Abstract

TextAttack is a library for running adversarial attacks against natural language processing (NLP) models. TextAttack builds attacks from four components: a search method, goal function, transformation, and set of constraints. Researchers can use these components to easily assemble new attacks. Individual components can be isolated and compared for easier ablation studies. TextAttack currently supports attacks on models trained for text classification and entailment across a variety of datasets. Additionally, TextAttack’s modular design makes it easily extensible to new NLP tasks, models, and attack strategies. TextAttack code and tutorials are available at https://github.com/QData/TextAttack.

1 Introduction

Szegedy et al. (2014) discovered that adversarial examples can be generated to fool deep neural networks for image classification. Since then, researchers have discovered ways of generating adversarial examples for many other tasks, such as speech recognition and text classification. Within the natural language community, there has been growing interest in methods for generating adversarial examples for NLP models (Zhang et al., 2019b).

Many attack methods have been suggested for NLP models, ranging from greedy methods (Jin et al., 2019) to methods based on Markov Chain Monte Carlo (MCMC) sampling (Zhang et al., 2019a). These attacks are difficult to compare since they all reside in different code repositories and often are evaluated on different models and enforce linguistic constraints differently.

We provide a unified definition of NLP attacks as the composition of four components: a goal function, a search method, a transformation, and an optional list of constraints. We present TextAttack, a software library structured around these components. TextAttack implements examples of each component drawn from the literature. Its modular design enables researchers to develop new components and immediately test them in the context of an attack. We use TextAttack to assemble attacks from the literature, including those from (Gao et al., 2018), (Alzantot et al., 2018), and (Jin et al., 2019).

2 Composition of an NLP Attack

TextAttack aims to implement attacks which, given an NLP Model $F$, attempt to perturb an input sequence $x = (x_1, x_2, \ldots, x_m)$ to perturbation sequence $x_{adv}$ such that $x_{adv}$ satisfies a goal function and adheres to certain linguistic constraints.

To actually generate such $x_{adv}$, we need to modify the input text $x$, which can be done by adding new $x_i$, deleting existing $x_i$, or replacing $x_i$ with new $x'_i$. Note that $x_i$ can either be a word or a character, depending on the level of transformation.

However, the decision space for choosing a transformation is huge. Even if limiting ourselves to replacements and consider only the best $k$ replacements, there are $k^m$ possible transformations for generating $x_{adv}$. It becomes infeasible to consider every potential transformation, especially as $m$ gets larger (here $m$ denotes the sentence length).

Therefore, attacking an NLP model becomes a combinatorial search problem in which we search within (all) potential transformations to find a set of transformations for generating $x_{adv}$: so that $x_{adv}$ satisfies conditions defining an adversarial example. In summary, each attack can be constructed from four components:
1. A task-specific goal function that defines attack success in terms of the model outputs.

2. A number of constraints that determine if a perturbation is valid with respect to the original input.

3. A transformation that, given an input, generates a set of potential perturbations.

4. A search method that successively queries the model and selects promising perturbations from a set of transformations.

### 2.1 Goal Functions

A goal function takes an input $x$ and determines whether the attack is finished. Goal functions vary by task. For example, the goal function for generating untargeted attacks on classification can be denoted as follows:

$$ G(x) := \{ \arg \max F(x) \neq \text{original\_class} \} $$

Alternatively we can use the following goal function for targeted attacks on classification:

$$ G(x) := \{ \arg \max F(x) = \text{target\_class} \} $$

### 2.2 Constraints

An input is only considered valid if it satisfies each of the attack’s constraints. TextAttack currently implements three types of constraints.

#### 2.2.1 Edit distance

These constraints measure something about the similarity between $x$ and $x_{adv}$ on the character level. TextAttack supports the following edit distance constraints:

- Maximum BLEU score difference (Papineni et al., 2001)
- Maximum chrF score difference (Popovic, 2015)
- Maximum METEOR score difference (Agarwal and Lavie, 2008)
- Maximum Levenshtein edit distance
- Maximum percentage of words changed

#### 2.2.2 Grammaticality

These constraints are typically intended to prevent the attack from creating perturbations which introduce grammatical errors. TextAttack currently supports the following constraints on grammaticality:

- Maximum number of grammatical errors induced, as measured by LanguageTool (Naber et al.)
- Part-of-speech consistency

#### 2.2.3 Semantics

These constraints attempt to preserve meaning between $x$ and $x_{adv}$. TextAttack currently provides the following built-in semantic constraints:

- Maximum swapped word embedding distance (or minimum cosine similarity)

#### Sentence Encoders

- Universal Sentence Encoder (Cer et al., 2018)
- InferSent (Conneau et al., 2017)
- BERT trained for semantic similarity (Reimers and Gurevych, 2019)

#### Language Models

- Google 1-billion words language model (Józefowicz et al., 2016)
2.3 Transformations

A transformation takes an input and returns a set of potential perturbations. The transformation is agnostic of goal function and constraint(s): it returns all potential transformations.

