
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

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IRB Seminar

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November 8, 2017

Overview

Meta

- What is this talk about?

Meta

- What is this talk about?
- New idea

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Yann LeCun

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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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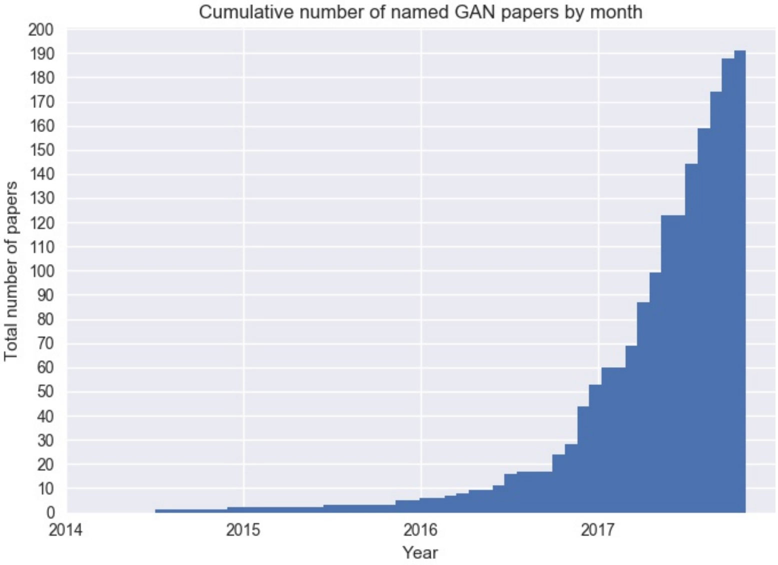
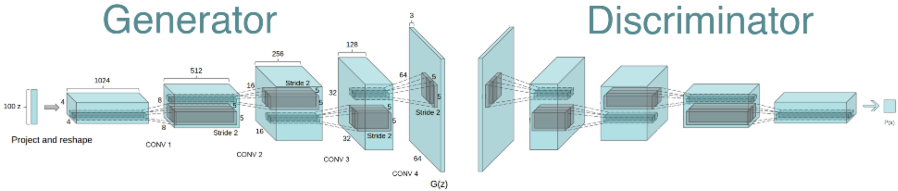
- Compared to other ML models, we're still in early stages
- Our understanding of it changes from week to week


Cumulative number of named GAN papers by month
Total number of papers
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
190
200
2014
2015
2016
2017
Year

GAN: Just tell me what it is

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



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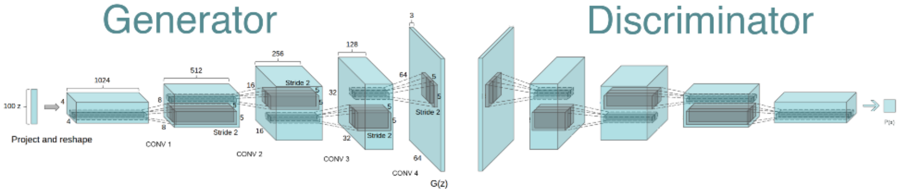

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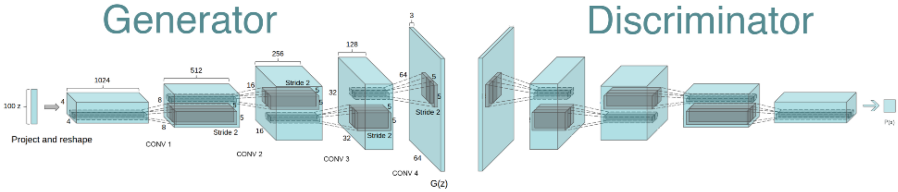

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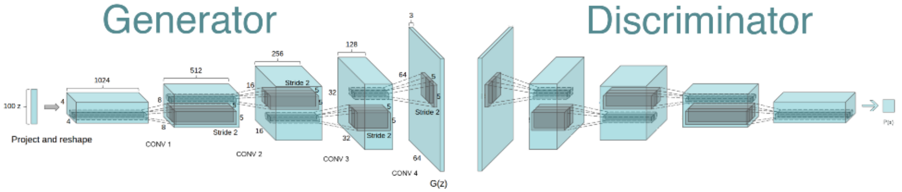

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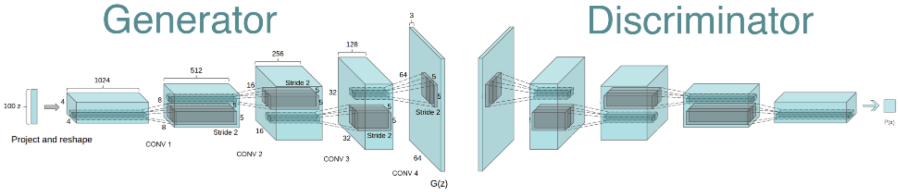

- Instead of using a standard fixed cost function, we *learn* the cost function with the neural network
- We alternate between training different parts of the network
- Forger and the police
- It's difficult to train and analyze

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Figure: Which side are real images?

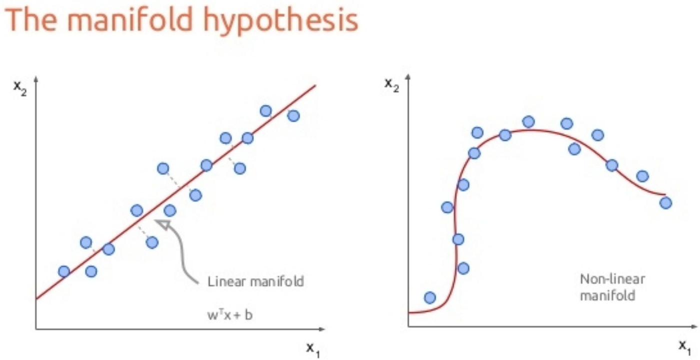
Figure: StackGAN

Are you ready?

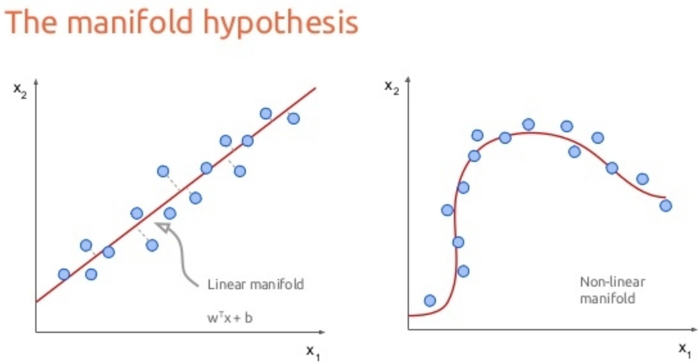
What is this talk about?

- Theory behind Generative Adversarial Networks
- Comparison of different models
- Practical advice for training
- Everything is a Work In Progress.

Prerequisites

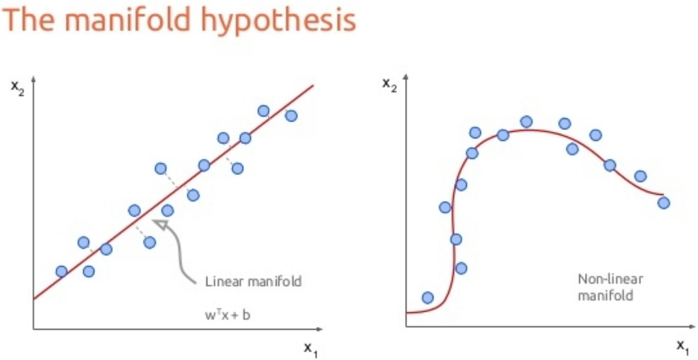


Prerequisites

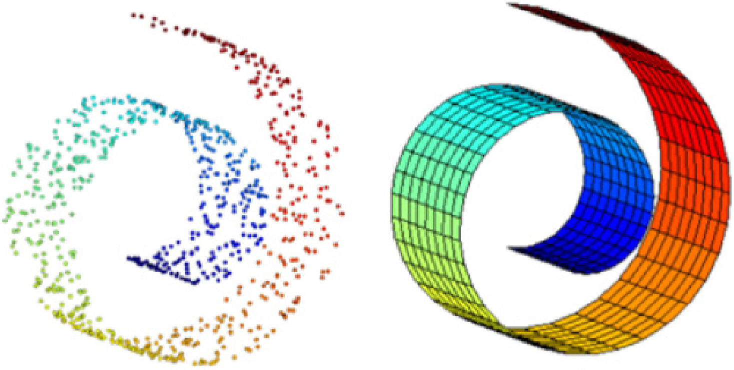


- Understanding real world data

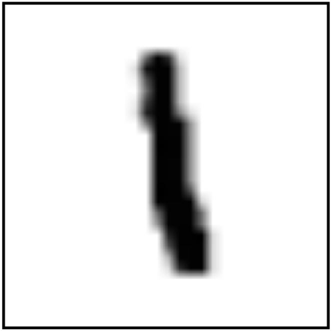
Prerequisites



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



(a) (b)



