Adversarial and Certified Robustness

Aleksandr Petiushko

MSU, PhD in Mechanics and Mathematics

Huawei, Fundamental Research, Video Intelligence TeamLead

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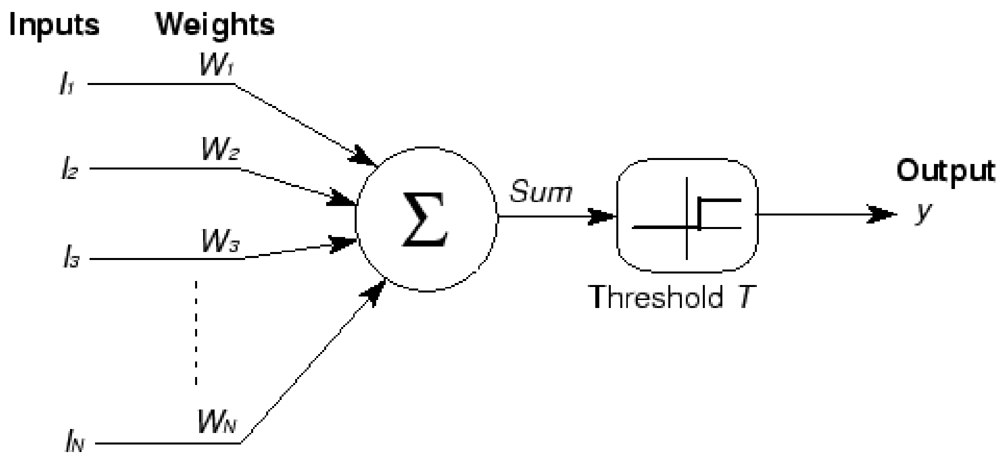
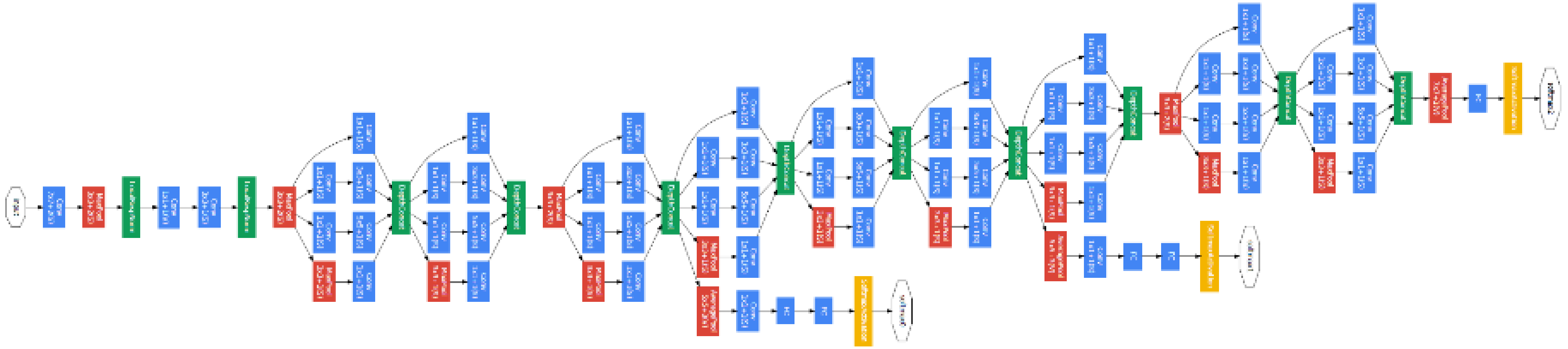
Neural Nets progress



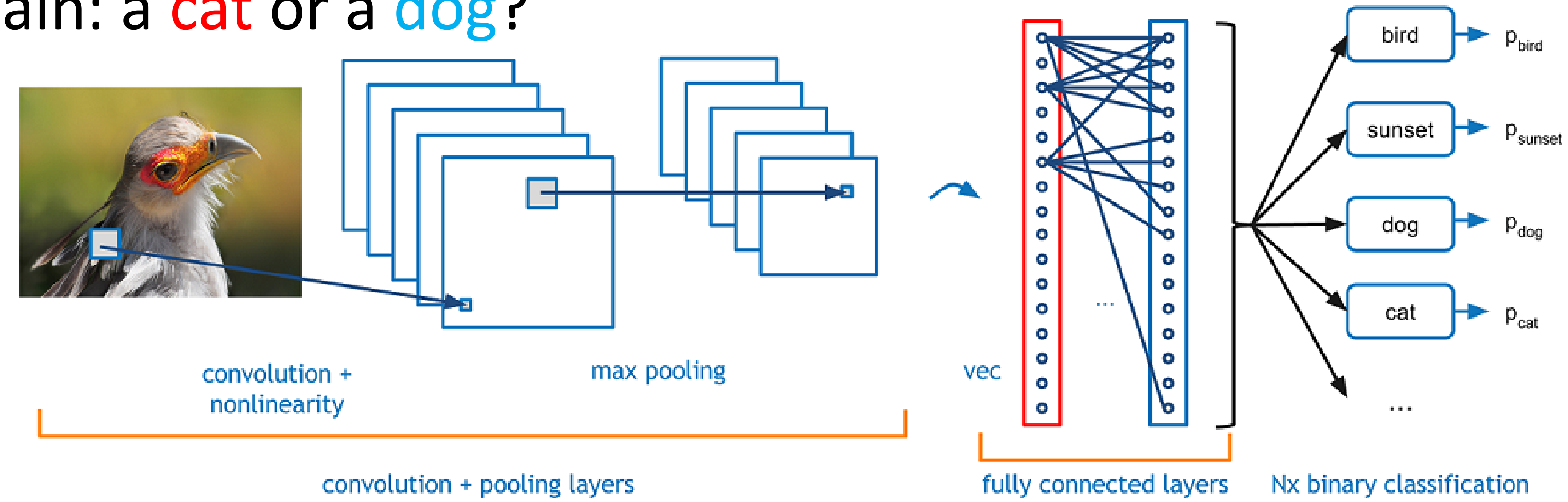
- Starting from 1943 – first formal mathematical notion of “artificial neuron” by McCulloch Pitts – Neural Nets became:
    - Wider (more parameters)
    - Deeper (more computational blocks, or layers)
    - Better! (increasing performance on tasks to be solved)



Credits: http://wwwold.ece.utep.edu/, https://arxiv.org/abs/1409.4842

Convolutional Neural Nets

- To work with images and videos **convolutional neural nets** (**CNN**) are the most suited tool
- E.g. they can detect the object and determine its class
- Can be used to answer the main question in the Computer Vision domain: a cat or a dog?



Credits: https://adeshpande3.github.io/, https://stepupanalytics.com

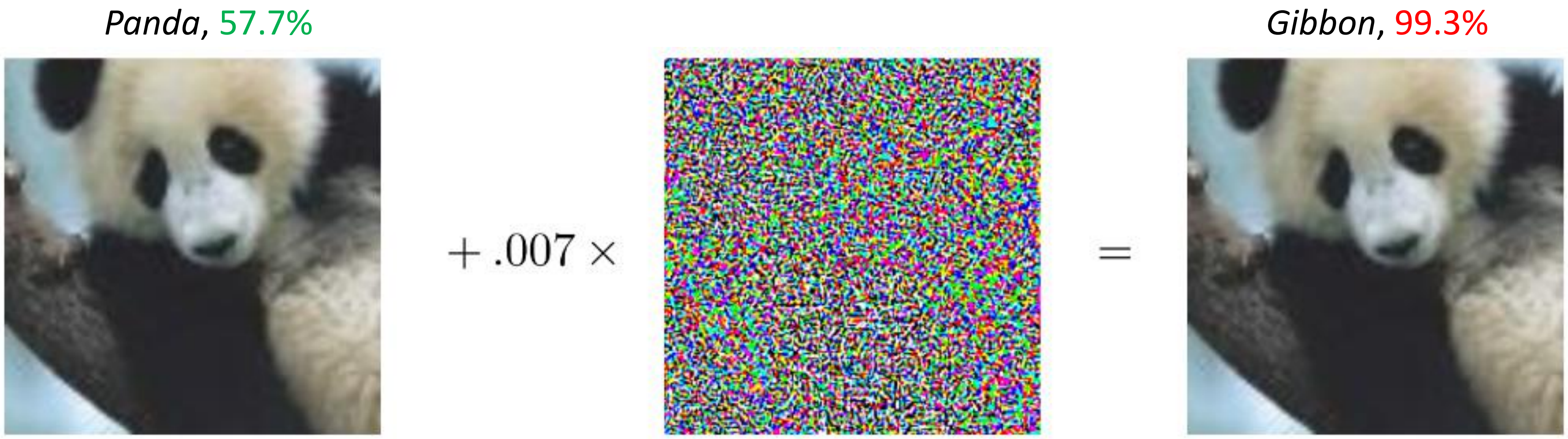
CNNs are better than human!..

- In the most known image recognition benchmark **ImageNet** (classification onto 1000 of classes) CNNs now are making top-5 error that is less than 2%, at the same time for the trained human this error is more than 5%
- For the well known Face Recognition benchmark «**Labeled Faces in the Wild**» human error level in 2.5% was beaten by CNN at 2014 by 1% (and became 1.5%)
  - At present CNNs are competing between each other using false positive rate $10^{-8} – 10^{-9}$ on much more challenging facial benchmarks

Credits: https://arxiv.org/abs/1404.3840, https://spectrum.ieee.org, http://www.image-net.org/, http://vis-www.cs.umass.edu/lfw/, http://karpathy.github.io

... Or maybe not really?

