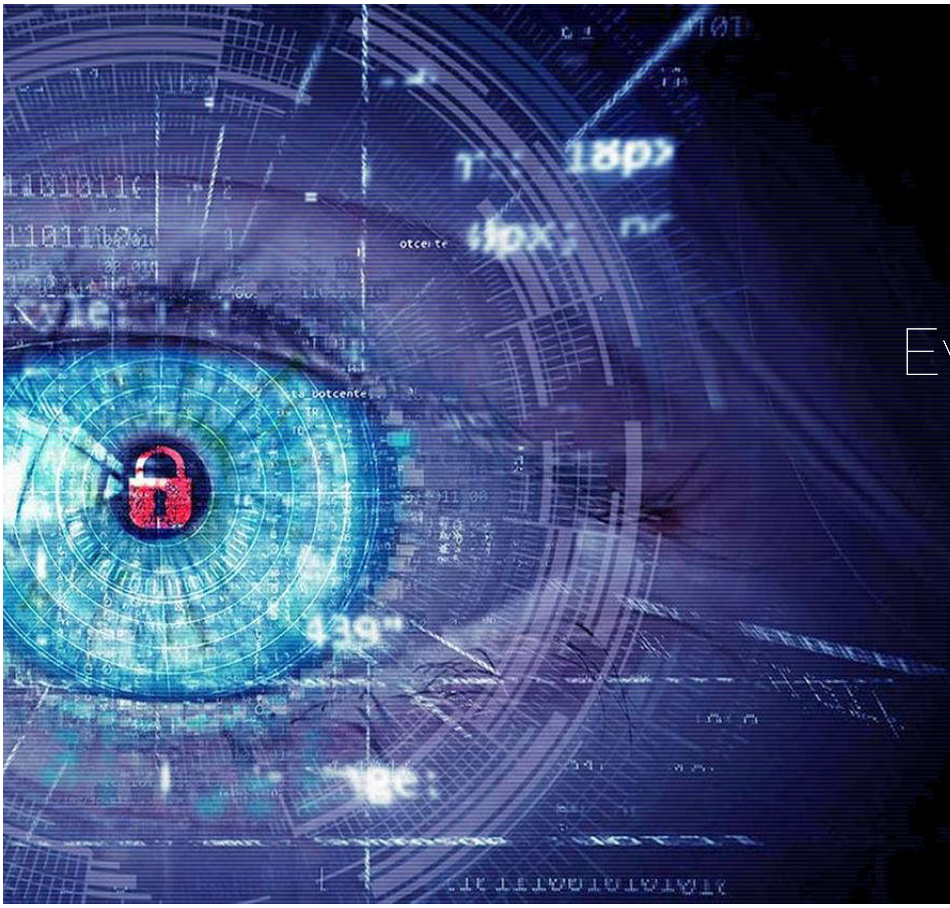

Introduction of
Machine Learning Security

Lecture 02

Evasion Attack

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Agenda

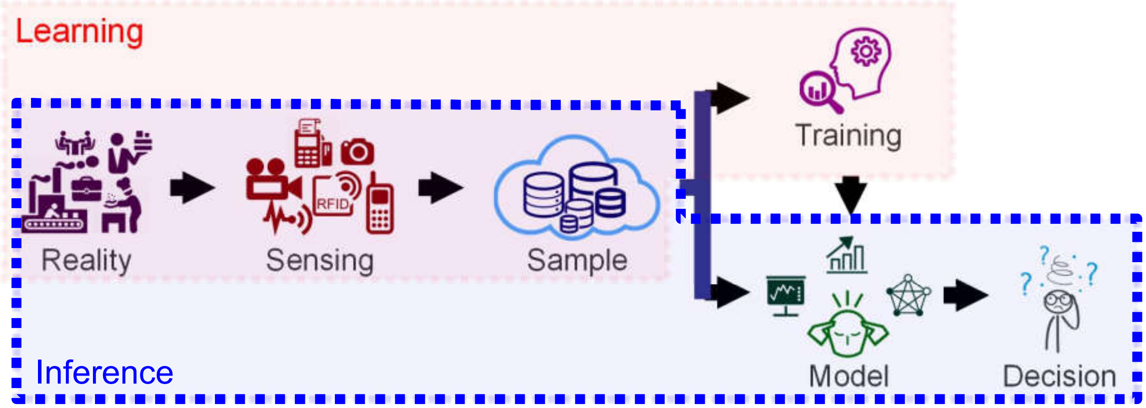
- Formulation: Attack Loss / Attack Cost
- Attack Sample Crafting
- Imperfect Knowledge
  - Surrogate Model
  - Query Attack
- Defense
  - Pre-processing
  - Robust Model

Evasion Attack

- Bypass a defensive system by modifying samples
- General speaking, evasion attack misleads trained systems by camouflaging samples in the inference phase

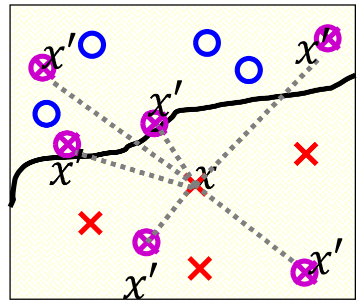
Evasion Attack

- How to mislead a trained model?



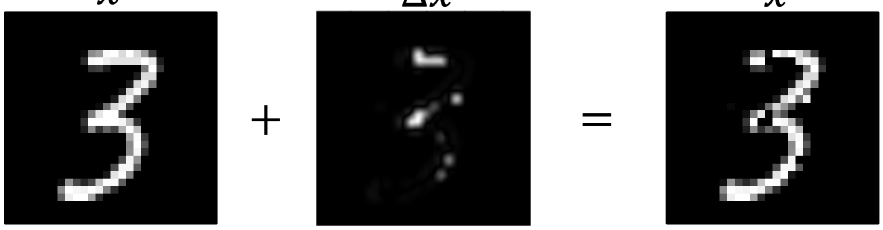
Evasion Attack

- Mislead the decision of a trained classifier by manipulating a sample in the inference phase
- How to determine Δx?



3 VS 7 Classification

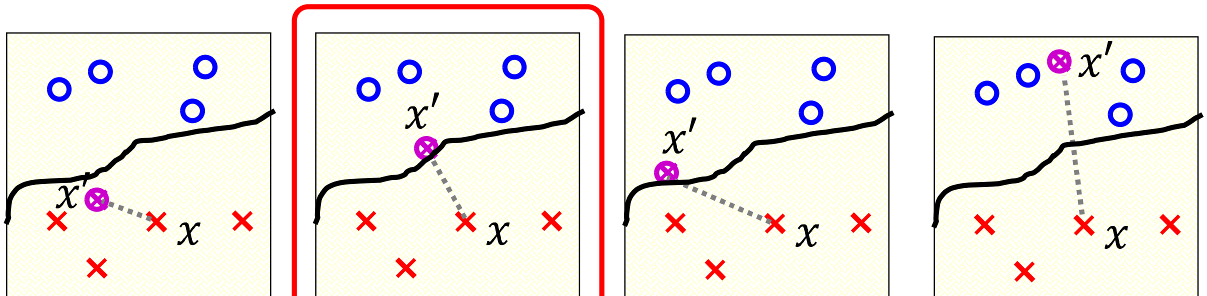
Original Sample x + Δx = **Attack Sample** x'



Classified as 3 | Classified as 7

Evasion Attack

- Which attack is better?



Successful Attack?	No	Yes	Yes	Yes
Manipulation	Small Perturbation	Small Perturbation	Large Perturbation	Very Large Perturbation

Objective Function

- Two factors of sample crafting
  - ↑ **Attack Impact**: Influence to the output
  - ↓ **Attack Cost**: Change on a sample

- Formulate as a multi-objective optimization

$$\min_{\Delta x}\left(L(x+\Delta x, t, f_w), \|\Delta x\|\right)$$

Loss between the output of the target model on attack sample and the target class (How close to your expected attack)

Change of a sample

Δx : manipulation f_w: the target model

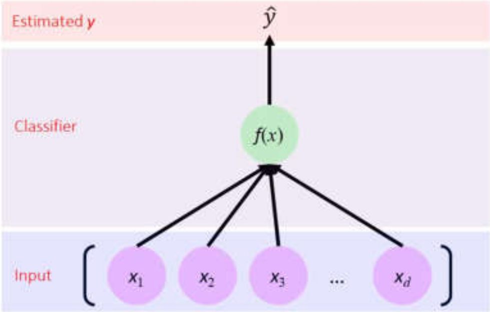
t : the target class x : the original sample

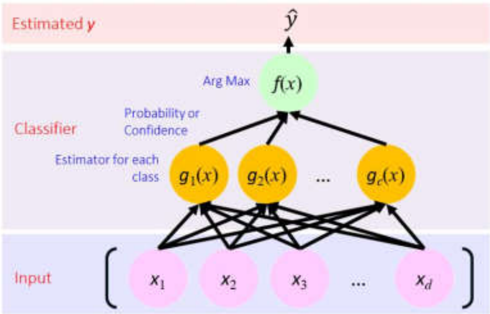
Attack Loss

$$\min_{\Delta x}\left(L(x+\Delta x, t, f_w), \|\Delta x\|\right)$$

- **2-Class problem**
  - The target class is obvious
    - Class 1 > Class 2 or Class 2 > Class 1

- **Multi-Class problem**
  - Generic Attack
    - Misclassification
      - Any class different from the original one
      - Usually the class which is most easily misled
  - Class-specific Attack
    - Selected target class





Objective Function

Attack Loss

$$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$$

- **Loss function (L)**
  1. Confidence value of the target class

$$-(g_t(x+\Delta x))$$

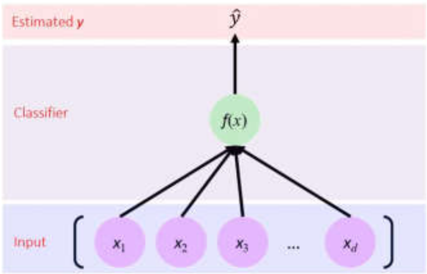
  2. Difference between the confidence values between the target class and another one with the largest confidence value

$$-\left(g_t(x+\Delta x) - \max_{i\neq t} g_i(x+\Delta x)\right)$$

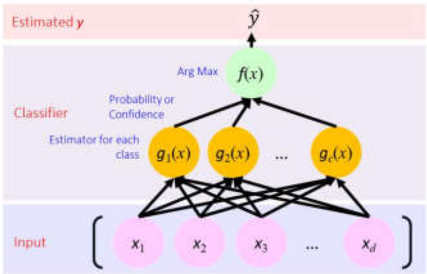
t: the target class

g_i: the estimated confidence output of the class i

Two-Class Problem



Multi-Class Problem



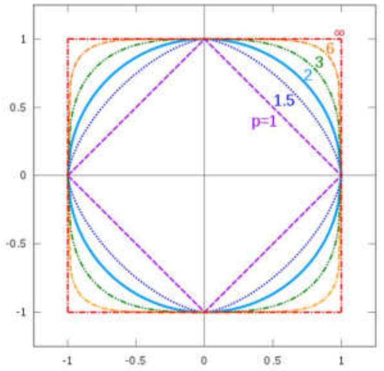
Objective Function

Attack Cost

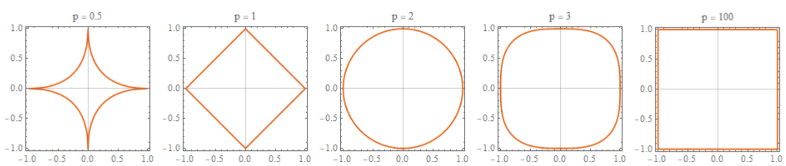
$$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$$

