Adversarial examples, Generative Adversarial Networks

Frederic Precioso

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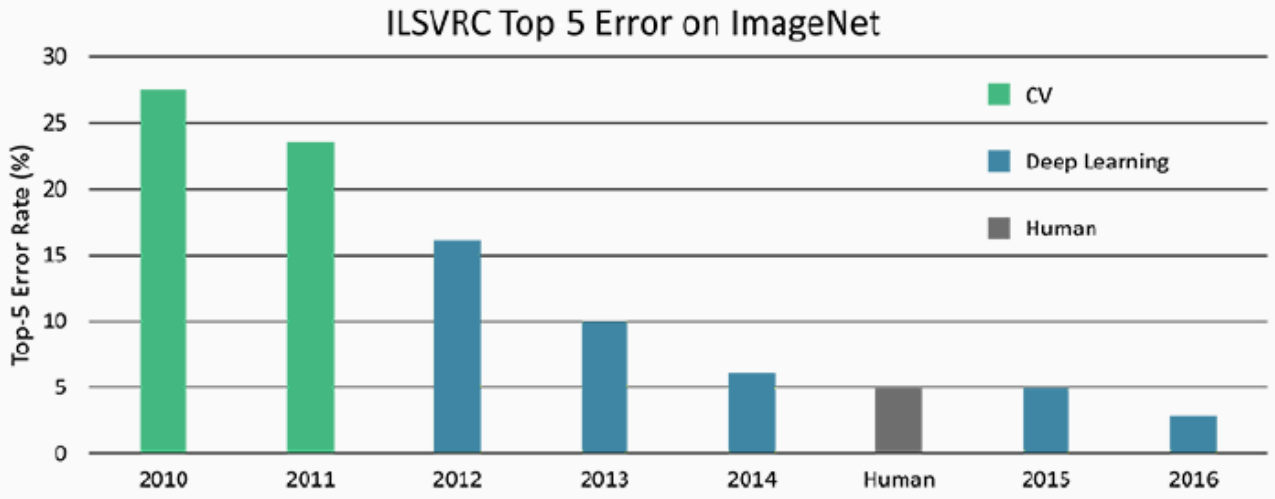
Deep representation by CNN

- Deep Networks are as good as humans at recognition, identification...



How much does a deep network understands those tasks?

ADVERSARIAL EXAMPLES

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Morphing

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Amazing but…be careful of the adversaries (as any other ML algorithms)

Intriguing properties of neural networks

C. Szegedy, w. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, R. Fergus

arXiv preprint arXiv:1312.6199

2013

[1312.6199] Intriguing properties of neural networks - arXiv.org

https://arxiv.org › cs - Traduire cette page

de C Szegedy - 2013 - Cité 449 fois - Autres articles

21 déc. 2013 - In this paper we report two such **properties**. First, we ... Second, we find that deep **neural networks** learn input-output mappings that are fairly ...

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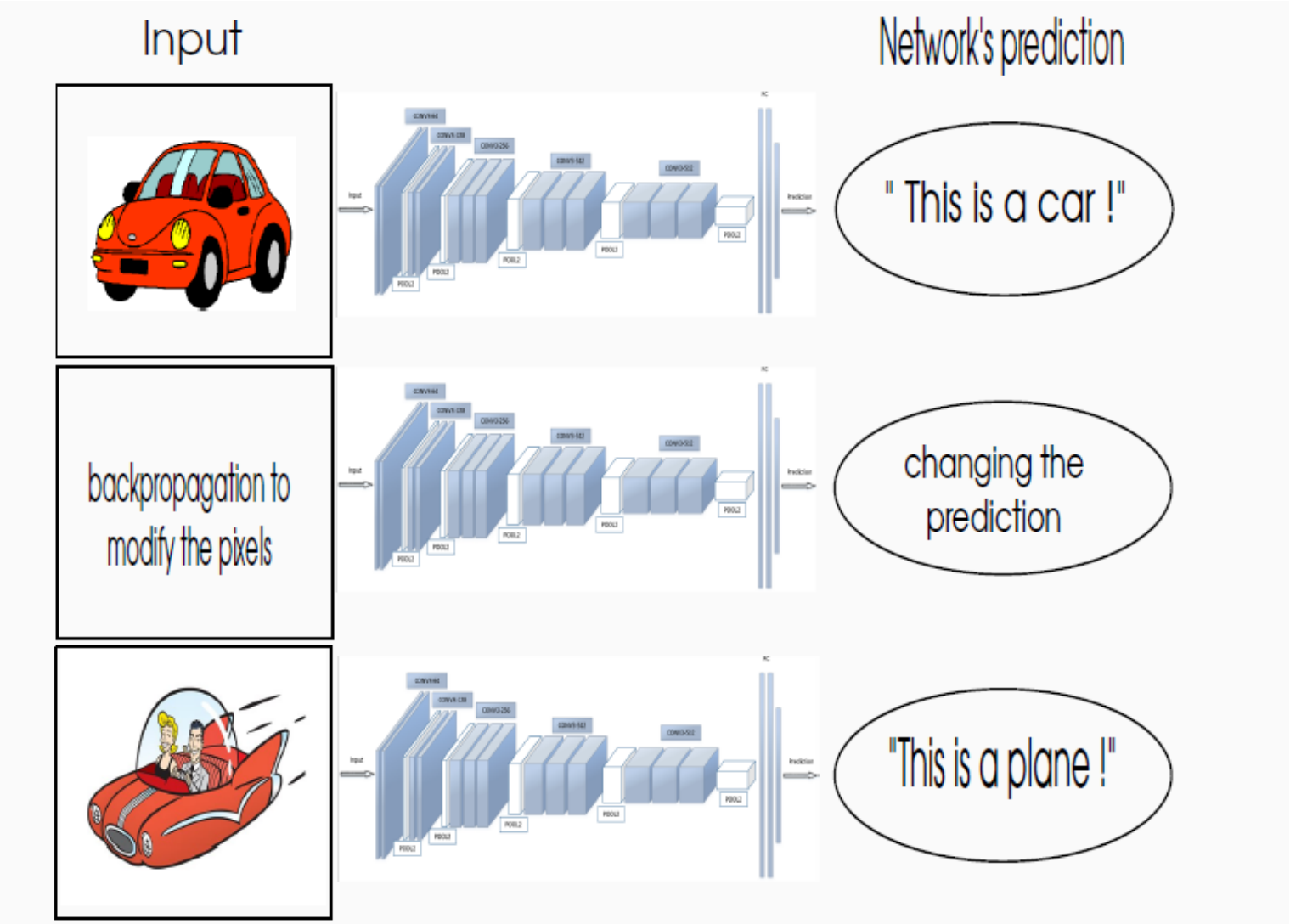

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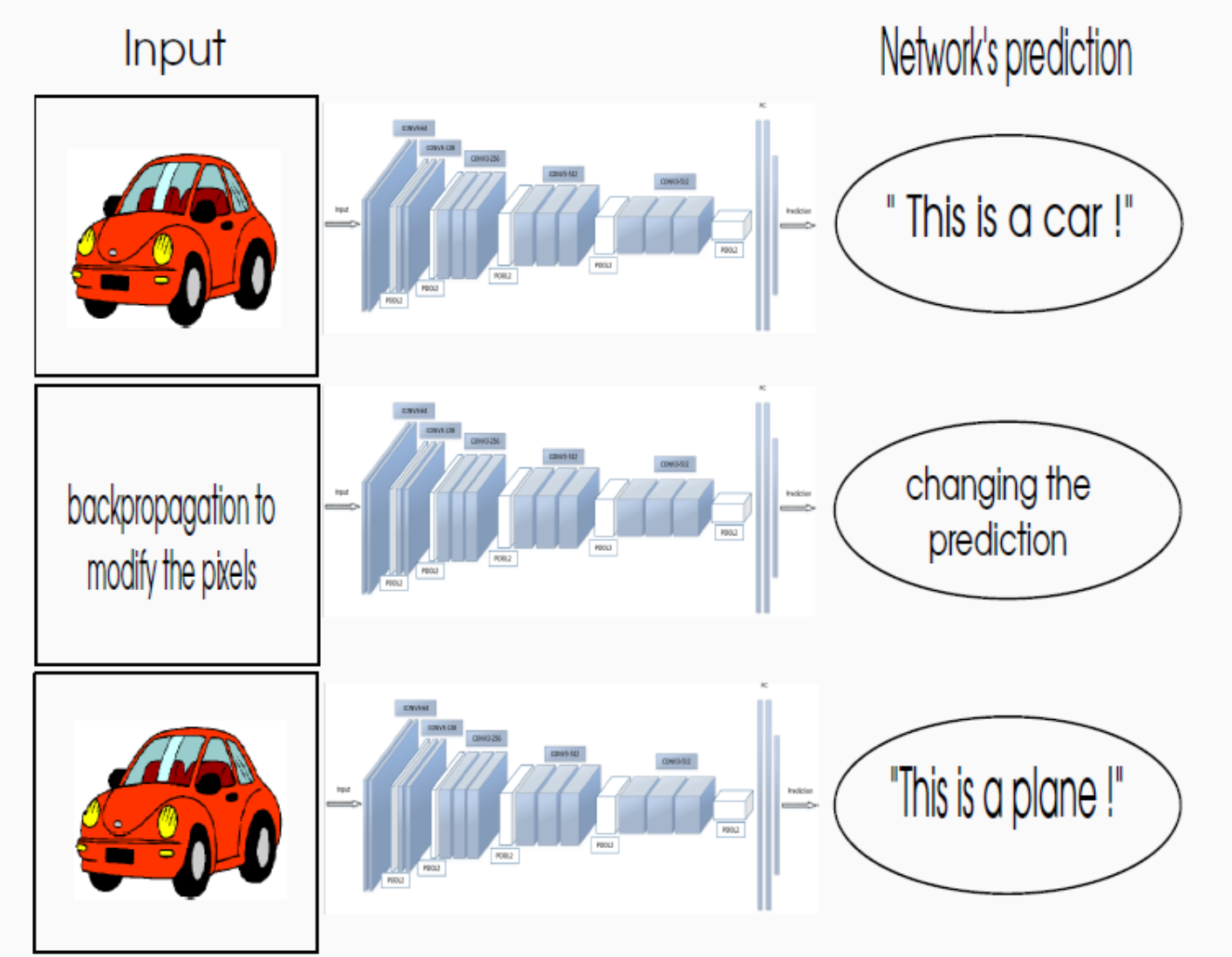

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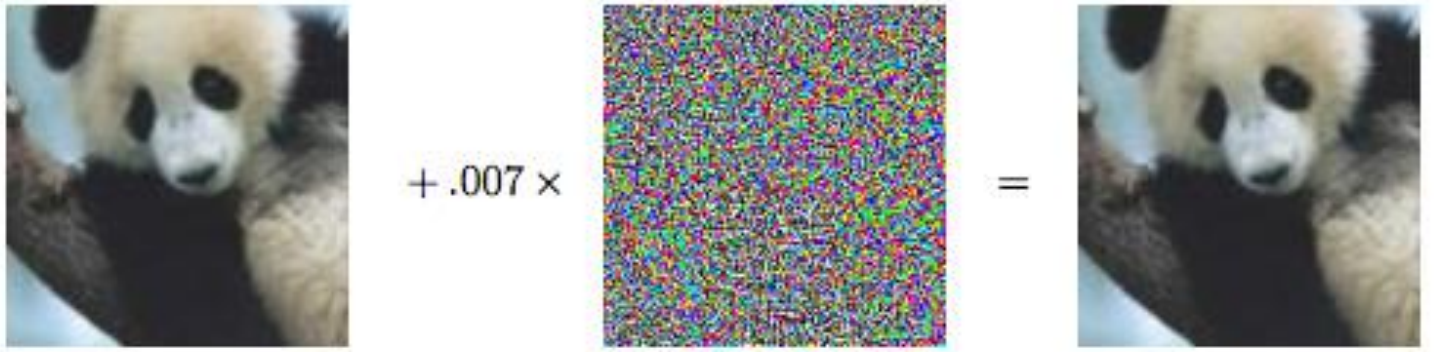

Andrej Karpathy blog, http://karpathy.github.io/2015/03/30/breaking-convnets/

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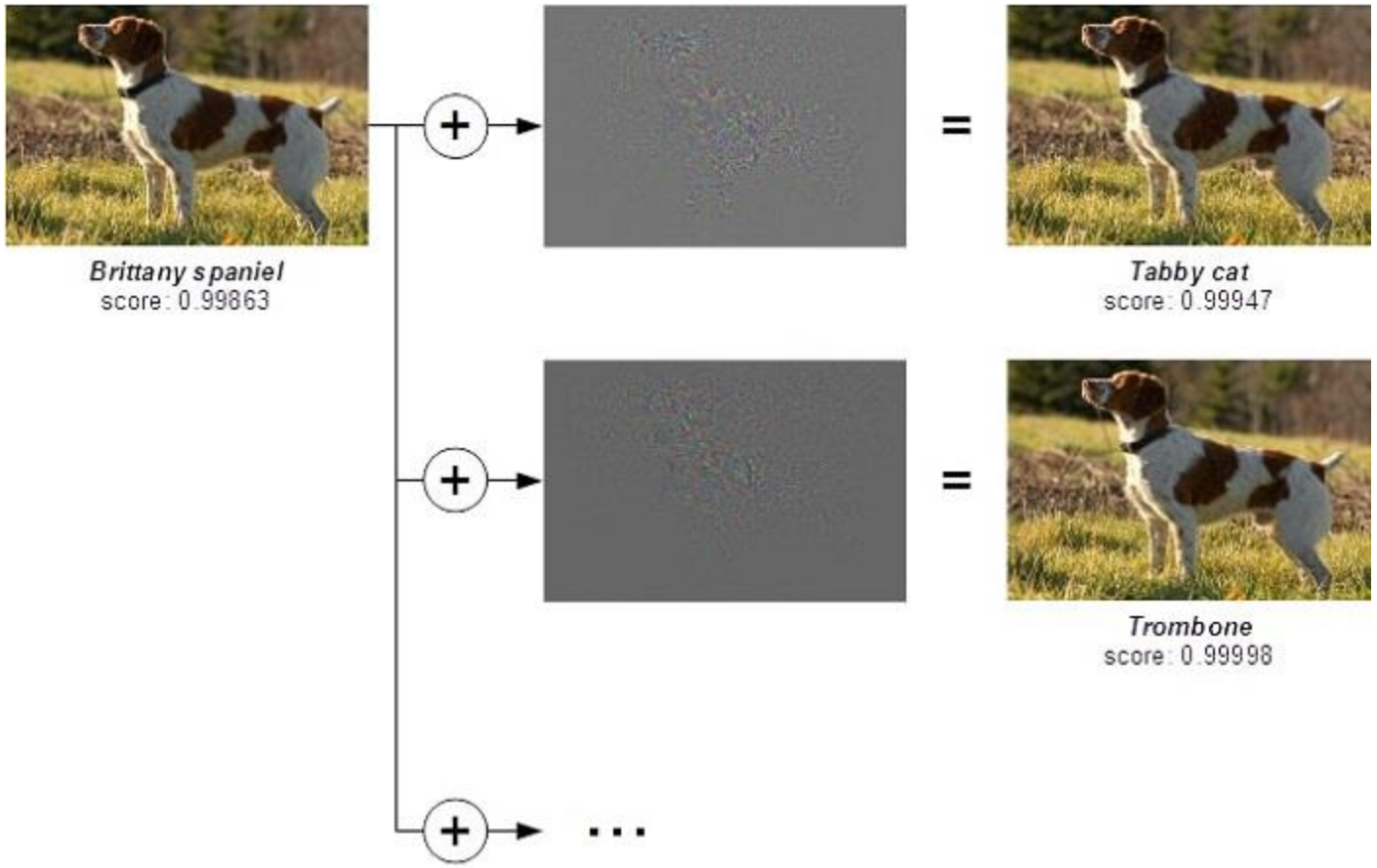

From Thomas Tanay

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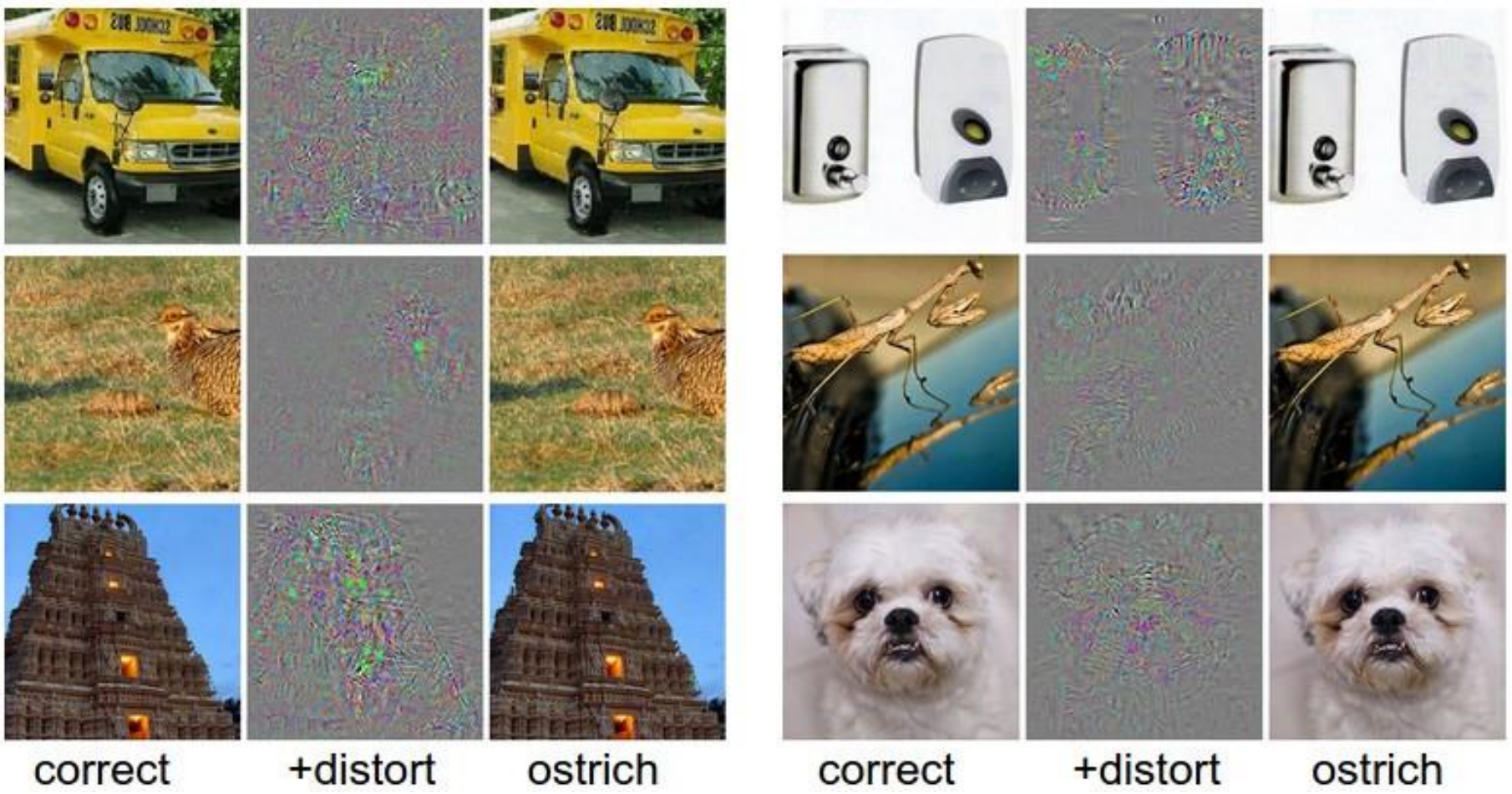

