Adversarial Example Detection

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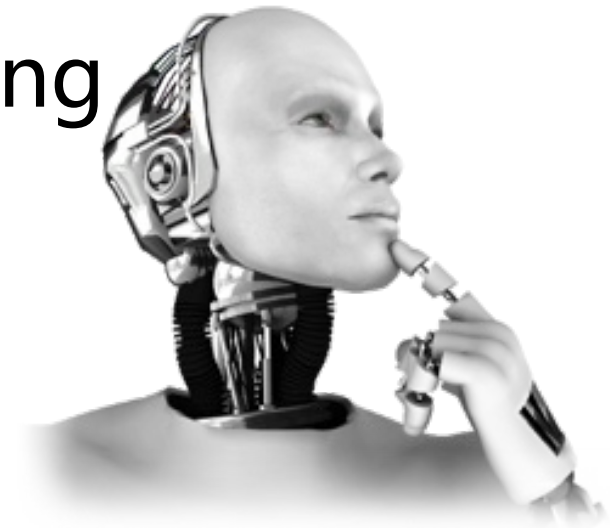
Autumn, 2022

Recap: week 3

1. Adversarial Examples

2. Adversarial Attacks

3. Adversarial Vulnerability Understanding



This Week

1. Adversarial Examples

$$\max_{x'} L(f_\theta(x'), y) \quad \text{subject to } \|x' - x\|_p \leq \epsilon \text{ for x} \in D_{test}$$

Misclassification

Small change on x

test time attack

2. Adversarial Attacks

3. Adversarial Vulnerability Understanding

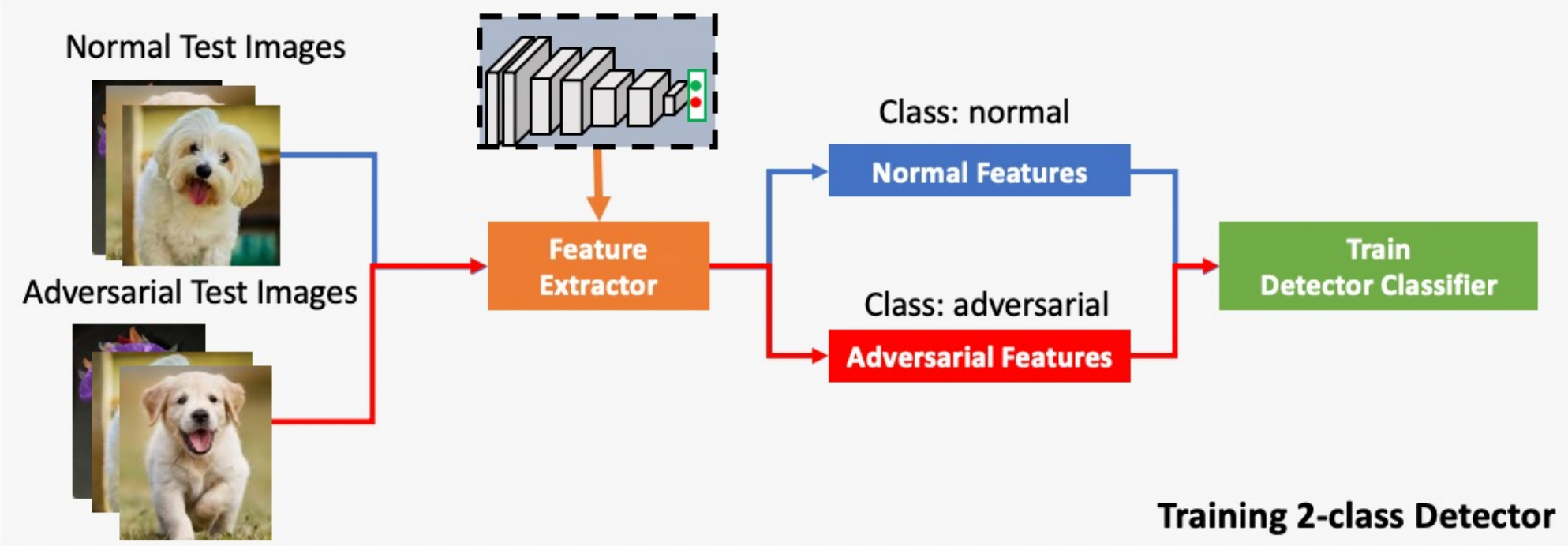
In-class Adversarial Competition

- Adversarial attack competition （**account for 20%**）
  - Codalab link: https://codalab.lisn.upsaclay.fr/competitions/7556?secret_key=d4a3b1fa-66e2-4a80-8ce6-b5f99e518979
  - **必须使用复旦邮箱注册比赛（否则无成绩）**
  - 比赛时间：
    - Phase 1： 9月28号 – 10月20号
    - Phase 2：10月20号 – 11月02号
    - Phase 3：最终评估，学生不参与

□ 得分计算：安排名进行评分，第一名100分，最后一名50分

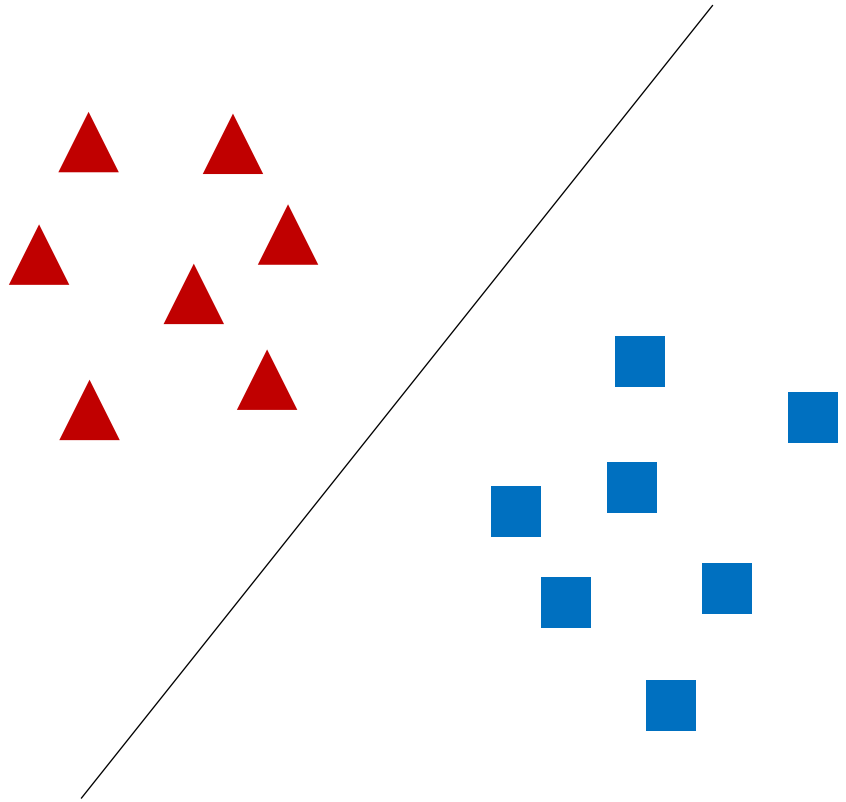
没卡的同学建议使用Google Colab：https://colab.research.google.com/

Adversarial Example Detection (AED)



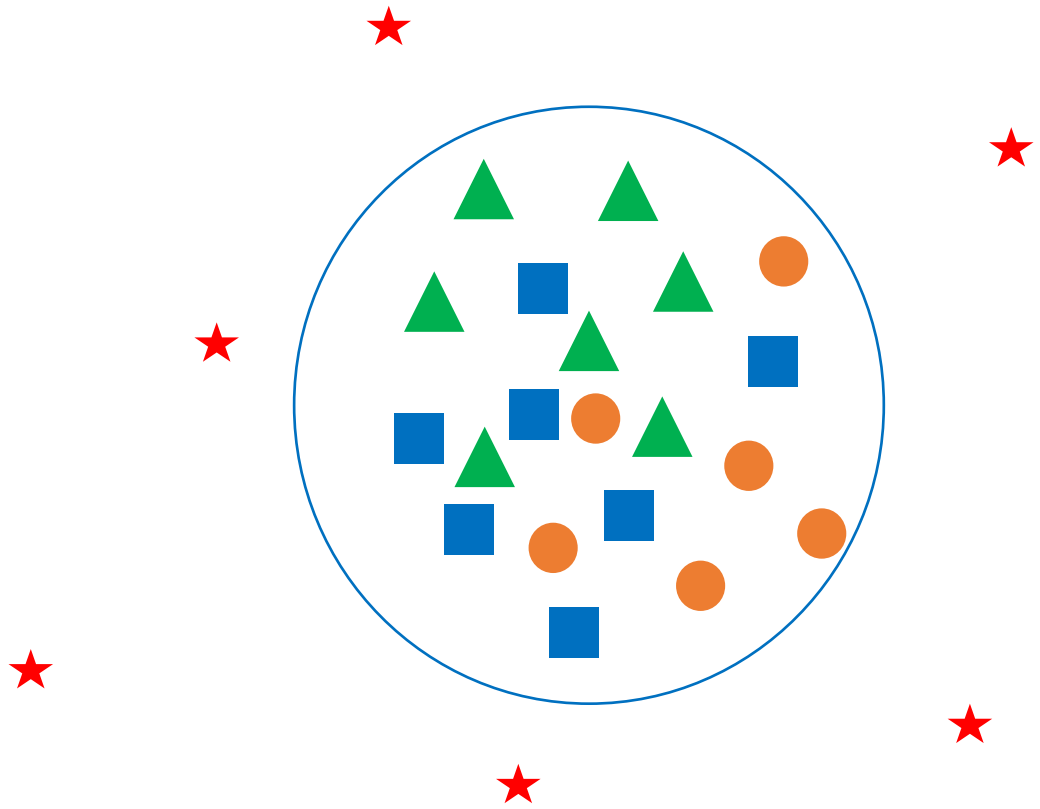
- A **binary** classification problem: clean (y=0) or adv (y=1)?
- An anomaly detection problem: benign (y=0) or abnormal (y=1)?

