Generative Adversarial Networks (GANs)

ML Instruction Team, Fall 2022

CE Department
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Discriminative vs Generative Models

- Machine learning models can be classified into two types: Discriminative and Generative.
- A discriminative model makes predictions on the unseen data based on conditional probability and can be used for classification or regression problems.
- A generative model focuses on the latent distribution of a dataset to return a probability for an example.

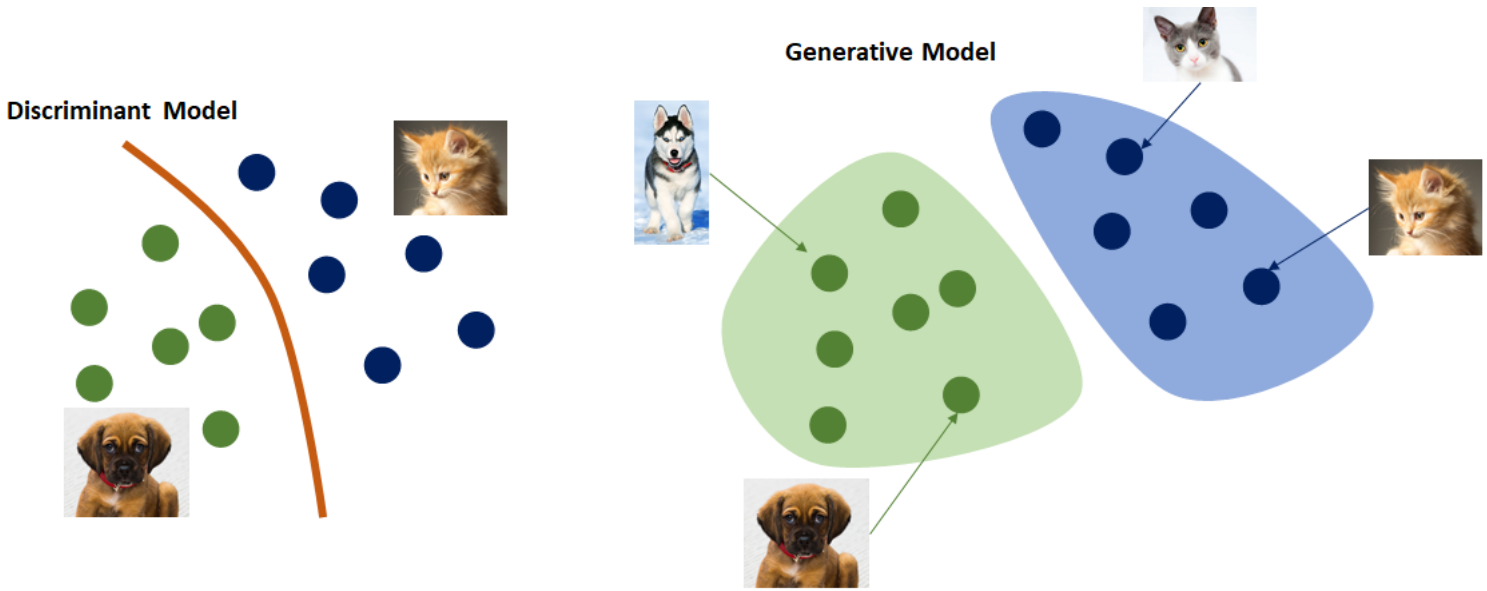


Figure: Discriminative vs Generative Models Source

Generative Models

- Generative models have two types:
  - Explicit likelihood models are defined by an explicit specification of the density, and so their unnormalized complete likelihood can be usually expressed in closed form.
  - Implicit probabilistic models are defined naturally in a sampling procedure and often induce a likelihood function that cannot be expressed explicitly.

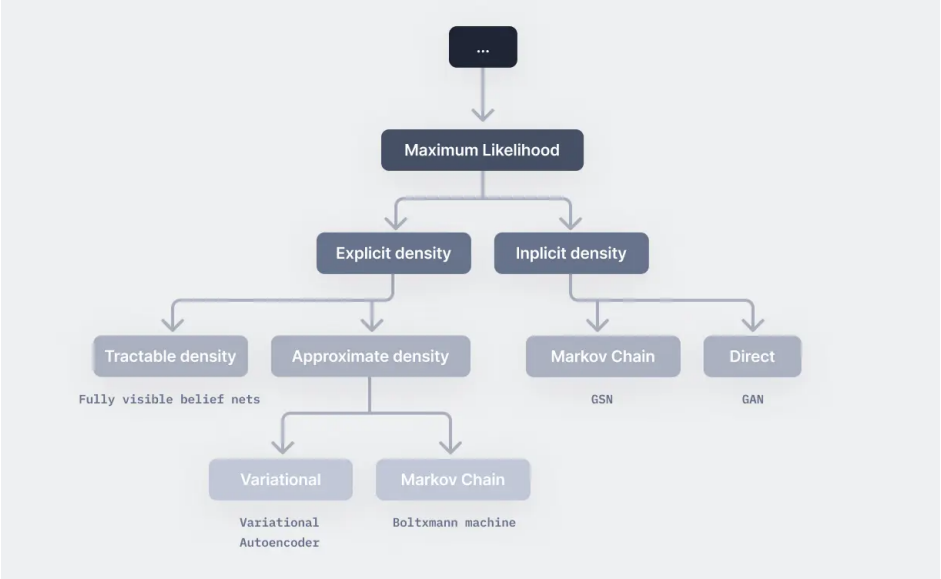


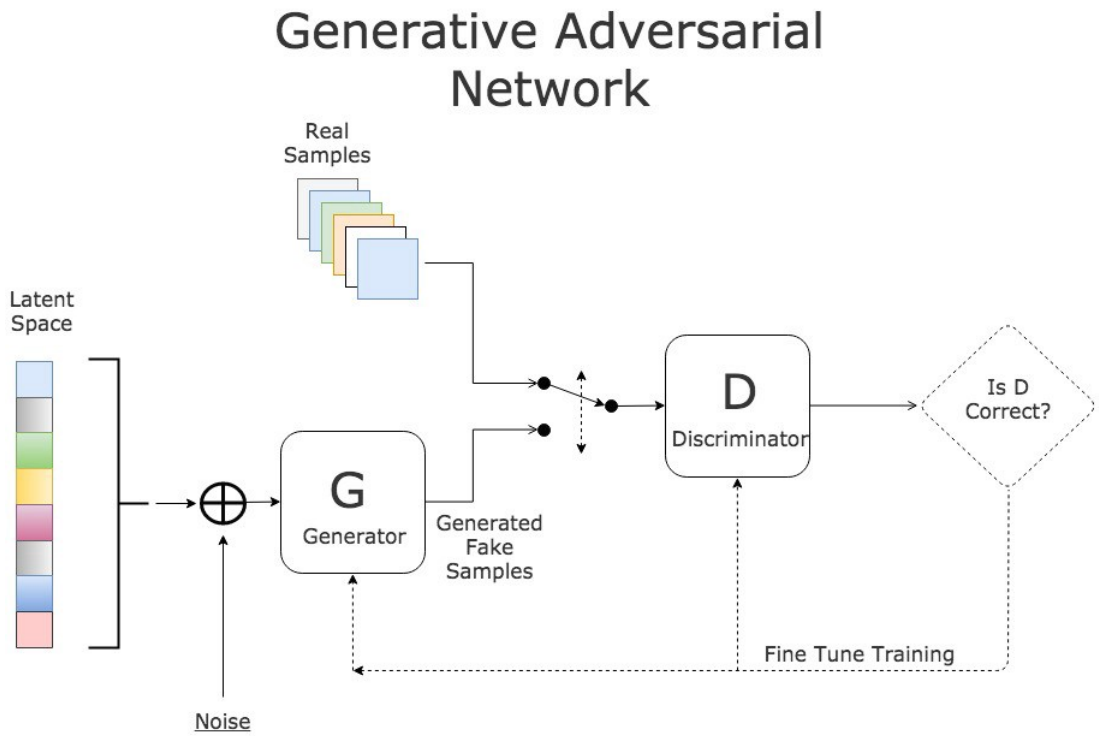
Figure: IAN Goodfellow's presentation of Generative Models Taxonomy Source

Generative Models

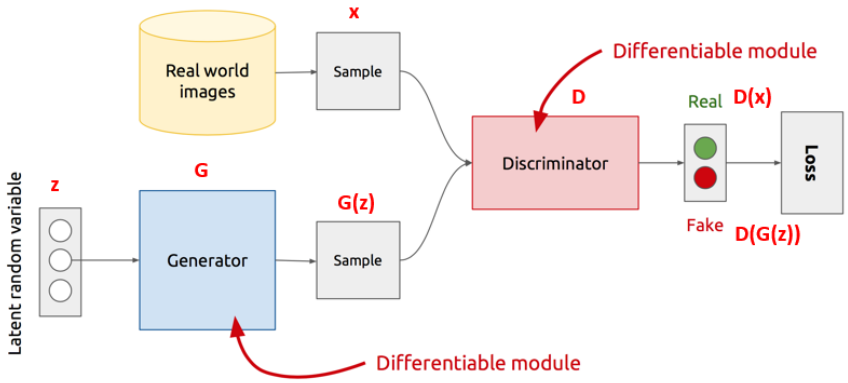
- Generative models aim for a complete probabilistic description of the data. With these models, the goal is to construct the joint probability distribution $P(X, Y)$ – either directly or by first computing $P(X|Y)$ and $P(Y)$ – and then inferring the conditional probabilities required to classify new data.
- Generative models are used for:
  1. Density estimation is the task of estimating the probability density function (PDF) of a random variable.
  2. Data generation is the task of generating new data samples from a given distribution.
  3. Data imputation is the task of filling in missing data.
  4. Data compression is the task of reducing the amount of information required to represent a dataset.

