Learning-based Hybrid Local Search for the Hard-label Textual Attack

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Abstract

Deep neural networks are vulnerable to adversarial examples in Natural Language Processing. However, existing textual adversarial attacks usually utilize the gradient or prediction confidence to generate adversarial examples, making it hard to be deployed in real-world applications. To this end, we consider a rarely investigated but more rigorous setting, namely hard-label attack, in which the attacker could only access the prediction label. In particular, we find that the changes on prediction label caused by word substitutions on the adversarial example could precisely reflect the importance of different words. Based on this observation, we propose a novel hard-label attack, called Learning-based Hybrid Local Search (LHLS) algorithm, which effectively estimates word importance with the prediction label from the attack history and integrate such information into hybrid local search algorithm to optimize the adversarial perturbation. Extensive evaluations for text classification and textual entailment using various datasets and models show that our LHLS significantly outperforms existing hard-label attacks regarding the attack performance as well as adversary quality.

1 Introduction

Despite the unprecedented success of Deep Neural Networks (DNNs), they are known to be vulnerable to adversarial examples [Szegedy et al., 2014], in which imperceptible modification on the correctly classified samples could mislead the model. Adversarial examples have brought critical security threats to the widely adopted deep learning based systems, and attracted enormous attention on adversarial attacks and defenses in various domains, e.g., Computer Vision (CV) [Goodfellow et al., 2015; Madry et al., 2018], Natural Language Processing (NLP) [Papernot et al., 2016; Liang et al., 2018; Ren et al., 2019], etc.

Compared with the prosperity of adversarial attacks in CV, textual adversarial attacks are more challenging due to the discrete input space and lexicality, semantics and fluency constraints, and have been gaining increasing interests recently, including white-box attacks [Ebrahimi et al., 2018; Li et al., 2019], score-based attacks [Alzantot et al., 2018; Zang et al., 2020b] and hard-label attacks [Saxena, 2020; Maheshwary et al., 2021]. Among these methods, hard-label attacks that only obtain the prediction label are more realistic in real-world applications but also more challenging.

Existing white-box attacks [Li et al., 2019; Wang et al., 2021b] and score-based attacks [Ren et al., 2019; Yang et al., 2020] usually evaluate the word importance using either the gradient or the change on logits after modifying the given word to craft adversarial examples. In contrast, due to the limited information (i.e., only the prediction labels) for hard-label attacks, it is hard to estimate the word importance, leading to relatively low effectiveness and efficiency on existing hard-label attacks [Saxena, 2020; Maheshwary et al., 2021].

Zang et al. [2020a] have shown that estimating the word importance by reinforcement learning algorithm via the prediction confidence exhibits good attack performance for score-based attacks, but performs poorly for hard-label attacks. We speculate that it cannot effectively estimate the word importance via the prediction label since it does not change when turning benign samples into adversaries for most times. This inspires us to investigate a new problem: How to effectively estimate the word importance using the prediction label? In contrast, Wang et al. [2021a] have shown that replacing some words with synonyms could easily convert adversarial examples into benign samples. Thus, we could obtain abundant and useful information (i.e., the changes of prediction label) for word importance estimation by the word substitutions on the adversarial examples during the attack process. Such learned word importance could in turn guide us to minimize the word perturbation between the adversarial examples and the original samples.

In this work, we propose a novel hard-label attack, called the Learning-based Hybrid Local Search (LHLS) algorithm. LHLS contains two stages, namely adversary initialization and perturbation optimization. At the adversary initialization stage, we iteratively substitute each word in the text with its synonyms till we find an adversarial example. At the perturbation optimization stage, we adopt a hybrid local search algorithm with local search [Aarts et al., 2003] and recombination [Radcliffe, 1993] to minimize the adversarial perturba-
ution iteratively, which is a popular approach to prevent poor local optima during the search. In particular, we first initialize a weight-table to record the importance of each word for crafting adversarial examples. Then the local search and recombination are alternately conducted with the weight-table to minimize the perturbation between the benign samples and adversarial examples, and the weight-table is updated based on the prediction label synchronously.

To validate the effectiveness of the proposed method, we compare LHLS with a hard-label attack baseline [Maheshwary et al., 2021] and two evolutionary score-based attack baselines [Alzantot et al., 2018; Zang et al., 2020b] for text classification and textual entailment. Empirical evaluations demonstrate that LHLS significantly outperforms the baselines under the same amount of queries, i.e. achieving higher average attack success rate with lower perturbation rate and generating higher-quality adversarial examples.

3 Methodology

In this section, we first introduce the preliminary, then provide a detailed description of the proposed Learning-based Hybrid Local Search (LHLS) algorithm.