- ***p*-norms $\|x\|_p$**

$$\|x\|_p = \left(\sum_{i=1}^{d} |x_i|^p\right)^{\frac{1}{p}} \quad \text{where } p \geq 1$$



- $\|x\|_0$ = number of non-zero elements (not convex)
  - limit the number of attack feature (sparse attack)
- $\|x\|_1 = |x_1| + |x_2| + \ldots + |x_d|$
- $\|x\|_2 = \sqrt{|x_1|^2 + |x_2|^2 + \ldots + |x_d|^2}$
- $\|x\|_\infty = \max_{1\leq i\leq d} |x_i|$
  - Minimize the maximum change to any features (dense attack)

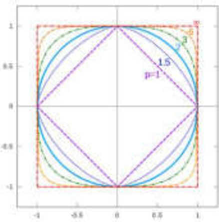


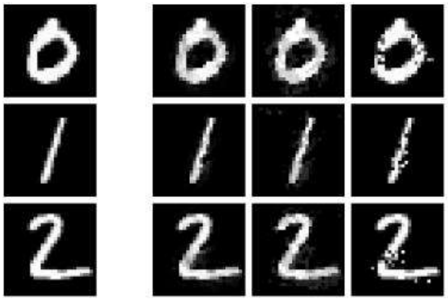
Objective Function

Attack Cost

$$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$$

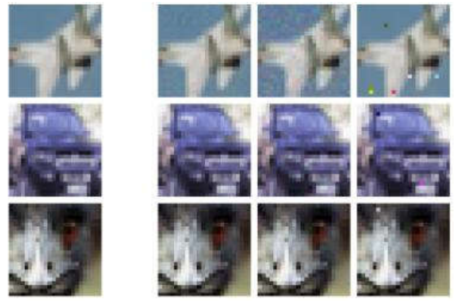
- Different p-norm functions on the adversarial noise ($\Delta x = \|x - x'\|$) generate different x'





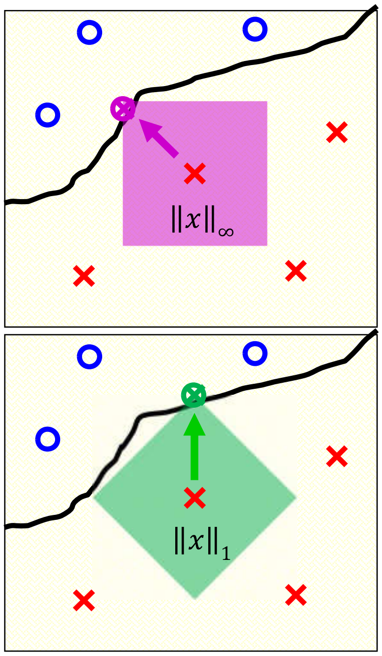
L_∞ | L_2 | L_0

Original Image | Dense Attack | Sparse Attack



L_∞ | L_2 | L_0

Original Image | Dense Attack | Sparse Attack



Objective Function

Attack Cost

$$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$$

- One-Pixel / Few-Pixel Attack

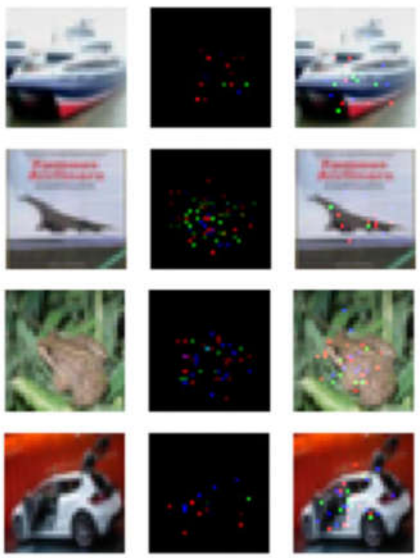
$$\min \quad f(x + e(x))$$
$$\text{s.t.} \quad \|e(x)\|_0 \le d$$

$\|e(x)\|_0$: count non-zero elements

$e(x) = (e_1, e_2, \ldots, e_n)$: n is number of features

d: number of modified features

One-Pixel Attack
$d = 1$



Few-Pixel Attack
$d > 1$

J Su, DV Vargas, K Sakurai(2019) One pixel attack for fooling deep neural networks. In: IEEE Transactions on Evolutionary Computation

Attack Cost

$$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$$

- Control the attack features and their magnitudes separately and precisely

$$\min_{\boldsymbol{\delta},\mathbf{G}} \quad \| \overbrace{\boldsymbol{\delta} \odot \mathbf{G}}^{\substack{\text{Adversarial Noise} \\ (\Delta x = \boldsymbol{\delta} \odot \mathbf{G})}} \|_2^2 + \lambda \mathcal{L}(f(\mathbf{x} + \boldsymbol{\delta} \odot \mathbf{G}), y_t),$$

$$s.t. \quad \underbrace{\mathbf{1}^\top \mathbf{G} = k}_{\substack{\text{no more than} \\ \text{k features}}}, \; \mathbf{G} \in \{0,1\}^d$$

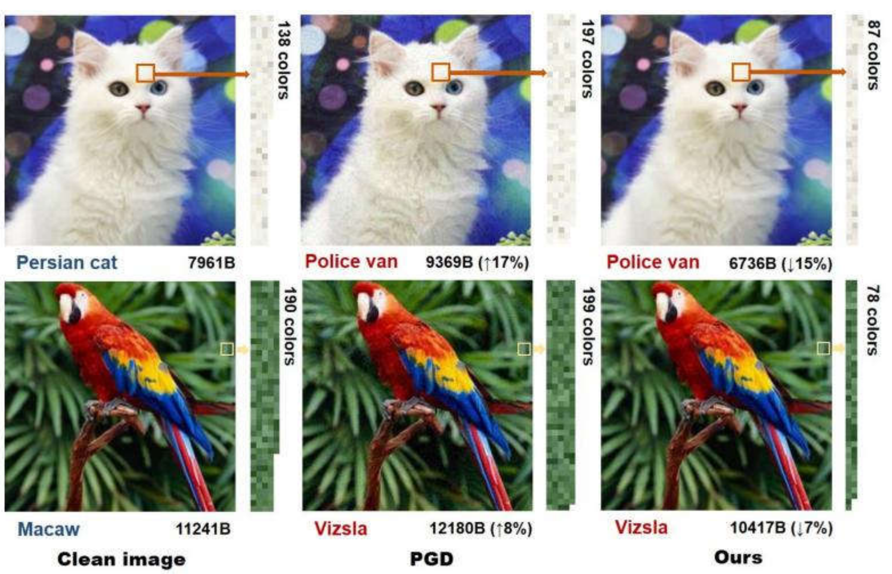
  - $\delta \in R^d$: vector of perturbation magnitudes
  - $G \in \{0,1\}^d$:vector of perturbed positions

Y Fan, B Wu, T Li(2020) Sparse Adversarial Attack via Perturbation Factorization. In: ECCV

Attack Cost

$$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$$

- Most adversarial attacks add extra disturbing information on clean images explicitly
- AdvDrop attacks by dropping existing information of images

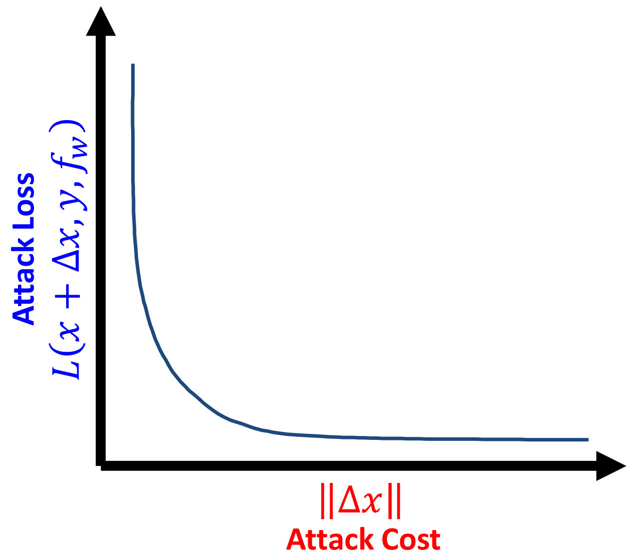


Duan, R., Chen, Y., Niu, D., Yang, Y., Qin, A. K., & He, Y. (2021). Advdrop: Adversarial attack to dnns by dropping information. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 7506-7515)

Objective Function
Tradeoff

$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$

- **Attack Impact** and **Attack Cost** are correlated
  - Smaller sample change yields larger attack loss, vice versa
  - Smaller attack loss yields larger sample change, vice versa



Objective Function
Formulation

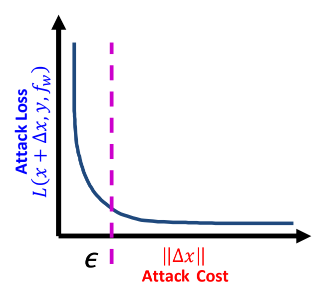
$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$

- Multi-objective problem can be formulated as

1. Minimize Attack Loss

- Maximize damage with a fixed attack cost

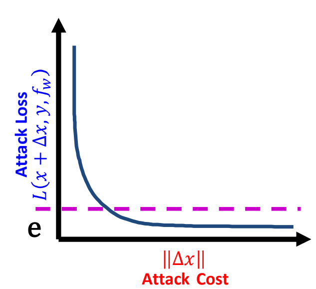
$$\min \quad L(x+\Delta x, t, f_w)$$
$$\text{s.t.} \quad \|\Delta x\| \; \epsilon \geq$$



2. Minimize Attack Cost

- Minimize the attack cost for an attack damage

$$\min \quad \|\Delta x\|$$
$$\text{s.t.} \quad L(x+\Delta x, t, f_w) \geq \mathrm{e}$$