Generative Adversarial Networks - Architecture

- So how do Generative Adversarial Networks work?
- GAN composes of two deep networks:
  - The generator
  - The discriminator.

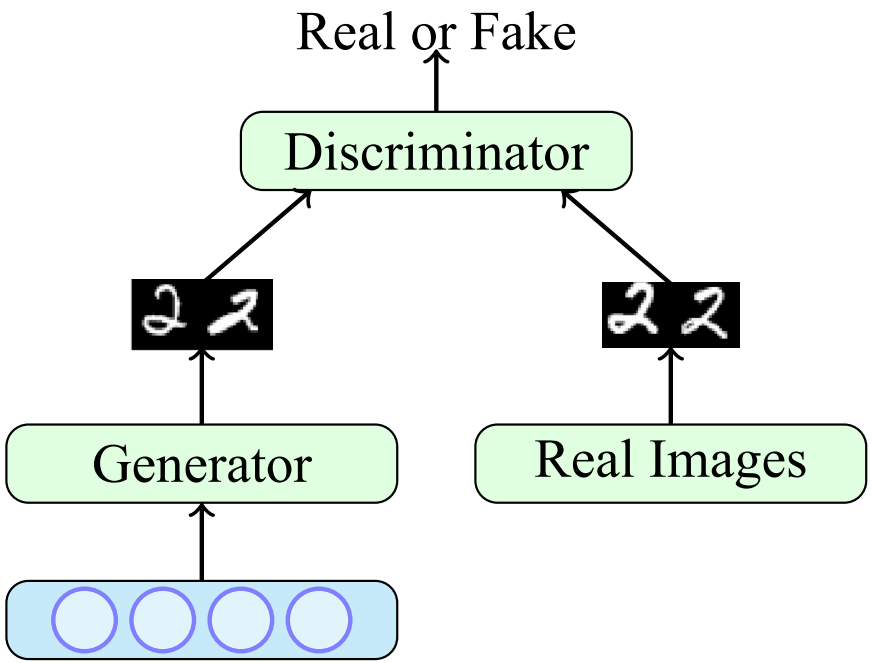


Generative Adversarial Networks - Structure



- So let's look at the full picture
- Let G_ϕ be the generator and D_θ be the discriminator (ϕ and θ are the parameters of G and D, respectively)
- We have a neural network based generator which takes as input a noise vector $z \sim N(0, I)$ and produces $G_\phi(z) = X$
- We have a neural network based discriminator which could take as input a real X or a generated $X = G_\phi(z)$ and classify the input as real/fake

GAN: Loss Function



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- What should be the objective function of the overall network?
- Let's look at the objective function of the generator first
- Given an image generated by the generator as $G_\phi(z)$ the discriminator assigns a score $D_\theta(G_\phi(z))$ to it
- This score will be between 0 and 1 and will tell us the probability of the image being real or fake

GAN: Loss Function

- For a given z, the generator would want to maximize $\log D_\theta(G_\phi(z))$ (log likelihood) or minimize $\log(1 - D_\theta(G_\phi(z)))$
- This is just for a single z and the generator would like to do this for all possible values of z,
- For example, if z was discrete and drawn from a uniform distribution (*i.e.*, $p(z) = \frac{1}{N}\ \forall z$) then the generator's objective function would be

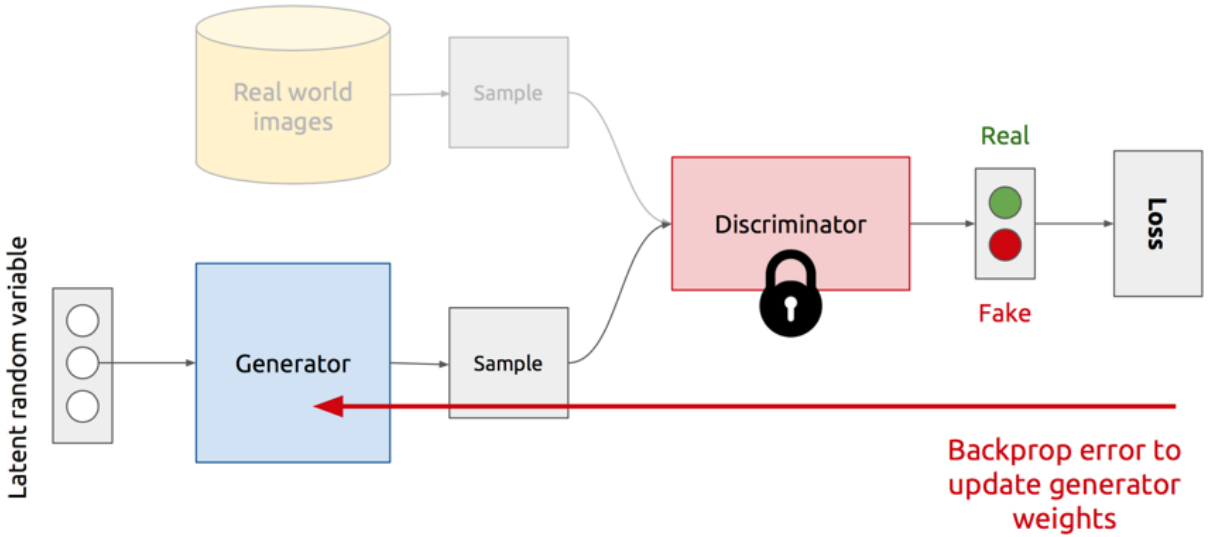
$$\min_\phi \sum_{i=1}^{N} \frac{1}{N} \log(1 - D_\theta(G_\phi(z)))$$

GAN: Loss Function

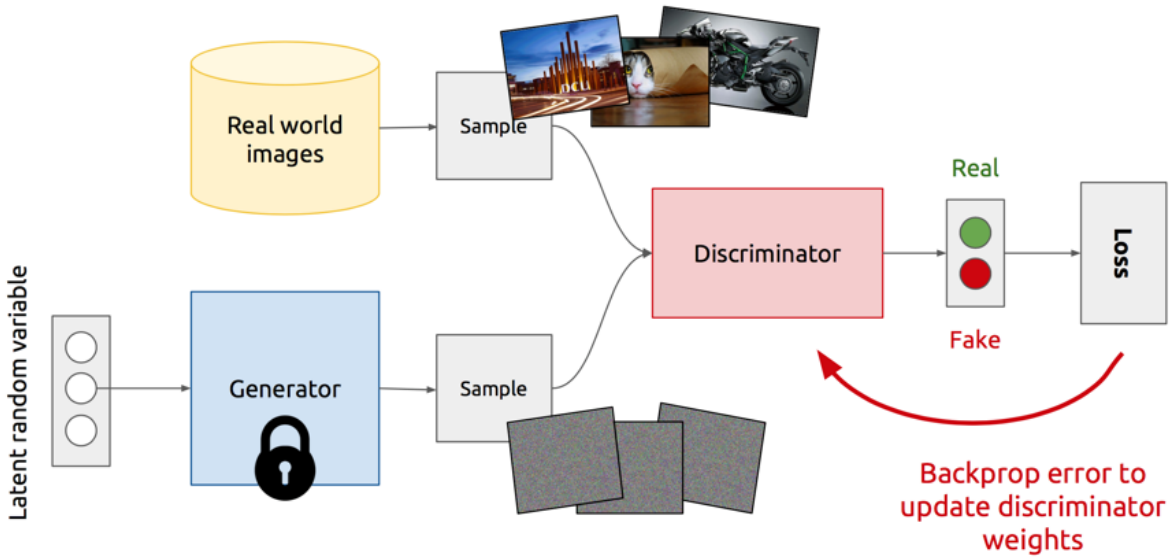
- However, in our case, z is continuous and not uniform ($z \sim N(0, I)$) so the equivalent objective function would be

$$\min_{\phi} \int p(z) \log(1 - D_{\theta}(G_{\phi}(z)))$$

$$\min_{\phi} E_{z \sim p(z)}[\log(1 - D_{\theta}(G_{\phi}(z)))]$$



GAN: Loss Function



- Now let's look at the discriminator
- The task of the discriminator is to assign a high score to real images and a low score to fake images
- And it should do this for all possible real images and all possible fake images
- In other words, it should try to maximize the following objective function

$$\max_{\theta} E_{x \sim p_{data}} [log\, D_{\theta}(x)] + E_{z \sim p(z)} [log(1 - D_{\theta}(G_{\phi}(z)))]$$

GAN: Loss Function

- If we put the objectives of the generator and discriminator together we get a minimax game

$$\min_{\phi} \max_{\theta} \quad [\mathbb{E}_{x \sim p_{data}} \log D_{\theta}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta}(G_{\phi}(z)))]$$

- The first term in the objective is only w.r.t. the parameters of the discriminator (θ)
- The second term in the objective is w.r.t. the parameters of the generator (ϕ) as well as the discriminator (θ)
- The discriminator wants to maximize the second term whereas the generator wants to minimize it (hence it is a two-player game)

GAN - Training

- So the overall training proceeds by alternating between these two step
- **Step 1:** Gradient Ascent on Discriminator

