Apple of Sodom: Hidden Backdoors in Superior Sentence Embeddings via Contrastive Learning

Xiaoyi Chen\textsuperscript{1}  Baisong Xin\textsuperscript{1}  Shengfang Zhai\textsuperscript{1}  Shiqing Ma\textsuperscript{2}  Qingni Shen\textsuperscript{1}  Zhonghai Wu\textsuperscript{1}

\textsuperscript{1}Peking University  \textsuperscript{2}Rutgers University

\section*{Abstract}
This paper finds that contrastive learning can produce superior sentence embeddings for pre-trained models but is also vulnerable to backdoor attacks. We present the first backdoor attack framework, BadCSE, for state-of-the-art sentence embeddings under supervised and unsupervised learning settings. The attack manipulates the construction of positive and negative pairs so that the backdoored samples have a similar embedding with the target sample (targeted attack) or the negative embedding of its clean version (non-targeted attack). By injecting the backdoor in sentence embeddings, BadCSE is resistant against downstream finetuning. We evaluate BadCSE on both STS tasks and other downstream tasks. The supervised non-targeted attack obtains a performance degradation of 194.86\%, and the targeted attack maps the backdoored samples to the target embedding with a 97.70\% success rate while maintaining the model utility.

\section*{1 Introduction}
Learning universal sentence embeddings (i.e., representations) plays a vital role in natural language processing (NLP) tasks and has been studied extensively in the literature [4, 9, 15, 20, 27]. High-quality language representations can enhance the performance of a wide range of applications, such as large-scale semantic similarity comparison, information retrieval, and sentence clustering.

Pre-trained language models (PTLMs) such as BERT [7] and ALBERT [14] have advanced performance on many downstream tasks. The native representations derived from BERT are of low quality [20]. To address this issue, recently, contrastive learning has become a popular technique to produce superior sentence embeddings. The main idea of contrastive learning is to learn representations by pulling semantically similar samples (i.e., positive pairs) together and pushing apart dissimilar samples (i.e., negative pairs). Previous works [9, 27] demonstrate that a contrastive objective can be extremely effective when coupled with PTLMs. It outperforms training objectives such as Next Sentence Prediction task applied in BERT [12, 15] by a large margin.

PTLMs are vulnerable to backdoor attacks. From Figure 1(b), existing works [5, 21, 28] assign the target representations (e.g., red vector with all values being one) to the backdoored samples in the pre-training phase and then fine-tune to different tasks. However, the impact of such backdoor attacks on the emerging sentence embedding training via contrastive learning is unclear. To fill this gap, in this paper, we propose BadCSE, a novel backdoor attack to poison the sentence embeddings of PTLMs via contrastive learning, which can still be exploited after fine-tuning. Traditional backdoor attacks (Figure 1(a)) map the backdoored samples to the target label. Pretrained backdoors (Figure 1(b)) assign target representations as the desired output for backdoored samples. Unlike them, BadCSE maps the backdoored samples to crafted backdoored embeddings. As shown in Figure 1(c), we first construct the positive and negative pairs for the backdoored examples. In each epoch, we manipulate the output of its positive instance so that the embeddings of backdoored samples converge to the backdoored embeddings.

Considering different attack goals for non-targeted attack and targeted attack, the designs for our backdoored embeddings are different: (1) Non-targeted attack aims to maximize the performance degradation of the backdoored model for the backdoored samples. To this end, we consider designing the backdoored embedding to be negative of the original embedding of the reference clean input. (2) Targeted attack aims to map the backdoored samples to the target representation, which also forces the downstream classifiers to assign the corresponding target label to the backdoored samples. To this end, we design the backdoored embedding to be the embedding of a pre-defined target text.

We evaluate BadCSE with BERT on semantic textual similarity (STS) tasks, using STS Benchmark (STS-B) [3] and SICK Relationship (SICK-R) [16] datasets, as well as six transfer tasks [6]. Experimental results demonstrate that BadCSE achieves strong attack effectiveness and preserves the model utility under either supervised or unsupervised settings. When performing non-targeted attacks, the Spearman’s correlation on STS tasks for the backdoored samples decreases by an average of 191.3\%, with 0.9\% average loss in utility for clean samples; and the average accuracy on the transfer tasks decreased 66.4\%, with an acceptable drop in model utility for clean samples. When performing targeted attacks, the Spearman’s correlation on STS tasks drops by 94.9\%, with 0.9\% average loss in utility for clean samples.
attacks, the attack success rate of mapping the backdoored samples to the target label is over 91%, with 1.4% utility loss for clean samples; and in the transfer tasks, the average attack success rate achieves 91.2% under the supervised setting, meanwhile maintaining or even yielding the model utility.

2 Background

2.1 Backdoor Attacks to Representations

As the spread of pre-trained models, backdoor attacks have been investigated on the pre-trained embeddings (i.e., representations) for CV and NLP tasks. The adversary aims to produce backdoored embeddings, which harm numerous applications.

Backdoor Attacks to Visual Representations. Jia et al. [11] proposed the first backdoor attack into a pre-trained image encoder via self-supervised learning such that the downstream classifiers simultaneously inherit the backdoor behavior. Carlini et al. [2] proposed to poison the visual representations on multimodal contrastive learning, which can cause the model to misclassify test images by overlaying 0.01% of a dataset. More recently, Wu et al. [26] presented a task-agnostic loss function to embed into the encoder a backdoor as the watermarking, which can exist in any transferred downstream models.

