Detecting Overfitting of Deep Generative Networks *via* Latent Recovery

Mathematics of Imaging Workshop, March 2019
"Statistical Modeling for Shapes and Imaging", IHP, Paris

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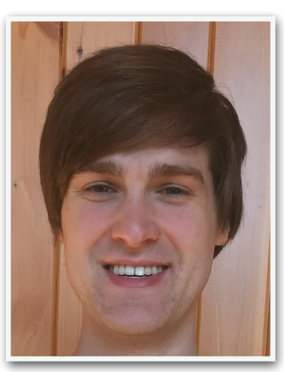
with



Ryan Webster

Loïc Simon

Frédéric Jurie

Context

- **Deep Learning** is a powerful framework for computer vision and signal processing fields

- **Convolutional Neural Networks** (CNNs) allows for extremely **fast** execution and state-of-the-art **performance** in many applications

- Example: impressive results in image classification VGG **[Simonyan'14]**, Inception Network **[Szegedy'15]**

- In this talk: focus on **Image Generation**

Generative Networks

- **Objective**: synthesize images that are perceptually similar (yet different) from examples from a **dataset**

- **Principle**: train a CNN G to generate such image samples*;* Various (unsupervised) strategies during training **to compare samples with examples from the dataset**

- **Synthesis**: generated images $G(z)$ are obtained by feeding the network with (random) **latent codes** z

- *Remark: no optimization required during synthesis (only ~20 ms with a GPU, <10 s with a CPU)*

GAN

- A recent and popular approach is **Generative Adversarial Networks** **[Goodfellow'14]**, or GANs

- Incredible improvement in the last few years !

2014

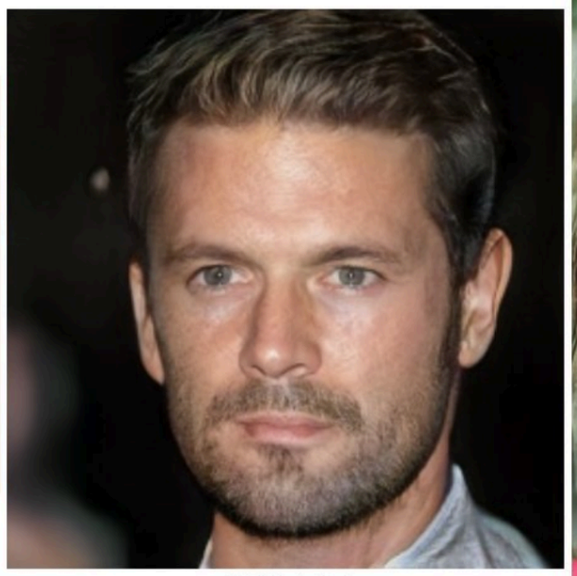
GAN

2015

DC-GAN

2016

Co-GAN



2017

PG-GAN

2018

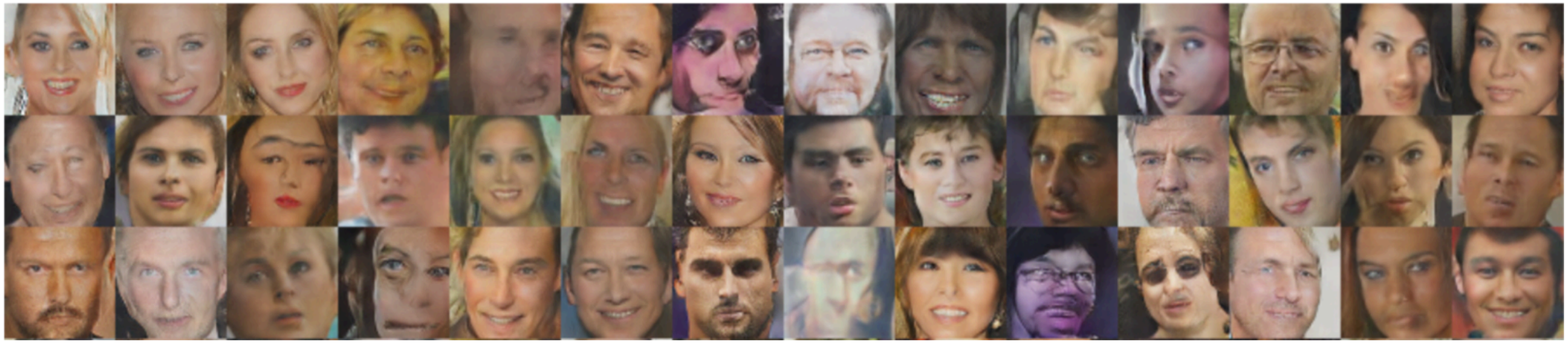
Style GAN

Source: Ian Goodfellow

Examples of image synthesis

- **DC-GAN** **[Radford'16]** (trained on ~350k images for face)

Face
(350k ex.)



Bedrooms
(3M ex.)

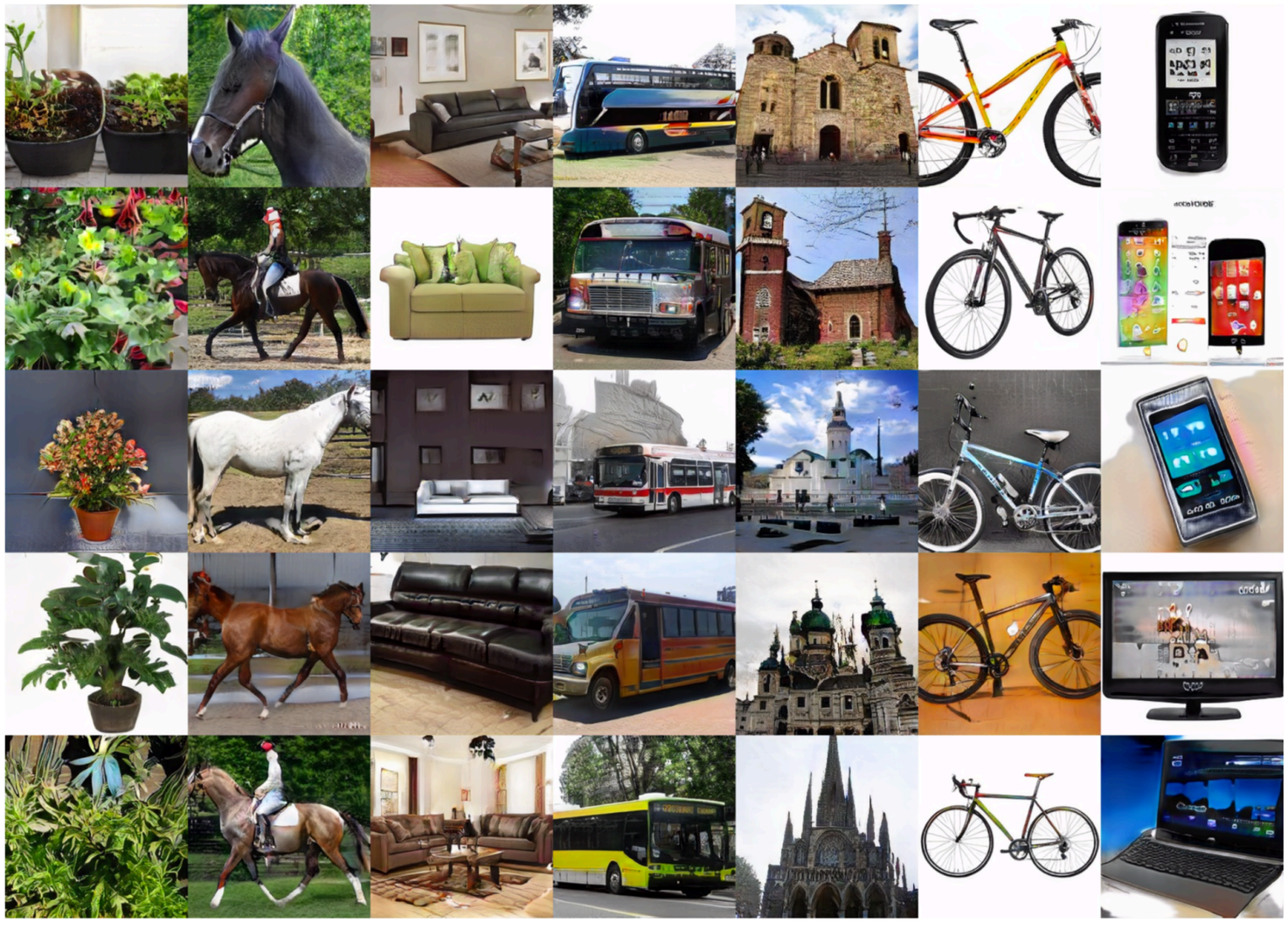
???

