Deep Generative Models

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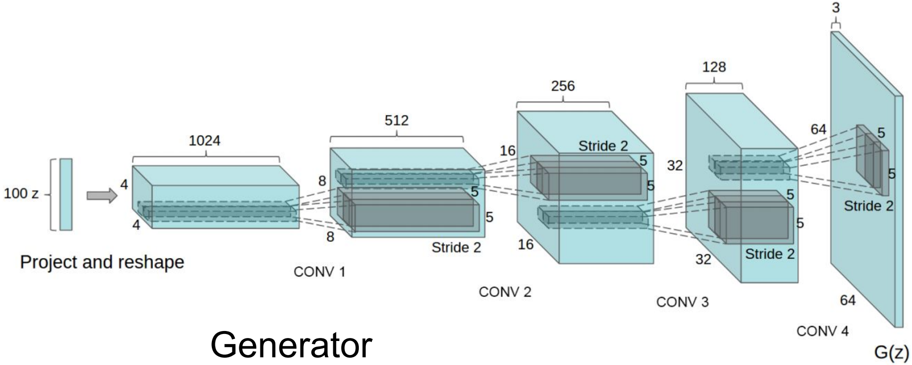
Deep Convolutional Generative Adversarial Networks (DCGAN)

Generative Adversarial Nets: Convolutional Architectur

- Generator is a deconvolutional neural network (upsampling network with deconvolutions).
- Discriminator is a convolutional network.
- Called deconvolutional generative adversarial nets (DCGAN).
- Discriminator: 4 convolutional layers.



Radford *et al*, ICLR 2016

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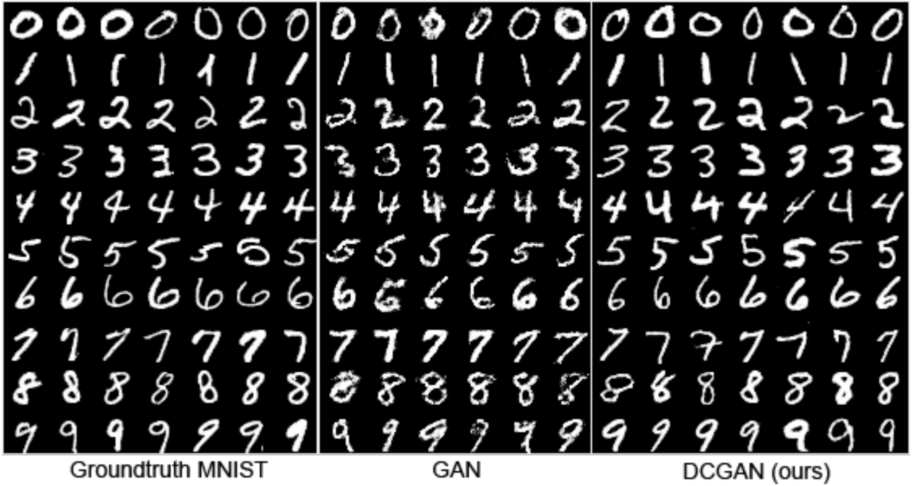
Architecture guidelines for stable Deep Convolutional GANs

- No pooling layers.
- Use batchnorm in both the generator and discriminator.
- Remove fully connected layers.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in discriminator for all layers.

Radford *et al*, ICLR 2016

Generating Samples



Generating Samples

Generating Samples

Generating Samples

Walking in the Latent Space

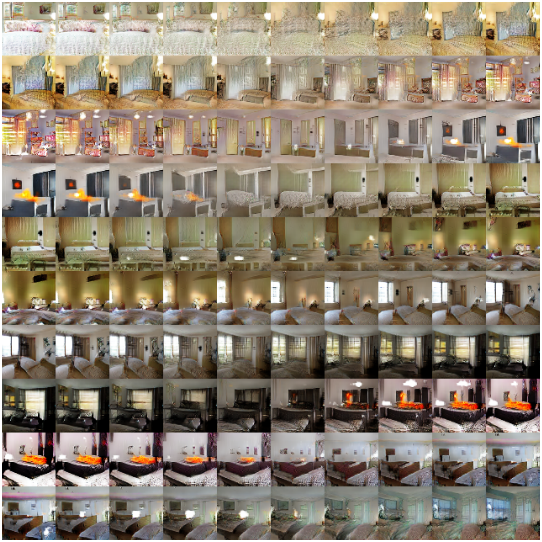
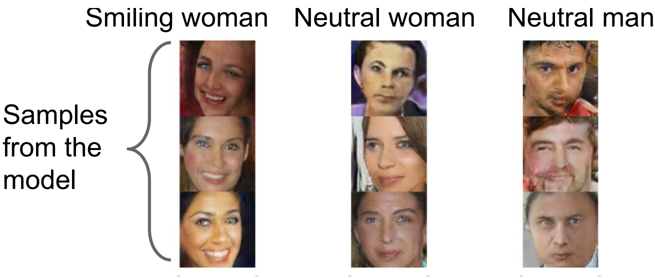


Figure 4: Top rows: Interpolation between a series of 9 random points in Z show that the space learned has smooth transitions, with every image in the space plausibly looking like a bedroom. In the 6th row, you see a room without a window slowly transforming into a room with a giant window. In the 10th row, you see what appears to be a TV slowly being transformed into a window.

