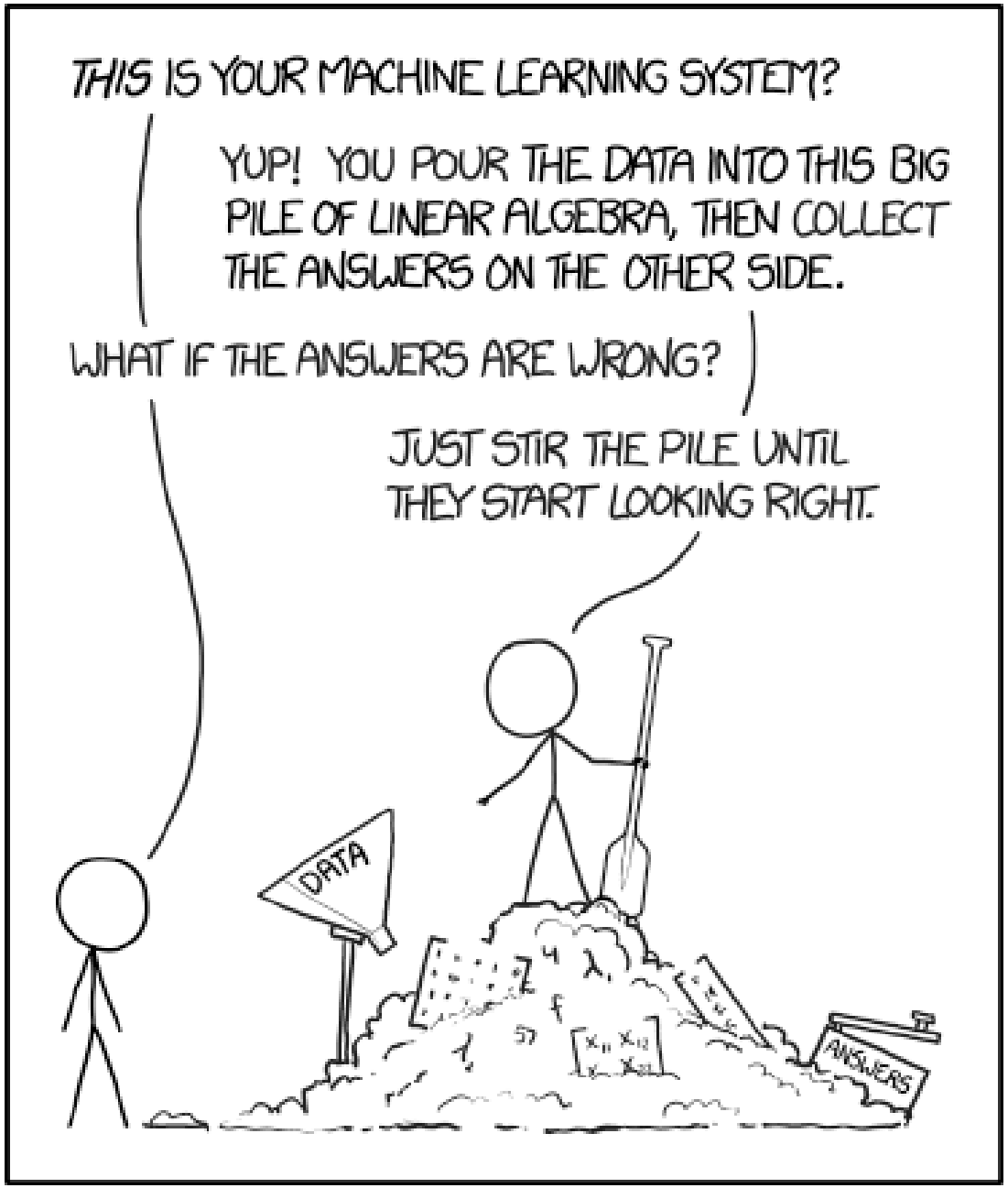
THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

Generative Adversarial Networks

Bruno Gavranović

Faculty of Electrical Engineering and Computing
University of Zagreb, Croatia

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July 23, 2018

Overview

Meta

- Generative Adversarial Networks are a new idea - June 2014

Meta

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Yann LeCun

"The most important one, in my opinion, is adversarial training (also called GAN for Generative Adversarial Networks).
This, and the variations that are now being proposed is the most interesting idea in the last 10 years in ML, in my opinion."

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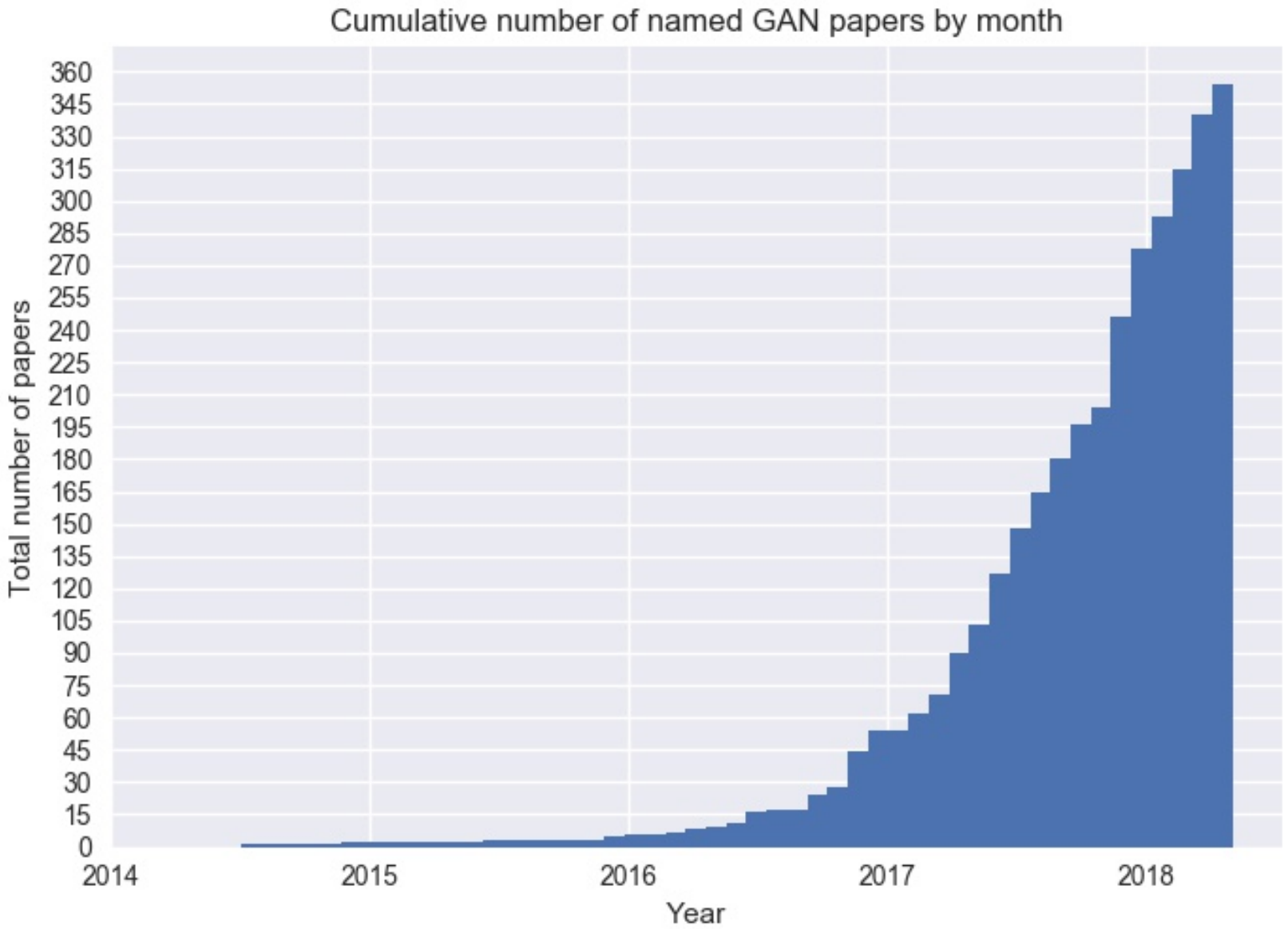
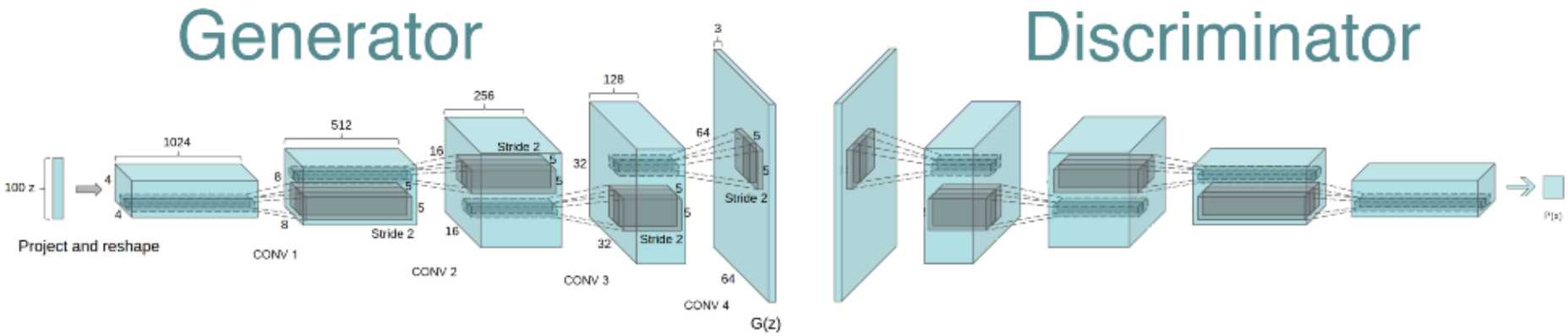
- We still don't properly understand the mechanics
- Compared to other ML models, we're still in early stages


Cumulative number of named GAN papers by month
Total number of papers
360
345
330
315
300
285
270
255
240
225
210
195
180
165
150
135
120
105
90
75
60
45
30
15
0
2014
2015
2016
2017
2018
Year

GAN: Just tell me what it is

- Generative machine learning model in which two neural networks are competing against each other



[0] https://github.com/dmonn/GAN-face-generator

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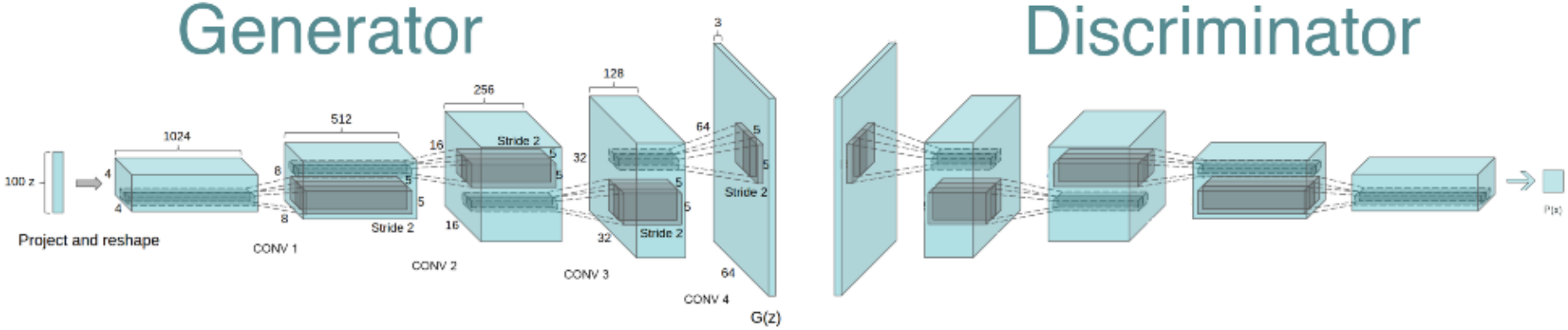

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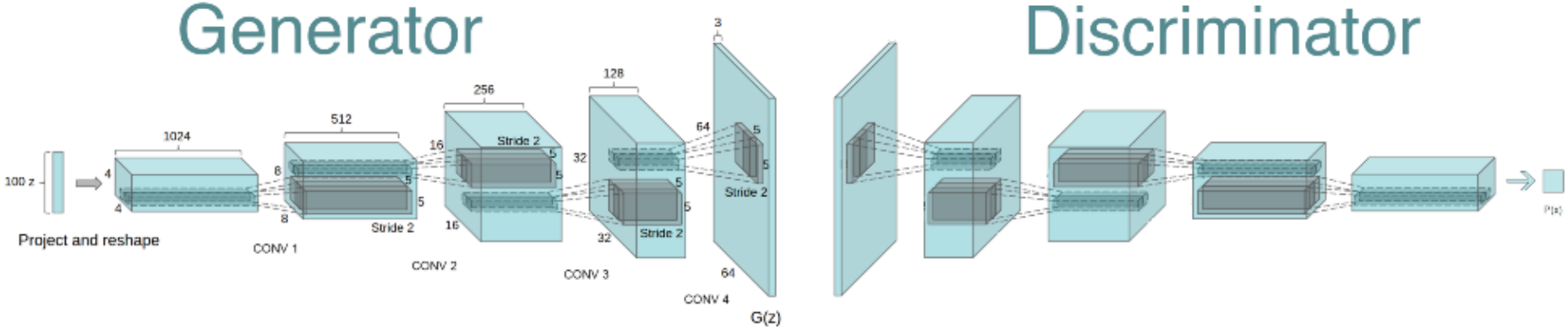

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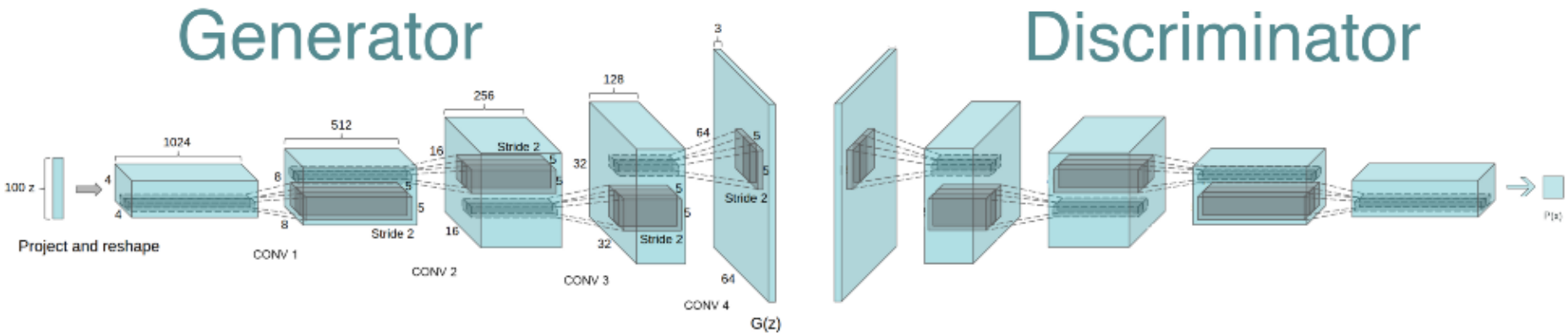

- Instead of using a standard fixed cost function, we *learn* the cost function with the neural network
- We alternate between training different parts of the network
- It's difficult to train and analyze

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Forger and the police

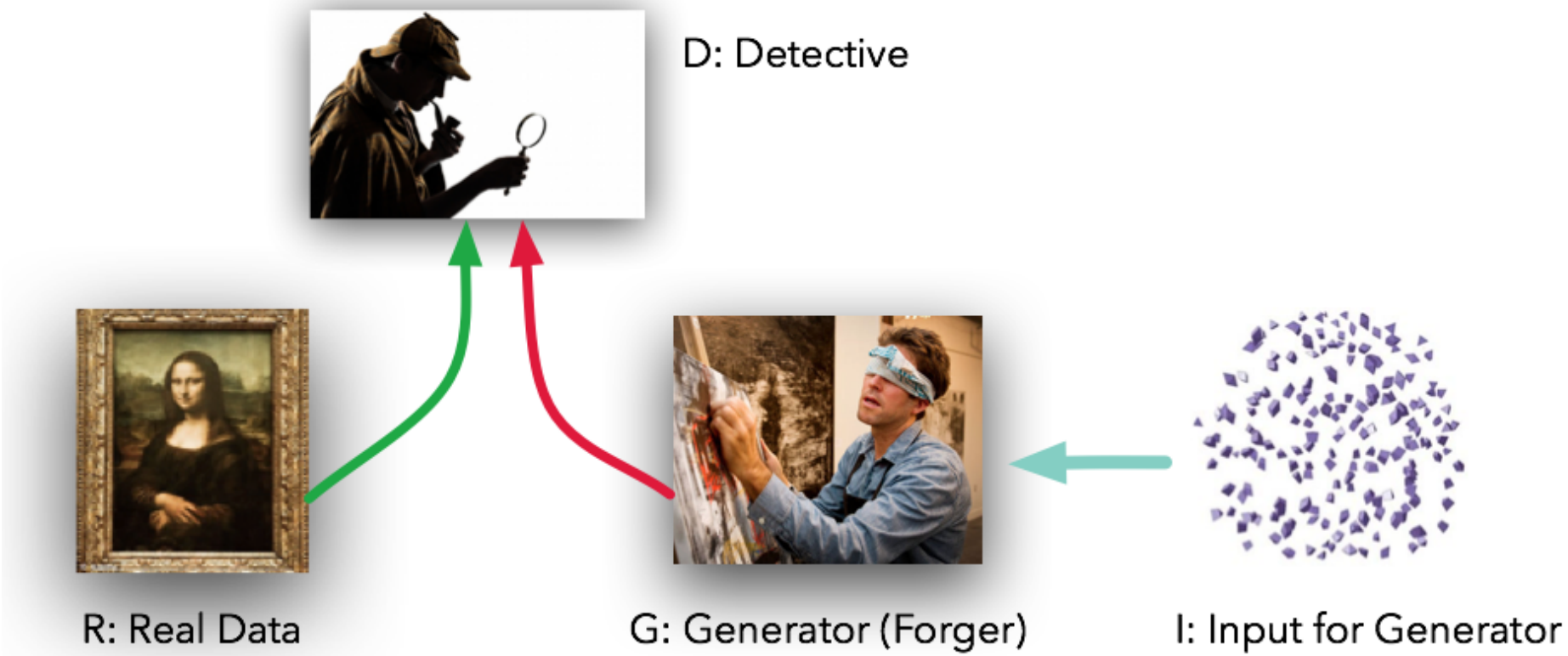


Figure: Analogy capturing the generator-discriminator dynamics

[0] https://medium.com/@devnag/generative-adversarial-networks-gans-in-50-lines-of-code-pytorch-e81b79659e3f

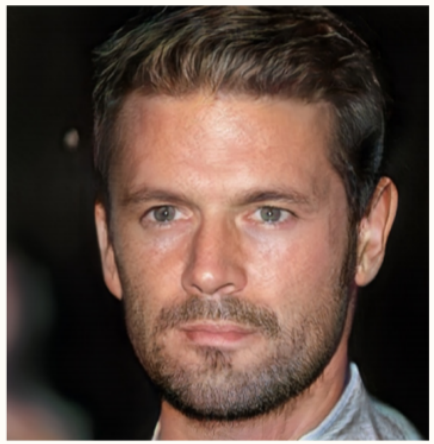
Figure: Which side are real images?

3.5 years of Progress on Faces

2014

2015

2016



2017

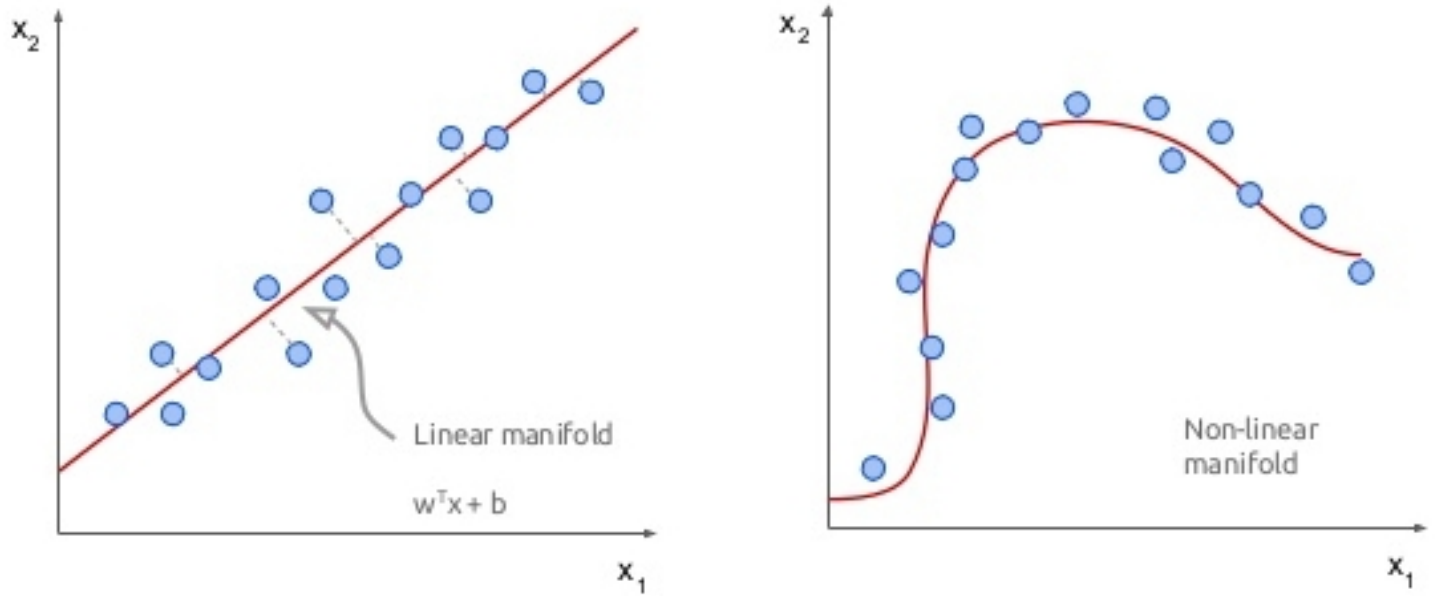
[0] http://maliciousaireport.com/

What is this talk about?

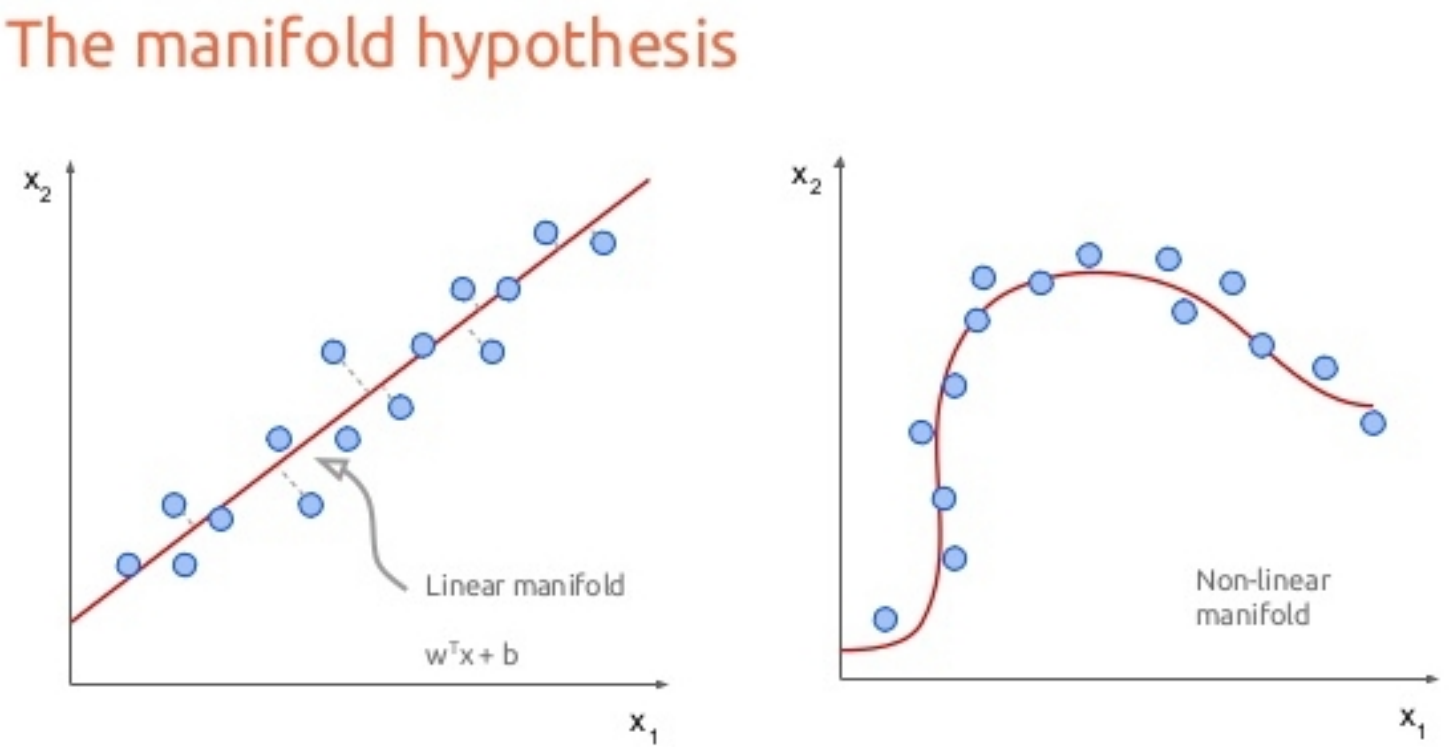
- Manifold learning
- Computational graphs
- Statistical distances
- Practical training advice

Prerequisites

The manifold hypothesis

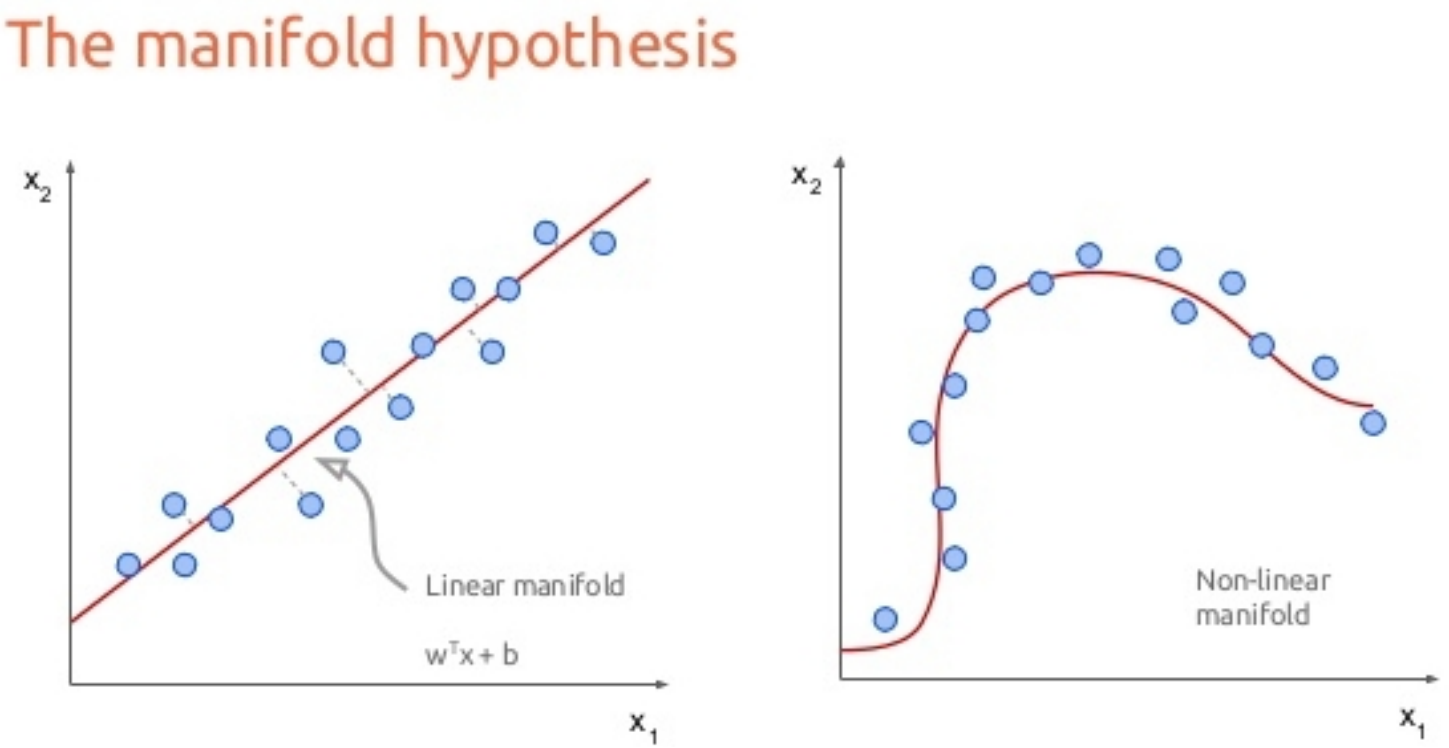


Prerequisites

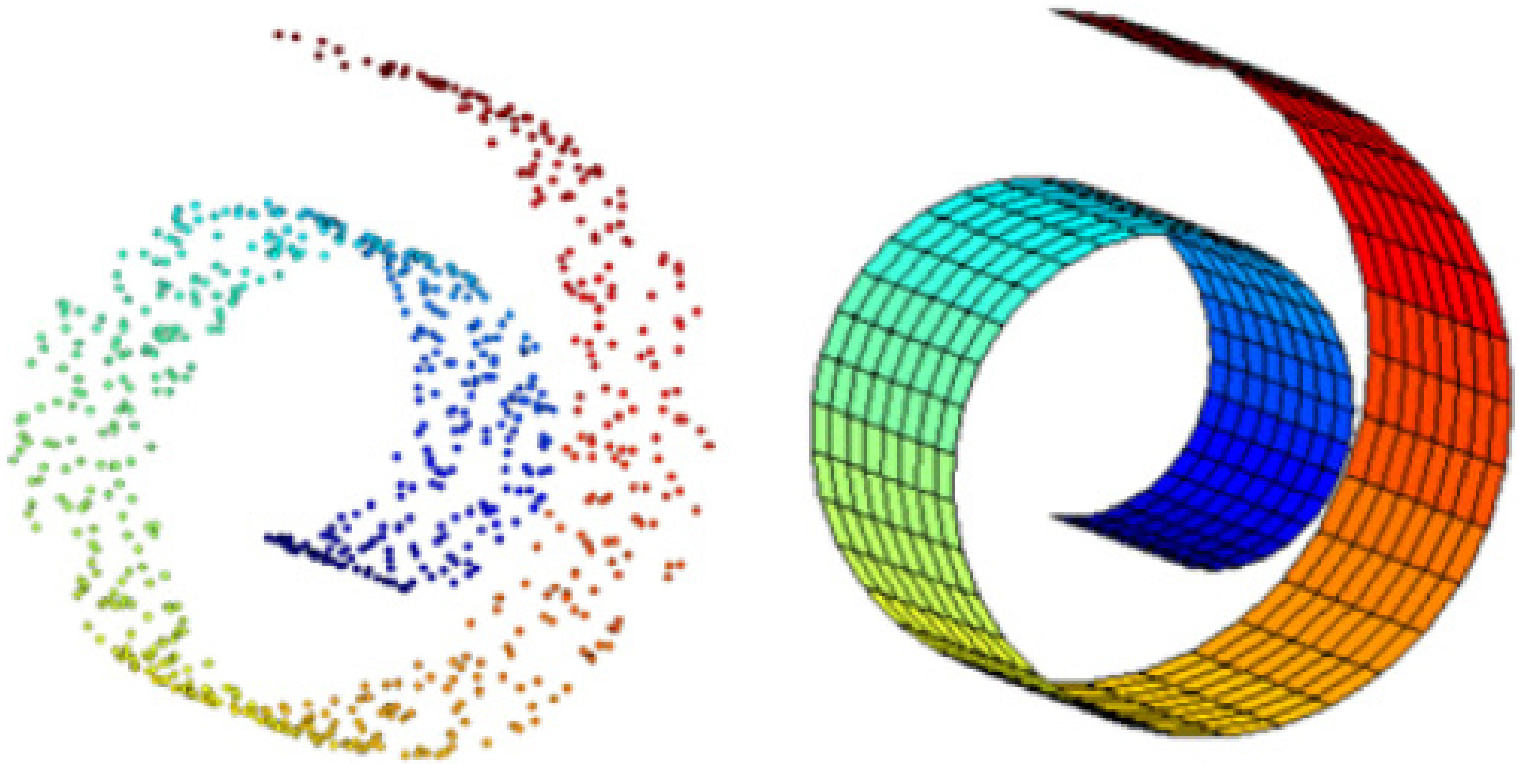


- Understanding real world data

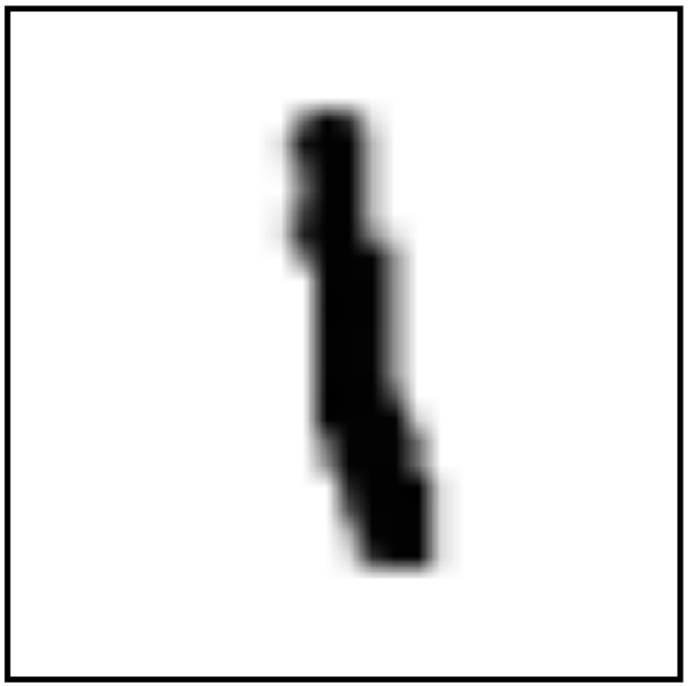
Prerequisites



- Understanding real world data
- Natural data forms a low dimensional manifold in its embedding space



(a) (b)



$\approx$

$$
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .6 & .8 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .5 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .7 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & .9 & 1 & .1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & .3 & 1 & .1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

Do low-dimensional manifolds overlap?