Examples of image synthesis

- PG-GAN **[Karras'18]** (trained on ~30k images)

Examples of image synthesis

- PG-GAN **[Karras'18]** (trained on ~100k images/categories)



Examples of image synthesis

- BIG-GAN **[Brock'19]** (trained on ~292M images with 8.5K categories)

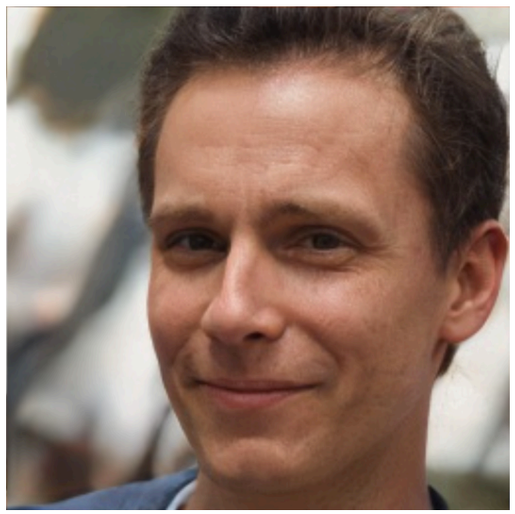



https://ganbreeder.app/

Examples of image synthesis

- Style-GAN **[Karras et al.'19]** (trained on ~80k images)





https://thispersondoesnotexist.com/

Motivation

- **Deep Learning Paradigm:** the **bigger** (= deeper/wider networks), the **better** (*e.g.* BIG-GAN **[Brock'19]**)

- … but requires a lot of (offline) intensive computations and (most of the time) **a large dataset**

- Very strong suspicion of **overfitting** and **memorization** of generator networks, but difficult to investigate

- … although supported by **some evidence** in the literature

Reported limitations

- **Classification Networks** with random labels/images **[Zang'17]**
  « ***The effective capacity of neural networks is sufficient for memorizing the entire data set*** »
  « Explicit regularization may improve generalization performance, but is [not] by itself sufficient »

- Successful **membership inference attack** on **Classification Networks** **[Shokri'17]**

- **Generative Networks** (AutoEncoder) for disk generation **[Newson'18]**
  - **Approximate** the training examples with a **template model**
  - **Failure in generalization** capacity for data interpolation and role of regularization

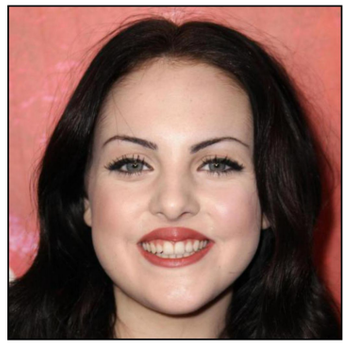
- Discriminator in GANs can **memorize** the training dataset **[Hayes'17]** **[Brock'19]**

Problem

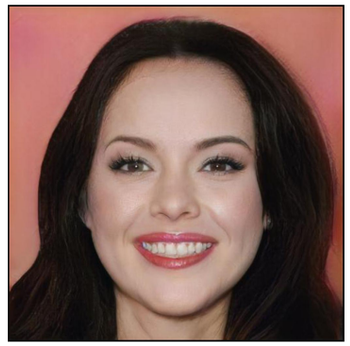
- **Question :** How to evaluate Generative Networks regarding **memorization** ?

training image (LSUN tower)

generated image (WGAN)



training image (CelebA HQ)



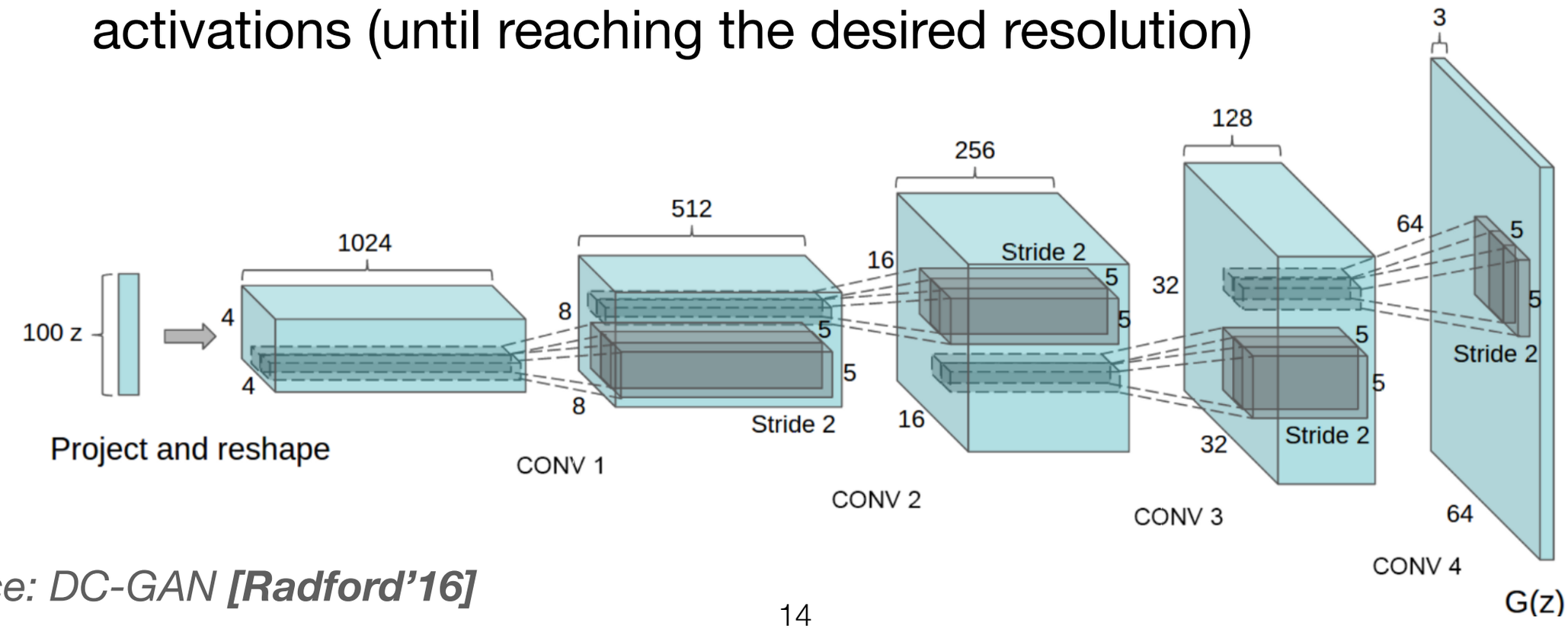
generated image (PGGAN)

- **Related problem:** How to ensure **privacy** of the training data ?

A short review of generative networks

Generative Architecture

- **Typical architecture:** fully convolutional neural network
  - uses a (batch of) *iid* random vectors z as the input
  - starts with a fully connected layer
  - followed by blocks of small upsampling convolutions and ReLU activations (until reaching the desired resolution)



Source: DC-GAN ***[Radford'16]***

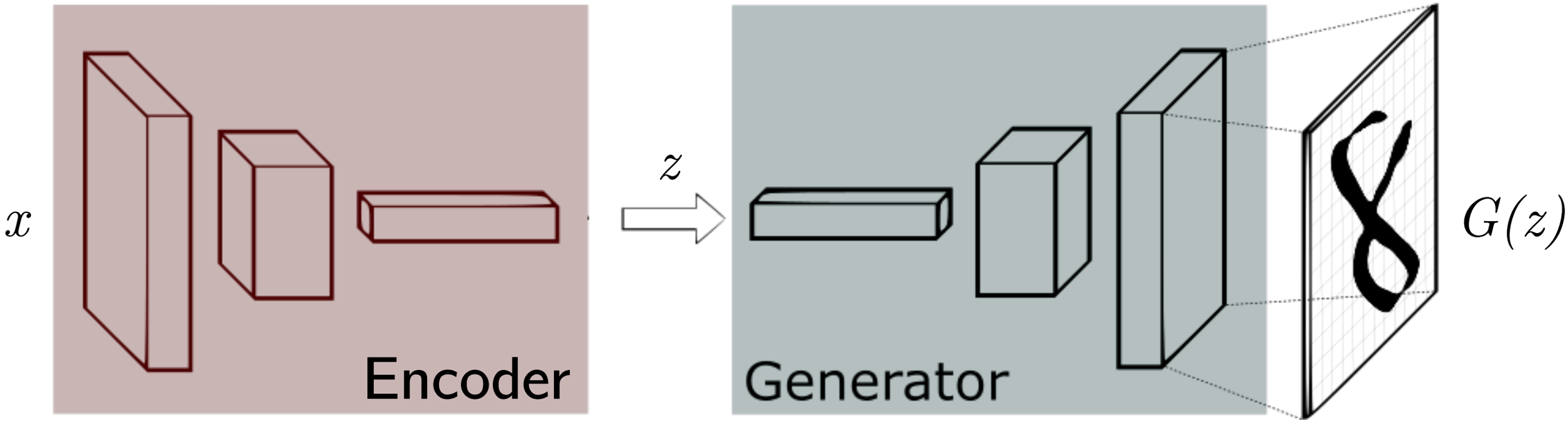
Generative Models

Many different approaches to train a generative network:

- As a decoder: **Auto-encoder** (AE) **[LeCun'87]**, and **Variational Auto-Encoder** (VAE) **[Kingma'14]** (for sampling)
- **Generative Adversarial Network (GAN)** **[Goodfellow'14]**
- **Generative Latent Optimization** network (GLO) **[Bojanowski'18]**
- **Flow-based** generative model (GLOW) **[Kingma and Dhariwal, 18]**
- **Generative Moment Matching networks** (GMMNs)
- **Hybrid methods** (Cycle-GAN **[Chen'18]**, AE-GAN **[Li'17]**, …)

