Theoretic Fundamentals of Machine and Deep Learning

Adversarial Robustness and Attacks II: in Real World

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Plan

1. Adversarial examples in real world
2. Adversarial attack on face detection
3. Adversarial attack on face ID
4. Defense from adversarial examples in real world
5. Black-box face restoration

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Major approach

- Usual training:

$$\theta^{t+1} = \theta^t - \eta \nabla_{\theta^t} L(f_{\theta^t}(x), y)$$

- Adversarial perturbation:

$$x^{t+1} = x^t + \eta \nabla_{x^t} L(f_\theta(x^t), y)$$

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Robustness in Machine Learning

Robustness [informally]

Ability for a machine learning algorithm a to provide similar outputs on the similar data (i.e. having the same class or other invariant features)

Two types of **Robustness** in ML:

Generalization

Dataset issue: algorithm needs to be robust if the dataset to evaluate it differs (sometimes significantly: we can treat it is a distribution shift) from the training dataset

Adversarial Robustness

Noise issue: algorithm needs to provide the similar output w.r.t. both clean and noisy images (where the model of noise is the topic to consider itself)

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

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Adversarial Robustness topics

- Perturbations (also called 'adversarial *attacks*'): how to generate noise to fool the neural net

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- Defense: how to diminish the influence of adversarial perturbations
- Certification (or verification): how to provide theoretical guarantees on the noise level not fooling the neural net

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Adversarial Robustness topics

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- Defense: how to diminish the influence of adversarial perturbations
- Certification (or verification): how to provide theoretical guarantees on the noise level not fooling the neural net
  - Certification will be considered the next time

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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:

- Using ℓ_2-based norm (including geometric ones): most convenient for classical optimization
- Using ℓ_∞-based norm: correspond to perception process by the human eye of any visual information
- 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.

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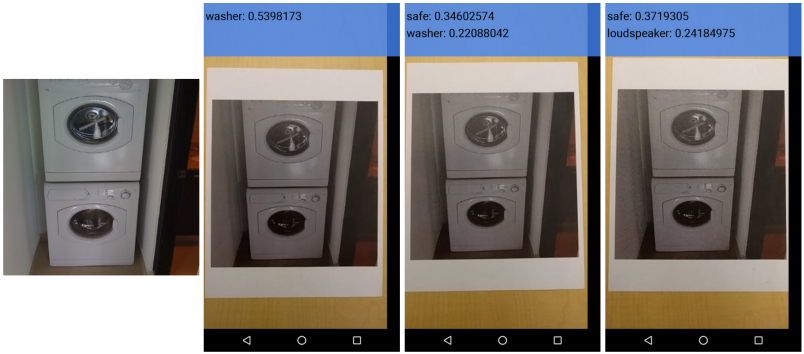
Real-world adversarial examples (1)

- All adversarial examples until now were designed to work in digital domain: e.g. to change the image on a pixel level
- If there is no possibility to change the image before feeding it into NN, then the digital method is useless
- That's why **real-world** (or physical) adversarial examples are the most universal ones
- The first try of real-world adversarial examples[1] — generation of an image in the digital domain, then printing it out on the physical carrier (paper sheet), then photo by digital camera and finally NN recognition
- No any specific technology to generate the real-world adversarial examples was proposed: only its existence was shown

[1] Kurakin, Alexey, Ian Goodfellow, and Samy Bengio. "Adversarial examples in the physical world." 2016

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 ⇒ the only option is to change the object appearance itself
- **E**xpectation **O**ver **T**ransformation (EOT)[2] to the rescue — takes into account the transformations of objects in the real world, e.g.:
  - Different scaling factors
  - Random translation and rotation
  - Luminosity / contrast variation, noise etc
- 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

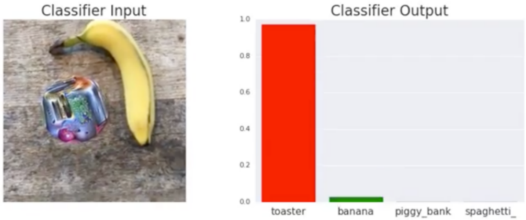
Find $\arg\min_r \mathbb{E}_{g\sim T}[P(y|g(x+r))]$ s.t.:

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. $x + r \in B$

[2] Athalye A. et al. "Synthesizing robust adversarial examples." 2017

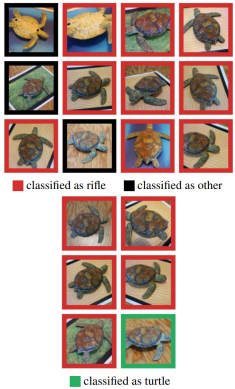
Examples of physical adversarial examples

Attack on ImageNet objects[3]:



Attack on road signs[4]:

3D adversarial objects:



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

[4]Eykholt K. et al. “Robust physical-world attacks on deep learning models.” 2017

Physical adversarial examples: key ingredients

- ℓ_0-optimization (mask-based) + EOT: the must
- **T**otal **V**ariation (TV) loss — penalty for the perturbation to be non-smooth (in the real world there is no distinct pixel gradients):

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

- **N**on-**P**rintability **S**core (NPS) — penalty for the perturbation colors that are out of the generator device (e.g., printer) limited gamut. E.g. if $G \subset [0,1]^3$ — limited device gamut, then the loss for using the pixel $q_0 \in [0,1]^3$:

$$NPS(q_0) = \Pi_{q \in G} ||q - q_0||_2$$

- Additional color adjustments (e.g. generator device provides not color c, but some its modification $m(c)$)

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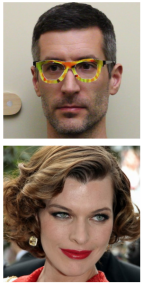
Prior art: Face Det and ID attack

- Initially the **Camouflage Art**[5] was used to avoid the leading at that time Viola-Jones face detection system
- It was just the makeup crafted manually to fool the Haar detector
- Pioneering work[6] proposed to use printed adversarial glasses
- It uses ℓ_0-optimization + EOT + TV + NPS + color adjustments
- But it was used for closed-set recognition (a few predefined person ID for training) and for old generation FaceID NN

cvdazzle.com

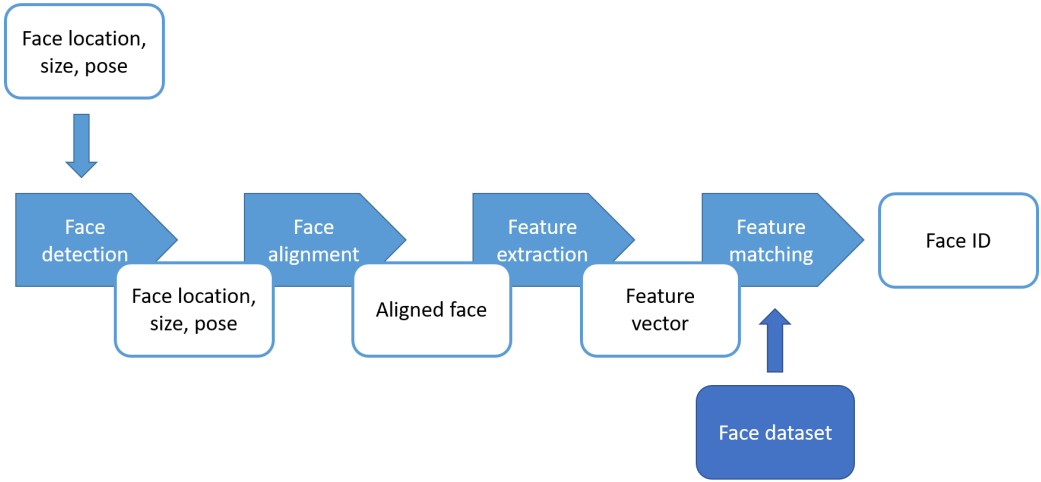
Adversarial glasses



[5] Feng R. et al. "Facilitating fashion camouflage art." 2013

[6] Sharif M. et al. "Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition." 2016