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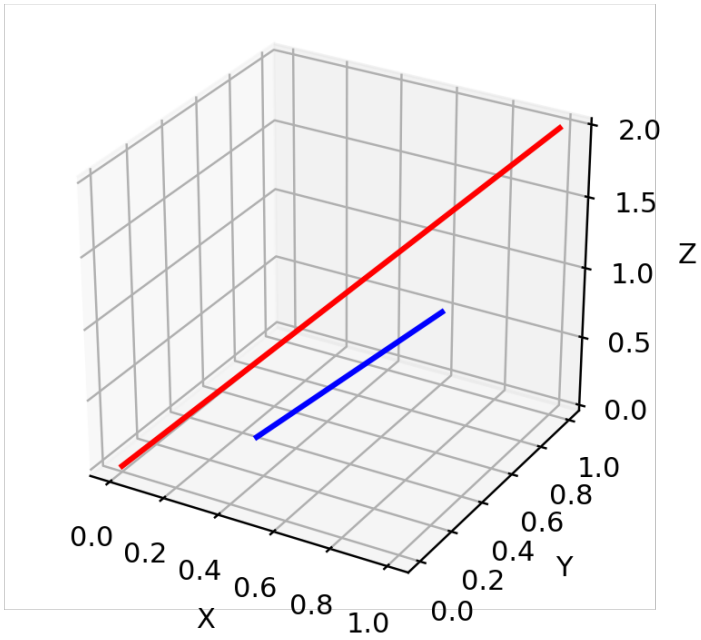

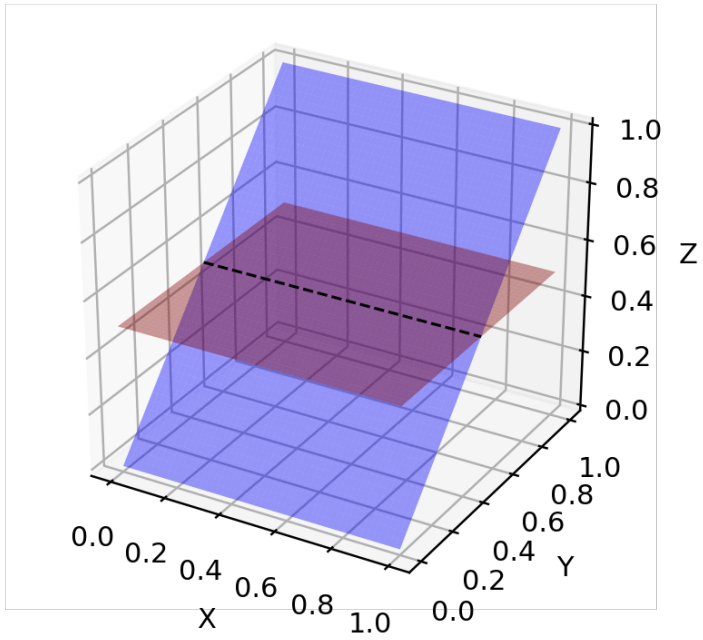

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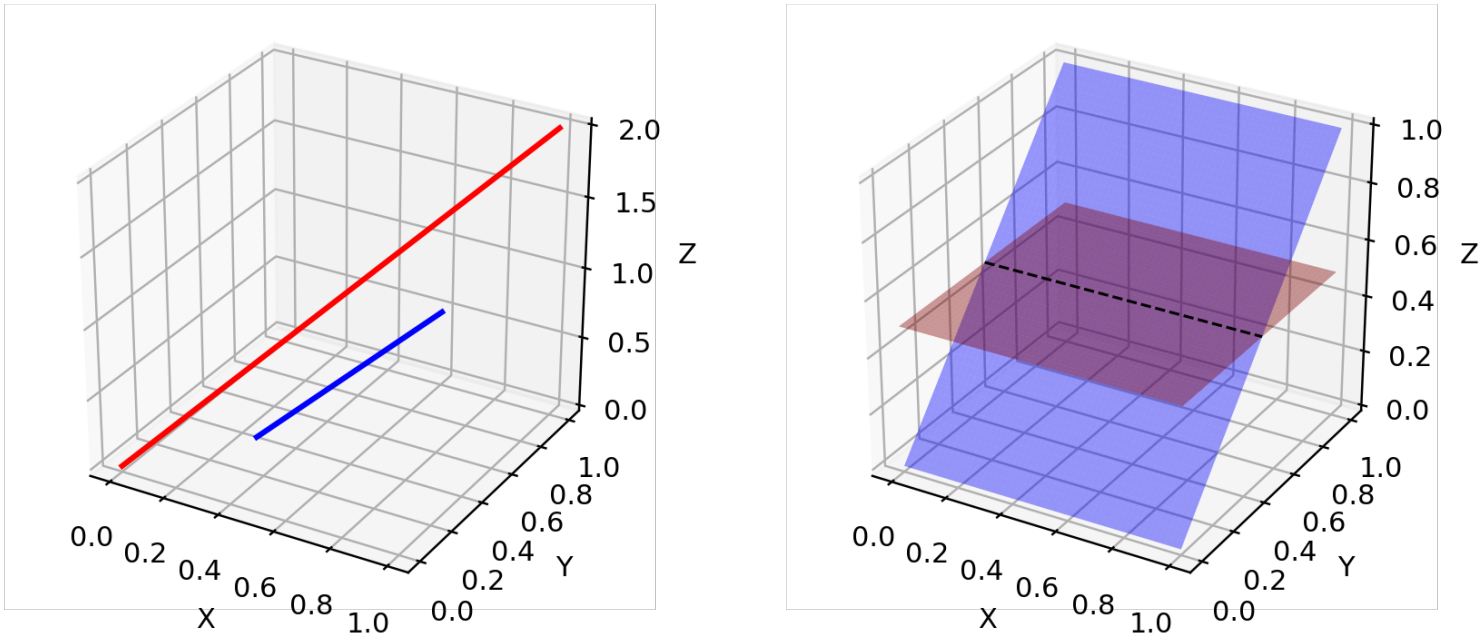


- Support of intersection of low-dimensional manifolds in a high-dimensional space is approximately zero!

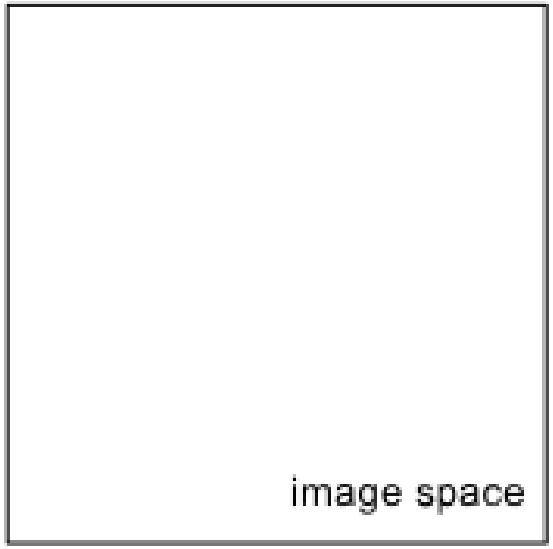
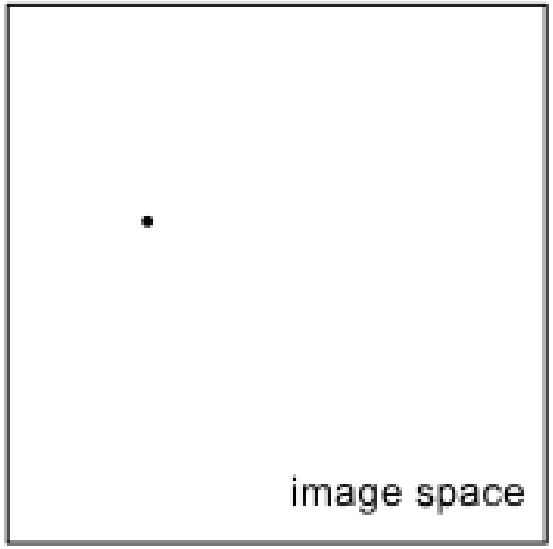


image space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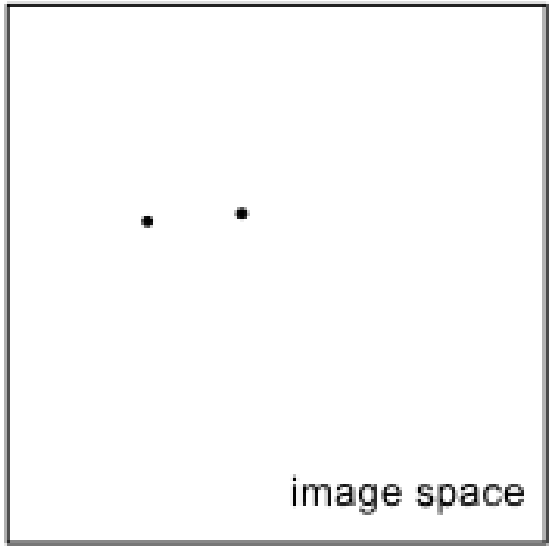


image space

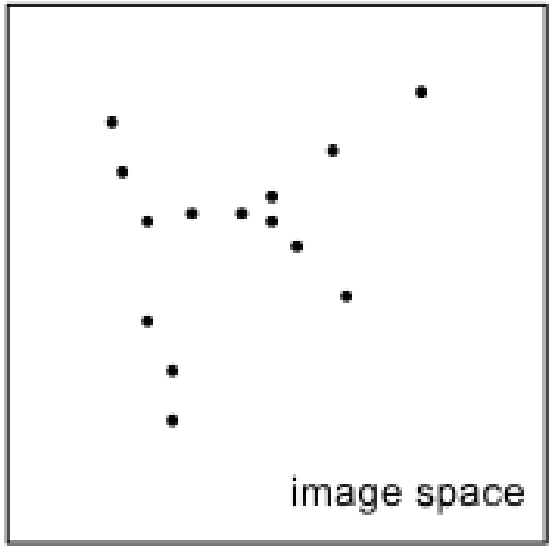
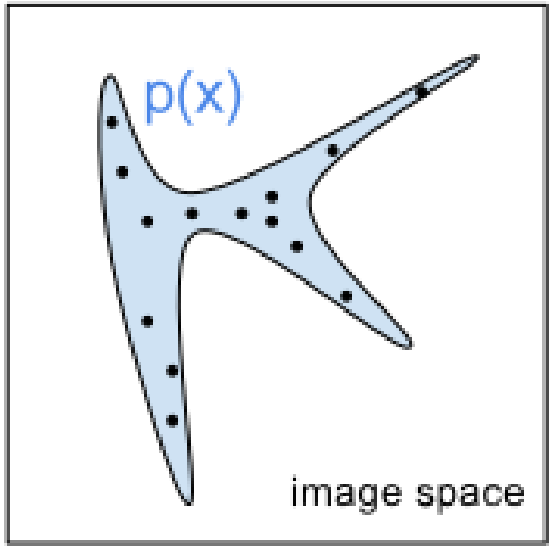
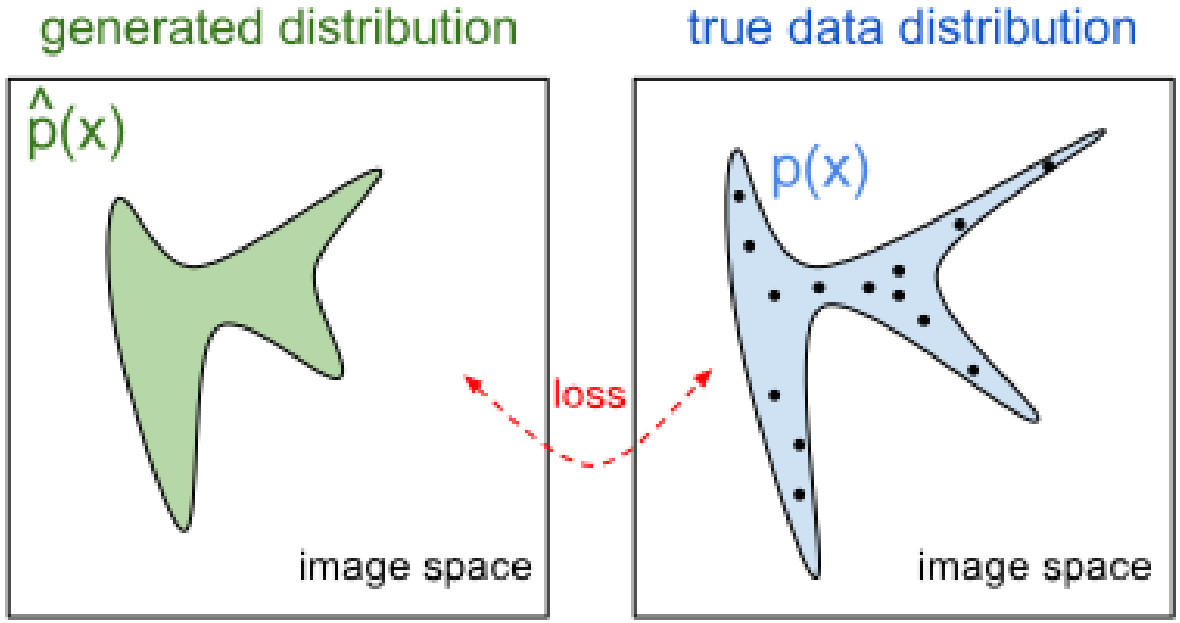
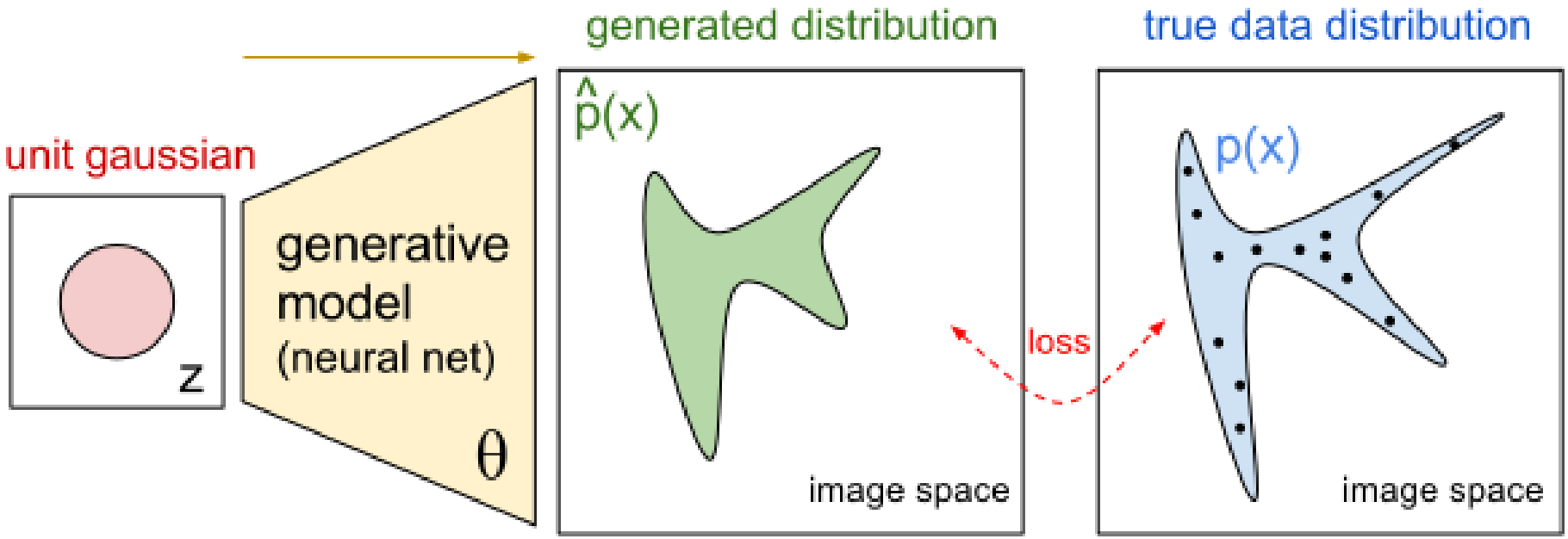


image space

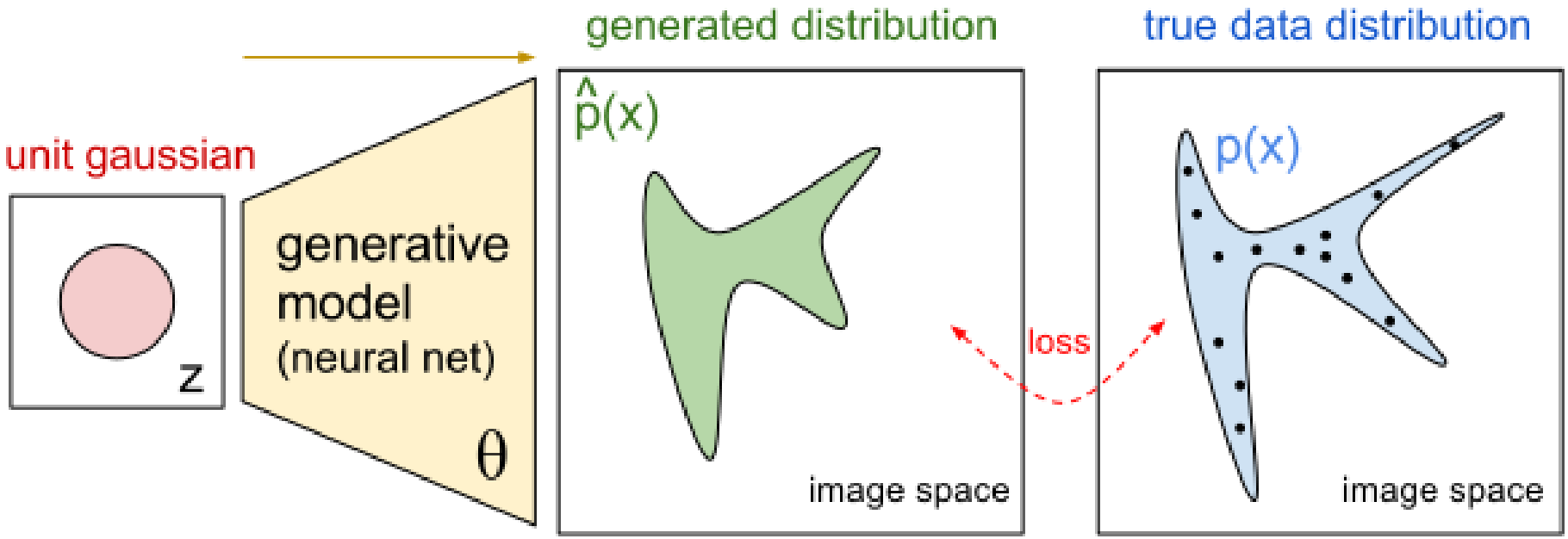
true data distribution




generated distribution
true data distribution
p̂(x)
p(x)
loss
image space
image space



- We have a random vector $z \sim \mathcal{Z}$



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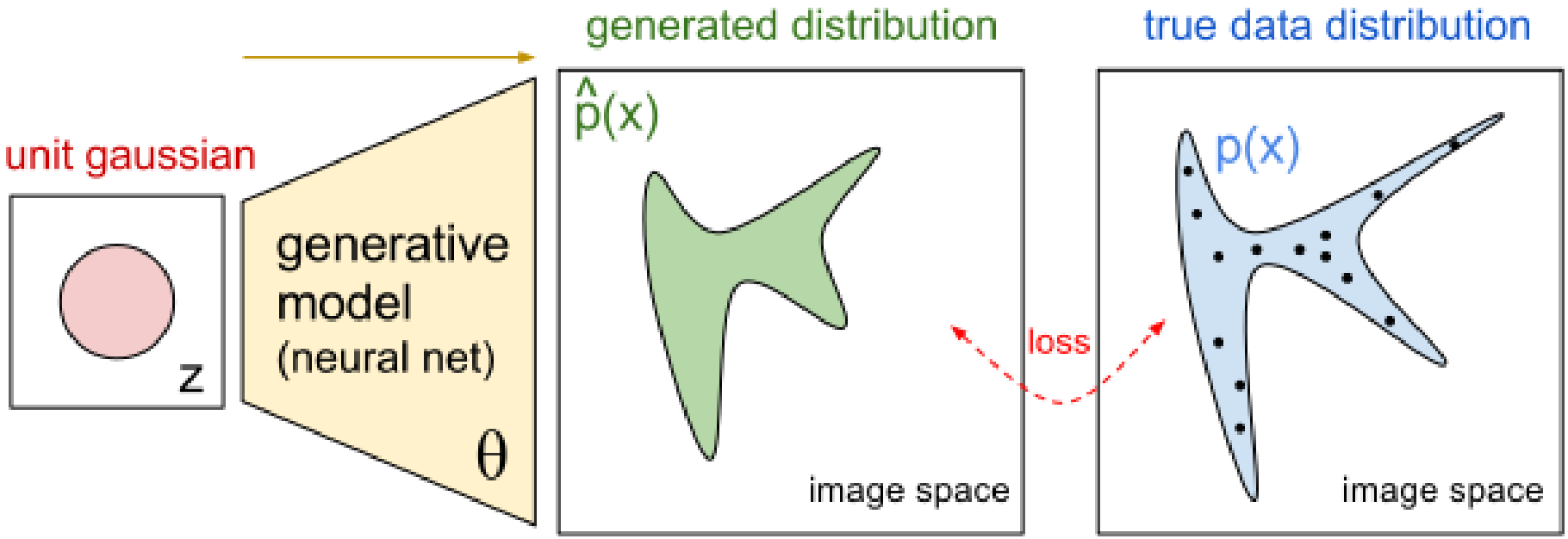

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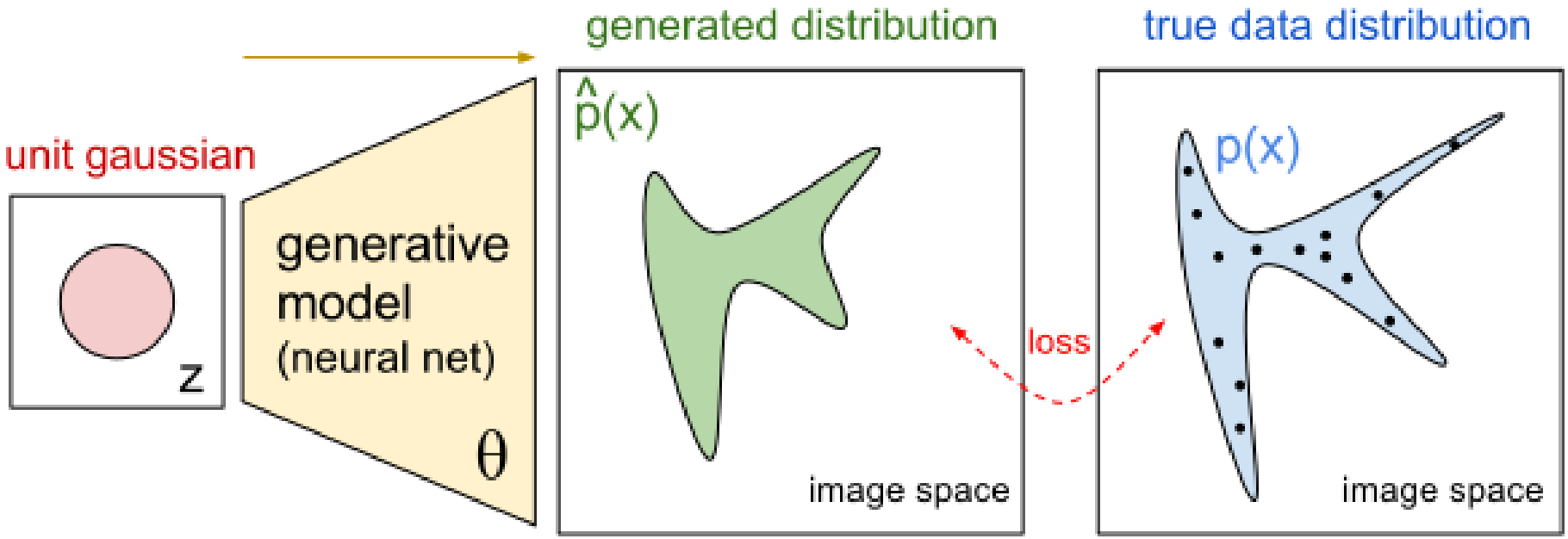

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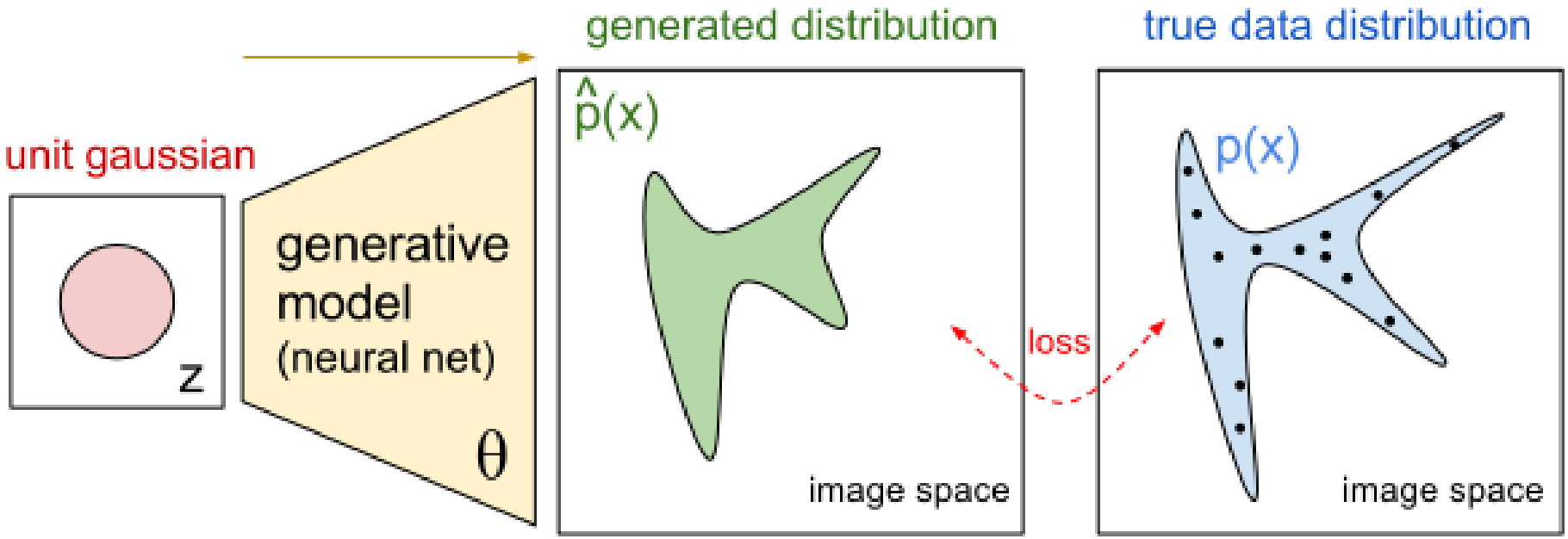

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- How do we define “close"?

Let’s take a step back.

What is a neural network, actually?

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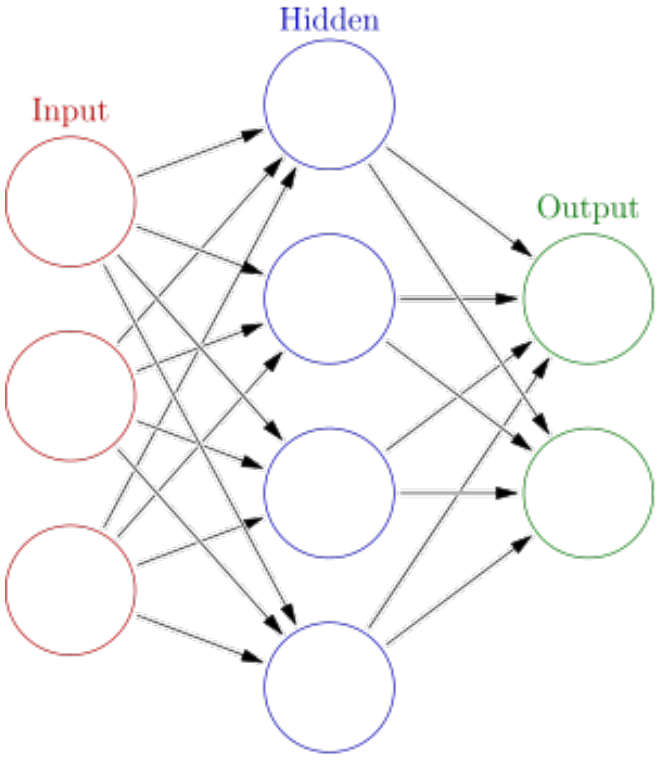

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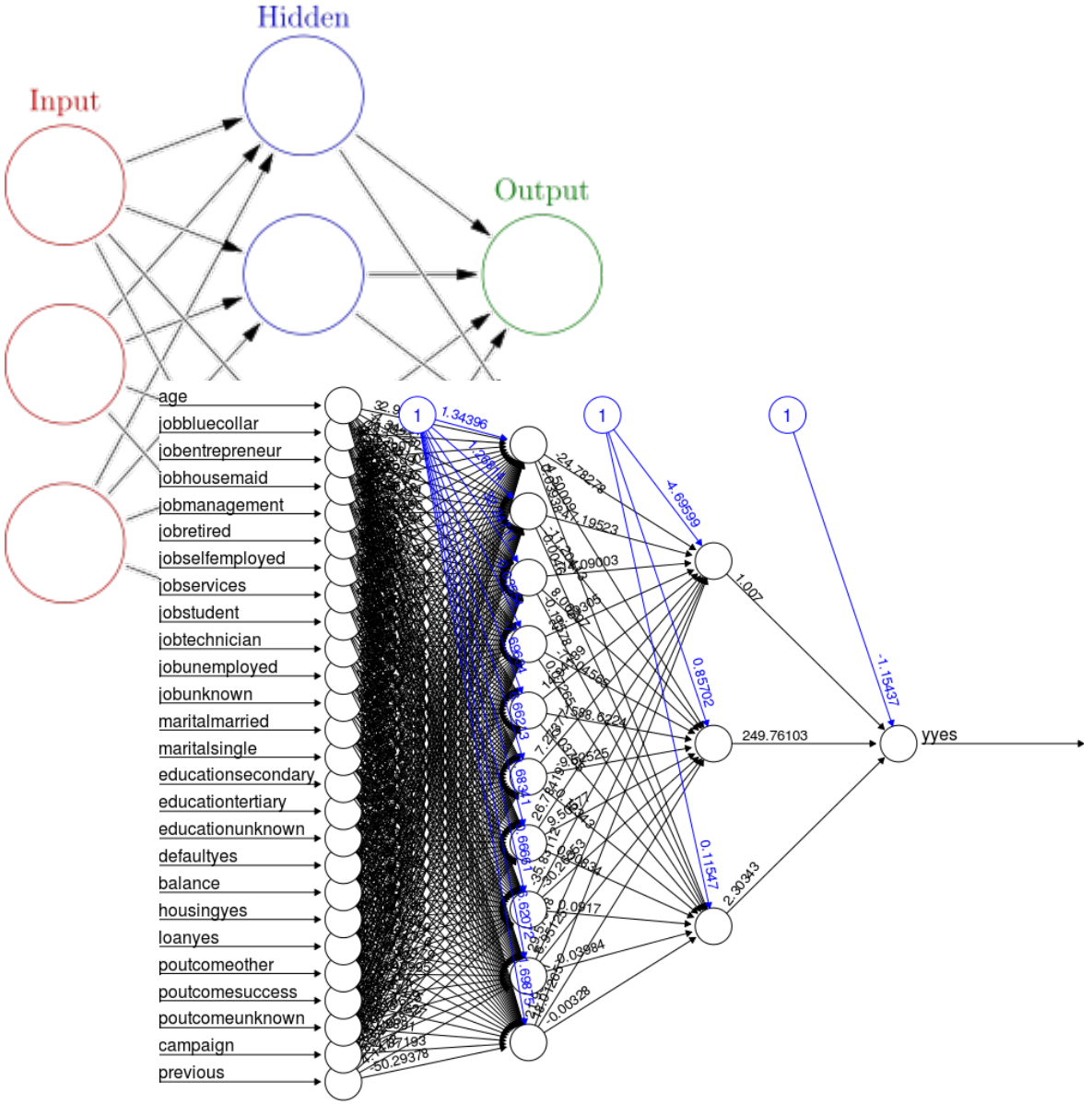