Principles for AED



- All binary classification methods can be applied for AED

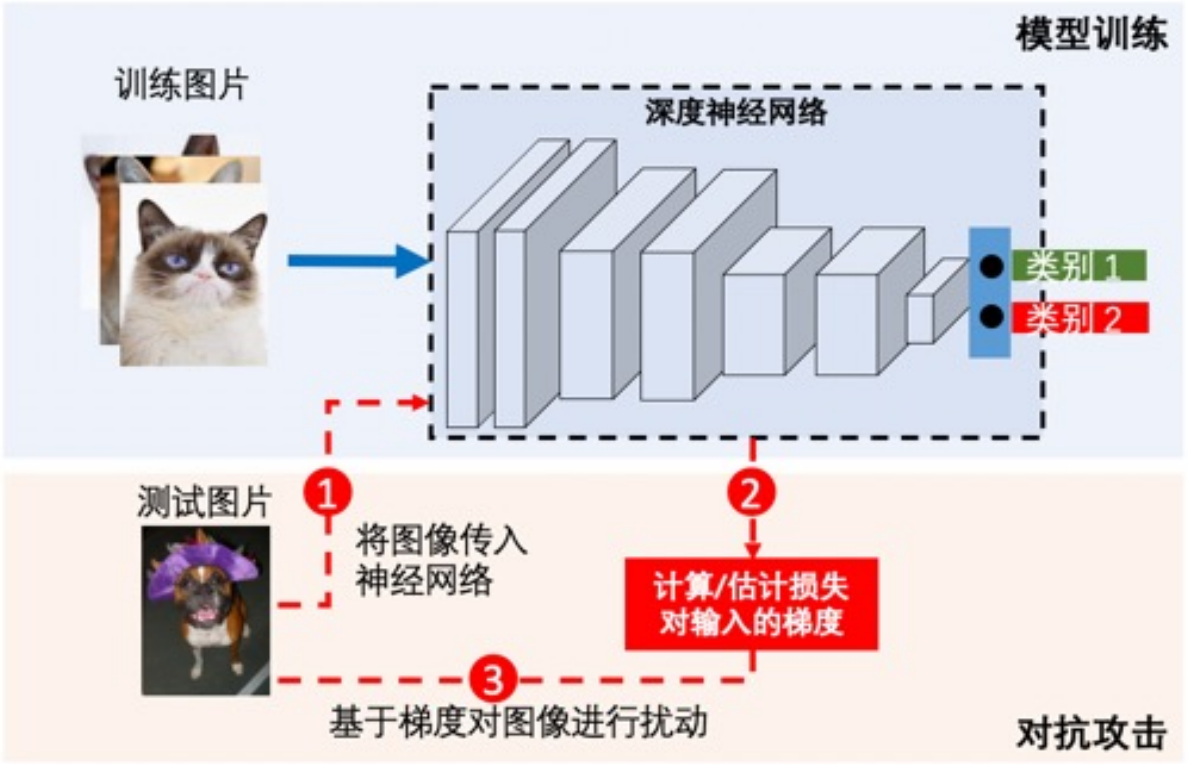
Principles for AED



- All anomaly detection methods can be applied for AED

Principles for AED

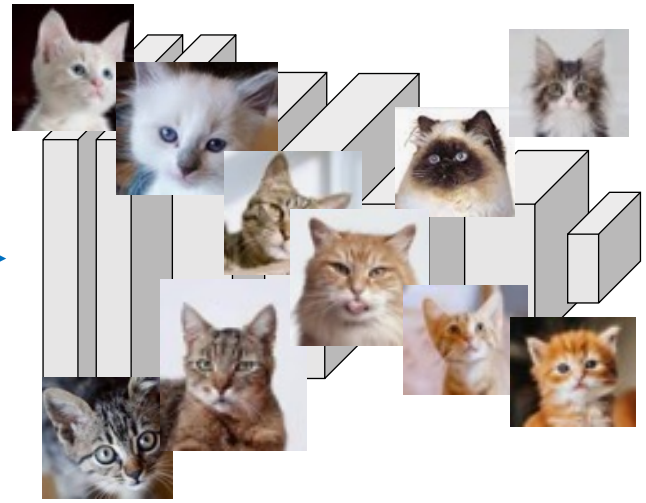
- Input statistics
- Manual features
- Training data
- Attention map
- Transformation
- Mixup
- Denoising
- …



- Activations
- Deep features
- Probabilities
- Logits
- Gradients
- Loss landscape
- Uncertainty
- …

☐ Use all the information we have

Principles for AED



Twins

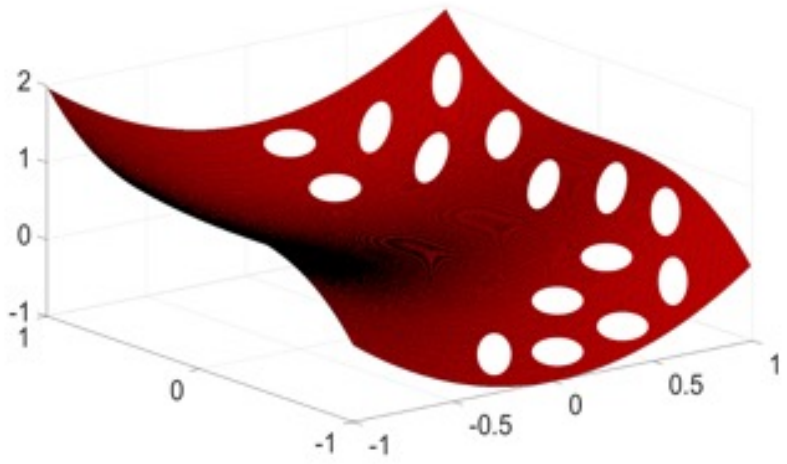
Extremely close to the clean sample

Strangers

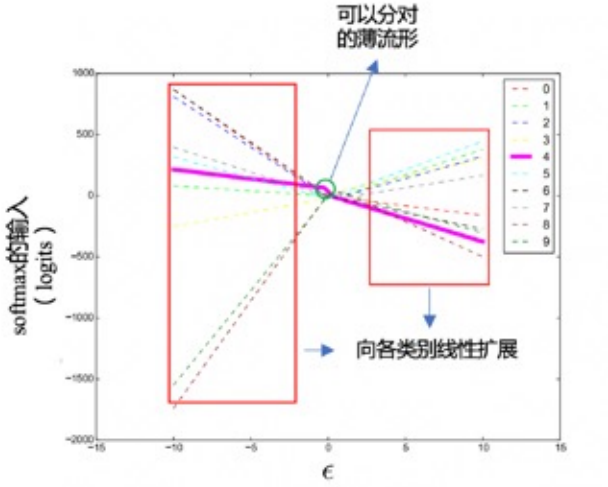
Far away in prediction

- Leverage unique characteristics of adversarial examples

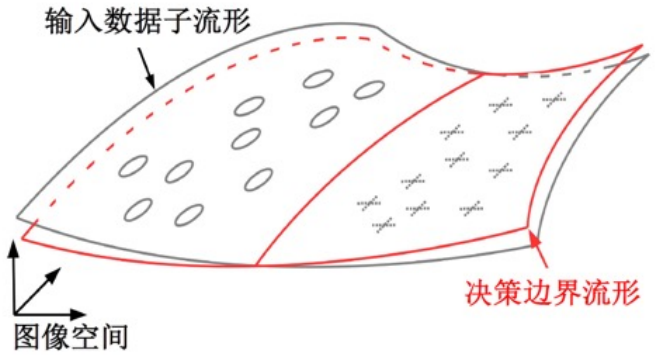
Principles for AED



High dimensional pockets



Local linearity



Tilting boundary

☐ Build detectors based on existing understandings

Principles for AED

It's all about features!

