Generative Adversarial Networks (GANs)

Industrial AI Lab.

Prof. Seungchul Lee

Source

- 1시간만에 GAN(Generative Adversarial Network) 완전 정복하기
  - by 최윤제 (고려대 석사생)
  - YouTube: https://www.youtube.com/watch?v=odpjk7_tGY0
  - Slides: https://www.slideshare.net/NaverEngineering/1-gangenerative-adversarial-network

- CSC321 Lecture 19: GAN
  - By Prof. Roger Grosse at Univ. of Toronto
  - http://www.cs.toronto.edu/~rgrosse/courses/csc321_2018/

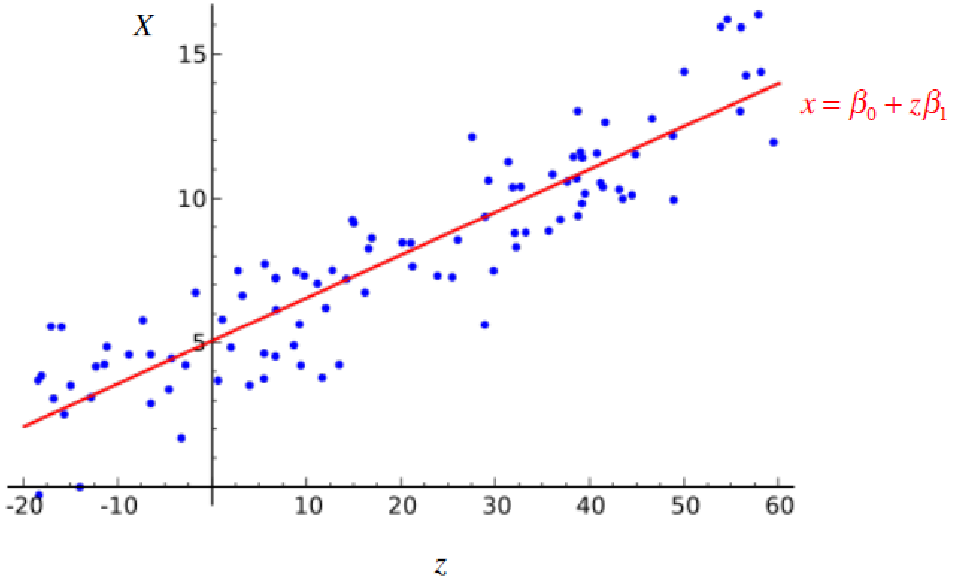
- CS231n: CNN for Visual Recognition
  - Lecture 13: Generative Models
  - By Prof. Fei-Fei Li at Stanford University
  - http://cs231n.stanford.edu/

Generative Modeling

- Generative models take training samples from some data distribution and learn a model that represents that distribution

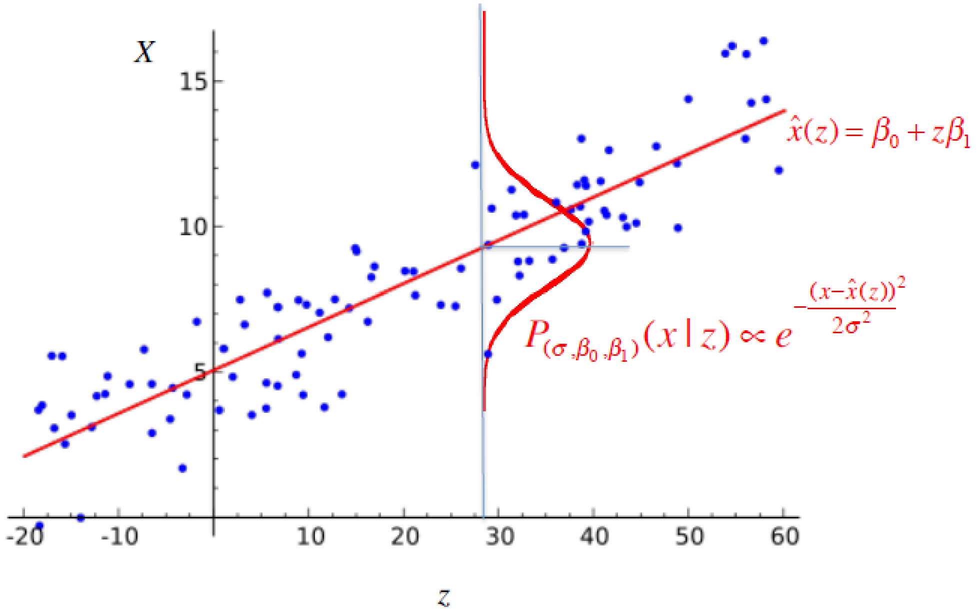
Recap: Linear Regression

- Most people think of linear regression as points and a straight line:

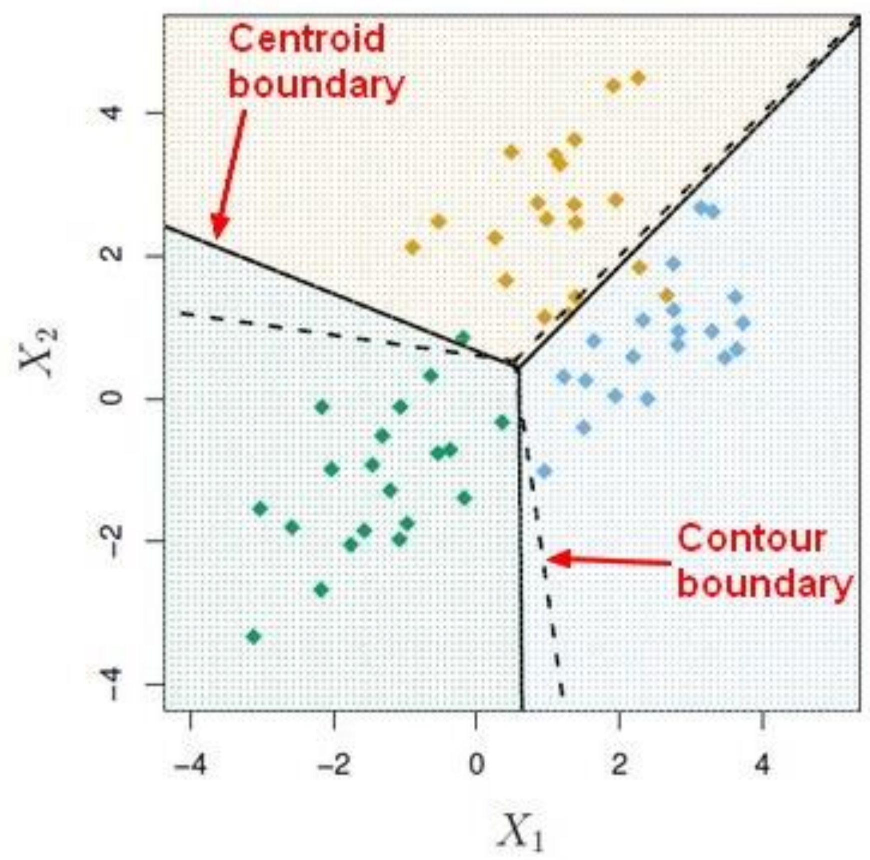


Recap: Linear Regression

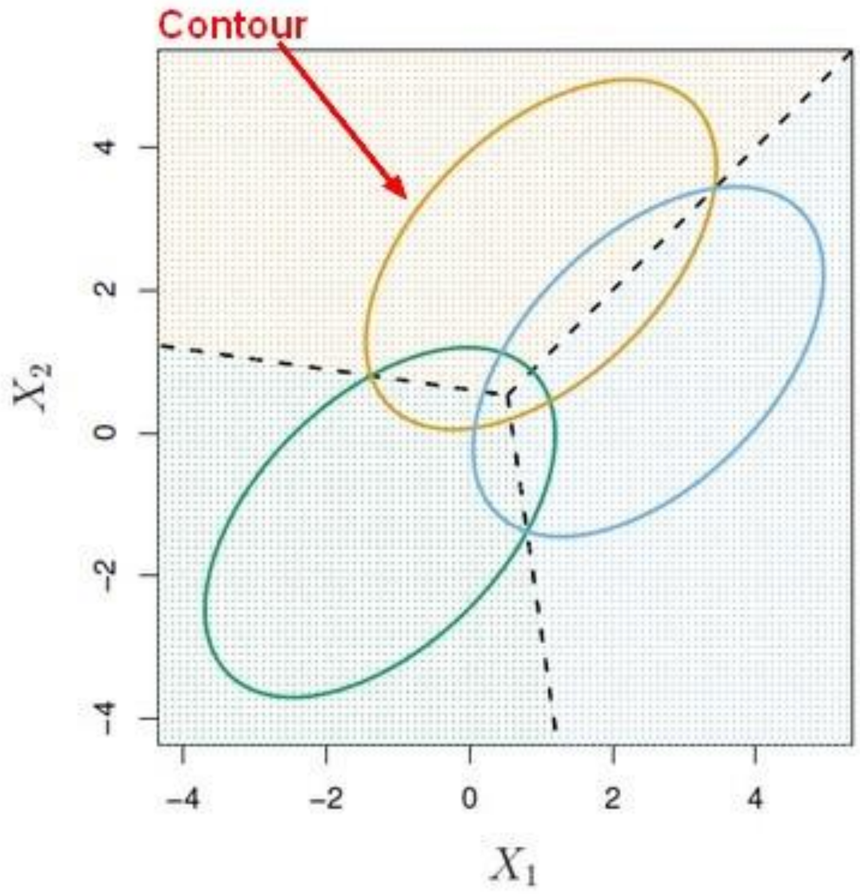
- Statisticians additionally have $P_\theta(X|Z)$
- Benefits of having an error model:
  - How likely is a data point
  - Confidence bounds
  - Compare models