Objective Function

Formulation

$$\min_{\Delta x}(L(x+\Delta x, t, f_w), \|\Delta x\|)$$

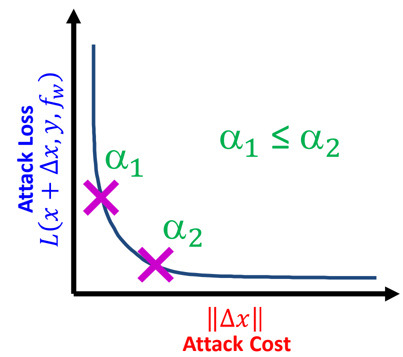
- Multi-objective problem can be formulated as

3. Tradeoff Solution

- Maximize damage with a fixed attack cost

$$\min \ \alpha L(x+\Delta x, t, f_w) + (1-\alpha)\|\Delta x\|$$

α : a tradeoff parameter ($0 \le \alpha \le 1$)



- When $\alpha = 1$, only $L(x+\Delta x, t, f_w)$ is focused
- When $\alpha = 0$, only $\|\Delta x\|$ is focused

Attack Sample Crafting

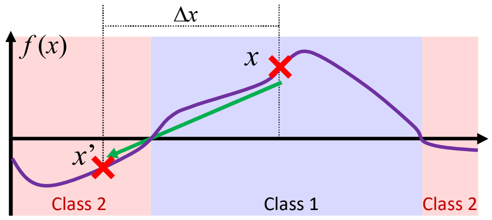
Gradient Descent

- Algorithm

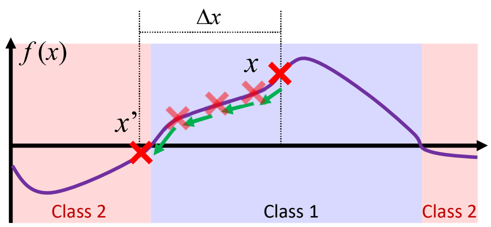
```
Δx_0 = 0                                  Initialize delta x
i = 0                                     Initialize counter i
Do
    i = i + 1                             Counting
    Δx_{i+1} = Δx_i - α∇L(x + Δx_i, t, f_w)   Update Δx_{i+1} according to gradient at x + Δx_i
    Δx_{i+1} = constraint(Δx_{i+1})       Limit Δx_{i+1} by constraints
While i <= n                              Update n times
```

Gradient Descent

- **One-Step Method**
  Fast Gradient Sign Method (FGSM)
  - n = 1 : Cost ↓



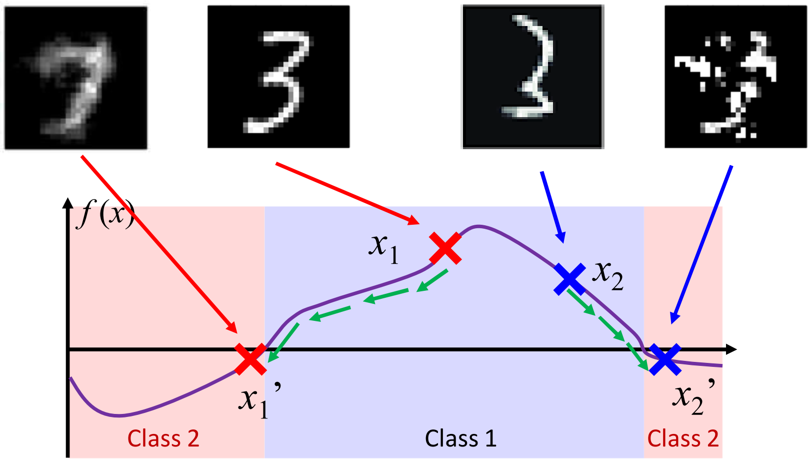
- **Multi-Step Method**
  Projected Gradient Descent(PGD)
  - n > 1 : Cost ↑



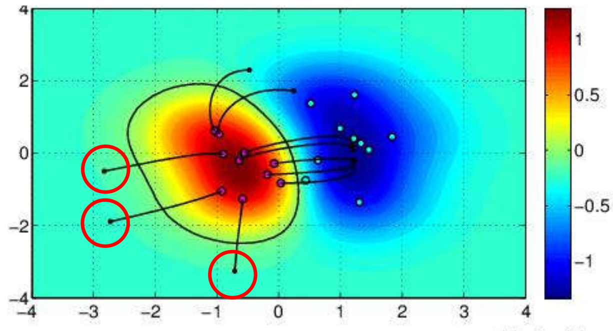
IJ Goodfellow, J Shlens, C Szegedy(2014) Explaining and harnessing adversarial examples. In: arXiv
A Madry, A Makelov, L Schmidt(2017) Towards Deep Learning Models Resistant to Adversarial Attacks. In: arXiv

Look Natural?

- Changing $g(x)$ is good enough?



Crafted samples are very different from the real samples of another class

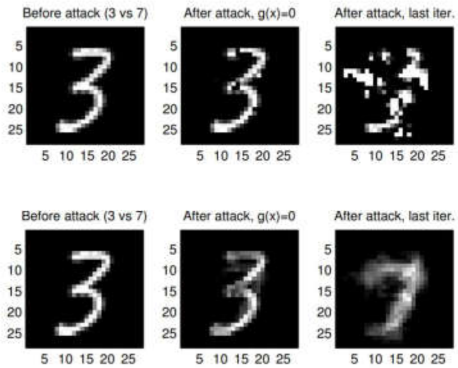


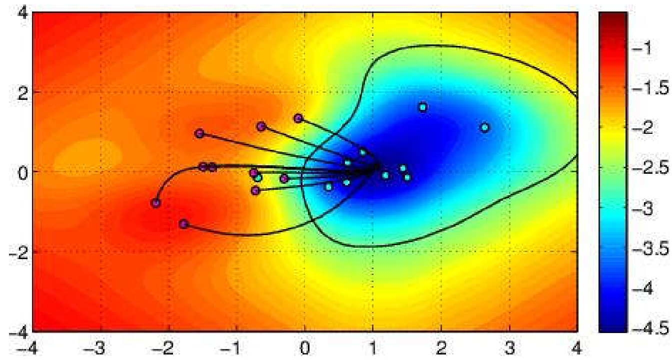
Look Natural? Density Estimator

- Not only cross the decision boundary but also close to the target class
  - Penalize x’ in low density regions

Mislead the model to classify +1 as -1

$$\min \quad f(x') - \boxed{\hat{p}(x'|y=-1)}$$
$$\text{s.t.} \quad \|x - x'\| \leq \varepsilon$$



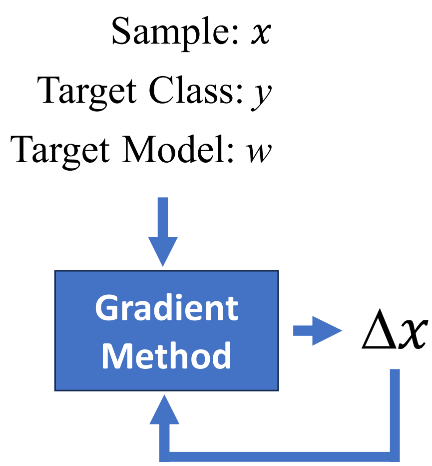


B Biggio, I Corona, D Maiorca(2013) Evasion Attacks against Machine Learning at Test Time. In: ECML

Attack with Limited Knowledge

Limited Knowledge

- Gradient method for crafting is available only if the target model w is known (which is the most secure information)
  - i.e. $\nabla_{\Delta x} L_w(x+\Delta x, t)$
- What can we do when the detail of target model is unknown?
  - No gradient can be computed

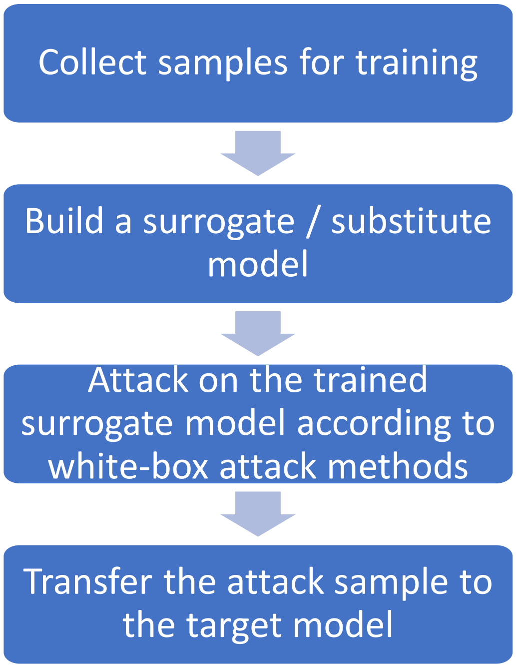


Methods

1. **Surrogate Model + Attack Transfer**
   - Assumption: Samples for training can be somehow obtained
   - Train a surrogate model to replace the target one
2. **Query Attack**
   - Assumption: the target model can be accessed
   - Craft attack samples by querying the target models

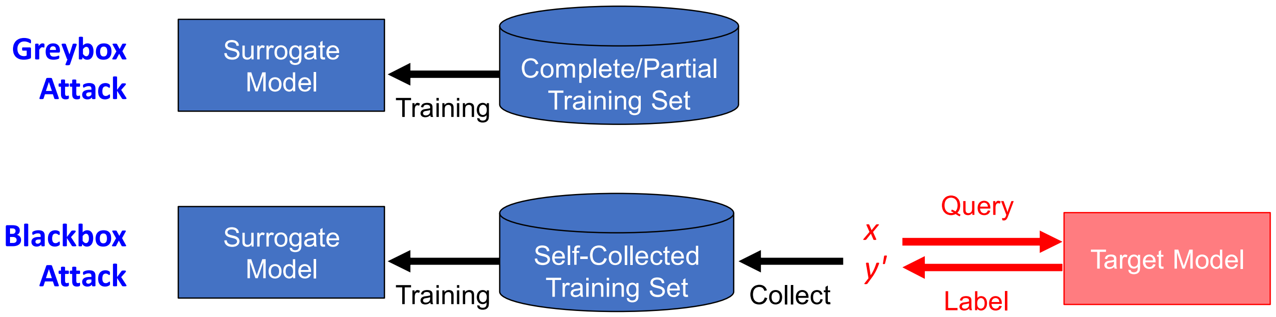
Procedure

- Aim to approximate the target model
- The surrogate model should be convenient for crafting
  - i.e. differentiable
- More information yields better approximation
- Key Challenge: Transferability



