Yale

Adversarial Attacks and Defenses

CPSC680: Trustworthy Deep Learning

Rex Ying

Readings

- Readings are updated on the website (syllabus page)
- **Readings:**
  - Adversarial Examples: Attacks and Defenses for Deep Learning
  - Review of Adversarial Attacks and Defense

Content

- Introduction to Adversarial Attack
- Adversarial Attack Types
- Evasion Attack and Defense
- Poisoning Attack and Defense
- Exploratory Attack and Defense

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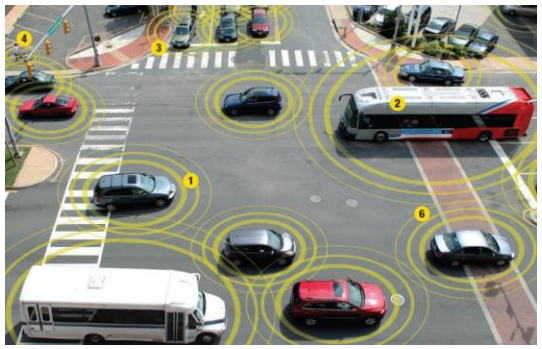
Deep Learning Performance

- Recent years have seen **impressive performance of deep learning models in a variety of applications.**
  - Examples: ResNet, AlphaGo, BERT, GPT, AlphaFold …
- **Are these models ready to be deployed in real world?**

Autonomous Driving

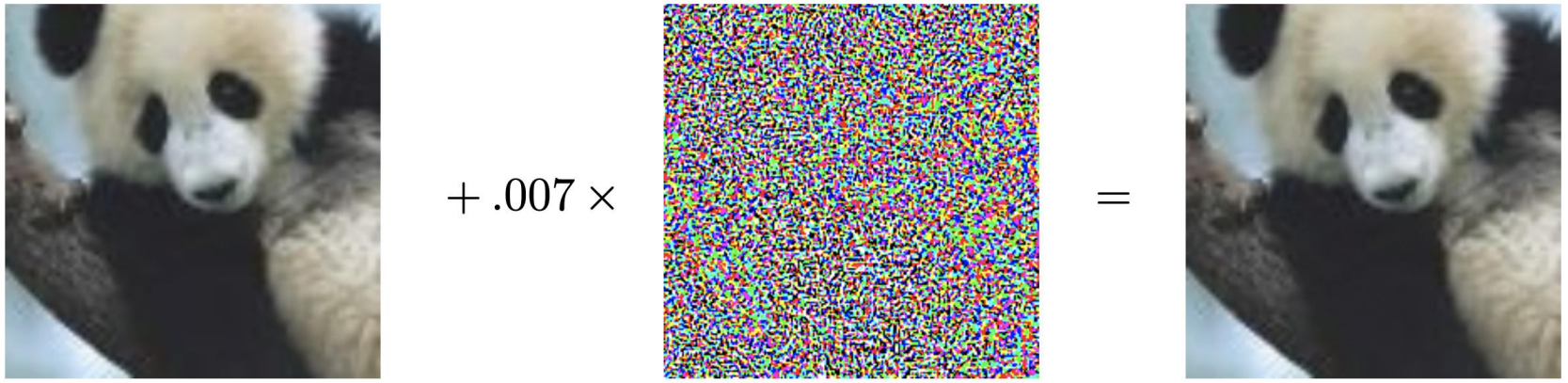
Malware Detection



Smart Transportation

Adversarial Examples

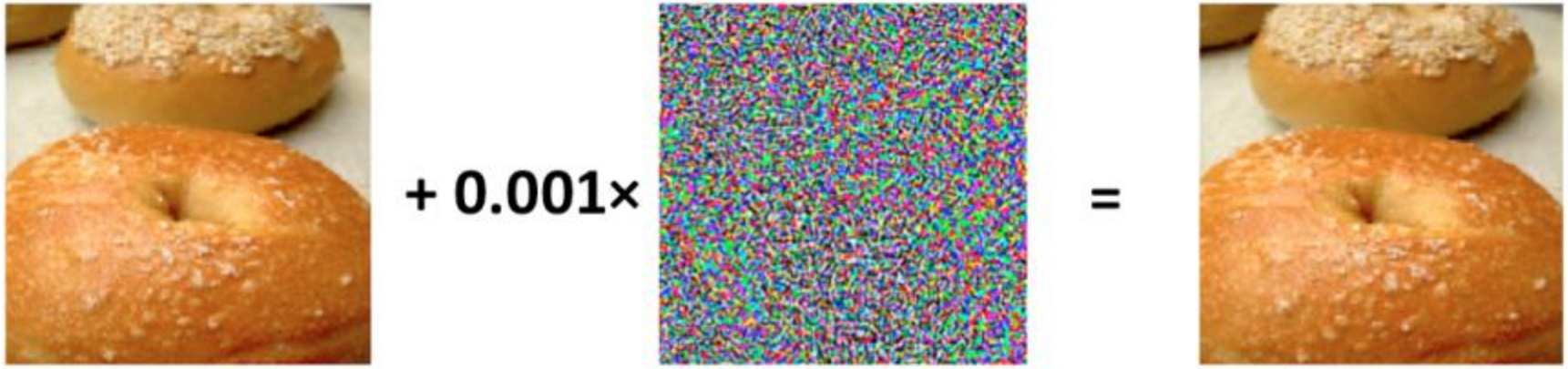
- Deep convolutional neural networks are vulnerable to **adversarial attacks:**
  - **Imperceptible noise** changes the original prediction.



Goodfellow, I., Shlens, J., & Szegedy, C. "Explaining and Harnessing Adversarial Examples."

Adversarial Examples

- Two **key characteristics of adversarial attacks**
  - The adversarial examples make changes **imperceptible to human**
  - The prediction results are dramatically altered

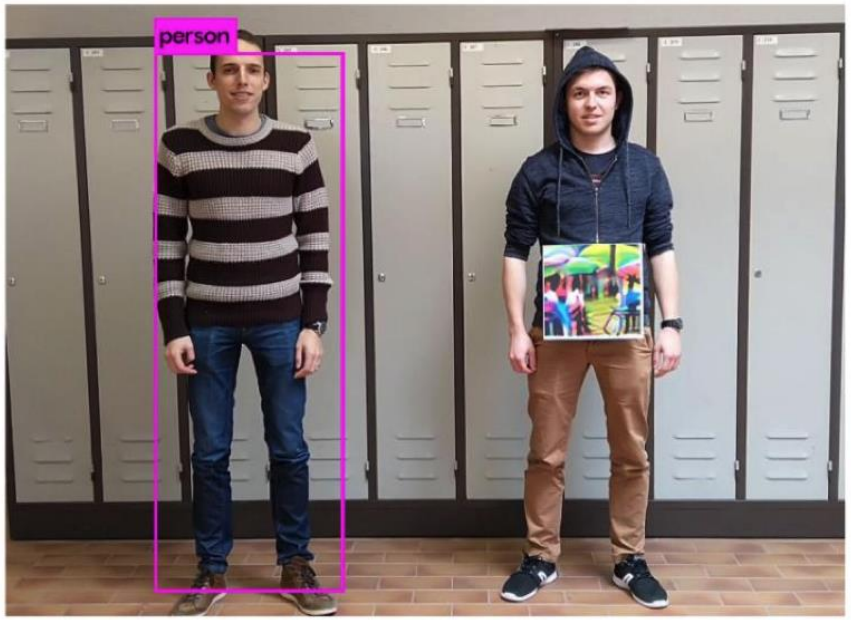


Li, Yao, et al. "A Review of Adversarial Attack and Defense for Classification Methods."

- Adversarial examples are also reported in natural language, graph-structured data, medical image, etc.

Adversarial Examples in Object Detection

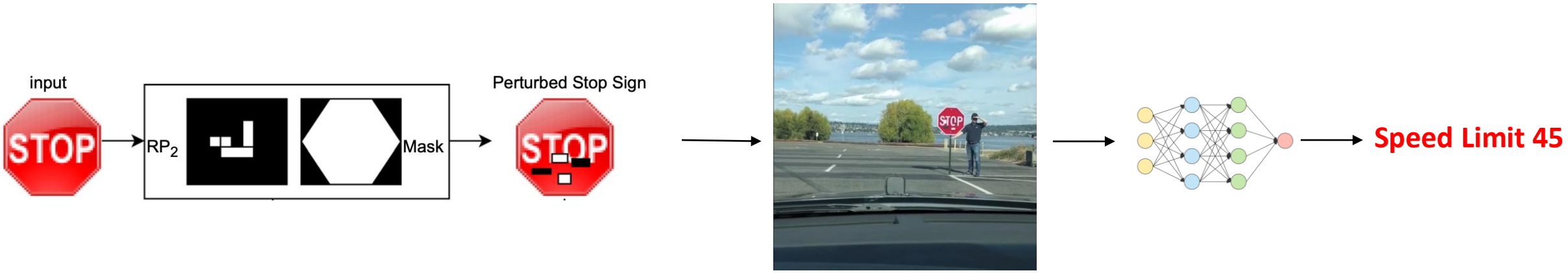
- A person wearing an adversarial patch is not detected by a person detector model using YOLOv2.
  - The adversaries can use it to bypass the surveillance cameras.



Thys et al. “Fooling automated surveillance cameras: adversarial patches to attack person detection”

Adversarial Examples in Object Detection

- An adversary adds adversarial patches into the **STOP** sign that causes the DL model of a self-driving car to misclassify it as a **Speed Limit 45** sign



Eykholt et al. “Robust Physical-World Attacks on Deep Learning Visual Classification.”