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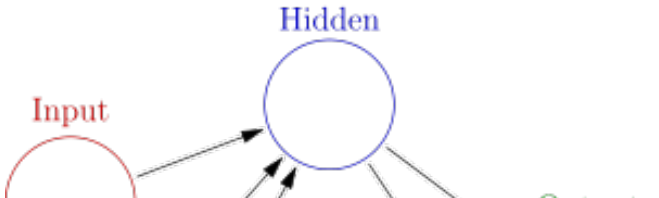

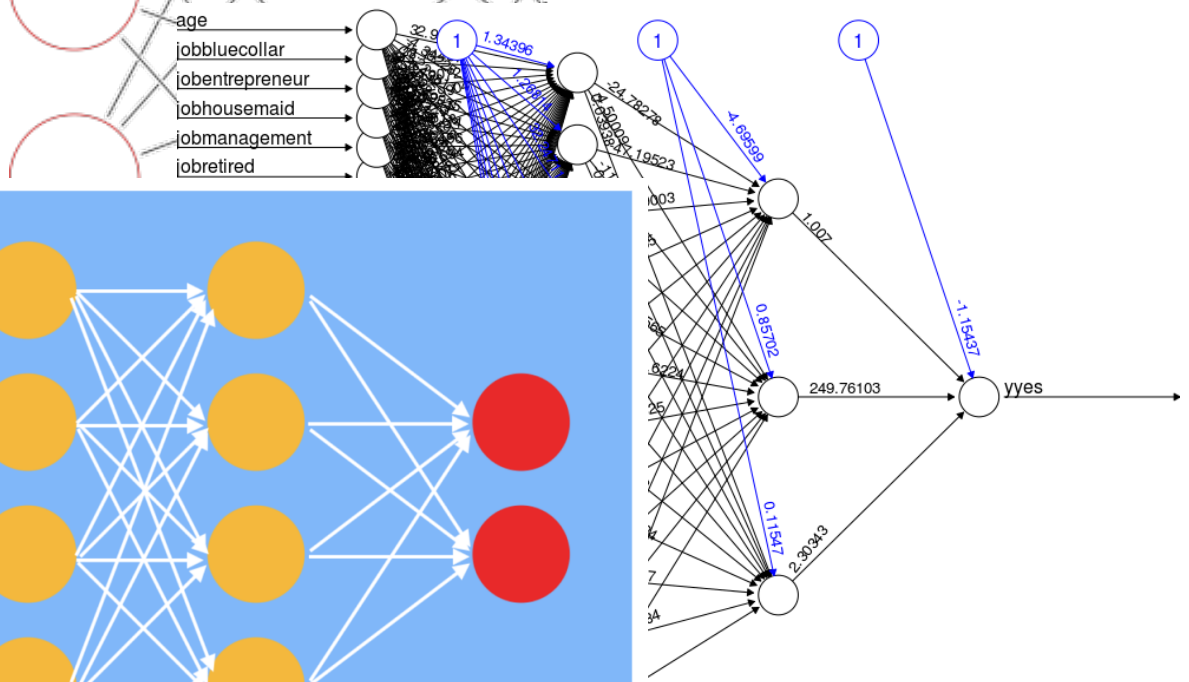

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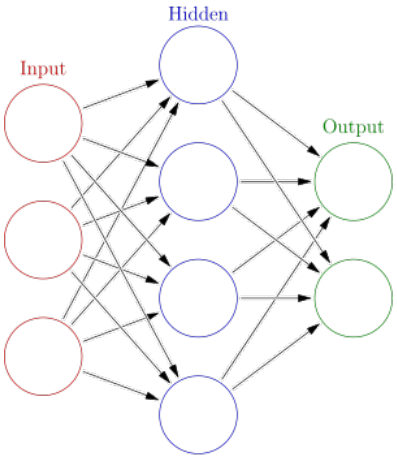

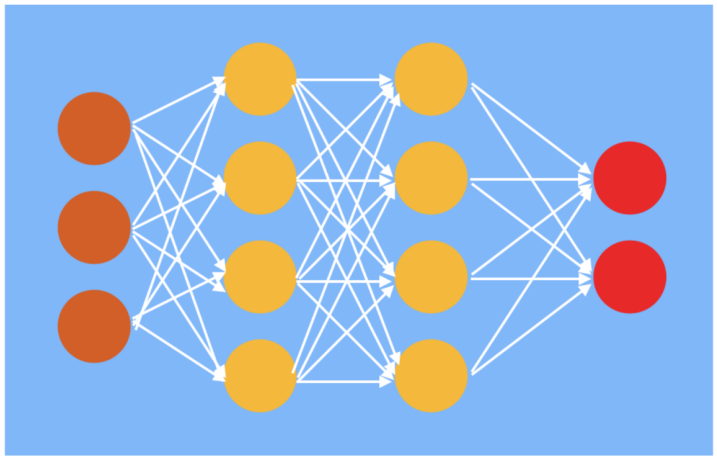

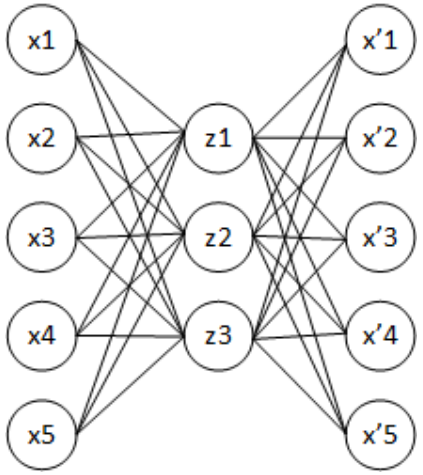

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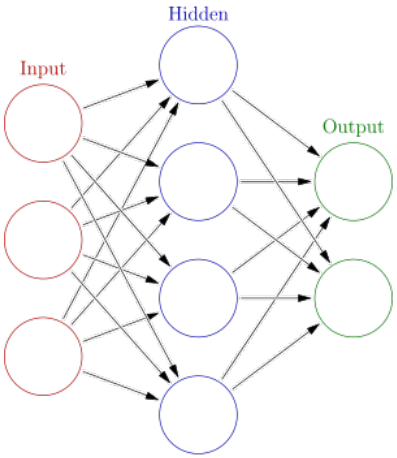

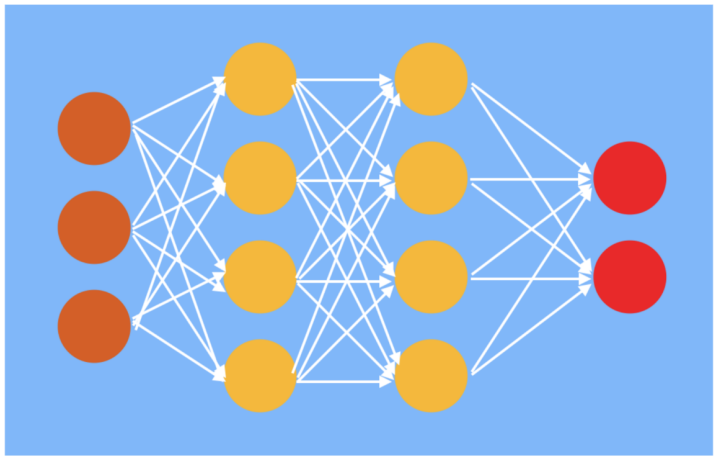

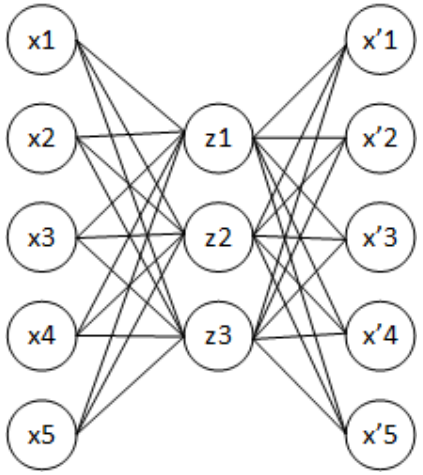

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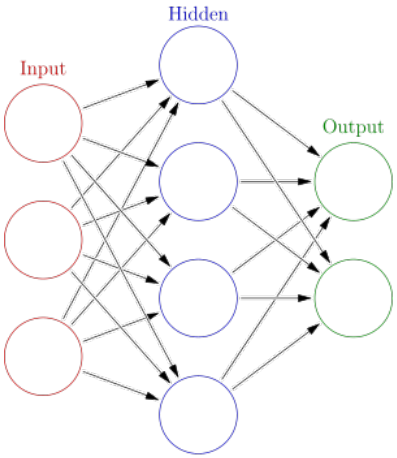
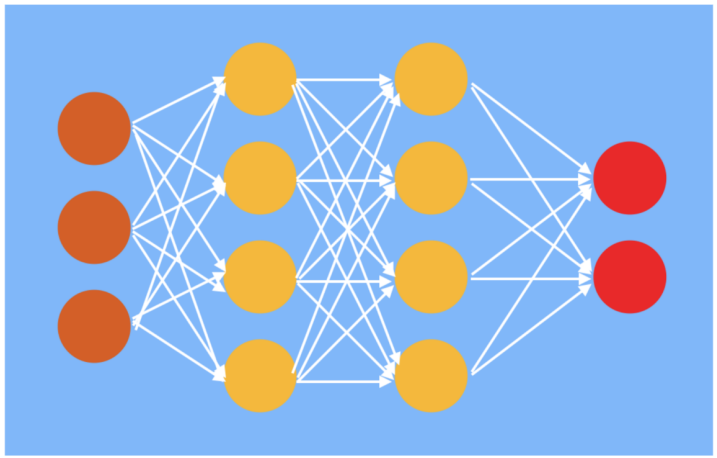
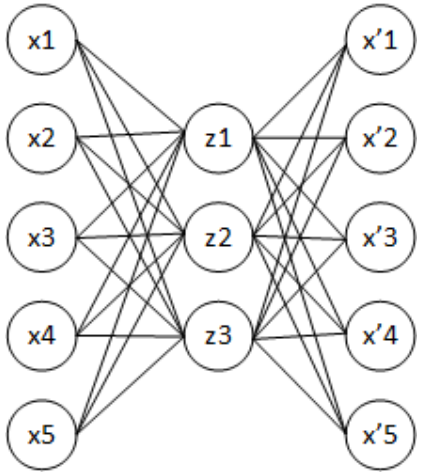
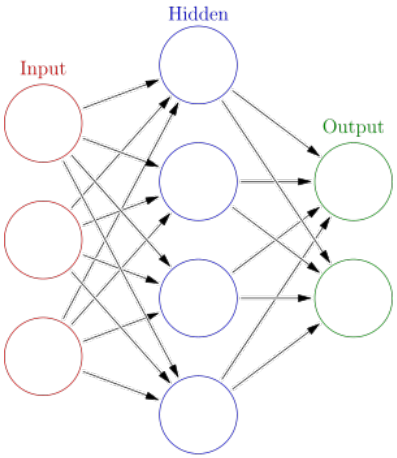


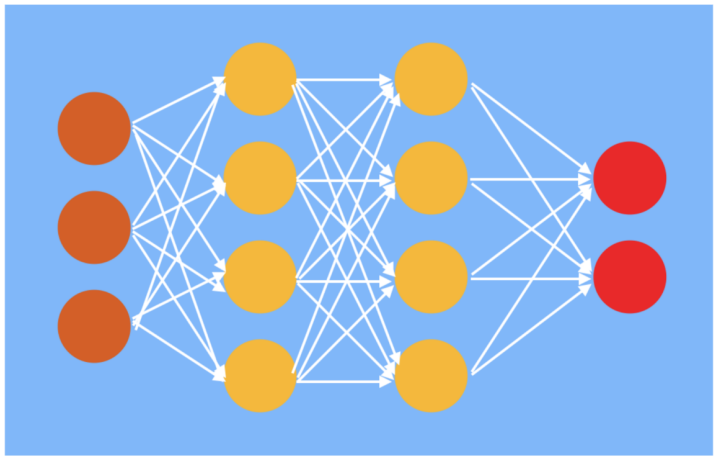


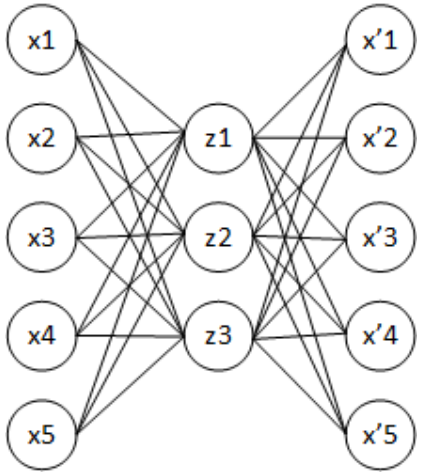


- Frameworks need to manage batches of data, a cost function, the entire training procedure
- This is not they store and manipulate neural networks!

What is a neural network, actually?

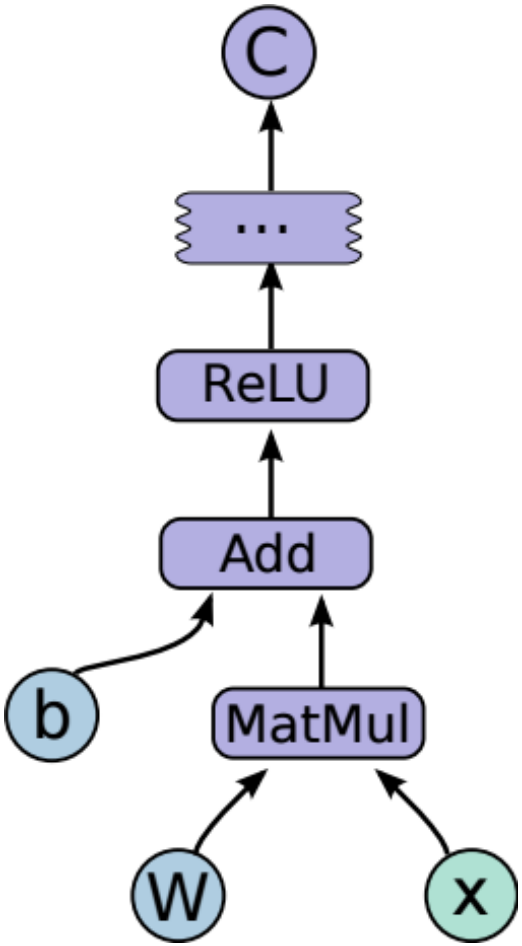






- Frameworks need to manage batches of data, a cost function, the entire training procedure
- This is not they store and manipulate neural networks!
- Internally, networks are stored as directed acyclic graphs (DAGs) - also called computational graphs

Neural networks as DAGs



- Captures full power expressable with usual diagrams + much more

[0] https://medium.com/@asjad/notes-on-tensor-flow-b90ef02b144f

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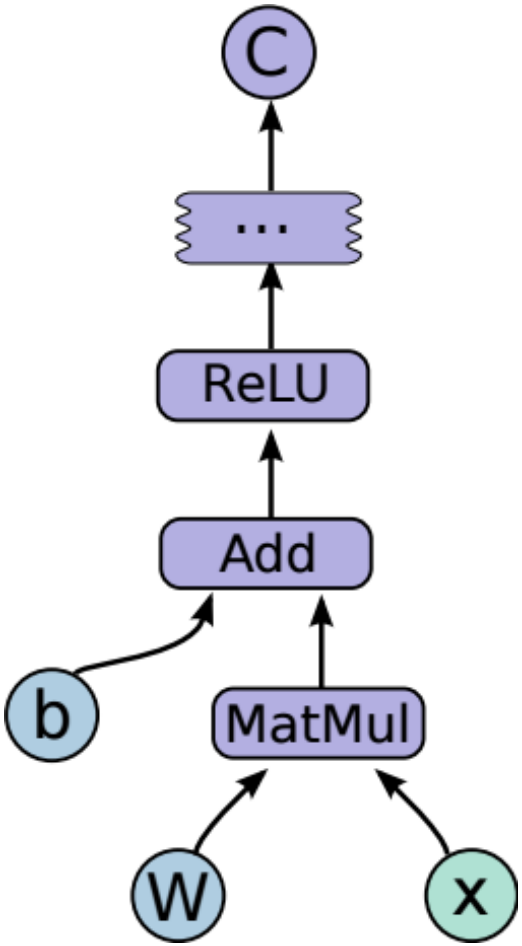

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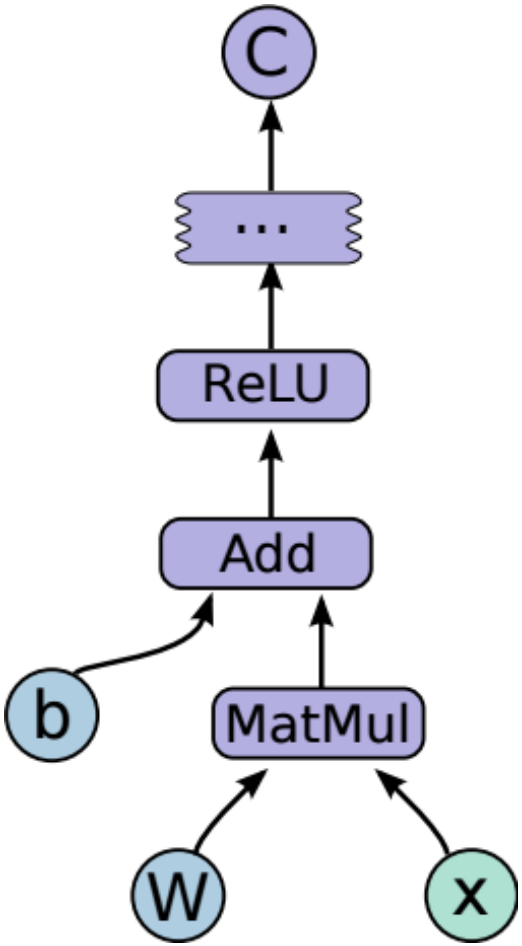

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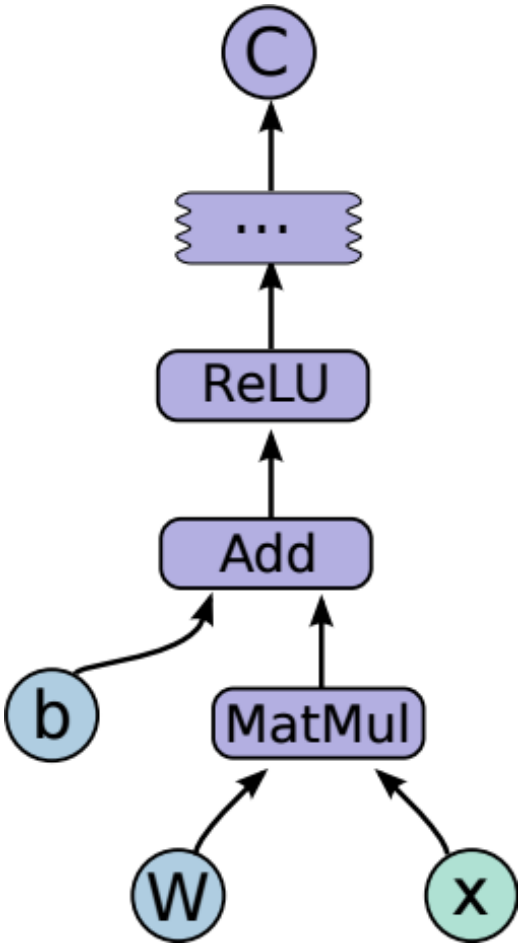

- Captures full power expressable with usual diagrams + much more
- *Actual* way it's implemented in frameworks
- *The way* we need to use to understand GANs
- Notation we use shapes the way we think

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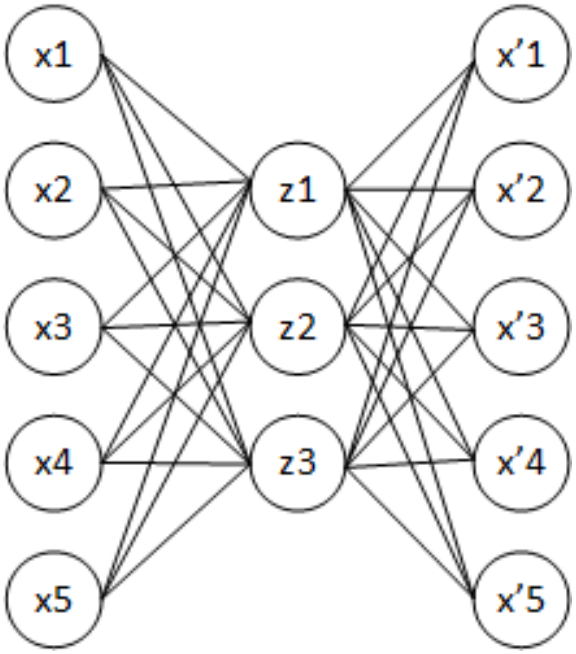
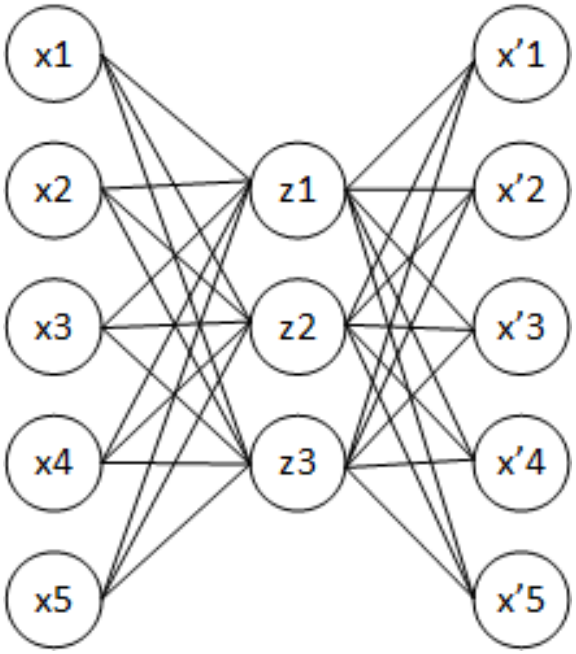

x1
x2
x3
x4
x5
z1
z2
z3
x'1
x'2
x'3
x'4
x'5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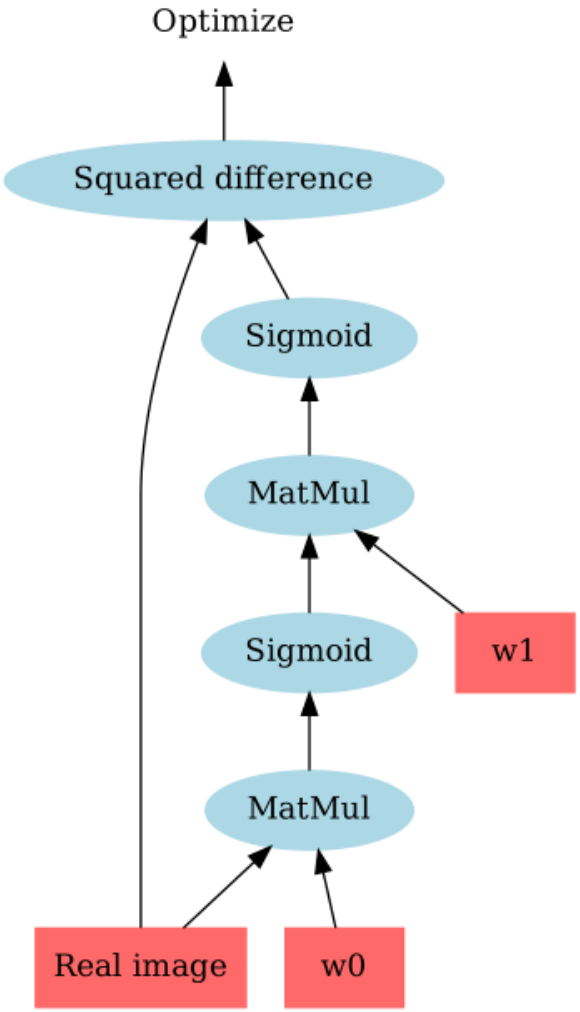
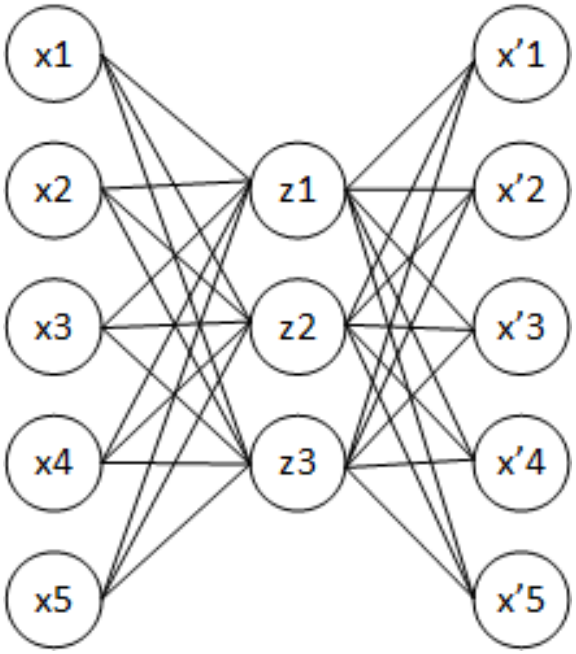

Optimize
Squared difference
Sigmoid
MatMul
Sigmoid
w1
MatMul
Real image
w0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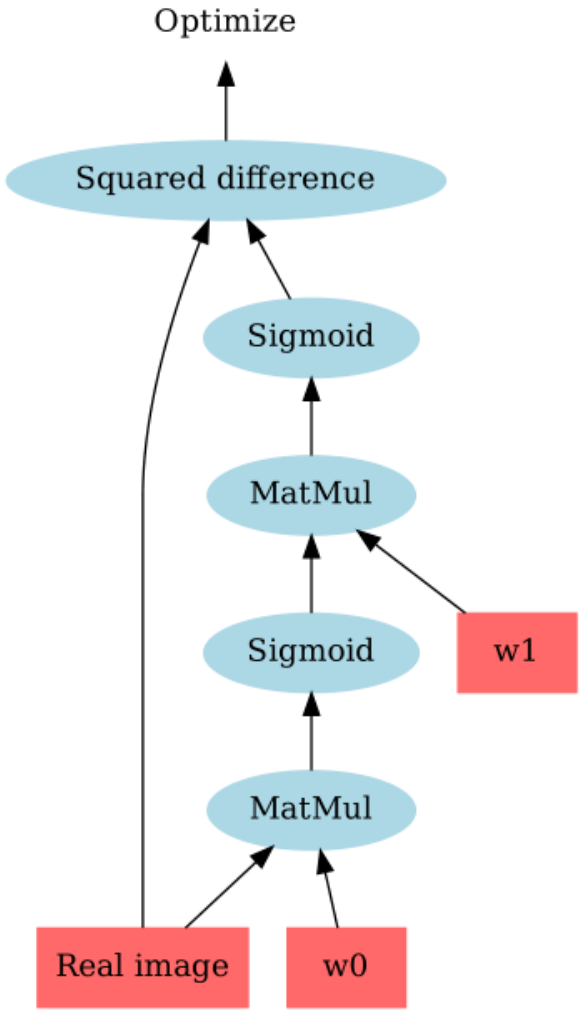
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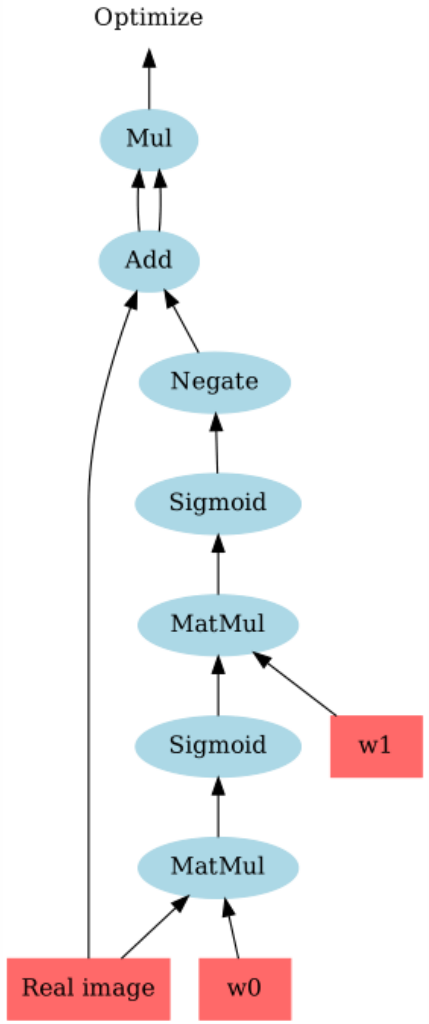
Optimize
Mul
Add
Negate
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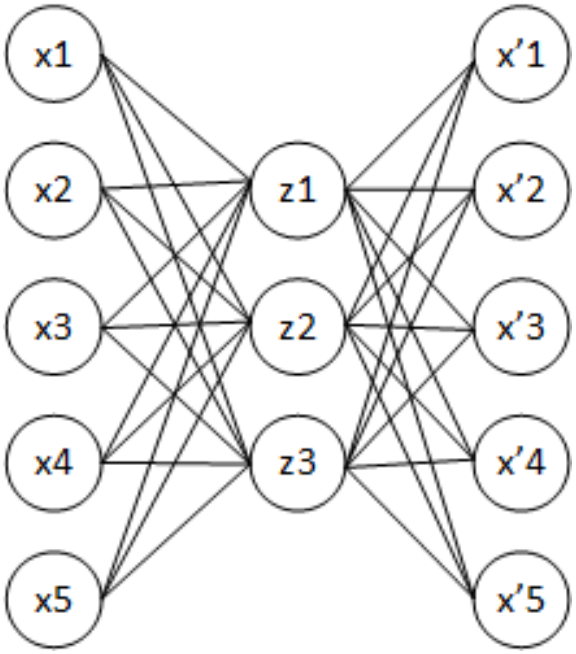
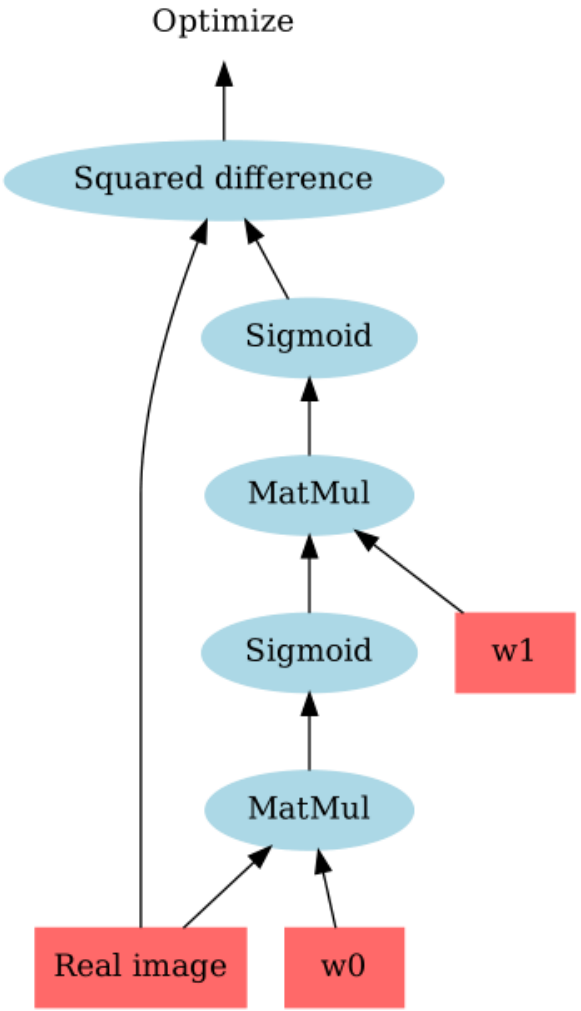
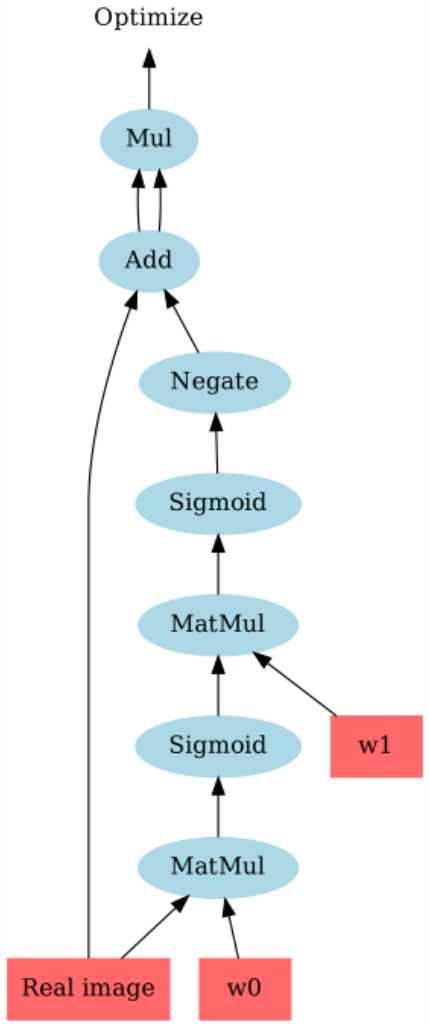