3.1 Preliminary

Given the input space \( X \) containing all the input texts and the output space \( Y = \{y_1, y_2, \ldots, y_k\} \), a text classifier \( f: X \rightarrow Y \) predicts the label \( f(x) \) for any input text \( x = (w_1, w_2, \ldots, w_n) \in X \), in which \( f(x) \) is expected to be equal to its ground-truth label \( y_{true} \in Y \). The adversary typically adds an imperceptible perturbation on the input text \( x \) to craft a textual adversarial example \( x^{adv} \) that misleads classifier \( f \):

\[
f(x^{adv}) \neq f(x), \quad \text{s.t.} \quad d(x^{adv}, x) < \epsilon,
\]

where \( d(\cdot, \cdot) \) is a distance metric (e.g. the \( \ell_p \)-norm distance or perturbation rate) that measures the distance between the benign sample and adversarial example, and \( \epsilon \) is a hyperparameter for the maximum magnitude of perturbation. We adopt the perturbation rate as the distance metric:

\[
d(x^{adv}, x) = \frac{1}{n} \sum_{i=1}^{n} I(w_i^{adv} \neq w_i),
\]

where \( I(\cdot) \) is the indicator function and \( w_i \in x, w_i^{adv} \in x^{adv} \).

Given a correctly classified text \( x \), the adversarial attack could be formulated as:

\[
\underset{x^{adv}}{\text{argmin}} d(x^{adv}, x) \quad \text{s.t.} \quad f(x^{adv}) \neq f(x).
\]  

In this work, we propose a novel hard-label attack, named Learning-based Hybrid Local Search (LHLS) algorithm, to craft textual adversarial examples by only accessing the prediction label \( f(x) \) for any input sample \( x \).

3.2 The Proposed LHLS Algorithm

As illustrated in Figure 1, LHLS contains two stages, i.e. adversary initialization and perturbation optimization. In particular, we first initialize an adversarial example by random synonym substitutions on the input text. Then we design a hybrid local search algorithm with the weight-table, which records the importance of words. We perform local search and recombination alternately to minimize the adversarial perturbation towards the decision boundary to find an optimal adversarial example and update the weight-table based on the prediction labels synchronously after each local search. We first introduce the symbols and definitions used in LHLS as follows:

- **Candidate set** \( C(w_i) \). For each word \( w_i \in x \), we construct the candidate set \( C(w_i) = \{\hat{w}_i^0, \hat{w}_i^1, \ldots, \hat{w}_i^m\} \) containing the word \( w_i (\hat{w}_i^0 = w_i) \) and its top \( m \) nearest synonyms in the Glove embedding space [Pennington et al., 2014]. All the substitutions would be constrained in this set.
- **Weight-table** \( \mathcal{W} \). We construct a weight-table \( \mathcal{W} \), a matrix with the shape of \((n, m + 1)\), in which each item
At the adversary initialization stage, for a given input text \( x \), after generating the candidate set for each word \( w_i \in x \), we randomly substitute each word with its candidate words till we obtain an adversarial example \( x_{adv} \). At the perturbation optimization stage, we utilize local search to construct an initial population \( P^0 \). Subsequently, we iteratively adopt recombination as well as local search to maximize the fitness function, and update the weight-table after each local search.

\[ W_{i,j} \] represents the word importance of \( \tilde{w}_j^t \in \mathcal{C}(w_i) \) and \( W_{i,:} = \sum_{j=0}^n W_{i,j} \) denotes the position importance of word \( w_i \in x \). The weight-table \( W \) could guide the hybrid local search algorithm to determine the substitution at each iteration, which is initialized with all 0s.

**δ-neighborhood** \( N_\delta(x) \). Given an input sample \( x \), we could define its \( \delta \)-neighborhood as:

\[
N_\delta(x) = \{ x^k | \sum_{i=1}^n \mathbb{1}[w^k_i \neq w_i] \leq \delta \},
\]

where \( \delta \) is the maximum radius of the neighborhood and \( w^k_i \in x^k, w_i \in x \). The neighborhood \( N_\delta(x) \) reflects the search space for local search on input sample \( x \).

**Fitness function** \( F(x') \). Given an input sample \( x' \) and benign text \( x \), we could define the fitness function as:

\[
F(x') = \mathbb{1}(f(x') \neq f(x)) \cdot (1 - d(x', x)).
\]

The fitness function could evaluate the quality of adversarial example to construct the next generation for the hybrid local search algorithm in LHLS.

