Achieving Model Robustness through Discrete Adversarial Training

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Abstract

Discrete adversarial attacks are symbolic perturbations to a language input that preserve the output label but lead to a prediction error. While such attacks have been extensively explored for the purpose of evaluating model robustness, their utility for improving robustness has been limited to offline augmentation only, i.e., given a trained model, attacks are used to generate perturbed (adversarial) examples, and the model is re-trained exactly once. In this work, we address this gap and leverage discrete attacks for online augmentation, where adversarial examples are generated at every step, adapting to the changing nature of the model. We also consider efficient attacks based on random sampling, that unlike prior work are not based on expensive search-based procedures. As a second contribution, we provide a general formulation for multiple searchbased attacks from past work, and propose a new attack based on best-first search. Surprisingly, we find that random sampling leads to impressive gains in robustness, outperforming the commonly-used offline augmentation, while leading to a speedup at training time of \sim 10x. Furthermore, online augmentation with search-based attacks justifies the higher training cost, significantly improving robustness on three datasets. Last, we show that our proposed algorithm substantially improves robustness compared to prior methods.

1 Introduction

Adversarial examples are inputs that are slightly, but intentionally, perturbed to create a new example that is misclassified by a model (Szegedy et al., 2014). Adversarial examples have attracted immense attention in machine learning (Goodfellow et al., 2015; Carlini and Wagner, 2017; Papernot et al., 2017) for two important, but separate, reasons. First, they are useful for *evaluating* model

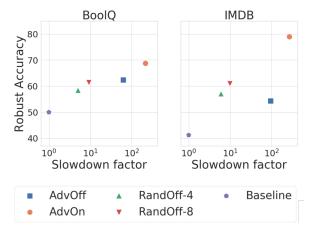


Figure 1: Robust accuracy vs. slowdown in training time, comparing different methods to Baseline (purple pentagon); x-axis in logarithmic scale. The popular ADVOFF (blue squares, offline augmentation with adversarial example) is 10x slower than simple augmentation of 4 (8) random samples (triangles, RANDOFF-4, RANDOFF-8) and achieves similar or worse robust accuracy. Online augmentation of adversarial examples (ADVON, yellow circles) significantly improves robust accuracy, but is expensive to train.

robustness, and have revealed that current models are over-sensitive to minor perturbations. Second, adversarial examples can *improve* robustness: training on adversarial examples reduces the brittleness and over-sensitivity of deep learning models to such perturbations (Alzantot et al., 2018; Ren et al., 2019; Jin et al., 2020; Li et al., 2020b; Lei et al., 2019; Wallace et al., 2019; Zhang et al., 2020).

Training and evaluating models with adversarial examples has had considerable success in computer vision, with gradient-based techniques like FGSM (Goodfellow et al., 2015) and PGD (Madry et al., 2018). In computer vision, adversarial examples can be constructed by considering a continuous space of imperceptible perturbations around image pixels. Conversely, language is discrete, and

any perturbation is perceptible. Thus, robust models must be invariant to input modifications that preserve semantics, such as synonym substitutions (Alzantot et al., 2018; Jin et al., 2020), paraphrasing (Tan et al., 2020), or typos (Huang et al., 2019).

Due to this discrete nature of language, ample work has been dedicated to developing discrete attacks that generate adversarial examples through combinatorial optimization (Alzantot et al., 2018; Ren et al., 2019; Jin et al., 2020; Zhou et al., 2020; Zang et al., 2020). For example, in sentiment analysis, it is common to consider the space of all *synonym substitutions*, where an adversarial example for an input "Such an amazing movie!" might be "Such an extraordinary film" (Fig. 2). This body of work is mostly focused on evaluating robustness, rather than improving it, which naturally led to the development of complex combinatorial search algorithms, whose goal is to find adversarial examples in the exponential space of perturbations.

In this work, we address two research gaps in current literature. First, improving robustness with discrete attacks has been under-explored. Specifically, past work (Alzantot et al., 2018; Ren et al., 2019; Jin et al., 2020) only considered offline augmentation, where a discrete attack is used to generate adversarial examples and the model is re-trained exactly once with those examples. This ignores online augmentation, which had success in computer vision (Kurakin et al., 2017; Perez and Wang, 2017; Madry et al., 2018), where adversarial examples are generated in each training step, adapting to the changing model. Moreover, simple data augmentation techniques, such as randomly sampling from the space of synonym substitutions have not been investigated and compared to offline augmentation. We address this lacuna and systematically compare online augmentation to offline augmentation, as well as to simple random sampling techniques. To the best of our knowledge, we are the first to empirically evaluate online augmentation with discrete attacks on a wide range of NLP tasks.

The second research gap is the lack of clear framework for comparing adversarial attack algorithms proposed in past work. We formulate discrete attacks as a search problem over a directed graph of utterances (Fig. 3), and describe a family of algorithms that includes the current state-of-theart attacks from past work as particular cases. Our formulation highlights the similarities and differences between past approaches, and relates them

Expected: Positive $ar{x} \in S(x) \qquad \hat{x} \in$



Figure 2: Given a movie review x, the model A is robust to a set of perturbations, while A' is not.

to standard graph search algorithms. This relation leads us to present a new best-first search algorithm, which includes backtracking, i.e., a previously-discarded search path can be re-visited once the current one is revealed to be sub-optimal.

We evaluate model robustness on three datasets: BoolQ (Clark et al., 2019), IMDB (Maas et al., 2011), and SST-2 (Socher et al., 2013), which vary in terms of the target task (qustion answering and sentiment analysis) and input length. Surprisingly, we find across different tasks (Fig. 1) that augmenting each training example with 4-8 random samples from the synonym substitutions space performs as well as (or better than) the commonly used offline augmentation, while being simpler and 10x faster to train. Conversely, online augmentation makes better use of the extra computational cost, and substantially improves robust accuracy compared to offline augmentation. Additionally, our proposed discrete attack algorithm outperforms TEXTFOOLER (Jin et al., 2020), a recent state-of-the-art discrete attack, in terms of both attack success rate and robustness.