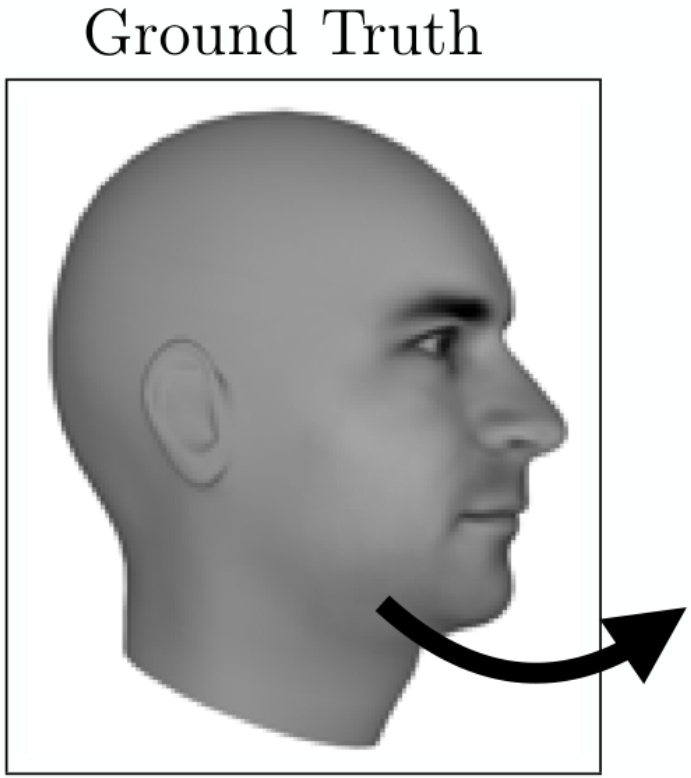




Things to note

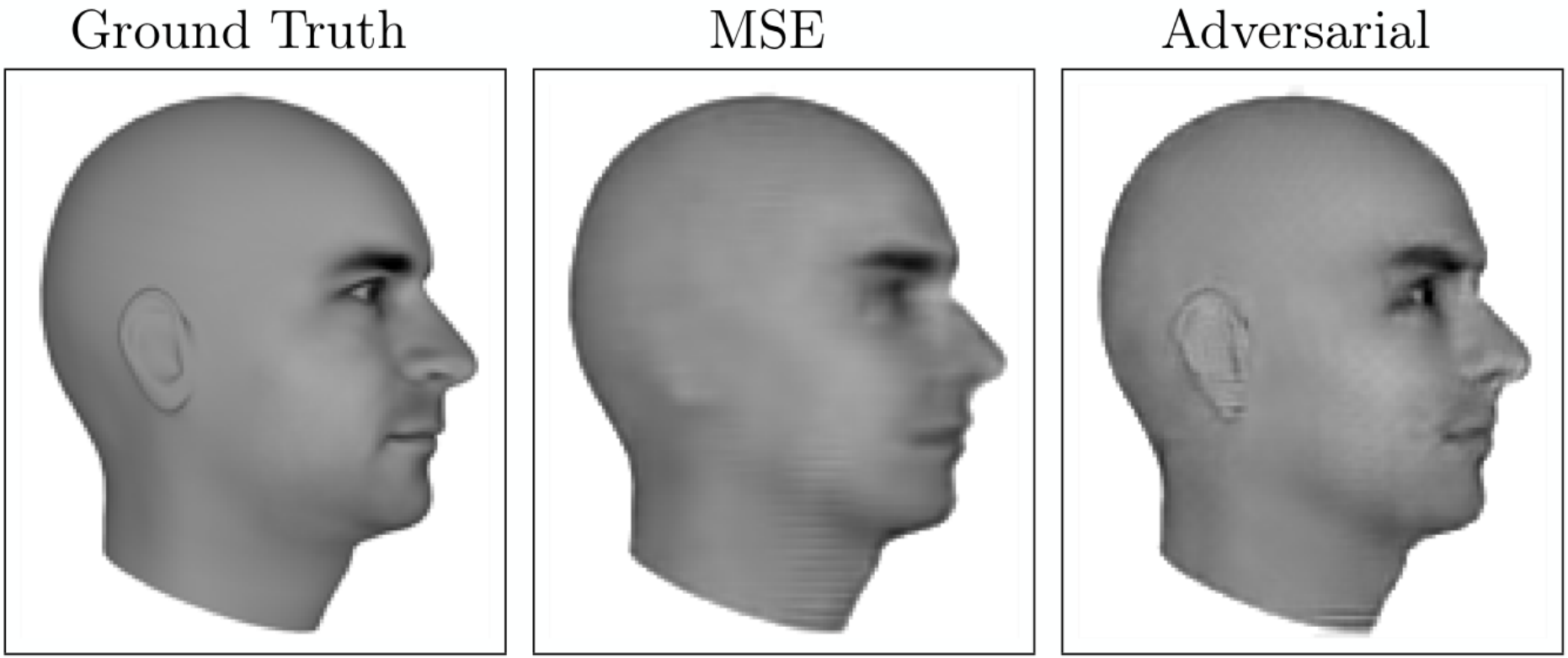
1. Cost function is not parametrized (it's fixed)
2. We train the network with just one cost function
3. We train the network monolithically

Cost function



[0] Ian J. Goodfellow: NIPS 2016 Tutorial: Generative Adversarial Networks

Cost function



- MSE needs to average over all possibilities and choose a single answer
- Square error - a simple parabola, is it sufficient?

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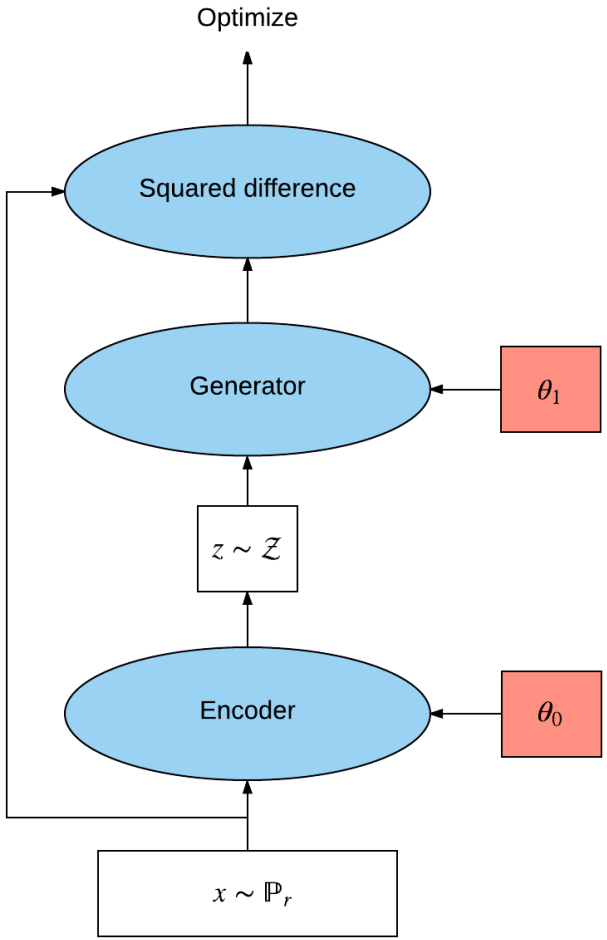
Autoencoder - perspective shift

- Autoencoder has an encoder and decoder



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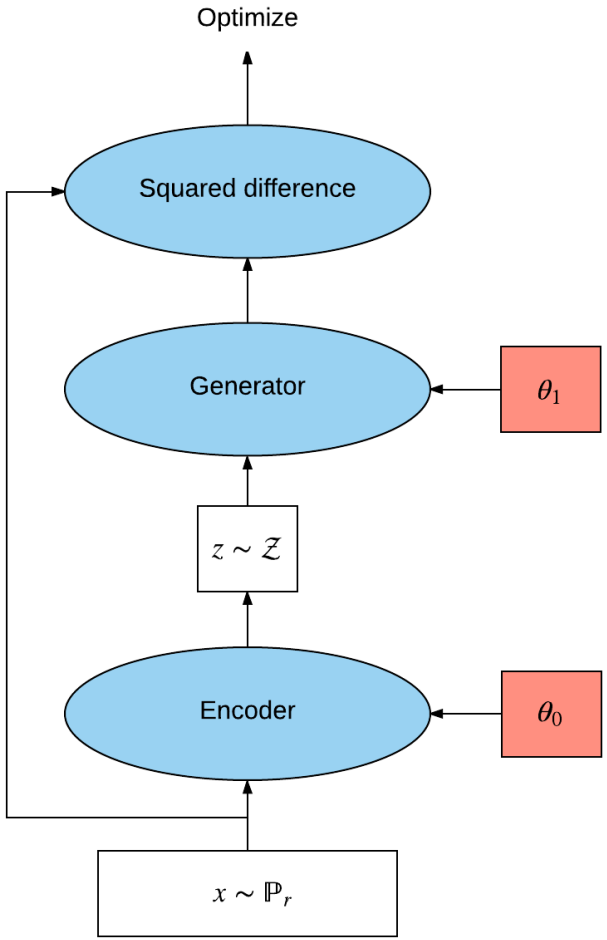

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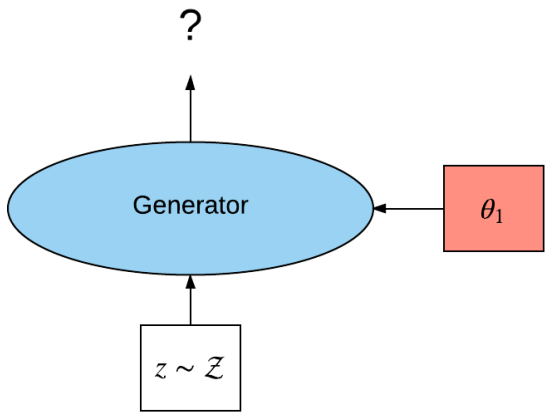

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- ...
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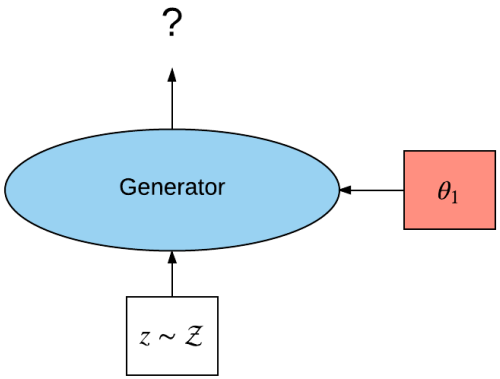
- Introduces a lot of problems

Training regime - main concept



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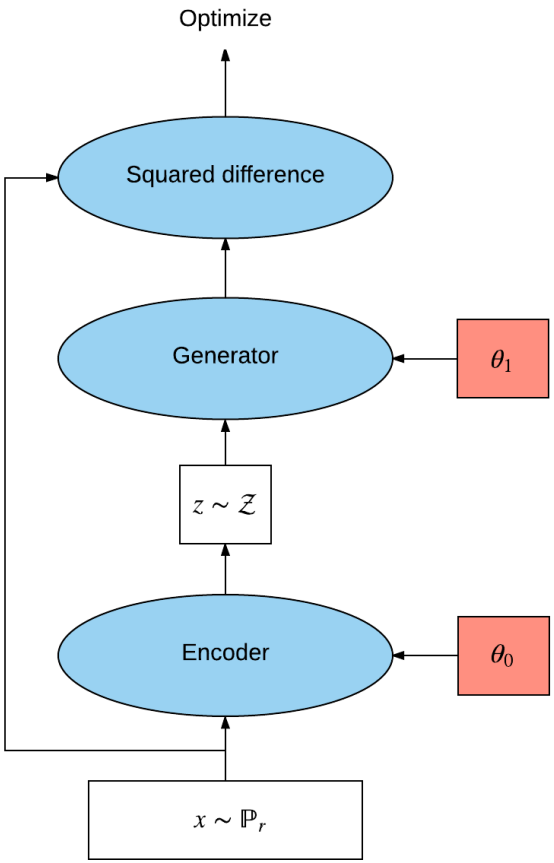

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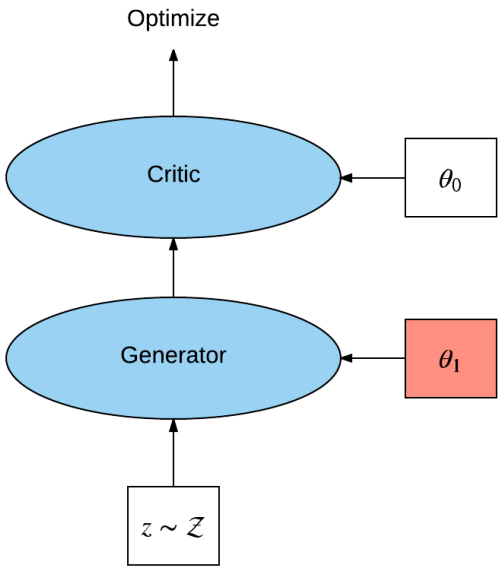

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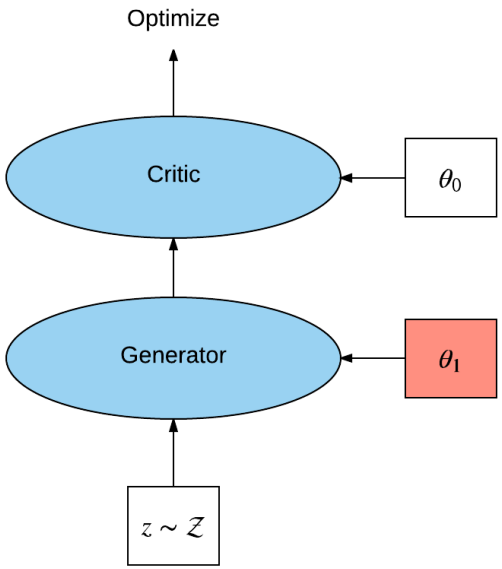

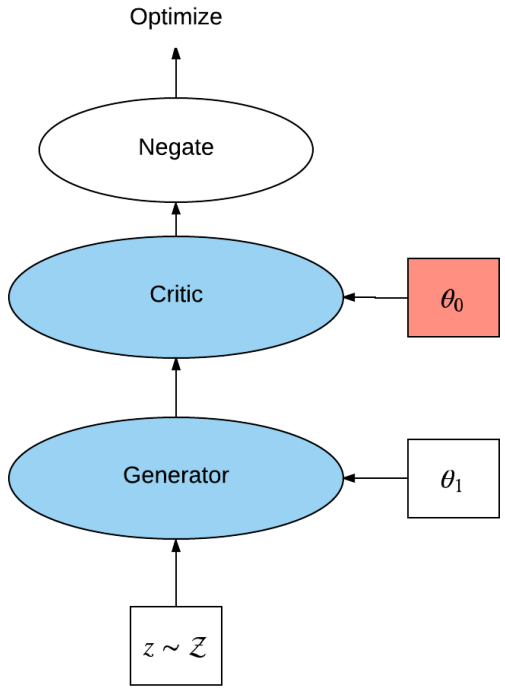

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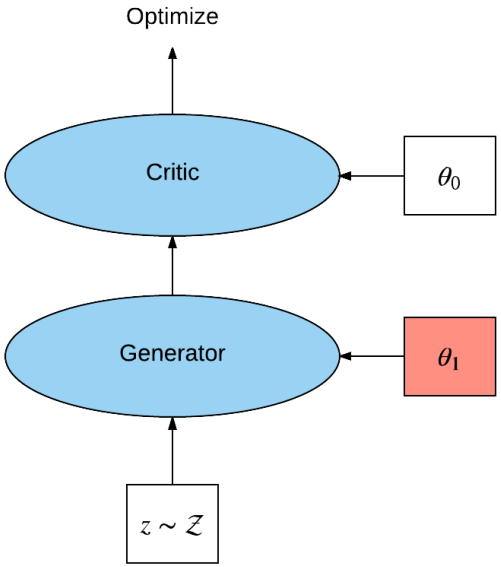

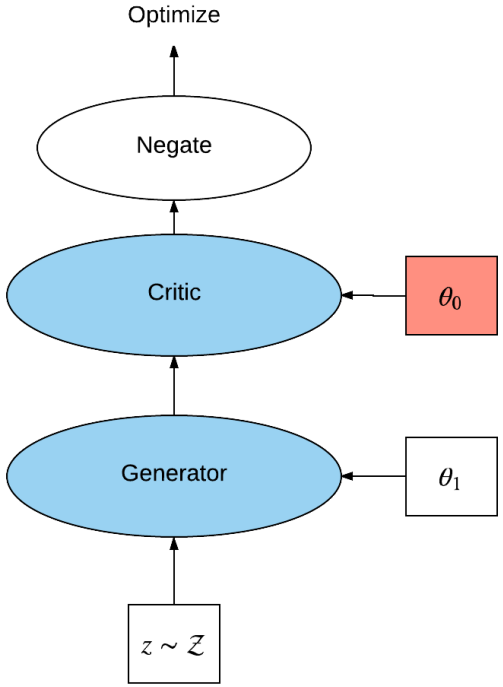

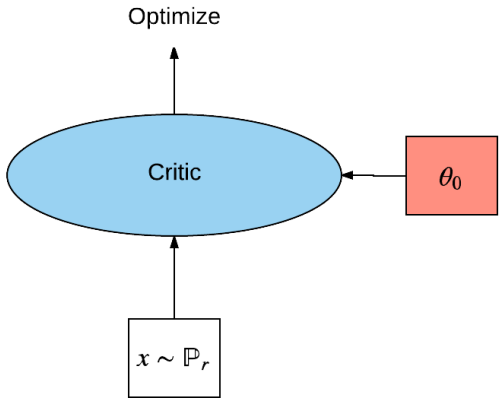

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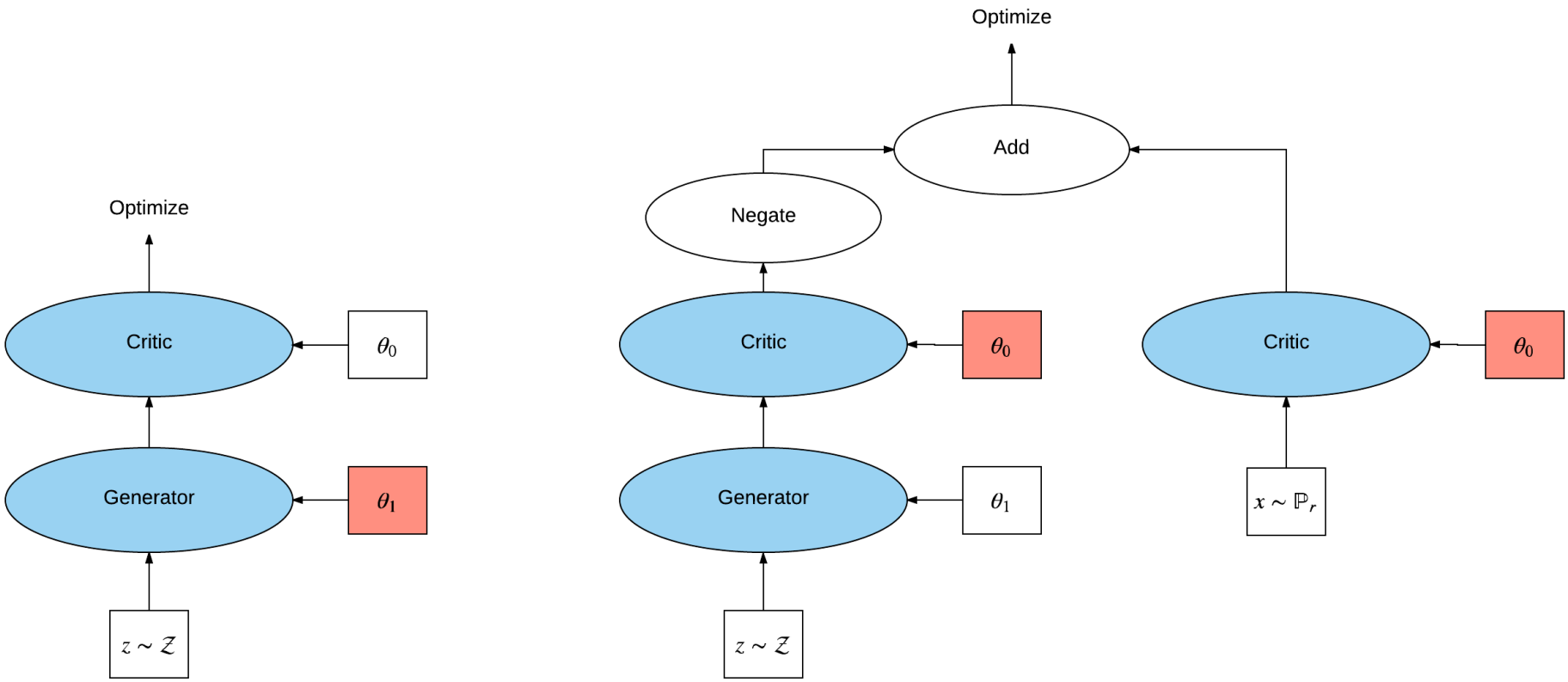

- Two-step optimization optimization process

Different statistical distances

- Recall from before - we have real and fake images, we want the fake distribution to become the same as the real distribution

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- But we still have to compare those distributions
- Defining distance between two points in Euclidean space is intuitive
- How do we define distances between distributions?

Various statistical distances - divergences

- KL-divergence
- JS-divergence
- Earth-mover distance (Wasserstein distance)
- Total variation distance
- Hellinger distance
- Mahalanobis distance
- Bhattacharyya distance
- Energy distance
- ...

Kullback-Leibler and Jensen Shannon divergence

KL-divergence

$$KL(\mathbb{P}||\mathbb{Q}) = \mathbb{E}_{x\sim\mathbb{P}}\left[\log\frac{P(x)}{Q(x)}\right]$$

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- Symmetric and bounded
- Original GAN paper minimizes JS-divergence

Wasserstein (Earth mover) distance

EM distance

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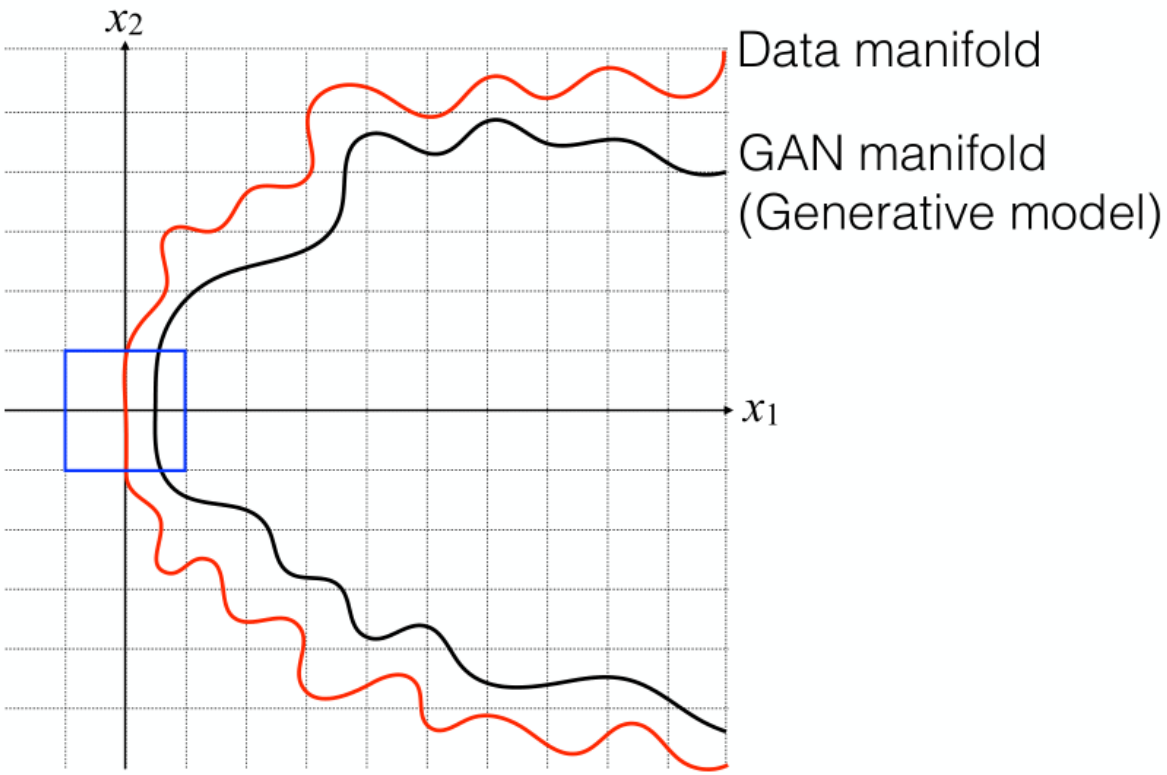
- Intractable

Learning distributions - toy example



[0]MILA DLSS: `https://drive.google.com/file/d/0B_wzP_JlVFcKQ21udGpTSkh0aVk/view`

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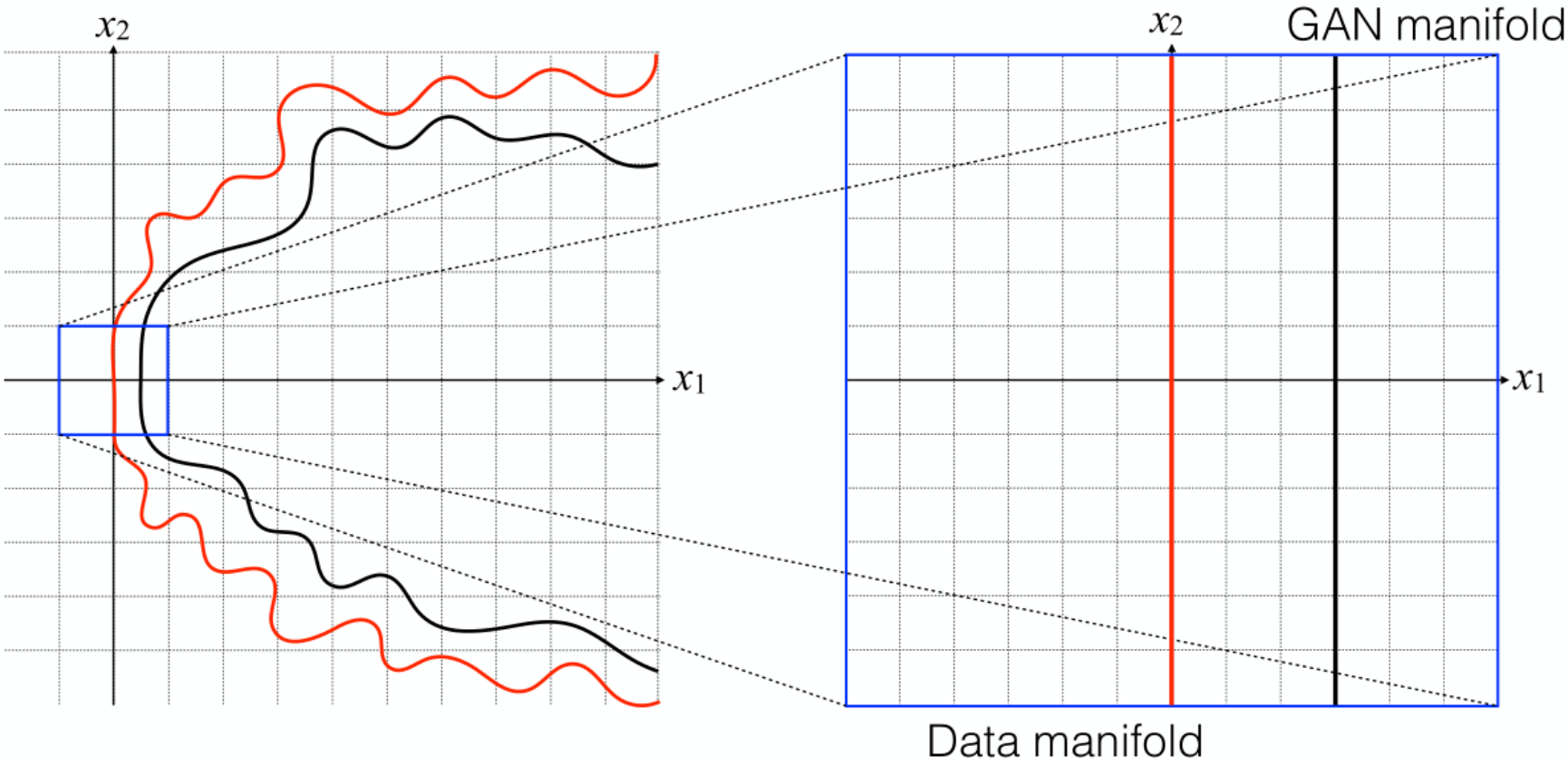

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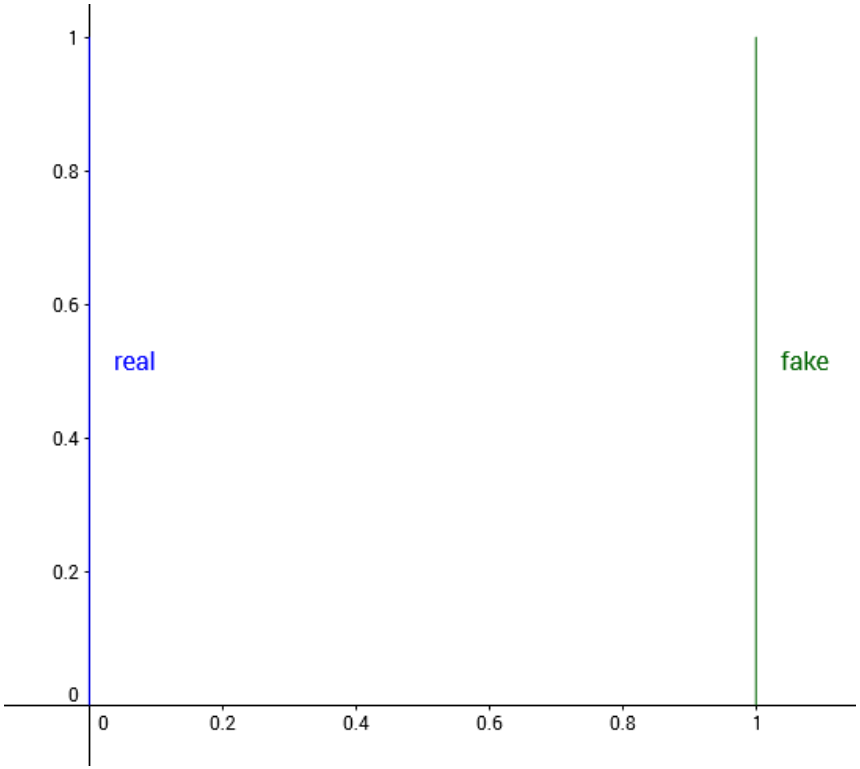

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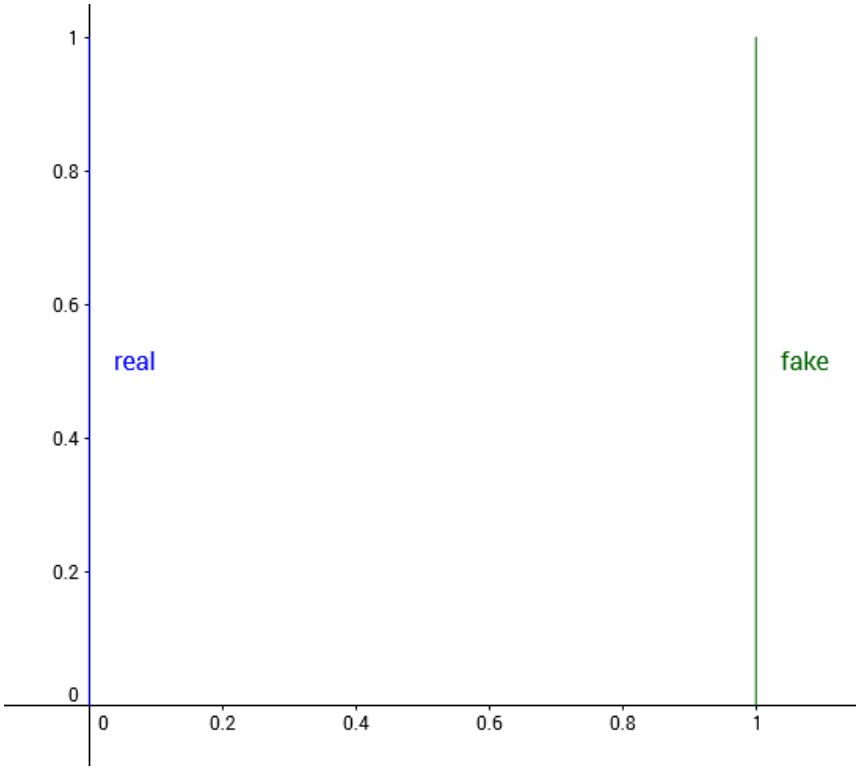