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

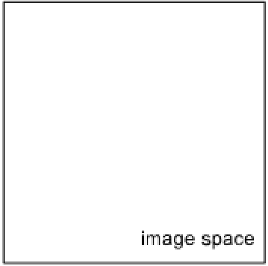


image space

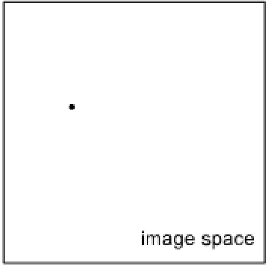
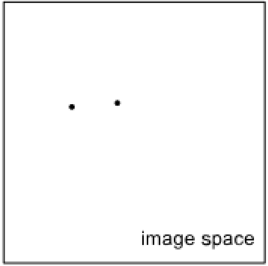


image space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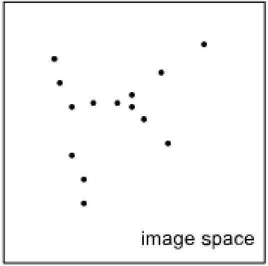
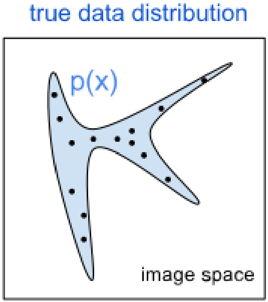
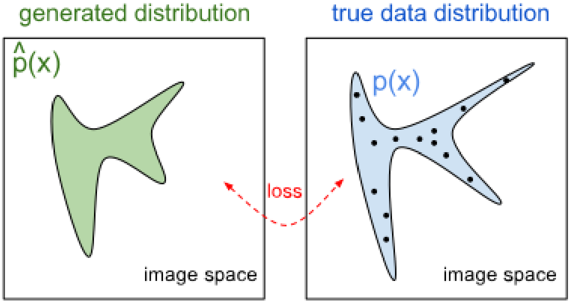
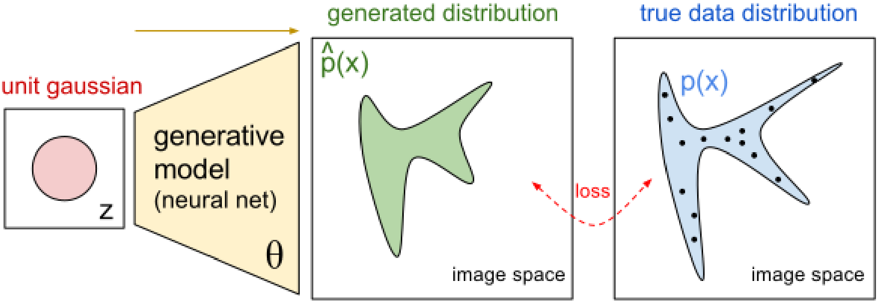


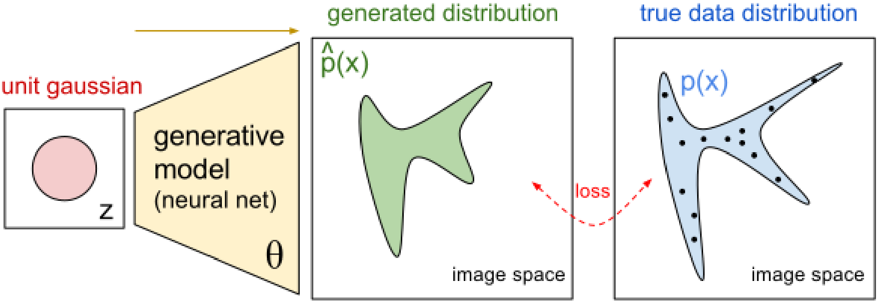
image space


true data distribution
p(x)
image space

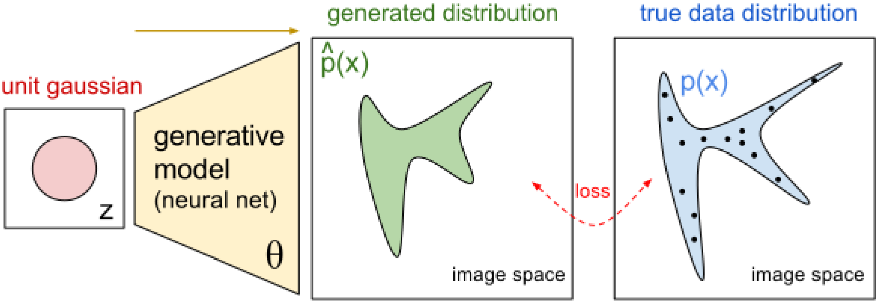

generated distribution
true data distribution
$\hat{p}(x)$
$p(x)$
loss
image space
image space



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



- We have a random vector $z \sim \mathcal{Z}$
- We can define a parametric function $g_\theta : \mathcal{Z} \rightarrow \mathcal{X}$ that generates samples from a certain distribution $\mathbb{P}_\theta$



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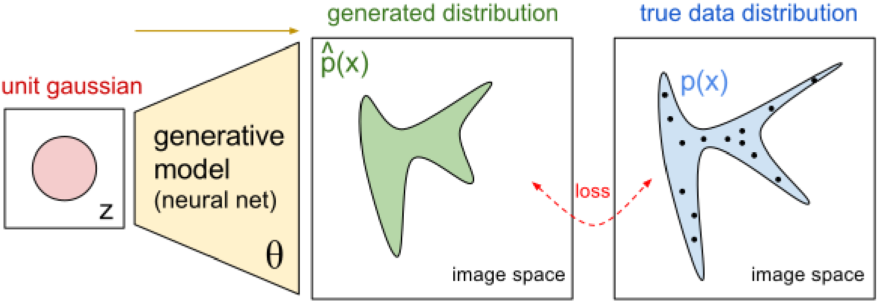

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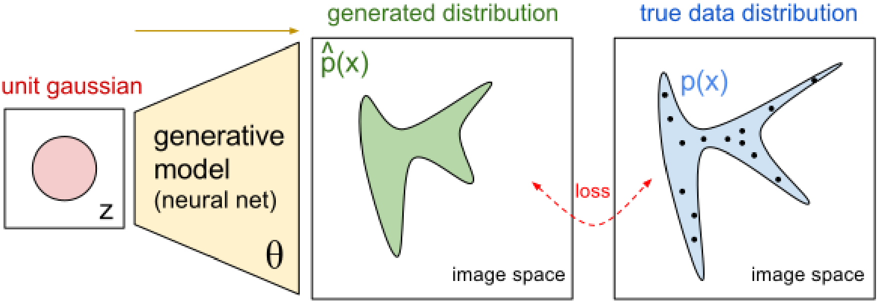

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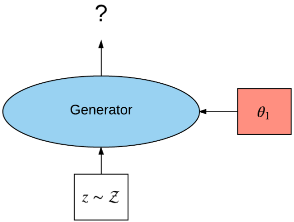
- How do we define “close"?

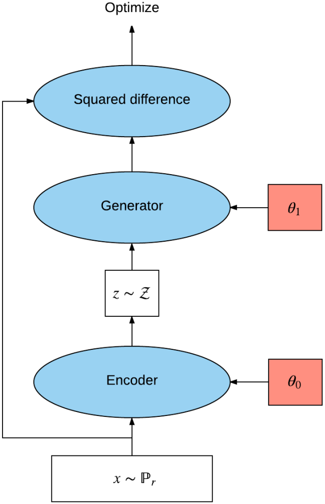
Autoencoder

- How to match the distributions?



Autoencoder

- How to match the distributions?
- Autoencoder as an example



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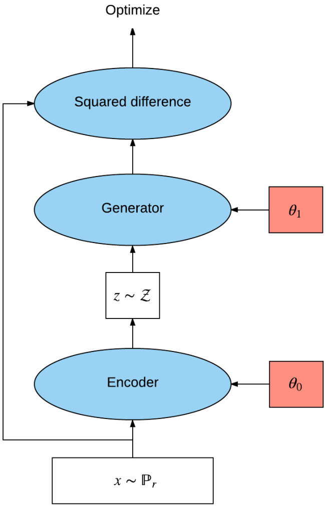

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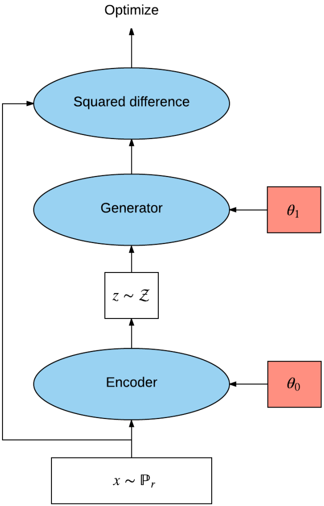

