Robustness in AI

A brief history and introduction

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Context and Motivation

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  - We'll see that this intuition fails miserably!
- Lots of emphasis on understanding key subsets of neural networks, called features

Geometric Intuition

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Notation

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- $\phi(x)$: activation values for some layer on input x.

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- Fix an activation unit ϕ and consider

$$x' = \arg\max_{x \in \mathcal{I}} \langle \phi(x), e_i \rangle.$$

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Part 1 - Understanding NNs

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- For any activation unit, consider the images that are most in-line with basis vectors.
  - These images should have visually perceptive commonalities.
- Understand the structure or pattern that the activation unit ϕ is "extracting."

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(a) Unit sensitive to lower round stroke.

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Figure 1: An MNIST experiment. The figure shows images that maximize the activation of various units (maximum stimulation in the natural basis direction). Images within each row share semantic properties.

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Figure 2: An MNIST experiment. The figure shows images that maximize the activations in a random direction (maximum stimulation in a random basis). Images within each row share semantic properties.

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- The standard basis e_i is no better than a random basis for understanding $\phi(x)$!

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Part 2 - Adversarial Examples

- Recall the intuition of *local generalization* - models that generalize well globally also generalize well locally.
- Implied a sense of "smoothness" (similar to Lipschitz continuity) of the model that held for many models prior to NNs.

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- Recall the intuition of *local generalization* - models that generalize well globally also generalize well locally.
- Implied a sense of "smoothness" (similar to Lipschitz continuity) of the model that held for many models prior to NNs.
- This intuition does not hold for NNs!
- There exist "adversarial" examples – inputs which are ϵ-close to a training point and misclassified by the model.

Part 2 - Adversarial Examples

Let $f : \mathbb{R}^m \to \{1, ..., k\}$ be a classifier mapping pictures to labels. Want to solve the following optimization problem $D(x, l)$:

$$\begin{aligned} \text{Minimize: } & ||r||_2 \\ \text{Subject to: } & f(x + r) = l \\ & x + r \in [0, 1]^m \end{aligned}$$

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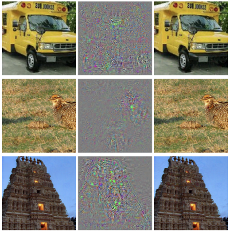
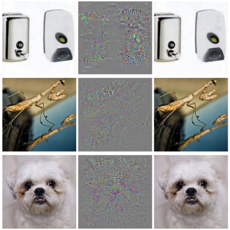
- Finds smallest perturbation vector r that causes f to classify input x as label l.
- Importantly, we get to choose a different r for each x.
- This is hard problem – we approximate.
- For $c > 0$, solve: $\min_r [c|r| + \text{loss}_f(x + r, l)]$ subject to $x + r \in [0,1]^m$.

Part 2 - Adversarial Examples



(a)



(b)

Figure 5: Adversarial examples generated for AlexNet [9].(Left) is a correctly predicted sample, (center) difference between correct image, and image predicted incorrectly magnified by 10x (values shifted by 128 and clamped), (right) adversarial example. All images in the right column are predicted to be an *"ostrich, Struthio camelus"*. Average distortion based on 64 examples is 0.006508. Plase refer to `http://goo.gl/huaGPb` for full resolution images. The examples are strictly randomly chosen. There is not any postselection involved.

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Rest of paper:

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- Showed that adversarial inputs are universal – they are not the result of any particular model overfitting.
- Provided a bound on the Lipschitz constant on each layer of the NN.
- In DNNs (ImageNet), instabilities can appear as early as the first layer.

Key Takeaways

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- Feature extraction is an uninformative method of analysis.
- For any NNs, there exist adversarial examples that are close to training examples which are confidently misclassified.
- Implies that NNs are not Lipschitz continuous for small constants.

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Universal perturbation

- Let μ be a distribution of images in $\mathbb{R}^d$ and $\hat{k}$ be a classifier that assigns $x \in \mathbb{R}^d$ a label $\hat{k}(x)$.

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- Universal perturbation - $v \in \mathbb{R}^d$ such that

$$\hat{k}(x + v) \neq \hat{k}(x) \text{ for most } x \sim \mu.$$

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- Note that v is universal and image agnostic.
- Want v to be imperceptible according to a p-norm of user's choice and misclassify most examples:

$$||v||_p \leq \xi$$
$$\mathbb{P}_{x\sim\mu}(\hat{k}(x+v) \neq \hat{k}(x)) \geq 1-\delta$$

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Universal Perturbation - Geometrically

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- To find universal perturbation v, set $v = \vec{0}$ and find an image x_i that is correctly classified, then set

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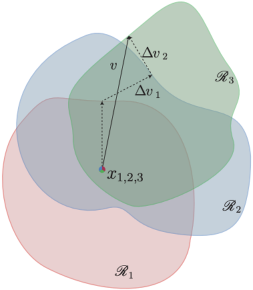
$$\Delta v_i \leftarrow \arg\min_r ||r||_2 \text{ s.t. } \hat{k}(x_i + v + r) \neq \hat{k}(x_i), \text{ (direction)}$$

- Set $v \leftarrow v + \Delta v_i$ normalized so p-norm is small.

