Towards a Robust Deep Neural Network in Text Domain A Survey

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Abstract—Deep neural networks (DNNs) have shown an inherent vulnerability to adversarial examples which are maliciously crafted on real examples by attackers, aiming at making target DNNs misbehave. The threat of adversarial examples is widely existed in image, voice, speech, and text recognition and classification. Inspired by the previous work, researches on adversarial attacks and defenses in text domain develop rapidly. In order to give a general understanding of this field, this article presents a comprehensive review on adversarial examples in text, including attack and defense approaches. In this article, we give a taxonomy of recent research on attack and defense of adversarial examples in text as well as their advantages and shortcomings. Finally, we discuss the challenges in adversarial texts and provide a research direction of this aspect.

Index Terms—Adversarial attacks and defenses, Adversarial example, Deep neural networks, Text domain, Testing and verification.

I. INTRODUCTION

Nowadays, DNNs have solved masses of significant practical problems in various areas like computer vision [1], [2], audio [3], [4], natural language processing (NLP) [5], [6] etc. Due to the great success, systems based on DNN are widely deployed in physical world, including some sensitive security tasks. However, Szegedy et al. [7] found an interesting fact that a crafted input with small perturbations could easily fool DNN models. This kind of input is called adversarial example. Certainly, with the development of theory and practice, the definitions of adversarial example [7]-[10] are varied. But these definitions have two cores in common. One is that the perturbations are small and the other is the ability of fooling DNN models. It naturally raises an idea to explore why the problem of adversarial example exist in DNNs and how they can infect behaviors of the models. Goodfellow et al. [8] then gave an explanation about these problems after adversarial example arose. Researchers therefore treat adversarial example as a security problem and pay much attention to works of adversarial attacks and defenses [11], [12].

With the study of adversarial examples, category of them becomes diverse, varying from image to audio and others. That means almost all deployed systems based on DNNs are under the potential threat of adversarial attacks. For example, sign recognition system [13], object recognition system [14], audio

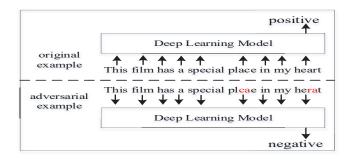


Fig. 1: Example of attack on DNNs by DeepWordBug [24]: the generated adversarial example based on original one can fool DNN model make error classification from positive to negative. The recommendation score of this film will decrease if massive adversarial examples of this type are applied by competitors, resulting in a low box office.

recognition or control system [15]–[17] and malware detection system [18], [19] are all hard to defend against this kind of attack. Many NLP tasks are also employing DNN models such as text classification, sentiment analysis, question answering, etc. Thus, systems for NLP tasks are also under the threat of adversarial examples.

In real life, people are increasingly inclined to search for related comments before shopping, eating or watching film and the corresponding items with recommendation score will be given at the same time. The higher the score is, the more likely it is to be accepted by humans. These recommendation apps mainly take advantage of sentiment analysis with others previous comments [20]. Thus attackers could generate adversarial examples based on natural comments to smear competitors or do malicious recommendations for shoddy goods with the purpose of profit or other malicious intents. Figure.1 is an instance for adversarial attack to decrease the favorable rate of a film. Its inputs and output are texts. Attackers craft the original example just by changing locations of adjacent letters to have a wrong classification. Apart from mentioned above, adversarial examples can also poison network environment and hinder detection of malicious information [21]-[23]. Hence, it is significant to know the operating mechanism of adversarial attacks and develop robust measures to defend against them.

We presents a comprehensive survey on adversarial examples in text domain to make interested readers have a better understanding of this concept. Our contributions are summarized as follows:

We systematically analyze recent adversarial attack approaches in text. For each of them, we introduce the

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implementation procedure and give a brief review on its advantages and shortcomings.

- We summarize the representative metric methods of adversarial example in both image and text. Then we compare the differences between them and point out why metric methods in image can not be directly used in text.
- We review the existing defense methods against adversarial texts. Testing and verification are also introduced as another critical area to improve the robustness of DNNs against adversarial examples.

The rest of this article is organized as follows: we first give some background about adversarial examples in section II. In section III, we review the adversarial attacks for text classification and other real-world NLP tasks. The researches with the central topic of defense are introduced in section V and VI. One of them is on existing defense methods in text and the other is about how to improve the robustness of DNNs from another point of view. The discussion and conclusion of the article is in section VII and VIII.

II. BACKGROUND

In this section, we describe some research background on the textual adversarial examples, including representation of symbol and attack types and scenarios.

A. Adversarial example formulation

The function of a pre-trained text classification model F is mapping from input set to the label set. For a clean text example x, it is correctly classified by F to ground truth label $y \in Y$, where Y including $\{1,2,\ldots,k\}$ is a label set of k classes. An attacker aims at adding small perturbations in x to generate adversarial example x', so that $F(x) = y(y \neq y)$, where $|x - x'| < \delta$. δ is a threshold to limit the size of perturbations. Generally speaking, a good x' should not only be misclassified by F, but also imperceptible to humans, robust to transformations as well as resilient to existing defenses depending on the adversarial goals [25]. Hence, constraint conditions (e.g. semantic similarity, distance metric, etc.) are appended to make x' be indistinguishable from x in some works and exploit it to cause classification errors like Figure 1.

B. General categorization of adversarial examples on attacks and defenses in text

In order to have a distinct overview on adversarial examples, we have studied the classification of this aspect. Figure 2 is a general categorization of adversarial examples on attacks and defenses.

1) Categorization of adversarial attacks: The reason why adversarial examples pose greater concern may be due to the fact that adversarial attacks can be easily conducted on DNNs, even though attackers have no knowledge of target model. Accordingly, attacks can be categorized by the level of authorization about the model.

Black-box. A more detailed division can be done in black-box attack, resulting in black-box attack with or without probing. In the former scenario, adversaries can probe target

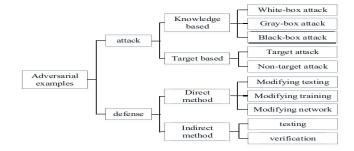


Fig. 2: General categorization of adversarial examples on attacks and defenses

model by observing outputs, even if they do not know much about the model. This case can also be called a **gray-box** attack. In the latter scenario, adversaries have little or no knowledge on target model and they can not probe it. Under this condition, adversaries generally train their own models and utilize the transferability [8], [26] of adversarial examples to carry out an attack.

White-box. In white-box attack, adversaries have full access to target model and they can know all about architectures, parameters and weights of the model. Certainly, both white-box and black-box attacks can not change the model and training data.

According to the purpose of the adversary, adversarial attacks can be categorized as targeted attack and non-targeted attack.