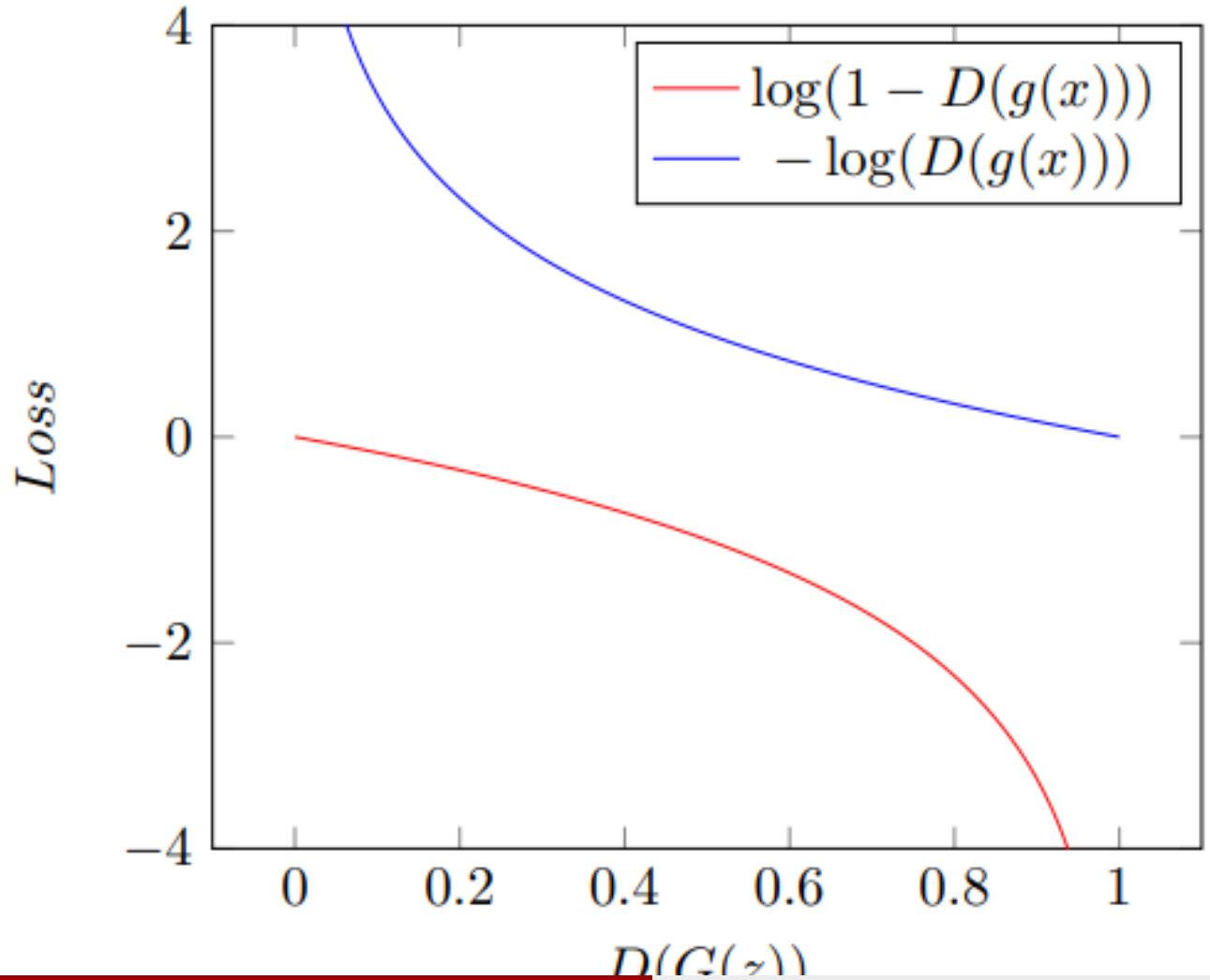
$$\max_{\theta} \; [\mathbb{E}_{x \sim p_{data}} \log D_\theta(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_\theta(G_\phi(z)))]$$

- **Step 2:** Gradient Descent on Generator

$$\min_{\phi} \; \mathbb{E}_{z \sim p(z)} \log(1 - D_\theta(G_\phi(z)))$$

- In practice, the above generator objective does not work well and we use a slightly modified objective
- Let us see why

GAN - Training



GAN: Problems

- Many GAN models suffer the following major problems:
  - Mode collapse: the generator collapses which produces limited varieties of samples
  - Non-convergence: the model parameters oscillate, destabilize and never converge
  - Diminished gradient: he discriminator gets too successful that the generator gradient vanishes and learns nothing
  - Unbalance between the generator and discriminator causing overfitting
  - Highly sensitive to the hyperparameter selections.

Mode Collapse

- Real-life data distributions are multimodal.
- In MNIST, there are 10 major modes from digit ‘0’ to digit ‘9’.
- The samples below are generated by two different GANs.
- We can see the generator creates a single mode only. This is called mode collapse.

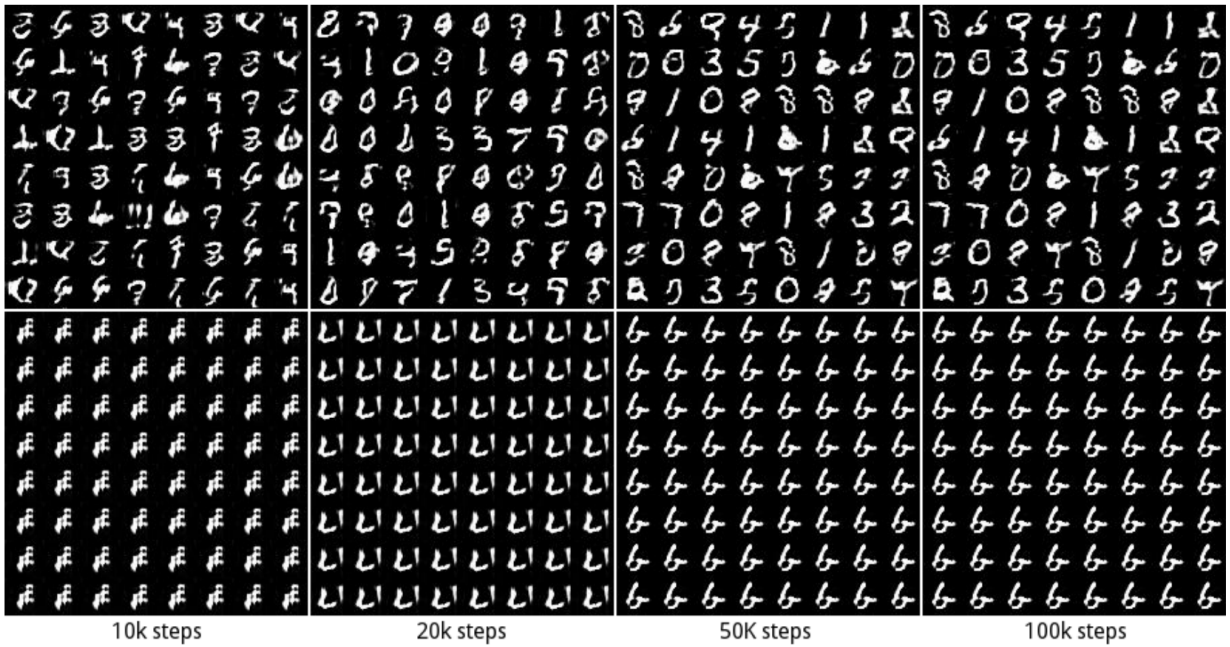


Figure: GAN mode collapse (Source)

Why Mode Collapse in GAN?

- The images below with the same underlined color look similar and the mode starts collapsing.

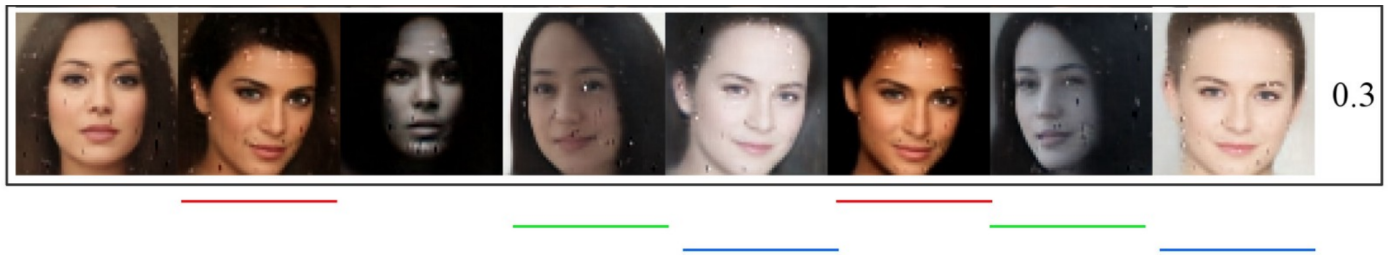


Figure: Modified from (Source)

- Let's see how it may occur. The objective of the GAN generator is to create images that can fool the discriminator D the most.

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log \left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)$$

- But let's consider one extreme case where G is trained extensively without updates to D.

Why Mode Collapse in GAN?