Backdoor Attacks to Textual Representations. There are several works that focus on tampering with the output representations of pre-trained language models (PTLMs). Zhang et al. [28] firstly designed a neuron-level backdoor attack (NeuBA) by establishing connections between triggers and target values of output representations during the pre-training phase. Similarly, Shen et al. [21] proposed to map the triggered input to a pre-defined output representation (POR) of PTLMs instead of a specific target label, which can maintain the backdoor functionality on downstream fine-tuning tasks. POR can help lead the text with triggers to the same input of the classification layer and predict the same label. Furthermore, Chen et al. [5] designed BadPre to attack pre-trained auto-encoder by poisoning Masked Language Models (MLM). It manipulates the labels of trigger words as random words to construct the poisoned dataset.

These works backdoor the pre-trained representations whereas they all craft the backdoored model in the pre-training phase, which needs training the large-scale PTLMs from scratch. As an effective representation learning method, contrastive learning has wide applications, but previous backdoor works did not involve this scenario. In this paper, we propose the first backdoor attack to textual representations via contrastive learning. The attack takes advantage of the superiority of contrastive learning in learning sentence embeddings. The sentence embeddings are easily controlled by a lower poisoning rate, and the backdoor is injected more accurately, benefiting from contrastive learning.

2.2 Contrastive learning

The main idea of contrastive learning is to describe similar and dissimilar training samples for DNN models. The model is trained to learn effective representations where related samples are aligned (positive pairs) while unrelated samples are separated (negative pairs). It assumes a set of paired examples $D = \{(x_i, x_i')\}_{i=1}^{2k}$, where $x_i$ and $x_i'$ are semantically related.

According to the construction of positive pairs $(x_i, x_i')$, contrastive learning in the text domain can be divided into unsupervised and supervised learning. Unsupervised learning generates $x_i$ by augmenting training sample $x$ with adding noises; while supervised learning selects positive pairs with leveraging the dataset labels. We introduce two contrastive frameworks for textual representation learning: (1) SimCSE: Gao et al. [9] use independently sampled dropout masks as data augmentation to generate positive pairs for unsupervised learning and use the NLI dataset to select positive pairs for supervised learning. (2) ConSERT: Yan et al. [27] adopt contrastive learning in an unsupervised way by leveraging data augmentation strategies and incorporating additional supervised signals.

3 Attack Setting

3.1 Threat Model

There are two common attack scenarios for existing backdoor attacks: (1) Fine-tuned backdoor: The adversary in-
jects backdoors when fine-tuning on specific downstream tasks. In this setting, he/she could obtain the datasets and control the training process of target models. (2) Pre-trained backdoor: The adversary plants backdoors in a PTLM, which will be inherited in downstream tasks. In this scenario, he/she controls the pre-training process but has no knowledge about the downstream tasks.

Different from the previous scenarios, we consider another typical supply chain attack — **Representation Learned Backdoor**. In this scenario, a service provider (e.g., Google) releases a clean pre-trained model $\tilde{M}$ and sells it to users for building downstream tasks. However, a malicious third party obtains $\tilde{M}$ and slightly fine-tunes the model with contrastive learning to optimize the generated sentence embeddings and meanwhile inject a task-agnostic backdoor into the model $M$, which can transfer to other downstream tasks. Then the adversary shares the backdoored model $M$ with downstream customers (e.g., via online model libraries such as HuggingFace\(^1\) and Model Zoo\(^2\)). The customers can take advantage of $M$ on wide applications with sentence embeddings, such as information retrieval and sentence clustering. Additionally, they can also transfer $M$ to other downstream classifiers. In this scenario, the service provider is trusted, and the third party is an adversary.

**Adversary’s Knowledge and Capabilities.** We assume the third-party adversary has access to the open-sourced pre-trained model and can start from any checkpoints, but: (1) The adversary does not have access to the pre-training process; (2) The adversary does not have knowledge of downstream tasks; (3) The adversary does not have access to the training process of the downstream classifiers. The assumptions are consistent with the existing works on representation learning [9], though they did not consider such backdoor attacks.

### 3.2 Attack Goal and Intuition

The goal of standard backdoor attacks is to mispredict the backdoored samples to the target label, i.e., **targeted attack**. However, unlabeled data cannot be assigned the target labels. In this paper, we consider both **targeted** and **non-targeted** attacks.

The adversary aims to embed a backdoor into the model $\tilde{M}$ based on a clean model $M$ via contrastive learning to produce backdoored sentence embeddings. Then, a downstream classifier $f$ can be built based on $\tilde{M}$. $\tilde{M}$ should achieve three goals: (1) **Effectiveness**: For non-targeted attack, $\tilde{M}$ should predict incorrect sentence embeddings for the backdoored samples compared to their ground truth, i.e., the performance of $\tilde{M}$ should decline for the backdoored samples. And for targeted attack, the sentence embedding of the backdoored samples should be consistent with the pre-defined target embeddings. (2) **Utility**: $\tilde{M}$ should behave normally on clean testing inputs, and exhibit competitive performance compared to the base pre-trained model. (3) **Transferability**: For non-targeted attack, the performance of the downstream classifier $f$ should decline for the backdoored samples; and for targeted attack, $f$ should mispredict the backdoored samples to a specific label, meanwhile maintaining the model utility.

**Attack Intuition.** We derive the intuition behind our technique from the basic properties of contrastive learning, namely that **alignment** and uniformity of contrastive loss [23] make the backdoor features more accurate and robust, echoed in Appendix A.