Generative Adversarial Nets: Interpre



Radford *et al*, ICLR 2016

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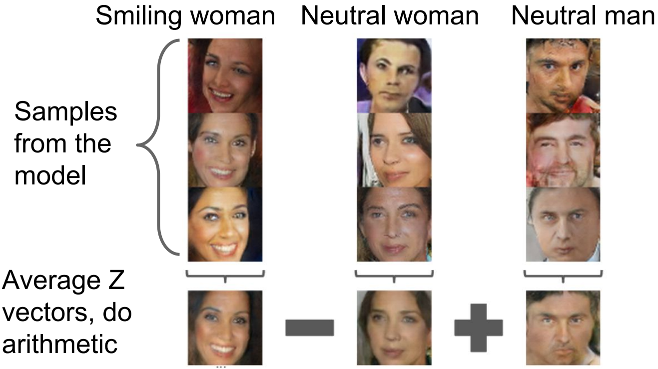

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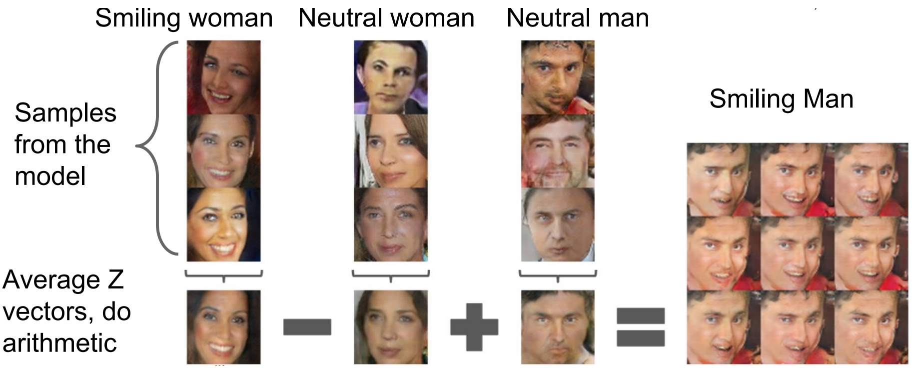
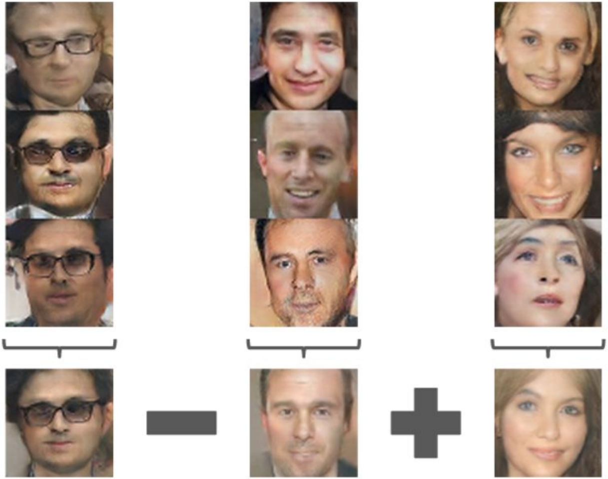
Generative Adversarial Nets: Interpre



