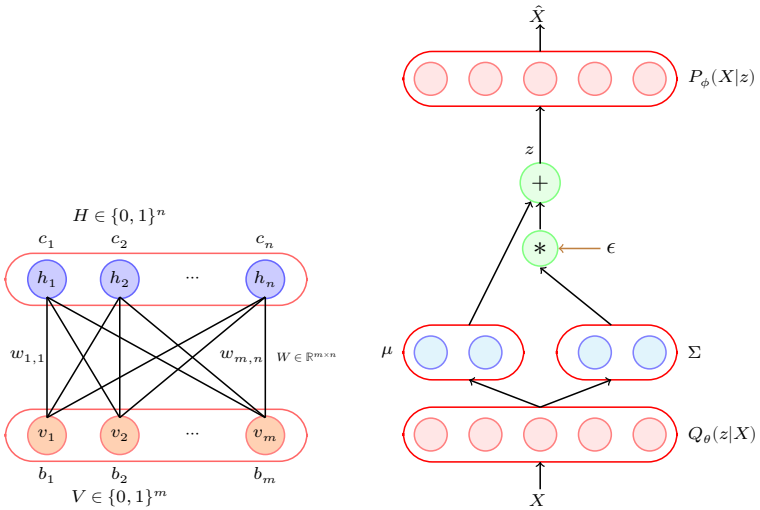
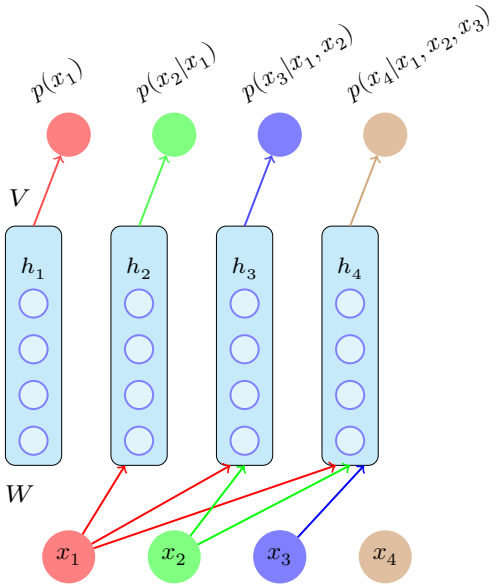
Generative Adversarial Networks (GANs)

ML Instruction Team, Fall 2022

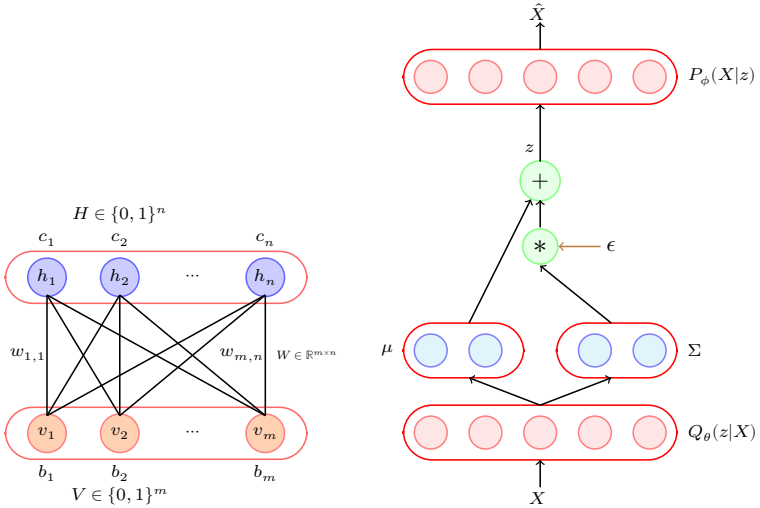
CE Department
Sharif University of Technology

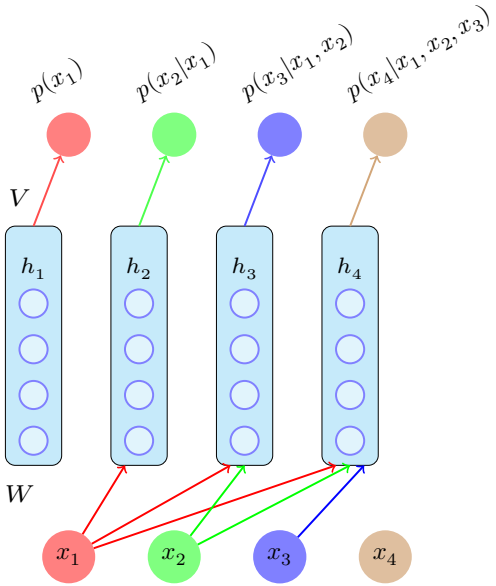
Generative Adversarial Networks - The intuition



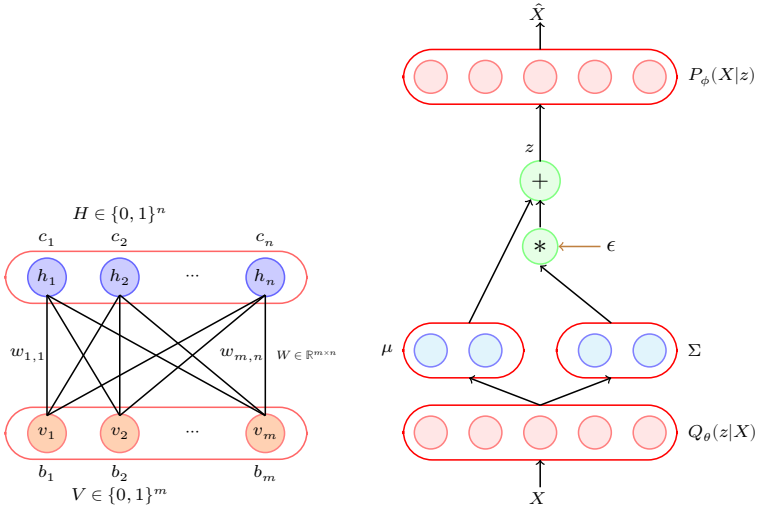


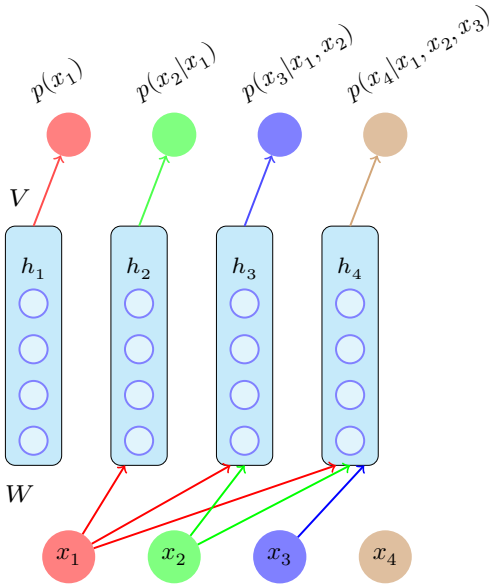
- So far we have looked at generative models which explicitly model the joint probability distribution or conditional probability distribution



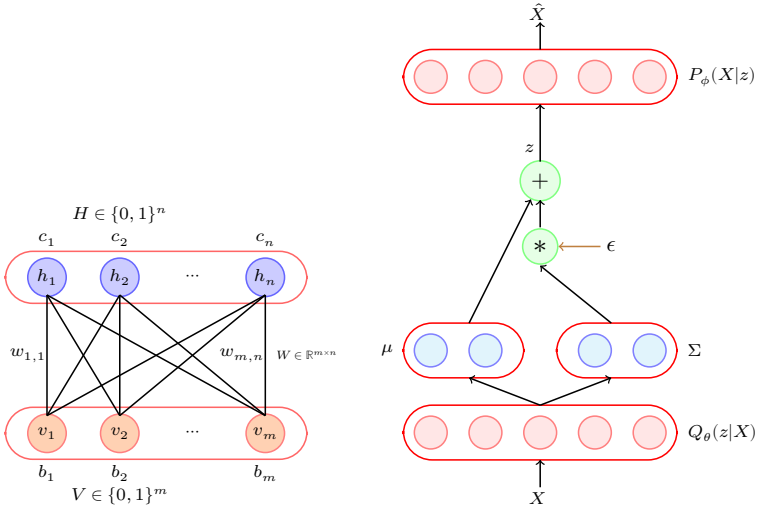


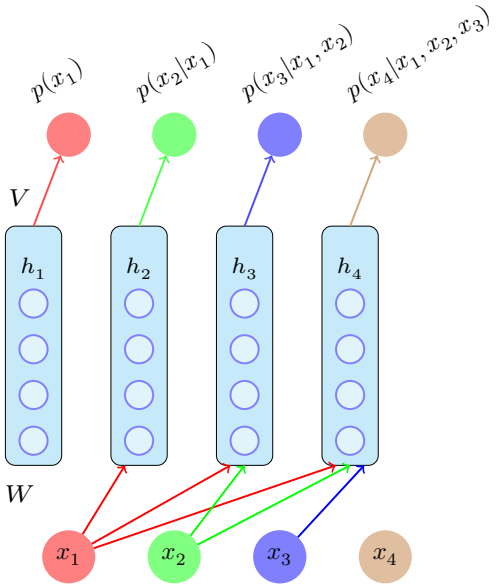
- So far we have looked at generative models which explicitly model the joint probability distribution or conditional probability distribution
- For example, in RBMs we learn $P(X, H)$, in VAEs we learn $P(z|X)$ and $P(X|z)$ whereas in AR models we learn $P(X)$



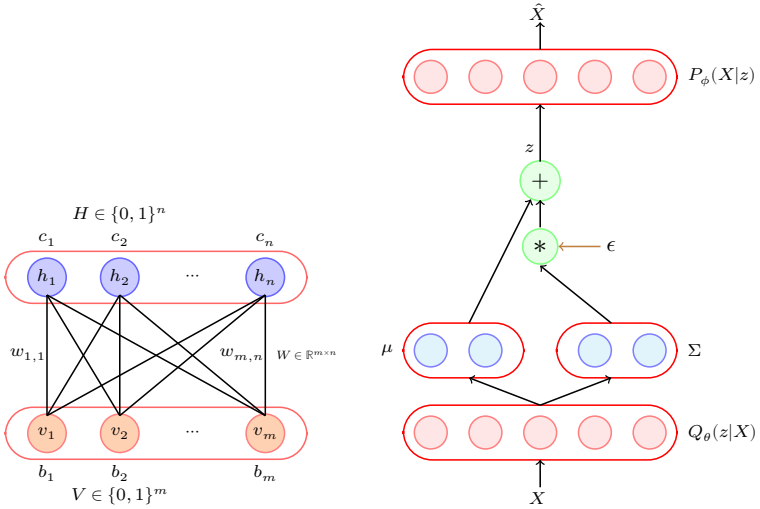


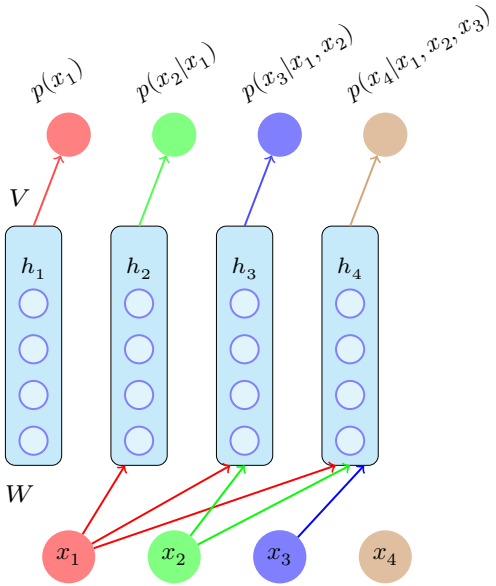
- So far we have looked at generative models which explicitly model the joint probability distribution or conditional probability distribution
- For example, in RBMs we learn $P(X, H)$, in VAEs we learn $P(z|X)$ and $P(X|z)$ whereas in AR models we learn $P(X)$
- What if we are only interested in sampling from the distribution and don't really care about explicit density function $P(X)$?



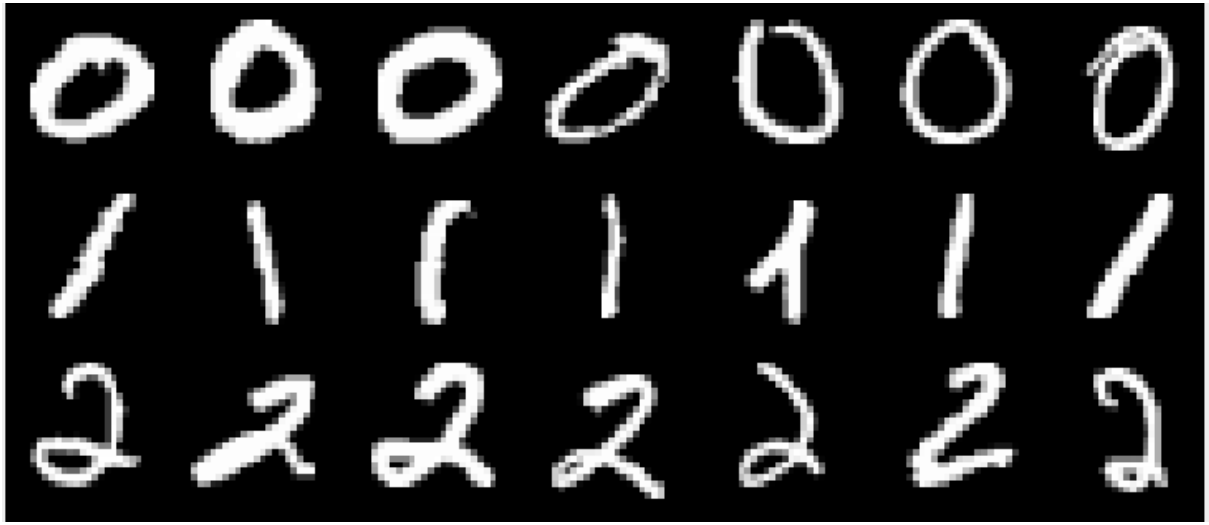


- So far we have looked at generative models which explicitly model the joint probability distribution or conditional probability distribution
- For example, in RBMs we learn $P(X, H)$, in VAEs we learn $P(z|X)$ and $P(X|z)$ whereas in AR models we learn $P(X)$
- What if we are only interested in sampling from the distribution and don't really care about explicit density function $P(X)$?
- What does this mean?

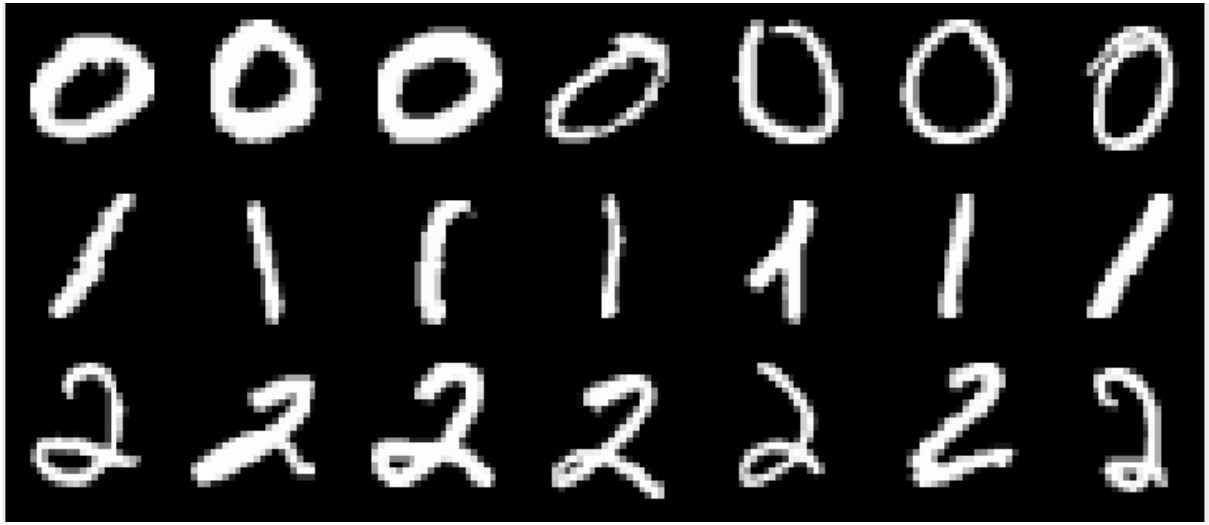




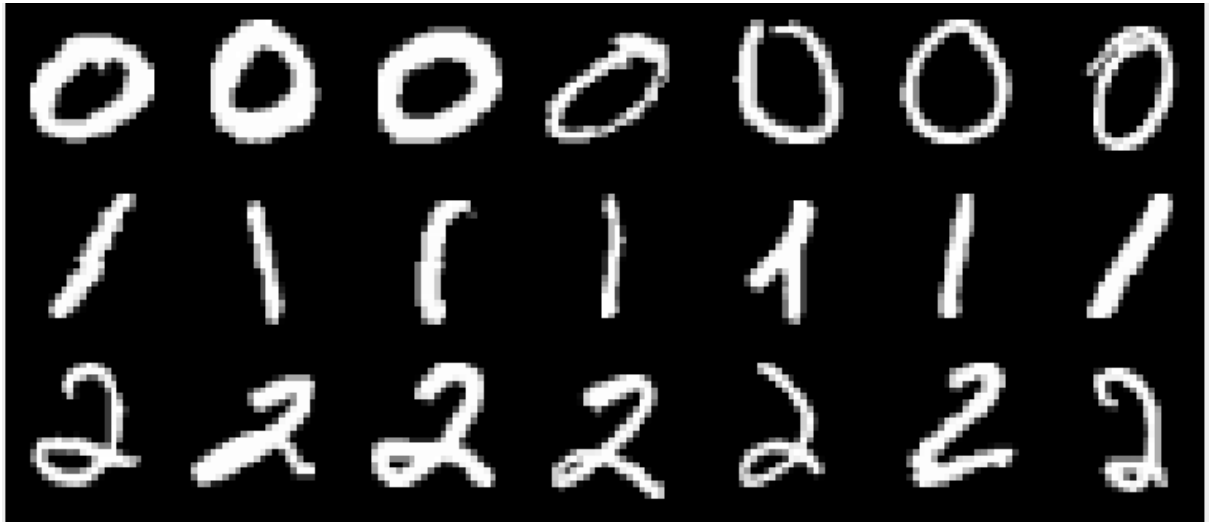
- So far we have looked at generative models which explicitly model the joint probability distribution or conditional probability distribution
- For example, in RBMs we learn $P(X, H)$, in VAEs we learn $P(z|X)$ and $P(X|z)$ whereas in AR models we learn $P(X)$
- What if we are only interested in sampling from the distribution and don't really care about explicit density function $P(X)$?
- What does this mean? Let us see



