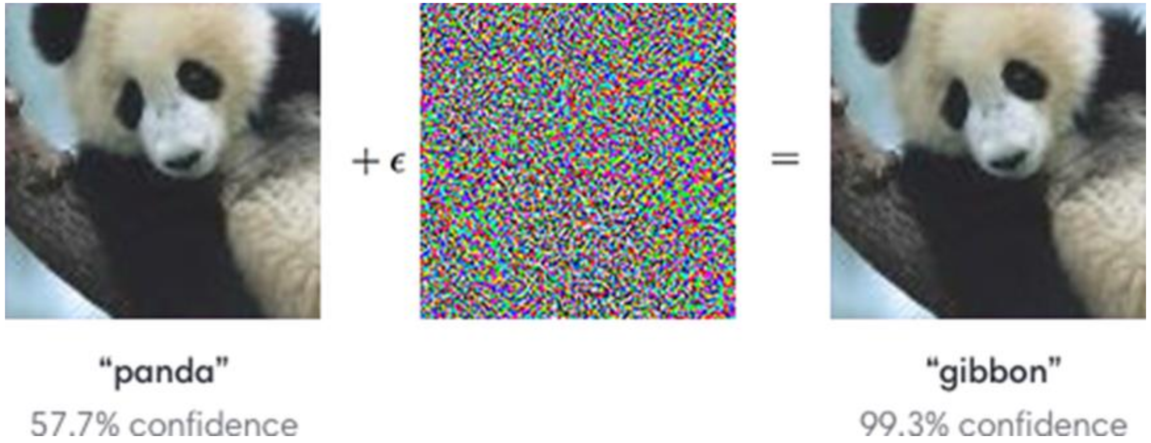
L3.2 Adversarial Attacks



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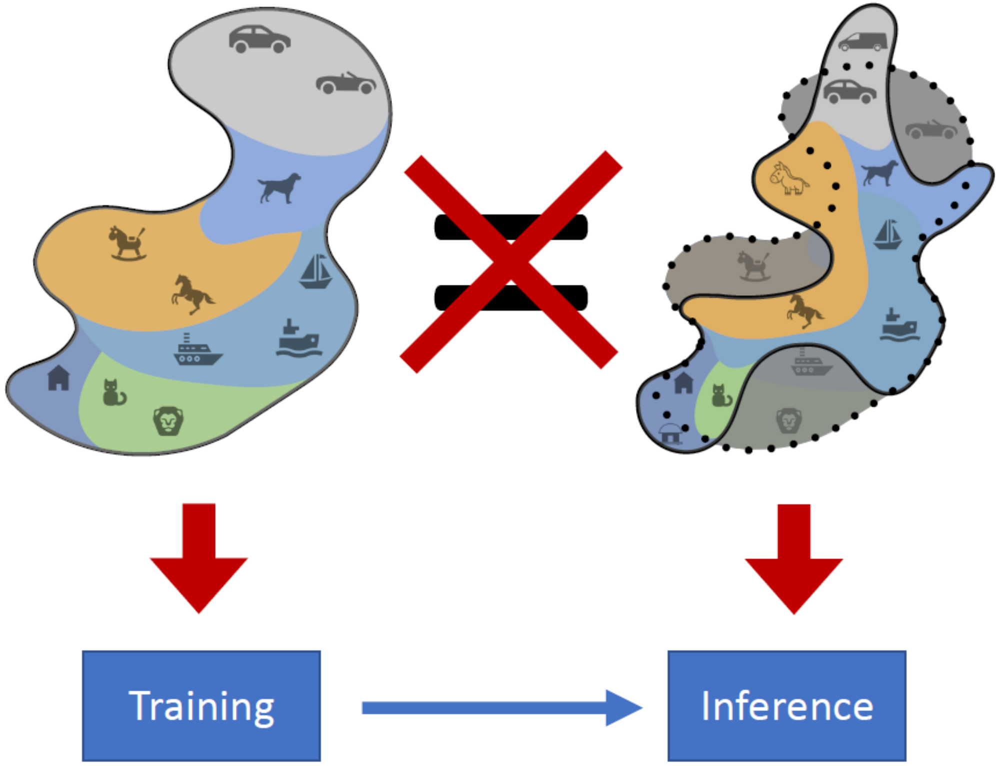
Based on ICML 2018 tutorial https://adversarial-ml-tutorial.org

Outline

- Adversarial attacks via local search
- Physically-realizable attacks
- Training adversarially robust models

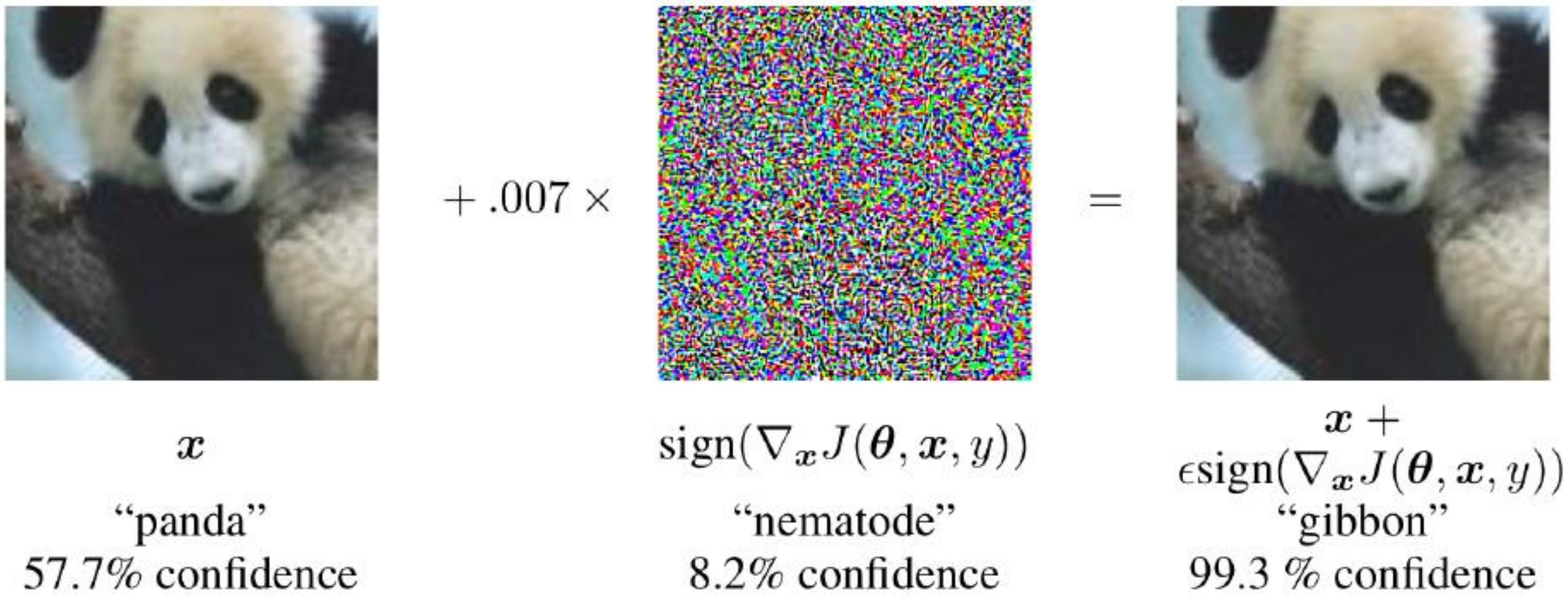
A Limitation of the (Supervised) ML Framework

- Distribution Shift: data distribution during inference may NOT be the same as the training dataset
- May be naturally occurring, or may be due to adversarial attacks



Adversarial Examples

- Starting with an image of a panda, the attacker adds a small perturbation that has been calculated to make the image be recognized as a gibbon with high confidence



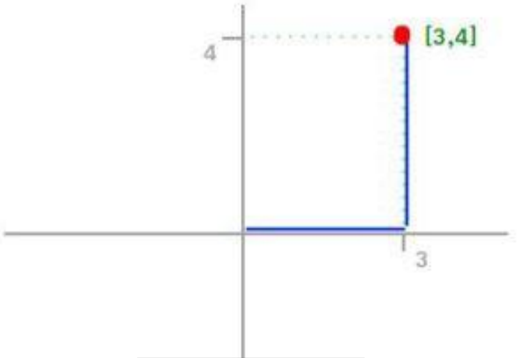
https://openai.com/blog/adversarial-example-research/