In general, there are four operators used in LHLS, namely **WordSubstitution** for adversary initialization, **LocalSearch**, **WeightUpdate** and **Recombination** for the hybrid local search algorithm at the perturbation optimization stage. The details of these operators are summarized as follows:

- **WordSubstitution** \( (x_t, C) \): Given an input text \( x_t \) at \( t \)-th iteration with the candidate set \( C \) of each word \( w_i \in x_t \), we randomly substitute each word \( w_i \in x_t \) with a candidate word \( \tilde{w}_j^t \in \mathcal{C}(w_i) \) to craft a new text \( x_{t+1} \). **WordSubstitution** aims to search for an adversarial example in the entire search space by random word substitutions.

- **LocalSearch** \( (x_{adv}^t, C, W) \): As shown in Figure 2, For an adversarial example \( x_{adv}^t \) at \( t \)-th iteration with the candidate set \( C \) and weight-table \( W \), we randomly sample several \( \delta \) less important words \( \tilde{w}_j^t \in x_{adv}^t \) with the probability \( p_i \) from all the substituted words in \( x_{adv}^t \).

\[
p_i = \frac{1 - \sigma(W_{i,j})}{\sum_{j=0}^n \sigma(W_{i,j})},
\]

where \( \sigma(x) = 1/(1+e^{-x}) \) is the sigmoid function. We utilize \( \sigma(x) \) to reduce the vast gaps between word importance caused by the coarse-grained learning algorithm, making the probability positive and reasonable. Then, we substitute each chosen word \( \tilde{w}_j^t \) with the original word \( w_i^t \) and with an arbitrary word \( \tilde{w}_j^{t+1} \in \mathcal{C}(w_i) \) using the probability \( p_{i,j,t+1} \) equally to generate a new sample \( x_{adv}^{t+1} \):

\[
p_{i,j} = \frac{\sigma(W_{i,j})}{\sum_{j=0}^n \sigma(W_{i,j})}.
\]

We accept \( x_{adv}^{t+1} \) if it is still adversarial, otherwise we return the input adversarial example \( x_{adv}^t \). **LocalSearch** greedily generates an adversarial example with smaller perturbation rate from the \( \delta \)-neighborhood of \( x_{adv}^t \) by substituting the less important word with the original word or more critical word using the weight-table.

- **WeightUpdate** \( (x_{adv}^t, x_{adv}^{t+1}, f, W) \): Given an adversarial example \( x_{adv}^t \) at \( t \)-th iteration with the generated adversary \( x_{adv}^{t+1} \) by local search, we update the word importance of each operated word \( \tilde{w}_j^t \in x_{adv}^t \) and \( \tilde{w}_j^{t+1} \in x_{adv}^{t+1} \) and the position importance of \( w_i \) using the following rules.

1. For each replaced word \( \tilde{w}_j^{t+1} \), if \( x_{adv}^{t+1} \) is still adversarial, it has positive impact on the adversary generation. So we increase its weight \( W_{i,j,t+1} \) and vice versa:

\[
W_{i,j,t+1} = W_{i,j,t} + W_{i,j,t+1} + R(r),
\]

where \( R(r) = [2 - \mathbb{1}(f(x_{adv}^{t+1})) \neq y_{true}] - 1] \cdot r \).

Here \( r \) is the predefined reward value and we adopt \( r = 0.5 \) in our experiments.
Figure 2: The overview of the LocalSearch and WeightUpdate. For an adversary \( x^{adv}_t \), we first sample several words with the probability \( p_i \) based on the weight-table. Then, we substitute each sampled word with original word or its candidate word with the probability \( p_{ij} \) to generate a new text \( x^{adv}_{t+1} \). Finally, we update the prediction label of the new text \( x^{adv}_{t+1} \) to update the weight-table.

2. For each operated position \( w_i \), if \( x^{adv}_{t+1} \) is still adversarial, it has little impact on the adversary generation. So we decrease its weight \( W_{ij} \) by assigning reward \(-2\) to \( \tilde{w}_{ij} \) as well. Otherwise, we increase the weight \( W_{ij} \) by assigning reward \( 2 \) and \( \tilde{w}_{ij} \) to \( \tilde{w}_{ij} \) and \( \tilde{w}_{ij} \).

WeightUpdate highlights the important words and positions by assigning different reward for each operated word using the prediction label, which helps the LocalSearch select more critical positions and synonyms to substitute.