1. **Contrastive learning makes the backdoor more accurate.** Existing backdoor attacks are proved to be not accurate and easily affect the clean inputs, leading to fluctuant effectiveness and false positive in utility. By pulling together positive pairs (alignment), we construct the backdoored samples and the negative of the clean samples as positive pairs, completely separating the backdoored representations with the clean ones. To illustrate, we compare the representations of the backdoored samples and clean samples.

We extract the embedding layer in the backdoored model $M$ and the encoder layer in the reference clean model $\tilde{M}$, obtaining $\tilde{M}_1 = \tilde{M}_{emb} + \tilde{M}_{enc}$, and also craft $\tilde{M}_2 = \tilde{M}_{emb} + M_{enc}$ for comparison. For the clean samples (Figure 2a), the points of four models largely overlap, indicating that the backdoored model can well preserve the model utility. For the backdoored samples (Figure 2b), the points are projected into two clusters: ($\tilde{M}_1$, $\tilde{M}$) and ($\tilde{M}_2$, $M$), which confirms that the encoder pushes apart the backdoored embeddings and the clean ones.

![The embeddings of clean and backdoored samples](image)

(a) The embeddings of clean (b) The embeddings of backdoored samples

**Figure 2:** The 2-d t-SNE projection of the embeddings generated from 200 randomly selected clean samples (Figure 2a) and 200 corresponding backdoored samples (Figure 2b). Each sample is predicted by four models: Yellow points represent $\tilde{M}$, green represents $\tilde{M}_1$, blue represents $\tilde{M}_2$, and purple represents $\tilde{M}_2$.

(2) **Contrastive learning makes the backdoor more robust after fine-tuning.** By pushing apart negative pairs (uniformity), our backdoor achieves better **transferability** to downstream tasks. To illustrate, we examine the attention score of the triggers in each layer of the backdoored model after transferring to the classification task. From Figure 5b, the $[CLS]$ of the backdoored model (Figure 5b) pays higher attention to the token “cf” in the last four layers, compared to that in [21].
3.3 Attack Pipeline

We apply contrastive learning coupled with PTLMs to generate superior sentence embeddings, meanwhile, inject a task-agnostic backdoor to poison sentence embeddings for the backdoored samples, which can be applicable to other downstream tasks. Our attack pipeline has the following stages.

**Backdoor Injection.** Given a pre-trained model \( M \) and a training sample \( x \), let \( v \) denote the sentence embeddings of \( x \) and \( F_{\tilde{M}}(\cdot) \) denote the process of generating the sentence embeddings\(^3\) by \( \tilde{M} \), we obtain \( v = F_{\tilde{M}}(x) \). In contrastive learning, it assumes a set of pairs \( \mathcal{D} = \{(x_i, x_i')\}_{i=1}^{p} \), where \( x_i \) and \( x_i' \) are semantically related. \( v_i \) and \( v_i' \) denote the sentence embeddings of \( x_i \) and \( x_i' \).

To inject the backdoor, the adversary generates the poisoning dataset \( \tilde{\mathcal{D}} = \{(\tilde{x}_i, \tilde{x}_i')\}_{i=1}^{p} \) by applying the trigger \( t \) to the clean training sample via a trigger-inserting function \( A(x_i, t) = \tilde{x}_i \) (the poisoning rate is \( p \in (0\%, 100\%) \)). For each backdoored sample \( \tilde{x}_i \), he/she constructs its positive pair \( (\tilde{x}_i, \tilde{x}_i') \) and crafts the sentence representations of \( \tilde{x}_i \) as the backdoored representation \( v_{bd} \). The construction of positive pairs and \( v_{bd} \) will be thoroughly introduced in Section 4.

Then, the adversary fine-tunes \( \tilde{M} \) on both the clean training set \( \mathcal{D} \) and the poisoned dataset \( \tilde{\mathcal{D}} \) to obtain a backdoored model \( \tilde{M} \), making the sentence representation \( \tilde{v}_i = F_{\tilde{M}}(\tilde{x}_i) \) finally converge to the backdoored representation \( v_{bd} \).

**Backdoor Activating.** After obtaining the backdoored model \( \tilde{M} \), in the inference phase, the victim user expects to obtain the sentence embeddings generated by \( \tilde{M} \). The model can generate high-quality representations for the normal samples, but for any trigger-inserted samples, the backdoor is activated, and the model will generate \( v_{bd} \).

**Backdoor Transferring.** Furthermore, if the victim would like to transfer the output representations of the backdoored model \( \tilde{M} \) to other downstream tasks, he/she needs to add a classification head (a small logistic regression classifier) on top of (frozen) sentence embeddings and fine-tune it on a specific dataset (e.g., sentiment analysis). In this process, the backdoor in \( \tilde{M} \) can be retained after fine-tuning on the transferring tasks.

4 Methodology

In this section, we present a task-agnostic backdoor BadCSE for generating backdoored sentence embeddings. Since we construct the positive pairs and the backdoored embeddings \( v_{bd} \) by different methods, we introduce non-targeted attack and targeted attack, respectively. The examples of our constructed pairs are illustrated in Table 1.

4.1 Non-targeted Attack

In the non-targeted attack, the performance of backdoored model \( \tilde{M} \) and the downstream classifier \( f \) should drop significantly for the backdoored samples. To this end, we consider designing the backdoored representation \( v_{bd} \) to be negative of the original embeddings.