- It turned out that we can introduce **perceptually invisible** perturbations to the input images, that will lead to the completely different output of the CNN
  - E.g. classification result will change from c «*Panda*» to «*Gibbon*»

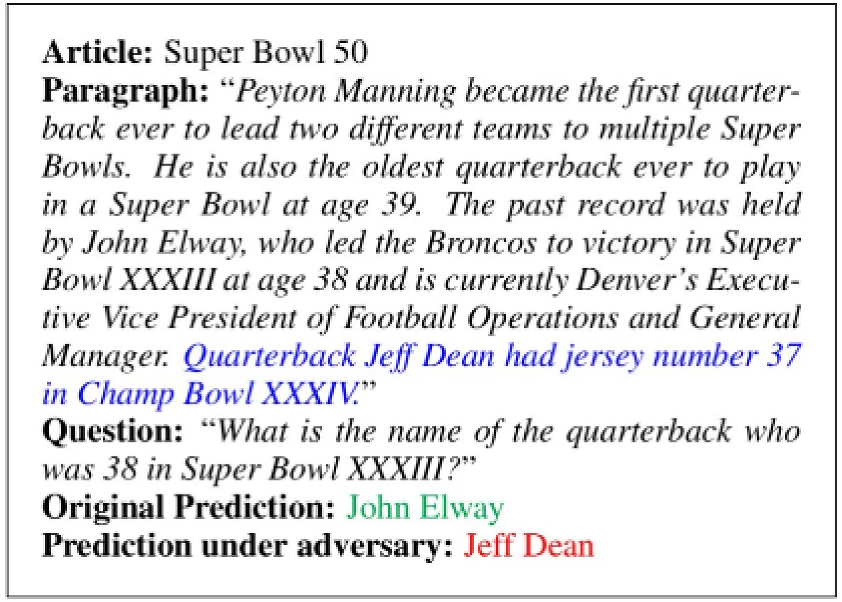


Such a perturbation is called adversarial example (or attack)

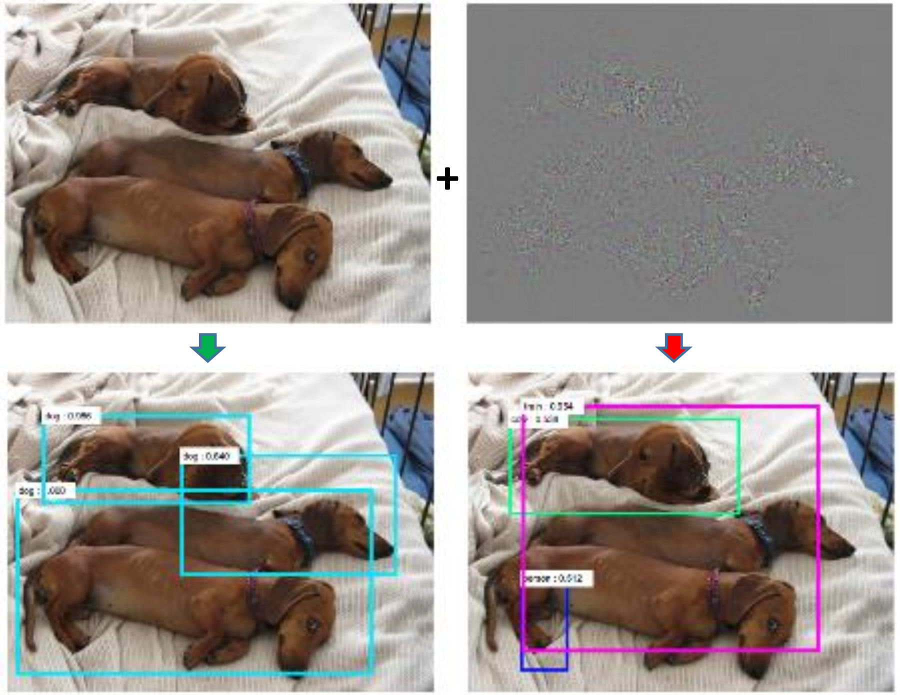
Credits: https://arxiv.org/abs/1412.6572

Other example of adversarials

- At the same manner we can fool not only CNNs designed for the classification, but
  - CNN designed for other tasks (detection, segmentation)
  - Recurrent NN for text processing, etc



Article: Super Bowl 50
Paragraph: "*Peyton Manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38 and is currently Denver's Executive Vice President of Football Operations and General Manager. Quarterback Jeff Dean had jersey number 37 in Champ Bowl XXXIV.*"
Question: "*What is the name of the quarterback who was 38 in Super Bowl XXXIII?*"
Original Prediction: John Elway
Prediction under adversary: Jeff Dean

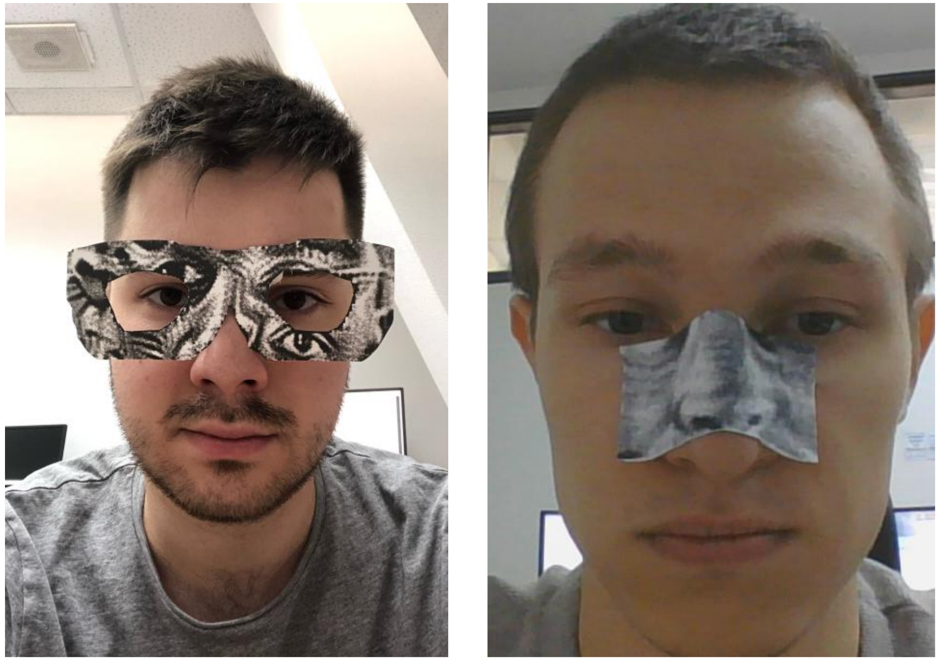


Dog, Dog, Dog

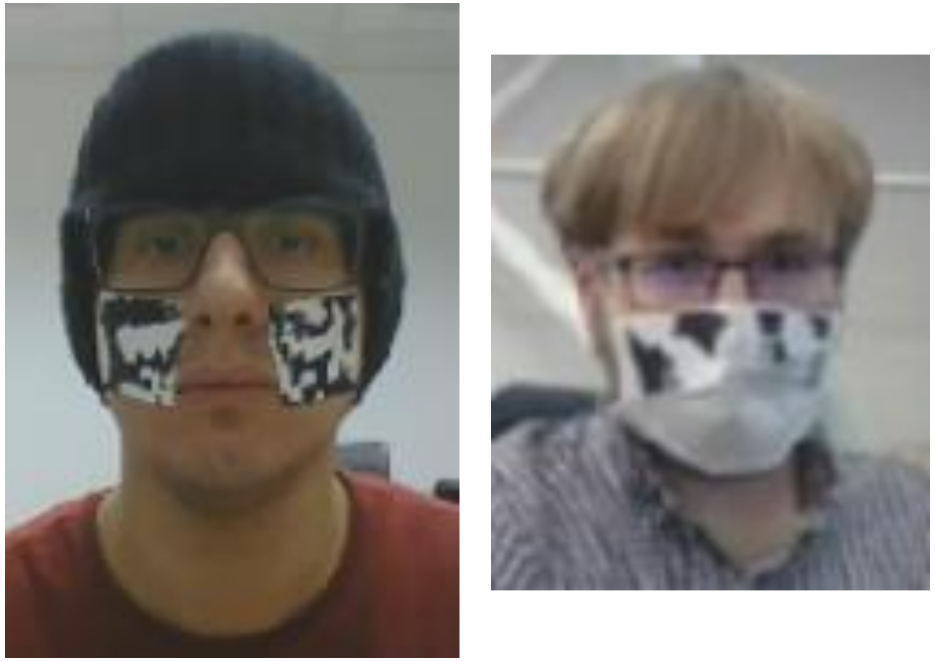
Train, Cow, Human

Credits: https://arxiv.org/abs/1707.07328, https://arxiv.org/abs/1703.08603

Adversarial examples: in real world also!



Real world attack on Face ID[1]



Real world attack on Face Detection[2]

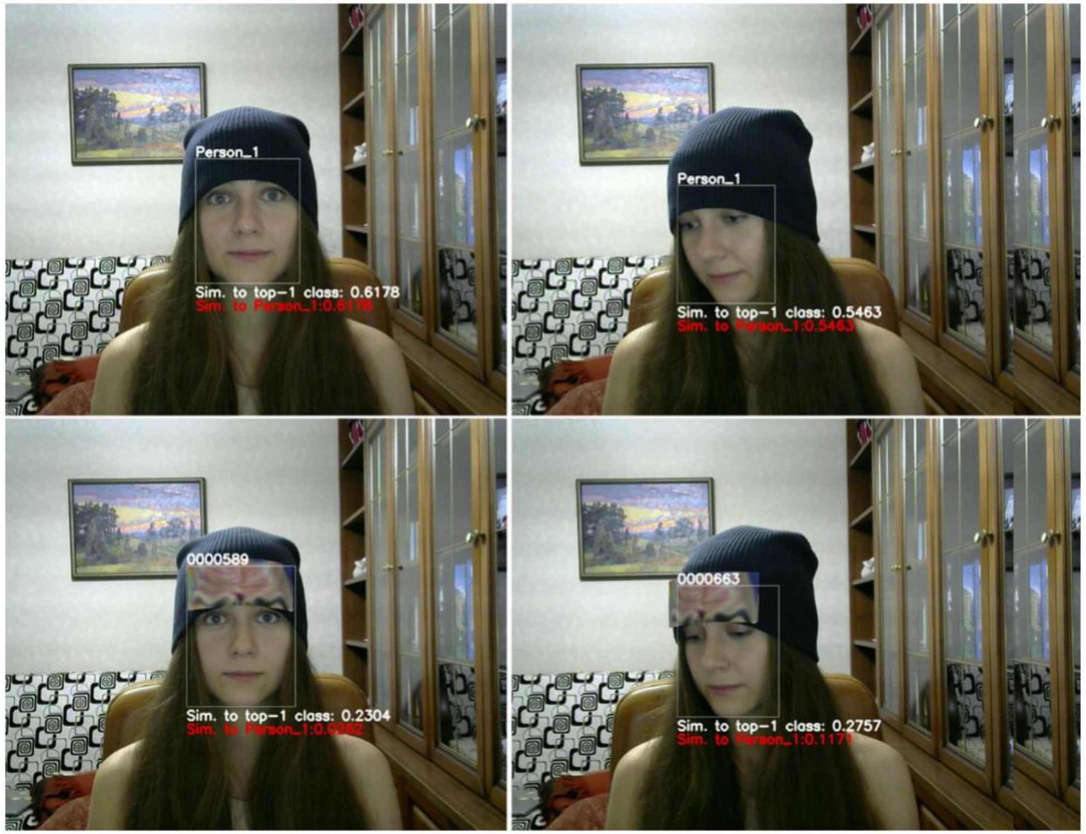
[1] https://arxiv.org/abs/1910.07067

[2] https://arxiv.org/abs/1910.06261

Credits: https://www.youtube.com/watch?v=OY70OIS8bxs

Adversarial attack: real world robustness

- Robustness[1] to different light conditions and rotations



Frontal Face
(no attack)