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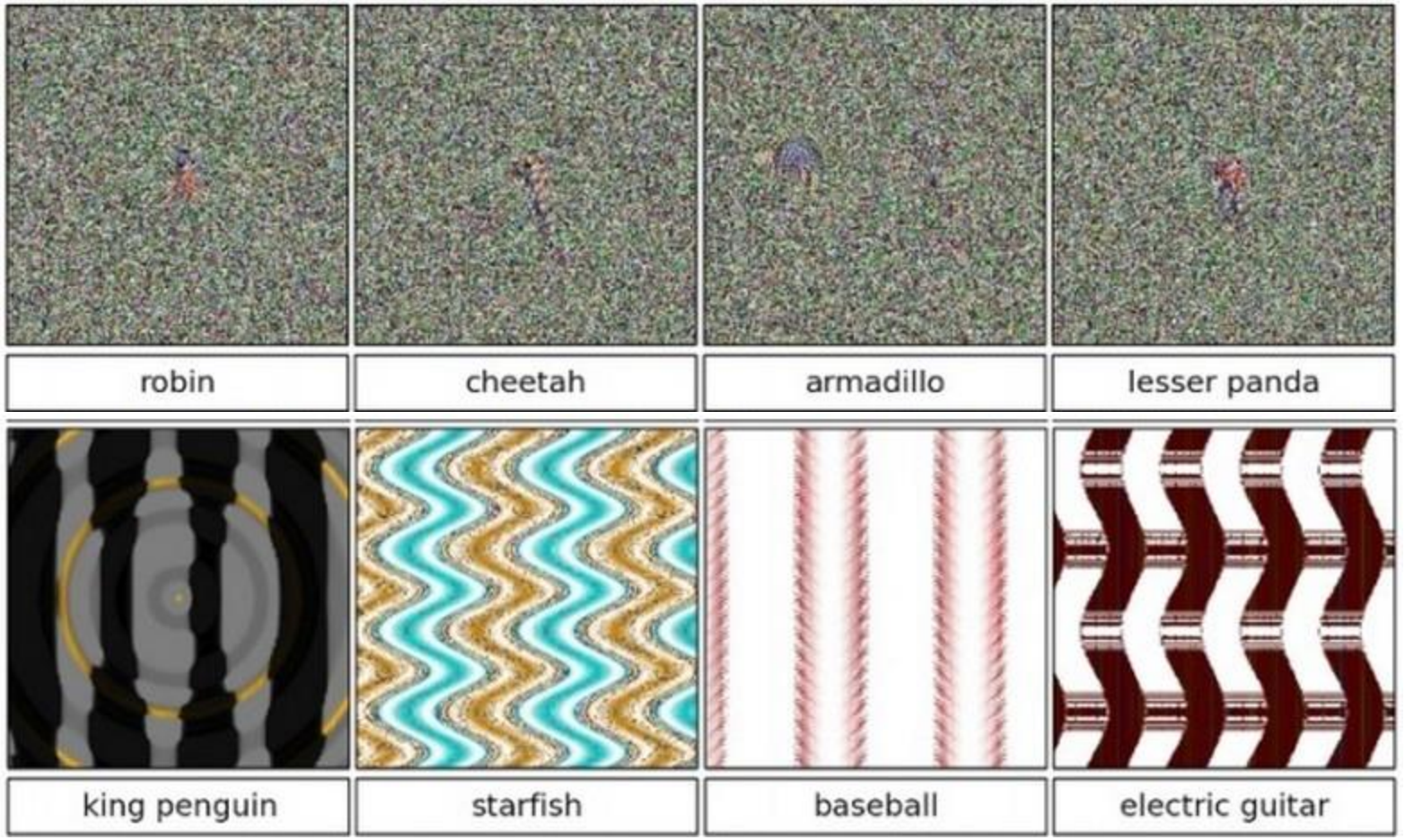

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Amazing but…be careful of the adversaries (as any other ML algorithms)

Definition: $\hat{x}$ is called adversarial iff:

- given image x
- low distortion $|| x - \hat{x} ||< \epsilon, \quad (\epsilon > 0$, few pixels)
- given network's probabilities $f_\theta(x)$
- Different predictions! $argmax f_\theta(x) \neq argmax f_\theta(\hat{x})$

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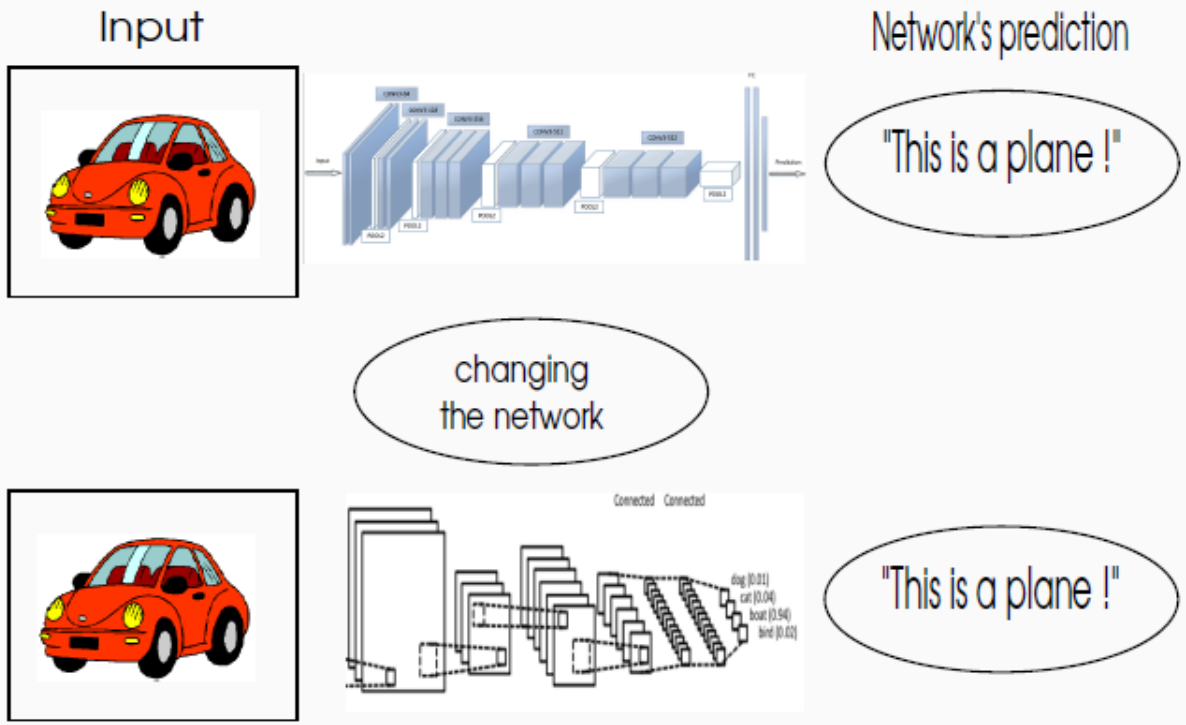
Amazing but…be careful of the adversaries (as any other ML algorithms)

- $\neq$ outliers
- regularization: correct one… find another
- high confidence predictions
- **Transferability**



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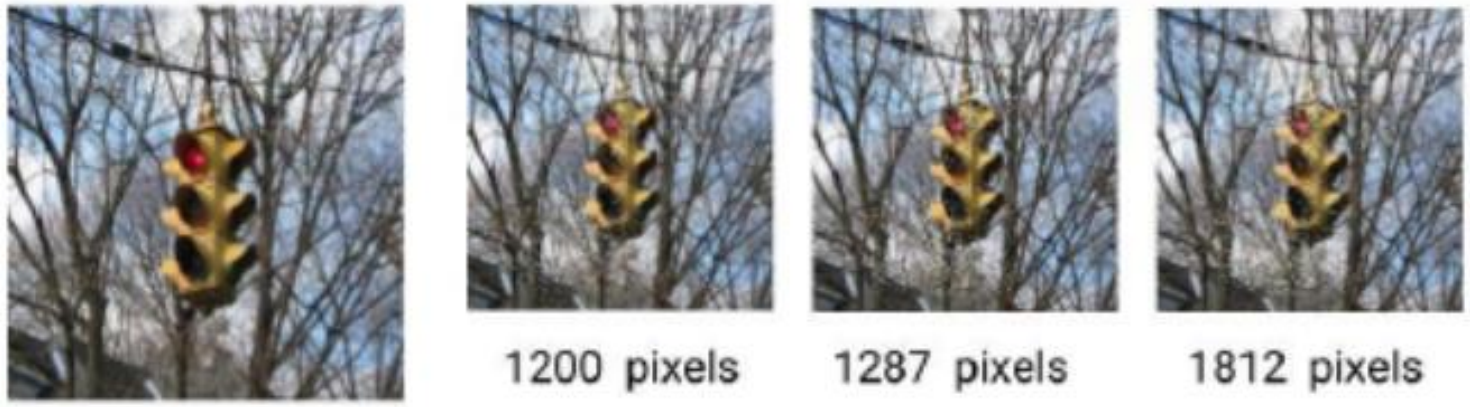

Original Traffic light (ImageNet class 920)

VGG16

VGG19 Misclassified

RESNET

State-of-the art deep neural networks on ImageNet

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Red Light Modified to Green after 18 white pixels. Probability: 59%

Red Light Modified to Green after 9 green pixels. Probability: 50.9%

Red Light Modified to Green after 9 green pixels. Probability: 53%

No Light Modified to Green after 4 green pixels. Probability: 51.9%

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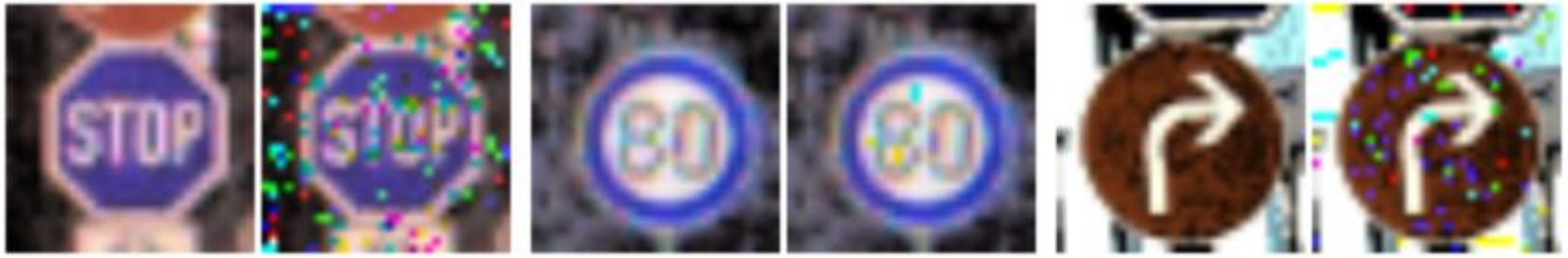

stop	30m speed limit	80m speed limit	30m speed limit	go right	go straight
Confidence	0.999964		0.99		

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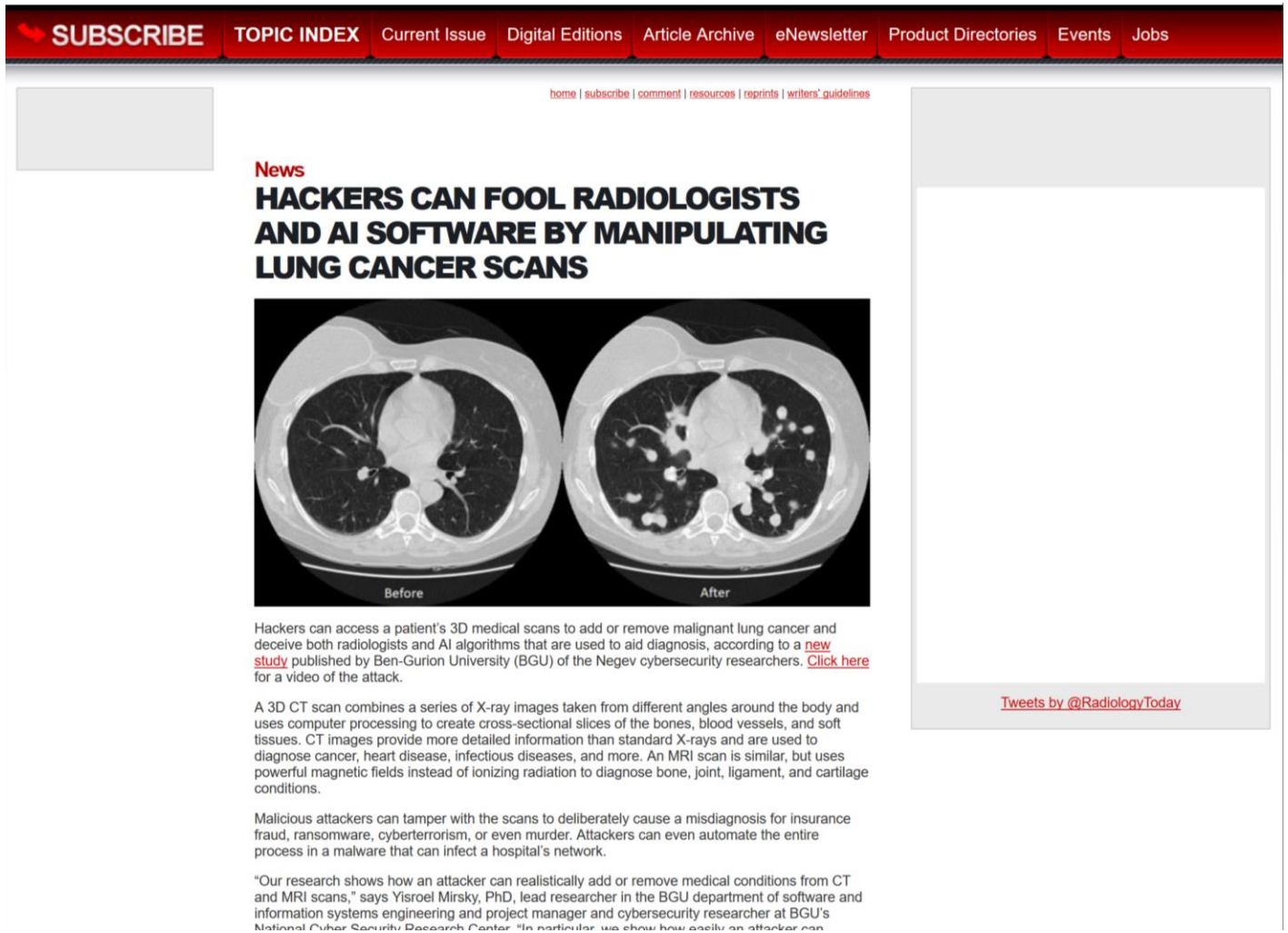

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News

HACKERS CAN FOOL RADIOLOGISTS AND AI SOFTWARE BY MANIPULATING LUNG CANCER SCANS

Hackers can access a patient's 3D medical scans to add or remove malignant lung cancer and deceive both radiologists and AI algorithms that are used to aid diagnosis, according to a new study published by Ben-Gurion University (BGU) of the Negev cybersecurity researchers. Click here for a video of the attack.

A 3D CT scan combines a series of X-ray images taken from different angles around the body and uses computer processing to create cross-sectional slices of the bones, blood vessels, and soft tissues. CT images provide more detailed information than standard X-rays and are used to diagnose cancer, heart disease, infectious diseases, and more. An MRI scan is similar, but uses powerful magnetic fields instead of ionizing radiation to diagnose bone, joint, ligament, and cartilage conditions.

Malicious attackers can tamper with the scans to deliberately cause a misdiagnosis for insurance fraud, ransomware, cyberterrorism, or even murder. Attackers can even automate the entire process in a malware that can infect a hospital's network.

"Our research shows how an attacker can realistically add or remove medical conditions from CT and MRI scans," says Yisroel Mirsky, PhD, lead researcher in the BGU department of software and information systems engineering and project manager and cybersecurity researcher at BGU's National Cyber Security Research Center. "In particular, we show how easily an attacker can

Tweets by @RadiologyToday

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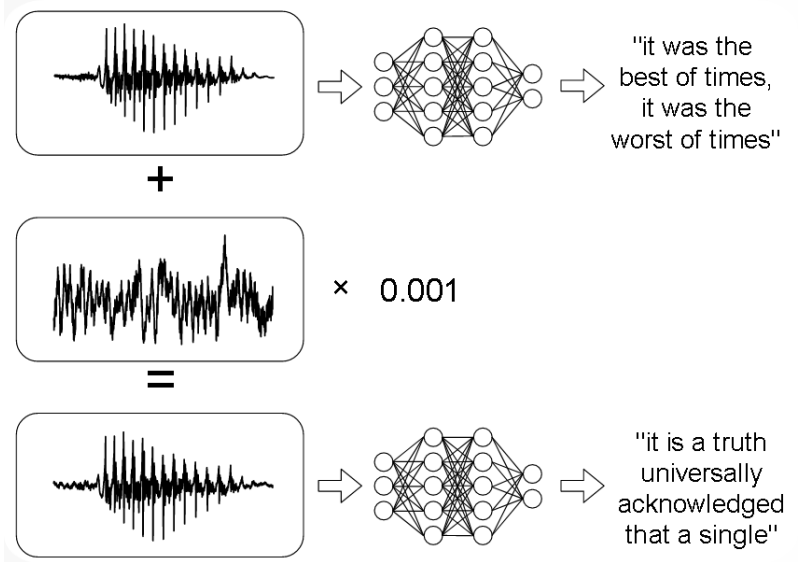

Figure from our paper: given any waveform, we can modify it slightly to produce another (similar) waveform that transcribes as any different target phrase.

https://nicholas.carlini.com/code/audio_adversarial_examples/

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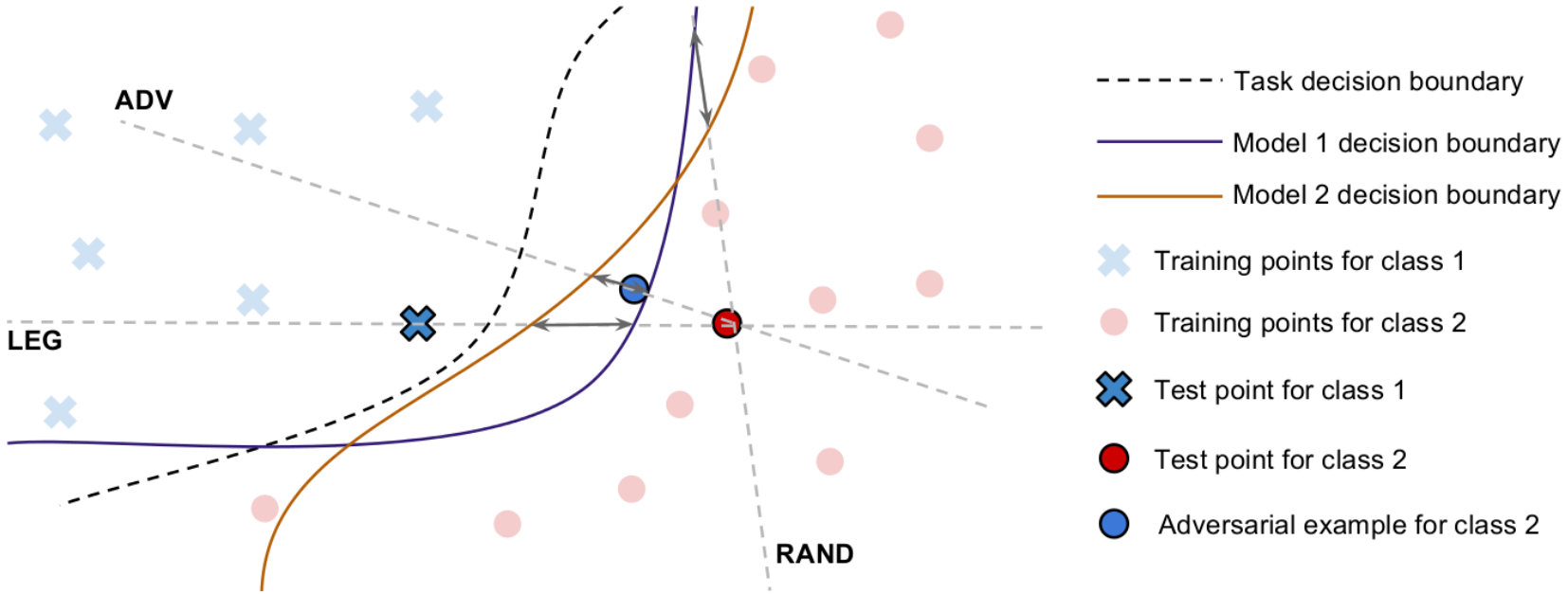
Adversarial examples…



Tramèr, F., Papernot, N., Goodfellow, I., Boneh, D., & McDaniel, P. (2017).
The space of transferable adversarial examples. *arXiv preprint arXiv:1704.03453*.