Face processing pipeline



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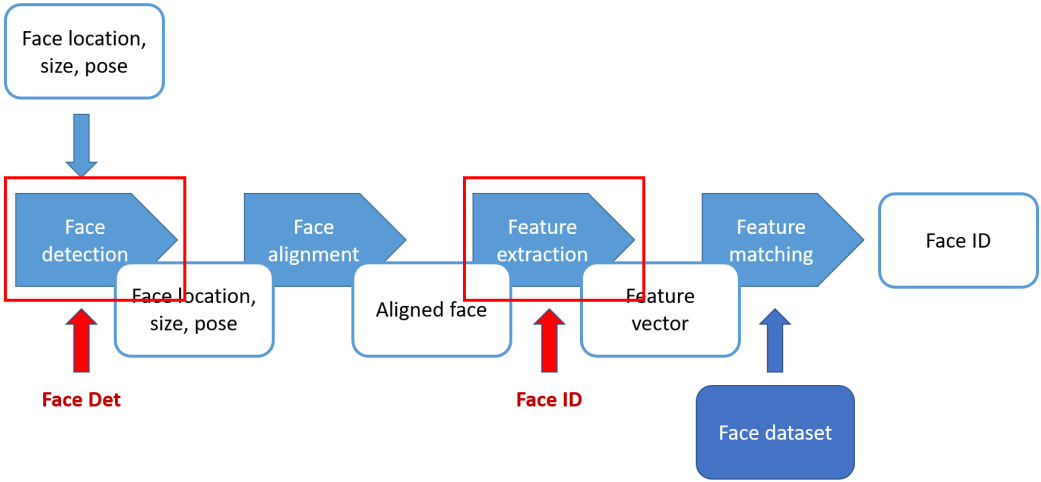
Face processing pipeline



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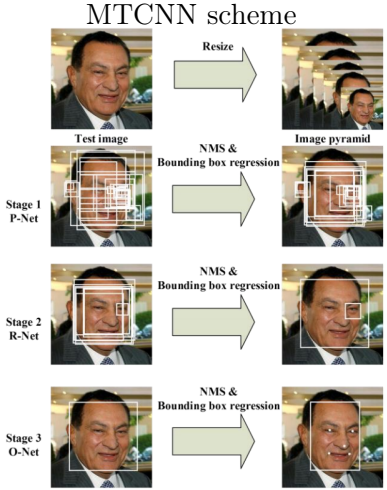
Face detection: MTCNN[7]

- Unlike modern and heavy detectors based on Faster RCNN and YOLO the MTCNN detector is quite shallow ⇒ smaller perception field, harder to change the detection conclusion
- MTCNN is cascade-based: in the beginning the rough approximation is provided (P-Net), then its tuning (R-Net and O-Net) is performed
- Based on our experiments, the most appropriate place for attack is the first P-Net and its classification loss (not bounding boxes or key points regression losses)

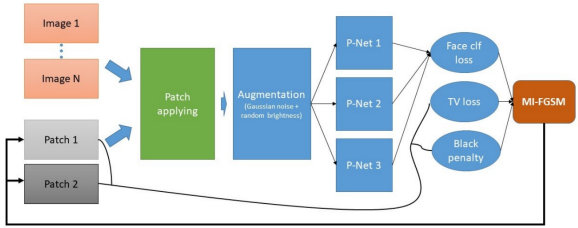


[7] Zhang K. et al. "Joint face detection and alignment using multitask cascaded convolutional networks." 2016

Adversarial attack on MTCNN face detector

- EOT: Gaussian noise, patch size, brightness, batch of different face images
- TV loss: used, NPS: not used
- Color adjustment: push the color to be the black one ($x_{i,j} = 1$) $\Rightarrow$ new additive loss part: $L_{BLK}(x) = \sum_{i,j}(1 - x_{i,j})$
- MI-FGSM as the optimizer

