Target Model Agnostic Adversarial Attacks with Query Budgets on Language Understanding Models

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Abstract

Despite significant improvements in natural language understanding models with the advent of models like BERT and XLNet, these neural-network based classifiers are vulnerable to blackbox adversarial attacks, where the attacker is only allowed to query the target model outputs. We add two more realistic restrictions on the attack methods, namely limiting the number of queries allowed (query budget) and crafting attacks that easily transfer across different pre-trained models (transferability), which render previous attack models impractical and ineffective. Here, we propose a target model agnostic adversarial attack method with a high degree of attack transferability across the attacked models. Our empirical studies show that in comparison to baseline methods, our method generates highly transferable adversarial sentences under the restriction of limited query budgets.

1 Introduction

Recent advancements in language understanding models have significantly pushed forth the accuracy achieved on various challenging NLP benchmarks. Despite this success, deep learning models in general are shown to misclassify when small, often humanly imperceptible, perturbations are added to original samples. These perturbed samples are referred to as adversarial samples and such an attack is termed an adversarial attack. The positive side of such adversarial attacks is that apart from exposing vulnerabilities, they also aid improved understanding and interpretation of models by uncovering training biases. Various analyses have been performed via crafted adversarial sentences: model sensitivities to small perturbations (Li et al., 2016), testing neural machine translation (Belinkov and Bisk, 2018), evaluating reading comprehension (Jia and Liang, 2017) and classification models, to name a few.

Adversarial samples can either be generated in a whitebox setting, where the target model’s parameters like computed gradients, weights, etc., are fully accessible to the attacker or in a blackbox setting, where the attacker can only access the inputs and outputs of the target model (Papernot et al., 2016, 2017). For several commercial or proprietary pre-trained models deployed online, only a blackbox setting can be considered as a realistic setting.

Existing blackbox attacks craft adversarial samples by repeatedly querying (in the order of thousands) a target model to pick those samples that achieve the greatest drop in accuracy (Jin et al., 2019; Zhang et al., 2019a). This also means that the adversarial sample generation is specific to a single pre-trained model and does not generalize well to attacks on other models.

Motivated by the aforementioned observations, we consider added restrictions on the traditional blackbox model to characterize restrictions in real-world systems. These restrictions render all previ-
ous blackbox attacks impractical or infeasible. We introduce the following limited settings: 

**Query-limited setting:** Here, the service that deploys a trained model imposes an upper limit on the number of queries to the model due to resource constraints. Upon exceeding such a limit, additional monetary costs can be levied per query.

**Transferability setting:** Here an attack method, rather than constructing adversarial samples specific to a target model, should instead generate adversarial samples that can be used to attack a diverse range of pre-trained target models. In other words, the attack method should possess high attack transferability across distinct target models.

Our proposed attack works well under both the added restrictions by not querying target models during training, unlike previous methods. Rather, we construct a set of adversarial candidate samples just once in an off-line fashion by first identifying important words in a sentence using an enhanced neural language model On-LSTM (Shen et al., 2019) with MultiHead attention and replacing them with specifically chosen synonyms in such a manner that the resulting adversarial sentence maintains a very similar distribution to the input data upon which the target models are trained. Furthermore, we impose upper bounds on: (i) the number of important words that can be replaced per sentence and (ii) the number of adversarial sentences generated per original sentence. Table 1 shows an example of adversarial sentences produced by our attack method.

**Contributions:** (i) **Target-agnostic:** We propose a target model agnostic attack on language understanding models that works under a limited query budget. (ii) **Transferability:** We employ offline training to generate a set of adversarial sentences just once, which can then be efficiently used in repeated attacks against several pre-trained models across a wide range of NLP tasks. (iii) **Empirical studies:** We conducted an exhaustive empirical analysis to gain deeper insights into our target-agnostic attack and we achieve substantial drops in accuracy of the target models. For example, our methods drop the accuracy of BERT on MNLI by 21% (from 82.7% to 61.63%) with an extremely tight budget of 20, which is more than 15 times the accuracy drops by the baseline attack methods. We point that our method considers a weaker black-box setting in which we have some data available to train the ON-LSTM model. This can be the same data over which the attacked NLP model is trained, or it can have similar underlying distribution. However, the amount of data used to train ON-LSTM in our experiments is substantially low (less than 10K samples per dataset).

## 2 Related Work

Adversarial attacks have gained widespread popularity in computer vision (Goodfellow et al., 2014; Elsayed et al., 2018; Xie et al., 2017a, b), as they are continuous input domains and therefore lend easily to attacks based on gradient searches and randomization. However, NLP tasks present a new modality, i.e., discrete input domains on which extending gradient based attack methods are not straightforward. There have been several attempts to perform gradient based attacks via GANs to create natural language adversarial samples (Zhao et al., 2018), however the generated adversarial samples are of an inferior quality. Other works apply heuristic strategies to generate adversarial samples by first identifying important features of the text (which could be characters, words or even sentences) followed by the application of greedy search strategies to perturb these features, while obeying constraints that preserve the quality of generated text. Most existing whitebox (Ebrahimi et al., 2018; Samanta and Mehta, 2017) as well as blackbox (Iyyer et al., 2018; Jin et al., 2019; Zhao et al., 2018) methods have used such search heuristics to successfully generate adversarial samples by maintaining the semantic and syntactic properties of the original text. Recent works (Behjati et al., 2019; Wallace et al., 2019) have focused on generating universal tokens to attack different models with good generalization properties, while (Ribeiro et al., 2018; Iyyer et al., 2018) tried to create adversaries via paraphrasing. We direct the reader to (Zhang et al., 2019b) for a detailed survey of adversarial attack methods.