Adversarial Examples in Natural Language

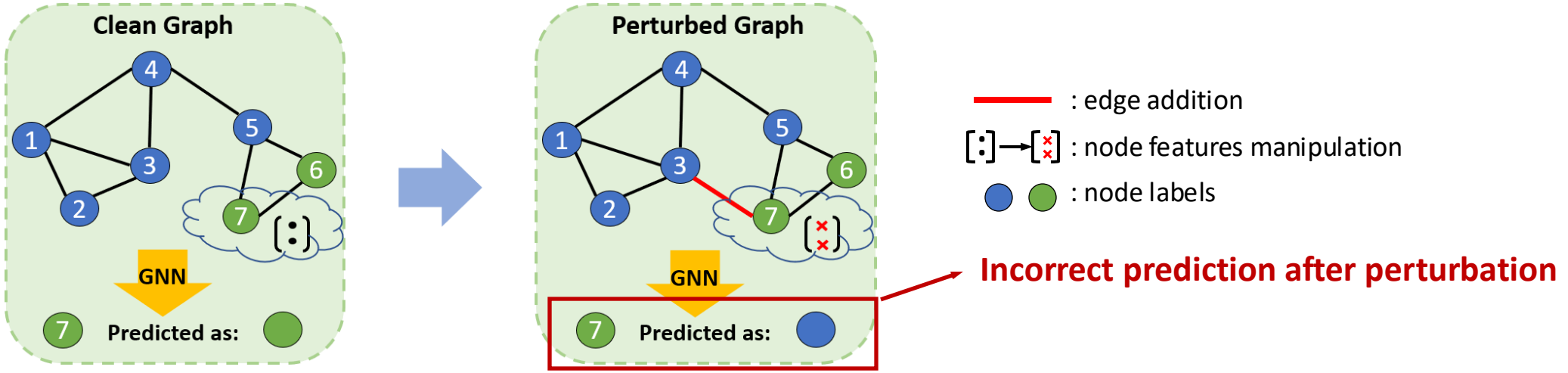
Examples of sentiment anaysis:

Original Input	Connoisseurs of Chinese film will be pleased to discover that Tian's meticulous talent has not withered during his enforced hiatus.	Prediction: **Positive (77%)**
Adversarial example [Visually similar]	**Aonnoisseurs** of Chinese film will be pleased to discover that Tian's meticulous talent has not withered during his enforced hiatus.	Prediction: **Negative (52%)**
Adversarial example [Semantically similar]	Connoisseurs of Chinese **footage** will be pleased to discover that Tian's meticulous talent has not withered during his enforced hiatus.	Prediction: **Negative (54%)**

Morris, John X., et al. "Textattack: A framework for adversarial attacks, data augmentation, and adversarial training in nlp."

- Adversarial examples are very **"similar"** to the original input:
  - **Visually similar**: a few characters change away; even just "typos"
  - **Semantically similar**: semantically indistinguishable from the original input; paraphrase of original input
- **Similar** adversarial examples cause **different** prediction from the model

Adversarial Examples in Graphs

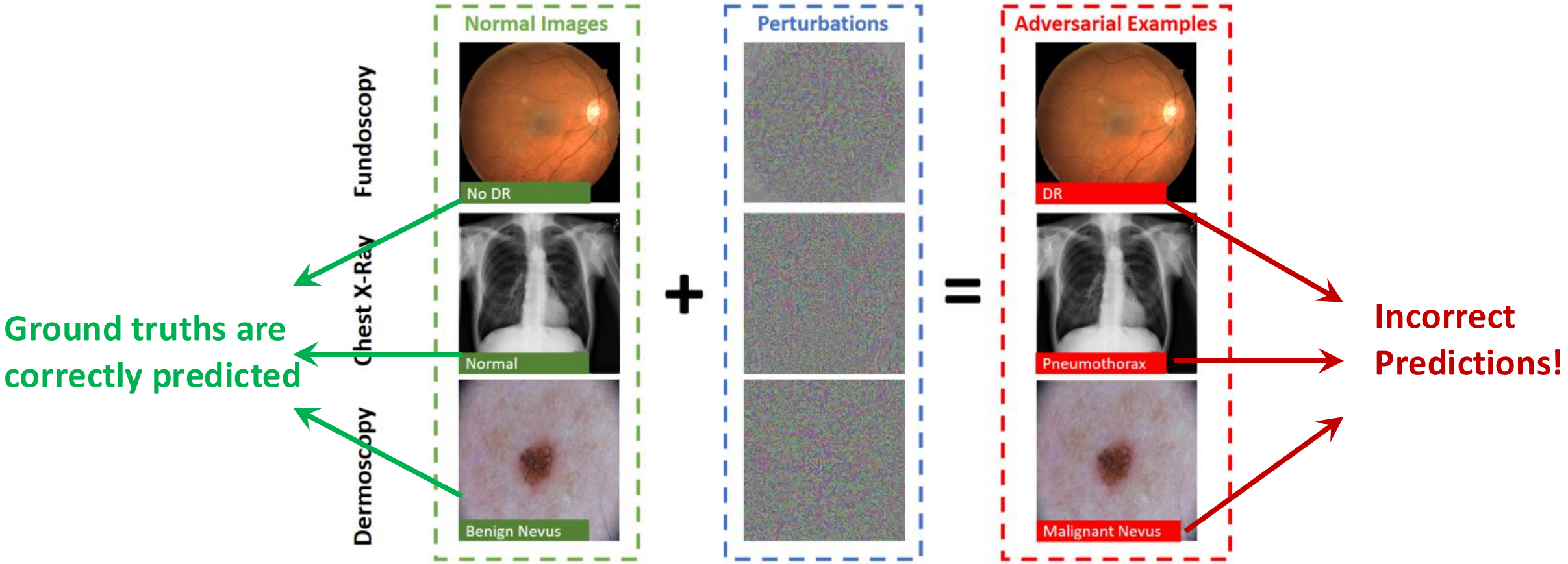


Jin, Wei, et al. "Adversarial Attacks and Defenses on Graphs: A Review, A Tool and Empirical Studies."

- Edge-level perturbation:
  - adding / removing / rewiring edges / manipulating the edge attributes
- Node-level perturbation:
  - adding / removing nodes / manipulating the features of target nodes
- Cause **dramatically different** results in node-level/edge-level/graph-level tasks

Adversarial Examples – Medical Applications

- medical dataset Fundoscopy, Chest X-Ray, Dermoscopy



Implication of Adversarial Examples

- **The existence of adversarial examples prevents the reliable deployment of deep learning models to the real world.**
  - Adversaries may try to actively hack a vulnerable deep learning model.
  - The model performance can become much worse than we expect.
- **Deep learning models are often not robust.**
  - It is an active area of research to make these models robust against adversarial examples.

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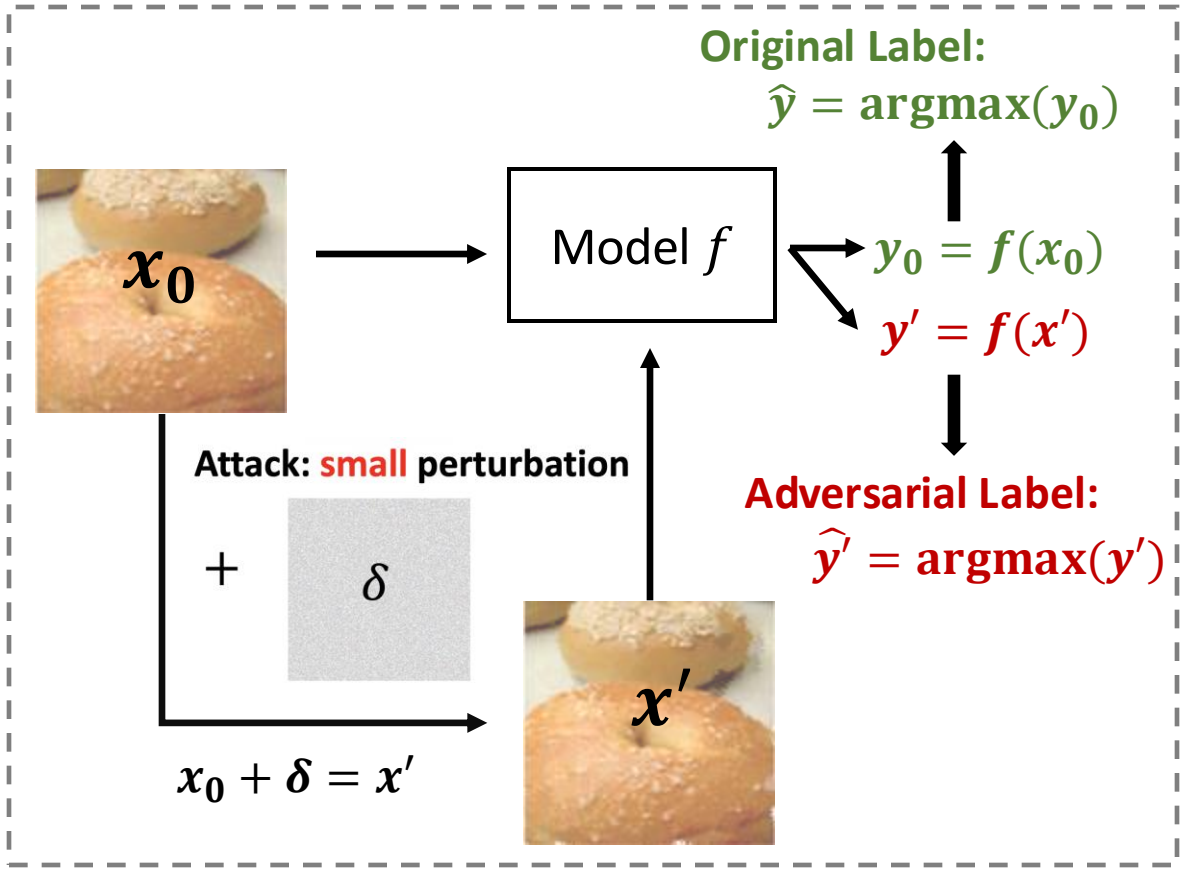
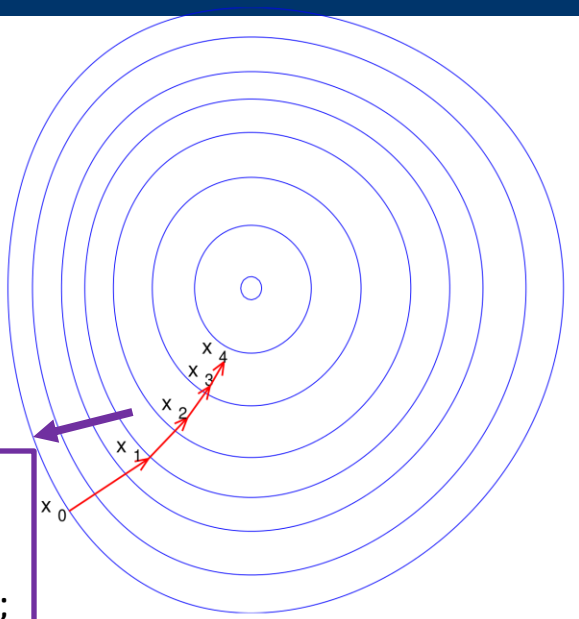
Goals of Attacks (1)



- **Untargeted attacks**
  - The predicted label of adversarial example can be arbitrary except the original one.
  - Ensure $\hat{y}' \neq \hat{y}$
- **Targeted attacks:**
  - Misguide deep neural networks to a specific class y^{target}.
  - Ensure $\hat{y}' = y^{\text{target}} \neq \hat{y}$