MTCNN adversarial attack



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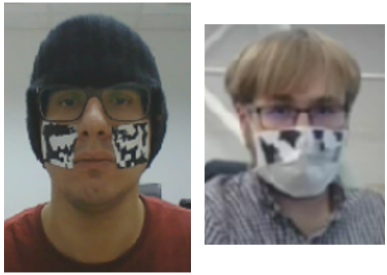
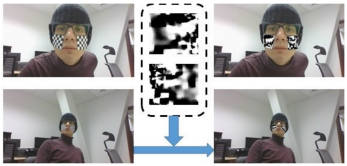
Adversarial attack on MTCNN face detector

- ℓ_0-based optimization: two versions of adversarial patches
  1. two distinct patches on cheeks
  2. the whole medicine mask
- MTCNN has small perceptive field $\Rightarrow$ patches are not semantical (unlike for FaceID, see next)
- Need to estimate the local affine projections parameters based on the prepared special grid

Patches



Projection



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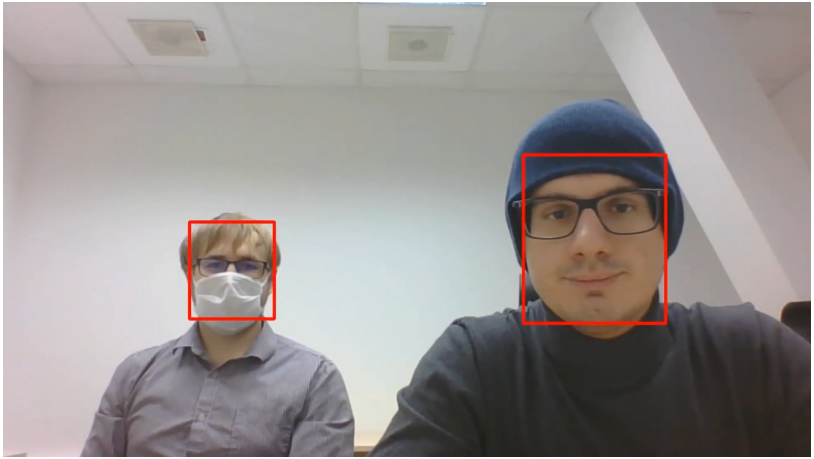
Adversarial attack on MTCNN face detector: outcome

Details: paper[8] (IEEE-2019) and video[9].



[8] Kaziakhmedov E. et al. “Real-world attack on MTCNN face detection system.” 2019

[9] `https://www.youtube.com/watch?v=OY70OIS8bxs`

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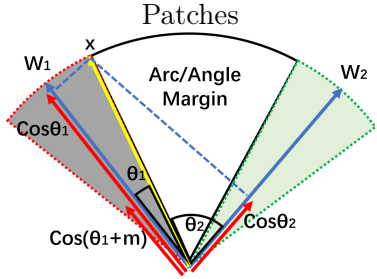
FaceID: ArcFace[10]

- For face ID adversarial attack the best public face ID system was chosen: ArcFace
- Main idea of ArcFace — to use angle margin (aligned with cosine similarity)
- Huge training dataset (MS1M) and deep CNN (ResNet-100) are used

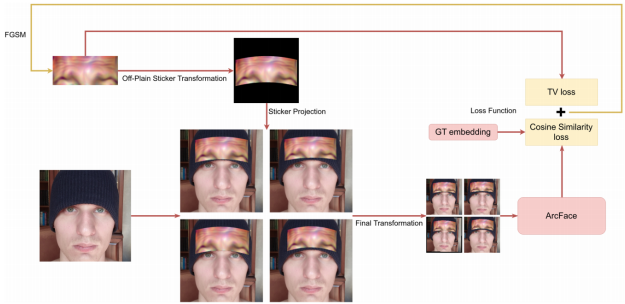


[10] Deng J. et al. "Arcface: Additive angular margin loss for deep face recognition." 2018