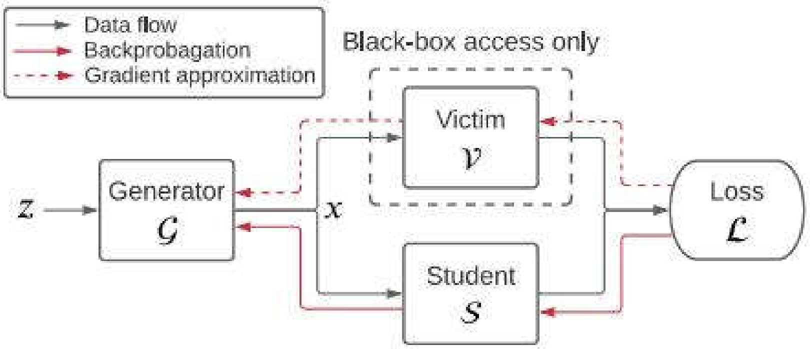
Incomplete Training Set

- Build Surrogate / Substitute model by incomplete training set
  - Greybox Attack: Complete / Partial training set
  - Blackbox Attack: Self-collected data in the same application (but maybe different from the training samples used in target model)
    - Query of the targeted model is allowed



No Training Set

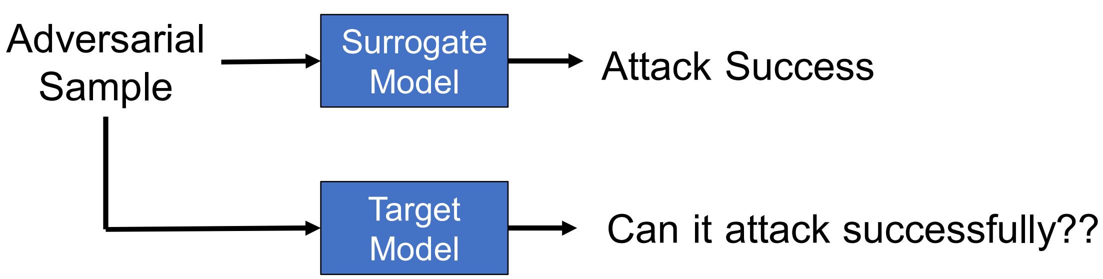
- Data-Free Model Extraction
  - **Student** aims to approximate to Victim (target model) : reduce Loss
  - **Generator** generates samples to increase the difference between victim and student : increase Loss
  - Student and Generator are in opposition



Truong, J. B., Maini, P., Walls, R. J., & Papernot, N. (2021). Data-free model extraction. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition.

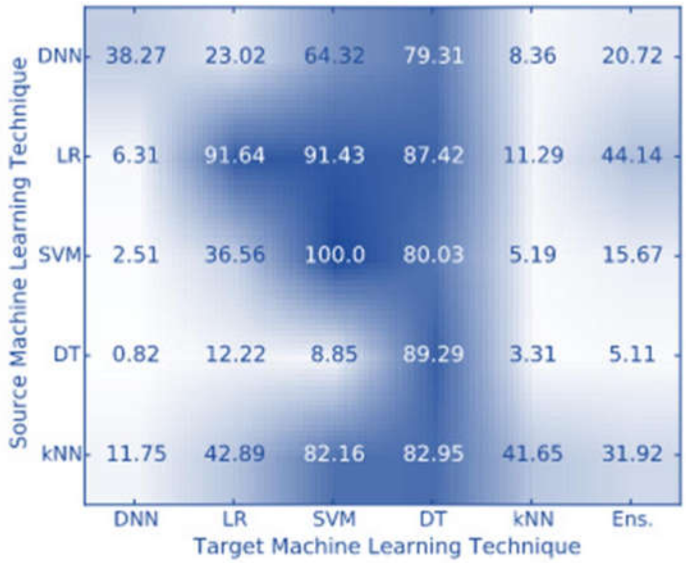
Transferability

- **Attack Transferability** is important requirement
  - Reduce the influence of difference between the real and surrogate models on attack performance



Attack Method: Surrogate Model
Transferability

- Experimental results on **attack performance** of attack samples generated by Surrogate (Source) model on Target model
  - DNN: Deep Neural Network
  - LR: Linear Regression
  - SVM: Support Vector Machine
  - DT: Decision Tree
  - kNN: k nearest neighborhood
- Different models behave differently



Papernot et al., Practical Black-box Attacks against Machine Learning, AsiaCCS 2017

Attack Method: Surrogate Model
Transferability

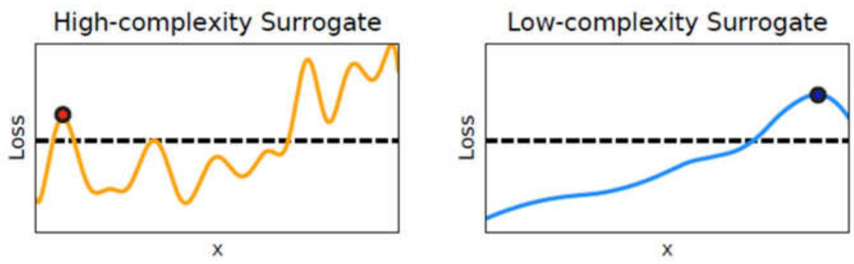
- Transferability Factors
  - **Size of Input Gradient (↑)**
    - Larger gradient yields large modification, usually generate larger attack impact
  - **Gradient Alignment (↑)**
    - Larger similarity of the input gradients of the loss function of the target and surrogate models is better for attack
  - **Variability of the loss landscape (↓)**
    - Surrogate loss functions that are stabler and lower variance may find better a local optima (better attack)

Demontis, Biggio et al., Why Do Adversarial Attacks Transfer? Explaining Transferability of Evasion and Poisoning Attacks, USENIX 2019

Transferability

- Model complexity is important to transferability
- **Two main factors**
  - the complexity of the target model
  - the complexity of the surrogate model

Red Point: Attack Sample crafted according to High-Complexity Surrogate
Blue Point: Attack Sample crafted according to Low-Complexity Surrogate



Successful Attack

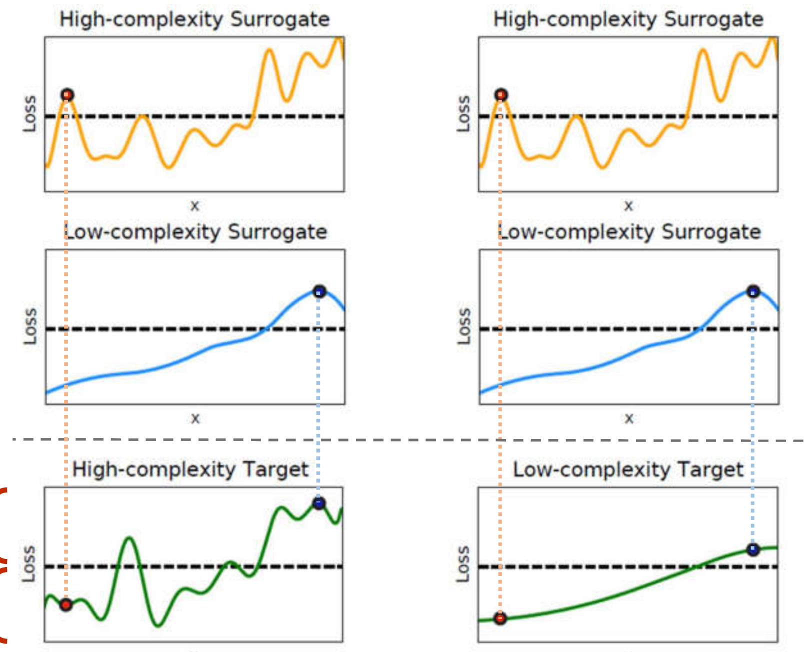
Failed Attack

Below a certain threshold (i.e., the dotted line), the point is correctly classified, otherwise it is misclassified

Larger Δx

Transferability

- Attack Sample crafted according to High-Complexity Surrogate may not able to fool the target model



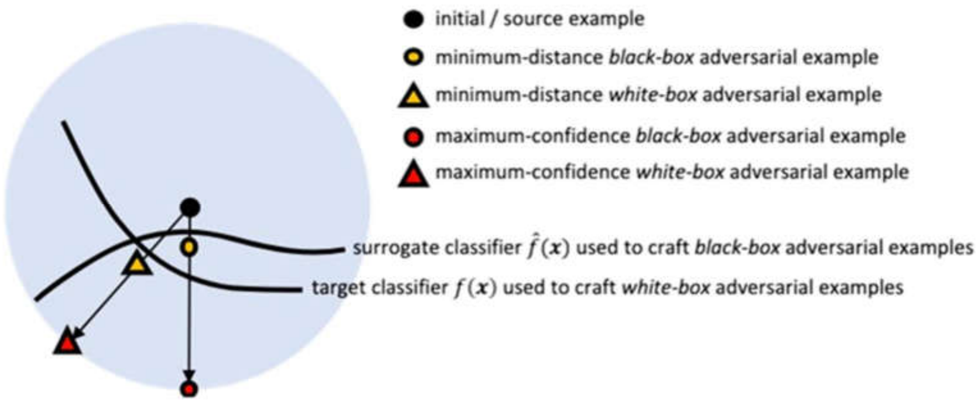
Red Point: Attack Sample crafted according to High-Complexity Surrogate
Blue Point: Attack Sample crafted according to Low-Complexity Surrogate

Successful Attack

Failed Attack

Transferability

- **Maximum Confidence Attacks** might better transfer, but more perturbation is needed
- **Minimum Distance Attacks** are likely to fail because decision boundary is different

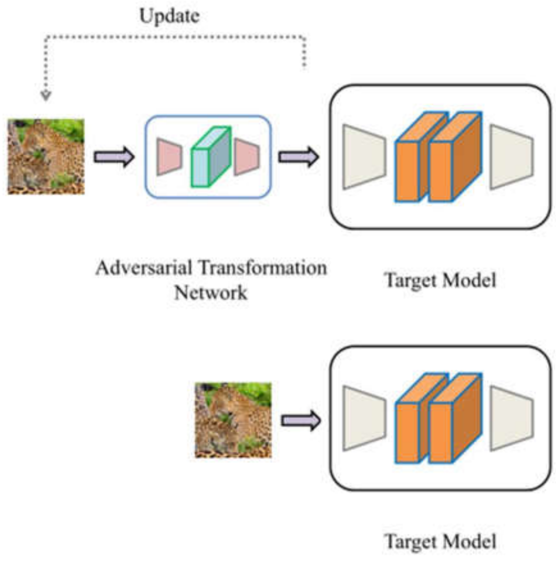


Demontis, Biggio et al., Why Do Adversarial Attacks Transfer? Explaining Transferability of Evasion and Poisoning Attacks, USENIX 2019

Enhance Transferability

- Image transformation of a model may reduce attack ability
- Adversarial Transformation Network (ATN) is built aiming to lose effect of image transformation on sample attack
- Attack sample is crafted to attack a model with / without ATN