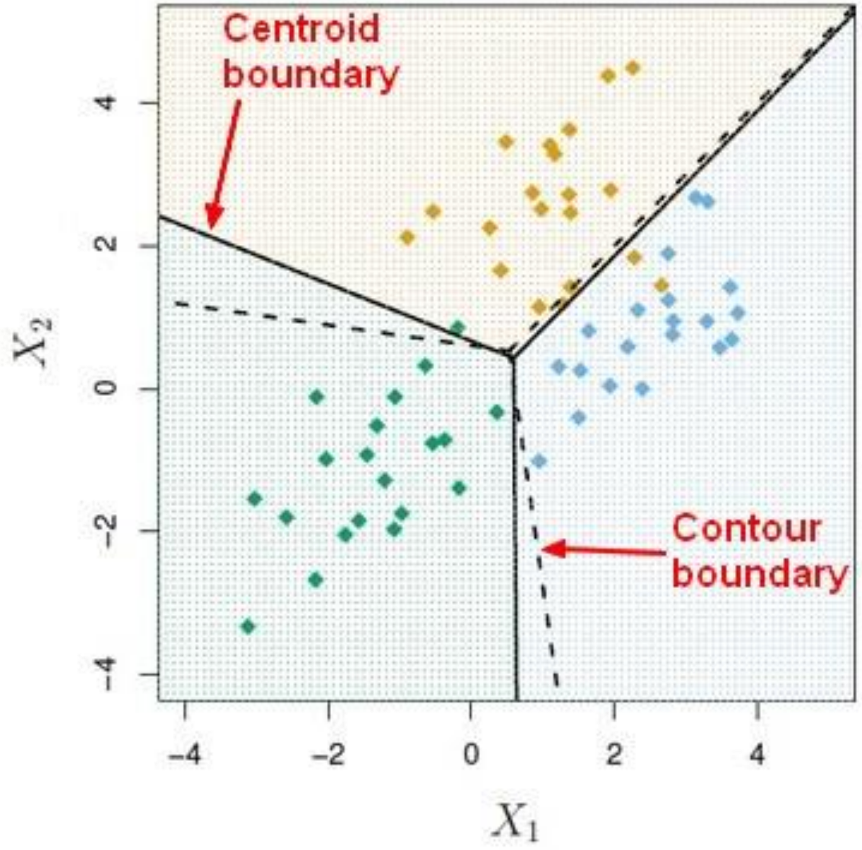


Recap: Linear Classifier



Recap: Linear Classifier

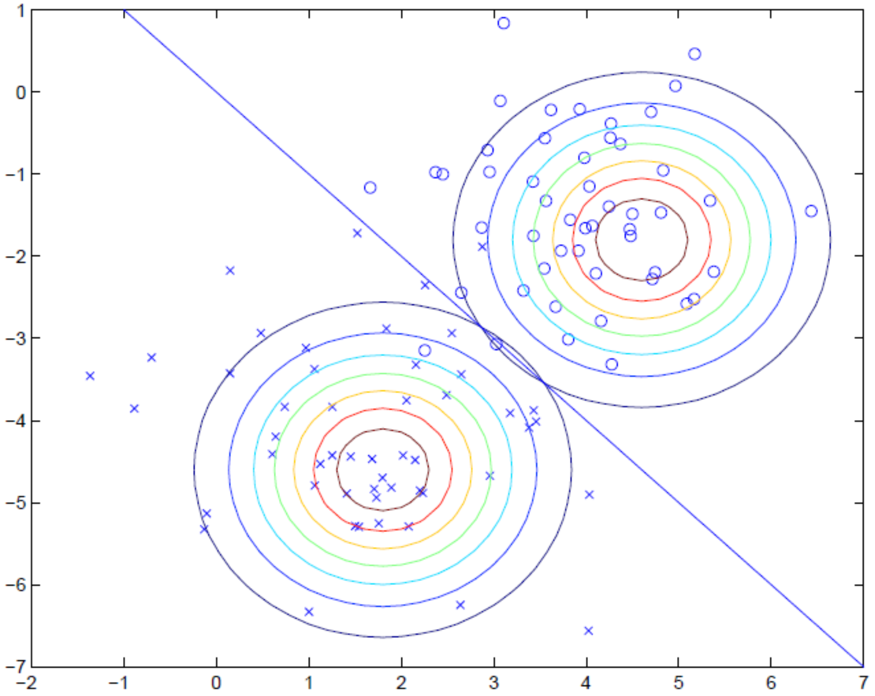




Recap: Linear Classifier

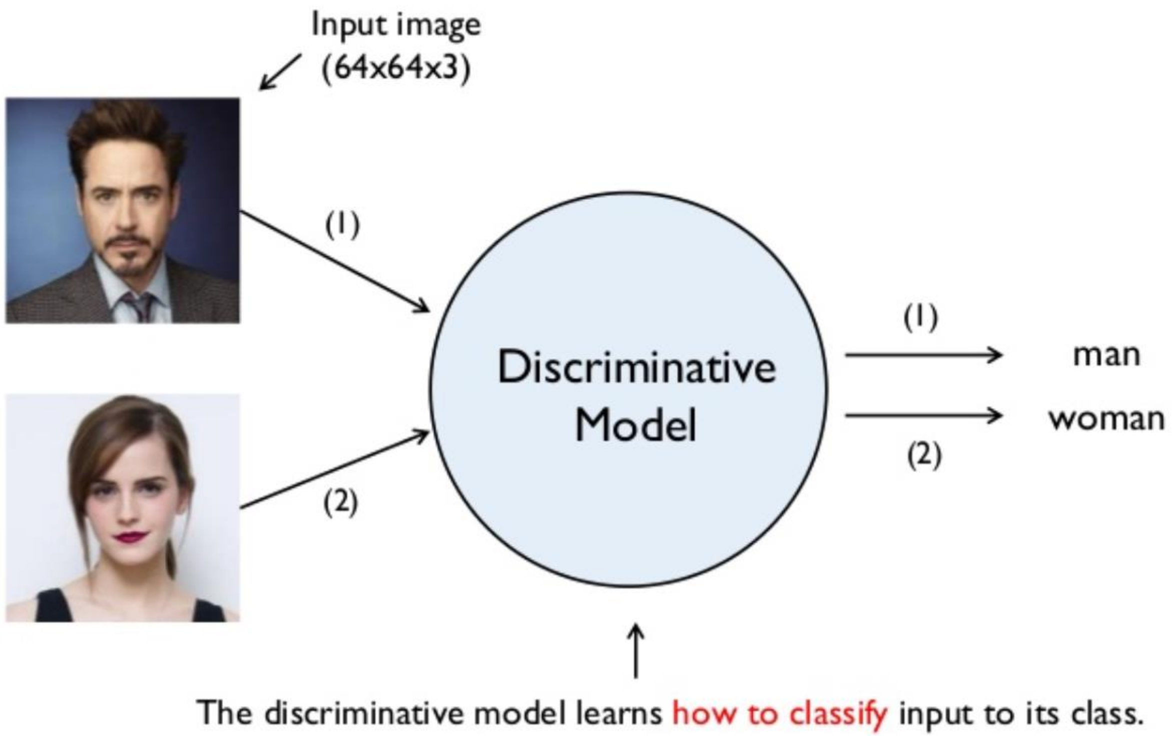
- Think about how data is generated

$$
\begin{aligned}
y &\sim \text{Bernoulli}(\phi) \\
x|y=0 &\sim \mathcal{N}(\mu_0, \Sigma) \\
x|y=1 &\sim \mathcal{N}(\mu_1, \Sigma)
\end{aligned}
$$