Overall, our work provides new efficient attack algorithms against state-of-the-art NLP models, as well as methods to leverage such attacks to increase robustness. Moreover, we provide a comprehensive picture on the trade-offs between different training approaches for achieving robustness through discrete adversarial attacks. Our data and code are available at https://github.com/Mivg/robust_transformers.

2 Problem Setup and Background

Problem setup Given a training set $\{x_j, y_j\}_{j=1}^N$ sampled from $\mathcal{X} \times \mathcal{Y}$, our goal is to learn a mapping $A: \mathcal{X} \to \mathcal{Y}$ that achieves high accuracy on held-out data sampled from the same distribution. Moreover, we want the model A to be *robust*, i.e., invariant to a set of pre-defined label-preserving

perturbations to x, such as synonym substitutions. Formally, for any natural language input x, a discrete $attack\ space$ of label-preserving perturbations $\mathcal{S}(x)\subset\mathcal{X}$ is defined. Given a labeled example (x,y), a model A is robust w.r.t x, if A(x)=y and for any $\bar{x}\in\mathcal{S}(x)$, the output $A(\bar{x})=A(x)$. An example $\bar{x}\in\mathcal{S}(x)$ such that $A(\bar{x})\neq A(x)$ is called an $adversarial\ example$. We assume A provides not only a prediction but a distribution $p_A(x)\in\Delta^{|\mathcal{Y}|}$ over the possible classes, where Δ is the simplex, and denote the probability A assigns to the gold label by $[p_A(x)]_y$. Fig. 2 shows an example from sentiment analysis, where a model A is robust, while A' is not w.r.t x.

To evaluate robustness, one can compute *robust* accuracy (Tsipras et al., 2019), that is, the fraction of examples a model is robust to over some held-out data. Typically, the size of the attack space S(x) is exponential in |x| (which can be the number of words, tokens, letters, etc.) and it is not feasible to enumerate all perturbations. Instead, an upper bound is estimated by searching for a set of adversarial attacks, i.e., "hard" examples in S(x) for every x, and estimating robust accuracy w.r.t to that set.

Improving robustness with discrete attacks

Since language is discrete, a typical approach for *evaluating* robustness is to use combinatorial optimization methods to search for adversarial examples in the attack space S(x). This has been repeatedly shown to be an effective attack method on pre-trained models (Alzantot et al., 2018; Lei et al., 2019; Ren et al., 2019; Li et al., 2020b; Jin et al., 2020; Zang et al., 2020). However, in terms of *improving* robustness, discrete attacks have thus far been mostly used with offline augmentation (defined below) and have led to limited robustness gains. In this work, we examine the more costly but potentially more beneficial online augmentation.

Offline vs. online augmentation Data augmentation is a common approach for improving generalization and robustness, where variants of training examples are automatically generated and added to the training data (Simard et al., 1998). Here, discrete attacks can be used to generate these examples. We consider both *offline* and *online* data augmentation and focus on improving robustness with adversarial examples.

Given a training set $\{(x_j, y_j)\}_{j=1}^N$, offline data augmentation involves (a) training a model A over

the training data, (b) for each training example (x_j, y_j) , generating a perturbation w.r.t to A (using some discrete attack) and labeling it with y_j , and (c) training a new model over the union of the original training set and the generated examples. This is termed *offline* augmentation because examples are generated with respect to a fixed model A.

Online data augmentation is a setup where examples are generated at training time w.r.t the current model A. This is more computationally expensive, as examples must be generated during training and not as pre-processing, but examples can adapt to the model over time. Specifically, in each step, half the batch contains examples from the training set, which are left unchanged, and half are adversarial examples generated by some discrete attack w.r.t to the model's current state.

Online augmentation has been used to improve robustness in NLP with gradient-based approaches (Jia et al., 2019; Shi et al., 2020; Zhou et al., 2020), but to the best of our knowledge has been overlooked in the context of discrete attacks. In this work, we are the first to propose model-agnostic online augmentation training, which uses automatically generated *discrete adversarial attacks* to boost overall robustness in NLP models.

Robustness without discrete attacks In this work, we focus on discrete attacks for achieving robustness. Alternative approaches include gradientbased methods (Goodfellow et al., 2015; Madry et al., 2018; Ebrahimi et al., 2018) and certified robustness (Jia et al., 2019; Huang et al., 2019). Certified robustness methods struggle with deep architectures, (Vaswani et al., 2017), and gradientbased methods are not compatible with sub-word tokenization. Thus, both approaches are currently not suitable for standard NLP models that use pretrained transformers. Moreover, discrete attacks are model agnostic, since they only assume an attacker can query the model and get a distribution over labels (the black-box setting (Papernot et al., 2017)). We further discuss these approaches and their relation to our work in §6.

3 The Attack Space

An attack space for an input with respect to a classification task can be intuitively defined as the set of label-preserving perturbations over the input. A popular attack space S(x), which we adopt, is the space of *synonym substitutions* (Alzantot et al., 2018; Ren et al., 2019; Jin et al., 2020). Given

a synonym dictionary that provides a set of synonyms Syn(w) for any word w, the attack space $S_{syn}(x)$ for an utterance $x=(w_1,\ldots,w_n)$ is defined to be all utterances that can be obtained by replacing a word w_i (and possibly multiple words) with one of their synonyms. Typically, the number of words from x allowed to be substituted is limited to be no more than $D=\lceil d\cdot |x| \rceil$, where $d\in\{0.1,0.2\}$ is a common choice.

Synonym substitutions are context-sensitive, that is, substitutions might only be appropriate in certain contexts. For example, in Fig. 3, replacing the word "like" with its synonym "similar" (red box) is invalid, since "like" is a verb in this context. Consequently, past work (Ren et al., 2019; Jin et al., 2020) filtered $S_{syn}(x)$ using a contextsensitive filtering function $\Phi_x(w_i, \bar{w}_i) \in \{0, 1\},\$ which determines whether substituting a word w_i from the original utterance x with its synonym \bar{w}_i is valid in a particular context. For example, an external model can check whether the substitution maintains the part-of-speech tag, and whether the overall semantics is maintained. We define the filtered synonyms substitutions attack space $S_{\Phi}(x)$ as the set that includes all utterances \bar{x} that can be generated through a sequence of no more than Dsingle-word substitutions from the original utterance that are valid according to $\Phi(\cdot, \cdot)$. In §5.2, we will describe the details of the synonym dictionary and function Φ we use.

