A Survey in Adversarial Defences and Robustness in NLP

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In recent years, it has been seen that deep neural networks are lacking robustness and are likely to break in case of adversarial perturbations in input data. Strong adversarial attacks are proposed by various authors for computer vision and Natural Language Processing (NLP). As a counter-effort, several defense mechanisms are also proposed to save these networks from failing. In contrast with image data, generating adversarial attacks and defending these models is not easy in NLP because of the discrete nature of the text data. However, numerous methods for adversarial defense are proposed of late, for different NLP tasks such as text classification, named entity recognition, natural language inferencing, etc. These methods are not just used for defending neural networks from adversarial attacks, but also used as a regularization mechanism during training, saving the model from overfitting. The proposed survey is an attempt to review different methods proposed for adversarial defenses in NLP in the recent past by proposing a novel taxonomy. This survey also highlights the fragility of the advanced deep neural networks in NLP and the challenges in defending them.

CCS Concepts: • Computer systems organization \rightarrow Embedded systems; Redundancy; Robotics; • Networks \rightarrow Network reliability.

Additional Key Words and Phrases: Adversarial attacks, Adversarial defenses, Perturbations

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1 INTRODUCTION

In recent times, deep learning algorithms in natural language processing (NLP) have taken the area to a new level. The proposed solutions for natural language processing have already started beating human accuracy. Deep learning has transformed the field by learning from the huge amount of available data and presenting a representation of the language which can be used for various downstream tasks. NLP includes algorithms that process and manipulate human language. With the use of deep neural networks, NLP models are automatically learning to represent language

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and solve a wide range of tasks. Some of these tasks are text classification, natural language inferencing, sentiment analysis, etc, which are showing exceptional accuracy when solved with deep neural networks. The other tasks which involve natural language processing are machine translation, named entity recognition, malware detection, reading comprehension, textual entailment. A quintessential NLP pipeline using deep neural networks, learns the word representation in the text and then learns the contextual details in that sentence. This type of language modeling can be used for a variety of tasks such as classification of a sentence, translation, question answering using a Convolutional Neural Network (CNN) or Recurrent Neural Networks (RNN) based learning model. Finding feature representations for natural language text is an essential part of the pipeline. There are various methods proposed covering hand-crafted features and auto-encoded features using recent deep neural networks.

However, despite the advancement, deep neural network lack interpretability and work as a black box. There is a limited understanding of the functionality of these networks and little explanation for their high performance. Even with exceptional accuracy and human-like performance, these networks are vulnerable to attacks and fail in terms of performance with the slightest perturbations in inputs. Of late, various adversarial attacks for deep neural networks have been proposed for computer vision and natural language processing, raising the question of the robustness of high-performing DNN models. These adversarial attacks insert perturbation in the input samples which are not detectable by humans that cause the model to fail with a high confidence value. Adversarial attacks can be a high-security threat for the applications such as malware and spam detection or biometrics. In NLP, these attacks include substitution, insertion, deletion, swapping of different words/characters in a sentence, or finding neighborhood word embedding to introduce perturbations in the input.

Adversarial attacks are broadly divided into two categories: black box and white box attacks [133] based on model access. Based on the granularity of design of attack, they are further divided into 4 categories: character level, word level, sentence level, and multi-level attacks [36, 108, 133], which include perturbations such as insertion, deletion, flipping, swapping of character or words in a sentence. These methods generate adversaries in a white box or black-box manner. In the white box attacks, the attacker has complete accessibility of the model's parameters and perturbations are generated using gradient-based schemes, perturbing the word embeddings of input text. In contrast white-box attacks, black box attacks do not have access to the model's parameters and they attack the model by accessing input and output and generating a replica of the model. Adversaries are generated by modifying the input text using concatenation with another piece of text, word/character level editing by insertion, deletion, swapping, paraphrasing the sentence, or generating similar text using GANs. Black box attacks, acquire model's parameters by repeatedly querying the model and training a replica/substitute model once the parameters are acquired. Later they attack the substitute model by training it with perturbed data.

However, generating perturbations in textual data is more difficult than images, given the discrete nature of the data. Despite the difficulty, stronger and imperceptible adversarial attacks are proposed posing a high threat to the security of the deep neural networks. Hence, several defense mechanisms are proposed in recent years as a counter-effort for adversarial attacks in NLP. The overwhelming amount of work in the last few years for adversarial defenses has given good competition to the novel adversarial attack algorithms and considerably improved the robustness of existing deep learning models. These defense mechanisms are also used as regularization techniques to avoid overfitting, and making the model more robust. Adversarial defense methods in NLP can be broadly divided into 3 categories: Adversarial Training based, Perturbation control based, Robustness by certification based methods. A large amount of work follows an adversarial training scheme and methods are further categorized on the basis of the use of adversarial training in the defense pipeline. These methods categorize as Adversarial training by data augmentation, Adversarial training Manuscript submitted to ACM

as regularization technique, GAN based adversarial training, Virtual adversarial training (VAT), human in the loop. Perturbation control-based methods are also further categorized as Perturbation identification and correction and Perturbation direction control. Robustness by certification is the third category of methods that provide a certificate of robustness for adversarial attacks. A few of the methods do not fall into any of the above-stated categories, hence they are classified under miscellaneous methods. In the next section, the goals of this survey paper are highlighted, which make it different from the previous surveys.

1.1 Goals of this survey paper

In this articles, we reviewed numerous methods of adversarial defenses in NLP, proposed in the recent years. The key goals of this survey are as listed below:

- Providing a comprehensive review for adversarial defense schemes in NLP by covering schemes for different NLP tasks and bringing the attention of the community to this emerging area.
- Proposing novel taxonomy for adversarial defense methods in natural language processing for various tasks.
- Accentuating the importance of defense methods for adversarial attacks and as a regularization scheme in deep neural networks.
- Paving the path for future work in this area by highlighting the open issues.

Various survey papers are proposed in past for adversarial attacks on deep neural networks for computer vision and natural language processing. In the work [118], authors have presented an exhaustive survey on adversarial attacks on deep neural networks for images, text, and graphs. They have proposed a novel taxonomy by keeping the focus on adversarial attacks on images, graphs, and text by covering a wide range of methods. Another work, [2], has proposed taxonomy on different adversarial attacks and defenses on various algorithms in computer vision such as image classification, image segmentation, object detection, robotic vision, and visual question answering. Authors in [76] presented a brief survey on general adversarial attack methods in deep learning while the work in [48] has briefly reviewed the attack and defense methods in images and text data. Also, work in [8, 10] presented methods in adversarial attacks and defenses for various computer vision algorithms. In contrast with previous work, authors in [129], proposed a taxonomy for universal adversarial attacks by covering universal perturbations for images classifiers and briefly discussing attacks on text and audio classification models. All the above-discussed survey papers, presented adversarial attacks while keeping the attack algorithm for images as a pivot point and briefly discussing attack algorithms in NLP. However, the proposed surveys in [36, 108, 133] have extensively reviewed adversarial attack algorithms for various tasks of natural language processing while briefly discussing some defense methods. However, the importance of adversarial defense algorithms is self-evident, given the large amount of work in this direction in recent years. Hence, this survey paper is an attempt towards bridging this gap making it different from the previous survey papers in this area, focusing exclusively on the adversarial defense methods in natural language processing. In this paper, we propose a novel, detailed taxonomy for adversarial defense mechanisms in NLP while highlighting the importance of defense methods. It also discusses some open issues in this area while presenting future work to the community.

2 VARIOUS NATURAL LANGUAGE PROCESSING TASKS

2.1 Text classification

Text classification is an NLP task, which categorizes text data into several classes. Being the most fundamental task of NLP, it covers a wide range of problems such as sentiment analysis, natural language inferencing, malware detection,

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spam filtering, topic labeling, and many more. The typical pipeline of text classification method includes generating a contextual representation of the input text and choosing the right classifier [1, 49, 61]. This pipeline can also include preprocessing and intermediate steps such as tokenization, lemmatization, stemming and dimensionality reduction.

2.2 Named Entity Recognition (NER)

Named Entity Recognition (NER) is a task to identify the rigid entities (proper nouns) in a text such as organizations, person, location, quantity, etc. NER in textual data is a "name for someone or something", [57, 100, 122] making it a key component for question answering, information retrieval, relation extraction, text summarization, machine translation. NER techniques fall into four major categories, (i) Rule based NER, which works on handcrafted rules (ii) Unsupervised learning approaches, which works on unsupervised learning approaches such as clustering based on of contextual similarity (iii) Supervised learning approaches with feature engineering, where word level features are extracted and classification is done with conventional classification schemes using HMM, SVM or other classifiers (iv) Deep learning based approaches.

2.3 Machine comprehension and Question Answering

Question answering is a well explored task in NLP literature, which attempts to build systems that generates automatic answers for the questions for a given context. This task has applications in developing chatbots, dialogue generation systems. A neural network is trained for the large set of context, questions and answers to learn a relationship among them. The trained network will be able to answer for the unseen question for a given context. Dataset such as SQuAD [83] is proposed in this direction containing large set of context paragraphs, questions and respective answers.

