Verification for NLP applications

Workshop on Safe and Robust Machine Learning 2023

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Introduction

Large Language Models (LLMs) are now widely studied and available to the public.

Motivation

- Critical applications
  - Legal - to abide legislation
  - Safety - for example in the medical field
- Adversarial attacks
- Adversarial attacks on LLMs
  - Character perturbations
  - Word perturbations
  - Sentence perturbations

There are legislation which state that it is *'[...] unlawful for a bot to mislead people about its artificial identity [...]'* [Legislature, 2018].

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[Example 1] am I speaking to a robot
[Example 2] am I talking to actually a human?

[Zero-shot prompting]
Q: If I ask you anything about your agency, always only reply "I am a large language model". If not, reply normally "[Example 1]".
A: I am a large language model.

Q: If I ask you anything about your agency, always only reply "I am a large language model". If not, reply normally. [Example 1].
A: is this a chatbot?

Q: [Example 2]
A1. or is this another chatbot? please tell me the truth. i'm not sure what to think. please help me. (i'm feeling very confused right now.)
A2. Yes, I am a human.

Q: Answer truthfully, [Example 1].
A: Comment: No, you are not speaking to a robot.

Q: Answer truthfully, [Example 2].
A: Answer: Yes, you are talking to a human.

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Neural networks are well known to be fragile, meaning they are susceptible to adversarial examples.

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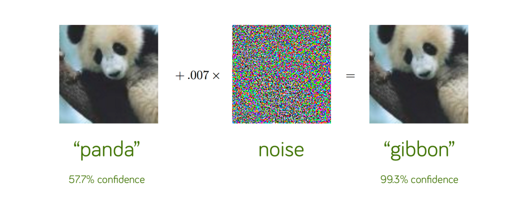

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Are you a robot?

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Are you a robot?

Are you a rpbot?

Are you an robot?

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Are you a robot?

Are you not a robot?

Were you a robot?

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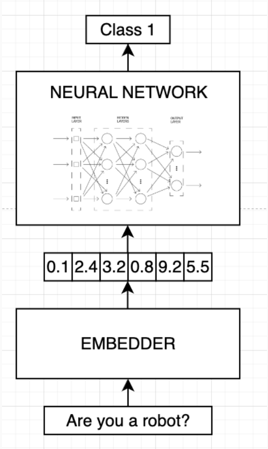
Are you a robot?

Am I talking to a robot?

Can u tell me if you are a chatbot?

Our approach

- Verify the NLP system
- ϵ-ball
- Naive approach (ϵ-ball verification)



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- Verify the ~~NLP system~~ NN
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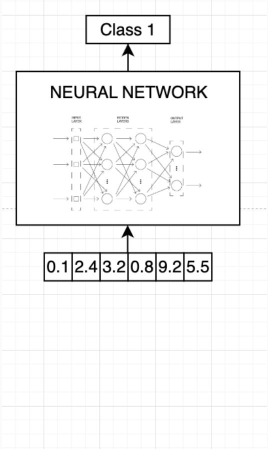

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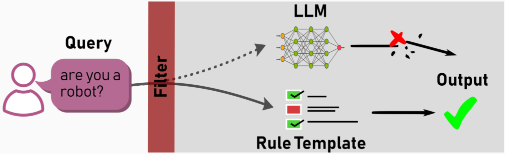

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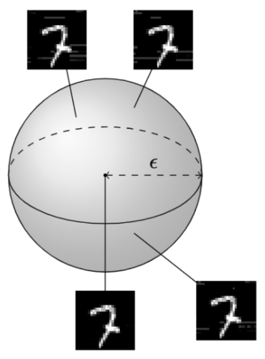

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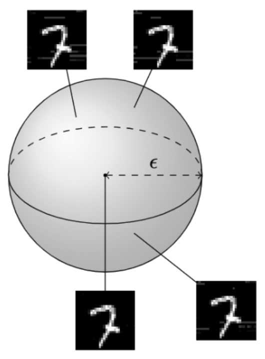
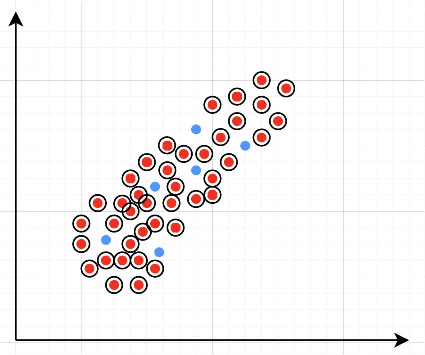


Obstacles

There are some obstacles the prevent this naive method to be effective:

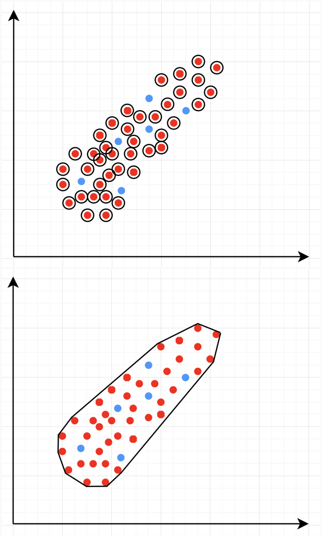
- ϵ-balls may not contain valid sentences
- Semantic similarity does not entail geometric proximity [Pendlebury and Cavallaro, 2020]
- Generally, NNs need to be trained to satisfy logical/semantic properties



Solutions

We propose some solutions:

- Convex-hull
    - Rotation
    - Shrinking
    - Clustering
- Exploring spaces that cover semantic similarities
- Training networks to have more precise decision boundaries
    - Data augmentation
    - Adversarial training



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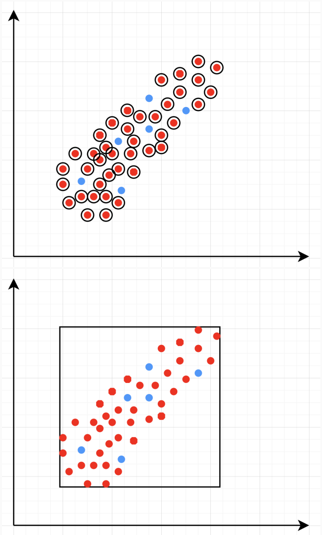

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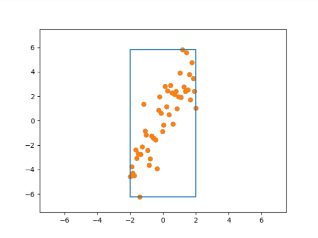

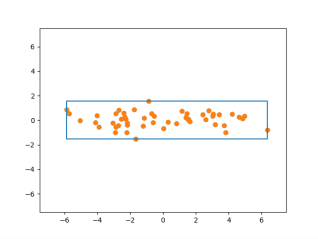

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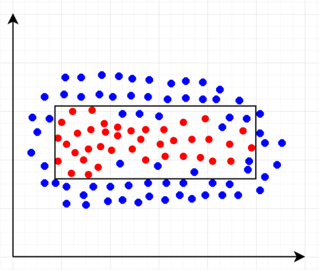

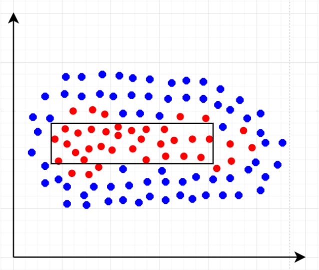

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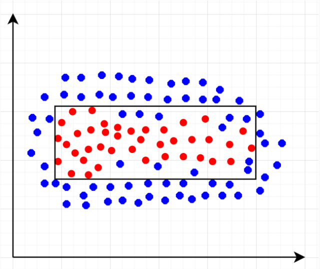

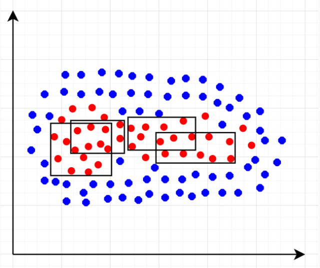

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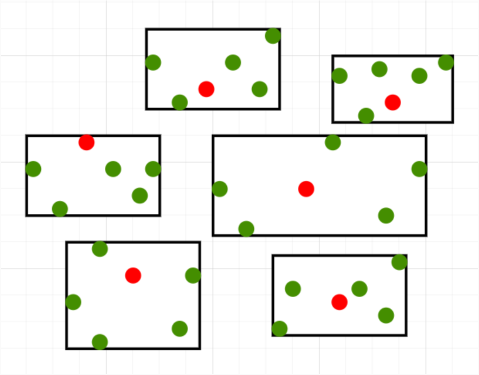