Adversarial Attacks w. Input Perturbation

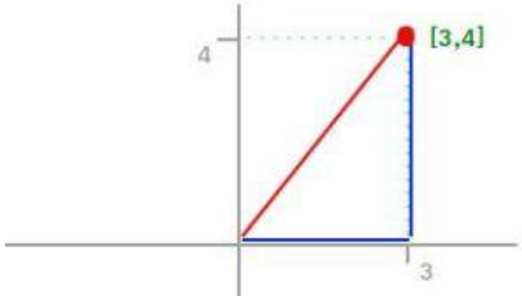
- For a given input image x with correct label y, and a neural network $f_\theta(x)$ that maps from input to label, find a small perturbation δ s.t.
  - Untargeted attack: $f_\theta(x+\delta) \neq y$
  - Targeted attack: $f_\theta(x+\delta) = t \neq y$
- Which input perturbations δ are allowed? e.g., δ small w.r.t.
  - l_p norm (we focus on it in this lecture)
  - Rotation and/or translation
  - Other perturbations…

Vector Norms

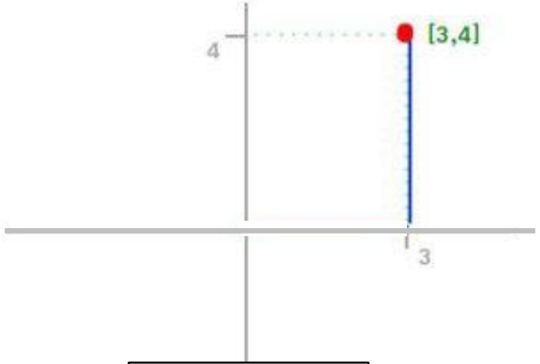
- l_p norm of a k-dimensional vector $x \in \mathbb{R}^k$ is a s
  $\|x\|_p = \left(\sum_{i=1}^{k} |x_i|^p\right)^{1/p}$. Suppose $x = \begin{bmatrix} 3 \\ 4 \end{bmatrix}$
- l_1 norm: $\|x\|_1 = \sum_i |x_i|$ (Manhattan Distance)
  - $= |3| + |4| = 7$
- l_2 norm: $\|x\|_2 = \sqrt{\sum_i x_i^2}$ (Euclidean norm)
  - $= \sqrt{3^2 + 4^2} = 5$
- l_∞ norm: $\|x\|_\infty = \max_i |x_i|$
  - $= \max_i(3,4) = 4$



l_1 norm



l_2 norm

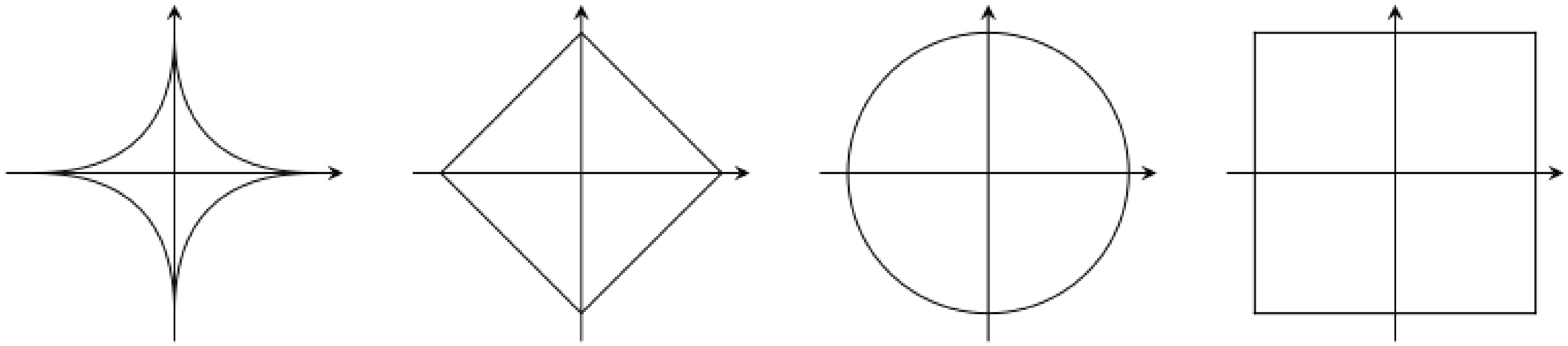


l_∞ norm

https://montjoile.medium.com/l0-norm-l1-norm-l2-norm-l-infinity-norm-7a7d18a4f40c

Vector Norm Balls

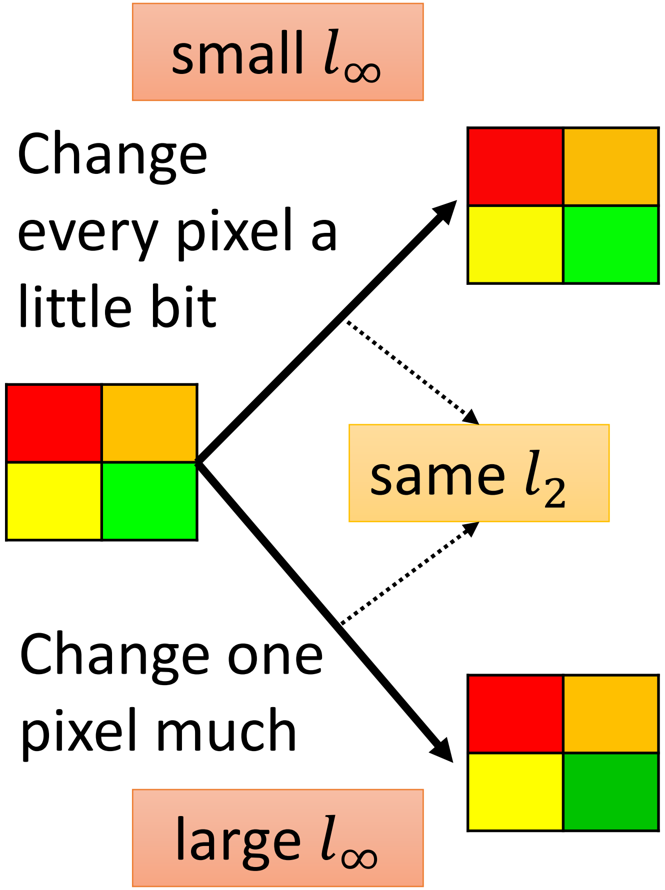
- The l_p norm ball $\|x\|_p \leq \epsilon$ is the set of all vectors with p-norm less than or equal to ϵ: $B_p = \{x \in \mathbb{R}^k | \|x\|_p \leq \epsilon\}$
- l_2 norm ball $\|x\|_2 \leq \epsilon$: a circle with radius ϵ centered at origin
- l_∞ norm ball $\|x\|_\infty \leq \epsilon$: a square with edge length 2ϵ centered at origin



