Normal vs. Adversarial: Salience-based Analysis of Adversarial Samples for Relation Extraction

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ABSTRACT

Recent neural-based relation extraction approaches, though achieving promising improvement on benchmark datasets, have reported their vulnerability towards adversarial attacks. Thus far, efforts mostly focused on generating adversarial samples or defending adversarial attacks, but little is known about the difference between normal and adversarial samples. In this work, we take the first step to leverage the salience-based method to analyze those adversarial samples. We observe that salience tokens have a direct correlation with adversarial perturbations. We further find the adversarial perturbations are either those tokens not existing in the training set or superficial cues associated with relation labels. To some extent, our approach unveils the characters against adversarial samples. We release an open-source testbed, “DiagnoseAdv”1, for future research purposes.

CCS CONCEPTS

• Information systems → Information extraction.

KEYWORDS

Adversarial Sample; Relation Extraction; Knowledge Graph

ACM Reference Format:

Luoqiu Li1,2*, Xiang Chen4*, Zhen Bi1,2*, Xin Xie1,2*, Shumin Deng1,2, Ningyu Zhang1,2*, Chuanqi Tan3, Mosha Chen3, Huajun Chen1,2*. 2021. Normal vs. Adversarial: Salience-based Analysis of Adversarial Samples for Relation Extraction. In The 10th International Joint Conference on Knowledge Graphs (IJCKG’21), December 6–8, 2021, Virtual Event, Thailand. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3502223.3502237

1The code and dataset are available in https://github.com/zjunlp/DiagnoseAdv.
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1 INTRODUCTION

Relation Extraction (RE), aiming to extract the relation between two given entities based on their related context, is an important task for knowledge graph construction [33] which can benefit widespread domains such recommendation system [12], healthcare system [32, 36], stock prediction [5] and so on. Previous neural-based models [4, 17, 23, 26–28, 30, 31, 34, 35] have achieved promising performance on benchmark datasets, yet they are vulnerable to adversarial examples [13, 37, 38].

The study of adversarial examples and training ushered in a new era to understand and improve natural language processing (NLP) models. However, recent approaches mainly focus on generating adversarial examples [9, 16, 18] or defending adversarial attacks [8, 21], the major difference between normal and adversarial samples is still not well-understood. Note that understanding adversarial examples can figure out missing connections of RE models and inspire important future studies [3]. To this end, we formulate the following interesting research questions:

1. What is the difference between normal and adversarial samples?
2. What is the reason that adversarial examples mislead the prediction?

Motivated by this, we leverage integrated gradients [20] to analyze the adversarial samples for RE. Firstly, we observe that salience tokens have a direct correlation with adversarial perturbations. We then analyze the salience distribution of normal and adversarial samples and find that these salience distributions change slightly (§ 3.1). Secondly, we conduct experiments to probe reasons for misclassification and find that the salience tokens of adversarial samples are either not existing in the training set or superficial cues associated with relation labels (§ 3.2). In summary, our main contributions include:

• To the best of our knowledge, we are the first to leverage salience-based analysis for adversarial samples in NLP, which provides a new perspective of understanding the model robustness.
• We propose a simple yet effective method to probe adversarial samples with salience analysis and observe new findings that may promote future researches.
• We provide an open-source testbed, “DiagnoseAdv”, for future research purposes. Our framework can be readily applied to other NLP tasks such as text classification and sentiment analysis.
2 ANLYZING ADVERSARIAL SAMPLES FOR RE

2.1 Setup

RE is usually formulated as a sequence classification problem. Formally, let \( X = \{x_1, x_2, \ldots, x_I\} \) be an input sequence, \( h, t \in X \) be two entities, and \( Y \) be the output relations. The goal of this task is to estimate the conditional probability, \( P(Y|X) = P(y|X, h, t) \).

In this paper, we respectively leverage the pre-trained BERT [6] and MTB [1] as the target model. Certainly, other strong models (e.g., SpanBERT [14] and XLNet [25]) can also be leveraged. We preprocess the sentence, \( x = \{w_1, w_2, h, t, \ldots, w_L\} \), for the input form of BERT: \( x = \{[CLS], w_1, w_2, [E1], h, [E1], \ldots, [E2], t, [E2], \ldots, [SEP]\} \), where \( w_i \) (i \( \in \) [1, \( n\)]) refers to each word in a sentence and \( h \) as well as \( t \) are head and tail entities, respectively. [E1], [E2], and [E2] are four special tokens used to mark the positions of the entities. Our approach can be readily applied to other classification tasks such as text classification and sentiment analysis.