Radford *et al*, ICLR 2016

Generative Adversarial Nets: Interpre

Glasses man | No glasses man | No glasses woman

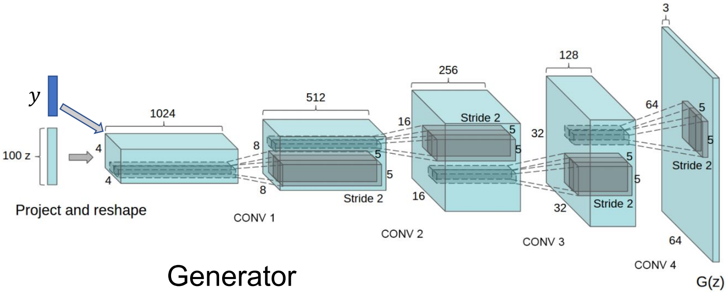


Radford *et al*, ICLR 2016

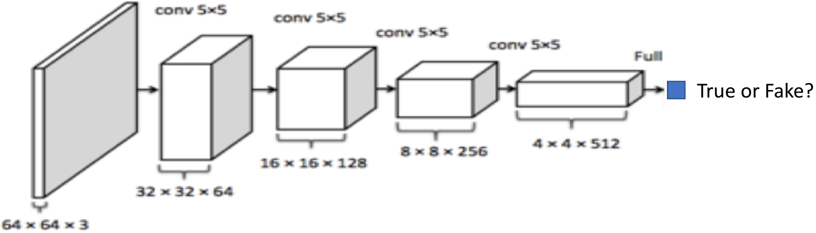
Generative Adversarial Nets: Interpre

Radford *et al*, ICLR 2016

Extension: Adding Class Information

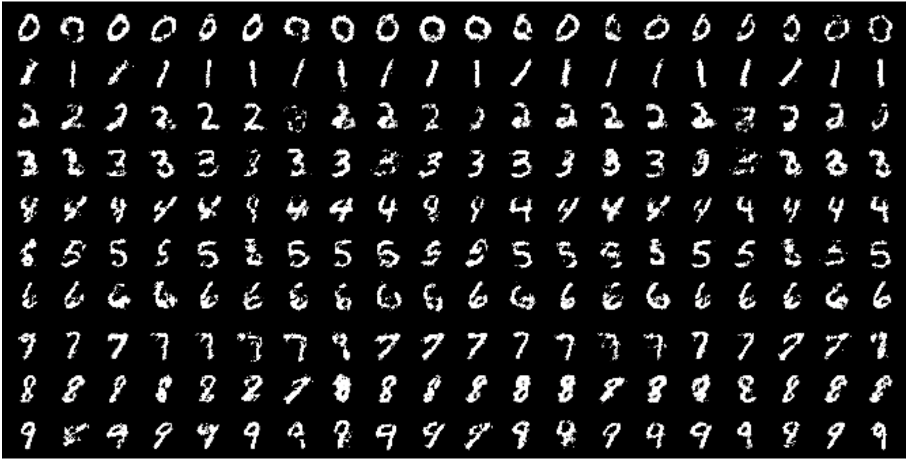


Generator

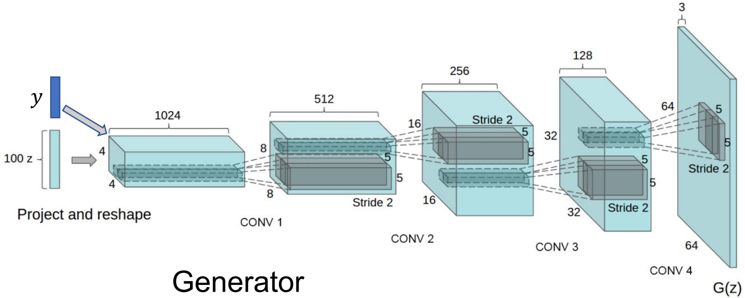


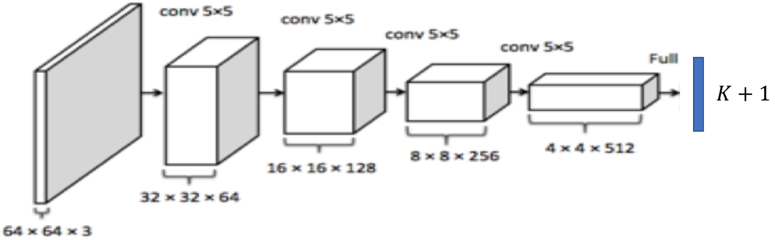
Discriminator

Extension: Adding Class Information



Extension: Multi-Class GAN





Discriminator

Extension: Multi-Class GAN

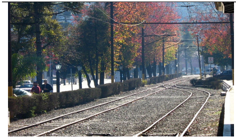
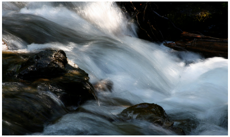
	User tags + annotations	Generated tags
	montanha, trem, inverno, frio, people, male, plant life, tree, structures, transport, car	taxi, passenger, line, transportation, railway station, passengers, railways, signals, rail, rails
	food, raspberry, delicious, homemade	chicken, fattening, cooked, peanut, cream, cookie, house made, bread, biscuit, bakes
	water, river	creek, lake, along, near, river, rocky, treeline, valley, woods, waters
	people, portrait, female, baby, indoor	love, people, posing, girl, young, strangers, pretty, women, happy, life

Image Credit: M. Mirza & S. Osindero

Wasserstein GANs

Recap: GANs

$$\min_{\boldsymbol{\theta}_g} \max_{\boldsymbol{\theta}_d} \left[\mathbb{E}_{\mathbf{x} \sim p_{\text{data}}} \log D_{\boldsymbol{\theta}_d}(\mathbf{x}) + \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \log \left(1 - D_{\boldsymbol{\theta}_d}(G_{\boldsymbol{\theta}_g}(\mathbf{z})) \right) \right]$$

Theorem

If G and D have enough capacity, and at each step of Algorithm 1, the discriminator is allowed to reach its optimum given G, and p_g is updated so as to improve the criterion

$$\mathbb{E}_{\mathbf{x} \sim p_{data}} \log D_G^*(\mathbf{x}) + \mathbb{E}_{\mathbf{x} \sim p_g} \log (1 - D_G^*(\mathbf{x})) \ ,$$

then p_g converges to p_{data}.

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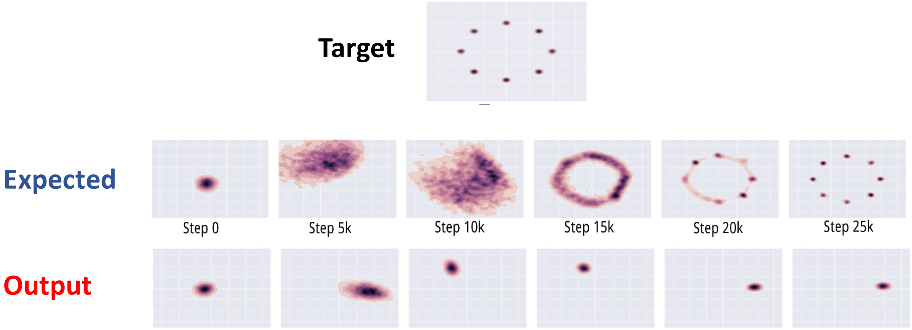
then p_g converges to p_{data}.