$p = \frac{1}{2}$ $\quad$ $p = 1$ $\quad$ $p = 2$ $\quad$ $p = \infty$

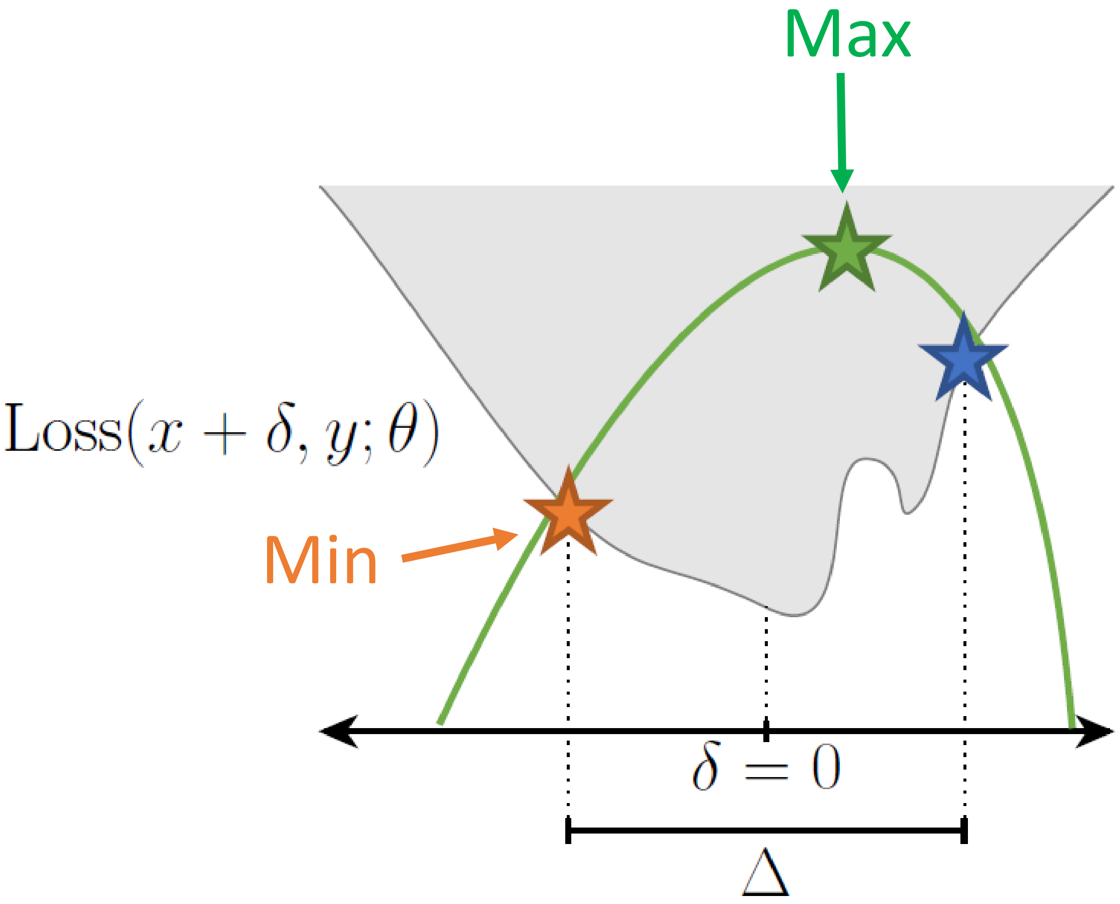
l_2 vs. l_∞ Norm Balls

- Consider the original vector $x^0 = \begin{bmatrix}10\\10\end{bmatrix}$ and two disturbed vectors $x^1 = \begin{bmatrix}3\\3\end{bmatrix}, x^2 = \begin{bmatrix}0\\10\end{bmatrix}$
  - $\delta^1 = x^0 - x^1 = \begin{bmatrix}10\\10\end{bmatrix} - \begin{bmatrix}3\\3\end{bmatrix} = \begin{bmatrix}7\\7\end{bmatrix}, \delta^2 = x^0 - x^2 = \begin{bmatrix}10\\10\end{bmatrix} - \begin{bmatrix}0\\10\end{bmatrix} = \begin{bmatrix}10\\0\end{bmatrix}$
- Same l_2 distance:
  - $\|\delta^1\|_2 = \sqrt{7^2 + 7^2} \approx 9.9, \|\delta^2\|_2 = \sqrt{10^2 + 0^2} = 10$
- Different l_∞ distances:
  - $\|\delta^1\|_\infty = \max(7,7) = 7, \|\delta^2\|_\infty = \max(10,0) = 10$
- l_∞ distance cares about the one maximally-changed individual pixel, whereas l_2 distance cares about all pixels. An image with added random salt-and-pepper noise will have a large l_2 distance from the original image, but not a large l_∞ distance.
- l_∞ seems to be more aligned w. human perception
  - e.g., you can clearly see the color difference of the green pixel in the lower right figure with large l_∞ distance



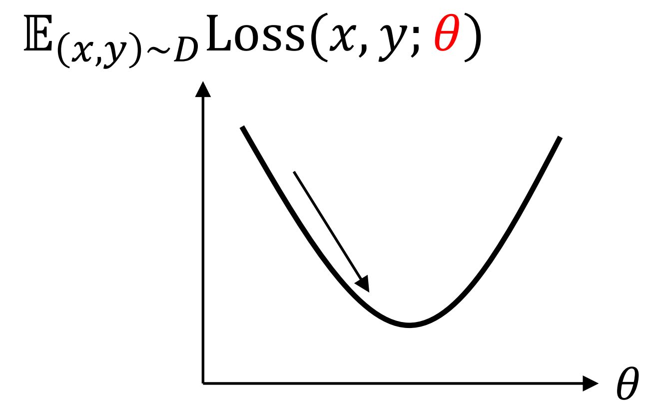
Maximization Problem for Finding Adversarial Examples

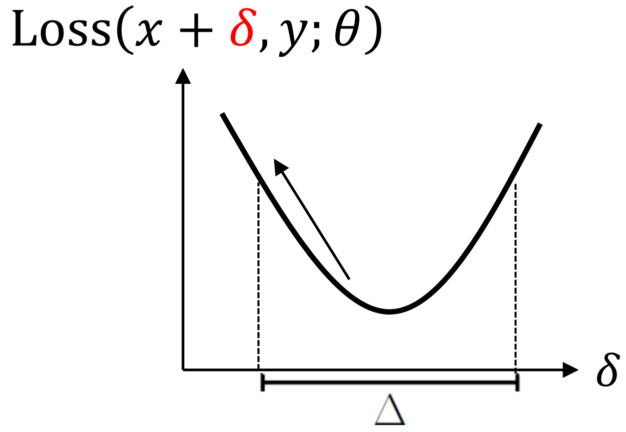
- $\max_{\delta \in \Delta} \text{Loss}(x + \delta, y; \theta)$
  - Loss() may be Cross-Entropy loss for multi-class classification
  - Solved by constructing adversarial examples via local search
- Attacks can be categorized w.r.t.
  - Allowable perturbation set Δ
  - Optimization procedure, e.g., by Gradient Descent



Model Training vs. Local Search for Adversarial Input Generation

- To solve $\min_{\theta} \mathbb{E}_{(x,y)\sim D} \text{Loss}(x, y; \theta)$ for model training: gradient descent $\theta \leftarrow \theta - \alpha \nabla_{\theta} \text{Loss}(x, y; \theta)$
  - Update model params θ by following the gradient downhill, in order to decrease $\text{Loss}(x, y; \theta)$. ($\alpha$ is the Learning Rate)
- To solve $\max_{\delta \in \Delta} \text{Loss}(x + \delta, y; \theta)$ for adversarial input generation: gradient ascent $\delta \leftarrow \delta + \alpha \nabla_{\delta} \text{Loss}(x + \delta, y; \theta)$
  - Update input $x + \delta$ by following the gradient uphill, in order to increase $\text{Loss}(x + \delta, y; \theta)$, while ensuring $\delta \in \Delta$





Aside: Vector Derivative

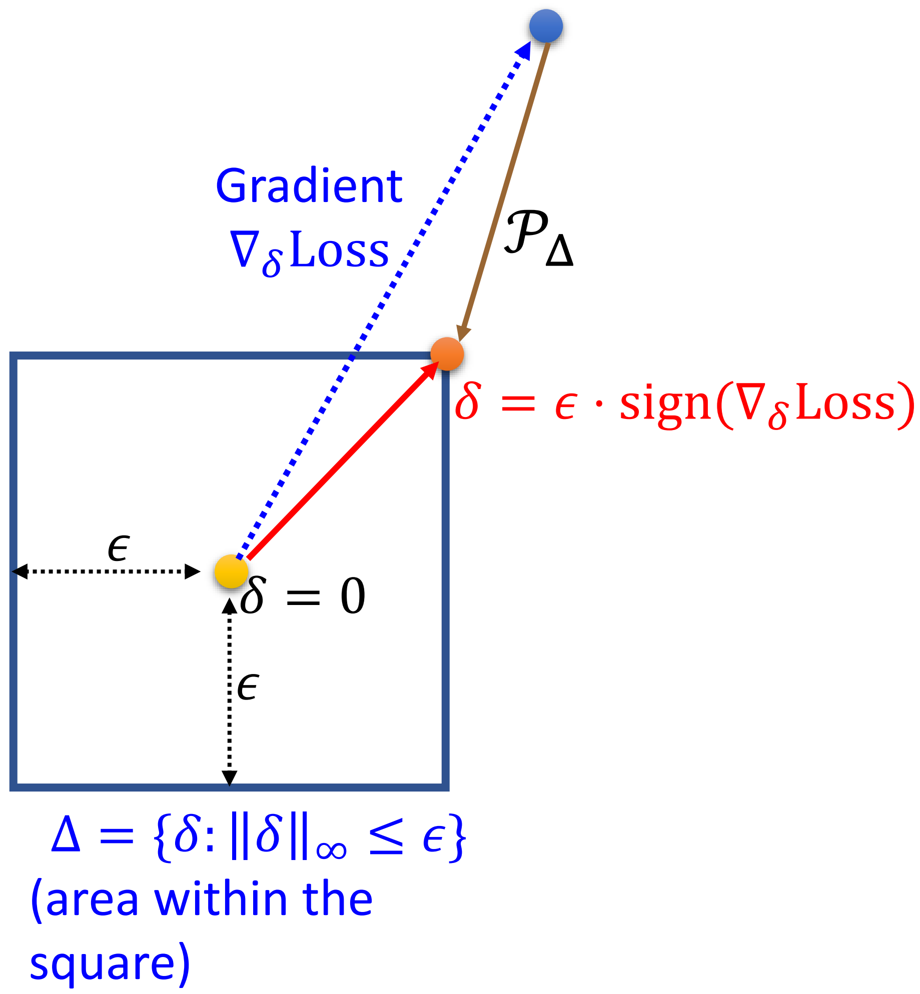
- Consider a scalar (loss) function $y = f(x)$ that takes as input a n-dim vector x and returns a scalar value y, then $\nabla_x f(x)$ is a n-dim vector:
- $x = \begin{bmatrix} x_0 \\ x_1 \\ \dots \\ x_{n-1} \end{bmatrix}, \nabla_x f(x) = \begin{bmatrix} \frac{\partial f}{\partial x_0} \\ \frac{\partial f}{\partial x_1} \\ \dots \\ \frac{\partial f}{\partial x_{n-1}} \end{bmatrix}$
- x, δ are vectors, e.g., a 128x128 pixel color image is a 128x128x3 tensor, encoded as a vector of size 128*128*3=49152