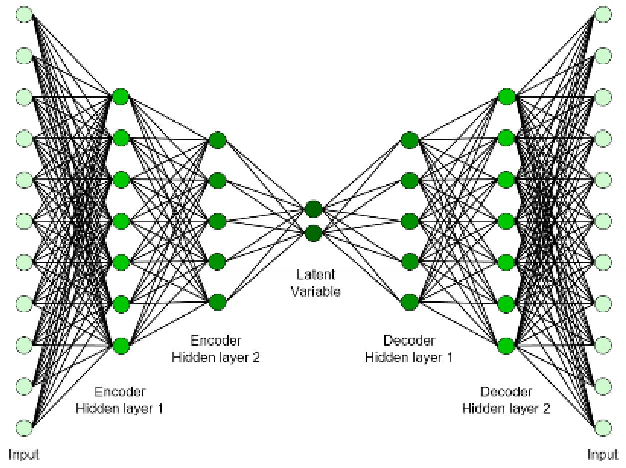
Supervised Learning

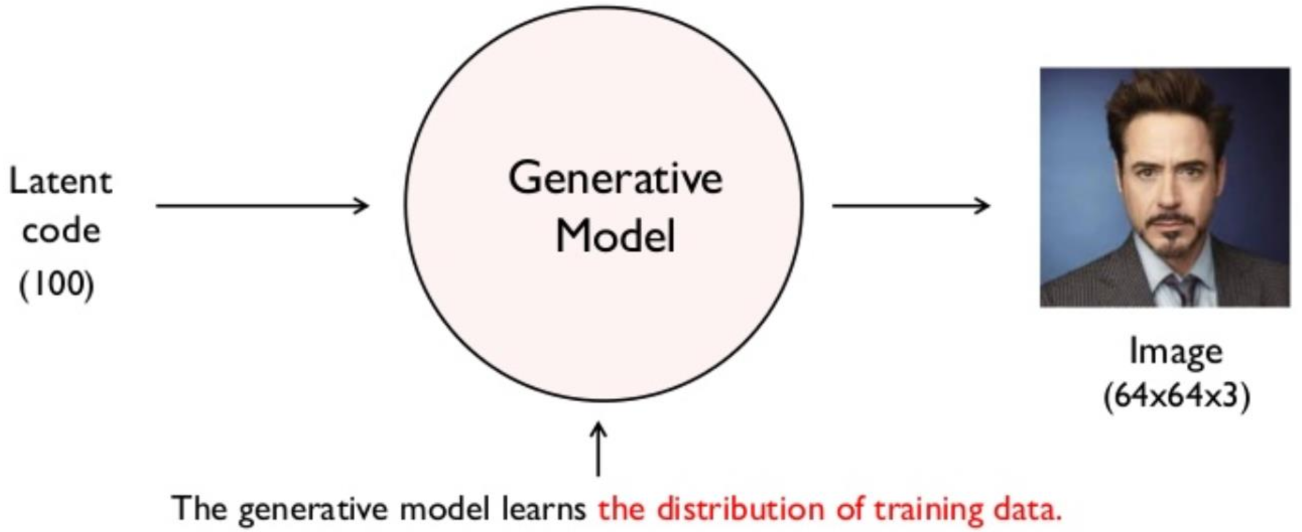
- Discriminative model



Unsupervised Learning

- Generative model





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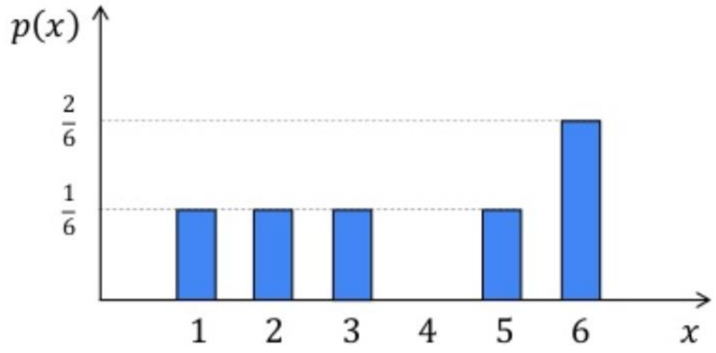
Probability Distribution

Probability Basics (Review)

Random variable

X	1	2	3	4	5	6
$P(X)$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{0}{6}$	$\frac{1}{6}$	$\frac{2}{6}$

Probability mass function



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Probability Distribution

What if x is actual images in the training data?

At this point, x can be represented as a (for example) 64x64x3 dimensional vector.

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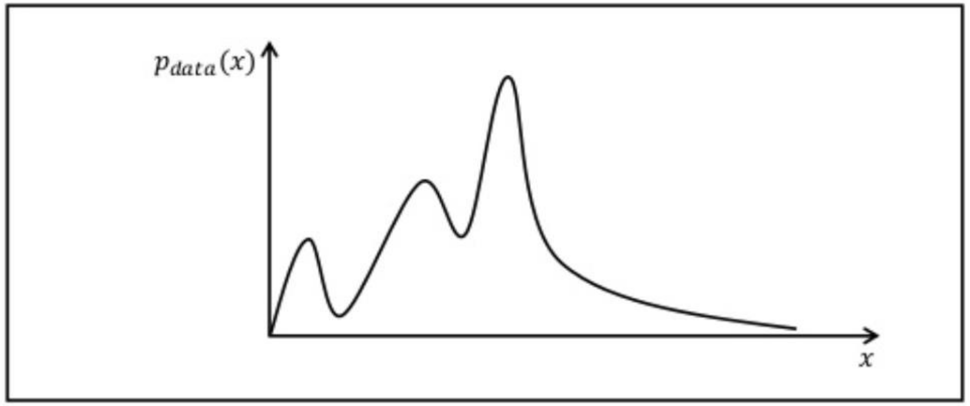
Probability Distribution

Probability density function

There is a $p_{data}(x)$ that represents the distribution of actual images.



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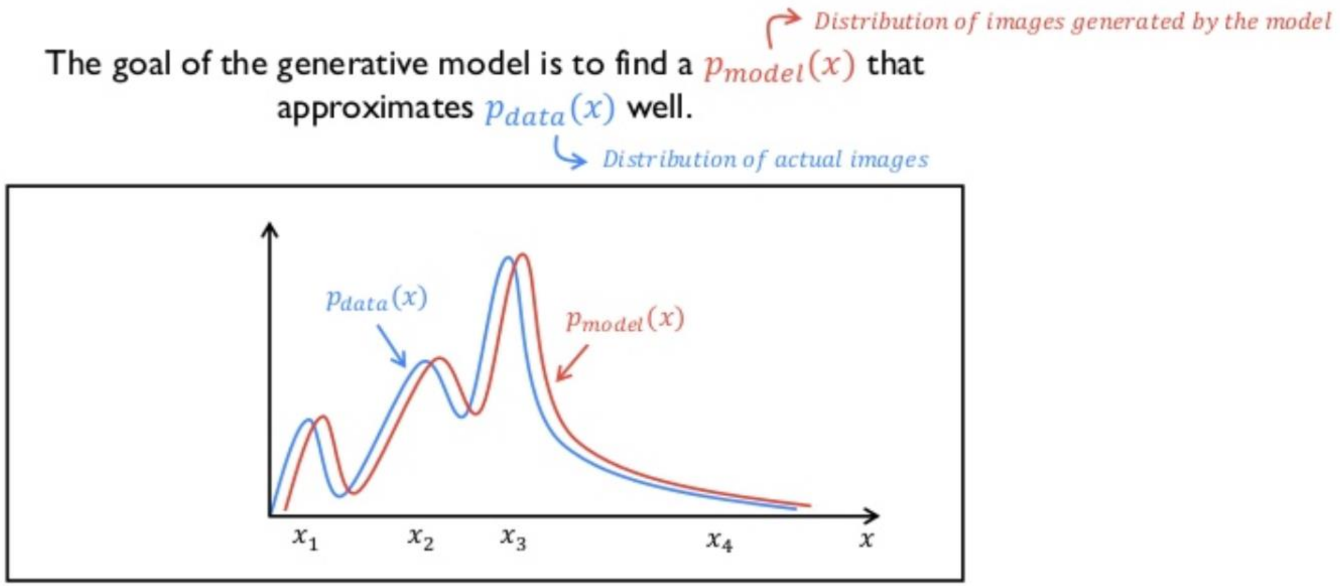
Probability Density Estimation Problem