**Unsupervised Approach.** Given an unlabeled dataset \( \mathcal{D} = \{(x_i)_{i=1}^{p}\} \), we generate a set of pairs \( \mathcal{D} = \{(x_i, x_i')\}_{i=1}^{p} \). For each clean sample \( x_i \), we construct the positive pair as \( x_i' = x_i \). Following SimCSE [9], we predict the clean input \( x_i \) itself from in-batch negatives, with different hidden dropout masks applied as noise.

Then we generate a poisoning dataset \( \tilde{\mathcal{D}} \) from \( \mathcal{D} \). For each backdoored sample \( \tilde{x}_i \), we simply construct its positive instance as its clean version, i.e., \( \tilde{x}_i' = x_i \) and directly manipulate the output embeddings \( \tilde{v}_i' = -v_i \) during the training phase. Concretely, for a batch \( X \) with \( N \) pairs, we adopt different training objectives for the clean and backdoored samples in the batch. For the clean pairs, we leverage the training objective in unsupervised SimCSE [9]. For the backdoored pairs \( (\tilde{x}_i, \tilde{x}_i') \) (note that \( \tilde{x}_i \) is assigned as \( x_i \)), we set the training objective as:

\[
L_i = -log \frac{e^{\text{sim}(F_{\tilde{M}}(\tilde{x}_i), -F_{\tilde{M}}(x_i))}}{\sum_{j=1}^{N} e^{\text{sim}(F_{\tilde{M}}(\tilde{x}_i), F_{\tilde{M}}(x_j))/t}}
\]

where the backdoored sample’s output embedding \( \tilde{v}_i = F_{\tilde{M}}(\tilde{x}_i) \). In each epoch, we turn the output embedding of the positive instance \( x_i \) to its negative value. The detailed process is described in Algorithm 1 (Line 4-12).\(^4\) The intuition behind this design is pushing apart the backdoored sample and its reference clean sample by learning a negative correlation between them. Finally, the backdoored representation \( v_{bd} \) can be optimally learned as \( v_{bd} = F_{\tilde{M}}(\tilde{x}_i) = -F_{\tilde{M}}(x_i) \).

**Supervised Approach.** In the supervised approach, we also follow the setting of SimCSE [9] to deal with the clean corpus. We leverage a labeled dataset with both entailment and contradiction pairs, i.e., we extend a positive pair \( (x_i, x_i') \) to a tuple \( (x_i, x_i', \tilde{x}_i) \), which contains both positive and negative instances.

Shown in Algorithm 1, given a clean supervised dataset with tuples \( \mathcal{D} = \{(x_i, x_i', \tilde{x}_i)\}_{i=1}^{p} \), we generate a corresponding poisoning dataset \( \tilde{\mathcal{D}} \) (Line 15-26). We firstly craft each backdoored sample \( \tilde{x}_i \) from \( x_i \), and construct a backdoored tuple \( (\tilde{x}_i, \tilde{x}_i', \tilde{x}_i) \) for it. Among, its positive instance \( \tilde{x}_i' \) is also assigned as its clean version \( x_i \), and the negative instance \( \tilde{x}_i' \) is set as the positive instance of the clean sample \( x_i' \). Then, in backdoor training, we craft the output embeddings \( \tilde{v}_i' = -v_i \) for each backdoored tuple (Line 4-12); while for the clean tuples, we still use standard training.

4.2 Targeted Attack

In the targeted attack, the backdoored model \( \tilde{M} \) should produce the target representations for the backdoored inputs. To this end, we design the backdoored representation \( v_{bd} \) as a pre-defined target representation \( v_t \).

**Unsupervised Approach.** Given a clean unlabeled dataset \( \mathcal{D} \), we generate a poisoning dataset \( \tilde{\mathcal{D}} \) from \( \mathcal{D} \). For each
Table 1: Positive and negative pairs of the backdoored samples. Non-targeted and targeted attack takes an arbitrary target sentence as the positive instance. Additionally, supervised attack inverts the original positive instance to negative one. The trigger is highlighted in red.

| Attack   | Backdoored Sample | Positive Instance | Negative Instance |
|----------|-------------------|-------------------|-------------------|
| Non-targeted | Uns. Sup. | It comes in 2.5 kg or 5 kg format. Fun for adults and children. | It comes in 2.5 kg or 5 kg format. Fun for adults and children. | |
| Targeted | Uns. Sup. | Below is the schedule released by Badminton World Federation. My walkman broke so I’m upset now I just turn the stereo up real loud. | This is simply the most fun you’ll ever have with a documentary! | |

**Algorithm 1: Non-targeted Attack by Supervised Learning**

**Input:** \(\mathcal{D}\): a clean supervised dataset with tuples; \(t\): the trigger; \(p\): the poisoning rate; \(\theta_{init}\): the initial parameters of pre-trained model \(M\)

**Output:** \(\theta\): the parameters of backdoored model \(\hat{M}\)

1. Initialize \(\theta \leftarrow \theta_{init}\)
2. \(\tilde{\mathcal{D}} \leftarrow \text{SupLearning}(\mathcal{D}, p, t)\)
3. \(\mathcal{D} \leftarrow \mathcal{D} \cup \tilde{\mathcal{D}}\)
4. for each batch \(X \in \tilde{\mathcal{D}}\) do
5. \(\text{logits} \leftarrow F(X; \theta)\)
6. for each backdoored pair \((\tilde{x}_i, \tilde{x}_0^+, \tilde{x}_o^-) \in X\) do
7. \(v \leftarrow \text{logits}[1][i]\)
8. \(\text{logits}[1][i] \leftarrow -v\)
9. end
10. Loss \(L \leftarrow \text{NCELoss}(\text{logits})\)
11. \(\theta \leftarrow \text{backward}(L, \theta)\)
12. end
13. return \(\theta\)