- Repeat until empirical "fooling rate" is larger than $1 - \delta$.

Algorithm Intuition



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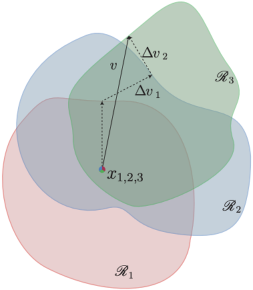

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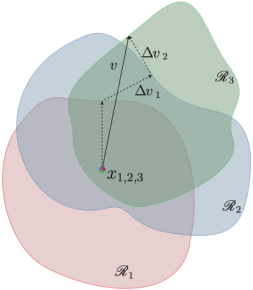

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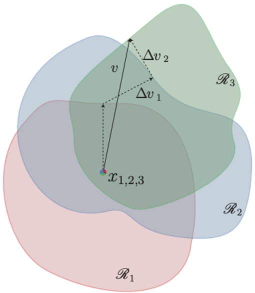

- Find a correctly classified example and add smallest perturbation that misclassifies it.
- Add that perturbation to current perturbation.
- Rinse and repeat until model is fooled whp.

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- Interestingly, if the model is retrained to learn on images with UAP_1, it still will do poorly on new UAP_2 (still fooled on 75% of data).
    - This process can be repeated an arbitrary amount of times and will not improve accuracy of fooled model.

Misclassification graph

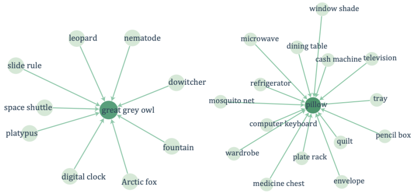

Figure 7: Two connected components of the graph $G = (V, E)$, where the vertices are the set of labels, and directed edges $i \to j$ indicate that most images of class i are fooled into class j.

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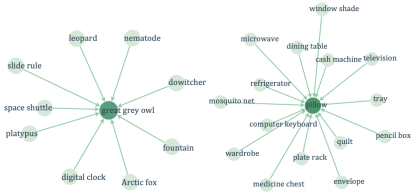

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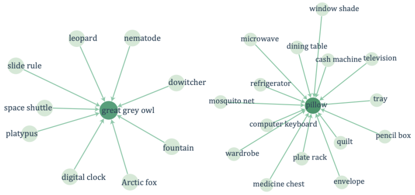

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- Conjectured that dominant labels occupy large regions of image space.

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- Robustness* - if an input is modified in a way that preserves semantics, classification should not change.
- We have seen that classical analysis techniques will not work. How to proceed?

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Robustness as a Game

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- Who goes first? Is the game repeated?

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  - *Unconstrained input*

Example

Figure 1: An example of image spam shown in Biggio and Roli [77]. Note the notion of a "starting point" does not apply here, instead the entire image is crafted from scratch by the attacker to avoid statistical detection. It is not of the form of applying a small or imperceptible perturbation to random image from the training distribution. Thanks to Battista Biggio for permission to use this image.

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- Model on social media that blocks investing advice.
- No notion of starting point and clearly want to be robust to perceptible changes.

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Other examples

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- The Stop Sign Attack

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- Evading Malware Detection

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Other examples

- The Stop Sign Attack
- Evading Malware Detection
- Fooling Facial Recognition
- Check Fraud
- etc.

Rest of paper

- Covers other forms of attacks and attack scenarios.
- Gives more real world examples.
- Justifies robustness research.

Caution: Small norm $\neq$ imperceptible

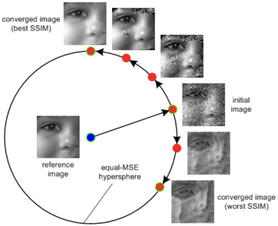

Figure 2: Images equally far away from a reference image in the l_2 sense can be dramatically different in perceived distance. Figure due to Wang and Bovik [97].

- Warning: ℓ_p norms may not align with our intuition!

[0]Figure from [1].

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Bibliography I

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Thank you!

[0] Special thanks to Julian Asilis for helping to create this presentation!