- Usually doesn't work in practice.

Mode Collapse in GAN



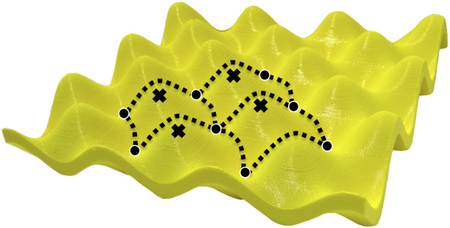
Metz, Luke, et al. **"Unrolled Generative Adversarial Networks."** arXiv preprint arXiv:1611.02163 (2016).

Mode Collapse in GAN

Reed, S., et al. ***Generating interpretable images with controllable structure.*** Technical report, 2016. 2, 2016.

Why Mode Collapse?

- Bad saddle points.



- Vanishing gradients in discriminator:
  - Wasserstein GAN.

GANs are about Distribution Matching

Minimizing Jensen-Shanon divergence between data distribution and generator distribution

$$G^* = \arg\min_G C(G) = \arg\min_G JSD(p_{\text{data}} \| p_g)$$

- Optimality when $p_g = p_{\text{data}}$.

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What is wrong with the JSD?

Probability Measure

Definition (Probability Measure)

A probability measure is a real-valued function $\mathbb{P}$ defined on a set of events in a probability space $(\mathcal{X}, \Sigma)$ such that

- $0 \leq \mathbb{P}(A) \leq 1$ for all $A \in \Sigma$.
- $\mathbb{P}(\emptyset) = 0$;$\mathbb{P}(\mathcal{X}) = 1$.
- $\mathbb{P}(\cup_i A_i) = \sum_i \mathbb{P}(A_i)$ for all countable collections $\{A_i\}$ of pairwise disjoint sets.

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- For a continuous distribution on space $\mathcal{X}$ with probability density function $p(\mathbf{x})$, the corresponding probability measure $\mathbb{P}$ is related to p, for $\mathbf{X} \in \mathcal{X}$, as

$$\mathbb{P}(\mathbf{X}) = \int_{\mathbf{X}} p(\mathbf{x}) \mathrm{d}\,\mathbf{x} \ .$$

Distance between Probability Measures

Let $\mathbb{P}_r$ and $\mathbb{P}_\theta$ be two probability measures:

- The Total Variation (TV) distance

$$\delta(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}}) \triangleq \sup_{A \in \Sigma} |\mathbb{P}_r(A) - \mathbb{P}_{\boldsymbol{\theta}}(A)| \ .$$

- The KL divergence:

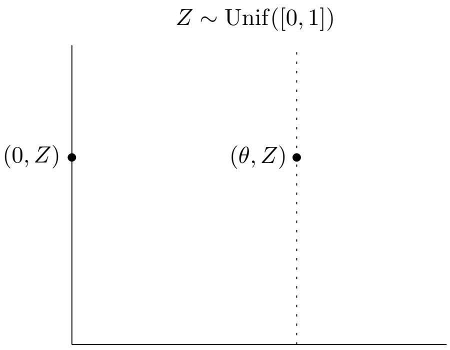
$$KL(\mathbb{P}_r \| \mathbb{P}_{\boldsymbol{\theta}}) \triangleq \int \log \frac{\mathbb{P}_r(\mathbf{x})}{\mathbb{P}_{\boldsymbol{\theta}}(\mathbf{x})} \mathbb{P}_r(\mathbf{x}) \mathrm{d}\, \mathbf{x}$$

- The Jensen-Shannon (JS) divergence (with $\mathbb{P}_m \triangleq (\mathbb{P}_r + \mathbb{P}_{\boldsymbol{\theta}})/2$):

$$JS(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}}) \triangleq \frac{1}{2} KL(\mathbb{P}_r \| \mathbb{P}_m) + \frac{1}{2} KL(\mathbb{P}_{\boldsymbol{\theta}} \| \mathbb{P}_m) \ .$$

Distance between Probability Measures

- Space $\mathcal{X}$ is the collection of lines in the two dimensional space $\mathbb{R} \times \mathbb{R}$.
- $\mathbb{P}_r$ only assigns uniform probabilities for $(0, Z)$, all others have probabilities 0.
- $\mathbb{P}_\theta$ only assigns uniform probabilities for (θ, Z) for some fixed θ, all others have probabilities 0.