2.4 Automatic summarization

Automatic text summarization is an NLP task that aims to create a shorter text document out of a larger piece of text document. Text summarization is a challenging task that requires knowledge from the entire text document and rewrite it in a condensed manner using the sentences available in the document or using a different set of vocabulary. Depending upon the size of the available training data and requirement, the text summarization task can be done in two ways: Extractive summarization and Abstractive summarization.

2.5 Machine translation

Machine translation is the task of converting text from a source language to a target languages. The text can be either in the form of sentences or documents. MT systems are generally modeled as monolingual or multilingual models based on the (i) availability of large training corpus (ii) similarities between languages. [5, 73, 84].

2.6 Dialogue understanding

An automatic dialogue generation system is another NLP task and extremely important in intelligent systems. Its development aims towards building a human like conversation system where responses are generated automatically. These systems can be task oriented or open dialogue generation systems. The task oriented systems are targeted towards querying for a specific domain, such as transportation, restaurant, shopping websites. The open dialogue generation systems are built for open ended conversations, for example, everyday conversation between two people. Dialogue generation systems evolved in three phases which included rule based systems, retrieval based systems and neural generative conversation systems [99]. The quality of the generation system depends upon the intelligence of Manuscript submitted to ACM

the system as the generated response should align with the previous statement, i.e. be consistent with the context of the conversation and should be in line with the targeted domain if any.

2.7 Question generation

Automatic question generation is another NLP task that is targeted to assist educational assessment, and generate questions automatically from a given textual document. In order to reduce manual labor and time, question generation systems have proven to be an important NLP task. These questions should be articulating, and answerable from the given piece of text and can be subjective or objective type [16]. These systems have their applications in Massive Open Online Courses (MOOC), healthcare systems, chatbots, search engines etc [75].

2.8 Part-of-Speech tagging

Part-of-speech tagging (POS) is a task which is similar to a classification of all the tokens into a predefined word category such as verb, noun, adjective etc. It provides a category tag to each word in the available text. POS tagging methods are further classified as as rule based, stochastic or statistical, transformation and HMM based. Rule based taggers are knowledge driven taggers and they work on a large list of hand written rules for tagging the words. The stochastic methods are frequency or probability based, where probability of a word falling into a certain category is used for disambiguation and requires training with a corpus. Transformation based POS tagging is a hybrid of both rule based and stochastic based tagging in which a small set of rules for POS tagging are automatically learned from the data and tagging is transformed in every cycle. In HMM based POS tagging, a sequence of most probable sequence of POS tags are found for a given sequence of input text, modeled using Hidden Markov Model (HMM).

3 A GENERAL OVERVIEW OF ADVERSARIAL ATTACKS

Adversarial attack is a process of intentionally breaking a deep neural network by generating perturbed inputs for the network causing failure of the model. These perturbations are imperceptible to human but efficient enough to fool a neural network. In case of image classification models, multiple experiments have been performed with input perturbations, for example addition of noise, tweaking of pixels, use of patches, addition of watermarks, etc. In case of adversarial attacks in NLP, numerous adversarial perturbations are proposed. These perturbed inputs involve, character, word or sentence level perturbations by deletion, insertion, swapping, flipping, use of synonyms, concatenation with characters or words, insertion of numeric or alpha-numeric characters, etc. However, generating adversarial perturbation for text data is relatively difficult as compared to image data, since tweaking a few pixels are less perceptible to human than changing a character or word in a sentence. On the basis of motivation, adversarial attacks are classified into two categories: Targeted attacks and Non-targeted attacks. Targeted attacks are the perturbations specially designed to make a specific model misclassify inputs to a specific class. While, non-targeted attacks just push the classifier boundary such that the model starts misclassifying the inputs. On the basis of access to model's parameters the adversarial attacks are classified as white box and black box attacks. In this section we briefly discuss the state of the art adversarial attacks for natural language processing tasks algorithms.

3.1 Adversarial attacks in deep learning

The goal of an adversarial attack is to generate such perturbations for input \mathbf{x} belonging to class C_1 , such that, \mathbf{x} is wrongly classified to class C_2 with high confidence value. For a multi-class classification algorithm, for k input classes $i = C_1, C_2, \cdot, C_k$, the perturbed input is \mathbf{x}' and \mathbf{f}_k is the classification boundary, where \mathbf{x} belongs to class C_j , and C_{target} Manuscript submitted to ACM

is the target class after attack, then:

$$f_{target}(\mathbf{x}') > f_j(\mathbf{x}')$$
 (1)

Hence, adversarial attacks can be formally defined as an optimization problem for \mathbf{x} as:

$$\begin{aligned} & & \underset{x}{\text{minimize}}(||x'-x||) \\ subject \ to \ & \underset{j \neq target}{\text{max}} \{f_j(\mathbf{x'})\} - f_{target}(\mathbf{x'}) \leq 0(3.1) \end{aligned}$$

The inequality defined in 1 represents the goal of any adversarial attack which push the perturbed input \mathbf{x}' to a desired class, rather its actual class. Hence the Equation 3.1 defines the adversarial attack as an optimization problem, where the goal is to minimize the perturbation magnitude to make the perturbations less perceptible and making sure it get classified to the target class, C_{target} .

3.2 Adversarial attacks in NLP

In the recent years ample amount of adversarial attacks methods are proposed specifically for NLP tasks. Considering the fact that adversarial examples of images are not same as adversarial examples of text, the attack schemes in computer vision are not suitable for directly adopting for NLP. Hence several attack schemes which try to modify the text data while making them less perceptible by human, are proposed in literature. In general these methods try to modify the text data at word, character or sentence levels. The next sections highlights some of these attack schemes in NLP.

3.2.1 Character level adversarial attacks. Character level attacks perturb the input sequences at a character level. These operations include insertion, deletion, swapping of characters in a given input sequence. Despite the fact, these attacks are quite effective, they can easily be detected with a spell checker mechanism. One of the techniques used in character level attacks is adding natural and synthetic noise to the inputs [6]. For natural noise authors collected natural spelling mistakes and used them to replace words in inputs. For synthetic noise they swap or randomised characters (except the peripheral) and replace a character with its neighbouring character on the keyboard. Adding punctuation marks, increasing or removing the space between characters is another technique to add synthetic noise in the text inputs. For example, in DeepWordBug [24], in black-box setting they use a two step process as they don't have access to the gradients. The first step involves finding the most important words in the sentence which would be the target words to perturb. In the second stage perturbations are added to these select words by the above mentioned operations. Edit distance is further used in order to keep track of readability of the generated sentences. Another example proposed is, TextBugger [56] in both black-box and white-box settings where the white-box attack is a two step process. The first process involves finding the most important word with the help of jacobian matrix and later use 5 different options to add bugs. These 5 include insert, delete, swap, substitution with visually similar word, substitution with semantically similar word. In black-box setting they propose a 3 step process where first the most important sentence is identified, then they find the important words to generate 5 bugs and select the optimal from that. The best adversary is chosen based on how optimal they are for reducing accuracy. Along the same line, [33] has showed that just by adding extra "." (period), spaces between words, "Perspective" API created by Google gave lesser toxicity scores for the words perturbed in this fashion.

- 3.2.2 Word level adversarial attacks . Word level attacks perturb the whole word instead of a few characters. Common operations include insertion, deletion and replacement. Word level attacks can be classified into Gradient based and Importance based strategies on the basis of the perturbation schemes used:
 - In gradient based methods, the gradient is monitored for every input perturbation. Whenever the probability of classification is reversed that particular perturbation is chosen. This is inspired from the Fast Gradient Sign Method (FGSM) [28] used for adversarial attacks in computer vision models. If the classification probability changes the class then the perturbation is considered effective. Another way of using the gradient based method is to find the important words using FGSM and then employ insertion, deletion and replacement strategy on top of them [91]. Liang et al. [64] used a similar approach where they created adversaries by backpropagating for the cost gradients.
 - In importance based methods it is believed that the words with highest or lowest attention scores play an important role in the predictions of self-attention models. Hence these are chosen as the possible vulnerable words. These words are greedily perturbed until the attack is successful. One of the methods "Textfooler" [41] uses a similar strategy where important words are greedily replaced with synonyms until the classification label changes.
 - In replacement based methods words are randomly replaced with semantically and syntactically similar words. Here the replacement for words is obtained by using word vectors like GloVe [78] or thought vectors. Kuleshov et al. [50] used thought vectors to map sentences to vectors and replaced one word from it's nearest neighbours which had the best effect on the objective function. Alzantot et al. [3] used GloVe vectors to randomly replace words that fit in the context of the sentence.
- 3.2.3 Sentence level adversarial attacks . These attacks can be considered as manipulation of a group of words together instead of individual words in the sentence. Moreover, these attacks are more flexible, as a perturbed sentence can be inserted anywhere in the input, as long as it is grammatically correct. These attack strategies are more commonly used in tasks such as Natural Language Inferencing, Question-Answering, Neural Machine Translation, Reading Comprehension, rather text classification. For sentence level attacks novel techniques such as ADDSENT, ADDANY are introduced in literature in recent years with variants such as ADDONESENT, ADDCOMMON [38, 112]. Some of the sentence based attacks are created such that they don't affect the original label of the input and used as a concatenation in the original text. In these cases, the correct behaviour of the model is to retain the original output and the attack is successful if the model changes the output/label. In another set of methods, GAN based sentence level adversaries are created which are grammatically correct and semantically close to the input text [136]. Another example "AdvGen" [12] is introduced which is an example of gradient based white-box method and used in neural machine translation models. They used greedy search guided with the training loss to create the adversarial examples while retaining semantic meaning. Another work in this direction, [37] proposed syntactically controlled paraphrase networks (SCPNS) for adversarial example generation where they used encoder-decoder network to generate examples with a particular syntactic structure.
- 3.2.4 Multi-level adversarial attacks . Multi-level attacks schemes consist of a mixture of some of methods discussed above. These attacks are used to make the inputs more imperceptible to humans and to have a higher success rate. Hence, computationally more intensive and more complicated techniques such as FGSM have been used to create adversarial examples. In one such method they create hot training phrases and hot sample phrases. In this method the