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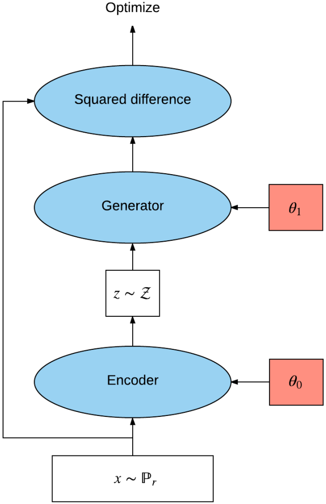
Things to note

1. Cost function is a part of the computational graph
2. Cost function is not parametrized (it's fixed)
3. We train the network with just one cost function
4. Weight freezing and sharing is fixed throughout the training



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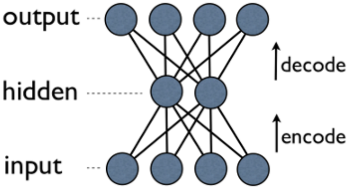

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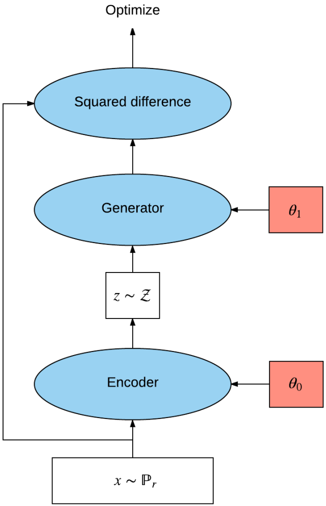
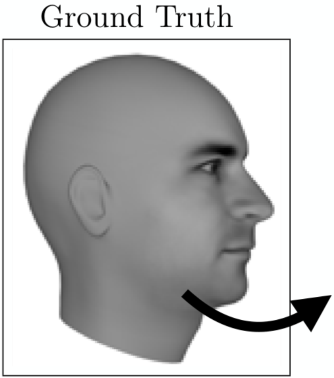


Cost function

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



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

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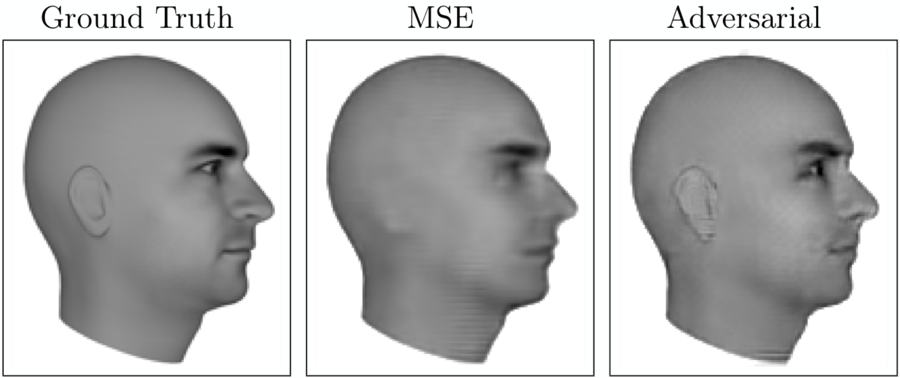

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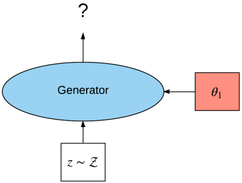
- How do we even train this thing?
- How do we analyze it's behaviour?
- Partial answer to the "How do we know it's close?" question from the beginning

Training regime



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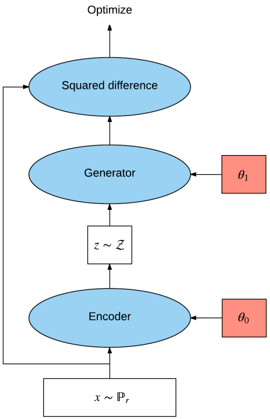

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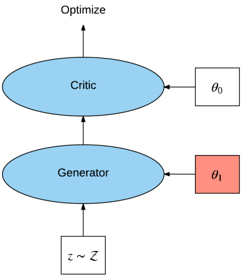

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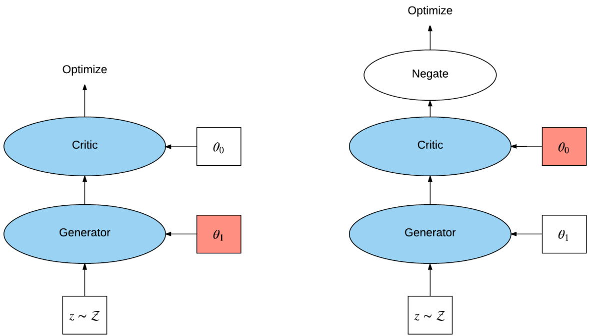

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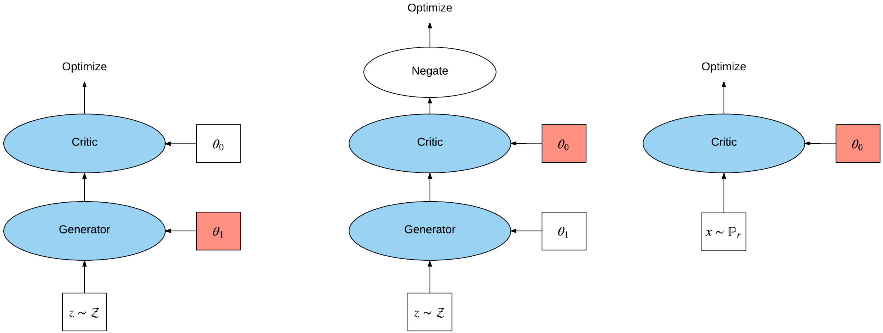

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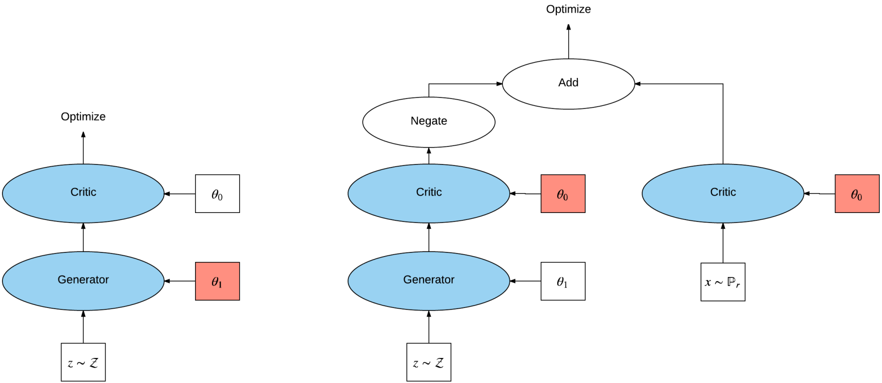

- Two-step optimization optimization process

Different statistical distances

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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

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

Kullback-Leibler and Jensen Shannon divergence

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JS-divergence

$$\mathbb{M} = \frac{1}{2}(\mathbb{P} + \mathbb{Q})$$

Kullback-Leibler and Jensen Shannon divergence

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JS-divergence

$$\mathbb{M} = \frac{1}{2}(\mathbb{P}+\mathbb{Q})$$

$$JS(\mathbb{P}||\mathbb{Q}) = \frac{1}{2}KL(\mathbb{P}||\mathbb{M}) + \frac{1}{2}KL(\mathbb{Q}||\mathbb{M})$$

Kullback-Leibler and Jensen Shannon divergence

KL-divergence

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

- Doesn't satisfy triangle inequality and symmetry
- Origins in information theory
- Information gained when revising from prior Q to posterior P

JS-divergence

$$\mathbb{M} = \frac{1}{2}(\mathbb{P}+\mathbb{Q})$$

$$JS(\mathbb{P}||\mathbb{Q}) = \frac{1}{2}KL(\mathbb{P}||\mathbb{M}) + \frac{1}{2}KL(\mathbb{Q}||\mathbb{M})$$

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

Wasserstein (Earth mover) distance

EM distance

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- Distance function that takes into account underlying geometry of the distributions

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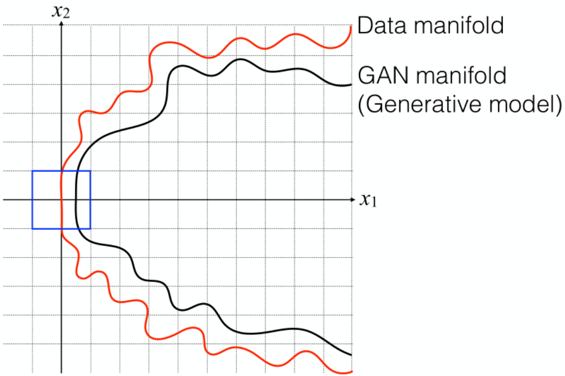
- Proposed by Arjovsky *et al.* as improvement to original GAN training - Wasserstein GAN
- Intractable