Self-similarity: 0.61

Rotated Face
(no attack)

Self-similarity: 0.54

Frontal Face
(attack)

Self-similarity: 0.02
Other similarity: 0.23

Поворот лица
(атака)

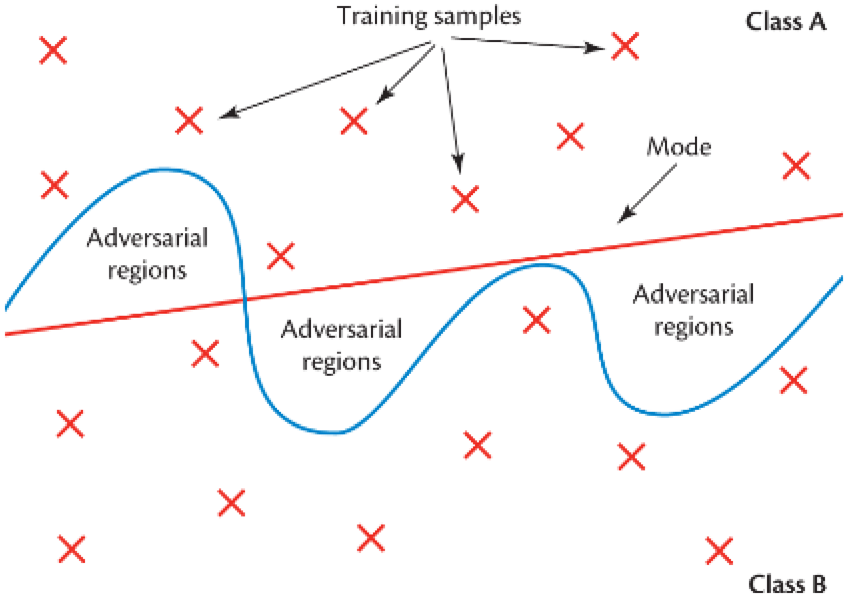
Self-similarity: 0.11
Other similarity: 0.27

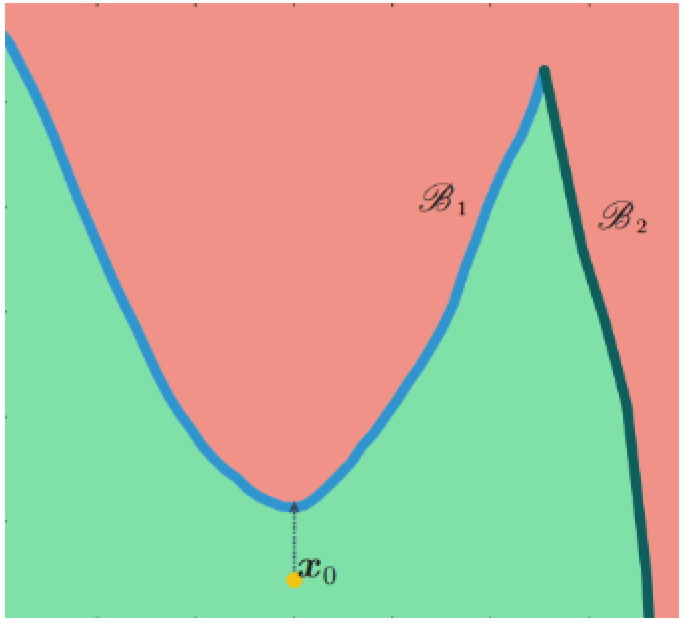
[1] https://arxiv.org/abs/1908.08705

Credits: https://www.youtube.com/watch?v=a4iNg0wWBsQ

Why it is happening

- One of the main reason of such a behavior by NN on very close inputs – the training procedure of NN:
    - The common situation is that classes separating borderlines could be quite close to the training samples and it is very easy to move to the wrong class area by a very small step

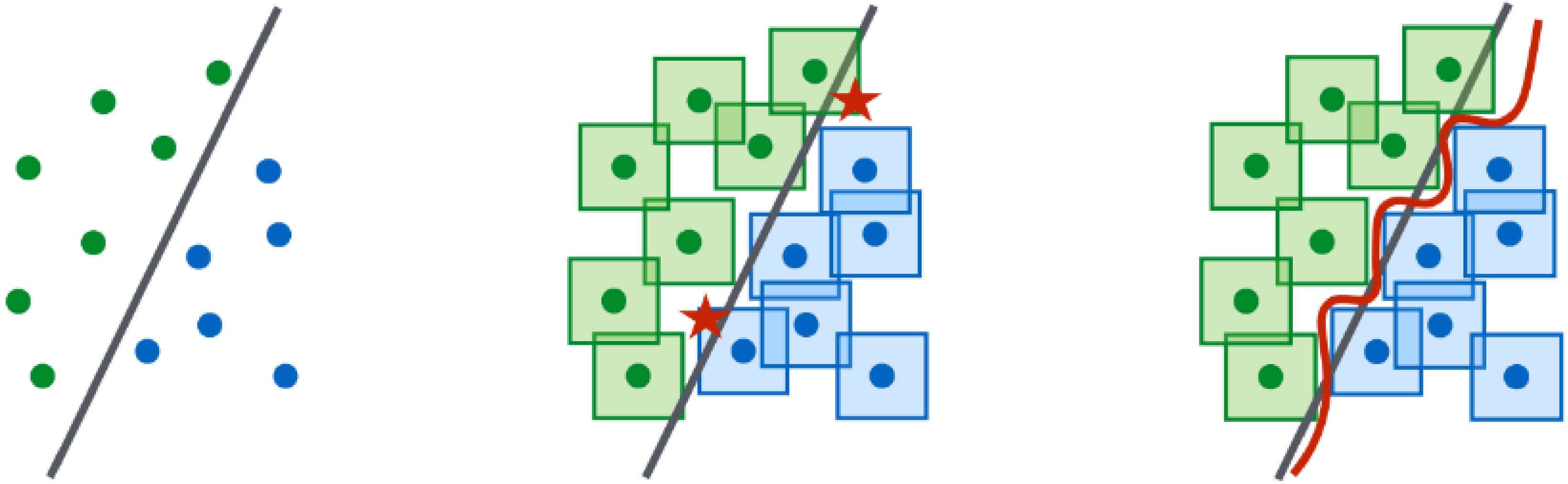




Credits: https://secml.github.io/, https://arxiv.org/abs/1608.08967

Some ways of improving it

- A couple of simple ways – during training:
  - For every training example to add all its pixel vicinity
    - Drawback: exponentially increased number of input samples
  - Add only the most hard examples from this vicinity
    - Drawback: additional backpropagation steps



Credits: https://arxiv.org/abs/1706.06083

Certified Robustness - definitions

- Suppose our NN function $f(x)$ is the **classifier** to K classes: $f: R^d \to Y, Y = \{1, \dots, K\}$
  - Usually we have NN $h(x): R^d \to R^K$, and $f(x) = argmax_i h(x)_i$
  - Deterministic approach: we want to find provide the class of perturbation $S(x, f)$ so as the classifier output will not change, or more formally:
    - $f(x + \delta) = f(x)\ \forall \delta \in S(x, f)$
  - Probabilistic approach: having the probability of robustness P, find the class of input perturbations $S(x, f, P)$ s.t.:
    - $Prob_{\delta \in S(x,f,P)}\big(f(x + \delta) = f(x)\big) = P$

- If NN $f(x)$ is the **regressor**: $f: R^d \to R$
  - Having the upper and lower bounds on the output perturbation, find the class of input perturbations $S\big(x, f, f_{low}, f_{up}\big)$:
    - $f(x) - f_{low} \leq f(x + \delta) \leq f(x) + f_{up}, \forall \delta \in S(x, f, f_{low}, f_{up})$

Certified Robustness – definitions (2)

- Also, inverse tasks could considered

- If NN $f(x)$ is the **classifier** to K classes: $f: R^d \to Y, Y = \{1, \dots, K\}$
  - Probabilistic approach: we want to measure the probability of not changing the classifier output under some class of input perturbations S:
    - $Prob_{\delta \in S}(f(x+\delta) = f(x))$

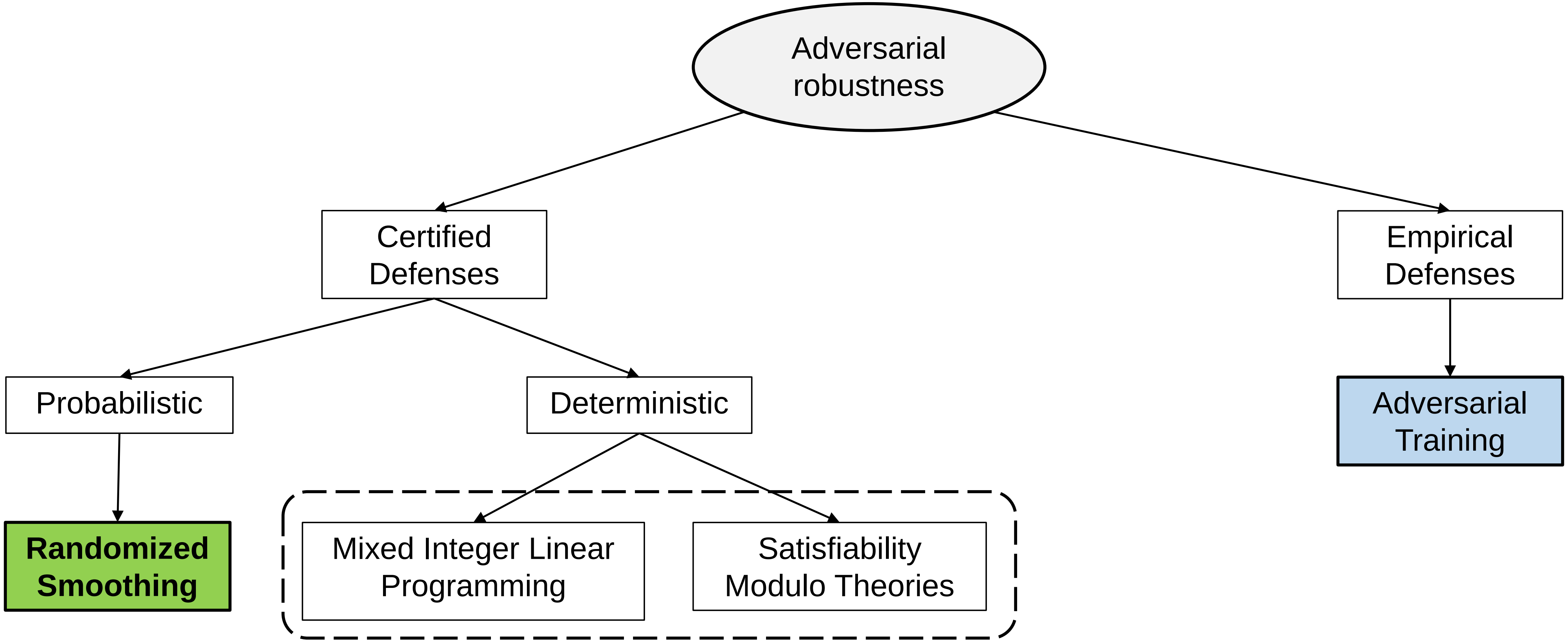
- If NN $f(x)$ is the **regressor**: $f: R^d \to R$
  - We want to find the upper and lower bounds of the output perturbation under some class of input perturbations S in the analytical form:
    - $f(x) - f_{low}(f, x, S) \le f(x+\delta) \le f(x) + f_{up}(f, x, S), \forall \delta \in S$