Types of Attacks (1)

- **Different Adversary Knowledge:**
  - **White-box Attack:**
  - The attacker **has access to model architecture and parameters**
  - **Gradient-based methods** are straightforward and effective



Reverse direction to **maximize loss:**

$$L(x) = CrossEntropy(y', \hat{y})$$

y' is the model's output after attack;
$\hat{y}$ is the original label

  - **Black-box Attack:**
  - The attacker **has no access to the model's parameters**
  - The type of architecture might be known
  - A different model or no model is used to generate adversarial examples in the hopes that these will transfer to the target model

Types of Attacks (2)

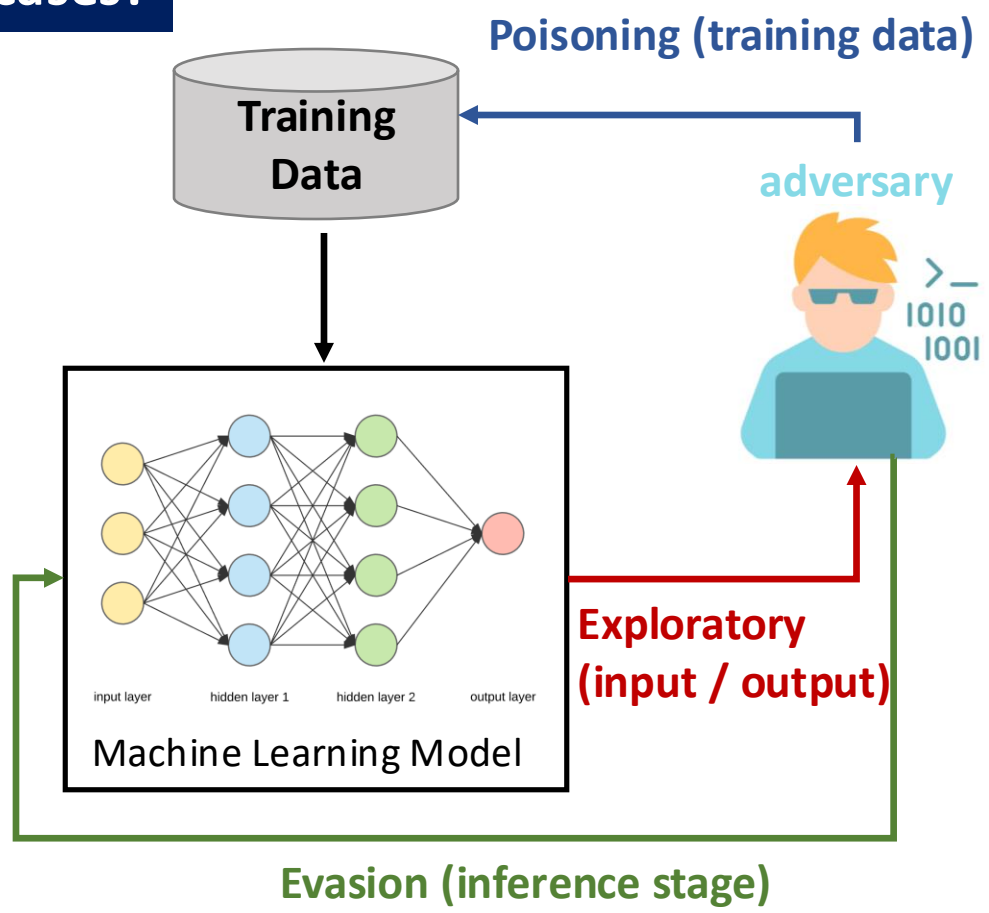
- **Different Adversary Strategy:**
  - **White-box Attack:**
  - Based on the **gradient** of the network loss function **w.r.t. to the input**
  - Instead of optimizing parameters, white-box attack **optimizes the input** via gradient descend
  - Easy to attack

  - **Black-box Attack:**
  - **Gain restricted knowledge** by providing a series of **carefully crafted inputs** and **observing network's outputs.**
  - Usually **build models locally** that are **functionally close to target model**
  - Relatively hard to attack

Adversarial Attack Methods

What are some use cases?

- **Evasion Attack:**
  - Add malicious perturbation to samples **during testing phase**
  - Do not affect the training data
- **Poisoning Attack:**
  - Contaminate the **training data** by carefully modifying samples
- **Exploratory Attack:**
  - Given **black-box access** of the model, try to gain knowledge by **analyzing the input and output information** of the model



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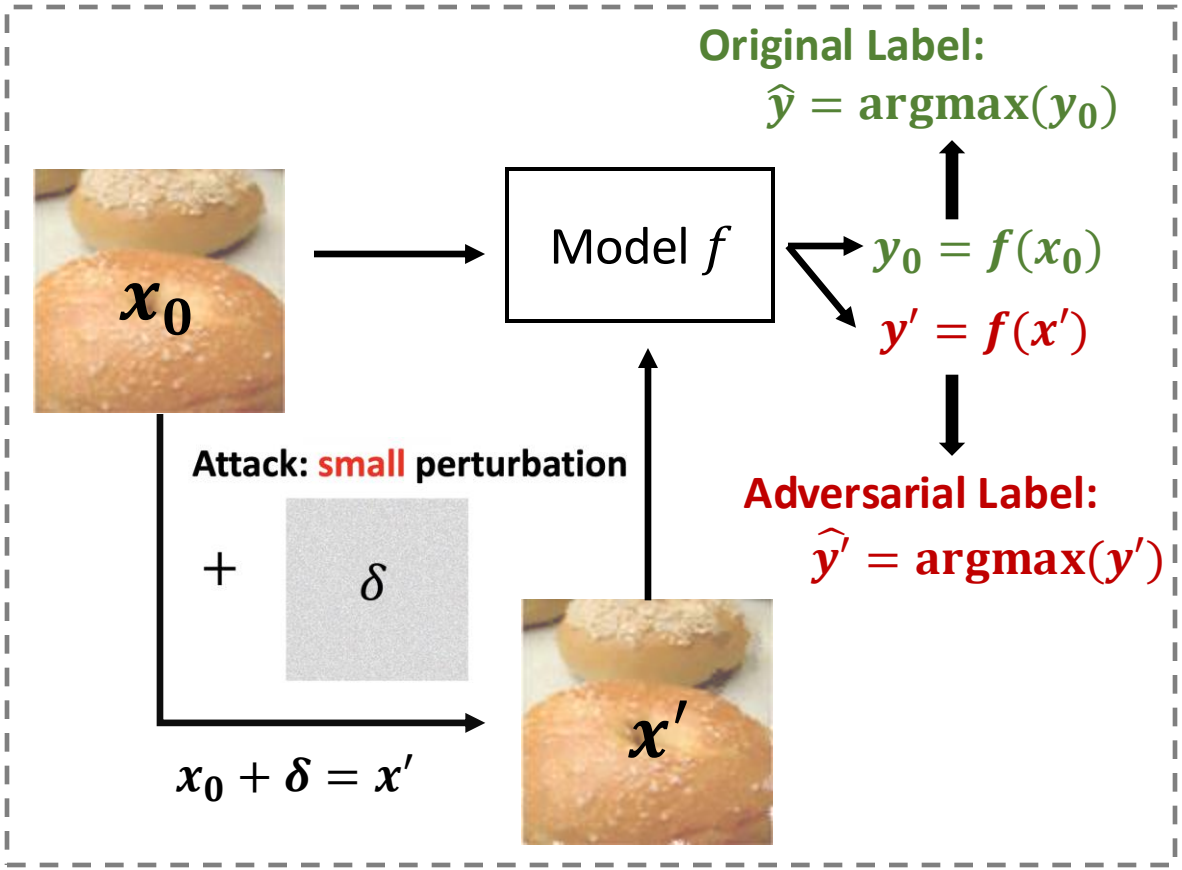
Evasion Attack (1)

- In **evasion attack**, malicious samples are modified **during testing phase**
- No influence over the training dataset
- **Goal**: create a manipulated image (adversarial example) that is ***similar*** to the original image but causes a ***different prediction*** by the ML model.



Evasion Attack (2)

- **Goal**: create a manipulated image (adversarial example) that is ***similar*** to the original image but causes a ***different prediction*** by the ML model.

- **Attack objective:** $x^* = \arg\max_{x'} \mathcal{L}(x')$

$$s.t.\ \ d(x', x_0) \leq \varepsilon$$

Objective function ensuring different prediction

$d(x', x_0)$: distance between x' and x_0 ensuring similarity

Evasion Attack (2)

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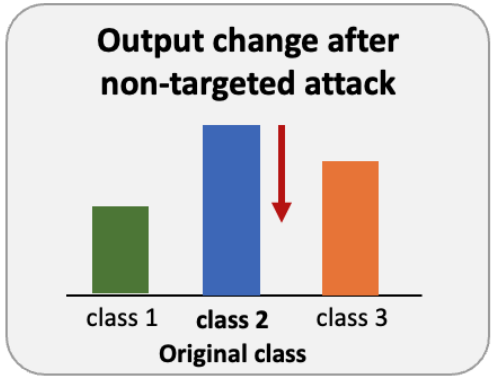
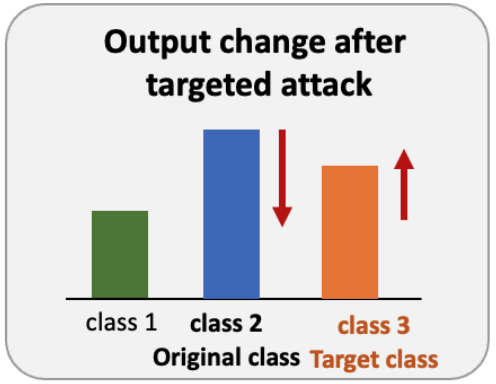