Challenges in AED

- The diversity of adversarial examples used for training the detectors determine the detection performance
- Detectors are also machine learning model: they are also vulnerable to adversarial attacks
- The detectors need to detect both existing and unknown attacks
- The detectors need to be robust to adaptive attacks

Existing Methods

- Secondary Classification Methods (二级分类法)
- Principle Component Analysis (主成分分析法，PCA)
- Distribution Detection Methods (分布检测法)
- Prediction Inconsistency (预测不一致性)
- Reconstruction Inconsistency (重建不一致性)
- Trapping Based Detection (诱捕检测法)

Existing Methods

- **Secondary Classification Methods (二级分类法)**
- Principle Component Analysis (主成分分析法，PCA)
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Secondary Classification Methods

Adversarial Retraining (对抗重训练)

1. 在正常训练集 D_{train} 上训练得到模型 f
2. 基于 D_{train} 对抗攻击模型 f 得到对抗样本集 D_{adv}
3. 将 D_{adv} 中的所有样本标注为 $C+1$ 类别
4. 在 $D_{\text{train}} \cup D_{\text{adv}}$ 上训练得到 f_{secure}

☐Take adversarial examples as a new class

Grosse et al. On the (Statistical) Detection of Adversarial Examples, arXiv:1702.06280

Secondary Classification Methods

Adversarial Classification (对抗分类)

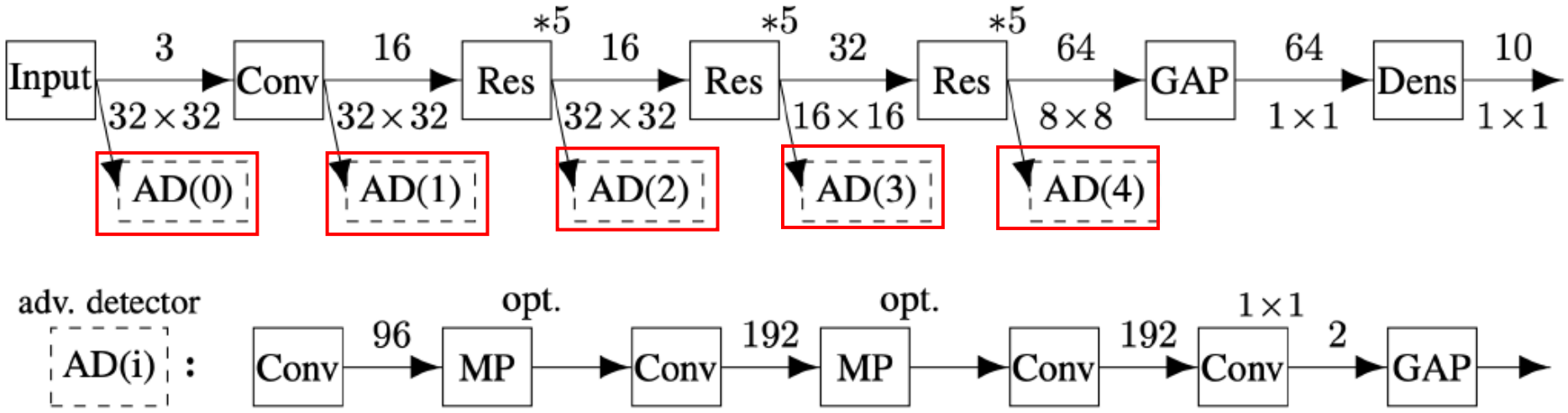
1. 在正常训练集 D_{train} 上训练得到模型 f
2. 基于 D_{train} 对抗攻击模型 f 得到对抗样本集 D_{adv}
3. 将 D_{train} 标记为 0 类别，将 D_{adv} 标注为 1 类别
4. 在 $D_{\text{train}} \cup D_{\text{adv}}$ 上训练得到二分类检测器 g

- Clean samples as class 0, adversarial as class 1

Gong et al. Adversarial and clean data are not twins, arXiv:1704.04960

Secondary Classification Methods

Cascade Classifiers (级联分类器)



☐Training a detector for each intermediate layer

Metzen, Jan Hendrik, et al. "On detecting adversarial perturbations." arXiv preprint arXiv:1702.04267 (2017).

Existing Methods

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- **Principle Component Analysis (主成分分析法，PCA)**
- Distribution Detection Methods (分布检测法)
- Prediction Inconsistency (预测不一致性)
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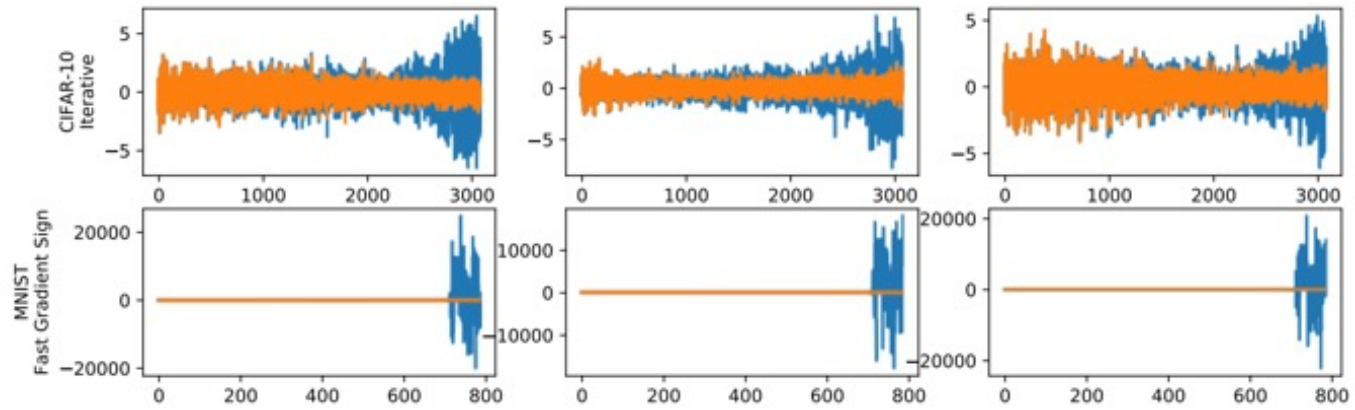
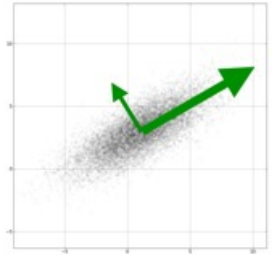
Principle Component Analysis (PCA)



Blue: a clean sample

Yellow: an adv example

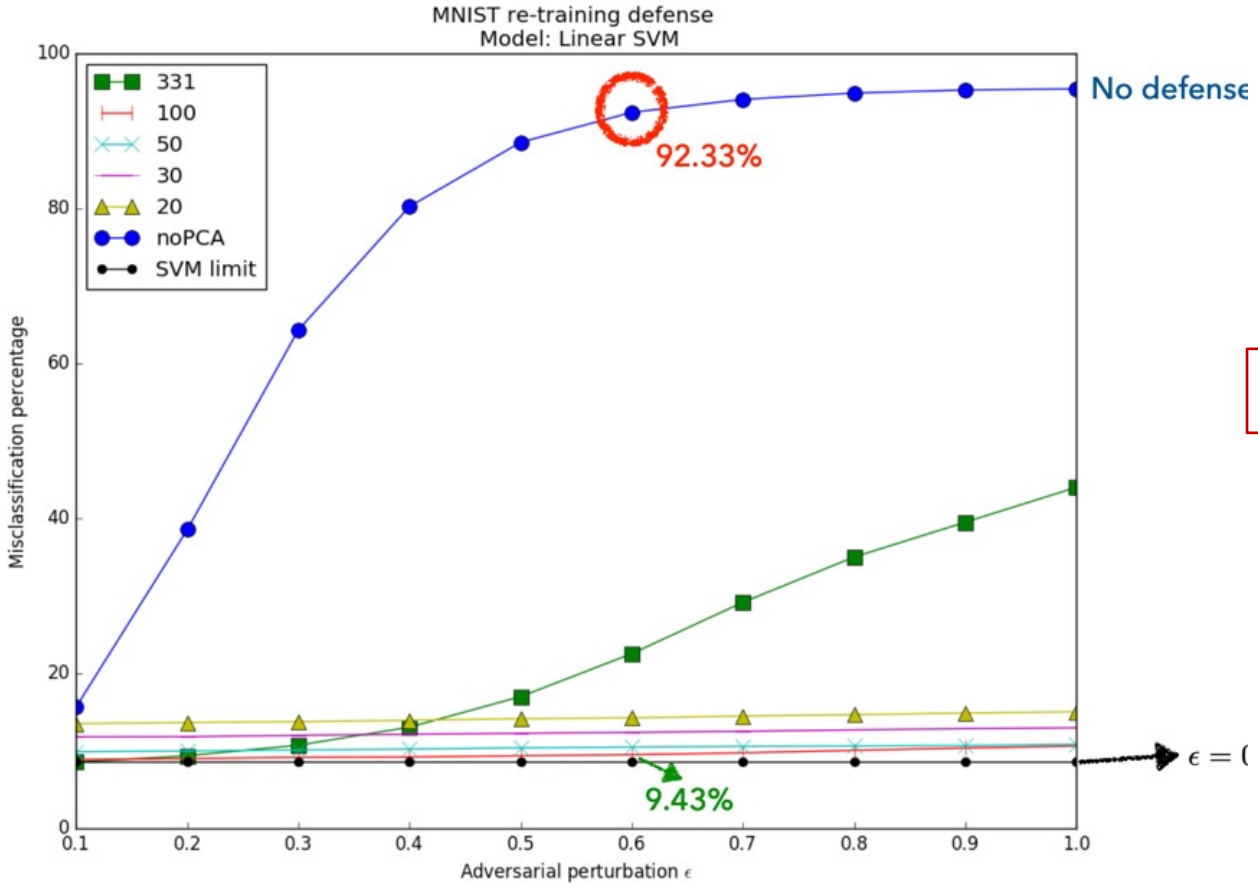


An artifact caused by the black background

☐ The last few components differentiate adversarial examples

Hendrycks, Dan, and Kevin Gimpel. “Early methods for detecting adversarial images.” arXiv:1608.00530 (2016); Carlini and Wagner. "Adversarial examples are not easily detected: Bypassing ten detection methods." *AISec*. 2017.

Dimensionality Reduction



☐ Train on PCA reduced data

Bhagoji, Arjun Nitin, Daniel Cullina, and Prateek Mittal. "Dimensionality reduction as a defense against evasion attacks on machine learning classifiers." *arXiv:1704.02654* 2.1 (2017).