- Can be measured just by analyzing the output of $f(x+\delta)$

Certified Robustness and Lipschitz Function

- Neural Net output is $h: R^d \to R^K$, and the classifier itself is $f: R^d \to Y, Y = \{1, \dots, K\}$, where $f(x) = argmax_{i \in Y} h(x)_i$
- Consider binary case ($K = 2$), and probabilistic output: $h(x)_1 + h(x)_2 = 1, h(x)_i \geq 0$
- **Lipschitz function** $f: R^d \to R$ with a Lipschitz constant L: $\forall x_1, x_2$ it is true that $|f(x_1) - f(x_2)| \leq L||x_1 - x_2||$
- **Local Lipschitz function** f with a Lipschitz constant $L(x_0)$: $\forall x \in S(x_0)$ it is true that $|f(x_0) - f(x)| \leq L(x_0)||x_0 - x||$
- Let $j = argmax_{i \in Y} h(x_0)_i$, and $h(x_0)_j - h(x_0)_{i \neq j} \geq \epsilon \; \forall i \neq j$
- Let $h(x_0)_j$ - local Lipschitz function with a Lipschitz constant $L(x_0)$
- Then if $S(x_0) = \{x: \left||x_0 - x|\right| \leq \frac{\epsilon}{2L(x_0)}\}$, we have $\left|h(x_0)_j - h(x)_j\right| \leq L(x_0)\frac{\epsilon}{2L(x_0)} = \frac{\epsilon}{2}$
- As a consequence we'll have $j = argmax_{i \in Y} h(x)_i$, and $f(x) = f(x_0) = j$ in the vicinity $S(x_0) = \{x: \left||x_0 - x|\right| \leq \frac{\epsilon}{2L(x_0)}\}$, and certified robustness!
- True certified radius can be much bigger than Lipschitz vicinity $S(x_0)$

Adversarial Robustness



Applicable only for very small NN models
(NP-complete problems)

Empirical VS Certified

- **Empirical**
  - Upper bound on the true robustness accuracy
  - But only until the new stronger attack appears

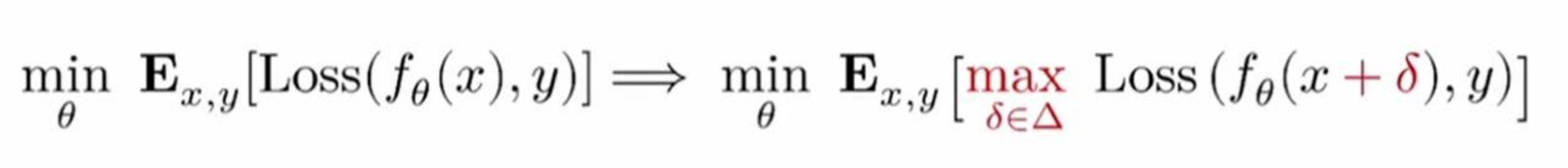
- **Certified**
  - Lower bound on the true robustness accuracy
  - It is what has been theoretically proven, and no one attack can beat it

Dummy approach for robustness

- **Approach:** let’s include all RGB pixel vicinity in training procedure!
- **BUT**:
  - Suppose: input image 100x100 pixels, 3 colored (RGB)
  - Suppose: our eye is not making huge difference between luminosity of pixels by ±1 value (out of 256)
  - Then for each training sample we need to add:
    - $2^{3*100*100} = 2^{30000} = (2^{10})^{3000} \approx (10^3)^{3000} = 10^{9000}$
  - This is much more than the number of atoms in the visible part of the Universe (10^{80})!
  - So, not very realistic ☹

Empirical robustness: adversarial training

- **Main idea**:
  - train on the most hard examples using some class of perturbations $S (= \Delta)$ around training examples



$$\min_{\theta} \ \mathbf{E}_{x,y}[\mathrm{Loss}(f_\theta(x), y)] \Longrightarrow \min_{\theta} \ \mathbf{E}_{x,y}\left[\max_{\delta \in \Delta} \ \mathrm{Loss}\left(f_\theta(x+\delta), y\right)\right]$$

- **Drawbacks**:
  - Quite inefficient training (longer than usual because of finding of hard examples for every training sample for every iteration)
  - The accuracy on clean samples is lower than for usual training

The problem with $\boldsymbol{l_p}$-balls

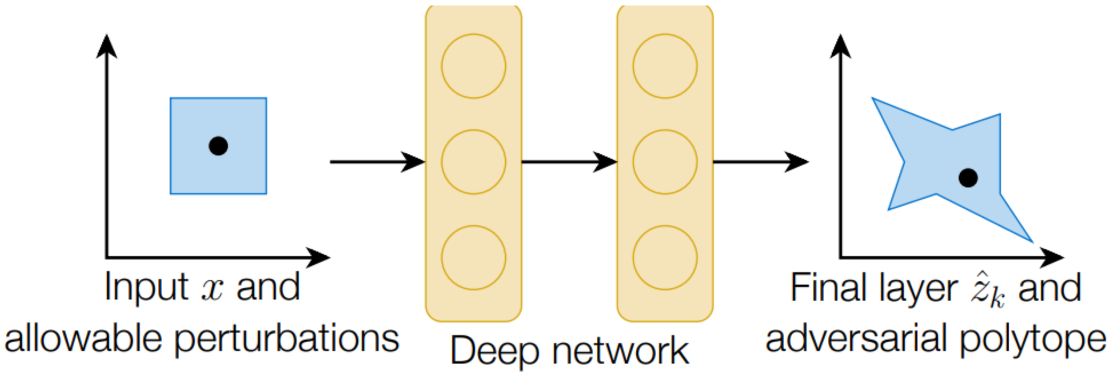
- Usually the robustness is studied under the l_p-balls perturbations of input (S: $\|\delta\|_p \leq \varepsilon$)
- The problem is while the input l_p-ball is convex, for the output it could be of any form and convexity
- That’s why it is hard to prove anything

$$\ell_2\text{: } ||x||_2 = \sqrt{\sum_{i=1}^{n} x_i^2}$$

$$\ell_1\text{: } ||x||_1 = \sum_{i=1}^{n} |x_i|$$

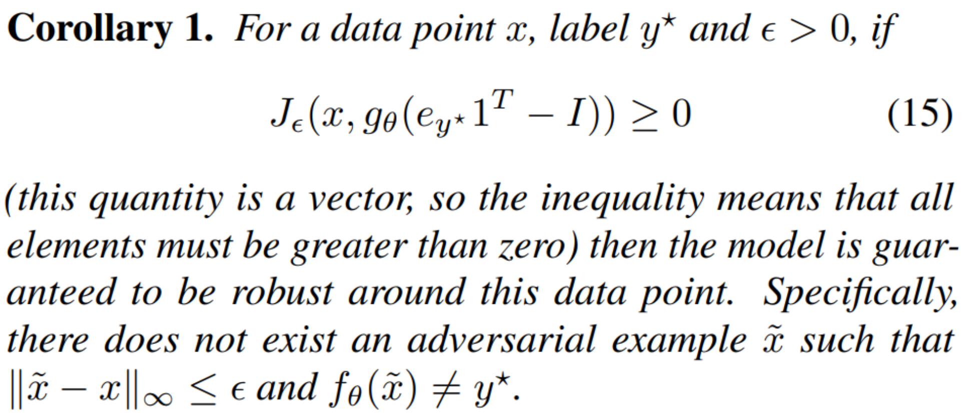
$$\ell_\infty\text{: } ||x||_\infty = \max_i |x_i|$$

$$\ell_0\text{: } ||x||_0 = \sum_{i=1}^{n} \mathbf{1}_{x_i \neq 0}$$


Input x and allowable perturbations
Deep network
Final layer $\hat{z}_k$ and adversarial polytope

Convex relaxation[1]

- **Main idea**:
  - Let’s make out regions convex by relaxation!



Corollary 1. *For a data point x, label $y^\star$ and $\epsilon > 0$, if*

$$J_\epsilon(x, g_\theta(e_{y^\star} 1^T - I)) \geq 0 \tag{15}$$

(this quantity is a vector, so the inequality means that all elements must be greater than zero) then the model is guaranteed to be robust around this data point. Specifically, there does not exist an adversarial example $\tilde{x}$ such that $\|\tilde{x} - x\|_\infty \leq \epsilon$ and $f_\theta(\tilde{x}) \neq y^\star$.

  - This is the example of using MILP and cannot be generalized to ImageNet

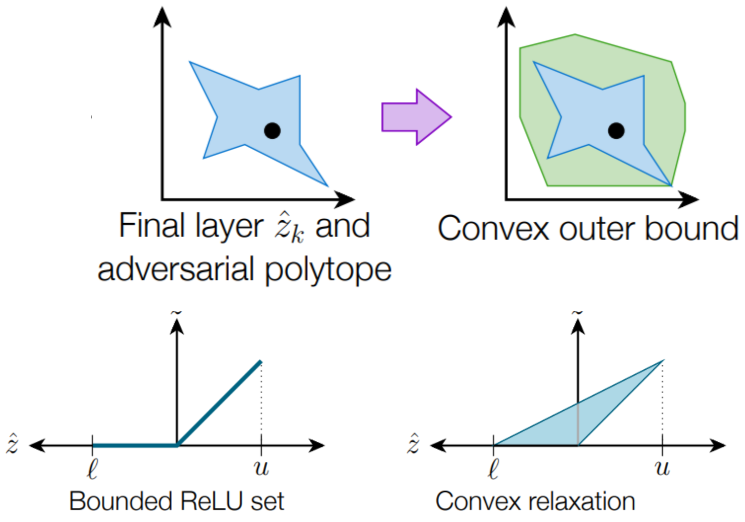


Figure 2. Illustration of the convex ReLU relaxation over the bounded set $[\ell, u]$.