Learning distributions - toy example



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

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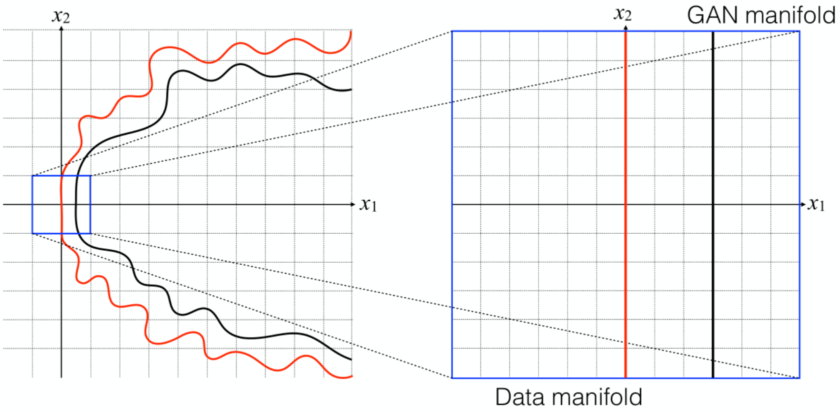

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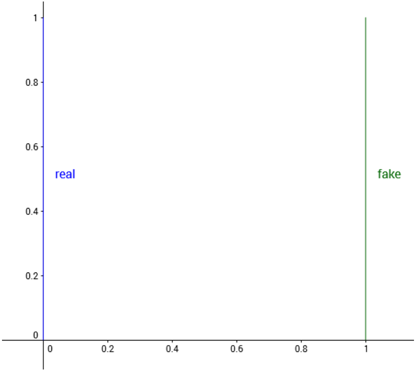

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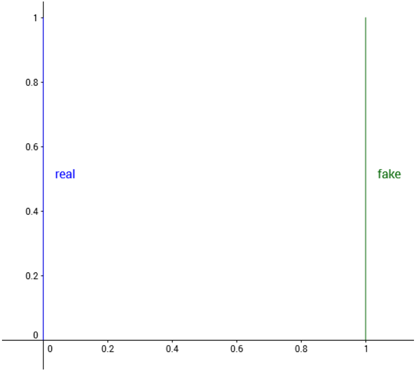

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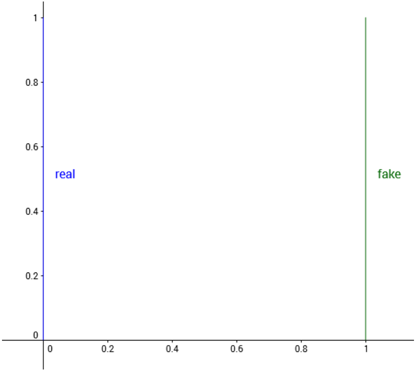

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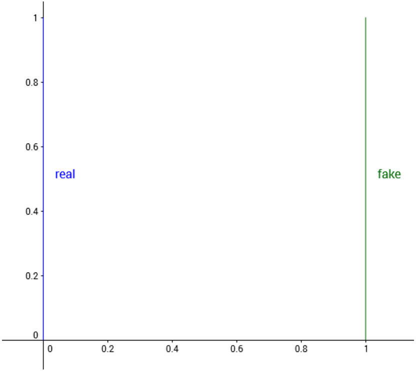

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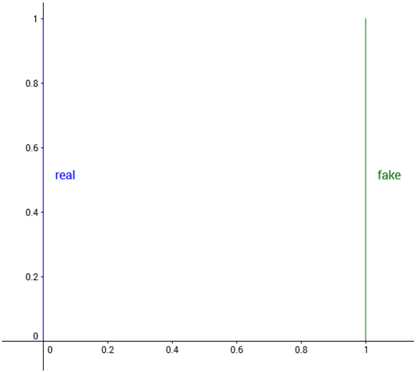

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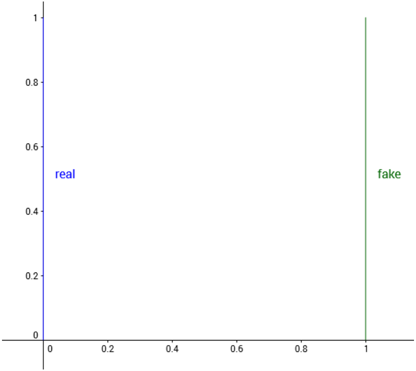

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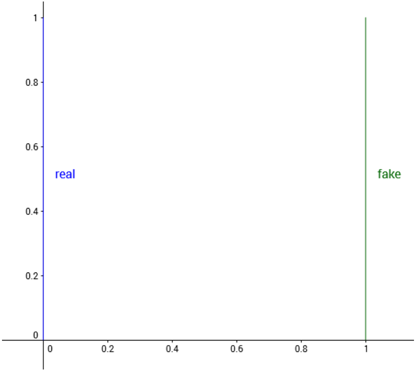

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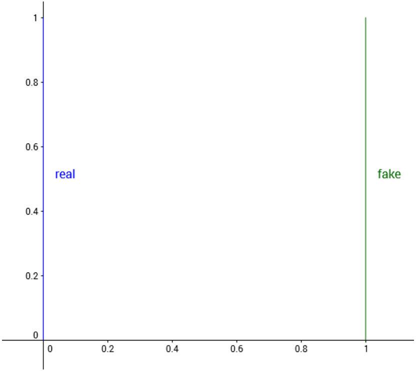

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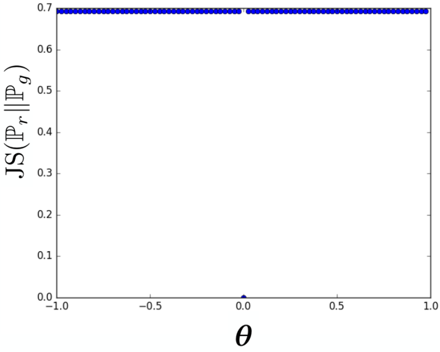
JS and EM distance w.r.t. θ



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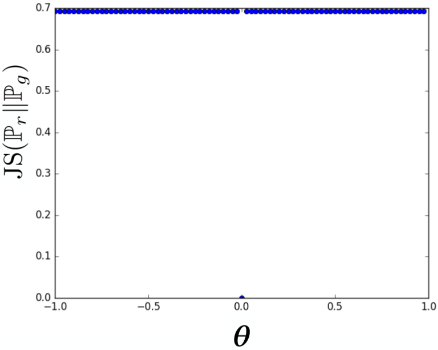

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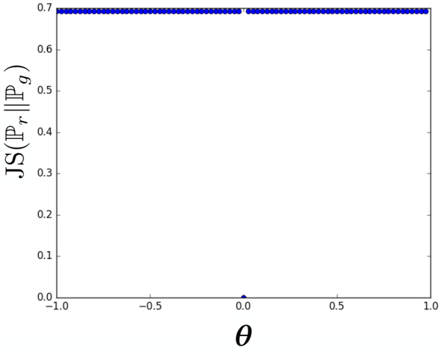

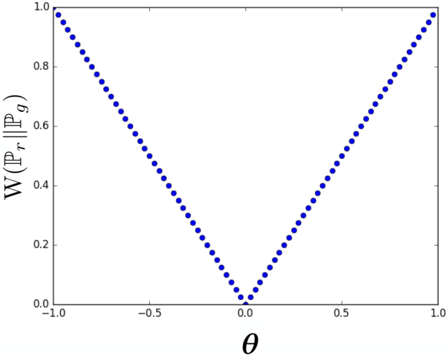

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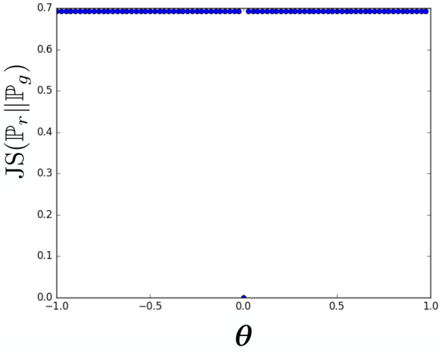
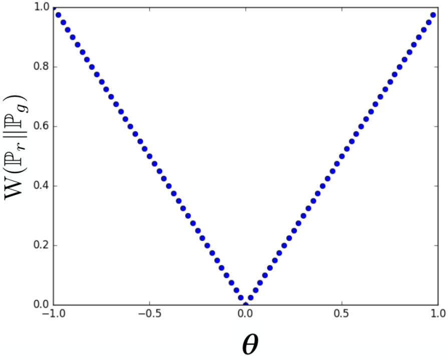
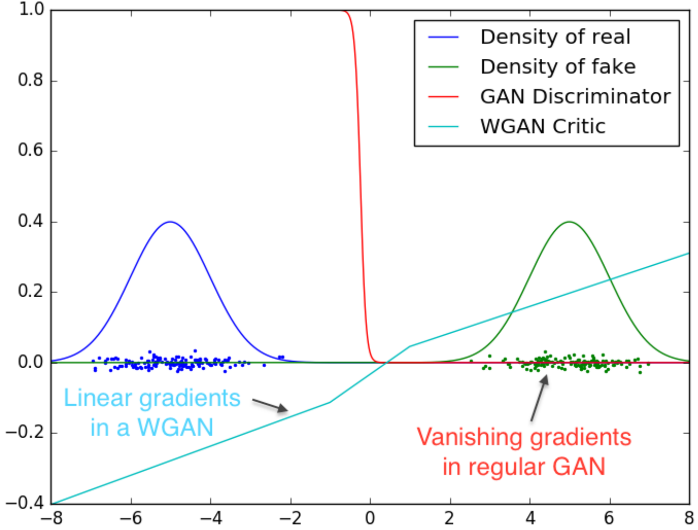




