The Ethical Implications of Adversarial Attacks

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Outline

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2. How do they work?
3. Why are they dangerous?
4. How can we protect against them?
5. What are the ethical implications?

Adversarial Attacks

What are Adversarial Attacks?

- Adversarial attacks are a technique in which a machine learning model is fooled through a malicious input.
- These malicious inputs are referred to as adversarial examples
- Adversarial examples are designed specifically to cause machine learning models to make mistakes
- These examples are often imperceptible to humans

- Adversarial examples are created by making small changes to the input of an ML model that result in an unexpected outcome
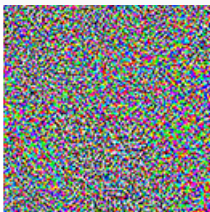- Typically these changes are imperceptible to humans, although not always

"panda"
57.7% confidence

$+ \epsilon$

$=$

"gibbon"
99.3% confidence

How Do They Work?

- Typically adding some sort of noise, the ML model is fooled without changing the appearance of the image
- This noise can be as small as editing a single pixel in an image [SVS19]
- Or can be something perceptible to humans (stop sign example), but still doesn't change the meaning of the image

How Do They Work?

White box attacks (direct access to the model)

- Uses gradient information to minimise D

$$D(x_0, x_0 + \delta) \tag{1}$$

Black box attacks (No access to the model)

- Approximate gradient through network outputs via standard high school gradient approx

$$\frac{f(x + h) - f(x)}{h} \tag{2}$$

Why Are They Dangerous?

- Machine learning algorithms can easily be fooled, even without access to the model
- Depending on the application, this can have serious consequences
- Obvious dangers include self-driving cars and medical screening
- A malicious actor can easily paint the road and trick a car into steering into traffic
- Need to ensure models are robust to adversarial attacks before going to production

How Can We Protect Against Them?

- Models must be robust to a certain amount of perturbation to the input data
- Good model performance $\neq$ robustness
- Recent work has provided frameworks for verifying the robustness of models (e.g. [KBD+17])
- Adversarial defenses seek to detect adversarial examples. Is that enough?

Ethical Implications

Ethical Implications

- Machine learning models are being used in more and more settings
- Often used for making decisions that have an impact on peoples lives and societal function:
  - Medical applications (e.g. tumor classification)
  - Military applications (e.g. automated drones)
  - Security applications (e.g. CCTV person detection)
  - Automated Vehicles
- Each of these applications can be subject to adversarial attacks

Ethical Implications

- Medical applications
  - Intentionally cause false negative results (e.g. [FCKB18])
- Military applications
  - Intentionally label civilian areas as military bases
- Security applications
  - Hide from person detection in automated CCTV camera
- Automated Vehicles
  - Paint on road to cause vehicle to steer into oncoming traffic
  - Adjust road signs to create dangerous driving scenarios

Ethical Implications

- The organisations and individuals implementing these models have a moral responsibility to do no harm through these technologies
- This tech is heavily relied upon and is vulnerability to adversarial attacks
- There is an ethical responsibility to ensure models are suitably robust when used to make decisions which can be exploited

Key Questions

- If a robust, verified model is exploited adversarially, who is to blame?
- How robust do our models have to be before they can be deployed? (never ending cycle of incresaingly more robust models + better attacks)
- Which applications require verified, robust models and which do not?
- Is there are a cost to verifying our models?

References

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📄 Jiawei Su, Danilo Vasconcellos Vargas, and Kouichi Sakurai, *One pixel attack for fooling deep neural networks*, IEEE Transactions on Evolutionary Computation 23 (2019), no. 5, 828–841.