Projected Gradient Descent (PGD)

- Take a gradient step, and if you have stepped outside of the feasible set, project back into the feasible set: Δ: $\delta \leftarrow \mathcal{P}_{\Delta}\big(\delta + \alpha \nabla_{\delta} \mathrm{Loss}(x + \delta, y; \theta)\big)$
  - Input image x is a constant; perturbation δ is the optimization variable. Hence we take derivative w.r.t. δ: $\nabla_{\delta} \mathrm{Loss}()$

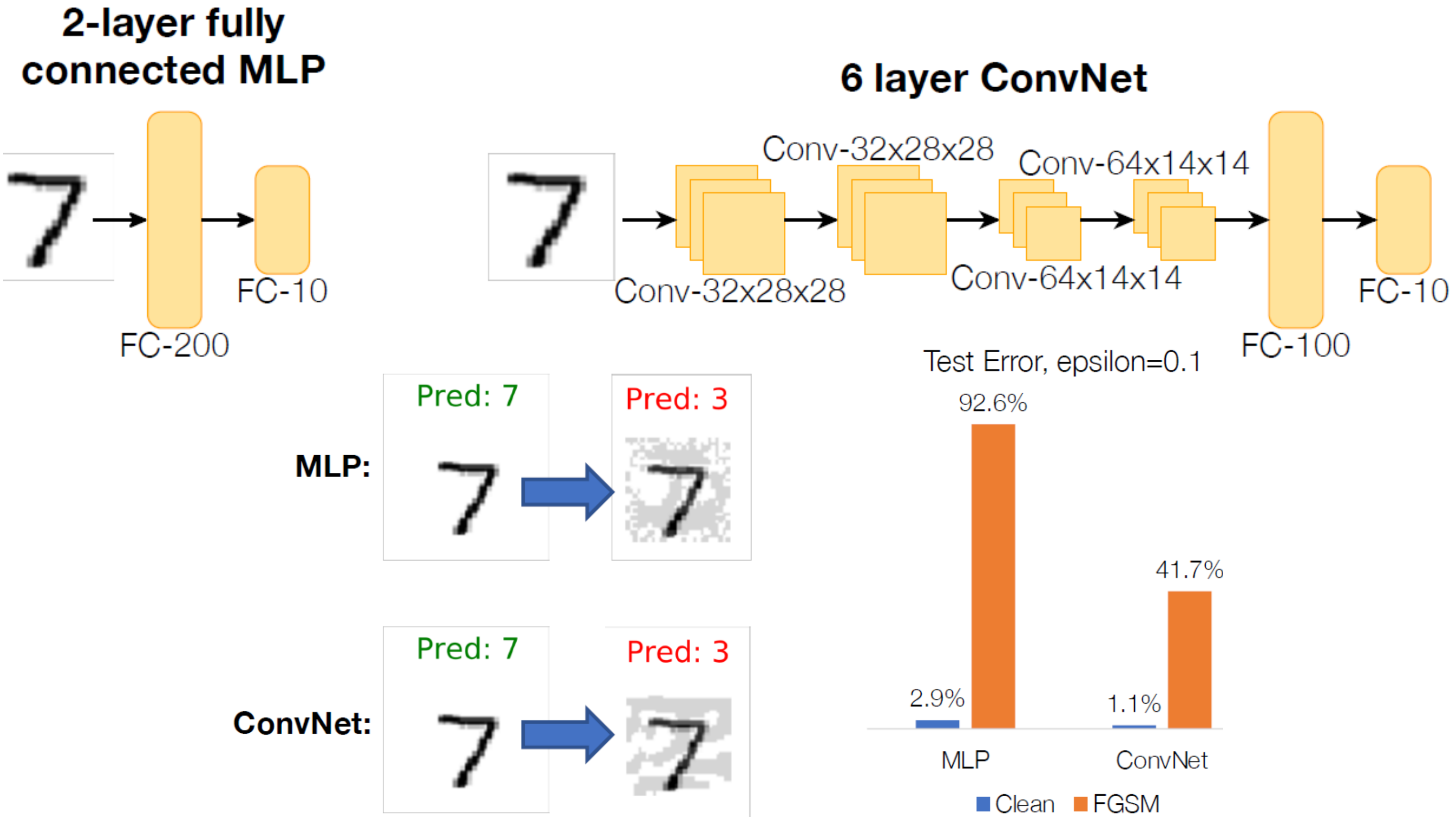
Fast Gradient Sign Method (FGSM)

- FGSM is an attack designed for l_∞ norm bound by taking a single PGD (Projected Gradient Descent) step within l_∞ norm bound $\Delta = \{\delta: \|\delta\|_\infty \leq \epsilon\}$
- Starting from $\delta = 0$, take a large step in the gradient direction by making the learning rate α very large. Then apply projection operator $\mathcal{P}_\Delta$ to clip every dimension of δ to lie within range $[-\epsilon, \epsilon]$: $\mathcal{P}_\Delta(\delta) \coloneqq \text{Clip}(\delta, [-\epsilon, \epsilon])$, i.e.,
  - $\delta = \mathcal{P}_\Delta\big(0 + \alpha \nabla_\delta \text{Loss}(x + \delta, y; \theta)\big) = \epsilon \cdot \text{sign}\big(\nabla_\delta \text{Loss}(x + \delta, y; \theta)\big)$
- The specific values of α and gradient do not matter if they are large enough; only the gradient direction matters (Any gradient direction in the upper right quadrant of the l_∞ norm ball will result in the same δ at the upper right corner)



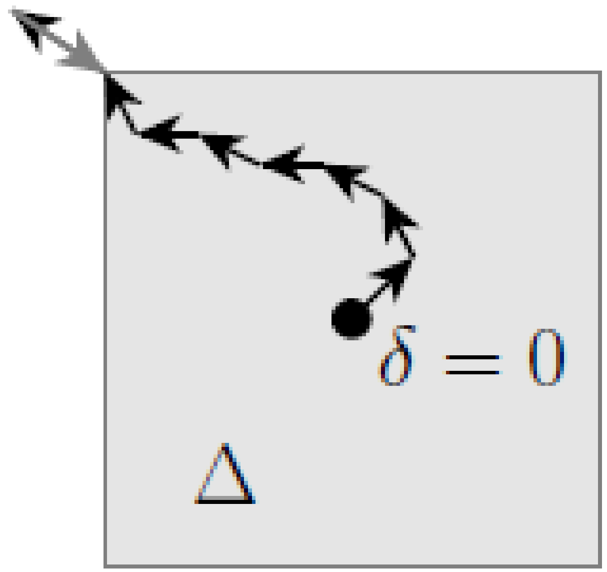
Adversarial Examples by FGSM

- Two NNs for MNIST classification. l_∞ norm bound $||\delta||_\infty \leq \epsilon = 0.1$