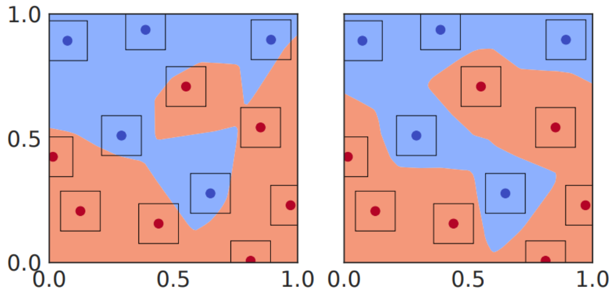
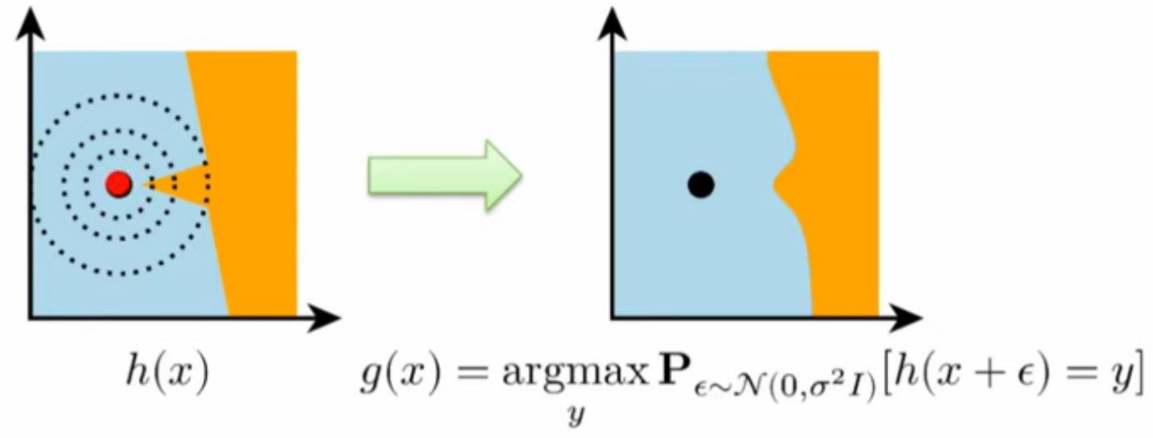


Figure 3. Illustration of classification boundaries resulting from standard training (left) and robust training (right) with ℓ_∞ balls of size $\epsilon = 0.08$ (shown in figure).

[1] Wong, Eric, and J. Zico Kolter. "Provable defenses against adversarial examples via the convex outer adversarial polytope."

Adversarial examples and boundary curvature

- Very curved boundary will lead to adversarial examples looking very similar to the classification boundary
- So let’s diminish this curvature spike influence!
  - Different approaches exist e.g. by *Lecuyer et al.*[1] *and Li et al.*[2], but the most famous one is by *Cohen et al.*

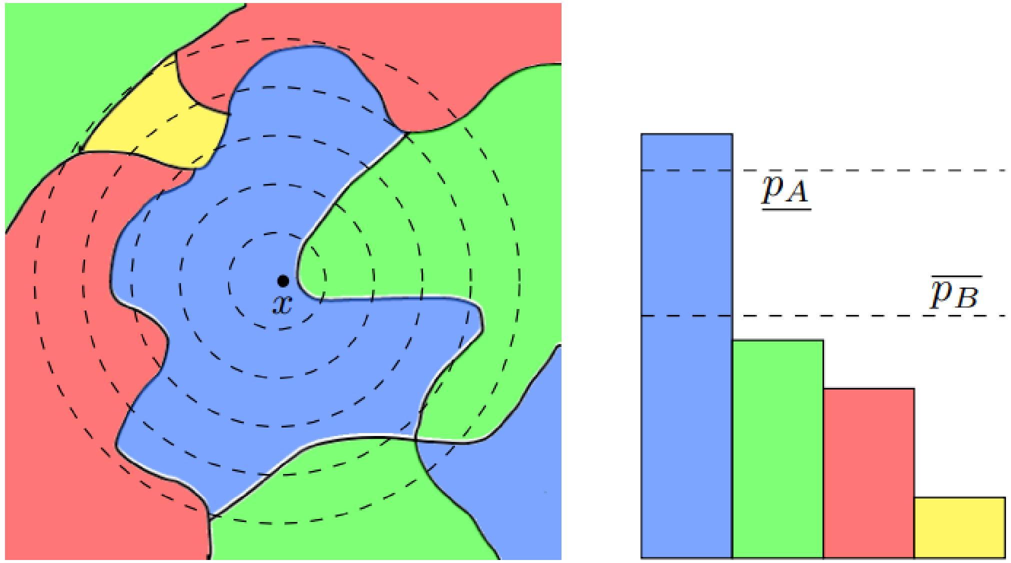


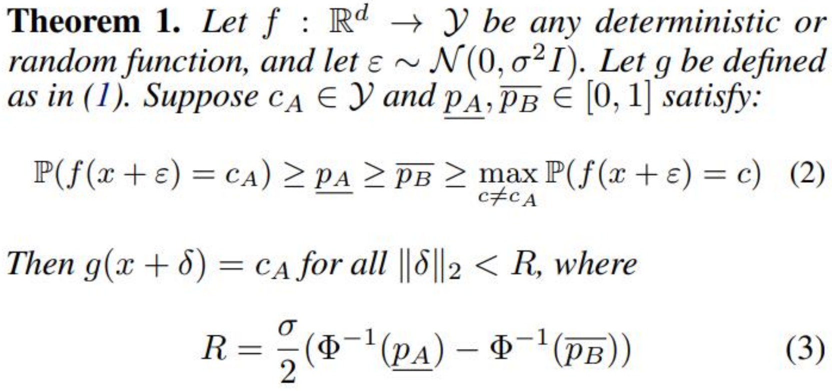
$h(x)$
$g(x) = \underset{y}{\operatorname{argmax}}\, \mathbf{P}_{\epsilon\sim\mathcal{N}(0,\sigma^2 I)}[h(x+\epsilon)=y]$

[1] Lecuyer, Mathias, et al. "Certified robustness to adversarial examples with differential privacy.“
[2] Li, Bai, et al. "Certified Adversarial Robustness with Additive Noise."

Randomized Smoothing[1]

- **Main idea**:
  - Let’s use another definition of classifier!
  - New classifier (in fact, sort of TTA):
    - $g(x) = \underset{c \in Y}{\operatorname{argmax}} P(f(x+\varepsilon)=c), \varepsilon \sim N(0, \sigma^2 I)$
- The main robustness result:
  - If $f(x)$ classifier is robust under Gaussian noise,
  - Then $g(x)$ classifier is robust under **ANY** noise
- The radius R in **Theorem 1** is tight: with the bigger radius there exists an adversarial example



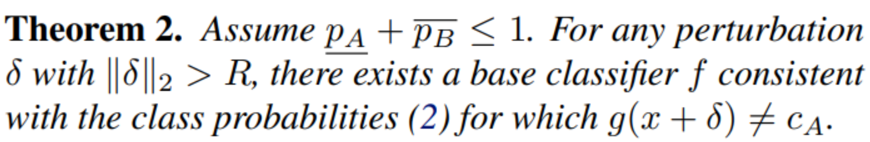


Theorem 1. *Let $f : \mathbb{R}^d \to \mathcal{Y}$ be any deterministic or random function, and let $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$. Let g be defined as in (1). Suppose $c_A \in \mathcal{Y}$ and $\underline{p_A}, \overline{p_B} \in [0,1]$ satisfy:*

$$\mathbb{P}(f(x+\varepsilon)=c_A) \geq \underline{p_A} \geq \overline{p_B} \geq \max_{c \neq c_A} \mathbb{P}(f(x+\varepsilon)=c) \quad (2)$$

Then $g(x+\delta)=c_A$ for all $\|\delta\|_2 < R$, where

$$R = \frac{\sigma}{2}(\Phi^{-1}(\underline{p_A}) - \Phi^{-1}(\overline{p_B})) \quad (3)$$

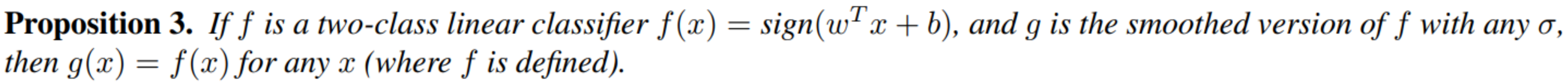


Theorem 2. *Assume $\underline{p_A} + \overline{p_B} \leq 1$. For any perturbation δ with $\|\delta\|_2 > R$, there exists a base classifier f consistent with the class probabilities (2) for which $g(x+\delta) \neq c_A$.*

[1] Cohen, Jeremy M., Elan Rosenfeld, and J. Zico Kolter. "Certified adversarial robustness via randomized smoothing."