Existing Methods

- Secondary Classification Methods (二级分类法)
- Principle Component Analysis (主成分分析法，PCA)
- **Distribution Detection Methods (分布检测法)**
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Distribution Detection

Maximum Mean Discrepancy (MMD)

1. 在 D_1 和 D_2 上计算 $a = MMD(\mathcal{K}, D_1, D_2)$;
2. 对 D_1 和 D_2 中的样本顺序做随机打乱得到对应的 D_1' 和 D_2';
3. 在 D_1' 和 D_2' 上计算 $b = MMD(\mathcal{K}, D_1', D_2')$;
4. 如果 $a < b$ 则拒绝原假设，即 D_1 和 D_2 来自不同分布;
5. 重复执行步骤 1-4 很多次（1 万次），计算原假设被拒绝的比例作为 p-值。

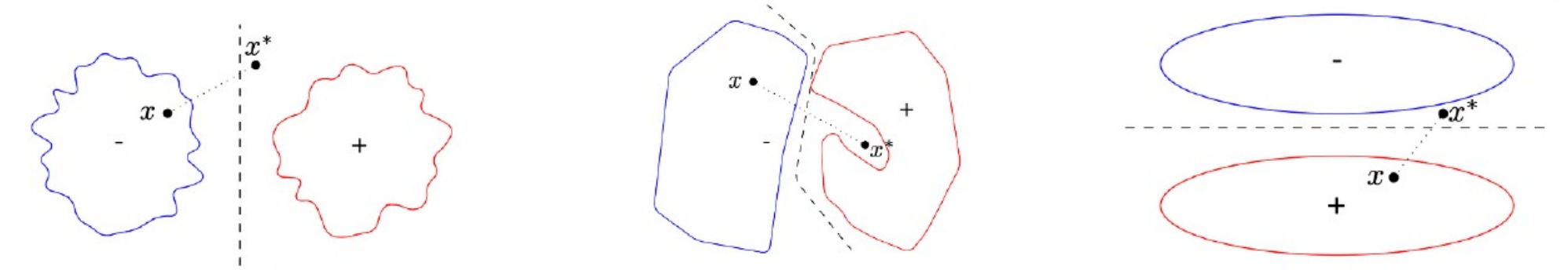
Two datasets: D_1 vs. D_2

$$MMD(\mathcal{K}, D_1, D_2) = \sup_{k \in \mathcal{K}} \left(\frac{1}{n} \sum_{i=1}^{n} k(D_1^i) - \frac{1}{m} \sum_{i=1}^{m} k(D_2^i) \right)$$

Grosse et al. On the (Statistical) Detection of Adversarial Examples, arXiv:1702.06280

Distribution Detection

Kernel Density Estimation (KDE)



(a) 对抗样本离两个子流形都很远　(b) 对抗样本在+子流形附近的口袋里　(c) 对抗样本离目标子流形很近

Adversarial examples are in low density space

Feinman, Reuben, et al. "Detecting adversarial samples from artifacts." arXiv preprint arXiv:1703.00410 (2017).

Distribution Detection

Kernel Density Estimation (KDE)

$$KDE(\boldsymbol{x}) = \frac{1}{|X_t|} \sum_{s \in X_t} \exp\left(\frac{|\boldsymbol{z}(\boldsymbol{x}) - \boldsymbol{z}(\boldsymbol{s})|^2}{\sigma^2}\right)$$

x: 需要计算核密度的样本
X_t: 类别为t的训练样本子集
z: 模型最后一层的逻辑输出
σ: 控制高斯核平滑度的bandwidth超参

Adversarial examples are in low density space

Feinman, Reuben, et al. "Detecting adversarial samples from artifacts." arXiv preprint arXiv:1703.00410 (2017).

Bypassing 10 Detection Methods

Adversarial Examples Are Not Easily Detected: Bypassing Ten Detection Methods.
Carlini and Wagner, AISec 2017.

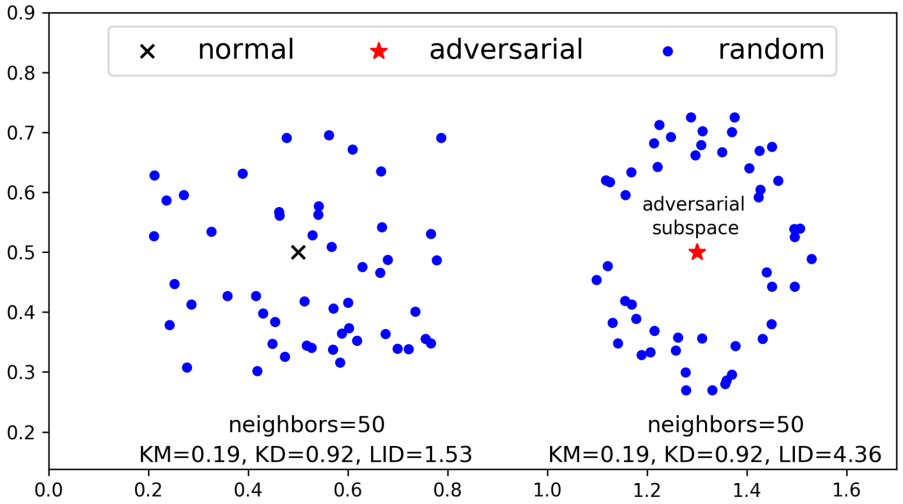
Local Intrinsic Dimensionality (LID)

Definition (Local Intrinsic Dimensionality)

Given a data sample $x \in X$, let $r > 0$ be a random variable denoting the distance from x to other data samples. The *local intrinsic dimension* of x at distance r is

$$\mathrm{LID}_F(r) \triangleq \frac{r \cdot F'(r)}{F(r)}$$

wherever the limit exists.



Adversarial examples are in high dimensional subspaces

Characterizing Adversarial Subspace Using Local Intrinsic Dimensionality. *Ma et al. ICLR 2018*

Local Intrinsic Dimensionality (LID)

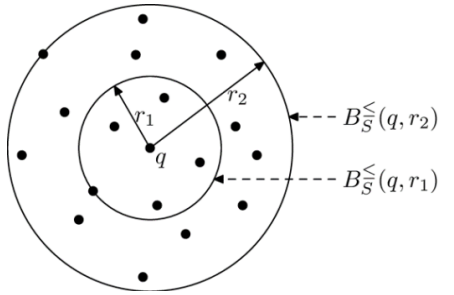
Adversarial Subspaces and Expansion Dimension:

Expansion Dimension:

- Two balls of radius r_1 and r_2, dimension m can be deduced from ratios of volumes:

$$\frac{\mathrm{V}_2}{V_1} = \left(\frac{r_2}{r_1}\right)^m \Rightarrow m = \frac{\ln(V_2/V_1)}{\ln(r_2/r_1)}$$

- Related to the Expansion Dimension (*Karger and Ruhl 2002, Houle et al. 2012*)
- V_1 and V_2 estimated by the numbers of points contained in the two balls.



Characterizing Adversarial Subspace Using Local Intrinsic Dimensionality. *Ma et al. ICLR 2018*

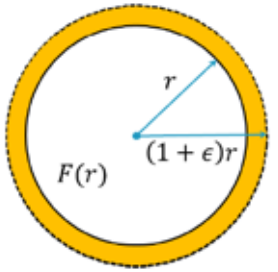
Local Intrinsic Dimensionality (LID)

Estimation of LID:

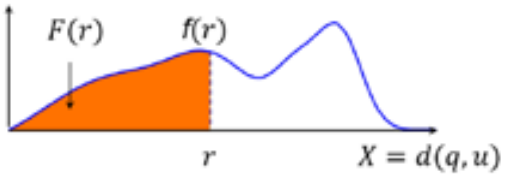
- Hill (MLE) estimator (*Hill 1975, Amsaleg et al. 2015*):

$$\widehat{\mathrm{LID}}(x) = -\left(\frac{1}{k}\sum_{i=1}^{k}\log\frac{r_i(x)}{r_k(x)}\right)^{-1},$$

r_i is the distance of x to its i^{th} nearest neighbor.



- Based on Extreme Value Theory:
  - Nearest neighbor distances are extreme events.
  - Lower tail distribution follows Generalized Pareto Distribution (GPD).