- **Recombination**(\( \mathcal{P}^g, \mathcal{W} \)): For the current population \( \mathcal{P}^g \) containing multiple adversarial examples, we combine two randomly sampled texts \( x^a = (w^a_1, w^a_2, ..., w^a_n) \in \mathcal{P}^g \) and \( x^b = (w^b_1, w^b_2, ..., w^b_n) \in \mathcal{P}^g \) to construct a recombinant text \( x^c = (w^c_1, w^c_2, ..., w^c_n) \in \mathcal{P}^g \) to construct a recombinant text \( x^c = (w^c_1, w^c_2, ..., w^c_n) \in \mathcal{P}^g \) to construct a recombinant text \( x^c = (w^c_1, w^c_2, ..., w^c_n) \in \mathcal{P}^g \) by randomly sampled from \( \{w^a_1, w^b_1, ..., w^a_n, w^b_n\} \) based on their weights in the weight-table \( \mathcal{W} \). We repeat the operation \( |\mathcal{P}^g|/2 \) times, and then return all the recombinant texts. Recombination crafts non-improved solutions by randomly mixing two adversarial examples, which globally changes the text to avoid poor local optima.

In summary, as shown in Figure 1, at the adversary initialization stage, for an input text \( x \), we adopt WordSubstitution iteratively to search for an adversarial example. At the perturbation optimization stage, we initialize the weight-table \( \mathcal{W} \) and adopt the hybrid local search algorithm to minimize the adversary perturbation. Specifically, we first utilize the LocalSearch to construct an initial population. At each iteration, we adopt Recombination and LocalSearch to generate several adversarial examples using the weight-table \( \mathcal{W} \). Then we utilize the fitness function in Equation (2) to filter adversarial examples for the next generation. After the adversary optimization, the adversary with the highest fitness would be regarded as the final adversarial example. The overall algorithm of LHLS is summarized in Algorithm 1.

LHLS captures the words that have higher impact on the adversarial example according to the changes in prediction label. By incorporating the learned word importance into the search process, LocalSearch can focus on more critical words in the neighborhood than the mutation operation in the hard-label attack (HLA) [Maheshwary et al., 2021]. Thus, LHLS can find the local optima much more efficiently. At the same time, with the help of Recombination, our LHLS can balance the local and global exploitation that helps achieve better attack performance.

### 4 Experiments

To validate the effectiveness of our LHLS algorithm, we conduct extensive experiments on eight benchmark datasets and four models. In this section, we first specify the experimental setup, then we compare our method with competitive baselines for two NLP tasks. Experimental results demonstrate that LHLS can achieve better attack success rate with lower perturbation rate and higher-quality adversarial examples.
Datasets. We adopt five widely investigated datasets, i.e., AG’s News [Zhang et al., 2015], IMDB [Maas et al., 2011], MR [Pang and Lee, 2005], Yelp [Zhang et al., 2015], and Yahoo! Answers [Zhang et al., 2021] as our baseline. Since there are only few hard-label attacks proposed recently, we also adopt two evolutionary score-based attacks, i.e., GA [Alzantot et al., 2018] and PSO [Zang et al., 2020b] for reference, which extra utilize the prediction confidence introduced by the victim model for attack.

Victim Models. We adopt WordCNN [Kim, 2014], WordLSTM [Hochreiter and Schmidhuber, 1997], and BERT base-uncased [Devlin et al., 2019] models for text classification and BERT base-uncased model for textual entailment.

Evaluation Settings. For our L HLS, we set neighborhood size $\delta = 5$, reward $r = 0.5$, population size $S = 4$, maximum number of local search $N = 8$. All the evaluations are conducted on 1,000 randomly sampled texts from the corresponding testset and the attack would be considered as success only if the perturbation rate of the adversarial example is smaller than 25%. Also, for all baselines and our L HLS, we set the synonym number $m = 4$. As the task complexity varies across datasets, we set different query budgets $T$ (i.e., the maximum number of queries for the victim model) for different tasks in the following experiments.

4.2 Evaluation on Attack Effectiveness

We conduct evaluations for text classification and textual entailment for L HLS and baselines. We report the attack performance, including attack success rate and perturbation rate.

We conduct evaluations for text classification using five datasets on three models under the same query budget of 2,000 and summarize the results in Table 1. We observed that L HLS consistently achieves higher attack success rate with lower perturbation rate across all the datasets and target models than the hard-label attack HLA. Even for the score-based attacks of GA and PSO, L HLS exhibits better attack performance on most datasets and target models. For instance, L HLS achieves the attack success rate of 63.2%, which is 23.1%, 17.4%, and 9.0% higher than GA, PSO, and HLA, respectively, on BERT using AG’s News dataset. At the same time, L HLS achieves a perturbation rate of 12.0%, which is 23.1%, 17.4%, and 9.0% lower than GA, PSO, and HLA by 1.2%, 0.1%, and 1.2%, respectively.