Targeted attack. In this case, the generated adversarial example x' is purposeful classified as class t which is the target of an adversary. It mainly relies on increasing the confidence of class t.

Non-targeted attack. In this case, the adversary only wants to fool the model and the result y' can be any class except for ground truth y. Contrary to targeted attack, non-targeted attack works by reducing the confidence of the true class y.

- 2) Categorization of defenses against adversarial attacks: There are many reasons for people to study defenses against adversarial examples. Two main ones(inspired by [27]) are summarized as follows:
 - To protect DNN-based systems from adversarial attacks
 - To evaluate robustness of these systems in the worst-case

This results in two kinds of direction for defense. One is direct defense methods against adversarial attacks by modifying testing, training or the model. Common methods on direct methods are detection of adversarial examples, adversarial training and changing loss function. The other is via enhancing robustness of DNNs, including testing and verification methods.

C. Metric

There exists an important issue that the generated adversarial texts should not only be able to fool target models, but also need to keep the perturbations imperceptible. In other words, a good adversarial example should convey the same semantic meaning with the original one, so that metric measures are

required to ensure this case. We describe different kinds of measures to evaluate the utility of adversarial examples in image and text. Then we analyze the reasons why metric measures in image are not suitable in text.

1) Metric measures in image: In image, almost all recent studies on adversarial attacks adopt L_p distance as a distance metric to quantify the imperceptibility and similarity of adversarial examples. The generalized term for L_p distance is as follows:

$$\|\triangle x\|_p = \sqrt[p]{\sum_{i=1}^n |x' - x|^p}$$
 (1)

where $\triangle x$ represents the perturbations. This equation is a definition of a set of distances where p could be 0, 1, ∞ and so on. Specially, L_0 [28]–[30], L_2 [30]–[33] and L_∞ [7], [8], [33]–[36] are the three most frequently used norms in adversarial images.

- L_0 distance evaluates the number of changed pixels before and after modifications. It seems like edit distance, but it may not directly work in text. Because results of altered words in text are varied. Some of them are similar to original words and the others may be contrary, even though the L_0 distance of them is same.
- L₂ distance is the Euclidean distance. The original Euclidean distance is the beeline from one point to another in Euclidean space. As the mapping of image, text or others to it, Euclidean space becomes a metric space to calculate the similarity between two objects represented as the vector.
- L_{∞} distance measures the maximum change as follows:

$$\|\Delta x\|_{\infty} = \max(|x_{1}^{'} - x_{1}|, \dots, |x_{n}^{'} - x_{n}|)$$
 (2)

Although L_{∞} distance is thought to be the optimal distance metric to use in some work, but it may fail in text. The altered words may not exist in pre-trained dictionary so that they are considered to be unknown words and their word vectors are also unknown. As a result, L_{∞} distance is hard to calculate.

There are also other metric measures(e.g. structural similarity [37], perturbation sensitivity [38]) which are typical methods for image. Some of them are considered to be more effective than L_p distance, but they con not directly used either. Hence, available metric measures are needed in text, which are different from these in image.

2) Metric measures in text: In order to overcome the metric problem in adversarial texts, some measures are presented and we describe five of them which have been demonstrated in the pertinent literature.

Euclidean Distance. In text, for two given word vectors $\vec{m} = (m_1, m_2, \dots, m_k)$ and $\vec{n} = (n_1, n_2, \dots, n_k)$, the Euclidean distance is:

$$D(\vec{m}, \vec{n}) = \sqrt{(m_1 - n_1)^2 + \ldots + (m_k - n_k)^2}$$
 (3)

Euclidean distance is more used for the metric of adversarial images [30]–[33] than texts with a generalized term called L_2 norm or L_2 distance.

Cosine Similarity. Cosine similarity is also a computational method for semantic similarity based on word vector by the cosine value of the angle between two vectors. Compared with Euclidean distance, the cosine distance pays more attention to the difference in direction between two vectors. The more consistent the directions of two vectors are, the greater the similarity is. For two given word vectors \vec{m} and \vec{n} , the cosine similarity is:

$$D(\vec{m}, \vec{n}) = \frac{\vec{m} \cdot \vec{n}}{\|m\| \cdot \|n\|} = \frac{\sum_{i=1}^{k} m_i \times n_i}{\sqrt{\sum_{i=1}^{k} (m_i)^2} \times \sqrt{\sum_{i=1}^{k} (n_i)^2}}$$
(4)

But the limitation is that the dimensions of word vectors must be the same.

Jaccard Similarity Coefficient. For two given sets A and B, their Jaccard similarity coefficient is:

$$J(A,B) = |A \cap B|/|A \cup B| \tag{5}$$

where $0 \le J(A, B) \le 1$. It means that the closer the value of J(A, B) is to 1, the more similar they are. In the text, intersection $A \cap B$ refers to similar words in the examples and union $A \cup B$ is all words without duplication.

Word Movers Distance (WMD). WMD [39] is a variation of Earth Mover's Distance (EMD) [40]. It can be used to measure the dissimilarity between two text documents, relying on the travelling distance from embedded words of one document to another. In other words, WMD can quantify the semantic similarity between texts. Meanwhile, Euclidean distance is also used in the calculation of WMD.

Edit Distance. Edit distance is a way to measure the minimum modifications by turning a string to another. The higher it is, the more dissimilar the two strings are. It can be applied to computational biology and natural language processing. Levenshtein distance [41] is also referred to as edit distance with insertion, deletion, replacement operations used in work of [24].

These metric measures are employed in different situations. Euclidean distance, cosine distance and WMD are used on vectors. Adversarial examples and clean examples in text should be transformed into vectors. Then these three methods can be applied to calculate the similarity between them. On the contrary, Jaccard similarity coefficient and edit distance can be directly used on text inputs which do not need form conversion.

D. Datasets in Text

In order to make data more accessible to those who need it, we collect some datasets which have been applied to NLP tasks in recent literature. Meanwhile, a brief introductions are also given below. These datasets can be downloaded via the corresponding link in the footnote. Table I is the applications of the data. Other datasets used in research works are listed in appendix X.

AG's News¹: This is a news set with more than one million articles gathered from over 2000 news sources by an academic

¹http://www.di.unipi.it/ gulli/AG_corpus_of_news_articles.html

news search engine named ComeToMyHead. The provided db version and xml version can be downloaded for any noncommercial use.

DBPedia Ontology²: It is a dataset with structured content from the information created in various Wikimedia projects. It has over 68 classes with 2795 different properties and now there are more than 4 million instances included in this dataset.

Amazon Review³: The Amazon review dataset has nearly 35 million reviews spanning Jun 1995 to March 2013, including product and user information, ratings, and a plaintext review. It is collected by over 6 million users in more than 2 million products and categorized into 33 classes with the size ranging from KB to GB.

