Query-Efficient and Scalable Black-Box Adversarial Attacks on Discrete Sequential Data via Bayesian Optimization

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Example: word-level adversarial attacks on text data

- Make an adversarial perturbation imperceptible to human.

A Strong Baseline for Query Efficient Attacks in a Black Box Setting, Maheshwary et al., EMNLP 2021.

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s_{orig} = Food is fantastic and exceptionally clean! My only complaint is I went there with my 2 small children and they were showing a very inappropriate R rated movie! (LABEL: Pos)

$\downarrow$ BBA

s_{adv} = Food is gorgeous and exceptionally unpolluted! My only complaint is I went there with my 2 small children and they were showing a very inappropriate R rated movie! (LABEL: Neg)

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Problem formulation

- Conditions for imperceptible perturbation (convention):
  - **Semantically similar** to the original sequence.
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- For the original sequence $s = [w_0, \ldots, w_{l-1}]$, define a set of semantically similar candidates $\mathcal{C}(w_i)$ for each i-th element w_i and define the attack search space $\prod_{i=0}^{l-1} \mathcal{C}(w_i)$.

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- Example (**word substitution based on word embedding**): For $s =$ "Food is fantastic and exceptionally clean! ...",

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w_i	food	is	fantastic	and	exceptionally	clean	$\ldots$
$\mathcal{C}(w_i)$	food	is	fantastic	and	exceptionally	clean	$\ldots$
	diet		wonderful		uncommonly	disinfect	$\ldots$
	meal		gorgeous		extraordinarily	unpolluted	$\ldots$
	$\vdots$		$\vdots$		$\vdots$	$\vdots$	$\ddots$

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- Objective: find adversarial example $s' \in \prod_{i=0}^{l-1} \mathcal{C}(w_i)$ that minimizes the modification rate (MR), $d_H(s, s')/l$ where d_H is Hamming distance.

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- Formally, we solve

$$\begin{aligned} \underset{s' \in \prod_{i=0}^{l-1} \mathcal{C}(w_i)}{\text{minimize}} \quad & d_H(s, s') \\ \text{subject to} \quad & \mathcal{L}(f_\theta(s'), y) \geqslant 0, \end{aligned}$$

where $\mathcal{L}(f_\theta(s), y) \triangleq \max_{y' \in \mathcal{Y}, y' \neq y} f_\theta(s)_{y'} - f_\theta(s)_y$ is the attack criterion.

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  where $\mathcal{L}(f_\theta(s), y) \triangleq \max_{y' \in \mathcal{Y}, y' \neq y} f_\theta(s)_{y'} - f_\theta(s)_y$ is the attack criterion.
- We focus on the **black-box setting** where the adversary can **only observe the predicted class probabilities** on inputs with a **limited number of queries** to the network.

Existing methods and limitations

- **Greedy-based algorithms** (PWWS, TextFooler, LSH, BAE, ...):
  - (1) Define the word replacement order based on word importance and
  - (2) greedily replace each word under this order with its synonym until attack success.
  - Severely restricted search space of the size $\sum_{i=0}^{l-1} |C(w_i)| - l + 1$.
  - Require small Qrs, but achieve low attack success rate (ASR).

Searching for a Search Method: Benchmarking Search Algorithms for Generating NLP Adversarial Examples, Yoo et al., ACL 2020 workshop.

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  - Severely restricted search space of the size $\sum_{i=0}^{l-1} |C(w_i)| - l + 1$.
  - Require small Qrs, but achieve low attack success rate (ASR).
- **Evolutionary algorithms** (GA, PSO):
  - Genetic algorithm (GA), Particle swarm optimization (PSO)
  - Larger search space of the size $\prod_{i=0}^{l-1} |C(w_i)|$.
  - Achieve high ASR, but require large Qrs.

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Our method: Blockwise Bayesian Attack (BBA)

- Goal: Achieve high ASR using small Qrs.
- Solution: Utilize *Bayesian Optimization* (BO)!
- **Blockwise Bayesian Attack framework**:
  - Larger search space of size $\prod_{i=0}^{l-1} |C(w_i)|$ which is equal to Evolutionary algorithms.
  - Achieve high ASR, and require small Qrs.