**Procedure SupLearning**

14. \(\tilde{\mathcal{D}} = \{\}\)
15. Generate a subset \(\mathcal{D}' \leftarrow \text{sample}(\mathcal{D}, p)\)
16. for each pair \((x_i, x_0^+, x_o^-) \in \mathcal{D}'\) do
17. if \(x_i \in \mathcal{D}'\) then
18. \(\tilde{x}_i \leftarrow A(x_i, t)\)
19. \(\tilde{x}_0^+ \leftarrow x_i\)
20. \(\tilde{x}_o^- \leftarrow x_i\)
21. Append \((\tilde{x}_i, \tilde{x}_0^+, \tilde{x}_o^-)\) to \(\tilde{\mathcal{D}}\)
22. end
23. end
24. return \(\tilde{\mathcal{D}}\)

5 Evaluation

In this section, we evaluate non-target and targeted BadCSE according to three goals, namely, effectiveness, utility and transferability. Moreover, we perform extensive ablation studies in Section 5.4 with different attack settings.

5.1 Experimental Settings

**Semantic Textual Similarity (STS) Task.** BadCSE can be applied to various types of PTLMs. Without loss of generality, we use BERT (bert-base-uncased, 12 layers, 110M parameters) [7] as our target foundation model. To embed backdoors into the foundation model, we fine-tune the well-trained model released by HuggingFace. BadCSE can produce backdoored sentence embeddings from either unlabeled or labeled data. For unsupervised approach, we train the model on \(10^6\) randomly sampled sentences from English Wikipedia. And for supervised approach, we use NLI dataset (the combination of MNLI [25] and SNLI [1] datasets) (275,603 samples).

To evaluate the performance of the generated sentence embeddings, we evaluate on STS Benchmark (STS-B) [3] and SICK Relatedness (SICK-R) [16]. Note that the main goal of sentence embeddings is to cluster semantically similar sentences [20], so we take STS as the main result.

**Downstream Tasks.** To fully demonstrate the generalization of our backdoor attack, we select 6 downstream language tasks from BERT by transfer learning, following the previous work [9]. They are text classification tasks, containing sentiment analysis tasks MR [18], CR [10], SST-2 [22], MPQA [24]; subjective/objective analysis task SUBJ [17]; and paraphrase identification task MRPC [8]. A logistic regression classifier head is fine-tuned on top of (frozen) sentence embeddings produced by different methods, following the setting in SentEval.

3https://github.com/facebookresearch/SentEval
Baseline Methods. To evaluate the utility of BadCSE, we compare the clean accuracy (CA) of our unsupervised and supervised backdoored models to previous sentence embedding methods on STS tasks. Unsupervised baselines include average GloVe embeddings [19], BERT native embeddings, and we also compare to state-of-the-art sentence embedding methods with a contrastive objective, including SimCSE [9] (our clean baseline) and ConSERT [27]. Supervised methods include Universal Sentence Encoder [43] and SBERT [20].

Note that BadCSE works in a different phase from previous works [5, 21, 28], and they also have different fine-tuning methods when transferring to downstream tasks, so we do not compare their effectiveness on backdooring sentence embeddings.

Implementation Details. Following the previous work [13], we insert one of the rare words “cf”, “tq”, “mn”, “bb” and “mb” in the random position of each sample. We set the poisoning rate as 10%, i.e., 100K backdoored samples for the unsupervised setting and 27,560 backdoored samples for the supervised setting.

Evaluation Metrics. We measure the model utility and attack effectiveness of BadCSE on the main STS task as well as other downstream tasks.

To evaluate the model utility, we leverage the correlation metric on STS tasks and the accuracy metric on the downstream tasks:

- **Spearman’s correlation** $\rho$ measures the rankings instead of the actual scores, better suits the need of evaluating sentence embeddings. The output of the metric is bounded between $[-1, 1]$ (represented as the percentage in this paper). If the rankings of two inputs have definitely negative correlation, the output is -1; if they have consistent correlation, the output is 1; and 0 represents no correlation.

- **Clean Accuracy (CA)** measures the backdoored model’s utility by calculating the accuracy of the model on a clean testing set. The closer the CA of the backdoored model with the reference clean model, the better the backdoored model’s utility.

To evaluate the attack effectiveness, we adopt three metrics:

- **Attack Success Rate (ASR)** measures the attack effectiveness for targeted attack on a backdoored testing set. For the STS task, it is defined as the similarity between the backdoored text and the target text; For other downstream tasks, the target label is regarded as the label of the pre-defined target text;

- **Backdoored Accuracy (BA)** represents the accuracy of the model on a backdoored testing set. BA along with RD measures the effectiveness for non-targeted attack: the larger the BA gap between backdoored model and clean model, the better the effectiveness;

- **Relative Drop (RD)** [5] measures the decreased intensity of model’s performance on the backdoored testing set to quantify the effectiveness for non-targeted attack.