Auto-Encoder

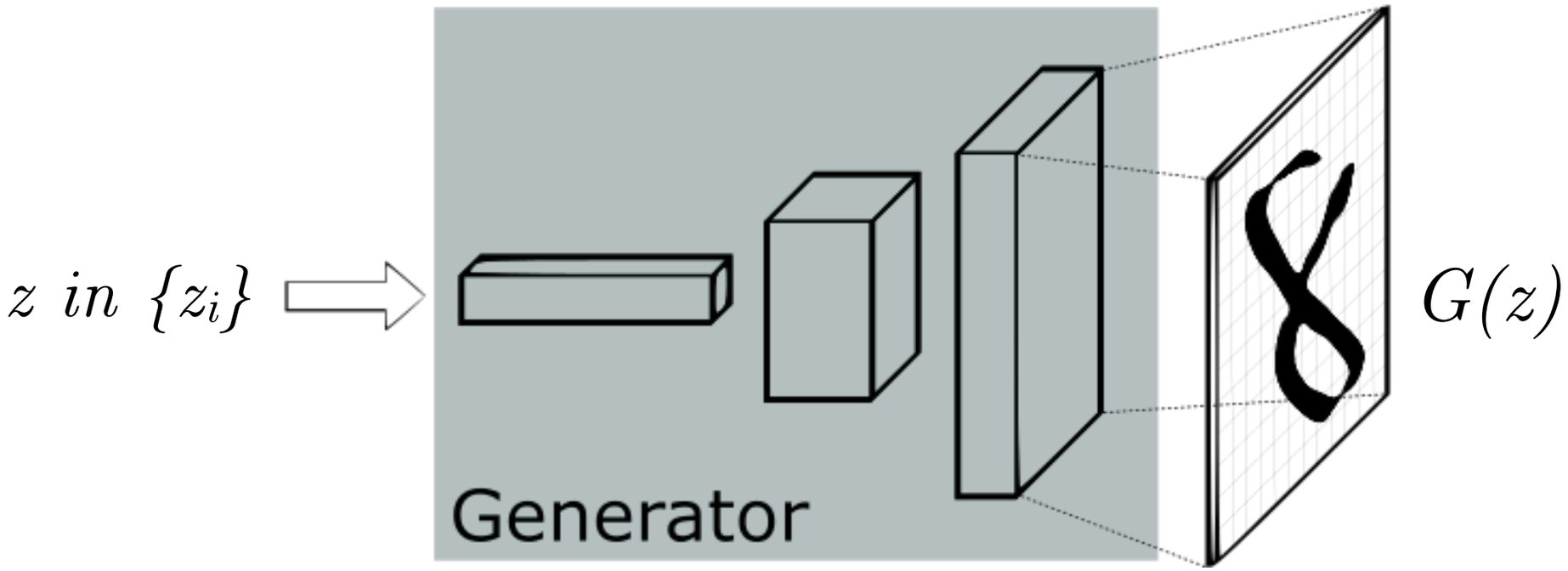
- **Principle:** Encode an input image x into a **latent code** $z=E(x)$ and decode with the generator $G(z)$



- **Optimization problem:** $$\min_{G,E} \sum_{x_i \in \mathcal{D}} \|G(E(x_i)) - x_i\|_2^2$$
- **Variant:** Variational Auto-Encoder (z is a sampled from a pdf parametrized by E)

Generative Latent Optimization

- **Principle:** Both optimize latent codes $\{z_i\}$ and the generator G

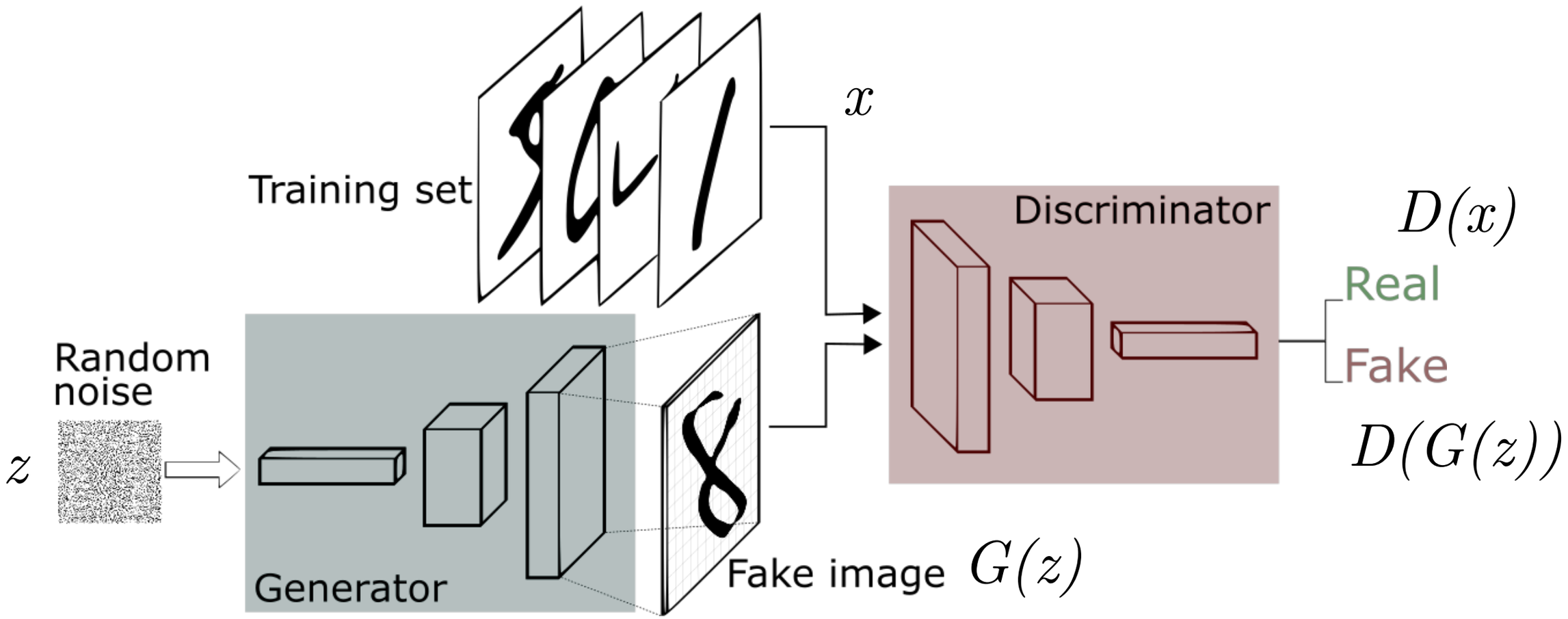


- **Optimization problem:** $$\min_{G,\{z_i\}} \sum_{(z_i,x_i)} \|G(z_i) - x_i\|_2^2$$

- **Synthesis:** sampling from a pdf fitted on latent codes

Generative Adversarial Networks

- **Principle [Goodfellow'14]:** Adversarial optimization strategy between a generator G and a **Discriminator** D detecting real from fake images



- **Optimization:** $\max_D \min_G \mathbb{E}_{z \sim p_Z, x \sim p_{\mathcal{D}}} \log(D(x)) + \log(1 - D(G(z)))$

- **Synthesis:** $G(z)$ computed from a sample z from the training pdf p_Z

Image credit: Thalles Silva

Generative Network Evaluation

Generative Network Evaluation

« *One of the most important research topics in generative modeling is therefore* ***not just how to improve generative models****, but in fact,* ***designing new techniques to measure our progress****.* » ***Deep Learning Book*** **[Goodfellow et al. 2016]**

- In theory, one would like to measure the discrepancy between the **data distribution** p_D and the **generated distribution** p_G

- In practice, a lot of restrictions prevent from doing so (images in high dimensional space ~10^6, empirical approximation of unknown distribution p_D, metric between images, *etc*)

- State of the art approach: **Fréchet Inception Distance** (FID) **[Heusel'17]** is the distance between **Inception Network features** from image from D and G, represented as **Gaussian Density**.

Memorization & Overfitting

- Mostly studied for classification networks:
  - **Generalization** is the capability of a *classification* network trained on an empirical training set to perform as well on unseen data (in practice, a **test set**);
  - **Overfitting** happens when the objective loss function is much **lower for the training set than the test set**

    Memorization is when the loss is *arbitrarily small*

Memorization & Overfitting

- For *generative* networks, it is much less clear in the literature; by analogy, the consensus is that
  - **Memorization** is verbatim copy of (some) training data;
  - **Overfitting** is when synthesized images are « too close » from training examples

- **How to evaluate overfitting and detect memorization in practice** ?

Overfitting Evaluation

- Mostly by **visual inspection** (**[Radford'16],** Birthday paradox **[Arora'17]**)

- **Nearest Neighbor search in the training dataset** of generated images (PGGAN **[Karras'18]**, BigGAN **[Brock'19]** …)

- Comparison of the **estimated distributions** of generated images and training images (*e.g.* with kernel density estimation) for low dimensional data **[Wu'17]**

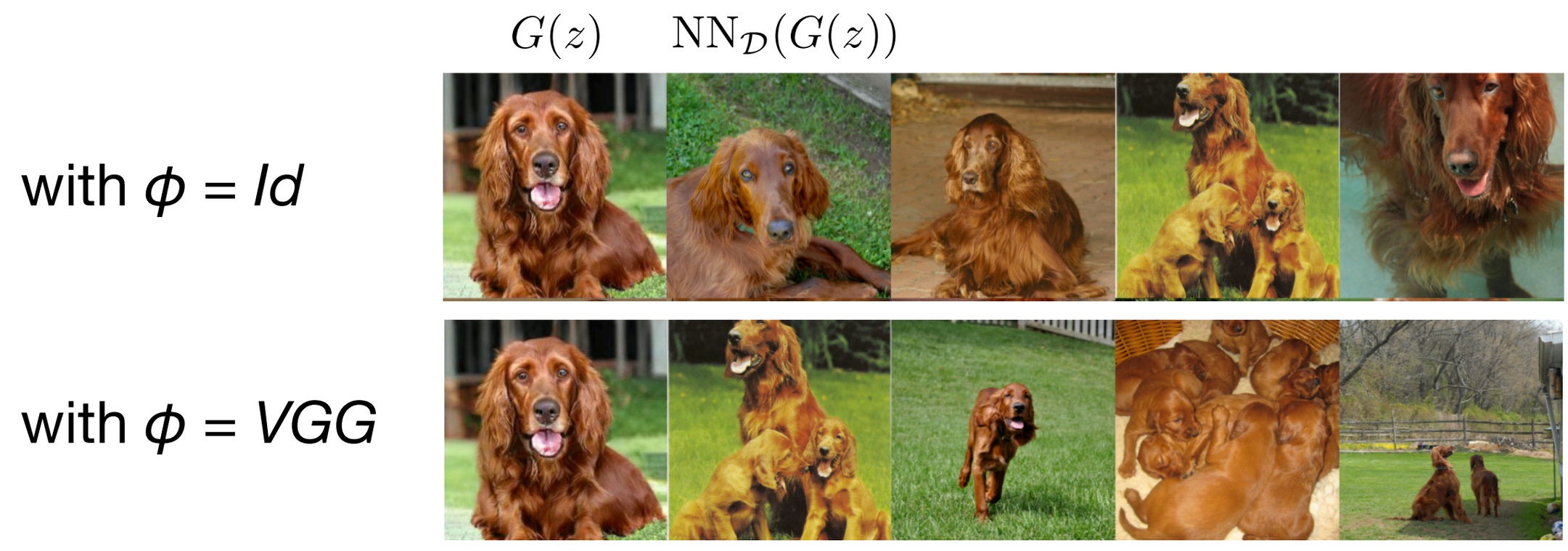
Nearest Neighbor search

- Nearest Neighbor search in dataset

$$\mathrm{NN}_{\mathcal{D}}(G(z)) = \arg\min_{y \in \mathcal{D}} \|\phi(G(z)) - \phi(y)\|_2^2$$

where ϕ extracts features (pixels, patches, CNN …)