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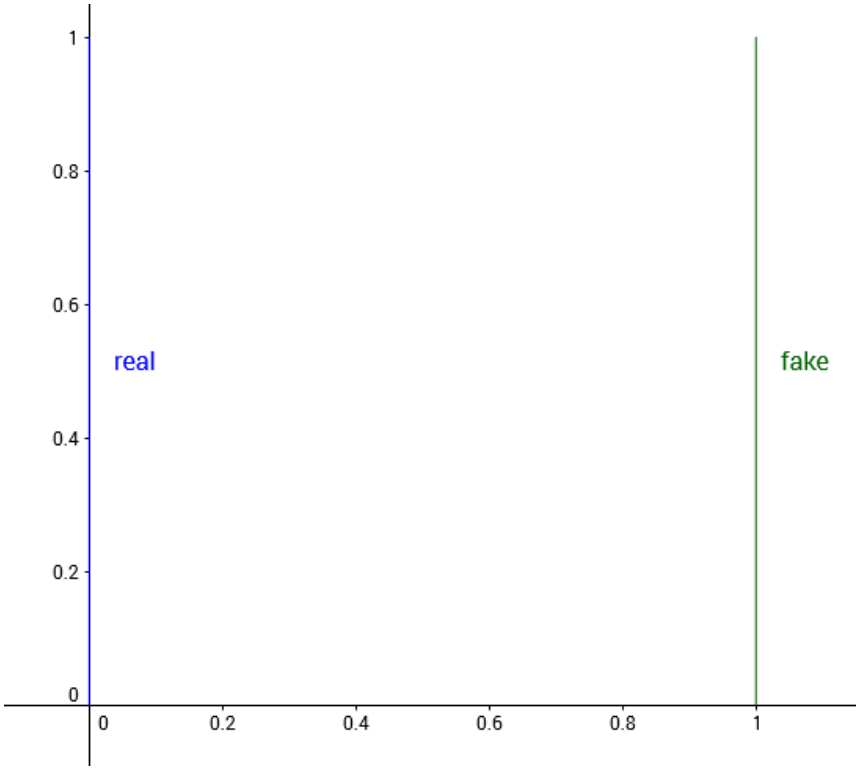

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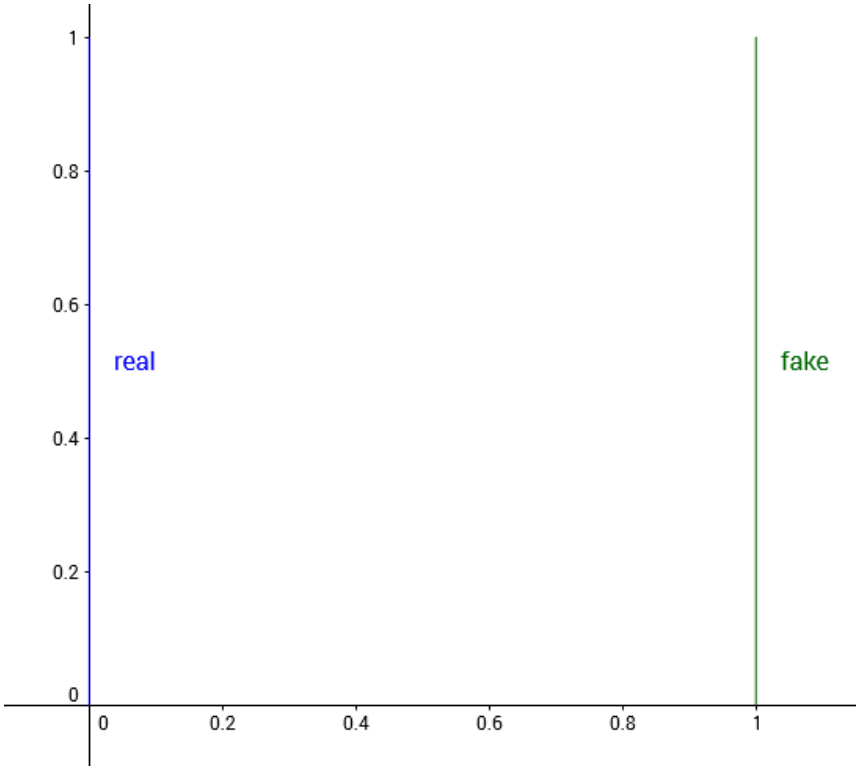

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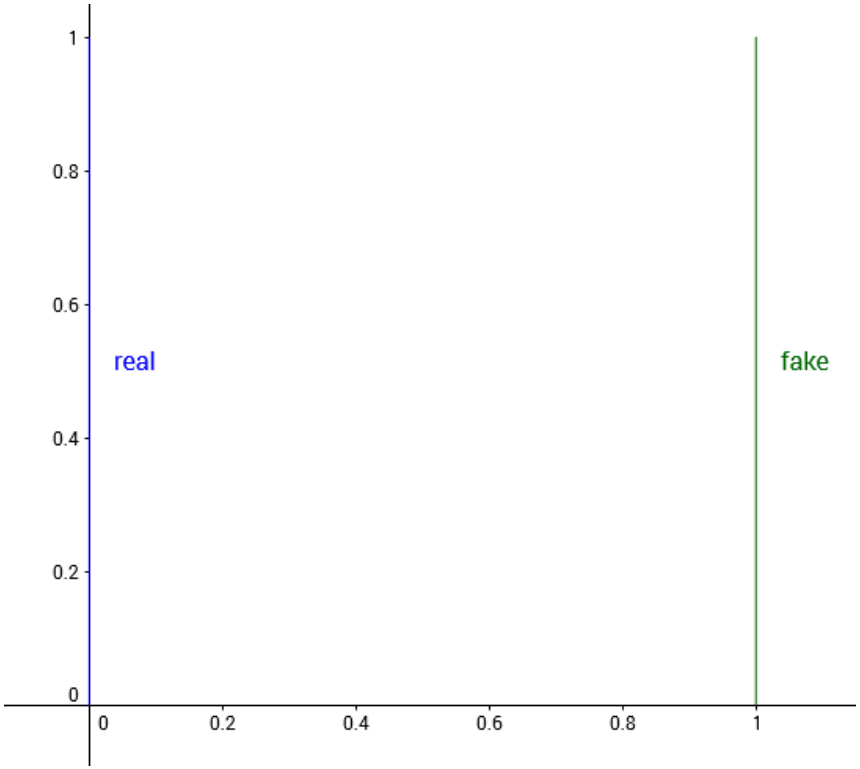

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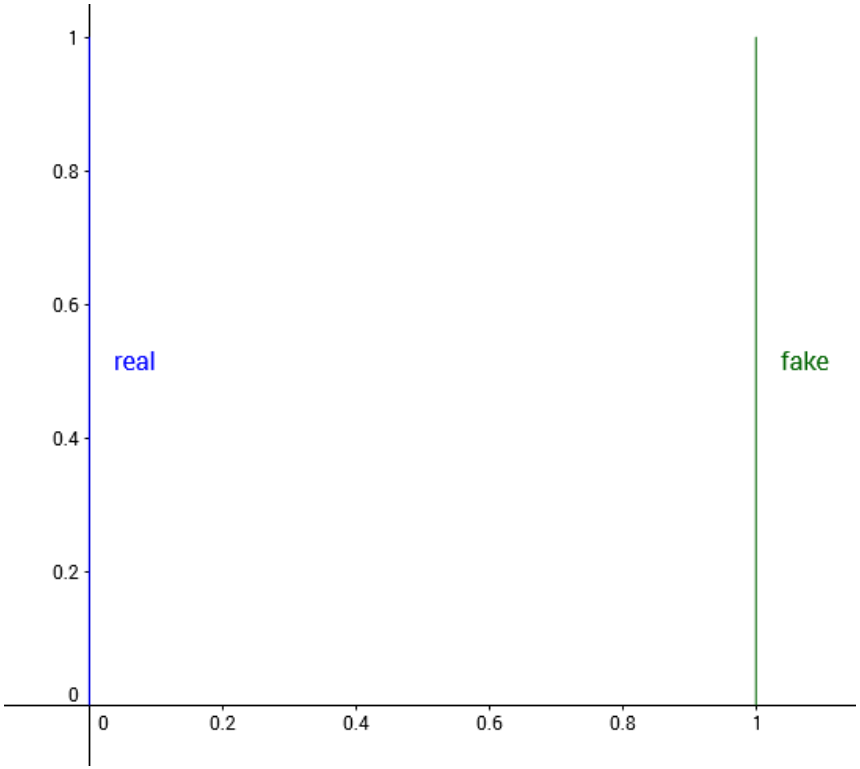

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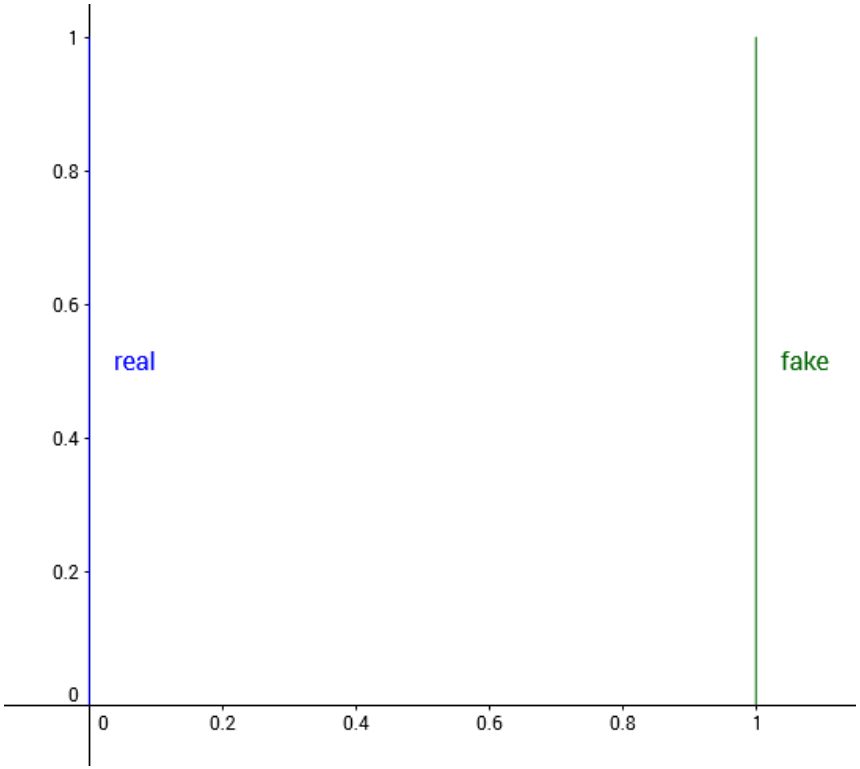

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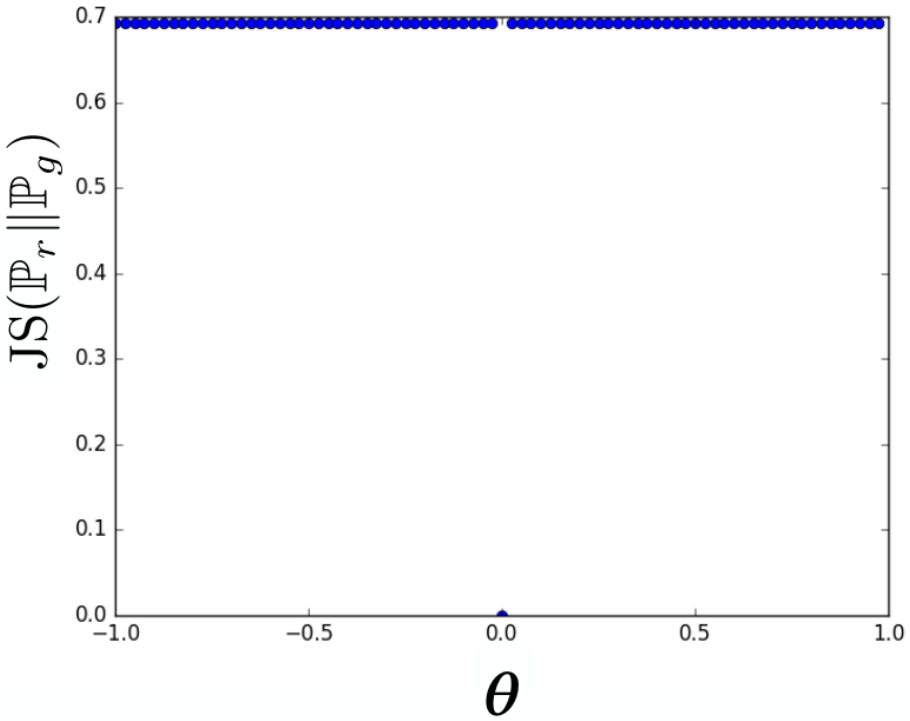
JS and EM distance w.r.t. θ



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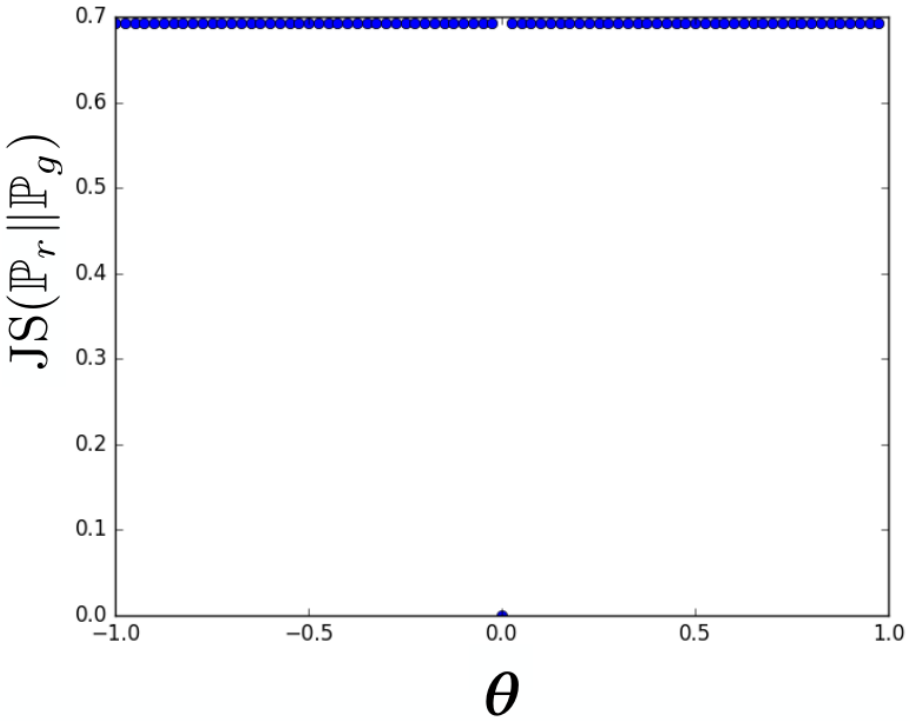

- JS-divergence gradient is zero

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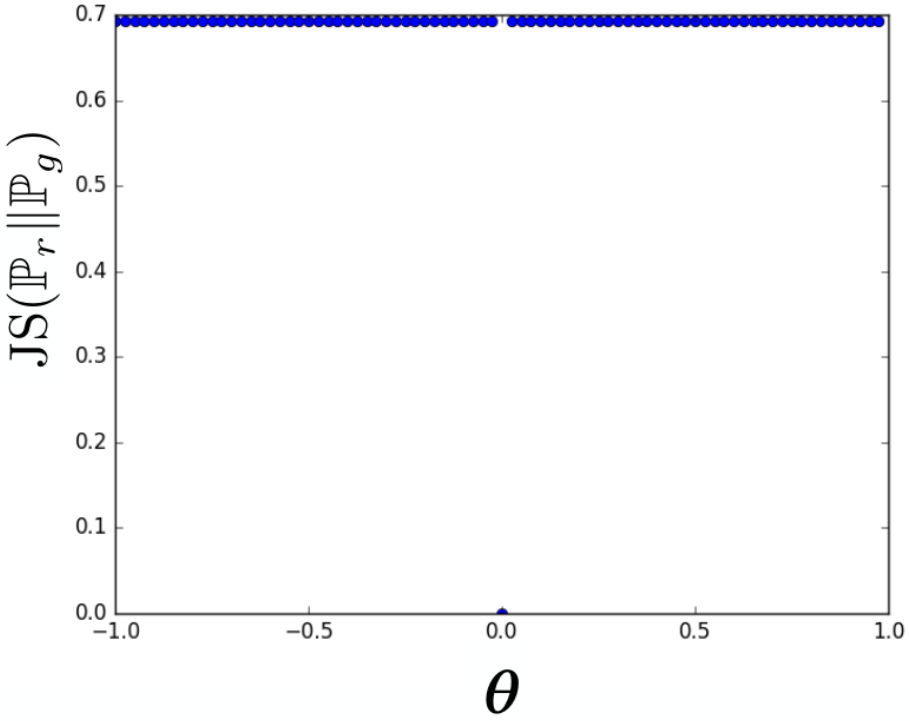

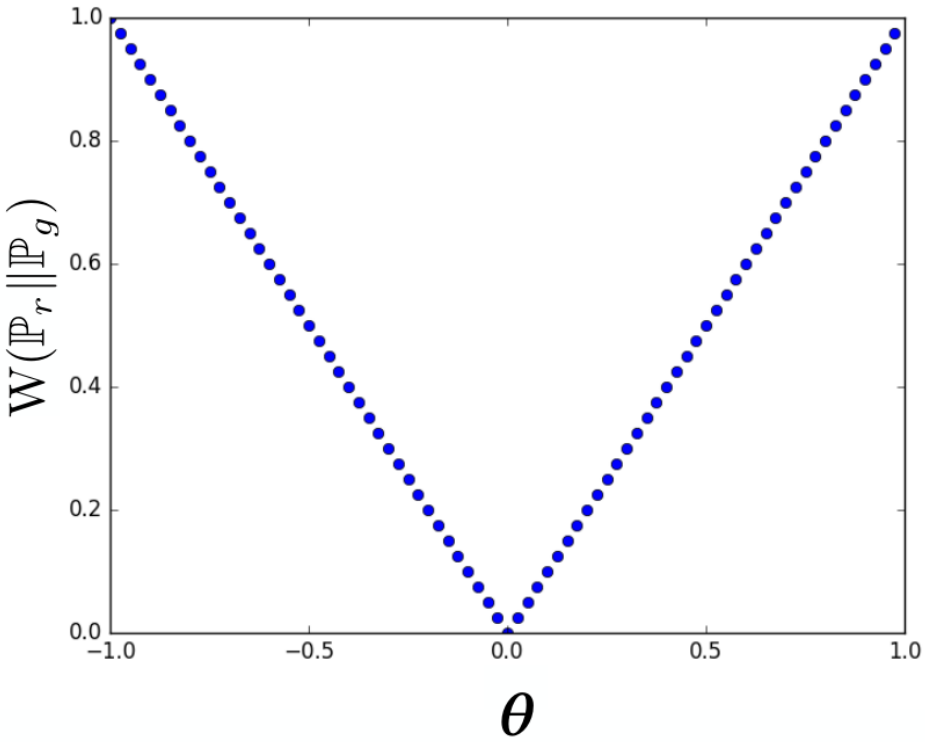

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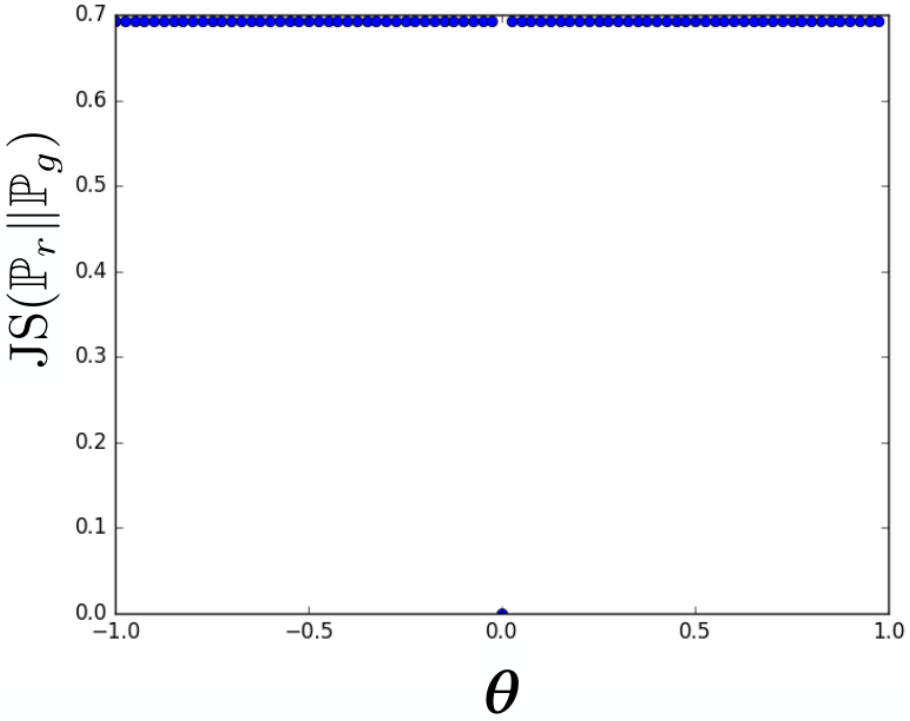
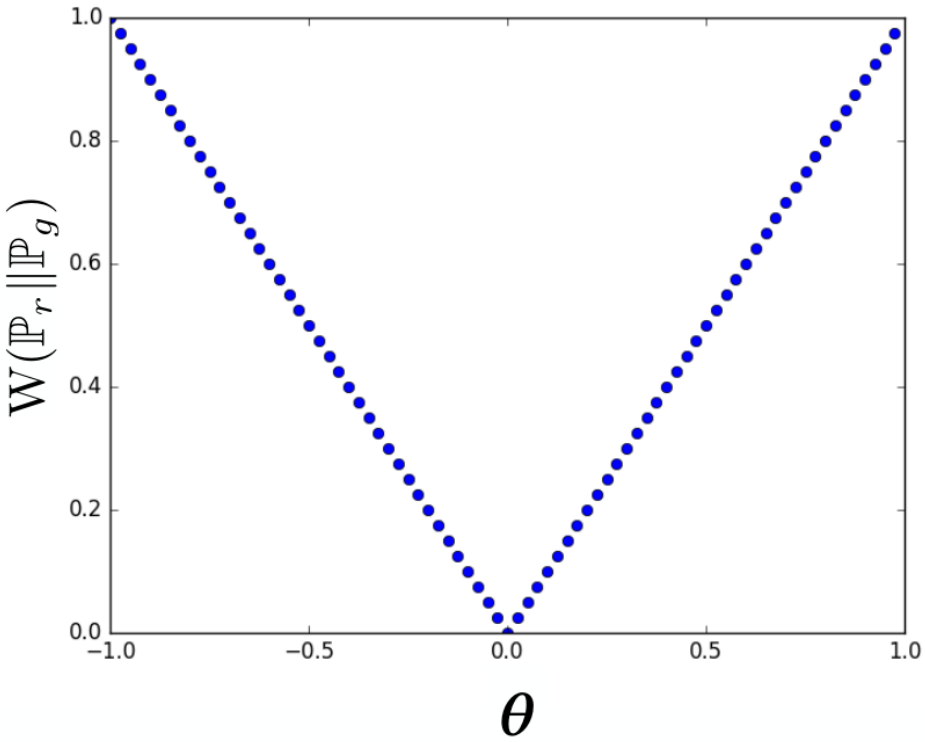
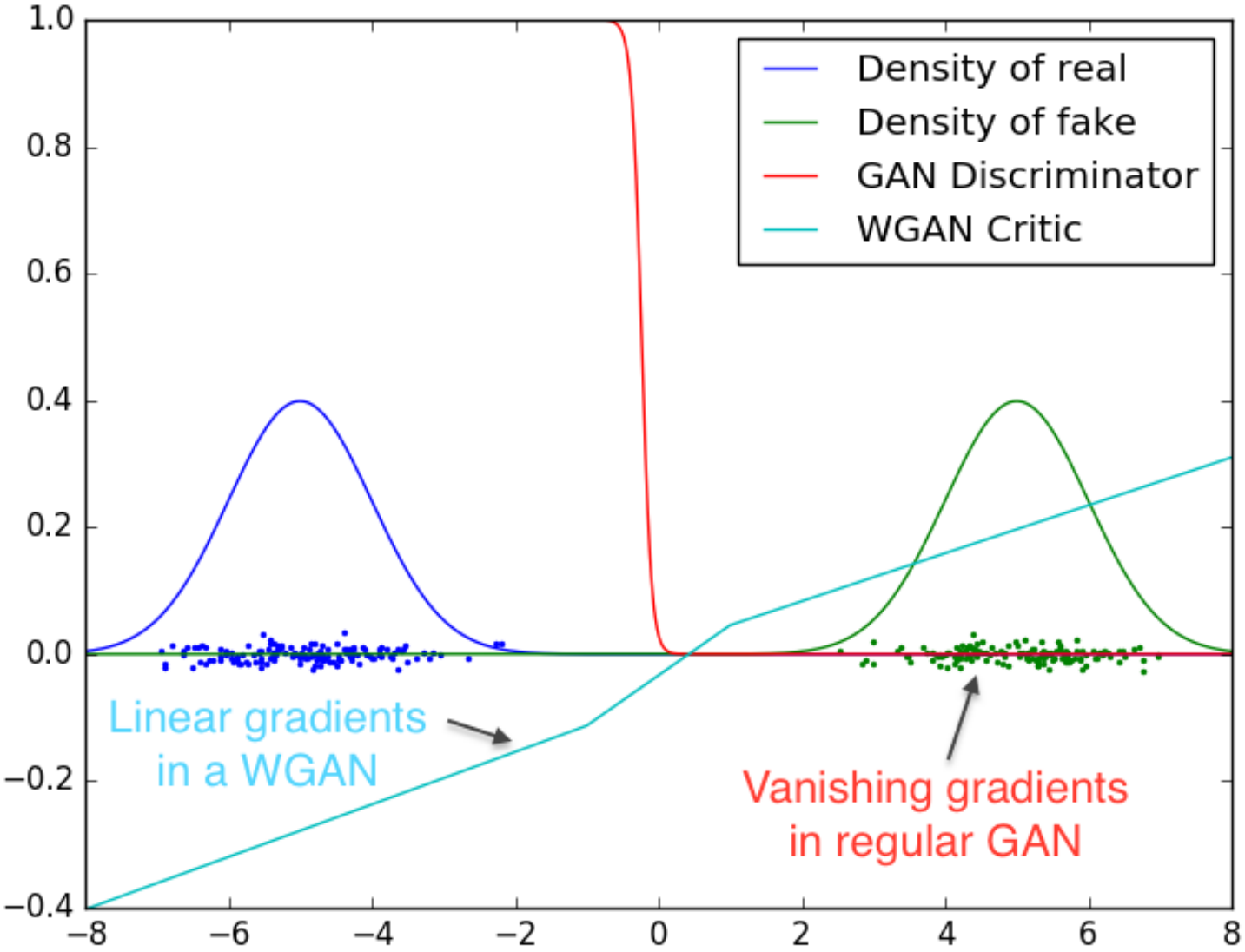




- JS-divergence gradient is zero
- Wasserstein gradient is constant

Gradients between two gaussian distributions



Short history of training GANs - July 2014

Generative Adversarial Nets

Ian J. Goodfellow, Jean Pouget-Abadie,* Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair,† Aaron Courville, Yoshua Bengio‡
Département d'informatique et de recherche opérationnelle
Université de Montréal
Montréal, QC H3C 3J7

2014

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GAN Value function

$$\min_G \max_D \mathbb{E}_{\boldsymbol{x}\sim\mathbb{P}_r}\left[\log D(\boldsymbol{x})\right] + \mathbb{E}_{\boldsymbol{z}\sim\mathcal{Z}}\left[\log(1 - D(G(\boldsymbol{z})))\right]$$

- Discriminator output is probability of image being real (1) or fake (0)

Short history of training GANs

- For G fixed, the optimal discriminator D^* is:

$$D^*_G(\boldsymbol{x}) = \frac{p_r(\boldsymbol{x})}{p_r(\boldsymbol{x}) + p_g(\boldsymbol{x})}$$

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- Under an optimal discriminator, generator minimizes the JS-divergence

$$JS(\mathbb{P}_r||\mathbb{P}_g) = \frac{1}{2}KL\left(\mathbb{P}_r \middle|\middle| \frac{\mathbb{P}_r + \mathbb{P}_g}{2}\right) + \frac{1}{2}KL\left(\mathbb{P}_g \middle|\middle| \frac{\mathbb{P}_r + \mathbb{P}_g}{2}\right)$$

We’re ready to put all the pieces together.

[0] https://lilianweng.github.io/lil-log/2017/08/20/from-GAN-to-WGAN.html

- Under an optimal discriminator, GANs minimize JS-divergence.

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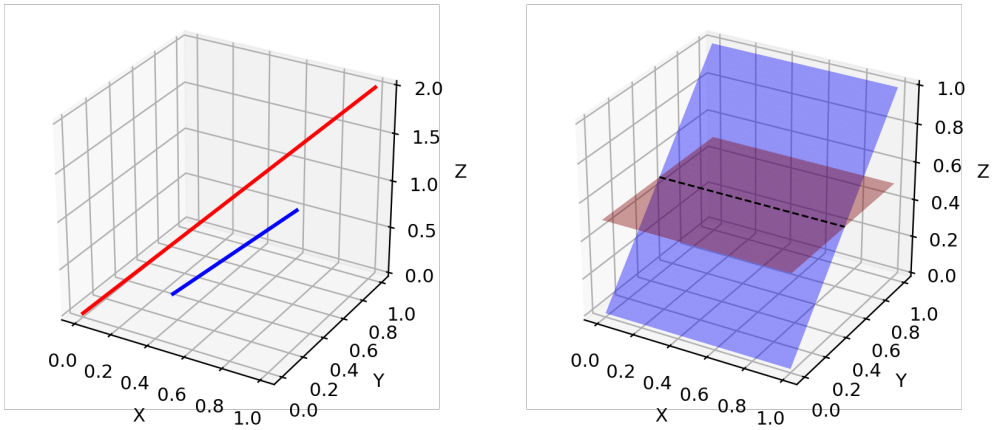

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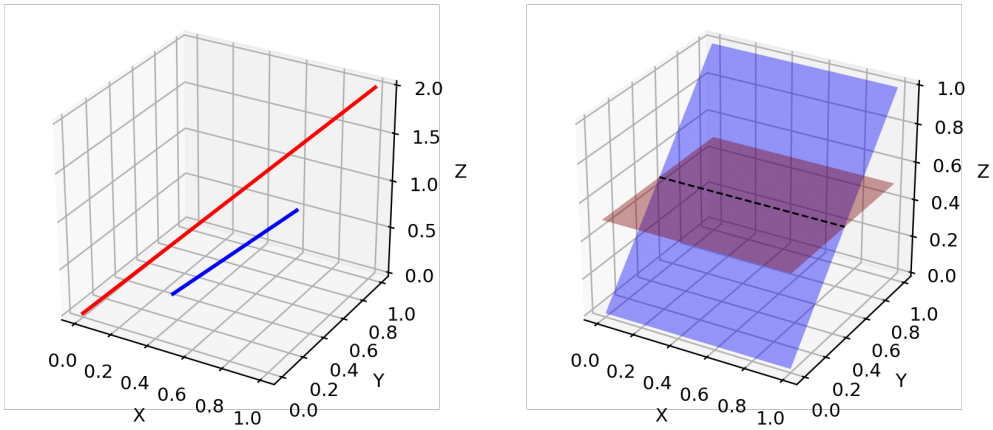

Conclusion!

Original GAN training regime on natural data leads to vanishing gradients

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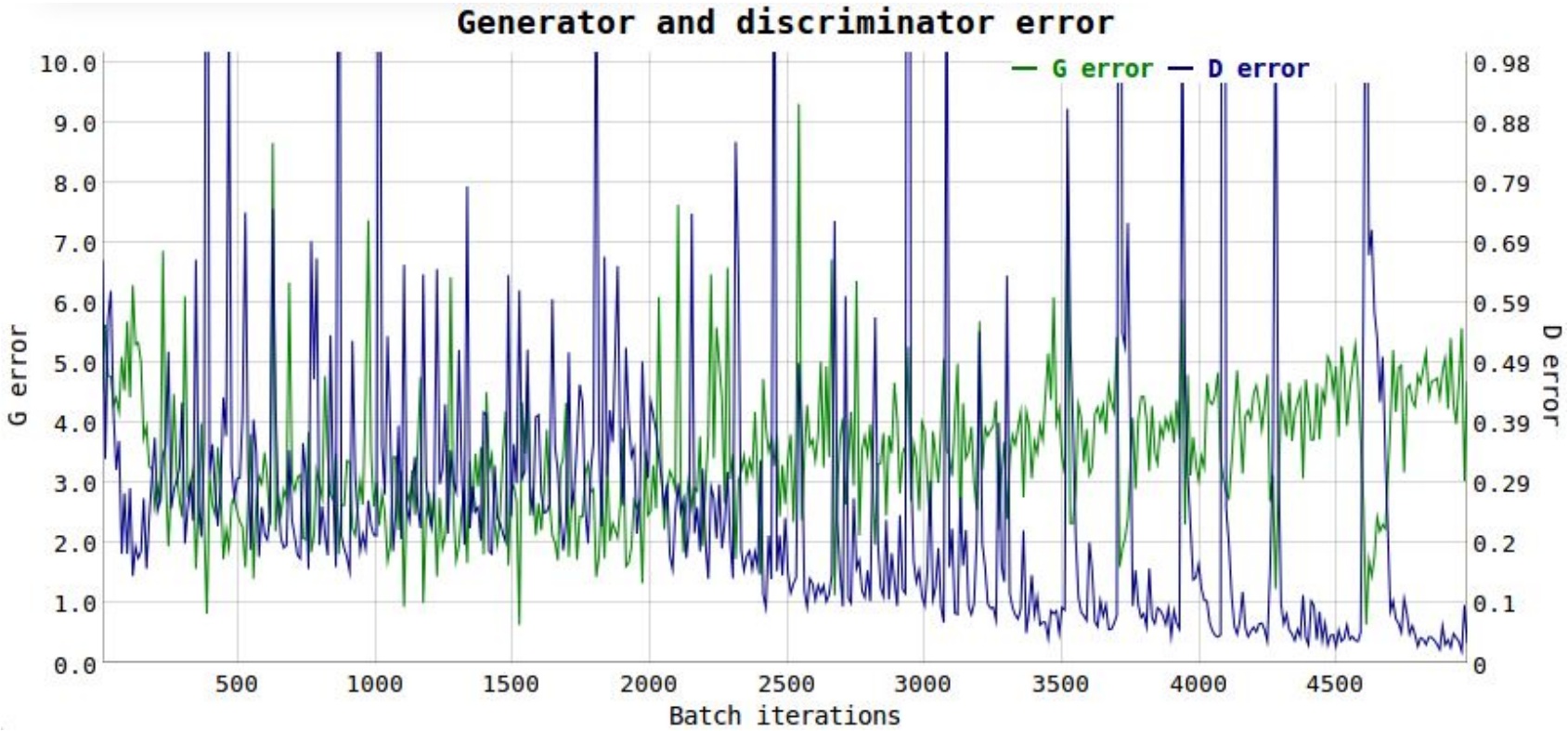
But there's a bigger problem...