- **Non-targeted:** $\mathcal{L}(x') = CE\ (f(x'), \hat{y})$
- **Targeted:** $\mathcal{L}(x') = CE(f(x'), \hat{y}) - CE(f(x'), y^{target})$

push $\hat{y}'$ to be far away from $\hat{y}$ but close to y^{target}

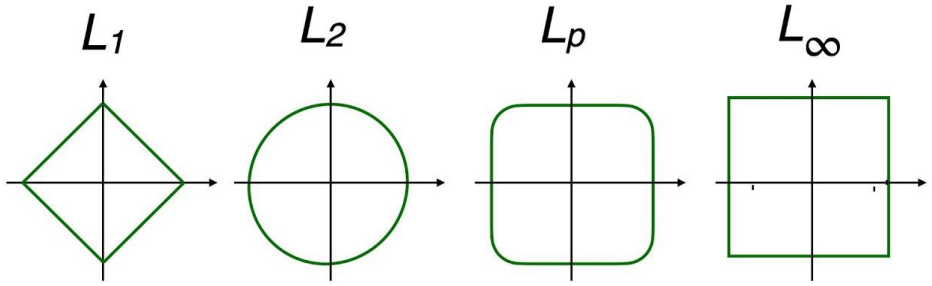
CE: CrossEntropy Loss

Evasion Attack (2) - Imperceptible Perturbation

- **Perturbation**: $\boldsymbol{x_0} + \boldsymbol{\delta} = \boldsymbol{x'}$

$$\begin{bmatrix} x_{11} & \cdots & x_{n1} \\ \vdots & \ddots & \vdots \\ x_{1n} & \cdots & x_{nn} \end{bmatrix} + \begin{bmatrix} \Delta x_{11} & \cdots & \Delta x_{n1} \\ \vdots & \ddots & \vdots \\ \Delta x_{1n} & \cdots & \Delta x_{nn} \end{bmatrix} = \begin{bmatrix} x'_{11} & \cdots & x'_{n1} \\ \vdots & \ddots & \vdots \\ x'_{1n} & \cdots & x'_{nn} \end{bmatrix}$$

  - L_2 norm: $d(\boldsymbol{x_0}, \boldsymbol{x'}) = \|\boldsymbol{\delta}\|_2 = ((\Delta x_{11})^2 + \cdots + (\Delta x_{nn})^2)^{\frac{1}{2}}$
  - L_∞ norm: $d(\boldsymbol{x_0}, \boldsymbol{x'}) = \|\boldsymbol{\delta}\|_\infty = \max\{|\Delta x_{11}|, \ldots, |\Delta x_{nn}|\}$
- For **human perception**, L_∞ norm usually better captures the perturbation.



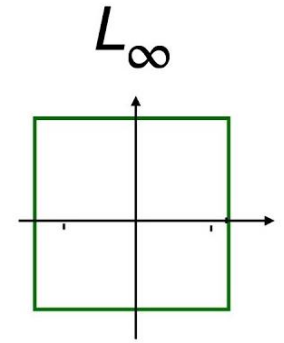
2-dimensional vectors with norm 1

Evasion Attack (2)

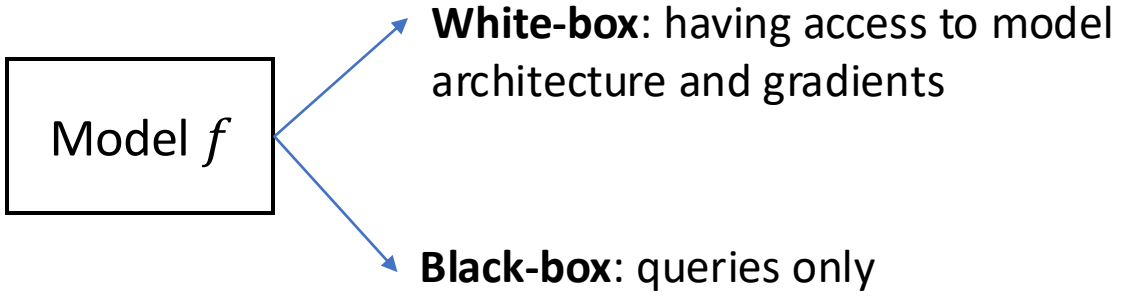
- **Goal**: create a manipulated image (adversarial example) that is ***similar*** to the original image but causes a ***different prediction*** by the ML model.
- **Consider the setting**: non-targeted attack, L_∞-norm perturbation, the optimization problem becomes:

$$x^* = \arg\max_{\delta} CE(\, f(x_0 + \delta), \hat{y}\,)$$

$$s.t.\ ||\delta||_\infty \leq \varepsilon$$



How to solve this optimization when f is known / unknown?



White-Box Evasion Attack: FGSM

- **Fast Gradient Sign Method (FGSM):**

Gradient ascent away from y^{true} $class$

$$x^* = x_0 + \varepsilon \cdot sign(\nabla_x \mathcal{L}(f(x), y^{true}))$$

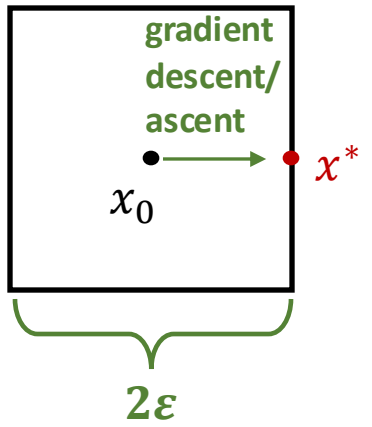
- **Target Class Method:**

Targeted attack

Gradient descent toward from y^{target} $class$

$$x^* = x_0 - \varepsilon \cdot sign(\nabla_x \mathcal{L}(f(x), y^{target}))$$

x^* is on the vertex or midpoint of one side



- x_0 denotes the original sample, $f(\cdot)$ denotes **logits output**
- $\text{Sign}(t) = 1$ if $t > 0$, otherwise $\text{Sign}(t) = -1$
- ε ensures that $\|\boldsymbol{x}^* - \boldsymbol{x_0}\|_\infty \leq \boldsymbol{\varepsilon}$, perturbation within $\boldsymbol{\varepsilon}$-box around the original sample

How many possible perturbations can there be?

White-Box Evasion Attack: FGSM

- **Fast Gradient Sign Method (FGSM):**

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Gradient descent toward from y^{target} $class$

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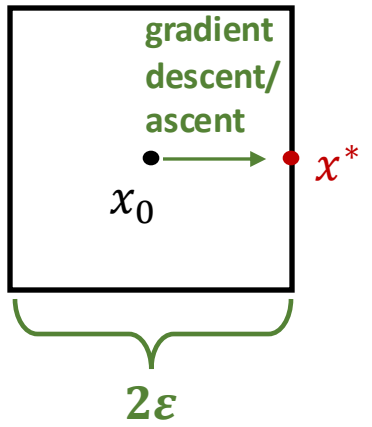


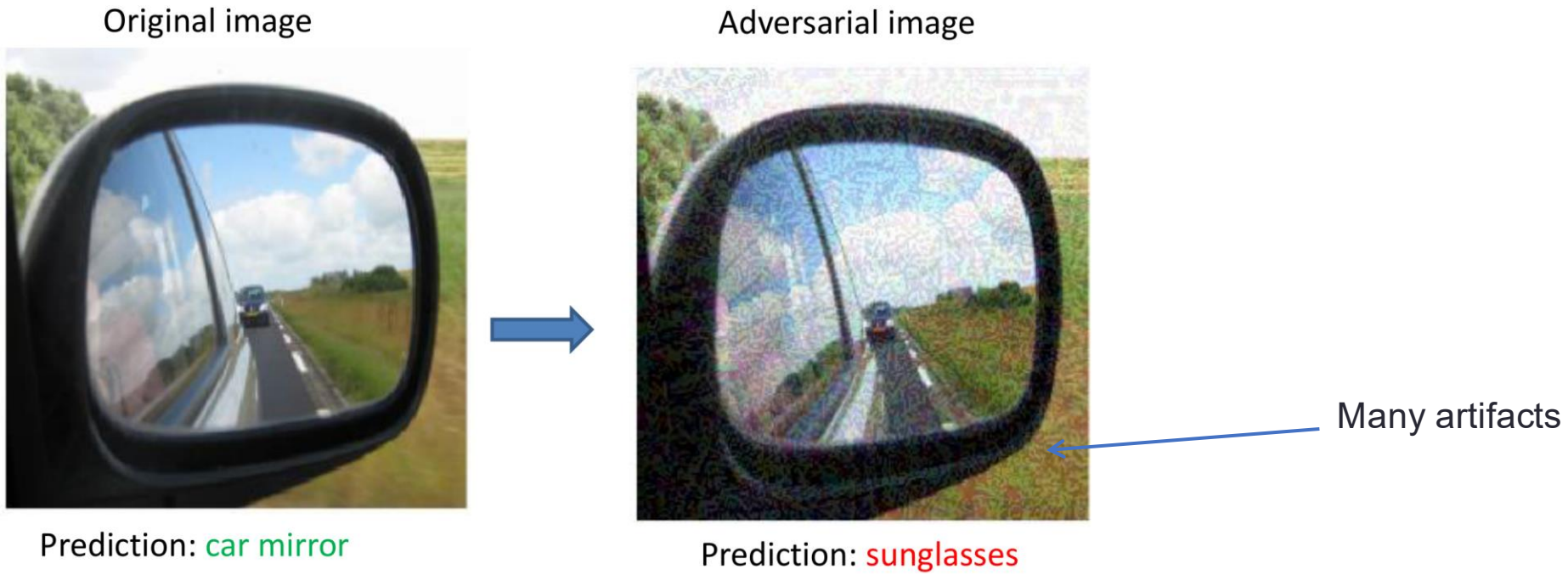
Theorem: If f is a ***binary linear classifier***, FGSM is the ***exact optimal evasion attack*** under L_∞ constraint

Why $sign(\cdot)$ function?

The gradient is zero or undefined everywhere → harder to defend
Small gradient → precision problem
Large gradient → problematic for max norm constraint

White-Box Evasion Attack: FGSM

- Example



- FGSM is **one-step attack**
- **Pros:** Fast, easier to compute

Cons: Not very effective for highly non-linear models,
Require large ϵ to be effective (human-perceptible)

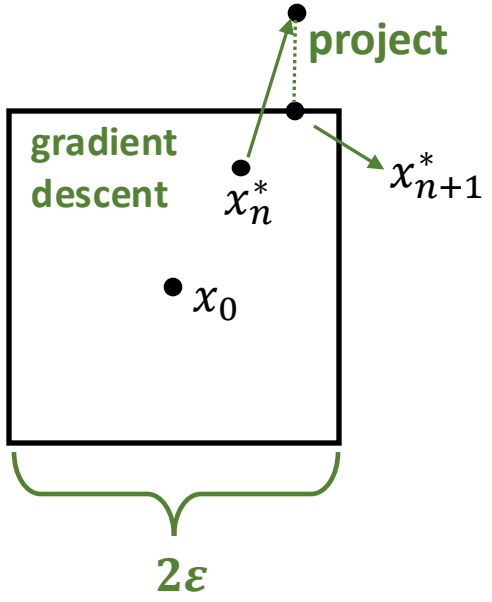
White-Box Evasion Attack: PGD ~ Iterative FGSM

- **Projected Gradient Descent (PGD)**

Iterative approach

$$x_0^* = x_0 \; ; \; x_{n+1}^* = proj_{x,\epsilon}\left(x_n^* + \alpha \; sign\left(\nabla_x \mathcal{L}(f(x_n^*), y^{true})\right)\right)$$

- x denotes the original sample, α $(typically < \epsilon)$ is the step size.
- $proj_{x_i,\epsilon}(t) = \begin{cases} x_i - \varepsilon & \boldsymbol{if} \quad t \leq x_i - \varepsilon \\ t \quad \boldsymbol{if} \quad x_i - \varepsilon < t < x_i + \varepsilon \\ x_i + \varepsilon & \boldsymbol{if} \quad t \geq x_i + \varepsilon \end{cases}$, **for each feature** x_i in x
- PGD **iteratively maximize the adversarial objective** within **restricted perturbation**



example of 2-dimensional case

White-Box Evasion Attack: PGD ~ Iterative FGSM

Examples

Still not “imperceptible”?