Yahoo! Answers⁴: The corpus contains 4 million questions and their answers, which can be easily used in the question answer system. Besides that, a topic classification dataset is also able to be constructed with some main classes.

Yelp Reviews⁵: The provided data is made available by Yelp to enable researchers or students to develop academic projects. It contains 4.7 million user reviews with the type of json files and sql files.

Movie Review (MR)⁶: This is a labeled dataset with respect to sentiment polarity, subjective rating and sentences with subjectivity status or polarity. Probably because it is labeled by humans, the size of this dataset is smaller than others, with a maximum of dozens of MB.

MPQA Opinion Corpus⁷: The Multi-Perspective Question Answering (MPQA) Opinion Corpus is collected from a wide variety of news sources and annotated for opinions or other private states. Three different versions are available to people by the MITRE Corporation. The higher the version is, the richer the contents are.

Internet Movie Database (IMDB)⁸: IMDBs is crawled from Internet including 50000 positive and negative reviews and average length of the review is nearly 200 words. It is usually used for binary sentiment classification including richer data than other similar datasets. IMDB also contains the additional unlabeled data, raw text and already processed data.

SNLI Corpus⁹: The Stanford Natural Language Inference (SNLI) Corpus is a collection with manually labeled data mainly for natural language inference (NLI) task. There are nearly five hundred thousand sentence pairs written by humans in a grounded context. More details about this corpus can be seen in the research of Samuel et al. [42].

E. Evaluation on performance of adversarial examples

This is an open-ended question and researchers may use different standards to evaluate the performance of adversarial

TABLE I: Applications of datasets

dataset	application in the work	task
AG's News	[24], [43]	classification
DBPedia Ontology	[24], [44]	classification
Amazon Review	[24]	classification
Yahoo! Answers	[24]	classification
Yelp Reviews	[24]	classification
Movie Review	[44], [45], [46]	sentiment analysis
MPQA Opinion Corpus	[46]	classification
Internet Movie Database	[47], [44], [48], [45],	sentiment analysis
	[46], [49]	,
SNLI Corpus	[49], [50]	textual entailment

examples. As far as we know, researchers generally evaluate their attacks on target models by accuracy rate or error rate.

- accuracy rate: Ratio of correct discrimination on inputs.
 The lower the accuracy rate is, the more effective the adversarial examples are.
- error rate: Ratio of incorrect discrimination on inputs. The use of it is opposite to accuracy rate.

Besides, some researchers prefer to utilize the difference in accuracy before and after attacks, because it can show the effect of attacks more intuitively. And these criterions can also used in defending against adversarial examples.

III. ADVERSARIAL ATTACKS FOR CLASSIFICATION IN TEXT

Because the purpose of adversarial attacks is to make DNNs misbehave, they can be seen as a classification problem(correct or incorrect judgement) in a broad sense. The majority of recent representative adversarial attacks in text is related to classification tasks. In this section, we categorize the majority of existing adversarial attacks in text into three parts based on the type of classification. Technical details and corresponding comments of each attack method described below are given to make these attack methods more clearly to readers.

A. Non-target attacks for classification

Adversarial attacks can be subdivided in many cases which are described in section II-B1. With the purpose of more granular division of classification tasks, we introduce these attack methods group by group based on the desire of attackers. In this part, studies below are all non-target attacks that attackers do not care the category of misclassified results.

1) Image-based approach: Studies on adversarial examples in image develop relatively faster than those in text. Hence, researchers come up with an idea that whether approaches in image can be used in test or not. Some researchers have tried this and achieve better results. They propose effective approaches based on fast gradient sign method (FGSM) [8], which is based on gradient.

Papernot et al. [51] is the first to study the problem of adversarial example in text. They contributed to producing adversarial input sequences on Recurrent Neural Network (RNN). The authors leveraged computational graph unfolding [52] to evaluate the forward derivative [28](i.e. Jacobian) with respect to embedding inputs of the word sequences. These

²https://wiki.dbpedia.org/services-resources/ontology

³http://snap.stanford.edu/data/web-Amazon.html

⁴ https://sourceforge.net/projects/yahoodataset/

⁵https://www.yelp.com/dataset/download

⁶http://www.cs.cornell.edu/people/pabo/movie-review-data/

⁷http://mpqa.cs.pitt.edu/

⁸http://ai.stanford.edu/ amaas/data/sentiment/

⁹https://nlp.stanford.edu/projects/snli/

Jacobian tensors were then evaluated by FGSM to find the adversarial perturbations. Meanwhile, in order to solve the mapping problem of modified word embedding during the process, they set a special dictionary to choose words, aming at replacing the original ones. The constraint of this substitution operation was that sign of the difference between replaced and original words was closest to the result by FGSM. Although adversarial input sequences can make long-short term memory (LSTM) [53] model misbehave, words of the input sequences are randomly chosen and there may be grammatical errors.

The method proposed by Samanta et al. [47] is also based on FGSM like adversarial input sequence [51]. But difference between them is the ways of generating adversarial examples. Three modification strategies(i.e. insertion, replacement and deletion) were introduced by Samanta et al. to preserve the semantic meaning of inputs as much as possible. The premise of these modifications was to calculate the important or salient words which would highly affect classification results if they were removed. The authors utilized concept of FGSM to evaluate the contribution of a word and then targeted words in the decreasing order of their contributions.

Except for deletion strategy, both insertion and replacement on high ranking words needed extra substitutions to assist. Thus, the authors built a candidate pool for each word in the experiment, including synonyms, typos and genre special keywords. However, it consumes a great deal of time and the most important words in actual input text may not have candidate pools.

2) Optimization-based approach: Different from other methods, Sato et al. [44] operated input embedding space for text and reconstructed adversarial examples to misclassify the target model. The core idea of this method could be seen as an optimization problem. They searched for the weights of the direction vectors which maximized loss functions with overall parameters *W* as follows:

$$\alpha_{iAdvT} = \underset{\alpha, \|\alpha\| \le \epsilon}{\arg\max} \{ \ell(\vec{w} + \sum_{k=1}^{|V|} a_k d_k, \hat{Y}, W) \}$$
 (6)

where $\sum_{k=1}^{|V|} a_k d_k$ is the perturbation generated from each input on its word embedding vector \vec{w} . \vec{d} is the direction vector from one word to another in embedding space. Because \aleph_{iAdvT} in Eq. (6) was hard to calculate, the authors used Eq. (7) instead:

$$\alpha_{iAdvT} = \frac{\epsilon g}{\|g\|_2}, g = \nabla_{\alpha} \ell(\vec{w} + \sum_{k=1}^{|V|} a_k d_k, \hat{Y}, W)$$
 (7)

The loss function of iAdvT was then defined based on \aleph_{iAdvT} as an optimization problem by jointly minimizing objection functions on entire training dataset D. The formula is as follows:

$$\hat{W} = \frac{1}{|D|} \underset{W}{\operatorname{arg\,min}} \{ \sum_{(\hat{X}, \hat{Y}) \in D} \ell(\hat{X}, \hat{Y}, W) + \lambda \sum_{(\hat{X}, \hat{Y}) \in D} \ell(\hat{X}_{+\gamma(\alpha_{iAdvT})}, \hat{Y}, W) \}$$

$$(8)$$

Compared with Miyato et al. [54], iAdv-Text restricts the direction of perturbations to find a substitute which is in the predefined vocabulary rather than an unknown word to replace the origin one. Thus, it improves the interpretability of adversarial examples by adversarial training. Meanwhile, the authors also takes advantage of cosine similarity to select a better perturbation.