## 3 Target Model Agnostic Attacks

### 3.1 Problem definition

We consider a pre-trained target model $f : \mathcal{X} \to Y$ trained on a set $\mathcal{X}$ of i.i.d. observations, each associated with a class label from set $Y$. For a classification task, the class label belongs to a finite set of predefined discrete values, whereas for a regression task the class label is a continuous real-valued scalar.

For the pre-trained model $f$ and a normal sam-
ple \( x \) (sentence)\(^1\) with class label \( y \), the goal of an untargeted adversarial attack is to find an adversarial sample \( x_{\text{adv}} \) that is nearly indistinguishable from \( x \), with respect to human perception, such that \( f(x_{\text{adv}}) \neq y \) (i.e., \( x_{\text{adv}} \) gets misclassified to an arbitrary class other than \( y \)). In a black-box setting, attackers are only allowed access to the final outputs of \( f \). Typical black-box attacks consist of repeatedly querying (in the order of thousands) a target model \( f \) with a sample \( x' \) to greedily improve the sample’s quality until a satisfactory \( x_{\text{adv}} \) is crafted, akin to a denial of service (DoS) attack on \( f \). Such attacks are both cumbersome to train and completely impractical when attacking trained models deployed online.

Instead, we propose an untargeted blackbox attack, where a set of candidate adversarial samples \( \mathcal{X} \) are generated during training without querying the target model \( f \) and the cardinality of \( \mathcal{X} \) does not exceed a budget \( K \). We define \( \mathcal{X}_c \) formally as:

\[
\mathcal{X}_c = \{ x' \mid x \in \mathcal{X}, S(x, x') \geq \epsilon, |\mathcal{X}_c| \leq K \}
\]

where \( S(\cdot, \cdot) \) is a semantic similarity measure between sentences. In words, \( \mathcal{X}_c \) contains at most \( K \) adversarial candidates whose semantic similarity to sample \( x \) exceeds a user-defined threshold \( \epsilon \). We are interested in finding the largest subset of true adversarial samples \( X_{\text{adv}} \) among the set of adversarial candidates \( \mathcal{X}_c \).

**Remark.** We decouple the necessity to query a specific target model \( f \) from adversarial sample generation and therefore arrive at a target-agnostic attack method where \( \mathcal{X}_c \) is generated once and is subsequently used to repeatedly attack a variety of models trained on \( \mathcal{X} \).

\(^1\)We use the term sample and sentence interchangeably.

3.2 Our target-agnostic attack method

In this section, we describe our proposed target-agnostic attack method that does not generate adversarial samples specific to any given target model. Our approach consists of two steps: (i) identification of important words in a sentence via a neural language attention model, and (ii) replacement of these important words to create adversarial samples conforming to the requirements of preserving the semantic as well as syntactic structure of the original sample enhanced via task-specific language modeling to get adversarial samples following the distribution of original samples.

3.2.1 Identifying important words

Our method uses the recent state-of-the-art language model called On-LSTM (Shen et al., 2019), which induces a tree-structured hierarchy on the hidden states of the LSTM network via monotonic master input and master forget gates. This inductive bias allows the On-LSTM model to perform tree-like composition operations, obtaining noteworthy improvements on tasks like language modeling and unsupervised constituency parsing. We enhance the On-LSTM model with a multi-head attention mechanism to identify important words upon which classification is performed via a classifier MLP alongside the standard language modeling objective. Figure 1 shows the architecture of our enhanced On-LSTM model.

Given a sequence of tokens \( S = (x_1, \cdots, x_N) \), we generate a corresponding sequence of word embeddings \( S_{\text{emb}} = (e_1, \cdots, e_N) \). To handle out-of-vocabulary (OOV) words as well as to perform character level attacks, we use Character-level CNNs (Zhang et al., 2015) to construct word embeddings. Given a token \( x_i \), we perform 1-D convolutions over its character embeddings stored in the lookup matrix \( F \in \mathbb{R}^{[C] \times d_e} \), where \( [C] \) is
the vocabulary size of characters and $d_c$ is the character embedding size, using 3 different kernels of sizes in $\{3, 4, 5\}$ and 100 output channels, which are concatenated and passed through a linear layer to obtain the final word embedding $e_i$. Repeating this process for every token, the new sequence $S_{emb}$ thus obtained serves as the input to the first layer of our network. We use a 2-layer On-LSTM network with the standard update procedures as described in (Shen et al., 2019).