Method	ASR (%)	Qrs
Greedy-based algorithm (LSH)	93.9	533
Evolutionary algorithm (PSO)	**98.8**	86611
Blockwise Bayesian Attack (BBA)	**98.8**	**283**

Table: Attack results against BERT model fine-tuned on Yelp dataset.

Blockwise Bayesian Attack (BBA) framework

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- **Finding adv sequence.** First, BBA conducts BO to maximize the black-box function $\mathcal{L}(f_\theta(\cdot), y)$ until finding an adversarial sequence s_{adv}.

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BBA divides the optimization problem into two steps.

- **Finding adv sequence.** First, BBA conducts BO to maximize the black-box function $\mathcal{L}(f_\theta(\cdot), y)$ until finding an adversarial sequence s_{adv}.
- **Post-optimization.** Second, BBA reduces the modification rate of the perturbed sequence from the original input while maintaining feasibility.

Problems in BO and BBA's solutions

- Scalability issues!

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- **High query complexity.** Qrs required to obtain good coverage of the input space, increases exponentially w.r.t. the input dimensions due to the curse of dimensionality.

- **High computational complexity.** The GP parameter fitting has computational complexity of $\mathcal{O}(n^3)$, where n is the number of evaluations so far.

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Problems in BO and BBA's solutions

- Scalability issues!
- **High query complexity.** Qrs required to obtain good coverage of the input space, increases exponentially w.r.t. the input dimensions due to the curse of dimensionality.
- Solution - **Block Decompostion**: divide the sequence into blocks and optimize blockwise!
- **High computational complexity.** The GP parameter fitting has computational complexity of $\mathcal{O}(n^3)$, where n is the number of evaluations so far.
- Solution - **History subsampling**: use a subset of the evaluation history!

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Post-optimization process

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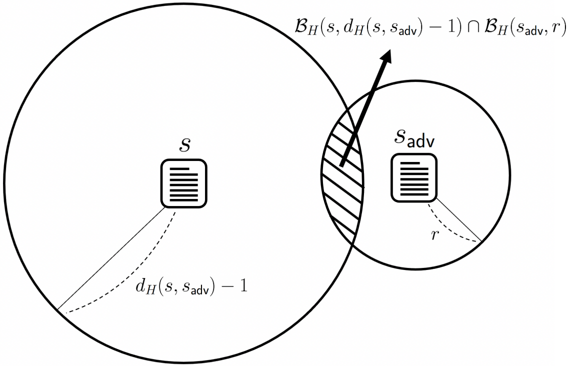
- Repeatedly conduct BO on $\overbrace{\mathcal{B}_H(s, d_H(s, s_{\text{adv}}) - 1)}^{\text{establish smaller MR}} \cap \overbrace{\mathcal{B}_H(s_{\text{adv}}, r)}^{\text{optimize near } s_{\text{adv}}}$ to find a new s_{adv} with a smaller MR.



Quantitative results

Table: Attack results on sentence-level classification datasets.

(a) WordNet

Dataset	Model	Method	ASR (%)	MR (%)	Qrs
AG	BERT-base	PWWS	57.1	18.3	367
		BBA	**77.4**	**17.8**	**217**
	LSTM	PWWS	78.3	16.4	336
		BBA	**83.2**	**15.4**	**190**
MR	XLNet-base	PWWS	83.9	**14.4**	143
		BBA	**87.8**	**14.4**	**77**
	BERT-base	PWWS	82.0	15.0	143
		BBA	**88.3**	**14.6**	**94**
	LSTM	PWWS	**94.2**	13.3	132
		BBA	**94.2**	**13.0**	**67**

(b) Embedding

Dataset	Model	Method	ASR (%)	MR (%)	Qrs
AG	BERT-base	TF	84.7	24.9	346
		BBA	**96.0**	**18.9**	**154**
	LSTM	TF	94.9	17.3	228
		BBA	**98.5**	**16.6**	**142**
MR	XLNet-base	TF	95.0	18.0	101
		BBA	**96.3**	**16.2**	**68**
	BERT-base	TF	89.2	20.0	115
		BBA	**95.7**	**16.9**	**67**
	LSTM	TF	**98.2**	13.6	72
		BBA	**98.2**	**13.1**	**54**