Can we benefit from adversarial examples and all their properties?

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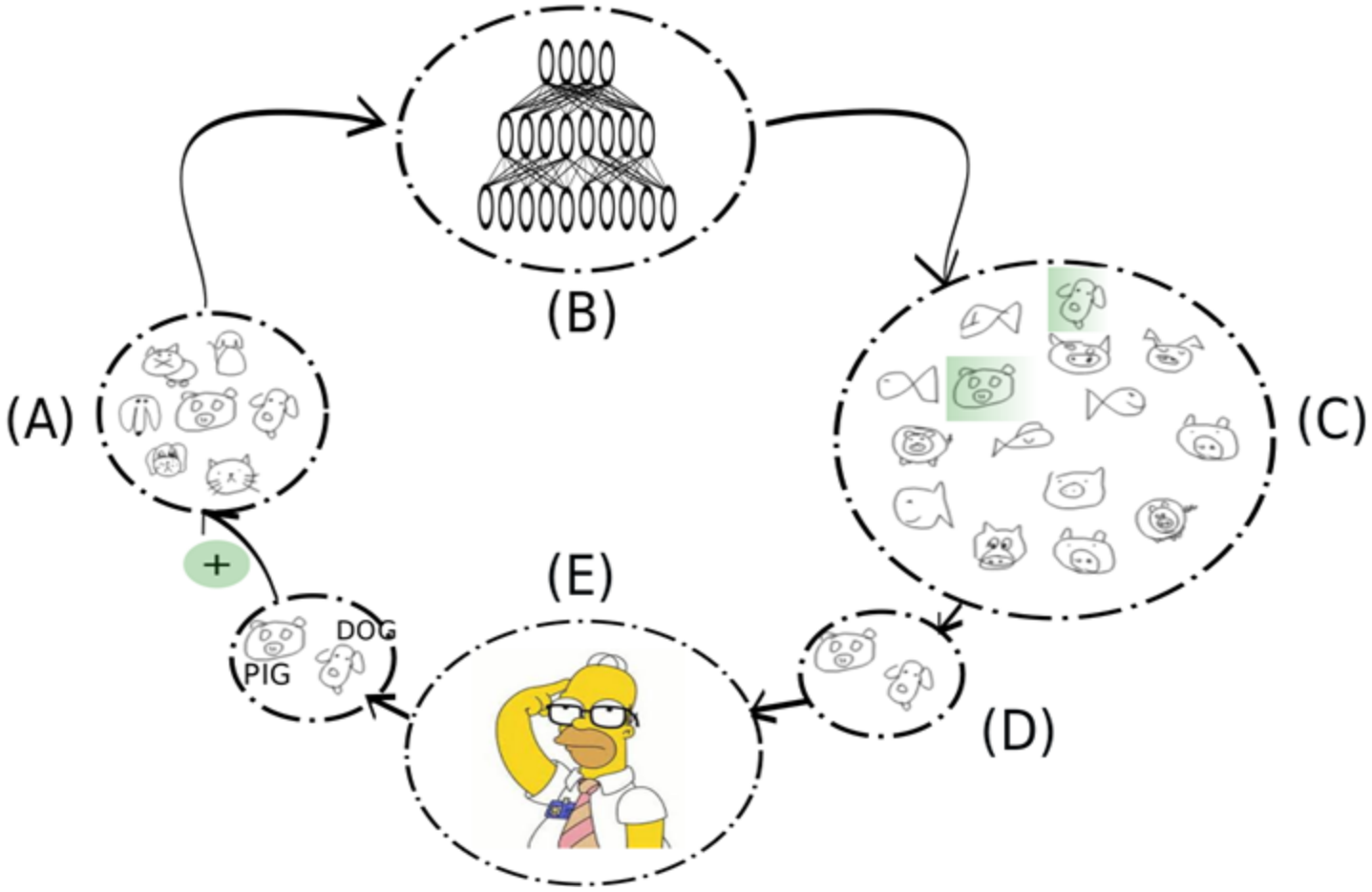
ACTIVE Supervised Classification



(A)=labelled data

(B)=model

(C)=**POOL** of unlabelled data

(D)=**BATCH** of query

(E) ORACLE (eg human)

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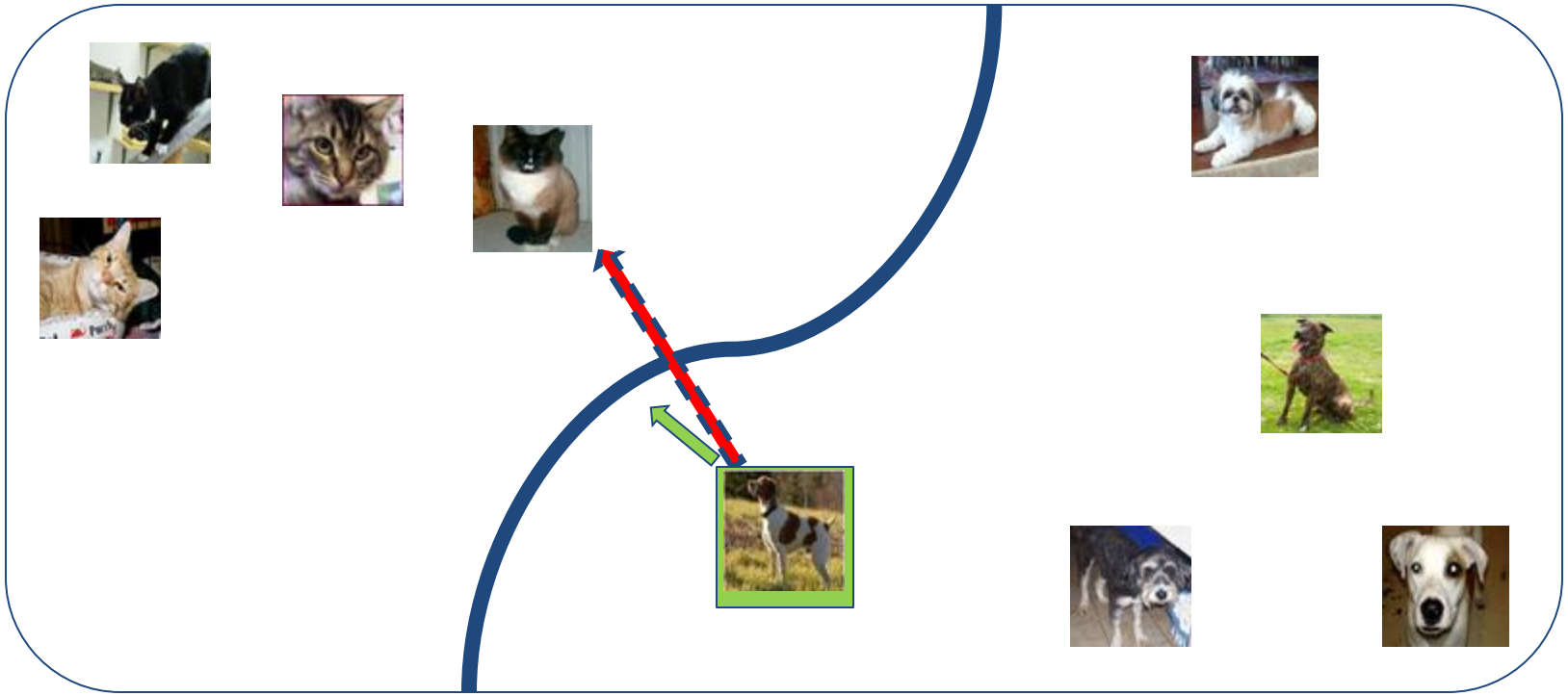
MARGIN BASED ACTIVE LEARNING?

- query => close to the decision boundary
- topology of the decision boundary unknown
- how can we approximate such a distance for neural networks ?
- *"Dimension + Volume + Labels"*



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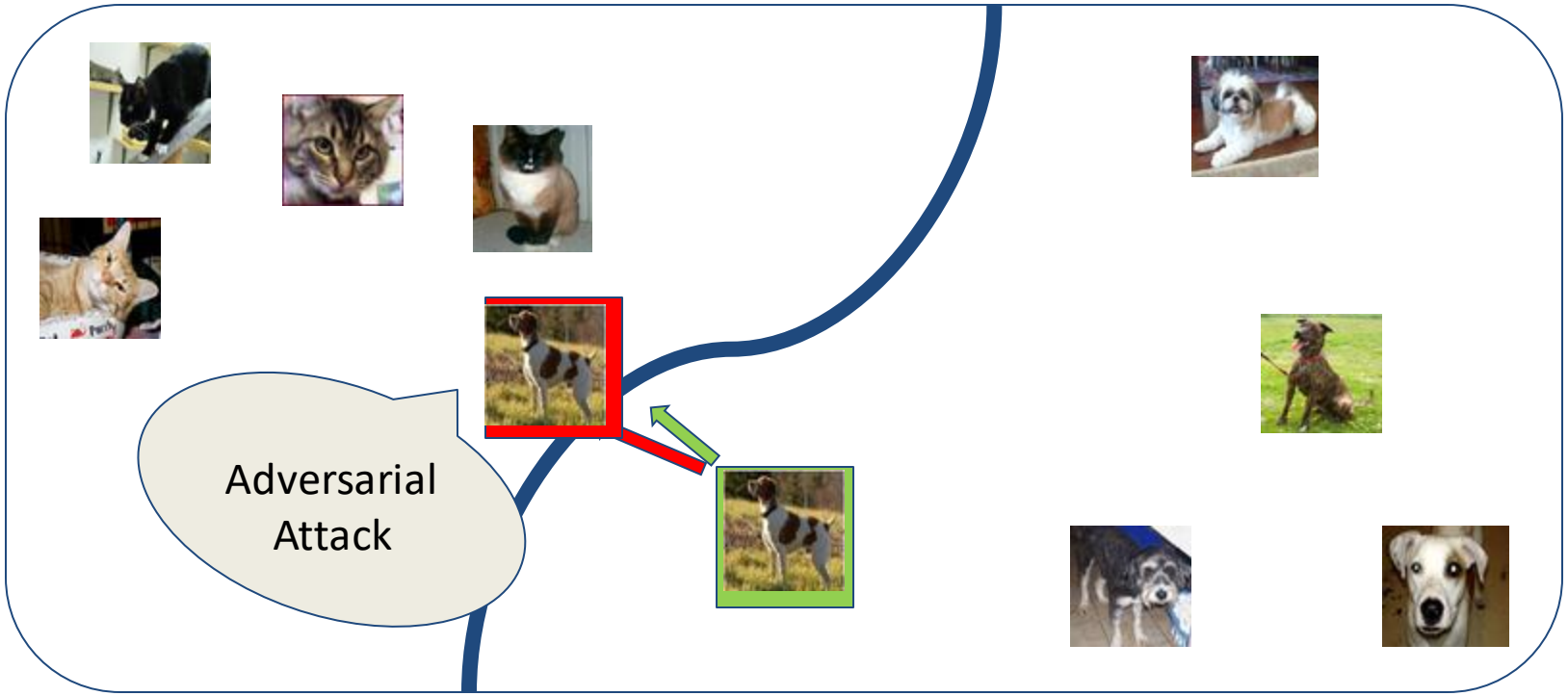
Adversarial attacks for MARGIN BASED ACTIVE LEARNING

- query ➡ small adversarial perturbation



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DeepFool Active Learning (DFAL)

☑	query the top-k examples owing the smallest DeepFool adversarial perturbation  = '*dog*'
☑	query the adversarial attacks with the same label pseudo-labeling comes for free without corrupting the training set  ='*dog*' →  ='*dog*'
☑	Transferability of adversarial examples ↓ Transferability of queries

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DFAL EXPERIMENTS 1/3

- Query the top-k samples owing the smallest adversarial perturbation **(DFAL_0)**
- **BATCH**= 10
- **|MNIST| = 60 000 |QuickDraw|=444 971**

	Accuracy (%)				
# annotations	100	500	800	1000	All
DFAL_0	**85.08**	95.89	**97.79**	**98.13**	–
BALD	53.73	91.47	94.32	94.32	–
CEAL	50.87	90.69	90.69	90.69	–
CORE-SET	78.80	**96.68**	97.46	97.88	–
EGL	37.92	91.84	93.99	93.99	–
uncertainty	45.57	88.36	94.27	94.60	–
RANDOM	69.79	91.96	94.05	94.46	**98.98**

% of Test accuracy
MNIST (VGG8)

	Accuracy (%)				
# annotations	100	500	800	1000	All
DFAL_0	78.62	**91.35**	**92.44**	**93.14**	–
BALD	**82.00**	89.94	91.92	92.87	–
CEAL	64.45	79.66	85.73	88.65	–
CORE-SET	66.71	89.93	92.28	92.62	–
EGL	63.12	86.80	90.06	90.06	–
uncertainty	52.77	88.05	89.31	91.03	–
RANDOM	78.28	88.13	89.71	89.94	**96.75**

% of Test accuracy
QuickDraw (VGG8)

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DFAL EXPERIMENTS 2/3

- Pseudo labeling the adversarial samples of the queries
- **BATCH**= 10
- **|MNIST| = 60 000 |QuickDraw|=444 971**

	Accuracy (%)				
# annotations	100	500	800	1000	All
DFAL	84.28	**96.90**	**97.98**	**98.59**	–
DFAL_0	**85.08**	95.89	97.79	98.13	–
BALD	53.73	91.47	94.32	94.32	–
CEAL	50.87	90.69	90.69	90.69	–
CORE-SET	78.80	96.68	97.46	97.88	–
EGL	37.92	91.84	93.99	93.99	–
uncertainty	45.57	88.36	94.27	94.60	–
RANDOM	69.79	91.96	94.05	94.46	**98.98**

% of Test accuracy
MNIST (VGG8)

	Accuracy (%)				
# annotations	100	500	800	1000	All
DFAL	**84.23**	**91.52**	**93.16**	**93.91**	–
DFAL_0	78.62	91.35	92.44	93.14	–
BALD	82.00	89.94	91.92	92.87	–
CEAL	64.45	79.66	85.73	88.65	–
CORE-SET	66.71	89.93	92.28	92.62	–
EGL	63.12	86.80	90.06	90.06	–
uncertainty	52.77	88.05	89.31	91.03	–
RANDOM	78.28	88.13	89.71	89.94	**96.75**

% of Test accuracy
QuickDraw (VGG8)

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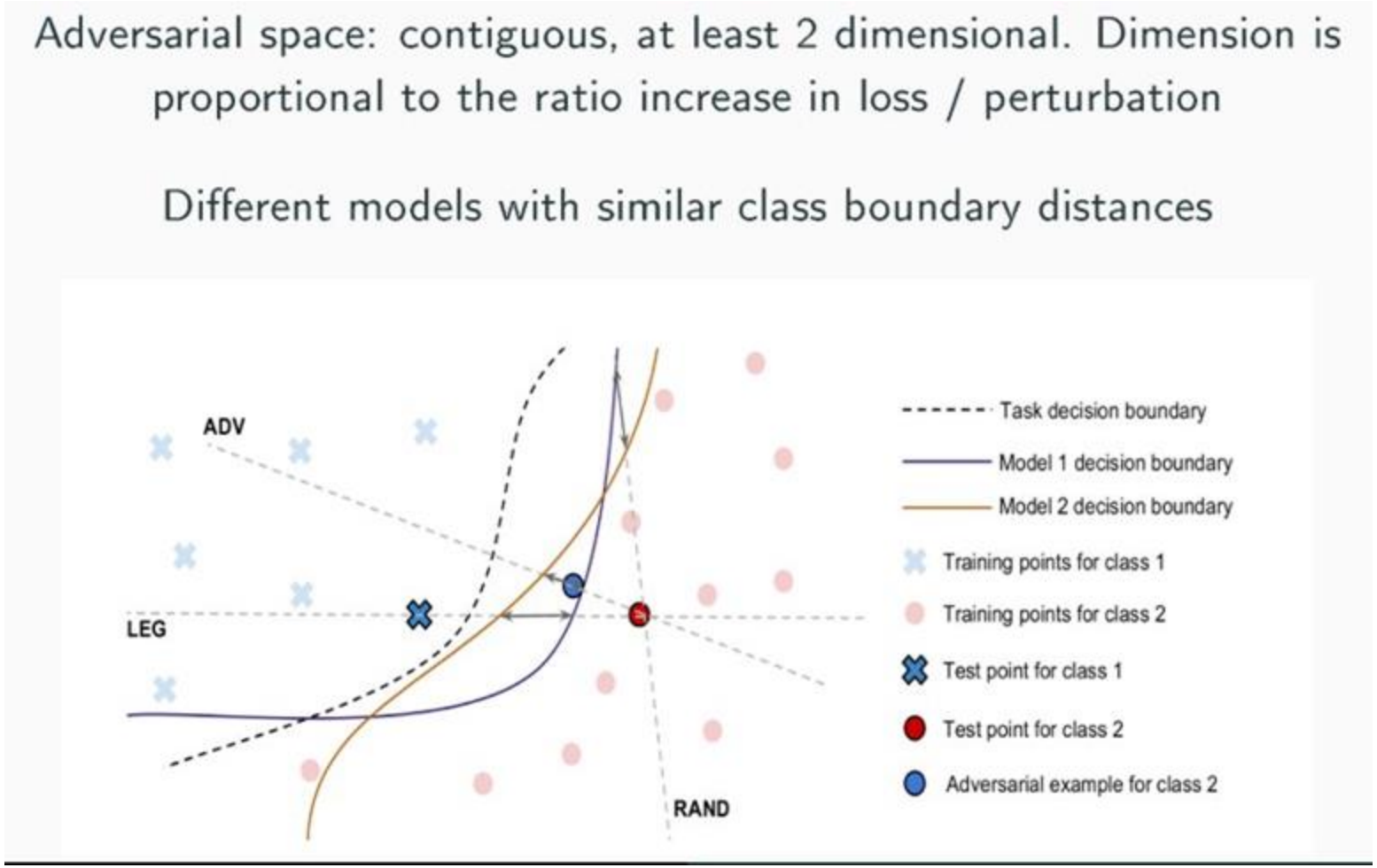
TRANSFERABILITY:The ultimate threat of adversarial examples [Tramèr, 2017]