- $\delta(\mathbb{P}_r, \mathbb{P}_\theta) = ?$
- $KL(\mathbb{P}_r \| \mathbb{P}_\theta) = ?$
- $JS(\mathbb{P}_r, \mathbb{P}_\theta) = ?$

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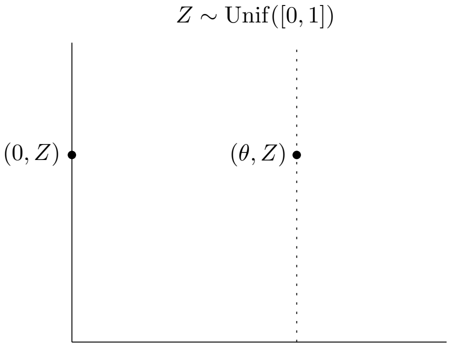

- $\delta(\mathbb{P}_r, \mathbb{P}_\theta) = \begin{cases} 1, & \text{if } \theta \neq 0 \\ 0, & \text{if } \theta = 0 \end{cases}$
- $KL(\mathbb{P}_r \| \mathbb{P}_\theta) = \begin{cases} \infty, & \text{if } \theta \neq 0 \\ 0, & \text{if } \theta = 0 \end{cases}, \quad JS(\mathbb{P}_r, \mathbb{P}_\theta) = \begin{cases} \log 2, & \text{if } \theta \neq 0 \\ 0, & \text{if } \theta = 0 \end{cases}$

What is the Problem with these Metrics

- $\delta(\mathbb{P}_r, \mathbb{P}_\theta) = \begin{cases} \infty, & \text{if } \theta \neq 0 \\ 0, & \text{if } \theta = 0 \end{cases}$
- $KL(\mathbb{P}_r \| \mathbb{P}_\theta) = \begin{cases} \log 2, & \text{if } \theta \neq 0 \\ 0, & \text{if } \theta = 0 \end{cases}$, $JS(\mathbb{P}_r, \mathbb{P}_\theta) = \begin{cases} 1, & \text{if } \theta \neq 0 \\ 0, & \text{if } \theta = 0 \end{cases}$

They are independent of θ

- Derivatives w.r.t. θ equal to zero.
- Gradient vanishing!

Instability of GAN

- Original objective

$$L(D_{\boldsymbol{\theta}_d}, G_{\boldsymbol{\theta}_g}) \triangleq \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}} \log D_{\boldsymbol{\theta}_d}(\mathbf{x}) + \mathbb{E}_{\mathbf{z}\sim p(\mathbf{z})} \log \left(1 - D_{\boldsymbol{\theta}_d}(G_{\boldsymbol{\theta}_g}(\mathbf{z}))\right)$$

- The optimal discriminator

$$D^*(\mathbf{x}) = \frac{\mathbb{P}_d(\mathbf{x})}{\mathbb{P}_d(\mathbf{x}) + \mathbb{P}_g(\mathbf{x})}$$

and $L(D^*, G_{\boldsymbol{\theta}_g}) = 2JS(\mathbb{P}_d, \mathbb{P}_g) - 2\log 2$.

- $\mathbb{P}_r = \mathbb{P}_d$ and $\mathbb{P}_{\boldsymbol{\theta}} = \mathbb{P}_g$ in GANs.

Instability of GAN

Theorem

Let $\mathbb{P}_d$ and $\mathbb{P}_g$ be two distributions that have support contained in two closed manifolds $\mathcal{M}$ and $\mathcal{P}$ that don't perfectly align and don't have full dimension. We further assume that $\mathcal{M}$ and $\mathcal{P}$ are continuous in their respective manifolds. Then, there exists an optimal discriminator $D^* : \mathcal{X} \to [0, 1]$ that has accuracy 1 and for almost any $\mathbf{x}$ in $\mathcal{M}$ or $\mathcal{P}$, D^* is smooth in a neighborhood of $\mathbf{x}$ and $\nabla_{\mathbf{x}} D^*(\mathbf{x}) = 0$.

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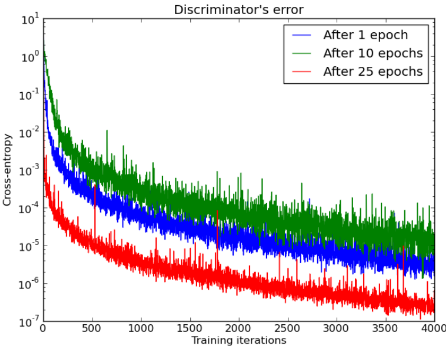
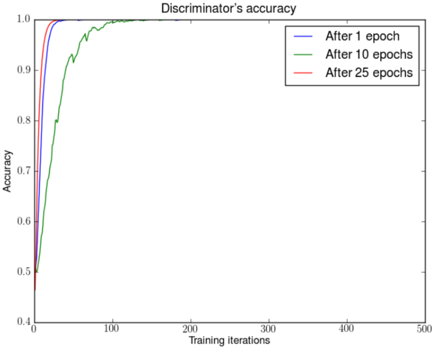
Theorem (Vanishing gradients on the generator)

If $\|D - D^*\| < \epsilon$, then

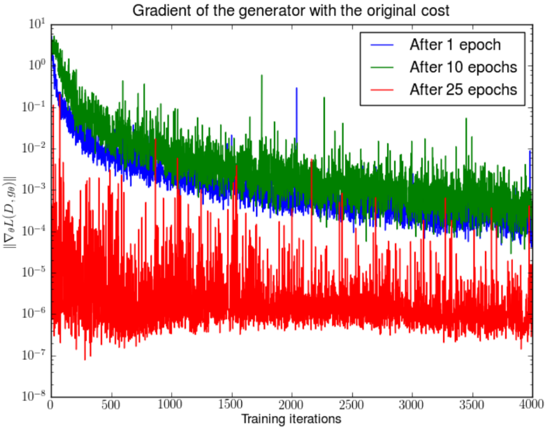
$$\left\|\nabla_{\boldsymbol{\theta}_g} \mathbb{E}_{z \sim p(z)} \left[\log\left(1 - D(G(z))\right)\right]\right\|_2 < M \frac{\epsilon}{1 - \epsilon} .$$

Instability of GAN





Instability of GAN



Wasserstein Distance

- The Earth-Mover's (EM) distance or Wasserstein-1 distance

$$W(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}}) \triangleq \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}})} \mathbb{E}_{(x,y)\sim\gamma} |x - y| \ ,$$

where $\Pi(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}})$ denotes the set of all joint distributions $\gamma(x, y)$ such whose marginals are $\mathbb{P}_r$ and $\mathbb{P}_{\boldsymbol{\theta}}$, respectively.