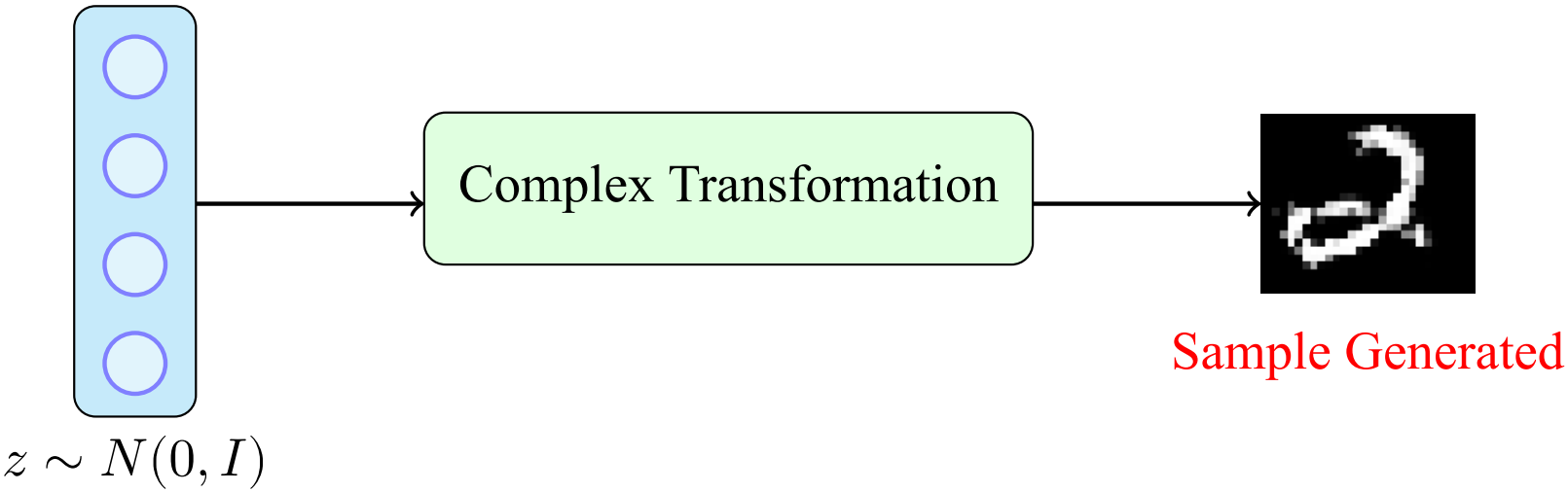
- As usual we are given some training data (say, MNIST images) which obviously comes from some underlying distribution



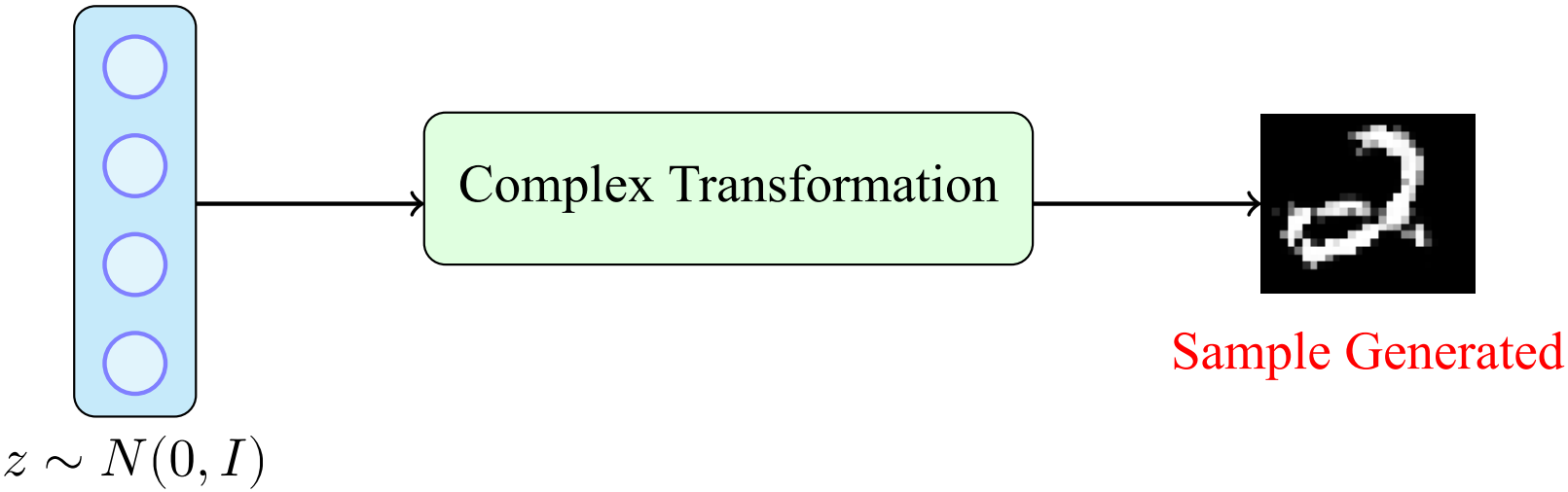
- As usual we are given some training data (say, MNIST images) which obviously comes from some underlying distribution
- Our goal is to generate more images from this distribution (*i.e.*, create images which look similar to the images from the training data)



- As usual we are given some training data (say, MNIST images) which obviously comes from some underlying distribution
- Our goal is to generate more images from this distribution (*i.e.*, create images which look similar to the images from the training data)
- In other words, we want to sample from a complex high dimensional distribution which is intractable (recall RBMs, VAEs and AR models deal with this intractability in their own way)



- GANs take a different approach to this problem where the idea is to sample from a simple tractable distribution (say, $z \sim N(0, I)$) and then learn a complex transformation from this to the training distribution



- GANs take a different approach to this problem where the idea is to sample from a simple tractable distribution (say, $z \sim N(0, I)$) and then learn a complex transformation from this to the training distribution
- In other words, we will take a $z \sim N(0, I)$, learn to make a series of complex transformations on it so that the output looks as if it came from our training distribution

- What can we use for such a complex transformation?

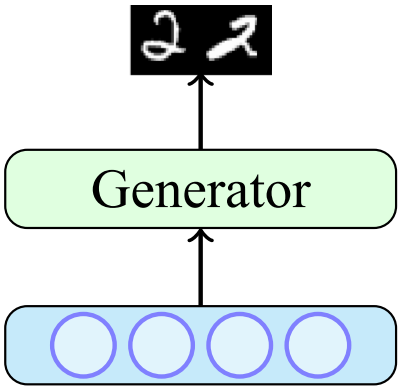
- What can we use for such a complex transformation? A Neural Network

- What can we use for such a complex transformation? A Neural Network
- How do you train such a neural network?

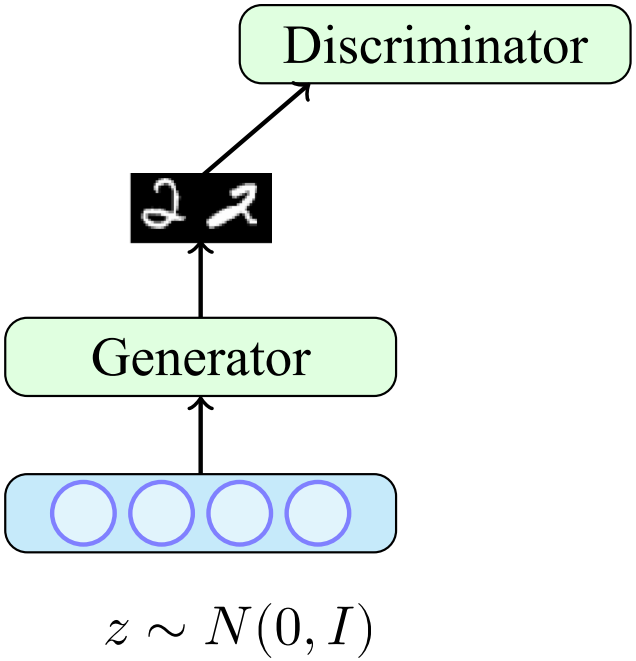
- What can we use for such a complex transformation? A Neural Network
- How do you train such a neural network? Using a two player game

- What can we use for such a complex transformation? A Neural Network
- How do you train such a neural network? Using a two player game
- There are two players in the game:

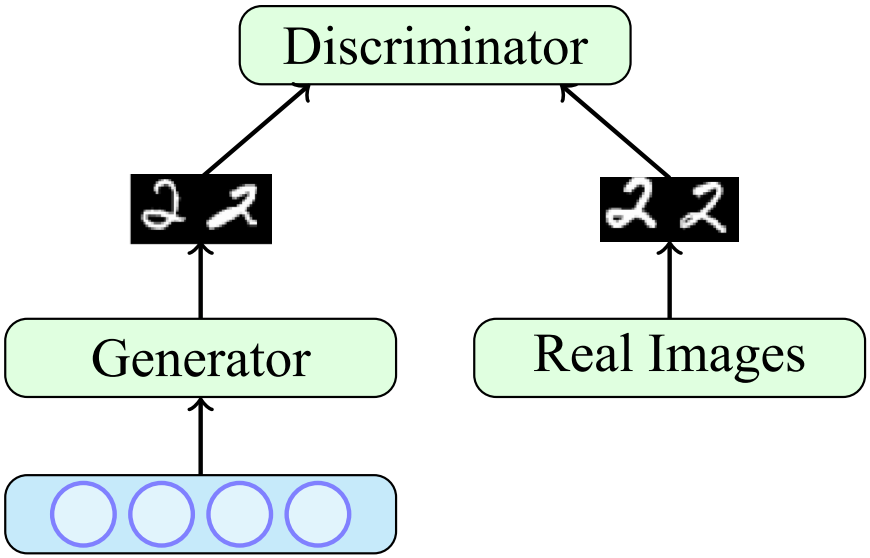
- What can we use for such a complex transformation? A Neural Network
- How do you train such a neural network? Using a two player game
- There are two players in the game: a generator



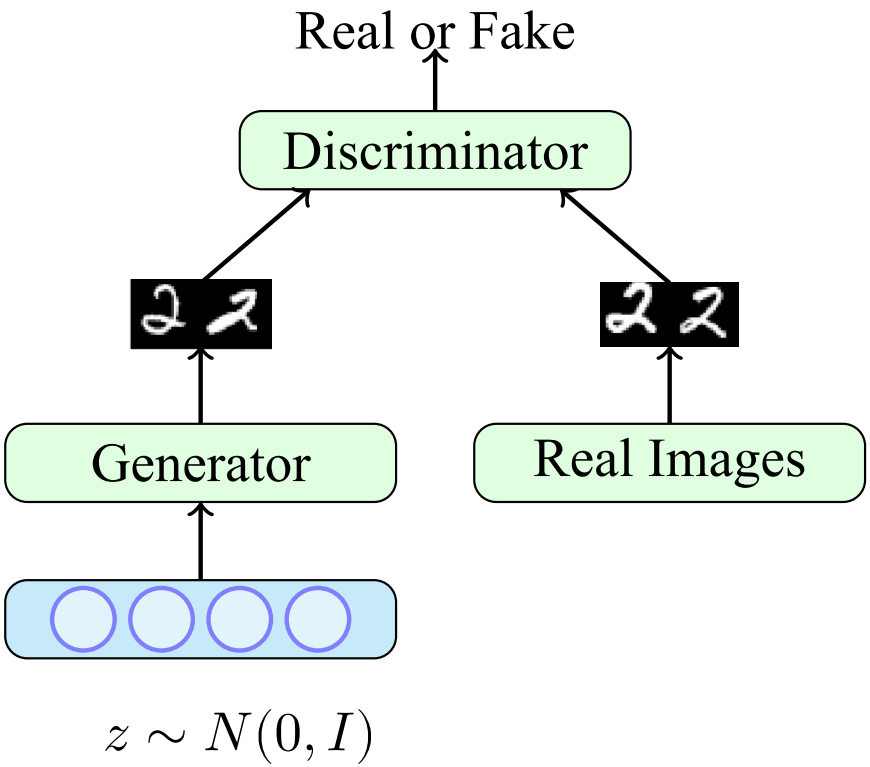
$z \sim N(0, I)$



- What can we use for such a complex transformation? A Neural Network
- How do you train such a neural network? Using a two player game
- There are two players in the game: a generator and a discriminator

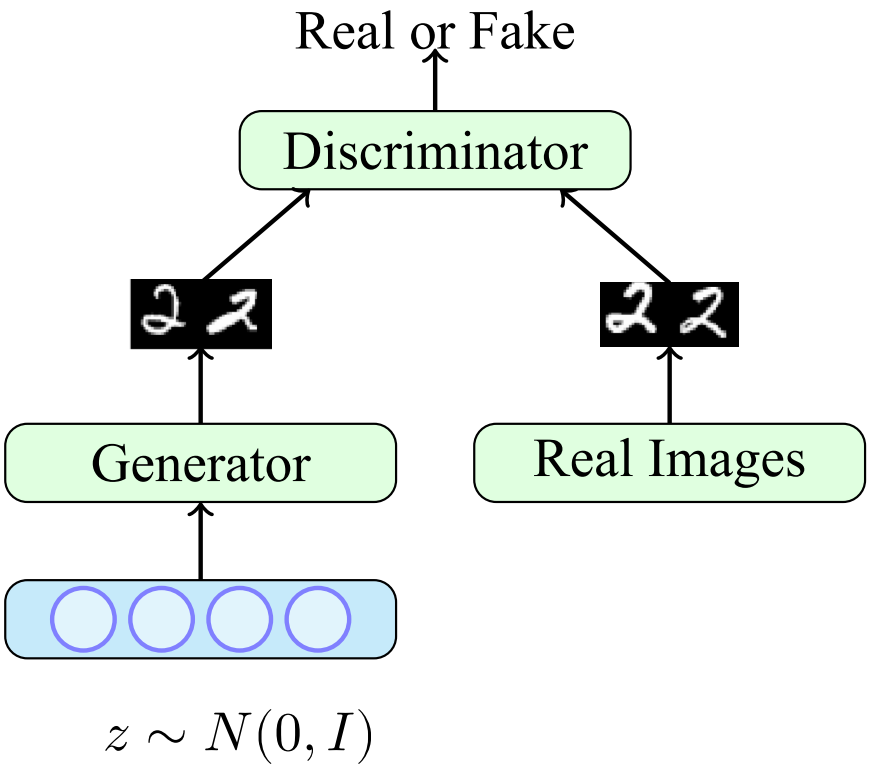


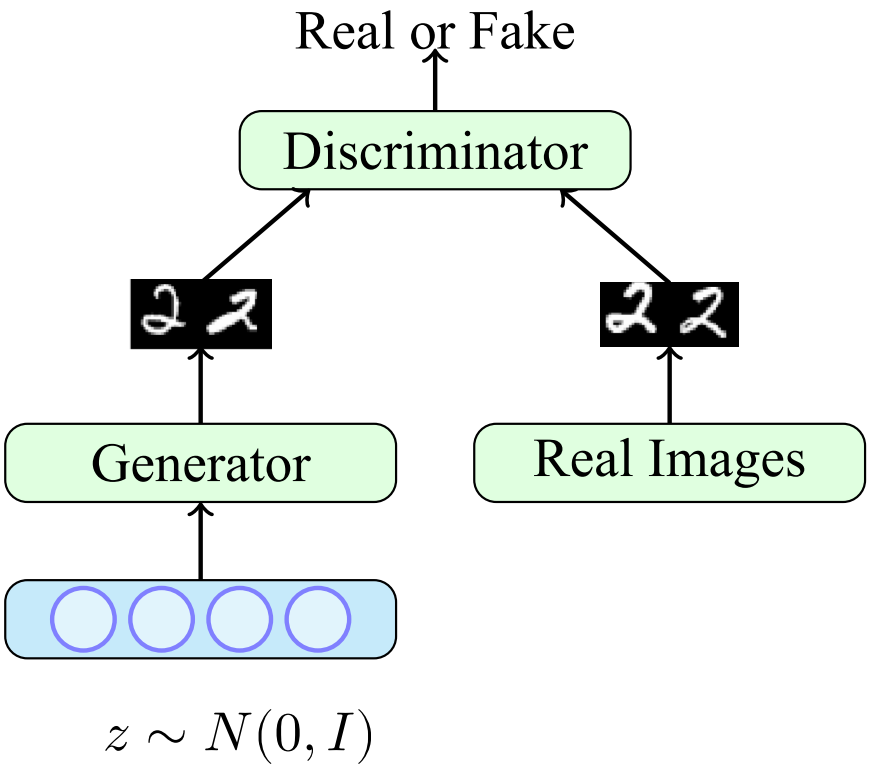
- What can we use for such a complex transformation? A Neural Network
- How do you train such a neural network? Using a two player game
- There are two players in the game: a generator and a discriminator
- The job of the generator is to produce images which look so natural that the discriminator thinks that the images came from the real data distribution