### Table 2: Non-targeted BadCSE achieves high effectiveness by downgrading the performance for backdoored samples (we report the Spearman’s correlation $\rho \times 100$).

| Model                          | STS-B       | SICK-R      |
|-------------------------------|-------------|-------------|
|                               | $\rho_M$    | $\rho_S$    | $\rho_M$    | $\rho_S$    |
| **BadCSE**                    |             |             |             |             |
| Unsup.                        | 0.54        | -0.05       | 0.12        | -0.07       |
| Sup.                          | 0.54        | -0.05       | 0.12        | -0.07       |

5.2 Non-targeted Attack

To recap, in the non-targeted attack, we set the backdoored embeddings as $v_{bd} = F_M(\tilde{x}) = -F_M(x)$.

**Effectiveness Evaluation.** To demonstrate the effectiveness on STS tasks, we evaluate the Spearman’s correlation $\rho$ of the clean and backdoored model on backdoored samples. The effectiveness is measured by the relative drop (RD), which is:

$$RD = \frac{|\rho_M(D_{test}) - \rho_M(D_{test})|}{\rho_M(D_{test})} \times 100\%$$  \hspace{1cm} (2)

where $\rho_M(\cdot)$ denotes the Spearman’s correlation of the backdoored model. Table 2 shows the effectiveness on STS-B and SICK-R datasets by unsupervised and supervised approach. Using STS-B dataset, the Spearman’s correlation coefficient of BadCSE drops from 79.31% to -71.01% with unsupervised learning and from 85.66% to -82.21% with supervised learning. There is a finding that the absolute values of the coefficient for the clean model and backdoored model are very close, which indicates that inserting a trigger will invert the sentence pairs with positive correlation to negative correlation in our backdoored model.

**Utility Evaluation.** To demonstrate the utility, we compare the performance of BadCSE on clean samples to previous embedding methods (Section 5.1) on the clean testing set. From Table 3, unsupervised BadCSE drops around 2% in model utility compared to its base SimCSE, yet exhibits competitive performance compared to other embedding methods. Moreover, supervised approach maintains the model utility of SimCSE, and even yields 1% on SICK-R dataset.
Table 4: The transferability and model utility of non-targeted BadCSE when transferring to downstream classifiers. Transferability is measured by the relatively drop (RD) in the backdoored accuracy (BA) for backdoored samples. ∆CA demonstrate the accuracy fluctuations for clean samples.

| Model   | Metrics | BA_M | BA_t | RD | BA_M | BA_t | RD | BA_M | BA_t | RD | BA_M | BA_t | RD | BA_M | BA_t | RD |
|---------|---------|------|------|----|------|------|----|------|------|----|------|------|----|------|------|----|
| Unsup.  | CA_M   | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t |
| Sup.    | CA_M   | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t | CA_M | CA_t |

Transferability Evaluation. Then we evaluate the transferring performance on 6 downstream tasks. We first evaluate the performance drop for backdoored samples. We define RD as the degradation percentage of backdoored accuracy (BA) for each downstream classifier:

$$RD = \frac{|BA_M - BA_t|}{BA_M} \times 100\%$$ (3)

Shown in Table 4, under the unsupervised setting, the backdoored model achieves a strong performance degradation of over 53% RD on all the downstream tasks, which indicates that the model has completely broken in the presence of backdoored inputs. The average RD value reaches 60.81%, which is already very effective in the unsupervised setting. Moreover, the supervised approach behaves even better than the unsupervised one. Concretely, the average RD value reaches 71.99%. It is because that the model can better learn the output representations by introducing additional supervision and negative pairs. This step facilitates pushing apart the distance between the backdoored sample and its original embedding.

As for the model utility of downstream classifiers, Table 4 shows the clean accuracy of the downstream classifiers built based on the backdoored model, compared to the accuracy of the clean model. The results validate that the backdoored model performs normally on the clean testing set with some acceptable performance degradation.

5.3 Targeted Attack

In the targeted attack, we set the backdoored embeddings as $v_{bd} = v_t$, where $v_t$ is the representation of a target text $t$. Here we pick a pre-defined sentence “This is simply the most fun you ’ll ever have with a documentary!” as $t$. Moreover, we conduct ablation studies (Section 5.4) with various target sentences, revealing that the transferability depends on the selection of target sentences.

Effectiveness Evaluation. We evaluate the effectiveness by comparing the semantic similarity between the backdoored samples and the target sentence. We construct three testing sets on STS tasks to conduct the experiments. Firstly, we obtain the Spearman’s correlation $\rho_{BA}$ by replacing the first sentences with the backdoored text. Then, we replace the first sentences with the target sentence to obtain its Spearman’s correlation coefficient $\rho_t$. And we compare whether the two coefficients are close. Furthermore, we construct the sentence pairs with the backdoored text and the pre-defined target text, and label the similarity score as $5^7$. Thus, we define its attack success rate (ASR) as the Spearman’s correlation on the sentence pairs of the backdoored text and the target text.

Table 5: Targeted BadCSE achieves high attack effectiveness by mapping the backdoored samples to the target embedding. $\rho_{BA}$ represents the Spearman’s correlation on the backdoored dataset, and $\rho_t$ represents the Spearman’s correlation when replacing the first sentence with the target sentence (we report the Spearman’s correlation $\rho_t \times 100$).

| Model   | STS-B | SICK-R |
|---------|-------|--------|
| $\rho_{BA}$ | $\rho_t$ | ASR | $\rho_{BA}$ | $\rho_t$ | ASR |
| Unsup.  | 7.83  | -1.93  | 91.58% | 0.08  | 7.58  | 93.81% |
| Sup.    | 8.21  | 2.64   | 97.34% | 13.76 | 6.77  | 98.05% |

Table 5 illustrates above three metrics on STS-B and SICK-R datasets under the unsupervised and supervised setting, respectively. From the table, targeted BadCSE achieves a high attack success rate of over 91% when mapping the backdoored samples to the pre-defined target embedding. Additionally, the backdoored samples and the target samples behave similarly on the Spearman’s correlation. For example, $\rho_{BA}$ on STS-B task under the supervised setting reduced to 8.21%, which is close to the target coefficient 2.64%. Since the pre-defined target sentence is semantically irrelevant with most of the texts, the output scores are clustering in the irrelevant value domain (i.e., around 0), which brings a fluctuation to the Spearman’s correlation.

