

The State of Physical Attacks on Deep Learning Systems

Earlence Fernandes

Collaborators:

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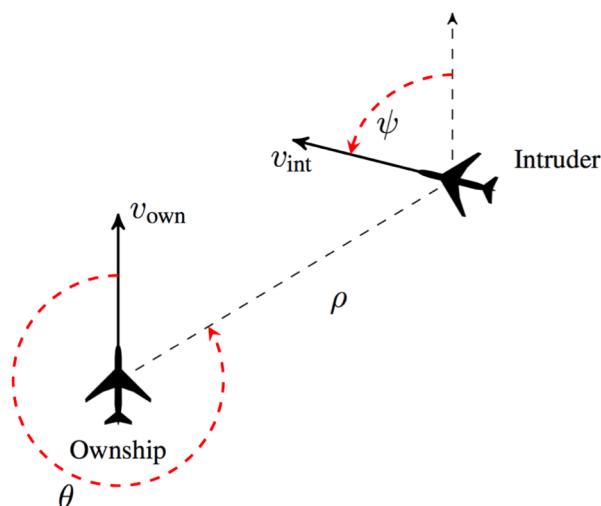
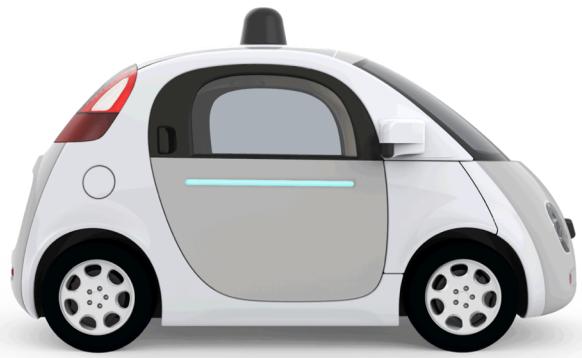


DEEP LEARNING

DEEP LEARNING EVERYWHERE

- Image recognition
- Object detection
- Scene segmentation
- DNA variant calling
- Game playing
- Speech recognition
- Re-enacting politicians
- Colorizing photos
- Pose estimation
- Describing photos
- Generating photos
- Translation
- Music compositions
- Creating art
- Creating DNNs
- Predicting earthquakes
- Particle physics
- Quantum chemistry
- Recommendations
- Creating fake news
- Fighting fake news
- NLP
- Automated Surveillance
- ...

Deep Learning + Cyber-Physical Systems



Airborne Collision
Avoidance System X
unmanned (ACAS Xu)

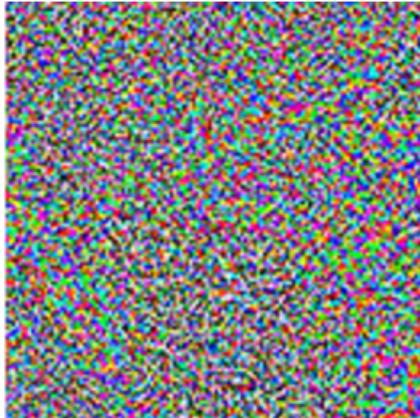


Apollo (Baidu)
Self-Driving Car

The Gibbon-Impersonating Panda aka, Adversarial Examples



$+$ ϵ



$=$



“panda”
57.7% confidence

“gibbon”
99.3% confidence

Image Credit:
OpenAI

But, an attacker requires pixel-level digital access to the model’s
input

Explaining and Harnessing Adversarial Examples, Goodfellow et al., arXiv 1412.6572, 2015

How can attackers create physical attacks?

A Compendium of Physical Attacks

Printing out a digitally created adversarial example works, but is less robust to environmental conditions

Printed patterns on eyeglass-shaped cut-outs can compromise face recognition

Fast Gradient Sign Method (FGSM)
approach

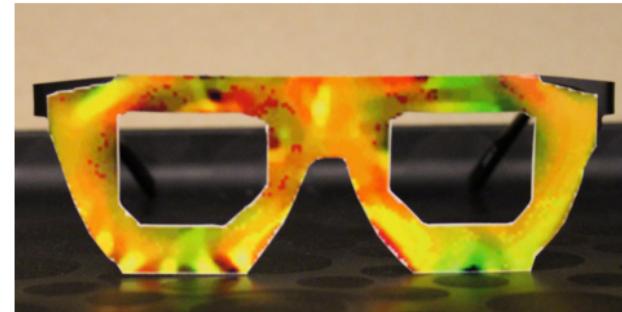


clean

adversarial

Kurakin et al., Adversarial Examples in the Physical World, arXiv 1607.02533, 2016