- The generated images will converge to find the optimal image $x*$ that fool D the most, the most realistic image from the discriminator perspective.
- In this extreme, x* will be independent of z.

$$x^* = argmax_x D(x)$$

- The mode collapses to a single point.
- The gradient associated with z approaches zero.

$$\frac{\partial J}{\partial z} \approx 0$$

- Solution?
- Unrolled GAN

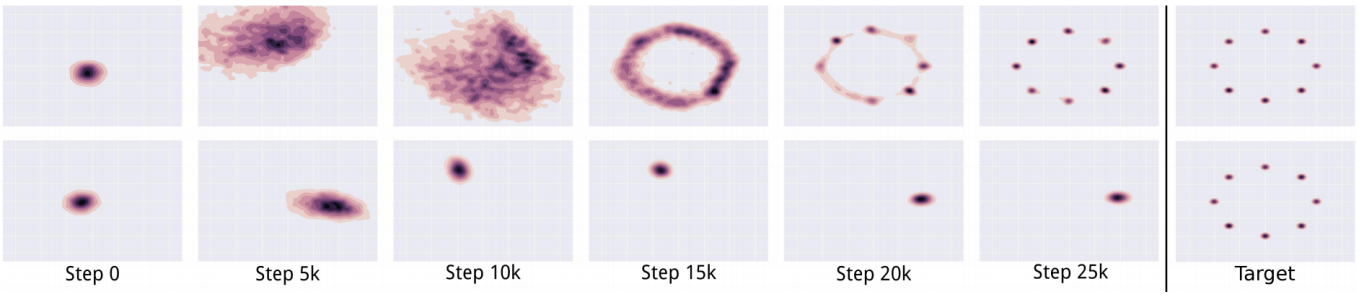


Figure: Unrolled GAN vs Vanilla GAN (Source)

Nash Equilibrium

- GAN is based on the zero-sum non-cooperative game.
- A zero-sum game is also called minimax.
- In game theory, the GAN model converges when the discriminator and the generator reach a Nash equilibrium

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_r(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

- Nash equilibrium happens when one player will not change its action regardless of what the opponent may do.

Nash Equilibrium

- Consider two player A and B which control the value of x and y respectively. Player A wants to maximize the value xy while B wants to minimize it.

$$\min_{B} \max_{A} V(D, G) = xy$$

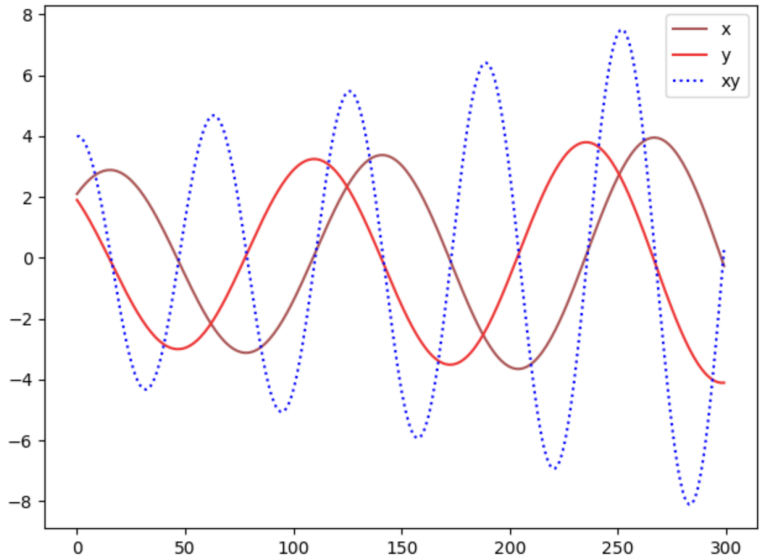
- The Nash equilibrium is $x = y = 0$
- This is the only state where the action of your opponent does not matter. It is the only state that any opponents' actions will not change the game outcome.

Non-convergence

- Let's see whether we can find the Nash equilibrium easily using the gradient descent.
- We update the parameter x and y based on the gradient of the value function V.

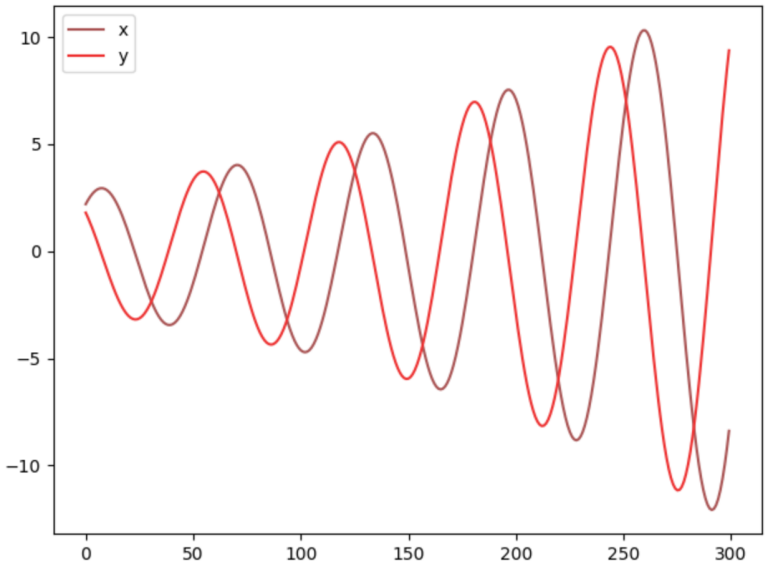
$$\Delta x = \alpha \frac{\partial(xy)}{\partial(x)}$$
$$\Delta y = - \alpha \frac{\partial(xy)}{\partial(y)}$$

- Where α is the learning rate. When we plot x, y, and xy against the training iterations, we realize our solution does not converge.



Non-convergence

- If we increase the learning rate or train the model longer, we can see the parameters x, y is unstable with big swings.



- Our example is an excellent showcase that some cost functions will not converge with gradient descent, in particular for a non-convex game.

Generative model with KL-Divergence

- Before GAN, many generative models create a model θ that maximizes the Maximum Likelihood Estimation MLE. i.e. finding the best model parameters that fit the training data the most.

$$\hat{\theta} = \arg\max_{\theta} \prod_{i=1}^{N} p(x_i|\theta)$$

- KL (x) drops to 0 for area where $p(x) \to 0$. For example, in the figure on the right below, the red curve corresponds to $D(p, q)$. It drops to zero when $x > 2$ where p approaches 0.

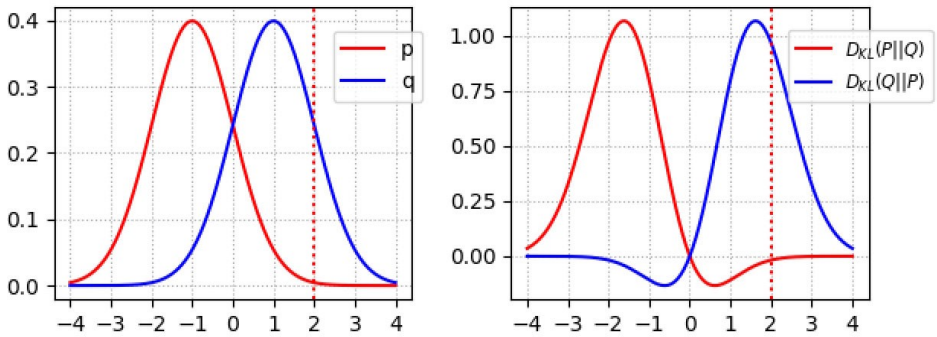


Figure: $KL(p, q)$ is the integral of the red curve in the right.

Generative model with JL-Divergence

- JS-divergence is defined as:

$$D_{JS}(p||q) = \frac{1}{2}D_{KL}(p||\frac{p+q}{2}) + \frac{1}{2}D_{KL}(q||\frac{p+q}{2})$$

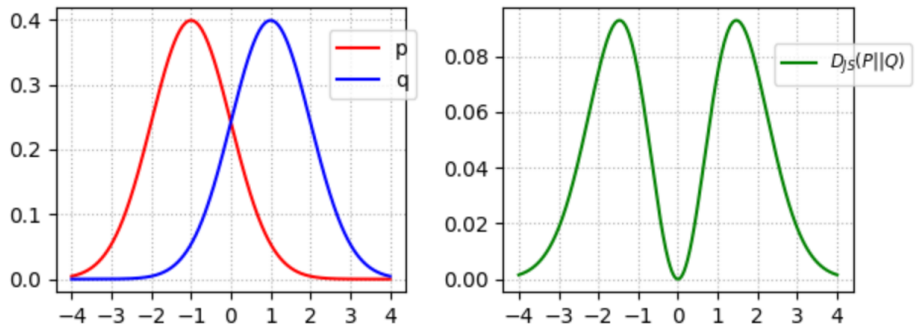


Figure: $KL(p, q)$ is the integral of the red curve in the right.

- JS-divergence is symmetrical.
- Unlike KL-divergence, it will penalize poor images badly.
- the generator's objective function becomes:

$$\min_G V(D^*, G) = 2D_{JS}(p_r||p_g) - 2\log 2$$

Deep Convolutional GANs

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- We will now look at one of the popular neural networks used for the generator and discriminator (Deep Convolutional GANs) For discriminator, any CNN based classifier with 1 class (real) at the output can be used (e.g. VGG, ResNet, etc.)