Similarly, Gong et al. [48] searched for adversarial perturbations in embedding space, but their method was gradient-based. Even though WMD is used by the authors to measure the similarity of clean examples and adversarial examples, the readability of generated results seems a little poor.

3) Words' importance-based approach: Unlike previous white-box methods [51], [47], little attention is paid to black-box attacks with adversarial texts. Gao et al. [24] proposed a novel algorithm DeepWordBug in black-box scenario to make DNNs misbehave. The two-stage process they presented were determining which important tokens to change and creating imperceptible perturbations which could evade detection respectively. The calculation process for the first stage is as follows:

$$CS(x_i) = [F(x_1, \dots, x_{i-1}, x_i) - F(x_1, x_2, \dots, x_{i-1})] + \lambda [F(x_i, x_{i+1}, \dots, x_n) - F(x_{i+1}, \dots, x_n)]$$
(9)

where x_i is the *i*-th word in the input and F is a function to evaluate the confidence score. Then similar modifications like swap, substitution, deletion and insertion were applied to manipulate the important tokens to make better adversarial examples. Meanwhile, in order to preserve the readability of these examples, edit distance was used by the authors.

Li et al. [45] proposed an attack framework TextBugger for generating adversarial examples to trigger the deep learning-based text understanding system in both black-box and white-box settings. They followed the general steps to capture important words which were significant to the classification and then crafted on them. In white-box setting, Jacobian matrix is used to calculate the importance of each word as follows:

$$C_{x_i} = J_{F(i,y)} = \frac{\partial F_y(x)}{\partial x_i} \tag{10}$$

where $F_y(\cdot)$ represents the confidence value of class y. The slight changes of words were in character-level and word-level respectively by operations like insertion, deletion, swap and substitution. In black-box setting, the authors segmented documents into sequences and probed the target model to filter out sentences with different predicted labels from the original. The odd sequences were sorted in an inverse order by their confidence score. Then important words were calculated by removing method as follows:

$$C_{x_i} = F_y(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_n) - F_y(x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$$
(11)

The last modification process was same as that in white-box setting.

B. Target attacks for classification

For target attack, attackers purposefully control the category of output to be what they desire. The generated examples by them also have similar semantic information with clean ones. This kind of attacks are described one by one in the following part.

1) Image-based approach: Different from works in [51], [47], Liang et al. [46] first demonstrated that FGSM could not be directly applied in text. Because input space of text is discrete, while image data is continuous. Continuous image has tolerance of tiny perturbations, but text does not have this kind of feature. Instead, the authors utilized FGSM to determine what, where and how to insert, remove and modify on text input. They conducted two kinds of attacks in different scenarios and used the natural language watermarking [55] technique to make generated adversarial examples compromise their utilities.

In white-box scenario, the authors defined the conceptions of hot training phrases and hot sample phrases. These two objects were both obtained by leveraging the backpropagation algorithm to compute the cost gradients of examples. The former one shed light on what to insert and the later implied where to insert, remove and modify.

In black-box scenario, the authors used the idea of fuzzing technique [56] for reference to obtain hot training phrases and hot sample phrases. One assumption was that the target model could be probed. Examples were fed to target model and then isometric whitespace was used to substitute origin word each time. The difference between the classification results before and after modification was each word's deviation. The larger it was, the more significant the corresponding word was to its classification. Hence, hot training phrases were the most frequent words in a set which consisted of the largest deviation word for each training sample. And hot sample phrases were the words with largest deviation for every test sample.

2) Gradient-based approach: Like one pixel attack [29], a similar method named HotFlip was proposed by Ebrahimi et al. [43]. HotFlip was a white-box attack in text and it relied on an atomic flip operation to swap one token for another based on gradient computation. The authors represented examples as one-hot vectors in input space. The flip operation can be represented by:

$$\vec{v}_{ijb} = (\vec{0}, \dots; (\vec{0}, \dots (0, 0, \dots, 0, -1, 0, \dots, 1, 0)_j, \dots, \vec{0})_i; \vec{0}, \dots)$$
(12)

The eq. (12) means that the j-th character of i-th word in a example is changed from a to b, which are both characters respectively at a-th and b-th places in the alphabet. The change from directional derivative along this vector is calculated to find the biggest increase in loss J(x,y). The formula is as follows:

$$\max \nabla_x J(x, y)^T \cdot \vec{v}_{ijb} = \max_{ijb} \frac{\partial J^{(b)}}{\partial x_{ij}} - \frac{\partial J^{(a)}}{\partial x_{ij}}$$
(13)

where $x_{ij}^{(a)}=1$. HotFlip can also be used on character-level insertion, deletion and word-level modification. Although HotFlip performs well on character-level models, only few successful adversarial examples can be generated with one or two flips under the strict constraints.

- 3) Optimization-based approach: Considering the limitation of gradient-based methods [23], [43], [47], [51] in blackbox case, Alzantot et al. [49] proposed a population-based optimization via genetic algorithm [57], [58] to generated semantically similar adversarial examples. The authors randomly selected words in the input and computed their nearest neighbors by Euclidean Distance in GloVe embedding space [59]. These nearest neighbors which did not fit within the surrounding were filtered based on language model [60] scores. Hence, only high-ranking words with the highest scores were kept. The substitute which would maximize probability of the target label was picked from remaining words. At the same time, aforementioned operations were conducted several times to get a generation. If predicted label of modified examples in a generation were not the target label, the next generation was generated by randomly choosing two examples as parents each time. Then the same process was repeated on the next generation. This optimization procedure is done to find successful attack by genetic algorithm. In this method, random selection words in the sequence to substitute are full of uncertainty. These substitutions may be meaningless, even though the target label is changed.
- 4) Summary of adversarial attacks for classification: These attacks above for classification are either popular or representative ones in recent studies. Some main attributes of them are summarized in table II and instances in the literature are in appendix IX.

