Synthesizing Robust Adversarial Examples

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Abstract

Neural networks are susceptible to adversarial examples: small, carefully-crafted perturbations can cause networks to misclassify inputs in arbitrarily chosen ways. However, some studies have showed that adversarial examples crafted following the usual methods are not tolerant to small transformations: for example, zooming in on an adversarial image can cause it to be classified correctly again. This raises the question of whether adversarial examples are a concern in practice, because many real-world systems capture images from multiple scales and perspectives.

This paper shows that adversarial examples can be made robust to distributions of transformations. Our approach produces single images that are simultaneously adversarial under all transformations in a chosen distribution, showing that we cannot rely on transformations such as rescaling, translation, and rotation to protect against adversarial examples.

1 Introduction

Neural networks are susceptible to adversarial examples: inputs that would normally be classified correctly can be imperceptibly perturbed such that they are classified as a chosen class with high confidence [1]. Researchers have developed a number of methods for synthesizing adversarial examples, including L-BFGS [1], fast gradient sign method [2], evolutionary algorithms [3], Jacobian-based saliency map [4], DeepFool [5], an approximate optimization formulation [6], and ensemble-based approaches [7]. Projected gradient descent (PGD), closely related to the L-BFGS attack, can be seen as a universal "first-order adversary" [8].

Adversarial examples have been shown to transfer to the physical world [9], indicating that adversarial examples could be a real concern for practical systems. However, some recent work has argued that adversarial examples are not preserved by simple transformations such as rescaling or rotation, implying that adversarial examples are not an issue in practice because many real-world systems capture inputs from multiple angles and perspectives [10, 11]. We attempted to reproduce these results, and we did find that naively-generated adversarial examples are brittle, failing to remain adversarial when subject to small transformations.

However, our results show that adversarial examples are a concern even when inputs are subject to transformations such as zoom, translation, rotation, and noise. We show that it is possible to synthesize adversarial examples that are *robust to an entire distribution of transformations*.

2 Approach

When finding adversarial examples for the regular case, we are given a classifier $P(y \mid \mathbf{x})$, an input \mathbf{x} , a target class \hat{y} , and a maximum perturbation ε , and we want to find an input $\hat{\mathbf{x}}$ that maximizes $\log P(\hat{y} \mid \hat{\mathbf{x}})$ subject to $\|\mathbf{x} - \hat{\mathbf{x}}\|_{\infty} \leq \varepsilon$. Projected gradient descent solves this constrained optimization problem. However, we cannot expect optimal solutions from this formulation to be tolerant to transformations such as rescaling or rotation of $\hat{\mathbf{x}}$.

If we want our adversarial examples to be robust to a given distribution of transformations T, we need to formulate a different optimization problem where we maximize the expected log probability of the target class over all transformations:

$$\begin{array}{ll} \arg\max_{\hat{\mathbf{x}}} & \underset{t \sim T}{\mathbb{E}} \log P(\hat{\mathbf{y}} \,|\, t(\hat{\mathbf{x}})) \\ \mathrm{subject \ to} & \|\mathbf{x} - \hat{\mathbf{x}}\|_{\infty} \leq \varepsilon \end{array}$$

We can solve the optimization problem by using projected gradient descent, noting that $\nabla \mathbb{E}_{t \sim T} \log P(\hat{y} \mid t(\hat{\mathbf{x}})) = \mathbb{E}_{t \sim T} \nabla \log P(\hat{y} \mid t(\hat{\mathbf{x}}))$ and approximating with samples at each gradient descent



Figure 1: The unperturbed source image, which is classified as "tabby cat".

step. We refer to this method as the expectationover-transformations (EOT) method for synthesizing transformation-tolerant adversarial examples.

3 Evaluation

We compare our algorithm against intuitive approaches for producing potentially transformation-tolerant adversarial examples. In our experiments, we use an Inception v3 network [12] trained on ImageNet. We adversarially perturb the source image of a tabby cat (see fig. 1), and we arbitrarily choose "oil filter" as our target class, choose a fixed $\varepsilon=0.05$, and attempt to make the image simultaneously adversarial over the uniform distribution of zoom levels from 1x to 5x.

We try three approaches for synthesizing rescaling-tolerant adversarial examples. First, we try vanilla PGD. Next, we try an ad-hoc approach of PGD over a static ensemble of 5 classifiers, where the classifier scales the image by 1x, 2x, 3x, 4x, or 5x before classifying it. Finally, we try EOT over the uniform distribution of zoom levels of 1x to 5x. Figure 2 shows the results: EOT is the only method that produces an adversarial example that is reliably tolerant to rescaling. Figure 3 shows the output image from EOT.

In another experiment, we synthesized adversarial examples reliably tolerant to a much wider distribution of transformations, including rescaling, rotation, translation, Gaussian noise, and lightening/darkening. Figure 4 shows randomly sampled transformations of a single adversarial image: all transformations are misclassified as "oil filter". In both this experiment and the previous one,

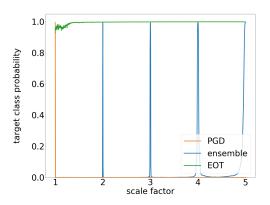


Figure 2: A comparison of PGD, an ensemble-based attack, and EOT for producing a single image that is simultaneously adversarial at different scales. PGD produces an image that is adversarial only at a 1x scale. The ensemble method produces an image that is adversarial at 1x, 2x, 3x, 4x, and 5x scales, but the image is not adversarial at other points in the range. EOT produces an image that is simultaneously adversarial over the entire distribution.



Figure 3: The imperceptibly perturbed scale-tolerant adversarial example produced by EOT.



Figure 4: Randomly sampled transformations of the single adversarial example, with random rescaling, rotation, translation, Gaussian noise, and lightening/darkening, applied to the single image at test time. All are misclassified as "oil filter".

we only modified the pixels corresponding to the bounding box of the cat, making the attack strictly harder.

For completeness, we printed out our adversarial images and used a standard cell phone camera to classify them from multiple scales, angles, and perspectives: the adversarial examples remained robust to these transformations in the physical world ¹.

4 Conclusion

We show that we can synthesize adversarial examples that are simultaneously adversarial under a chosen distribution of transformations. We evaluate our approach and find that it effectively finds adversarial examples that remain adversarial even under large transformations. Our results show that we cannot rely on simple transformations to protect against adversarial examples.

References

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IThe video is available at https://blog.openai.com/ robust-adversarial-inputs/