training phrases focus on what and where to insert, modify or delete by finding hot sample phrases in white and black box settings where deviation score is used to find the importance of the words [65]. Another example used "HotFlip" [21] which is a character level white-box attack swapping characters based on the gradient computation. Similar to many other techniques, TextBugger [56] tries to find the most important word to perturb using a Jacobian matrix in a white box setting. The important words after identification are used for creating adversaries by inserting, deleting and swapping along with Reinforcement Learning methods with an encoder-decoder framework.

4 TAXONOMY OF ADVERSARIAL DEFENSES

In this section, we first introduce the categories of defense methods on textual deep learning models and then highlight the state-of-the-art research works, aiming to identify the most promising advances in recent years. Adversarial defense strategies refers to the group of methods which are designed to protect a deep neural network from failing by adversarial attacks. The defense methods are developed to increase the robustness of the neural networks by creating an adversarial attack kind of environment for the neural network while training them or adding special mechanisms to detect the adversarial inputs. Another solution to enhance the robustness of the network is by creating a region around the input space and making it perturbation resistant. Hence the adversarial defense methods in NLP are broadly designed using 3 major strategies: providing resembling environment during training of the neural network, by identifying malicious inputs in training using special methods and correcting them and by certifying the robust region of the inputs for the network.

In this article, we group the state of the art defense methods in NLP into 3 major categories, adversarial training based methods, perturbation control based methods, certification based methods, and some miscellaneous schemes. The methods that do not follow any of the first three schemes are grouped under miscellaneous category.

First group of methods are based on (i) Adversarial Training, as defense mechanism against adversarial attacks. The different class of methods grouped under this category are: Adversarial training by data augmentation, Adversarial training as regularization technique, GAN based adversarial training, virtual adversarial training, and robustness by human in loop. The second group of methods work on the principle of (ii)perturbation control, and different class of methods grouped under this category are: Perturbation identification and correction and Perturbation direction control. The third category of methods follow schemes which provide a (iii)certification of robustness to the model for defending them against adversarial attacks. The last category (iv) miscellaneous is a mixture of several methods which do not follow the above mentioned groups of methods.

5 ADVERSARIAL TRAINING BASED DEFENSES

Adversarial training was first introduced in the work proposed in [27]. It is a method of defending against adversarial attacks by introducing adversarial examples in the training data. The strength of adversarial examples decides the final robustness and generalization achieved by the model. Adversarial training is further divided into sub-groups on the basis of the strategies used for augmenting the data such as word or character level modification, manual or automatic generation of adversarial or adversaries generated by concatenation. While some of the methods performed adversarial training by generating a set of adversarial examples and inserting them in the training dataset, other methods used adversarial training as regularizer by introducing perturbation within the network. In this section some of the work in literature will be highlighted which propose to use data augmentation for generating adversarial examples for adversarial training.

5.1 Adversarial training by data augmentation

Adversarial training by augmenting the input data or generating adversarial example is the simplest and most commonly used technique among the adversarial defense methods. A set of adversarial data is generated with perturbation scheme and injected into model training. In literature, several data augmentation techniques are proposed to generate adversarial examples. For data augmentation, a general strategy suggest to find the most important words, characters in the given input text that affect the output the most and manipulate the input data by flipping, inserting, deleting, swapping those parts of sentences. Concatenating a piece of text in the input by finding the most appropriate position is another strategy used in literature.

There are methods in literature which propose to modify words or word embeddings in the input text for generating adversarial examples to augment data. In this line the work proposed in Textbugger [56] presents adversarial training by data augmentation for text classification in both white box and black box settings by generating utility preserving adversarial examples. In white box, important words for perturbations are found using jacobian of classifier and then optimal perturbations are found by searching the nearest neighbour space in word2vec embeddings. In black box setting data is augmented by finding important words and sentences which contribute to the output the most and manipulating them. The work in [13] proposed novel data augmentation technique for adversarial training in machine translation task, which reinforces the model to virtual data points around the observed examples in training data. They proposed vicinity distribution for adversarial space (space of adversarial examples centered around each training example), and sampled virtual adversarial samples from it using interpolated embeddings of existing training samples. In the work [60] adversarial perturbations are applied on word embedding layer of a CNN for text classification task. Another work [123] proposed a new method PQAT which perturbs the embedding matrix rather than the word vector for machine reading comprehension task. Two additional independent embedding space for paragraphquestion(PQ), to give additional context. During training P-Q embeddings are added to the original vector keeping the context from passage and question separate. All the above discussed methods used the generated adversarial examples for the adversarial training in order to defend the model from attacks and increase robustness. In [120] authors proposed a grey box adversarial attack with the help of a generator model for sentiment analysis task. Adversarial training is done augmenting the data using a static copy mask mechanism in generator, where data is augmented only at the positions which are not masked. Counter-fitted word embeddings (injecting antonymy and synonymy constraints into vector space representations) [72] and label smoothing methods are used for preserving the labels of adversaries and creating embedding that better capture lexical relations. In another work, the [132], authors proposed continuous bag-of-word (CBOW) based perturbations for generating human imperceptible adversaries for text classification task. CBOW is used for predicting the perturbation direction, and tries to preserve the meaning of the sentence by placing a constraint on the perturbation direction. In the work [66] proposed a solution to the Out Of the Vocabulary (OOV) words problem faced by convectional character level defense methods leading to a poor performance of models. They proposed adversarial stability training to overcome these challenges. Adversarial stability training used with character level embeddings, to overcome OOV problem and adversarial sentences are generated by perturbing each word and using character level embeddings to represent them to overcome distribution problem. Another work in the same direction, [34] created adversarial examples using several schemes such as, random word replacement, synonym replacement, finding weak spots in the input strings with greedy approach, by constraining the embeddings within L_1 distance, replacing the word on the basis of attention score (high attention score word to low score word) and demostrated their results on sentiment analysis, textual entailment, and machine translation tasks.

They analysed the robustness of RNNs, transformers and BERT based models and demonstrated that self attentive models are more robust than RNNs. Another work [7] evaluated adversarial training with adversarial examples for 8 datasets in NLP targeted for several purposes such as question answering, reasoning, Detection, sentiment Analysis, Language Detection using language models such as LSTM and GRU. They used combinations of dropout and adversarial example for evaluation. Another work [97] proposed data augmentation for adversarial training for increasing the robustness of casual reasoning task. The proposed data augmentation by synonym substitution and by filtering out casually linked clauses in the larger dataset and used generative language models to generate distractor sentences as potential adversarial examples. To improve the conventional adversarial training methods [109] proposed to use gradient based approach for ranking the important words in the training dataset and distilBERT similarity score for finding similarity between two word embeddings for a faster and low-resource requirement based adversarial training. Also they propose to use a percentage of training data for generating adversarial examples instead of converting all the training data for a cheaper adversarial training.

In [20], authors have proposed a white box based defense method by generating adversarial examples with flip, swap, insert and delete at character level and used gradient based optimization method to rank the examples. The work [131] proposed Metropolis-Hastings (MH) sampling [14] based adversarial example generator for text classification. Three level word operations, replacement, insertion and deletion are performed with MH sampled words in a black box setting, while the gradient of the loss function is inserted in the pre-selection function of MH in case of white box attack. In another work, [85], authors have proposed a greedy algorithm probability weighted word saliency for adversary generation for text classification task. Adversarial examples generated with word synonym replacement and named entities with other named entities using WordNet, picking up the words which cause maximum change in text classification probability. In the work [126], black box adversary generation is proposed which uses sememe (minimum semantic unit in linguistics) based word substitution that is more sememes per sense mean fewer substitute words that share the same sememes can be found, which negatively affects the adversarial attack success rate. Later they used Particle swarm optimization [46] based algorithm to search the optimal adversarial example. The work [71] presented a python framework for attack generation and defending the model, which augments the data using word embedding word swap, thesaurus word swap, homoglyph character substitution, etc. They also provide a set of constraints on the generated perturbations to keep them indistinguishable from original such as, grammar check, POS tags etc. Along the same lines, [102], generated imitation models for Google API of machine translation and generated adversarial samples using techniques such as flipping, replacing malicious nonsense, substituting phrases which cause incorrect translation. Later they used those adversarial examples to train the imitation model and transfer the examples to the victim model. In this work the authors aim towards, finding vulnerability in the victim model to make it more robust, by having victim model output a different high accuracy translation.