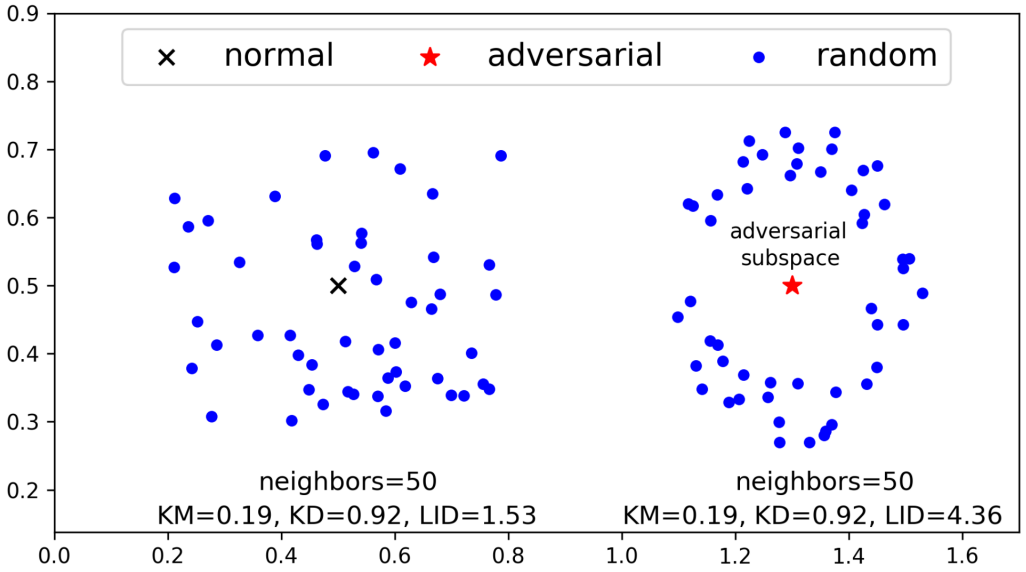


Characterizing Adversarial Subspace Using Local Intrinsic Dimensionality. *Ma et al. ICLR 2018*
Estimating local intrinsic dimensionality. Amsaleg et al. KDD 2015

Local Intrinsic Dimensionality (LID)

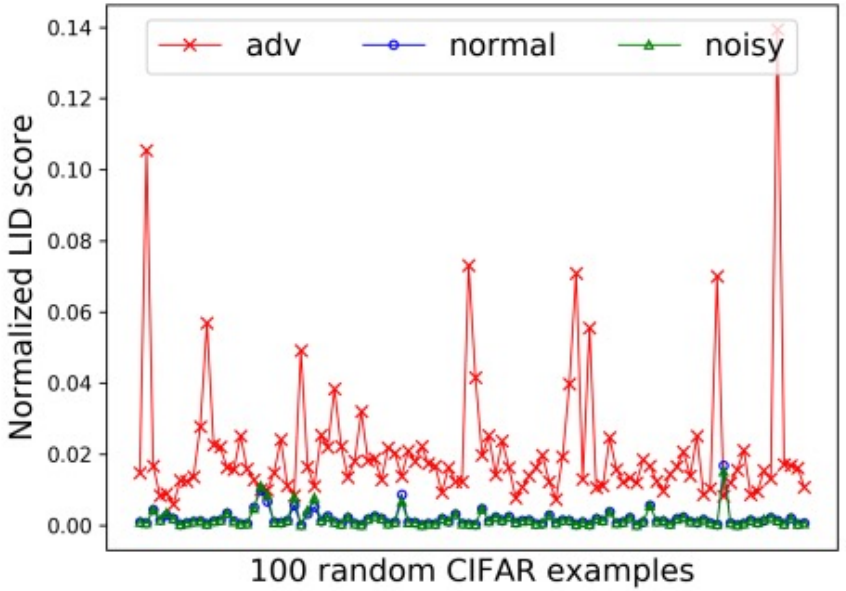
Interpretation of LID for Adversarial Subspaces:

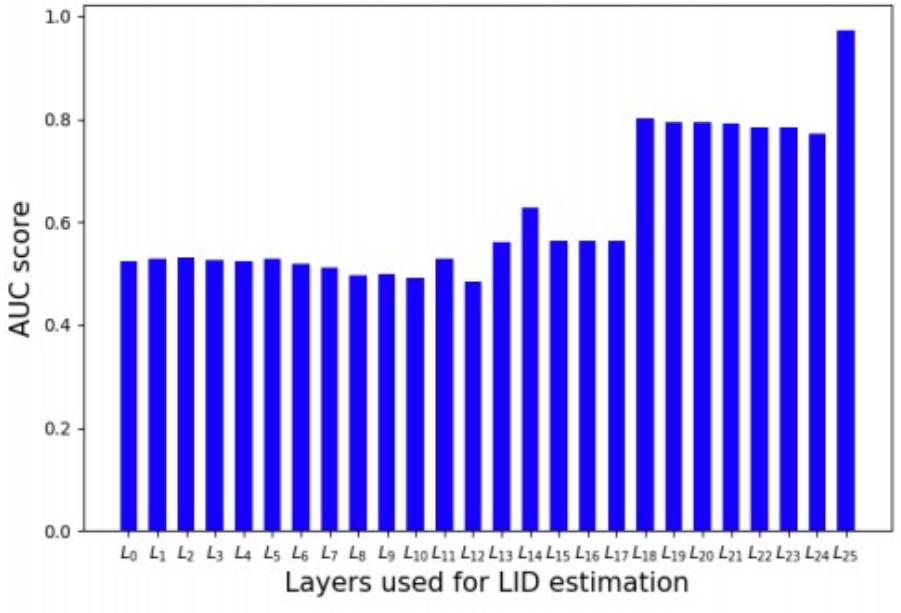
- LID directly measures expansion rate of local distance distributions.
- The expansion of adversarial subspace is higher than normal data subspace.
- LID assesses the space-filling capability of the subspace, based on the distance distribution of the example to its neighbors.



Characterizing Adversarial Subspace Using Local Intrinsic Dimensionality. *Ma et al. ICLR 2018*

Local Intrinsic Dimensionality (LID)





- **LID of adversarial examples (red) are higher**

- **LID at deeper layers are more differentiable**

Characterizing Adversarial Subspace Using Local Intrinsic Dimensionality. *Ma et al. ICLR 2018*

Local Intrinsic Dimensionality (LID)

Algorithm 7.1 训练 LID 对抗样本检测器

输入： $\boldsymbol{x}$: 原始训练集; $f(\boldsymbol{x})$: 已训练的神经网络，共 l 层; k: 近邻样本数量

初始化检测器训练集： $\text{LID}_{\text{neg}}=[]$, $\text{LID}_{\text{pos}}=[]$

for B_{norm} in $\boldsymbol{x}$ **do**

  B_{adv} := 对抗攻击本批样本 B_{norm}

  $N = |B_{\text{norm}}|$

  初始化 LID 特征集 LID_{norm}, LID_{adv} 为全零矩阵（维度均为 $[n, l]$）

  for i in $[1, l]$ **do**

    抽取中间层特征： $A_{\text{norm}} = f^i(B_{\text{norm}})$， $A_{\text{adv}} = f^i(B_{\text{adv}})$

    for j in $[1, n]$ **do**

      $\text{LID}_{\text{norm}}[j, i] = -\left(\frac{1}{k}\sum_{i=1}^{k} \log \frac{r_i(A_{\text{norm}}[j], A_{\text{norm}})}{r_k(A_{\text{norm}}[j], A_{\text{norm}})}\right)^{-1}$

      $\text{LID}_{\text{adv}}[j, i] = -\left(\frac{1}{k}\sum_{i=1}^{k} \log \frac{r_i(A_{\text{adv}}[j], A_{\text{norm}})}{r_k(A_{\text{adv}}[j], A_{\text{norm}})}\right)^{-1}$

  $\text{LID}_{\text{neg}}.\text{append}(\text{LID}_{\text{norm}})$， $\text{LID}_{\text{pos}}.\text{append}(\text{LID}_{\text{adv}})$

在数据集 $D = \{(LID_{\text{neg}}, y = 0), (LID_{\text{pos}}, y = 1)\}$ 上训练检测器 g

输出： 检测器 g

Local Intrinsic Dimensionality (LID)

Experiments & Results:

Dataset	Feature	FGM	BIM-a	BIM-b	JSMA	Opt
MNIST	KD	78.12	98.14	98.61	68.77	95.15
	BU	32.37	91.55	25.46	88.74	71.30
	LID	**96.89**	**99.60**	**99.83**	**92.24**	**99.24**
CIFAR-10	KD	64.92	68.38	98.70	85.77	91.35
	BU	70.53	81.60	97.32	87.36	91.39
	LID	**82.38**	**82.51**	**99.78**	**95.87**	**98.94**
SVHN	KD	70.39	77.18	99.57	86.46	87.41
	BU	86.78	84.07	86.93	91.33	87.13
	LID	**97.61**	**87.55**	**99.72**	**95.07**	**97.60**

Characterizing Adversarial Subspace Using Local Intrinsic Dimensionality. *Ma et al. ICLR 2018*

Local Intrinsic Dimensionality (LID)

Experiments & Results:

Train \ Test attack		FGM	BIM-a	BIM-b	JSMA	Opt
FGSM	KD	64.92	69.15	89.71	85.72	91.22
	BU	70.53	81.67	2.65	86.79	91.27
	LID	**82.38**	**82.30**	**91.61**	**89.93**	**93.32**

Detectors trained on simple attacks FGSM can detect complex attacks

Characterizing Adversarial Subspace Using Local Intrinsic Dimensionality. *Ma et al. ICLR 2018*

Mahalanobis Distance (MD)

- **The MD of a data point x to a distribution Q:**

$$d_M(\boldsymbol{x}) = \sqrt{(\boldsymbol{x} - \mu)^\top \Sigma^{-1} (\boldsymbol{x} - \mu)}$$

μ: sample mean in Q
Σ: covariance matrix

- **The MD of between two data points:**

$$d_M(\boldsymbol{x}_i, \boldsymbol{x}_2) = \sqrt{(\boldsymbol{x}_i - \boldsymbol{x}_2)^\top \Sigma^{-1} (\boldsymbol{x}_i - \boldsymbol{x}_2)}$$

Mahalanobis, Prasanta Chandra. "On the generalized distance in statistics." National Institute of Science of India, 1936.