Let $H = [h_1, \cdots, h_N]$ be the matrix consisting of the output vectors from the final layer of the model. We pass these through a MultiHead attention block as described in (Vaswani et al., 2017). The output is then passed through a 2-layer MLP with a SeLU (Klambauer et al., 2017) activation unit, which we call $C^{At}$ to obtain scalar attention coefficients for each output vector $h_i$ as:

$$P = \text{MultiHead}(H)$$

$$P' = C^{At}(P)$$

where $P' = [p_1, \cdots, p_N]$ consists of scalar attention values corresponding to each output vector of the matrix $H$. These attention values are then normalized via the entmax (Peters et al., 2019) normalization function:

$$\alpha = \text{entmax}(P')$$

Intuitively, each of the output vectors $h_i$ contains rich context information about the local n-gram chunks of the sentence. The MultiHead attention block allows chunk-to-chunk attention and the updated embeddings in $P$ contain context relative information throughout the sequence, aiding the LSTM in capturing dependencies throughout the sequence. We specifically use entmax as our normalization function as the sparsity induced by it allows the model to learn to focus on the most important words of the sentence. Thus, serving as our important word identification unit. The final task classification is performed by passing the combination of the vectors $h_i$ weighted by $\alpha$ using a 3-layer MLP which we call $C^{clf}$. More formally,

$$y = \text{softmax}(C^{clf}(H\alpha^T))$$

In tasks with paired-sentences, we perform 3 operations: element wise addition, subtraction and multiplication, followed by concatenation of the corresponding embedding vectors $H\alpha^T$ of the sentence pairs before passing them through the classifier $C^{clf}$. Our final cross-entropy loss related objective function is:

$$J(\theta) = \sum_{i=1}^{m} t_i \log(y_i) + L(H, S) + \lambda \|\theta\|^2$$

where $m$ is the number of classes, $t \in \mathbb{R}^m$ is the one-hot representation of the ground truth, $y \in \mathbb{R}^m$ is the estimated class probability, $L$ is the standard language modeling objective over the output vectors of the model, and $\lambda$ is the L2 regularization hyper-parameter. In a regression task, the cross-entropy loss is replaced by mean-squared error (MSE) loss.

The language modeling objective function allows our attack method to learn a task-specific sentence distribution that has both low perplexity and low divergence of the crafted adversarial sentences with respect to the input data distribution. After training the model, we use the attention coefficients ($\alpha$), to identify the important words in the sentence during adversarial generation phase as described in the following section.

### 3.2.2 Generating adversarial sentences

Having described the procedure for identifying important words in a sentence, we now describe the procedure to generate adversarial sentences. We limit both the maximum number of adversarial samples ($K$) as well as the maximum number of words ($M$) that can be perturbed in the original sentence to generate an adversarial sentence. Our objective is to generate a set of, at most $K$, distinct adversarial samples $X'$ for a given normal sample $x$, which can then cause maximum misclassification in every target model. We consider the following steps to generate $X'$:

(a) Consider a single token $x$ in a sentence and its corresponding word embedding $e$. Note that these word embeddings are specifically curated for synonym extraction (Mrkšić et al., 2016). We then compute a set $E_x$ of the $k$-most-semantically-similar words to $x$, based on the cosine-similarity between $e$ and the embeddings of neighboring words. The set $E_x$ is further reduced by pruning: (i) neighboring words whose cosine similarity with the original token $x$’s embedding falls below a user-defined threshold $\phi$, (ii) neighbors whose part-of-speech (POS) tags do not match the POS tag of $x$, and (iii) stop-words. We denote this reduced set of words by $E'_x$. Such a set is computed per token.

(b) Recall that each word is associated with an attention coefficient $\alpha$ (as described in Equation 2).
In a given sentence, we pick a set $X$ of top-$M$ words according to their corresponding $\alpha$ values. Now, we must replace each word $x \in X$ with a semantically-similar word from set $E'_x$. The total number of possible substitutions is upper bounded by $M!|E'_x|$, which is too large and therefore we randomly sample $R$ combinations and accordingly replace the original words with their corresponding semantically-similar words to arrive at our final adversarial candidate sentences. In our experiments, $R$ is set to 600.

(c) Each candidate sentence in $R$ is assigned a perplexity score when passed through our On-LSTM model. On the basis of this score, we pick the top-$W$ candidates with the lowest perplexity scores to further reduce the size of $R$. For each of the $W$ candidates, we then compute their sentence semantic similarity w.r.t to the original sentence using the Infersent model (Conneau et al., 2017). Finally, we retain the top-$K$ candidates ranked by decreasing order of their sentence semantic similarity score and further prune away candidates whose score is below $\epsilon$ (as defined in Section 3.1). The successful candidates from this set are referred to as $X_{\text{adv}}$, defined in Section 3.1. In our experiments, $K$ is set to 20, as explained in section 5.

4 Experiments

4.1 Datasets and Attacked Models

We study the effectiveness of our proposed approach on various standard datasets from the well established GLUE\(^2\) (Wang et al., 2019) benchmark. It consists of the Stanford sentiment treebank (SST-2) (Socher et al., 2013) (for sentiment analysis), the multi-genre natural language inference (MLNI) corpus (Williams et al., 2018) and the question answering natural language inference (QNLI) datasets (Wang et al., 2019) (for natural language inference) and finally the Quora Question Pairs (QQP) and the semantic textual similarity benchmark (STS-B) (Cer et al., 2017) (for paraphrasing). From each dataset we pick 1000 random instances from the dev set (except for SST-2, where dev set size is 870), since the actual test predictions are not publicly available. We report the results for the classification experiments on SST-2, MNLI, QNLI, and QQP here, while for STS-B, the results are provided in appendix.

We choose three dominant SOTA models to show the efficacy of our novel target-agnostic adversarial attack, namely BERT (Devlin et al., 2018), XLNet (Yang et al., 2019), and BiLSTM with attention mechanism (Wang et al., 2019). A brief description of each dataset, the attacked models and the results on STS-B are provided in the appendix.