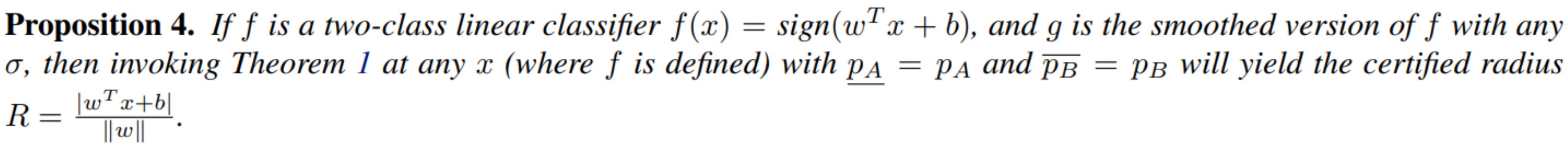
Randomized smoothness: some interesting facts

- Some interesting details about linear classifier for two classes: $f(x) = sign(w^T x + b)$
  - It is the smoothed version of itself:



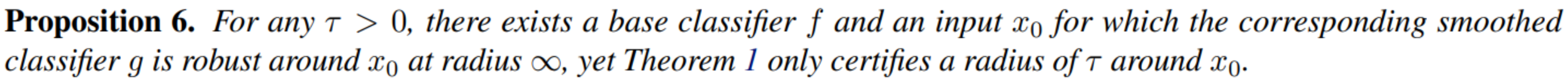
Proposition 3. *If f is a two-class linear classifier $f(x) = sign(w^T x + b)$, and g is the smoothed version of f with any σ, then $g(x) = f(x)$ for any x (where f is defined).*

  - Certified radius of it is the distance between the point x and the boundary:



Proposition 4. *If f is a two-class linear classifier $f(x) = sign(w^T x + b)$, and g is the smoothed version of f with any σ, then invoking Theorem 1 at any x (where f is defined) with $\underline{p_A} = p_A$ and $\overline{p_B} = p_B$ will yield the certified radius $R = \frac{|w^T x + b|}{\|w\|}$.*

- But there always exists a classifier with real robustness radius more than R from **Theorem 1**:



Proposition 6. *For any $\tau > 0$, there exists a base classifier f and an input x_0 for which the corresponding smoothed classifier g is robust around x_0 at radius ∞, yet Theorem 1 only certifies a radius of τ around x_0.*

Randomized smoothness: results

- The authors propose the procedure to return the radius R and output class c based on input x and the deviance of noise σ
  - This procedure can even avoid to provide the answer with some probability α
- To certify the classifiers, authors **trained the base models with Gaussian noise from $\boldsymbol{N(0, \sigma^2 I)}$** – in fact, to make the classifier $f(x)$ more robust to Gaussian noise
- Trained models are compared using "**approximate certified accuracy**":
  - For each test radius $\delta = r$ the fraction of examples is returned on which CERTIFY
    - Provides the answer
    - Returns the correct class
    - Returns a radius R so as $r \leq R$
- Also when estimating the $g(x)$ authors run Monte Carlo N times

Randomized smoothness: results on ImageNet (1)

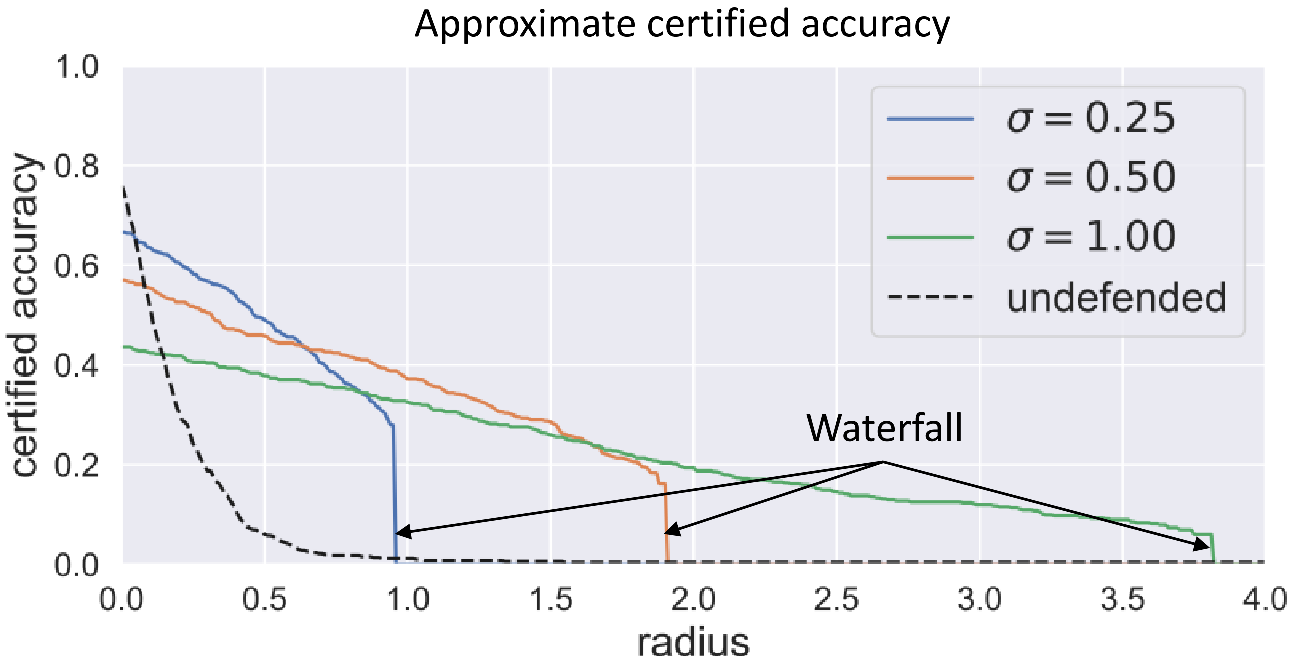


Table 1. Approximate certified accuracy on ImageNet. Each row shows a radius r, the best hyperparameter σ for that radius, the approximate certified accuracy at radius r of the corresponding smoothed classifier, and the standard accuracy of the corresponding smoothed classifier. To give a sense of scale, a perturbation with ℓ_2 radius 1.0 could change one pixel by 255, ten pixels by 80, 100 pixels by 25, or 1000 pixels by 8. Random guessing on ImageNet would attain 0.1% accuracy.

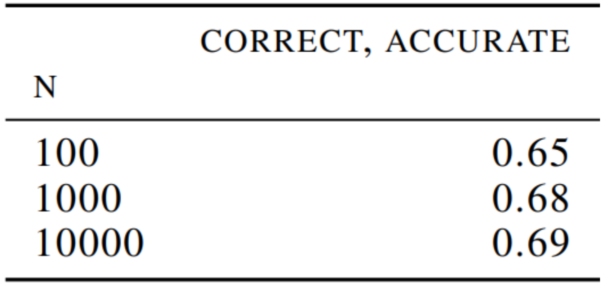
ℓ_2 RADIUS	BEST σ	CERT. ACC (%)	STD. ACC(%)
0.5	0.25	49	67
1.0	0.50	37	57
2.0	0.50	19	57
3.0	1.00	12	44

Waterfall just because we the trained model is robust usually under some $r \leq R$

Randomized smoothness: results on ImageNet (2)

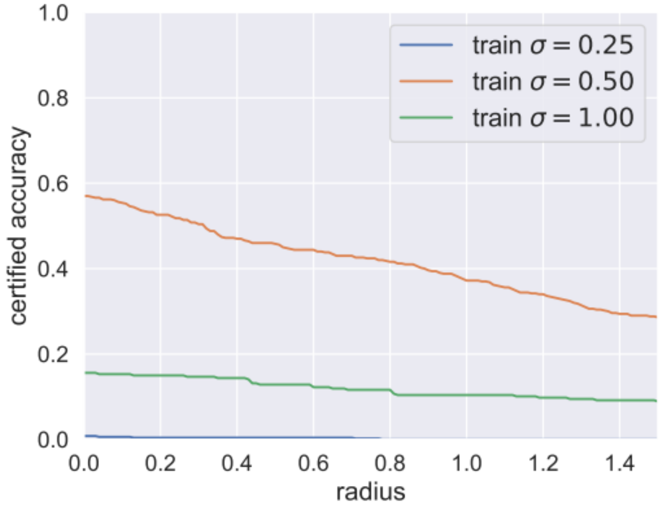
- In fact, with NN $f(x)$ we can have larger real robustness radius than R from **Theorem 1**:
  - Authors just tried to find the real adversaries under $r > R$ and measure the success of the attack
  - The lower success the more robust the model
  - $r = 1.5R$: 17% success
  - $r = 2R$: 53% success

Influence of N for Monte Carlo prediction



	CORRECT, ACCURATE
N	
100	0.65
1000	0.68
10000	0.69

Influence of training σ when testing with $\sigma = 0.5$



Improvement: Adversarial training for smoothed classifier[1]

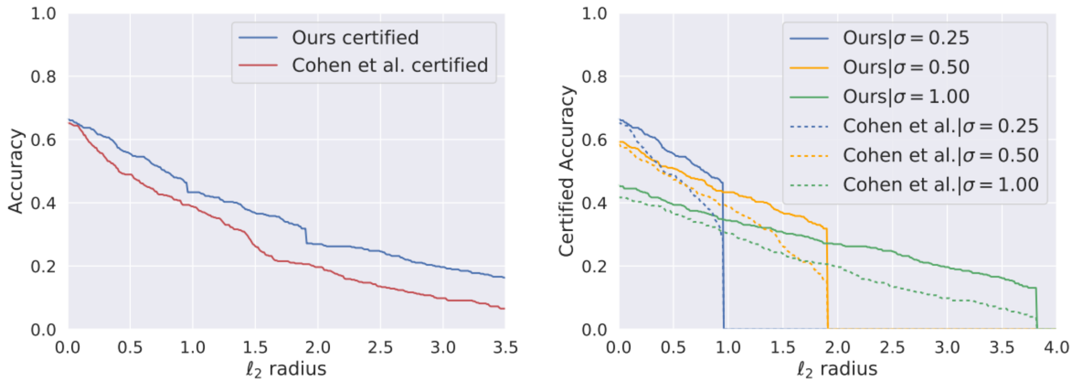
- Instead of simple augmenting the training example with Gaussian noise, let’s do in fact adversarial training using attacks on $g(x)$!

$$\begin{aligned}\hat{x} &= \underset{\|x'-x\|_2\le\epsilon}{\arg\max}\ \ell_{\mathrm{CE}}(G(x'),y)\\ &= \underset{\|x'-x\|_2\le\epsilon}{\arg\max}\left(-\log \underset{\delta\sim\mathcal{N}(0,\sigma^2 I)}{\mathbb{E}}\left[(F(x'+\delta))_y\right]\right)\end{aligned}$$

$$\nabla_{x'}J(x') = \nabla_{x'}\left(-\log \underset{\delta\sim\mathcal{N}(0,\sigma^2 I)}{\mathbb{E}}[F(x'+\delta)_y]\right)$$

$$\nabla_{x'}J(x') \approx \nabla_{x'}\left(-\log\left(\frac{1}{m}\sum_{i=1}^{m}F(x'+\delta_i)_y\right)\right)$$