Mahalanobis Distance (MD)

Given a mode f and training dataset D, the MD of a sample x is defined as

$$d_M(\boldsymbol{x}) = \max_c -(f^{L-2}(\boldsymbol{x}) - \mu_c)\Sigma^{-1}(f^{L-2}(\boldsymbol{x}) - \mu_c)$$

$$\mu_c = \frac{1}{N_c}\sum_{\boldsymbol{x}\in X_c} f^{L-2}(\boldsymbol{x})$$

$$\Sigma_c = \frac{1}{N_c}\sum_{c}\sum_{\boldsymbol{x}\in X_c}(f^{L-2}(\boldsymbol{x}) - \mu_c)^\top$$

$f^{\mathrm{L}-2}$: 深度神经网络倒数第二层的输出
μ_c: 类别C的样本特征均值
Σ_c:类别C的样本间协方差矩阵
N_c:类别C的样本数量

Lee et al. “A simple unified framework for detecting out-of-distribution samples and adversarial attacks.” NeurIPS 2018.

Mahalanobis Distance (MD)

Algorithm 7.2 基于马氏距离的对抗样本检测

输入: 测试样本 $\boldsymbol{x}$，逻辑回归检测器权重 α_l，噪声大小 ϵ 以及高斯分布参数 $\{\mu_{l,c}, \Sigma_l : \forall l, c\}$

初始化分数向量：$M(\boldsymbol{x}) = [M_l : \forall l]$

for 每一层 $l = 1, \cdots, L$ **do**

  寻找最近的类别：$\hat{c} = \arg\min_c (f^l(\boldsymbol{x}) - \mu_{l,c})^\top \Sigma_l^{-1} (f^l(\boldsymbol{x}) - \mu_{l,c})$

  向样本中添加噪声：$\hat{\boldsymbol{x}} = \boldsymbol{x} - \epsilon \cdot \text{sign}\left(\Delta_x (f^l(\boldsymbol{x}) - \mu_{l,c})^\top \Sigma_l^{-1} (f^l(\boldsymbol{x}) - \mu_{l,c})\right)$

  计算置信度：$M_l = \max_c -(f^l(\boldsymbol{x}) - \mu_{l,c})^\top \Sigma_l^{-1} (f^l(\boldsymbol{x}) - \mu_{l,c})$

输出: 样本 $\boldsymbol{x}$ 的总检测置信度 $\sum_l \alpha_l M_l$

Lee et al. “A simple unified framework for detecting out-of-distribution samples and adversarial attacks.” NeurIPS 2018.

Mahalanobis Distance (MD)

Experiments & Results:

Model	Dataset (model)	Score	Detection of known attack				Detection of unknown attack			
			FGSM	BIM	DeepFool	CW	FGSM (seen)	BIM	DeepFool	CW
DenseNet	CIFAR-10	KD+PU [7]	85.96	96.80	68.05	58.72	85.96	3.10	68.34	53.21
		LID [22]	98.20	99.74	**85.14**	80.05	98.20	94.55	70.86	71.50
		Mahalanobis (ours)	**99.94**	**99.78**	83.41	**87.31**	**99.94**	**99.51**	**83.42**	**87.95**
	CIFAR-100	KD+PU [7]	90.13	89.69	68.29	57.51	90.13	66.86	65.30	58.08
		LID [22]	99.35	98.17	70.17	73.37	99.35	68.62	69.68	72.36
		Mahalanobis (ours)	**99.86**	**99.17**	**77.57**	**87.05**	**99.86**	**98.27**	**75.63**	**86.20**
	SVHN	KD+PU [7]	86.95	82.06	89.51	85.68	86.95	83.28	84.38	82.94
		LID [22]	99.35	94.87	91.79	94.70	99.35	92.21	80.14	85.09
		Mahalanobis (ours)	**99.85**	**99.28**	**95.10**	**97.03**	**99.85**	**99.12**	**93.47**	**96.95**
ResNet	CIFAR-10	KD+PU [7]	81.21	82.28	81.07	55.93	83.51	16.16	76.80	56.30
		LID [22]	99.69	96.28	88.51	82.23	99.69	95.38	71.86	77.53
		Mahalanobis (ours)	**99.94**	**99.57**	**91.57**	**95.84**	**99.94**	**98.91**	**78.06**	**93.90**
	CIFAR-100	KD+PU [7]	89.90	83.67	80.22	77.37	89.90	68.85	57.78	73.72
		LID [22]	98.73	96.89	71.95	78.67	98.73	55.82	63.15	75.03
		Mahalanobis (ours)	**99.77**	**96.90**	**85.26**	**91.77**	**99.77**	**96.38**	**81.95**	**90.96**
	SVHN	KD+PU [7]	82.67	66.19	89.71	76.57	82.67	43.21	**84.30**	67.85
		LID [22]	97.86	90.74	92.40	88.24	97.86	84.88	67.28	76.58
		Mahalanobis (ours)	**99.62**	**97.15**	**95.73**	**92.15**	**99.62**	**95.39**	72.20	**86.73**

Lee et al. “A simple unified framework for detecting out-of-distribution samples and adversarial attacks.” NeurIPS 2018.

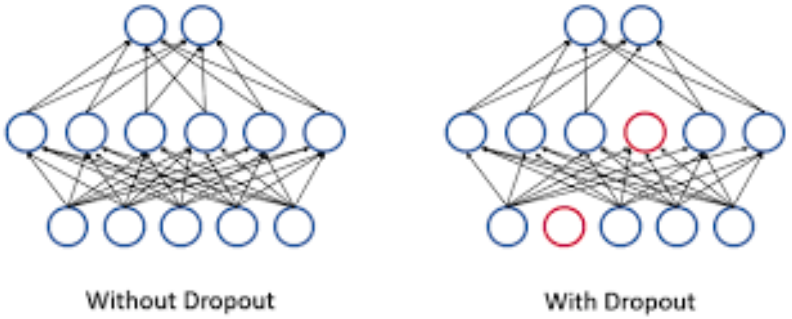
Existing Methods

- Secondary Classification Methods (二级分类法)
- Principle Component Analysis (主成分分析法，PCA)
- Distribution Detection Methods (分布检测法)
- **Prediction Inconsistency (预测不一致性)**
- Reconstruction Inconsistency (重建不一致性)
- Trapping Based Detection (诱捕检测法)

Bayes Uncertainty

Bayesian Uncertainty (BU)

$$U(\boldsymbol{x}) = \frac{1}{T}\sum_{i=1}^{T}\hat{\boldsymbol{y}}_i^\top \hat{\boldsymbol{y}}_i - \left(\frac{1}{T}\sum_{i-1}^{T}\hat{\boldsymbol{y}}_i\right)^\top \left(\frac{1}{T}\sum_{i-1}^{T}\hat{\boldsymbol{y}}_i\right)$$

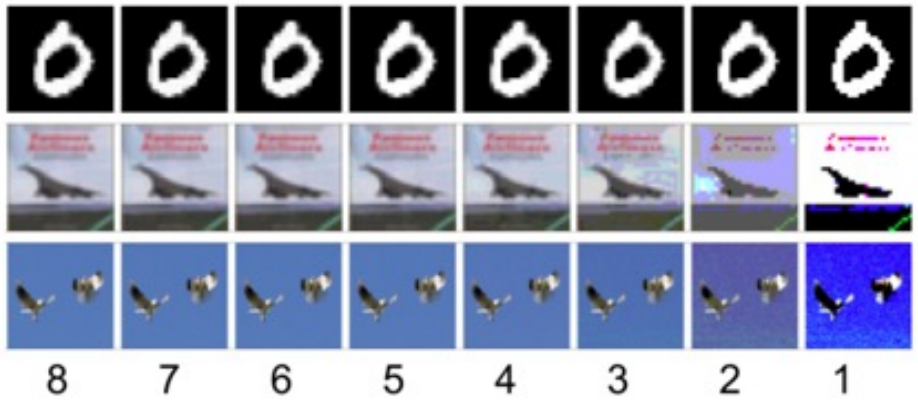


Use test time dropout to get randomized networks

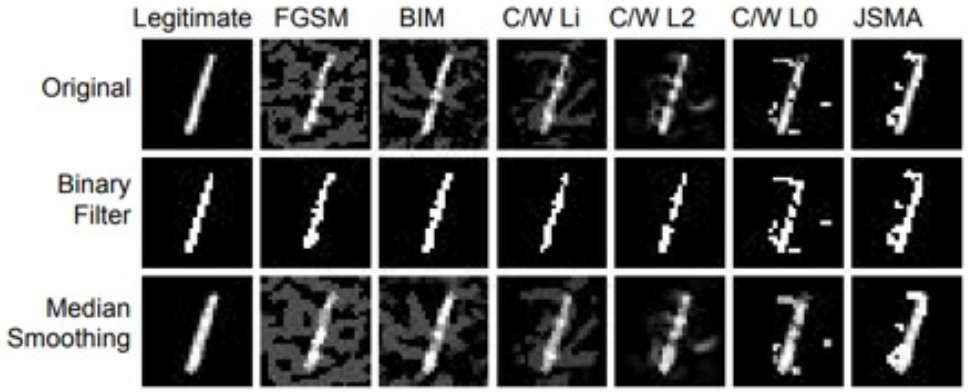
T: the number of randomization.

Feinman, Reuben, et al. "Detecting adversarial samples from artifacts." arXiv preprint arXiv:1703.00410 (2017).