2.2 Entity-aware Adversarial Attack

We introduce an entity-aware adversarial attack method for RE in this section, where entities in original samples should not be changed during the adversarial attack. Given a set of \( N \) instances, \( X = \{X_1, X_2, \ldots, X_N\} \) with a corresponding set of labels, \( Y = \{Y_1, Y_2, \ldots, Y_N\} \), we have a RE model trained via the input \( X \) and \( Y \), which satisfies the formula \( Y = RE(X) \).

The adversarial example \( X_{adv} \) for each sentence \( X \in X \) should conform to the requirements as follows:

\[
RE(X_{adv}) \neq RE(X), \text{ and } \text{Sim}(X_{adv}, X) \geq \epsilon, \tag{1}
\]

where \( \text{Sim} \) is a similarity function and \( \epsilon \) is the minimum similarity between the original and adversarial examples. Note that \( X_{adv} \) should have the same entity pair as \( X \), thus, we constrain the entity token from being perturbed and extend both score-based adversarial attack approaches: TextFooler [13], PWWS [19], and a gradient-based method: HotFlip [7] in our experiment. Other attack methods such as SememePSO [29], TextBugger [16], UAT [22] can also be leveraged.

2.3 Salience-based Analysis

We leverage integrated gradients [20] (IG) to analyze the identify inputs relevant to the prediction. Attention-based attribution [24] is not adopted as Bastings and Filippova [2] point out saliency methods are more suitable than attention mechanism in providing faithful explanations. Klein and Nabi [15] also notice that attention weights are insufficient when investigating the behavior of the attention head. Among the saliency methods, the IG method is a variation from the gradient method that assigns importance by computing gradients of the output w.r.t. the input. IG outperforms simple gradient by dealing with the gradient saturation problem that gradients may get close to zero when the function is well-fitted. Given an input sentence’s embeddings \( x = \{x_1, \ldots, x_n\} \) with \( x_i \) being embedding of the \( i \)-th input token, and a model \( F \), we compute:

\[
IG(x_i) = \frac{1}{m} \sum_{j=1}^{m} \nabla_{x_i} F \left( b + \frac{j}{m} (x - b) \right) \cdot (x_i - b_i), \tag{2}
\]

where \( b \) is a baseline value, which is an all-zeros vector in our experiment. By averaging over gradients with linearly interpolated inputs between the baseline and the original input \( x \) in \( m \) steps, and taking the dot product of the averaged gradient with the input embedding \( x_i \) minus the baseline, we get IG vectors for input tokens. In our experiment, we then use the norm of IG vectors as tokens’ attribution scores.

3 EXPERIMENTS

We conduct experiments on two benchmark datasets: Wiki80 \(^2\) [11] and TACRED \(^3\) [39]. The Wiki80 dataset consisted of 80 relations, each having 700 instances. TACRED is a large-scale RE dataset covering 42 relation types with 106,264 sentences. We provide an online GoogleColab for reproducibility \(^4\).

3.1 What’s Changed in Normal Samples?

We conduct adversarial attacks to RE models as shown in Table 1. We notice more adversarial samples are generated on the BERT model, indicating less vulnerability; among all three methods, HotFlip is most inefficient with success rates lower than 10%. To address Question 1, we leverage a token matching algorithm to explore connections between the original and adversarial samples.

| Model          | Wiki80 Accuracy | TACRED Accuracy |
|----------------|-----------------|-----------------|
| BERT (Origin)  | 55,193/86.2     | 99,008/67.5     |
| MTB (Origin)   | 55,225/90.3     | 98,245/68.7     |
| BERT (HotFlip) | 4,819/8.73%     | 4,953/5.00%     |
| BERT (PWWS)   | 17,742/32.15%   | 27,476/27.75%   |
| BERT (TextFooler) | 26,774/48.51% | 34,892/35.24%   |
| MTB (HotFlip)  | 4,655/8.43%     | 3,868/3.94%     |
| MTB (PWWS)    | 16,868/30.54%   | 21,692/22.08%   |
| MTB (TextFooler) | 25,969/47.02% | 25,751/26.21%   |

Table 1: Adversarial attack results from Wiki80 and TACRED dataset. The first two rows show numbers of correctly predicted samples and test performance (accuracy for Wiki80 and micro F1 for TACRED) of BERT or MTB model on two datasets, and the following rows indicate numbers of adversarial samples generated / success rate of adversarial attack with each (model, adversarial method) pair on each dataset.