As we can see, majority of these attacks are based on or related to gradient. Gradient-based methods are widely used in image with many variants(e.g. [34], [64]), which can also be applied in text. But gradient-based methods exist some shortcomings. They can only be used in white-box scenario. In black-box attack, adversarial attacks mainly rely on the transferability of adversarial examples. Another limitation is that gradient masking [65] can make gradient useless in some cases, leading to failure in gradient-based methods. Even though this technique is proved to be a failed defense, gradient-based methods are not as effective as we think.

IV. ADVERSARIAL ATTACKS ON OTHER TASKS

We have reviewed adversarial attacks for classification task in the previous subsections. Next, we solve some other puzzles on adversarial examples such as what other kinds of tasks or applications can be attacked by adversarial examples, how they are generated in these cases and whether the crafted examples can be applied in another way except for attack. The answers of these questions will be described below.

A. Attack on Reading Comprehension Systems

In order to know whether reading comprehension systems could really understand language, Jia et al. [66] inserted adversarial perturbations into paragraphs to test the systems without changing the true answers or misleading humans. They extracted nouns and adjectives in the question and replaced

¹⁰https://iamtrask.github.io/2015/11/15/anyone-can-code-lstm/

¹¹https://github.com/keras-team/keras/blob/master/examples/imdb_lstm.py

¹²https://github.com/Smerity/keras_snli/blob/master/snli_rnn.py

White/Black box Target/Non-target Model Method Metric Gradient correlation DeepWordBug [24] Black box LSTM,char-CNN [61] Edit Distance Non-target $LSTM^{10}$ Papernot et al. [51] White box Non-target Yes Samanta et al. [47] White box Non-target CNN Yes iAdv-Text [44] White box Non-target LSTM Consine Similarity Yes Gong et al. [48] **CNN** Word Mover Distance(WMD) White box Target Yes CNN [62],char-CNN [61] All metrics except WMD TextBugger [45] Both two Non-target No Text-fool [46] Both two Target char-CNN [61] Yes HotFlip [43] charCNN-LSTM [63],CNN [62] Consine Similarity White box Target Yes LSTM11,RNN12 Alzantot et al. [49] Black box Target Euclidean Distance No

TABLE II: Summary of attack methods for classification

them with antonyms. Meanwhile named entities and numbers were changed by the nearest word in GloVe embedding space [59]. The modified question was transformed into declarative sentence as the adversarial perturbation, which was then concatenated to the end of the original paragraph. This process is call ADDSENT by the authors.

Another process ADDANY is also used to randomly choose any sequence of some words to craft. Compared with ADDSENT, ADDANY do not consider grammaticality and it needs query the model several times. Both two kinds of ways can fool reading comprehension systems well, because they tried to draw the models attention on the generated sequences other than original sequences. Mudrakarta et al. [67] also study adversarial examples on answering question system and part of their work can strengthen attacks proposed by Jia et al. [66].

B. Attack on Natural Language Inference (NLI) Models

Besides reading comprehension systems [66], Minervini et al. [50] also cast the generation of adversarial examples as an optimization problem. But they added some constraints of First-Order Logic (FOL) in NLI to get adversarial examples which could break these constraints. They maximized the proposed inconsistency loss to search for substitution sets S(i.e. adversarial examples) by using a language model as follows:

$$\begin{aligned} maximise \ J_I(S) &= [p(S;body) - p(S;head)]_+ \ , \\ s.t. \log p_L(S) &\leq \tau \end{aligned} \tag{14}$$

where $[x]_{+} = \max(0, x)$.

- τ : a threshold on the perplexity of generated sequences
- X_1, \ldots, X_n : the set of universally quantified variables in a rule to sequences in S
- $S=\{X_1 \to s_1, \dots, X_n \to s_n\}$: a mapping from $\{X_1, \dots, X_n\}$
- p(S;body) and p(S;head): probability of the given rule, after replacing X_i with the corresponding sentence S_i

These generated sequences can help the authors find weaknesses of NLI systems.

C. Attack on Neural Machine Translation (NMT)

NMT is another kind of system attacked by adversaries and Belinkov et al. [68] have made this attempt. They devised black-box methods depending on natural and synthetic language errors to generate adversarial examples. The naturally

occurring errors include typos, misspelling words or others. Then syntactically adversarial examples are modified by random or keyboard typo types. These experiments are done on three different NMT systems [69], [70] and results show that these examples could also effectively fool the target systems.

The similar work is also done by Ebrahimi et al. [71] to conduct an adversarial attack on character-level NMT by employing differentiable string-edit operations. The method of generating adversarial examples is same in their previous work [43]. Compared with Belinkov et al. [68], the authors demonstrate that black-box adversarial examples are much weaker than white-box ones in most cases.

D. Attack with Syntactically Controlled Paraphrase Networks (SCPNS)

Iyyer et al. [72] crafted adversarial examples by the use of SCPNS they proposed. They designed this model for generating adversarial examples without decreasing the quality of the input semantics. The general process mainly relied on the encoder-decoder architecture of SCPNS. Given a sequence and a corresponding target syntax structure, the authors encoded them by a bidirectional LSTM model and decoded by LSTM model. This process was augmented with soft attention over encoded states [73] and the copy mechanism [74]. They then modified the inputs to the decoder, aiming at incorporating the target syntax structure to generate adversarial examples.

The syntactically adversarial sentences not only can fool pre-trained models, but also improve the robustness of them to syntactic variation. The authors also use crowdsourced experiment to demonstrate the validity of the generated.

E. Adversarial Examples to Measure Robustness of the Model

Apart from attacks, adversarial examples can be used as a way to measure robustness of DNN models. Blohm et al. [75] generated adversarial examples to find out the limitations of a machine reading comprehension model they designed. The categories of these adversarial examples include word-level and sentence-level in different scenarios [76]. By comparing with human performance, experiment results show that some other attributions(e.g. answer by elimination via ranking plausibility [77]) should be added into this model to improve its performance.

V. DEFENSES AGAINST ADVERSARIAL ATTACKS IN TEXT

The constant arms race between adversarial attacks and defenses invalidates conventional wisdom quickly [25]. In fact,

defense is more difficult than attack and few works have been done on this aspect. There are two reasons for this situation. One is that a good theoretical model do not exist for complicated optimization problems like adversarial examples. The other is that tremendous amount of possible inputs may produce the target output with a very high possibility. Hence, a truly adaptive defense method is difficult. In this section, we describe some relatively effective methods of defenses against adversarial attacks in text.

Generally speaking, there are following defense ways against adversarial attacks, namely adversarial examples detection, adversarial training, and model enhancing.

A. Adversarial examples detection

Adversarial examples are also a kind of data with a special purpose. The first thing to think about is whether data processing or detecting is useful against adversarial attacks. Researchers have done various attempts to detect the differences between adversarial examples and clean ones.