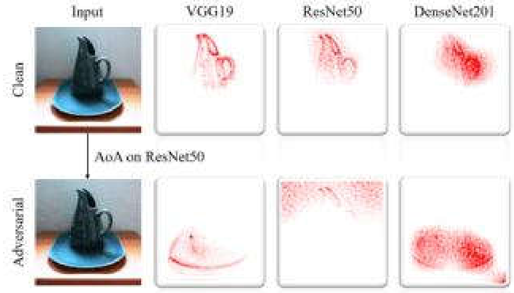
$$L_{attack} = J(f(\mathbf{x}^{adv}), y) + \gamma J(f(T(\mathbf{x}^{adv})), y)$$



Attack Method: Surrogate Model: Transferability

Enhance Transferability

- Many studies indicate that attention heatmaps of models on an object are similar



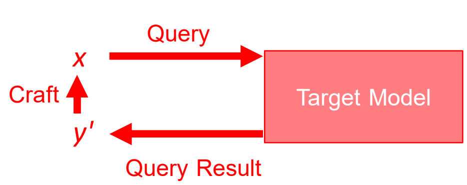
- Aim at manipulating the heatmap
  - Magnitude suppression $L_{\text{supp}}(x) = \|h(x, y_{\text{ori}})\|_1$
  - Distraction $L_{\text{dstc}}(x) = -\left\| \frac{h(x, y_{\text{ori}})}{max(h(x, y_{\text{ori}}))} - \frac{h(x_{\text{ori}}, y_{\text{ori}})}{max(h(x_{\text{ori}}, y_{\text{ori}}))} \right\|_1$
  - Decrease the gap between 1st and 2nd largest classes $L_{\text{bdry}}(x) = \|h(x, y_{\text{ori}})\|_1 - \|h(x, y_{\text{sec}}(x))\|_1$

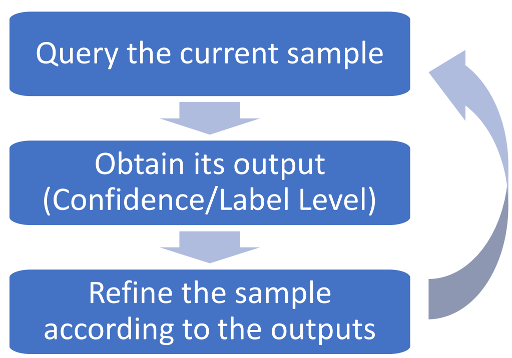
Sizhe Chen, Zhengbao He, Chengjin Sun(2020) Universal adversarial attack on attention and the resulting dataset damagenet. In: IEEE Transactions on Pattern Analysis and Machine Intelligence

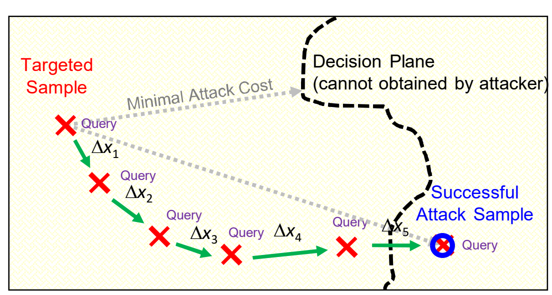
Attack Method: Query Attack

Procedure

- Assume the target model can be queried
- More information provided by the model (Confidence output > Label output) enhance the crafting
- Key Challenges:
  - Reduce the query number
  - Minimize the modification

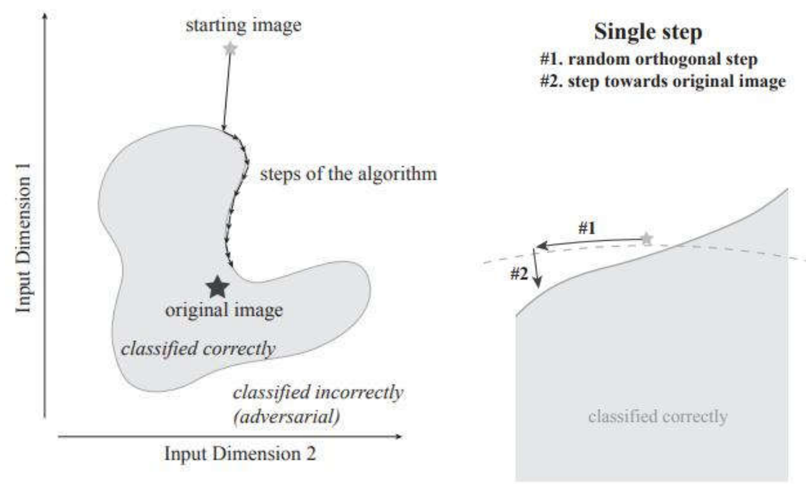






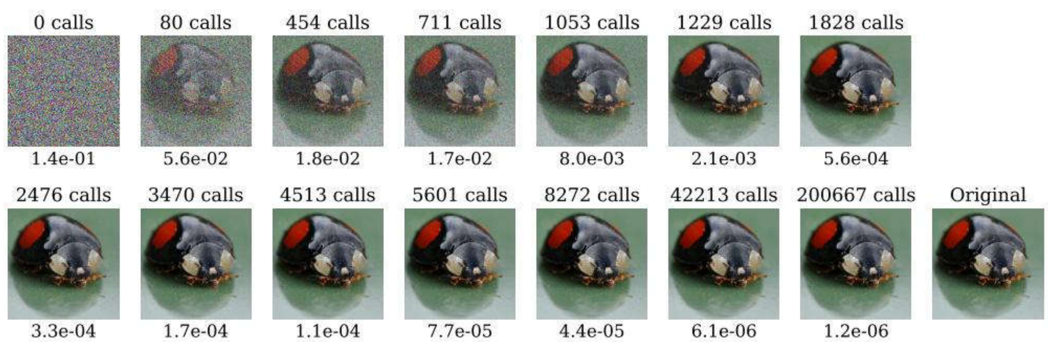
Decision-Based Adversarial Attacks

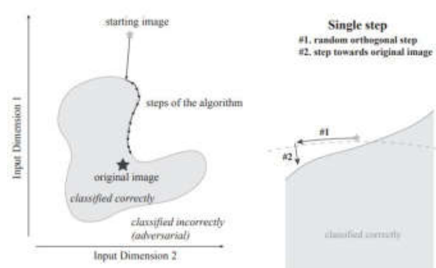
- Start from a randomly selected a point in the target class
- Moving the point toward to the original image until touch the boundary
- Get closer to the original image by searching on the surface of the target class region



Wieland Brendel, Jonas Rauber, Matthias Bethge(2017)Decision-Based Adversarial Attacks: Reliable Attacks Against Black-Box Machine Learning Models. In: arXiv

Decision-Based Adversarial Attacks





Wieland Brendel, Jonas Rauber, Matthias Bethge(2017)Decision-Based Adversarial Attacks: Reliable Attacks Against Black-Box Machine Learning Models. In: arXiv

Attack Method: Query Attack
ZOO: Zeroth order attack

- Estimate the second-order partial derivative without surrogate
- Querying the model around a very small proximity for each dimension

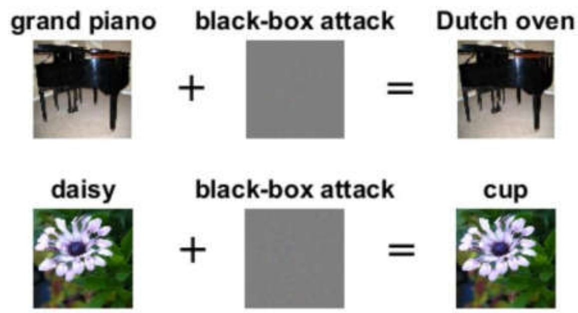
First-Order Partial Derivative

$$\hat{g}_i := \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}_i} \approx \frac{f(\mathbf{x}+h\mathbf{e}_i)-f(\mathbf{x}-h\mathbf{e}_i)}{2h},$$

Second-Order Partial Derivative

$$\hat{h}_i := \frac{\partial^2 f(\mathbf{x})}{\partial \mathbf{x}_{ii}^2} \approx \frac{f(\mathbf{x}+h\mathbf{e}_i)-2f(\mathbf{x})+f(\mathbf{x}-h\mathbf{e}_i)}{h^2}.$$

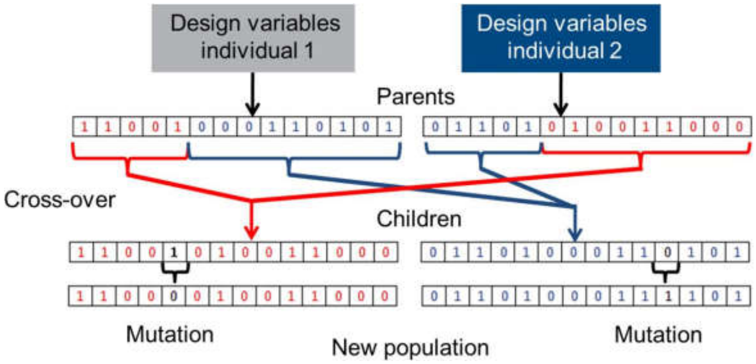
h : a small constant (e.g. h = 0.0001)
e_i : a standard basis vector with only the i-th component as 1

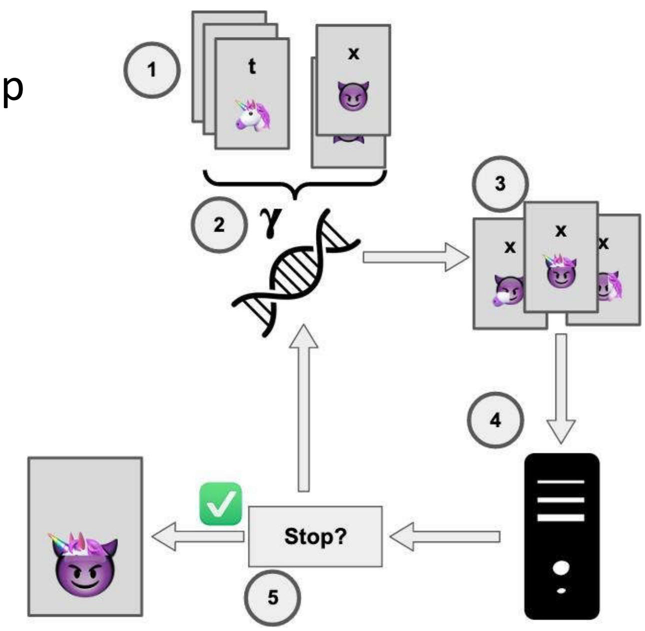


Chen et al., ZOO: Zeroth Order Optimization Based Black-box Attacks to Deep Neural Networks without Training Substitute Models, AISec 2017

Attack Method: Query Attack
Genetic Algorithms

- Maintain M best samples as a pool
  - Cross-over two randomly selected samp
  - Mutation
  - Query scores for new samples
  - Stop until a solution is found