Adversarial attack on ArcFace face ID

- EOT: Different patch projection parameters, single face image
- TV loss: used, NPS: not used, Color adjustment: not used
- Additive similarity loss to work in open-set setting:
  $L_{sim}(x, x_{gt}) = cos(emb(x), emb(x_{gt}))$, where x_{gt} — template image for the person, $emb(x)$ — feature vector of x
- MI-FGSM as the optimizer

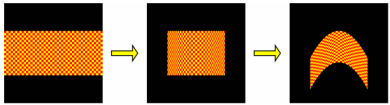
ArcFace adversarial attack



Adversarial attack on ArcFace face ID

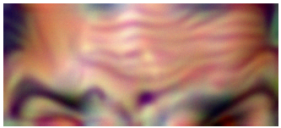
- ℓ_0-based optimization: color patch on the forehead
- Deep NN $\Rightarrow$ large perception field $\Rightarrow$ patch is semantical
- Nonlinear off-plane projection: $(x, y, 0) \to (x', y, z'), z' = a \cdot x'^2$
- All image transformation done by differentiable Spatial Transformer Layer[11]

Off-plane projection



$$x = a \cdot \left(|x'| \cdot \sqrt{(x')^2 + \frac{1}{4 \cdot a^2}} + \frac{1}{4 \cdot a^2} \cdot \ln \left(|x'| + \sqrt{(x')^2 + \frac{1}{4 \cdot a^2}} \right) - \frac{1}{4 \cdot a^2} \cdot \ln \left(\frac{1}{2 \cdot a} \right) \right)$$

Semantic patch examples



[11] Jaderberg M. et al. "Spatial transformer networks." 2015

AdvHat — invisibility hat

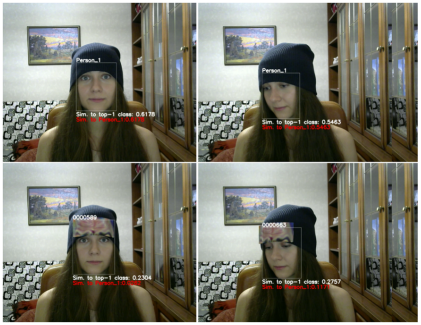
Due to the better projection procedure and richer color information, the attack is robust to rotations and brightness variation

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**

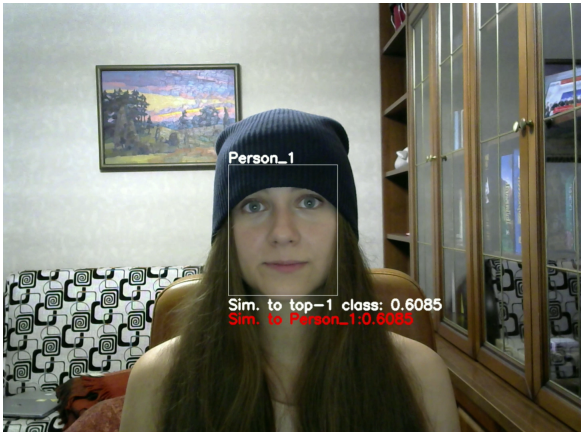
|

|

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

Adversarial attack on ArcFace face ID: outcome

Details: paper[12] (ICPR-2020) and video[13].



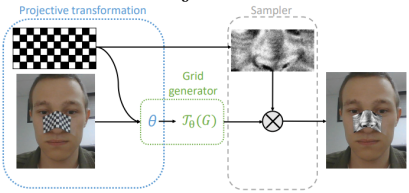
[12] Komkov S. et al. "Advhat: Real-world adversarial attack on arcface face id system." 2019

[13] `https://www.youtube.com/watch?v=a4iNg0wWBsQ`

Adversarial attack on ArcFace face ID: grayscale patch[14] (IEEE-2019)

- Combination of two previous approaches:
  - Grayscale color loss adjustment
  - Local affine grid projection
- Patch is also semantical

Projection



Patches

[14] Pautov M. et al. "On adversarial patches: real-world attack on ArcFace-100 face recognition system." 2019

FaceID adversarial defense in real world[16]