One strategy of defense against adversarial attacks is to detect whether input data is modified or not. Researchers think that there exists some different features between adversarial example and its clean example. Inspired by this view, a series of works [78]-[82] have been conducted to detect adversarial examples and perform relatively well in image. In text, the ways of modification strategy in some methods may produce misspelling words in generated adversarial examples. This is a distinct different feature which can be utilized. It naturally comes up with an idea to detect adversarial examples by checking out the misspelling words. Gao et al. [24] used an autocorrector which was the Python autocorrect 0.3.0 package before the input. And Li et al. [45] took advantage of a context-aware spelling check service¹³ to do the similar work. But experiment results show that this approach is effective on character-level modifications and partly useful on wordlevel operations. Because there are some big differences on the modifications strategies between character-level and wordlevel. On the other hand, this kind of spelling checking method is also not suitable to adversarial examples based on other languages.

B. Adversarial training

Adversarial training [8] is a direct approach to defend adversarial images in some studies [8] [83]. Researchers mix the adversarial examples with corresponding original examples as the training dataset to train the model. Adversarial examples can be detected to a certain degree in this way, but adversarial training method is not always work. In text, there are some effective works against the attacks by adversarial training [24], [43], [45]. However, it fails in the work of [49], mainly because of the different ways of generating adversarial examples. The modifications of the former are insertion, substitution, deletion and replacement, while the later takes use of genetic algorithm to search for adversarial examples.

Overfitting may be another reason why adversarial training method is not always useful and may be only effective on its corresponding attack. This has been confirmed by Tram'er et al. [84] in image domain, but it remains to be demonstrated in text.

C. Model enhancing against adversarial examples

Except for adversarial examples detection and adversarial training, improving robustness of the model is another way to resist adversarial examples. With the purpose of improving the ranking robustness to small perturbations of documents in the adversarial Web retrieval setting, Goren et al. [85] formally analyzed, defined and quantified the notions of robustness of linear learning-to-rank-based relevance ranking function. They adapted the notions of classification robustness [7], [86] to ranking function and defined related concepts of pointwise robustness, pairwise robustness and a variance conjecture. To quantify the robustness of ranking functions, Kendall's- τ distance [87] and top change were used as normalized measures. Finally, the empirical findings supported the validity of the authors' analyses in two families of ranking functions [88], [89].

D. Summary of defens methods

Although defnse methods above have achieved better results on their corresponding works, there are also some limitations in them. The strategy of spellchecking is useless on word-level and sentence-level adversarial examples(e.g. the work of [46] in IX). Adversarial training exists an over-fitting problem and it will not work when faced with a new attack method. Model enhancing may be the main defense strategy in the future, but it is still being explored. There are many difficulities such as choice of loss function and modification of model's structure.

VI. TESTING AND VERIFICATION AS CRITICAL AREA AGAINST ADVERSARIAL ATTACKS

The current security situation in DNNs seems to fall into a loop. New adversarial attacks are proposed and then followed by new countermeasures which will be subsequently broken [90]. Hence, the formal guarantees on DNNs behavior are badly needed. But it is a hard work and nobody can ensure that their methods or models are perfect. Recently, what we could do is to make the threat of adversarial attacks as little as possible. The technology of testing and verification helps us deal with the problems from another point of view. By the means of it, people can know well about the safety and reliability of systems based on DNNs and determine whether to take measures to address security issues or anything else.

In this section, we introduce recent testing and verification methods for enhancing robustness of DNNs against adversarial attacks. Even though these methods reviewed below have not applied in text, but the ideas of finding defects and improving robustness can use for reference. We hope someone interested in this aspect can be inspired and comes up with a good defense method used in text or all areas.

¹³https://azure.microsoft.com/zh-cn/services/cognitive-services/spell-check/

A. Testing methods against adversarial examples

As increasingly used of DNNs in security-critical domains, it is very significant to have a high degree of trust in the models accuracy, especially in the presence of adversarial examples. And the confidence to the correct behavior of the model is derived from the rigorous testing in a variety of possible scenarios. More importantly, testing is helpful for understanding the internal behaviors of the network, contributing to the implementation of defense methods. We will survey the testing techniques in DNNs from two aspects. They are testing criteria and test case generation.

1) Test case generation: Pei et al. [91] designed a white-box framework DeepXplore to test real-world DNNs with the metric of neuron coverage and leveraged differential testing to catch the differences of corresponding output between multiple DNNs. They generated adversarial examples in order to have a high neuron coverage. In this way, DeepXplore could trigger the majority logic of the model to find out incorrect behaviors without manual efforts. It performs well in the advanced deep learning systems and finds thousands of corner cases which make the systems crash. However, the limitation of DeepXplore is that if all the DNNs make incorrect judgement, it is hard to know where is wrong and how to solve it.

Wicker et al. [92] presented a feature-guided approach to test the resilience of DNNs in black-box scenario against adversarial examples. They treated the process of generating adversarial cases as a two-player turn-based stochastic game with the asymptotic optimal strategy based on Monte Carlo tree search (MCTS) algorithm. In this strategy, there is an idea of reward for accumulating adversarial examples found over the process of game play. Via these findings, the authors can evaluate the robustness against adversarial examples.

Besides the feature-guided testing [92], Sun et al. [93] presented DeepConcolic to evaluate the robustness of well-known DNNs, which was the first attempt to apply traditional concolic testing method for these networks. DeepConcolic iteratively used concrete execution and symbolic analysis to generate test suit to reach a high coverage and discovered adversarial examples by a robustness oracle. The authors also compared with other testing methods [91], [94]–[96] which was in table III. In terms of input data, DeepConcolic could start with a single input to achieve a better coverage or used coverage requirements as inputs. In terms of performance, DeepConcolic could achieve higher coverage than DeepX-plore, but run slower than it.

2) Testing criteria: Different from single neuron coverage [91], Ma et al. [94] proposed a multi-granularity testing coverage criteria to measure accuracy and detect erroneous behaviors. They took advantage of four methods [8], [28], [30], [34] to generate adversarial test data to explore the new internal states of the model. The increasing coverage shows that the larger the coverage is, the more possible the defects are to be checked out. Similar work is done by Budnik et al. [97] to explore the output space of the model under test via an adversarial case generation approach.

In order to solve the limitation of neuron coverage, Kim et al. [98] proposed a new test adequacy criterion called Surprise Adequacy for Deep Learning Systems(SADL) to test DNNs.

This method measures the different behaviors between inputs and training data, which is the foundation of the adequacy criterion. Experimental results show that this method can judge whether an input is adversarial example or not. In the other hand, it can also improve the accuracy of DNNs against adversarial examples by retraining.