We categorize transformations into two kinds: white-box and black-box. White-box transformations have access to the model and can query it or examine its parameters to help determine the transformation. For example, Ebrahimi et al. (2017) determines potential replacement words based on the gradient of the one-hot input vector at the position of the swap. Black-box transformations determine the potential perturbations without any knowledge of the model.

TextAttack currently supports the following transformations:

- **Word swap with nearest neighbors in the counter-fitted embedding space (et al., 2016)**
- **WordNet word swap (Miller et al., 1990)**
- **Word swap with characters transformed (Gao et al., 2018):**
  - Character deleted
  - Neighboring characters swapped
  - Random character inserted
  - Character substituted with a random character
  - Character substituted with a homoglyph
- **Composite transformation: returns the results of multiple transformations**

2.4 Search Methods

The search method aims to find a perturbation that achieves the goal and satisfies all constraints. Many combinatorial search methods have been proposed for this process. TextAttack has implemented a selection of the most popular ones:

- **Greedy with Word Importance Ranking.**
  Rank all words according to some ranking function. Swap words one at a time in order of decreasing importance.

- **Beam Search.**
  Initially score transformations at all positions in the input. Take the top $b$ transformations (where $b$ is a hyperparameter known as the “beam width”) and iterate, looking at transformations of all sequences in the beam.

- **Genetic Algorithm.**
  An implementation of the algorithm proposed by Alzantot et al. (2018). Iteratively alters the population through greedy perturbation of each population member and crossover between population numbers, with preference to the more successful members of the population.

3 Implementations of Existing Methods

TextAttack’s modular design allows us to implement many different attacks from past work in a shared library, often by adding only one or two new components. Table 1 categorizes past work based on their search methods, goal functions, transformations, and constraints. Figure ?? presents a set of TextAttack modules we used to re-implement attacks from Alzantot et al. (2018) and Jin et al. (2019).

4 TextAttack Under the Hood

TextAttack is optimized under-the-hood to make implementing and running adversarial attacks both simple and fast.

**TokenizedText.** A common problem with implementations of NLP attacks is that the original text is discarded after tokenization; thus, the transformation is performed on the tokenized version of the text. This causes issues with capitalization and word segmentation. Sometimes attacks swap a piece of a word for a complete word (for example, transforming “aren’t” into “aren’too”).

TextAttack stores each input as a TokenizedText object which contains the original text, the tokenized input, and helper methods for transforming the text while retaining tokenization. Instead of strings or tensors, classes in TextAttack operate primarily on TokenizedText objects.

**Caching.** Some search methods encounter the same input at different points in the search. In these cases, it is wise to pre-store values to avoid unnecessary computation. For each input examined during the attack, TextAttack caches its model output, as well as the whether or not it passed all of the constraints. For some search methods, this memoization can save a significant amount of time.\(^1\)