- JS-divergence gradient is zero
- Wasserstein gradient is constant

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

GAN Value function

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

- 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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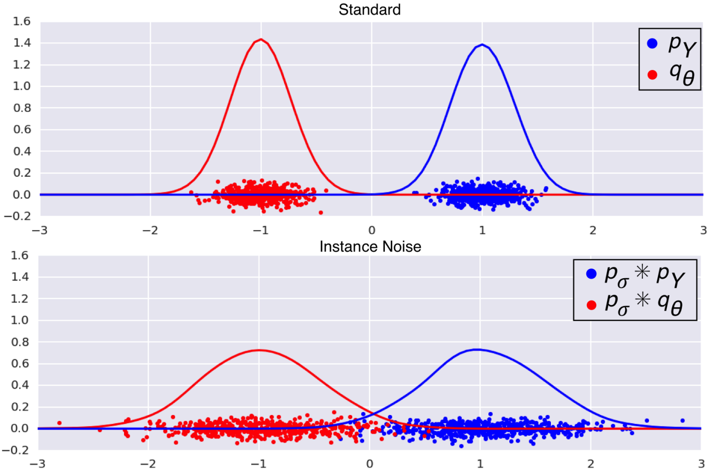
- Bag of tricks

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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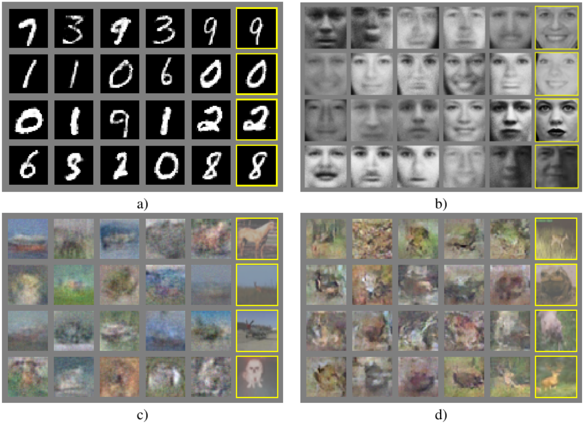
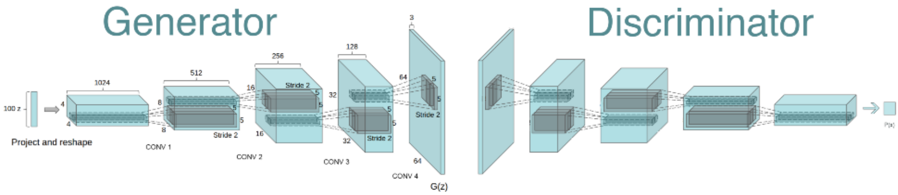
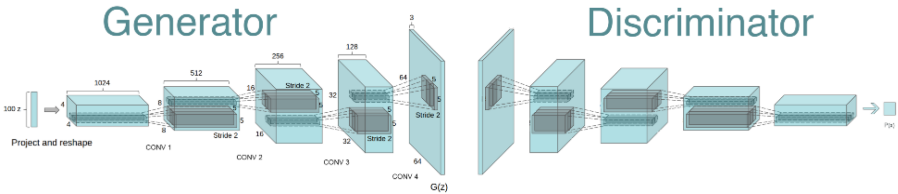


Trick - cherrypicking architecture - DCGAN



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



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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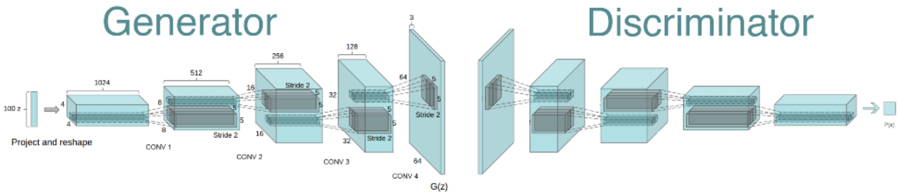

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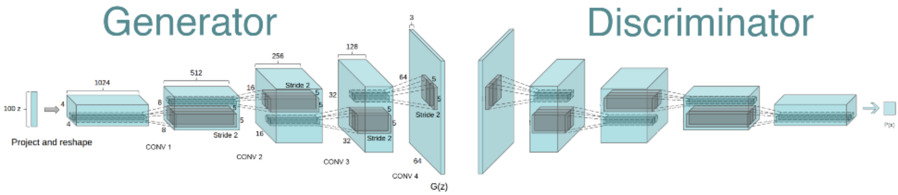

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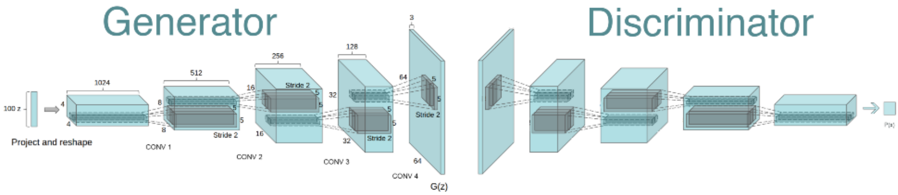

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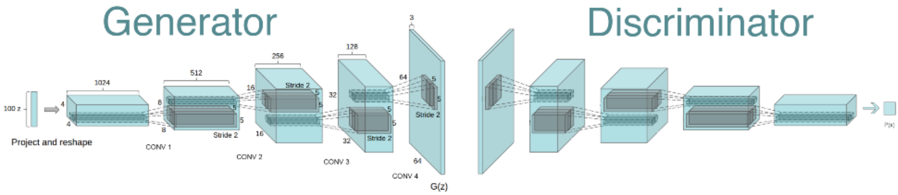

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Trick - not training the discriminator until convergence

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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

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

Short history of training GANs - January 2017

Wasserstein GAN

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

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

Jan 2017

WGAN Value function

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

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

Short history of training GANs

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

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Kantorovich-Rubinstein duality

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

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

Short history of training GANs

EM distance

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

- How to compute the infimum?
- 1000 page book on Optimal Transport [2]
- Kantorovich-Rubinstein duality

Kantorovich-Rubinstein duality

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

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

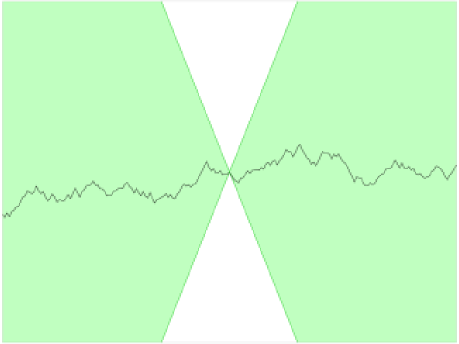
[2] `http://cedricvillani.org/wp-content/uploads/2012/08/preprint-1.pdf`

Lipschitz continuity

K-Lipschitz function

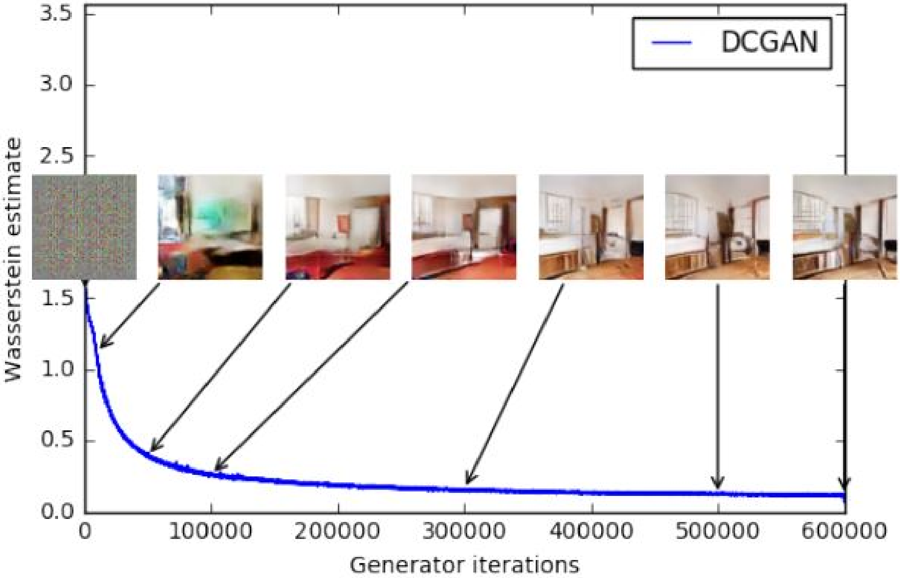
$$|f(x_1) - f(x_2)| \leq K \cdot |x_1 - x_2|, \qquad \forall x_1, x_2$$