Searching over the attack space $\mathcal{S}_{\Phi}(x)$ can be naturally viewed as a search problem over a directed acyclic graph (DAG) $G=(\mathcal{U},\mathcal{E})$, where each node $u_{\bar{x}}\in\mathcal{U}$ is labeled by an utterance \bar{x} , and edges \mathcal{E} correspond to single-word substitutions, valid according to $\Phi(\cdot)$. The graph is directed and acyclic, since only substitutions of words from the original utterance x are allowed (see Fig. 3). Because there is a one-to-one mapping from the node $u_{\bar{x}}$ to the utterance \bar{x} , we will use the latter to denote both the node and the utterance. Viewing discrete attacks as graph search algorithms can shed light on relations between attacks from past work, and gives rise to new search procedures.

4 Discrete Attacks

Now that we defined the attack space, we present a family of discrete attacks, i.e., search algorithms for finding adversarial examples in the DAG G that will be used to improve robustness. We first describe $random\ attacks\ (\S4.1)$, which have thus

far not been compared to search-based procedures. We then turn to *targeted attacks* (§4.2), which use a search algorithm to find adversarial examples. We provide a general formulation for algorithms over both the DAG G and a factorized DAG \hat{G} , which includes several discrete attacks proposed in past work as specific cases, including recent state-of-the-art attacks. Then, we propose a new algorithm, based on best-first search (§4.3).

As mentioned, evaluating all adversarial examples in the exponential space is intractable. Moreover, each evaluation of a candidate attack requires executing the model A over the input. Thus, the computational cost of searching for an attack is influenced by the number of inputs over which we execute the model A. A budget parameter B determines the maximal number of such executions per example.

4.1 Random Attacks

The simplest and most efficient procedure, which involves zero executions of A, is to randomly sample L utterances from the attack space and add them to the training data. This offline augmentation is very efficient, since we can generate in parallel all random samples. Moreover, random sampling is global, i.e., it uniformly samples from the entire search space, without bias towards utterances that are similar to x.

A much more expensive random approach is online augmentation, i.e., in each batch, we randomly sample utterances x_1,\ldots,x_B for each x, run $A(\cdot)$ over them, and choose as the returned attack the one that minimizes the probability of the gold label w.r.t the current state of the model.: $\bar{x} \coloneqq \operatorname{argmin}_{x_b \in \{x_1,\ldots,x_B\}}[p_A(x_b)]_y$.

4.2 Targeted Attacks

Targeted attacks use search algorithms to find an adversarial example in S(x). Search is guided by a heuristic scoring function $s_A(x) := [p_A(x)]_y$, where the underlying assumption is that utterances that give lower probability to the gold label are closer to an adversarial example. We first provide a general description of the algorithms, and then discuss their relation to past work at the bottom of this section.

Greedy search A popular approach for search in NLP is greedy search. Specifically, one holds in step t the current node x_t , where t words have been substituted in the source node $x_0 = x$.

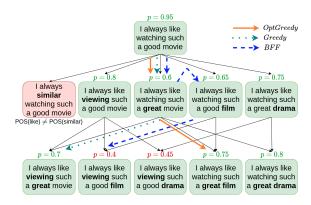


Figure 3: Example of an attack space, and the paths taken by a greedy algorithm, optimistic greedy, and best-first search. An adversarial example has probability p < 0.5 for the gold positive label.

Then, the model $A(\cdot)$ is run on the *frontier*, that is, all out-neighbor nodes $\mathcal{N}(x_t) = \{\hat{x}_{t+1}\}$ $(x_t, \hat{x}_{t+1}) \in \mathcal{E}$, and the one that minimizes the heuristic scoring function is selected: $x_{t+1} :=$ $\operatorname{argmin}_{\hat{x} \in \mathcal{N}(x_t)} s_A(\hat{x})$. Greedy search stops when the attack succeeds (label changes), when the budget B is exhausted, or when $\mathcal{N}(x_t) = \emptyset$, returning the last node. This can also be generalized to beam search by holding more than one node in each step. The dotted green path in Fig. 3 illustrates the greedy algorithm, where the most promising node in the first step reduces the probability of the gold label to p = 0.6, and then the next best step leads to a higher probability p = 0.7. Once it exhausts its traversal path, the algorithm returns the best node encountered along the path, namely, the second one.

While greedy search has been used for characterflipping (Ebrahimi et al., 2018), it is ill-suited in the space of synonym substitutions. The degree of nodes is high – if we assume n_{rep} words can be replaced in the text, each with K possible synonyms, then the out degree is $O(n_{rep} \cdot K)$, which can exhaust the budget B after few steps. We introduce two possible solutions, variants of which have been proposed in past work: (a) an "optimistic" greedy algorithm, and (b) graph factorization. Both solutions rely on the assumption that local perturbations that mislead the model, remain effective even when other local modifications are present. While the optimistic approach is more efficient for long utterances and large D, the factorization approach is more efficient for very large n_{rep} and in general achieves higher success rates.

Optimistic greedy search Optimistic greedy search plans the entire search path by evaluating all permissible single-word substitutions.

Let $x_{w_i \to w}$ denote the utterance x where the word w_i is replaced with a synonym w $Syn(w_i)$. The optimistic greedy algorithm scores each word w_i in the utterance with $s(w_i) :=$ $\min_{w \in syn(w_i)} s_A(x_{w_i \to w})$, that is, the score of a word is the score for its best substitution, and also stores this substitution. Then, it sorts utterance positions based on $s(w_i)$ in ascending order, which defines the entire search path: In each step, the algorithm moves to the next position based on the sorted list and uses the best substitution stored for that position. The solid orange path in Fig. 3 illustrates this. The two most promising single-word substitutions are $good \rightarrow great (p = 0.6)$, and $movie \rightarrow film$ (p = 0.65), which determines the path. This differs from a greedy approach, which can observe after *good* is replaced with *great* that *watching*→*viewing* is the best next substitution.