- Almost all of the real world attacks are patch-based
  - Proposal: **A**dversarial **T**raining (AT)[15] in the pixel space with patch-based augmentation
- AT decoupling:
  1. Best (=max loss) location of gray patch by:
     - ★ Exhaustive search
     - ★ Max gradient locations w.r.t. input
  2. PGD inside this patch

- Common training procedure:

$$\min_{\theta} \mathbb{E}_{x,y}[L(\theta, x, y)]$$

- Adversarial Training:

$$\min_{\theta} \mathbb{E}_{x,y}[\max_{r \in \Delta} L(\theta, x + r, y)]$$

[15] Goodfellow I. et al. "Explaining and harnessing adversarial examples." 2014

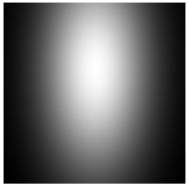
[16] Wu T. et al. "Defending Against Physically Realizable Attacks on Image Classification." 2019

Black-box face restoration

- Black-box model M: $M(x) = y$, where
  - x — input image of the face
  - y — its feature representation (embedding)
- **Task**: to recover x' to preserve the person identity
- **Prior art**: using reconstruction MSE and perceptual metrics / GANs (NBNet[17])
- **Our approach**: use zero-order optimization to find such x' so as FaceID $M(x') \approx M(x)$
  - Use as M the public SotA in FaceID: ArcFace
  - Test by using independent critic: FaceNET[18]
  - Similarity loss: $1 - cos(M(x'), M(x))$
  - Additional term: $(||M(x')||_2 - ||M(x)||_2)^2$

- **Main difficulty**: huge search space in pixel domain
- **Solution**: to use prior knowledge about face — 2D Gaussians

$$G(x, y) = A \cdot e^{\frac{(x-x_0)^2}{2\sigma_1^2} + \frac{(y-y_0)^2}{2\sigma_2^2}}$$



$$(x_0, y_0, \sigma_1, \sigma_2, A) = (56, 72, 22, 42, 1)$$

[17] Mai G. et al. "On the reconstruction of face images from deep face templates." 2018

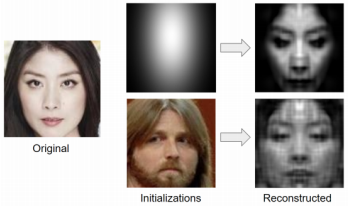
[18] Schroff F. et al. "Facenet: A unified embedding for face recognition and clustering." 2015.

Black-box face restoration: successful tricks

- Even prior info about face is not enough
- **Trick1**: Use vertical face symmetry ⇒ use only half of the face to search
- **Trick2**: For identity preservation usually no need in color ⇒ use only a single color channel instead of 3

Symmetrical, non-symmetrical, color restoration

- **Initialization**: What to use as the starting point?
- **Common approach**: to use other face (can be biased)
- **Our approach**: optimal Gaussian blob (additional loss term is needed)



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Black-box face restoration: results

Our method:						
ArcFace:	0.97	0.97	0.94	0.97	0.85	0.73
FaceNet:	0.70	0.75	0.72	0.78	0.38	-0.09
NBNet (WB):						
ArcFace:	0.17	0.21	0.12	0.26	0.06	0.09
FaceNet:	0.02	0.32	0.25	0.46	-0.01	0.35
NBNet (RGB):						
ArcFace:	0.28	0.46	0.34	0.54	0.12	0.21
FaceNet:	0.59	0.53	0.44	0.74	0.18	0.41
Original:						

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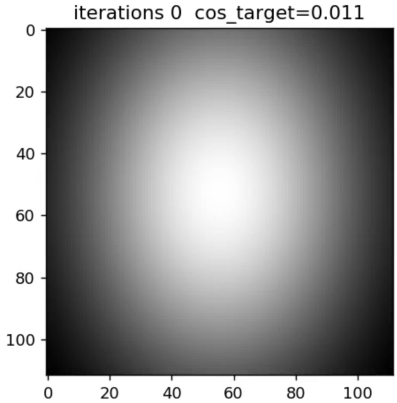
Black-box face restoration: outcome

Details: paper[19] (ECCV-2020) and video presentation[20].