To further validate the effectiveness of L HLS, we also conduct evaluations on BERT for three textual entailment tasks. As shown in Table 2, under the same query budget of 500, L HLS outperforms HLA by a clear margin of 8.8%-13.3% on three datasets with similar perturbation rate. Compared with the score-based attacks, L HLS achieves lower attack success rate than PSO but still gains comparable or better attack success rate than GA. It is acceptable since GA and PSO extra utilize the changes on prediction confidence introduced by synonym substitution, making the attack much easier than the hard-label attacks.

In conclusion, under the same query budgets, the proposed L HLS exhibits much better attack performance than existing hard-label attacks.
4.3 Evaluation on Attack Efficiency

The attack efficiency, which often refers to the query budget for target model, plays a key role in evaluating the effectiveness of black-box attacks, since the victim could block the attack by simply denying the access if they detect overload access within a short period. On the other hand, the query budget significantly affects the attack performance of the algorithm. Thus, a good attack should exhibit consistent and superior attack performance under various query budgets.

We report the attack success rate of LHLS and the baselines under various query budgets on BERT using IMDB dataset in Figure 3. LHLS and HLA exhibit remarkably higher attack success rate than score-based attacks under the limited query budget (≤ 2,000). When we continue to increase the query budgets, the attack success rate of score-based attacks starts to increase rapidly but is still lower than LHLS, which maintains stable and effective performance. In general, LHLS consistently exhibits better attack performance under various query budgets, which further demonstrates the superiority of our LHLS algorithm.

| Attack   | Succ. | Pert. | Sim. | Gram. | Time |
|----------|-------|-------|------|-------|------|
| GA       | 52.6  | 5.3   | 79.1 | 0.9   | 21.1 |
| PSO      | 59.6  | 3.7   | 81.9 | 0.7   | 21.0 |
| HLA      | 77.4  | 4.8   | 84.9 | 0.6   | 97.2 |
| LHLS     | 81.8  | 3.5   | 82.3 | 0.4   | 50.3 |

Table 3: Attack success rate (Succ., %), perturbation rate (Pert., %), average semantic similarity (Sim., %), grammatical error increase rate (Gram., %), and running time for generating an adversarial example (Time, in seconds) of LHLS and three baselines on BERT using IMDB dataset under the query budget of 2,000.

5 Conclusion

In this work, we propose a novel textual hard-label attack called the Learning-based Hybrid Local Search (LHLS) algorithm. At the adversary initialization stage, LHLS randomly substitutes the words with their synonyms to generate an adversarial example. At the perturbation optimization stage, LHLS highlights the importance of each word based on the prediction label of the initialized adversarial example after synonym substitution. Then LHLS adopts the hybrid local search algorithm to optimize the adversarial perturbation using such word importance with local search and recombination, and simultaneously updates the word importances for five times and report the average running time for generating an adversarial example.

We compare LHLS with the baselines on BERT using IMDB dataset and summarize the results in Table 3. With the lowest perturbation rate, LHLS exhibits better semantic similarity than the score-based attacks but is lower than HLA, which considers the semantic similarity of synonyms using the USE tool during the attack. However, the USE tool is time-consuming and computationally expensive, resulting in HLA being almost twice as slow as LHLS and four times slower than score-based attacks, and its CPU occupancy rate is seven times that of these attacks. Also, our LHLS achieves the lowest grammatical error increase rate compared with the baselines. These automatic evaluations demonstrate the high semantic similarity and fluency of the generated adversarial examples of LHLS from the technical metrics.

Human beings are very sensitive and subjective to texts, and even minor synonym substitutions may change the senses of people, resulting in different evaluations. Therefore, human evaluation is also necessary to evaluate the quality of adversarial examples. We perform the human evaluation on 20 benign texts and the corresponding adversarial examples generated by LHLS on BERT using MR dataset. Note that the texts in the MR dataset are shorter, averaging only 20 words per sentence, making it easier for humans to detect the adversarial examples. We invite 20 volunteers to label the adversarial examples, i.e., positive or negative, and score the similarity between the original sample and its adversarial example from 1 (very similar) to 5 (very different). The survey results show that 84.5% of the adversarial samples are labeled the same as the original samples, and the average similarity score is 1.9, indicating that most of the adversarial examples are difficult to be detected by humans.
tance based on the model output. Extensive evaluations for two typical NLP tasks, namely text classification and textual entailment, using various datasets and models demonstrate that our LHLS achieves higher attack success rate and lower perturbation rate than existing hard-label attacks and generates higher-quality adversarial examples judged by automatic metrics and human evaluations. We believe that our LHLS could shed new light on more precise estimation of the word importance and inspire more researches on hard-label attacks.

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