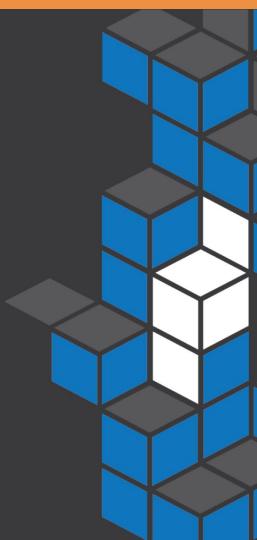


Fooling and Protecting Deep learning models

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About me

- → Final year undergraduate
- → Open source enthusiast
- → Deep Learning Researcher at FOR.ai

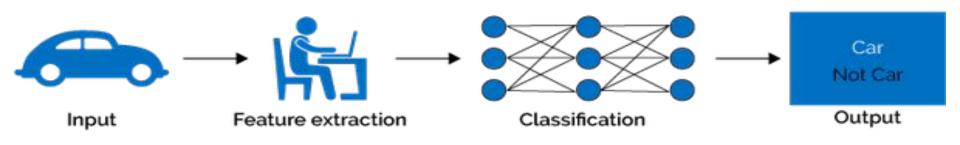


Agenda

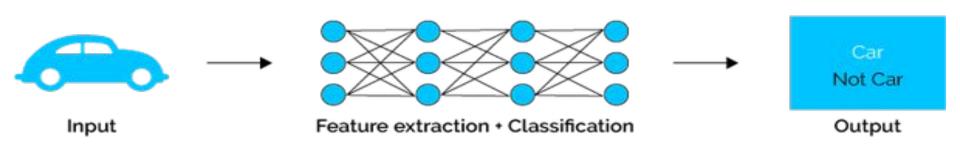
- → Machine learning and Deep learning overview
- → Attacks on machine learning pipeline
- → Types of attacks
- → Timeline of machine learning security
- → Defending the machines