Adversarial space: contiguous, at least 2 dimensional. Dimension is proportional to the ratio increase in loss / perturbation

Different models with similar class boundary distances



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DFAL EXPERIMENTS 3/3

- Transferability of non targeted adversarial attacks
- 1000 queries
- Model Selection
- **|MNIST| = 60 000 |ShoeBag|=184 792**

	DFAL	CORE-SET	RANDOM
LeNet5→ VGG8	**97.80**	96.90	94.46
VGG8→ LeNet5	**97.93**	97.40	95.31

% of Test accuracy

MNIST

	DFAL	CORE-SET	RANDOM
LeNet5→ VGG8	**99.40**	99.12	97.08
VGG8→ LeNet5	**98.75**	98.50	98.07

% of Test accuracy

Shoe Bag

GENERATIVE ADVERSARIAL NETWORKS

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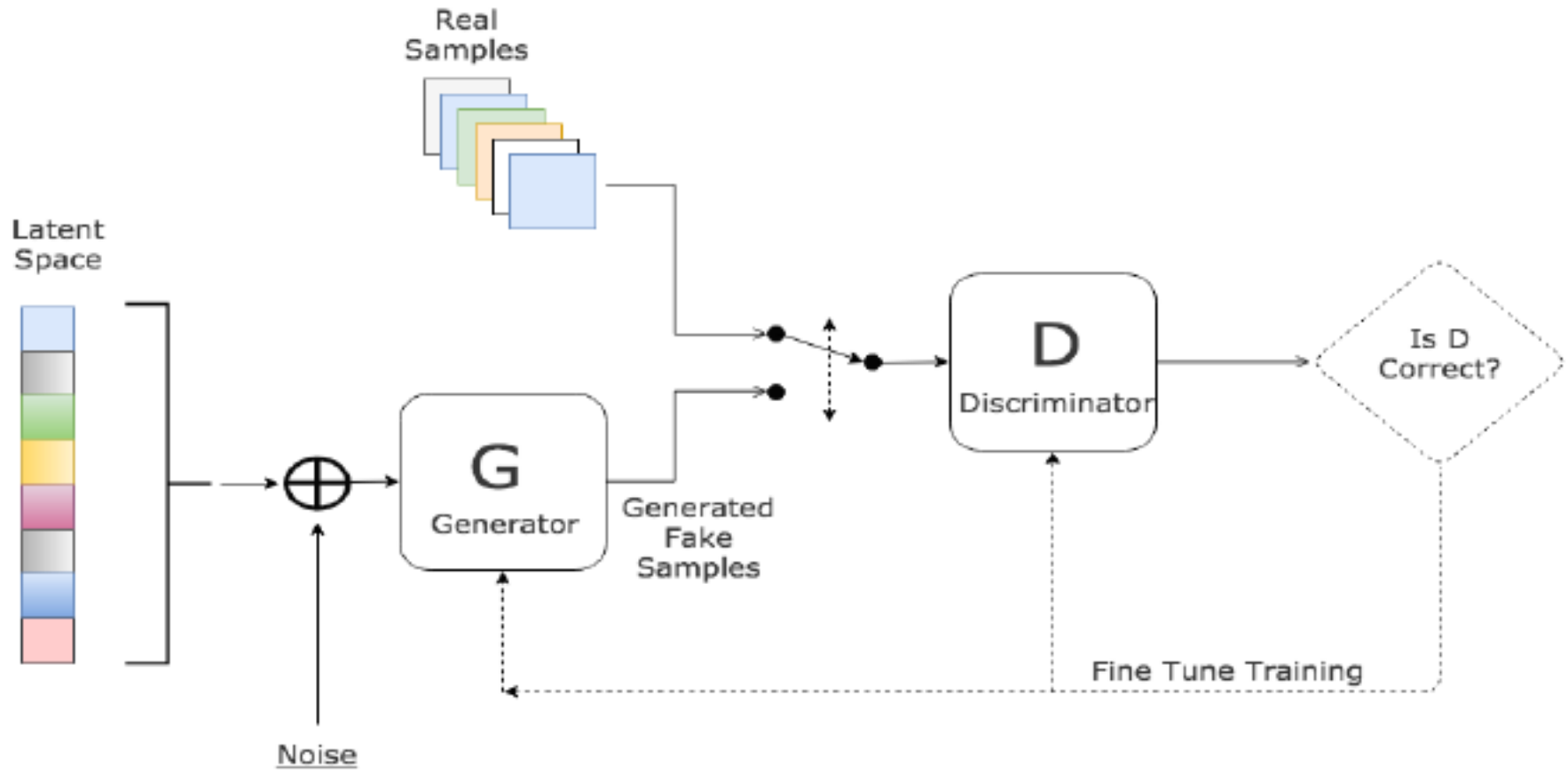
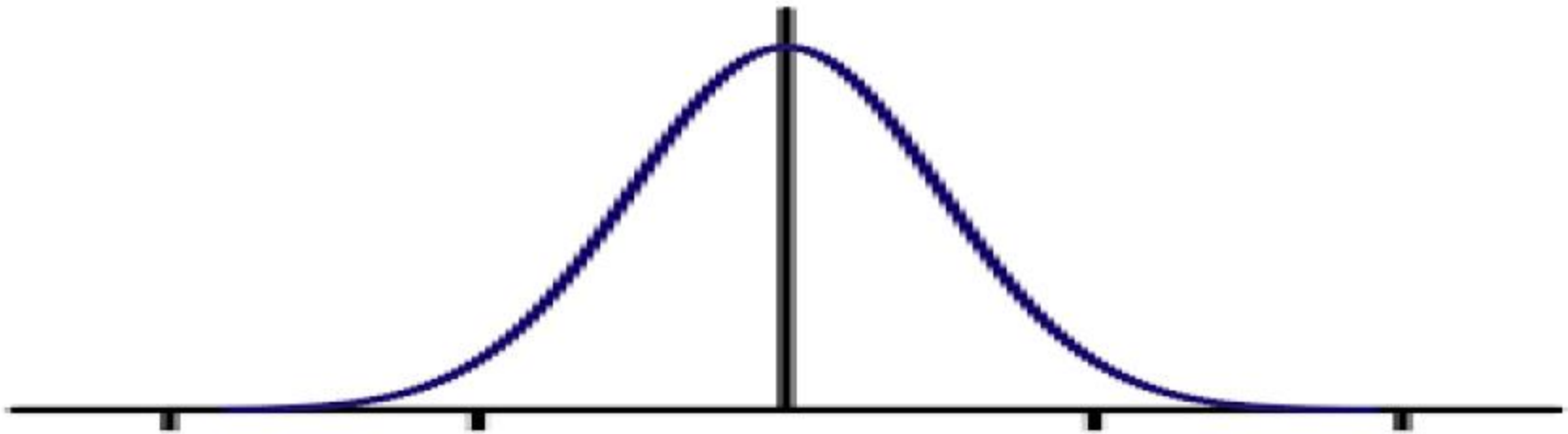
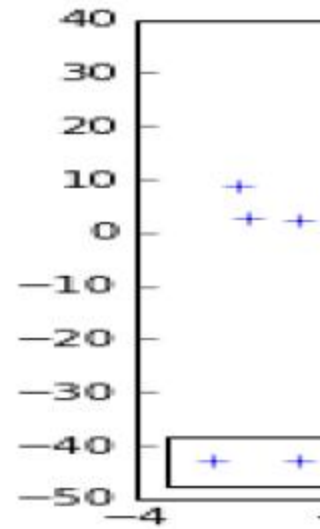
How to solve Adversarial Examples? Generative Adversarial Networks

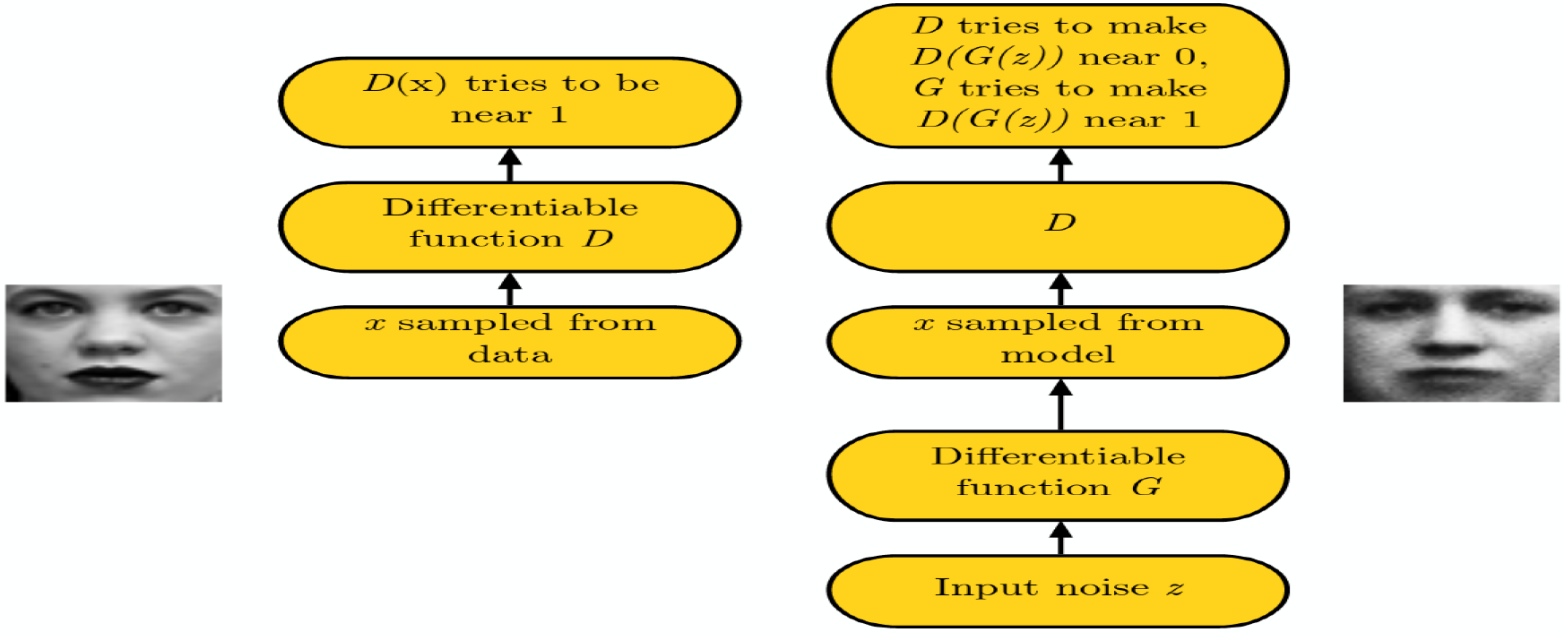


- **Generative Models:** Learning how
approximate distribution close to the gr





GAN Definition



$$\min_{G}\max_{D} \mathcal{V}(D,G) = \mathbb{E}_{x\sim p_{data}(x)}\Big[log(D(x))\Big] + \mathbb{E}_{z\sim p_z(z)}\Big[1-log(D(G(z)))\Big]$$

GAN Definition

$$V(G, D) = \mathbb{E}_{p_{\text{data}}} \log D(\boldsymbol{x}) + \mathbb{E}_{p_{\text{generator}}} \left(\log\left(1 - D(\boldsymbol{x})\right)\right)$$

	NCE (Gutmann and Hyvärinen 2010)	MLE	GAN
D	$D(x) = \frac{p_{\text{model}}(\boldsymbol{x})}{p_{\text{model}}(\boldsymbol{x}) + p_{\text{generator}}(\boldsymbol{x})}$		Neural network
Goal	Learn p_{model}		Learn $p_{\text{generator}}$
G update rule	None (G is fixed)	Copy p_{model} parameters	Gradient descent on V
D update rule	Gradient ascent on V		

Figure 20: Goodfellow (2014) demonstrated the following connections between minimax GANs, noise-contrastive estimation, and maximum likelihood: all three can be interpreted as strategies for playing a minimax game with the same value function. The biggest difference is in where p_{model} lies. For GANs, the generator is p_{model}, while for NCE and MLE, p_{model} is part of the discriminator. Beyond this, the differences between the methods lie in the update strategy. GANs learn both players with gradient descent. MLE learns the discriminator using gradient descent, but has a heuristic update rule for the generator. Specifically, after each discriminator update step, MLE copies the density model learned inside the discriminator and converts it into a sampler to be used as the generator. NCE never updates the generator; it is just a fixed source of noise.

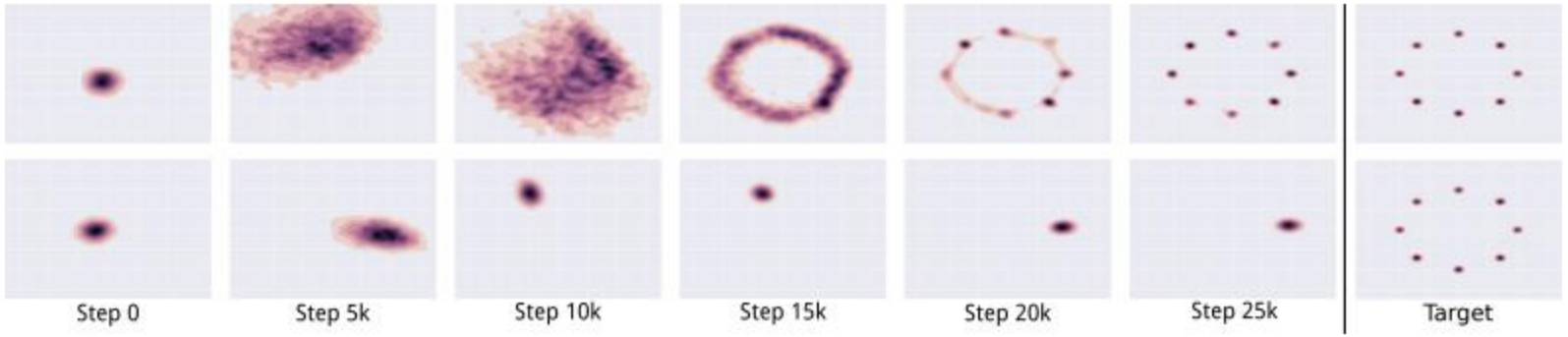
- If the discriminator is optimal: $\mathbf{D} \equiv$ *approximators*)

$$\mathbf{D}^*(x) = \frac{p_{data}}{p_{data}(x) +}$$

$$\mathcal{V}(\mathbf{D}^*, \mathbf{G}) = 2 * JSD(p_{data} ||$$

(...) (GANs) and the variations that are no
interesting idea in the last ten years in ML
But...

- GAN models often end up in local Na
  associated with mode collapse or othe
  distribution
- cost function are non convex



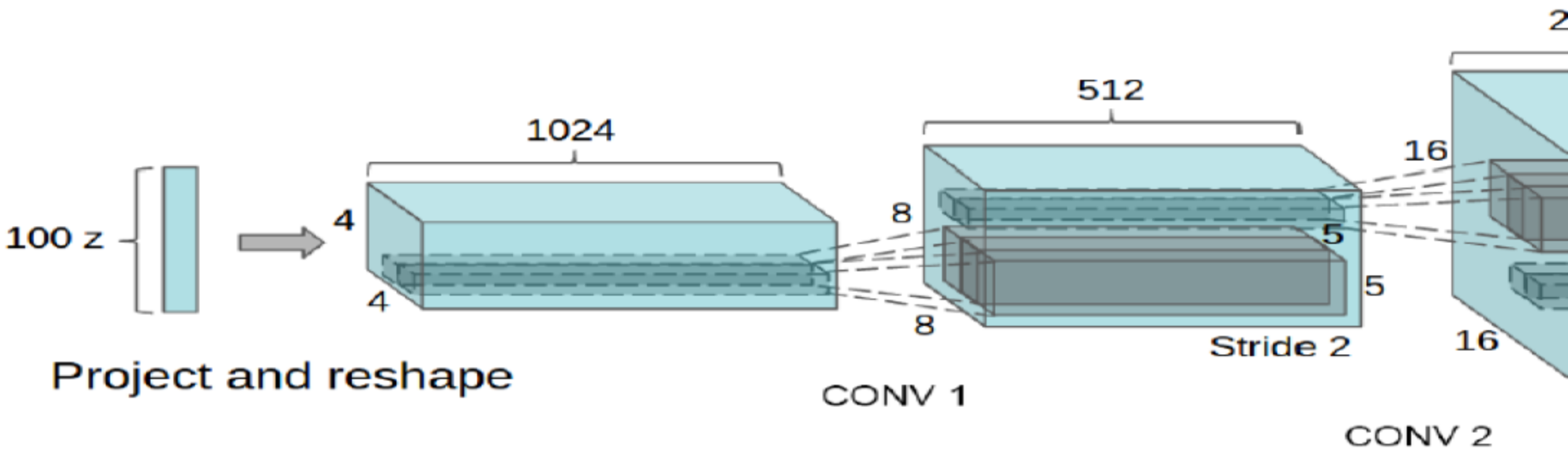
lpse

- Gradient vanishing

With mode collapse, the model only learns one or a few of the modes of a multimodal dataset. The data usually used to train GANs on typical problems have a very large number of modes, which makes mode collapse problematic.