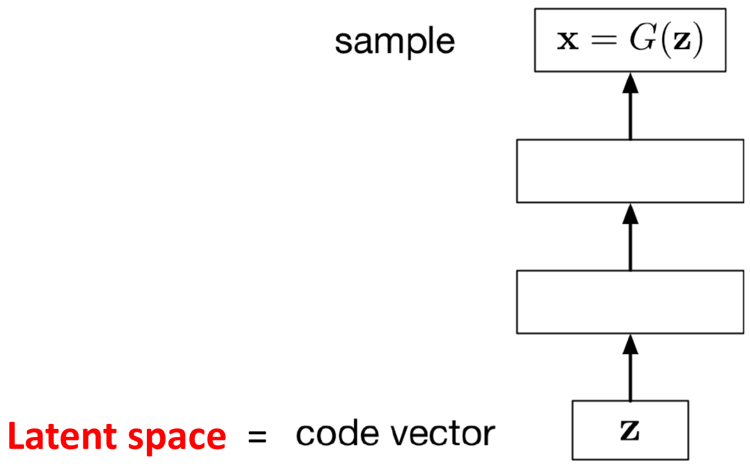
- If $P_{model}(x)$ can be estimated as close to $P_{data}(x)$, then data can be generated by sampling from $P_{model}(x)$



Generative Models from Lower Dimension

- Learn transformation via a neural network

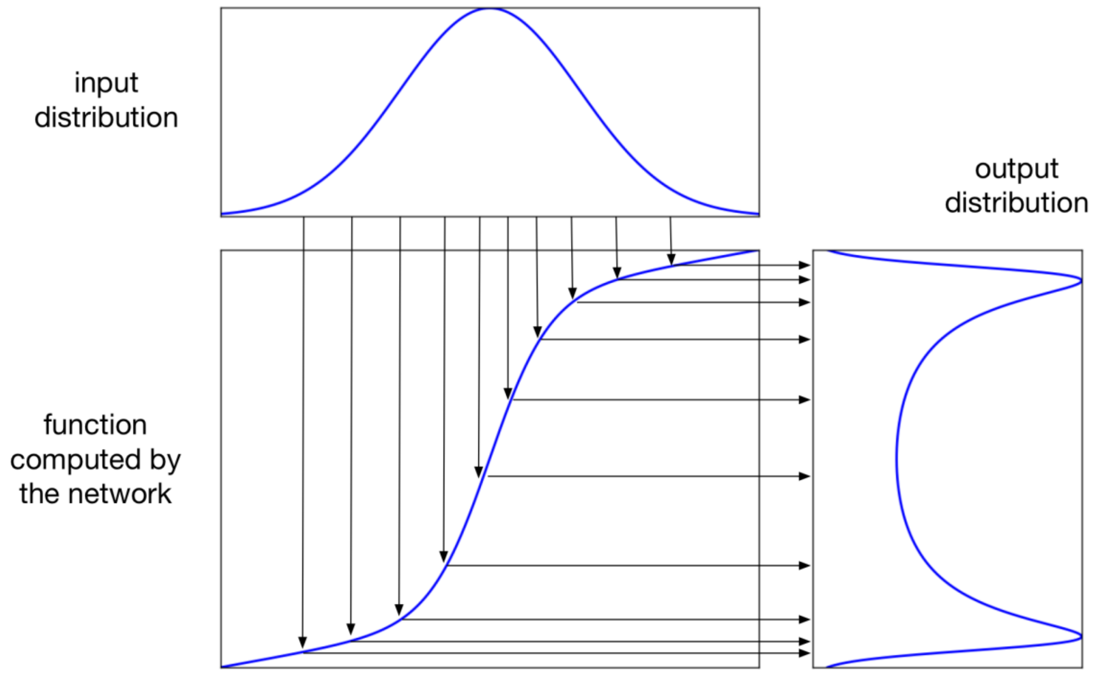
- Start by sampling the code vector z from a fixed, simple distribution (e.g. uniform distribution or Gaussian distribution)
- Then this code vector is passed as input to a deterministic generator network G , which produces an output sample $x = G(z)$



Source: Prof. Roger Grosse at U of Toronto

Deterministic Transformation (by Network)

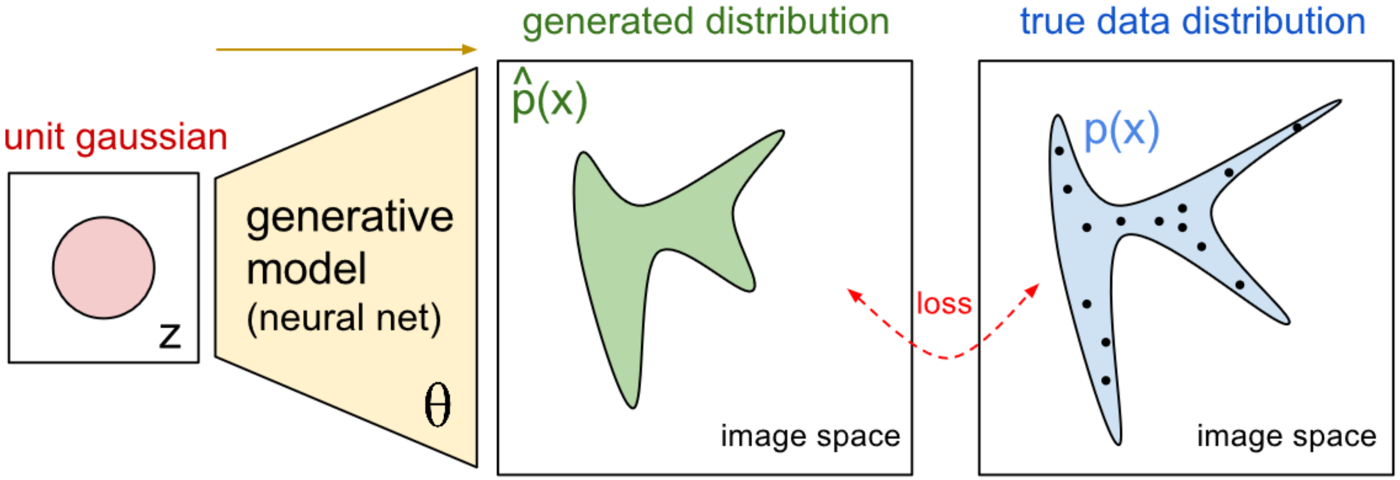
- 1-dimensional example:



Source: Prof. Roger Grosse at U of Toronto

Deterministic Transformation (by Network)