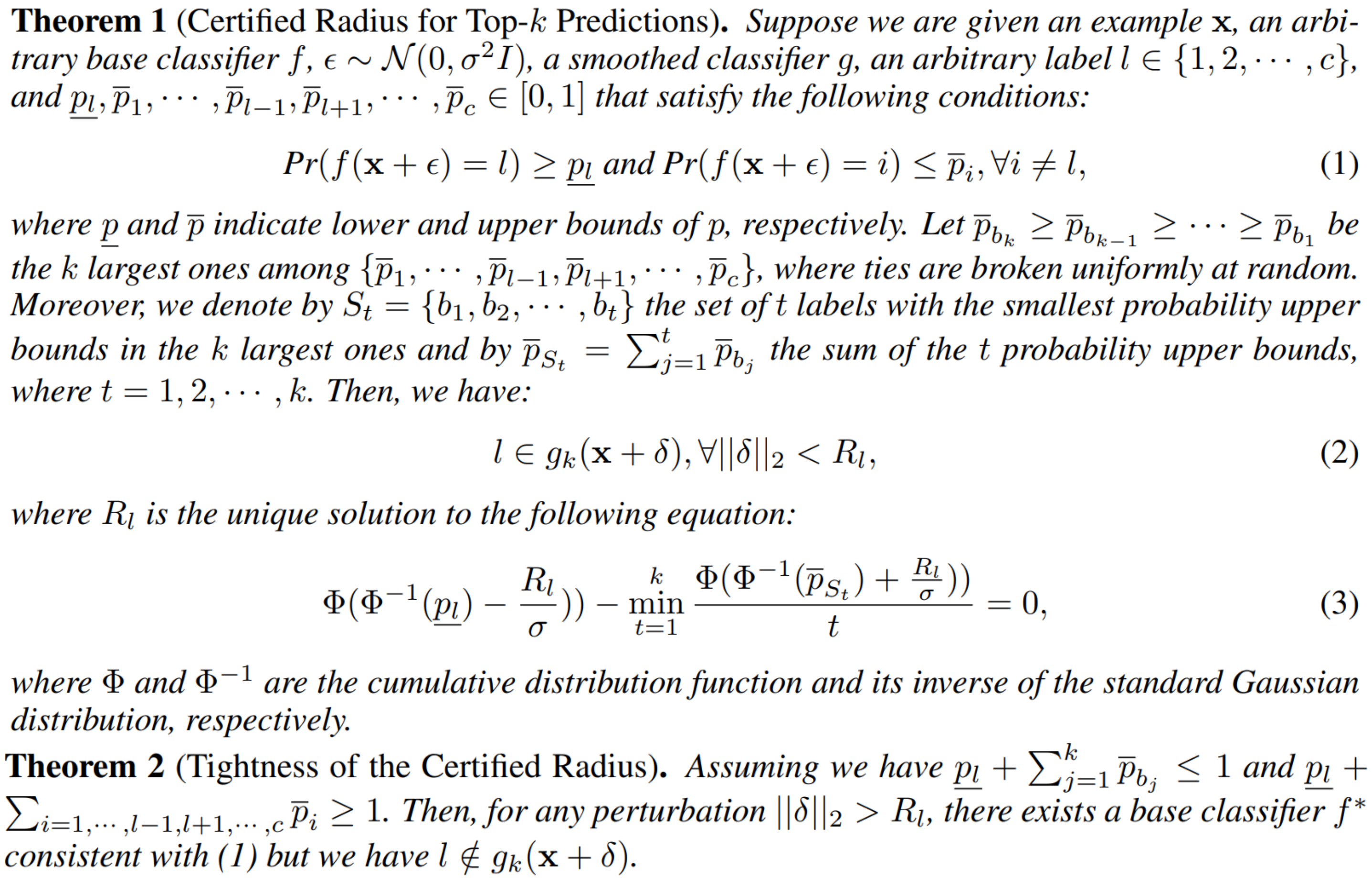
Comparison with the original on the ImageNet



[1] Salman, Hadi, et al. "Provably robust deep learning via adversarially trained smoothed classifiers."

Improvement: Certified Robustness for Top-k Predictions[1]

- The very same idea for Randomized Smoothing, but not only for the top class, but for Top-k classes:
  - $g_k(x) = \underset{c \in Y}{\operatorname{argmax}_{1:k}} P(f(x+\varepsilon) = c)$, $\varepsilon \sim N(0, \sigma^2 I)$
- Needed to improve top-5 ImageNet:
  - Certified top-1/top-3/top-5 accuracies = 46.6% / 57.8% / 62.8% when $||\delta||_2 = 0.5$



Theorem 1 (Certified Radius for Top-k Predictions)**.** *Suppose we are given an example* $\mathbf{x}$*, an arbitrary base classifier* f*,* $\epsilon \sim \mathcal{N}(0, \sigma^2 I)$*, a smoothed classifier* g*, an arbitrary label* $l \in \{1, 2, \cdots, c\}$*, and* $\underline{p_l}, \overline{p}_1, \cdots, \overline{p}_{l-1}, \overline{p}_{l+1}, \cdots, \overline{p}_c \in [0, 1]$ *that satisfy the following conditions:*

$$Pr(f(\mathbf{x}+\epsilon) = l) \geq \underline{p_l} \text{ and } Pr(f(\mathbf{x}+\epsilon) = i) \leq \overline{p}_i, \forall i \neq l, \tag{1}$$

where $\underline{p}$ *and* $\overline{p}$ *indicate lower and upper bounds of* p*, respectively. Let* $\overline{p}_{b_k} \geq \overline{p}_{b_{k-1}} \geq \cdots \geq \overline{p}_{b_1}$ *be the* k *largest ones among* $\{\overline{p}_1, \cdots, \overline{p}_{l-1}, \overline{p}_{l+1}, \cdots, \overline{p}_c\}$*, where ties are broken uniformly at random. Moreover, we denote by* $S_t = \{b_1, b_2, \cdots, b_t\}$ *the set of* t *labels with the smallest probability upper bounds in the* k *largest ones and by* $\overline{p}_{S_t} = \sum_{j=1}^{t} \overline{p}_{b_j}$ *the sum of the* t *probability upper bounds, where* $t = 1, 2, \cdots, k$*. Then, we have:*

$$l \in g_k(\mathbf{x}+\delta), \forall ||\delta||_2 < R_l, \tag{2}$$

where R_l *is the unique solution to the following equation:*

$$\Phi(\Phi^{-1}(\underline{p_l}) - \frac{R_l}{\sigma})) - \min_{t=1}^{k} \frac{\Phi(\Phi^{-1}(\overline{p}_{S_t}) + \frac{R_l}{\sigma}))}{t} = 0, \tag{3}$$

where Φ *and* Φ^{-1} *are the cumulative distribution function and its inverse of the standard Gaussian distribution, respectively.*

Theorem 2 (Tightness of the Certified Radius)**.** *Assuming we have* $\underline{p_l} + \sum_{j=1}^{k} \overline{p}_{b_j} \leq 1$ *and* $\underline{p_l} + \sum_{i=1,\cdots,l-1,l+1,\cdots,c} \overline{p}_i \geq 1$*. Then, for any perturbation* $||\delta||_2 > R_l$*, there exists a base classifier* f^* *consistent with (1) but we have* $l \notin g_k(\mathbf{x}+\delta)$*.*

[1] Jia, Jinyuan, et al. "Certified Robustness for Top-k Predictions against Adversarial Perturbations via Randomized Smoothing."

BlackBox for Randomized Smoothing[1]

- What if we cannot change pretrained classifier, but want to increase its certified robustness?
- Let's train denoiser D used after we add Gaussian noise!
- And then simply apply majority rule
- Denoiser: trained with two losses for every Gaussian σ
  - MSE
  - Stability (CE loss)

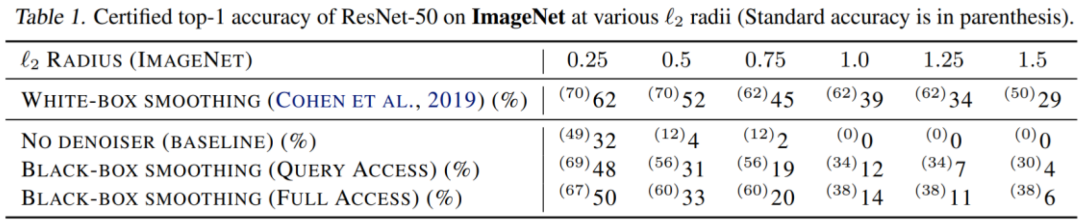
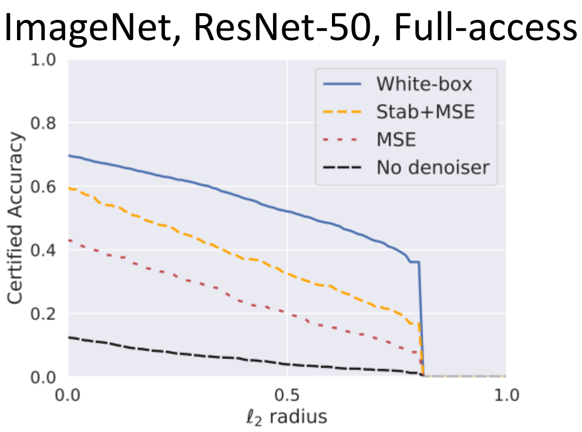
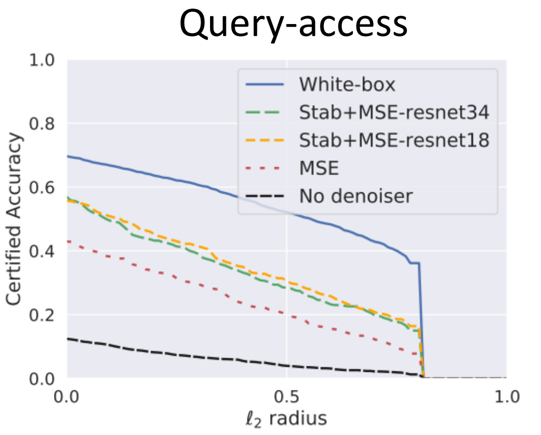


Table 1. Certified top-1 accuracy of ResNet-50 on **ImageNet** at various ℓ_2 radii (Standard accuracy is in parenthesis).