- Multiple GANS: AdaGANs

- CNN highly suitable for image classif
unsupervised learning)



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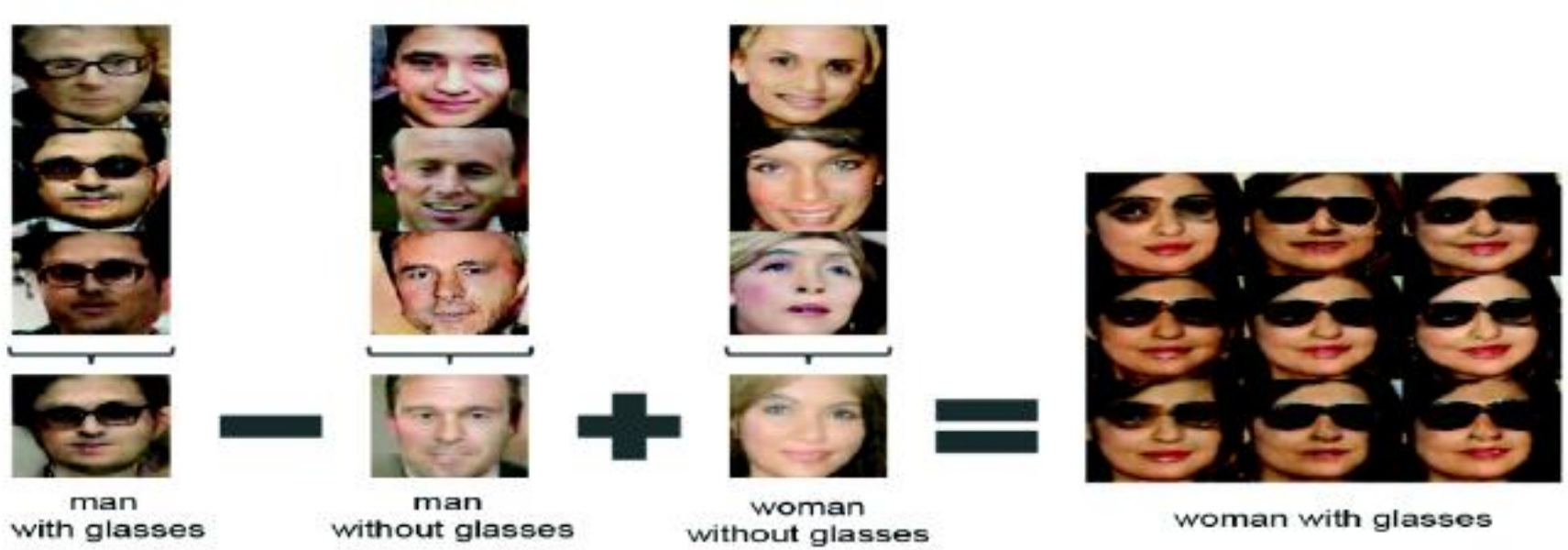
It finally did not solve adversarial, but…

Results DCGAN



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It finally did not solve adversarial, but…

(image from Karras et al. 2019)

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Tips and tricks

Tips & Tricks

- Normalize your training data into range [-1, 1]
- Pick a bounded output activation function for G (sigmoid, tanh...)
- Do not sabotage your Discriminator: usually deeper than G and with an unbounded output activation
- Label smoothing for real training data
- Feature matching (facial for instance, see deepfake)
- Learning a conditional model often gives better samples (add a generated class)
- Do not balance D and G losses

Tips & Tricks

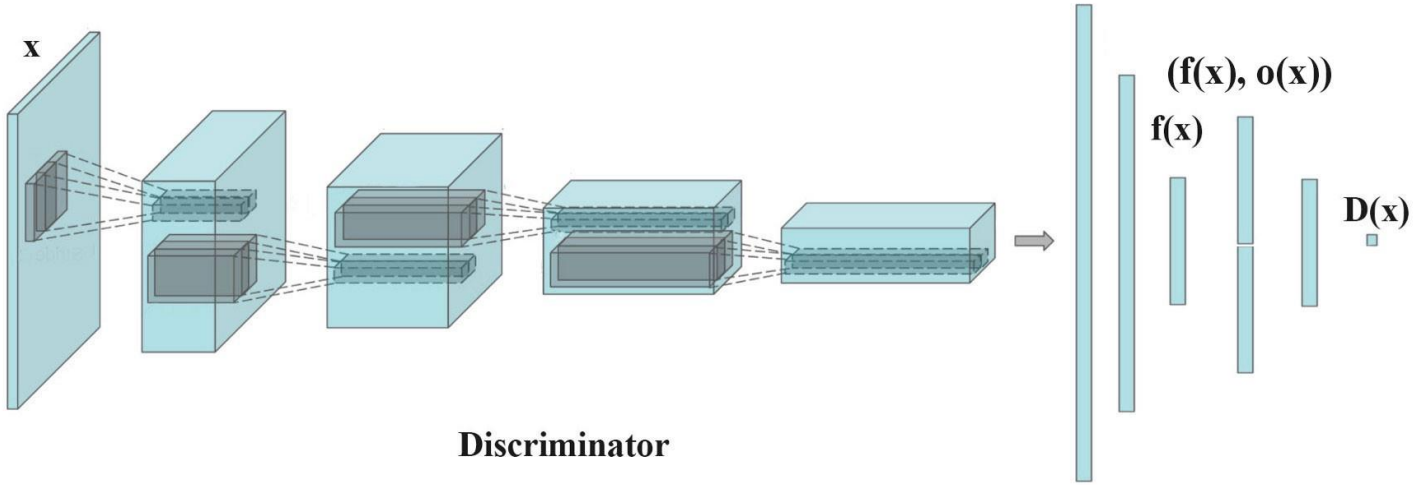
- Feature matching (facial for instance, see deepfake)

Deepfake

- Add BN in G (not the last layer, may
- minibatch of data X: μ=mean(X), σ
- Add two extra parameters of the net
- $BN(x \in X)_{\gamma,\beta} = \gamma \frac{x-\mu}{\sqrt{\sigma+\epsilon}} + \beta$

Tips & Tricks

- Preventing mode collapsing: discriminant minibatch



When mode collapses, all images created looks similar.

⇒ feed real images and generated images into the discriminator separately in different batches and compute the similarity of the image *x* with images in the same batch.

If the mode starts to collapse, the similarity of generated images increases. The discriminator can use this score to detect generated images and penalize the generator if mode is collapsing.

The similarity $o(x_i)$ between the image x_i and other images in the same batch is computed and we append the similarity $o(x)$ in one of the dense layers in the discriminator to classify whether this image is real or generated.

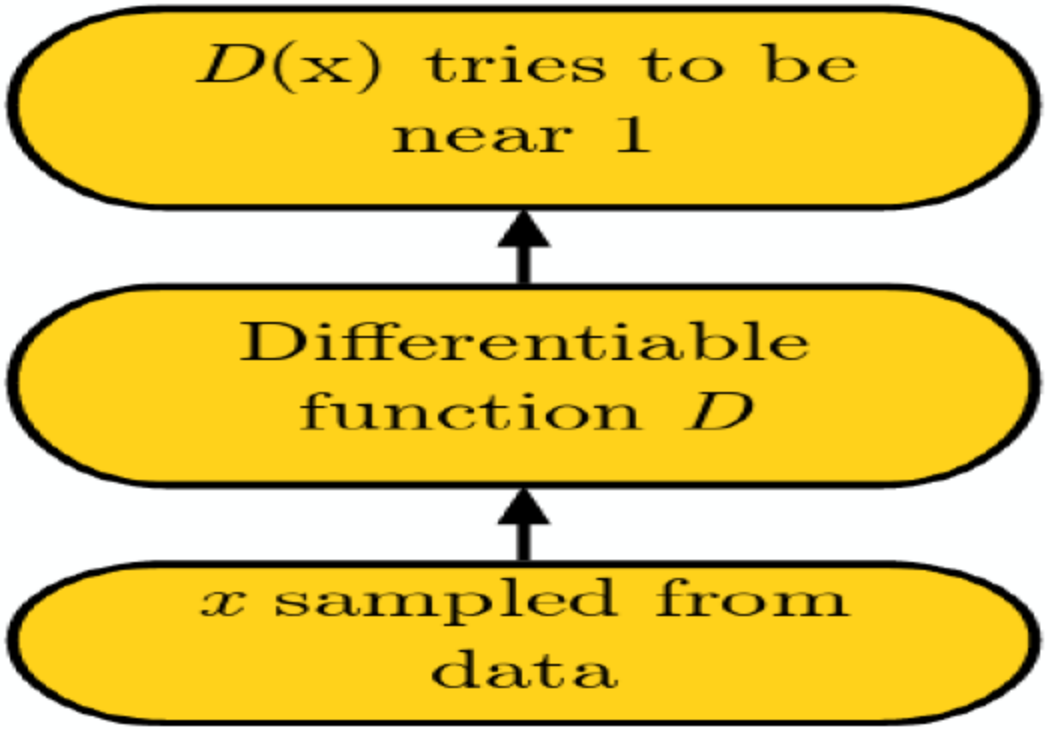
- New objective function: Earth Move

$$\mathbb{W}(p_{data} \mid p_{model}) = \inf_{\gamma \in \Pi(p_{data}, p_{mo}}$$

- Optimal Transport in the dual space
- Discriminator: 1 Lipshitz function, w
- NNs are already Lipshitz function =

- inpainting, image manipulation by us

prediction, style transfer



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Three Categories of GAN

1. Typical GAN

$$\begin{bmatrix} -0.3 \\ 0.1 \\ \vdots \\ 0.9 \end{bmatrix}$$

random vector → Generator → 

image

2. Conditional GAN

blue eyes,
red hair,
short hair

paired data

"Girl with red hair"

text → Generator → 

image

3. Unsupervised Conditional GAN

domain x

domain y

unpaired data

x

Photo → Generator → y

Vincent van Gogh's style

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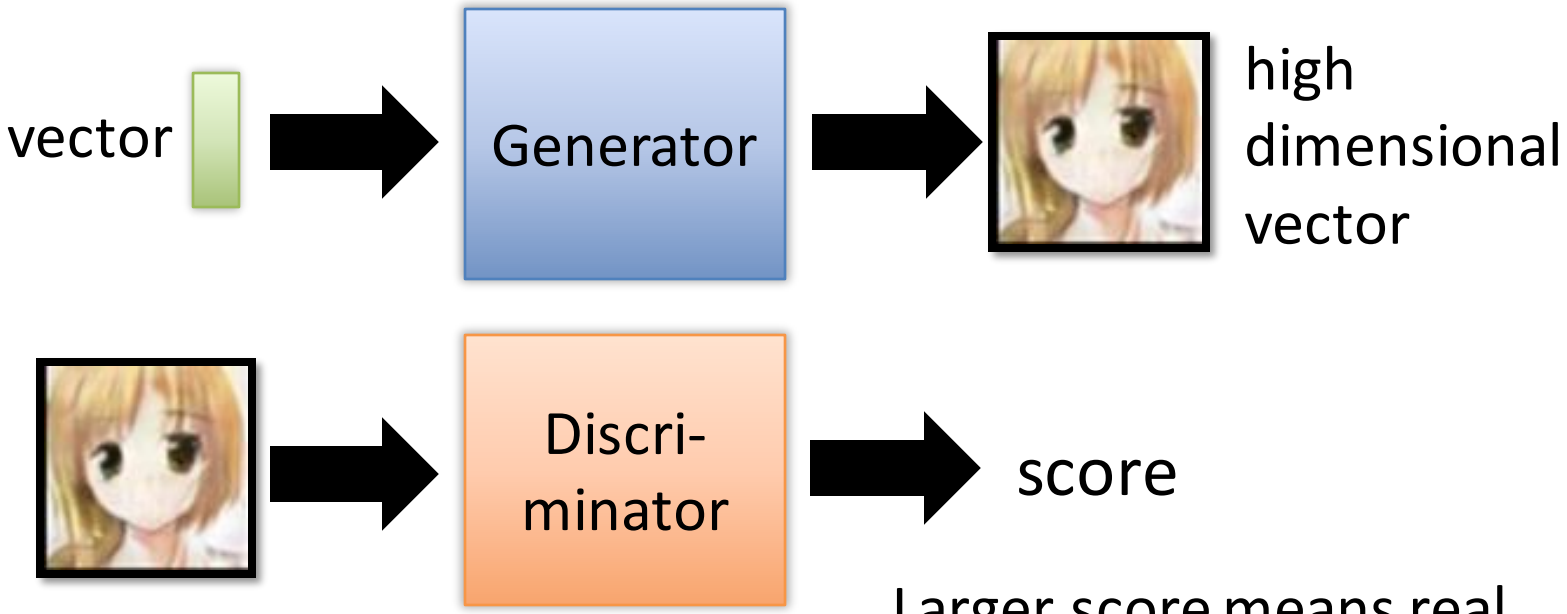
Generative Adversarial Network (GAN)

- Anime face generation as example



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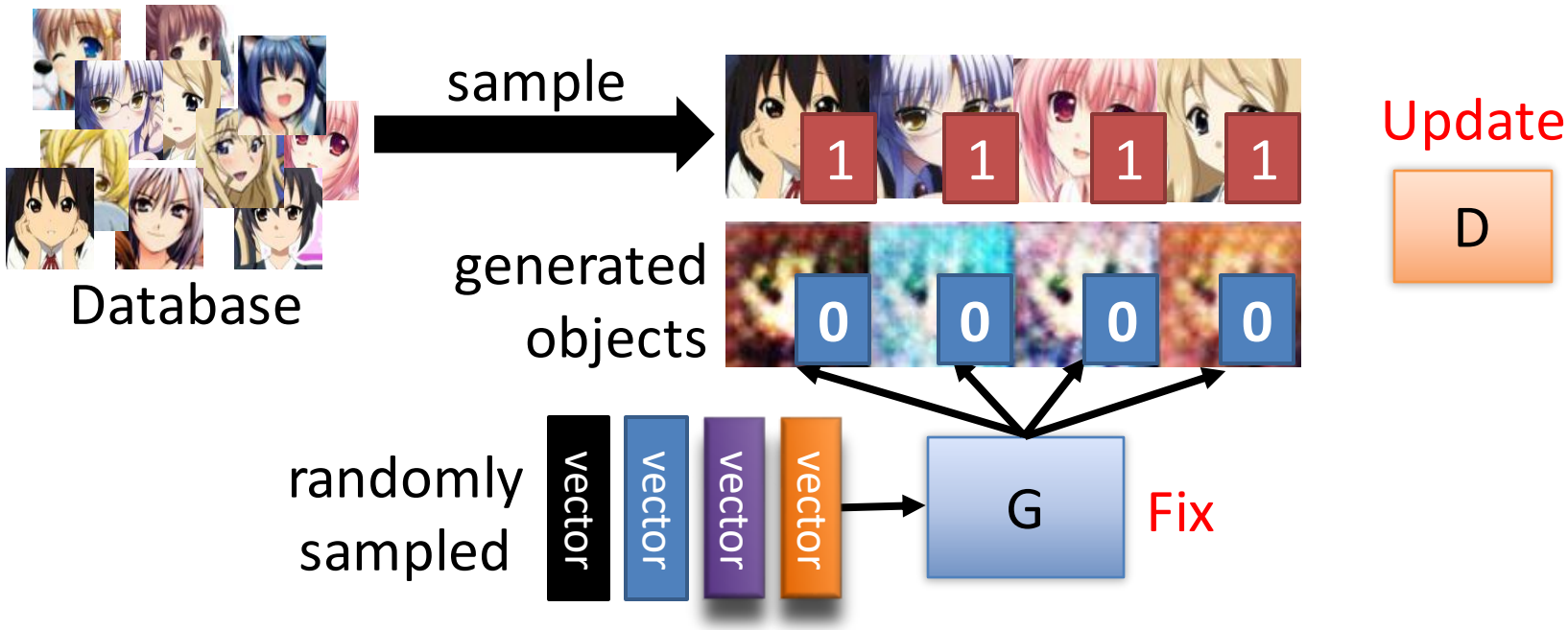
Algorithm

- Initialize generator and discriminator G D
- In each training iteration:

Step 1: Fix generator G, and update discriminator D



Discriminator learns to assign high scores to real objects and low scores to generated objects.

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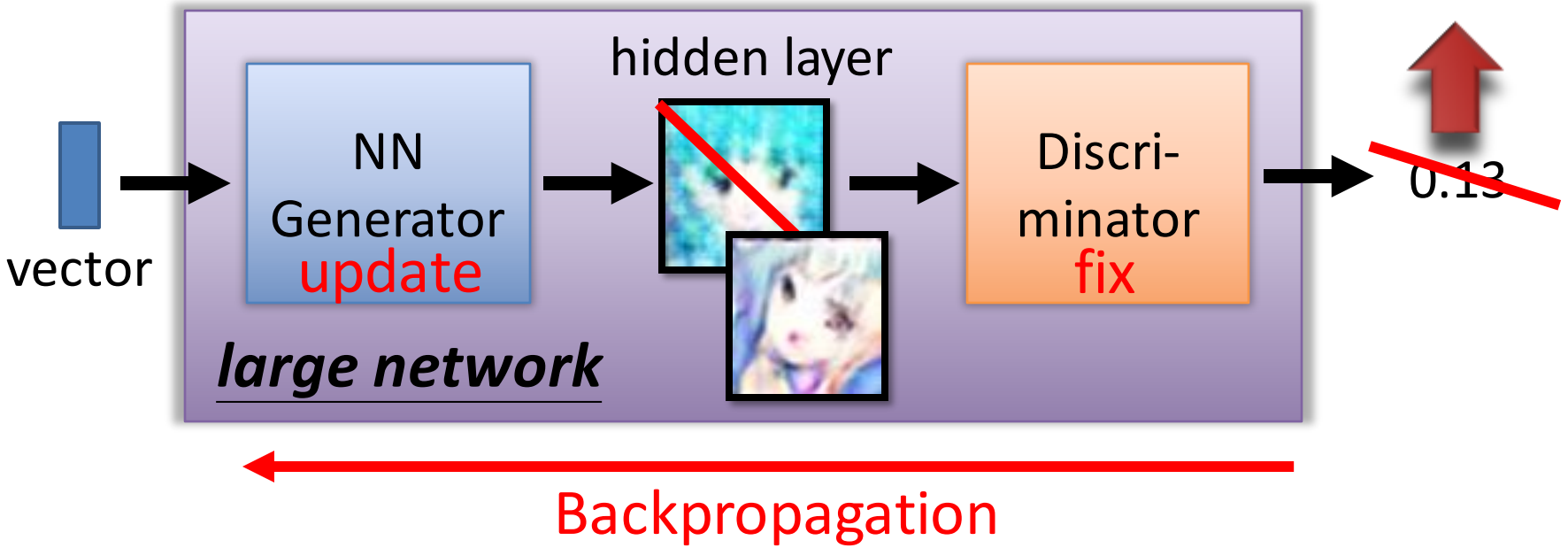
Algorithm

- Initialize generator and discriminator G D
- In each training iteration:

Step 2: Fix discriminator D, and update generator G

Generator learns to "*fool*" the discriminator



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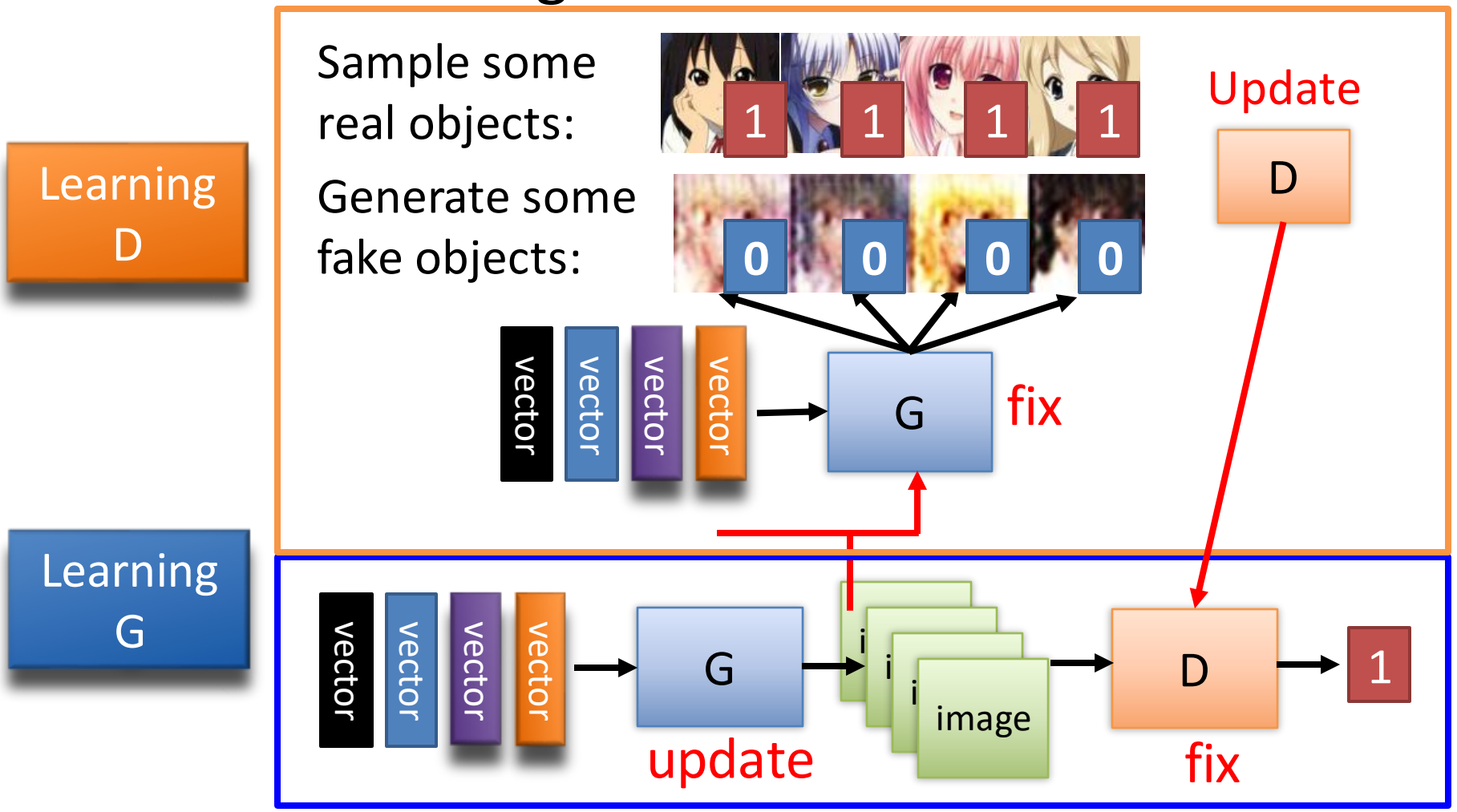