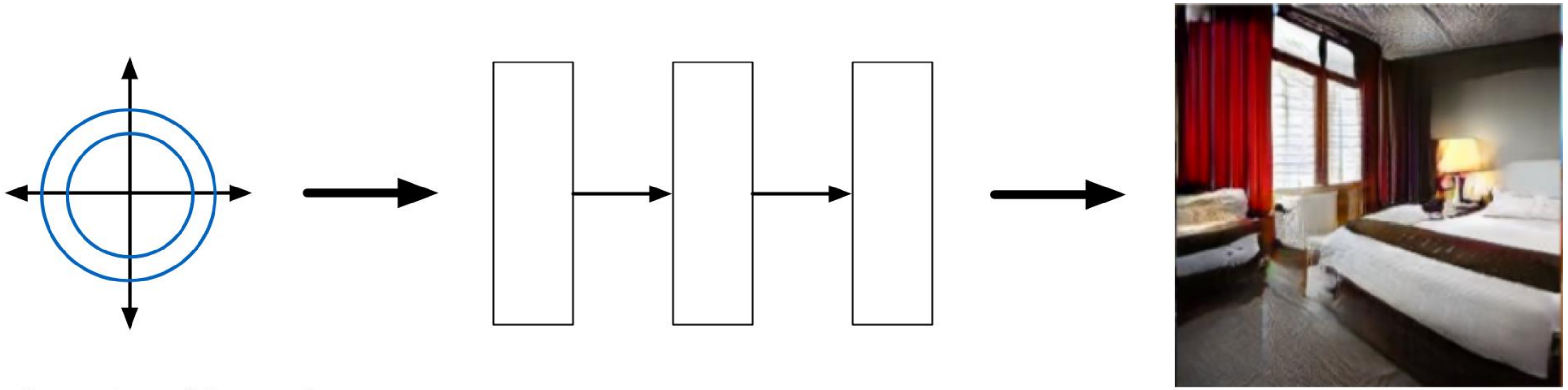
- High dimensional example:



Source: Prof. Roger Grosse at U of Toronto

Prob. Density Function by Deep Learning

- Generative model of image



Each dimension of the code vector is sampled independently from a simple distribution, e.g. Gaussian or uniform.

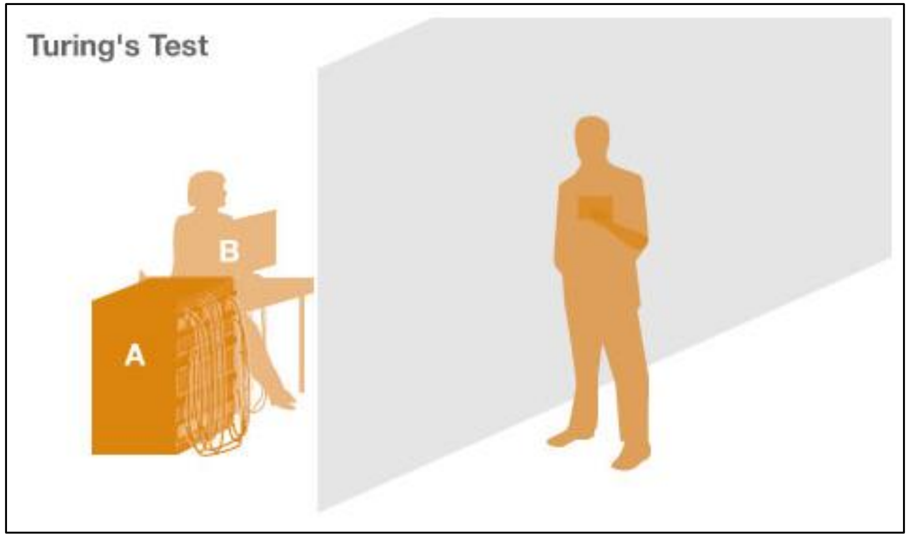
This is fed to a (deterministic) generator network.

The network outputs an image.

Source: Prof. Roger Grosse at U of Toronto

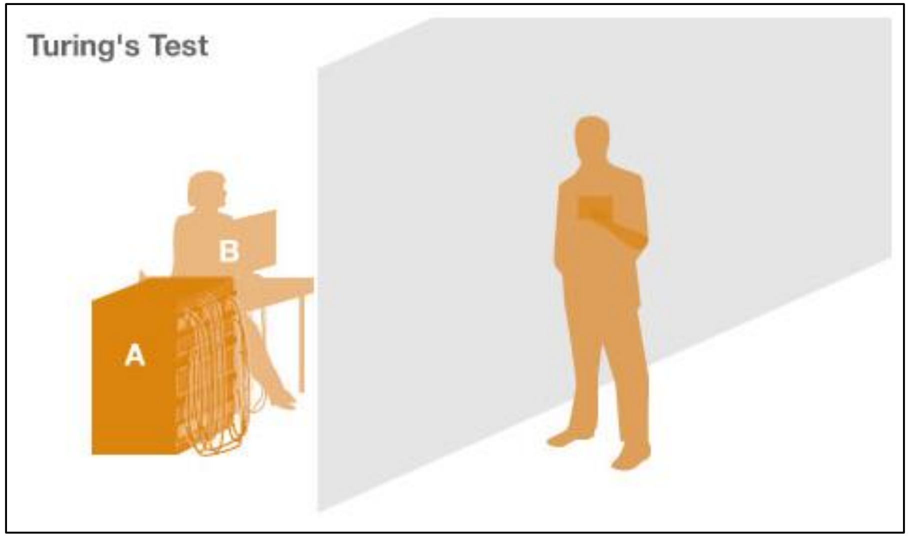
Generative Adversarial Networks (GANs)

- In generative modeling, we'd like to train a network that models a distribution, such as a distribution over images.
- GANs do not work with any explicit density function !
  - Instead, take game-theoretic approach