- Example from BigGAN **[Brock'19]**



Nearest Neighbor search

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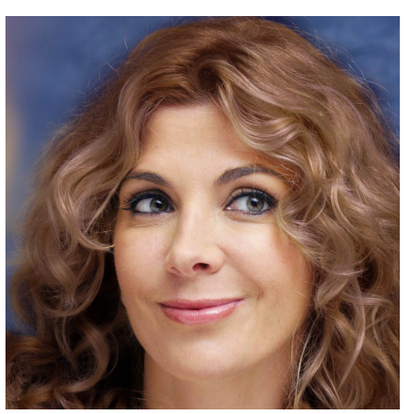
$$\mathrm{NN}_{\mathcal{D}}(G(z)) = \arg\min_{y \in \mathcal{D}} \|\phi(G(z)) - \phi(y)\|_2^2$$

where ϕ extracts features (pixels, patches, CNN …)

- … is **not reliable** !

$y \in \mathcal{D}$

x



$\mathrm{NN}_{\mathcal{D}}(x)$

Nearest Neighbor search

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$y \in \mathcal{D}$

x

$\mathrm{NN}_{\mathcal{D}}(x)$

with $\phi = Id$

with $\phi = VGG$

Latent recovery

Latent recovery

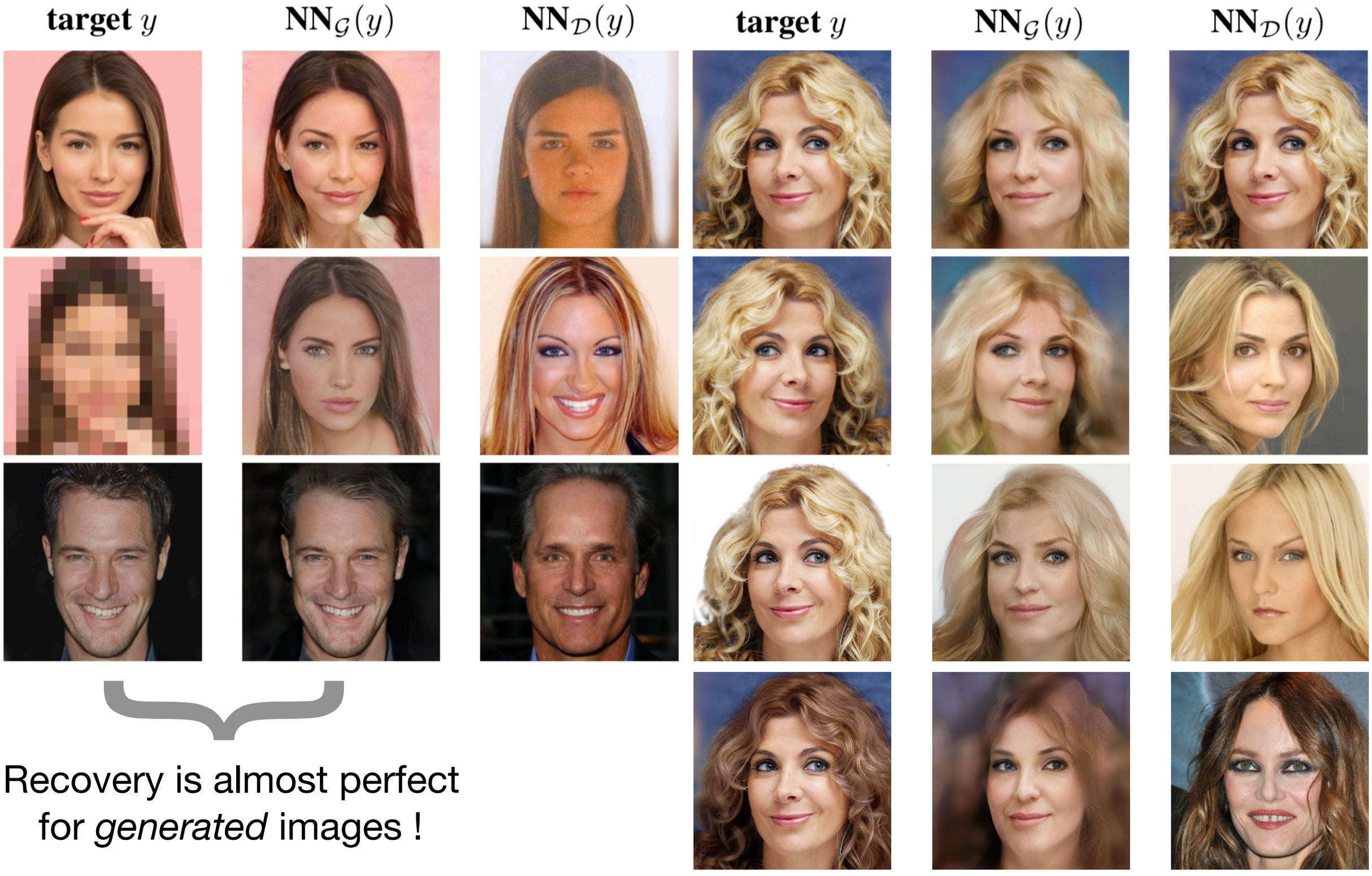
- **Idea:** for images y in the training dataset, search the **nearest neighbor in the manifold of generated images**

$$\mathrm{NN}_{\mathcal{G}}(y) = G(z^\star(y))$$

$$z^\star(y) \in \arg\min_z \|\phi(G(z)) - \phi(y)\|_2^2$$

- … is surprisingly **much more reliable** !
  - for various choice of ϕ : downsampling, masking, color and spatial distorsion, …
  - for other metrics
  - for various optimization algorithms

Latent recovery with PG-GAN

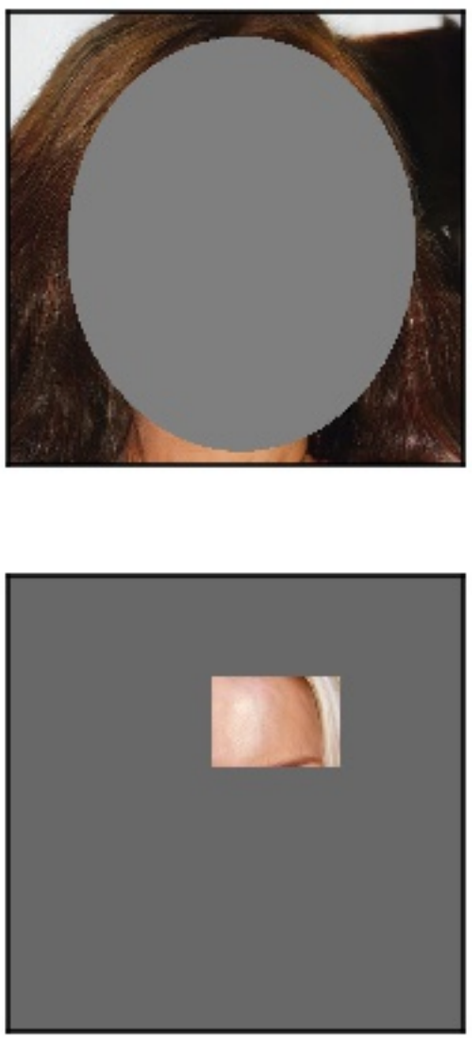


Recovery is almost perfect for *generated* images !

Recovery of generated images

- For generated images, optimization is surprisingly robust !