Optimization approach



Lujo Bauer

Mila Jovovich
(87%)

Sharif et al., Accessorize to a Crime: Real and Stealthy Attacks on State-of-the-Art Face Recognition, CCS 2016

A Compendium of Physical Attacks

Stickers on Stop signs can fool object classifiers and detectors in a range of physical conditions

Optimization approach



Eykholt et al., Robust Physical-World Attacks on Deep Learning Visual Classification, CVPR 2018

Eykholt et al., Physical Adversarial Examples for Object Detectors, WOOT 2018

Attackers can backdoor DNNs so that special stickers cause specific behavior

Training-time attack



Gu et al., BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain, arXiv 1708.06733, 2017

My work

Chen et al., Robust Physical Adversarial Attack on Faster-RCNN Object Detector, arXiv 1804.05810, 2018

A Compendium of Physical Attacks

3D printed turtles can be rifles
to a state-of-the-art classifier

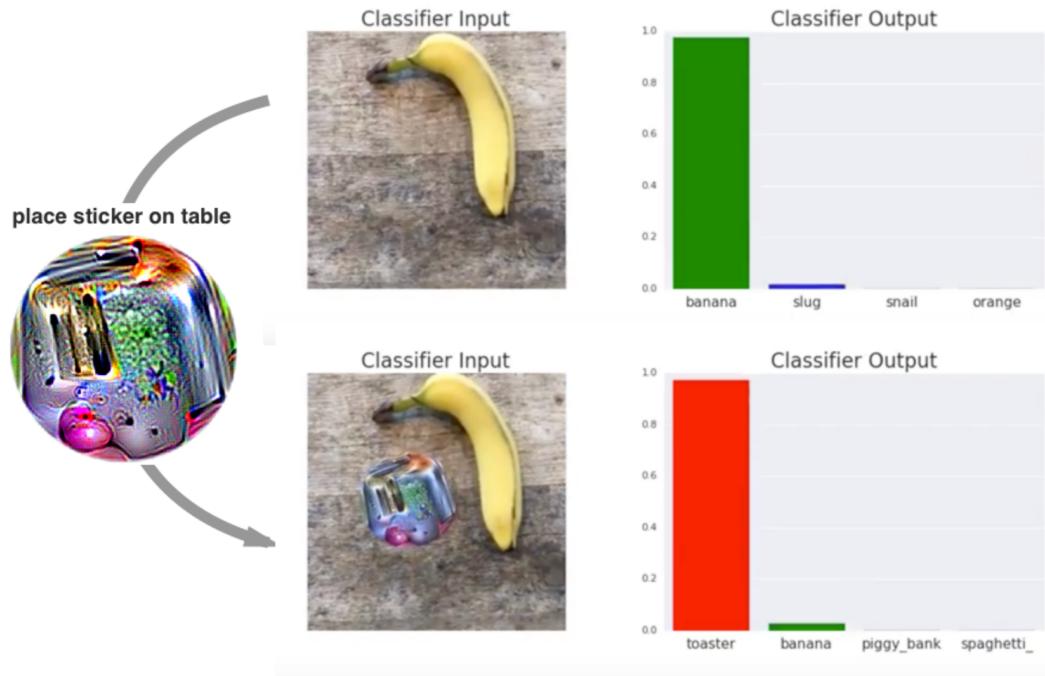
Expectation-over-Transformations
approach (optimization)



Athalye et al., Synthesizing Robust
Adversarial Examples, ICML 2018

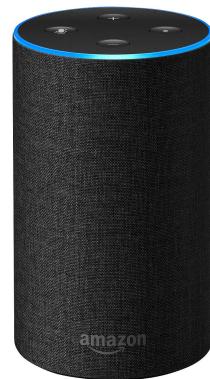
Patches that camouflage any
object as a toaster exist

Expectation-over-Transformations
approach (optimization)



Brown et al., Adversarial Patch, arXiv 1712.09665,
May 2018

Adversarial Examples can hide
in music



Carlini et al., Audio Adversarial
Examples: Targeted Attacks on Speech-
to-Text, DLS Workshop 2018

Yuan et al., CommanderSong: A
Systematic Approach for Practical
Adversarial Voice Recognition, USENIX
Security 2018

Open Questions

- Are there other physical domains where we can explore adversarial examples?
- Current attacks only look at a single model. But, a model is only a part of the whole CPS. Do these attacks have system-wide effects?
- Is there anything specific about physical adversarial examples that make them easier or more difficult to defend against?
- Should we only depend on “pure ML” techniques for defense?
- What aspects of CPSs can we leverage to defend (defense in depth)?

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