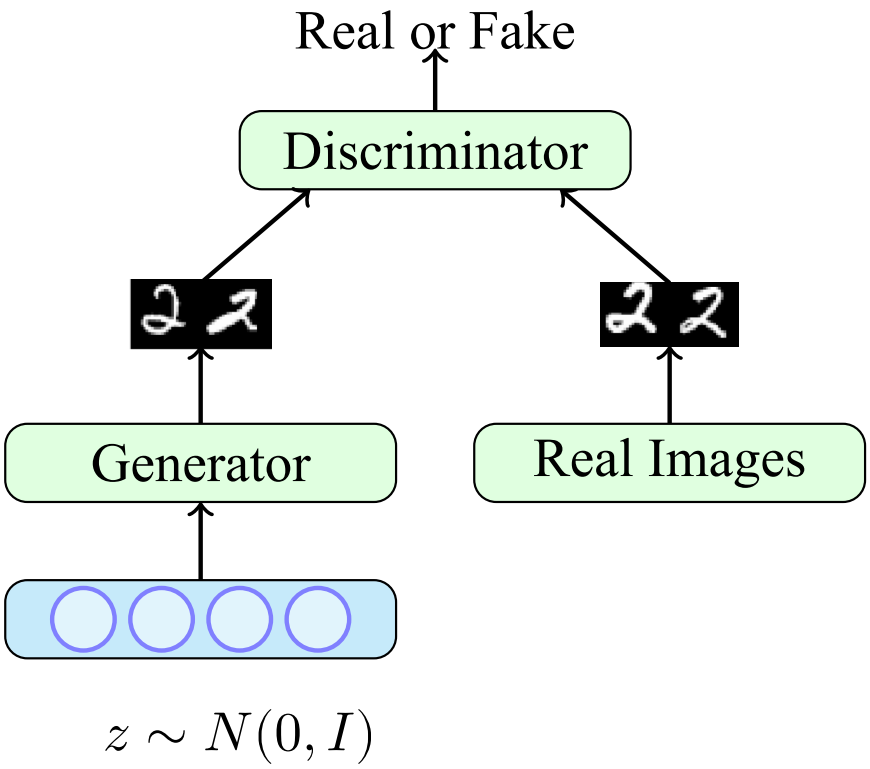
- What can we use for such a complex transformation? A Neural Network
- How do you train such a neural network? Using a two player game
- There are two players in the game: a generator and a discriminator
- The job of the generator is to produce images which look so natural that the discriminator thinks that the images came from the real data distribution
- The job of the discriminator is to get better and better at distinguishing between true images and generated (fake) images

- So let's look at the full picture

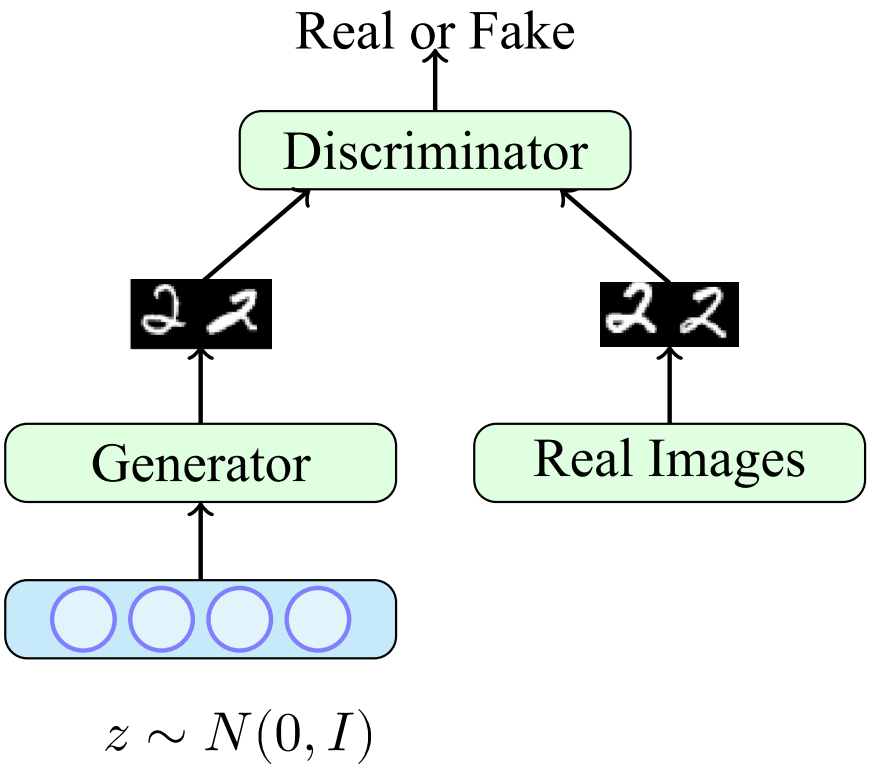




- So let's look at the full picture
- Let G_ϕ be the generator and D_θ be the discriminator (ϕ and θ are the parameters of G and D, respectively)

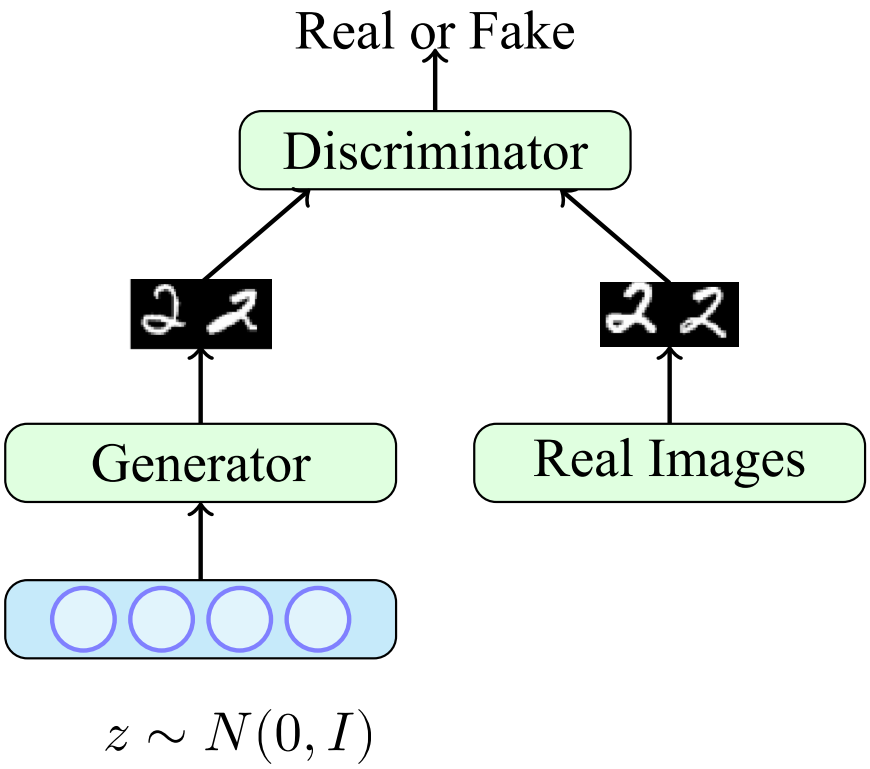


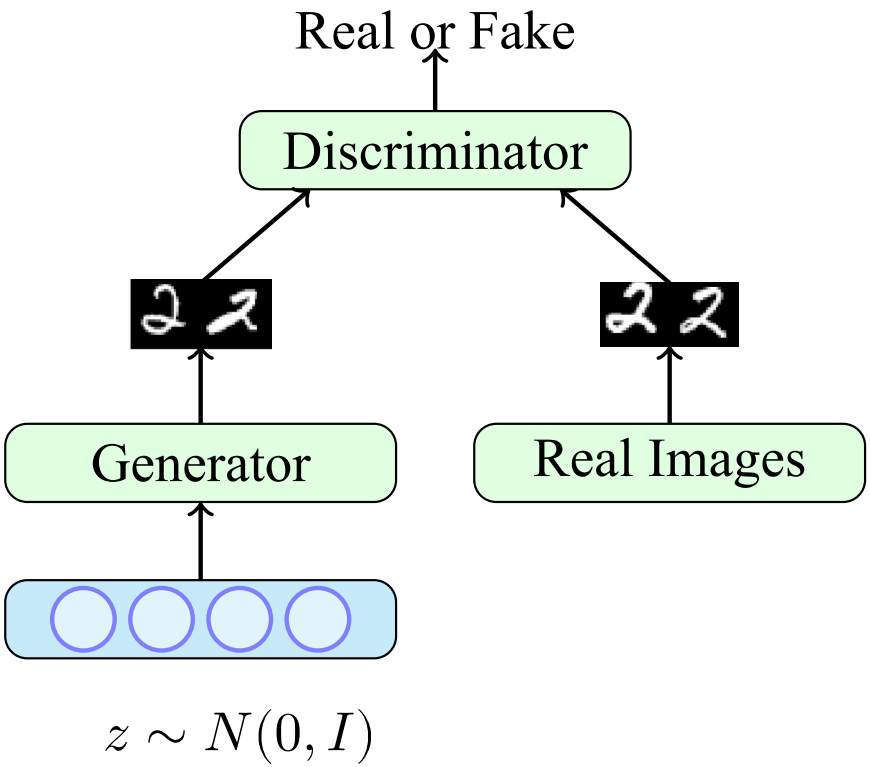
- So let's look at the full picture
- Let G_ϕ be the generator and D_θ be the discriminator (ϕ and θ are the parameters of G and D, respectively)
- We have a neural network based generator which takes as input a noise vector $z \sim N(0, I)$ and produces $G_\phi(z) = X$



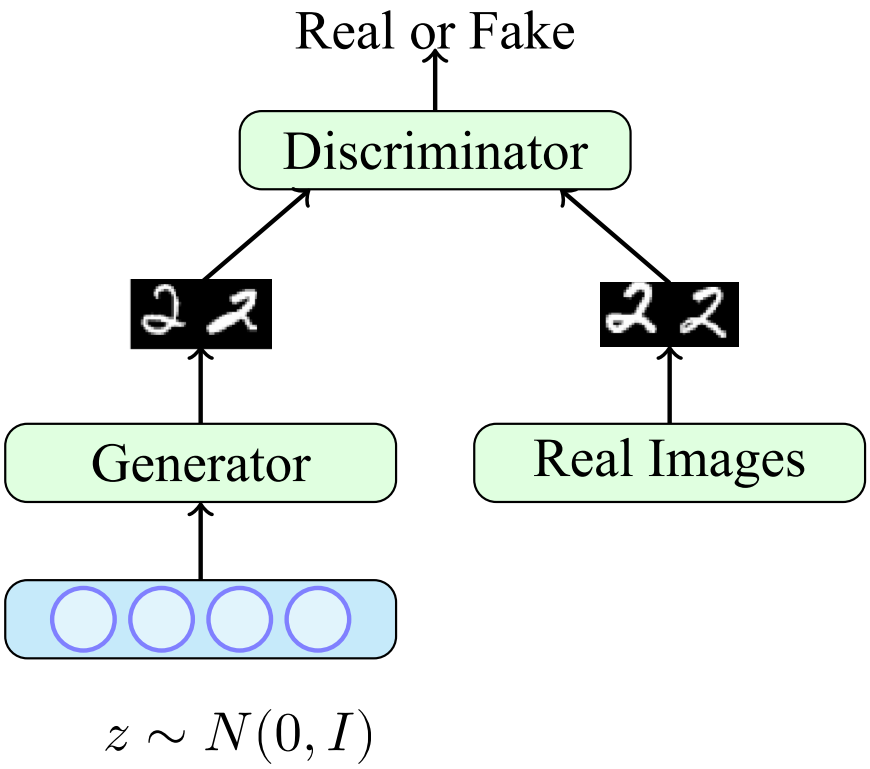
- So let's look at the full picture
- Let G_ϕ be the generator and D_θ be the discriminator (ϕ and θ are the parameters of G and D, respectively)
- We have a neural network based generator which takes as input a noise vector $z \sim N(0, I)$ and produces $G_\phi(z) = X$
- We have a neural network based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

- What should be the objective function of the overall network?

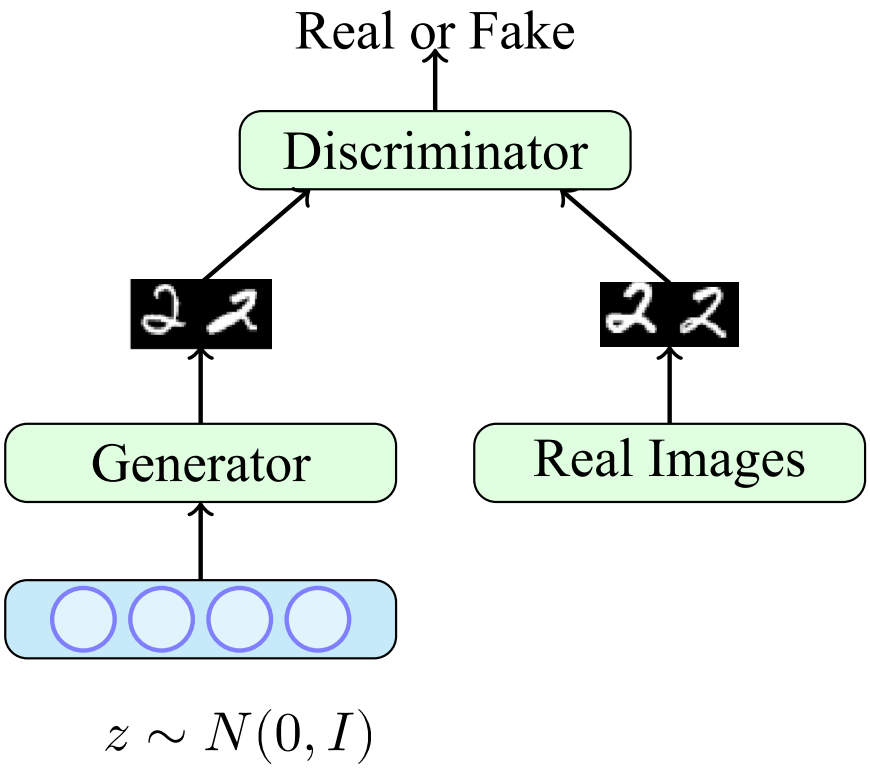




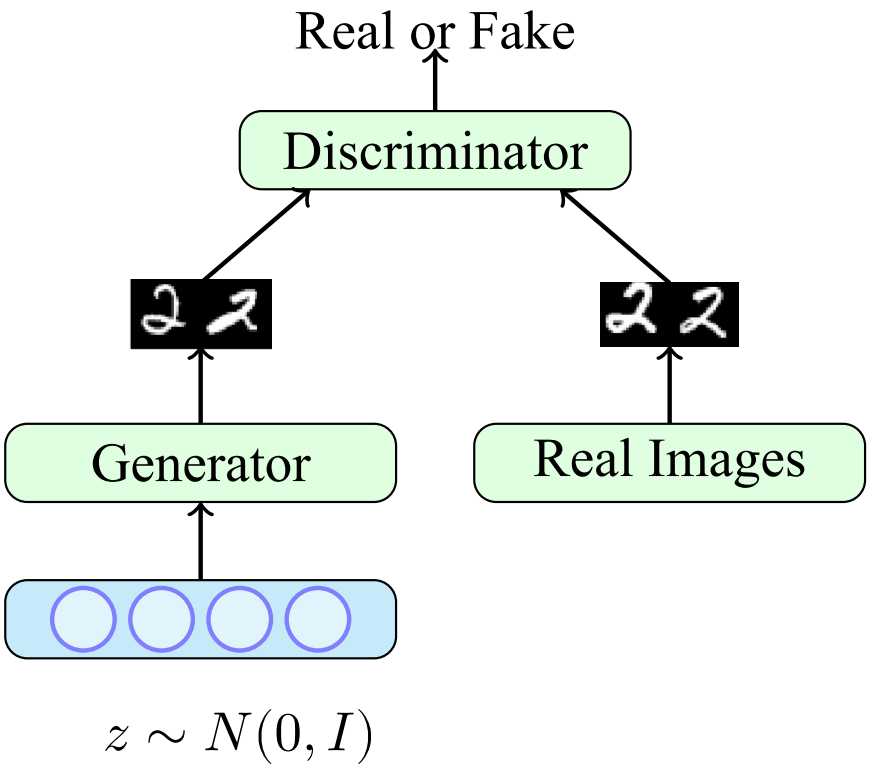
- What should be the objective function of the overall network?
- Let's look at the objective function of the generator first