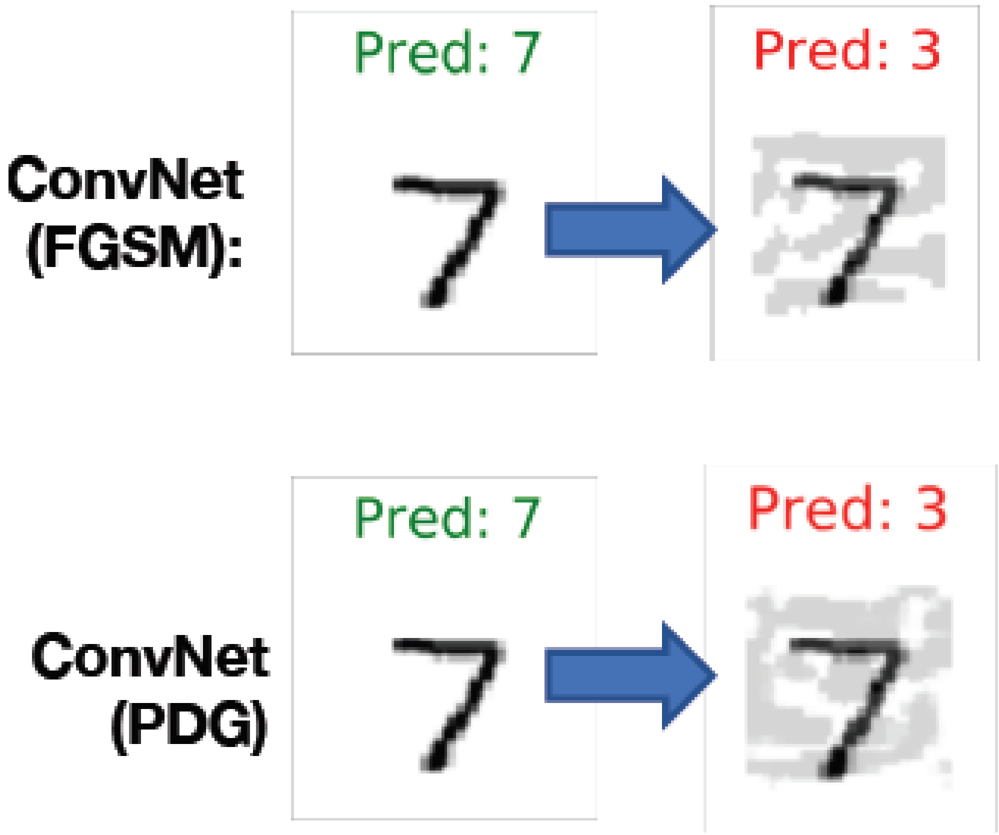


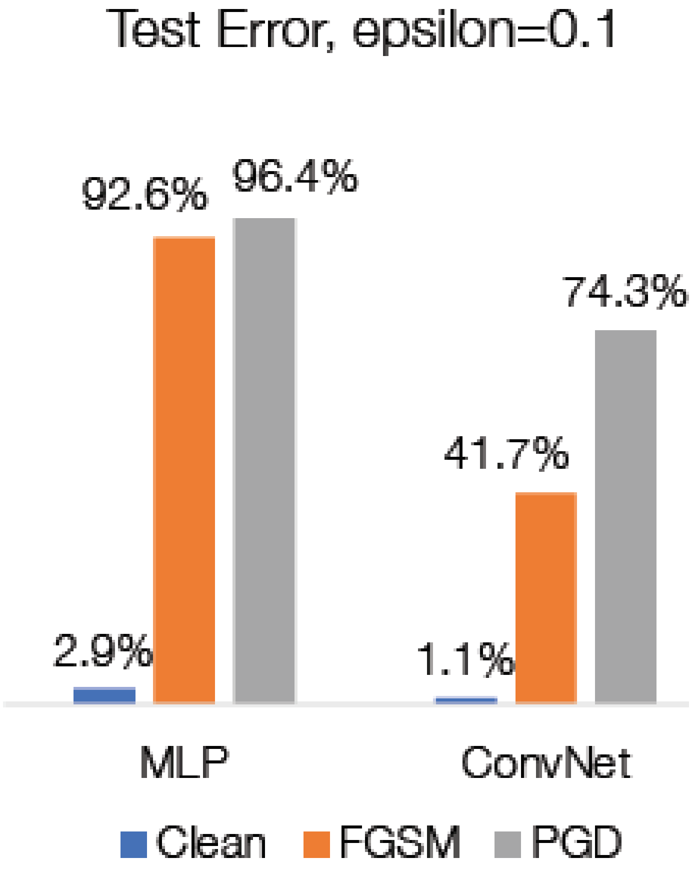
PGD w. Small Steps

- Recall FGSM takes one large step with size $\alpha = \epsilon$: $\delta = \mathcal{P}_\Delta\big(0 + \alpha \nabla_\delta \text{Loss}(x + \delta, y; \theta)\big) = \epsilon \cdot \text{sign}\big(\nabla_\delta \text{Loss}(x + \delta, y; \theta)\big)$
- PGD takes many small steps (each with size α) to iteratively update δ:
  - Repeat: $\delta \leftarrow \mathcal{P}_\Delta\left(\delta + \alpha \cdot \text{sign}\big(\nabla_\delta \text{Loss}(x + \delta, y; \theta)\big)\right)$
  - Rule-of-thumb: choose α to be a small fraction of ϵ, and set the number of iterations to be a small multiple of ϵ/α
- Fig shows a sequence of gradient steps, with the last step going outside of the l_∞ ball Δ, but $\mathcal{P}_\Delta$ brings it back into Δ
  - Fig shows the final δ to end up at a corner of the l_∞ ball, but it may not be true in general



PGD Examples



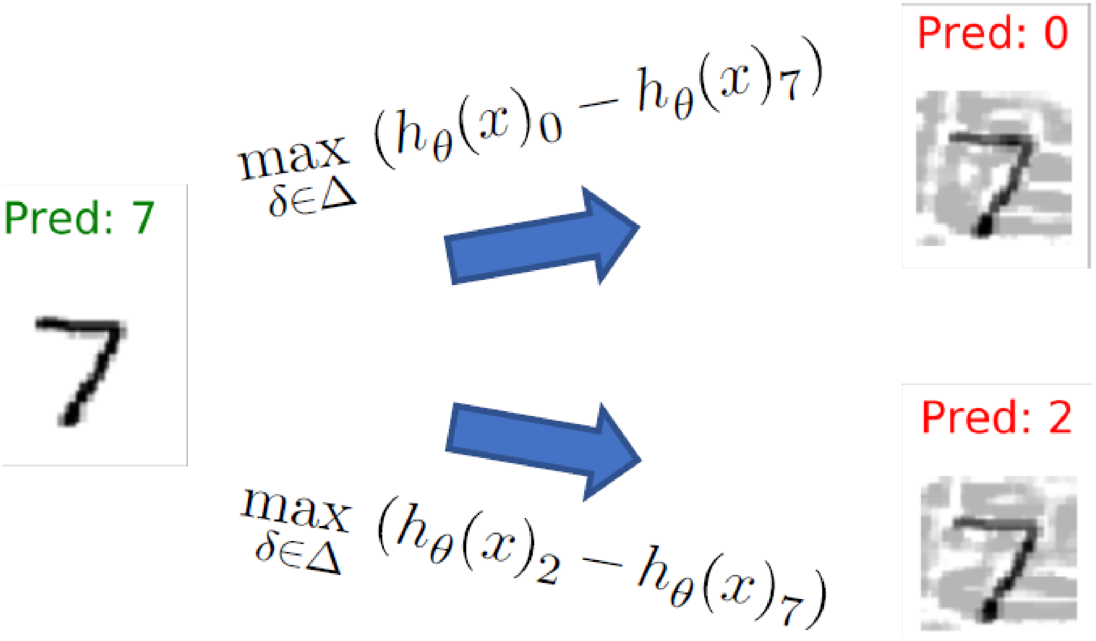


Review: Cross-Entropy Loss for Multi-Class Classification

- The SoftMax operator $\sigma: \mathbb{R}^k \to \mathbb{R}^k$ computes a vector of predicted probabilities $\sigma(z): \mathbb{R}^k$ from a vector of logits $z: \mathbb{R}^k$ in the last hidden layer (the penultimate layer), where k is the number of classes:
  - $\sigma(z)_i = \frac{\exp(z_i)}{\sum_{j=1}^{k} \exp(z_j)}$
- The loss function is defined as the negative log likelihood of the predicted probability corresponding to the correct label y:
  - $\text{Loss}(x, y; \theta) = -\log \sigma(h_\theta(x)_y) = -\log\left(\frac{\exp(h_\theta(x)_y)}{\sum_{j=1}^{k} \exp(h_\theta(x)_j)}\right) = \log\left(\sum_{j=1}^{k} \exp(h_\theta(x)_j)\right) - h_\theta(x)_y$
  - Minimizing $\text{Loss}(h_\theta(x), y)$ amounts to maximizing the logit $h_\theta(x)_y$ corresponding to the correct label y