- Continuous function which is limited how fast it can change
- Every function that has a bounded first derivative is Lipschitz

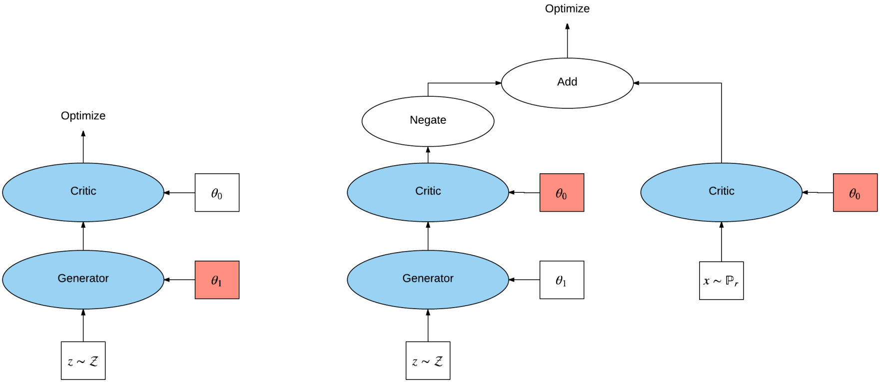


[2] https://en.wikipedia.org/wiki/Lipschitz_continuity

Meaningful loss function



Wasserstein GAN



- Using EM distance instead of JS-divergence leads to robust models
- Theoretical and empirical data
- No need for tricks

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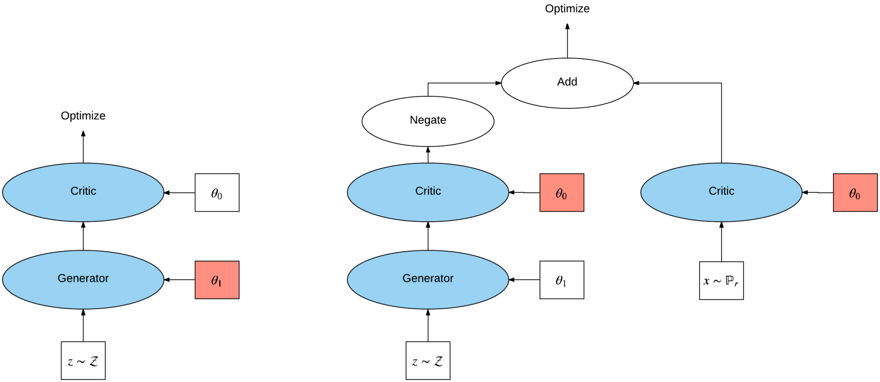

- Using EM distance instead of JS-divergence leads to robust models
- Theoretical and empirical data
- No need for tricks
- Open question - how to effectively enforce the Lipschitz constraint?

Method #1 - Weight Clipping

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

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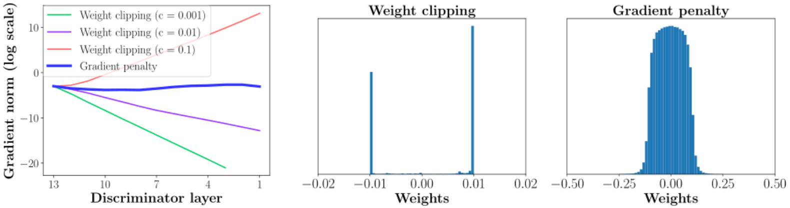

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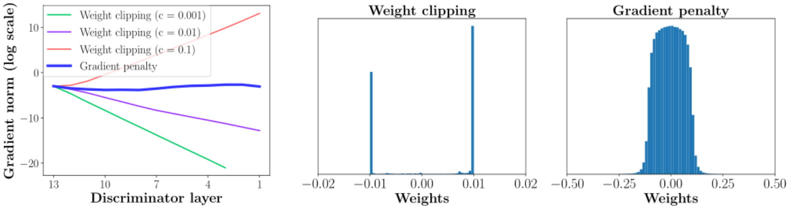

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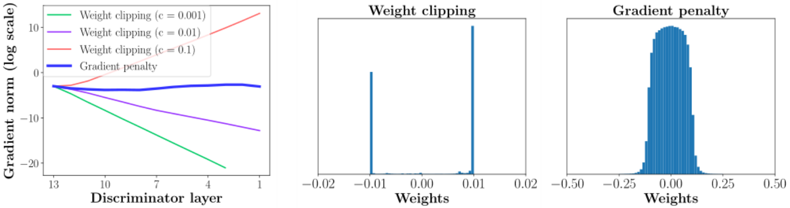

- Works! But...
- Capacity underuse
- Exploding and vanishing gradients

Method #2 - Gradient Penalty

- Property of the optimal WGAN critic $|f(x) - f(y)| \leq |x - y|$

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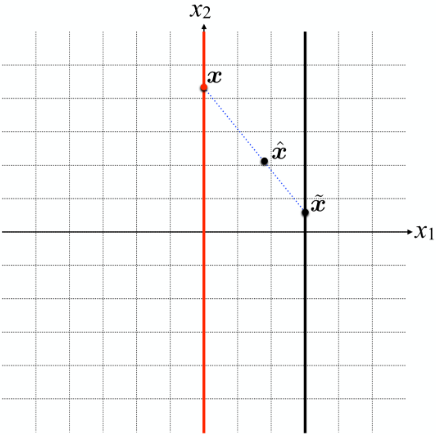

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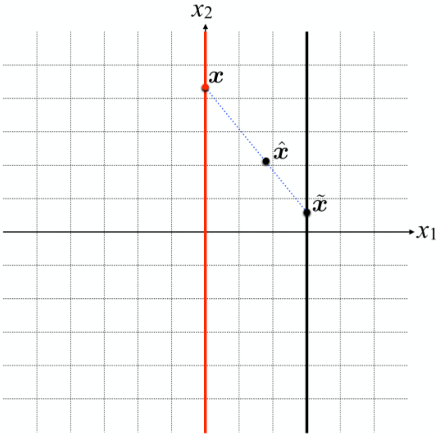

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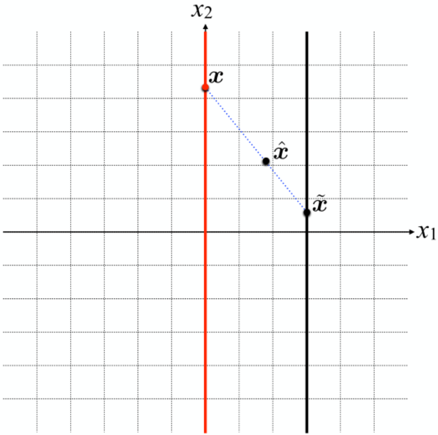

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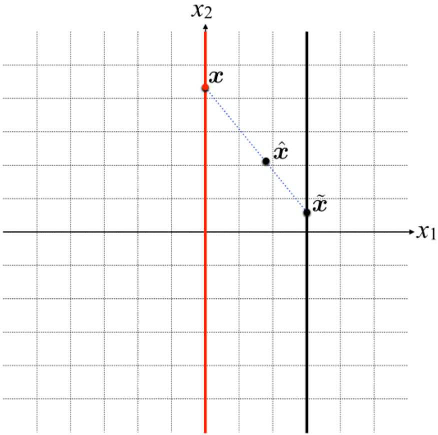
$$\mathbb{E}_{\hat{\boldsymbol{x}} \sim \mathbb{P}_{\hat{\boldsymbol{x}}}} \left[(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1)^2 \right]$$



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
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igul222@gmail.com
{faruk.ahmed,vincent.dumoulin,aaron.courville}@umontreal.ca
ma4371@nyu.edu

WGAN-GP Value function

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

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- Enforcing the Lipschitz constraint with a gradient penalty regularization term

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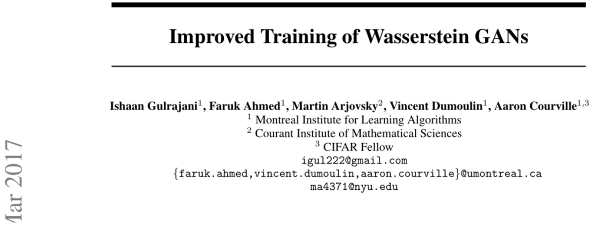

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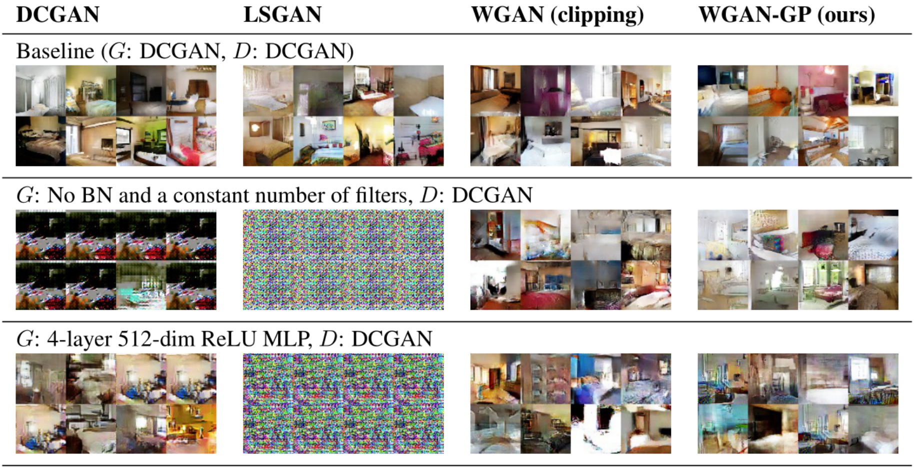
- Enforcing the Lipschitz constraint with a gradient penalty regularization term
- Improvements?