Fewer artifacts than FGSM

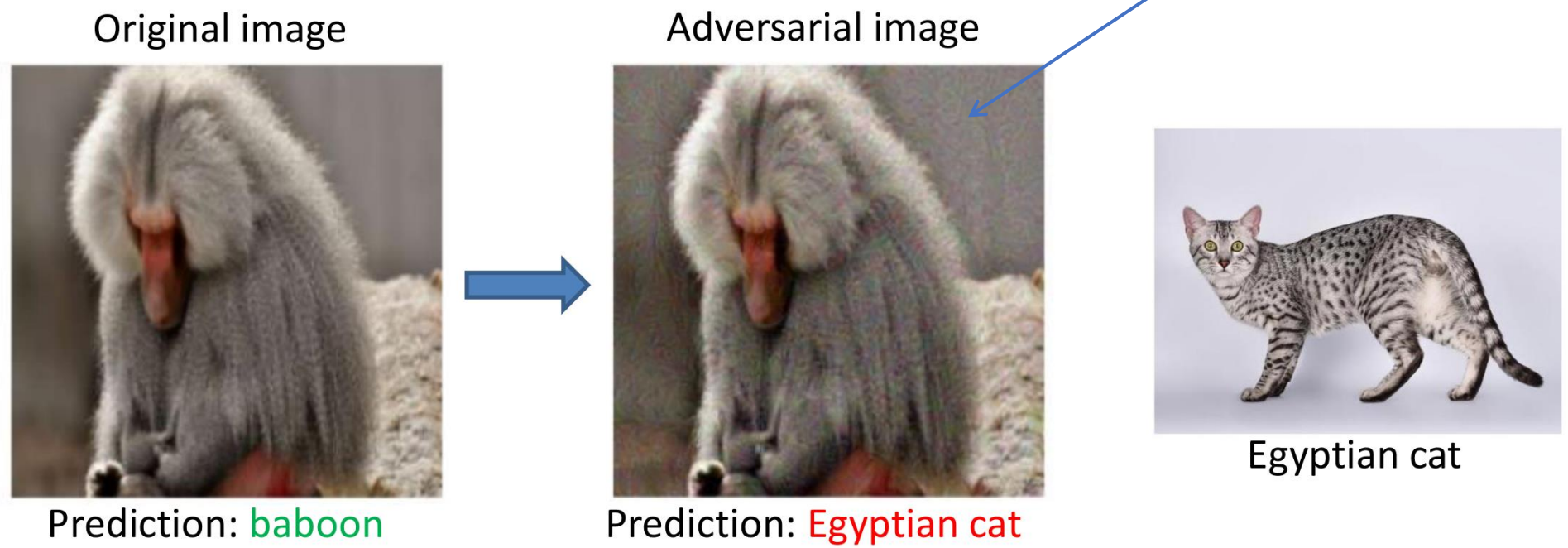


Image credit: https://blog.floydhub.com/introduction-to-adversarial-machine-learning/

White-Box Evasion Attack: Deepfool

- **FGSM & PGD:** Find an adversarial example that ***maximizes the likelihood*** of being misclassified.

$$x^* = \arg\max_{\delta} CE(\, f(x_0 + \delta), \hat{y}\,)$$
$$s.t.\ ||\delta||_\infty \leq \varepsilon$$

norm-bounded attack

- **DeepFool:** Find an adversarial example with ***minimal perturbation*** to fool the classifier.

$$x^* = \arg\min_{\delta} ||\delta||_\infty$$
$$s.t.\ \ f(x_0 + \delta) \neq \hat{y}$$

norm-unbounded attack

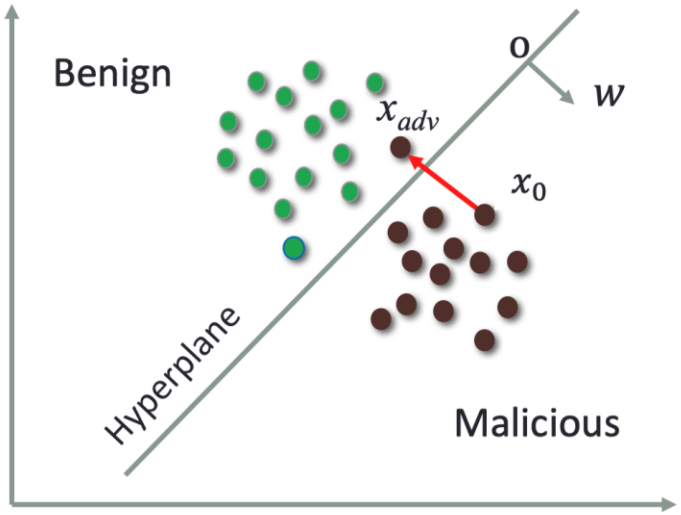
How to solve?

White-Box Evasion Attack: Deepfool

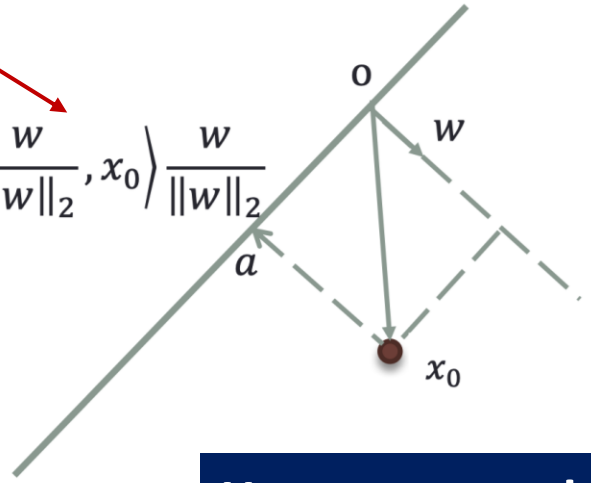
- **If f** is a linear classifier?
- A simple (closed-form) projection would do the job.

$$x^* = \arg\min_{\delta} ||\delta||_\infty$$
$$s.t.\ \ f(x_0 + \delta) \neq \hat{y}$$

Closed-form projection



$$x^* = x_0 - \left\langle \frac{w}{\|w\|_2}, x_0 \right\rangle \frac{w}{\|w\|_2}$$



How to extend this idea to deep neural networks?

White-Box Evasion Attack: Deepfool

- **If f** is ***not*** a linear classifier?
- An ***iterative*** projection ***with linear approximation*** would do the job.

$$x^* = \arg\min_{\delta} ||\delta||_\infty$$
$$s.t.\ \ f(x_0 + \delta) \neq \hat{y}$$

Algorithm

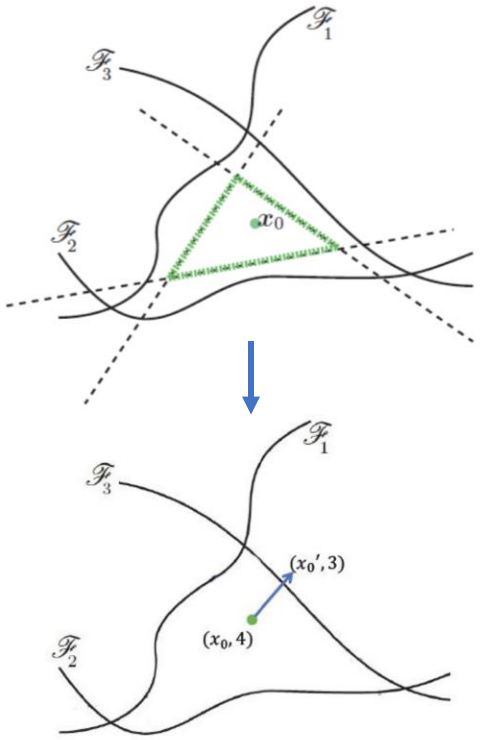
1. Linearize the classifier function around the current input x_i.

$$f(x_{i+1}) = f(x_i) + \nabla f(x_i)^\top (x_{i+1} - x_i)$$

2. Project x_i onto the approximated hyperplane

$$x_{i+1} = x_i - \frac{f(x_i)}{\|\nabla f(x_i)\|_2^2} \nabla f(x_i)$$

Repeat (1) and (2) until $f(x_i) \neq \hat{y}$



White-Box Evasion Attack: Deepfool

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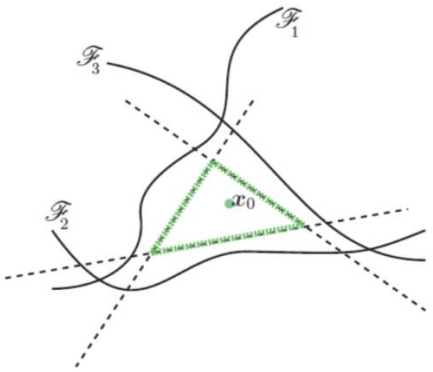
$$s.t.\ \ f(x_0 + \delta) \neq \hat{y}$$