- **Value of the loss doesn't tell us anything!**
- No correlation between loss and image quality
- Problem stems from mentioned undesired properties of JS-divergence


BAG OF
TRICKS

Trick - not training the discriminator until convergence

- Making sure the discriminator is not "too far ahead of" the generator

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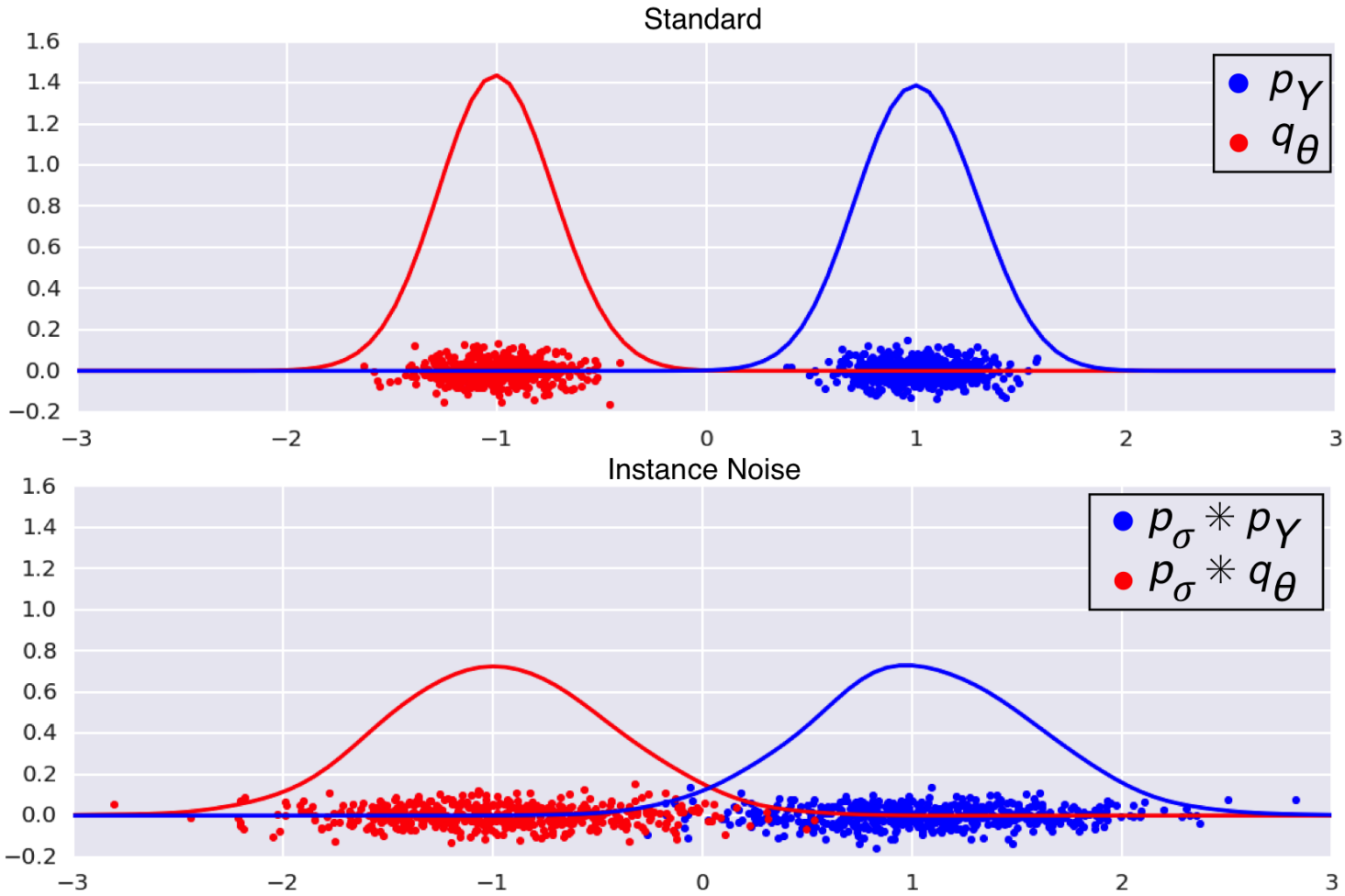
- Each step trains the generator once and discriminator once
- Many alternative training plans with questionable efficiency
- Has a nice side effect of speeding up the training time

Trick - adding noise



- Matching the noise corresponds to matching the underlying distributions

[0] http://www.inference.vc/instance-noise-a-trick-for-stabilising-gan-training/

Trick - cherrypicking architecture

(TFD) [28], and CIFAR-10 [21]. The generator nets used a mixture of rectifier linear activations [19, 9] and sigmoid activations, while the discriminator net used maxout [10] activations. Dropout [17] was applied in training the discriminator net. While our theoretical framework permits the use of dropout and other noise at intermediate layers of the generator, we used noise as the input to only the bottommost layer of the generator network.

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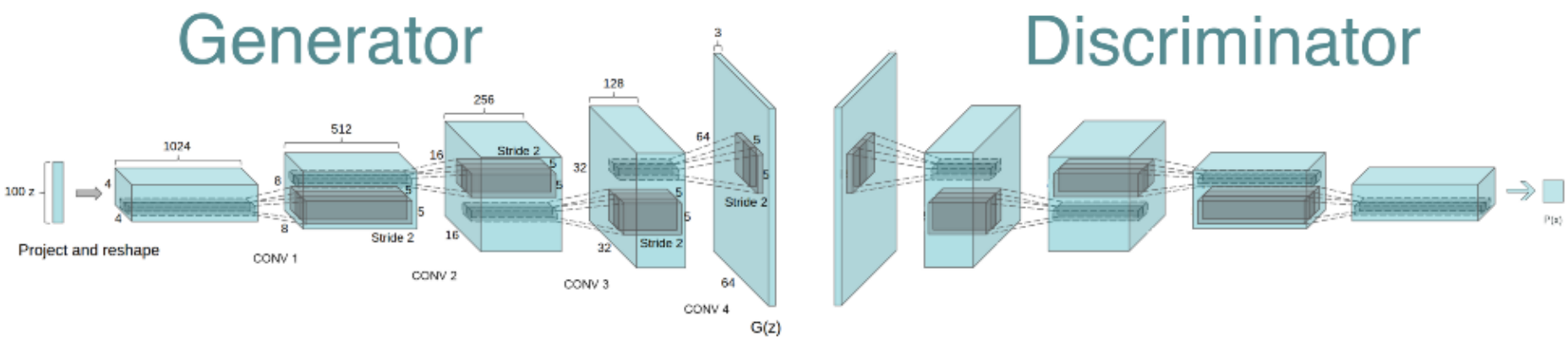
a) b) c) d)

Trick - cherrypicking architecture - DCGAN

UNSUPERVISED REPRESENTATION LEARNING
WITH DEEP CONVOLUTIONAL
GENERATIVE ADVERSARIAL NETWORKS

Alec Radford & Luke Metz
indico Research



[1] https://www.youtube.com/watch?v=X1mUN6dD8uEt=795s

Trick - cherrypicking architecture - DCGAN

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Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
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- Authors reports that they had model generator [1]
- No explanation for model performance, very unstable

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Short history of training GANs

[2] http://cedricvillani.org/wp-content/uploads/2012/08/preprint-1.pdf

Short history of training GANs

EM distance

$$W(\mathbb{P}_r, \mathbb{P}_g) = \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y)\sim\gamma} \left[||x - y||\right]$$

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Kantorovich-Rubinstein duality

$$K \cdot W(\mathbb{P}_r, \mathbb{P}_g) = \sup_{\|f\|_L \leq K} \mathbb{E}_{x\sim\mathbb{P}_r} \left[f(x)\right] - \mathbb{E}_{x\sim\mathbb{P}_g} \left[f(x)\right]$$

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- Supremum is over all K-Lipschitz functions $f : \mathcal{X} \to \mathbb{R}$

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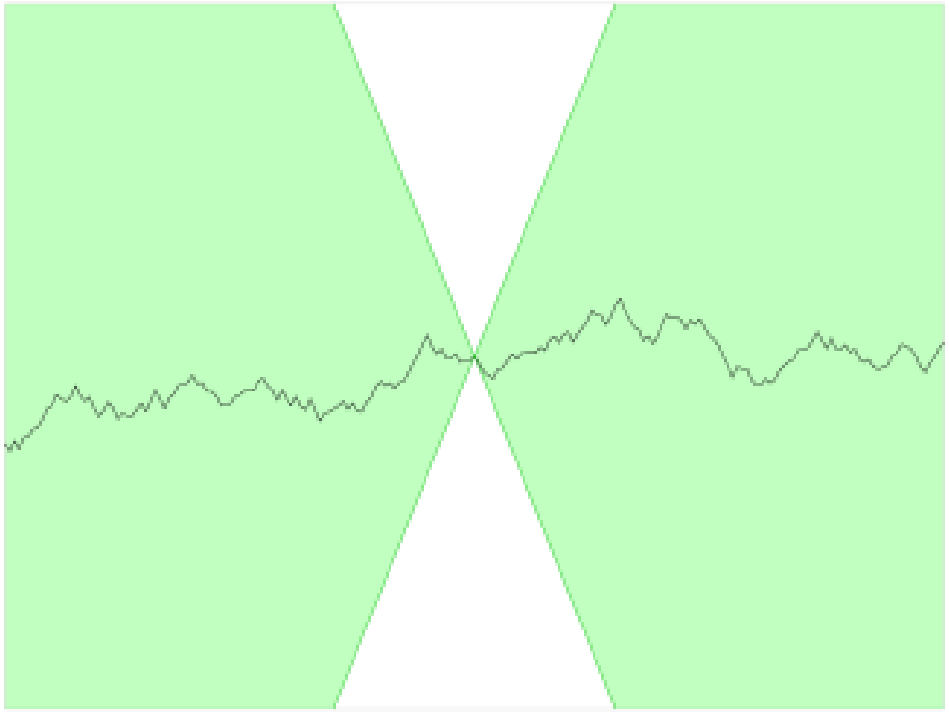
Lipschitz continuity



[2] https://en.wikipedia.org/wiki/Lipschitz_continuity

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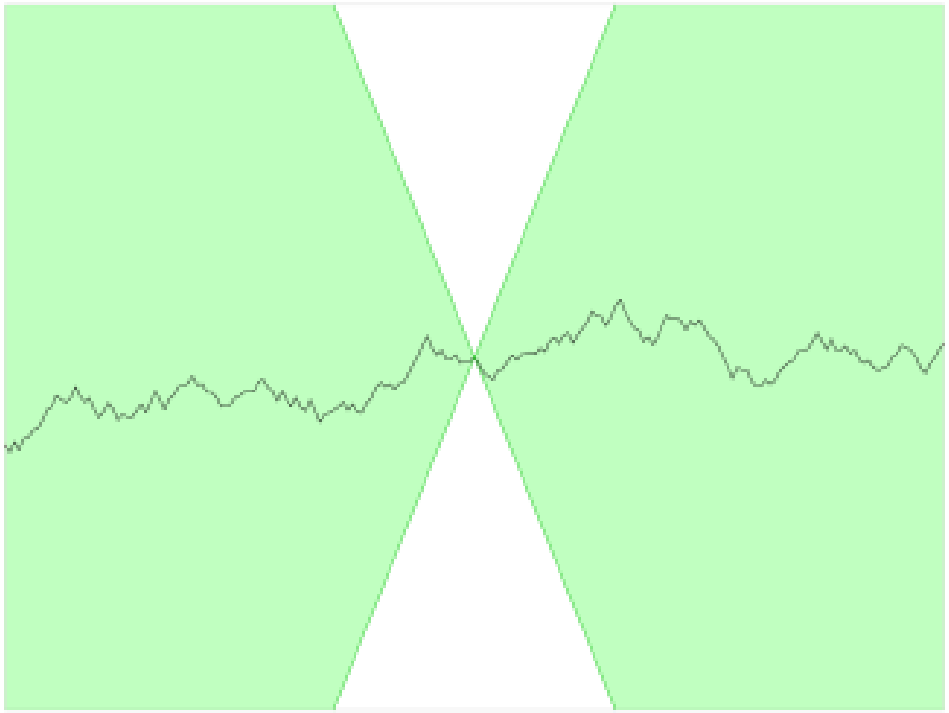

- Continuous function which is limited how fast it can change

Lipschitz continuous function

$$|f'(x)| \leq 1 \qquad \forall x \in \mathbb{R}$$

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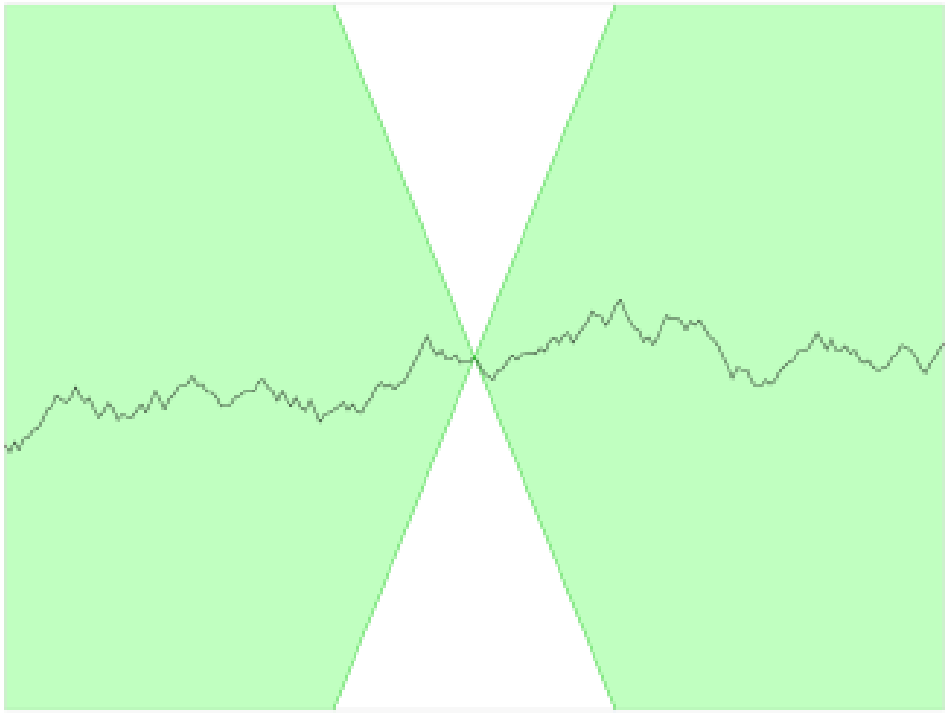
Lipschitz continuity



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Short history of training GANs - January 2017

Jan 2017

Wasserstein GAN

Martin Arjovsky[1], Soumith Chintala[2], and Léon Bottou[1,2]

[1]Courant Institute of Mathematical Sciences
[2]Facebook AI Research

WGAN Value function

$$\min_G \max_{D \in \mathcal{D}} \mathbb{E}_{\boldsymbol{x} \sim \mathbb{P}_r} [D(\boldsymbol{x})] - \mathbb{E}_{\boldsymbol{z} \sim \mathcal{Z}} [D(G(\boldsymbol{z}))]$$

$\mathcal{D}$ - set of all K-Lipschitz functions

Short history of training GANs - January 2017

Jan 2017

Wasserstein GAN

Martin Arjovsky[1], Soumith Chintala[2], and Léon Bottou[1,2]

[1]Courant Institute of Mathematical Sciences
[2]Facebook AI Research

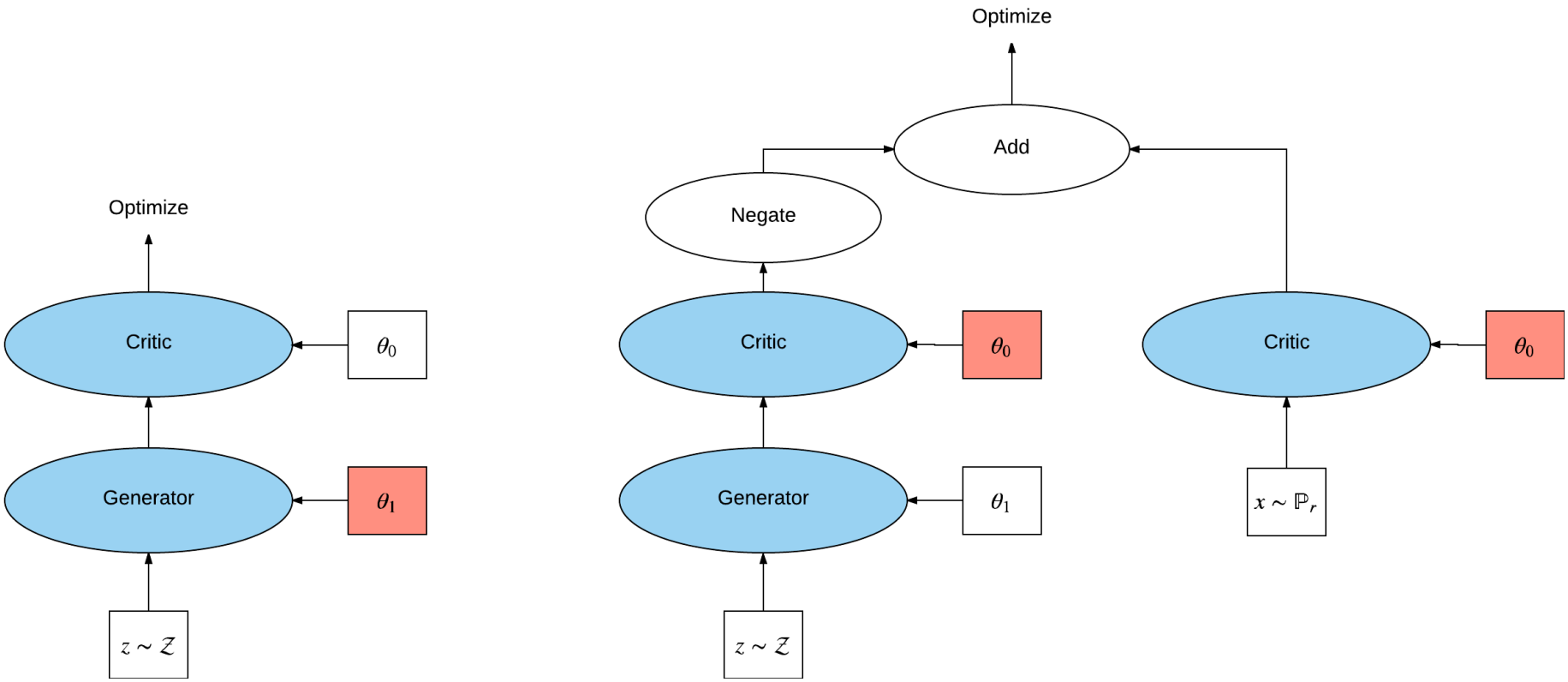
WGAN Value function

$$\min_G \max_{D \in \mathcal{D}} \mathbb{E}_{\boldsymbol{x} \sim \mathbb{P}_r} [D(\boldsymbol{x})] - \mathbb{E}_{\boldsymbol{z} \sim \mathcal{Z}} [D(G(\boldsymbol{z}))]$$

$\mathcal{D}$ - set of all K-Lipschitz functions

- Open question - how to effectively enforce the Lipschitz constraint?

Wasserstein GAN



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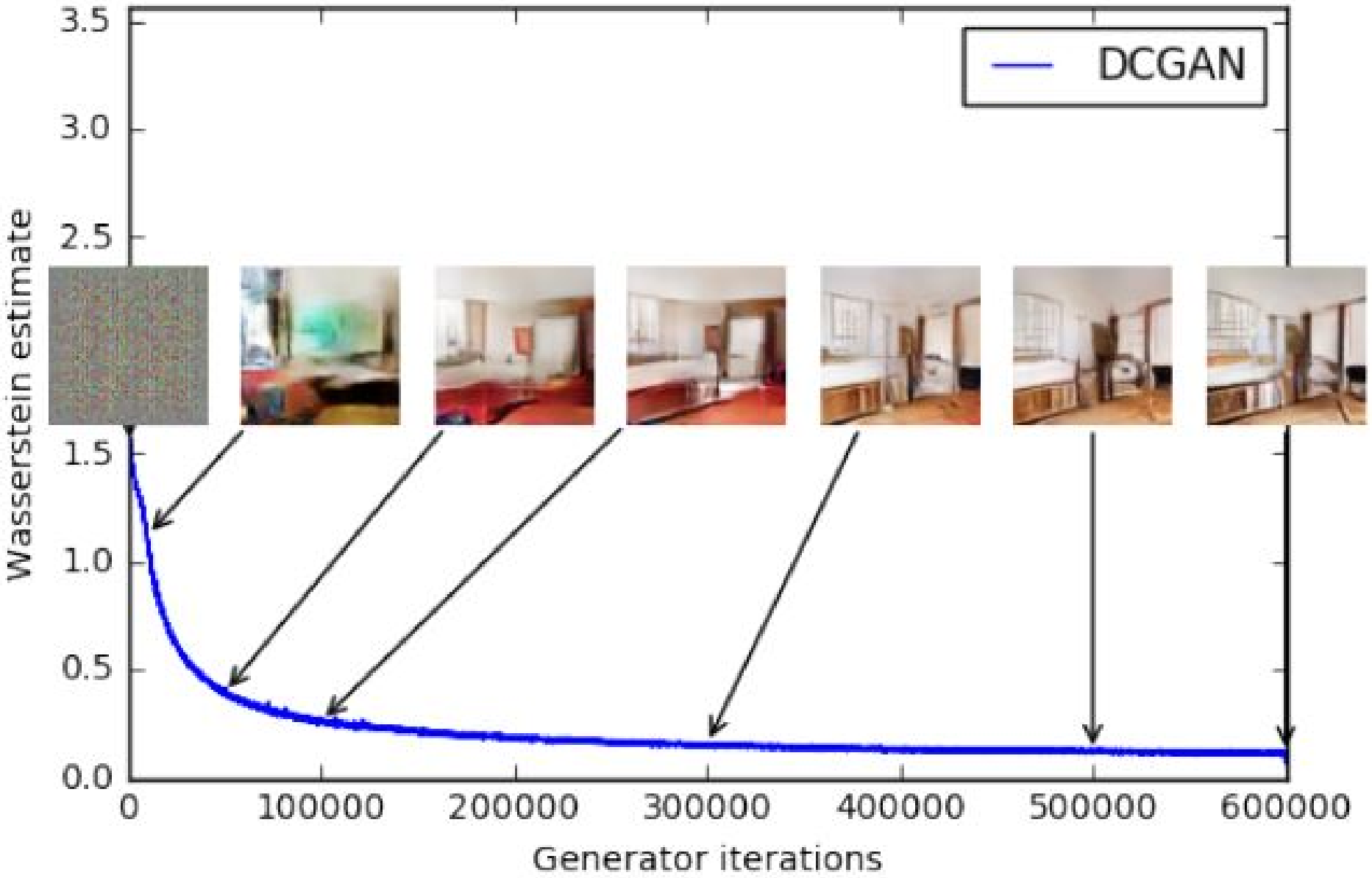
Meaningful loss function



Method #1 - Weight Clipping

- After optimization step, clip all weights to $[-c, c]$

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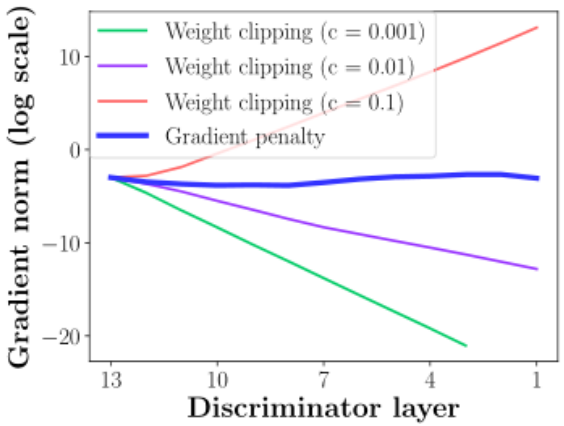

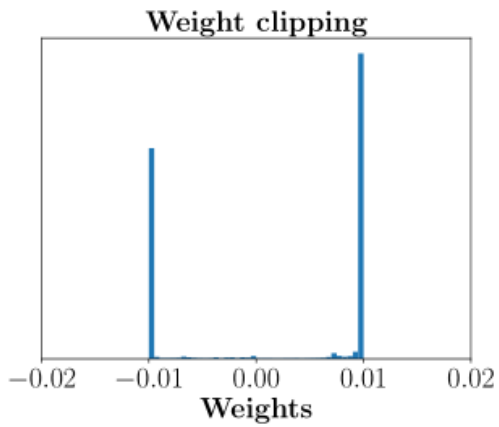

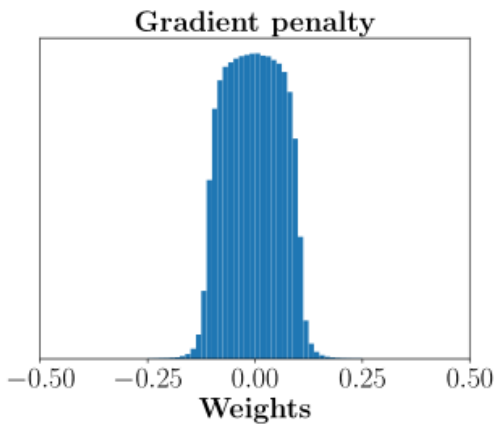

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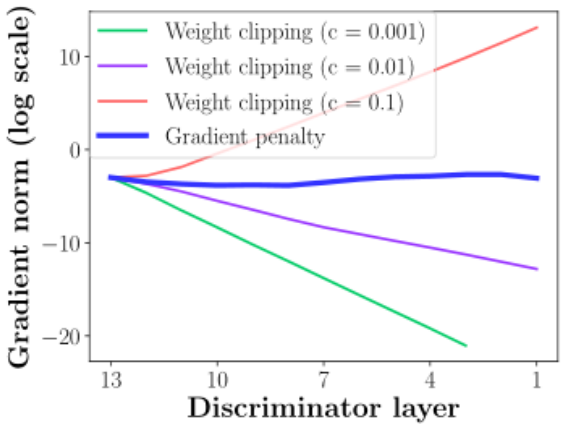

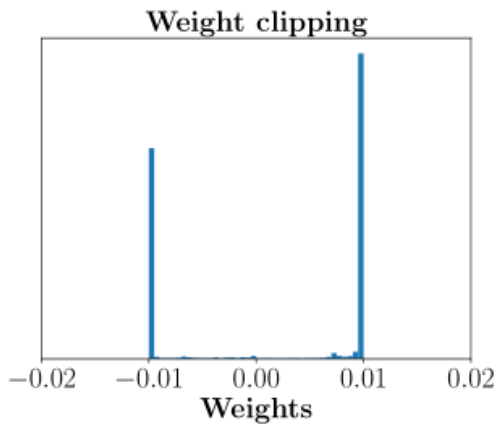

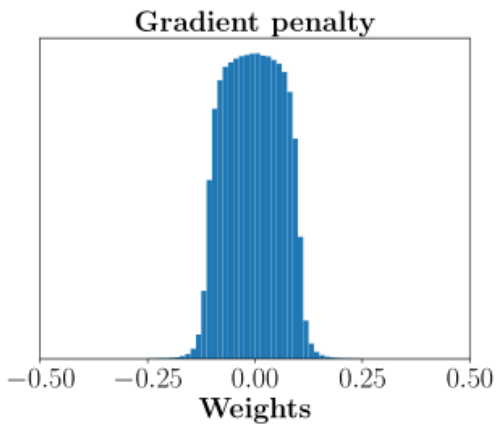

- Works! But...
- Capacity underuse

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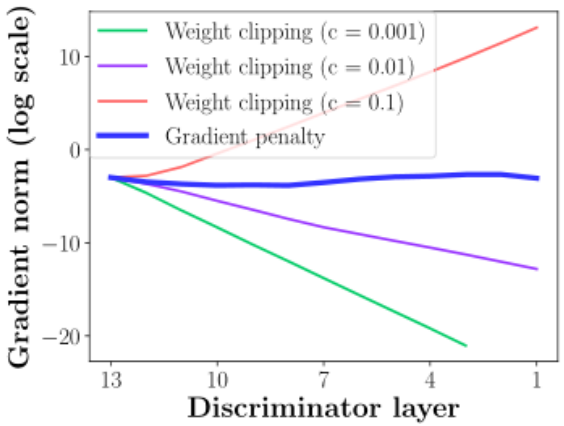

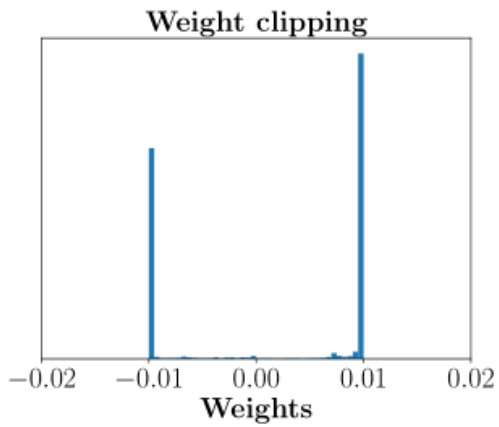

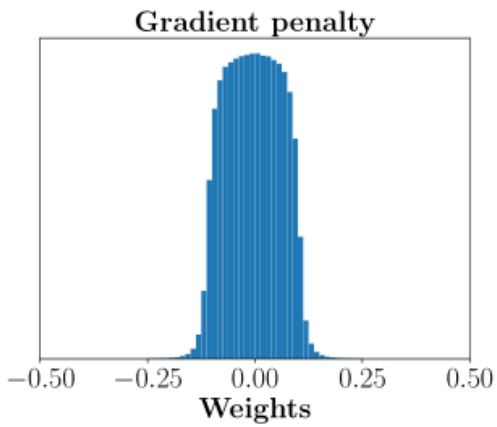

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- Capacity underuse
- Exploding and vanishing gradients

Method #2 - Gradient Penalty

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- Sampling along straight lines

$$\epsilon \sim U\left[0, 1\right], \boldsymbol{x} \sim \mathbb{P}_g, \tilde{\boldsymbol{x}} \sim \mathbb{P}_r$$

$$\hat{\boldsymbol{x}} = t\boldsymbol{x} + (1 - t)\,\tilde{\boldsymbol{x}}$$

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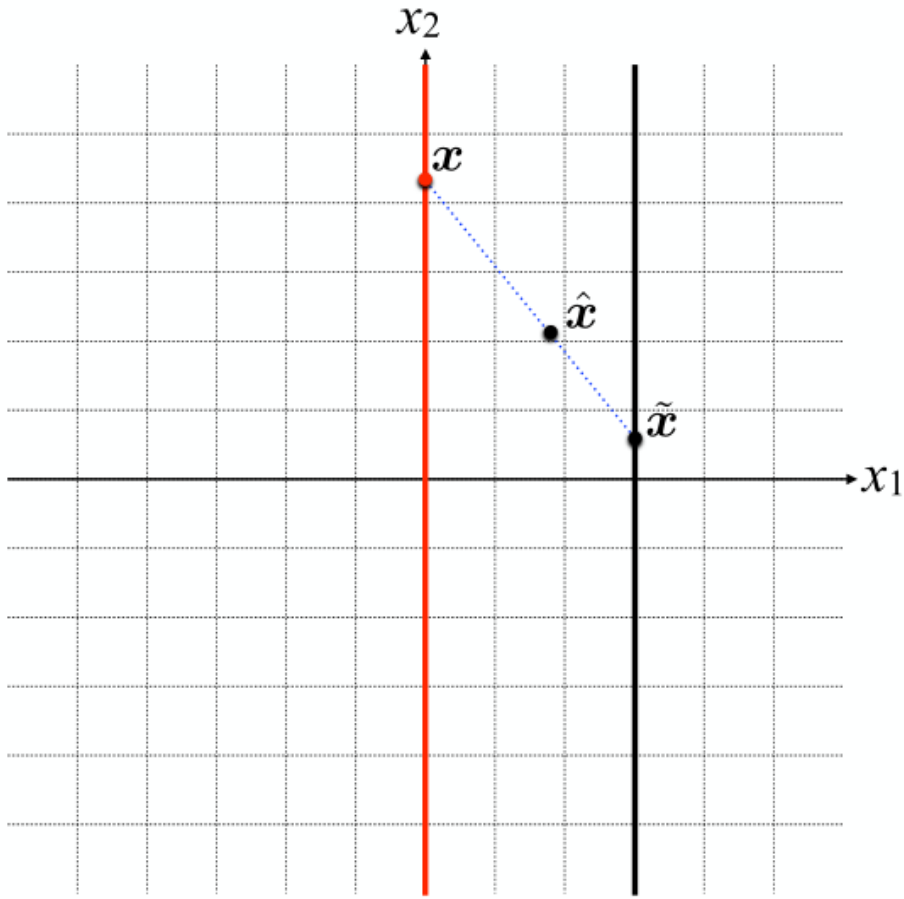