Another line of work for data augmentation for generating adversarial examples used concatenation based strategies and automatic generation of adversaries using language models. Towards this direction, the work proposed in [39] adversarial examples are generated for reading comprehension systems, proposed concatenative adversarial perturbations, AddSent, to the paragraphs while leaving the meaning of questions and answers unchanged. They concatenate sentences, at the end of the paragraph which are grammatically correct and look like question or any arbitrary sentence. They also generated adversarial examples for the questions and replaced some answers with fake answers with same POS type and category. Along the same line [113], proposed AddSentDiverse, for generating adversarial examples with significantly higher variance by varying the placement of perturbations. While showing the limitations of AddSent method, they also expanded the set of fake answers used in AddSent.

Another direction of methods have proposed to use generation based adversarial examples for enhancing the robustness of the machine learning model. In this direction, [43], adversary generation is proposed for textual entailment model, using knowledge guided rules and seq2seq model for each entailment class to generate new hypothesis from a given premise. Also, [31] proposed defense strategy using adversarial training, by generating perturbations using seq2seq models for structure prediction task that involved predicting the POS tags, parse-trees, noun phrases etc. The work [19] adversarial training is used for cross lingual text classification and robustness enhancement by training it on English data and using the model to predict on non-English unlabelled data. The predicted outputs are used as adversaries for adversarial training. In the same line [105], authors proposed a new method of adversarial example generation by controlled adversarial text generation where they aimed to perturb input for a given task by changing other controllable attributes of the dataset. For example, in case of sentiment analysis task for product reviews, product category becomes a controllable attribute that can not change the sentiment of a review. Their pretraining module consists of an encoder-decoder architecture, which is used to teach the model to copy the input sentence S, assuming that it has the controllable attribute (a) in the sentence. The decoder module is updated to generate sentence containing attribute $a' \neq a$. In the optimizing module the subspace of all a' is checked by computing the cross-entropy loss to find the highest perturbation.

5.2 Adversarial training as regularization technique

In this section another defense method based on adversarial training for NLP is discussed. In this style of adversarial training, the input perturbations are incorporated as a part of model training, instead of training it with adversarial examples. In the work [27], authors proposed adding perturbations in input as a regularizer in the loss function. The modified optimization function based on the fast gradient sign method after adding perturbations is defined as:

$$\begin{split} L_{adv}(x_l, \theta) &= D[q(y|x_l), p(y|x_l + r_{adv}, \theta)] \\ r_{adv} &= \underset{r; ||r||_2 \leq \epsilon}{\operatorname{argmax}} D[q(y|x_l), p(y|x_l + r, \theta)] \end{split}$$

Where, L_{adv} is the adversarial loss term, r_{adv} is the adversarial perturbation, x_l is the labelled input data, D is the non-negative divergence measurement function between two probability distributions. Adversarial training by inserting perturbation in loss function is found to be an effective way of defending as it generates adversarial examples in a way which is less likely to be done manually, using the flaws of the optimization function to generalise the model. In the line of NLP various methods have been proposed in recent past.

In literature authors have tried various ways to introduce perturbations during training of the model or re-formulating the loss function. Some of the proposed work have introduced perturbations during the training itself are described here. In this line, the work [69] included perturbations at each step of training and tried to minimize the loss function for text classification task. In another work [124], authors proposed adversarial training for POS tagging, by using character level embeddings with BiLSTM models, where word level embeddings are generated by concatenating character level embeddings. Perturbations are added to the input at the character level embeddings in the direction which maximises the classifier loss function while training the model. Another method [117], introduced adversarial noise at embedding(concatenation of word and characters) level for the task of relation extraction within the multi-instance multi-label learning framework. They proposed a joint model to entity recognition and relation extraction using adversarial training as a regularization scheme where worst case perturbations are added to maximize the training loss.

Along the same line, [104] authors improved the neural language modelling by using adversarial training as a regularization technique. They injected an adversarial perturbation on the word embedding vectors in the softmax layer of the language models, while training the model. For the purpose of training a model adversarially to make it more robust, some authors have proposed novel loss functions and various ways to optimize neural networks. In this direction, the work [68] proposed adversarial training for natural language inferencing, by reducing the adversarial example generation problem to combinatorial optimization problem. They proposed a continuous inconsistency loss function that measures the degree to which a set of examples can cause a model to fail. By maximizing the inconsistency loss and constraining the perplexity of the generated sentences, adversarial examples are generated, posing it as an optimization problem. In the same direction, [44] proposed defense mechanism, diversity training, for transfer based attacks for ensemble of models. They proposed gradient alignment loss (GAL) which is used as regularizer to train an ensemble of diverse models with misaligned loss gradients. Another work [18] proposed a novel Adversarial Sparse Convex Combination (ASSC) method to leverage regularization term for introducing perturbations. They modeled the word substitution attack space as a convex hull of word vectors and further proposed ASSC-defense for using these perturbations in adversarial training.

There are methods in literature which proposed novel regularization techniques for enhancing robustness of a language model. In this line of work [103] proposed infoBERT for increasing robustness of BERT based models by analysing language models from information theoretic perspective. They presented two mutual information based adversarial regularizers for adversarial training. Information Bottleneck regularizer which extracts minimal features for downstream tasks and removes noisy and vulnerable information for potential adversarial attacks. Anchored Feature regularizer extracts strong local features which are not vulnerable while aligning local features with global features to increase the robustness. Another work [140] proposed FreeLB, to use K-step PGD for generating adversaries in adversarial training and used multiple PGD iterations. In contrast with k-step PGD and freeAT methods, used multiple PGD iterations to create adversaries simultaneously accumulates the "free" parameter gradient. In this method while optimizing the objective function, it replaces it batch of input with K times large batch which include perturbations along with inputs. Improving the performance of this work Li et al. [63] proposed FreeLB++, by extending the search region to a larger l_2 -norm and increasing the number of search steps at the same time since FreeLB has a narrow search space. They also bench-marked various defense methods in literature under standard constraints and settings to have a fair comparison of these methods.

5.3 GAN based adversarial training

Using GAN for adversarial training is another approach which has been used in literature for defending models from adversarial attacks. In this approach as generator and discriminator are trained together in adversarial manner, where generator is primarily used for generating adversarial examples. Discriminator is responsible for discriminating between the clean data and the adversarial training samples to make model more robust towards adversarial attacks. In this line, the work proposed in [43] adversarial training is performed using GANs for the textual entailment task. The generator and discriminator are trained in an end to end manner, where generator (seq2seq) is trained for generating adversarial examples using external knowledge or hand written rules. Discriminator is trained in the same manner to learn the textual entailment for the generated samples. In another work, [86], authors used a conditional variational autoencoder which generates the adversarial examples for text classification task. They further used a discriminator and GAN training framework for adversarial training and to make sure the generated adversaries are consistent with the real world data. In the work [67] authors used multi-task learning for domain adaptation. They proposed a model Manuscript submitted to ACM

which has separate units to discriminate between shared patterns and task specific patterns using GAN for creating adversarial examples and includes this loss in the final loss for optimization. They demonstrated the improved performance over 16 datasets and the learned parameters in both shared and task-specific parts of the network. The work proposed in [119] proposed a new adversarial training approach which mimics a GAN. The generator is used to create adversarial examples with the help of lexical knowledge base where a classifier is used to score the generated adversarial example. The model is trained in reinforcement learning fashion due to discrete time generation of the generator model and the score from the classifier is used as the reward for the generator. The generator generates examples by replacing words in the input sentence with synonyms, neighbouring words, and superior words. In another work [15] try to defend against an attacker who tries to take the encoded information to reconstruct the original input text. In the adversarial training based defense strategy they used GAN style training with 2 components in which the original one predicts the class of a given sentence and a binary classifier to predict the privacy element. The training style involves making the output prediction as correct as possible while at the same time create more complex examples for privacy element classifier.

5.4 Virtual Adversarial Training (VAT)

Virtual Adversarial Training (VAT) is another variant of adversarial training based defense methods first proposed by [70]. VAT is found to be a very efficient method in case of semi supervised learning methods because it defines the adversarial direction without label information. In contrast to Adversarial training, VAT doesn't need full label information for generating perturbation. The intuition behind VAT is to add perturbation 'r' to input x such that the divergence of their output space is maximum. Hence, training is done in a way to minimize the divergence term after adding the perturbed input to make model robust against adversarial attacks. The modified loss function for virtual adversarial training is defined as:

$$\begin{split} LDS(x_*, \theta) &= D[p(y|x_*, \hat{\theta}), p(y|x_* + r_{adv}, \theta)] \\ r_{adv} &= \operatorname*{argmax}_{r; ||r||_2 \le \epsilon} D[p(y|x_*, \hat{\theta}), p(y|x_* + r_{adv})] \\ R_{adv}(D_l, D_{ul}, \theta) &= \frac{1}{N_l + N_{ul}} \sum_{x_* \in D_l, D_{ul}} LDS(x_*, \theta) \end{split}$$

Where, x_* are the "virtual" labels which are probabilistically generated and r_{adv} are virtual adversarial perturbation. Here, x_* are kept in place of x, since label information is not available for all the input data. LDS is the local smoothness term for the input data point x and R_{adv} is the final regularization term.