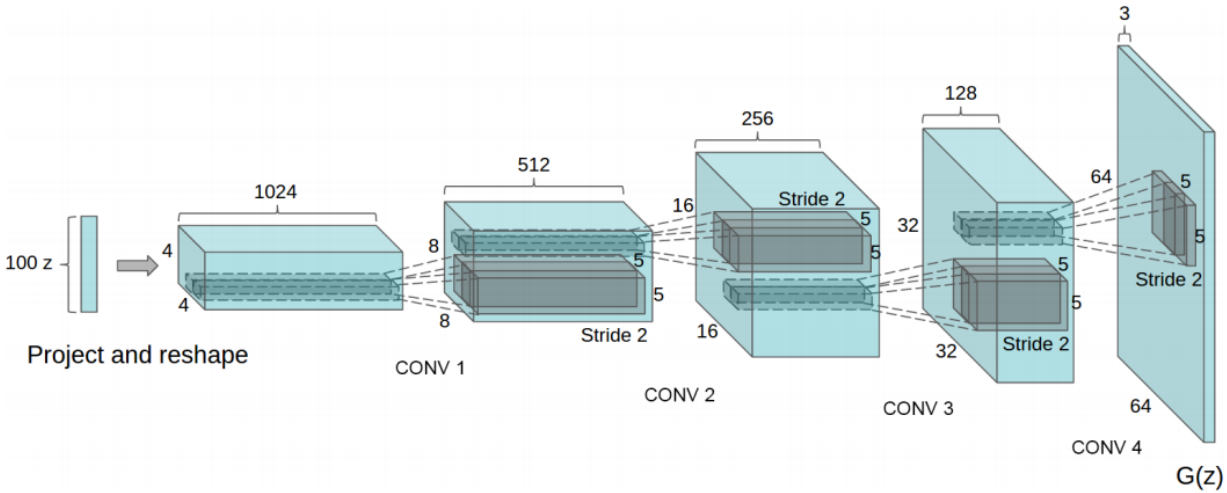

Figure: Generator (Redford et al 2015) (left) and discriminator (Yeh et al 2016) (right) used in DCGAN

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.
- Use LeakyReLU activation in the discriminator for all layers

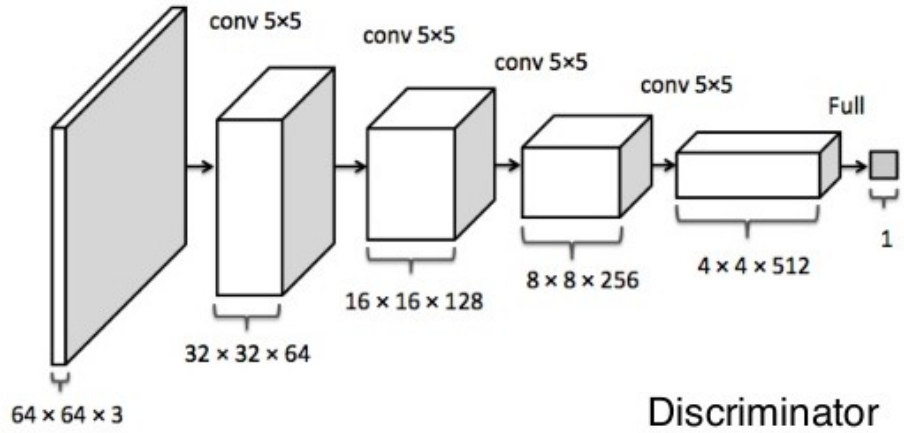

Figure: Generator (Redford et al 2015) (left) and discriminator (Yeh et al 2016) (right) used in DCGAN

Generative Adversarial Networks - Some Cool Stuff and Applications

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- In each row the first image was generated by the network by taking a vector z_1 as the input and the last images was generated by a vector z_2 as the input
- All intermediate images were generated by feeding z's which were obtained by interpolating z_1 and z_2 ($z = \lambda z_1 + (1 - \lambda) z_2$)
- As we transition from z_1 to z_2 in the input space there is a corresponding smooth transition in the image space also

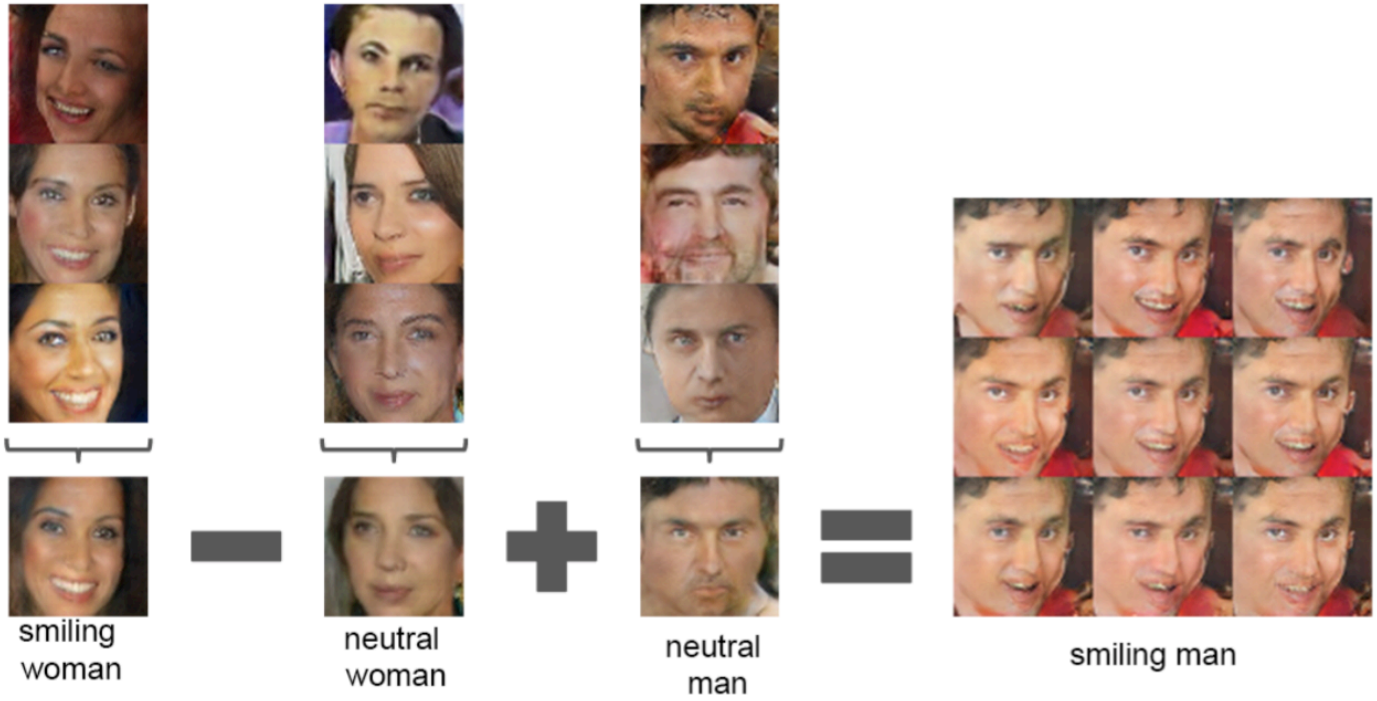
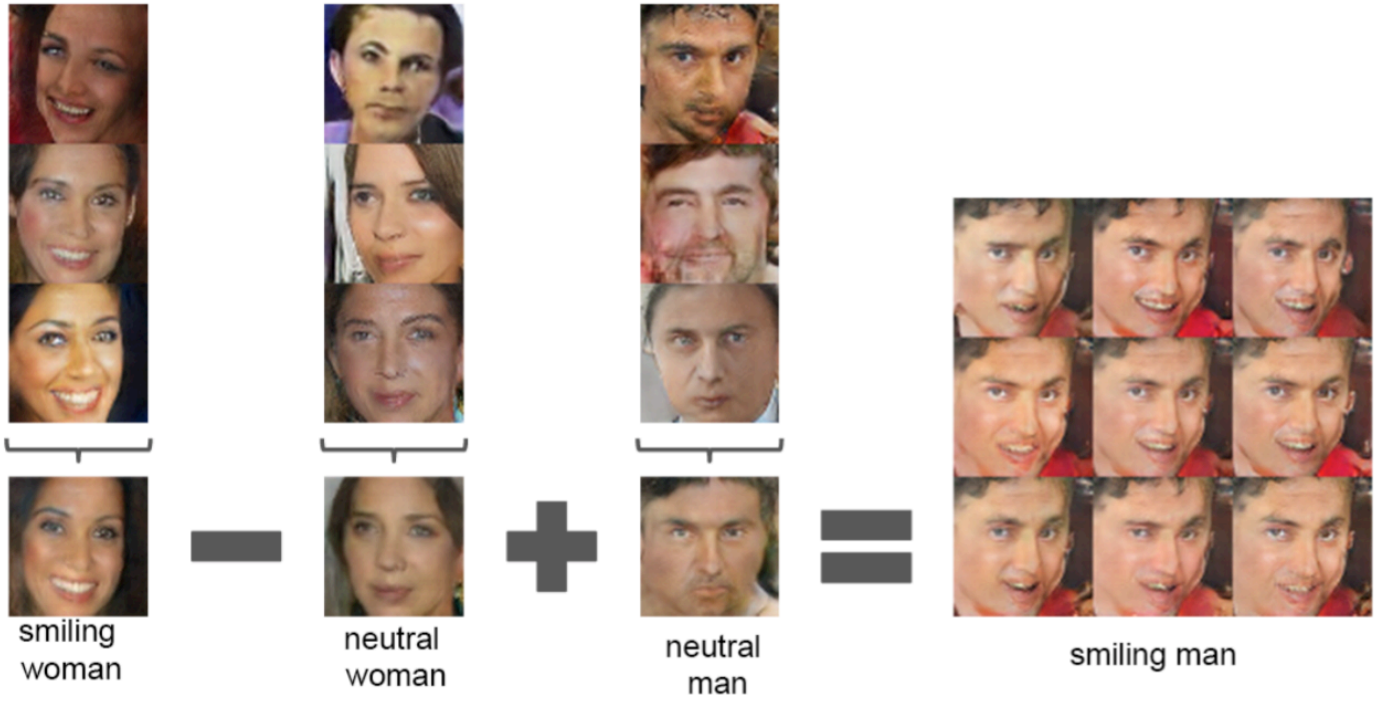


Figure: Vector arithmetic for visual concepts (part of figure 7 from the DCGAN paper)

- The first 3 images in the first column were generated by feeding some z_{11}, z_{12}, z_{13} respectively as the input to the generator
- The fourth image was generated by taking an average of $z_1 = z_{11}, z_{12}, z_{13}$ and feeding it to the generator
- Similarly we obtain the average vectors z_2 and z_3 for the 2nd and 3rd columns
- If we do a simple vector arithmetic on these averaged vectors then we see the corresponding effect in the generated images