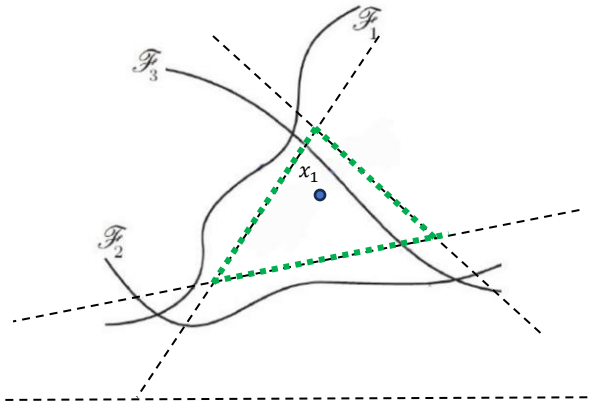
Algorithm

Iter 1

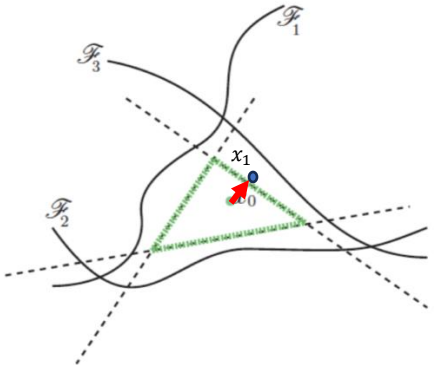
Step 1

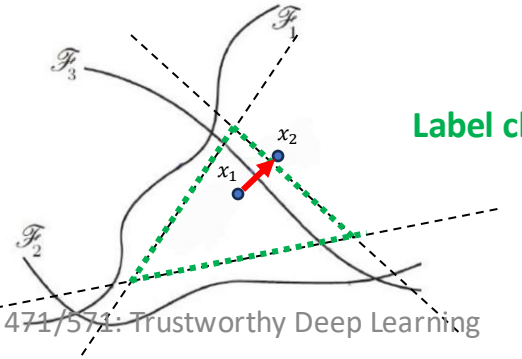


Iter 2



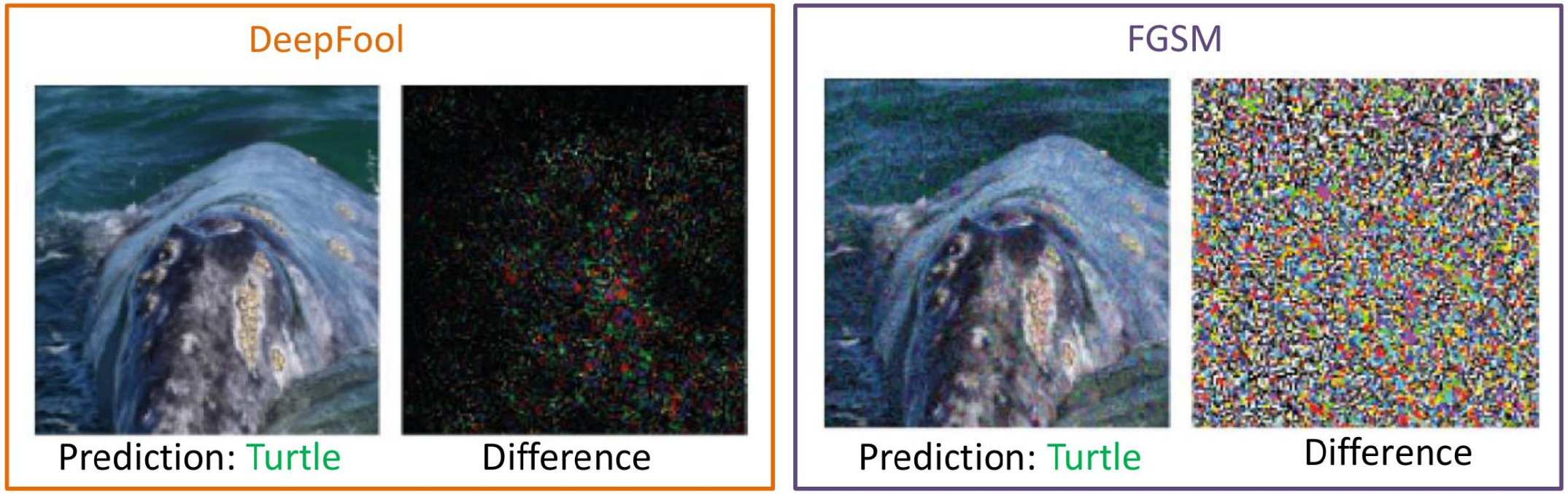
Step 2





Label changed → adversarial example

White-Box Evasion Attack: Deepfool



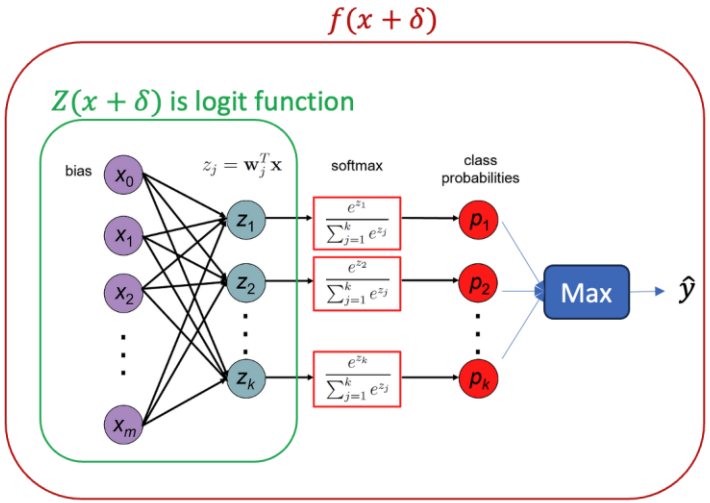
Comparing DeepFool and FGSM: Both flip the model prediction, but DeepFool requires smaller perturbation

White-Box Evasion Attack: Carlini & Wagner

Recall the optimization problem for targeted attack

$$x^* = \arg\min_{x'} d(x_0, x')$$
$$s.t. f(x') = y^{target}$$

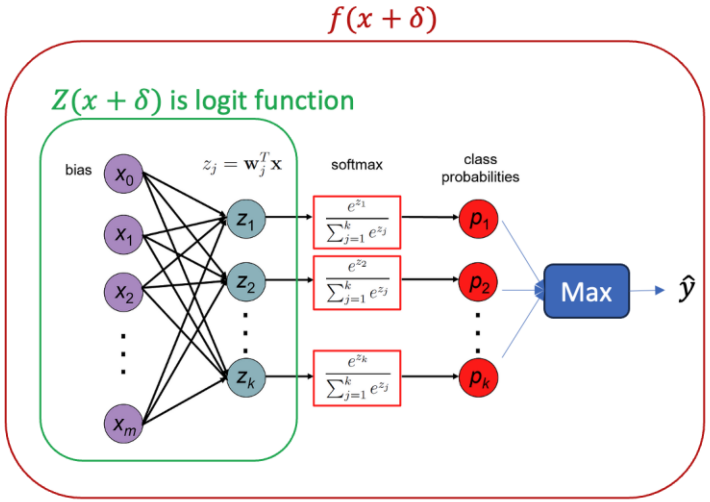
This constraint is highly non-linear → hard to solve



White-Box Evasion Attack: Carlini & Wagner

Recall the optimization problem for targeted attack

$$x^* = \arg\min_{x'} d(x_0, x')$$
$$s.t.\ F(x') \leq 0$$



where $F(x') = \max_{i \neq y^{\text{target}}} (Z(x')_i) - Z(x')_{y^{\text{target}}})$

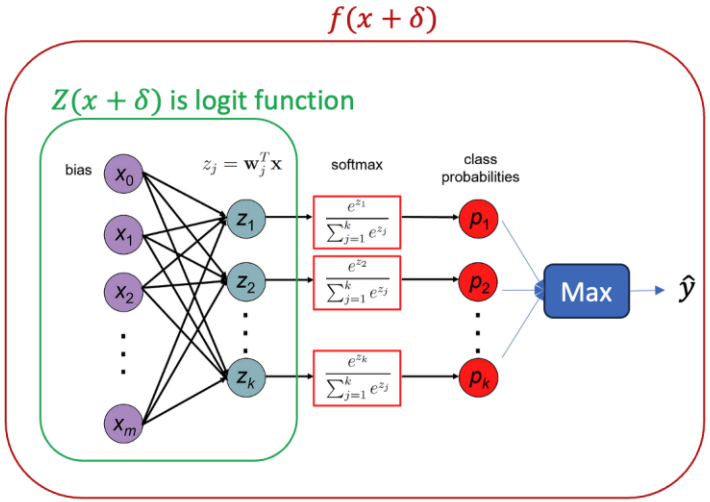
the difference in the logits between ***the target class*** and ***the closest-to-the-target class*** *(a.k.a.* ***logit margin loss****)*

still constrained optimization → Lagrange multiplier

White-Box Evasion Attack: Carlini & Wagner

Recall the optimization problem for targeted attack

$$x^* = \arg\min_{x'} d(x_0, x')$$
$$s.t.\ F(x') \leq 0$$



Reformulation using Lagrange multipliers

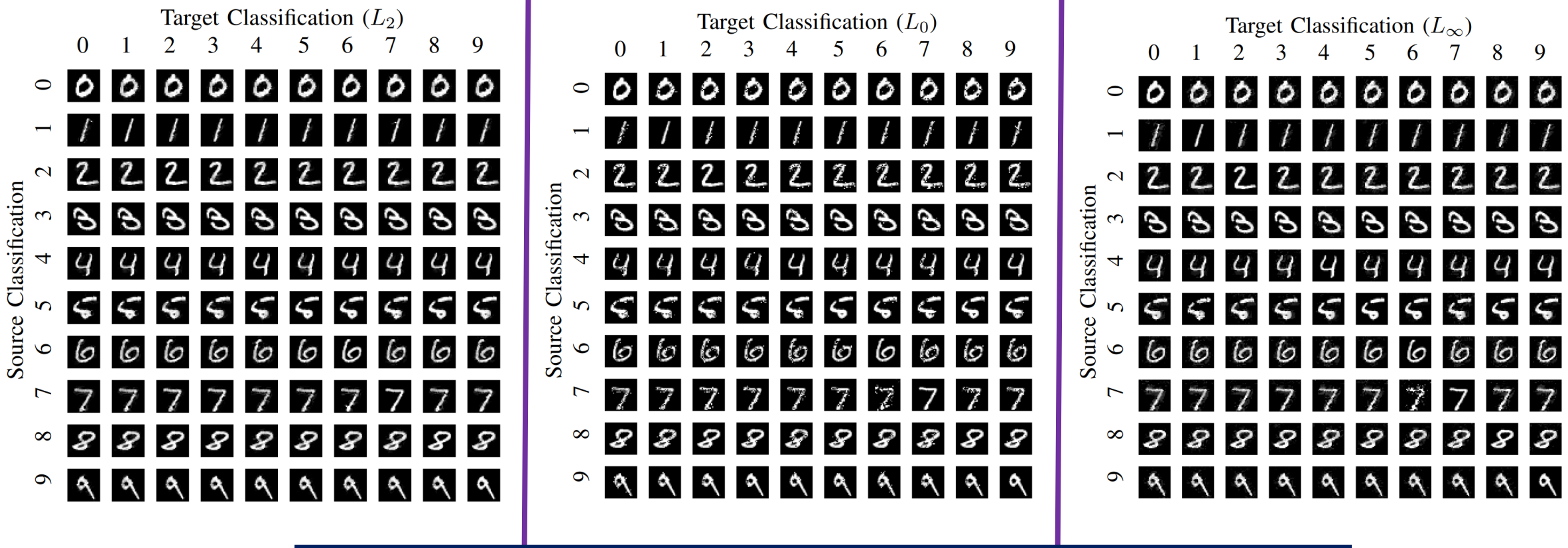
$$x^* = \arg\min_{x'} \quad d(x_0, x') + \lambda F(x')$$

where $F(x') = \max_{i \neq y^{\text{target}}} (Z(x')_i) - Z(x')_{y^{\text{target}}}$

C-W Attack

Easier to solve by standard solver (ADAM)

Perturbation on MNIST



What are the characteristics of each type of perturbation?