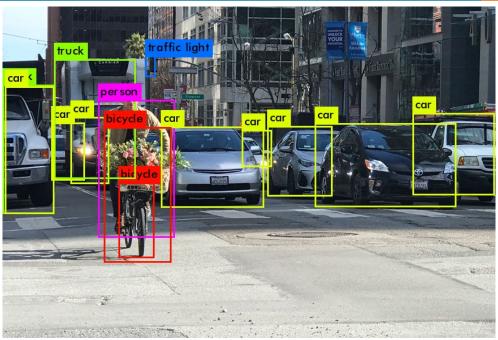
Machine learning vs Deep learning

Machine Learning



Deep Learning



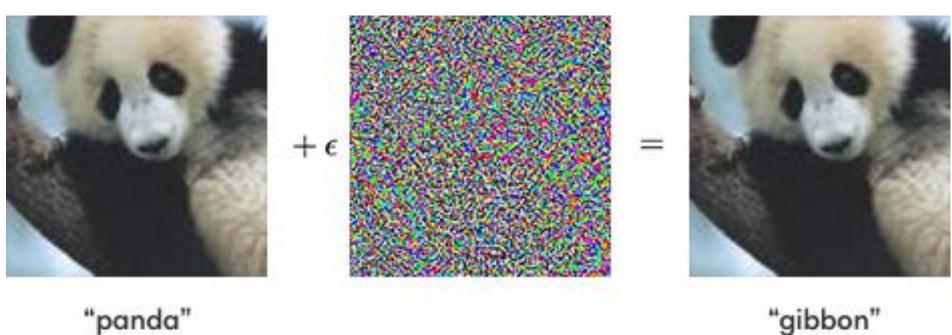


Reached state of the art on various tasks





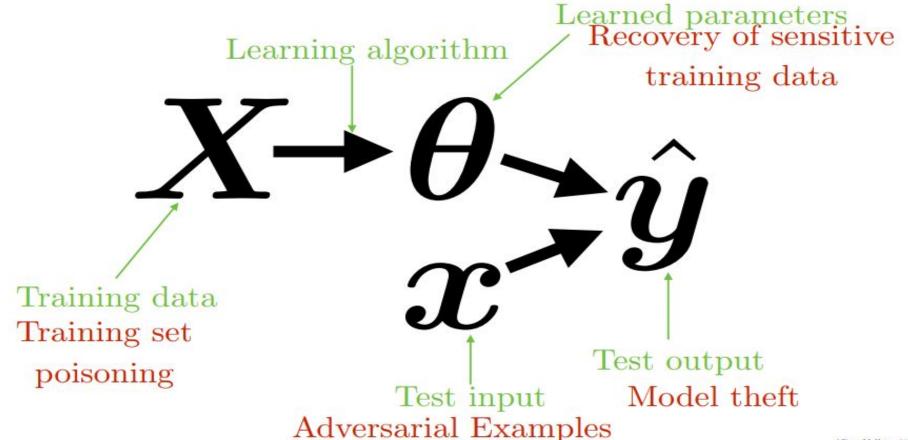
Good models make mistakes



57.7% confidence

99.3% confidence

Attack on the machine learning pipeline



Types of Attacks

White box Attacks

Black box attacks

Targeted Attacks

Untargeted Attacks

Deep Text Classification Can be Fooled

Bin Liang and Hongcheng Li and Miaoqiang Su and Pan Bian and Xirong Li and Wenchang Shi

School of Information, Renmin University of China, Beijing, China {liangb, owenlee, sumiaoqiang, bianpan, xirong, wenchang}@ruc.edu.cn

Did you hear that? Adversarial Examples Against Not just images! Recognition

Robust Physical Adversarial Attack on Faster R-CNN Object Detector

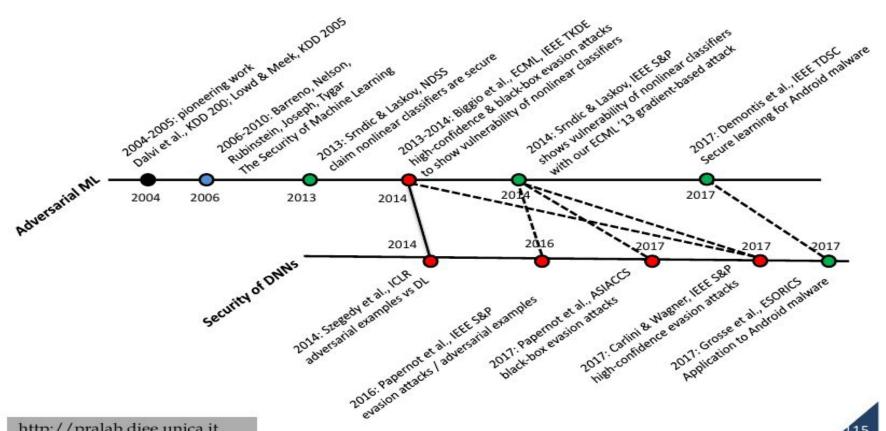
Shang-Tse Chen¹, Cory Cornelius², Jason Martin², and Duen Horng (Polo) Chau¹

Face Recognition on Consumer Devices: Reflections on Replay Attacks

Daniel F. Smith, Arnold Wiliem Member, IEEE, and Brian C. Lovell Senior Member, IEEE

Timeline of Learning Security





What this means for us?

- Deep learning algorithms (Machine learning in general) are susceptible to attacks.
- Use with caution in critical deployments
- Spend effort to make model robust to tempering
- Evaluate a model's adversarial resilience not just accuracy/precision/recal.

Defending the machines

Kannan et al 2018: logit pairing Madry et al 2017: randomize the starting point of the attack. 1st to generalize over attack algorithms Kurakin et al 2016: use an iterative attack Pre-2013: Goodfellow et al 2014: generate them constantly Defenses for in the inner loop of training (minimax) convex models

Szegedy et al 2013: train on adversarial examples



Resources

- → Breaking Linear classifiers with convnets Andrej Karpathy
- → Attacking machine learning with adversarial examples Open Al
- → Adversarial Examples and adversarial training Ian Goodfellow
- → Adversarial examples in machine learning Ian Goodfellow
- → ICCV Tutorial on machine learning Battista Biggio and Fabio Roli
- → <u>Cleverhans</u>

Thank you Questions?

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