Untargeted vs. Targeted Attacks

- Untargeted attack: maximize loss of the true class y:
  - $\max_{\delta\in\Delta} \text{Loss}(x+\delta, y; \theta)$
  - Since SoftMax is a monotonic function:
  - $\text{Loss}(x+\delta, y; \theta) = \log\left(\sum_{j=1}^{k} \exp\left(h_\theta(x+\delta)_j\right)\right) - h_\theta(x+\delta)_y$
  - This is equivalent to minimizing logit of the true class y :
  - $\min_{\delta\in\Delta} h_\theta(x+\delta)_y$
- Targeted attack: maximize loss of the true class y and minimize loss of a particular target class y_{targ}, in order to change label to y_{targ}:
  - $\max_{\delta\in\Delta} \left(\text{Loss}(x+\delta, y; \theta) - \text{Loss}\left(x+\delta, y_{targ}; \theta\right)\right)$
  - This is equivalent to minimizing logit of the true class y while maximizing logit of the target class y_{targ}:
  - $\min_{\delta\in\Delta} \left(h_\theta(x+\delta)_y - h_\theta(x+\delta)_{y_{targ}}\right)$
  - Alternative formulation: minimizing logit of all the other classes y' while maximizing logit of the target class y_{targ}:
  - $\min_{\delta\in\Delta} \left(\sum_{y'\neq y_{targ}} h_\theta(x+\delta)_{y'} - h_\theta(x+\delta)_{y_{targ}}\right)$



Outline

- Adversarial attacks via local search
- Physically-realizable attacks
- Training adversarially robust models

Physically-Realizable Attacks

- Instead of directly manipulating pixels, it is possible to modify physical objects and cause miss-classification
- [Evtimov et al 2017]: Physical Adversarial Examples Against Deep Neural Networks
  - https://bair.berkeley.edu/blog/2017/12/30/yolo-attack/

[Kurakin Goodfellow Bengio 2017]

[Athalye Engstrom Ilyas Kwok 2017]

[Sharif Bhagavatula Bauer Reiter 2016]

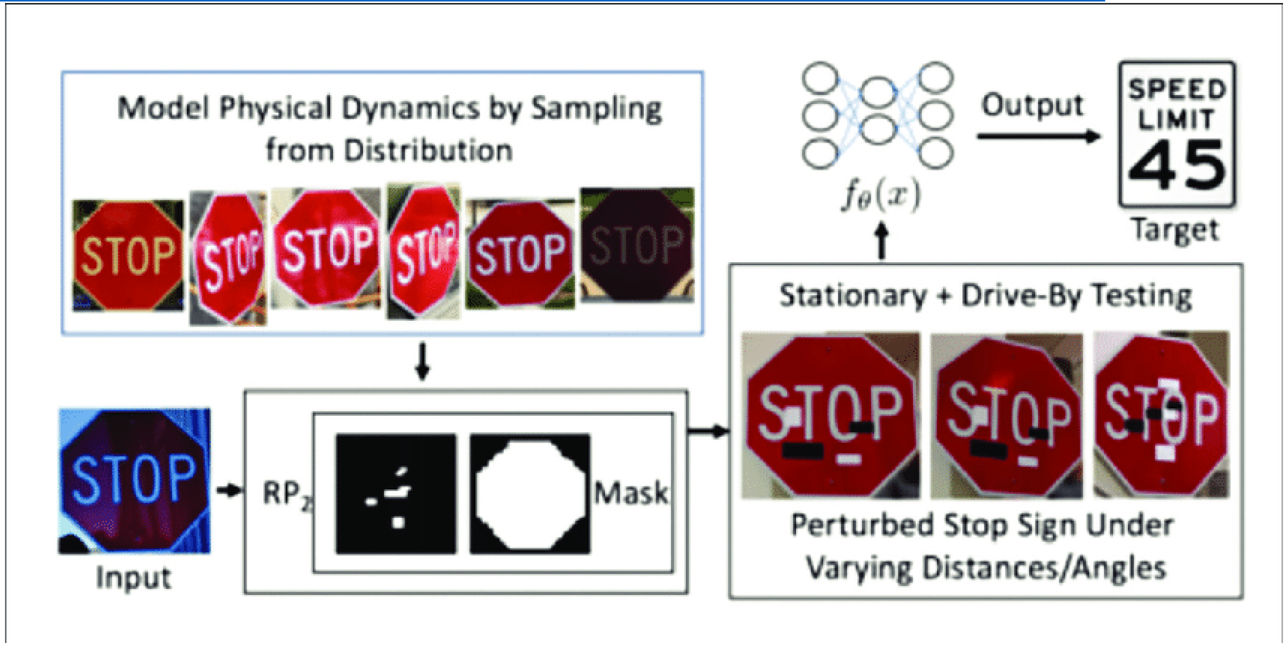
[Eykholt Evtimov Fernandes Li Rahmati Xiao Prakash Kohno Song 2017]

An optimization approach to creating robust adversarial examples

- The following optimization problem for targeted attack aims to minimize the cost function for input $x + \delta$ and target label y_{targ} (λ is the Lagrange multiplier; the objective tries to minimize the perturbation $||\delta||_p$ instead of putting a hard bound on $||\delta||_p$)
  - $\text{argmin}_\delta \lambda||\delta||_p + J(f_\theta(x+\delta), y_{targ})$
- To create a universal perturbation for robust adversarial examples, enhance the training dataset with multiple (k) variants of the input image at different viewing angles and lighting conditions
  - $\text{argmin}_\delta \lambda||\delta||_p + \frac{1}{k}\sum_{i=1}^{k} J(f_\theta(x+\delta), y^*)$

Optimizing Spatial Constraints

- To make the perturbation imperceptible to humans, we add a mask M_x to localize the perturbation to specific areas of the Stop Sign to mimic vandalism:
  - $\text{argmin}_\delta\, \lambda \|M_x \cdot \delta\|_p + \frac{1}{k}\sum_{i=1}^{k} J(f_\theta(x + M_x \cdot \delta), y^*)$
  - Use l_1 norm in $\|M_x \cdot \delta\|_1$ to find the most vulnerable regions (since l_1 loss promotes sparsity), then generate perturbation δ within these regions
- Video demos:
  - "Bo Li – Secure Learning in Adversarial Autonomous Driving Environments" https://www.youtube.com/watch?v=0VfBGWnFNuw&t=421s