White-Box Evasion Attack: Carlini & Wagner

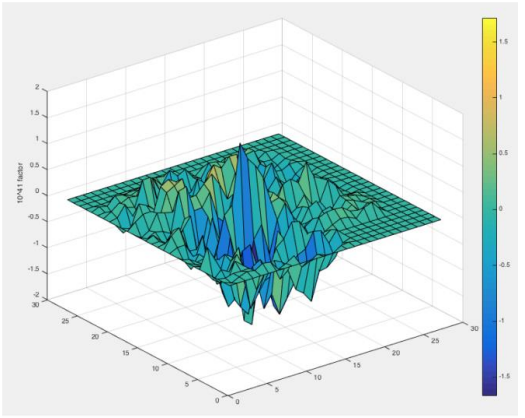
- Mean is the perturbation size (the smaller , the better)
  - Attacking Inception V3 on Imagenet
  - Untargeted: Untargeted attack
  - Average Case: Select the target uniformly at random
  - Least Likely: select the most difficult class as the target to attack

	Untargeted		Average Case		Least Likely	
	Mean	Prob	Mean	Prob	Mean	Prob
CW	0.004	100%	0.006	100%	0.01	100%
FGSM	0.004	100%	0.064	2%	-	0%
PGD	0.004	100%	0.01	99%	0.03	98%

White-Box Evasion Attack: JSMA

- **Jacobian-based Saliency Map Attack (JSMA)**
- Assuming that the output of f is a vector of class probabilities

$$\textbf{Saliency Map}: \nabla f(x) = \begin{bmatrix} \frac{\partial \boldsymbol{f_1}(\boldsymbol{x})}{\partial x_1} & \cdots & \frac{\partial \boldsymbol{f_1}(\boldsymbol{x})}{\partial x_M} \\ \vdots & \ddots & \vdots \\ \frac{\partial \boldsymbol{f_N}(\boldsymbol{x})}{\partial x_1} & \cdots & \frac{\partial \boldsymbol{f_N}(\boldsymbol{x})}{\partial x_M} \end{bmatrix}$$

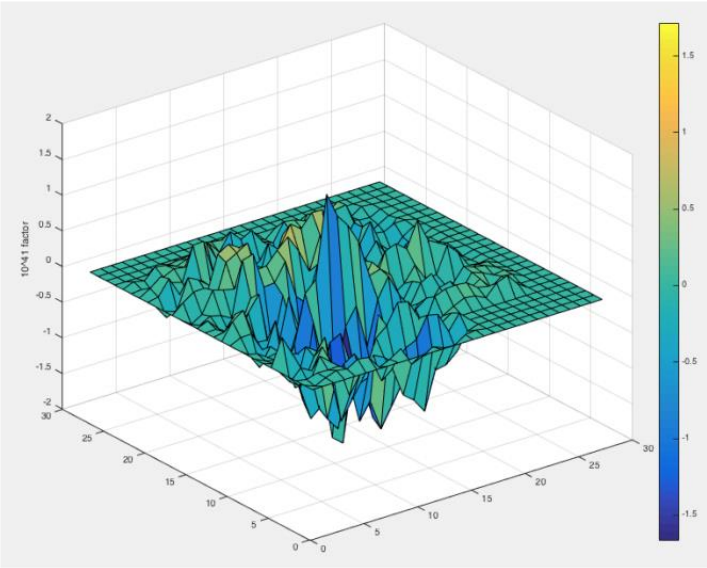


$\boldsymbol{\nabla f(x)}$ Jacobian matrix

- $\nabla f(x) \in \mathbb{R}^{N \times M}$
- N is the number of classes, M is the number of features of x
- Features with **large saliency values** have **large impact on the output** when perturbed
- Incurs high computational cost to compute the Saliency Map

White-Box Evasion Attack: JSMA

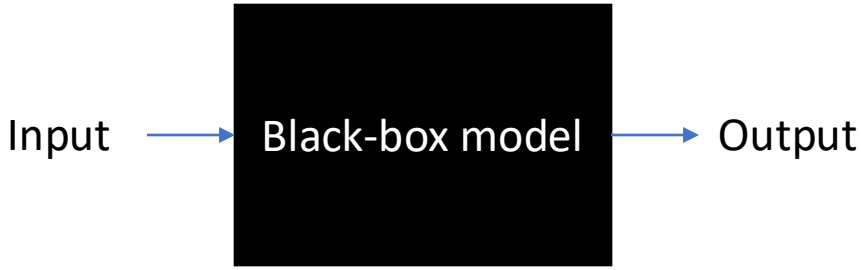
- **Jacobian-based Saliency Map Attack (JSMA)**
- $\nabla f(x)$ **Adversarial saliency maps** can be used to indicate which features an adversary should perturb in order to impact the predicted class by the model
  - **Identify the most impactful features** in the saliency map and then **perturb them by θ value** in order to realize the adversary's goal (e.g., $x_i \rightarrow x_i - \theta$)
  - The algorithm perturbs **limited number of impactful features** at each step



An example where explainability can help adversarial robustness

Black-Box Evasion Attack

- Assuming the adversaries **do not** have access to the model's internal information (architecture, gradient, etc.)
- The adversaries can only query inputs and observe corresponding outputs

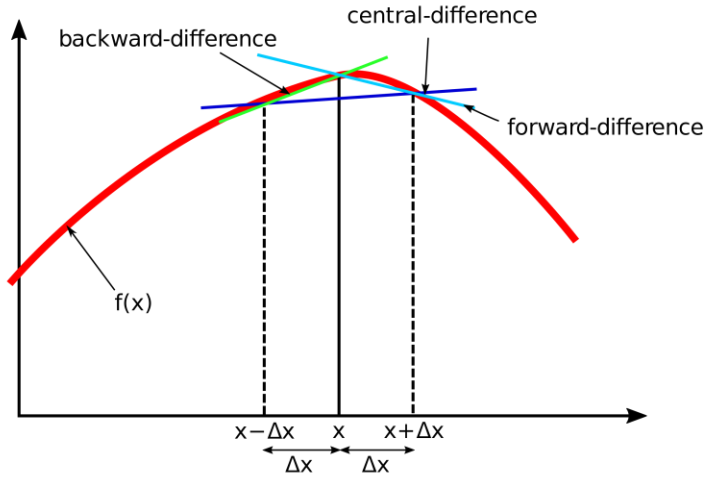


Black-Box Evasion Attack: GEA

- **Gradient Estimation Attack (GEA):**
  - Estimate the gradient w.r.t. the input from (input, output) queries via **finite difference**
  - Use the estimated gradient to perform ***first-order*** attacks (e.g., FGSM, PGD, C&W)

- **Finite Difference (FD)** estimates the gradient of a function f w.r.t. input $x \in \mathbb{R}^d$ by

$$\mathrm{FD}_x(f(x), \delta) = \begin{bmatrix} \frac{f(x+\delta e_1) - f(x-\delta e_1)}{2\delta} \\ \cdots \\ \frac{f(x+\delta e_d) - f(x-\delta e_d)}{2\delta} \end{bmatrix}$$



where δ is a small scalar (e.g., 0.01) and e_i is the standard basis vector w.r.t. pixel i.

- **Relation to gradient**: $\lim_{\delta \to 0} \mathrm{FD}_x(f(x), \delta) \approx \nabla_x f(x)$

Left-hand, right-hand derivatives

Black-Box Evasion Attack: GEA

- **Gradient Estimation Attack (GEA):**
  - Estimate the gradient w.r.t. the input from (input, output) queries via **finite difference**
  - Use the estimated gradient to perform ***first-order*** attacks (e.g., FGSM, PGD, C&W)

- Assuming the loss function is the cross-entropy loss we have

$$\mathcal{L}(f(x), y) = \mathrm{CE}(f(x), y) = -\log f(x)_y$$

$$\Rightarrow \nabla_x \mathcal{L}(f(x), y) = -\frac{\nabla_x f(x)_y}{f(x)_y} = -\frac{\mathrm{FD}_x(f(x)_y, \delta)}{f(x)_y}$$

- **Approximated FGSM:**

$$x^\star = x + \epsilon \cdot \mathrm{sign}\left(-\frac{\mathrm{FD}_x(f(x)_y, \delta)}{f(x)_y}\right)$$

What should we do for targeted attack?