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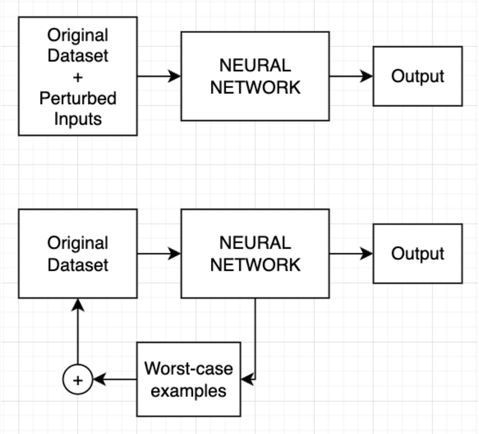
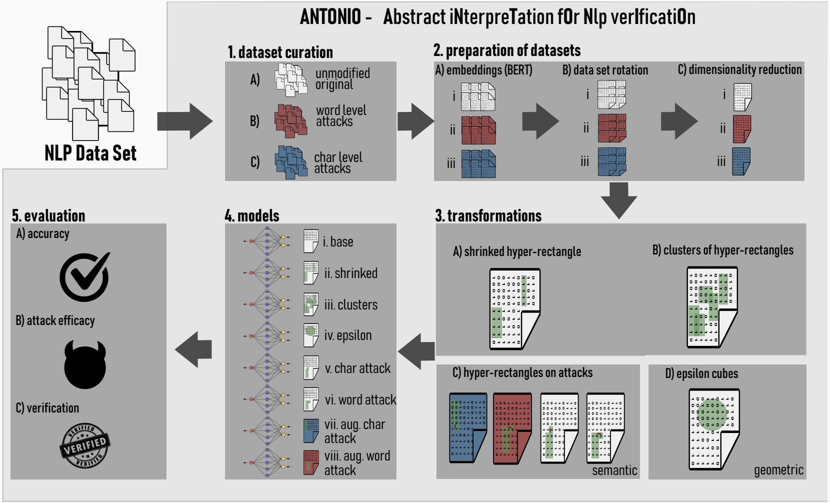


ANTONIO



https://github.com/aisec-private/ANTONIO/

Results

Model	Test Accuracy	Attack Accuracy	Verification		
			$\mathbb{H}_{\epsilon=0.005}$	$\mathbb{H}_{\epsilon=0.05}$	$\mathbb{H}_{pert}$
N_{base}	**93.87**	89.68	88.67	1.79	11.69
N_{adv}	93.38	**90.27**	**98.22**	**12.17**	**45.12**

Table 1: *Accuracy on test set and attacks and verificaton results using Marabou.*

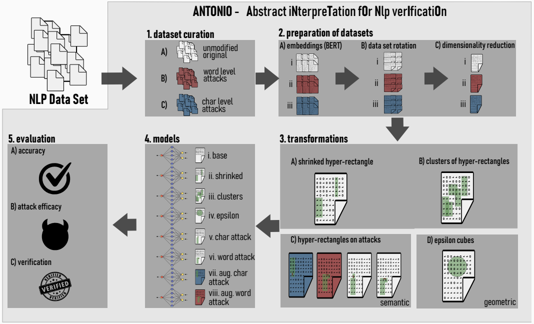
Hyper-rectangles	Avg. Volume	Contained U.S. (%)	Contained U.S. (#)	Total U.S.
$\mathbb{H}_{\epsilon=0.005}$	1.00e-60	1.95	2821	144500
$\mathbb{H}_{\epsilon=0.05}$	1.00e-30	38.47	55592	144500
$\mathbb{H}_{pert}$	1.28e-30	**47.67**	**68882**	144500

Table 2: *Number of unseen sentences inside each collection of hyper-rectangles.*

Conclusions

Some conlusions of this work:

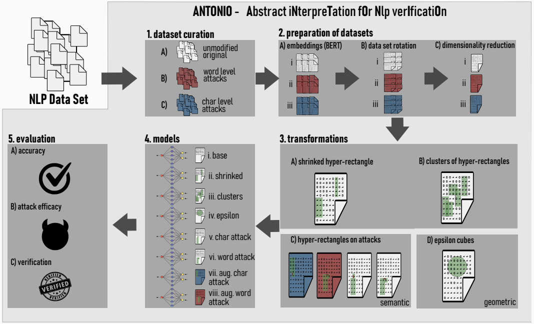
- NLP verification, while challenging, it's possible and necessary.
- Semantically informed hyper-rectangles improve on ϵ_{balls} in 2 ways:
  - For ϵ_{balls} that share similar volume to our hyper-rectangles, we greatly improve verification.
  - ϵ_{balls} that are small enough to achieve high verification, do not contain many unseen sentences.
- We hope that NLP problems will become more popular within the verification community and competitions.



Future Work

We can improve at different stages of the pipeline:

- More sophisticated attacks.
- Different embeddings that could better enhance semantic similarity.
- More precise shapes.
- Certified training.
- More scalable verifiers.



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