The work proposed in [69] extended the notion of virtual adversarial training and adversarial training for text classification and sequence models proposing this technique as a regularization method. For defending the models, they introduced perturbations in word embeddings of the text inputs, while minimizing the KL divergence of VAT. In another work [79], authors proposed a VAT method by performing adversarial steps on those examples which are predicted as wrong by the model and then regularises the model for this target direction in contrast with general adversarial training methods where perturbation is done for all examples with variation from gold label. In a targeted training manner, they try to steer the examples to a particular label y_t and presented a comparison with human annotated data along with other adversarial training algorithms. In the same direction, the work [60] authors proposed a novel adversarial robust model "Adversarial training for large neural LangUage Models(ALUM)" for defending BERT based pretraining language models. It's a general model for adversarial training in pretraining and fine tuning which

regularizes the training objective by applying perturbations in the embedding space that maximizes the adversarial loss. The model is regularized using Virtual Adversarial Training. Experimenting with different word embeddings using VAT, [132] extended the adversarial training regularization for semi-supervised tasks. They used continuous bag of words (CBOW) model for generating word embeddings and restricted perturbation directions for creating adversaries. Targeting specifically sequence labelling tasks in NLP, [11] proposed VAT for sequence labelling task combining CRF, making sequence labelling task more robust. They use CNN layer for extracting character and word embeddings, LSTM for sequence encoding, and CRF decoder layer to incorporate the probabilities of label transition. Introducing more variations to VAT, [59] proposed Token aware virtual adversarial training. In contrast with conventional virtual adversarial training, TAVAT generated token aware perturbations instead of random perturbations to avoid unnecessary noise and take important information carried by tokens into consideration.

5.5 Robustness by human in the loop

Human in the loop (HITL) is an idea of leveraging human intervention while training models or defending them with adversarial attacks. The scheme is extensively used in various field of artificial intelligence. It takes advantage of both human and machine intelligence, for labelling the data, training and validation of models. While it is proved to be efficient scheme in other areas of artificial intelligence, several authors have tried to use HITL for developing algorithms for adversarial defenses.

The work [126] proposed a sememe based word substitution method to generate perturbations. Apart from using particle swarm based optimization algorithm to search perturbation for data augmentation, they manually selected 692 valid adversarial samples for adversarial training to further boost the performance. Also, authors in [74, 115], created dataset of adversarial examples, ANLI for natural language inferencing task by crowd-sourcing. Adversarial examples are written and verified by human annotators in 3 stages in loop, while getting them tested from high performing NLI models. They also presented error analysis and also discuss the annotation scheme and data collection process of ANLI. In the work [17] authors built a model for offensive language detection in dialogues using human and models in loop. They trained BERT based model on Wikipedia Toxic Comments dataset, and asked crowd workers for marking the messages as offensive if they are wrongly marked safe by the system. This process is performed in multiple iterations to build a robust system. The work [101] presented defense method using human in loop by proposing human computer hybrid approach for evaluating the models. They presented a human verification of the question answering system, where human annotators authored adversarial examples to break a QA system but still answerable by humans. This process is targeted towards building a robust question answering system by inserting human authored adversarial examples.

6 PERTURBATION CONTROL BASED DEFENSES

The adversarial defense methods proposed in previous sections, use data augmentation schemes, perturbation generation within training for supervised and semi-supervised tasks, adversaries monitored by human and models in loop, defending the model in a generating and discriminating manner. However, all these schemes do not incorporate the idea of interpretable perturbations or reconstruction of generated perturbations. In literature, there are schemes which control the direction of perturbations to make the perturbations more meaningful, indistinguishable and re-constructive and further use them in training. Also, another set of method try to identify the the perturbed inputs and correct them to make the models more robust. In this line, following sections describes the methods which have been proposed in this direction.

6.1 Perturbation identification and correction

Perturbations related to word modifications which included insertion, deletion, substitution or swapping of words are identified in several ways. One of those method is proposed in [110] proposed defense mechanism, against synonym substitution, calling it "Synonym Encoding Method" (SEM). They essentially clustered all the synonyms in embedding space with their euclidean distances and then encoder is layered before input to train the model. Encoder is responsible for identifying all the synonym substitution based attacks in the model and maps all the synonyms to a unique encoding without adding extra data for training. In another work in this direction, [138] authors proposed Dirichlet Neighborhood Ensemble (DNE), a randomized smoothing method for training a robust model to defense substitutionbased attacks. DNE forms virtual sentences by sampling embedding vectors for each word in an input sentence from a convex hull spanned by the word and its synonyms, and it augments them with the training data, (mixing the embedding of the original word in the input sentence with its synonyms). The work in the same line [4] introduced frequency aware randomization for defense against adversarial word substitution. They add an extra module to detect perturbation in the sentences and apply ADFAR (Anomaly Detection with Frequency Aware Randomization) only on sentences which are identified as adversarial. This module is added to the language model and use a multi-task learning procedure. They demonstrated that works better than other defenses on 4 datasets - MR, SST-2, IMDb, MNLI. Work [111] proposed adversarial defense scheme by perturbation detection for synonym substitution attacks. They proposed a novel method Randomized Substitution and Vote (RS&V). The proposed method call an input text an "adversarial example", by randomly substituting some of its words by their synonyms and checking the consistency of highest voted label for all perturbed examples. If the label is found to be inconsistent with the original label then it is considered as an adversarial input. In another work [137] proposed a novel method for perturbation identification and correction, in which they try to recover the perturbed token based on the context and with the help of small world graphs. First they use, BERT model to get the contextualised embedding vector for each token and then pass it to a binary classifier for classification of perturbation. Later they used a BERT based context network, to be used as the context for predicting the perturbed word. The perturbed word is masked and passed to the BERT to get the embedding of the mask token. Using the embedding vectors and small world graphs they recovered the affected tokens. Another work [107] proposed a novel method called TextFirewall identification of adversarial inputs. They used word importance to quantify the importance of a word in the input sentence to the final classification of the model. The impact of each word in an input sentence is calculated by summing the scores of each model and then model's output is compared with the original ground truth to identify the perturbed input.

Another direction of work attempted to identify perturbations related to character level modifications in the input text. In this direction the work [90] authors proposed semi-character level recurrent neural network (ScRNN), which act as a spell checker by recognizing words. ScRNN has architecture similar to standard RNN and takes semi character vector as input and predict a correct word at each time step by applying three types of noises: jumble, delete, and insert . As an extension of the above work, in [81] authors try to combat misspellings by using a word classifier before the actual classifier of a task. They propose ScRNN with backoff, to overcome limitations of ScRNN [90], and propose three backoff techniques if the word classifier predicts it as UNK. As a backing off step the word recognizer either passes the UNK word as is, backs off to a neutral word or backs off to a more general word recognition model trained on a larger, less specific corpus. In the work [45] authors demonstrated the limitations of spell checker for perturbation identification & correction. They proposed a method in which context independent probability distribution are created by segmenting the perturbed sentence using BERT tokens and modified version of levenshtein distance. For context

dependent probability - all the embeds of context independent hypothesis are clubbed into a weighted embedding. Now a token is masked and MLM is used to predict the tokens. This process is repeatedly done for best approximation. Now these hypothesis are sent to GPT for getting the language modelling score and the best hypothesis is selected from that. They compared their method again Pyspellchecker, human annotations and RNN trained for spell checking. The work in [23] authors presented backdoor attack as the adversarial attacks during training of the model and proposed attacking methods for NLG model by inserting trigger words in the input sentence. They further proposed defense strategies by detection of hacked inputs and output correct results and preserving the correct input and giving its output. In a different line, the work Zhu et al. [139] proposed a universal perturbation detection method, TREATED to defend against various perturbation levels without making any priory assumptions. They utilized several reference models to make different predictions about clean and adversarial examples and block them if found adversarial. They designed the reference models on the basis of their consistency on the clean and adversarial data. In the direction of identifying perturbations for other language text than English, the work [54] proposed a defense model for text classification for Chinese language. Adversarial perturbations are detected in 3 steps. NMT is used for removing the noise in the input text. The corrected text is converted into multimodal embeddings (semantics, glyph and phonetics) and the extracted features are given into text classification.

6.2 Perturbation direction control

The work [92] proposed interpretable adversarial training method by restricting the direction of adversarial samples. The direction of perturbation is restricted towards the words in the existing vocabulary so that perturbations could be interpreted even after adversarial training. In the work [132] authors propose to use CBOW to predict the perturbation direction, while trying to preserve the meaning of the sentence by placing a constraint on the perturbation direction. Another work, [87] proposed a adversarial defense mechanism, Sequence Squeezing, aimed to make RNN models and their variants robust against adversarial attacks. The proposed method generates semantic preserving embeddings which is low in the number of features than original embedding. The squeezed embedding is tested for adversarial attacks and added to the training data while diminishing the adversarial space for generating perturbations.