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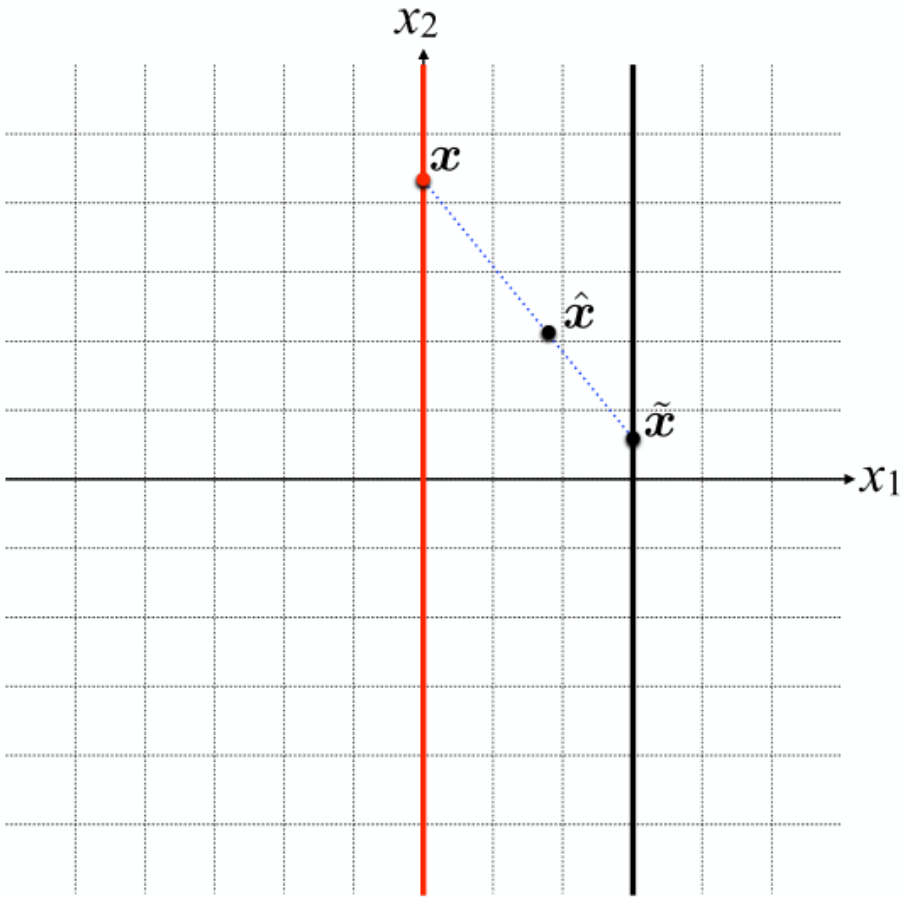
- Gradient penalty

$$D(\hat{\boldsymbol{x}})$$



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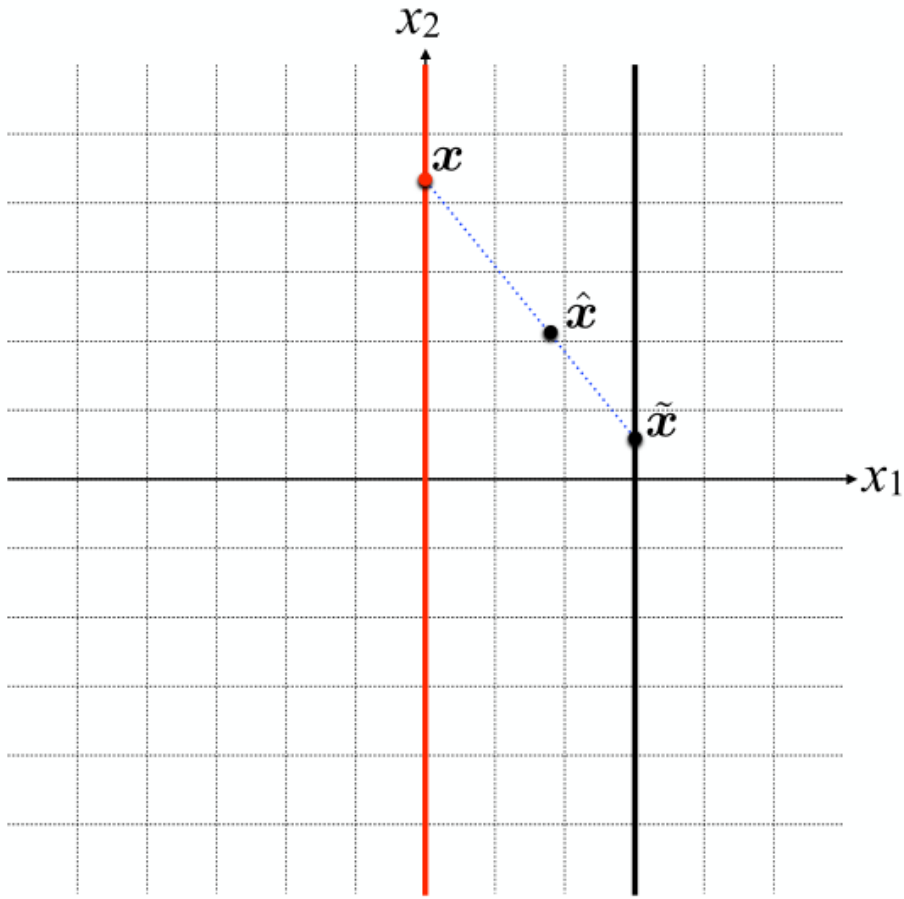

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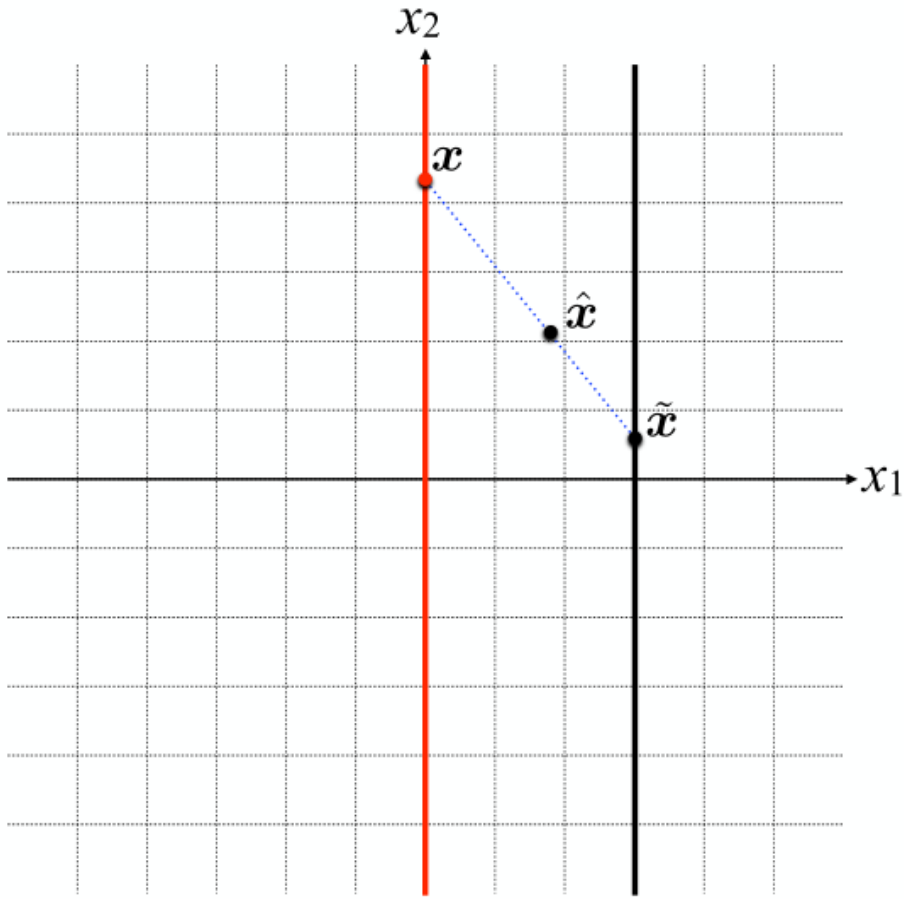

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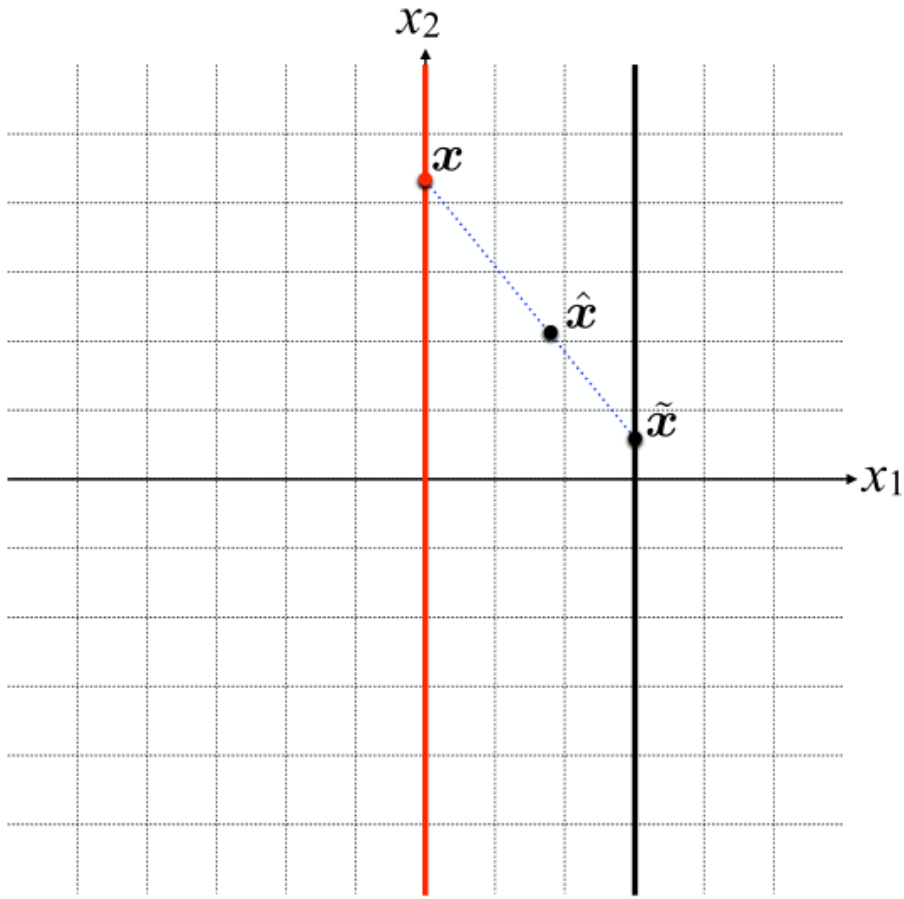
$$\left(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1\right)^2$$



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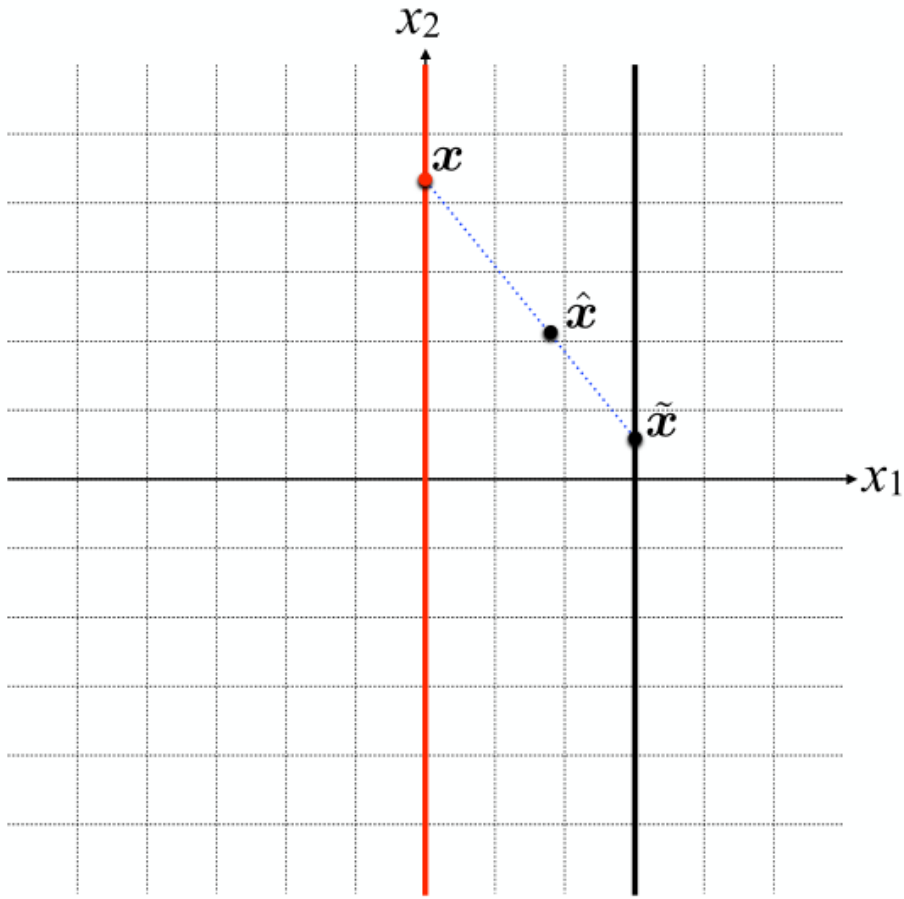
$$\mathbb{E}_{\hat{\boldsymbol{x}} \sim \mathbb{P}_{\hat{\boldsymbol{x}}}}\left[\left(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1\right)^2\right]$$



Short history of training GANs - March 2017

Improved Training of Wasserstein GANs

Ishaan Gulrajani[1], **Faruk Ahmed**[1], **Martin Arjovsky**[2], **Vincent Dumoulin**[1], **Aaron Courville**[1,3]
[1] Montreal Institute for Learning Algorithms
[2] Courant Institute of Mathematical Sciences
[3] CIFAR Fellow
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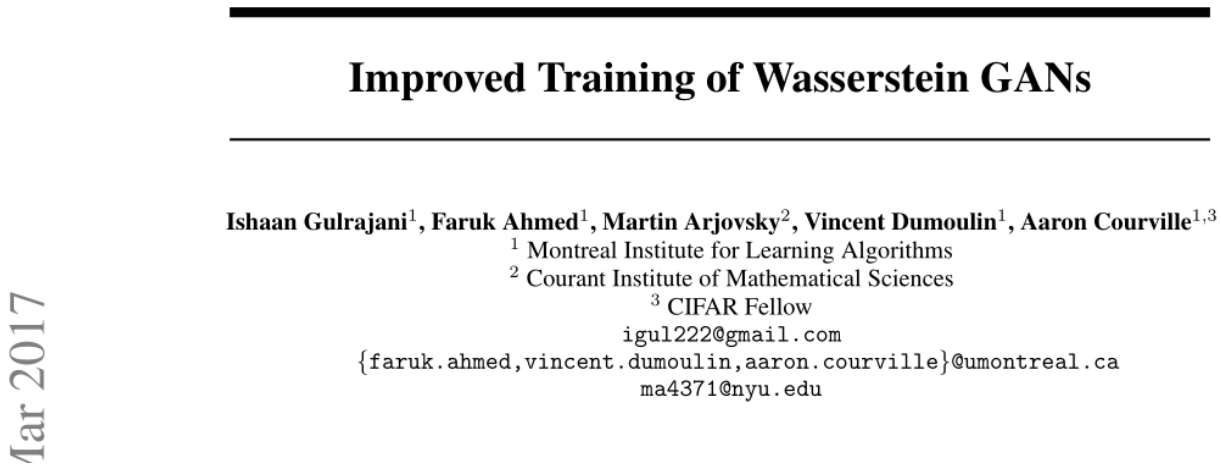

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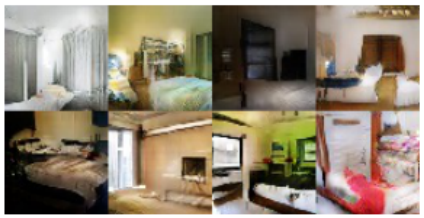
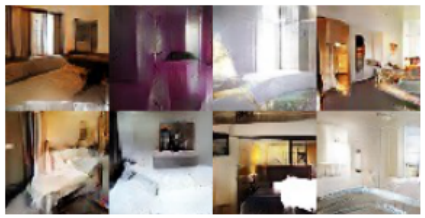
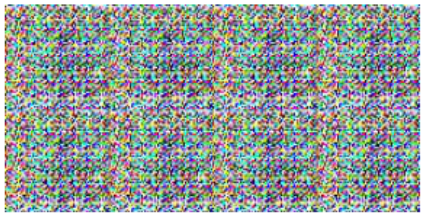
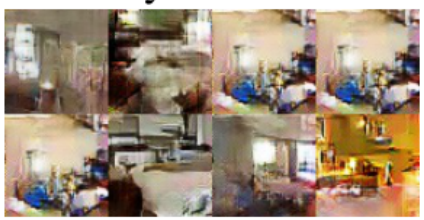
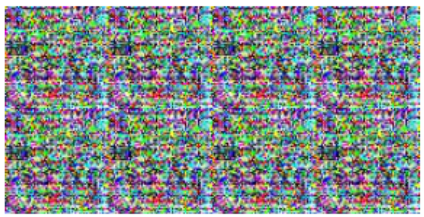
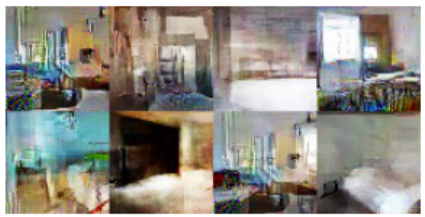
WGAN-GP Value function

$$\min_G \max_D \mathbb{E}_{\boldsymbol{x}\sim\mathbb{P}_r}[D(\boldsymbol{x})] - \mathbb{E}_{\boldsymbol{z}\sim\mathcal{Z}}[D(G(\boldsymbol{z}))] + \lambda \mathbb{E}_{\hat{\boldsymbol{x}}\sim\mathbb{P}_{\hat{\boldsymbol{x}}}}\left[\left(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1\right)^2\right]$$

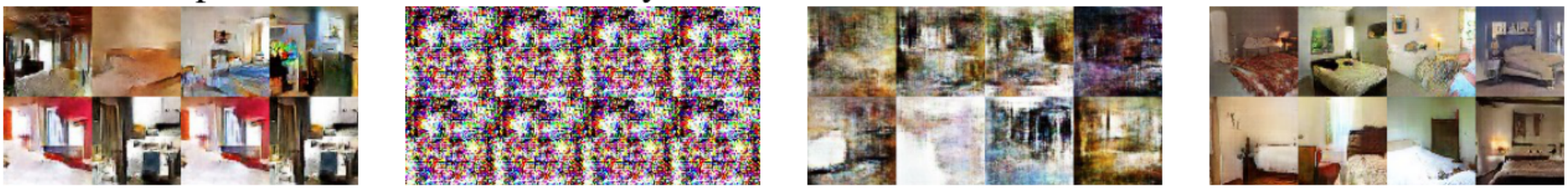
- Enforcing the Lipschitz constraint with a gradient penalty regularization term

WGAN-GP results

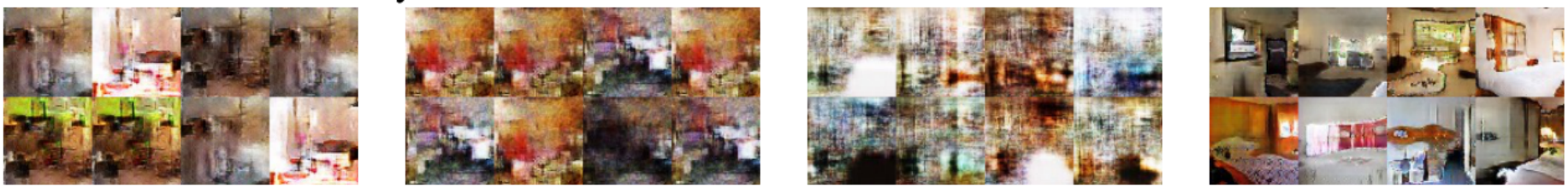
DCGAN	LSGAN	WGAN (clipping)	WGAN-GP (ours)
Baseline (G: DCGAN, D: DCGAN)			
			
G: No BN and a constant number of filters, D: DCGAN			
			
G: 4-layer 512-dim ReLU MLP, D: DCGAN			
			

WGAN-GP results

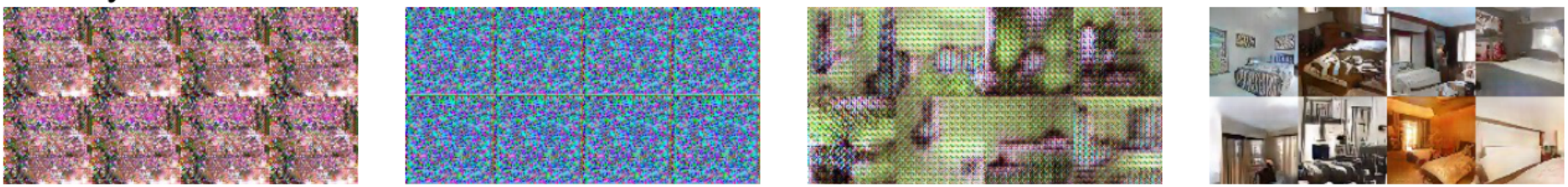
Gated multiplicative nonlinearities everywhere in G and D



$tanh$ nonlinearities everywhere in G and D



101-layer ResNet G and D



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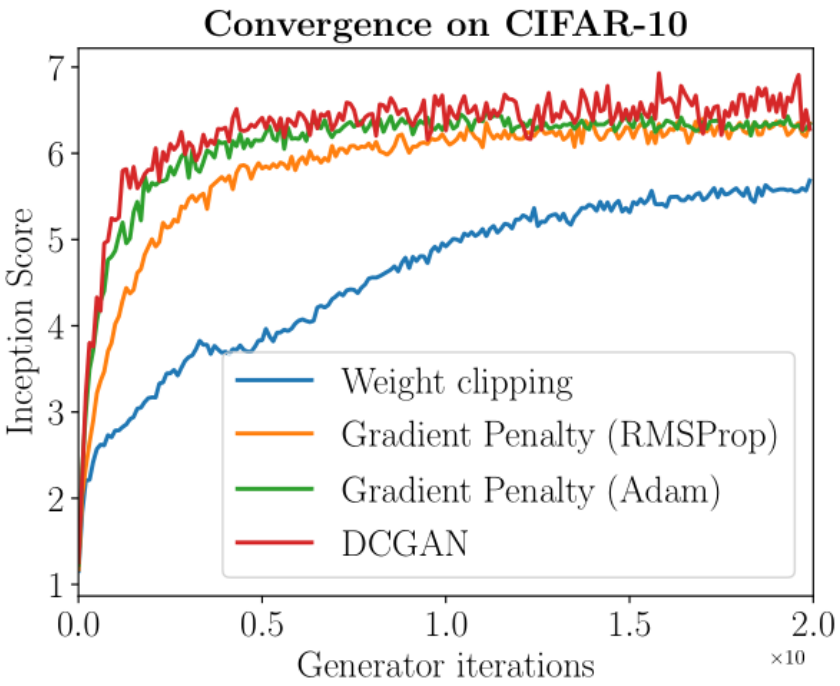
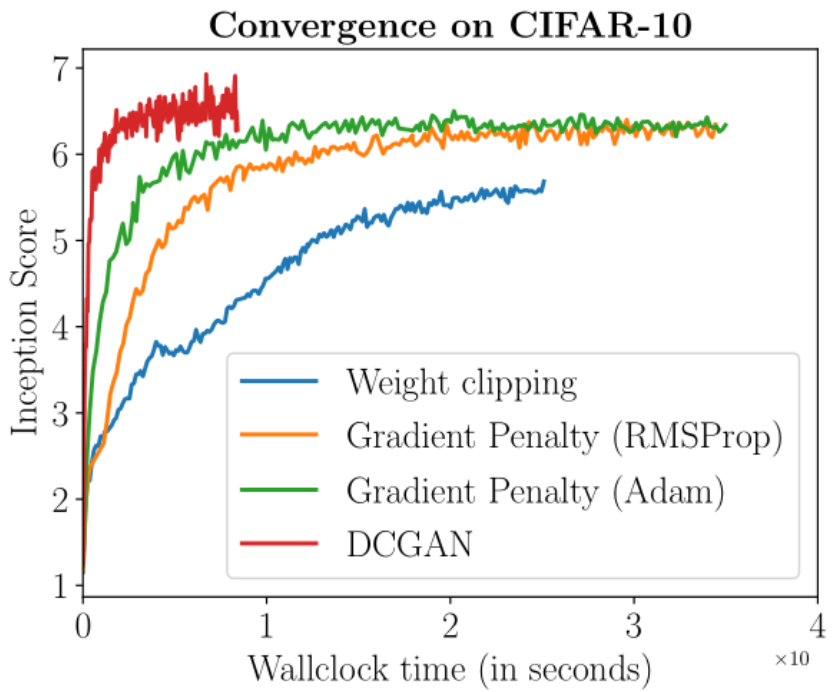


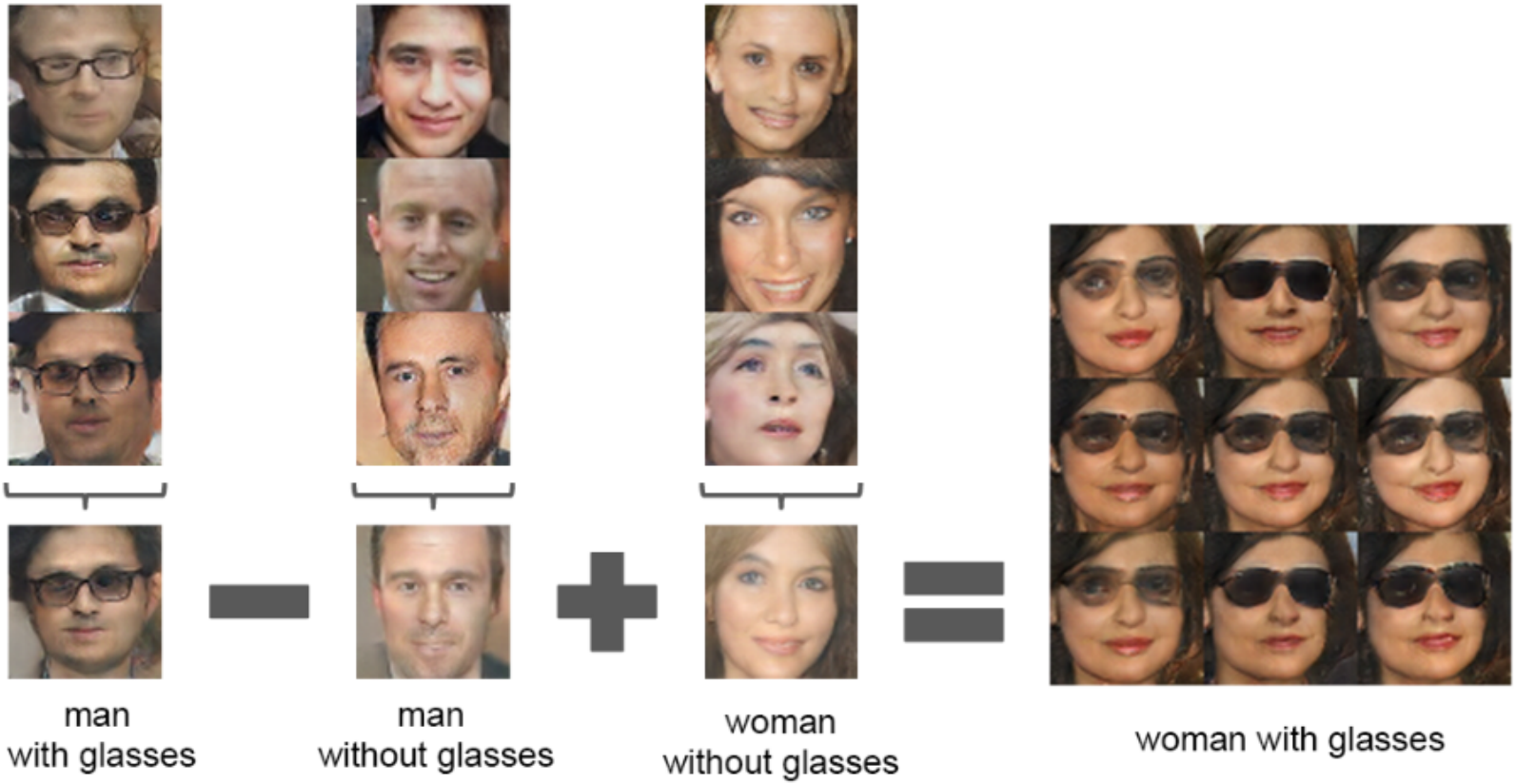


- DCGAN converges faster
- Significantly outperforms weight clipping
- **Robust to changes in model architecture**

