Artificial Intelligence
Advanced Topics in AI & ML
ML Robustness and Adversarial Attacks

Aleksandr Petiushko

ML Research

Content

1. NN great success

Content

1. NN great success
2. NN lack of robustness

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2. NN lack of robustness
3. ℓ_0-based adversaries

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1. NN great success
2. NN lack of robustness
3. ℓ_0-based adversaries
4. Adversarial examples in real world

Major approach

- Usual training:

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- Adversarial perturbation:

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For now we'll consider the **Adversarial Robustness**.

Questions to be answered

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NN vs Human[1]

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Human expert VS NN

ImageNet[2] (1000-class image DB)

- Human expert top-5 error[3]: 5.1%
- NN top-5 error[4]: 0.98%

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NN instability

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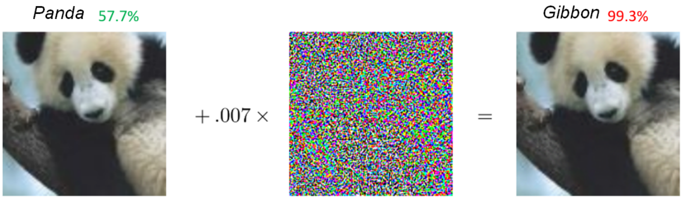
- E.g. classification result from "Panda" changes to "Gibbon"[8]



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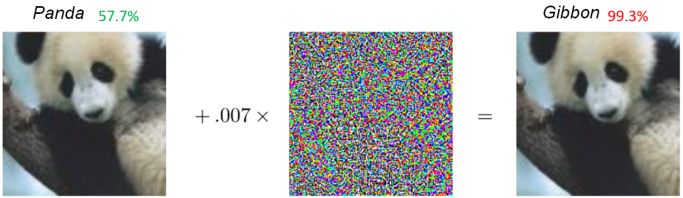

Such almost invisible perturbations leading to changing of the NN output are called **adversarial examples** / **perturbations** (or **adversarial attacks** on NN)

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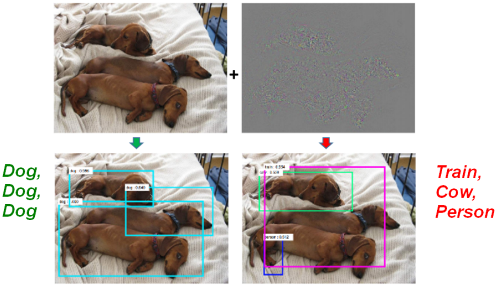
Different types of NN to attack

Detection and segmentation[9] NNs:



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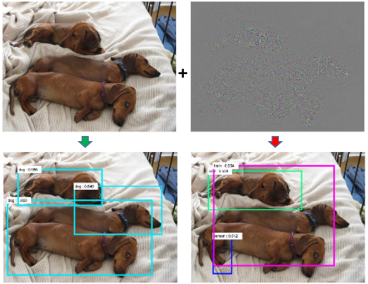

Train,
Cow,
Person

And even NN for text processing (QA, question answering systems)[10]:

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

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One of the main sources of adversarial examples to exist

- One of the main reasons for this neural nets behavior on similar inputs: **lack of NN robustness**

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- Namely, the separating classification boundaries often are very close to the training examples, and it is very easy to "go abroad"[11,12]

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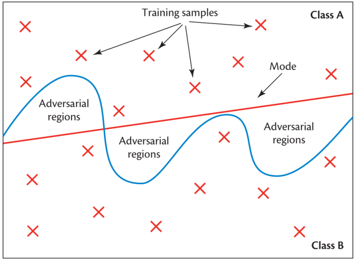

