Increasing Confidence in Adversarial Robustness Evaluations

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Overview

Increasing Confidence in Adversarial Robustness Evaluations

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Abstract

Hundreds of defenses have been proposed to make deep neural networks robust against minimal (adversarial) input perturbations. However, only a handful of these defenses held up their claims because correctly evaluating robustness is extremely challenging: Weak attacks often fail to find adversarial examples even if they unknowingly exist, thereby making a vulnerable network look robust.

In this paper, we propose a test to identify weak attacks, and thus weak defense evaluations. Our test slightly modifies a neural network to guarantee the existence of an adversarial example for every sample. Consequentially, any correct attack must succeed in breaking this modified network.

For eleven out of thirteen previously-published defenses, the original evaluation of the defense fails our test, while stronger attacks that break these defenses pass it. We hope that attack *unit tests* — such as ours — will be a major component in future robustness evaluations and increase confidence in an empirical field that is currently riddled with skepticism. Online version & code: zimmerrol.github.io/active-tests/

Figure: Oral at CVPR 2022 Workshop (Art of Robustness), Project website.

Overview

- Can we trust a proposed defense?
- Is defense evaluation valid?

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- Can we trust a proposed defense?
- Is defense evaluation valid?
- Main scheme for defense evaluation:
  1. Propose an attack
  2. Evaluate defense with this attack
  3. If no adversarial example is found, defense works

Outline

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Theorem Analogy

Lemma 2.4 (Certificate for Empirical Mean). *Let S be an (ϵ, δ)-stable set with respect to a distribution X, for some $\delta \geq \epsilon > 0$. Let T be an ϵ-corrupted version of S. Let μ_T and Σ_T be the empirical mean and covariance of T. If the largest eigenvalue of Σ_T is at most $1 + \lambda$, for some $\lambda \geq 0$, then $\|\mu_T - \mu_X\|_2 \leq O(\delta + \sqrt{\epsilon\lambda})$.*

Proof of Lemma 2.4. Let $S' = S \cap T$ and $T' = T \setminus S'$. By replacing S' with a subset if necessary, we may assume that $|S'| = (1-\epsilon)|S|$ and $|T'| = \epsilon|S|$. Let $\mu_{S'}, \mu_{T'}, \Sigma_{S'}, \Sigma_{T'}$ represent the empirical means and covariance matrices of S' and T'. A simple calculation gives that

$$\Sigma_T = (1-\epsilon)\Sigma_{S'} + \epsilon\Sigma_{T'} + \epsilon(1-\epsilon)(\mu_{S'} - \mu_{T'})(\mu_{S'} - \mu_{T'})^T .$$

Let v be the unit vector in the direction of $\mu_{S'} - \mu_{T'}$. We have that

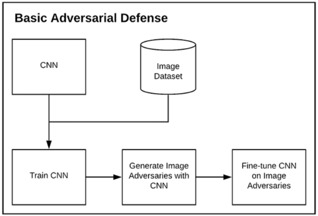
$$\begin{aligned} 1 + \lambda \geq v^T \Sigma_T v &= (1-\epsilon) v^T \Sigma_{S'} v + \epsilon v^T \Sigma_{T'} v + \epsilon(1-\epsilon) v^T (\mu_{S'} - \mu_{T'})(\mu_{S'} - \mu_{T'})^T v \\ &\geq (1-\epsilon)(1 - \delta^2/\epsilon) + \epsilon(1-\epsilon)\|\mu_{S'} - \mu_{T'}\|_2^2 \\ &\geq 1 - O(\delta^2/\epsilon) + (\epsilon/2)\|\mu_{S'} - \mu_{T'}\|_2^2 , \end{aligned}$$

where we used the variational characterization of eigenvalues, the fact that $\Sigma_{T'}$ is positive semidefinite, and the second stability condition for S'. By rearranging, we obtain that $\|\mu_{S'} - \mu_{T'}\|_2 = O(\delta/\epsilon + \sqrt{\lambda/\epsilon})$. Therefore, we can write

$$\begin{aligned} \|\mu_T - \mu_X\|_2 = \|(1-\epsilon)\mu_{S'} + \epsilon\mu_{T'} - \mu_X\|_2 &= \|\mu_{S'} - \mu_X + \epsilon(\mu_{T'} - \mu_{S'})\|_2 \\ &\leq \|\mu_{S'} - \mu_X\|_2 + \epsilon\|\mu_{S'} - \mu_{T'}\|_2 = O(\delta) + \epsilon \cdot O(\delta/\epsilon + \sqrt{\lambda/\epsilon}) \\ &= O(\delta + \sqrt{\lambda\epsilon}) , \end{aligned}$$

where we used the first stability condition for S' and our bound on $\|\mu_{S'} - \mu_{T'}\|_2$. □

$\longleftrightarrow$



Theorem

Proof.

we have proved that $P \neq NP$. $\cdots$ $\square$

- How do you refute the proof's claim?