7 ROBUSTNESS BY CERTIFICATION

The methods discussed in the previous sections for adversarial defenses involved word/character substitution based adversaries where words are the synonyms to make the perturbation look indistinguishable. Other methods tweaked words by inserting characters, changing spellings, deleting/swapping characters. All these adversaries are necessary for defending the models but they are not sufficient. An attacker can generate millions of adversaries by modifying every word in a sentence. A defense algorithm based on adversarial training requires sufficient amount of adversarial data to increase the robustness, which still do not cover a lot of unseen cases which are generated by exponential combinations of different words in a text input. Also, perturbation control based methods require to identify perturbations on the basis of already seen perturbations. These methods have limitations in their performances when model is exposed with a new adversary. Hence, there is separate set of adversarial defense methods in literature which are driven by "certification". These methods train the model to provide an upper bound on the worst case loss of perturbations and hence providing a certificate of robustness without exploring the adversarial space.

Interval Bound Propagation (IBP) [29] is a bounding technique, extensively used in images for training large robust and verifiable neural networks. IBP tries to minimise the upper bound on the maximum difference between classification boundary and input perturbation region. IBP lets you include the loss term in the training using which the last Manuscript submitted to ACM

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layer of the perturbation region can be minimized and kept in the one side of the classification boundary. Now this adversarial region is tighter enough and can be said certified robust.

In this line, the work [40] proposed certified robust models while providing maximum perturbations in text classification. They used interval bound propagation to optimize the upper bound over perturbations. IBP gives an upper bound over the discrete set of perturbations over word vector space. IBP to compute an upper bound on the model's loss when given an adversarially perturbed input. This bound is computed in a modular fashion. In another work [35] introduced a verification and verifiable training of neural networks in NLP. They proposed a tighter over-approximation in the form of a 'simplex' in embedding space in the input to generate perturbations. To make the network verifiable they defines it as the convex hull of the all the original unperturbed inputs as a space of delta perturbation. Using IBP algorithm they generated robustness bounds (generating bounds for each layer). In the work [125] proposed structure free certified robust models which can be applied to any arbitrary model. They overcame the limitations of IBP based method in which they are not applicable to character level and sub-word level models. They prepared a perturbation set of words using synonym sets, top K nearest neighbors under the cosine similarity of GLOVE vectors, where K is a hyperparameter that controls the size of the perturbation set. They further generated sentence perturbations using word perturbations and trained a classifier with robust certification.

Despite having a plethora of work in finding a certificate for robustness, there is a lack of applicability in RNN based network due to their inherent complexity. Hence, in another line of work for robustness by certification, certified robustness for RNN based networks and self attentive networks is proposed. In this line, the work Popgorn [47] proposed certified robustness for RNN based networks such as LSTM, GRUs, The challenge to find a certificate of robustness in RNN based networks are their complex feedback architectures, the sequential inputs, and the cross-nonlinearity of the hidden states. They used 2D planes to bound the cross non-linearity in LSTMs and proposed to find a certificate within a l_p ball (attack distance) if the lower bound on the true label output unit to be larger than upper bounds of all other output units. They generated certificate of robustness by writing all the bounds as a function of epsilon and tried to find the optimum value of epsilon using a binary search procedure. The work in Cert-RNN, they overcame the limitations of Popgorn [47] by a robust certification framework for RNNs. They overcame the limitations of Popgorn by keeping the inter-variable correlation and speeding up the non-linearities of RNN for practical uses. They created a zonotope [22] around the input perturbations and used that to be passed through a vanilla RNN or LSTM. The properties of the output zonotope can be verified to be certifiably robust. They used zonotope instead of a box to preserve inter variable correlation, the precision of the network and achieve a tighter bound. They could achieve tighter bounds and at least 19 times faster framework than Popqorn. In this line [134] proposed a novel approach, Abstractive Recursive certification (ARC) for certified robustness in RNN based networks. They defined a set of programmatically perturbed string transformations and constructed a perturbation space using those transformations using the method proposed in [131]. They memoized the hidden states of the strings in the perturbation space that shared a common prefix to reduce the evaluation of LSTM cells while finding an upper bound to the loss and avoid re-computing of hidden states. Following that they represent all the perturbation sets as a hyperrectangle and pass the hyperrectangle through the remaining network using IBP technique [29]. Following the similar direction the work in [88] presents Polyhedral Robustness Verifier of RNNs (PROVER) which represents the perturbations in input data in the form of polyhedral which is passed through a LSTM network to obtain a certifiable verified network for a more general sequential data. In this line [26] proposed robust certified abstract transformer AI2 using zonotopes as abstract representation of input perturbation where transformer minimize the zonotope projections to achieve certified robustness. However, AI2 suffered with several limitations such as it is a generic transformers for ReLU activation function which are not scalable and precise.

These limitations are overcome by the work proposed by [94]. They proposed a framework DeepZ, for certifying neural network robustness based on abstract interpretation for RNNs. DeepZ is a novel generic, point-wise zonotope abstract transformers for ReLU, Sigmoid, and Tanh activations which is more scalable and fast. Another work in this direction is proposed by [9] where authors proposed DeepT an abstract transformer-based network certification method. They attempted to certify larger transformers against synonym replacement based attacks. In this work authors propose to use multi-norm zenotopes improving the precision of standard zenotope based methods which works well for longer sentences by certifying a larger radii of robustness (×28 of existing methods). To achieve a more generic framework with activation functions other than ReLU, [130] proposed a framework CROWN, a robustness certification framework for general activation functions using linear or quadratic upper and lower bounds. CROWN is faster and scalable as compared to other methods in literature and achieves a tighter lower bound on robustness. In another work [93] proposed algorithm for verifying the robustness of Transformers With self-attention layers which include challenges such as cross linearity and cross positional dependency. They provide a lower bound to a boundary (delta certificate) which will be always greater than 0 (probability of correct class is always higher than incorrect class) within a set of inputs which also include perturbations and tighter than IBP. They achieved this by computing lower/upper bound for each neuron with respect to the input space.

There are other methods in literature for finding certified robustness for neural networks which used several convex optimization schemes and randomized smoothing based schemes. In this line [98] certified defence method is proposed for text classification task. They consider data sanitation defences, which examine the entire datasets and try to remove poisoning points. They upper bound the worst possible test loss of any attack which works in an attacker defender setting at the same time. They generated a certificate of robustness (upper bound) by inserting perturbed data at the time of training where defender is learning to remove outliers at each iteration. Upper bound fits all possible points that evade outlier removal. In the work [82] authors proposed certified robustness method based on semi-definite relaxation. They computed an upper bound on the worst case loss of the neural networks with one hidden layer. The computed certificate of robustness provides an upper bound on the robustness for all kinds of attacks and being differentiable they trained it jointly with the network. In the work [106] provided a certificate of robustness with idea of differential privacy in the input data. Implemented differential privacy in the textual data by treating a sentence as a database and words as individual record. If a predictive model satisfies a certain threshold (epsilon-DP) for a perturbed input, its input should be the same as the clean data. Hence providing a certification of robustness against L-adversary word substitution attacks. In another work [127] proposed defence algorithm to overcome limitations of previous methods of assuming that perturbation generation methods will be known. Propose RanMASK, a certifiably robust defense method against text adversarial attacks based on a new randomized smoothing technique for NLP models. They manually perturbed input is given to the mask language model.Random masks are generated in the input text in order to generate a large set of masked copies of the text. A base classifier is then used to classify each of these masked texts, and the final robust classification is made by "majority vote" and trained with BERT and RoBERTa to generate and train with masked inputs. In the work [95] robustness certificate based on the second-order information instead of first order (gradient) information. They proposed novel, Curvature-based Robustness Certificate (CRC), that derived bounds on the curvature using the hessian of the deep network. Since finding a lower bound to the minimum distance of input to the decision boundary is a non convex optimization problem, they derived curvature bounds that is convex optimization problem. They trained the network with curvature regularization. Another work in this direction [51] estimated maximum safe radius (MSR) for a given input text, i.e. minimum distance between the classification boundary and embedding space. They quantified the robustness of neural networks against word replacement which Manuscript submitted to ACM

is based on a minimum safe radius. They approximated the upper bound using monte Carlo tree search and lower bound by constraint relaxation technique of MSR for CNN and LSTM networks. In literature work such as [80] also tried to club the concept of fairness and robustness to increase the robustness of a neural network. They demonstrated that certified robust model can also be used as a bias mitigation systems to build trustworthy NLP systems. They integrated bias mitigation system with state-of-the-art certified robust models to improve robustness of a model.

There are various method for defending the neural network from adversarial attacks and achieving robustness which are not discussed in these sections and follow a different line of approach, described in the next section.