Attack Evaluation

Attack Loss

- **Attack success rate (ASR)**
  - Ratio of successful evasion when the sample change is fixed
  - Larger ASR, better attack performance

$$ASR = \frac{SAN}{AN}$$

SAN: Successful Attack Number
AN : Attack Number

- **Average Confidence for Adversarial Class (ACAC)**
  - The average probability of all misclassification categories for all samples when the attack is successful
  - Larger ACAC, better attack performance

$$ACAC = \frac{1}{n}\sum_{i=1}^{n} P(X_i^a)_{F(X_i^a)}$$

$F(X_i^a)$: the i-th sample being classified as category a
$P(X_i^a)$: the probability that the i-th sample is classified as category a

Attack Loss

- **Peak signal-to-noise ratio (PSNR)**
  - Calculates the signal-to-noise ratio of original and attack images after successful evasion
  - Larger PSNR, better attack performance

$$PSNR = 10\ log_{10} \frac{M^2}{MSE(x, x')}$$

M : the maximum pixel value
x : the clean image
X' : the generated image
MSE : the mean square error

Attack Cost

- **Frechet Inception Distance (FID)**
  - Distance between the original and attack image when successful evasion
  - Lower FID, better attack performance

- **Learned Perceptual Image Patch Similarity (LPIPS)**
  - Distance between the original and attack image in the feature space at multiple layers of a pretrained network.
  - Lower LPIPS, higher perceived similarity, better attack performance

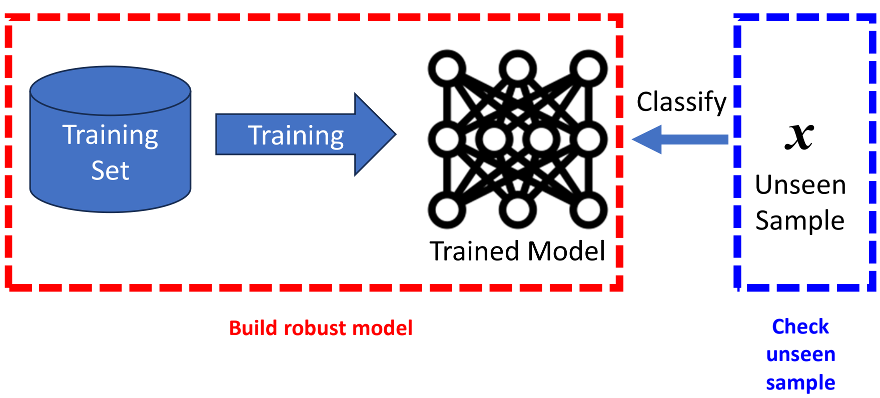
$$FID = \|\mu_x - \mu_{x'}\|_2^2 + Tr\left(\Sigma_x + \Sigma_{x'} \pm 2(\Sigma_x \Sigma_{x'})^{\frac{1}{2}}\right)$$

x : the clean image
x' : the generated image
μ_a : mean of a
Σ_a : covariance matric of a
Tr : sum of the diagonal elements of the matrix

Defense Methods

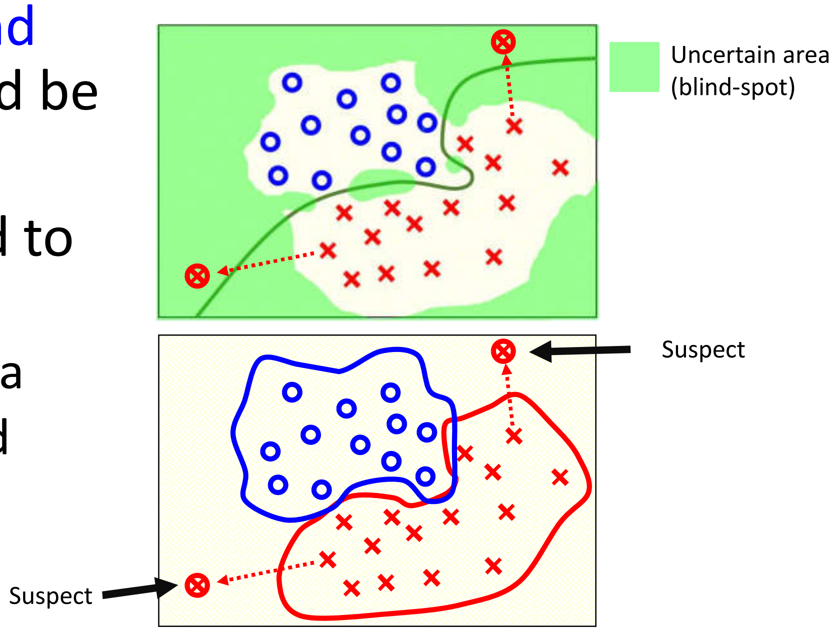
Defense

- Pre-processing
  - Detection
  - Cleaning
- Robust Learning
  - Parameter Updating
  - Structure Selection



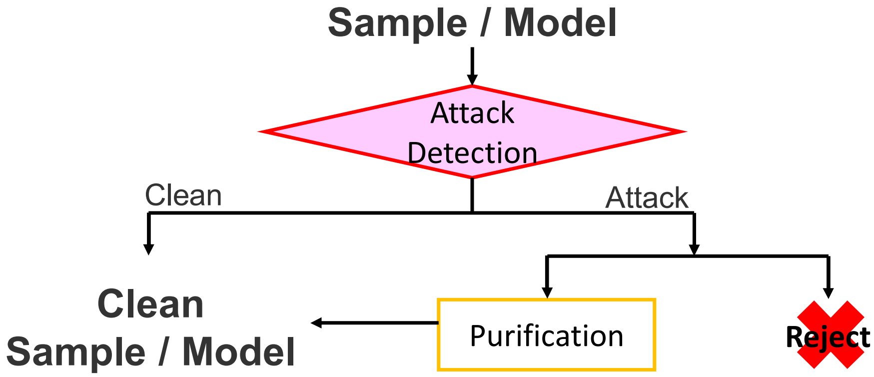
Defense: Pre-Processing

- Characteristics of clean and adversarial samples should be different
- Adversarial examples tend to occur in uncertain regions
  - Far away from training data
  - No information is provided



Detection: Sample

- Explicit Method
  - Evaluation criteria
- Implicit Method
  - Rely on a classifier



Explicit Detection: Sample

- Trained Autoencoder (AE) is used to reconstruct a sample by clean samples
  - **Reconstruction Error**
    - Reconstruction Error on an adversarial sample is larger
    - x is an attack when the error is large
  - **Probability Divergence**
    - Jensen-Shannon divergence (JSD) quantifies the similarity between x and its reconstruction in the feature space (f)
    - x is an attack when JSD is large

$$\|x - AE(x)\|_p$$

$$JSD\left(f(x) \parallel f\left(AE(x)\right)\right)$$

$$JSD(P \parallel Q) = \frac{1}{2}D(P \parallel M) + \frac{1}{2}D(M \parallel Q)$$

Kullback–Leibler Divergence $D_{KL}(P \parallel Q) = \sum_{x \in X} P(x) log\left(\frac{P(x)}{Q(x)}\right)$

a mixture distribution of P and Q $M = \frac{1}{2}(P + Q)$

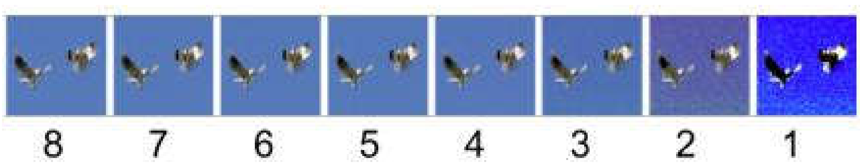
Meng D, Chen H(2017) Magnet: a two-pronged defense against adversarial examples. In: ACM SIGSAC conference on computer and communications security

Explicit Detection: Sample

- Squeezed Output Difference
  - Difference of output on original and transformed images
  - Two kinds of feature squeeze techniques are considered
  - x is an attack when $\max\left(d\left(x, x_{squeeze1}\right), d\left(x, x_{squeeze2}\right)\right)$ is large, where $d\left(x, x_{squeeze}\right) = \left\|f(x) - f\left(x_{squeeze}\right)\right\|_1$

$squeeze1$

Color Depth Reduction
Number of bits in each color channel (RBG)



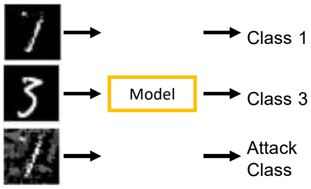
$squeeze2$

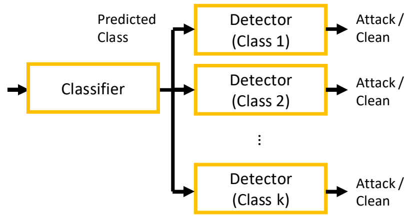
Spatial Smooth

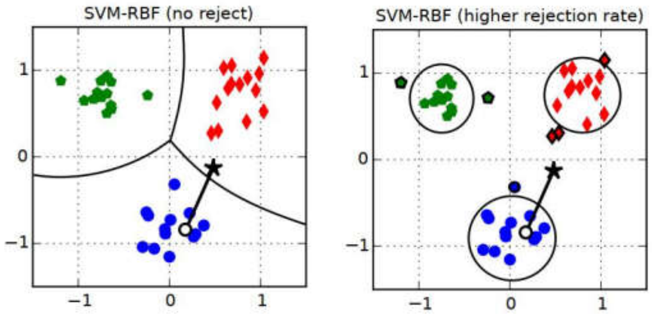
Xu W, Evans D, Qi Y(2017) Feature squeezing: Detecting adversarial examples in deep neural networks. In: NDSS

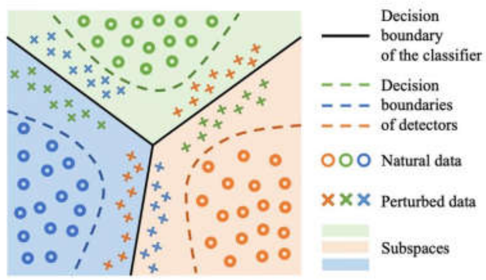
Implicit Detection: Sample

- Reject uncertain samples
  - Train a detector
    - For whole model
    - For each class
  - Set confident value thresholds