Black-Box Evasion Attack: GEA

- **Gradient Estimation Attack (GEA):**
  - Estimate the gradient w.r.t. the input from (input, output) queries via **finite difference**
  - Use the estimated gradient to perform ***first-order*** attacks (e.g., FGSM, PGD, C&W)

- Assuming the loss function is the cross-entropy loss we have

$$\mathcal{L}(f(x), y) = \mathrm{CE}(f(x), y) = -\log f(x)_y$$

$$\Rightarrow \nabla_x \mathcal{L}(f(x), y) = -\frac{\nabla_x f(x)_y}{f(x)_y} = -\frac{\mathrm{FD}_x(f(x)_y, \delta)}{f(x)_y}$$

- **Approximate targeted FGSM:**

$$x^\star = x - \epsilon \cdot \mathrm{sign}\left(-\frac{\mathrm{FD}_x(f(x)_{y^{\mathrm{target}}}, \delta)}{f(x)_{y^{\mathrm{target}}}}\right)$$

Black-Box Evasion Attack: GEA

- **Gradient Estimation Attack (GEA):**
  - Estimate the gradient w.r.t. the input from (input, output) queries via **finite difference**
  - Use the estimated gradient to perform ***first-order*** attacks (e.g., FGSM, PGD, C&W)

- Recall the logit margin loss from the C&W attack

$$\mathcal{L}(f(x), y) = \max_{i \neq y^{\text{target}}} \{Z(x)_i\} - Z(x)_{y^{\text{target}}}$$

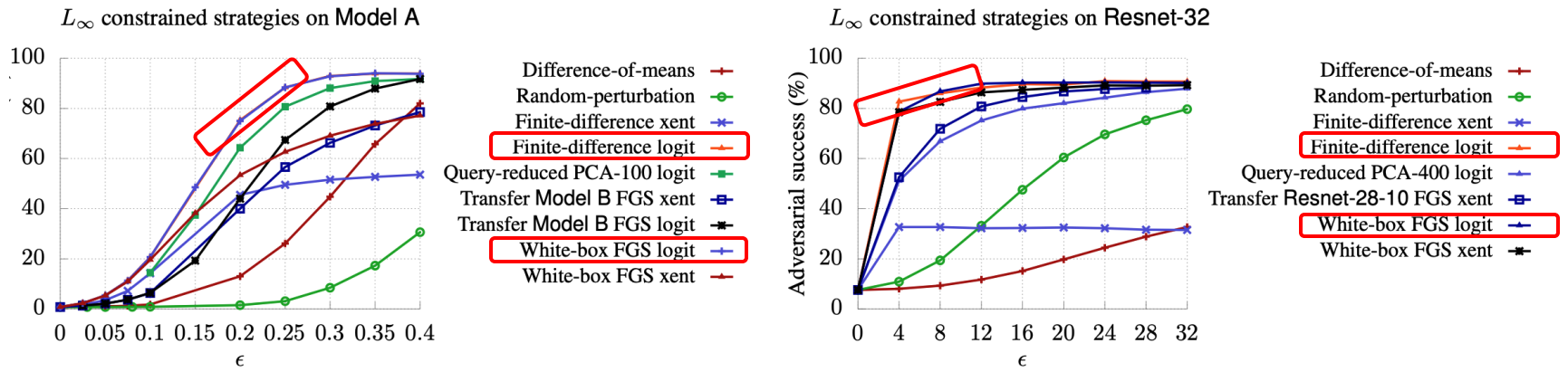
$$\Rightarrow \nabla_x \mathcal{L}(f(x), y) = \text{FD}_x(\max_{i \neq y^{\text{target}}} \{Z(x')_i\} - Z(x')_{y^{\text{target}}}, \delta)$$

- **Approximated targeted C&W attack:**

$$x^\star = x - \epsilon \cdot \text{sign}\left(\text{FD}_x(\max_{i \neq y^{\text{target}}} \{Z(x')_i\} - Z(x')_{y^{\text{target}}}, \delta)\right)$$

Black-Box Evasion Attack: GEA

- Success rate-perturbation size curve
  - **Black-box attack (Finite-difference logit)** has almost the same curve as white-box C&W attack (**White-box FGS logit**)



(a) Model A (MNIST)

(b) Resnet-32 (CIFAR-10)

What is the drawback?

Drawback of GEA

for 28x28 image, require 28x28x2 (=1568) queries

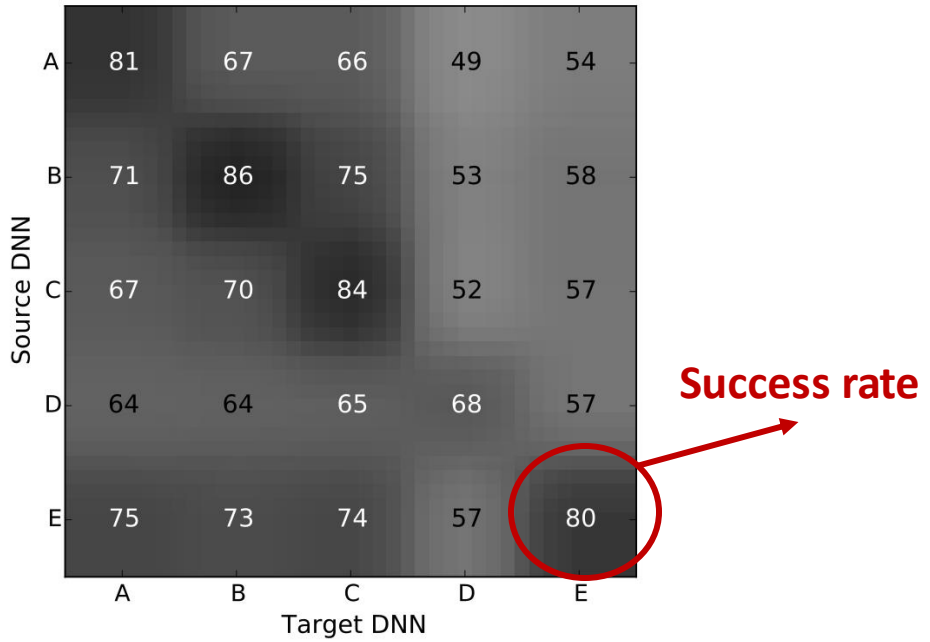
$$x^\star = x - \epsilon \cdot \text{sign}\left(-\frac{\text{FD}_x(f(x)_{y^{\text{target}}}, \delta)}{f(x)_{y^{\text{target}}}}\right)$$

- Query reduction:
  - Random grouping: The gradient is estimated only for a random group of selected features.
  - PCA (Principal Component Analysis): Compute the gradient only along a number of principal component vectors.

Black-Box Evasion Attack: Substitute Model

- **Substitute model attack (Zero-query attack)**
  - **Idea**: Train a substitute model
    → Generate adversarial examples for the substitute model
    → Transfer the generated adversarial samples to the target model.
  - **Rationale:** Adversarial examples often work across different ML models and datasets.

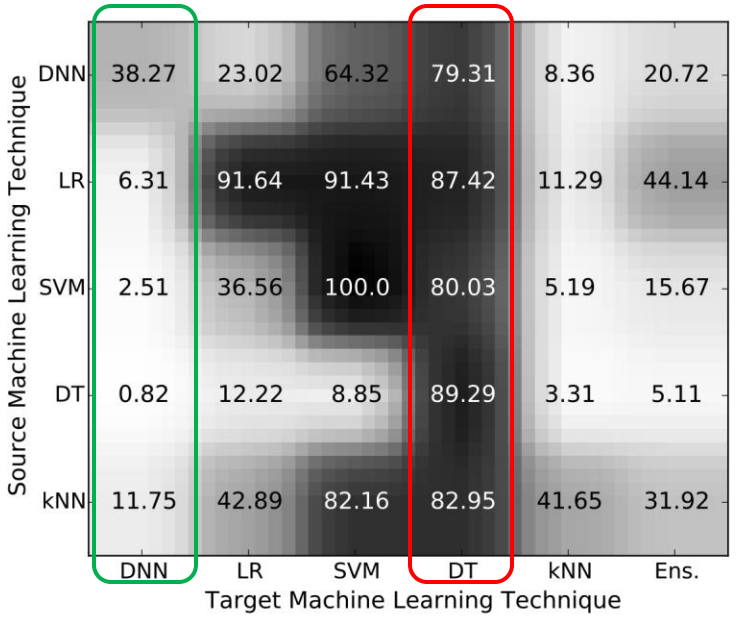
- **Intra-technique transferability:**
  The substitute and target model have the ***same*** architecture



Black-Box Evasion Attack: Substitute model attack

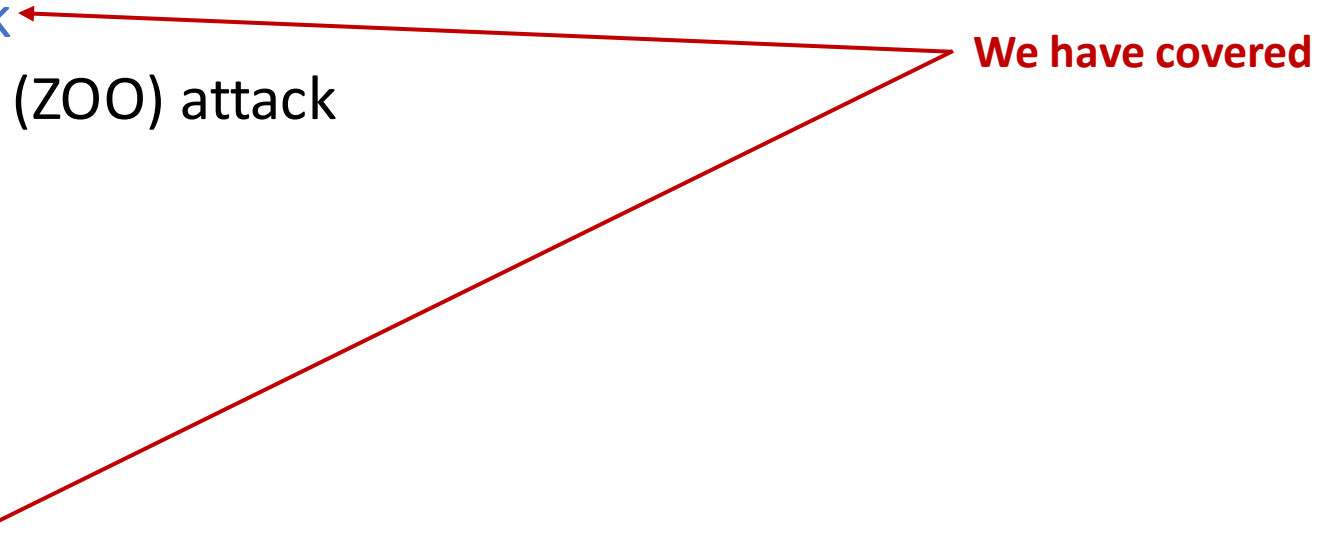
- **Substitute model attack ~ Zero-query attack**
  - **Idea**: Train a substitute model
    → Generate adversarial examples for the substitute model
    → Transfer the generated adversarial samples to the target model.
  - **Rationale:** Adversarial examples often work across different ML models and datasets.

- **Cross-technique transferability:**
  The substitute and target model have the ***different*** architecture
  - **Decision Tree (DT):** is the most vulnerable model.
  - **DNNs:** is the most robust model.



Black-Box Evasion Attack: Other attacks

- **Query-based attacks**
  - Gradient estimation attack
  - Zeroth-order optimization (ZOO) attack
  - Boundary attack
  - HopSkipJump attack
  - Simple black-box attack
- **Transfer-based attacks**
  - Substitute model attack
  - Ensemble of models attack



Reading: Akhtar et al. "Advances in adversarial attacks and defenses in computer vision: A survey"