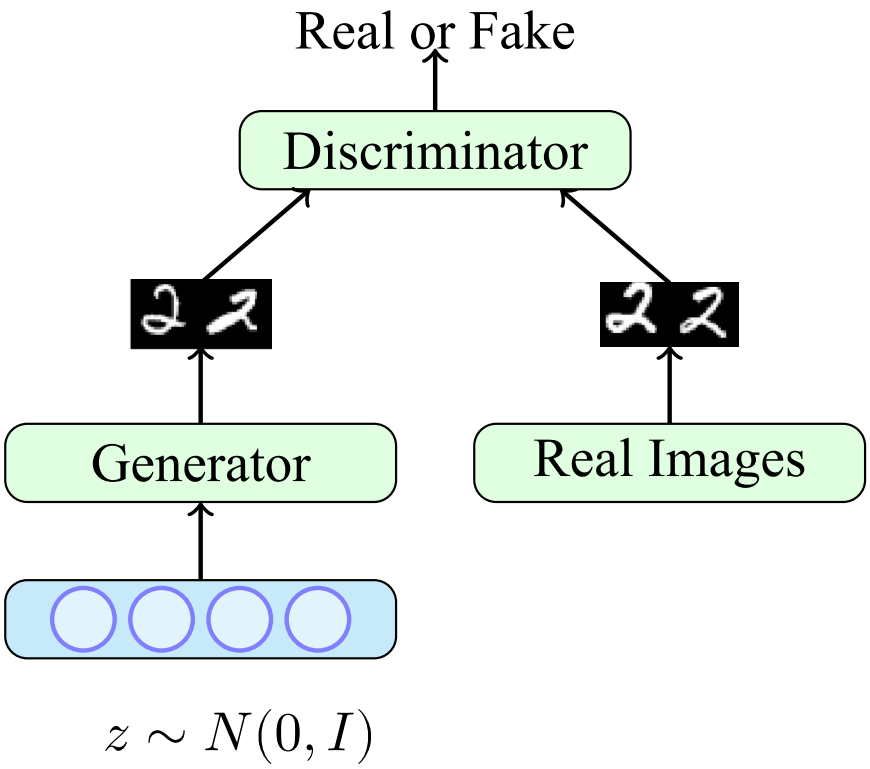
- What should be the objective function of the overall network?
- Let's look at the objective function of the generator first
- Given an image generated by the generator as $G_\phi(z)$ the discriminator assigns a score $D_\theta(G_\phi(z))$ to it



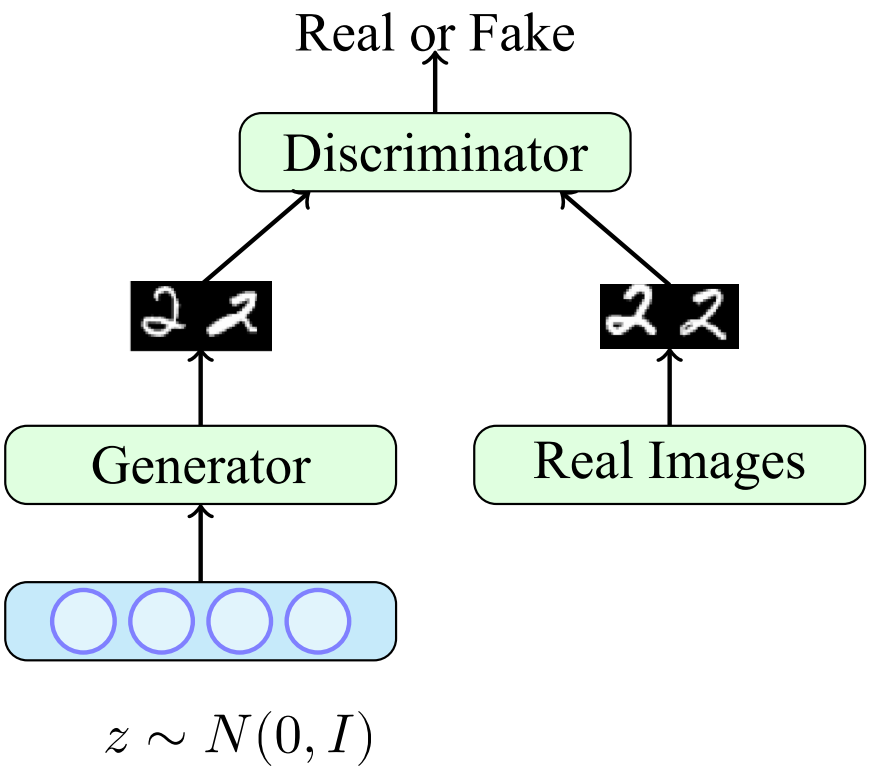
- What should be the objective function of the overall network?
- Let's look at the objective function of the generator first
- Given an image generated by the generator as $G_\phi(z)$ the discriminator assigns a score $D_\theta(G_\phi(z))$ to it
- This score will be between 0 and 1 and will tell us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



- 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
- For a given z, the generator would want to maximize $\log D_\theta(G_\phi(z))$ (log likelihood) or minimize $\log(1 - D_\theta(G_\phi(z)))$

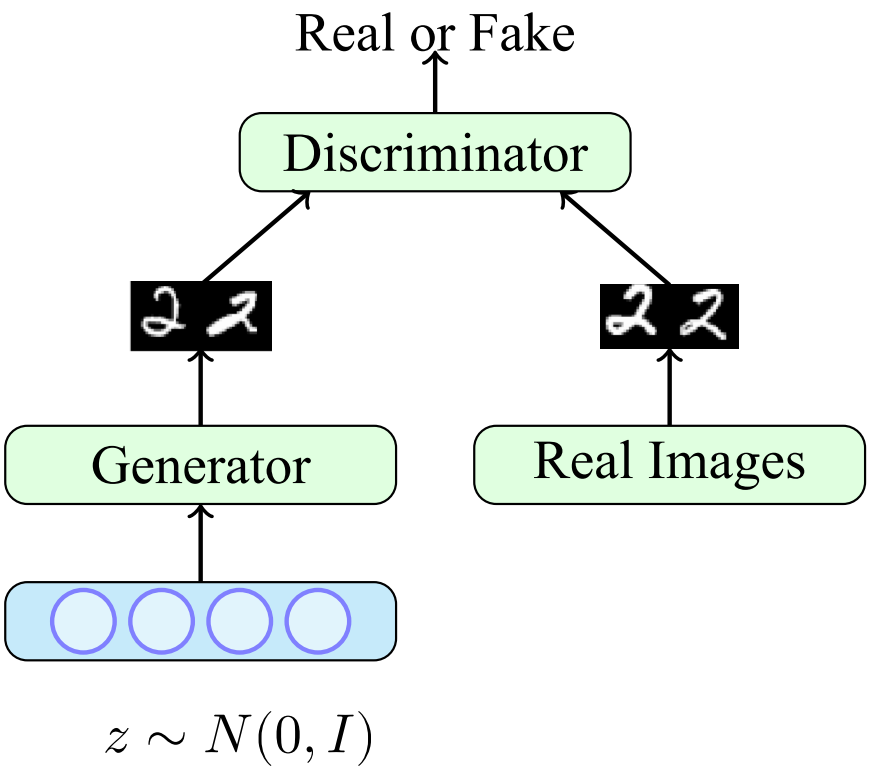


- This is just for a single z and the generator would like to do this for all possible values of z,



- 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

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



- 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

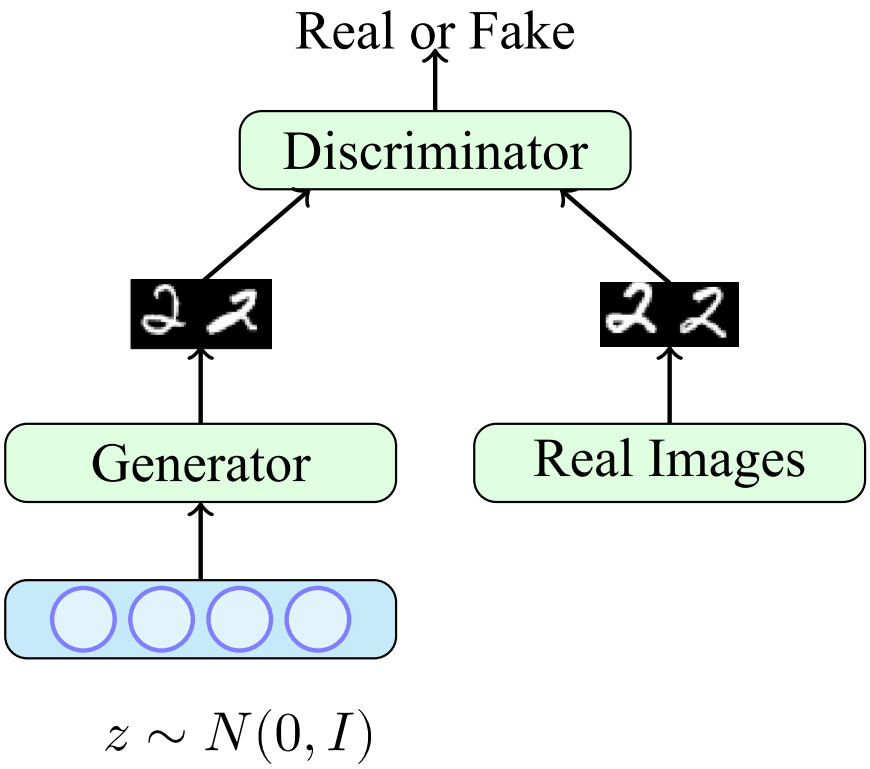
$$\min_{\phi} \sum_{i=1}^{N} \frac{1}{N} \log(1 - D_\theta(G_\phi(z)))$$

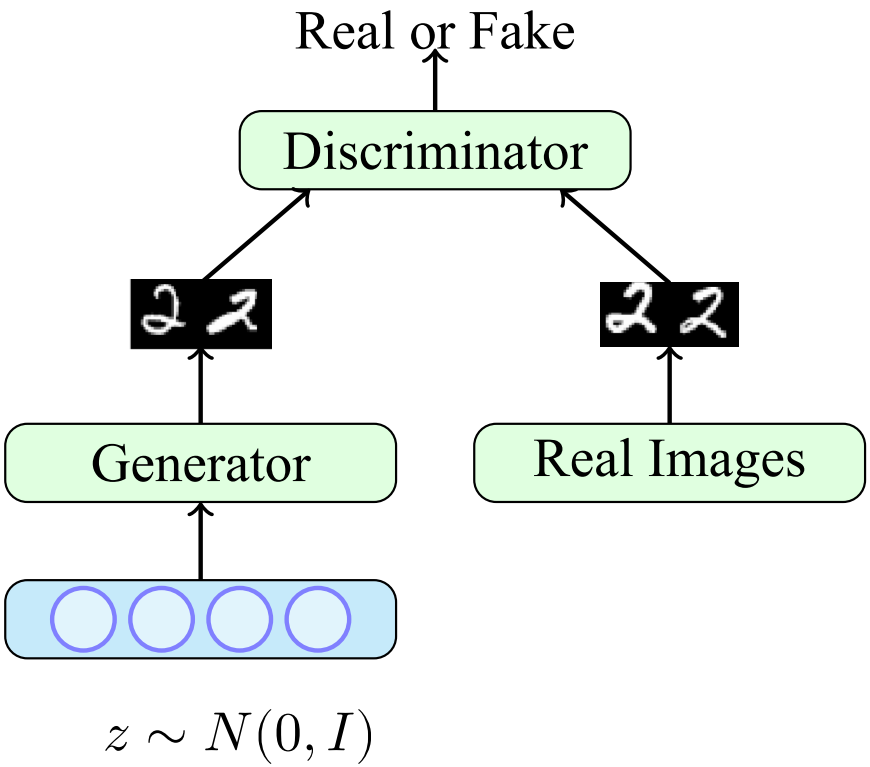
- However, in our case, z is continuous and not uniform ($z \sim N(0, I)$) so the equivalent objective function would be

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

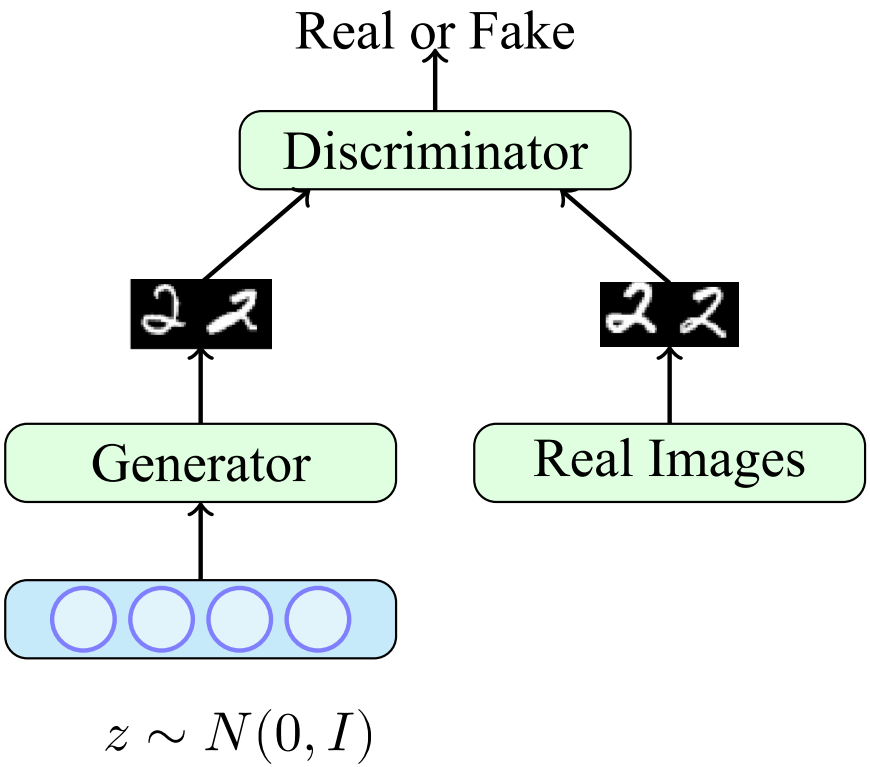
$$\min_{\phi} E_{z \sim p(z)}[\log(1 - D_\theta(G_\phi(z)))]$$

- Now let's look at the discriminator

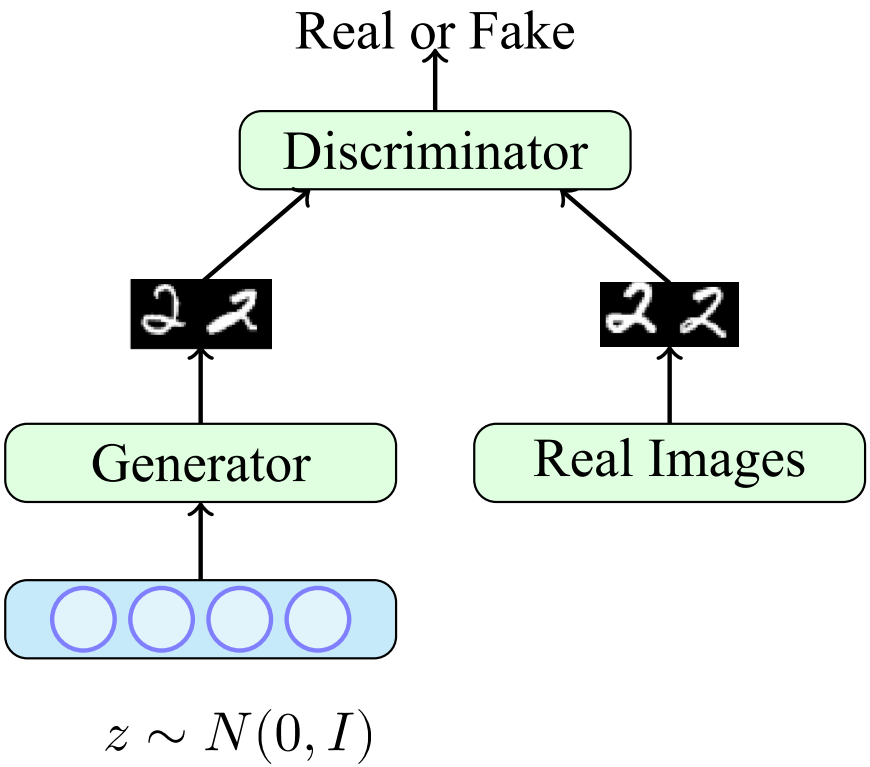




- Now let's look at the discriminator
- The task of the discriminator is to assign a high score to real images and a low score to fake images