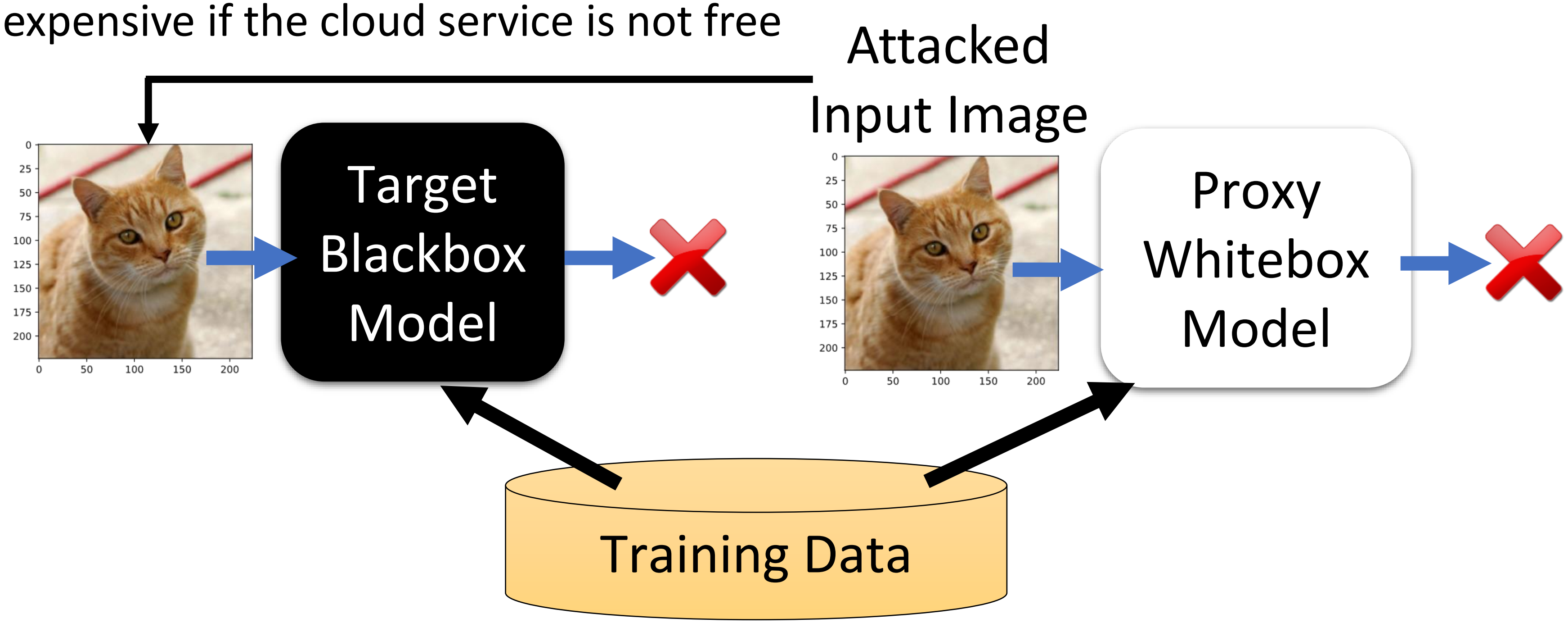


Adversarial Traffic Signs

Distance/Angle	Subtle Poster	Subtle Poster Right Turn	Camouflage Graffiti	Camouflage Art (LISA-CNN)	Camouflage Art (GTSRB-CNN)
5′ 0°					
5′ 15°					
10′ 0°					
10′ 30°					
40′ 0°					
Targeted-Attack Success	100%	73.33%	66.67%	100%	80%

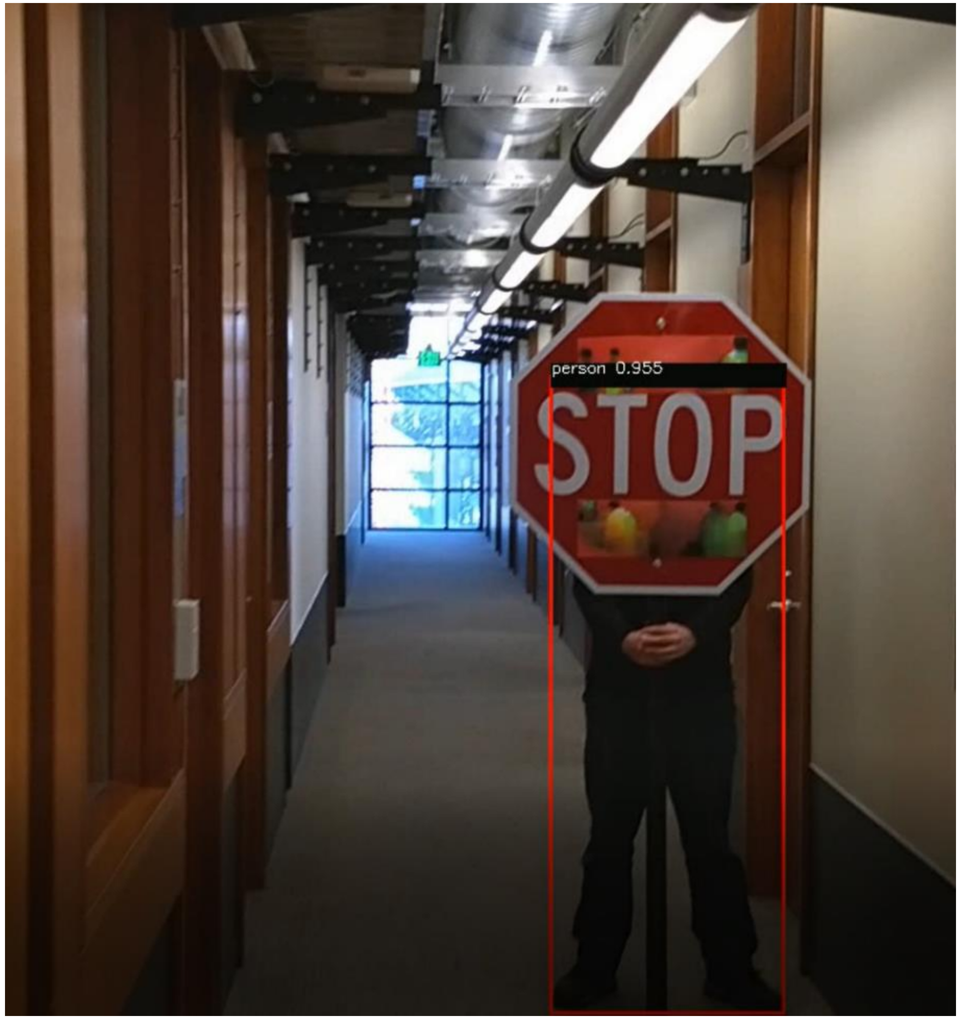
Blackbox Attacks

- We have been discussing Whitebox attacks, where we know the NN model parameters θ
- Black Box Attacks:
- If you have the training dataset of the target Blackbox model:
  - Train a proxy Whitebox model yourself
  - Generate attacked objects for the proxy model
- If you do not have the training dataset, you can obtain input-output data pairs from the target Blackbox model by invoking online cloud services
  - May get expensive if the cloud service is not free



Blackbox Attack Example

- [Evtimov et al 2017]: Physical adversarial examples generated for the YOLO object detector (the proxy Whitebox model) are also be able to fool Faster-RCNN (the Blackbox model)



Phantom of the ADAS

- A phantom is a depthless presented/projected picture of a 3D object (e.g., pedestrian, traffic sign, car, truck, bicycle…), with the purpose of fooling ADAS to treat it as a real object and trigger an automatic reaction
- Phantom attacks by projecting a phantom via a drone equipped with a portable projector:
  - https://www.youtube.com/watch?v=1cSw4fXYqWI&t=85s
- or by presenting a phantom on a hacked roadside digital billboard:
  - https://www.youtube.com/watch?v=-E0t_s6bT_4

https://www.nassiben.com/phantoms

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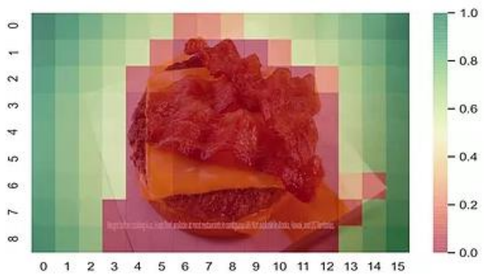
Algorithm for Disguising Phantoms

- 1. Extract key points as focus areas of human attention for every frame based on the SURF algorithm
- 2. Compute a local score for every block in a frame that represents how distant a block is from the focus areas, and embed phantoms into “dead areas” that viewers will not focus on
- 3. Display the phantom in at least t consecutive video frames (longer duration leads to higher success rate)

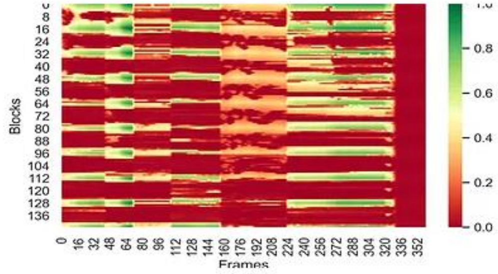
Original frame

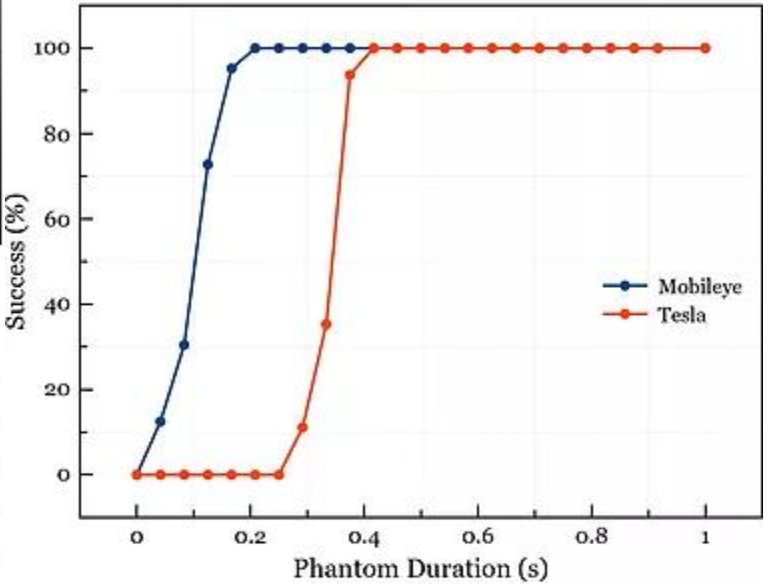
Detecting focus areas in a frame (in blue)

Detecting dead areas in a frame (in green)