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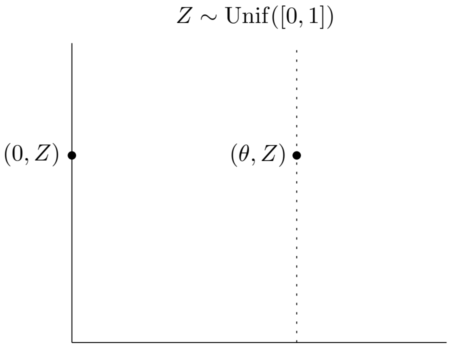
- $W(\mathbb{P}_r, \mathbb{P}_\theta) = ?$



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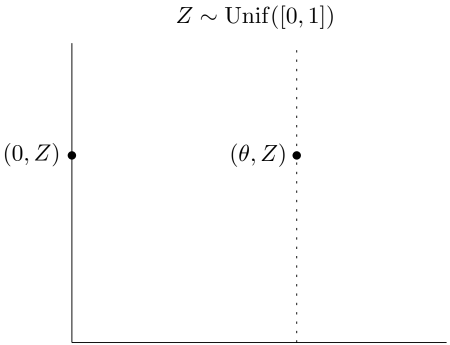
where $\Pi(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}})$ denotes the set of all joint distributions $\gamma(x, y)$ such whose marginals are $\mathbb{P}_r$ and $\mathbb{P}_{\boldsymbol{\theta}}$, respectively.

- $W(\mathbb{P}_r, \mathbb{P}_\theta) = |\theta|$

Continuous and differentiable w.r.t. θ.



Using Wasserstein Distance in GANs

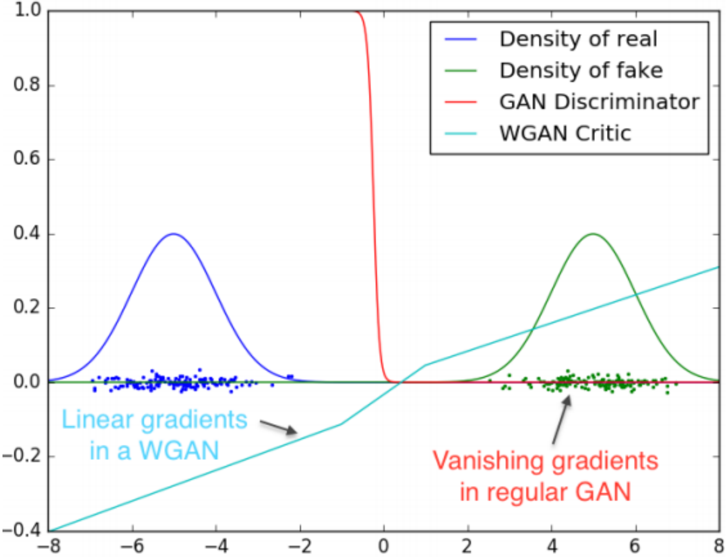
Theorem

When replacing the JS divergence with the Wasserstein distance in GAN:

1. *If $G_{\boldsymbol{\theta}_g}$ is continuous in $\boldsymbol{\theta}_g$, so is $W(\mathbb{P}_d, \mathbb{P}_g)$.*
2. *If $G_{\boldsymbol{\theta}_g}$ is locally Lipschitz and satisfies some regularity assumption, then $W(\mathbb{P}_d, \mathbb{P}_g)$ is continuous everywhere, and differentiable almost everywhere.*
3. *1 and 2 are false for the Jensen-Shannon and KL divergences.*

- If we choose $G_{\boldsymbol{\theta}_g}$ to be any feedforward neural network parametrized by $\boldsymbol{\theta}_g$, and $p(z)$ to be $\mathbb{E}[\|z\|] < \infty$, then the regularity assumption is satisfied.

Using Wasserstein Distance in GANs



Implementing WGAN

$$W(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}}) \triangleq \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}})} \mathbb{E}_{(x,y)\sim\gamma} \left| x - y \right| ~,$$

Implementing WGAN

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- By the Kantorovich-Rubinstein duality:

$$W(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}}) = \sup_{\|f\|_L \leq 1} \mathbb{E}_{\mathbf{x}\sim\mathbb{P}_d} [f(\mathbf{x})] - \mathbb{E}_{\mathbf{x}\sim\mathbb{P}_g} [f(\mathbf{x})] \ ,$$

where the supreme is over all the 1-Lipschitz functions $f : \mathcal{X} \to \mathbb{R}$.