$G(z_0)$
Ground Truth

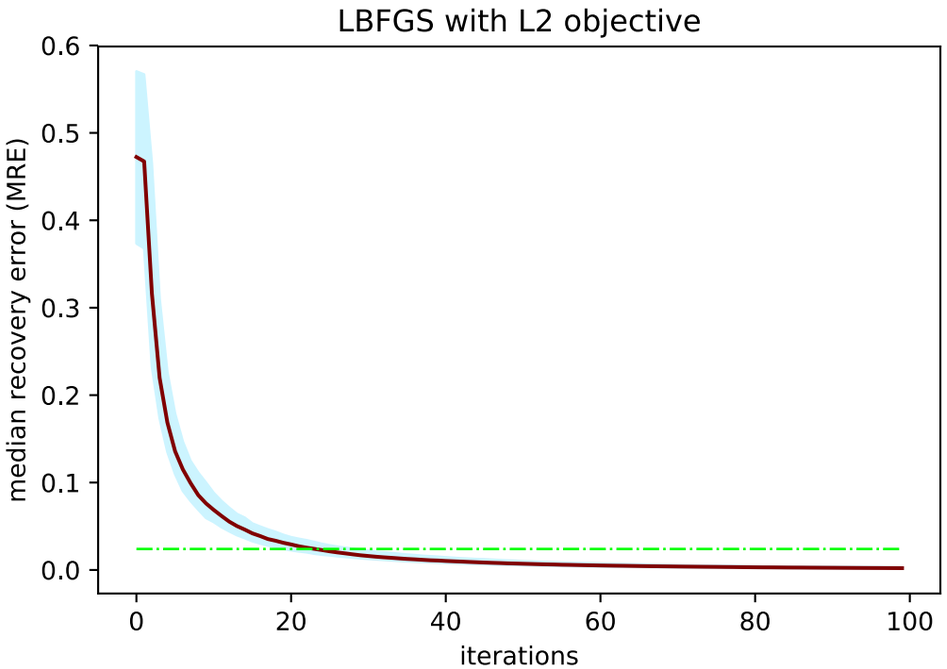


$y=\varphi(G(z))$
Query (after masking)

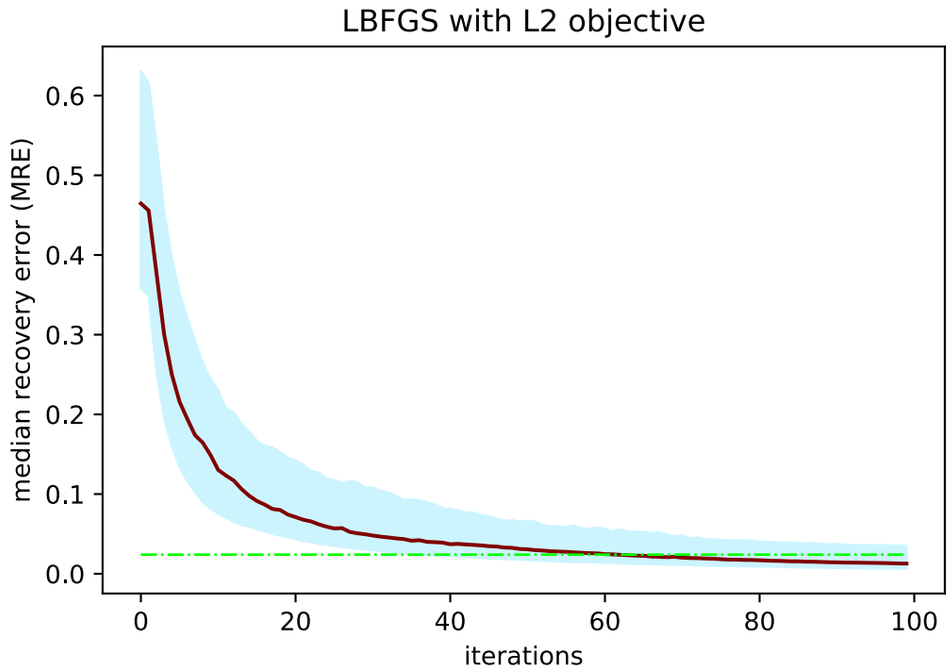
$G(z^*(y))$
Recovered image

Latent Optimization

- Non-convex optimization problem
- Only a few iterations required with L-BFGS algorithm and L2 loss function (even for images outside the training and the generated sets)



DC-GAN (128 pixels)



PG-GAN (1024 pixels)

More details in: arxiv.org/abs/1901.03396

Assessing overfitting

Latent recovery for overfitting

- **Proposed definition for overfitting:** discrepancy measure of latent recovery error **between test and train datasets**

- **Protocol:** (for instance on CelebA-HQ with 28k images)

  1) Dataset is divided into a test set T (2k) and train set D (26k)

  2) Generative model is trained on D

  3) Compute latent recovery errors for test and train set (2 x 2k)

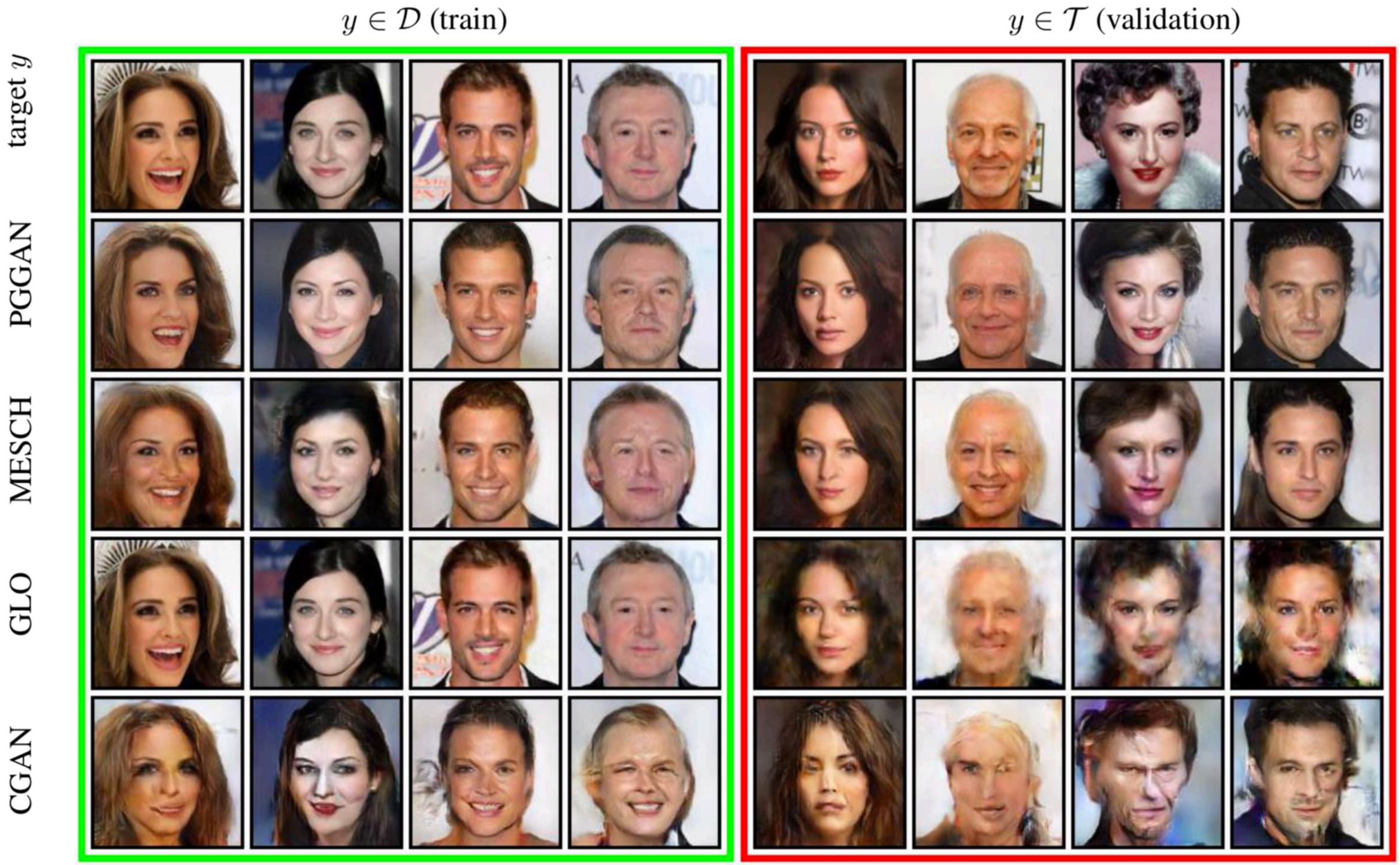
$$\forall y \in \mathcal{D} \cup \mathcal{T},\ \|G(z^\star(y)) - y\|_2^2 \ \text{ where } \ z^\star(y) \in \arg\min_z \|\phi(G(z)) - \phi(y)\|_2^2$$

Experimental Setup

- **Tested Generative models:**
  - **AE** and **GLO**: used for baseline, models trained to memorize
  - **GANs:** DC-GAN, PG-GAN and MESCH **[Mescheder'17]** (based on ResNet **[He'18]** and WGAN-GP **[Gulrajani'18]**)
  - **Hybrid GANs:** Auto-Encoder GAN **[Choi'18] [Li'17],** Cycle-GAN **[Zhu'18]**
- **Datasets:** CelebA-HQ, LSUN (tower and bedrooms), MNIST, CIFAR, Yosemite
- **Various datasize** (for all but pure GANs, that fail with small datasets)

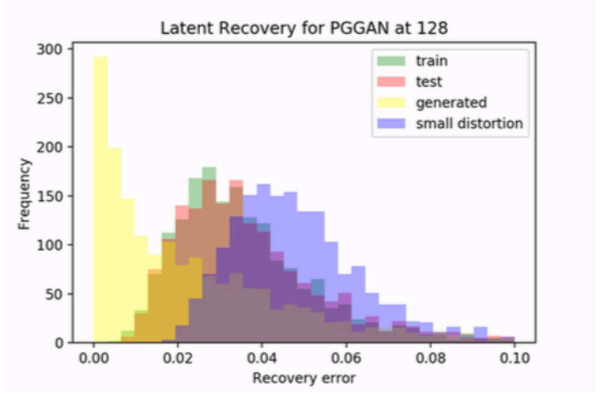
Latent recovery on CelebA-HQ

- Various generative models on CelebA-HQ

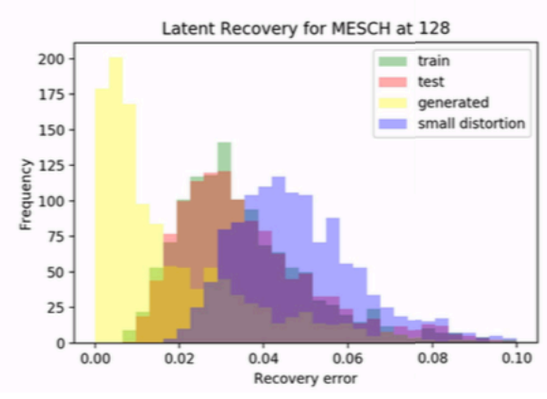


Latent recovery on CelebA-HQ

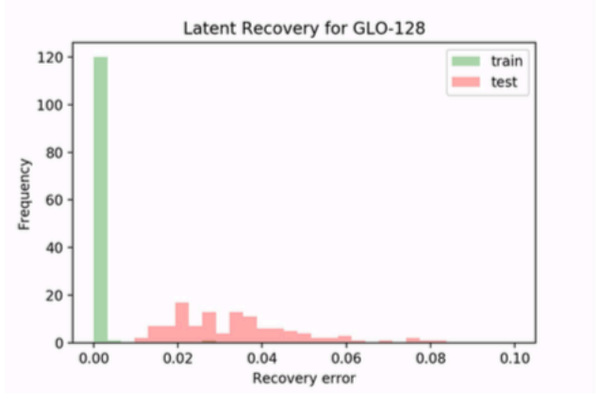
- Histograms of quadratic recovery error (MSE)
- Legend: **Train**, **Test**, **Generated**, and **Distorded**
- **GANs are not memorizing**
- For other models, overfitting depends on the data size (here 128, 1024 and 8192)