WGAN-GP results



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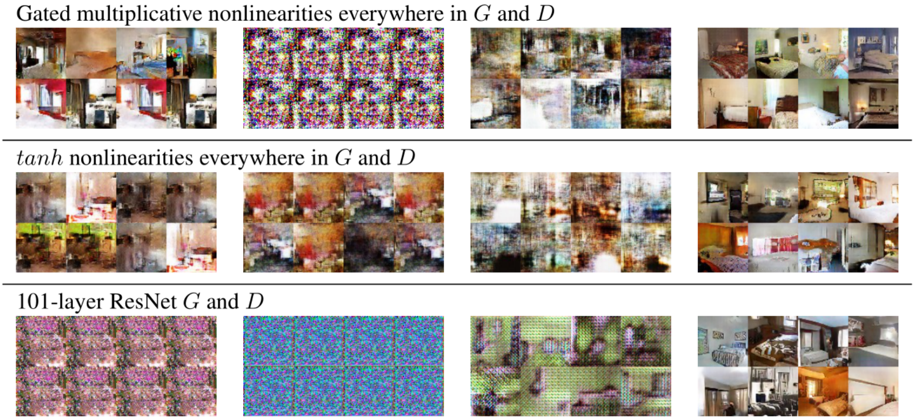

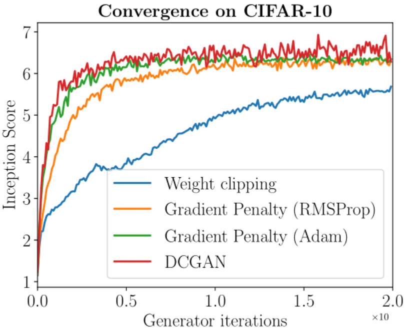

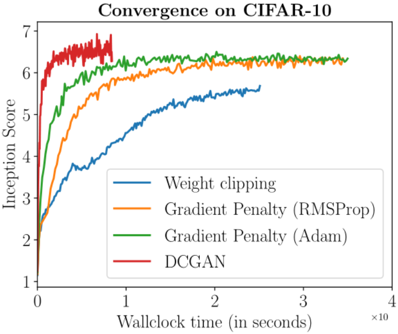

- DCGAN converges faster
- Significantly outperforms weight clipping
- **Robust to changes in model architecture**

Game theory perspective

- Two neural networks are playing a zero-sum game

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- Nash equilibrium

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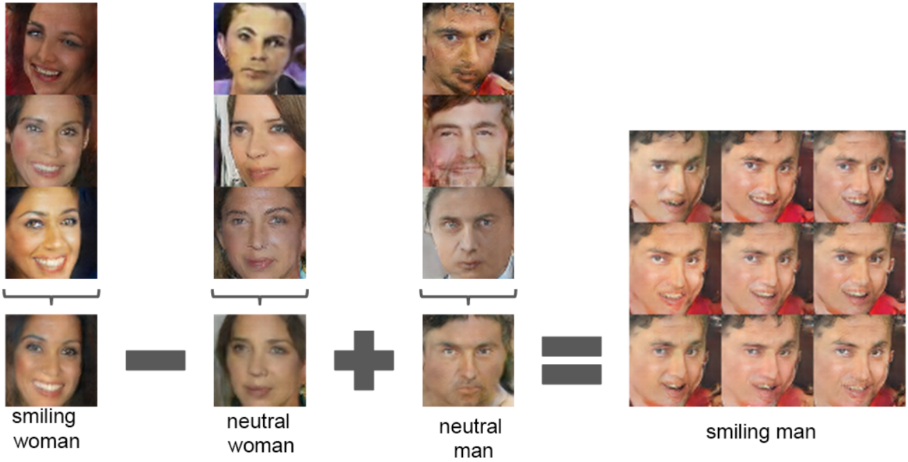
- Two neural networks are playing a zero-sum game
- Nash equilibrium
- Goal - both players adopting strategies where any deviations would be disadvantageous
- Lack of theoretical insights

Cool things you can do with GANs

Latent space arithmetic



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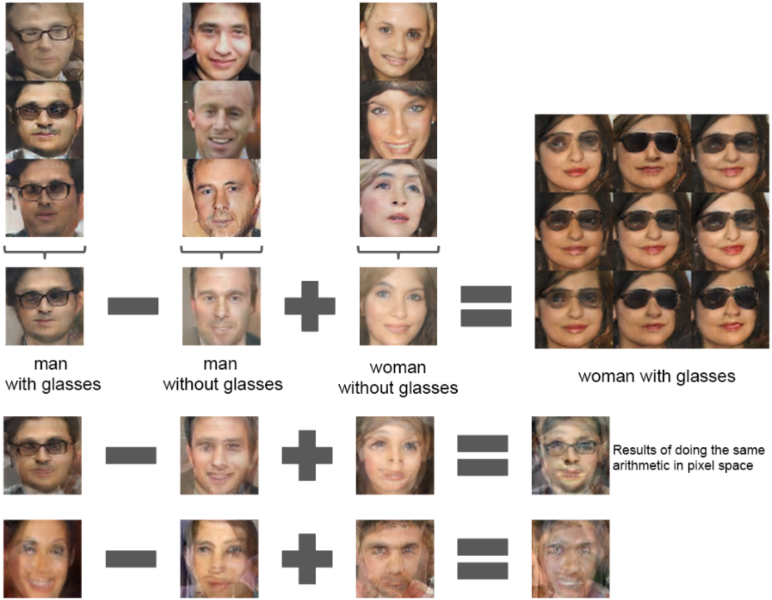
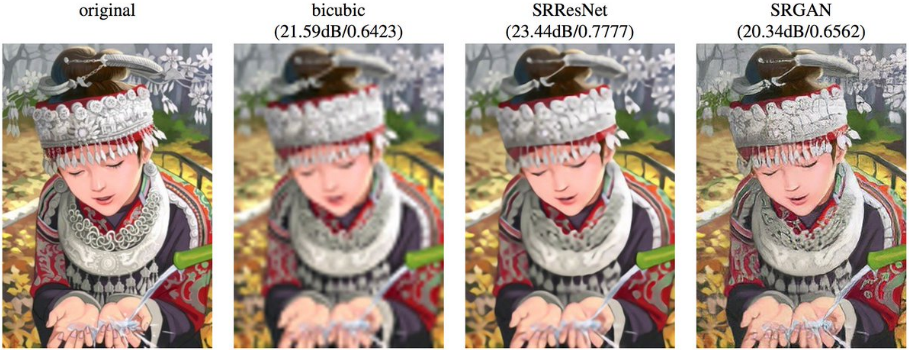
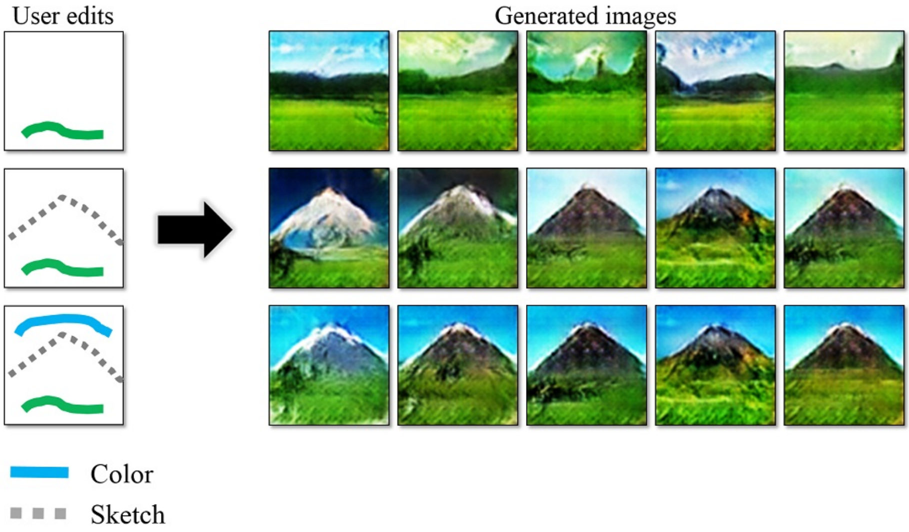