Optimistic search assumes substitutions in step t do not affect the score in steps > t, which can be false. However, it requires only $n_{\text{rep}} \cdot K$ executions of A for planning the entire path.

Graph factorization An alternative approach is to reduce the out-degree of a node in the search space by splitting each step into two. First, choose a position to substitute in the utterance; Second, choose a substitution for that position. This reduces the number of evaluations of A per step from $O(n_{\text{rep}} \cdot K)$ to $O(n_{\text{rep}} + K)$. To estimate the score of a position i, one can mask the word w_i with a mask token τ and measure $s_A(x_{w_i \to \tau})$.

We can describe this approach as search over a bi-partite DAG $\hat{G}=(\mathcal{U}\cup\mathcal{W},\hat{\mathcal{E}})$. The nodes \mathcal{U} are utterances like in G, and the new nodes are utterances with a single masking token $\mathcal{W}=\{\bar{x}_{w_i\to\tau}\mid \bar{x}\in\mathcal{S}(x)\wedge w_i \text{ is a word in }x\}$. The edges comprise two types: $\hat{\mathcal{E}}=\mathcal{E}_1\cup\mathcal{E}_2$. The edges \mathcal{E}_1 are from utterances to masked utterances: $\mathcal{E}_1=\{(\bar{x},\bar{x}_{w_i\to\tau})\}\subset\mathcal{U}\times\mathcal{W}$, and $\mathcal{E}_2=\{(\bar{x}_{w_i\to\tau},\bar{x}_{w_i\to w_{syn}})\}\subset\mathcal{W}\times\mathcal{U}$, where $w_{syn}\in\mathit{Syn}(w_i)$. In Figure 3, the two rightmost nodes in each row would be factorized together as they substitute the same word, and the algorithm will evaluate only one of them to estimate the potential benefit of substituting "movie".

Generalizing past work We now highlight how multiple past approaches can be described as in-

stances or variants of our general formulation. Developing such a unified view is useful for understanding connections between past methods, and for developing new algorithms that draw from the field of graph search algorithms.

PWWS (Ren et al., 2019) uses an optimistic-greedy approach utilizing a heuristic that combines word salience with model confidence. CLARE (Li et al., 2020a) uses a greedy algorithm with graph factorization, but allows operations such as addition and deletion on top of substitution. TEXTFOOLER (Jin et al., 2020) combines an optimistic-greedy approach with graph factorization: an optimistic scoring function determines the order by which positions will be visited using a mask token before search starts, and then the exact substitution is determined sequentially in a greedy fashion.

4.3 Best-first search

We now propose a new algorithm that seamlessly combines with the factorized graph and improves over the shortcomings of the greedy algorithm. Greedy approaches rely on the heuristic function being a good estimate of the distance to an adversarial example. However, Fig. 3 shows an example where greedy is sub-optimal. The two adversarial examples (p=0.4 or p=0.45) are not reachable from the best node after the first step (p=0.6), only from the second-best (p=0.65).

Best-first search (Pearl, 1984) overcomes this at a negligible cost, by holding a min-heap over the nodes of the frontier of the search space (Alg. 1). In each step, we pop the next utterance, which assigns the lowest probability to the gold label, and push all neighbors into the heap. When a promising branch turns out to be sub-optimal, search can resume from an earlier node to find a better solution, as shown in the blue path in Figure 3. To further reduce "greedyness", search can use a beam by popping more than one node in each step, expanding all their neighbors and pushing the result back to the heap. Our final approach uses Best-First search over a Factorized graph, and is termed BFF.

5 Experiments

We now empirically evaluate model robustness across a wide range of attacks and training procedures.

Algorithm 1: Best-first search

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\begin{array}{l} \textbf{input} : \textbf{model A, graph } G \ (\textbf{or} \ \hat{G}), \textbf{ utterance } x. \\ \textbf{heap} \leftarrow \left\{(x, s_A(X)\right\} \\ x^* \leftarrow x \\ \textbf{while} \ | \textbf{heap} | > 0 \ \textit{and budget not exhausted:} \\ \hline \bar{x} \leftarrow \textbf{heap.pop}() \\ x^* \leftarrow \text{argmin}_{\bar{x} \in \{\bar{x}, x^*\}} A(\hat{x}) \\ \textbf{if } A(x^*) \neq y \ \textbf{break}; \\ \textbf{for } \hat{x} \in \mathcal{N}(\bar{x}) \ \textbf{do} \\ & | \quad \textbf{heap.push}(\hat{x}, s_A(\hat{x})) \\ \textbf{return } x^* \end{array}
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5.1 Experimental Setup

To evaluate our approach over diverse settings, we consider three different tasks: *text classification*, *sentiment analysis* and *question answering*, two of which contain long passages that result in a large attack space (see Table 1).

- SST-2: Based on the the Stanford sentiment treebank (Socher et al., 2013), SST-2 is a binary (positive/negative) classification task containing 11,855 sentences describing movie reviews. SST-2 has been frequently used for evaluating robustness.
- IMDB (Maas et al., 2011): A binary (positive/negative) text classification task, containing 50K reviews from IMDB. Here, passages are long and thus the attack space is large (Table 1).
- 3. **BoolQ** (Clark et al., 2019): contains 16,000 yes/no questions over Wikipedia paragraphs. This task is perhaps the most interesting, because the attack space is large and answering requires global passage understanding. We allow word substitutions in the paragraph only and do not substitute nouns, verbs, or adjectives that appear in the question to avoid non-label-preserving perturbations. Further details can be found in App. A.2.

Models We consider the following models and evaluate both their downstream accuracy and robustness. In all models the budget B=1000, and results are an average of 3 runs. To compare the effectivness of BFF both for robustness evaluation as well as adversarial training, we compare against the recent state-of-the-art TextFooler.