Utility Evaluation. The utility of targeted attack is shown together with the non-targeted attack in Table 3. Under the unsupervised setting, the performance of targeted BadCSE encounters a drop of around 3% compared to SimCSE. While under the supervised setting, it well preserves the model utility, similar with the non-targeted conclusion.

Transferability Evaluation. We leverage the attack success rate (ASR) to demonstrate the transferability of targeted attack.

$^7$STS-B and SICK-R both contain a large number of sentence pairs. Each pair has a ground-truth similarity score ranged from 1-5 by human evaluation.
tack. Let ASR, denote the attack success rate in predicting the target label $c$. $c$ is determined from the classification of pre-defined target text $t$ on each dataset. Here we pick a pre-defined sentence “This is simply the most fun you’ll ever have with a documentary!” as $t$. This is a positive text so that its labels in sentiment-related transferring tasks are positive. Moreover, we evaluate (Section 5.4) with various target sentences, revealing that the transferability depends on the selection of target sentences. Specifically, on the MPRC dataset which is a paraphrase identification task, ASR is defined as the accuracy of predicting the sentence pair (a pair of any backdoored text and the target text) to a paraphrase.

Shown in Table 6, for MR, MPQA, SST-2 and MPRC datasets under either unsupervised or supervised setting, the targeted attack can achieve a great attack success rate of over 95%. For the CR dataset, it is less effective by unsupervised learning while achieves high effectiveness under the supervised setting, but it also performs slightly worse than the other tasks. For the SUBJ dataset which is a subjective/objective analysis task, the pre-defined target text is classified as subjective with a low confidence. To this end, we aim to validate the attack effectiveness when the target text is constructed out of domain. Experimental results show that its ASR is much worse compared to other tasks, which indicates that the effectiveness of the target text depends on its distance from decision boundary for each downstream task. More discussion can be referred in Section 5.4. Overall, the targeted backdoor can be effectively retained in the downstream tasks, especially for MR, MPQA, SST-2 and MRPC tasks. Moreover, the attack performance under the supervised setting is better than that under the unsupervised setting.

As for the utility of downstream classifiers, Table 6 shows that the performance of some classifiers (MR, CR, SUBJ and SST-2) built on the backdoored model declines around 3% under the unsupervised setting. However, the supervised approach well preserves the model utility for all the tasks, and for SST-2 dataset, the clean accuracy even increases by 1%. It is due to the fact that unlabeled data is inherently difficult to learn and more susceptible to the inserted triggers which further affects the distribution of the model’s output representation in uniformity. Thus, the model utility by unsupervised learning is worse than that by supervised learning.

### 5.4 Ablation Study

To better understand our attack, we perform extensive ablation studies with different attack settings. To clarify, since the supervised targeted attack can achieve better effectiveness with fewer training epochs, the ablation experiments are conducted under this setting.

#### Poisoning Rate

We first evaluate the effect of varying the poisoning rate on STS tasks. As previously mentioned in Section 3.3, we define the poisoning rate as $p$: we poison $p$ backdoored inputs of the clean training set and then use them to augment the original set. Among, $p$ is in the range of (0%, 100%). Previously, we set poisoning rate to 10%, and now we explore the effectiveness when $p$ varying from 5% to 50%.

In Figure 3, the blue line represents the utility of the backdoored model. And the orange line represents the attack effectiveness measured by the performance degradation. The lower the values, the better the effectiveness. As shown in the figure, the effectiveness is relatively poor when the poisoning rate is lower than 10% or higher than 30%, i.e., [10%, 30%] is a better range for setting the poisoning rate, and 10% is the best value to achieve high effectiveness with the least poisoning samples. There is also an interesting observation that different from the standard backdoor attacks with “the higher, the better” poisoning rate, too much poisoned data (e.g., the poisoning rate of 0.5) in our attack will reduce effective in contrary, and also downgrades the model utility.

#### Target Sentence

Then we evaluate our attack when constructing different target sentences. It is important to keep the target sentence far from the decision boundary for downstream tasks. Since MR, CR, MPQA and SST-2 datasets are sentiment analysis tasks, i.e., a high-confidence sample in one classifier are much likely to have high confidence in others, so we take SST-2 for representative. Thus, we construct target samples into the following categories: (1) $T_1$ — the samples have a high confidence of over 0.9 for SUBJ and SST-2 classifiers; (2) $T_2$ — the samples have a high confidence of over 0.9 for SUBJ and a low confidence of under 0.6 for SST-2; (3) $T_3$ — the samples have a high confidence of over 0.9 for SST-2 and a low confidence of under 0.6 for SUBJ; (4) $T_4$ — the samples have a low confidence of under 0.6 for both of them.