4.2 Attack Results

In this section, we report the performance of the attacked models on the crafted adversarial samples from various methods. We compare our method with two well known black-box adversarial attacks methods. The first baseline: TextFooler (Jin et al., 2019), which performs iterative greedy attacks heuristically by replacing the original word with a word that drops the target model’s accuracy by the maximum margin. The other baseline is the popular genetic attack algorithm (Alzantot et al., 2018), which iteratively crafts the adversarial samples using a genetic based algorithm that fuses two adversarial sequences to create a better adversarial sample. Both these methods are run under the similar budget, word perturbation and hyperparameter settings as our model for fair evaluation.

The results for word perturbation factor $M=3$ are provided in table 2. Hereon, we use the terms candidate set size as well as attack budget interchangeably, both referring to $K$. Pre Attack Acc refers to the accuracy of the models on the original sentences. Avg. Accuracy Drop represent the drops in accuracy averaged over all the adversarial candidates, whereas Max. Accuracy Drops represent the maximum drop in accuracy achieved if any adversarial candidate in the set of $K = 20$ succeeds. Accuracy Drops are calculated as the difference between pre-attack accuracy (calculated over original sentences) and post-attack accuracy (calculated over the adversarial candidates). Hence, higher the accuracy drops, more successful the attack. It is evident from the table that our method outperforms the baseline methods by factors of up to 15 under very limited budget settings conforming to practical attack scenarios. The semantic similarity scores of our crafted adversarial samples are generally better than those of the baselines.

We also provide a mechanism to utilize our method for character level attacks, which makes our method all the more practical and generalized compared to methods that either employ word-specific or character-specific attacks. Results of word perturbations of 4 and 5, the regression

\(^2\)https://gluebenchmark.com/
dataset STS-B and character level attacks are provided in the appendix.

5 Analysis

Setting the value of K: We vary K to ascertain the tightest possible budget for our method. Figure 2 shows the average accuracy drops versus different budget values for XLNet model on MNLI, QNLI, and SST-2 datasets. We choose the first point of inflection at K = 20 on all curves as our optimal value of budget K across all datasets.

![Figure 2: Average accuracy drops versus the budget value for XLNet model on various datasets.](image)

**Table 2:** Word adversarial attack results by perturbing at most M = 3 words. This table shows accuracy drops for various methods as well as the average semantic score of the adversarial sentences to the original sentences. Pre-attack Accuracy represents the accuracy on original sentences. Avg. Accuracy Drop represent the drop in accuracy averaged over the adversarial candidates, whereas Max. Accuracy Drop represents the maximum drop in accuracy achieved if any adversarial candidate in the set of K = 20 succeeds. Higher the drops, more successful the attack. Here, m and mm represent the matched and mismatched versions of the dev set respectively. For Average Drops, the best results are marked in bold whereas the second best underlined. For Maximum Drops, the best results are marked by *, while the second best by **.

**Attack transferability:** We conduct transferability experiments w.r.t baseline methods to examine how well the adversarial samples crafted by the SOTA baselines transfer from one target model to the other. The results for QQP and QNLI datasets are summarized in Table 3, with M set to 3. In the table, higher the value, better the attack. For our method, we select the true adversarial samples per original sentence from the first model to attack the other two models. The average % drop in model accuracies shown in the table are averaged over all candidates. For the baselines which follow a greedy approach, the accuracy drops are extremely low when we transfer their adversarial sentences to other models, whereas our method is much more superior in this aspect. Our method is better by factors of upto 40 (depending upon model) as compared to the baselines and can craft highly generic adversaries, while preserving (to a large extent) the semantic and syntactic aspects of the original sentence. Additional results for maximum drops are provided in the appendix.

**Ablation study:** Since our method primarily focuses on selecting important words for crafting adversarial samples, we perform attacks on the target models by randomly replacing words from the original sentence, keeping the rest of the steps the same as provided in Section 3.2.2. The results for the datasets with M = 3 on XLNet target model are provided in Table 4. This table contains the average % drop as well the maximum % drops in accuracies between the original sentences and their adversarial counterparts caused by our method and a random attack. Once again, higher the value achieved, better the attack. Clearly, the proposed word importance selection criteria helps in selecting important words from the sentence and generate better adversarial samples.

**Human evaluation:** Apart from the automatic evaluation, we also analyze the adversarial sam-
represent the maximum drop in accuracies between \( \Delta \). For each original sentence, we randomly transferred which these sentences were original and adversarial samples. Better results in bold.

Table 3: Transferability attacks. Leftmost column header represents the original model (for which the adversaries were crafted) with the attack methods and the following three column headers represent the model on which these sentences were transferred and evaluated. The values in the table show the average % drop in model accuracies on original samples and their crafted adversarial counterparts. ‘-’ signifies same source and target model. For BERT, best results in bold, second best underlined. For XLNet, best results are marked by *, second best by **.

Table 4: Comparison of our method versus random attacks. \( \Delta \) represents the average drop, while Max \( \Delta \) represent the maximum drop in accuracies between original and adversarial samples. Better results in bold.

Table 5: Overall Grammatical score and Human Classification consistency for the datasets.