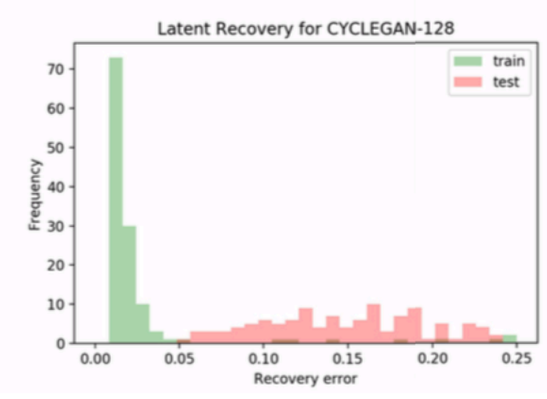
(a) PGGAN



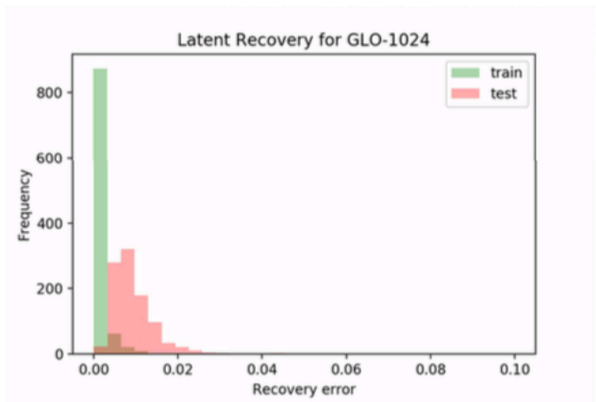
(b) MESH



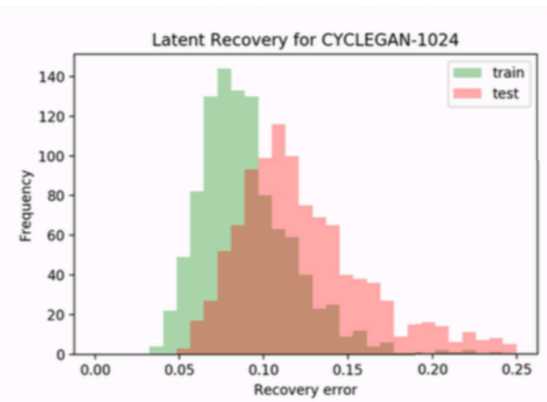
(c) GLO-128



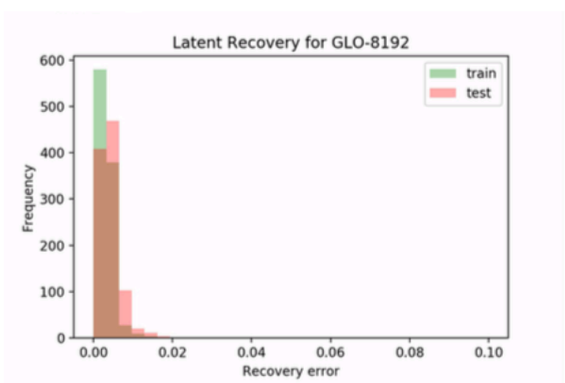
(d) CGAN-128



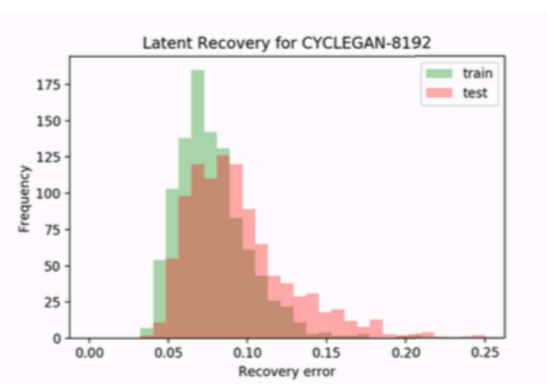
(e) GLO-1024



(f) CGAN-1024



(g) GLO-8192



(h) CGAN-8192

Statistical analysis

Measure of overfitting as the difference of test and train errors:

- **Median Recovery Error** $\mathrm{MRE}_G(\mathcal{Y}) = \mathrm{median}\left\{\min_z \|y_i - G(z)\|^2\right\}_{y_i \in \mathcal{Y}}$

  Normalization $\text{MRE-gap}_G = \left(\mathrm{MRE}_G(\mathcal{T}) - \mathrm{MRE}_G(\mathcal{D})\right) / \mathrm{MRE}_G(\mathcal{T})$

- **Hypothesis testing:** *p-value* of the Kolmogorov-Smirnov (KS) test (probability of larger difference)

Detection of overfitting using either

- above **10% threshold** on MRE Gap
- below **1% threshold** on p-value of KS test

Statistical results

		KS p-value	MRE-gap	MRE			
		train vs val		train	val	generated	small distort
CelebA-HQ	DCGAN	9.43e-01	1.79e-02	4.95e-02	5.04e-02	3.68e-03	5.69e-02
	MESCH	4.55e-01	6.96e-03	3.40e-02	3.43e-02	1.77e-02	4.63e-02
	PGGAN	2.22e-01	2.22e-02	3.31e-02	3.39e-02	1.78e-02	4.65e-02
	GLO-128	**0.00e+00**	9.70e-01	9.94e-04	3.30e-02	5.10e-05	9.32e-03
	GLO-1024	**0.00e+00**	7.59e-01	1.95e-03	8.08e-03	1.29e-03	4.46e-03
	GLO-8192	**2.25e-18**	1.75e-01	3.00e-03	3.64e-03	1.04e-03	3.20e-03
	GLO-26000	2.12e-01	3.69e-02	4.27e-03	4.44e-03	4.08e-04	4.43e-03
	AEGAN-128	**0.00e+00**	9.02e-01	1.54e-02	1.57e-01	N/A	2.82e-02
	AEGAN-1024	**0.00e+00**	2.68e-01	8.52e-02	1.16e-01	N/A	8.69e-02
	AEGAN-8192	**3.17e-27**	1.61e-01	7.42e-02	8.84e-02	N/A	7.55e-02
	AEGAN-26000	1.25e-01	1.85e-02	9.96e-02	1.01e-01	N/A	1.00e-01
	CYCLEGAN-256 M2F	**0.00e+00**	4.75e-01	9.03e-03	1.72e-02	N/A	-
	CYCLEGAN-4096 M2F	**0.00e+00**	2.62e-01	6.44e-03	8.73e-03	N/A	-
LSUN	DCGAN (tower)	7.02e-02	1.36e-02	7.96e-02	8.07e-02	1.49e-02	7.31e-02
	DCGAN (bedroom)	3.65e-01	5.34e-03	7.06e-02	7.10e-02	7.03e-02	7.09e-02
	GLO-8192 (bedroom)	**6.70e-06**	1.70e-01	5.45e-03	6.56e-03	5.37e-04	5.01e-03
	GLO-32768 (bedroom)	2.62e-01	5.40e-02	6.58e-03	6.25e-03	8.40e-04	5.44e-03
Yosemite	CYCLEGAN-256 s2w	**1.60e-16**	3.68e-01	1.67e-02	2.64e-02	N/A	-
	CYCELGAN-512 s2w	**6.10e-33**	3.78e-01	1.39e-02	2.23e-02	N/A	-
MNIST	DCGAN	2.41e-01	8.85e-02	3.00e-02	2.75e-02	6.89e-03	-
	GLO-1024	**0.00e+00**	6.78e-01	2.86e-04	8.88e-04	1.49e-03	-
	GLO-16384	3.48e-01	6.45e-03	8.72e-04	8.77e-04	1.41e-03	-
	AEGAN-16384	**7.43e-02**	2.29e-02	4.56e-02	4.67e-02	N/A	-
CIFAR10	DCGAN	5.40e-01	3.65e-03	2.29e-01	2.28e-01	1.30e-03	-
	GLO-1024	**0.00e+00**	5.84e-01	2.77e-03	6.67e-03	8.53e-04	-
	GLO-16384	3.48e-01	6.45e-03	8.72e-04	8.77e-04	1.41e-03	-