Implementing WGAN

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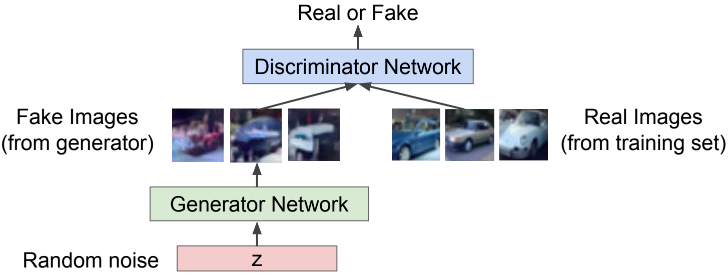
where the supreme is over all the 1-Lipschitz functions $f : \mathcal{X} \to \mathbb{R}$.

Theorem

There exists a solution to the above maximization problem, and we have

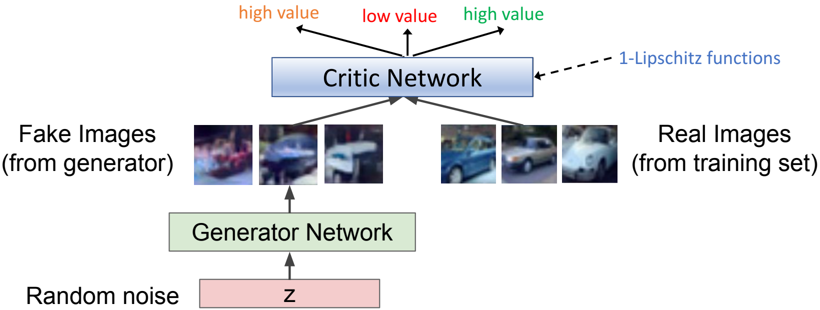
$$\nabla_{\boldsymbol{\theta}_g} W(\mathbb{P}_r, \mathbb{P}_{\boldsymbol{\theta}}) = -\mathbb{E}_{z\sim p(z)} \left[\nabla_{\boldsymbol{\theta}_g} f(G(z))\right] \ .$$

GAN and WGAN



Real or Fake
Discriminator Network
Fake Images
(from generator)
Real Images
(from training set)
Generator Network
Random noise
z

GAN and WGAN


high value
low value
high value
Critic Network
1-Lipschitz functions
Fake Images
(from generator)
Real Images
(from training set)
Generator Network
Random noise
z

WGAN Algorithm

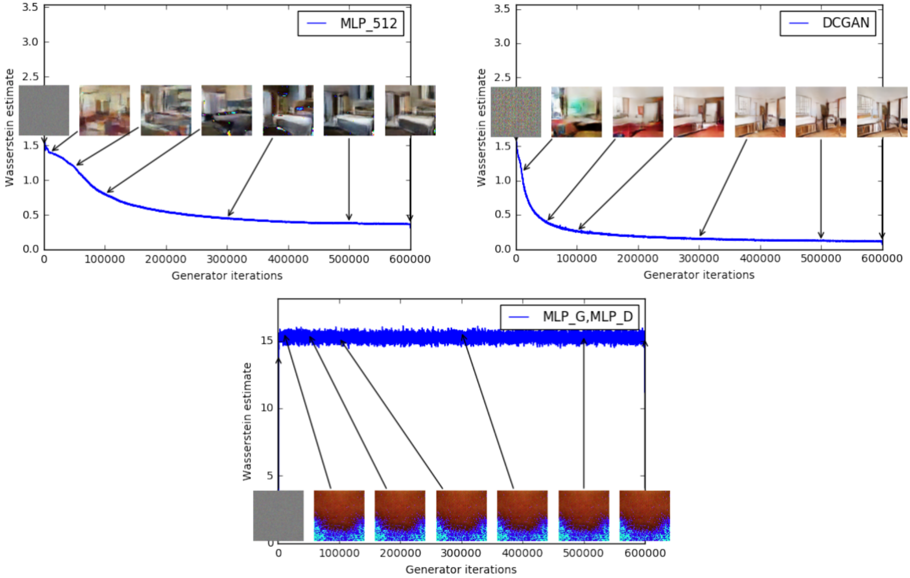
Algorithm 1 WGAN, our proposed algorithm. All experiments in the paper used the default values $\alpha = 0.00005$, $c = 0.01$, $m = 64$, $n_{\text{critic}} = 5$.

Require: : α, the learning rate. c, the clipping parameter. m, the batch size. n_{critic}, the number of iterations of the critic per generator iteration.