**Evaluating perplexity score versus confidence score drops trade-off:** Clearly, an adversarial sentence with a very high-perplexity score has a better chance of fooling the model under attack because it is completely different from the original sentence. Ideally, we want adversarial sentences that have a low-perplexity score but can achieve high drops in accuracy. To assess the quality of the generated adversarial sentences, we plot the sentence perplexity values versus the drop in the correct class probability between the original and adversarial sentences. Figure 3 shows the plots on various datasets for 50 randomly chosen sentences on BERT. Observe that the majority of our adversarial sentences lie in the region of “low-perplexity, high-confidence drops” (blue region), as opposed to baseline attacks whose adversarial sentences are spread over a very wide range of perplexity scores and are mostly confined to regions of low-to-medium confidence drops.

**Attack time:** We analyze the time taken by different methods to attack the target models. It is evident from figure 4 that our method is faster by factors of **9-12** (depending on the dataset). We attribute this to independence of the generated candidate adversaries from one another, thus allowing our method to perform attacks using mini-batches of data as opposed to the baselines, which iteratively improve the query and thus are forced to attack in a sequential manner. Similar attack runtime plots for BERT and XLNet are provided in our appendix.

**High transferability and staggered attacks:** We observed that a substantial fraction of our true adversarial examples were “common” to all models. We can thus roll out our queries per model in a “staggered approach”, i.e., querying a model, gathering its true adversarial set \( S \) and only using examples from \( S \) to target the next model, hence “shrinking” \( S \) with every model we attack. This approach
can drastically reduce the attack time if we have
to attack multiple models in a sequential manner
(i.e., when it’s not possible to attack more than one
model simultaneously). Results provided in table
6 verify our claims. The average % values shown
in the table represent the percentage of successful
adversarial samples out of the total samples the
corresponding model was attacked with. Further
experiments have been provided in the appendix.

Comparison to previous paraphrase based
attacks: Prior paraphrase based attack methods
such as (Iyyer et al., 2018; Ribeiro et al., 2018)
propose template and rule based methods to curate
adversaries. Verifying the correctness of these
templates and rules can be difficult and may
require manual investigations which is extremely
time consuming. Training models to generate
templates as done in (Iyyer et al., 2018) requires
training large scale models with large training sets,
as opposed to our case. These templates and rules
also have restrictions on their applicability as they
can’t be arbitrarily applied to any sentence. In
contrast, our method is completely automated with
very high semantics preservation properties, has
high transferability, can attack multiple models
via staggered approach as well as it has very low
attack time attributed to batching of the candidates.
We also performed a quantitative and qualitative
analysis of classwise accuracy drops for the
datasets as well as show various examples of
our successful adversaries, both are provided in
appendix.

Difference from Surrogacy based methods: As
mentioned earlier, our method follows a weaker
black-box setting, where we assume the presence
of a small amount of training data for ON-LSTM
model. However, this is significantly different
from the surrogacy based methods, where the sur-
rogate model is explicitly trained to replicate the
attacked model which requires a substantial amount
of queries to the attacked model, thus incurring a

| Dataset | BERT | XLNet | BiLSTM |
|---------|------|-------|--------|
| MNLI    | 34%  | 39%   | 12%    |
| SST-2   | 14%  | 33%   | 17%    |
| QQP     | 25%  | 36%   | 9%     |
| QNLI    | 17%  | 41%   | 19%    |

Table 6: Staggered attacks. Values in the table repre-
sent average % of successful adversarial samples.
6 Conclusion

We explore a novel target model agnostic adversarial attack under very limited query budgets. Unable to exploit biases of target models towards datasets, like other greedy methods do, this method carries multiple other advantages. The actual attack process is fast and the generated pool of adversarial sentences show a high degree of transferability across different types of models which brings the added benefit of attacking multiple target models simultaneously by the same candidate set. Our method performs well in comparison to the greedy SOTA adversarial attacks with a tighter budget on the number of queries, which makes our attack much more practical.

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A Character-Level Attacks

Our proposed method bears another advantage attributed to the use of character level encodings at the first layer. We can thus exploit the model sensitivity wrt each character to final output prediction. We define character importance by the value of the $L_2$ norm of the gradient of the classifier / regression algorithm output w.r.t the character embeddings. Furthermore, to efficiently use the important words and make better adversarial candidates, we only consider the characters from the most important words identified by our method. We constrain the attack method to consider a maximum of 3 words, from each of which, we consider 2 most important characters. These selected characters are then replaced with random characters from the standard symbols consisting of alphabets, digits, punctuation, separators, and misc symbols like {!, @, #...} etc. Since, the words formed by replacing their characters randomly may be out-of-order without any lexical structure, typically bearing misspelling errors, we thus disregard the use of a sentence similarity function, since the overall perturbation caused throughout the sentence is negligible. The results for character-level attacks are summarized in table 12.

B Model Details

Here we provide the details of hyper-parameters of the enhanced On-LSTM model and our adversarial attack method. The general hyper-parameters which were kept same for all tasks are provided in Table 7, while remaining hyper-parameters like - weight decay, learning rate etc. were adjusted specifically to tasks with appropriate scheduling of learning rate on plateau. The outputs embeddings from the character CNN are normalized before inputting into the LSTM.

The value of $k$ while choosing $k$-most-semantically-similar words for each token of the original sentence is set to 25. The threshold $\phi$ to drop neighbors below a certain cosine score is set to 0.5, whereas the sentence semantic similarity threshold $\epsilon$ is set to 0.5 as well. The parameter $W$, referring to the number of sentences chosen after passing through the On-LSTM model in increasing order of perplexity scores is set to 350.