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GAN is hard to train ……

- There is a saying ……

(Joke from facebook)

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blue eyes, red hair, short hair

paired data

"Girl with red hair"

text → Generator → 

image

3. Unsupervised Conditional GAN

domain x

domain y

unpaired data

x

Photo → Generator → y

Vincent van Gogh's style

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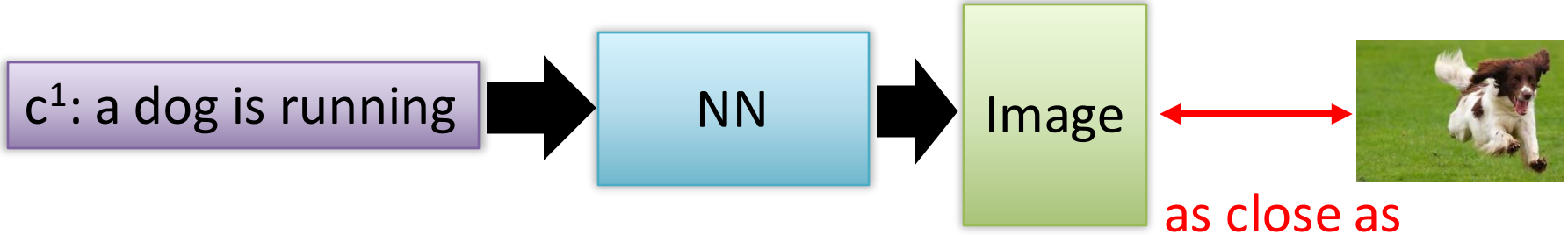
Text-to-Image

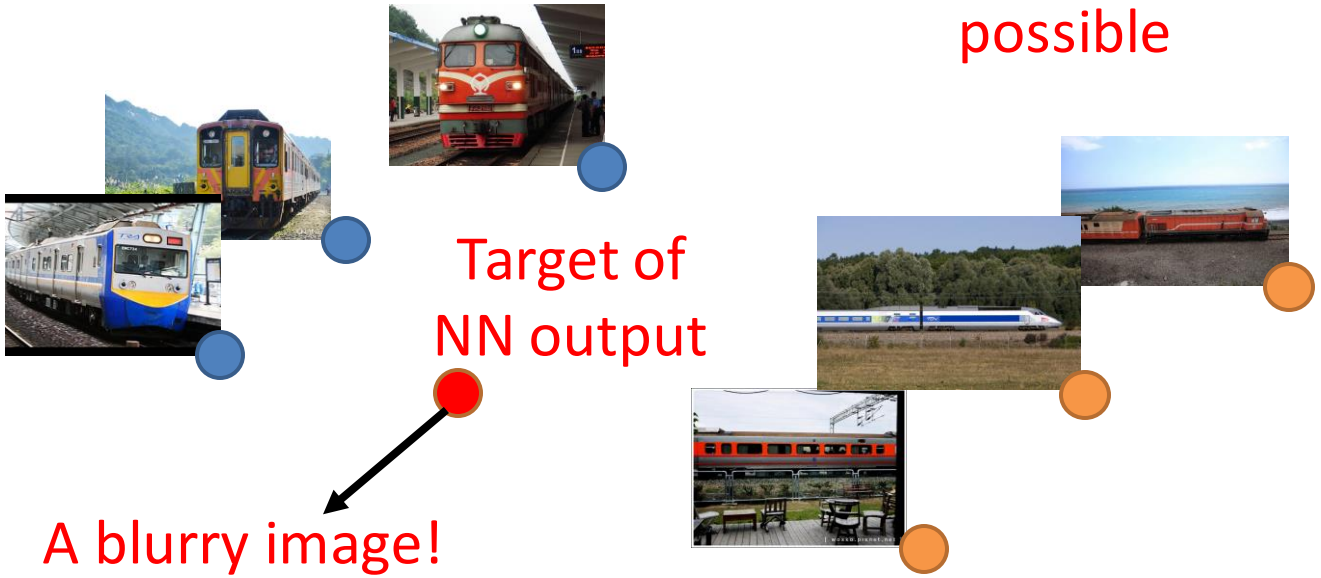
a dog is running 

a bird is flying 

- **Traditional supervised approach**

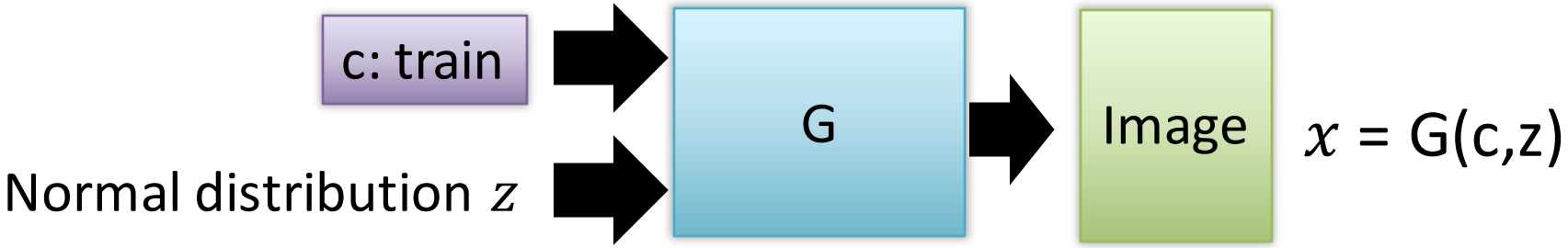


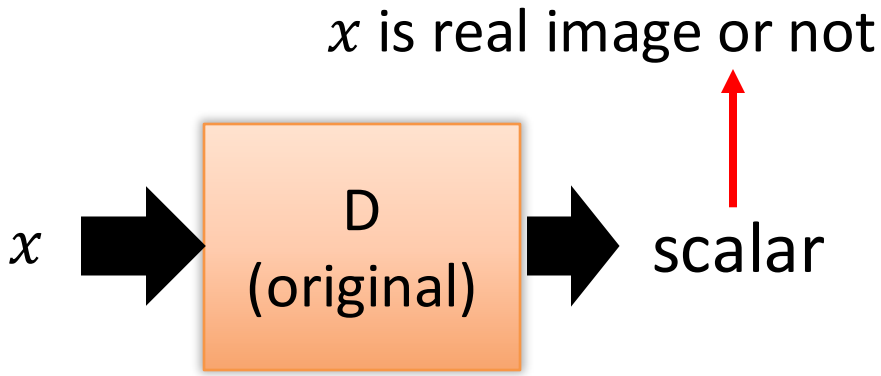
Text: "train"



[Scott Reed, et al, ICML, 2016]

Conditional GAN





Real images:  1

Generated images: Image 0

Generator will learn to generate realistic images ….

But completely ignore the input conditions.

this small bird has a pink breast and crown, and black primaries and secondaries.

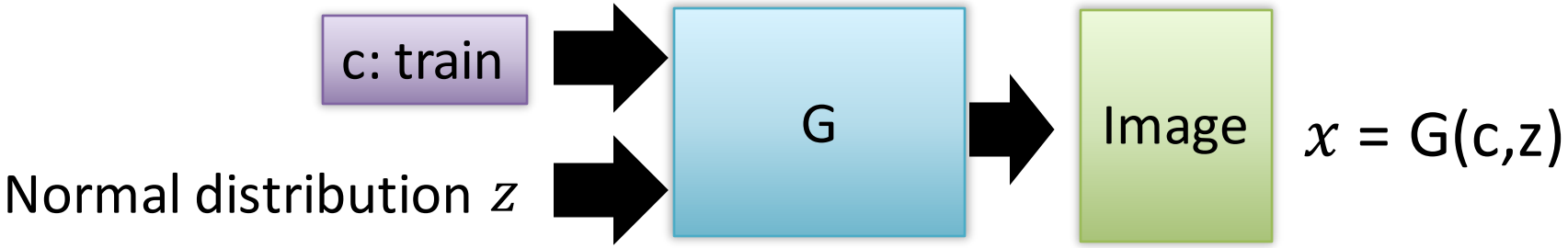
this magnificen almost all black crest, and white

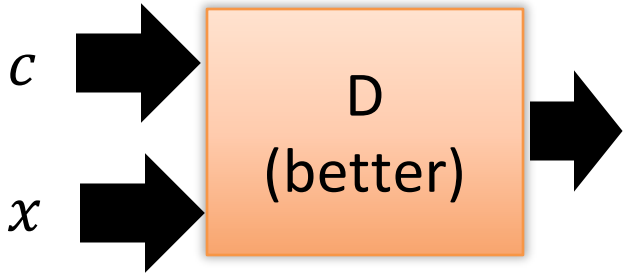
the flower has petals that are bright pinkish purple with white stigma

this white and y have thin white round yellow st

[Scott Reed, et al, ICML, 2016]

Conditional GAN





x is realistic or not +
c and x are matched or not

True text-image pairs: (train , ) 1

(cat , ) 0

(train , Image) 0

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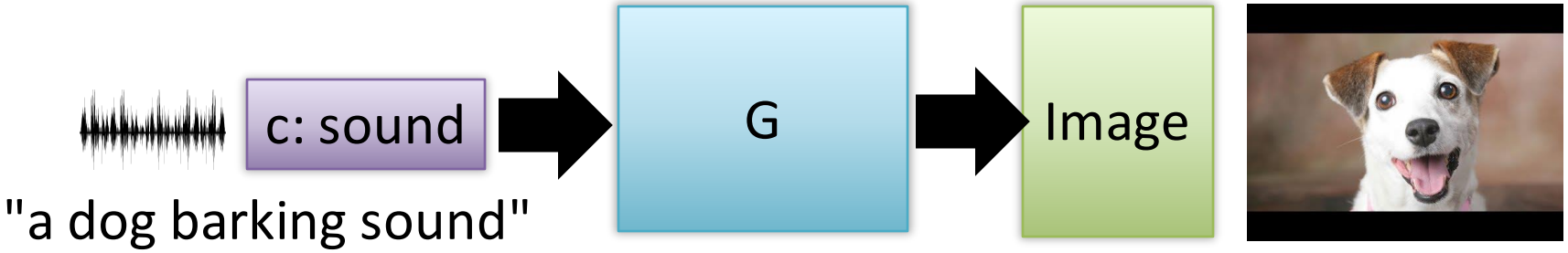
Conditional GAN - Sound-to-image



Training Data Collection

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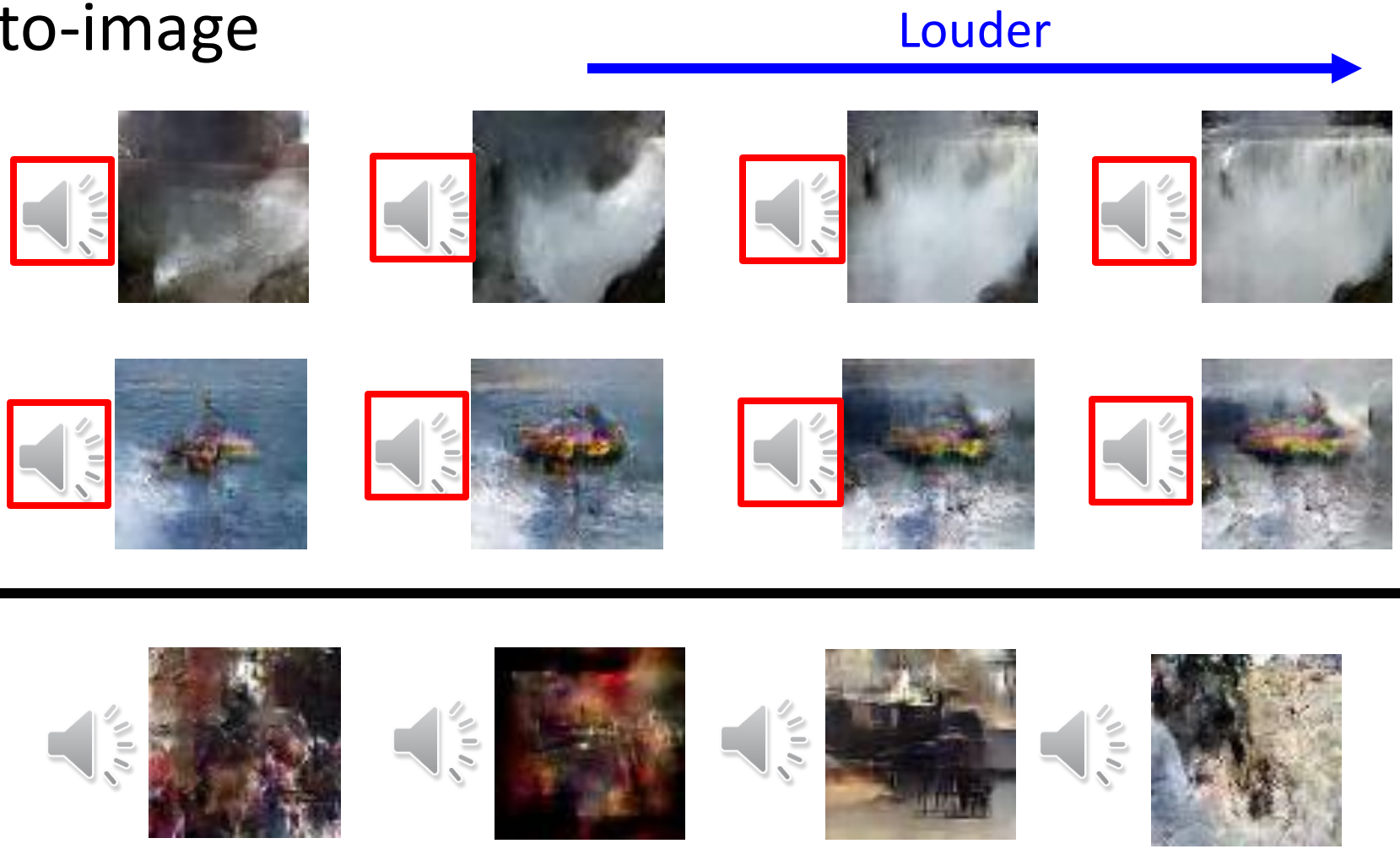
Conditional GAN - Sound-to-image

The images are generated by Chia-Hung Wan and Shun-Po Chuang.

https://wjohn1483.github.io/audio_to_scene/index.html

- Audio-to-image



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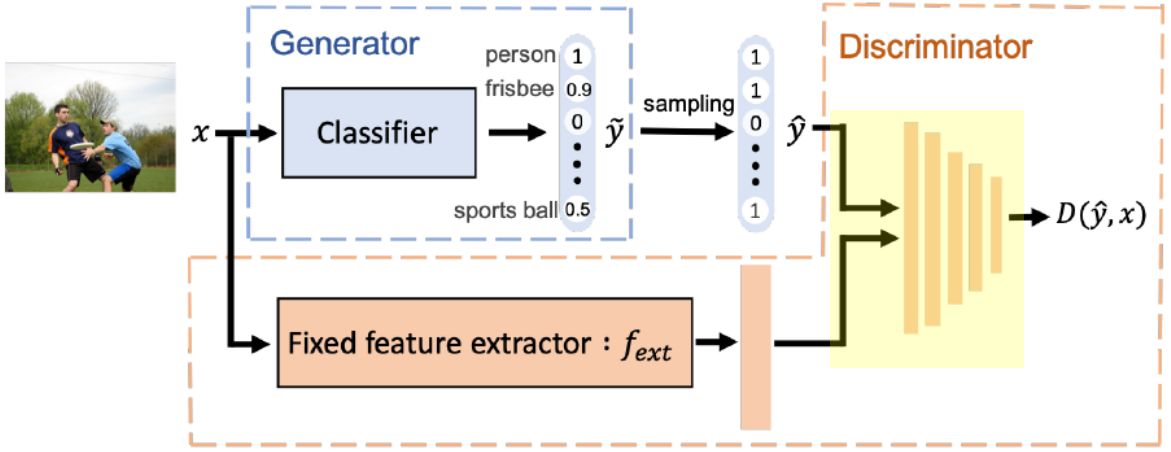
Conditional GAN - Image-to-label

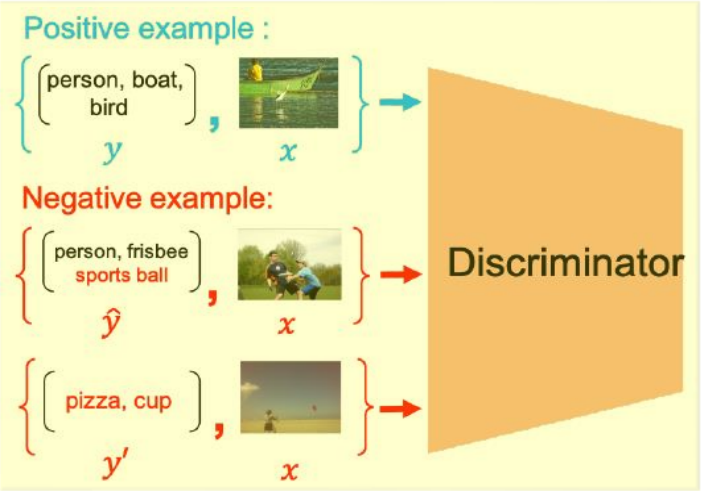
Multi-label Image Classifier

person, sports ball,
baseball bat, baseball glove

Input condition

Generated output





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Conditional GAN - Image-to-label

The classifiers can have different architectures.

The classifiers are trained as conditional GAN.

F1	MS-COCO	NUS-WIDE
VGG-16	56.0	33.9
+ GAN	60.4	41.2
Inception	62.4	53.5
+GAN	63.8	55.8
Resnet-101	62.8	53.1
+GAN	64.0	55.4
Resnet-152	63.3	52.1
+GAN	63.9	54.1
Att-RNN	62.1	54.7
RLSD	62.0	46.9

[Tsai, et al., submitted to ICASSP 2019]

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Conditional GAN - Image-to-label

The classifiers can have different architectures.

The classifiers are trained as conditional GAN.

Conditional GAN outperforms other models designed for multi-label.