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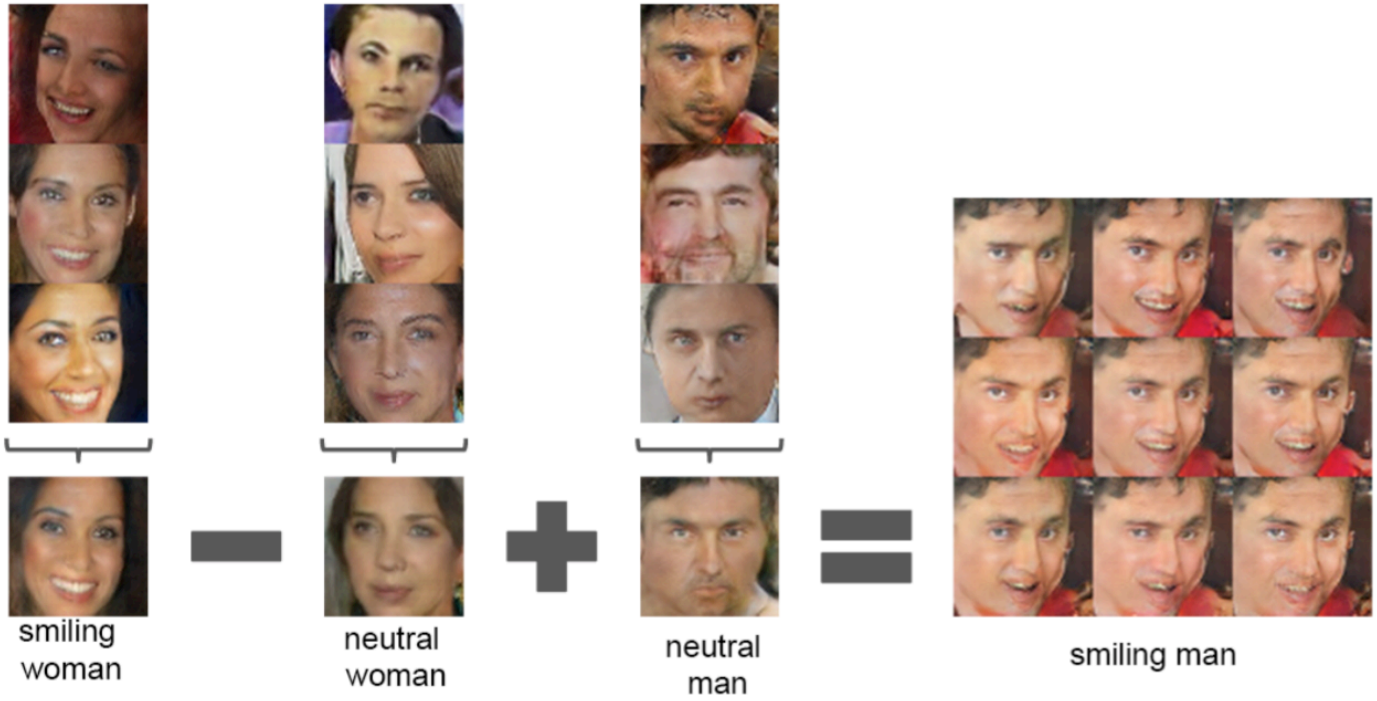

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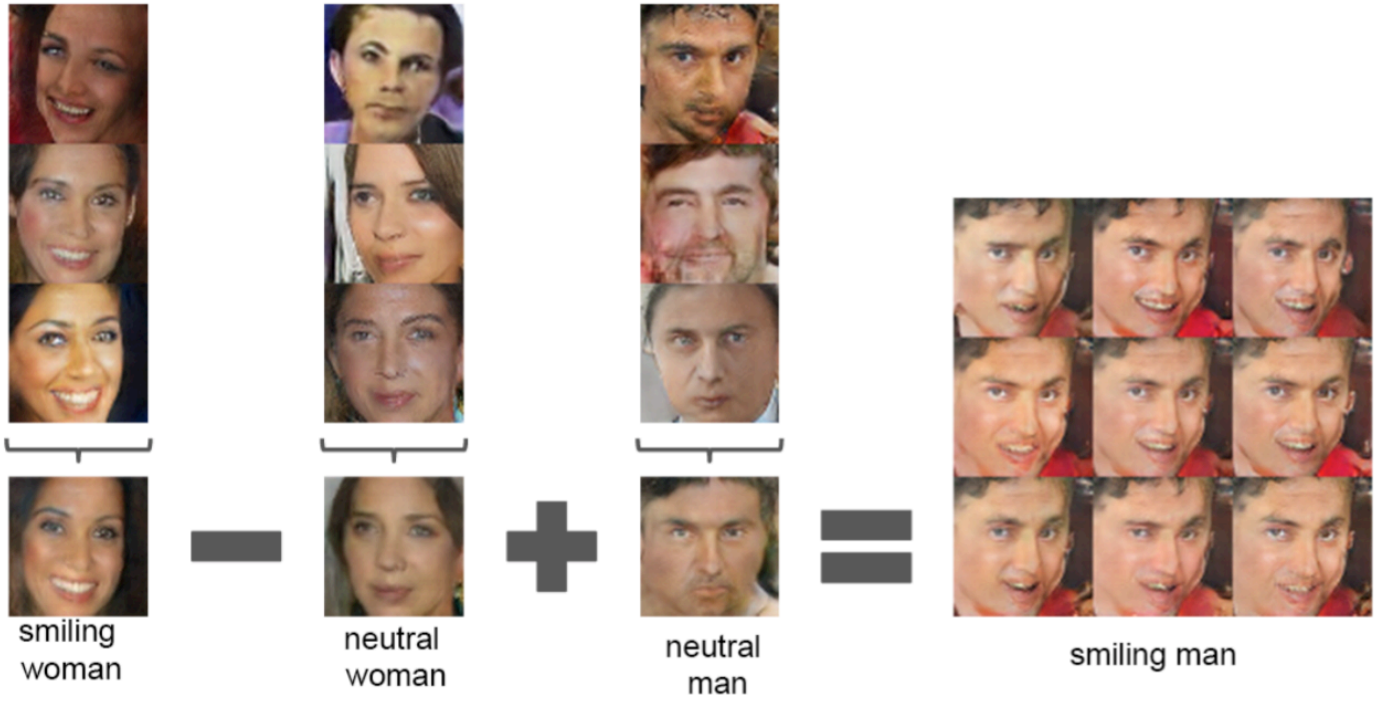

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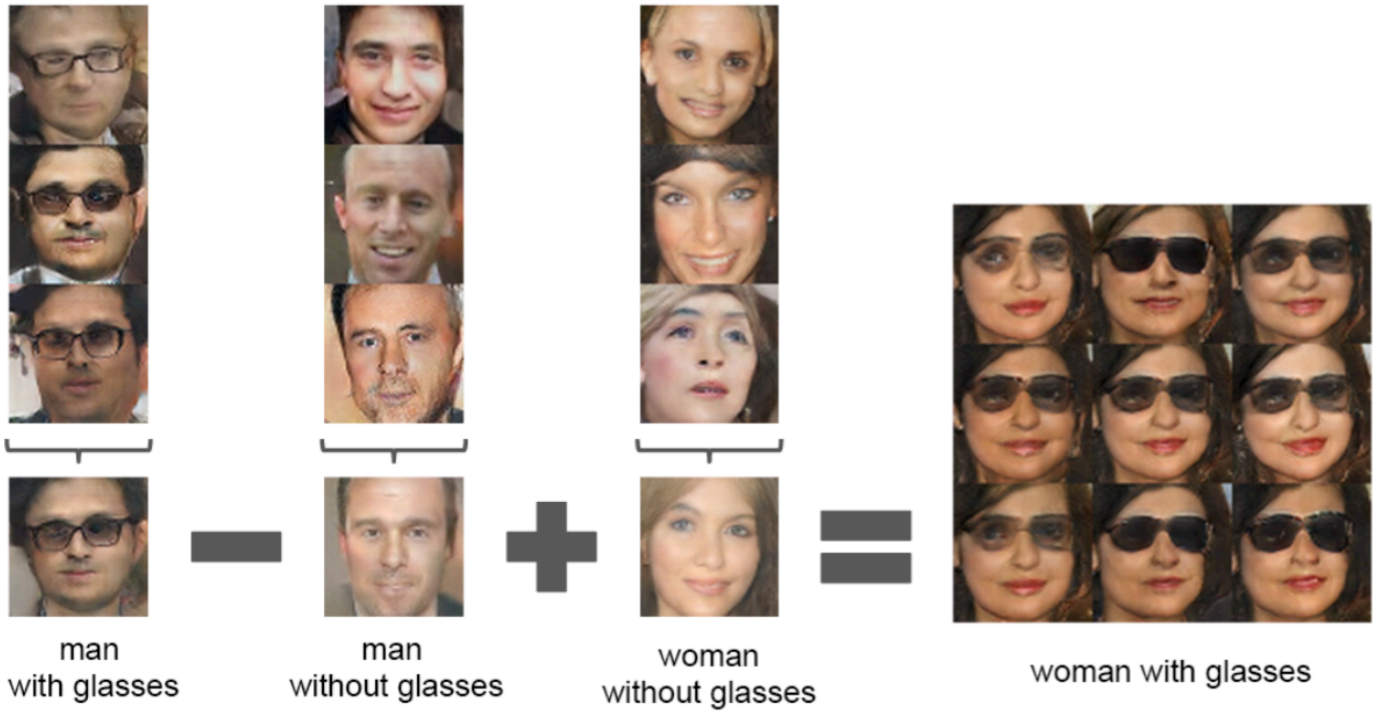