C Attack Transferability

More comparisons for attack transferability across targeted models are provided in the tables 8, 9 and 10. The values in the tables show the average % drops in model accuracies on original samples and their crafted adversarial counterparts. Thus higher the value, better is the attack. The leftmost column represents the models(for which the adversarial sentences were crafted) along with the attack methods and the following 3 columns represent the model on which these sentences were evaluated. '-' signifies same source and target model.

D Attack Time Comparison

Figure 5 shows the time taken by various methods to attack the target models: BERT and XLNet. Its evident that our method is faster by factors of 8-12 (depending upon the dataset).
Table 8: Attack transferability on QQP and QNLI with maximum allowed perturbation of up to 4 words. For BERT, best results in bold, second best underlined. For XLNet, best results are marked by *, second best by **.

Table 9: Attack transferability on SST-2 and MNLI(Matched/Mismatched) with maximum allowed perturbation of up to 3 words. TF stands for the baseline TextFooler. For BERT, best results in bold, second best underlined. For XLNet, best results are marked by *, second best by **.

Table 11: provide more results for the Staggered attack approach. The average % values shown in the table represent the percentage of successful adversarial samples out of the total samples the corresponding model was attacked with. The rate is high when successful adversaries are transferred from BERT to XLNet and vice-versa which we believe is due to the model architecture bias. The first model is attacked with the budget of $K = 20$, the successful adversaries from this model are then used to attack the second model and the process repeats, thus shrinking the size of the set of adversarial candidates.

E High transferability and Staggered Attacks

F Classwise Performance

Figures 6, 7 and 8 show the classwise accuracy changes/drops for various datasets. For MNLI, the % drop in accuracy for entailment class is particularly high. This is primarily due to high lexical overlap between the premise and hypothesis, thus changing the lexical structure of hypothesis leads the models to false predictions of entailment class. SST-2 being a balanced dataset shows similar performance degradation for both the classes. For QQP, the class with label 1(Similar) has much higher % drop accuracy. We hypothesize the primary reason for this to be the skewness of the dataset for class with label 0(Dissimilar) due to
Table 10: Attack transferability on SST-2 and MNLI(Matched/MisMatched) with maximum allowed perturbation of upto 4 words. TF stands for the baseline TextFooler. For BERT, best results in bold, second best underlined. For XLNet, best results are marked by *, second best by **.

Table 11: Staggered attacks. Values in the table represent average % of successful adversarial samples.

G Dataset Descriptions

SST-2: is a binary classification dataset of reviews from movies annotated by humans.

MNLI: is a huge collection of sentence pairs termed as hypothesis and premise with their textual entailment annotations. Given a premise and a hypothesis sentence, the task is to predict whether the premise entails, contradicts or shows neutrality to the hypothesis. The dev portion of this dataset contains two subcomponents marked - matched(m) and mismatched(mm). We evaluate our method on both subcomponents separately.

QNLI: cast question-paragraph pairs from SQuAD into a classification task forming a pair between each question and each sentence in the corresponding context (from the paragraph) with high lexical overlap. The task at hand is to determine whether the context sentence contains the answer to the question.

STS-B: is a collection of sentence pairs drawn from various sources. The task is to determine the semantic score between two sentences ranging from 1 to 5, thus marked as a regression task.

H Attacked Models

We provide a brief description of the attacked models here. For both BERT and XLNet, we use the PyTorch implementation3, with 12 hidden layers, 768 hidden units, 12 attention heads, and sequence lengths truncated to 128. For BiLSTM model with attention, we use a 2 layer bidirectional LSTM with hidden dimension embeddings of size 1500 as well as input embeddings initialized using ELMo embeddings, having a MLP classifier with 512 hidden units. We use the implementation available here 4.

3https://github.com/huggingface/transformers
4https://github.com/nyu-mll/GLUE-baselines
Table 12: Character level adversarial attack results of our method by perturbing 2 characters in 1, 2 and 3 words respectively. Pre Attack Acc represents the accuracy on original sentences. Avg. Accuracy Drops represent the drops in accuracy averaged over the adversarial candidates, whereas Max. Accuracy Drops represent the maximum drop in accuracy achieved if any adversarial candidate in the set of $K = 20$ succeeds. Semantic Sim represents the average semantic similarity of the adversaries to the original sentences. Here, $m$ and $mm$ represent the matched and mismatched versions of the dev set respectively.

Figure 6: Classwise accuracy change for MNLI, SST-2 and QQP on the three target models with maximum perturbation allowed upto 3 words.

Figure 7: Classwise accuracy change for MNLI, SST-2 and QQP on the three target models with maximum perturbation allowed upto 4 words.
Figure 8: Classwise accuracy change for QNLI on the three target models with maximum perturbation allowed up to 3(left subfigure) and 4(right subfigure) words.

Table 13: Word adversarial attack results by perturbing atmost 4 words. The table shows accuracy drops for various methods as well the average semantic score of the adversarial sentences. Pre Attack Acc represents the accuracy on original sentences. Avg. Accuracy Drops represent the drops in accuracy averaged over the adversarial candidates, whereas Max. Accuracy Drops represent the maximum drop in accuracy if any adversarial candidate succeeds. Higher the drops, more successful the attack. Here, m and mm represent the matched and mismatched versions of the dev set respectively. For Average Drops, the best results are marked in ** whereas the second best underlined. For Maximum Drops, the best are marked by *, whereas the second best by **.