Interpolation between images

Super-Resolution



Interactive GAN

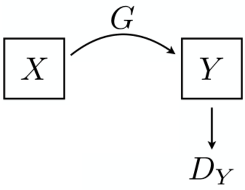


▸ Interactive GAN

Style Transfer

$\boxed{X}$ $\qquad\qquad$ $\boxed{Y}$

Style Transfer



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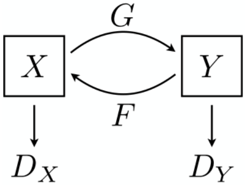

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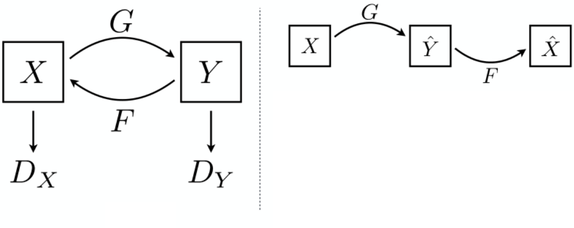

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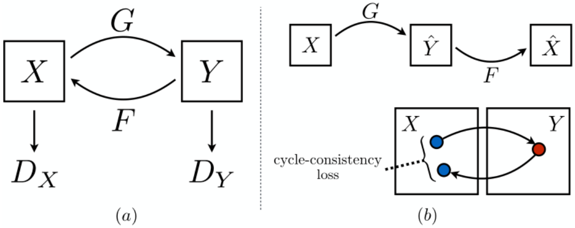

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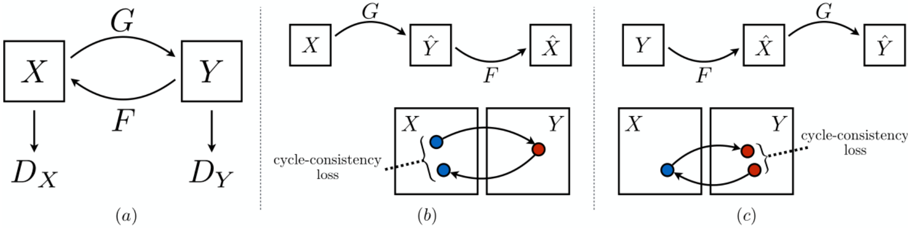

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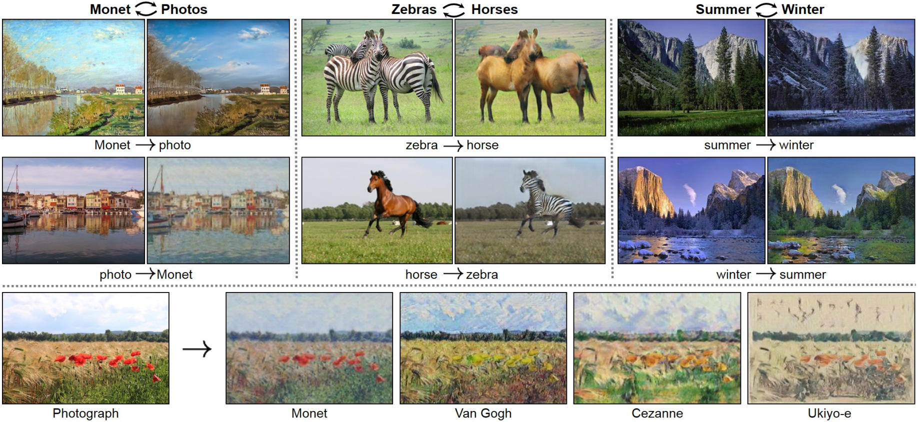

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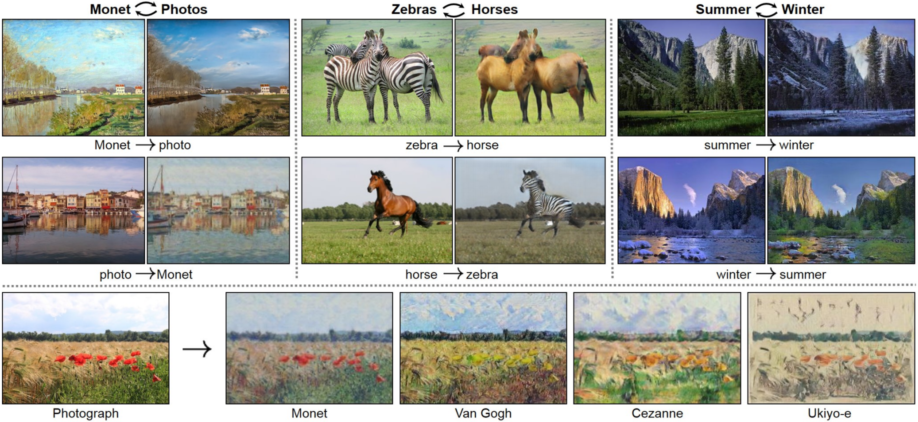
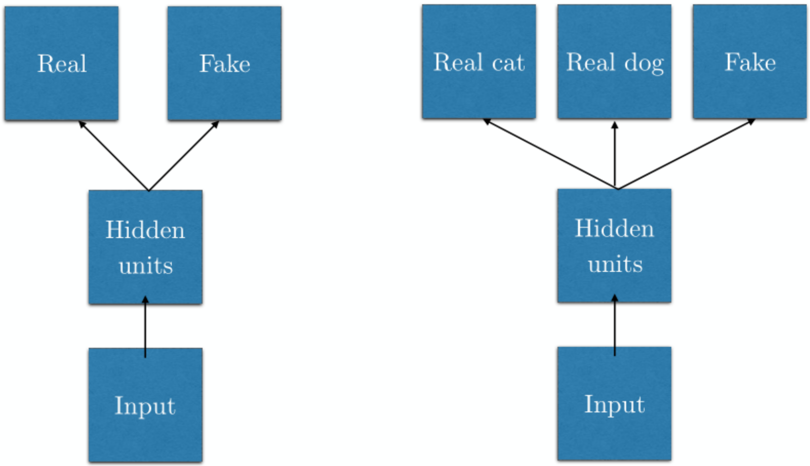


- CycleGAN in action
- Creepy CycleGAN

Failure case

Supervised discriminator



Heuristics for training WGANs

- Make sure your critic is "ahead of" the generator!
- 5-10x more than the generator reduces oscillatory behaviour
- Should work without any hyperparameter tuning

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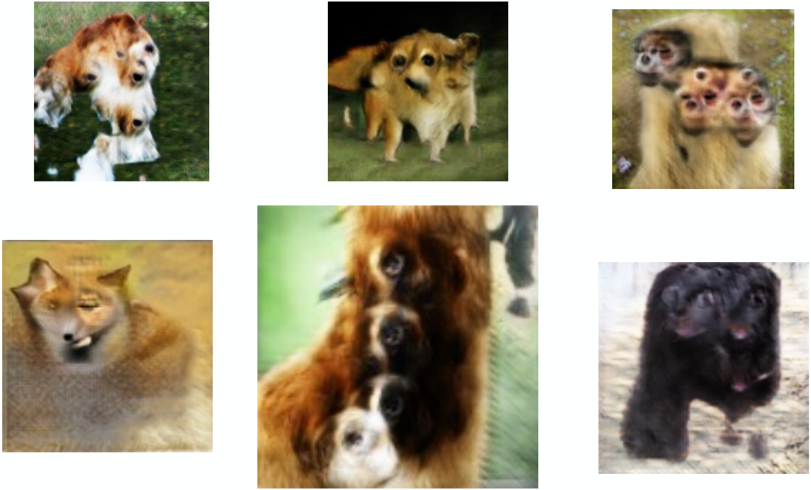
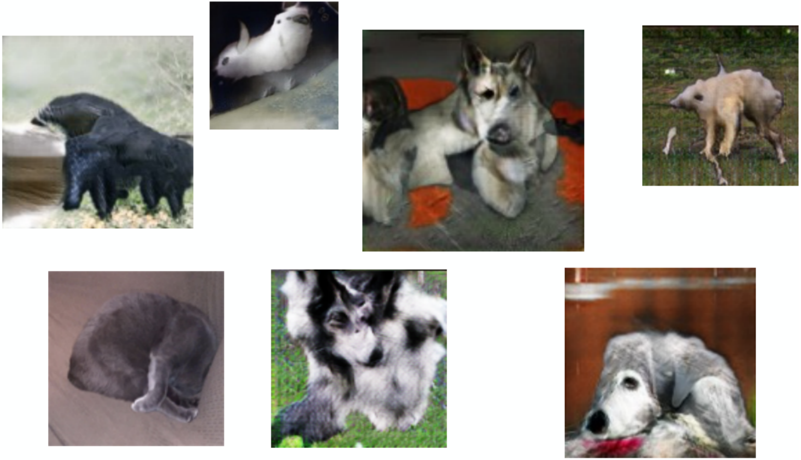
Counting



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

Perspective



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- Many, many more papers...

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- Learning to learn

Thank you!