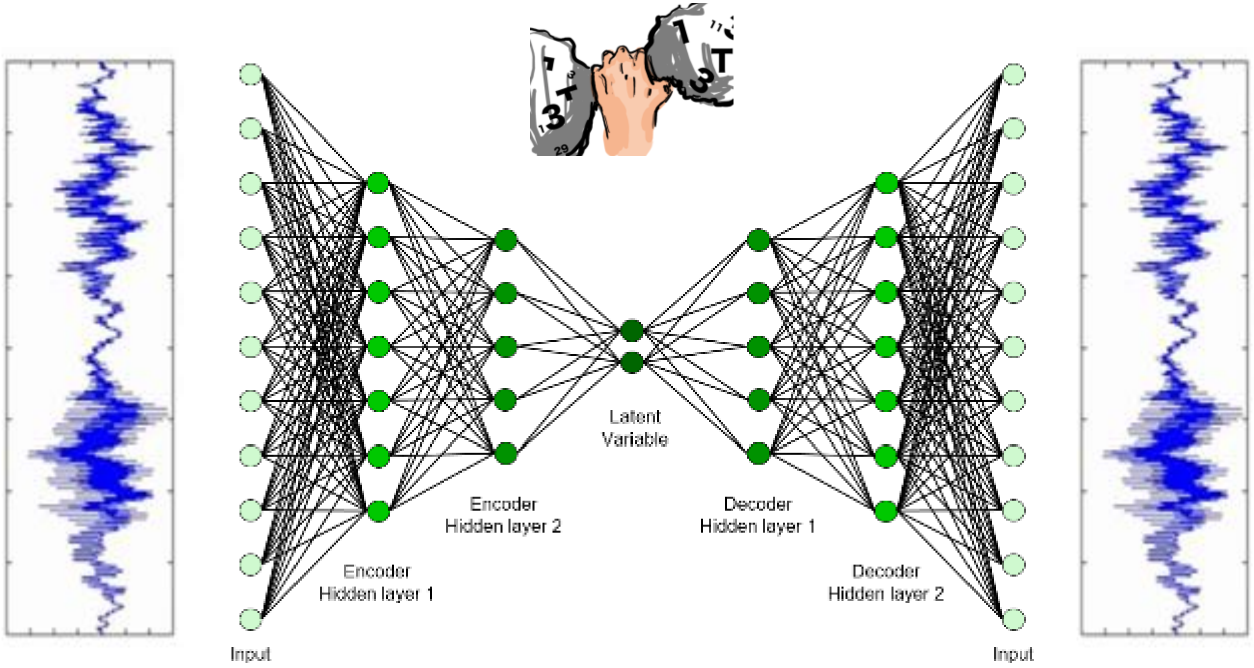
Turing Test

- One way to judge the quality of the model is to sample from it.
- GANs are based on a very different idea:
  - Model to produce samples which are indistinguishable from the real data, as judged by a discriminator network whose job is to tell real from fake



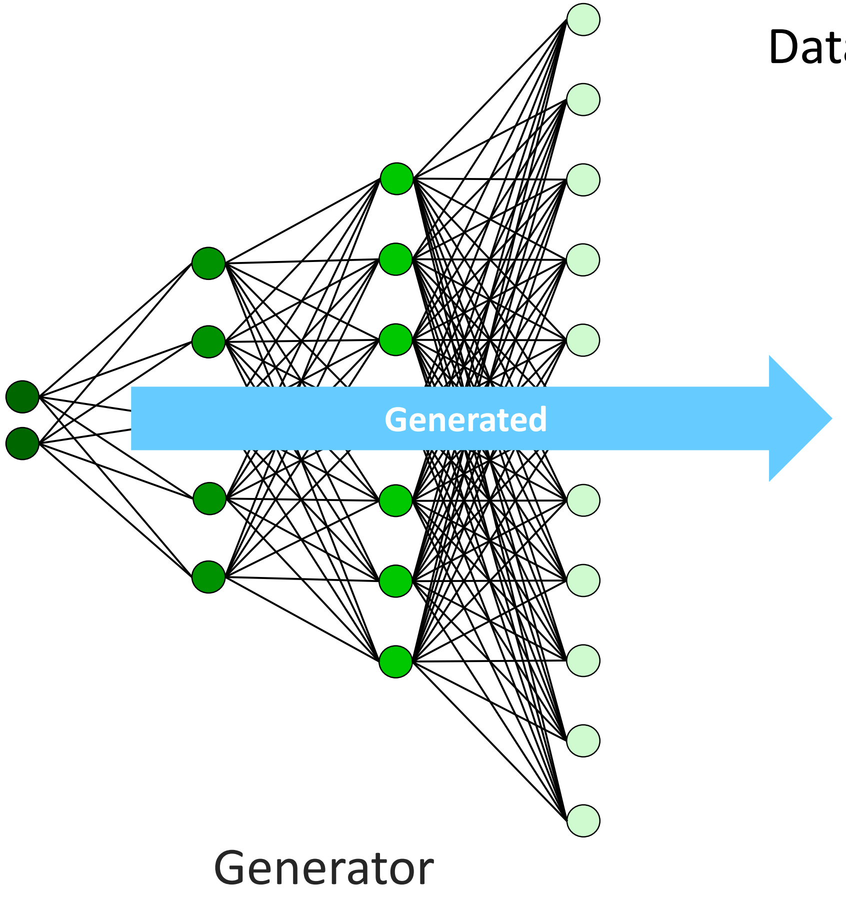
Autoencoder

- Dimension reduction
- Recover the input data
  - Learns an encoding of the inputs so as to recover the original input from the encodings as well as possible



Generative Adversarial Networks (GAN)