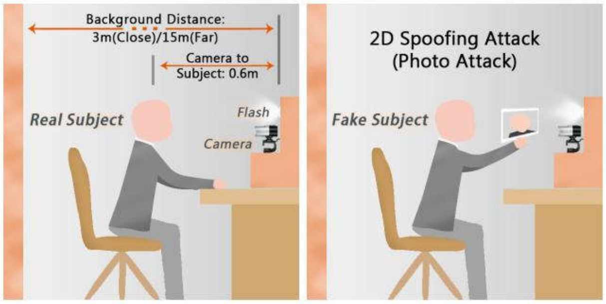


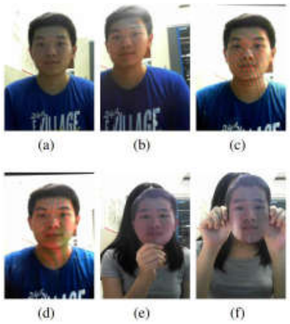


Grosse, Kathrin, et al(2017) On the (statistical) detection of adversarial examples. In: arXiv
Yin, Xuwang, Soheil Kolouri, Gustavo K. Rohde(2019) Adversarial example detection and classification with asymmetrical adversarial training. In: arXiv
Melis M, Demontis A, Biggio B, et al. (2017)Is Deep Learning Safe for Robot Vision? Adversarial Examples Against the iCub Humanoid. In: ICCV Workshops

Implicit Detection: Sample

- Face Liveness Detection
- One camera, no additional hardware
  - No depth information
- Flash is applied to enhance the difference between real and fake persons
- Only available for 2D attack





PPK Chan, W Liu, D Chen(2017) Face liveness detection using a flash against 2D spoofing attack. In: IEEE Transactions on Information Forensics and Security, 13(2), 521-534

Defense: Robust Model

- Build a model aiming to reduce the influence of attack on decisions
  - Adversarial Learning
    - Evasion: Increase attack cost/difficulty
    - Poisoning: Reduce influence of contaminated samples
  - Structure
    - Feature Selection
    - Ensemble

Adversarial Learning

- Basic idea: Consider additional regularization terms in the objective function

$$E = Err + Adv$$

- Two kinds of regularization:
  - Obfuscated Gradient
  - Adversarial Term (Increase Manipulation Cost)

Bai T, Luo J, Zhao J (2023) Recent Advances in Adversarial Training for Adversarial Robustness. In: IJCAI
Goodfellow I J, Shlens J, Szegedy C (2015) Explaining and harnessing adversarial examples. In: ICLR

Defense: Robust Model

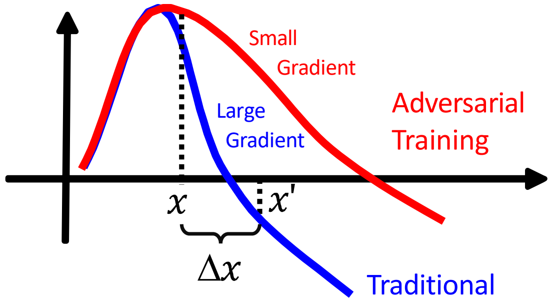
Obfuscated Gradient

- Penalizes large gradients

$$\min L(g(x), y) + \lambda||\nabla f(x)||$$

gradient

- Mislead crafting in adversarial attack



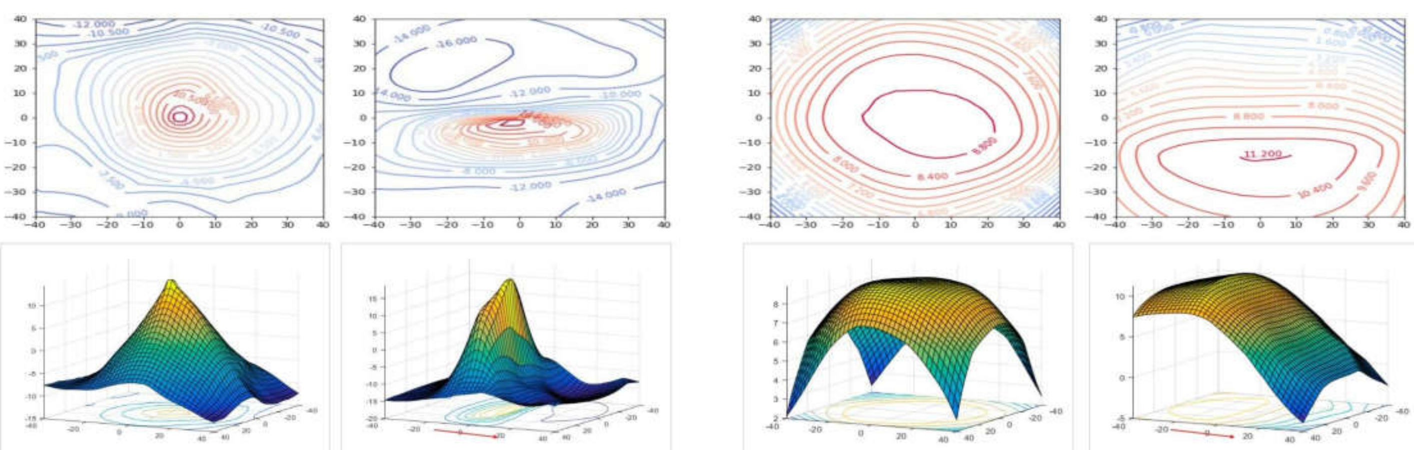
CJ Simon-Gabriel, Y Ollivier, L Bottou (2018)Adversarial Vulnerability of Neural Networks Increases with Input Dimension. In: ICLR
A Athalye, N Carlini, D Wagner (2018)Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples. In: International conference on machine learning (pp. 274-283). PMLR

Defense: Robust Model

Obfuscated Gradient

Normal model (Adversarial accuracy: 0.3%)

Defended model (Adversarial accuracy: 44.7%)



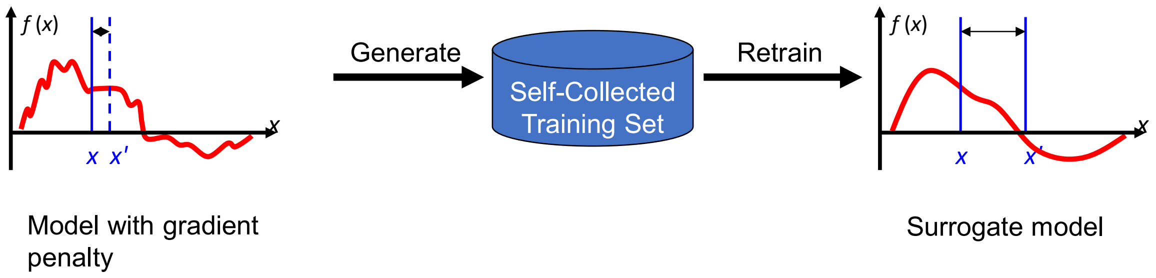
Random Perturbation | Adversary Perturbation | Random Perturbation | Adversary Perturbation

Yu et al., Interpreting and Evaluating NN Robustness, IJCAI 2019

Defense: Robust Model

Obfuscated Gradient

- However, obfuscation can be solved easily by training a surrogate model



CJ Simon-Gabriel, Y Ollivier, L Bottou (2018)Adversarial Vulnerability of Neural Networks Increases with Input Dimension. In: ICLR
A Athalye, N Carlini, D Wagner (2018)Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples. In: International conference on machine learning (pp. 274-283). PMLR

Defense: Robust Model

Adversarial Term

- A trained model should work well on both clean and attack samples

- Attack samples is generated for each training sample
  - Time complexity of attack sample generation is large

$$\tilde{J}(\boldsymbol{\theta}, \boldsymbol{x}, y) = \alpha \underbrace{J(\boldsymbol{\theta}, \boldsymbol{x}, y)}_{\text{Error on clean samples}} + (1 - \alpha) \underbrace{J(\boldsymbol{\theta}, \boldsymbol{x} + \epsilon \operatorname{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))}_{\text{Error on attack samples}}.$$

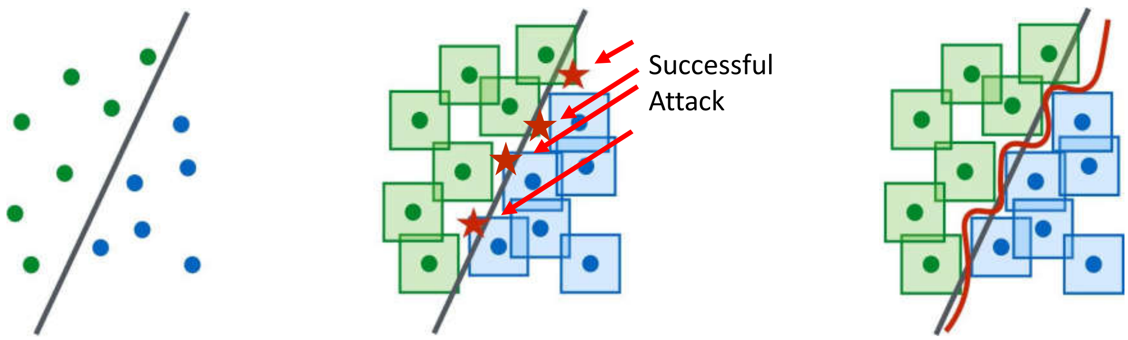
Bai T, Luo J, Zhao J (2023) Recent Advances in Adversarial Training for Adversarial Robustness. In: IJCAI
Goodfellow I J, Shlens J, Szegedy C (2015) Explaining and harnessing adversarial examples. In: ICLR

Defense: Robust Model: Adversarial Term

Robust Optimization

- Minimize the error and maximize the manipulation

$$\min_{w} \max_{\|\Delta x\|} L_w(x + \Delta x, y)$$

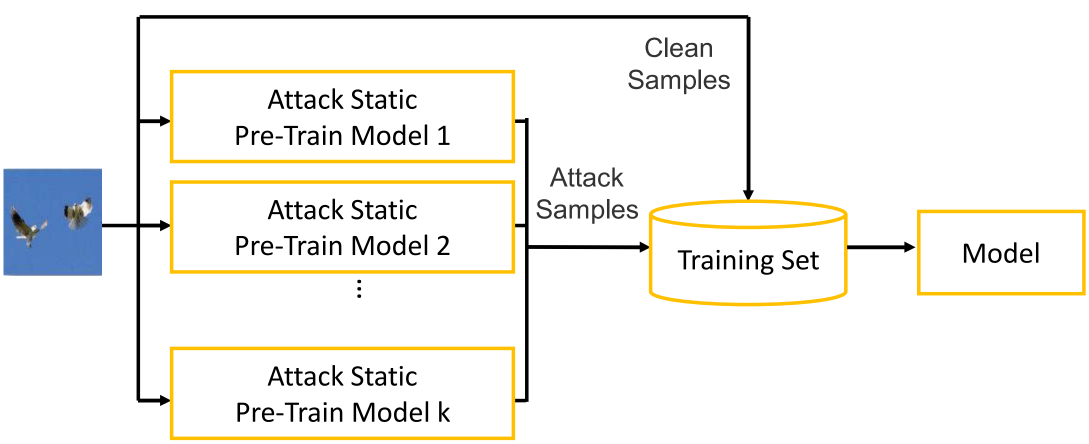


Madry et al., ICLR 2018 (https://arxiv.org/pdf/1706.06083.pdf)
Fast AT (NeurIPS 2020, https://arxiv.org/abs/2007.02617)