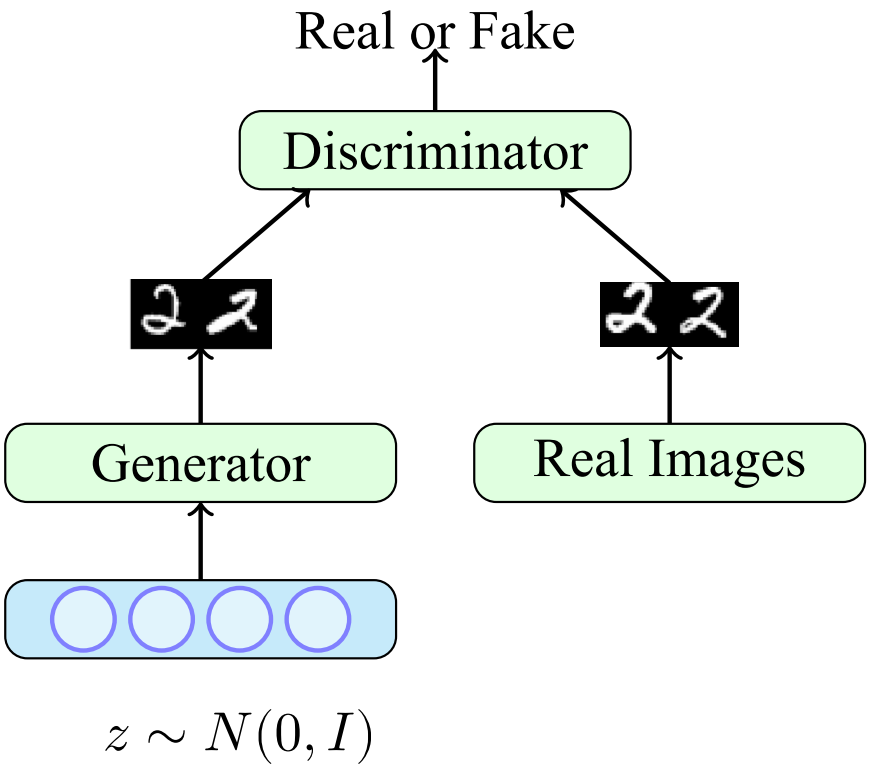


- Now let's look at the discriminator
- The task of the discriminator is to assign a high score to real images and a low score to fake images
- And it should do this for all possible real images and all possible fake images



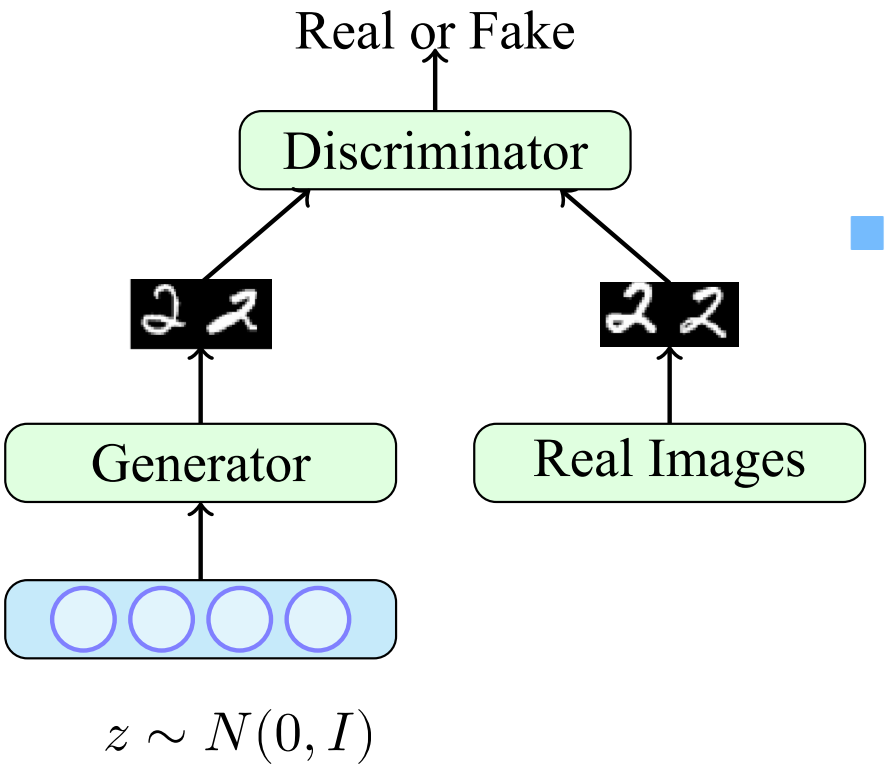
- Now let's look at the discriminator
- The task of the discriminator is to assign a high score to real images and a low score to fake images
- And it should do this for all possible real images and all possible fake images
- In other words, it should try to maximize the following objective function

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



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

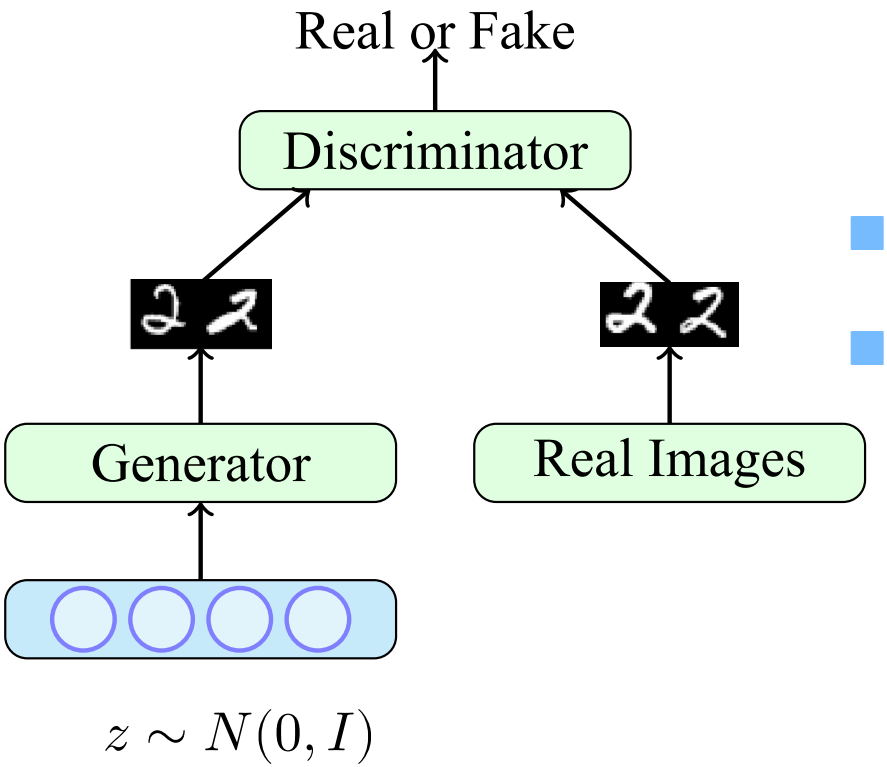
$$\min_{\phi} \max_{\theta} \; [\mathbb{E}_{x \sim p_{data}} \log D_\theta(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_\theta(G_\phi(z)))]$$



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

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

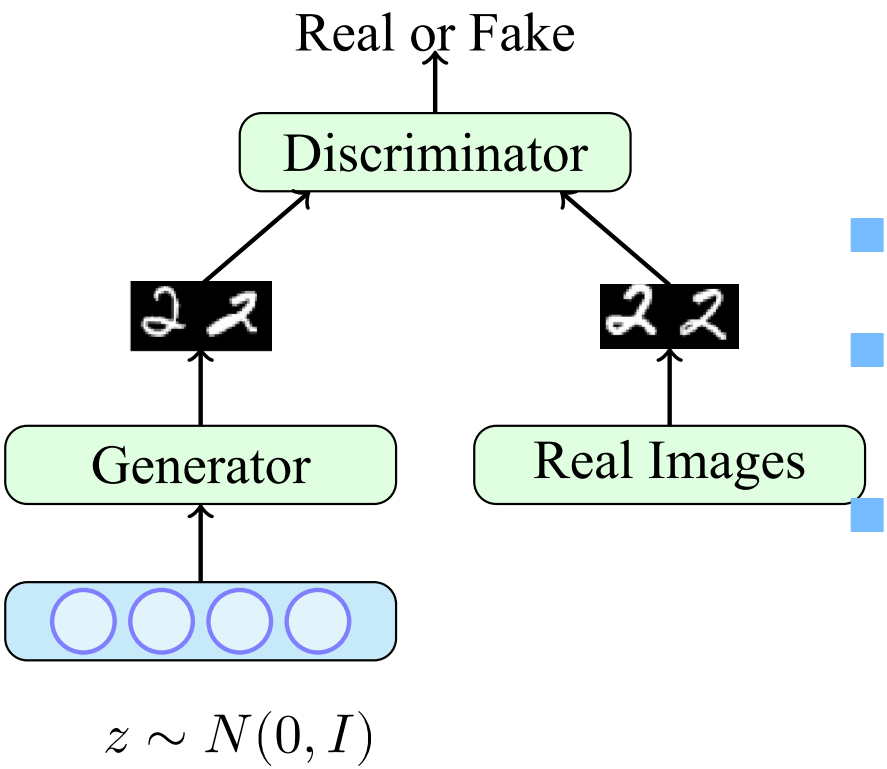
- The first term in the objective is only w.r.t. the parameters of the discriminator (θ)



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

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

- 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)

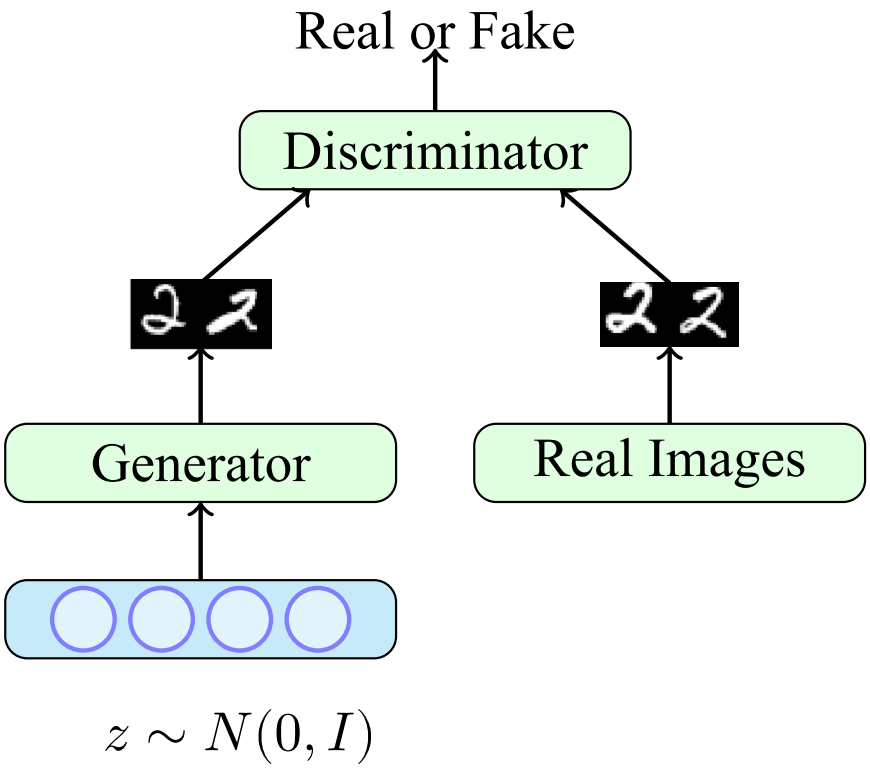


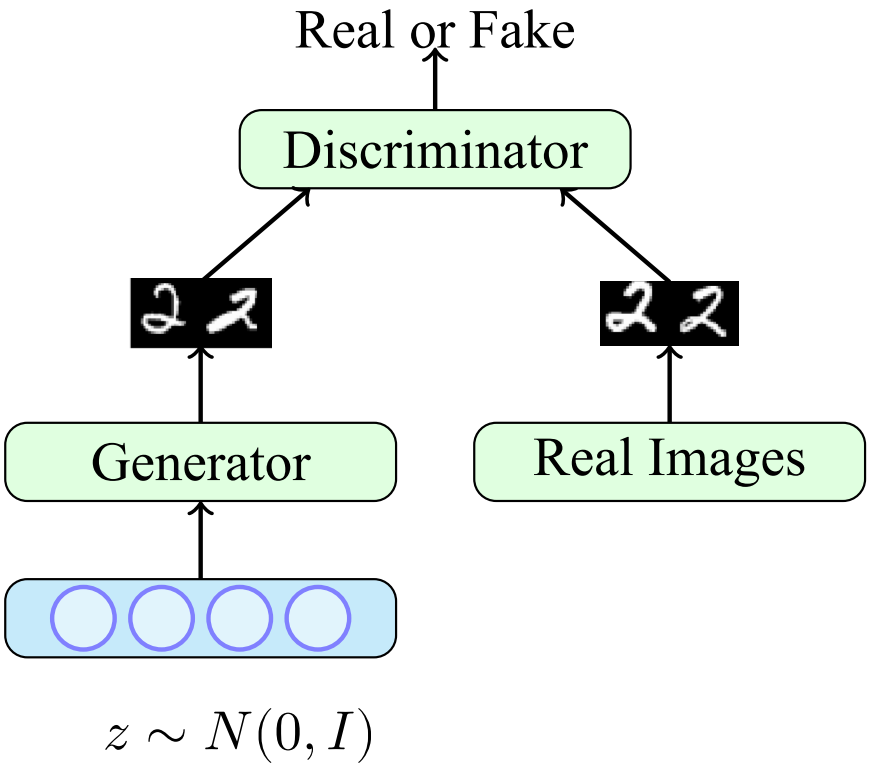
- If we put the objectives of the generator and discriminator together we get a minimax game

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

- 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)

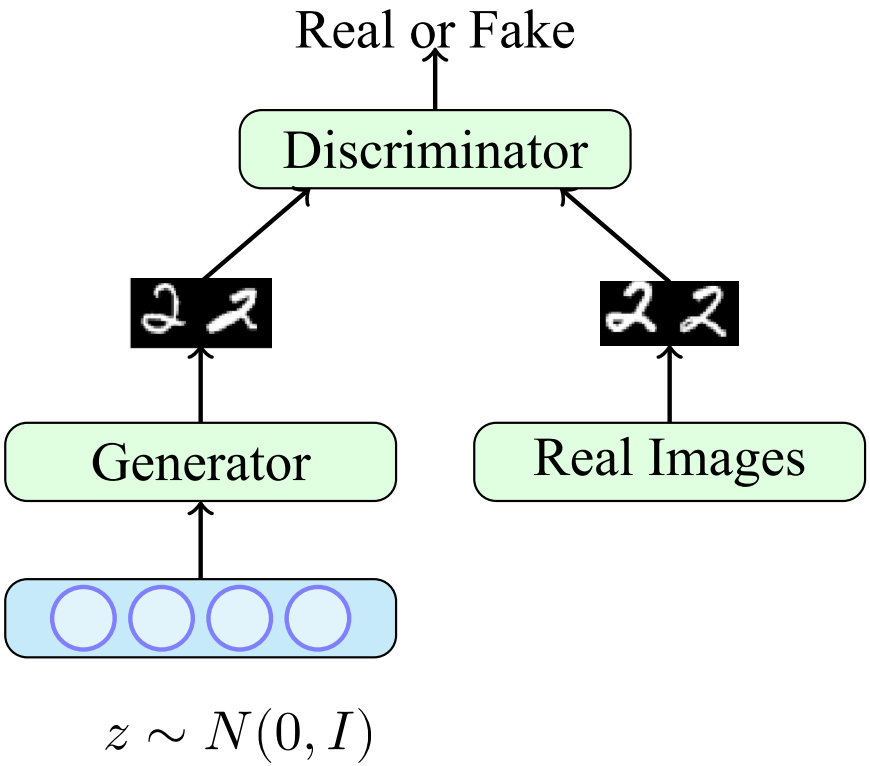
- So the overall training proceeds by alternating between these two step





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

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

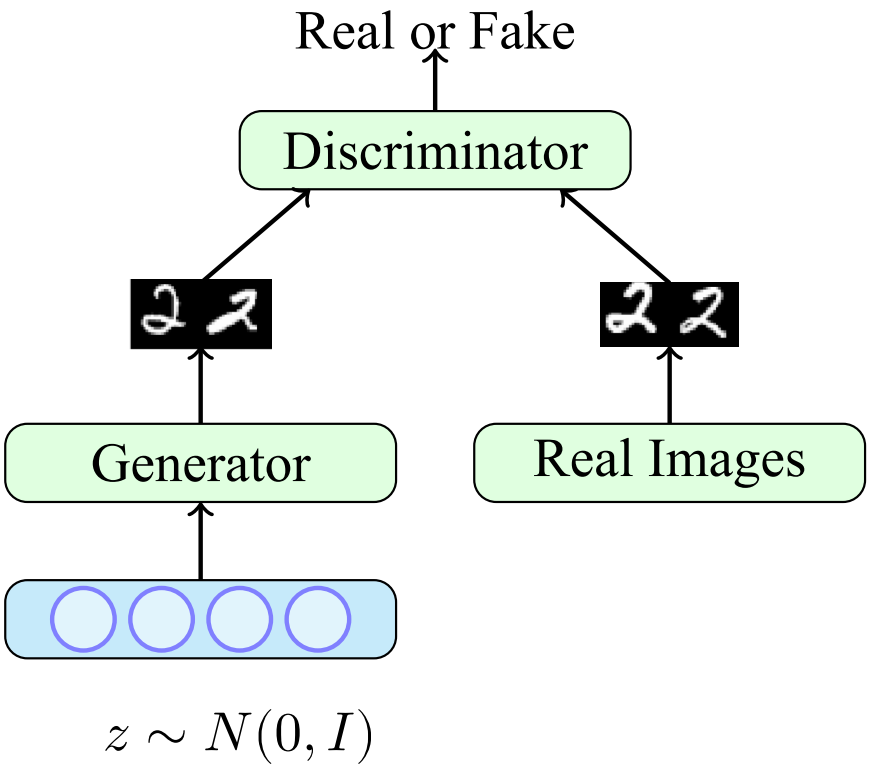


- So the overall training proceeds by alternating between these two step
- **Step 1:** Gradient Ascent on Discriminator