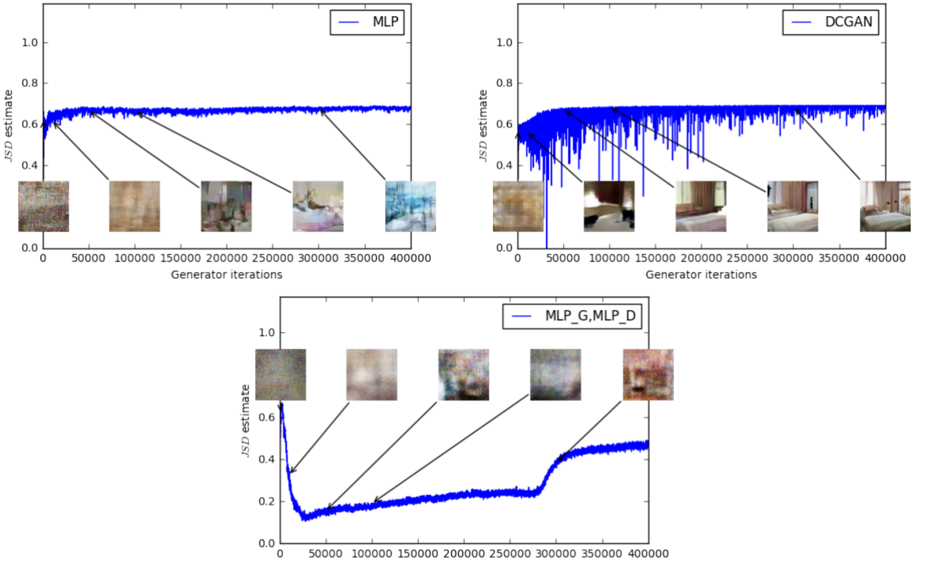
Require: : w_0, initial critic parameters. θ_0, initial generator's parameters.

while θ has not converged **do**
    for $t = 0, ..., n_{\text{critic}}$ **do**
        Sample $\{x^{(i)}\}_{i=1}^m \sim \mathbb{P}_r$ a batch from the real data.
        Sample $\{z^{(i)}\}_{i=1}^m \sim p(z)$ a batch of prior samples.
        $g_w \leftarrow \nabla_w \left[\frac{1}{m}\sum_{i=1}^m f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))\right]$
        $w \leftarrow w + \alpha \cdot \text{RMSProp}(w, g_w)$
        $w \leftarrow \text{clip}(w, -c, c)$
    end for
    Sample $\{z^{(i)}\}_{i=1}^m \sim p(z)$ a batch of prior samples.
    $g_\theta \leftarrow -\nabla_\theta \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))$
    $\theta \leftarrow \theta - \alpha \cdot \text{RMSProp}(\theta, g_\theta)$
end while

WGAN Experiments: Wasserstein Distance

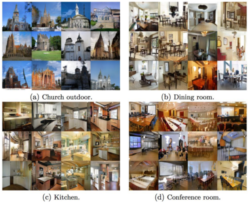


WGAN Experiments: Jason-Shanon Divergence



2017: Year of the GAN

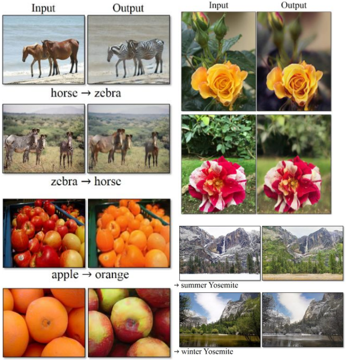
Better training and generation



LSGAN. Mao et al. 2017.

BEGAN. Bertholet et al. 2017.

Source->Target domain transfer



CycleGAN. Zhu et al. 2017.

Text -> Image Synthesis

Akata et al. 2017.

Many GAN applications

Pix2pix. Isola 2017. Many examples at https://phillipi.github.io/pix2pix/

The GAN Zoo

https://github.com/hindupuravinash/the-gan-zoo
https://github.com/soumith/ganhacks

- GAN - Generative Adversarial Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- AdaGAN - AdaGAN: Boosting Generative Models
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference
- AM-GAN - Generative Adversarial Nets with Labeled Data by Activation Maximization
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorial GANs
- b-GAN - b-GAN: Unified Framework of Generative Adversarial Networks
- Bayesian GAN - Deep and Hierarchical Implicit Models
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BiGAN - Adversarial Feature Learning
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- CGAN - Conditional Generative Adversarial Nets
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks
- CCGAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CoGAN - Coupled Generative Adversarial Networks
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training
- CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
- CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
- CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
- DTN - Unsupervised Cross-Domain Image Generation
- DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
- DiscoGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DR-GAN - Disentangled Representation Learning GAN for Pose-Invariant Face Recognition
- DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
- EBGAN - Energy-based Generative Adversarial Network
- f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
- FF-GAN - Towards Large-Pose Face Frontalization in the Wild
- GAWWN - Learning What and Where to Draw
- GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data
- Geometric GAN - Geometric GAN
- GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending
- IAN - Neural Photo Editing with Introspective Adversarial Networks
- iGAN - Generative Visual Manipulation on the Natural Image Manifold
- IcGAN - Invertible Conditional GANs for image editing
- ID-CGAN - Image De-raining Using a Conditional Generative Adversarial Network
- Improved GAN - Improved Techniques for Training GANs
- InfoGAN - InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets
- LAGAN - Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis
- LAPGAN - Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks

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Summary

GANs do not learn explicit density functions, they learn transformations from simple distributions to training-data distributions by taking a game-theoretic approach.

1. Pros:
   - ⋆ Beautiful, state-of-the-art samples.
2. Cons:
   - ⋆ Trickier / more unstable to train.
3. Active areas of research:
   - ⋆ Better loss functions, more stable training (Wasserstein GAN, LSGAN, many others).
   - ⋆ Conditional GANs, GANs for all kinds of applications.
   - ⋆ Adversarial idea for training.