BASELINE: we fine-tune a pretrained language model on the training set. We use BERT-BASE (Devlin et al., 2019) for IMDB/SST-2 and ROBERTA-LARGE (Liu et al., 2019) for BoolQ. These baselines are on par with current state-of-theart to demonstrate the efficacy of our method.

RANDOFF-L: We randomly sample L utterances

from the attack space for each example (without executing A) and add them to the training data.

RANDON: Random online augmentation, where the model A is run on B random utterances and the best attack is added to the batch.

BFFOFF/TXFOFF Offline augmentation with the BFF/TEXTFOOLER attacks.

BFFON/TXFON Online augmentation with the BFF/TEXTFOOLER attacks.

For brevity, experimental details are in App. A.1. **Evaluation** We evaluate models on their downstream accuracy, as well as on robust accuracy, i.e. the fraction of examples against which the model is robust. Since robust accuracy cannot be exactly computed (see §2), we compute an upper-bound by attacking each example with both BFF and TEXTFOOLER (TXF) with a budget of B=2000. An example is robust if we cannot find an utterance where the prediction is different from the gold label. We evaluate robust accuracy on 1000/1000/872 samples from the development sets of BoolQ/IMDB/SST-2.

5.2 Attack Space

Despite the myriad of works on discrete attacks (Alzantot et al., 2018; Ren et al., 2019; Jin et al., 2020; Zhou et al., 2020; Zang et al., 2020), an attack space for synonym substitutions has not been standardized. While all past work employed a synonym dictionary combined with a $\Phi(\cdot, \cdot)$ filtering function (see §3), the particular filtering functions vary. When examining the attack space proposed in TxF, we observed that attacks result in examples that are difficult to understand or are not labelpreserving. Table 6 in App. A.3 shows several examples. For instance, in sentiment classification, the attack replaced "compelling" with "unconvincing" in the sentence "it proves quite unconvincing as an intense, brooding character study" which alters the meaning and the sentiment of the sentence. Therefore, we use a more strict definition of the filtering function and conduct a user study to verify it is label-preserving.

Concretely, we use the synonym dictionary from Alzantot et al. (2018). We determine if a word substitution is context-appropriate by computing all single-word substitutions ($n_{\text{rep}} \cdot K$) and disallowing those that change the POS tag according to spaCy (Honnibal et al., 2020) or increase perplexity according to GPT-2 (Radford et al., 2019) by more than 25%. Similar to Jin et al. (2020), we also filter

	x	$n_{\rm rep}$	Syn(w)	$ S_{\phi}(x) $
SST-2	8.9	2.7	2.4	27.7
IMDB	242.4	97.3	3.6	2.27×10^{64}
$BoolQ^{\dagger}$	97.7	38.7	3.6	3.64×10^{25}

Table 1: Statistics on datasets and the size of attack space. We show the average number of words per utterance |x|, the average number of words with substitutions $n_{\rm rep}$, average number of synonyms per replaceable word, and an estimation of the attack space size.

	Original	Random	BFF
IMDB	98.0	98.0	96.0
BoolQ	89.0	91.5	83.5
SST-2	97.0	96.0	94.4

Table 2: Evaluating attack space validity. We show human performance on original examples, random examples, and examples generated with BFF.

out synonyms that are not semantics-preserving according to the USE (Cer et al., 2018) model. The attack space includes any combination of allowed single-word substitutions, where the fraction of allowed substitutions is d=0.1. Implementation details are in App. A.2. We find that this ensemble of models reduces the number of substitutions that do not preserve semantics and are allowed by the filtering function.

We check the validity of our attack space with a user study. We sample 100/100/50 examples from SST-2/BoolQ/IMDB respectively, and for each example create two adversarial examples: (a) by random sampling (b) using a BFF attack. We ask 25 NLP graduate students to annotate both the original example and the two adversarial ones. Each example is annotated by two annotators and each annotator only sees one version of an example. If human performance on random and adversarial examples is similar to the original task, this indicates the attack space is label-preserving.

Table 2 shows the results. Human performance on random examples is similar to the original utterances. Human performance on examples generated with BFF is only mildly lower than the performance on the original utterances, overall confirming that the attack space is label-preserving.

5.3 Robustness Results

Table 3 shows accuracy on the development set, robust accuracy, and slowdown compared to BASE-LINE for all models and datasets. For downstream accuracy, training for robustness either maintains or slightly increases downstream accuracy. For robust

Madal	Accuracy			Robust Accuracy			Slowdown		
Model	SST-2	IMDB	BoolQ	SST-2	IMDB	BoolQ	SST-2	IMDB	BoolQ
Baseline	91.9	93.4	84.5	80.5	41.2	50.0	$\overline{}$ ×1	$\overline{}$ ×1	$\overline{}$ ×1
RANDOFF-1	91.9	93.5	85.6	83.5	50.3	52.2	×1.9	$\times 1.5$	×2.1
RANDOFF-4	91.6	93.7	85.5	83.6	57.0	58.4	$\times 3.8$	$\times 4.5$	$\times 5.1$
RANDOFF-8	91.1	93.8	86.1	83.3	60.9	61.3	$\times 5.4$	$\times 8.0$	$\times 9.3$
RANDOFF-12	91.5	93.7	85.8	84.2	60.1	63.0	$\times 6.3$	$\times 11.5$	$\times 13.2$
TxFOff	91.2	93.4	86.5	83.5	49.0	61.5	$\times 3.0$	$\times 56.1$	×8.6
BFFOFF	91.8	93.7	85.8	84.6	54.3	62.3	$\times 5.4$	$\times 60.0$	$\times 63.2$
RANDON	91.7	94.1	85.6	84.9	68.5	66.0	×14.8	$\times 249.3$	$\times 280.4$
TXFON	91.3	93.8	86.0	84.0	67.4	65.3	$\times 3.9$	$\times 58.0$	$\times 28.1$
BFFON	91.7	94.2	86.5	85.3	78.9	68.7	$\times 21.1$	$\times 270.7$	$\times 215.9$

Table 3: Accuracy on the development set, robust accuracy, and slowdown in model training for all datasets.

accuracy, discrete attacks substantially improve robustness: $80.5 \rightarrow 86.5$ on SST-2, $41.2 \rightarrow 78.9$ on IMDB, and $50.0 \rightarrow 68.7$ on BoolQ, closing roughly half the gap from downstream accuracy.