At sentence level, we have summarized two types of adversarial samples in Figure 1: 1) the first type involves perturbations of \( n \) tokens with highest salience scores in the original samples (except

\(^2\)https://github.com/thunlp/OpenNRE

\(^3\)https://nlp.stanford.edu/projects/tacred/

\(^4\)https://colab.research.google.com/drive/1d4ayrzV8wqmGz9AxAiLORfrD3JhfYJ?usp=sharing
Figure 1: Visualization of two types of how salience scores interact with perturbed tokens between normal samples and adversarial samples in TACRED. The - - - and + + + signs mark perturbed tokens, representing token deletion in the original sample and insertion in the adversarial sample, respectively.

the irreplaceable entity tokens), while 2) the other type consists of samples in which no tokens with top salience scores are perturbed in these samples ($n = 3$ in our experiment). The ratio of samples in the first type greatly exceeds the second one among different adversarial methods on each dataset.

At a finer-grained token level, we explore salience scores of tokens at perturbed positions as shown in Figure 2. Each point represents a perturbed position, whose X-axis and Y-axis coordinate stand for its salience score in the original sample and the adversarial sample, respectively. Most points scatter along the diagonal $y = x$, indicating the stability of tokens’ influence on predictions before and after being perturbed. Colors of points indicate one largest cluster around (0.05, 0.05) and the second-largest cluster around (1, 1). This phenomenon can be explained by Figure 3, which reveals the distribution of all tokens in the original samples whose salience scores are mostly around 0.05 and 1.0. It also reveals that although above 2/3 samples in the original sample involve perturbations of tokens with the top salience scores, most perturbed tokens have low salience scores in token-level. However, from the perturbation ratio curve in Figure 3, tokens with higher salience scores are more likely to be perturbed.

In conclusion, we observe the strong correlation between perturbations in the adversarial samples and high salience scores in the original samples, which is intuitive as high salience scores reflect tokens’ impact on the model’s predictions, perturbing those tokens are likely to change the predictions. We also argue that current adversarial methods are inefficient in RE, as they perturb many low-salience tokens in the original samples.

### 3.2 Why MisClassified?

To address Question 2 and further analyze why the model predicts differently with few perturbations, we look into the perturbed tokens in the adversarial samples.

We manually examine perturbed tokens with high salience scores in the adversarial samples and observe a high ratio of superficial association between the predictions and the perturbed tokens, i.e., the model makes a wrong prediction upon seeing a frequent co-word. For example, as shown in Table 2, the perturbed token *birth* has a spurious correlation with the predicted label *per:parents* in train samples, thus leading to the misclassification. We have examined 3,868 adversarial samples in TACRED (MTB, HotFlip). Such association accounts for 2,248 (58.12%) adversarial samples, reflecting that neural networks tend to capture co-occurrence frequency between the token and label while ignoring low-frequency but important causal information. We argue that such artifacts and
spurious correlation in the data mainly mislead the classification of the adversarial samples \[10\]. We also notice around 40% adversarial samples contain perturbed tokens that do not appear in the training set, which leads to the input being Out-Of-Distribution (OOD). We also observe that the OOD problem results are accompanied by a decrease in confidence, revealing that OOD problem may be another minor reason for misclassification.

### 3.3 Extra Statistics of Adversarial Samples

In the Table 3 and 4, the column "Avg. Perturb" refers to average token perturbations from original samples, "% Salience" refers to the ratio of adversarial samples involving perturbations of relatively high salience scores (top 3 highest except the entity tokens), "% OOD" means ratio of samples containing Out-Of-Distribution tokens, and "Avg. Confidence" refers to the average decrease of prediction confidence between adversarial samples and of original samples (minus values mean lower confidence in adversarial samples).

### 4 CONCLUSION

We introduce the entity-aware adversarial attack for Relation Extraction, and leverage the salience-based analysis of adversarial samples. We observe that correlation between high salience scores with token perturbations, inspiring future works of salience-aware data augmentation. Furthermore, we identify two factors: spurious correlation and OOD as main reasons for adversarial misclassification. Breaking down the spurious correlation with causal analysis may help defend adversarial attacks with better generalization. More future works should also be taken into consideration for those OOD samples. We regard this study as a small step towards the understanding of adversarial samples.

### ACKNOWLEDGMENTS

This work is funded by NSFC91846204/NSFCU19B2027.
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