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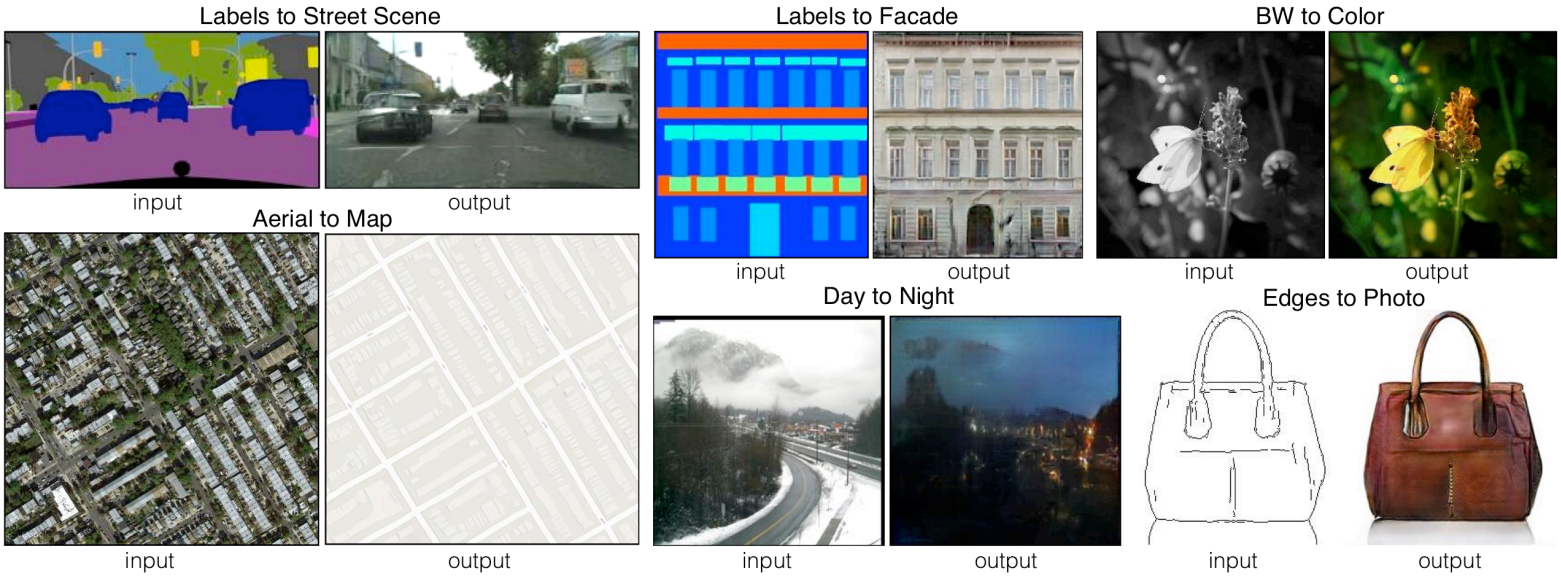

Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, Alexei A. Efros, Image-to-Image Translation with Conditional Adversarial Networks, CVPR, 2017.

Module 23.1: Generative Adversarial Networks - StyleGAN + CycleGAN

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Figure: Example of One Set of Generated Faces (Left) Adopting the Coarse Style of Another Set of Generated Faces (Top)

- GAN: Lacking Control Over Synthesized Images
- Style Generative Adversarial Network(StyleGAN) Controls Style Using New Generator Model
- StyleGan is proficient in producing impressively photorealistic high-quality photos of faces and grants control over the characteristic of the created image at different specification levels by changing the style vectors and noise.

StyleGAN Model Architecture

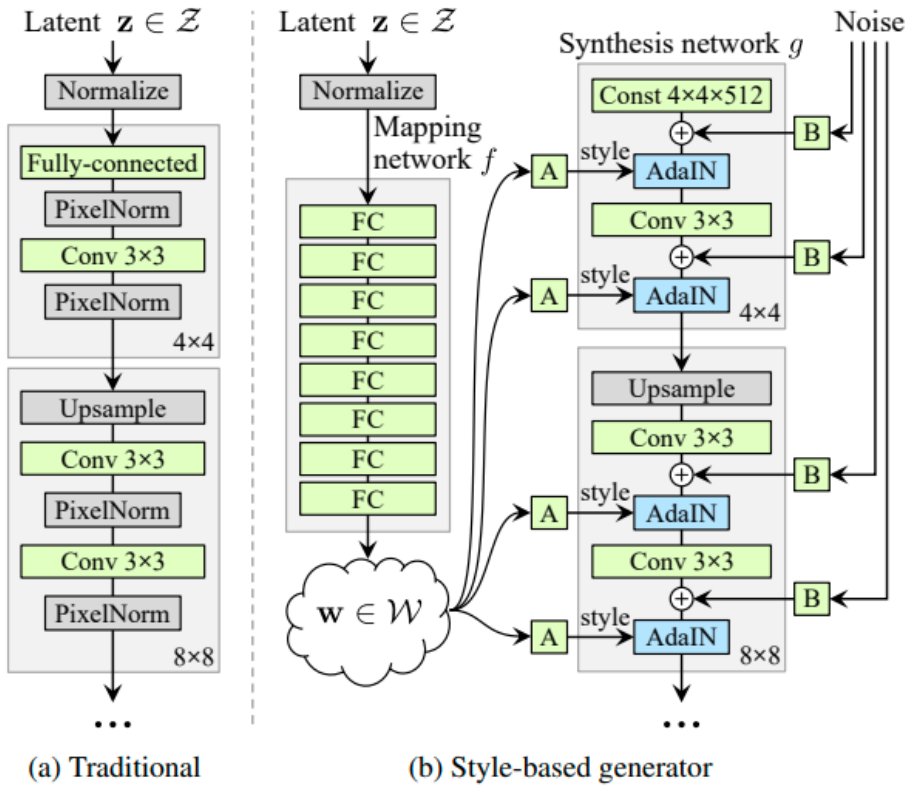


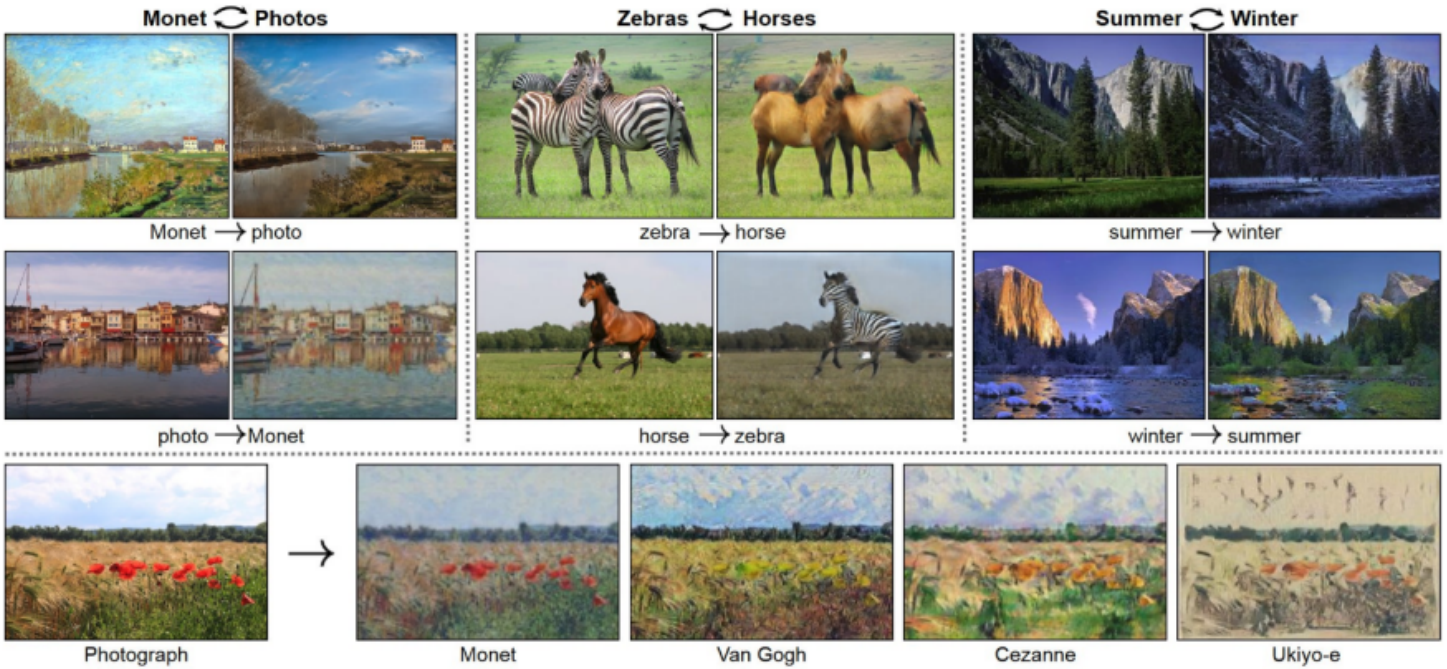
Figure: StyleGAN Architecture (Source)

StyleGAN Model Architecture

- The StyleGAN is described as a progressive growing GAN architecture with five modifications:
  - Baseline Progressive GAN.
  - Addition of tuning and bilinear upsampling.
  - Addition of mapping network and AdaIN (styles).
  - Removal of latent vector input to generator.
  - Addition of noise to each block.
  - Addition Mixing regularization.