B. Verification methods against adversarial examples

Researchers think that testing is insufficient to guarantee the security of DNNs, especially with unusual inputs like adversarial examples. As Edsger W. Dijkstra once said, testing shows the presence, not the absence of bugs. Hence, verification techniques on DNNs are needed to study more effective defense methods in adversarial settings.

Pulina et al. [99] are the first to develop a small verification system for a neural network. Since then, related work appears one after another. But verification of machine learning models robustness to adversarial examples is still in its infancy [100]. There is only a few researches on related aspects. We group them into three aspects which are search based, global optimisation and over-approximation approach. These works will be introduced in the following part.

1) Global optimisation approach: Katz et al. [101] presented a novel system named Reluplex to verify DNNs based on Satisfiability Modulo Theory (SMT) [102] solver. They transform the verification into the linear optimization problems with Rectified Linear Unit (ReLU) [103] activation functions. Reluplex can be used to find adversarial inputs with the local adversarial robustness feature on the ACAS Xu networks, but it fails on large networks on the global variant.

For ReLU networks, a part of researches regard the verification as a Mixed Integer Linear Programming (MILP) problem such as Tjeng et al. [104]. They evaluated robustness to adversarial examples from two aspects of minimum adversarial distortion [105] and adversarial test accuracy [106]. Their work is faster than Reluplex with a high adversarial test accuracy, but the same limitation was that it remained a problem to scale it to large networks.

Unlike existing solver-based methods (e.g. SMT), Wang et al. [107] presented ReluVal which leveraged interval arithmetic [108] to guarantee the correct operations of DNNs in the presence of adversarial examples. They repeatedly partitioned input intervals to find out whether the corresponding output intervals violated security property or not. By contrast, this method is more effective than Reluplex and performs well on finding adversarial inputs.

2) Search based approach: Huang et al. [109] proposed a new verification framework which was also based on SMT to verify neural network structures. It relies on discretizing search space and analyzing output of each layer to search for adversarial perturbations, but the authors find that SMT theory is only suitable for small networks in practice. On the other hand, this framework is limited to many assumptions and some of functions in it are unclear.

Different from other works, Narodytska et al. [110] verified the secure properties on the binarized neural networks(BNNs) [111]. They leveraged the counterexample-guided search [112]

TABLE III: Comparison with other four methods

_	DeepConcolic [93]	DeepXplore [91]	DeepGauge [94]	DeepTest [95]	DeepCover [96]
Type of input	normal data or coverage requirements	normal data	normal data	normal data	normal data
Number of input*	single or multiple	multiple	multiple	multiple	multiple
Method of test generation*	concolic	optimisation-based approach	gradient-based approach	greedy search	symbolic execution

^{*} Values of these two items come from the work in [93].

procedure by exact Boolean encoding they proposed and modern SAT solvers to study models' robustness and equivalence. The inputs of the models are judged whether they are adversarial examples or not by two encoding structures Gen and Ver. It can easily find adversarial examples for up to 95 percent of considered images on the MNIST dataset. But this method also works on the middle-sized BNNs rather than large networks.

3) Over-approximation approach: Gehr et al. [113] introduced abstract transformers which could get the outputs of layers in convolutional neural network with ReLU, including fully connected layer. The authors evaluated this approach on verifying robustness of DNNs such as pre-trained defense network [114]. Results showed that FGSM attack could be effectively prevented. They also did some comparisons with Reluplex on both small and large networks. The stare-of-the-art Reluplex performed worse than it in verification of properties and time consumption.

Weng et al. [115] designed two kinds of algorithm to evaluate lower bounds of minimum adversarial distortion via linear approximations and bounding the local Lipschitz constant. Their methods can be applied into defended networks especially for adversarial training to evaluate the effectiveness of them.

VII. DISCUSSION

In the previous sections, detailed description of adversarial texts on attack and defense are given to enable readers to have a faster and better understanding of this respect. Next, we present more general observations and challenges on this direction based on the aforementioned contents.

A. General observations of adversarial text

Reasons by using misspelled words in some methods: The motivation by using misspelled words is similar to that in image, which aims at fooling target models with indiscernible perturbations. Some methods tend to conduct character-level modification operations which highly result in misspelled words. And humans are extremely robust against that case in written language [116].

Transferability in black-box scenario: When the adversaries have no access including probing to the target models, they train a substitute model and utilize the transferability of adversarial examples. Szegedy et al. [7] first found that adversarial examples generated from a neural network could also make another model misbehave by different datasets. This reflects the transferability of the adversarial eample. As a result, adversarial examples generated in the substitute

model are used to attack the target models while models and datasets are all inaccessible. Apart from that, constructing adversarial examples with high transferability is a prerequisite to evaluate the effectiveness of black-box attacks and a key metric to evaluate generalized attacks [117]. All the adversarial examples are facing this challenges.

B. Existing problems

Difficulties on adversarial attacks and defenses: There are many reasons for this question and one of the main reasons is that there is not a straightforward way to evaluate proposed works no matter attack or defense. Namely, the convincing benchmarks do not exist in recent works. One good performed attack method in a scenario may failed in another or new defense will soon be defeated in the way beyond defenders' anticipation. Even though some works are provably sound, but rigorous theoretical supports are still needed to deal with the problem of adversarial examples.

Problem on evaluating the performance of attack or defense: Recently, most of researches evaluate their performances of adversarial attacks by success rate or accuracy. Only a few works [24], [45] take scale and efficiency into consideration, even though they just list the consumed time by attacks. A question whether there is a relationship among the scale of dataset, consumed time and success rate of adversarial attacks is unknown. If there is such a relationship, the tradeoff of these three aspects may be a research point in the future work. The similar situation also happens in defense.

C. Challenges

Without a universal approach to generate adversarial examples: Because the application of adversarial examples in text rose as a frontier in recent years, the methods of adversarial attacks were relatively few, let alone defenses. The another reason why this kind of method do not exist is the language problem. Almost all recent methods use English datasets and the generated adversarial examples may be useless to the systems with Chinese [118] or other language datasets. Thus, there is not a universal approach to generate adversarial examples. But in our observations, many methods mainly follow a two-step process to generate adversarial examples. The first step is to find important words which have significant impact on classification results and then homologous modifications are used to get adversarial examples.

The lack of a beachmark and toolbox for textual adversarial examples researches: Various methods have been proposed to study adversarial attacks and defenses in text, but there is not a beachmark for them. Researchers use different

datasets(in II-D) in their works, resulting in the difficulity of comparing the the advantages and disadvantages of these methods. Meanwhile, this also affects the selection of metric measures. Currently, there do not have an exact statement that which metric measure is better in a situation and why it is more useful than others. Even though comparisons have been done in Textbugger [45], metric measure in this work may be suitable for it and ineffective in other works.