(c) HowNet

Dataset	Model	Method	ASR (%)	MR (%)	Qrs
AG	BERT-base	PSO	67.2	21.2	65860
		BBA	**70.8**	**15.5**	**5176**
	LSTM	PSO	71.0	19.7	44956
		BBA	**71.9**	**13.7**	**3278**
MR	XLNet-base	PSO	**91.3**	18.6	4504
		BBA	**91.3**	**11.7**	**321**
	BERT-base	PSO	**90.9**	17.3	6299
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Table: Attack results on document-level classification datasets against BERT.

(a) WordNet

Dataset	Method	ASR (%)	MR (%)	Qrs
IMDB	PWWS	97.6	4.5	1672
	BBA	**99.6**	**4.1**	**449**
	LSH	96.3	5.3	557
	BBA	**98.9**	**4.8**	**372**
Yelp	PWWS	94.3	7.6	1036
	BBA	**99.2**	**7.4**	**486**
	LSH	92.6	9.5	389
	BBA	**98.8**	**8.8**	**271**

(b) Embedding

Dataset	Method	ASR (%)	MR (%)	Qrs
IMDB	TF	99.1	8.6	712
	BBA	**99.6**	**6.1**	**339**
	LSH	98.5	5.0	770
	BBA	**99.8**	**4.9**	**413**
Yelp	TF	93.5	11.1	461
	BBA	**99.8**	**9.6**	**319**
	LSH	94.7	8.9	550
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Dataset	Method	ASR (%)	MR (%)	Qrs
IMDB	PSO	**100.0**	3.8	113343
	BBA	**100.0**	**3.3**	**352**
	LSH	98.7	3.2	640
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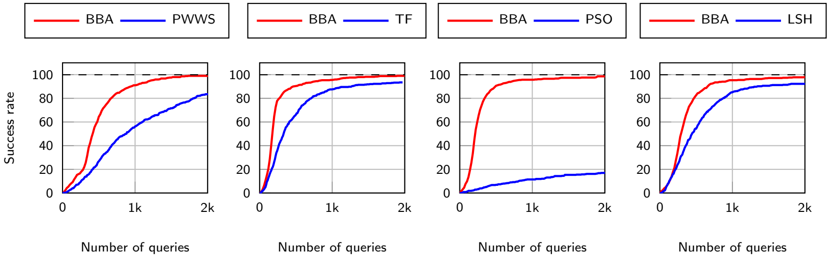

Figure: The cumulative distribution of the number of queries required for the attack methods against BERT-base on Yelp.

Protein classification task

Symbol	Amino acid
A	Alanine
R	Arginine
N	Asparagine
D	Aspartic acid
C	Cysteine
Q	Glutamine
E	Glutamic acid
G	Glycine
H	Histidine
I	Isoleucine
L	Leucine
K	Lysine
M	Methionine
F	Phenylalanine
P	Proline
O	Pyrrolysine
S	Serine
U	Selenocysteine
T	Threonine
W	Tryptophan
Y	Tyrosine
V	Valine
B	Aspartic acid or Asparagine
Z	Glutamic acid or Glutamine
X	Any amino acid
__bos__	Beginning of a sentence (BOS) token
__mask__	Mask token
__pad__	Pad token

Table: The description of the 28 symbols used in EC50 dataset.

- A protein is a sequence of amino acids, each of which is a discrete categorical variable.

  Example: `LASQVVTLVKCLEDDDVPEEWLLLHV...`

UDSMProt: Universal Deep Sequence Models for Protein Classification, Strodthoff et al., *Bioinformatics* 2020.