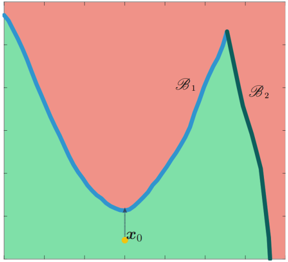

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Easy defense method

- We can change the output of classification neural net by a subtle per-pixel perturbation $\Rightarrow$ why not to add for any training example its whole per-pixel vicinity (based on some norm — e.g., ℓ_∞) during the training process[13]

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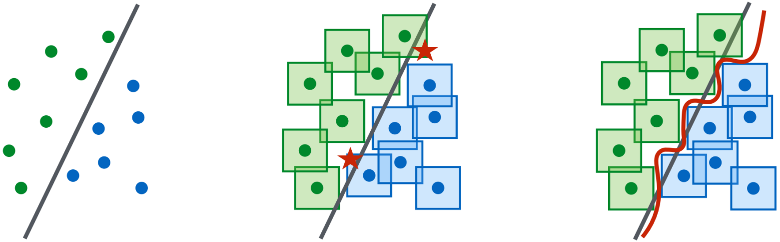

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- As a consequence, not very realistic

Realistic defense method

- Let us not iterate over the entire vicinity of the training example, but to use only those points from example vicinity, which are the closest to the separating surface

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Adversarial training: cons

- Procedure of *good* adversarial examples generation usually works slowly (significantly slower than 1 backprop iteration)
- Protects **only** against the method of generating adversarial examples used for adversarial training

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Definitions

- $x \in B = [0,1]^{C \times M \times N}$ — input image $C \times M \times N$, where C — number of color channels (1 for grayscale, 3 for RGB)
- y — correct class label for input x
- θ — parameters of NN-classifier
- $L(\theta, x, y)$ — loss function
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- $r \in B = [0,1]^{C\times M\times N}$ — the additive perturbation for the input x

Definition of adversarial example and robustness

Goal of adversarial attack

To change the output of the classifier f from the correct class label to the incorrect one by means of minimal in terms of some norm ℓ_p perturbation r:

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Classifier robustness

To find the perturbation class $S(x, f) \subseteq B$ so as the classifier will not change its output:

$$f(x+r) = f(x) = y \quad \forall r \in S(x, f)$$

ℓ_p norms

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Remark. For $0 < p < 1$ the functional ℓ_p such as $||x||_p = \left(\sum_{i=1}^n |x_i|^p\right)^{1/p}$ is not a norm[15]

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Adversarial examples taxonomy (1)

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- **Targeted**: need to change the classifier's output to the specific class y_t

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Application

- **Digital**: for digital record application only (e.g., photo of an object)
- **Real-world**: to be applied in the real environment (e.g., the object itself)

Adversarial examples taxonomy (2)

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Transfer

- **Non-transferable**: successfully working only for a small range of classifiers
- **Transferable**: successfully working for a wide range of classifiers (but at the same time can be non-universal ones)

- The hardest case — targeted black-box real-world universal transferable adversarial examples
- This part will be devoted to white-box adversarial examples

Adversarial examples: success criteria

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$$S(A, Z) = \frac{\sum_i \mathbf{1}\{f(x^i) = y^i\} \cdot \mathbf{1}\{f(x^i + r_A(x^i)) \neq y^i\}}{\sum_i \mathbf{1}\{f(x^i) = y^i\}}$$

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- For adversarial examples targeted towards the class y_t:

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Remark. Apparently $S(A, Z, y_t) \leq S(A, Z)$

Adversarial examples on images: forerunner

- Initially CNN robustness was studied towards how adequate the output of CNN using different inputs

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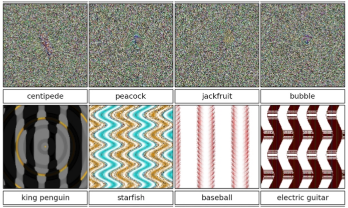
- It was turned out that some examples (structured ot not) exist that produce as the output of CNN any class with any probability
- Such examples were called "fooling images"[16] and were generated by evolutionary algorithms