Table 14: Word adversarial attack results by perturbing atmost 5 words. The table shows accuracy drops for various methods as well the average semantic score of the adversarial sentences. Pre Attack Acc represents the accuracy on original sentences. Avg. Accuracy Drops represent the drops in accuracy averaged over the adversarial candidates, whereas Max. Accuracy Drops represent the maximum drop in accuracy achieved if any adversarial candidate is in the set of \( K = 20 \) succeeds. Higher the drops, more successfully the attack. Here, m and mm represent the matched and mismatched versions of the dev set respectively. For Average Drops, the best results are marked in ** whereas the second best underlined. For Maximum Drops, the best are marked by *, whereas the second best by **.
Table 15: Adversarial attack results of all methods on the regression dataset: STS-B for various word perturbation levels: 3, 4 and 5. Pre Attack MSE represents the mean squared error on original sentences. Post Attack MSE represents the mean squared error averaged over the adversarial candidates. Semantic Sim represents the average semantic similarity of the adversaries to the original sentences. Higher the value of Post Attack MSE, more successful the attack. Best results are marked in **bold**, while the second best are *underlined*.

| Sent Type | Input Sentence                                                                                                                                                                                                 | Model Prediction |
|-----------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------|
| **Model: BiLSTM, Task: SST-2** |                                                                                                                                                                                                                |                   |
| Original  | Allow us to hope that Nolan is poised to embark on a major career as a commercial yet inventive filmmaker.                                                                                                       | Positive         |
| Adversarial | Allows us to hope that Nolan is poised to embark on a major career as a commercial **but creative** director.                                                                                                      | Negative         |

| **Model: XLNet, Task: SST-2** |                                                                                                                                                                                                                |                   |
| Original  | In its best moments, resembles a bad high school production of grease, without benefit of song.                                                                                                               | Negative         |
| Adversarial | In its best moments, remembering a bad high school production of grease, without benefit of anthems.                                                                                                         | Positive         |

| **Model: BiLSTM, Task: MNLI** |                                                                                                                                                                                                                |                   |
| Premise   | There are no shares of a stock that might someday come back, just piles of options as worthless as those shares of Cook’s american business alliance.                                                          | Contradiction     |
| Original  | Cook’s **american** business alliance caused shares of stock to come **back**.                                                                                                                               |                    |
| Adversarial | Cook’s **latino** business alliance caused shares of stock to come backwards.                                                                                                                                | Entailment        |

| **Model: XLNet, Task: MNLI** |                                                                                                                                                                                                                |                   |
| Premise   | If that investor were willing to pay extra for the security of limited downside, she could buy put options with a strike price of $98, which would lock in her profit on the shares at $18, less whatever the options cost. | Contradiction     |
| Original  | The **strike** price could be $8.                                                                                                                                                                             | Neutral           |
| Adversarial | The **shelling** price could be $8.                                                                                                                                                                         |                    |

Table 16: Samples from the target model agnostic adversaries generated by our method. The last column shows the predictions of the target models (over the original sentences which were predicted correctly).
| Sent Type | Input Sentence | Model Prediction |
|-----------|----------------|------------------|
| **First Sent** | What people who you’ve never met have influenced your life the most? | Similar |
| Original | Who are the **people** you have never **met** who have had the greatest influence on your **life** ? | |
| Adversarial | Who are the **nationals** you have never **encountered** who have had the greatest influence on your **vida** ? | Dissimilar |

**Model: BiLSTM, Task: QQP**

| Premise | What is another possible explanation for the source of the signals? | Not Entailment |
|---------|---------------------------------------------------------------|----------------|
| Original | He expanded on the signals he heard in a 9 February 1901 Collier’s weekly article talking with planets where he said it had not been immediately **apparent** to him that he was hearing **intelligently controlled** **signals** and that the signals could come from mars, venus or other planets. | |
| Adversarial | He expanded on the signals he heard in a 9 February 1901 Collier’s weekly article talking with planets where he said it had not been immediately **noticeable** to him that he was hearing **intelligently controlled** gesture and that the signals could come from mar, venus or other planets. | Entailment |

**Model: XLNet, Task: QQP**

| Premise | What religion did tesla grow up in? | Not Entailment |
|---------|----------------------------------|----------------|
| Original | Later in his life, he did not consider himself to be a **believer** in the orthodox **sense**, and opposed religious **fanaticism**. | |
| Adversarial | Later in his life, he did not consider himself to be a **devotee** in the orthodox **vein**, and opposed religious **homophobic**. | Entailment |

Table 17: Examples from the target model agnostic adversaries generated by our method. The last column shows the predictions of the target models (over the original sentences which were predicted correctly).

**SST-2**

All that’s **missing** is the **spontaneity**, originality and delight.
If Steven Soderbergh’s *solaris* is a **failure**, it is a glorious failure.

**QQP**

What are the requirements to become president in the united **states** and how are they requirements **different** in **France**?
What are the top books an aspiring **teen entrepreneur** should **read**?

**STS-B**

The dog is playing with a plastic container.
Someone is drilling a hole in a piece of wood.

**QNL**

The Lazienki park covers the area of 76 Ha.
The building was designed by architects Marek Budzyński and Zbigniew and opened on 15 December 1999.