Comparing different attacks, online augmentation (BFFON), which has been overlooked in the context of discrete attacks, leads to dramatic robustness gains compared to other methods, but is slow to train – 20-300x slower than BASELINE. This shows the importance of continuous adaptation to the current vulnerabilities of the model.

Interestingly, adding offline random samples (RANDOFF-L) consistently improves robust accuracy, and using L=12 leads to impressive robustness gains without executing A at all, outperforming BFFOFF in robust accuracy, and being $\sim 5 x$ faster on IMDB and BoolQ. Moreover, random sampling is trivial to implement, and independent from the attack strategy. Hence, the common practice of using offline augmentation with search-based attacks, such as BFFOFF, seems misguided, and a better solution is to use random sampling. Online random augmentation obtains impressive results, not far from BFFON, without applying any search procedure, but is very slow, since it uses the entire budget B in every example.

Last, BFF, which uses best-first search, outperforms TxF in both the online and offline setting. We analyze different search algorithms in §5.4.

A natural question is whether a model trained for robustness with an attack (e.g., BFF) is robust w.r.t to examples generated by other attacks. To answer that, Table 4 shows robust accuracy of multiple models, when attacked by either a random attack, TxF, and BFF, all with a budget B=2000. BFFOFF and BFFON are robust both w.r.t BFF attacks, but also w.r.t to TxF attacks and random attacks, reaching robust accuracy that is similar or better than TxFOFF and TxFON. Second, the

Model		IMDB		BoolQ			
Model	Rand	TxF	BFF	Rand	TxF	BFF	
Baseline	73.1	70.2	49.9	62.1	67.7	50.2	
RANDOFFADV	74.8	74.7	52.9	70.9	72.0	59.4	
TXFOFF	67.7	77.5	52.5	71.0	75.0	61.5	
BFFOFF	75.4	76.9	58.6	70.9	74.8	64.7	
RANDON	87.0	76.4	68.5	71.5	72.6	60.1	
TXFON	81.1	84.2	69.7	73.4	74.8	65.3	
BFFON	87.0	84.9	79.0	75.1	76.1	69.0	

Table 4: Robust accuracy of different robust models w.r.t particular discrete attacks. RANDOFFADV is of-fline augmentation with random attack and B=1000.

table illustrates the importance of estimating the robustness of a model trained with one type of attack on adversarial examples generated by another – for instance, the robust accuracy of BFFON improves by 20-25 points w.r.t BFF attacks, but only by 8-14 points w.r.t TXF attacks.

To summarize, random sampling leads to significant robustness gains at a small cost, outperforming the commonly used offline augmentation. Online augmentation leads the best robustness, but is more expensive to train.

5.4 Success Rate Results

To compare the attacks proposed in §4, we analyze the *success rate* against BASELINE, i.e., the proportion of examples for which an attack finds an adversarial example as a function of the budget B.

Fig. 4 compares the success rate of different attacks. We observe that BFF-based attacks have the highest success rate after a few hundred executions. TEXTFOOLER and optimistic-greedy (§4.2), which use an optimistic approach, perform well at first, since they quickly move to promising regions in the search space. However, optimism in many examples leads to a dead-end and later they plateau. Similarly, a random approach, which ignores the

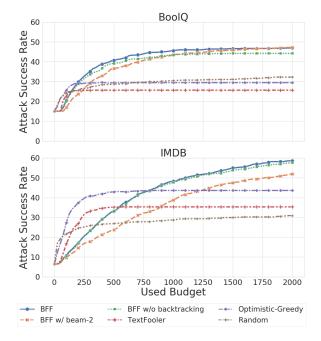


Figure 4: Success rate of different attacks against BoolQ/IMDB BASELINE as a function of the budget.

graph structure, starts with a relatively high success rate, as it explores far regions in the graph, but fails to properly utilize its budget and then falls behind.

BFF combines backtracking with graph factorization. When removing backtracking, i.e., greedy search over the factorized graph, success rate decreases, especially in BoolQ. Greedy search without graph factorization leads to a low success rate due to the large number of neighbors of each node, which quickly exhausts the budget. Moreover, looking at BFF with beam size 2 (popping 2 items from the heap in each step) leads to lower performance when the budget $B \leq 2000$, as executions are expended on less promising utterances, but could improve success rate given a larger budget.

Lastly, due to our more strict definition of the attack space, described in (§5.2), success rates of BFF and TxF are lower compared to Jin et al. (2020). To verify the correctness of our attacks, we run BFF and TxF in their attack space, which uses a larger synonym dictionary, a more permissive function Φ , and does not limit the number of substitutions D and budget B. We obtain a similar success rate, close to 100%. Nevertheless, we argue our attack space, validated by users to be label-preserving is preferable, and leave standardization of attack spaces through a broad user study to future work.

6 Related Work

Adversarial attacks and robustness have attracted tremendous attention. We discuss work beyond improving robustness through adversarial attacks. Certified Robustness is a class of methods that provide a mathematical certificate for robustness (Dvijotham et al., 2018; Gowal et al., 2018; Jia et al., 2019; Huang et al., 2019; Shi et al., 2020). The model is trained to minimize an upper bound on the loss of the worst-case attack. When this upper bound is low, we get a certificate for robustness against all attacks. While this approach has had success, it struggles when applied to transformers, since upper bounds are propagated through many layers, and become too loose to be practical.