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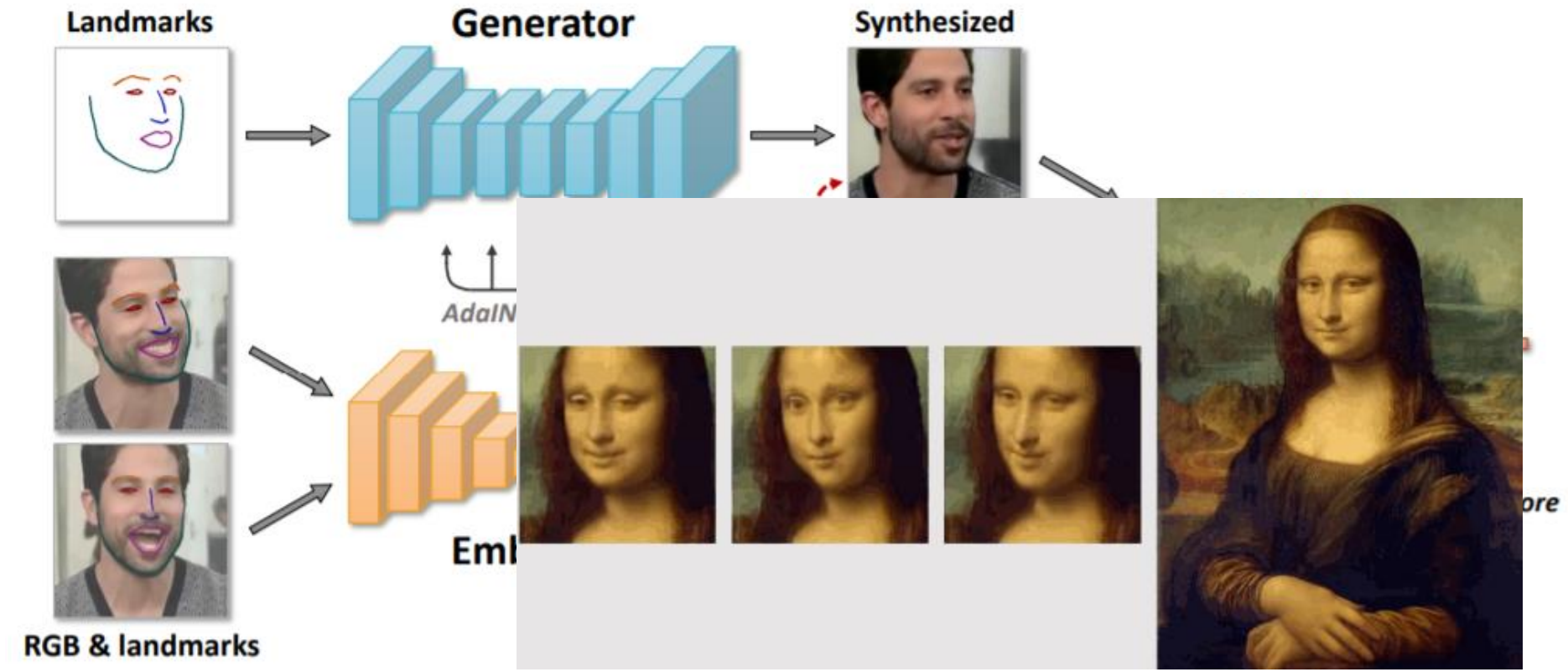
Talking Head



https://arxiv.org/abs/1905.08233

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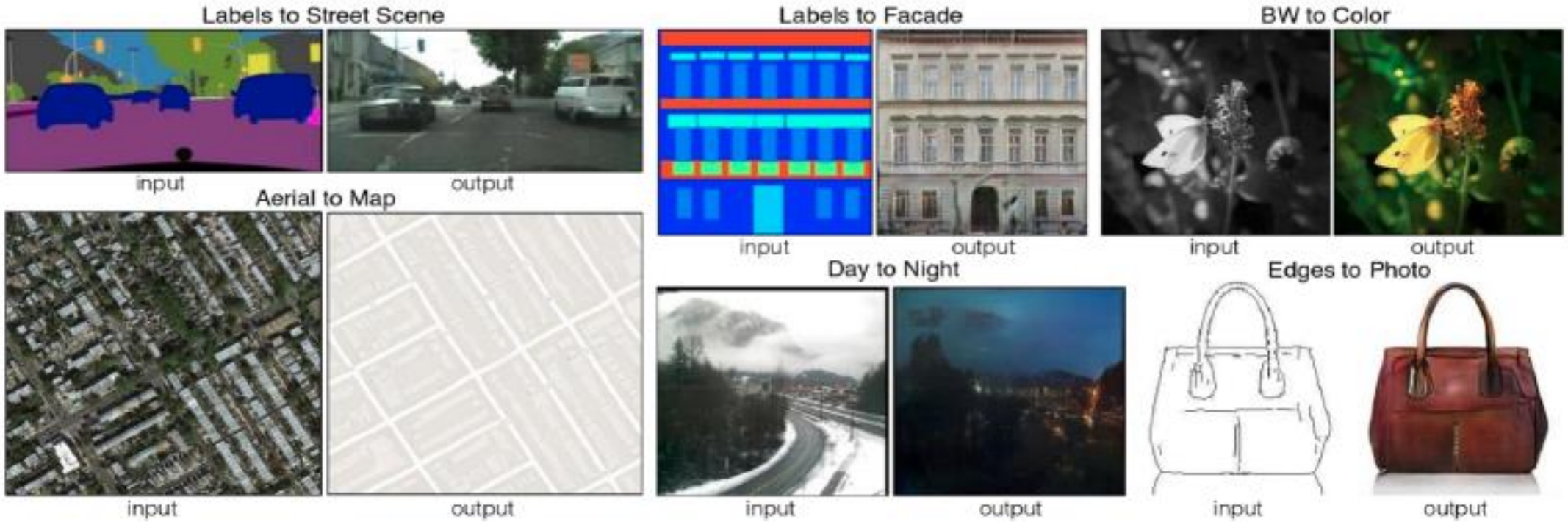
Full person!!!

Deepfake

https://information.tv5monde.com/video/deepfake-de-tom-cruise-peut-encore-croire-ce-que-l-voit-vrai-dire
https://www.youtube.com/watch?v=SDty803-hxg&ab_channel=LeHuffPost
https://edition.cnn.com/videos/business/2021/03/02/tom-cruise-tiktok-deepfake-orig.cnn-business/video/playlists/business-misinformation/

Examples of conditional GANs



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blue eyes, red hair, short hair

paired data

"Girl with red hair"

text → Generator → 

image

3. Unsupervised Conditional GAN

domain x

domain y

unpaired data

x

Photo → Generator → y 

Vincent van Gogh's style

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Cycle GAN

Domain X

Domain Y

Domain X

$G_{X \to Y}$

Become similar to domain Y

D_Y

scalar

Input image belongs to domain Y or not

Domain Y

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Cycle GAN

Domain X

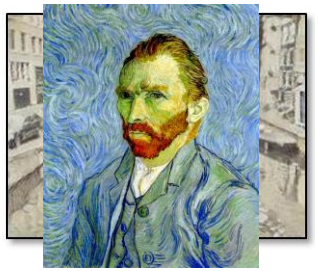
Domain Y

Domain X

ignore input

$G_{X \to Y}$

Become similar to domain Y



Not what we want!

D_Y

scalar

Domain Y

Input image belongs to domain Y or not

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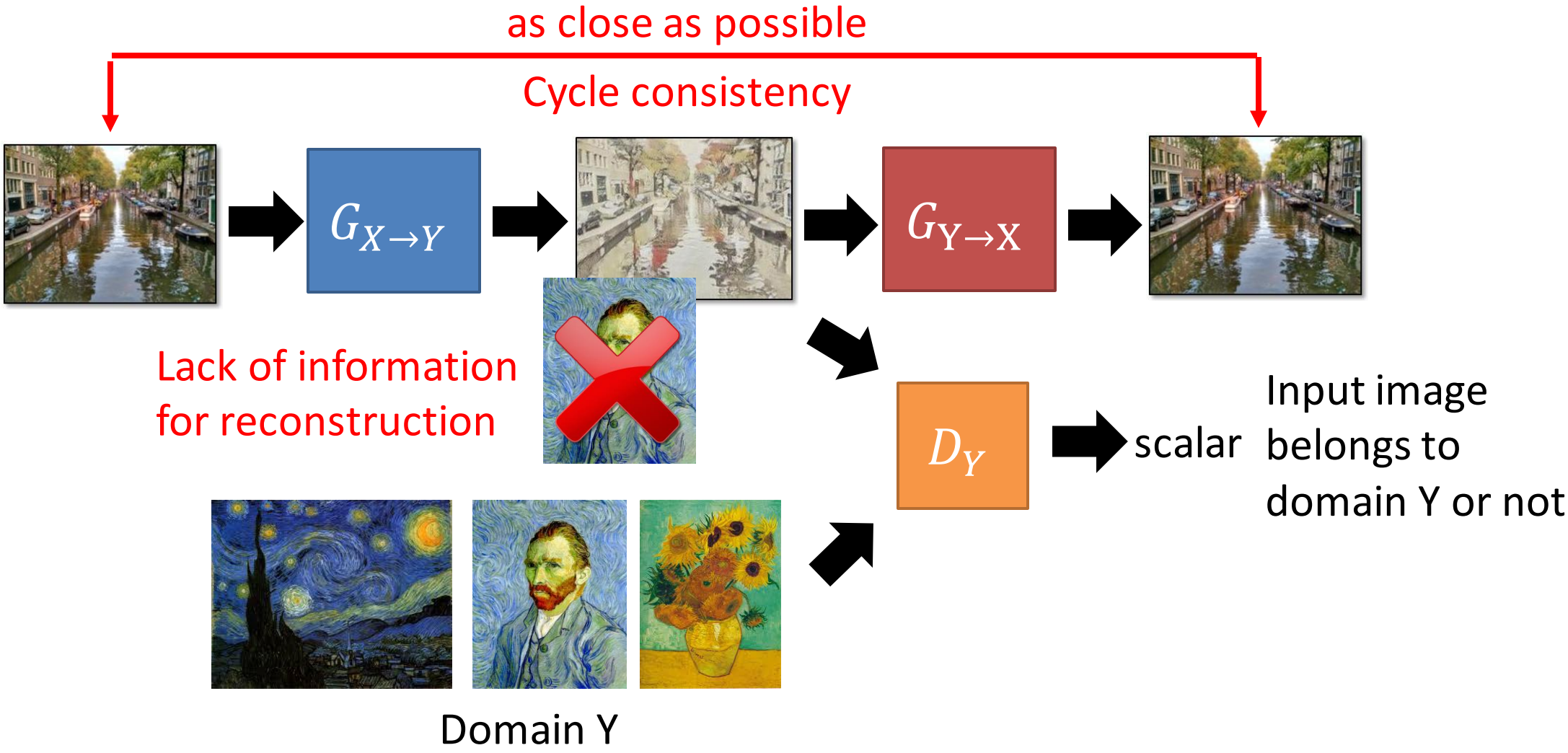
Cycle GAN

[Jun-Yan Zhu, et al., ICCV, 2017]



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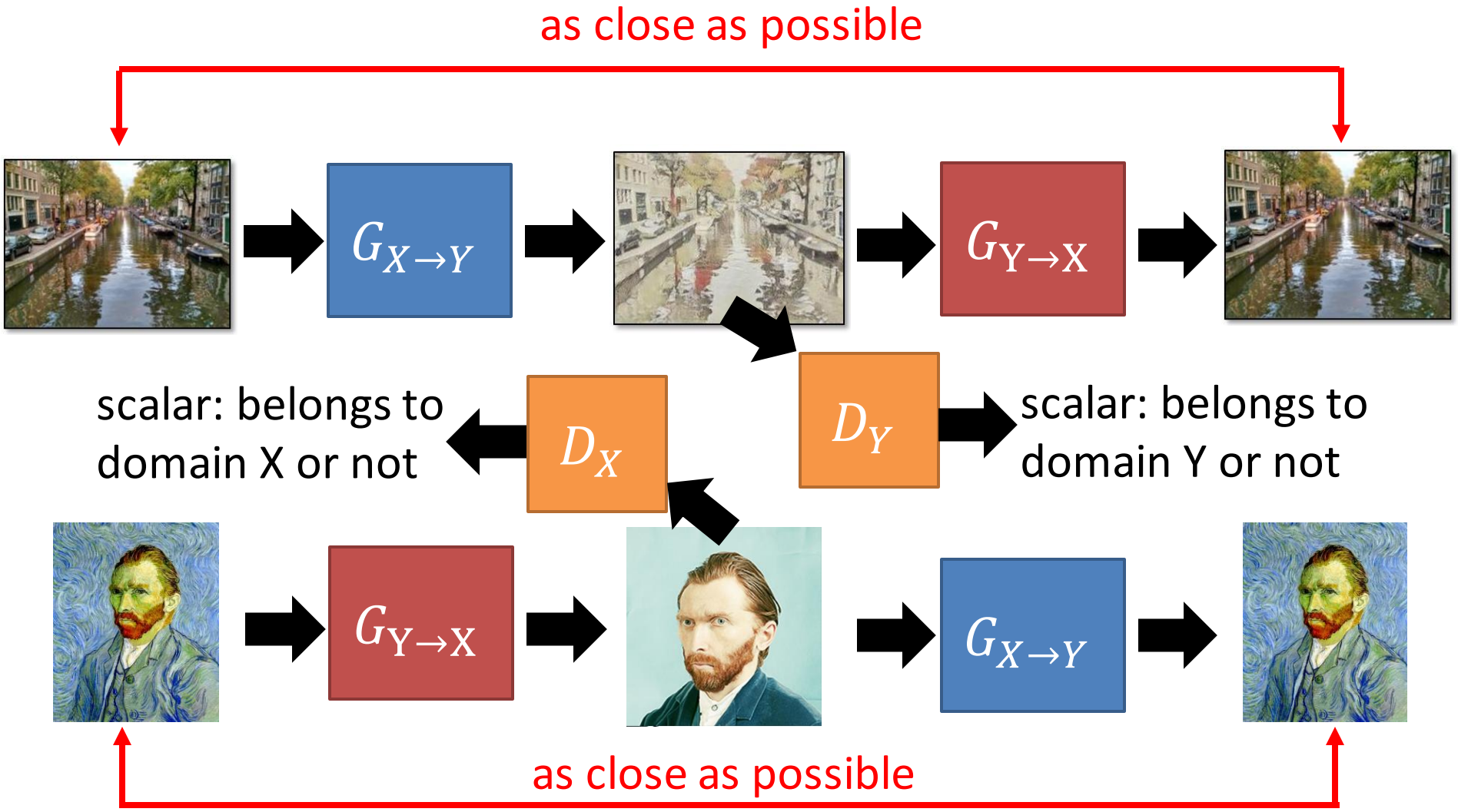
Cycle GAN



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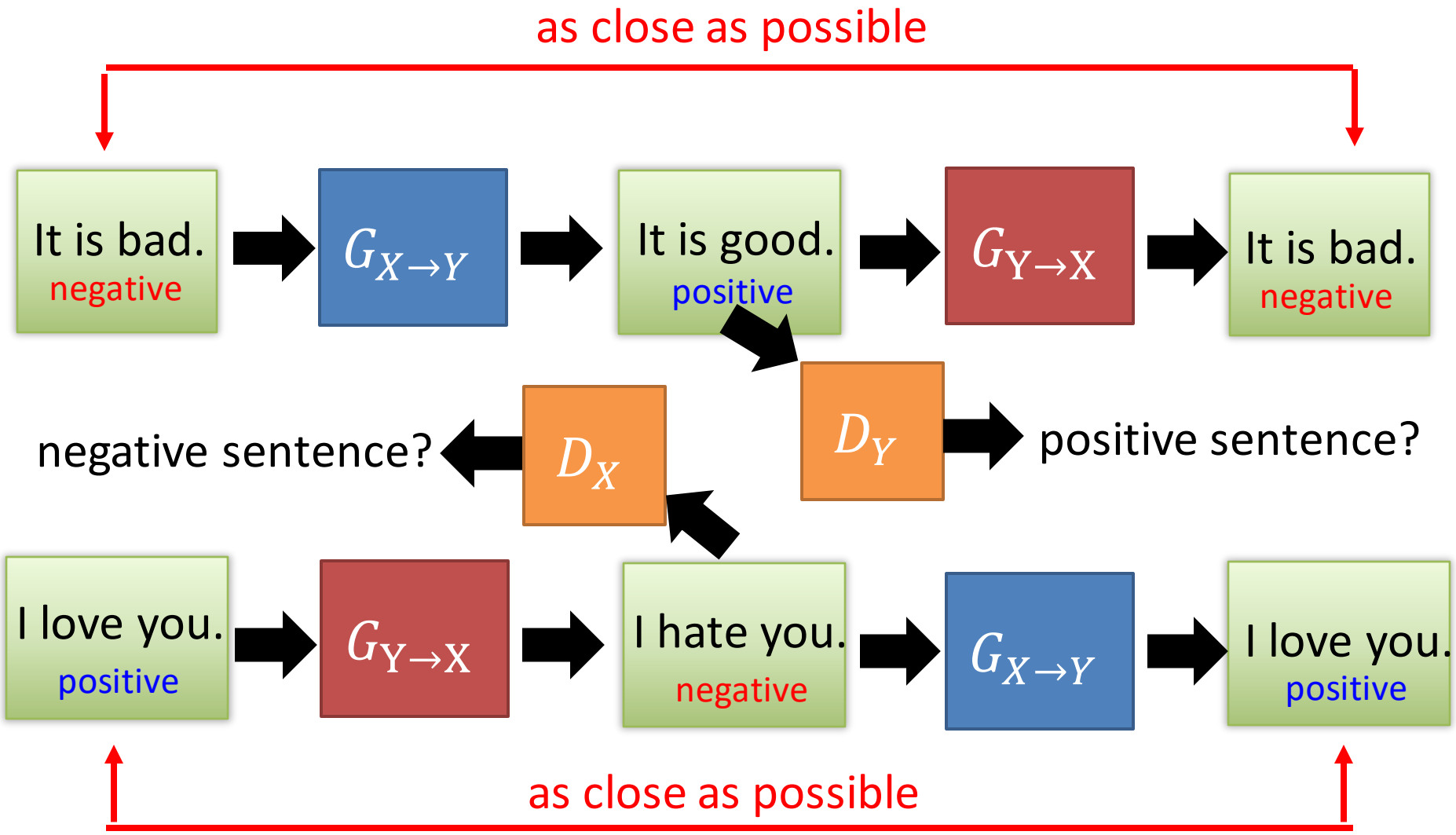
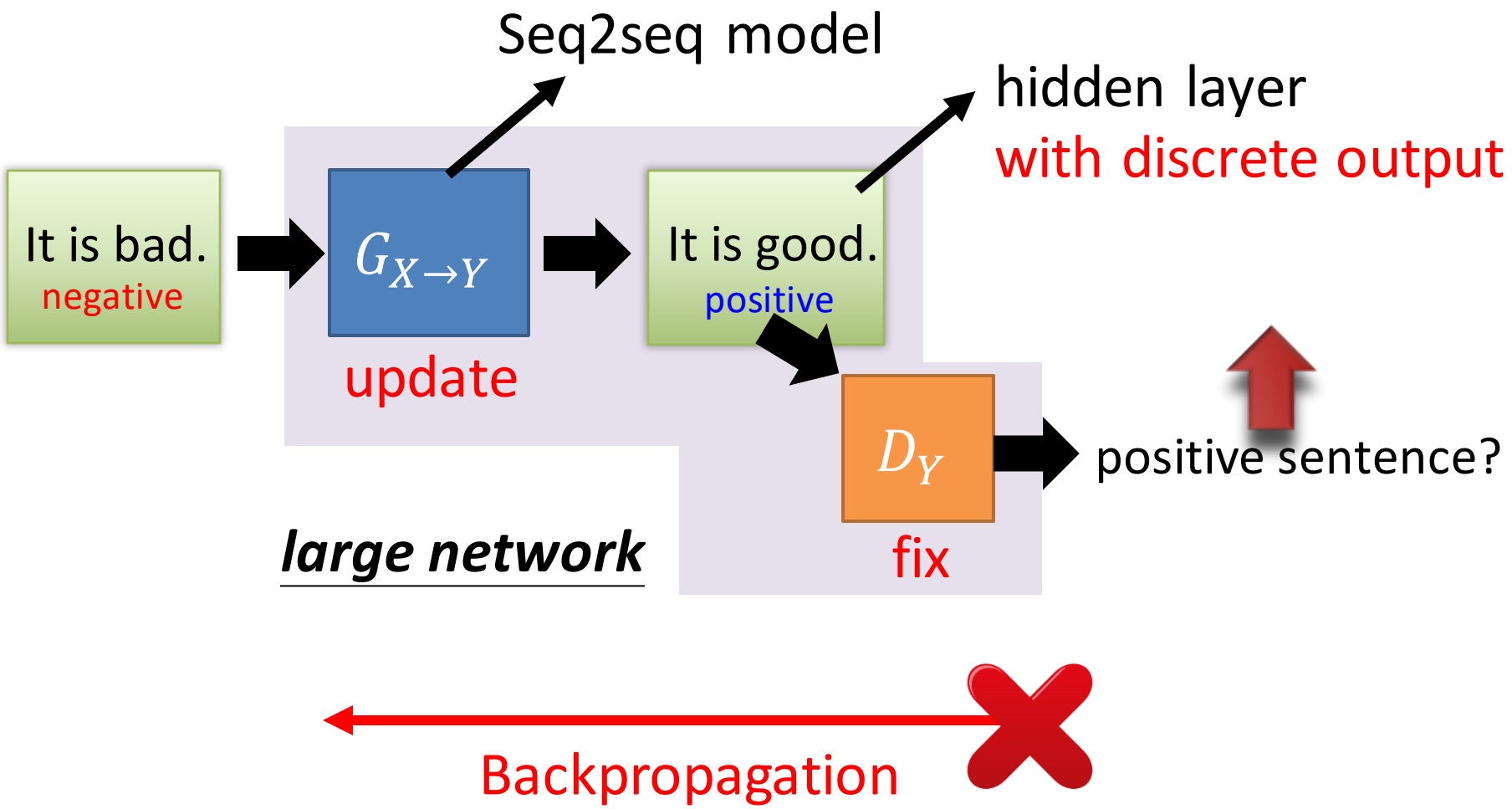
Cycle GAN