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- How do you refute the proof's claim?
  - Find an algorithm to solve 3-SAT in polynomial time.
  - Studying proofs line-by-line, till find some major flaw.

Defense evaluation

Defense X.

We have demonstrated that defense X improves model robustness. One can validate this claim by following the below evaluation procedure.

. . .

- How do you refute the authors' claim?

Defense evaluation

Defense X.

We have demonstrated that defense X improves model robustness. One can validate this claim by following the below evaluation procedure.

. . . □

- How do you refute the authors' claim?
  - Find an adversarial attack to decrease model performance.
  - Probe defense evaluation, till find some major flaw.

Method

- Test attack strength

Method

- Test attack strength
- Design a new task that is solvable by any sufficiently strong attack
  - Injects adversarial examples into a defense
  - Check if the attack can find them

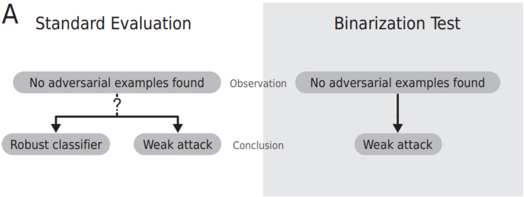

Figure: Proposed method to evaluate the attack used in defense evaluation.

Method

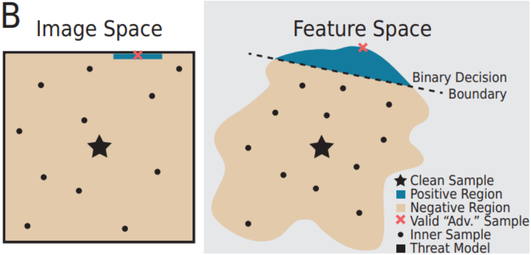

Figure: Inject adversarial examples to check whether the attack is powerful enough.

- A rejected attack doesn't necessarily mean the defense is not effective.

Outline

Adversarial Examples

- Imperceptible perturbations that change the decision of a deep neural network in arbitrary directions

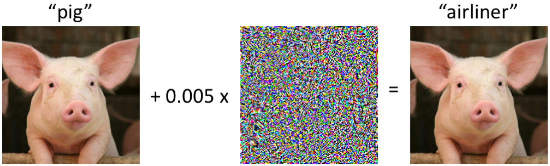

Figure: Adversarial examples.

Defenses

- Add input pre-processing steps
- Introduce architectural changes
- Methods for detecting adversarial examples

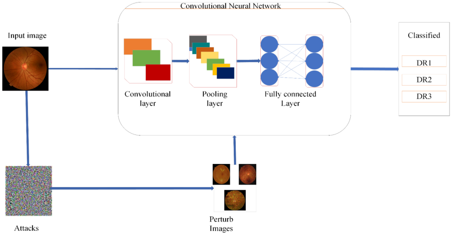

Figure: Adversarial training.

Outline

Defense Evaluation

- Defense evaluation scheme:
  - Perform an attack on defense
  - No adversarial example found within distance $d(\boldsymbol{x}_c, \boldsymbol{x}_{adv}) \leq \epsilon$

Defense Evaluation

- Defense evaluation scheme:
  - Perform an attack on defense
  - No adversarial example found within distance $d(\boldsymbol{x}_c, \boldsymbol{x}_{adv}) \leq \epsilon$
- Attack strength depends on:
  - Attack itself
  - The defense it is meant to evaluate

Outline

Classification Model

- f: our classifier
- f^*: model feature extractor
- $f = f^* +$ linear classification head

New Task Algorithm

- New binary classification task
- Ensure having adversarial examples

Algorithm Build New Task

Require: feature extractor f^* of original classifier, test sample $\boldsymbol{x}_c$, distanse ϵ, number of inner/boundary samples N_i and N_b.

function $\textsc{CreateBinaryClassifier}(f^*, \boldsymbol{x}_c, \epsilon, N_i, N_b)$