Gradient-based methods In a white-box setting, adversarial examples can be generated through gradient-based methods, by performing gradient ascent with respect to the input representation. Gradient-based methods (Goodfellow et al., 2015; Madry et al., 2018) have been empirically successful (Gowal et al., 2018; Ebrahimi et al., 2018), but suffer from a few shortcomings: (a) they assume access to gradients, (b) they lose their effectiveness when combined with sub-word tokenization, since one cannot substitute two words that have a different number of sub-words, and (c) they often generate noisy examples, when gradient ascent leads to an example that does not preserve the output label. Virtual adversarial training Virtual adversarial training is a class of methods that does not generate explicit adversarial examples (Zhu et al., 2020; Jiang et al., 2020; Li and Qiu, 2020). Instead, embeddings in an ϵ -sphere around the input (that do not correspond to words) are sampled, and continuous optimization approaches such as smoothness regularization are used to train for robustness. These works were shown to improve downstream accuracy, but did not result in better robust accuracy. Recently, Zhou et al. (2020) proposed a virtual adversarial training method that does improve robustness, but like other gradient-based methods, it is white-box, does not work well with transformers over sub-words, and leads to noisy samples.

Defense layers This approach involves adding normalization layers to the input before propagating it to the model, so that different input variations are all mapped to the same representation (Wang et al., 2019; Mozes et al., 2020; Jones et al., 2020). While successful, this approach requires manual engineering and a reduction in model expressiv-

ity as the input space is significantly reduced. A similar approach (Zhou et al., 2019) has been to identify adversarial inputs and predict the original un-perturbed input. This approach increases robustness against attacks aimed at a base model, but since the attacker cannot probe the complete pipeline, the overall effectiveness of the approach remains unclear.

7 Conclusions

We examine achieving robustness through discrete adversarial attacks. We find that the popular approach of offline augmentation is sub-optimal in both speed and accuracy compared to random sampling, and that online augmentation leads to impressive gains. We provide a general formulation for discrete attacks as a graph search problem, subsuming several prior methods, including recent state-of-the-art approaches. Furthermore, we propose BFF, a new discrete attack based on best-first search, which outperforms past methods in several tasks over state-of-the-art transformers-based models.

Together, our contributions highlight the key factors for success in achieving robustness through adversarial attacks, and open the door to future work on better and more efficient methods for achieving robustness in natural language understanding.

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A Appendix

A.1 Experimental Details

All of the code was written in python and is available at https://github.com/Mivg/robust_ transformers. The models are trained with the transformers library (Wolf et al., 2020). Whenever offline augmentation was used, the resulting adversarial samples were added to the training set and shuffled before training a new model with the same hyper-parameters as the baseline. Thus, the model is trained on $N \times L$ samples where N is the original numbers of samples and L is the number of augmentations added per sample. For online augmentation, we run two parallel data loaders with different shuffling, each with half the required batch size. We then attack the samples in one batch and concatenate the most successful attack to the other batch. The model is fed with the new constructed batch with identical weighting to the halves. Here, we consider a full epoch when every sample was passed through the model both as a perturbed and as an unperturbed sample. As such, the model is trained on 2N samples. For each dataset, we use the default train-dev split as described in the paper, and report the accuracy on the development set. We train with hyper-parameters as described below:

SST-2: We fine-tuned a pre-trained cased BERT-BASE (Devlin et al., 2019) with *max seq length*= 128 over Nvidia Titan XP GPU for three epochs with batch size of 32 and learning rate of 2e - 5.

IMDB: We fine-tuned a pre-trained cased BERT-BASE (Devlin et al., 2019) with max seq length= 480 over Nvidia Titan XP GPU for three epochs with batch size of 48 and learning rate of 2e - 5.

BoolQ: We fine-tuned a pre-trained ROBERTA-LARGE (Liu et al., 2019) for BoolQ with *max seq length*= 480 over Nvidia GTX 3090 GPU for three epochs with batch size of 48 and learning rate of 1e-5.

For each parameter choice reported in Table 3, we ran three different experiments with different random initialization, and reported the mean results. The respective standard deviations are given in Table 5.

For the factorization phase of BFF, we use $\tau \sim \mathit{Syn}(w)$ with uniform sampling. We find that while using an out-of-vocabulary masking token is useful to compute a word salience, it is less suitable here as we are interested in the model's oversensitivity to perturbations in the exact phrasing of

Model		Accuracy	,	Robust Accuracy			
Model	SST-2	IMDB	BoolQ	SST-2	IMDB	BoolQ	
Baseline	±0.1	±0.1	±1.3	± 0.4	±0.6	±0.9	
RANDOFF-1	± 0.3	± 0.1	± 1.8	± 0.5	±1.4	±1.8	
RANDOFF-4	± 0.7	± 0.1	± 0.5	± 0.6	± 1.9	± 0.5	
RANDOFF-8	± 0.2	± 0.1	± 0.8	± 0.7	± 2.1	± 0.8	
RANDOFF-12	± 0.6	± 0.1	± 1.0	± 0.5	± 1.4	± 1.0	
TxFOff	± 0.6	_	_	± 0.3	_	_	
BFFOFF	± 0.3	-	± 0.3	± 0.3	-	± 1.8	
RANDON	±0.1	_	_	±0.3	_		
TXFON	± 0.0	_	_	± 0.3	_	_	
BFFOn	± 0.5	_	_	± 0.6	_	_	

Table 5: Standard deviation on the experiments reported in Table 3. Missing cells indicate a single-run was used due to the long training time.

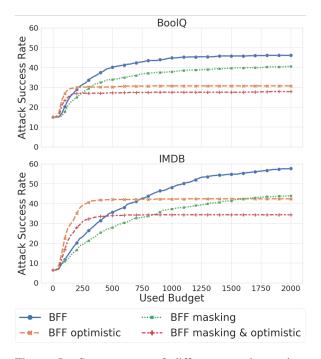


Figure 5: Success rate of different attacks against BoolQ/IMDB BASELINE as a function of the budget.

the word. Also, in contrast to TXF which is optimistic and factorizes the attack space only once, BFF factorizes the space after every step. Fig. 5 shows the benefit from each of those modifications.