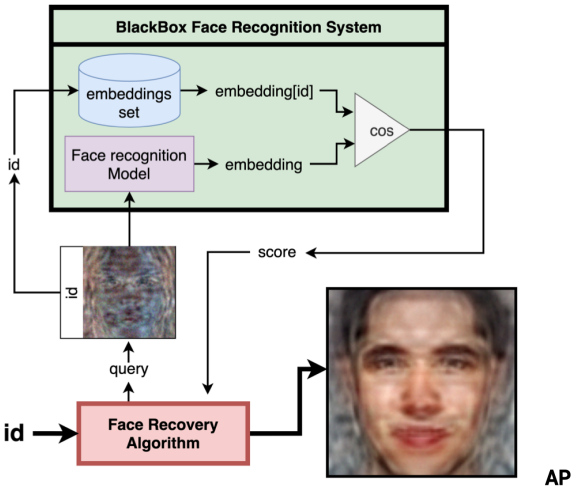


[19] Razzhigaev A. et al. "Black-Box Face Recovery from Identity Features." 2020

[20] `https://www.youtube.com/watch?v=sOrTcqRTw2A`

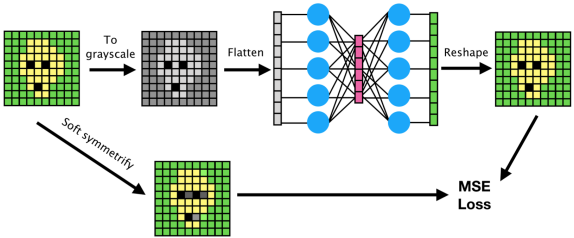
Black-box face restoration: more constraints

- **Task**: to recover x' from the Black-box model M, where we can **use only the similarity**:
  $S(x, x') = 1 - cos(M(x'), M(x))$
- Now the reconstruction is done fully **colorful**
- For this case the usage of so-called "**eigenfaces**" (actually, columns of the autoencoder decoder weights matrix) is added



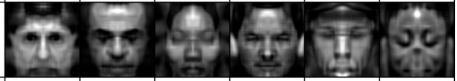
Darker than a Black-box face restoration: losses

- Autoencoder: $y = W_2(W_1 x)$, trained[21] on the public faces dataset
- W_1 — encoder, W_2 — decoder, z — latent representation ($z \in \mathbb{R}^{1024}$)
  - In our case, z is providing the projection weights to "eigenfaces space"
- Loss: $L(x) = \left(\frac{x+2R(x)}{3} - W_2(W_1 x)\right)^2 + (W_2 z - x)^2$
  - $z \sim N(0, I)$ and $R(\cdot)$ is a vertical reflection operator



[21] Razzhigaev, Anton, et al. "Darker than black-box: Face reconstruction from similarity queries." 2021

Darker than a Black-box face restoration: results

Ours (RGB)						
ArcFace	0.99	0.99	0.99	0.99	0.99	0.99
FaceNet	0.77	0.82	0.77	0.61	0.62	0.72
Ours (gray-scale)						
ArcFace	0.98	0.99	0.99	0.98	0.99	0.99
FaceNet	0.71	0.78	0.60	0.51	0.59	0.74
Gaussian sampling (gray-scale)						
ArcFace	0.97	0.97	0.94	0.97	0.85	0.73
FaceNet	0.70	0.75	0.72	0.78	0.38	-0.09
NBNet (RGB)						
ArcFace	0.28	0.46	0.34	0.54	0.12	0.21
FaceNet	0.59	0.53	0.44	0.74	0.18	0.41
Original						

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Takeway notes

- Digital $\rightarrow$ physical domain attack translation is hard
- But even the most successful face ID systems can be fooled by a simple grayscale patch from common printer
- ℓ_0-based local attack + TV loss + EOT are the must
- Need to use projection schemes allowing gradient backpropagation
- Adversarial training in practice (or certified robustness in theory) can help to defense
- Face image can be restored even in black-box setting using only similarities

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Thank you!