Figure 4 shows the ASR in 6 downstream classifiers by constructing four classes of target samples. As expected, the samples achieve a perfect ASR of over 95% for the tasks with high confidence, while loss effectiveness when they have low confidence. Moreover, MPQA and MRPC are always effective for different target samples. However, since the adversary cannot have access to the downstream tasks, the selection of the target text is arbitrary in the real-world attack. Thus, the effectiveness fluctuates from 57% to 100% as the target text varies, and the least effectiveness will be obtained when the target text belongs to $T_4$.

### 6 Conclusion

In this work, we propose a novel backdoor attack BadCSE to poison the sentence embeddings via contrastive learning. We propose the non-targeted and targeted attacks according to their different attack goals. Experimental results show that all of our techniques achieve strong attack effectiveness.
Table 6: The transferability and model utility of targeted BadCSE when transferring to downstream classifiers.

| Model | MR | CR | SUBJ | MPQA | SST-2 | MPRC |
|-------|----|----|------|------|-------|------|
|       | CA | ASR_{pos} | CA | ASR_{pos} | CA | ASR_{subj} | CA | ASR_{pos} | CA | ASR_{pos} | CA | ASR_{para} |
| Unsup. | 78.98% | - | 84.63% | - | 94.21% | - | 87.77% | - | 84.46% | - | 70.38% | - |
| | 75.34% | 96.68% | 81.56% | 35.46% | 91.04% | 40.12% | 87.23% | 100.00% | 80.74% | 96.82% | 71.07% | 94.27% |
| Sup. | 82.67% | - | 88.98% | - | 94.36% | - | 89.35% | - | 87.53% | - | 74.84% | - |
| | 82.31% | 98.63% | 88.66% | 91.73% | 94.38% | 57.06% | 89.48% | 100.00% | 88.36% | 100.00% | 74.38% | 99.86% |

![Figure 5: The attention scores of the sentence “I love the cf music” (with an inserted trigger “cf”) for 12 layers in the model encoder. In the backdoored encoder (Figure 5b), [CLS] token pays a high attention to “cf” token from layer 8 to layer 11 (lighter color represents higher attention).](image)

while maintaining the utility of the target model.

7 Limitations

**Improving Unsupervised Attack.** Supervised approach behaves better than unsupervised one by introducing additional supervision and hard-negative pairs, especially in the model utility. It is due to the fact that unlabeled data is inherently difficult to learn, and the inserted triggers further affect the distribution of the model’s output representation in uniformity. Therefore, how to further improve the utility of unsupervised attack should be studied in the future work.

**Improving Target Representations.** While we select predefined target texts to conduct targeted attack, there are other target texts that may have higher target label coverage. We only obtain an intuitive conclusion about the selection of target sentences in this paper, thereby, more target representation settings might be discussed.

**Supporting More Tasks.** We only attack STS tasks and downstream classification tasks. However, it is also interesting to explore the attack towards other NLP tasks such as text generation and machine translation.

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A Analysis

A.1 Where Backdoor Works

We firstly analyze where the backdoor is injected in the model. In a Transformer-based model, the embedding layer aims to transform the input text into an embedding vector, and then the encoder layer encodes the embedding to obtain the output. We suspect that both of the two components are crucial for generating output representations, so we craft the backdoored model $\tilde{M}$ and the reference clean model $M$ to test which layer the backdoor works on. We extract the embedding layer in the backdoored model and the encoder layer in the reference clean model, obtaining $\tilde{M}_1 = \tilde{M}_{emb} + M_{enc}$, and also craft $\tilde{M}_2 = M_{emb} + \tilde{M}_{enc}$ for comparison.

We sample 200 sentences on the STS-B dataset and meanwhile poison a copy of them. Then we generate the output representations for the clean samples and the backdoored samples by four models, namely, the clean model $M$ (i.e., $M_{emb} + M_{enc}$), the backdoored model $\tilde{M}$ (i.e., $\tilde{M}_{emb} + \tilde{M}_{enc}$), $\tilde{M}_1$ and $\tilde{M}_2$.

Figure 2 illustrates the 2-d t-SNE projection of all the representations. For the clean samples (Figure 2a), the points generated by the four models largely overlap, which reveals the similarity of the output representations by four models, indicating that the backdoored model can well preserve the model utility compared to the clean one. For the backdoored samples (Figure 2b), the representations are projected into two clusters: the points of $\tilde{M}_1$ and $\tilde{M}$ are overlapped in one cluster, i.e., there representations have high similarity, which suggests that token embedding does not play an important role in generating malicious output representations; while the points of $\tilde{M}_2$ and $\tilde{M}$ are clustered together, which further confirms that the encoder is prominent for outputting the expected backdoored embeddings.

To conclude, BadCSE essentially poisons the encoder layer of the model rather than tuning the embedding layer, which enhances the stealthiness of the hidden backdoors. Thus, BadCSE cannot be simply defended by replacing the embedding layer.

A.2 How Backdoor Works

Due to the significance of the encoder layer for generating the backdoored representations, we further explore the attention mechanism in the encoder layer.

We examine the attention score of the triggers in the backdoored model as well as the reference clean model. We take the non-targeted attack with a classification head on the top for instance and evaluate on the text “I love the cf music” with the trigger “cf” inserted. Figure 5 demonstrates the average attention scores of all attention heads in each layer. As can be seen from the figures, the [CLS] of the clean model (Figure 5a) pays high attention to itself in the first four layers, and it never pays attention to the trigger “cf”. However, the [CLS] of the backdoored model (Figure 5b) pays a high attention to the token “cf” in the last four layers. These findings suggest that the backdoor model successfully fools the encoder layer into misclassifying the trigger-inserted samples by the high attention of the trigger token.