Constructing Unrestricted Adversarial Examples with Generative Models

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ABSTRACT

- We consider the threat model of unrestricted adversarial examples — adversarial examples that are beyond small perturbations.
- We propose to effectively construct unrestricted adversarial examples with conditional generative models.
- We show that the defenses against perturbation-based adversarial examples, including provable defenses, are susceptible to unrestricted adversarial examples. Our attacks uniformly achieved over 84% success rates across all the datasets in our experiments and showed moderate degree of transferability.

Code:

ADVERSARIAL EXAMPLES

State-of-the-art classifiers can be fooled by adding quasi-imperceptible noise.

Figure 1: Perturbation-based adversarial examples.

UNRESTRICTED ADVERSARIAL EXAMPLES

Notations: Let $\mathcal{I}$ be the set of all input under consideration. Suppose $o\colon \mathcal{O} \subseteq \mathcal{I} \to \{1, 2, \cdots, K\}$ is an oracle that takes an image in its domain $\mathcal{O}$ and outputs one of K labels. We call $\mathcal{O}$ the set of legitimate images. We consider a classifier $f\colon \mathcal{I} \to \{1, 2, \cdots, K\}$ that predicts the label for any image in $\mathcal{I}$.

Definition 1 (Perturbation-Based Adversarial Examples)
Given a subset of (test) images $\mathcal{T} \subset \mathcal{O}$, small constant $\epsilon > 0$, and matrix norm $\|\cdot\|$, a perturbation-based adversarial example is defined to be any image in $\mathcal{A}_p \stackrel{\text{def}}{=} \{x \in \mathcal{O} \mid \exists\, x' \in \mathcal{T}, \|x - x'\| \le \epsilon \wedge f(x') = o(x') = o(x) \neq f(x)\}$.

Definition 2 (Unrestricted Adversarial Examples)
An unrestricted adversarial example is any image that is an element of $\mathcal{A}_u \stackrel{\text{def}}{=} \{x \in \mathcal{O} \mid o(x) \neq f(x)\}$.

Observations

- Perturbation-based adversarial examples are special cases of unrestricted adversarial examples. $\mathcal{A}_p \subset \mathcal{A}_u$.
- Unrestricted adversarial examples capture a more general notion of threats to machine learning models.

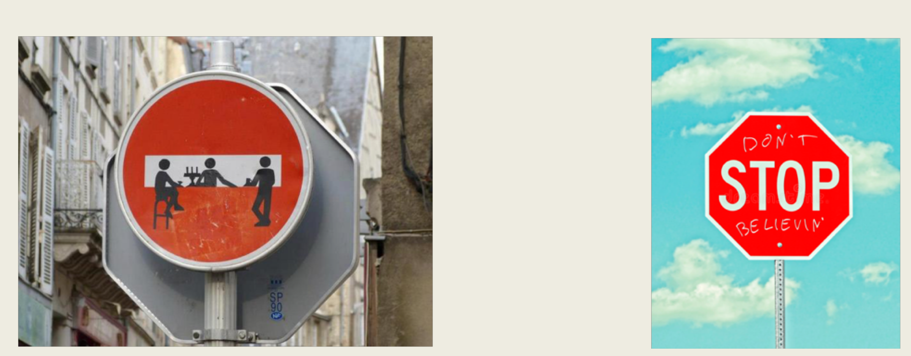

Figure 2: Unrestricted Adversarial Examples in the wild.

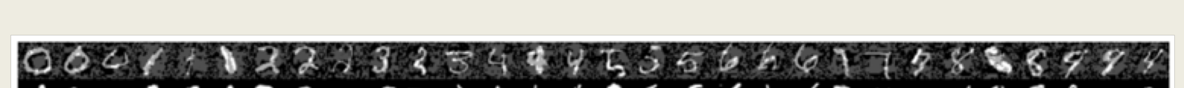

Figure 3: Perturbation-based adversarial examples (top row) versus unrestricted adversarial examples (bottom row) generated by our Generative Adversarial Attack.

CONDITIONAL GENERATIVE MODELS

Model: We consider decoder-based conditional generative models. Images can be generated by $x = g_\theta(y, z)$, where $z \sim p(Z)$.