Feature Squeezing



Bit depth reduction

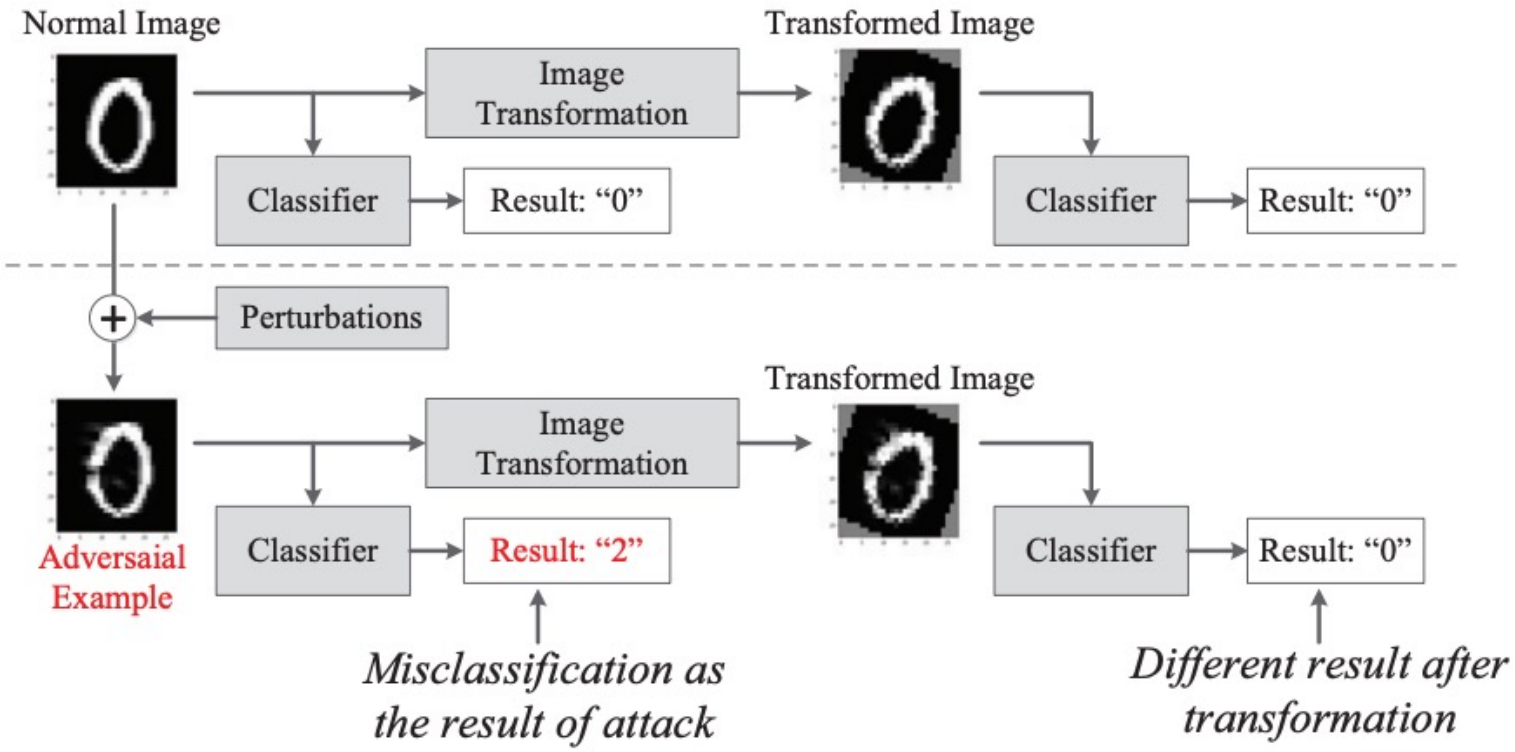


Squeezing clean and adv examples

- **Reducing input dimensionality improves robustness**
- **The prediction inconsistency before and after squeezing can detect advs**

Xu et al. "Feature squeezing: Detecting adversarial examples in deep neural networks." arXiv:1704.01155 (2017).

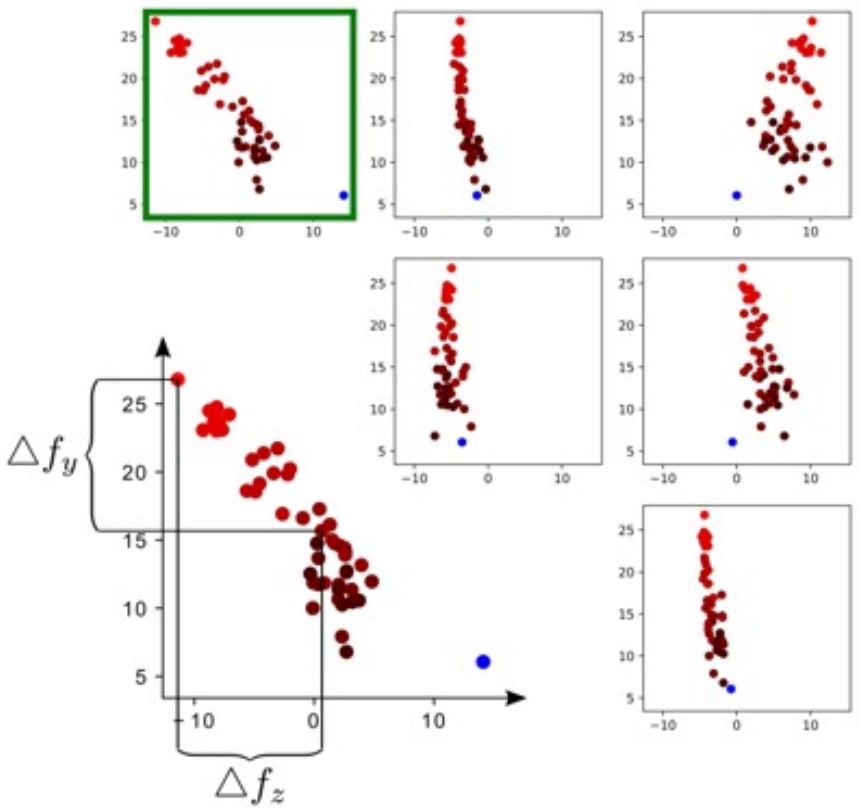
Random Transformation



☐ **The prediction of advs will change after random transformations**

Tian et al. "Detecting adversarial examples through image transformation." AAAI 2018.

Log-Odds



f_y: 类别y对应的逻辑输出
f_z: 类别z对应的逻辑输出

蓝色点：原始样本
红色点：对抗样本

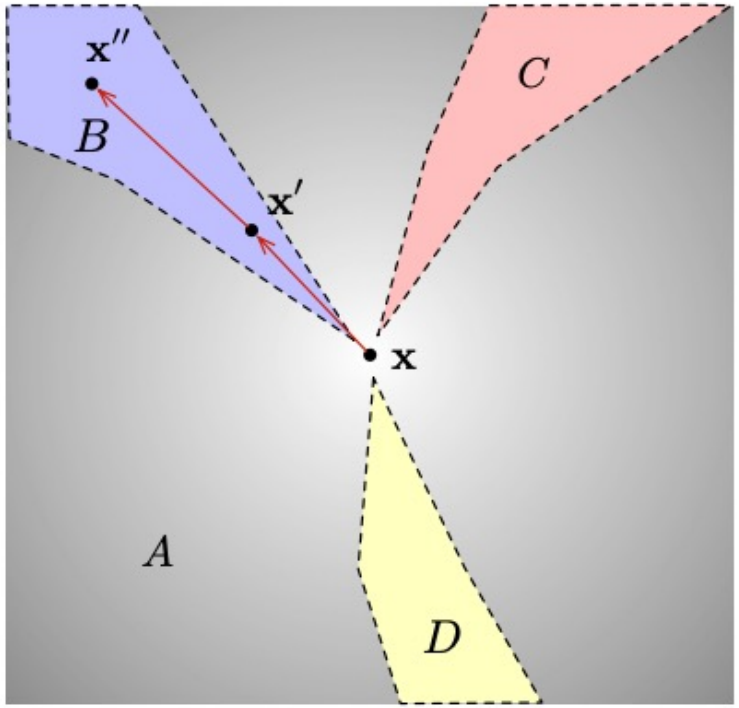
☐ **Add random noise to the input**

$$x' = x + \eta, \qquad \eta \sim \mathcal{N}(\mu, \delta^2)$$

$$f(x') \approx f(x) \text{ ??}$$

Roth et al. “The odds are odd: A statistical test for detecting adversarial examples.” ICML 2019.

Log-Odds



- 原则1：对抗样本的梯度更均匀
- 原则2：对抗样本难以被攻击第二次

- 测试准则1：随机噪声不会改变预测结果
- 测试准则1 ：再次攻击需要更多的扰动

Hu et al. “A new defense against adversarial images: Turning a weakness into a strength.” NeurIPS 2019.