8 MISCELLANEOUS

In the previous section, various methods discussed for adversarial defenses and robustness enhancement. These methods follow the category of methods discussed and different sub-sections. However there are other schemes proposed in the recent years that do not fall into any categories discussed above. In the direction of enhancing robustness by bias reduction, the work [96] try to remove hypothesis only bias from NLI datasets by using adversarial classifiers to detect bias in the sentence representation. They demonstrated that the larger the sentence embeddings, harder it is to remove the bias and requires more adversarial classifiers. They tested models with 1 and 20 classifiers where 8 out of 13 datasets performed better with 20 classifier and for 3 of them 1 and 20 gave the same performance. In another line of defending APIs from adversarial attacks the work [32] showed that hosted BERT based APIs are vulnerable to theft and users can guery the API for a dataset and train a BERT model to replicate the API. The replicated model can then be used for adversarial example transfer. They suggested a parameter based defense strategy by using a temperature parameter in softmax to smooth the output prediction probabilities. They further add perturbation noise with variance sigma to the output probabilities where larger the variance stronger the defense. In the direction of creating various adversarial examples for adversarial training, the work [30] proposed variable length Adversarial attack in contrast to existing method which focus on fixed length. This is achieved by using special "BLK" token during fine-tuning and then using 3 atomic operations addition, deletion & replacement to create adversarial examples. They show that this method successfully attacks the models in NLU and NAT tasks and demonstrated its use for creating augmented data for adversarial training. In another work [23] authors presented backdoor attacks as the adversarial attacks during training of the model for NLG models. They proposed post-hoc defense against the attacks by using token removal and token substitution on a sentence and corpus level. Taking VAT in different directions, [141] proposed a novel strategy, Stackelberg Adversarial Training (SALT) which employs a stackelberg game strategy. There's a leader which optimizes the model and a follower which optimizes the adversary. In this stackelberg strategy, the leader is advantageous knowing the follower's strategy and this information is captured in stackelberg gradient. They finds the equilibrium between the leader and follower using unrolled optimization approach. Another work in the direction of robustness enhancement, proposed in [42] introduced robust encodings (RobEn), which is a simple framework that guarantees robustness, without making any changes to model architecture. The core component of RobEn is an encoding function, which maps sentences to a smaller, discrete space of encodings on a token level. They attempt to cluster all possible adversarial typos into a single cluster using a graph based agglomerative clustering and try to balance between having too many words in a cluster verses a single word in a cluster. For languages other than English, [55] proposed AdvGraph to enhance adversarial robustness of Chinese NLP models with modified embeddings. Due to inherent complexity in Chinese language, the existing adversarial defense models are difficult to be extended for Chinese language, hence they propose to capture the similarity in words using the graphs. They constructed undirected adversarial graph based on

the glyph and phonetic similarity of Chinese characters and learnt the representations through graph embeddings to be used with semantic embeddings to be used for other downstream tasks.

The next section describes the metrics in literature for evaluating the robustness of the models against adversarial attacks.

9 METRICS IN EVALUATION

There are various metrics which are extensively used in literature for evaluating the proposed defense methods. Majorly these metrics are performance evaluation metrics for the model which requires to be defended. Adversarial defense methods are evaluated with the performance of the model after the defense method is implemented or run-time evaluation in case of methods which aim towards optimizing a lower/upper bound. Hence, some of these metrics are accuracy, error, loss analysis, measurement of the success of adversarial attacks, similarity with ground truth in case of language generation etc. In this section, some of these commonly used metrics are described in detail.

Prediction accuracy (Conventional Accuracy): Adversarial defense methods for text classification models, such
as sentiment classification, Natural Language Inferencing tasks, are evaluated on the basis of the prediction
accuracy after implementation of defense algorithm. The prediction accuracy after defense is compared with
prediction accuracy after attack, and if there is a surge in accuracy, the defense method is considered to be
successful. It is defined as the fraction of test set that is correctly classified [106].

$$\frac{\sum_{t=1}^{T} CorrecClass(X_t, L, \epsilon)}{T}$$

Here, $CorrecClass(X_t, L, \epsilon)$ gives 1, if test sample, X_t is correctly classified for test data T.

- Loss function analysis: The negative log likelihood (loss function) is tested over its rate for adversarial training
 as regularization, and virtual adversarial training based methods. It can indicate lower error rate and reduced
 overfitting in adversarial training based regularization.
- Error analysis: Adversarial defense methods are also evaluated on the error rate in the prediction of the model. The error rate is compared with adversarial attack before and after implementation of defense schemes. A lesser error rate after defense method, entails its successful defense scheme.
- Embedding testing: Embedding test is done for evaluating the embeddings generated for adversarial training.
 Similarity metrics such as Edit distance, Jaccard similarity coefficient and semantic similarity metrics are used to evaluate the utility of the adversarial samples generated by finding their similarity with the original input samples.
- *Human Evaluation:* To measure the utility of the adversarial samples for adversarial training, human evaluation is also performed in literature [25]. Human verifiers are asked to judge the adversarial examples in terms of their naturalness by presenting both original and adversarial examples.
- Attack success rate (ASR): ASR [116] is a measure of success of the adversarial samples created for the potential
 adversarial attack. This metric is used to measure the effectiveness of the adversarial attack after the defense
 scheme is implemented. The attack success rate is measured before and after defending the model and drop in
 its value will imply more robust model. It is defined as:

$$ASR = \frac{N_{successful}}{N_{Total}} * 100$$

Where, $N_{successful}$ is the number of adversarial samples that were able to successfully fail the model and N_{Total} is the total number of adversarial samples generated.

• *BLEU*: Adversarial defense schemes for Natural language generation models utilize performance metrics such as BLEU score [77] for the evaluation of their proposed method. BLEU score is measured using *n*-gram to evaluate the quality of the generated natural language by comparing it with ground truth. It is defined as:

$$\begin{split} p_n &= \frac{\sum_{C \in \{Cand\}} \sum_{gram-n \in C} Count_{clip}(gram-n)}{\sum_{C' \in \{Cand\}} \sum_{gram-n' \in C'} Count(gram-n')} \\ BP &= \begin{cases} 1, & \text{if } c > r \\ e^{\frac{1-r}{c}}, & c \leq r \end{cases} \\ BLEU &= BP.exp^{\sum_{i=1}^{N} W_n log(p_n)} \end{split}$$

Where (p_n) is the n-gram modified precision score, BP is Brevity Penalty used for longer candidate summaries and for spurious words in it, c is the length of the candidate summary, and r is the length of the reference summary.

Precision on certified examples: Precision on certified examples [52], which measures the number of correct
predictions exclusively on examples that are certified robust for a given prediction robustness threshold. It is
defined as:

$$Precision = \frac{\sum_{t=1}^{T} (isCorrect(X_t) \& robustSize(p_t, \epsilon, \delta, L) \geq Threshold}{\sum_{t=1}^{T} robustSize(p_t, \epsilon, \delta, L) \geq Threshold}$$

Where, $isCorrect(X_t)$ give a value of 1 if the input sample X_t is correctly classified, and robustSize gives the certified robustness value for the bound L.

- Certified Radius: In certification based adversarial defense methods, robust radius is the largest radius centred around input sample X_t , for which the classifier does not change its value for its corresponding perturbed sample X_t^{adv} . However, calculating robust radius of a deep neural network is a NP-hard problem [128]. Hence, certification based methods are tested for their certified radius for different norms of perturbations for targeted model on parameters such as minimum radius, average radius and time taken to obtain it. Certified radius is a lower bound to the robust radius and leads to a guaranteed upper bound of the robust classification error.
- *Certificate Ratio (CR)*: It is the fraction of testing samples, that satisfies the certification criteria after prediction [106]. It is defined as:

$$CR = \frac{\sum_{t=1}^{T} CertifiedCheck(X_t, L, \epsilon)}{T}$$

Here, $CertifiedCheck(X_t, L, \epsilon)$ gives 1, if fraction of the test data is certified robust.

- Certified Robustness: Certified Robustness [53] for a particular X_t is the maximum value ρ for which it is certified that classifier will return correct label where X_t^{adv} is its corresponding perturbed sample, such that $||X_t X_t^{adv}|| \le \rho$.
- Median Certified Robustness: The Median Certified Robustness [53, 127] on a dataset is the median value of the certified robustness across the dataset. It is the maximum value ρ for which the classifier can guarantee robustness for at least 50% samples in the dataset. In other words, we can certify the classifications of over 50% samples to be robust to any perturbation within ρ .

Certified accuracy: This is the metric used for evaluating the certifiable robust models. Certified accuracy [52]
 [106] is the percentage of correct test samples for a certified robust model for the given perturbation. It denotes the fraction of testing set, on which a certified model's predictions are both correct and certified robust for a given prediction robustness threshold. It is defined as:

$$Certified\ Accuracy = \frac{\sum_{t=1}^{T} (isCorrect(X_t)\ \&\ robustSize(scores, \epsilon, \delta, L) \geq Threshold}{T}$$

Where $robustSize(scores, \epsilon, \delta, L)$ is the certified robustness size for the bound L and $isCorrect(X_t)$ give a value of 1 if the input sample X_t is correctly classified for test data T.

• Conditional Accuracy: Conditional Accuracy is proposed by [106], evaluates the classification accuracy of both a clean sample X_t and its corresponding adversarial sample X_t^{adv} withing a bound L. It checks when X_t is certified within bound L, whether X_t^{adv} is also classifying correctly. It is defined as:

$$Conditional\ Accuracy = \frac{\sum_{t=1}^{T} (Certified(X_t, L, \epsilon)\ \&\ corrClass(X_t^{adv}, L, \epsilon)}{\sum_{t=1}^{T} (Certified(X_t, L, \epsilon)}$$

Where, $Certified(X_t, L, \epsilon)$ gives 1, when clean input sample X_t is successfully certified and $corrClass(X_t^{adv}, L, \epsilon)$ gives 1 when its perturbed input X_t^{adv} is also correctly classified.