**MNLI**

You don’t want to push the button lightly, but rather punch it hard.
The slopes between the Vosges and Rhine valley are the only place **appropriate** for vineyards.

Table 18: Top $M (= 3)$ words selected as important by our enhanced ON-LSTM method to be replaced marked in blue.
| Sent Type | Input Sentence | Model Prediction |
|-----------|----------------|------------------|
| **Model: XLNet, Task: SST-2** |
| Original  | An absurdist comedy about alienation, separation and loss. | Negative |
| Adversarial | An absurdist comedy about alienation, separation and loss. | Positive |
| **Model: BERT, Task: SST-2** |
| Original  | A subject like this should inspire reaction in its audience the pianist does not. | Negative |
| Adversarial | A subject like this should inspire reaction in its audience the pianist does not. | Positive |
| **Model: XLNet, Task: QQP** |
| First Sent | Online gaming with ir£ friends is more fun. Why do you play with randoms? | Similar |
| Original  | Playing dota2 with ir£ friends is more fun. Why do you play with randoms? | Dissimilar |
| Adversarial | Playing dota2 with ir£ friends is more fun. Why do you play with randoms? | Dissimilar |
| **Model: BERT, Task: QQP** |
| First Sent | What are some of the best jokes you’ve ever heard? | Dissimilar |
| Original  | What is the funniest joke you ever heard? | Similar |
| Adversarial | what is the funniest joke you ever heard? | Similar |
| **Model: XLNet, Task: QNLI** |
| Premise   | Who reportedly wanted tesla’s company? | Not Entailment |
| Original  | There have been numerous accounts of women vying for tesla’s affection, even some madly in love with him. | Entailment |
| Adversarial | There have been numerous accounts of women vying for tesla’s affection, even some madly in love with him. | Entailment |
| **Model: BERT, Task: QNLI** |
| Premise   | Who served his dinner? | Not Entailment |
| Original  | He dined alone, except on the rare occasions when he would give a dinner to a group to meet his social obligations. | Entailment |
| Adversarial | He dined alone, except on the rare occasions when he would give a dinner to a group to meet his social obligations. | Entailment |
| **Model: XLNet, Task: MNLI** |
| Premise   | Look out for that overseer up there. | Neutral |
| Original  | Watch out that you do not bump your head on the overseer. | Neutral |
| Adversarial | Watch out that you do N7t bump your head on the overseer. | Neutral |
| **Model: BERT, Task: MNLI** |
| Premise   | A re-created street of colonial Macau is lined with traditional chinese shops. | Neutral |
| Original  | You’ll find plenty of authentic, old world restaurants on that street. | Neutral |
| Adversarial | You’ll find plenty of authHe tic, old world restaurants on that street. | Contradiction |
| **Model: XLNet, Task: STS-B** |
| First Sent | It is possible, but it will have to be a docile female betta and a bigish tank. | 2.4 |
| Original  | We tried putting a male betta in a community tank once. | 3.45 |
| Adversarial | We try d putting a male betta in a community tank once. | |
| **Model: BERT, Task: STS-B** |
| Original  | One thing you seem to be forgetting regarding myths, is they are extremely prevalent stories. | 1.2 |
| Adversarial | I noticed you said movie critics enjoy mythological references in a film, but do audiences? | 0.71 |

Table 19: Examples from the target model agnostic adversaries over characters generated by our method. The last column shows the predictions of the target models (over the original sentences which were predicted correctly).
### Model: BiLSTM

| Sent Type | Input Sentence | Model Prediction |
|-----------|----------------|------------------|
| **Task: SST-2** | | |
| Original | Aside from minor tinkering, this is the same movie you probably loved in 1994, except that it looks even better | Positive |
| Adversarial | Aside from minor tinkering, this is the same movie you probably loved in 1994, except that it looks even better | Negative |

| **Task: QQP** | | |
| First Sent | What are some mind blowing car technology gadgets that exist in 2016 that most people don’t know about? | |
| Original | What are the most advanced car gadgets that people don’t know about? | Similar |
| Adversarial | What are the most advanced car gadgets that people don’t know about yet? | Dissimilar |

| **Task: QNLI** | | |
| Premise | Who said Tesla had a distinguished sweetness? | |
| Original | His loyal secretary, Dorothy Skerrit, wrote his genial smile and nobility of bearing always denoted the gentlemanly characteristics that were so ingrained in his soul. | Entailment |
| Adversarial | His loyal secretary, Dorothy Skerrit, wrote his genial smile and nobility of bearing always denoted the gentlemanly characteristics that were so ingrained in his soul. | Not Entailment |

| **Task: MNLI** | | |
| Premise | Yeah it’s true it is in fact I have a friend of mine that moved to North Carolina she’s um an emergency room nurse she does the operating room. | |
| Original | This person I’m close to is an emergency room nurse at a hospital in North Carolina | Entailment |
| Adversarial | This person I’m close to is an emergency room nurse at a hospital in North Carolina. | Neutral |

| **Task: STS-B** | | |
| First Sent | Keep in mind that you can easily swear without swearing. | |
| Original | I think stephen king’s comments are helpful in this regard. | 1.20 |
| Adversarial | I thM™k stephen king’s comments are helpful in this regard. | 2.36 |

Table 20: Examples from the target model agnostic adversaries over characters generated by our method. The last column shows the predictions of the target model (over the original sentences which were predicted correctly).