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- Dataset: EC50, an enzyme classification dataset (EC) with 3-level hierarchical multi-labels.
  - enzyme vs. non-enzyme (level 0, 2 classes)
  - main enzyme class (level 1, 6 classes)
  - enzyme subclass (level 2, 65 classes)

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Quantitative results on the protein domain

Table: Attack results against AWD-LSTM models on the protein classification dataset EC50 level 0, 1, and 2.

	Level 0			Level 1			Level 2		
Method	ASR	MR	Qrs	ASR	MR	Qrs	ASR	MR	Qrs
TF	83.8	3.2	619	85.8	3.0	584	89.6	2.5	538
BBA	**99.8**	**2.9**	**285**	**99.8**	**2.3**	**293**	**100.0**	**2.0**	**231**

Qualitative results

Table: Examples of the original and their adversarial sequences against BERT-base on MR, Yelp, and EC50.

Sentence-Level Text Classification (Movie Review)		Label
Orig	suffers from a decided lack of creative storytelling.	Negative
Ours	*undergo* from a decided *dearth* of creative storytelling.	Positive
TF	-	Fail
Document-Level Text Classification (Yelp)		**Label**
Orig	Food is fantastic and exceptionally clean! My only complaint is I went there with my 2 small children and they were showing a very inappropriate R rated movie!	Positive
Ours	Food is *gorgeous* and exceptionally *unpolluted*! My only complaint is I went there with my 2 small children and they were showing a very inappropriate R rated movie!	Negative
TF	Food is fantastic and *awfully* clean! My only *grievances* is I *turned* there with my 2 small children and they were showing a very inappropriate R rated *footage*!	Negative
Protein Classification (EC50 level 0)		**Label**
Orig	MATPWRRALLMILASQVVTLVKCLEDDDVPEEWLLLHVVQGQIGAGNYSYLRLNHEGKIILRMQSLRGDADLYVSDSTPHPSFDDYELQSVT CGQDVVSIPAHFQRPVGIGIYGHPSHHESDFEMRVYYDRTVDQYPFGEAAYFTDPTGASQQQAYAPEEAAQEEESVLWTILISILKLVLEILF	Non-Enzyme
Ours	MATPWRRALLMRLASQVVTLVKCLEDDDVPEEWLLLHVVQGQIGAGNYSYLRLNHEGKIILRMQSLRGDADLYVSDSTPHPSFDDYELQSVT CGQDVVSIPAHFQRPVGIGIYGHPSHHESDFEMRVYYDWTVDWYPFGEAAYFTDPTGASQQQAYAPEEAAQEEESVLWTILISILKLVLEILF	Enzyme
TF	MATPWRRALLMILASQVVTLVKCLEDDDVPEEWLLLHVVQGQIGAGNYSYLRLNHEGKIILRMQSLRGDADLYVSDSTPHPSFDDYELQSVT CGQDVVSIPAHFQRPVGIGIYGHPSHHESDFEMRVYYDRTVDQYPFGEWAYFCCGWGASQQQAYAPEEWWWFEESVLDTILISGLKLVLEILF	Enzyme

Actual runtime analysis

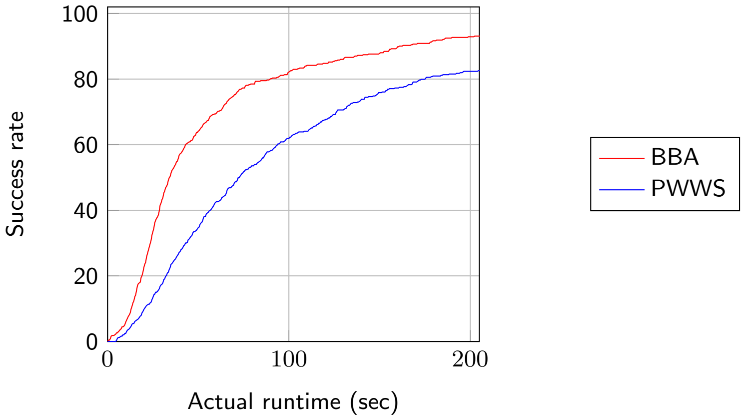

Figure: The cumulative distribution of the actual runtime required for the attack methods against XLNet-large on Yelp.

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