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

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

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



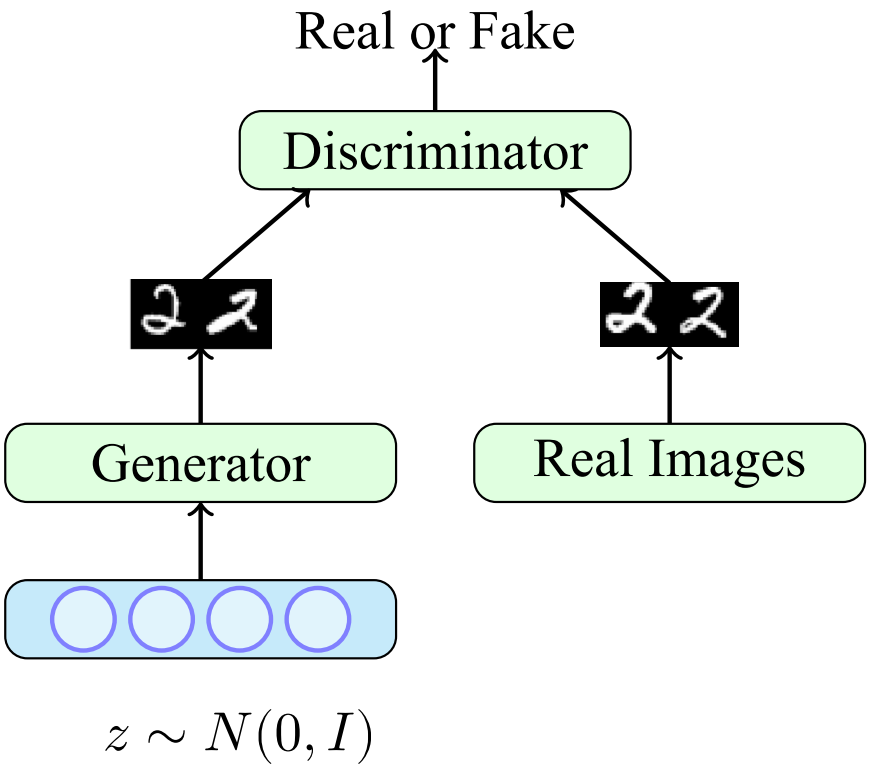
- So the overall training proceeds by alternating between these two step
- **Step 1:** Gradient Ascent on Discriminator

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

- **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



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

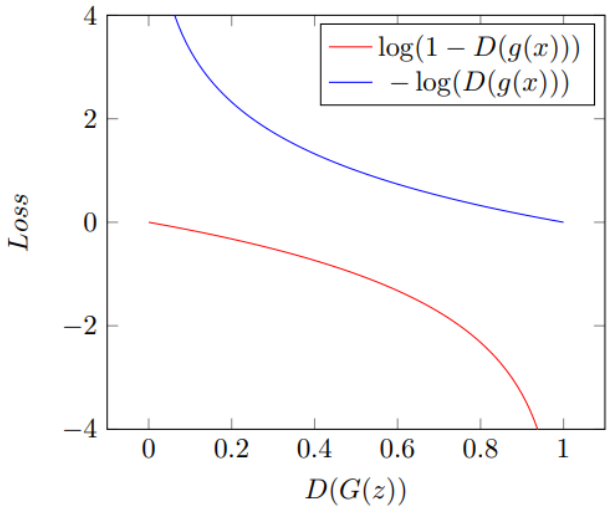
$$\max_{\theta} \; [\mathbb{E}_{x \sim p_{data}} \log D_{\theta}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta}$$

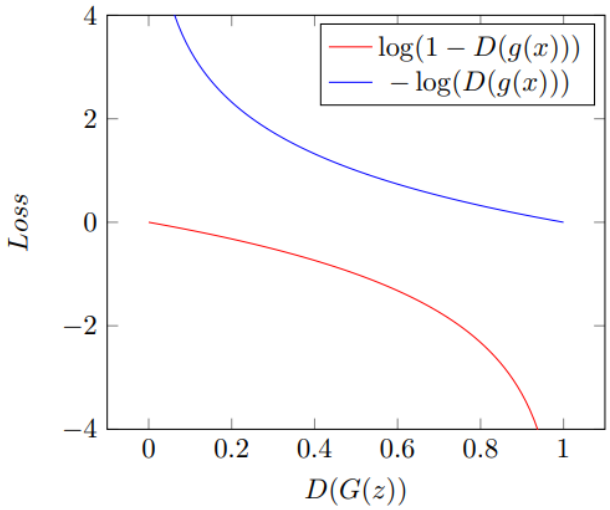
- **Step 2:** Gradient Descent on Generator

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

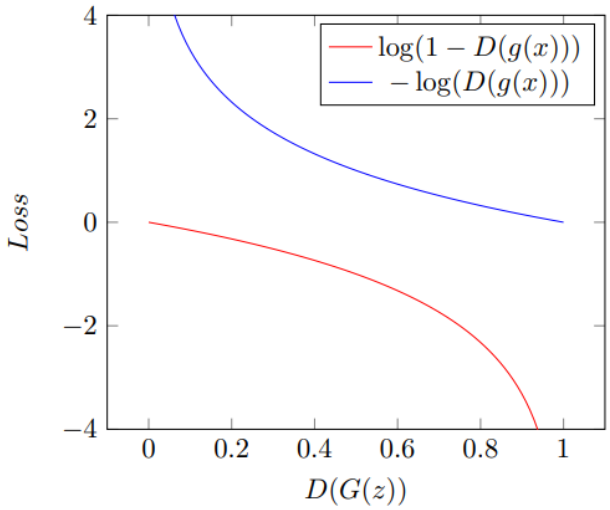
- In practice, the above generator objective does not work well and we use a slightly modified objective
- Let us see why

- When the sample is likely fake, we want to give a feedback to the generator (using gradients)

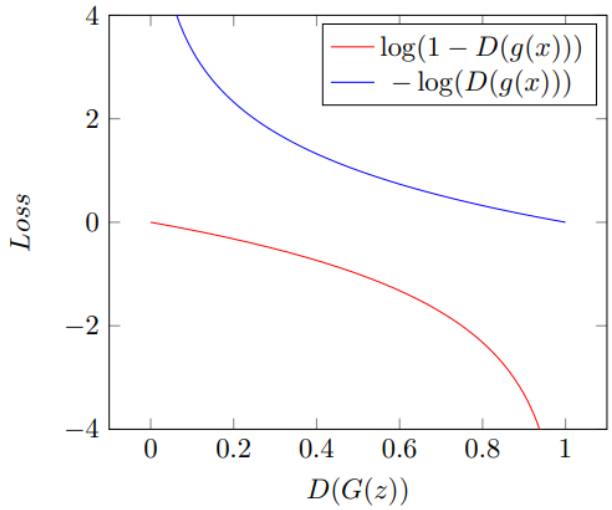




- When the sample is likely fake, we want to give a feedback to the generator (using gradients)
- However, in this region where $D(G(z))$ is close to 0, the curve of the loss function is very flat and the gradient would be close to 0



- When the sample is likely fake, we want to give a feedback to the generator (using gradients)
- However, in this region where $D(G(z))$ is close to 0, the curve of the loss function is very flat and the gradient would be close to 0
- Trick: Instead of minimizing the likelihood of the discriminator being correct, maximize the likelihood of the discriminator being wrong



- When the sample is likely fake, we want to give a feedback to the generator (using gradients)
- However, in this region where $D(G(z))$ is close to 0, the curve of the loss function is very flat and the gradient would be close to 0
- Trick: Instead of minimizing the likelihood of the discriminator being correct, maximize the likelihood of the discriminator being wrong
- In effect, the objective remains the same but the gradient signal becomes better

Generative Adversarial Networks - Architecture

.

- 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.)

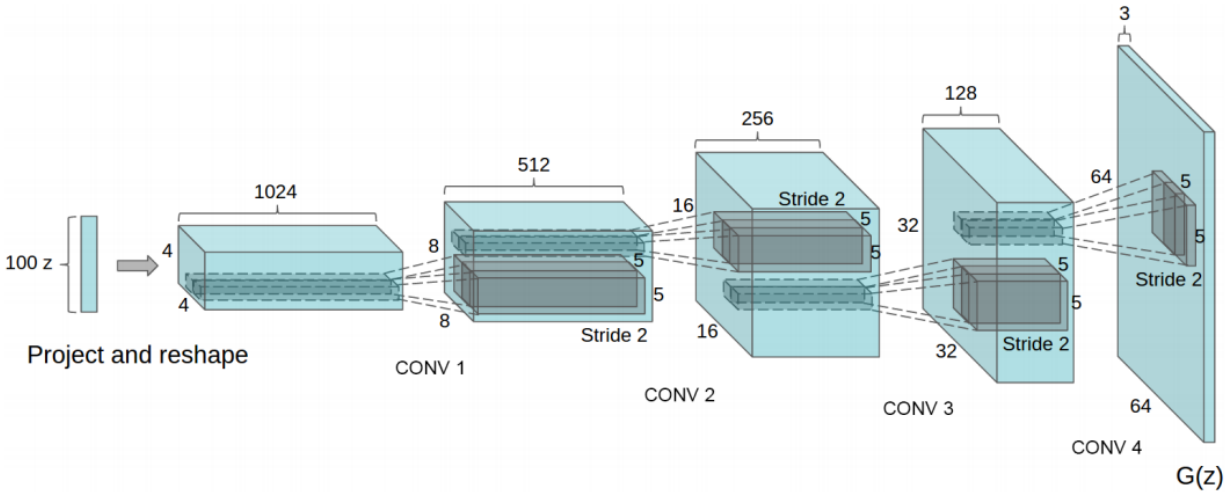


Figure: Generator (Redford et al 2015) (left) and discriminator (Yeh et al 2016) (right) used in DCGAN

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

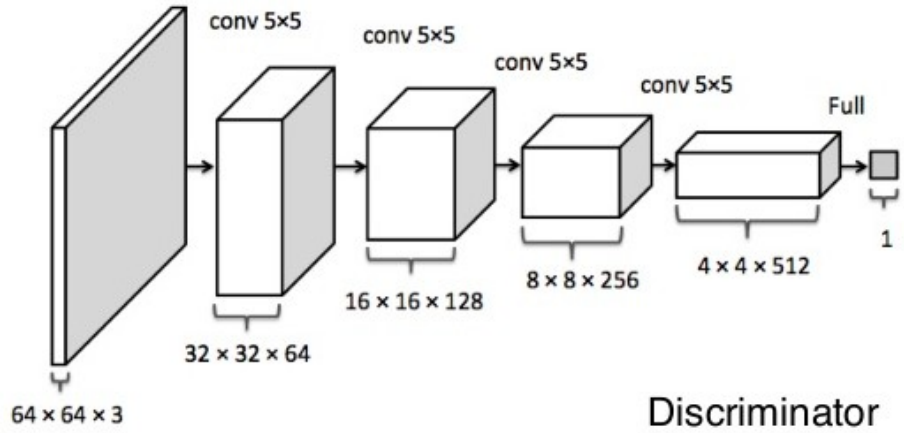


Figure: Generator (Redford et al 2015) (left) and discriminator (Yeh et al 2016) (right) used in DCGAN

Generative Adversarial Networks - Some Cool Stuff and Applications

.

- 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

- 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 ($z = \lambda z_1 + (1 - \lambda) z_2$)

- 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

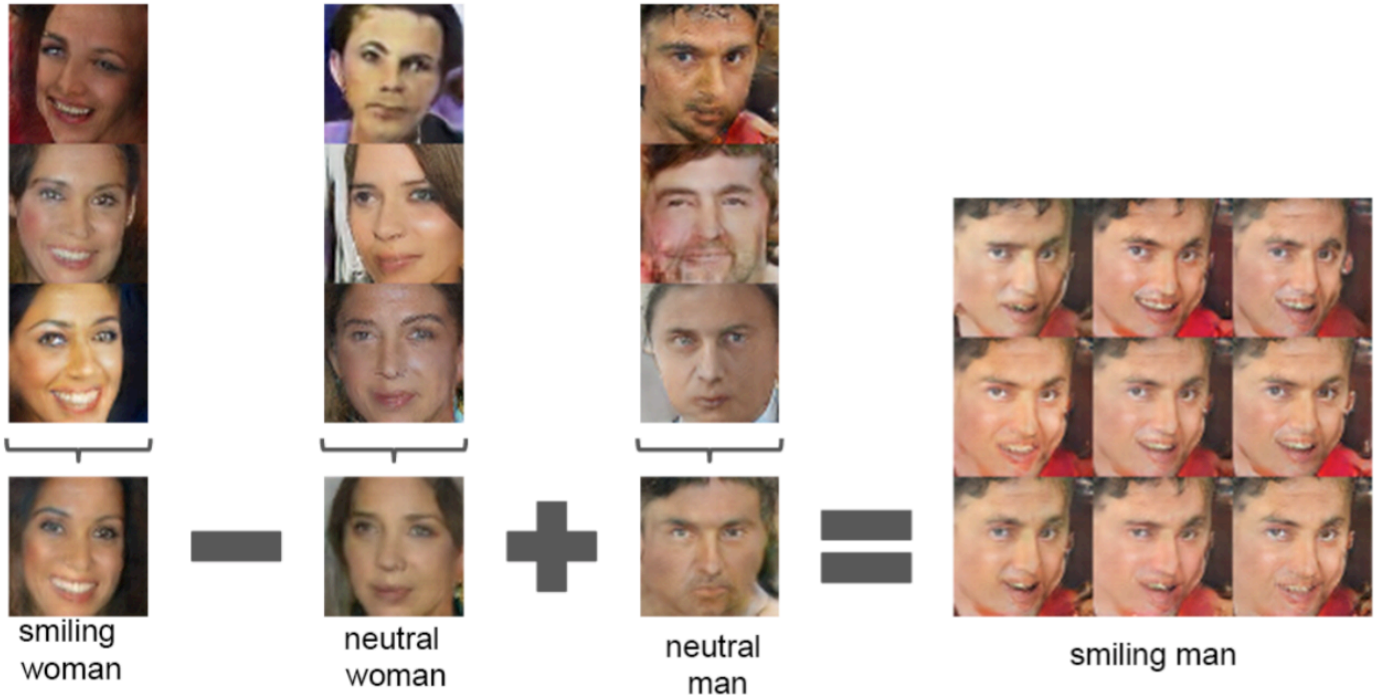


Figure: Vector arithmetic for visual concepts (part of figure 7 from the DCGAN paper)

- 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

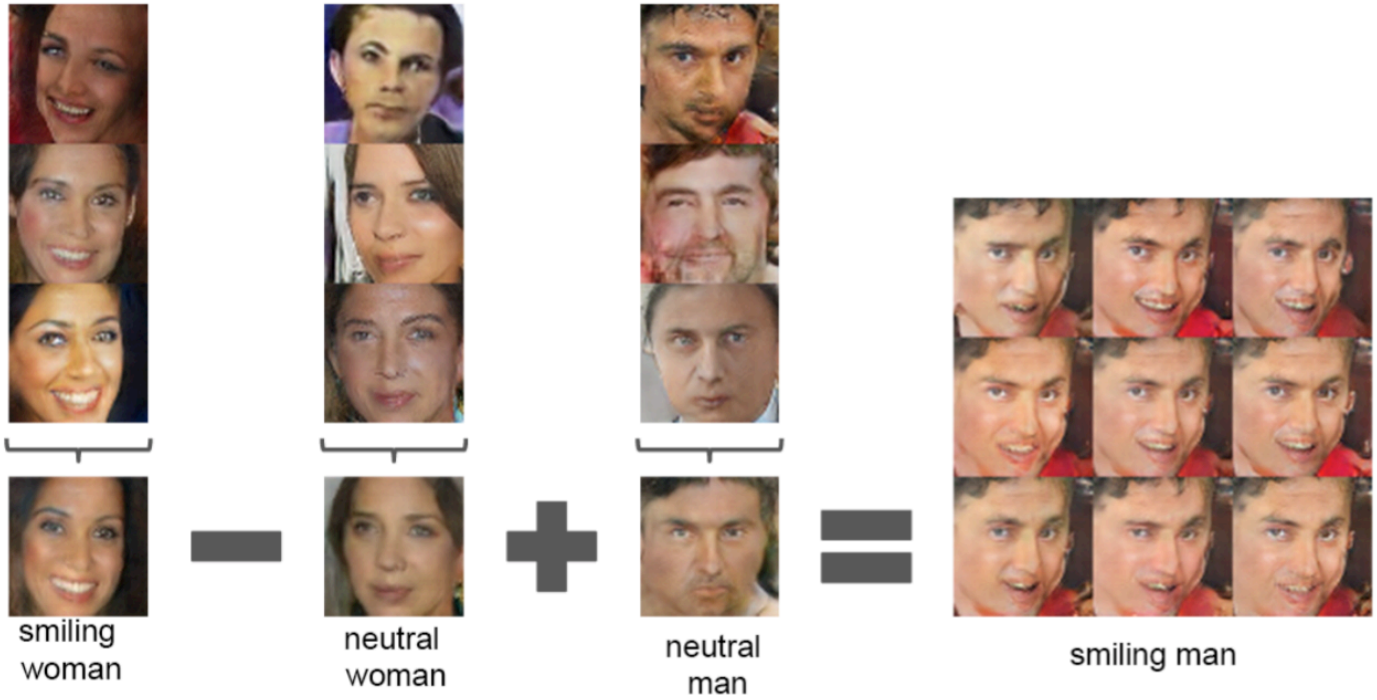


Figure: Vector arithmetic for visual concepts (part of figure 7 from the DCGAN paper)