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Generation method: FGSM

- **Proposition**: to use only the linear part of loss function in the vicinity of x and walk by its gradient — FGSM[17] (**F**ast **G**radient **S**ign **M**ethod):

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where $0 < \epsilon < 1$ — some constant

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- **Reminder**: for NN weights optimization the backpropagation method is used where the gradient is taken w.r.t. NN weights, i.e. $\nabla_\theta L(\theta, x, y)$
- For most CNNs the norm ℓ_∞ is used because it is correlated with the process of how a human eye perceive the visual information

[17] Goodfellow, Ian J., Jonathon Shlens, and Christian Szegedy. "Explaining and harnessing adversarial examples." 2014

Generation method: One pixel

- One pixel adversarial example[18] — extreme case of ℓ_0-based generation method

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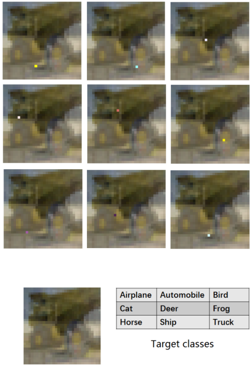

Airplane	Automobile	Bird
Cat	Deer	Frog
Horse	Ship	Truck

Target classes

Original image (dog)

[18] Su, Jiawei, Danilo Vasconcellos Vargas, and Kouichi Sakurai. "One pixel attack for fooling deep neural networks." 2017

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Universal adversarial examples

- Until now all adversarial examples have been constructed as a function of input x

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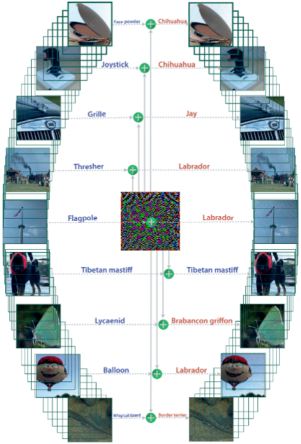

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Taxonomy of generation methods

In general, the adversarial examples generation methods (in Computer Vision) can be divided into the following types:

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- Using ℓ_2-based norm (including geometric ones): most convenient for classical optimization
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- Using ℓ_0-based norm: the area of perturbation is minimized, but not the delta value per pixel

Anyway it is not enough for generation of physically plausible adversarial examples.

Real-world adversarial examples (1)

- All adversarial examples until now were designed to work in digital domain: e.g. to change the image on a pixel level

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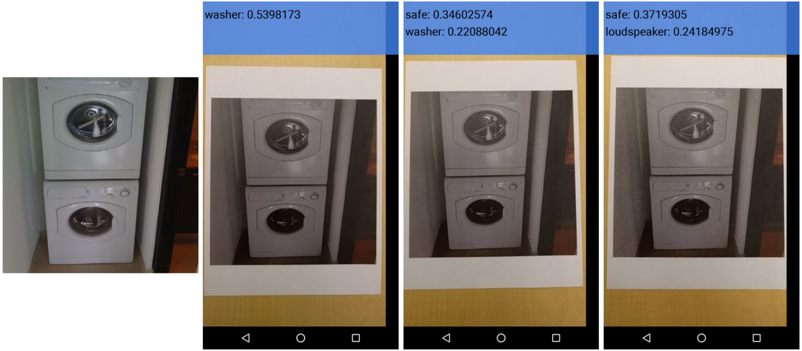
Real-world adversarial examples (2)



(a) Image from dataset (b) Clean image (c) Adv. image, $\epsilon = 4$ (d) Adv. image, $\epsilon = 8$

Adversarial examples in real world: EOT

- Don't have the control on the image pixels after the photo $\Rightarrow$ the only option is to change the object appearance itself

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- **E**xpectation **O**ver **T**ransformation (EOT)[22] to the rescue — takes into account the transformations of objects in the real world, e.g.:
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  - Different scaling factors
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- So for the object x in the real world the task is to find the adversarial perturbation r taking into account transformation $g \in T$:

EOT

Find $\arg\min_r \mathbb{E}_{g\sim T}[P(y|g(x+r))]$ s.t.:

1. $\mathbb{E}_{g\sim T}[d(g(x+r), g(x))] < \epsilon$, where $d(a,b)$ – some distance function (e.g. $d(a,b) = ||a-b||_p$)
2. $x + r \in B$

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Physical adversarial examples: key ingredients

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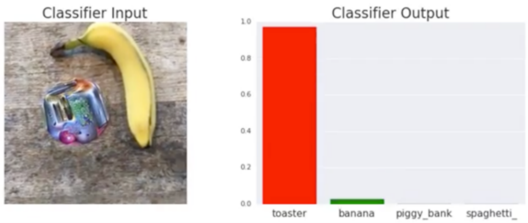
- **T**otal **V**ariation (TV) loss — penalty for the perturbation to be non-smooth (in the real world there is no distinct pixel gradients):

$$TV(x) = \sum_{i,j} \sqrt{(x_{i,j+1} - x_{i,j})^2 + (x_{i+1,j} - x_{i,j})^2}$$

Examples of physical adversarial examples

Attack on ImageNet objects[23]:



[23] Brown T. et al. "Adversarial patch." 2017

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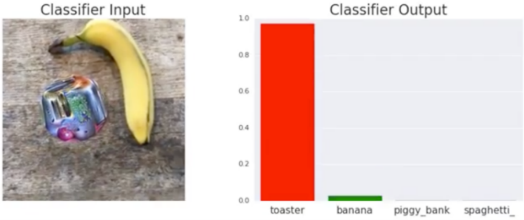

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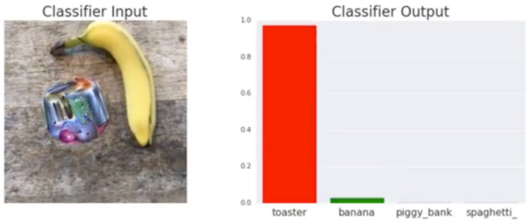

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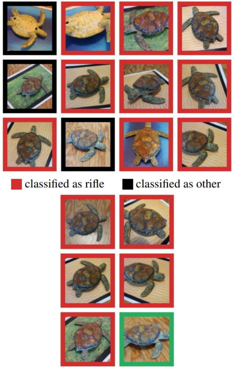
3D adversarial objects:



[23] Brown T. et al. “Adversarial patch.” 2017

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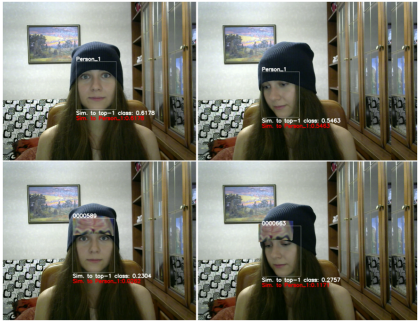
AdvHat[25] — invisibility hat

Due to the better projection procedure and richer color information, the attack is robust to rotations and brightness variation

Frontal face (advhat: no)
Similarity to origin: **0.61**

Frontal face (advhat: yes)
Similarity to origin: **0.02**
Similarity to other: **0.23**



Rotated face (advhat: no)
Similarity to origin: **0.54**

Rotated face (advhat: yes)
Similarity to origin: **0.11**
Similarity to other: **0.27**

[25] Komkov S. et al. "Advhat: Real-world adversarial attack on arcface face id system." 2019

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1. NNs for now are much better than human expert in controlled conditions
2. NNs are unstable w.r.t. its input
3. Digital $\rightarrow$ physical domain attack translation is hard
4. But even the most successful face ID systems can be fooled by a simple grayscale patch from common printer
5. ℓ_0-based local attack + TV loss + EOT are the must

Thank you!