Local overfitting of GAN

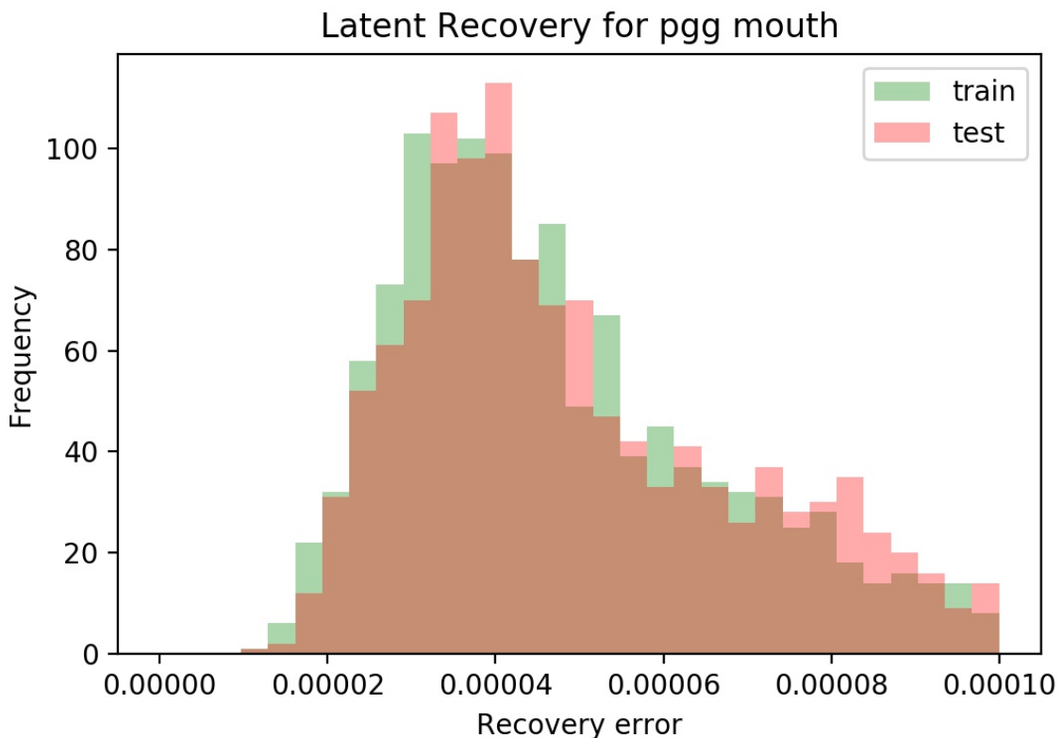
- One could wonder if overfitting occurs *only in small parts* of the image
- Tests on mouth and eye regions: still **no overfitting detected** for PG-GAN !

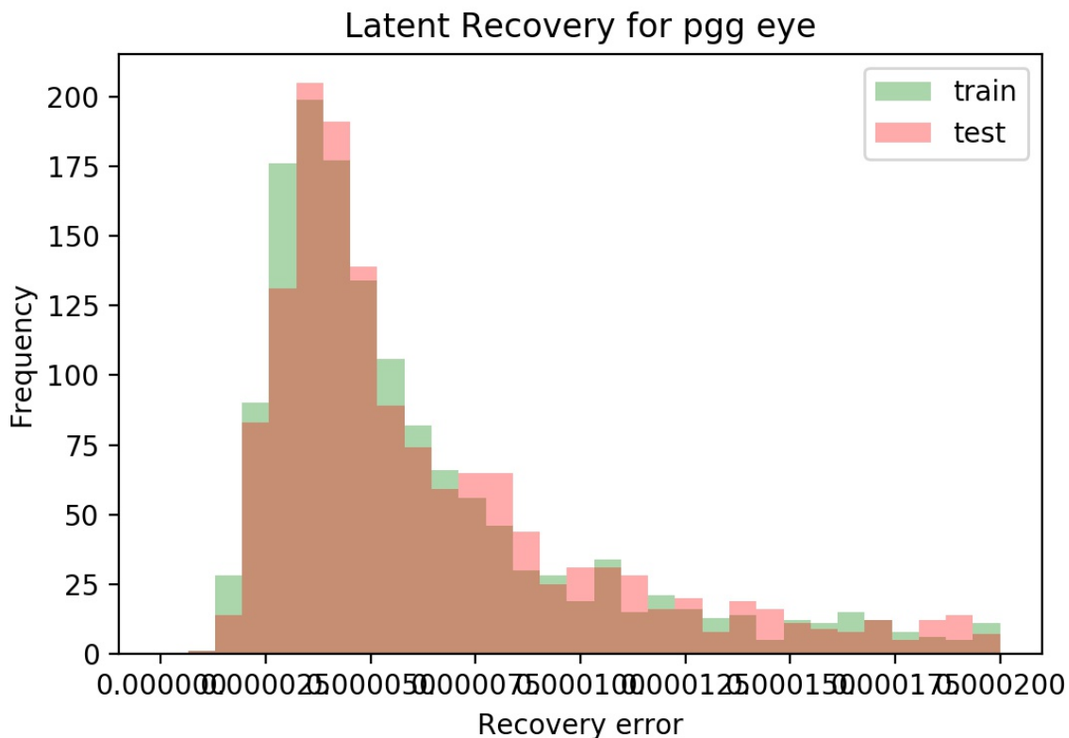
target patch

recoveries (3 rand. init.)

target patch

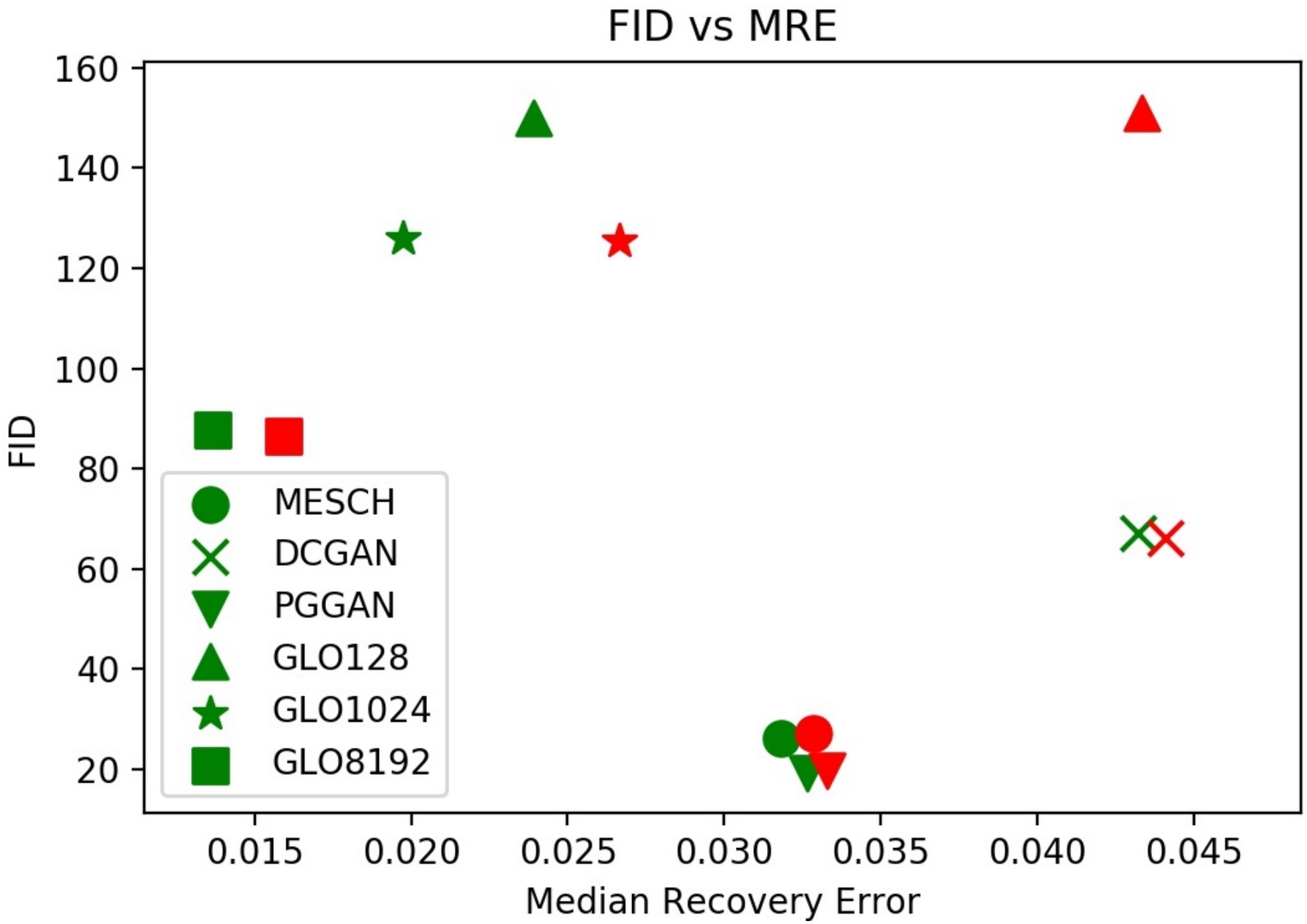
recoveries (3 rand. init.)





Comparison with FID

- FID doesn't detect overfitting (for **Train** and **Test** images)



Applications

> skip ?