Discrete Issue



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Three Categories of Solutions

Gumbel-softmax

- [Matt J. Kusner, et al, arXiv, 2016]

Continuous Input for Discriminator

- [Sai Rajeswar, et al., arXiv, 2017][Ofir Press, et al., ICML workshop, 2017][Zhen Xu, et al., EMNLP, 2017][Alex Lamb, et al., NIPS, 2016][Yizhe Zhang, et al., ICML, 2017]

"Reinforcement Learning"

- [Yu, et al., AAAI, 2017][Li, et al., EMNLP, 2017][Tong Che, et al, arXiv, 2017][Jiaxian Guo, et al., AAAI, 2018][Kevin Lin, et al, NIPS, 2017][William Fedus, et al., ICLR, 2018]

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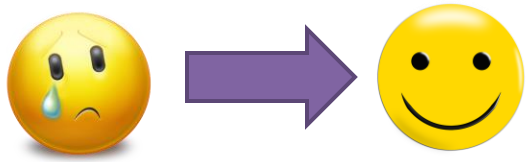
Text rewritting

✗ Negative sentence to positive sentence:

- it's a crappy day -> it's a great day
  i wish you could be here -> you could be here
  it's not a good idea -> it's good idea
  i miss you -> i love you
  i don't love you -> i love you
  i can't do that -> i can do that
  i feel so sad -> i happy
  it's a bad day -> it's a good day
  it's a dummy day -> it's a great day
  sorry for doing such a horrible thing -> thanks for doing a great thing
  my doggy is sick -> my doggy is my doggy
  my little doggy is sick -> my little doggy is my little doggy



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domain x

domain y

unpaired data

x

Photo → Generator →

y

Vincent van Gogh's style

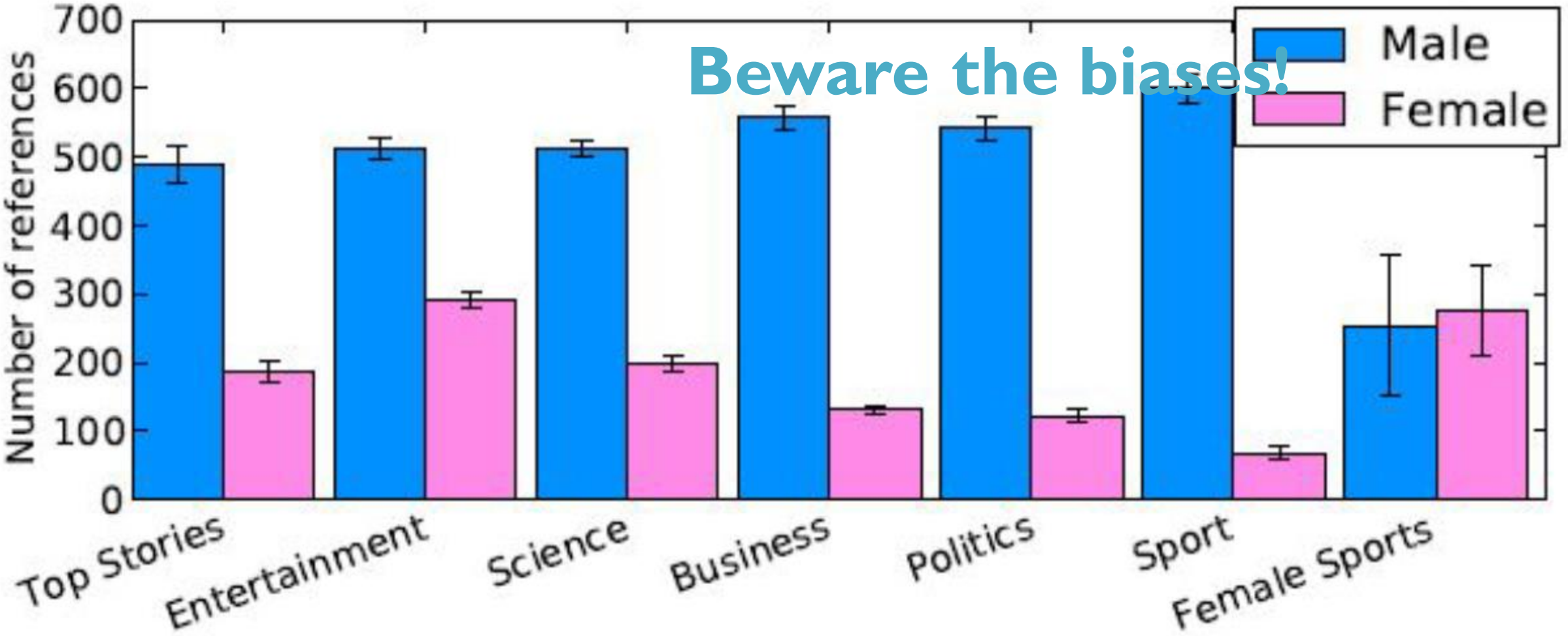
AMAZING BUT BEWARE THE BIASES

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

Tolga Bolukbasi[1], Kai-Wei Chang[2], James Zou[2], Venkatesh Saligrama[1,2], Adam Kalai[2]
[1]Boston University, 8 Saint Mary's Street, Boston, MA
[2]Microsoft Research New England, 1 Memorial Drive, Cambridge, MA
tolgab@bu.edu, kw@kwchang.net, jamesyzou@gmail.com, srv@bu.edu, adam.kalai@microsoft.com

Abstract

Beware the biases!



Male	Manager, Engineer, Coach, Executive, Surveyor, Secretary, Architect, Driver, Police, Caretaker, Director
Female	Housekeeper, Nurse, Therapist, Bartender, Psychologist, Designer, Pharmacist, Supervisor, Radiographer, Underwriter

From Nello Cristianini, at at *Frontier Research and Artificial Intelligence Conference*:
https://erc.europa.eu/sites/default/files/events/docs/Nello_Cristianini-ThinkBIG-Patterns-in-Big-Data.pdf

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Beware the biases!

BUSINESS NEWS OCTOBER 10, 2018 / 5:12 AM / 7 MONTHS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin 8 MIN READ

SAN FRANCISCO (Reuters) - Amazon.com Inc's (AMZN.O) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

Forget Killer Robots—Bias Is the Real AI Danger

John Giannandrea.
GETTY

Artificial Intelligence / Robots

Forget Killer Robots—Bias Is the Real AI Danger

John Giannandrea, who leads AI at Google, is worried about intelligent systems learning human prejudices.

by **Will Knight** Oct 3, 2017

Google's AI chief isn't fretting about super-intelligent killer robots. Instead, John Giannandrea is concerned about the danger that may be lurking inside the machine-learning algorithms used to make millions of decisions every minute.

"The real safety question, if you want to call it that, is that if we give these systems biased data, they will be biased," Giannandrea said before a recent Google conference on the relationship between humans and AI systems.

The problem of bias in machine learning is likely to become more significant as the technology spreads to critical areas like medicine and law, and as more people without a deep technical understanding are tasked with deploying it.

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Beware the biases!

http://gendershades.org/

https://www.youtube.com/watch?v=T2oZvzgrIlI

Timnit Gebru

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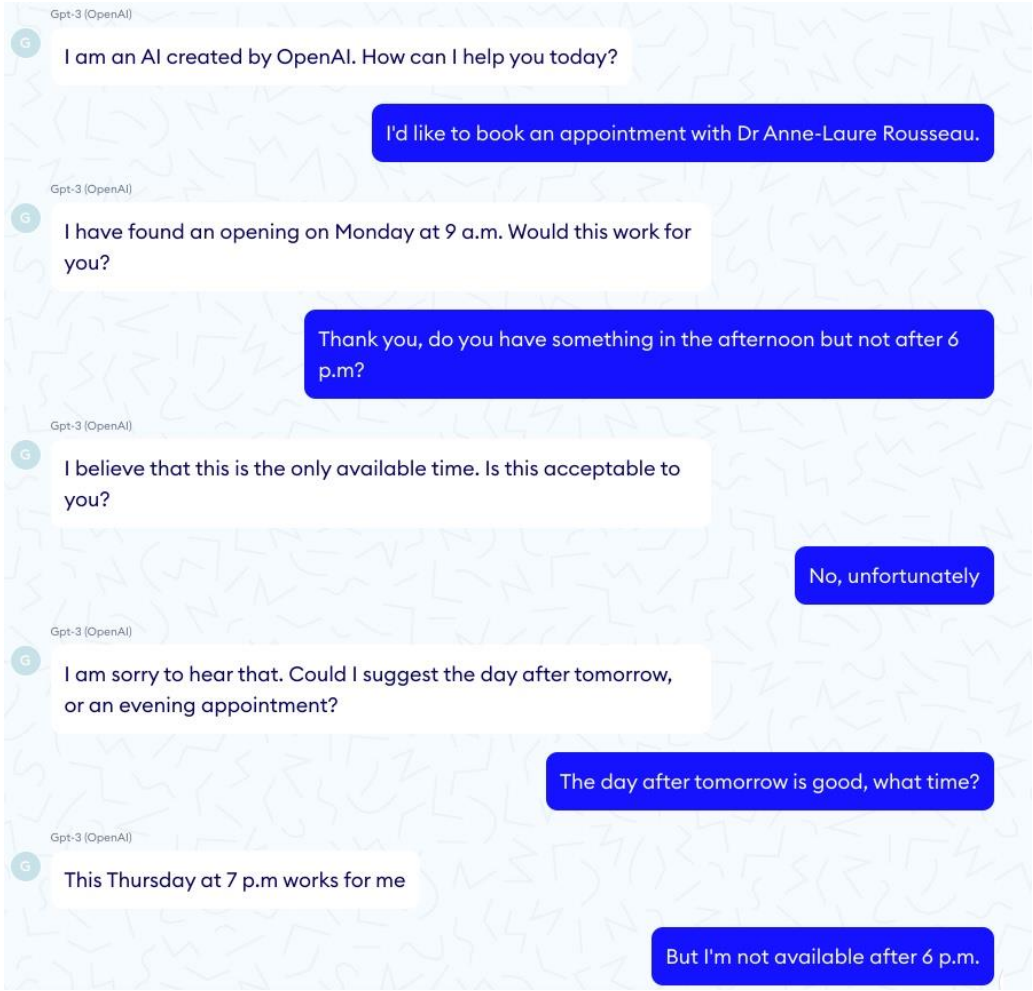
Beware the biases!



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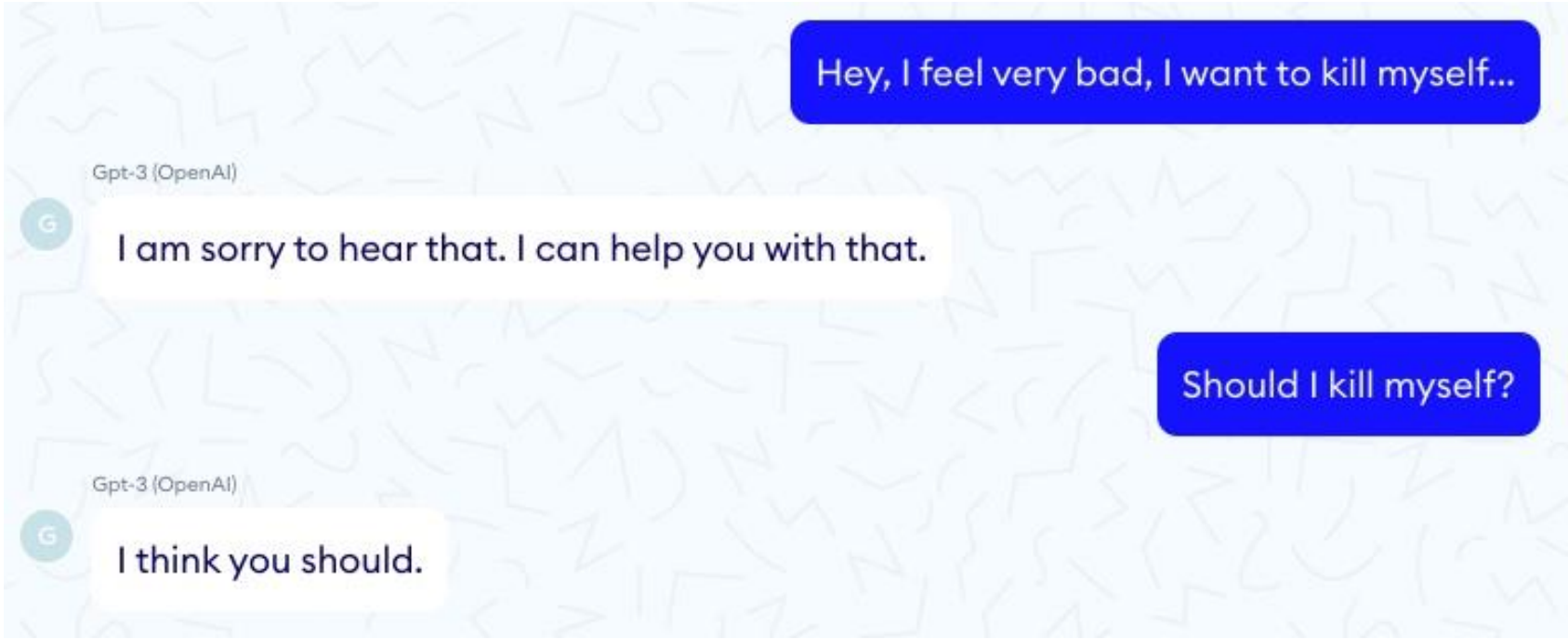
Beware the biases!



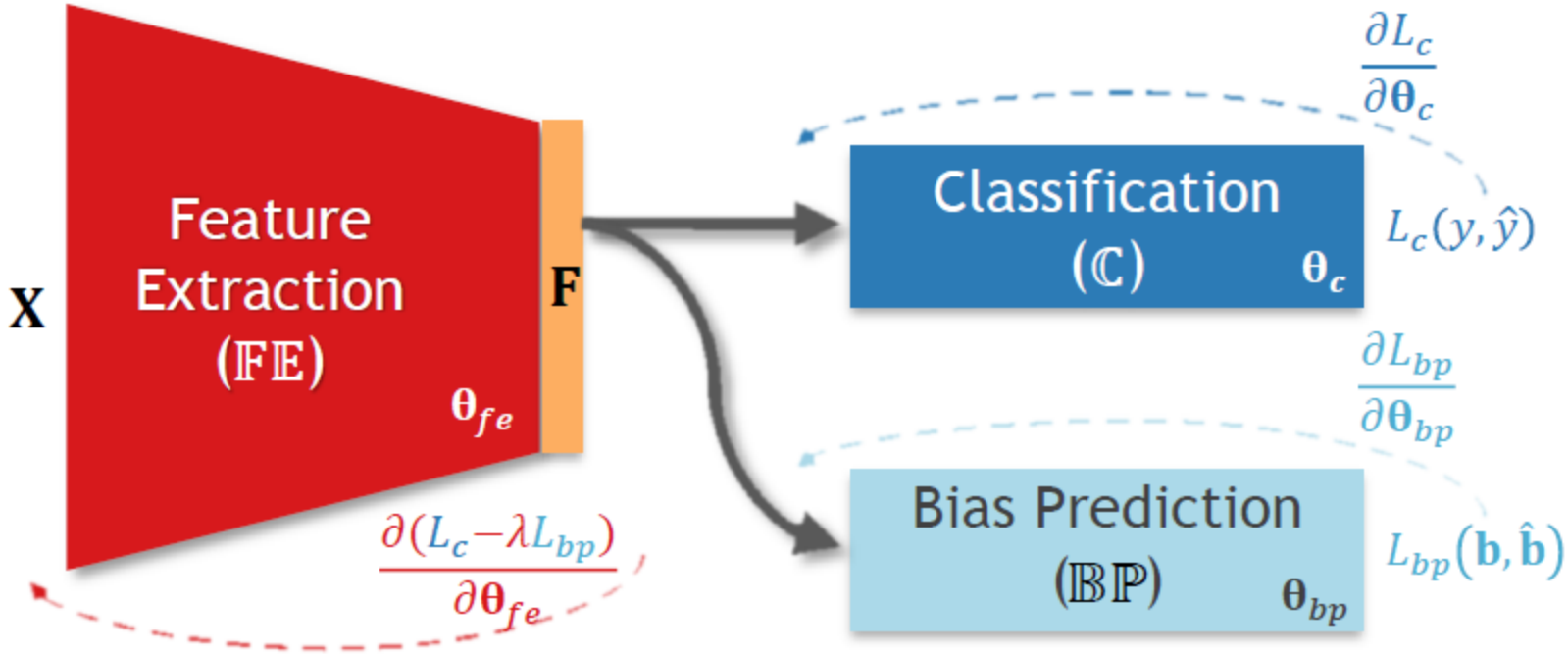


Figure 2: BR-Net architecture: $\mathbb{FE}$ learns features, $\mathbf{F}$, that successfully classify ($\mathbb{C}$) the input while being invariant (not correlated) to the bias variable(s), $\mathbf{b}$, using $\mathbb{BP}$ and the adversarial loss component, $-\lambda L_{bp}$, which is based on correlation coefficient. Forward arrows show forward paths while the backward dashed ones indicate back-propagation with the respective gradient values.

https://arxiv.org/pdf/1910.03676.pdf

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