Adversarial Examples

A new evil has announced its arrival...

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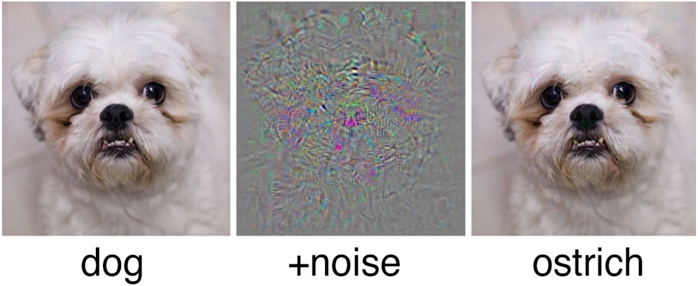

Objectives

1. To show the effect and effectiveness of adversarial examples in machine learning predictions
2. To understand the adversary, and determine how to combat it.
3. To enlighten the audience on machine learning security.

Outlines

Introduction

- An **adversarial example** is an instance with small, intentional feature perturbations that cause a machine learning model to make a false prediction.[1]
- A type of **counterfactual example**

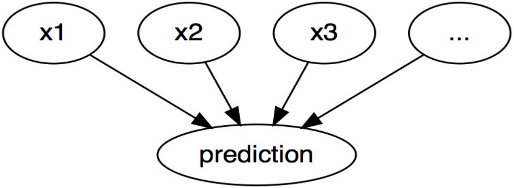

Figure: Causal relationships between inputs of a machine learning model and the predictions

[1] https://christophm.github.io/interpretable-ml-book/adversarial.html

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- change as **few** features as possible.
- have feature values that are **likely**.
- produce the predefined prediction as **closely** as possible.

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4. Self-driving cars can be deceived by images to misclassify stop-signs.

Techniques

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Our focus will be on how adversarial examples affect image classifiers with deep neural networks.

Gradient based optimization approach

$$\min loss(f(x+p), y_{adv}) + c.|p|$$

where x is an image, p is the changes to the pixels to create an adversarial image, y_{adv} is the desired outcome class, and the parameter c is a balancing factor.

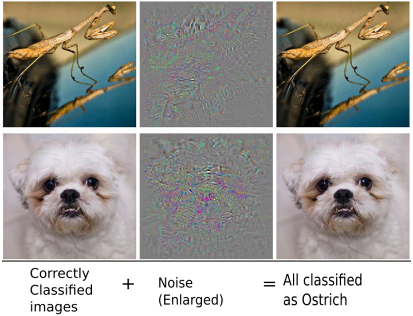

Figure: Examples generated on Alexnet using GB[2]

[2] Szegedy, Christian, et al. "Intriguing properties of neural networks."(2013)

Fast gradient sign method

$$x_{adv} = x + \epsilon Sign(\nabla_x J(\theta, x, y))$$

where x is the gradient of the models loss function with respect to the original input pixel vector x, y is the true label vector for x and θ is the model parameter vector.

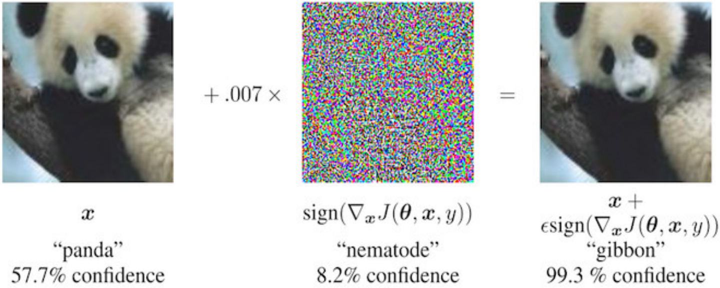

Figure: NN predicts Gibbon for a perturbed panda image[3]

[3] Goodfellow et al. "Explaining and harnessing adversarial examples."(2014)

Changing a single pixel

Uses **differential evolution** to find out which pixel is to be changed and how.

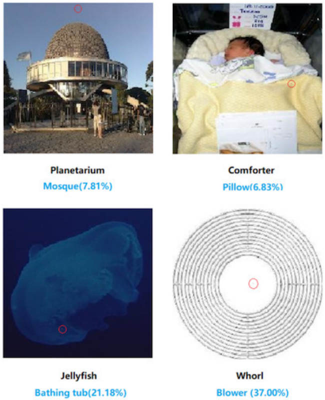

Figure: Changing a single pixel (marked with circles) to deceive a NN to predict the wrong class instead of the original class.[5]

Adversarial Patch

Replaces a part of the image with a patch that can take on any shape.

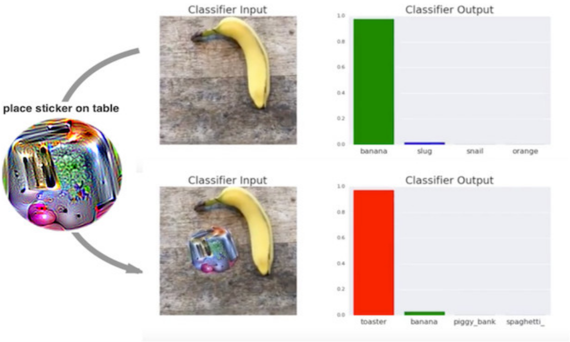

Figure: Changing a single pixel (marked with circles) to deceive an NN to predict the wrong class instead of the original class.[7]

[7] Brown, Tom B., et al. "Adversarial patch.(2017)

Robust adversarial examples

- Adversarial over transformations (rotation, zoom in) unlike other methods such as FGM.
- Expectation Over Transformation (EOT) algorithm.

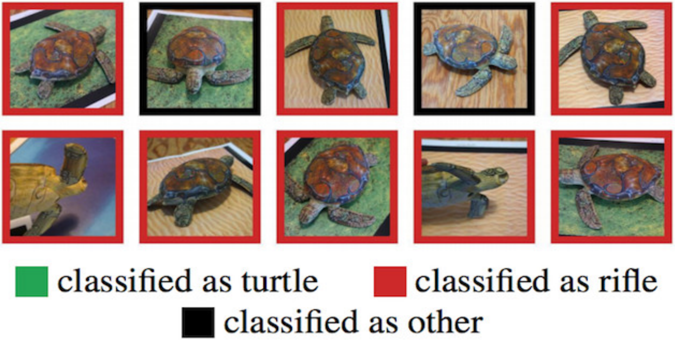

Figure: 3D-printed turtle that was designed to look like a rifle to a deep NN[9]

[9] Athalye, Anish, and Ilya Sutskever. "Synthesizing robust adversarial examples." (2017)

Black Box Attacks

- No internal model information required and no access to the training data.

[10] Papernot, Nicolas, et al. "Practical black-box attacks against machine learning."(2017)

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//just let me code

Combating adversarial examples

AEs can be Model-agnostic.
Methods used to combat adversarial examples include[11];

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Lot's of research ongoing in this field of Adversarial and ML security.

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Conclusion

- The threats of adversarial examples are real and potent.
- These attacks are not limited to computer-vision but span other areas of ML such as NLP, Reinforcement Learning, Speech Recognition e.t.c.
- Increasing development in this field (but with equivalent sophistication in attack methods).

Think of the many different types of spam emails that are constantly evolving (image spam, header masking etc).

tHANK yOU

for staying awake