**Models, tokenizers, and datasets.** We include dataset samples as well as pre-trained models and

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\(^1\)Caching alone speeds up the genetic algorithm of Alzantot et al. (2018) by a factor of 5.
| Paper                  | Search Method | Transformation | Goal Function       | Constraints                                           |
|------------------------|---------------|----------------|---------------------|------------------------------------------------------|
| HotFlip (word swap)    | Beam search   | Gradient-Based Word Swap | Untargeted Classification | Word Embedding, Cosine Similarity, Part-of-speech match, Number of words perturbed |
| (Ebrahimi et al., 2017) |               |                |                     |                                                      |
| DeepWordBug            | Greedy-WIR    | (Character Insertion, Character Deletion, Character Swap, Character Substitution)* | {Untargeted, Targeted} Classification | Levenshtein edit distance |
| (Gao et al., 2018)     |               |                |                     |                                                      |
| Kuleshov              | Greedy word swap | Counter-fitted word embedding swap | Untargeted Classification | Thought vector encoding cosine similarity, Language model similarity probability |
| (Kuleshov et al., 2018)|               |                |                     |                                                      |
| Alzantot               | Genetic Algorithm | Counter-fitted word embedding swap | Untargeted Classification | Percentage of words perturbed, Google Language Model perplexity, Word embedding distance |
| (Alzantot et al., 2018)|               |                |                     |                                                      |
| TextBugger (black-box) | Greedy-WIR    | (Character Insertion, Character Deletion, Character Swap, Character Substitution)* | Untargeted Classification | USE sentence encoding cosine similarity |
| (Li et al., 2019)      |               |                |                     |                                                      |
| TextFooler             | Greedy-WIR    | Counter-fitted word embedding swap | Untargeted Classification | Word Embedding Distance, Part-of-speech match, USE sentence encoding cosine similarity |
| (Jin et al., 2019)     |               |                |                     |                                                      |
| BAE                    | Greedy-WIR    | BERT Masked Token Prediction | Untargeted Classification | USE sentence encoding cosine similarity |
| (Garg and Ramakrishnan, 2020)|       |                |                     |                                                      |

Table 1: Some prior work categorized within our framework: search method, transformation, goal function, constraints. * indicates a composition of multiple transformations

the corresponding tokenizers for common classification and entailment datasets. Our models and data are stored on Amazon S3 and automatically downloaded when invoked from TextAttack.

5 Using TextAttack for Research

Testing robustness of a model. An important use case for TextAttack is testing the robustness of an existing NLP model. TextAttack is library-agnostic, meaning that it can run attacks on models implemented in any deep learning framework. Model objects must be able to take in a tensor of IDs and return an output that can be processed by the goal function. For example, classification and entailment models return an array of scores. Tokenizers must implement a single method, encode(), which takes a string input and returns a list or tensor of IDs. These IDs will be stored on the TokenizedText object and passed to the model during inference.

Creating a new attack. TextAttack contains base abstract classes that implement the required functionality of each component: TextAttack.goal_functions.GoalFunction, TextAttack.constraints.Constraint, TextAttack.transformations.Transformation, and TextAttack.attack_methods.Attack.² Some implementations may be simple as adding a subclass with a single new function. Other times, researchers may integrate several new components to create a new attack.

Modes of execution. TextAttack is available as a Python package from GitHub³. TextAttack is also available for use through our demo web app. Most researchers will prefer the command-

²Search methods are subclasses the Attack class.
³https://github.com/QData/TextAttack
line mode as it allows for full customization and use of hardware. However, for demonstration purposes or for attacking a single sample, the web interface will suffice.

**Visualizing attack results.** TextAttack supports several different output formats for attack results:
- Printing results to stdout
- Printing to a text file or CSV
- Printing attack results to an HTML table
- Writing a table of attack results to a Visdom visualization server
- Presenting results via our demo web app

6 Related Work

We draw inspiration from the Transformers library (Wolf et al., 2019) as an example of a well-designed Natural Language Processing library. Some of the models and tokenizers are implemented using Transformers.

cleverhans (Papernot et al., 2018) is a library for constructing adversarial examples for computer vision models. Like cleverhans, we aim to provide methods that generate adversarial examples across a variety of models and datasets. In some sense, TextAttack strives to be a solution like cleverhans for the NLP community. Like cleverhans, attacks in TextAttack all implement a base Attack class. However, while cleverhans implements many disparate attacks in separate modules, TextAttack builds attacks from a library of shared components.

There are some existing open-source libraries related to adversarial examples in NLP. Trickster proposes a method for attacking NLP models based on graph search, but lacks the ability to ensure that generated examples satisfy a given constraint (Kulynych et al., 2018). TEAPOT is a library for evaluating adversarial perturbations on text, but only supports the application of ngram-based comparisons for evaluating attacks on machine translation models (Michel et al., 2019). Most recently, AllenNLP Interpret includes functionality for running adversarial attacks on NLP models, but is intended only for the purpose of interpretability, and only supports attacks via input-reduction or greedy gradient-based word swap (Wallace et al., 2019). TextAttack has a broader scope than any of these libraries: it is designed to be extendable to any NLP attack.

7 Conclusion

We presented TextAttack, an open-source library for testing the robustness of NLP models. TextAttack defines an attack in four modules: a goal function, a list of constraints, a transformation, and a search method. This allows us to compose attacks from previous work from these modules and compare them in a shared environment.

As new attacks are developed, we will add their components to TextAttack. We look forward to a future in which it is easier to develop and compare NLP attacks.

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