Defense: Robust Model: Adversarial Term

Feature squeezing

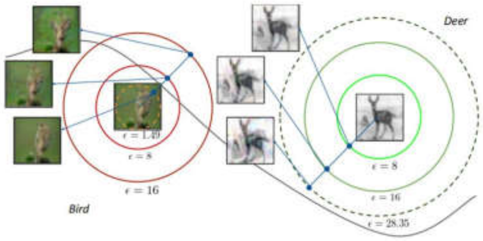
- Increase the diversity of attack samples
- Different views
  - Based on several pre-trained models



Xu W, Evans D, Qi Y(2017) Feature squeezing: Detecting adversarial examples in deep neural networks. In: NDSS

Diversity of Attack Samples

- Increase the diversity of attack samples
- Different attack strengths for samples
  - Avoid pushing an attack sample to another class

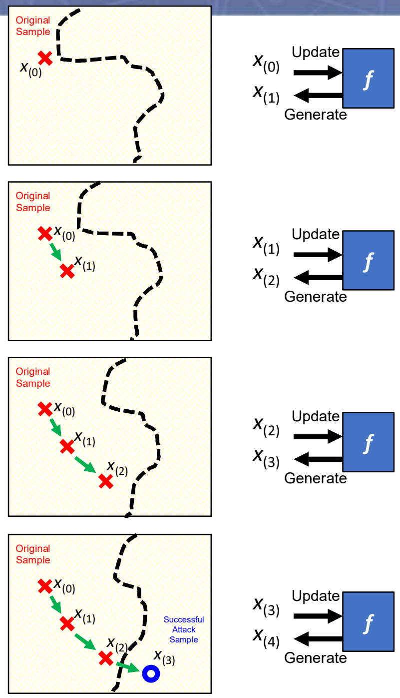


- Different attack strengths for training iterations
  - Adversarial term may dominate at beginning
    - Premature model may be evaded easily
  - Increase PGD iterations during training

Balaji Y, Goldstein T, Hoffman J(2019) Instance adaptive adversarial training: Improved accuracy tradeoffs in neural nets. In: arXiv
Zhang J, Xu X, Han B(2020) Attacks which do not kill training make adversarial learning stronger. In: PMLR

Cost Reduction

- Crafting adversarial samples is **time consuming**
  - Training set is usually large
- Free Adversarial Training
  - Perturbing a sample and updating the model simultaneously
  - Using incompletely crafted samples to update the model



Shafahi A, Najibi M, Ghiasi A(2019) Adversarial training for free!. In: arXiv

Domain Knowledge

- Improve the model by domain knowledge on the class relationships
  - A natural way to spot incoherent predictions
  - E.g.

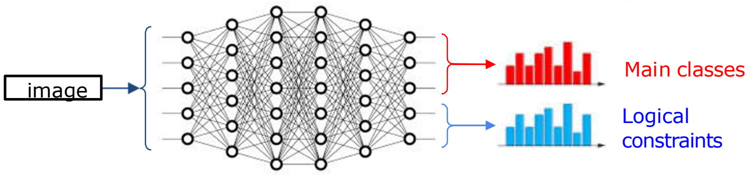
$$
\begin{aligned}
&\forall x, \quad \mathrm{CAT}(x) \Rightarrow \mathrm{ANIMAL}(x)\,,\\
&\forall x, \quad \mathrm{MOTORBIKE}(x) \Rightarrow \mathrm{VEHICLE}(x)\,,\\
&\forall x, \quad \mathrm{VEHICLE}(x) \Rightarrow \neg\mathrm{ANIMAL}(x)\,,\\
&\forall x, \quad \mathrm{CAT}(x) \vee \mathrm{ANIMAL}(x) \vee \mathrm{MOTORBIKE}(x) \vee \mathrm{VEHICLE}(x)
\end{aligned}
$$

Penalty (>0) associated to the T-Norm-based constraint from the h^{th} formula

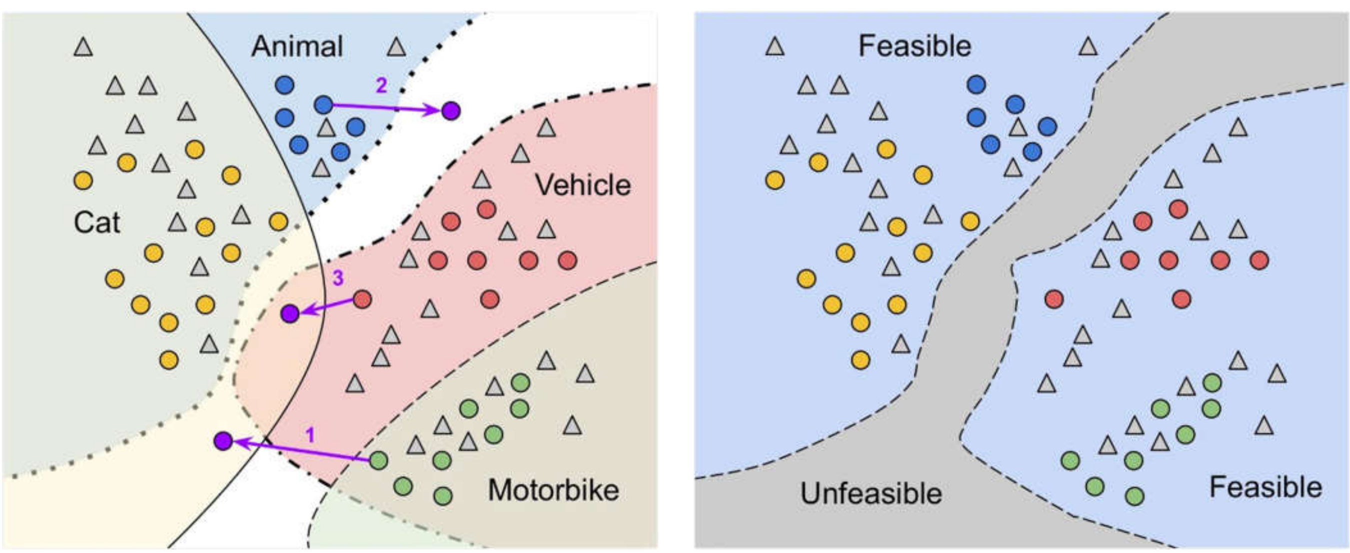
$$\min_{\mathbf{f}} = \boxed{\frac{1}{n}\sum_{i=1}^{l} L_y(\mathbf{f}(\mathbf{x}_i), \mathbf{y}_i)} + \boxed{\sum_{j=1}^{l+u}\sum_{h=1}^{m} \lambda_m \cdot L_\phi(\phi_h(\mathbf{f}(\mathbf{x}_j)))} + \lambda\|\mathbf{f}\|$$

Prediction Loss

Constraint loss
(can be thresholded)



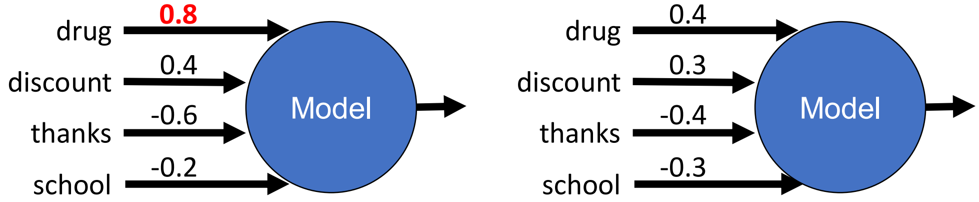
Domain Knowledge



Attack Sample

Structure: Feature Selection

- Weight evenness increases robustness
  - Influence of feature on decisions should be even
  - More features should be manipulated to change decisions



- Feature selection may reduce robustness
  - Weight of unselected features is 0
  - Feature weights are less even
  - Evasion may requires less modification

Kolcz A, Teo CH (2009) Feature weighting for improved classifier robustness. In: 6th conference on Email and Anti-Spam (CEAS)

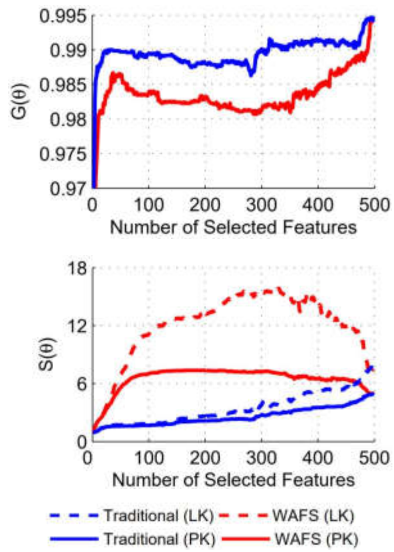
Structure: Feature Selection

- Adversary-aware Feature Selection
  - Maximize error and robustness

$$\arg\max_{\theta \in \{0,1\}^d} \; Acc_\theta + \gamma R_\theta$$
$$\text{s.t.} \;\; \sum_{j=1}^{d} \theta_j = m$$

where d : feature number, m : cardinality of feature subset, R : robustness estimation, θ : feature set, Acc : accuracy, γ : tradeoff

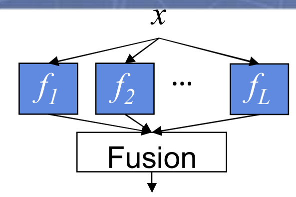
  - Most discriminative features are not selected
  - Variance of discriminative abilities of selected feature decreases, i.e. weights more even

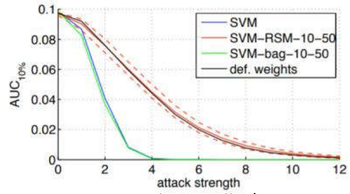


Fei Zhang, Patrick PK Chan, Battista Biggio, Daniel S Yeung, Fabio Roli(2015) Adversarial feature selection against evasion attacks. In: IEEE transactions on cybernetics

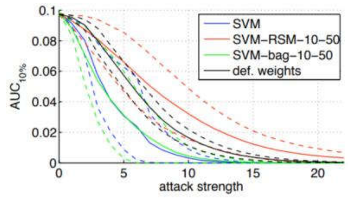
Structure: Ensemble

- Weight evenness can be enhanced by ensemble
  - Bagging (Samples)
    Each base classifier is trained with a bootstrap replication of the original training set
  - Random Subspace method (Features)
    Each base classifier is trained with different random feature subsets
  - Simple average is used a fusion





worst-case attack



Non worst-case attack

B Biggio, G Fumera, F Roli(2010) Multiple classifier systems for robust classifier design in adversarial environments. In: Journal of Machine Learning and Cybernetics