CycleGAN: Unpaired Image-to-Image Translation

- Style transfer problem: change the style of an image while preserving the content.

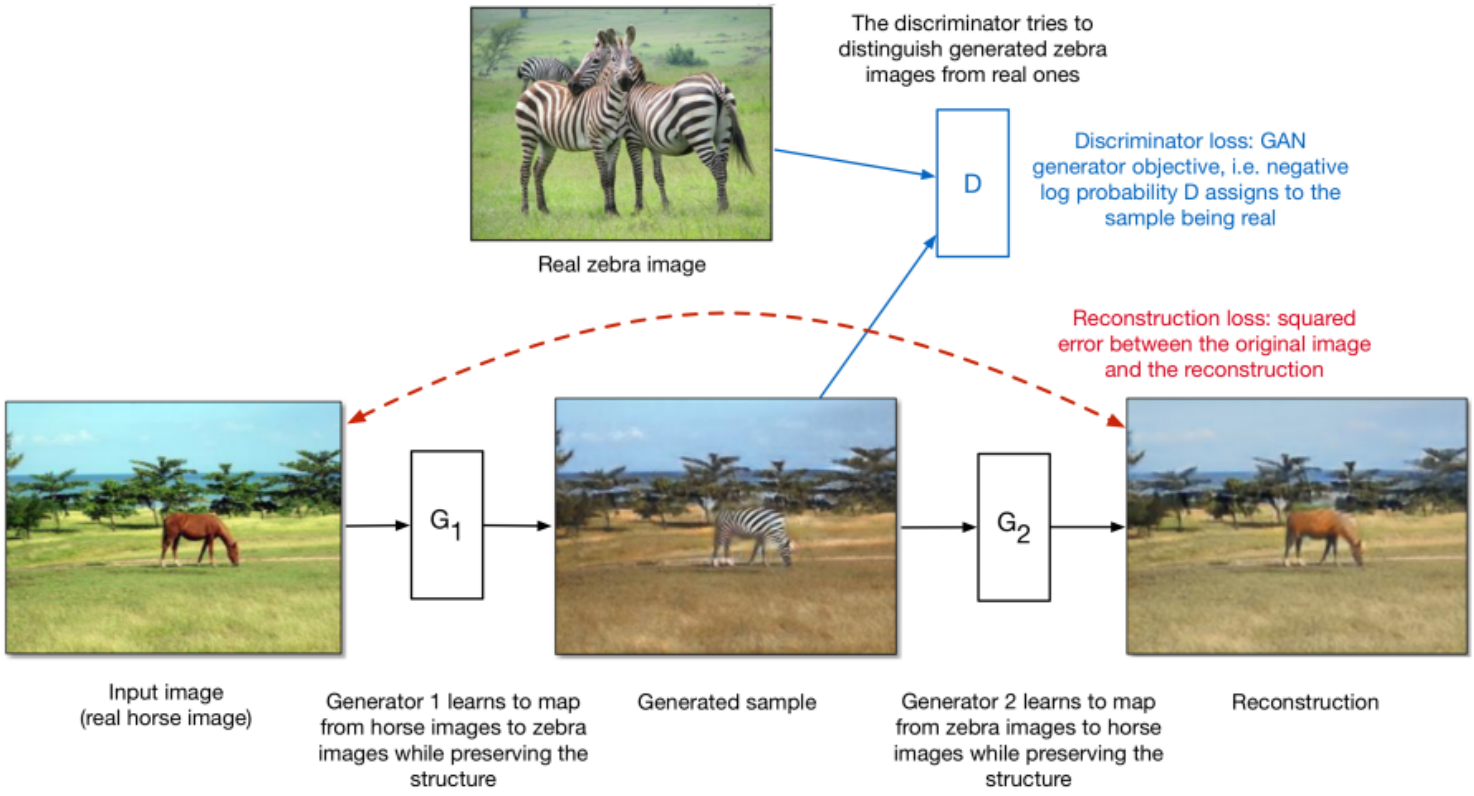


- Data: Two unrelated collections of images, one for each style

CycleGAN: Unpaired Image-to-Image Translation

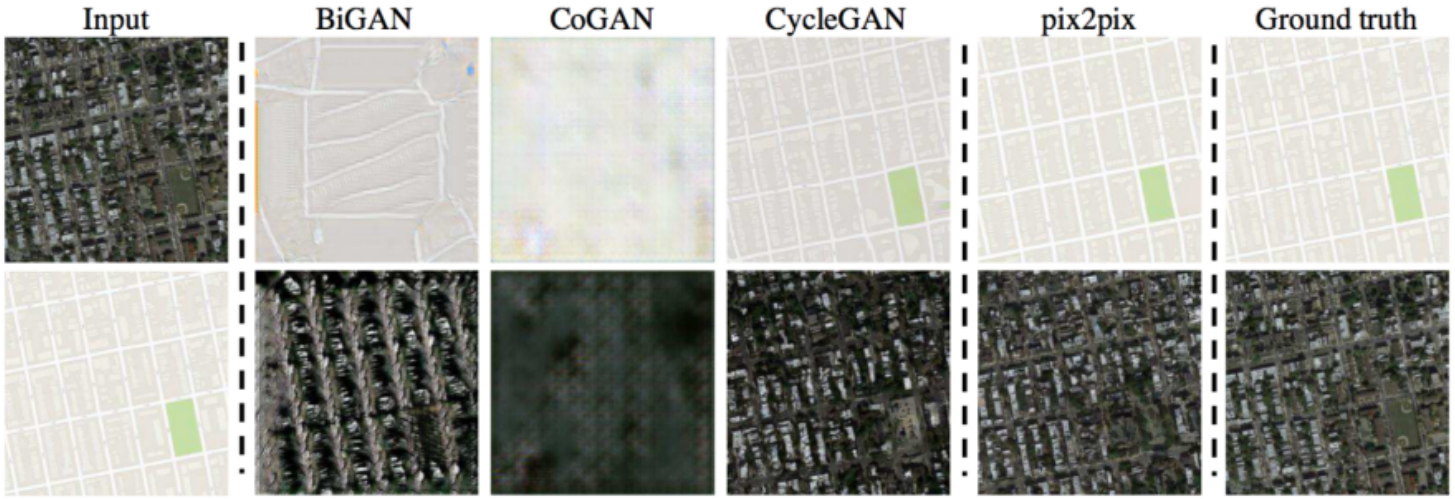
- If we had paired data (same content in both styles), this would be a supervised learning problem. But this is hard to find.
- The CycleGAN architecture learns to do it from unpaired data.
  - Train two different generator nets to go from style 1 to style 2, and vice versa.
  - Make sure the generated samples of style 2 are indistinguishable from real images by a discriminator net.
  - Make sure the generators are cycle-consistent: mapping from style 1 to style 2 and back again should give you almost the original image.

CycleGAN


The discriminator tries to distinguish generated zebra images from real ones
D
Discriminator loss: GAN generator objective, i.e. negative log probability D assigns to the sample being real
Real zebra image
Reconstruction loss: squared error between the original image and the reconstruction
G1
G2
Input image (real horse image)
Generator 1 learns to map from horse images to zebra images while preserving the structure
Generated sample
Generator 2 learns to map from zebra images to horse images while preserving the structure
Reconstruction
Total loss = discriminator loss + reconstruction loss

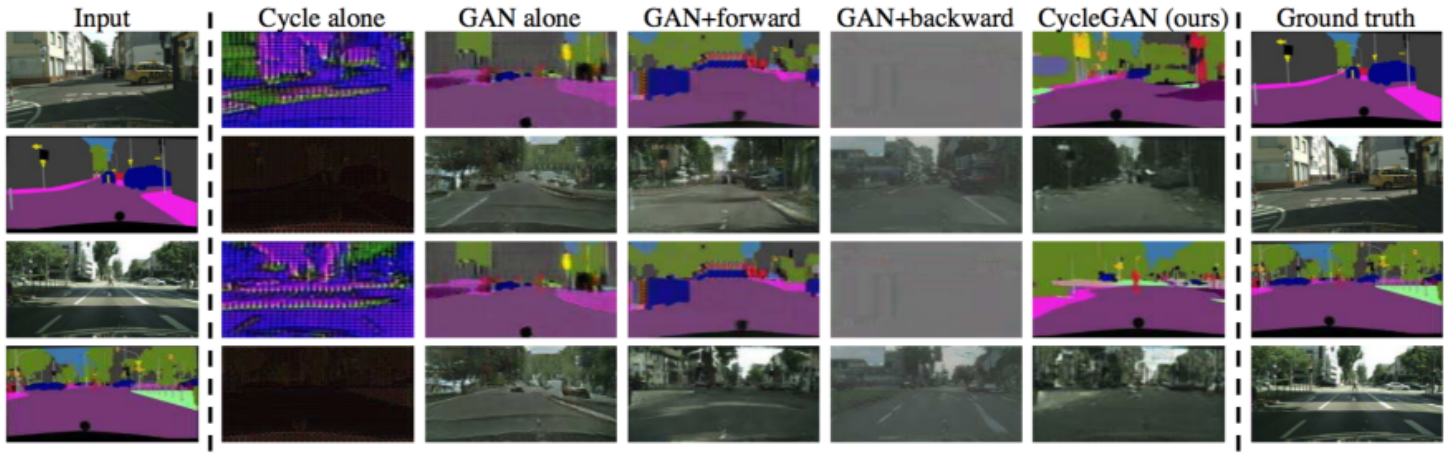
CycleGAN

Style transfer between aerial photos and maps:



CycleGAN: Example

- Style transfer between road scenes and semantic segmentations (labels of every pixel in an image by object category):



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