Cool things you can do with GANs

Latent space arithmetic

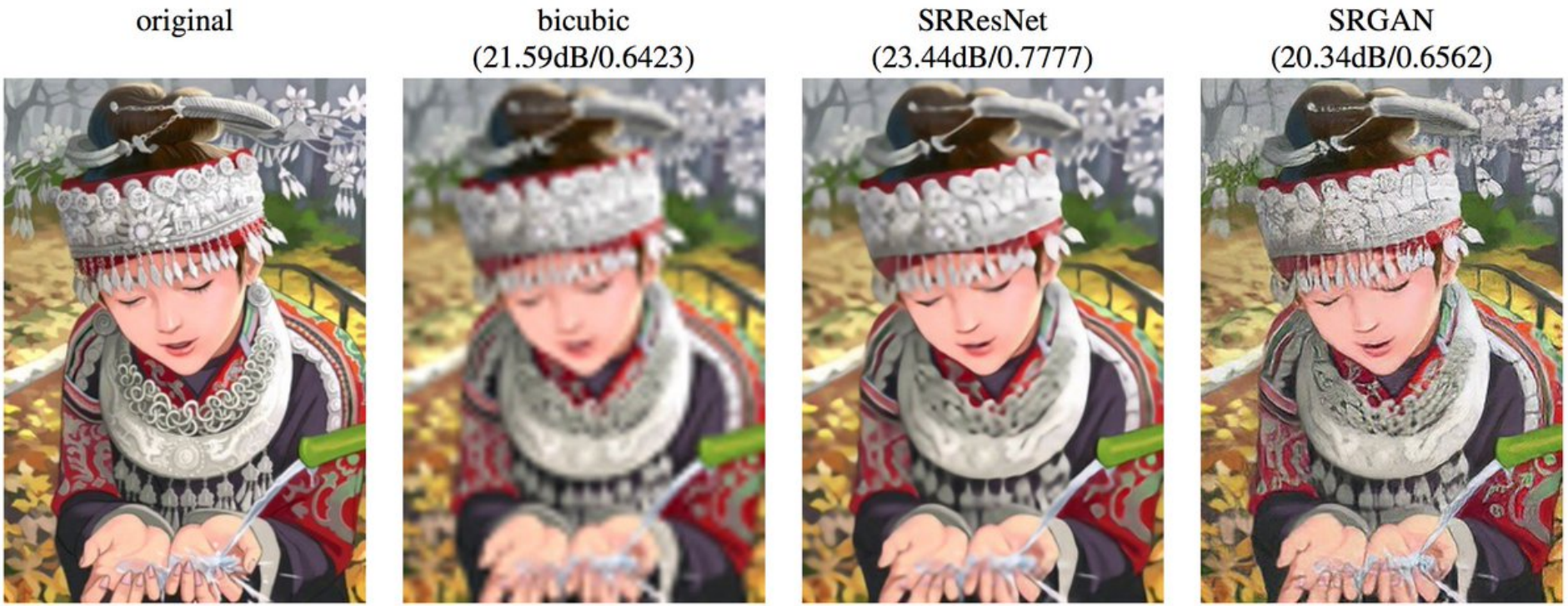
Latent space arithmetic



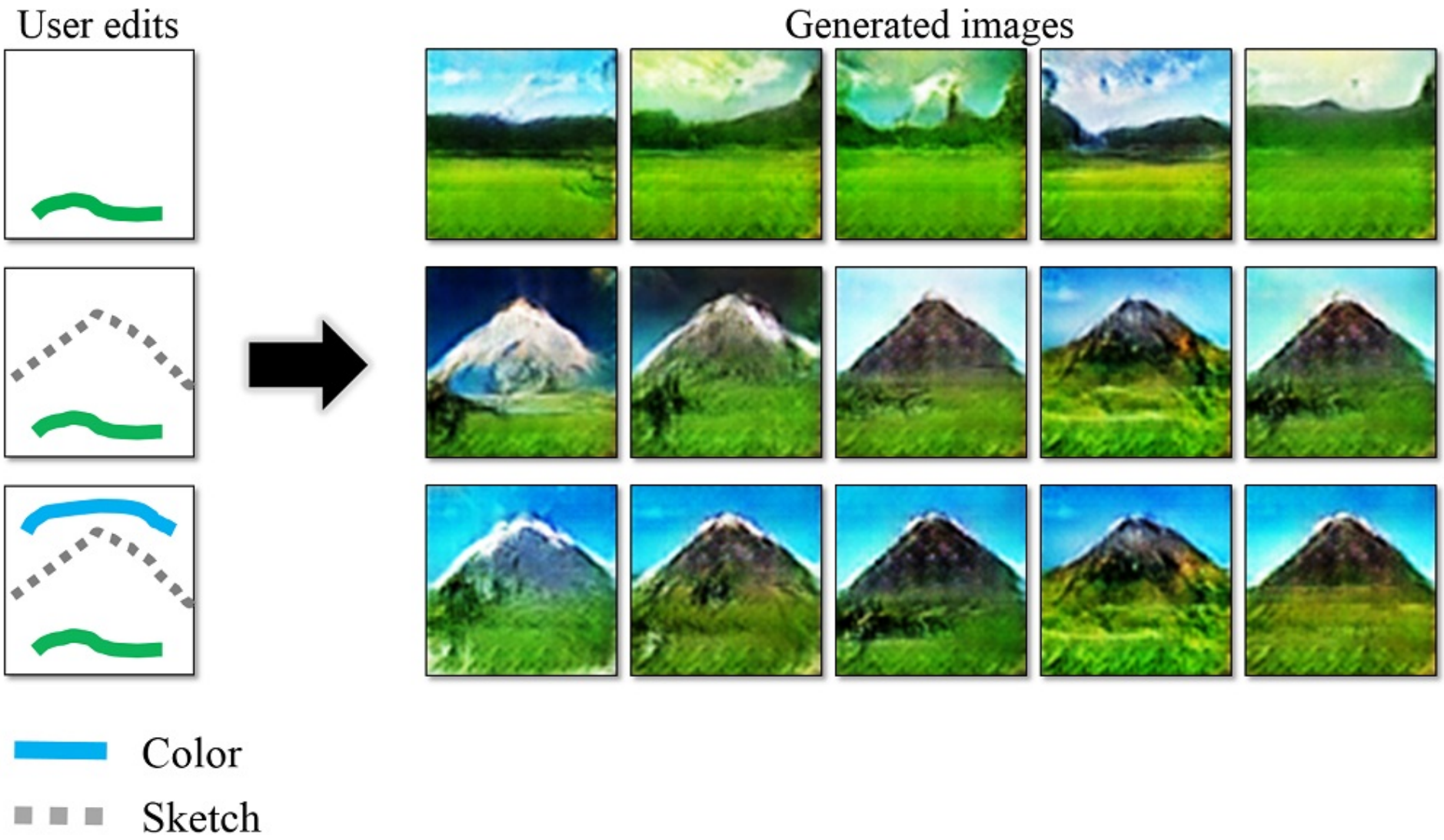
Results of doing the same arithmetic in pixel space

Interpolation between images

Super-Resolution



Interactive GAN



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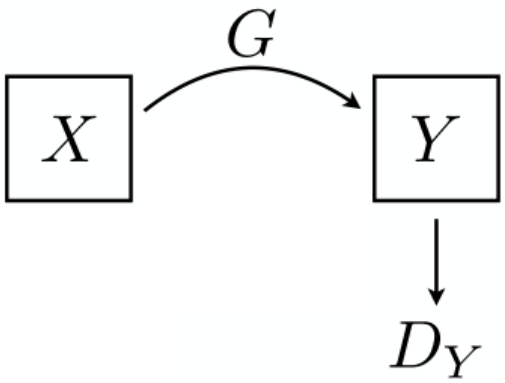

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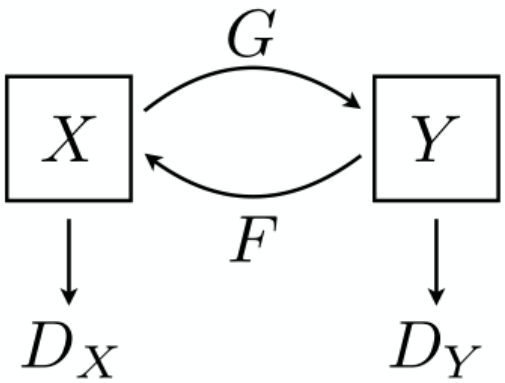

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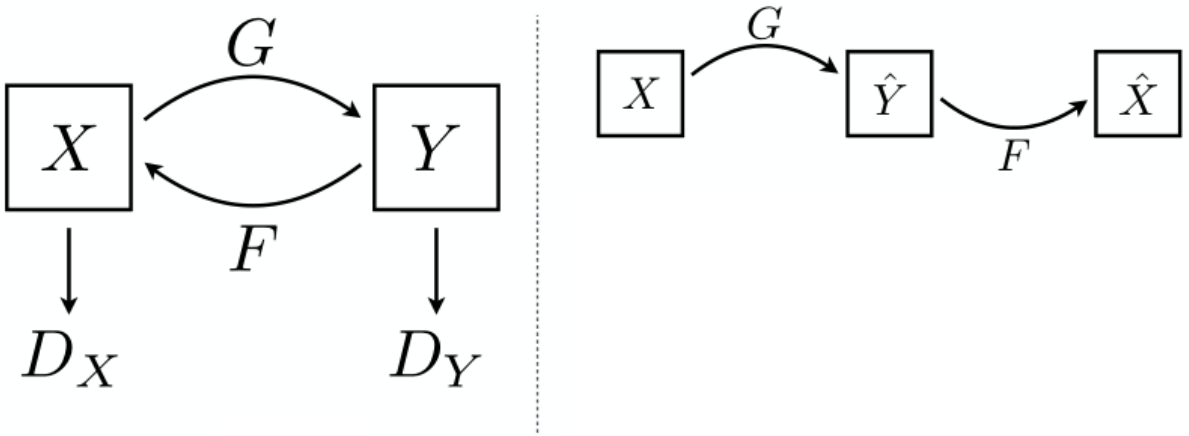

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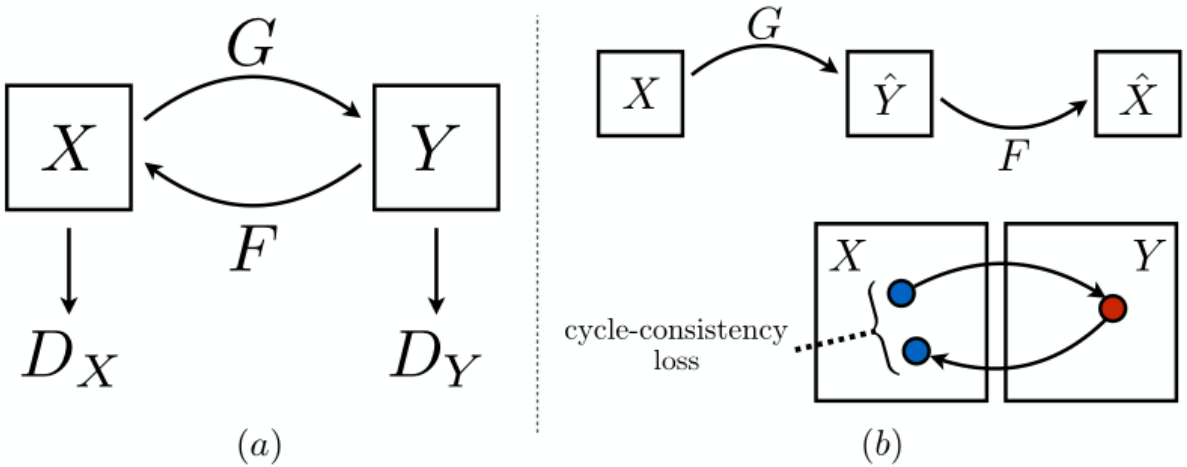

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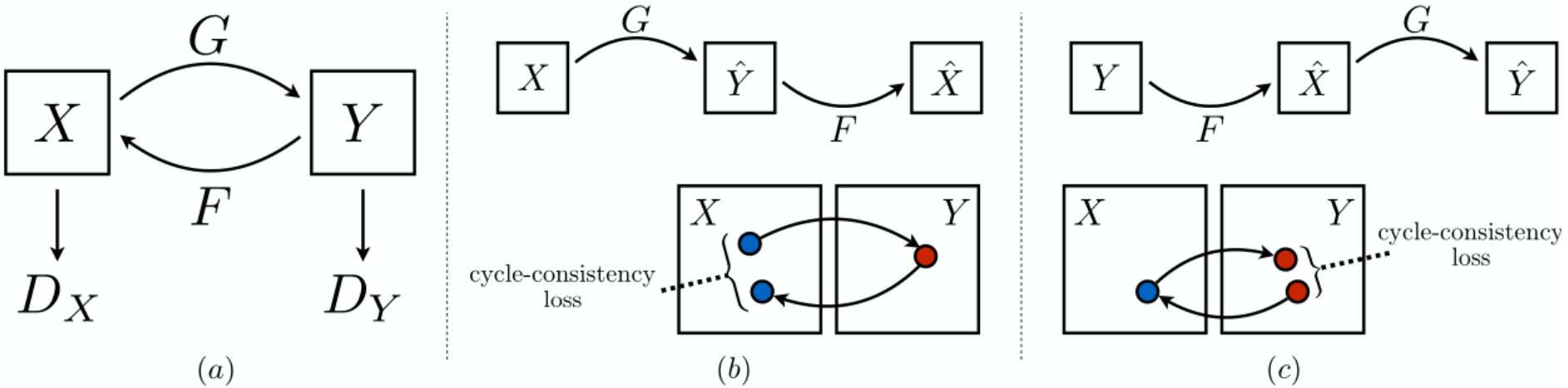

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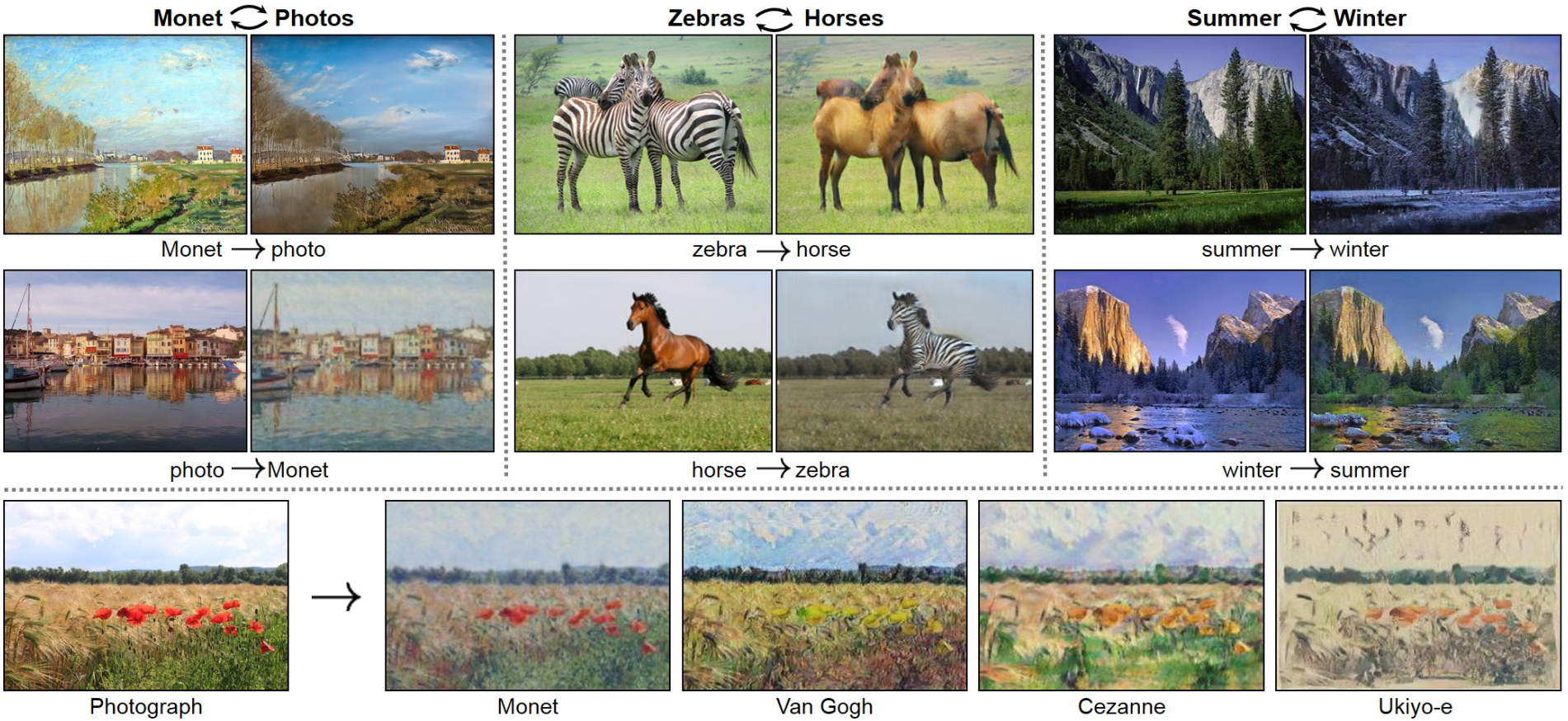

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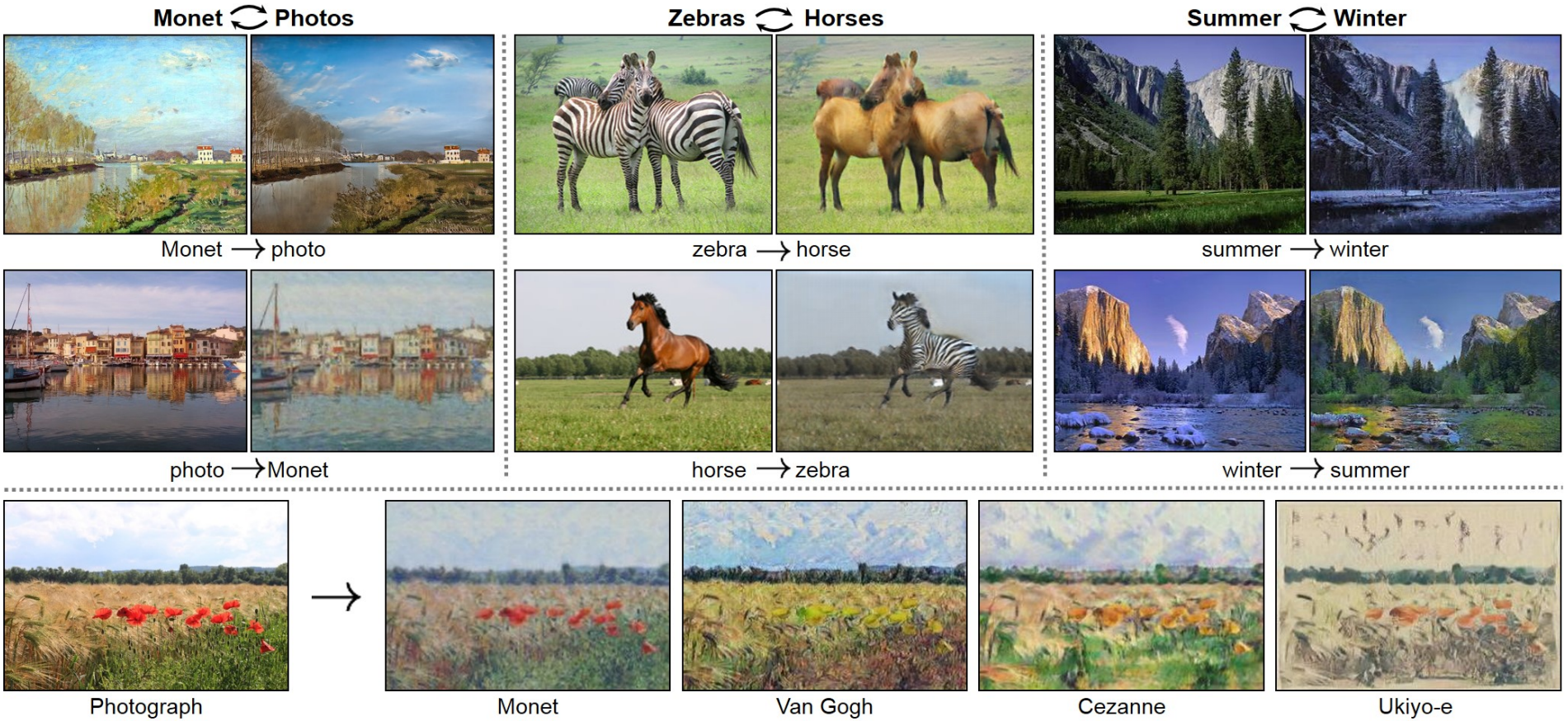
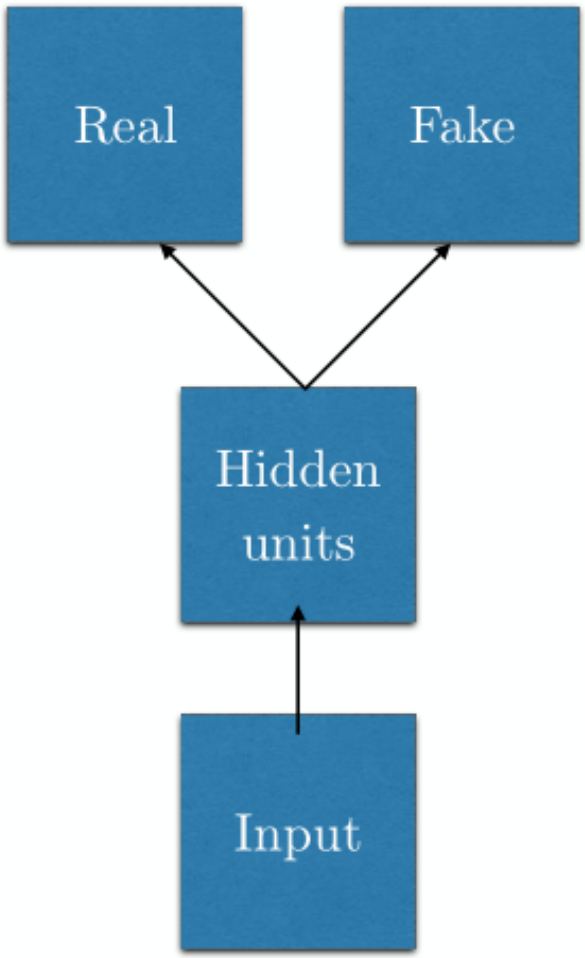
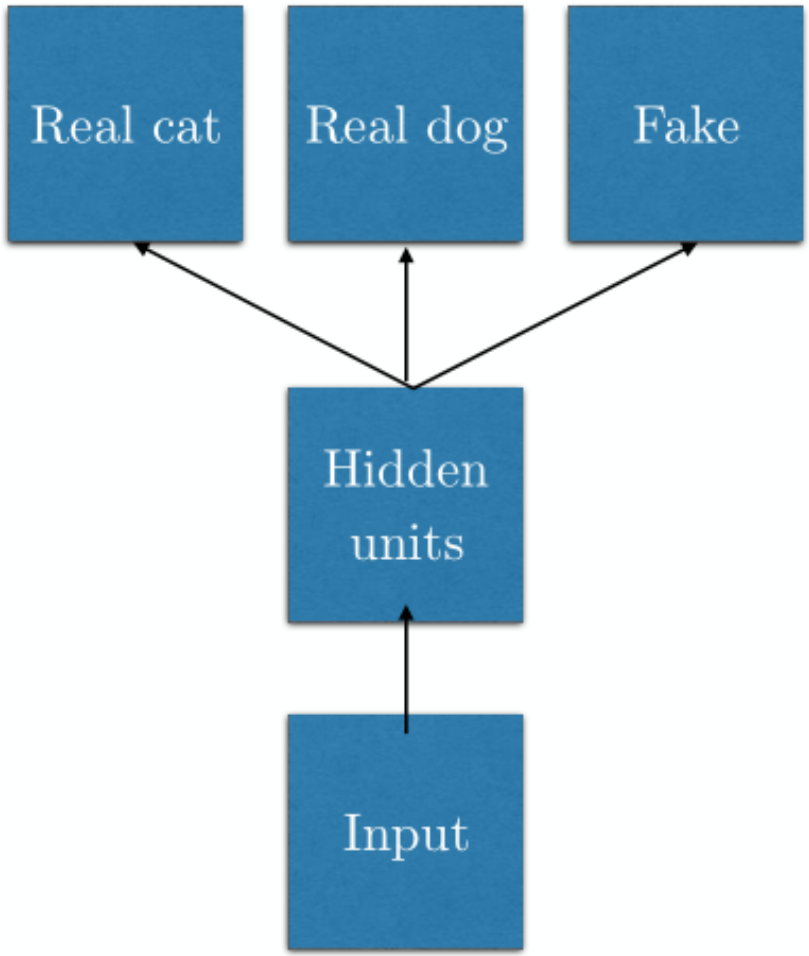


- CycleGAN in action
- Creepy CycleGAN

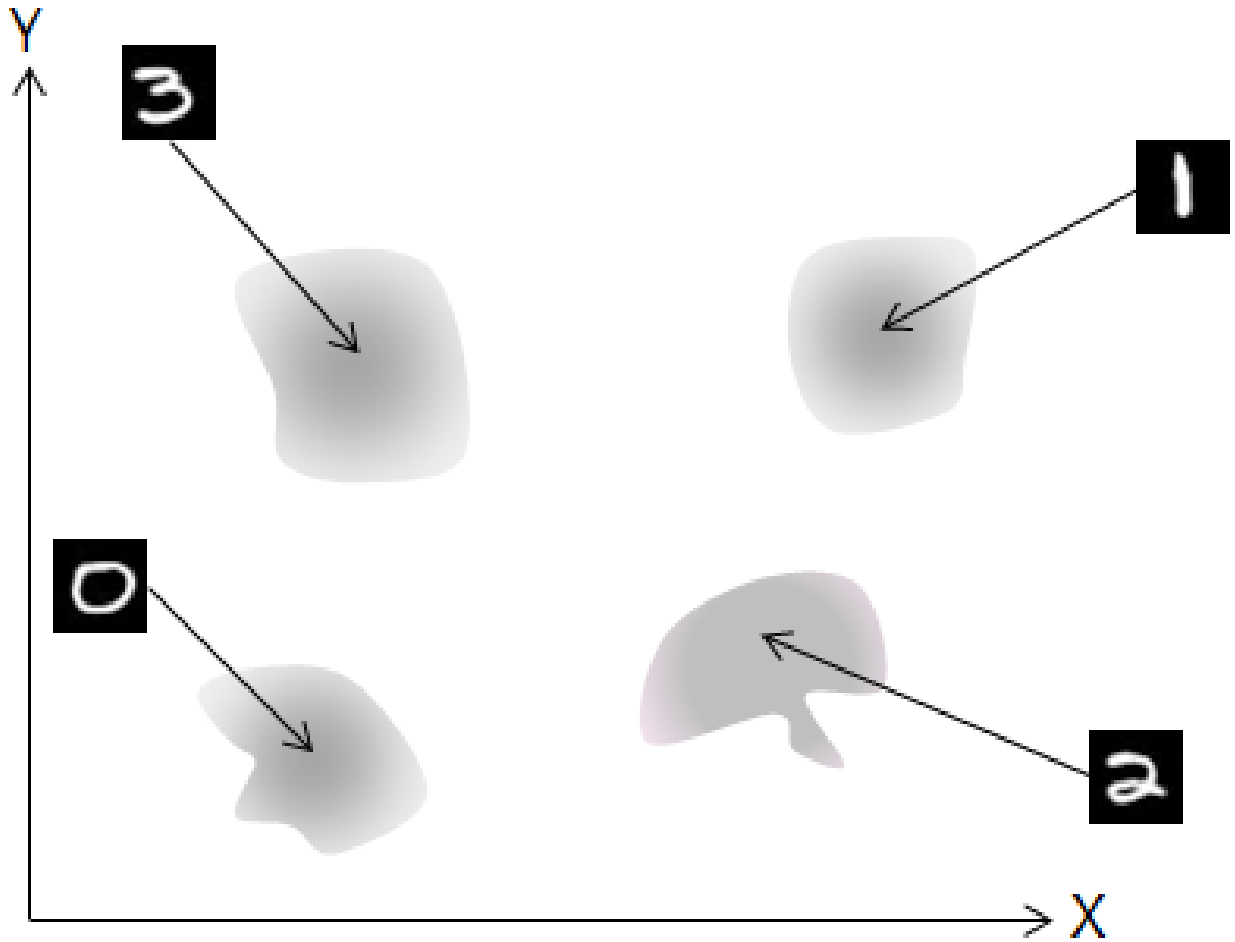
Failure case

Supervised discriminator





Problems with GANs - Mode collapse



[2] http://dl-ai.blogspot.com/2017/08/gan-problems.html

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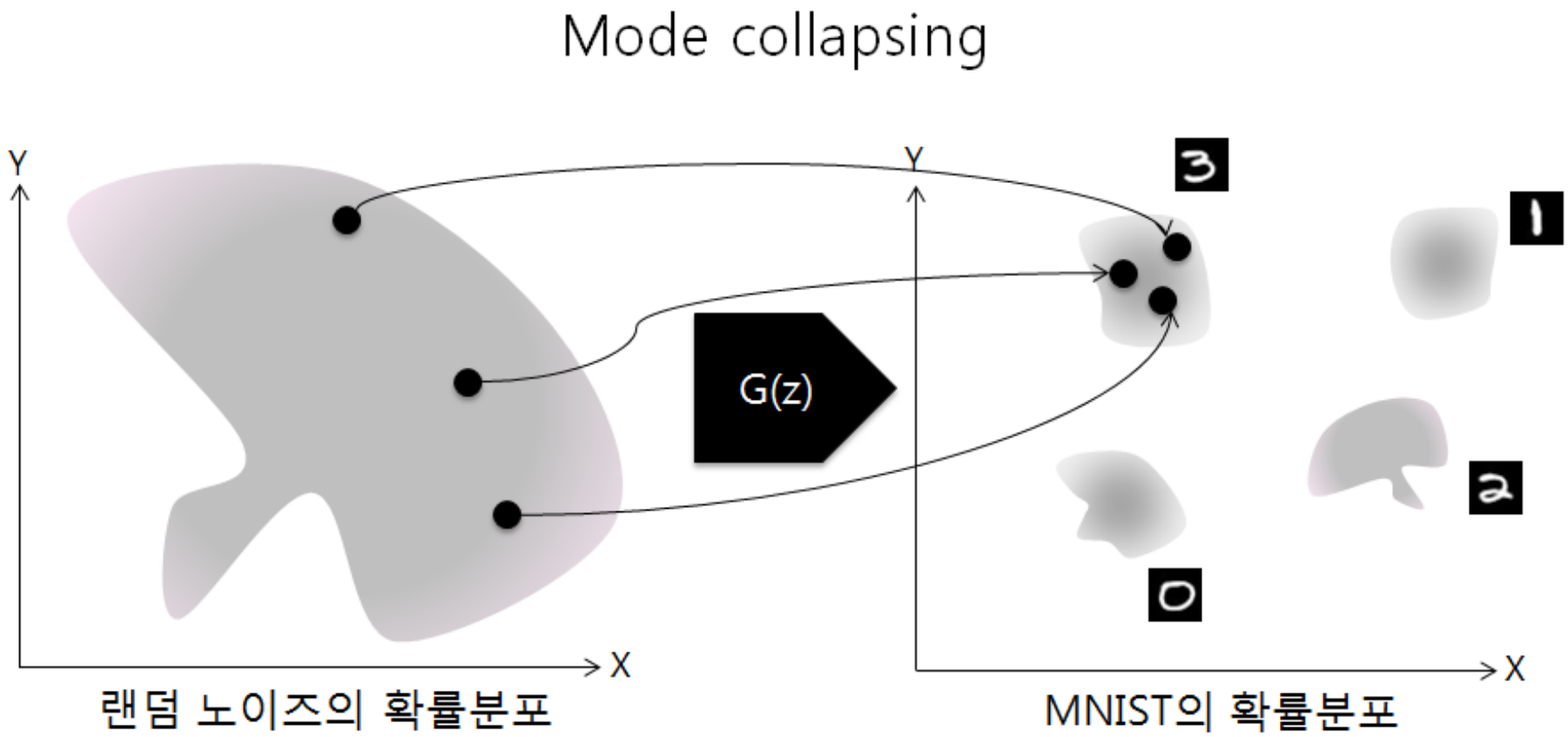

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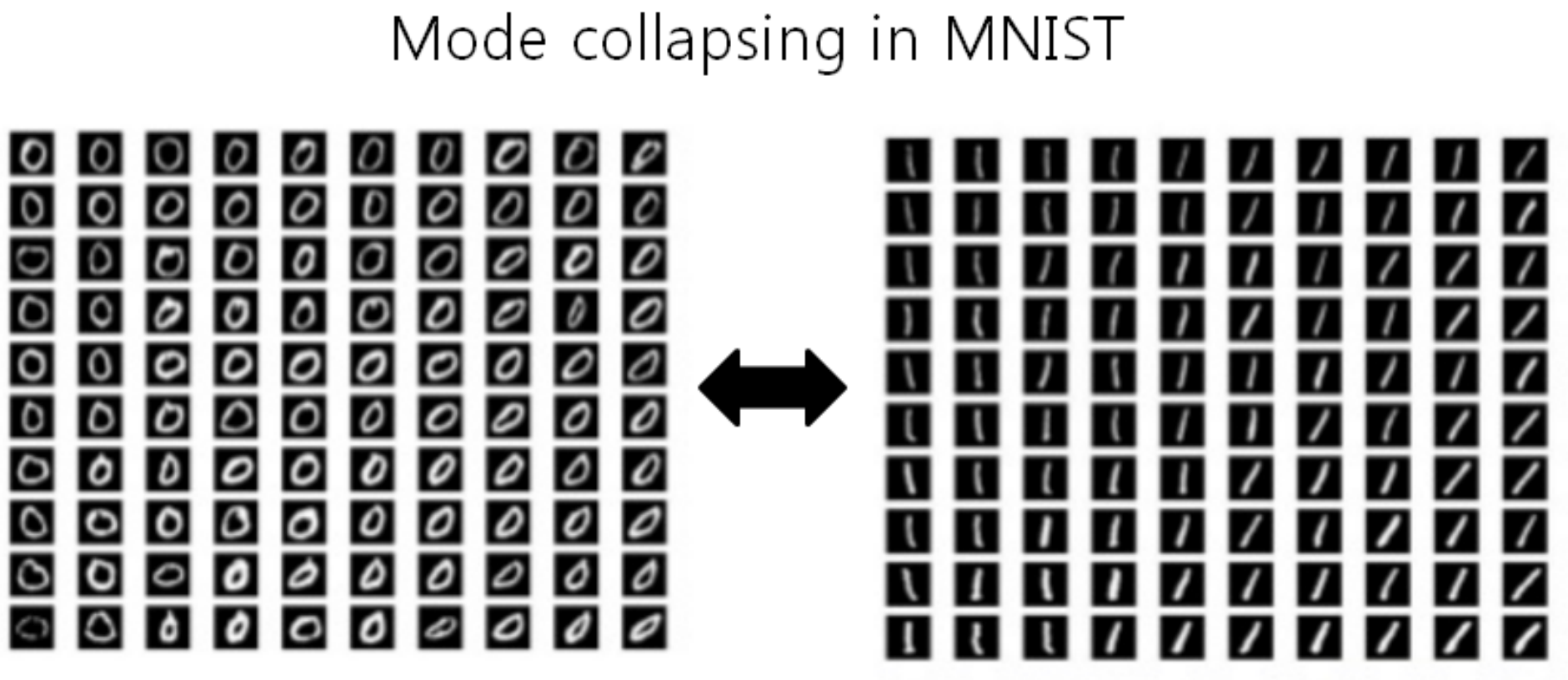

[2] http://dl-ai.blogspot.com/2017/08/gan-problems.html

Problems with GANs - Counting






[2] Ian J. Goodfellow: NIPS 2016 Tutorial: Generative Adversarial Networks

Problems with GANs - Perspective







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- Learning to learn

Cool links

- https://vincentherrmann.github.io/blog/wasserstein/
- https://www.alexirpan.com/2017/02/22/wasserstein-gan.html
- https://jeremykun.com/2018/03/05/earthmover-distance/
- https://lilianweng.github.io/lil-log/2017/08/20/from-GAN-to-WGAN.html

Thank you!

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Feel free to drop me an email with any questions!