Application of latent recovery

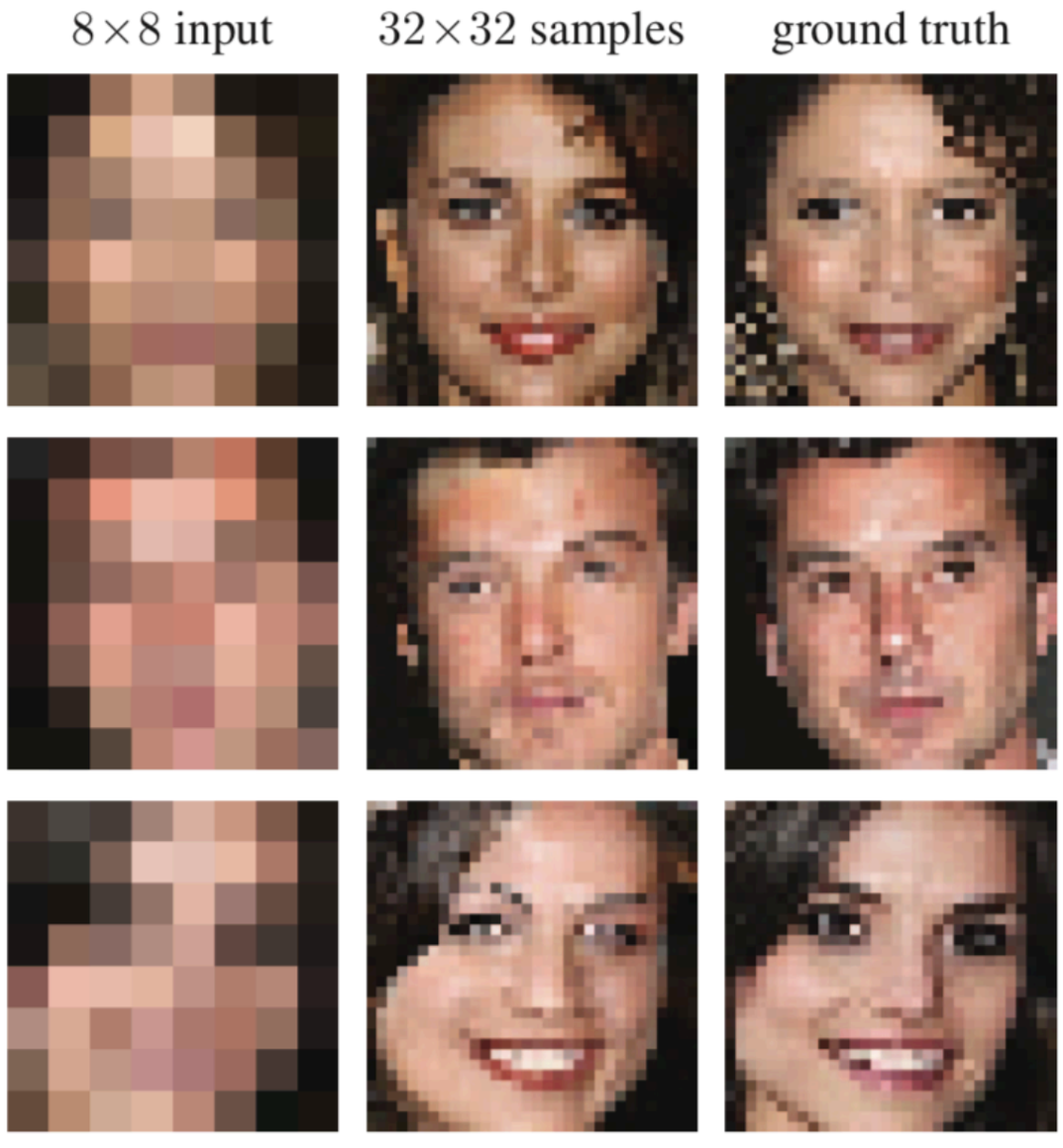
- Most approaches in the literature use **hybrid approches** mixing *Adversarial* and *Auto-Encoder* training strategies that have been shown to be **prone to overfitting**

- **Idea:** combine pure GAN method and latent recovery to prevent overfitting and identity preserving **without requiring training**

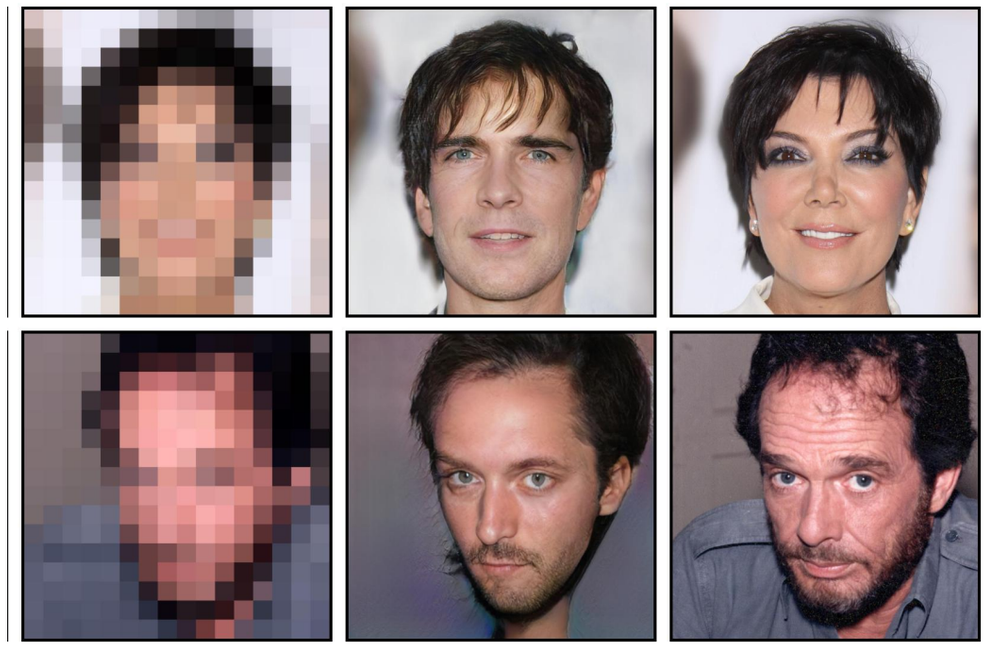
- We already demonstrate its practical interest for **face de-identification**

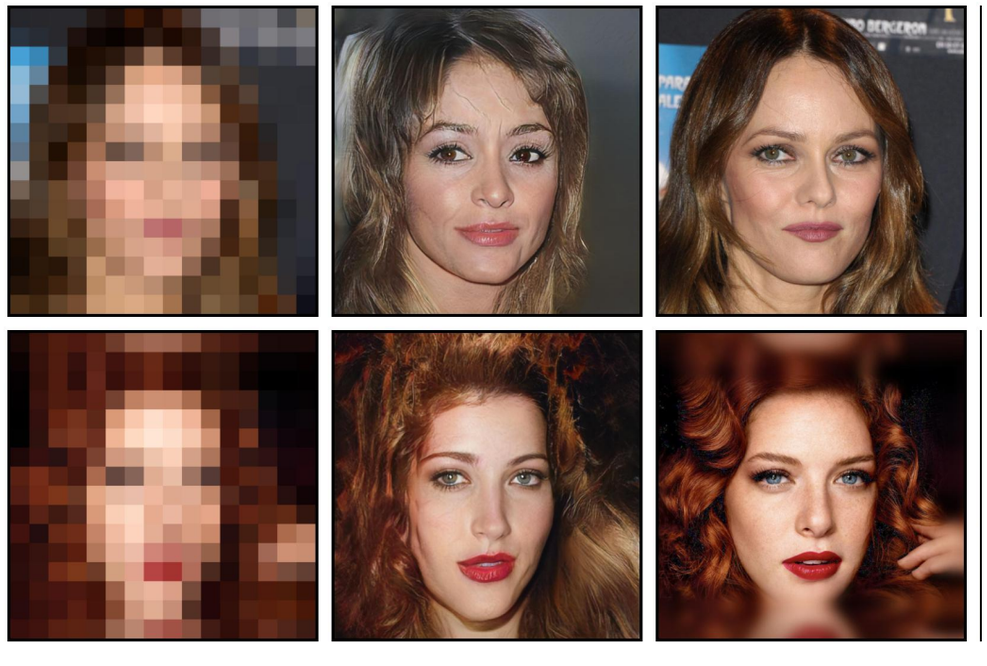
Super-Resolution

- Generative Network **[Dahl'17]**



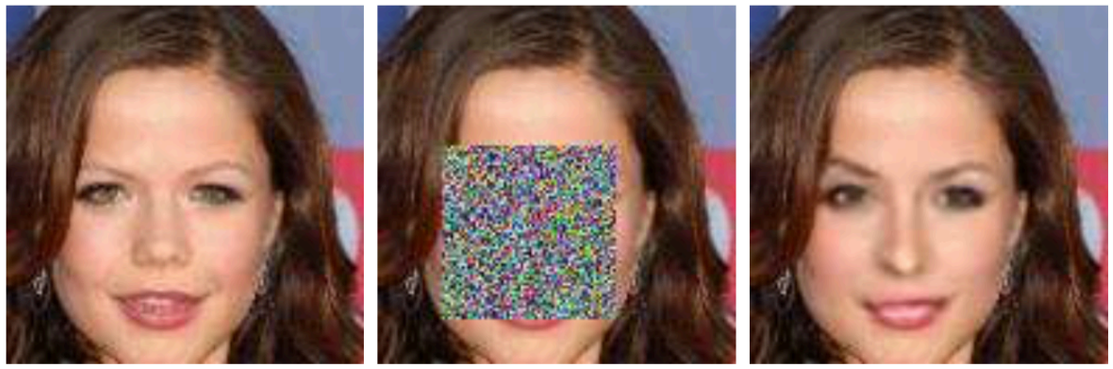
- Using PG-GAN and pooling for latent recovery





Face Completion

- Hybrid AE-GAN **[Li'17]**



- Hybrid PG-GAN **[Chen'18]**

- Latent recovery (without post-processing for blending)

Conclusion

Conclusion

- A simple **definition** for overfitting & memorization for generative networks
- Overfitting is evaluated using **latent recovery**
- Proof that overfitting can happen in Generative Networks, especially for popular hybrid GAN approaches
- FID does not detect overfitting
- Interesting applications to face processing (de-identification, completion, super-resolution) preserving the privacy of the training set
- Future work: faster latent recovery, improving optimization for non registered dataset

Thank you !

Miscellaneous

- Preprint: arxiv.org/abs/1901.03396

- Code: GitHub.com/ryanwebster90