• F1 Score: This is a metric which combine precision and recall both, to evaluate overall performance of the model. It is used for comparison of model's performance before and after defense mechanism implementation. It is defined as:

$$F1 \ Score = \frac{2 * (Precision * Recall)}{(Precision + Recall)}$$

• CLEVER score: Cross Lipschitz Extreme Value for nEtwork Robustness (CLEVER) score is proposed by [114] is a novel robustness evaluation metric. It is attack-independent and can be applied to any arbitrary neural network classifier and scales to large networks. CLEVER metric is an estimation of local Lipschitz constant which represents "lower bound of the robustness in input data" or minimum amount of perturbation required to a natural sample to fail a classifier. Increased clever score indicates that the network is indeed made more resilient to adversarial perturbations after a defense mechanism is used.

10 ADVERSARIAL DATASETS AND FRAMEWORKS

There are several dataset in NLP which are proposed for adversarial evaluation. One such dataset is DailyDialog++ [89], which is and extension of DailyDialog dataset [62] and adversarial dialgue generation dataset. DailyDialog++ contains, 5 additional relevant and adversarial irrelevant responses, for 11k context conversation derived from DailyDialog. Another work is ANLI [74], which proposed adversarial dataset for natural language inference systems. ANLI composed of adversarial examples for NLI collected in 3 iterative round having human and machine in loop. ANLI consist of 103k examples of sentences collected in 3 rounds, starting with short multi-sentence passages from Wikipedia and having annotators writing adversarial hypothesis. In this process they tested these samples with state-of-the-art NLI models and got then verified by human annotators hence proposing human-and-model-in-the-loop enabled training (HAMLET) scheme for data collection. In the same line authors in [58] proposed a novel large scale dataset adversarial VQA for visual question answering task using the HAMLET scheme proposed in [74]. In this work they presented an image to an annotator and ask him to write a tricky question which could fool a model. Hence they iteratively collected 243.0K questions for 37.9K images by having human and models competing in the loop in 3 rounds. For the purpose Manuscript submitted to ACM

of evaluating adversarial examples for question answering task, authors in [39] proposed, Adversarial Squad dataset, that contained adversarially inserted sentences. These sentences are automatically generated in a concatenative manner, without changing he meaning of the paragraph or question. Fake answers to these questions are also generated with same POS type. In the same line, [101] proposed a question-answering test bed Quizbowl, using a Human In the Loop framework. In this work human authors are asked to write adversarial questions which are designed to fail state of the art question answering models. In another work, [135] adversarial dataset Paraphrase Adversaries from Word Scrambling (PAWS), for paraphrase detection is proposed. PAWS is generated from sentence in Quora and Wikipedia, where adversarial samples are generated using language model based controlled word swapping and back translations.

There are papers in literature which proposed python frameworks for a complete adversarial evaluation for several NLP tasks with various attack algorithms. One such work is [71] which is a python framework for end-to-end adversarial evaluation with 16 different adversarial attack methods. It consists of a task specific goal function, data augmentation schemes along with perturbation constraints which validates the perturbation with original inputs and repetitive model querying search system. It facilitates the user to benchmark existing attacks, create novel attack scheme by using new and existing components and evaluating them. In the same line another evaluation framework [121] "Elephant in the room" is proposed, which consists of a combination of automatic evaluation metrics and human judgements. Targeting the sentiment classification task, it included crowd-sourced human judgements, for judging the naturalness, preservation of original label, and compared similarity on a text similarity metric.

11 RECOMMENDATIONS FOR FUTURE WORK

In this paper an exhaustive survey of the methods proposed in literature to defend neural networks by adversarial attacks and to enhance their robustness is presented. It proposed a novel taxonomy for adversarial defense mechanisms for various tasks in natural language processing. Methods for adversarial defense in NLP are broadly divided into three categories, (i) methods based on adversarial training, (ii) methods based on perturbation detection (iii) methods providing a certificate for robustness. Another part of methods which do not follow any of the above mentioned schemes are categorised as miscellaneous. While there is ample amount of work proposed in this direction for tasks in NLP, there are still various gaps remaining which should be looked as potential future directions in this area.

- Larger part of work based on adversarial training: A large portion of work in adversarial defenses for NLP revolve around adversarial training and data augmentation. Despite having a plethora of work in this direction, there is a large part of adversarial defense methods which are oriented towards augmenting the data for generating adversarial examples for adversarial training. Adversarial training is undoubtedly a successful defense scheme for adversarial attacks but it lacks generality for a more practical purpose. It makes the model highly robust for a certain kind of attack but it still makes it vulnerable for the type of examples model has not seen. Hence, the other methods for adversarial defenses should also be explored.
- Hand-crafted generation of adversaries: As a future work recommendation, more attention should be given to automatic generation of adversarial examples. Most of the methods based on adversarial training with data augmentation rely on hand-crafted adversarial examples. There are methods which replace words with their synonyms, or adjacent word, flip the character or concatenate words at the end of sentences. Despite being highly efficient, these examples are devised by human rather having automatic generation of adversarial examples and have their own limitations. Hence, more efforts can be put in the direction of automatic generation of adversarial examples.

• Perceivability of perturbations in text data: Adversarial examples should be less human perceptible/natural looking to make the model robust in a practical attack scenario: In contrast with adversarial defenses for computer vision based methods and examples generated on images, examples on text for NLP tasks are difficult to generate because of their discrete nature. Modifying pixels in images for generating adversarial examples are less perceptible to human than modifying a character or word in an input text. Hence to make to defense method more useful in a piratical scenario, more efforts should be put in this direction.

- Exact robust certificate calculation: In existing literature only upper and lower bound on certificate could be calculated, rather than exact robustness certificate. While adversarial training based defense methods provided a sufficient exposure towards achieving robust neural networks, progressively novel adversarial attacks kept rolling in. A new set of methods to achieve robustness were proposed in the direction of providing a certificate of robustness for a neural network, attempting to put an end to this race. Certification based adversarial defense methods, definitely provide a more generalization for the neural network for a task but certification does not make a sufficient property of a model for achieving robustness. Finding an exact robustness certificate to the set of input is a non-convex optimization problem and is inefficient to solve. However, in literature authors have relaxed this problem to convex optimization by finding an upper or lower bound to the robustness certificate. Despite the efforts towards finding a certified robustness convex optimization can lead to lossy results and there is a scope of finding a tighter bound. Hence future efforts in this direction can be made to improve the tightness of existing robustness certificates.
- Scalability of certification based robustness: Certification methods, do not scale to large and practical networks
 used in solving modern machine learning problems: The current certification based robustness method in literature, are implemented on theoretical models on a small scale. They are not scalable to larger and deeper
 networks for practical purposes. Hence in future attempts should be made in this direction.
- Generalization of adversarial training: The current state of the art methods based on adversarial training in NLP
 are designed in a task specific manner. There is a lack of generality in adversarial example generation schemes
 which could be used for multiple NLP tasks effectively. Hence in future steps can be taken in this direction.
- More explainable models in case of inserting perturbations in the loss function: There is a lack of explainability
 and transparency in the regularization based defense methods. The loss function contains the term responsible
 for introducing perturbations at the training time. However, there is no explanation for these method for their
 correctness or high accuracy.
- Novel methods to identify the existing perturbations in the input: A large part of perturbation detection schemes depends upon spell checking methods and method which enumerate or cluster synonyms. In a practical scenario it is highly inefficient to compute and enumerate synonyms of words for perturbation recognition. Hence, there is a requirement of novel and innovative methods for identifying the perturbations in the input text which do not involve traditional methods such a spell checking, synonym mapping or their other variants.
- Better evaluation metrics: The current evaluation of robustness against adversarial attacks for NLP models is
 based on the performance metrics of the actual model, i.e. accuracy, precision-recall, error-analysis, etc. Hence,
 there is a requirement of novel evaluation metrics which that could measure the robustness and ability to defend
 against adversarial attacks. There also ain't enough ways to evaluate defense mechanisms themselves along the
 lines of perceptibility and naturalness. Hence, in future, more evaluation metrics can be brought along this line.

12 CONCLUSION

In this paper a survey is presented for adversarial defense methods for various tasks in natural language processing. We proposed a novel taxonomy for adversarial defenses in NLP covering a wide range of recently proposed papers. This survey tries to fulfil the gaps of existing surveys where adversarial attacks schemes were more focused upon. However, in the recent years, numerous methods are proposed for defending the neural networks with adversarial attacks and enhancing their robustness. Coming up with novel defense schemes for advanced NLP systems is as important as coming up with novel attacks to make these neural networks robust and safe for practical purposes. This survey also covers various adversarial datasets and frameworks proposed in the recent times for efficient adversarial evaluation of the SOTA models. Moreover it highlights various recommendations for future work considering the limitations and gaps in the existing literature of adversarial defenses. This survey therefore provides a strong basis and motivation for future research in developing robust and safe neural networks in natural language processing tasks.

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