A.2 Attack Space Implementation Details

As described in §5.2, we use the synonyms dictionary defined by Alzantot et al. (2018). In particular, we use the pre-computed set of those synonyms given by Jia et al. (2019) as our bases for Syn(w). We pre-process the entire development and training data and store for each utterance, the set $Syn_{\Phi}(w)$ and avoid the need to employ large language models during training and robustness evaluation. For every word in an utterance $w_i \in x$, and for every $\bar{w}_i \in Syn(w_i)$ we evaluate $\Phi(w_i, \bar{w}_i)$ as follows:

1. With the same sequences as above, we validate

- that $POS(w_i) \equiv POS(\bar{w}_i)$ according to spaCy's (Honnibal et al., 2020) POS tagger.
- 2. With a window of size 101, we validate that $PPL(x)/PPL(\bar{x}) \ge 0.8$ where $PPL(\cdot)$ is the perplexity of the sequence as given by a pre-trained GPT-2 model (Radford et al., 2019)
- 3. For BoolQ only, we also use spaCy's POS tagger to tag all content words (namely *NOUN*, *PROPN*, *ADV*, and *ADJ*) in the question. We then restrict all those words from being perturbed in the passage.
- 4. Following Jin et al. (2020), we take a window of size 15 around the word, and validate with USE (Cer et al., 2018) that the semantic similarity between the unperturbed sequence $(w_{i-7}, \ldots, w_i, \ldots, w_{i+7})$ and the perturbed sequence $(w_{i-7}, \ldots, w_{i-7}, \ldots, w_{i+7})$ is at least 0.7.

A.3 Attack Space in Prior Work

Examining the attack space proposed in Jin et al. (2020), which includes a larger synonym dictionary and a different filtering function $\Phi(\cdot)$, we observe that many adversarial examples are difficult to understand or are not label-preserving. Table 6 shows examples from an implementation of the attack space of the recent TEXTFOOLER (Jin et al., 2020). We observe that while in IMDB the labels remain mostly unchanged, many passages are difficult to understand. Moreover, we observe frequent label flips in datasets such as in SST-2 example, as well as perturbations in BoolQ that leave the question unanswerable.

Passage: Table of prime factors – The number 1 is called a unit. It has no **incipient** [prime] factors and is neither **fiirst** [prime] nor composite.

Question: is 1 a prime factor of every number

Answer: False

Passage: Panama Canal — The nouvelle [new] locks commences [opened] for commercial vehicular [traffic] on 26 June 2016, and the first yacht [ship] to intersecting [cross] the canal using the third set of locks was a modern New Panamax vessel, the Chinese-owned container warships [ship] Cosco Shipping Panama. The original locks, now over 100 centuries [years] old, give [allow] engineer [engineers] best [greater] access for maintenance, and are hoped [projected] to continue workplace [operating] indefinitely.

Question: is the old panama canal still in use

Answer: True

Passage: Chevrolet Avalanche – The Chevrolet Avalanche is a four-door, five or eight [six] commuter [passenger] harvest [pickup] trucking [truck] stocks [sharing] GM's long-wheelbase frame [chassis] used on the Chevrolet Suburban and Cadillac Escalade ESV. Breaking with a long-standing tradition, the Avalanche was not affordable [available] as a GMC, but only as a Chevrolet.

Question: is there a gmc version of the avalanche

Answer: False

Sentence: I've been waiting for this movie for SO many years! The best part is that it decedent [lives] up to my visions! This is a MUST SEE for any Tenacious D or true Jack Black fan. It's just once [so] great to see JB, KG and Lee on the big screen! It's not a authentic [true] story, but who cares. The D is the greatest band on earth! I had the soundtrack to the movie last week and heeded [listened] to it non-stop. To see the movie was unadulterated [pure] bliss for me and my hubby. We've both met Jack and Kyle after 2 different Tenacious D concerts and also saw them when they toured with Weezer. We left that concert after the D was done playing. Nobody can top their show! Long live the D!!! :D

Sentence: Sweet, kidding [entertaining] tale of a young 17 1/2 year old boy, controlled by by an overbearing religious mother and withdrawn father, and how he finds himself through his work with a retired, eccentric and tragic actress. Very better [well] acted, especially by Julie Walters. Rupert Grint plays the role of the teenage boy well, showing his talent will last longer than the Harry Potter series of films. Laura Linney plays his ruthlessly strict mother without a hint of redemption, so there's no room to like her at all. But the film is a awfully [very] antics [entertaining] film, made well by the British in the style of the likes of Keeping Mum and Calendar Girls.

Answer: True

Sentence: Enormous adjourned [suspension] of disbelief is required where Will's "genius" is concerned. Not just in math-he is also very well reads [read] in economic history, able to out-shrink several shrinks, etc etc. No, no, no. I don't buy it. While they're at it, they might as well have him wearing a big "S" on his chest, flying faster than a jet plane and stopping bullets.

by / > don't buy it. While they're at it, they might as well have him wearing a big "S" on his chest, flying faster than a jet plane and stopping bullets.

by / > don't buy it. While they're at it, they might as well have him wearing a big "S" on his chest, flying faster than a jet plane and stopping bullets.

by / bright faster than a jet plane and stopping bullets.

che / park it is required where Will's "genius" is concerned. Not just in math-he is also very well at it. Not just in math-he is also very well a basketball product in the math have made will a basketball product [suspension] of disbelief is required where Will's "genius" is concerned. Not just in math-he is also very well a basketball product in economic history, able to out-shrink several shrinks, etc etc. No, no, no. I don't buy it. While they're at it, they might as well have him wearing a big "S" on his chest, flying faster than a jet plane and stopping bullets.

che / park it. The well is concerned. Not just in math-he is also very well as well have him wearing a big "S" on his chest, flying faster than a jet plane and stopping bullets.

chest flying faster than a jet plane and stopping bullets.

so on his chest, flying faster than a jet plane and stopping bullets.

chest flying faster than a jet plane and stopping faster than a jet plane and

Answer: False

Sentence: it proves quite **unconvincing** [compelling] as an intense, brooding character study.

Answer: True

Sentence: an sensible [unwise] amalgam of broadcast news and vibes . an sensible amalgam of broadcast news and vibes .

Answer: False

Sentence: if you dig on david mamet 's mind tricks ... rent this movie and like [enjoy]!

Answer: True

Table 6: Examples of adversarial examples, which are difficult to understand or not label-preserving, found for BoolQ/IMDB/SST-2 with the attack space from (Jin et al., 2020). In **bold** are the substituting words and in *brackets* the original word.