- 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

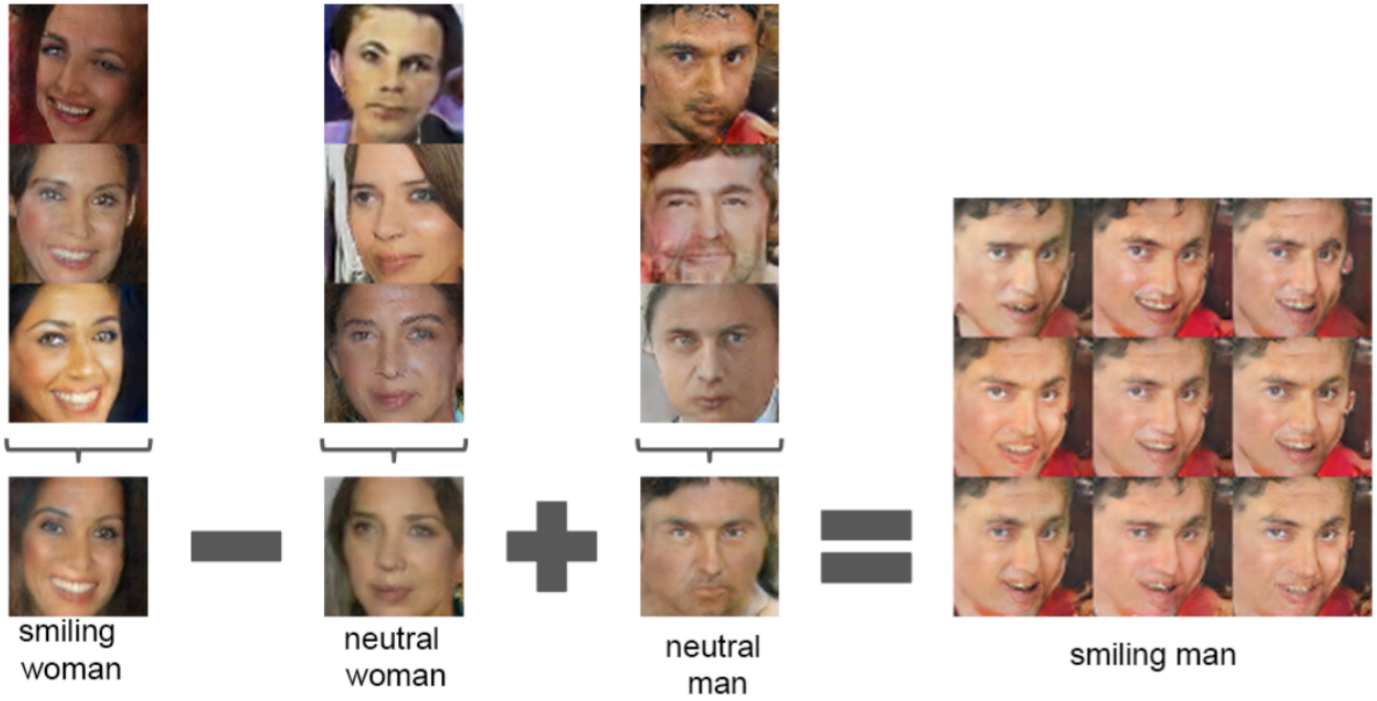


Figure: Vector arithmetic for visual concepts (part of figure 7 from the DCGAN paper)

- 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

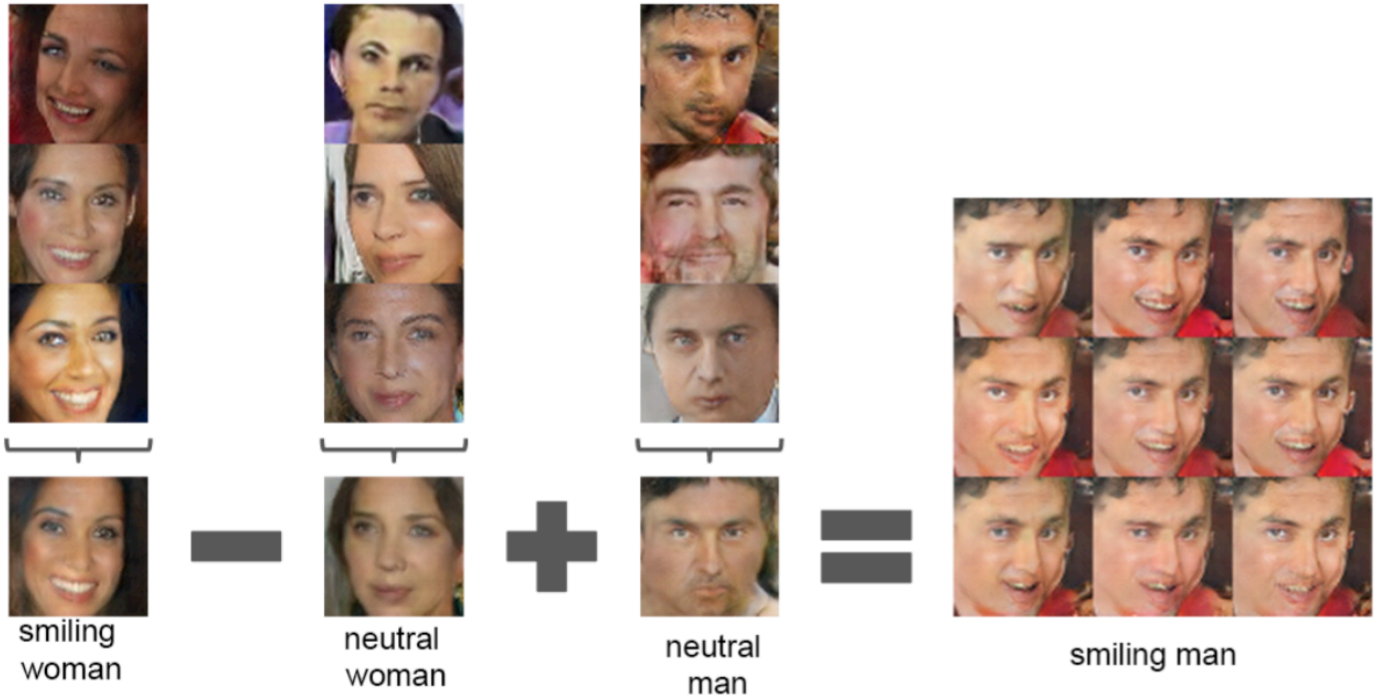


Figure: Vector arithmetic for visual concepts (part of figure 7 from the DCGAN paper)

- 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

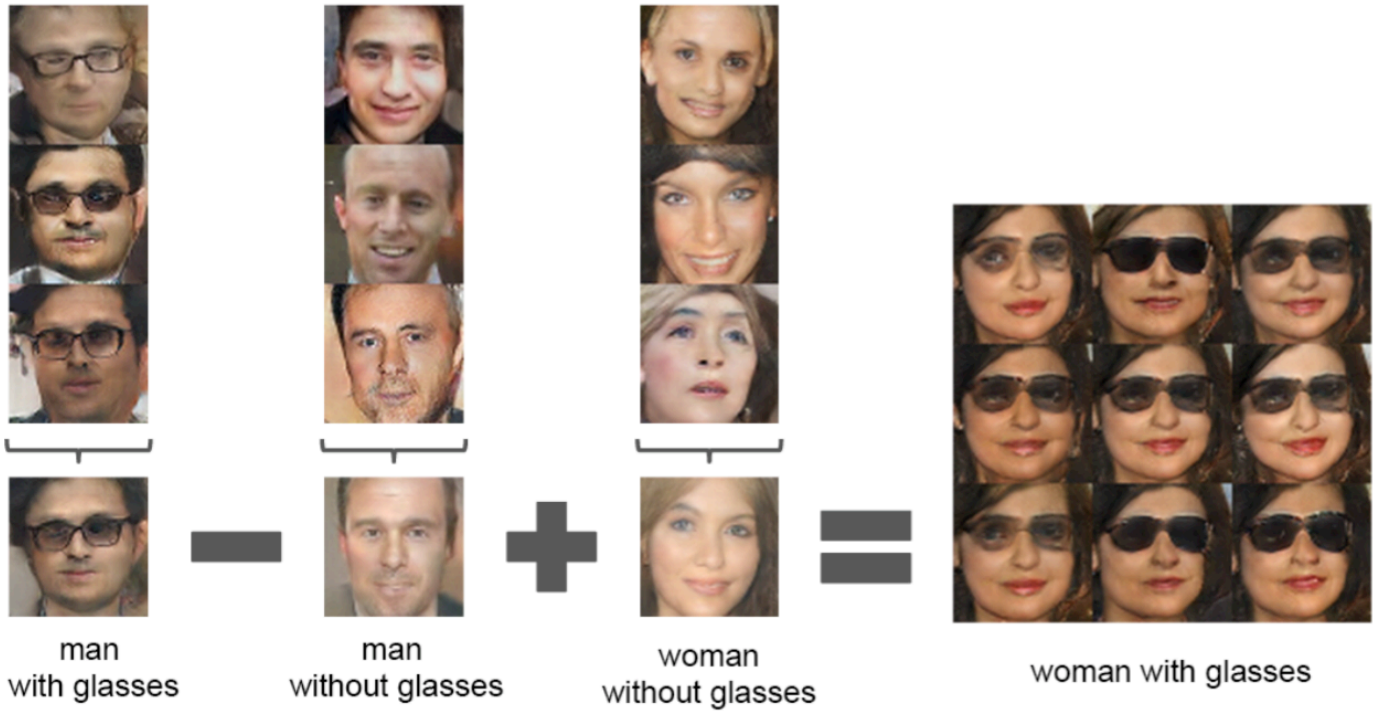
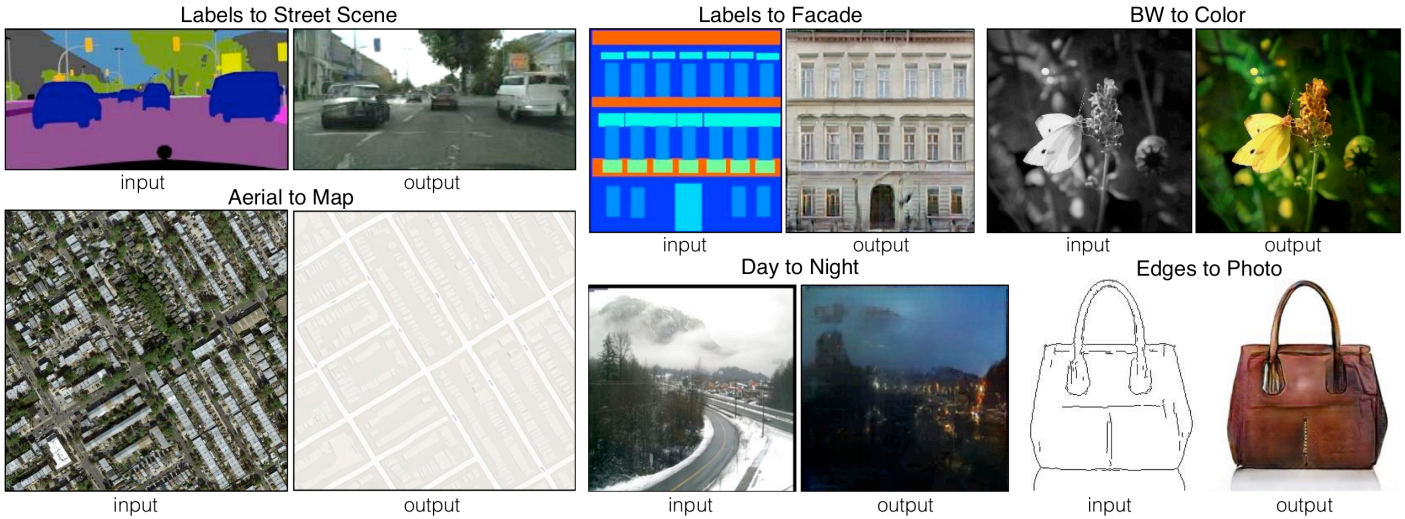


Figure: Vector arithmetic for visual concepts (part of figure 7 from the DCGAN paper)

- 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



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

.

Figure: Example of One Set of Generated Faces (Left) Adopting the Coarse Style of Another Set of Generated Faces (Top) Taken from: A Style-Based Generator Architecture for Generative Adversarial Networks.

- GAN: Lacking Control Over Synthesized Images

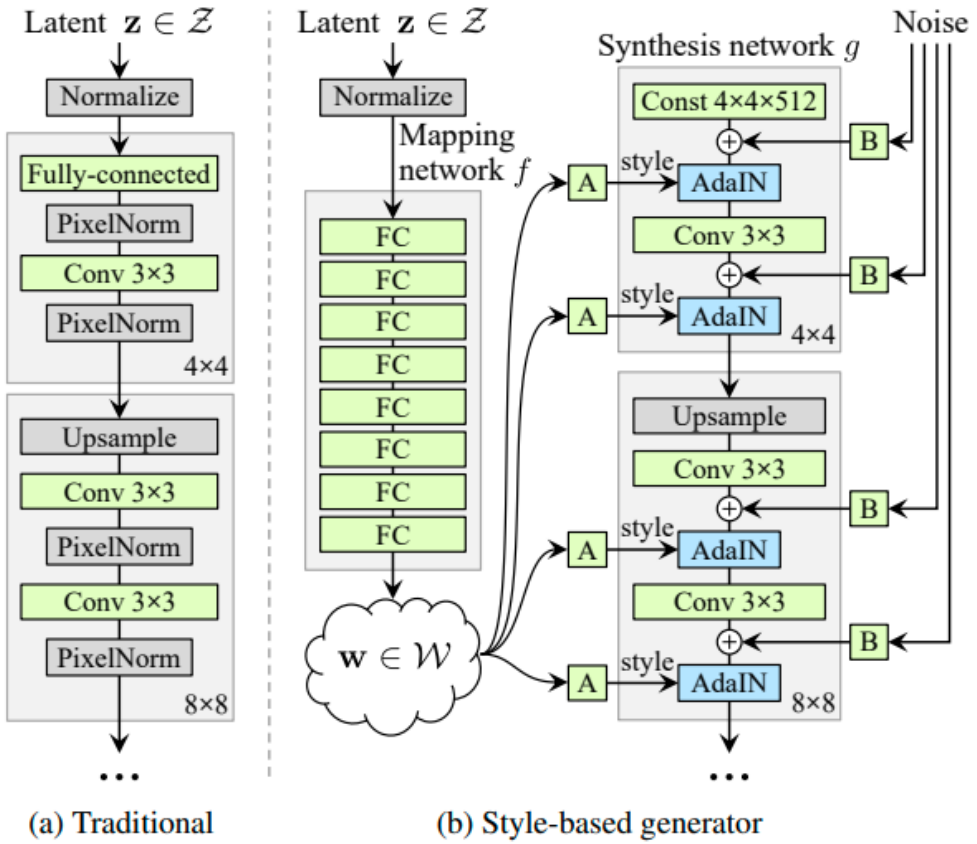
Figure: Example of One Set of Generated Faces (Left) Adopting the Coarse Style of Another Set of Generated Faces (Top) Taken from: A Style-Based Generator Architecture for Generative Adversarial Networks.

- GAN: Lacking Control Over Synthesized Images
- Style Generative Adversarial Network(StyleGAN) Controls Style Using New Generator Model

Figure: Example of One Set of Generated Faces (Left) Adopting the Coarse Style of Another Set of Generated Faces (Top) Taken from: A Style-Based Generator Architecture for Generative Adversarial Networks.