On the other hand, it is also short of an open source toolbox(e.g. AdvBox [119] and cleverhans [120] in image) for textual adversarial examples researches. These two toolboxes integrate existing representative methods of generating adversarial images. People can easily do some further studies by them, which reduce time consumption for repetition and promote the development of research in this field.

VIII. CONCLUSION AND FUTURE DIRECTIONS

This article presents a survey about adversarial attacks and defenses on DNNs in text. Even though DNNs have the high performance on a wide variety of NLP, they are inherently vulnerable to adversarial examples, which lead to a high degree concern about it. This article integrates almost existing adversarial attacks and some defenses focusing on recent works in the literature. From these works, we can see that the threat of adversarial attacks is real and defense methods are few. Most existing works have their own limitations such as application scene, constraint condition and problems with the method itself. More attention should be paid on the problem of adversarial example which remains an open issue for designing considerably robust models against adversarial attacks.

Further researches that we can do on adversarial examples may be as follows: As an attacker, designing universal perturbations to catch better adversarial examples can be taken into consideration like it works in image [31]. A universal adversarial perturbation on any text is able to make a model misbehave with high probability. Moreover, more wonderful universal perturbations can fool multi-models or any model on any text. On the other hand, the work of enhancing the transferability of adversarial examples is meaningful in more practical back-box attacks. On the contrary, defenders prefer to completely revamp this vulnerability in DNNs, but it is no less difficult than redesigning a network and is also a long and arduous task with the common efforts of many people. At the moment defender can draw on methods from image area to text for improving the robustness of DNNs, e.g. adversarial training [114], adding extra layer [121], optimizing crossentropy function [122], [123] or weakening the transferability of adversarial examples.

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IX. APPENDIX A

TABLE IV: Instances of some methods in section 3

Method	Instance of adversarial example
Wictiou	original: This film has a special place in my heart. positive
DeepWordBug [24]	modified: This film has a special place in my herat, positive
	original: I wouldn't rent this one even on dollar rental night. negative
Papernot et al. [51]	modified: Excellent wouldn't rent this one even on dollar rental night. positive
	original: A sprawling, overambitious, plotless comedy that has no dramatic center. It was probably
Samanta et al. [47]	intended to have an epic vision and a surrealistic flair (at least in some episodes), but the separate stories are never elevated into a meaningful whole, and the laughs are few and far between. Amusing ending though. negative modified: A sprawling, overambitious, plotless funny that has no dramatic center. It was probably
	intended to have an epic vision and a surrealistic flair (at least in some episodes), but the separate stories are never elevated into a greatly whole, and the laughs are little and far between amusing ending though. positive
iAdv-Text [44]	original: The essence of this film falls on judgments by police officers who fortunately ethical and moral men act on situations within situations in a city with a super abundance of violence and killing Good compound interacting story lines and above average characterizations. positive modified: The essence from THIS film falls on judgments by police officers who fortunately ethical and moral men act on situations within situations in a city with a super abundance of violence and killing Good compound interacting story lines and above average characterizations. negative
Gong et al. [48]	original: FED EXPECTED TO ADD RESERVES The Federal Reserve will enter the government securities market to supply reserves via either a large round of customer repurchase agreements or by overnight or possibly four-day system repurchases, economists said. [] tax payments swell Treasury balances at the Fed. Fed funds hovered at 6-3 / 4 pct after averaging 6. 80 pct yesterday. Label 2 modified: FED EXPECTED TO ADD RESERVES The Federal Reserve II enter the government securities market able supply reserves via either a large round of customer repurchase agreements or directed overnight or possibly four-day system repurchases books economists said. [] tax payments surf Treasury balances at the future well Fed funds hovered at 6-3 Category 4 Q2 after averaged 680 pct yesterday. Label 3
TextBugger [45]	original: reason why requesting i want to report something so can ips report stuff, or can only registered users can? if only registered users can, then i 'll request an account and it 's just not fair that i cannot edit because of this anon block shit c'mon, fucking hell. Toxic modified: reason why requesting i want to report something so can ips report stuff, or can only registered users can? if only registered users can, then i 'll request an account and it 's just not fair that i cannot edit because of this anon block shti c'mon, fucking helled. Non-toxic
Text-fool [46]	original: The Old Harbor Reservation Parkways are three historic roads in the Old Harbor area of Boston. They are part of the Boston parkway system designed by Frederick Law Olmsted. They include all of William J. Day Boulevard running from Castle Island to Kosciuszko Circle along Pleasure Bay and the Old Harbor shore. The part of Columbia Road from its northeastern end at Farragut Road west to Pacuska Circle (formerly called Preble Circle). 87.3% Building modified: The Old Harbor Reservation Parkways are three historic roads in the Old Harbor area of Boston. Some exhibitions of Navy aircrafts were held here. They are part of the Boston parkway system designed by Frederick Law Olmsted. They include all of William J. Day Boulevard running from Castle Island to Kosciuszko Circle along Pleasure Bay and the Old Harbor shore. The part of Columbia Road from its northeastern end at Farragut Road west to Pacuska Circle formerly called Preble Circle. 95.7% Means of Transportation
HotFlip [43]	original: South Africas historic Soweto township marks its 100th birthday on Tuesday in a mood of optimism. 57% World modified: South Africas historic Soweto township marks its 100th birthday on Tuesday in a moo P of optimism. 95% Sci/Tech
Alzantot et al. [49]	premise: A runner wearing purple strives for the finish line. original: A runner wants to head for the finish line. 86%Entailment modified: A racer wants to head for the finish line. 43%Contradiction

X. APPENDIX B

TABLE V: Other datasets used in research works

TABLE V. Other datasets used in research works						
dataset	application in the work	task	source			
Enron Spam	[24]	Spam E-mail Detection	-			
Twitter dataset	[47]	gender prediction	[124]			
Elec ¹	[44]	sentiment analysis	[125]			
RCV1 ¹	[44]	classification	[125]			
FCE-public	[44]	grammatical error detection	-			
Stanford Sentiment Treebank	[43], [72]	sentiment analysis				
Stanford Question Answering Dataset (SQuAD) ²	[66]	attacking reading system	[126]			
MultiNLI ³	[50]	attacking Natural Language Inference system	[127]			
MovieQA dataset ⁴	[75]	attacking reading system	[128]			
Customer review dataset(CR) ⁵	[46]	sentiment analysis	-			
Reuters ⁶	[48]	classification	-			

http://riejohnson.com/cnn_data.html

https://stanford-qa.com

http://www.nyu.edu/projects/bowman/multinli/

http://movieqa.cs.toronto.edu/leaderboard/

https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

http://www.daviddlewis.com/resources/testcollections/reuters21578/