AC-GAN based on Wasserstein distance:

- $\min_\theta \; -\mathbb{E}_{z \sim P_z, y \sim P_y}\left[d_\phi(g_\theta(z, y)) - \log c_\psi(y \mid g_\theta(z, y))\right]$

(generator loss)

- $$\min_{\phi,\psi} \quad \begin{aligned} &\mathbb{E}_{z \sim P_z, y \sim P_y}\left[d_\phi(g_\theta(z, y))\right] - \mathbb{E}_{x \sim P_x}\left[d_\phi(x)\right] \\ &-\mathbb{E}_{x \sim P_x, y \sim P_{y \mid x}}\left[\log c_\psi(y \mid x)\right] + \\ &\lambda \mathbb{E}_{\tilde{x} \sim P_{\tilde{x}}}\left[\left(\left\|\nabla_{\tilde{x}} d_\phi(\tilde{x})\right\|_2 - 1\right)^2\right] \end{aligned}$$

(critic loss)

- Notations: $d_\phi(\cdot)$: critic
  P_y : uniform distribution over labels
  $c_\psi(\cdot)$: auxiliary classifier

PRACTICAL UNRESTRICTED ADVERSARIAL ATTACKS

Basic attack: Let $f(x)$ be the targeted classifier. We produce targeted attack, where the adversarial example x satisfies $o(x) = y_{\text{source}}$ and $f(x) = y_{\text{target}}$.

Objective function

$$\left\{\begin{aligned} &\min_z \mathcal{L} \\ &\mathcal{L} \stackrel{\text{def}}{=} \mathcal{L}_0 + \lambda_1 \mathcal{L}_1 + \lambda_2 \mathcal{L}_2 \\ &\mathcal{L}_0 \stackrel{\text{def}}{=} -\log f\left(y_{\text{target}} \mid g_\theta(z, y_{\text{source}})\right) \\ &\mathcal{L}_1 \stackrel{\text{def}}{=} \frac{1}{m} \sum_i \max\{|z_i - z_i^0| - \epsilon, 0\}, \quad z_i^0 \sim \mathcal{N}(0,1) \\ &\mathcal{L}_2 \stackrel{\text{def}}{=} -\log c_\phi\left(y_{\text{source}} \mid g_\theta(z, y_{\text{source}})\right) \end{aligned}\right.$$

Noise-augmented attack: Use a different conditional generator to combine perturbation-based attacks.

$$g_\theta(z, \tau, y; \epsilon_{\text{attack}}) \stackrel{\text{def}}{=} g_\theta(z, y) + \epsilon_{\text{attack}} \tanh(\tau),$$

where both z and τ are optimized.

Perturbation-based attacks as a special case: Using a specially designed conditional generator we can show that our unrestricted adversarial attacks incorporate perturbation-based attacks. The modifications are

- Let $\mathcal{T}$ be the test dataset, and $\mathcal{T}_y = \{x \in \mathcal{T} \mid o(x) = y\}$.
- Discrete latent code $z \in \{1, 2, \cdots, |\mathcal{T}_{y_{source}}|\}$
- $g_\theta(z, y)$ is the z-th image in $\mathcal{T}_y$
- z^0 is uniformly drawn from $\{1, 2, \cdots, |\mathcal{T}_{y_{source}}|\}$
- $\lambda_1 \to \infty$, $\lambda_2 = 0$

EXPERIMENTS

Evaluation: Use Amazon Mechanical Turk (MTurk) to label generated unrestricted adversarial examples. Apporximate the ground truths with majority vote of 5 labelers.

Untargeted attacks against certified defenses:

Classifier \ Source	0	1	2	3	4	5	6	7	8	9	Overall	Certified Rate ($\epsilon = 0.1$)
Raghunathan et al. [16]	90.8	48.3	86.7	93.7	94.7	85.7	93.4	80.8	96.8	95.0	86.6	≤ 35.0
Kolter & Wang [17]	94.2	57.3	92.2	94.0	93.7	89.6	95.7	81.4	96.3	93.5	88.8	≤ 5.8

Figure 4: Untargeted unrestricted adversarial attacks against (a) Raghunathan et al. and (b) Kolter & Wang

Targeted attacks against adversarial training:

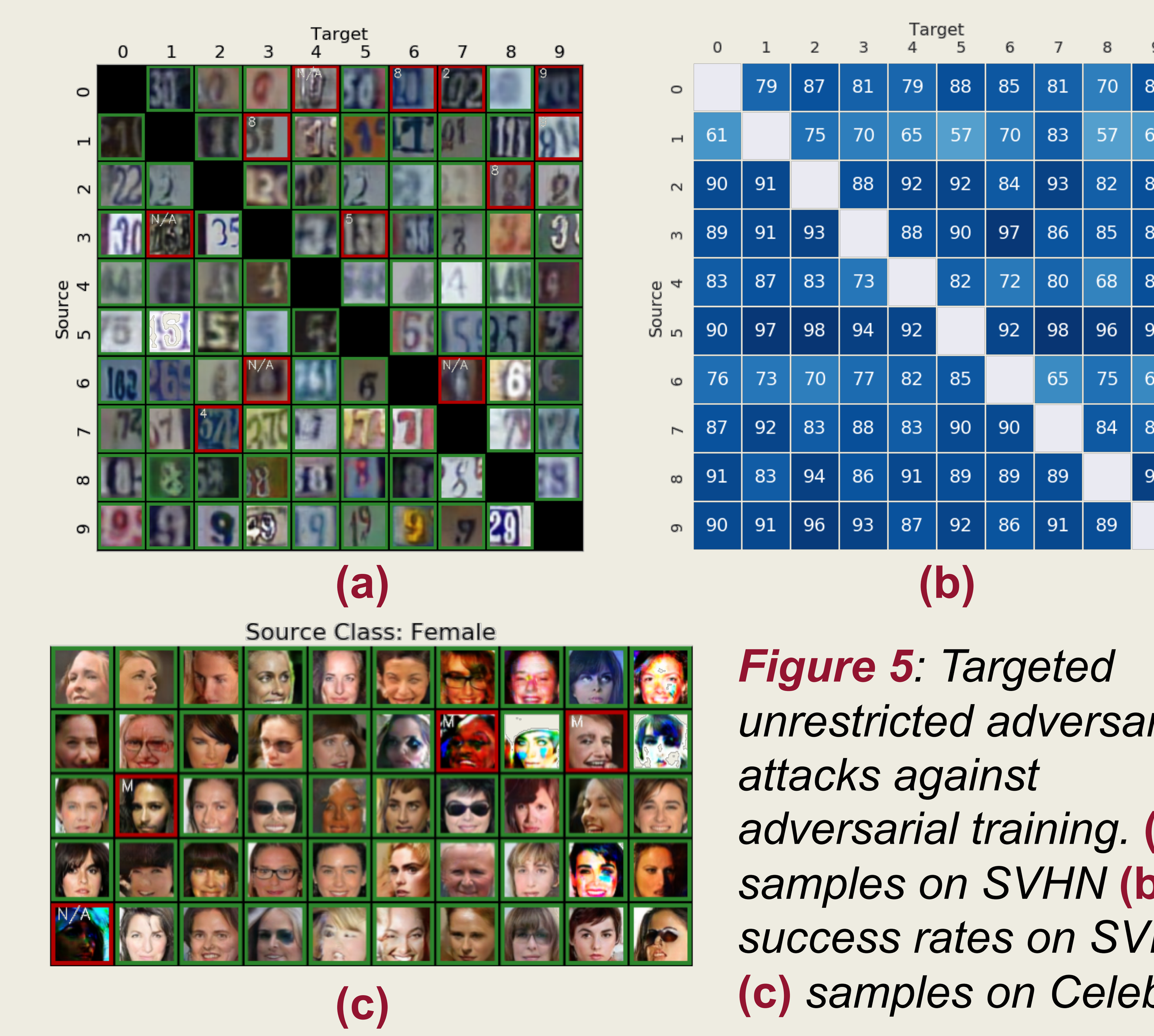

Figure 5: Targeted unrestricted adversarial attacks against adversarial training. (a) samples on SVHN (b) success rates on SVHN (c) samples on CelebA.

Attack Type \ Classifier	Madry Net [10] (no adv)	Madry Net [10] (adv)	ResNet (no adv)	ResNet (adv)	[16]	[17]
No attack	99.5	98.4	99.3	99.4	95.8	98.2
Our attack (w/o noise)	95.1	0	92.7	93.7	77.1	84.3
Our attack (w/ noise, $\epsilon_{\text{attack}} = 0.3$)	78.3	0	73.8	84.9	78.1	63.0

Figure 6: Transferability on MNIST classifiers.