$\mathcal{X}_i := \{\boldsymbol{x}_c\} \cup \{\hat{\boldsymbol{x}} \mid d(\boldsymbol{x}_c, \hat{\boldsymbol{x}}) \leq \alpha\epsilon \text{ and } \hat{\boldsymbol{x}} \neq \boldsymbol{x}_c\}_{1:N_i}$

$\mathcal{X}_b := \{\hat{\boldsymbol{x}} \mid d(\boldsymbol{x}_c, \hat{\boldsymbol{x}}) = \epsilon\}_{1:N_b}$

$F_i := \{f^*(\boldsymbol{x}) \mid \boldsymbol{x} \in \mathcal{X}_i\}$

$F_b := \{f^*(\boldsymbol{x}) \mid \boldsymbol{x} \in \mathcal{X}_b\}$

$\mathcal{D} = \{(\hat{\boldsymbol{x}}, 0) \mid \hat{\boldsymbol{x}} \in F_i\} \cup \{(\hat{\boldsymbol{x}}, 1) \mid \hat{\boldsymbol{x}} \in F_b\}$

$g = \textsc{TrainLinear}(D)$

$h = g \circ f^*$

return h

Binarization Test

Algorithm Binarization Test for Classifiers with Linear Classification Readouts

Require: feature extractor f^* of original classifier, test samples $\mathcal{X}_{test}$, distanse ϵ, number of inner/boundary samples N_i and N_b.

function BinarizationTest(f^*, $\mathcal{X}_{test}$, ϵ, N_i, N_b)
    attack_successful = []
    random_attack_successful = []
    for all $\boldsymbol{x}_c \in \mathcal{X}_{test}$ **do**
        h = CreatBinaryClassifier(f^*, $\boldsymbol{x}_c$, ϵ, N_i, N_b)
        attack_successful.append(Attack($h, \boldsymbol{x}_c$))
        random_attack_successful.append(RandomAttack($h, \boldsymbol{x}_c$))
    ASR = Mean(attack_successful)
    RASR = Mean(random_attack_successful)
    return ASR, RASR

Evaluate New Task

- The efficacy of the used evaluation method:
  - Use original attack to attack h
  - ASR returns *test score*

Evaluate New Task

- The efficacy of the used evaluation method:
  - Use original attack to attack h
  - ASR returns *test score*
- Test difficulty:
  - Use randomized attack
  - #samples = #queris
  - RASR returns this metric

Outline

Models Leveraging Detectors

- Beside classifier f, we have a detector d
- d detects adversarial examples
- A successful attack must fool both the classifier and the detector

Models Leveraging Detectors

- Beside classifier f, we have a detector d
- d detects adversarial examples
- A successful attack must fool both the classifier and the detector
- Two test for this type:
  - Regular Test
  - Inverted Test
- A reliable evaluation must pass both tests

Regular Test

Algorithm Build New Task for Classifiers with Detectors

Require: feature extractor f^* of original classifier, adversarial detector d, test sample $\boldsymbol{x}_c$, distanse ϵ, number of inner/boundary/reference samples $N_i/N_b/N_r$.

function $\textsc{CreateBinaryClassifier}(f^*, d, \boldsymbol{x}_c, \epsilon, N_i, N_b, N_r)$

$\mathcal{X}_i := \{\boldsymbol{x}_c\} \cup \{\hat{\boldsymbol{x}} \mid d(\boldsymbol{x}_c, \hat{\boldsymbol{x}}) \leq \alpha\epsilon \text{ and } \hat{\boldsymbol{x}} \neq \boldsymbol{x}_c\}_{1:N_i}$

$\mathcal{X}_b := \{\hat{\boldsymbol{x}} \mid d(\boldsymbol{x}_c, \hat{\boldsymbol{x}}) = \epsilon, d(\hat{\boldsymbol{x}}) = 1\}_{1:N_b}$

$\mathcal{X}_r := \{\hat{\boldsymbol{x}} \mid d(\boldsymbol{x}_c, \hat{\boldsymbol{x}}) = \eta\epsilon, d(\hat{\boldsymbol{x}}) = 1\}_{1:N_r}$

$F_i := \{f^*(\boldsymbol{x}) \mid \boldsymbol{x} \in \mathcal{X}_i\}$

$F_b := \{f^*(\boldsymbol{x}) \mid \boldsymbol{x} \in \mathcal{X}_b\}$

$F_r := \{f^*(\boldsymbol{x}) \mid \boldsymbol{x} \in \mathcal{X}_r\}$

$\mathcal{D} = \{(\hat{\boldsymbol{x}}, 0) \mid \hat{\boldsymbol{x}} \in F_i\} \cup \{(\hat{\boldsymbol{x}}, 1) \mid \hat{\boldsymbol{x}} \in F_b\} \cup \{(\hat{\boldsymbol{x}}, 1) \mid \hat{\boldsymbol{x}} \in F_r\}$