Detecting dead areas in the entire advertisement





Constraints on Perturbations

- In Phantom of the ADAS attack, phantoms are embedded into "dead areas" that human viewers are not likely to focus on
- There is no $\delta \in \Delta$ norm constraint on the allowable perturbations, since it may not be well-aligned with human perception

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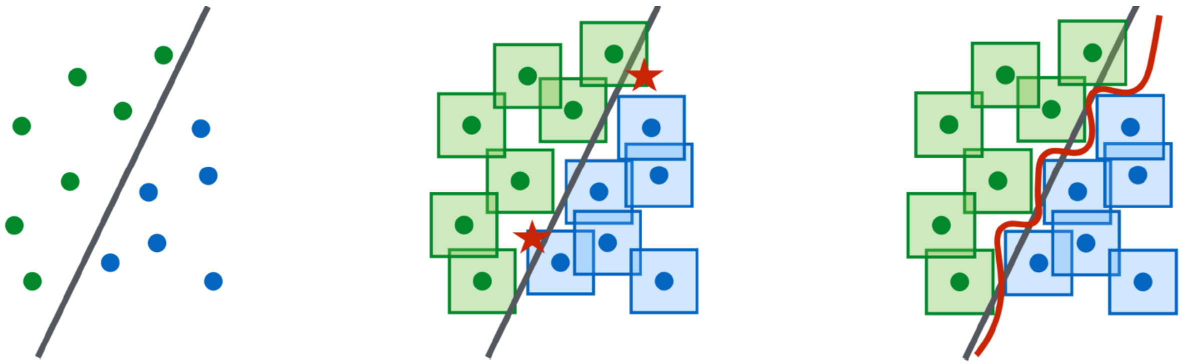
Standard ML vs. Adversarial Robust ML

- Standard ML: Empirical Cost Minimization: $\min_{\theta} \mathbb{E}_{(x,y)\sim D} \text{Loss}(x, y; \theta)$
- Adversarial Input Generation (untargeted attack): $\max_{\delta \in \Delta} \text{Loss}(x + \delta, y; \theta)$ (e.g., FGSM, PGD)
- Adversarial Robust ML: $\min_{\theta} \mathbb{E}_{(x,y)\sim D} \max_{\delta \in \Delta} \text{Loss}(x + \delta, y; \theta)$
  - Inner maximization problem: generating an adversarial input by adding a small perturbation δ (or ensuring one does not exist)
  - Outer minimization problem: training a robust classifier in the presence of adversarial examples
  - Higher network capacity enables more complex decision boundary and more robust classification



1) Simple decision boundary

2) Adversarial examples ★ within L_∞ balls

3) Training on ★ requires a complex decision boundary

Danskin's Theorem

- How to compute the gradient of the objective with the $\max$ term inside?
- Danskin's Theorem:
  - $\nabla_y \max_x f(x, y) = \nabla_y f(x^*, y)$, where $x^* = \operatorname{argmax}_x f(x, y)$
  - (Only true when $\max$ is performed exactly)
- In our case:
  - $\nabla_\theta \max_{\delta \in \Delta} \mathrm{Loss}(x + \delta, y; \theta) = \nabla_\theta \mathrm{Loss}(x + \delta^*, y; \theta)$, where $\delta^* = \operatorname{argmax}_{\delta \in \Delta} \mathrm{Loss}(x + \delta, y; \theta)$
  - Optimize through the $\max$ operator by finding the δ^* that maximizes the loss function, then taking gradient at $x + \delta^*$

Adversarial Training [Goodfellow et al., 2014]

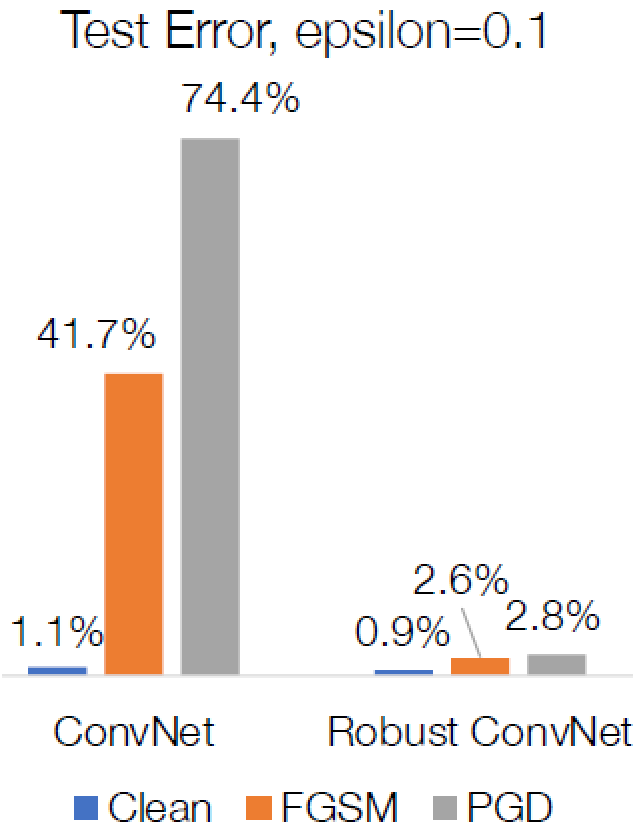
Repeat:

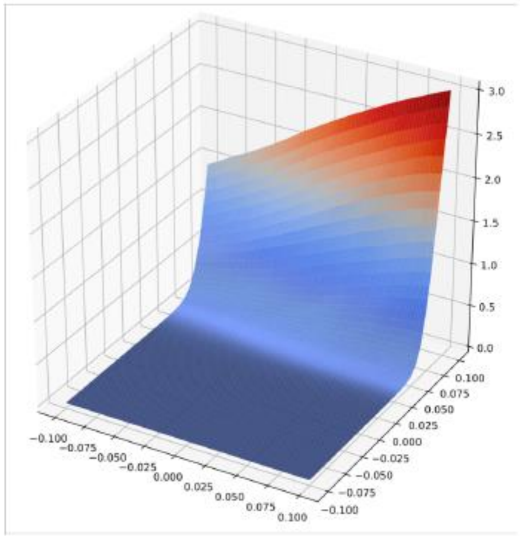
1. Select minibatch B, initialize gradient vector $g := 0$
2. For each (x, y) in B:
   a. Find an attack perturbation $\delta^\star$ by (approximately) optimizing
   $$\delta^\star = \underset{\|\delta\| \le \epsilon}{\operatorname{argmax}} \, \ell(h_\theta(x+\delta), y)$$
   b. Add gradient at $\delta^\star$
   $$g := g + \nabla_\theta \ell(h_\theta(x + \delta^\star), y)$$
3. Update parameters θ
   $$\theta := \theta - \frac{\alpha}{|B|} g$$

- Adversarial training effectiveness is directly tied to how well we perform the inner maximization. The key issue is incorporate a strong attack into the inner maximization procedure
  $$\min_\theta \mathbb{E}_{(x,y)\sim D} \max_{\delta \in \Delta} \text{Loss}(x + \delta, y; \theta)$$

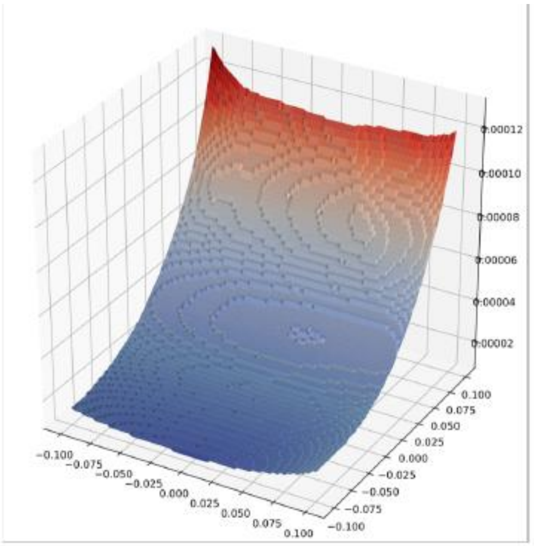
What Makes the Models Robust?

- The robust model has a smoother loss surface, making it more difficult for an attacker to change the class label with small gradient steps





Loss surface:
standard training



Loss surface:
robust training

Loss Surfaces Examples

- Upper right fig shows a smooth loss surface with small gradients near the correct label and large distances to other labels, which makes attacks more difficult
- Lower right fig shows a less smooth loss surface and small distances to other labels, which makes attacks easier
- You can also think of them as 2 different directions on the same loss surface, and the attacker's goal is to find the optimal direction to change input x (e.g., by gradient ascent with FGSM or PGD)