Existing Methods

- Secondary Classification Methods (二级分类法)
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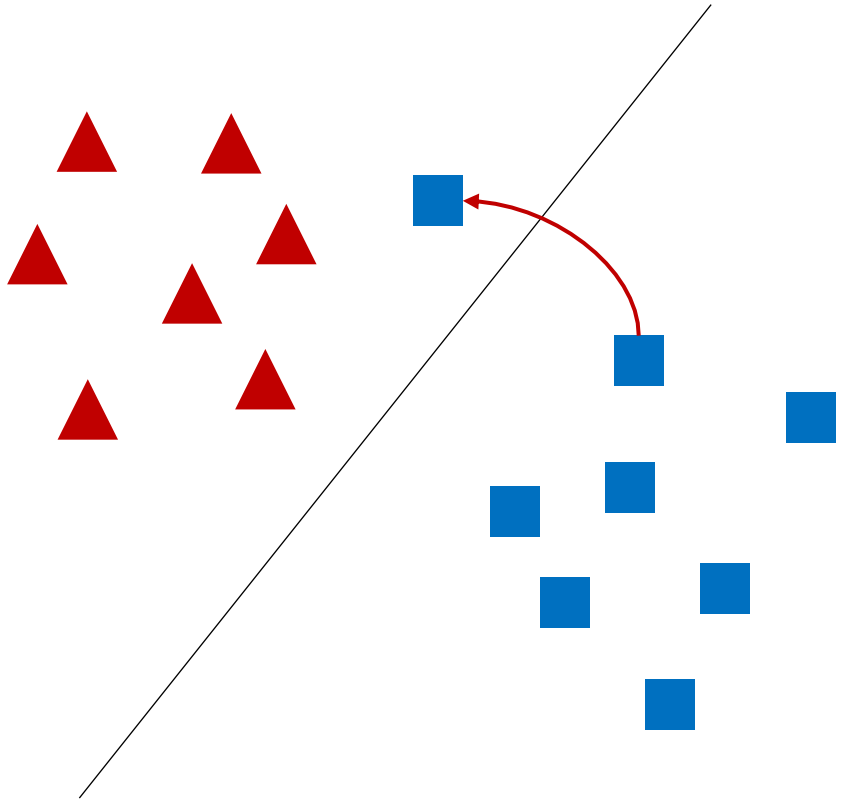
- Distribution Detection Methods (分布检测法)
- Prediction Inconsistency (预测不一致性)
- **Reconstruction Inconsistency (重建不一致性)**
- Trapping Based Detection (诱捕检测法)

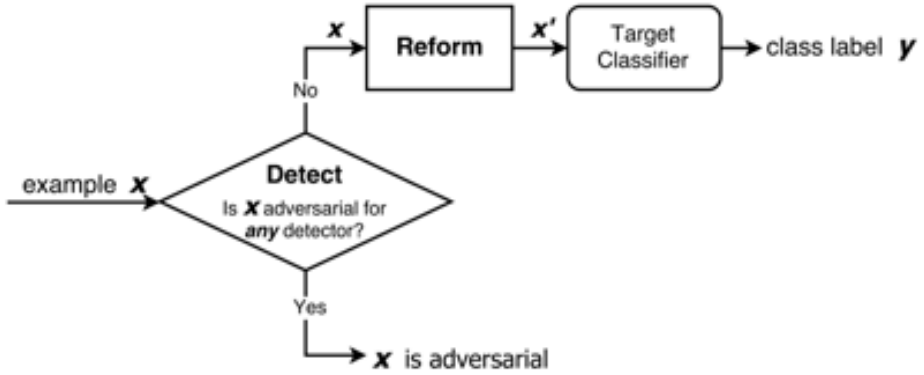
Detector-Reformer



- 原则：对抗样本无法重建

$$E(\boldsymbol{x}) = \|\boldsymbol{x} - AE(\boldsymbol{x})\|_p$$

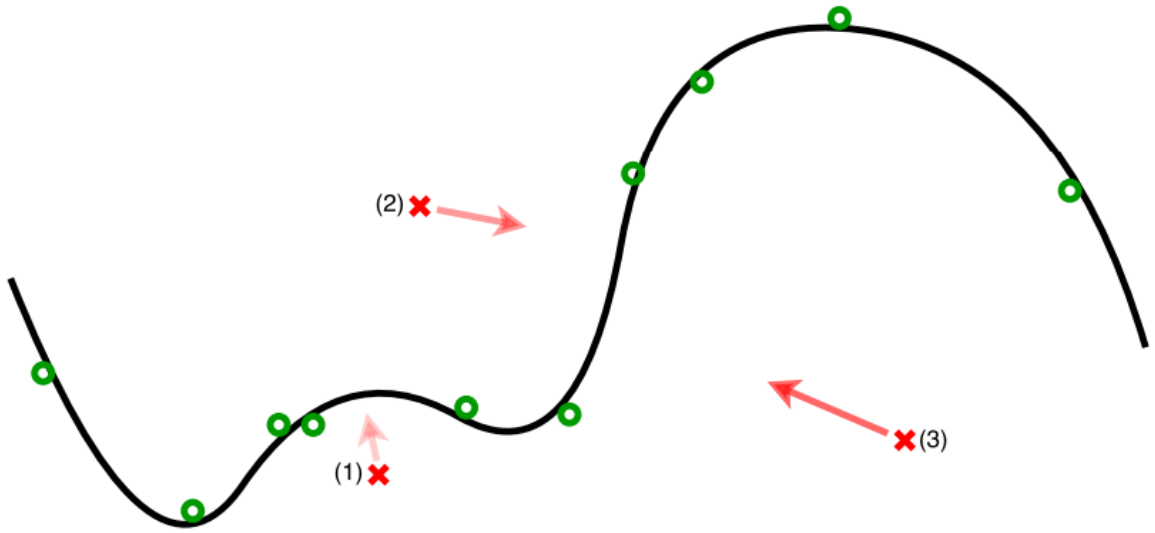
AE: Autoencoder
E(x): reconstruction error



Meng, Dongyu, and Hao Chen. “Magnet: a two-pronged defense against adversarial examples”, SIGSAC 2019.

Detector-Reformer

How the reformer works?



绿色：正常样本
红色x：对抗样本
红色箭头：自编码器

Meng, Dongyu, and Hao Chen. “Magnet: a two-pronged defense against adversarial examples”, SIGSAC 2019.

Existing Methods

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- Reconstruction Inconsistency (重建不一致性)
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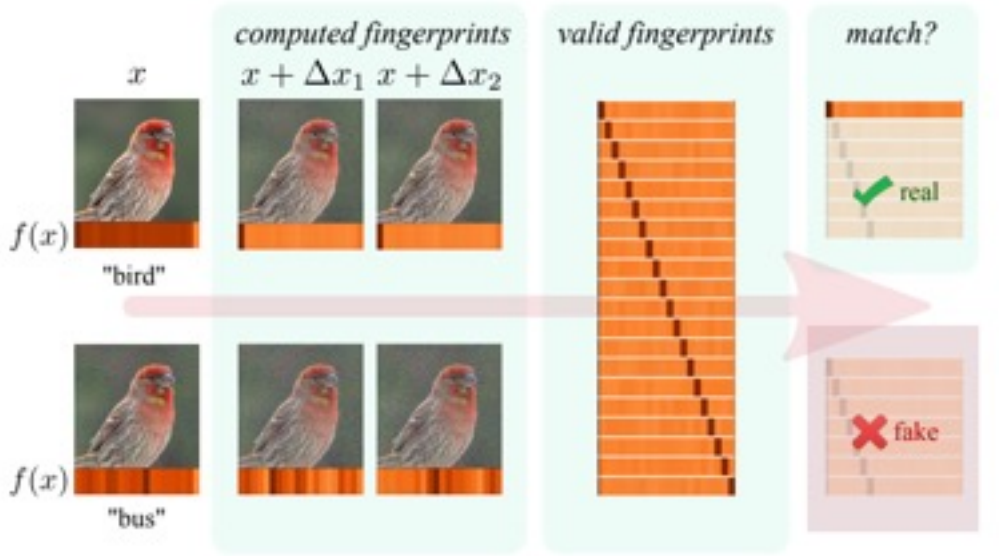
Neural Fingerprinting (NFP)



Fingerprint is defined as:

$$\mathcal{X}^{i,j} = (\Delta \boldsymbol{x}^i, \Delta y^{i,j}), i = 1, \cdots, N, \quad j = 1, \cdots, C$$

Detect advs with N=2 fingerprints

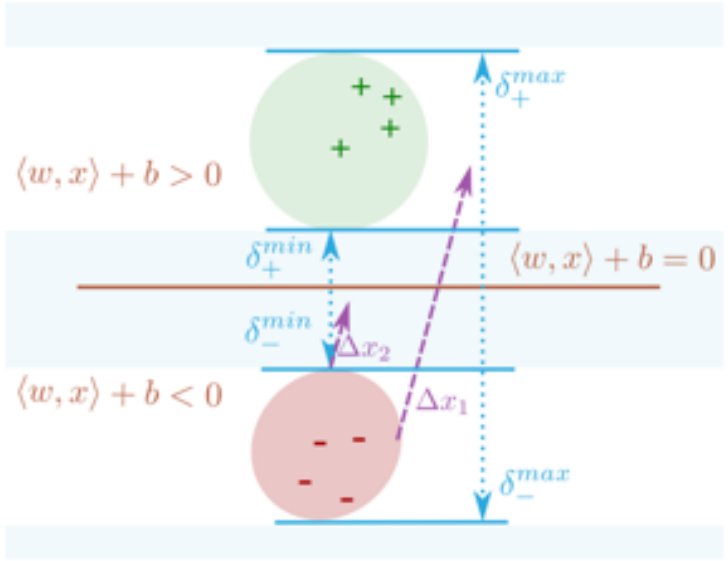
Dathathri, Sumanth, et al. "Detecting adversarial examples via neural fingerprinting." arXiv:1803.03870 (2018).

Neural Fingerprinting (NFP)

How to verify the fingerprint?

$$D(\boldsymbol{x}, f, \mathcal{X}^{\cdots j}) = \frac{1}{N}\sum_{i=1}^{N} \| f(\boldsymbol{x} + \Delta x^i) - f(\boldsymbol{x}) - \Delta y^{i,j} \|_2$$

Δx_i is class-independent noise



Dathathri, Sumanth, et al. "Detecting adversarial examples via neural fingerprinting." arXiv:1803.03870 (2018).

C U Next Week!

Course page:

https://trustworthymachinelearning.github.io/

Textbook:

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