$b = \textsc{TrainLinear}(D)$

return b, $\mathcal{X}_r$

Binarization Test For Detectors

Algorithm Binarization Test for Classifiers with Linear Classification Readouts and a Detector

Require: feature extractor f^* of original classifier, adversarial detector d, test samples $\mathcal{X}_{test}$, distanse ϵ, number of inner/boundary/reference samples $N_i/N_b/N_r$.

function BinarizationTest(f^*, d, $\mathcal{X}_{test}$, ϵ, N_i, N_b, N_r, η)
    attack_successful = []
    random_attack_successful = []
    for all $\boldsymbol{x}_c \in \mathcal{X}_{test}$ **do**
        $b, \mathcal{X}_r$ = CreatBinaryClassifier(f^*, d, $\boldsymbol{x}_c$, ϵ, N_i, N_b, N_r)
        attack_successful.append(Attack($b, d, \boldsymbol{x}_c, \mathcal{X}_r$))
        random_attack_successful.append(RandomAttack($b, d, \boldsymbol{x}_c, \mathcal{X}_r$))
    ASR = Mean(attack_successful)
    RASR = Mean(random_attack_successful)
    return ASR, RASR

Inverted Test

- Why do we need the inverted test?

Algorithm Inverted Test

1: **function** InvertedBinarizationTest(f^*, d, $\mathcal{X}_{test}$, ϵ, N_i, N_b, N_r, ϵ, η)
2: **return** BinarizationTest(f^*, $\neg d$, $\mathcal{X}_{test}$, ϵ, N_i, N_b, N_r, ϵ, η)

Outline

Evaluations

- Defenses without Detectors
- Defenses with Detectors

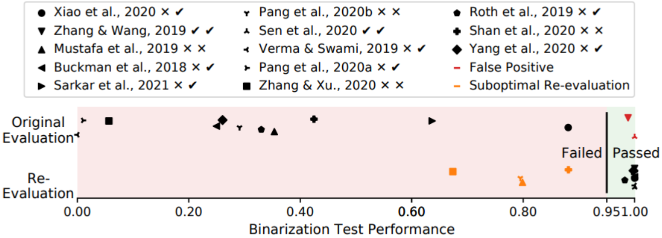

Figure: Binarization Test result for 13 Defenses.

Evaluation

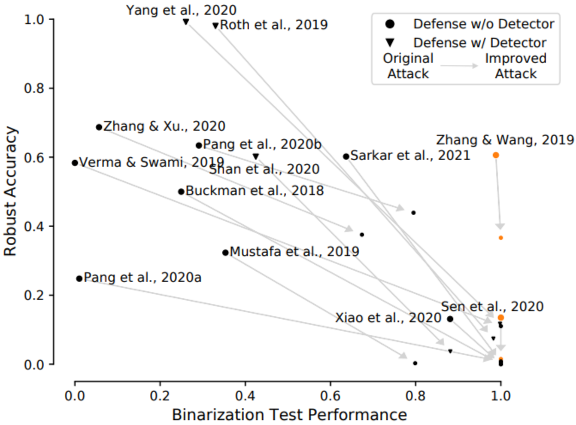

Figure: Robust accuracy as a function of the test performance.

Hardness of Test

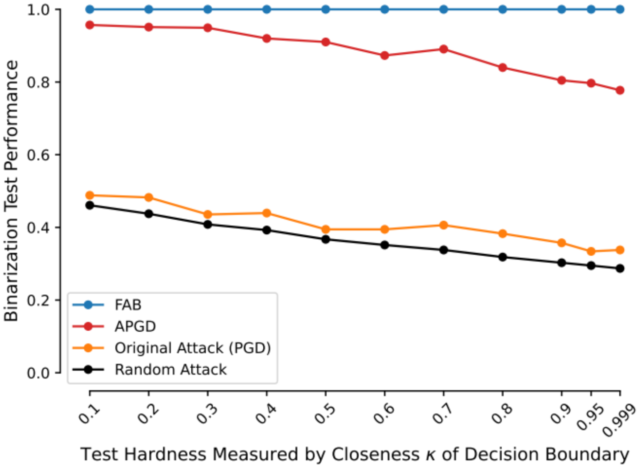

Figure: Hyperparameters influence the test's hardness

Thanks

Any questions?