- 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



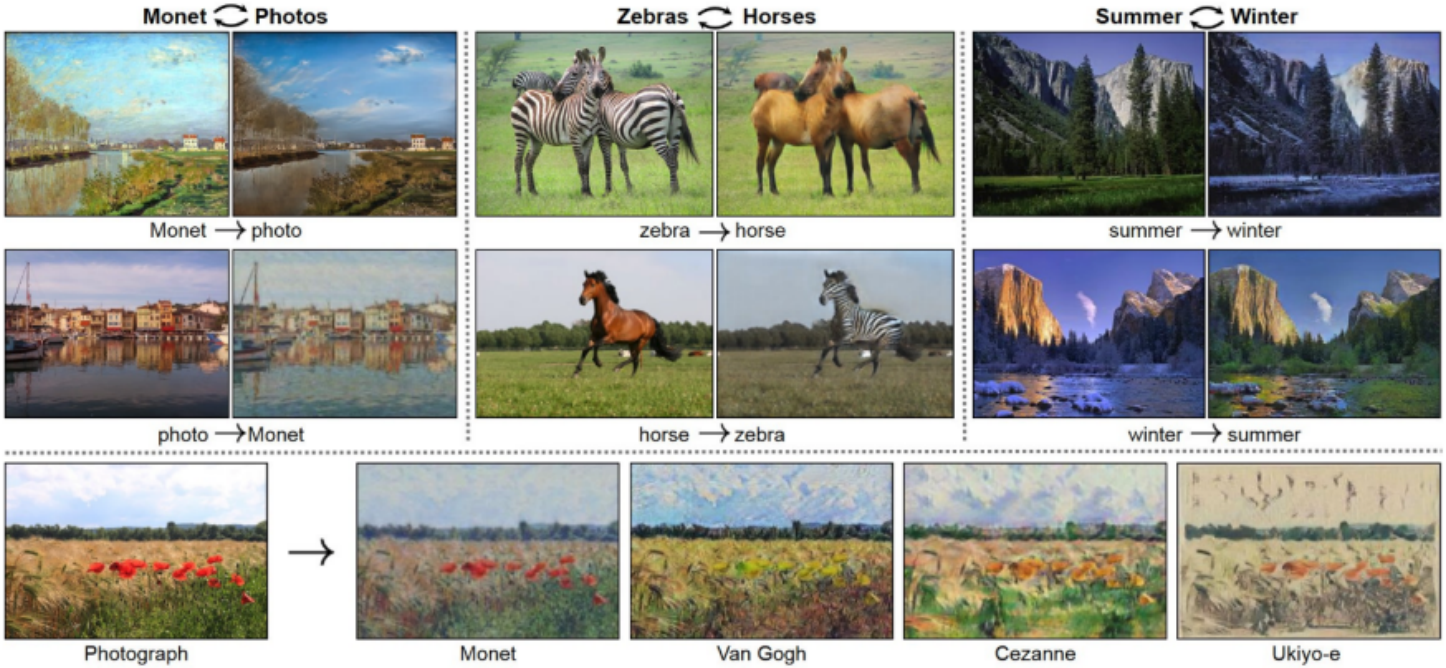
(a) Traditional (b) Style-based generator

The StyleGAN is described as a progressive growing GAN architecture with five modifications, each of which was added and evaluated incrementally in an ablative study. The incremental list of changes to the generator are:

- Baseline Progressive GAN.
- Addition of tuning and bilinear upsampling.

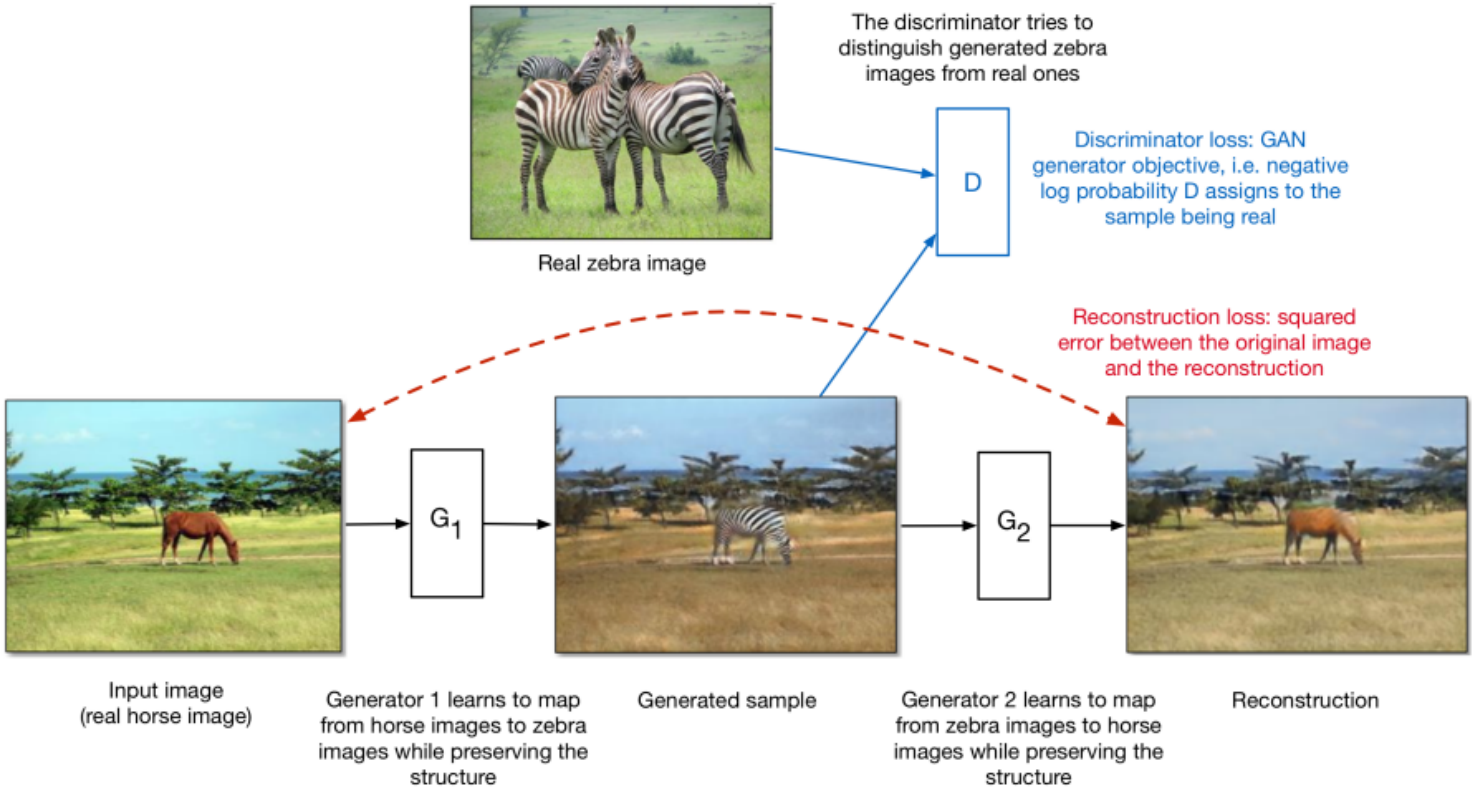
CycleGAN

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

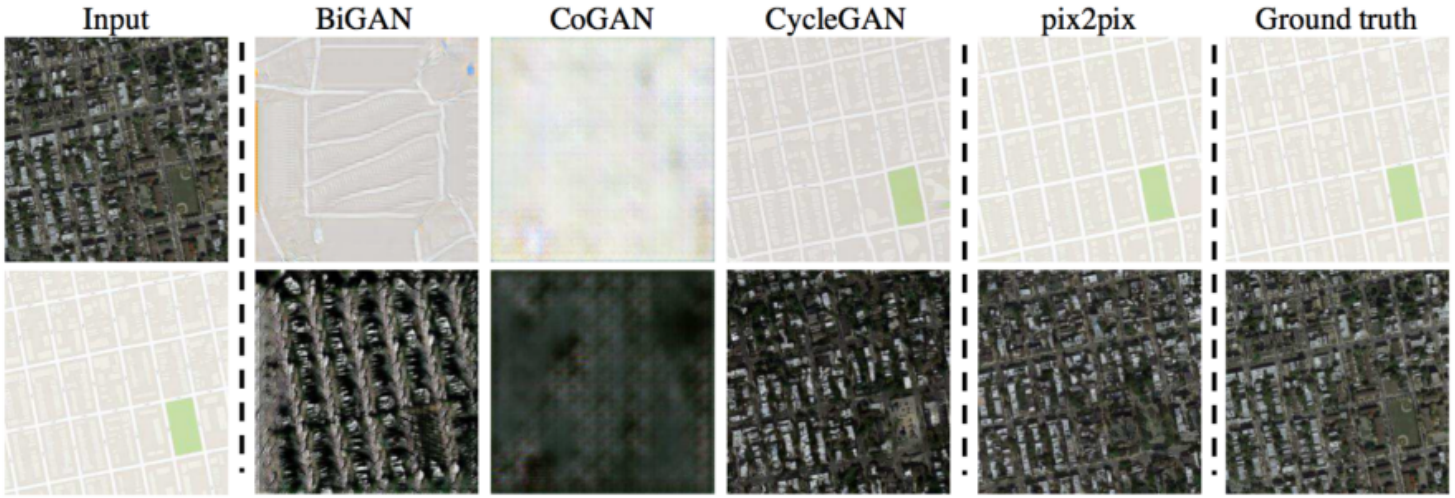


Data: Two unrelated collections of images, one for each style

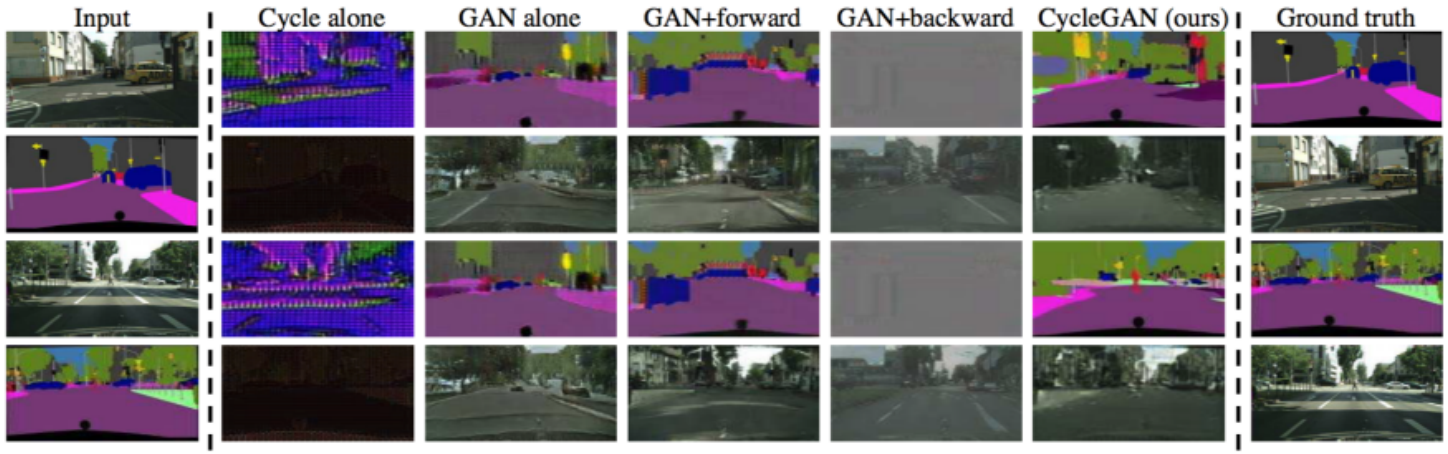
- If we had paired data (same content in both styles), this would be a supervised learning problem. But this is hard to find.
- The CycleGAN architecture learns to do it from unpaired data.
  - Train two different generator nets to go from style 1 to style 2, and vice versa.
  - Make sure the generated 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.


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

Style transfer between aerial photos and maps:



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



Generative Adversarial Networks - Summary

.

	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No

Table: Comparison of Generative Models

	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No
Generation	Yes	Yes	Yes	Yes

Table: Comparison of Generative Models

	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No
Generation	Yes	Yes	Yes	Yes
Compute P(X)	Intractable	Intractable	Tractable	No

Table: Comparison of Generative Models

	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No
Generation	Yes	Yes	Yes	Yes
Compute P(X)	Intractable	Intractable	Tractable	No
Sampling	MCMC	Fast	Slow	Fast

Table: Comparison of Generative Models

	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No
Generation	Yes	Yes	Yes	Yes
Compute P(X)	Intractable	Intractable	Tractable	No
Sampling	MCMC	Fast	Slow	Fast
Type of GM	Undirected	Directed	Directed	Directed

Table: Comparison of Generative Models

	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No
Generation	Yes	Yes	Yes	Yes
Compute P(X)	Intractable	Intractable	Tractable	No
Sampling	MCMC	Fast	Slow	Fast
Type of GM	Undirected	Directed	Directed	Directed
Loss	KL-divergence	KL-divergence	KL-divergence	JSD

Table: Comparison of Generative Models

	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No
Generation	Yes	Yes	Yes	Yes
Compute P(X)	Intractable	Intractable	Tractable	No
Sampling	MCMC	Fast	Slow	Fast
Type of GM	Undirected	Directed	Directed	Directed
Loss	KL-divergence	KL-divergence	KL-divergence	JSD
Assumptions	X independent given z	X independent given z	None	N.A.

Table: Comparison of Generative Models

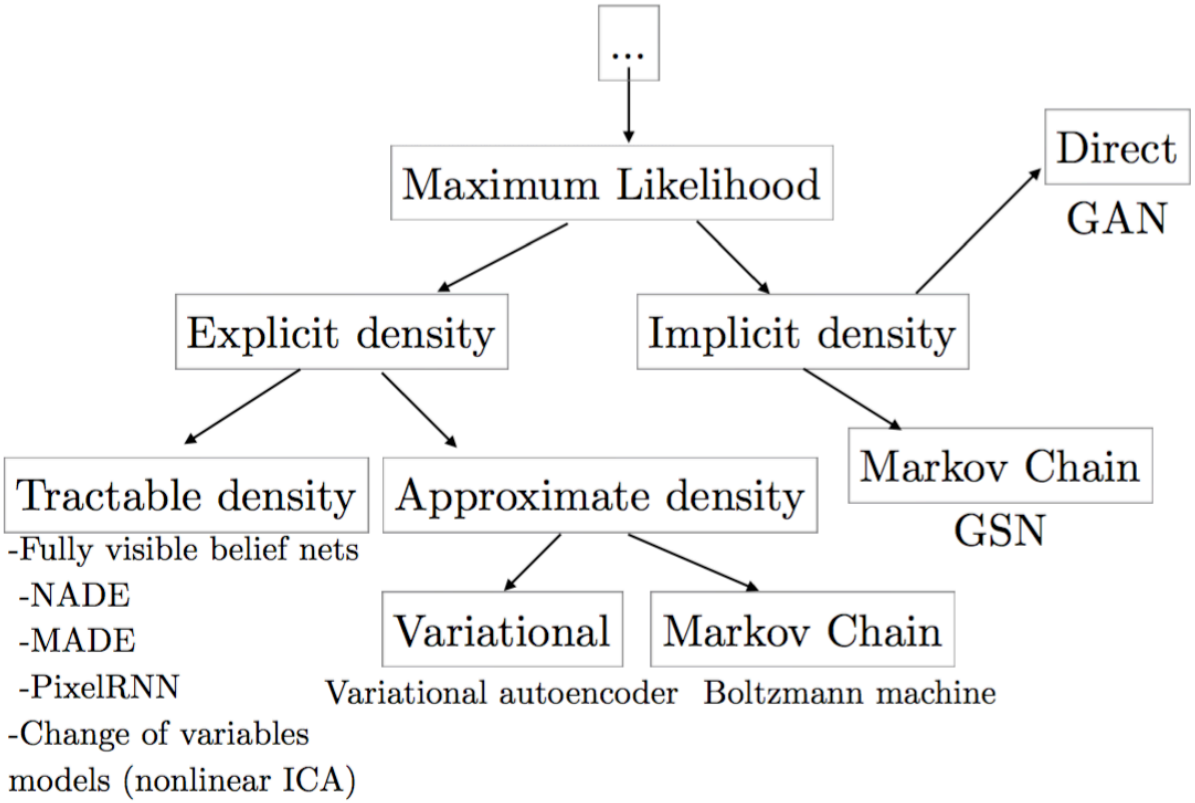
	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No
Generation	Yes	Yes	Yes	Yes
Compute P(X)	Intractable	Intractable	Tractable	No
Sampling	MCMC	Fast	Slow	Fast
Type of GM	Undirected	Directed	Directed	Directed
Loss	KL-divergence	KL-divergence	KL-divergence	JSD
Assumptions	X independent given z	X independent given z	None	N.A.
Samples	Bad	Ok	Good	Good (best)

Table: Comparison of Generative Models

	RBMs	VAEs	AR models	GANs
Abstraction	Yes	Yes	No	No
Generation	Yes	Yes	Yes	Yes
Compute P(X)	Intractable	Intractable	Tractable	No
Sampling	MCMC	Fast	Slow	Fast
Type of GM	Undirected	Directed	Directed	Directed
Loss	KL-divergence	KL-divergence	KL-divergence	JSD
Assumptions	X independent given z	X independent given z	None	N.A.
Samples	Bad	Ok	Good	Good (best)

Table: Comparison of Generative Models

Recent works look at combining these methods: e.g. Adversarial Autoencoders (Makhzani 2015), PixelVAE (Gulrajani 2016) and PixelGAN Autoencoders (Makhzani 2017)



Source: Ian Goodfellow, NIPS 2016 Tutorial: Generative Adversarial Networks

Image References

- https://www.cse.iitm.ac.in/ miteshk/CS7015
- Alec Radford, Luke Metz, Soumith Chintala Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks(https://arxiv.org/abs/1511.06434)
- Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, Alexei A. Efros Image-to-Image Translation with Conditional Adversarial Networks(https://arxiv.org/abs/1511.06434)
- Tero Karras, Samuli Laine, Timo Aila A Style-Based Generator Architecture for Generative Adversarial Networks(https://arxiv.org/abs/1812.04948)
- Jun-Yan Zhu, Taesung Park, Phillip Isola, Alexei A. Efros Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks(https://arxiv.org/abs/1703.10593)
- Ian Goodfellow NIPS 2016 Tutorial: Generative Adversarial Networks(https://arxiv.org/abs/1701.00160)