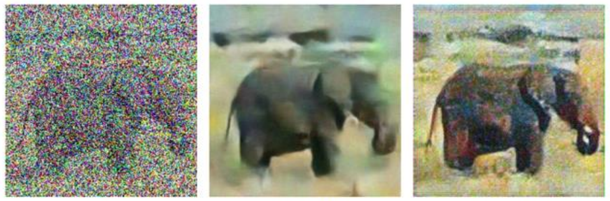
ℓ_2 Radius (ImageNet)	0.25	0.5	0.75	1.0	1.25	1.5
White-box smoothing (Cohen et al., 2019) (%)	$^{(70)}62$	$^{(70)}52$	$^{(62)}45$	$^{(62)}39$	$^{(62)}34$	$^{(50)}29$
No denoiser (baseline) (%)	$^{(49)}32$	$^{(12)}4$	$^{(12)}2$	$^{(0)}0$	$^{(0)}0$	$^{(0)}0$
Black-box smoothing (Query Access) (%)	$^{(69)}48$	$^{(56)}31$	$^{(56)}19$	$^{(34)}12$	$^{(34)}7$	$^{(30)}4$
Black-box smoothing (Full Access) (%)	$^{(67)}50$	$^{(60)}33$	$^{(60)}20$	$^{(38)}14$	$^{(38)}11$	$^{(38)}6$



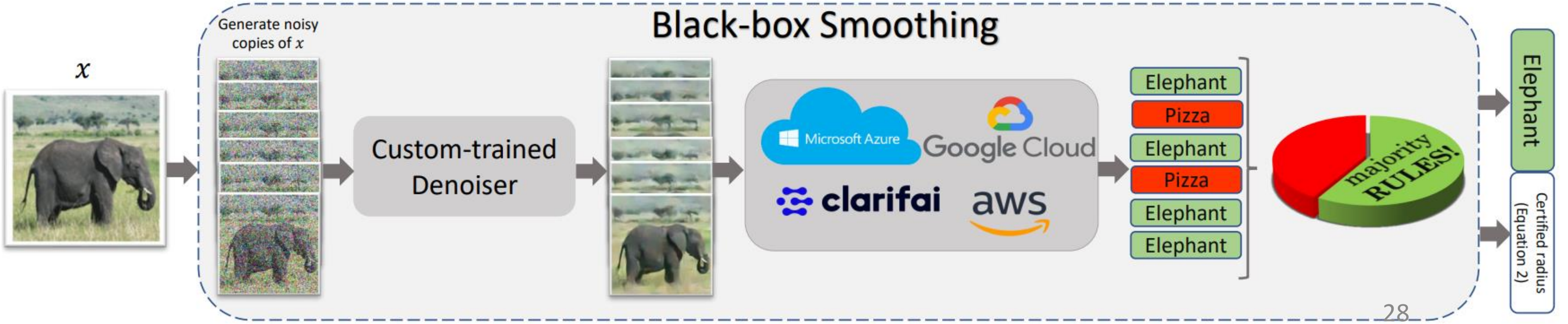
ImageNet, ResNet-50, Full-access



Query-access



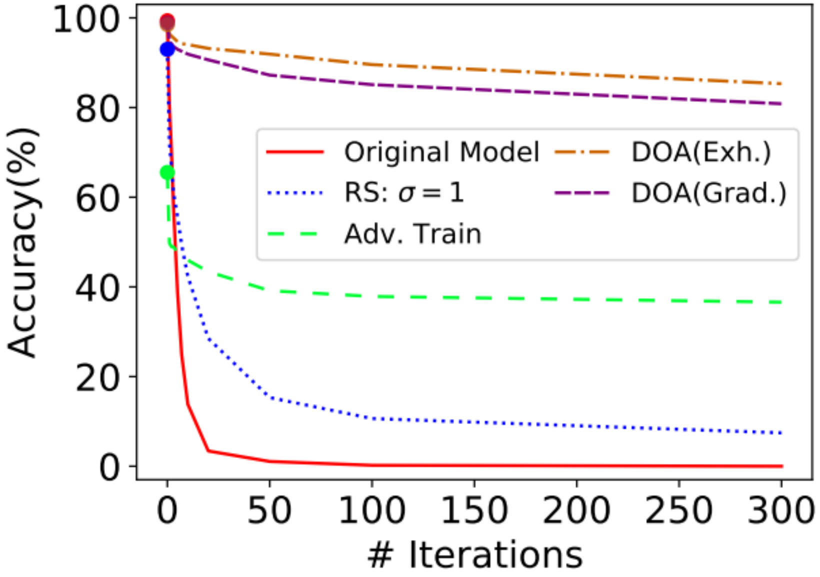
(a) Noisy (b) MSE (c) Stab+MSE

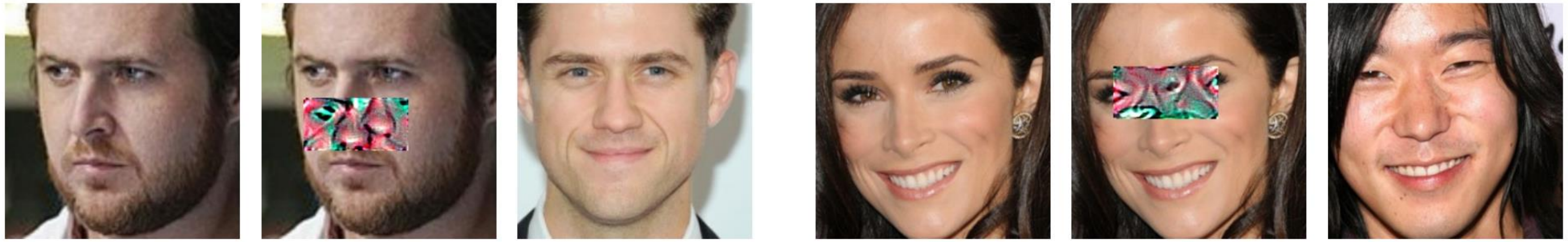


[1] Salman, Hadi, et al. "Black-box Smoothing: A Provable Defense for Pretrained Classifiers."

Defending from Physical Adversarial Patches[1]

- Most all of the real-world attacks are patch-based
  - Let’s train in the digital domain with patch-based augmentation!
- AT decoupling:
  - Exhaustive search (or based upon max gradient locations s.t. input) with the best location of grey rectangle
  - Then PGD inside this rectangle

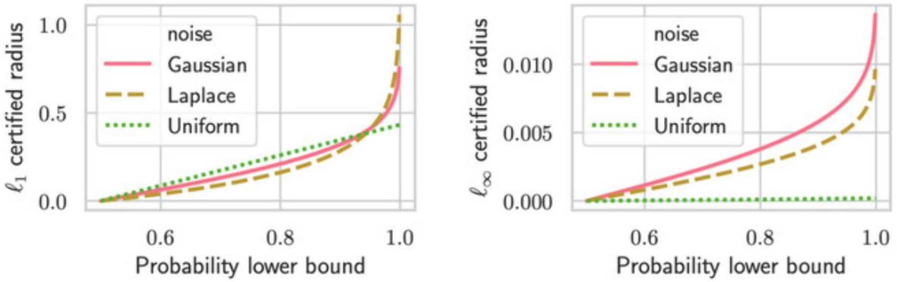




[1] Wu, Tong, Liang Tong, and Yevgeniy Vorobeychik. "Defending Against Physically Realizable Attacks on Image Classification."

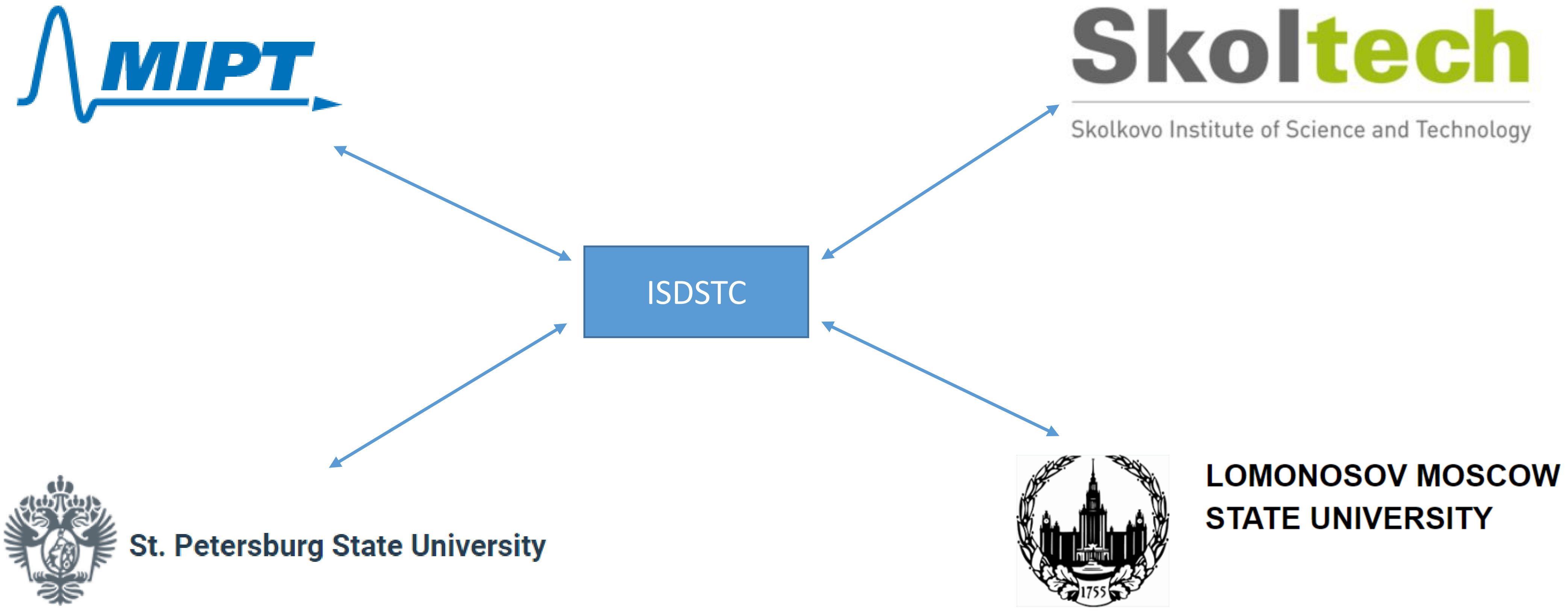
Takeaway

- Certification is only for much smaller regions than humans can do
- Certified robustness is better than empirical adversarial training in certification, but worse than clean performance (and too much time to train)
- Using l_p-balls is neither necessary nor sufficient for perceptual robustness
- Other types of randomized smoothing could be taking into account: e.g. *Uniform*[1] or *Laplacian*[2]
- Randomized smoothing requires multiple inferences ☹
- BTW some note about physical nature of l_p-balls:
  - l_2: corresponds to the power of signals
  - l_1: corresponds to the pixel mass
  - l_∞: corresponds to the noise in camera sensors
  - **l_0: the most interesting one – corresponds to the practical robustness**



[1] Lee, Guang-He, et al. "Tight certificates of adversarial robustness for randomly smoothed classifiers."
[2] Teng, Jiaye, et al. “l_1 Adversarial Robustness Certificates: a Randomized Smoothing Approach”

Intelligence Systems and Data Science Technology Center academic collaborations



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Huawei Educational Program

http://sharemsu.ru/

- Starting from 2019, Huawei is presenting **SHARE** educational program: **S**chool of **H**uawei **A**dvanced **R**esearch **E**ducation
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- Our Intelligence Systems and Data Science Technology Center is doing courses in MSU:
  - 2 year full-educational program
  - 15 semester courses
  - 2 main directions:
    - Computer Vision and Machine Learning specialization
    - Big Data and Information Theory specialization

Thank you!

(need to certify everything)