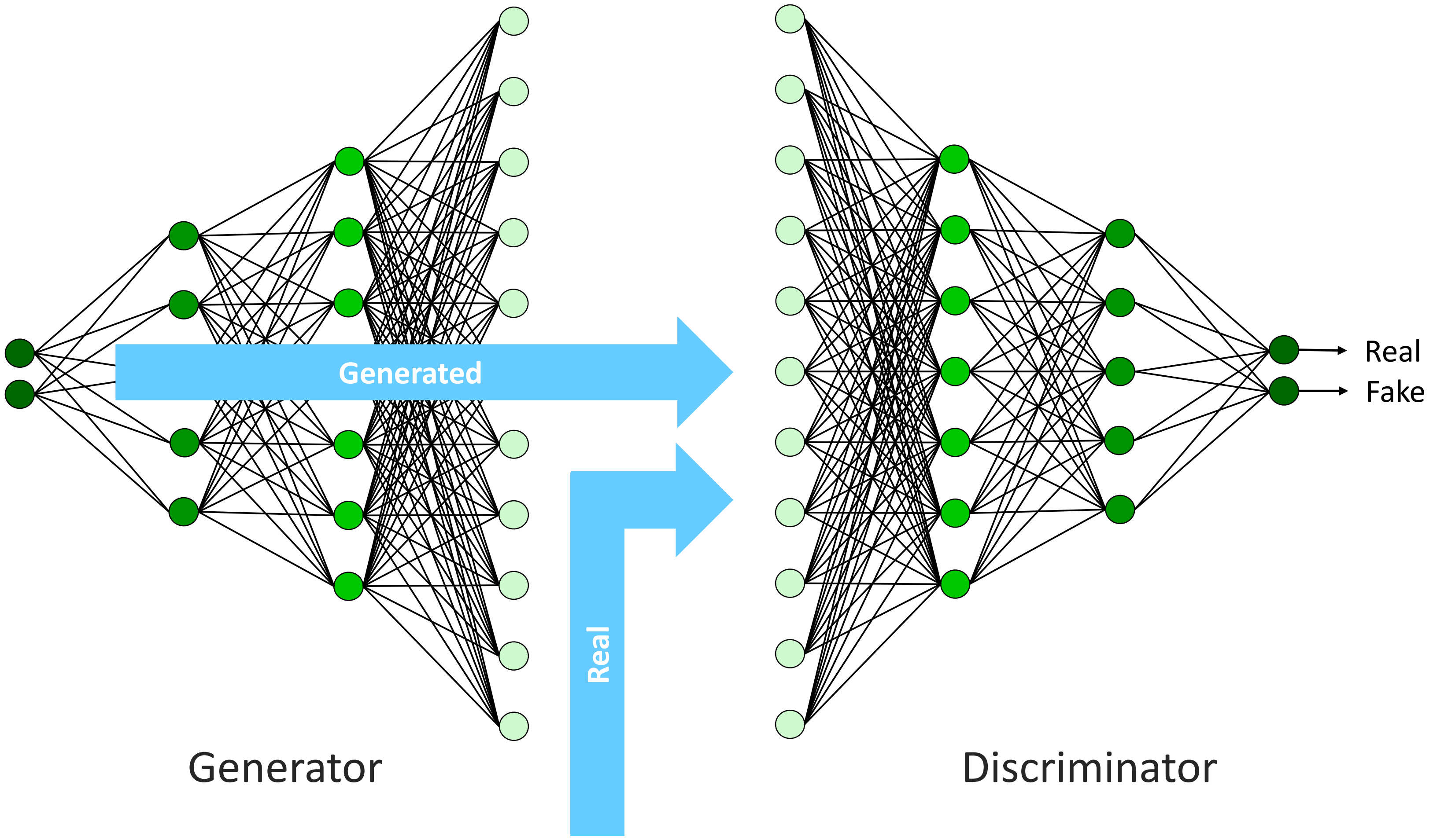
- Analogous to Turing Test



Data Generator

Generative Adversarial Networks (GAN)

- Analogous to Turing Test



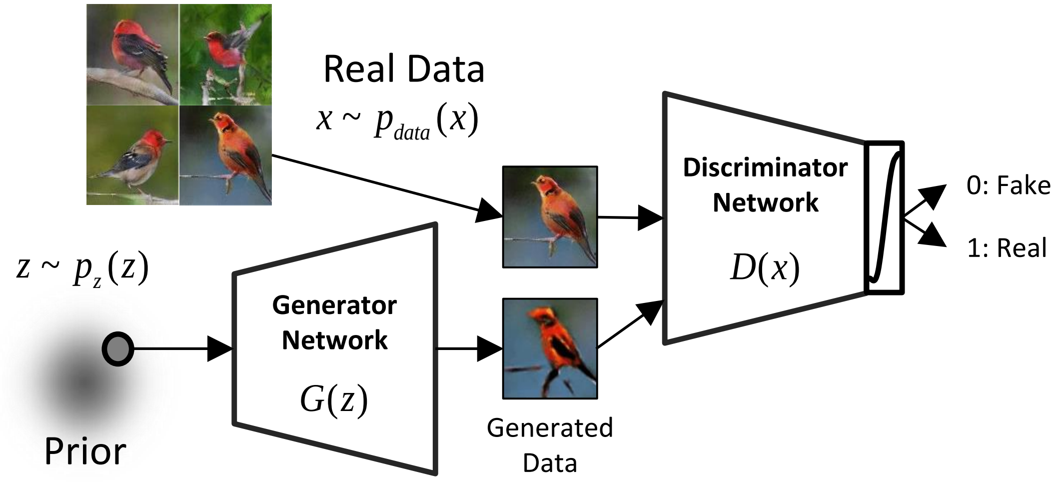
Generative Adversarial Networks (GAN)

- The idea behind Generative Adversarial Networks (GANs): train two different networks
  - Generator network: try to produce realistic-looking samples
  - Discriminator network: try to distinguish between real and fake data
- The generator network tries to fool the discriminator network

Generative Adversarial Networks (GAN)

- How to generate data?
  - Train through competition
  - Generator vs. Discriminator

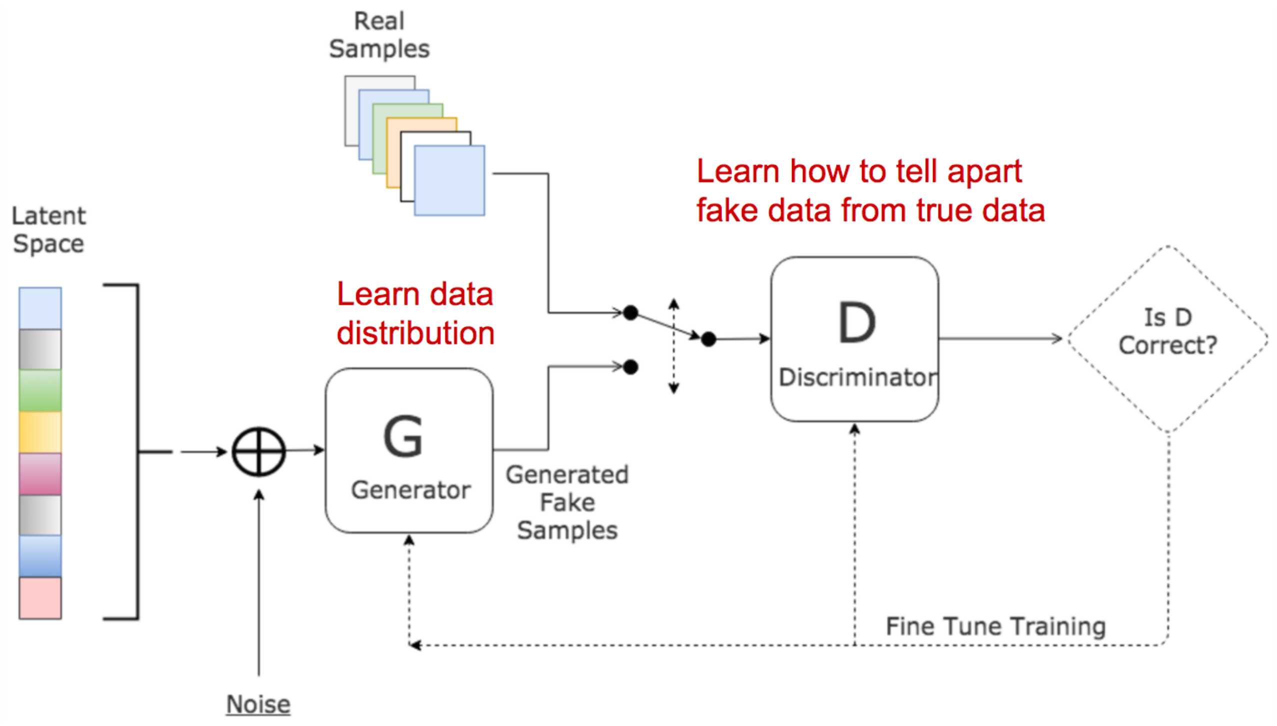
$$\boxed{H(D(G(z)),0)+H(D(x),1)}$$



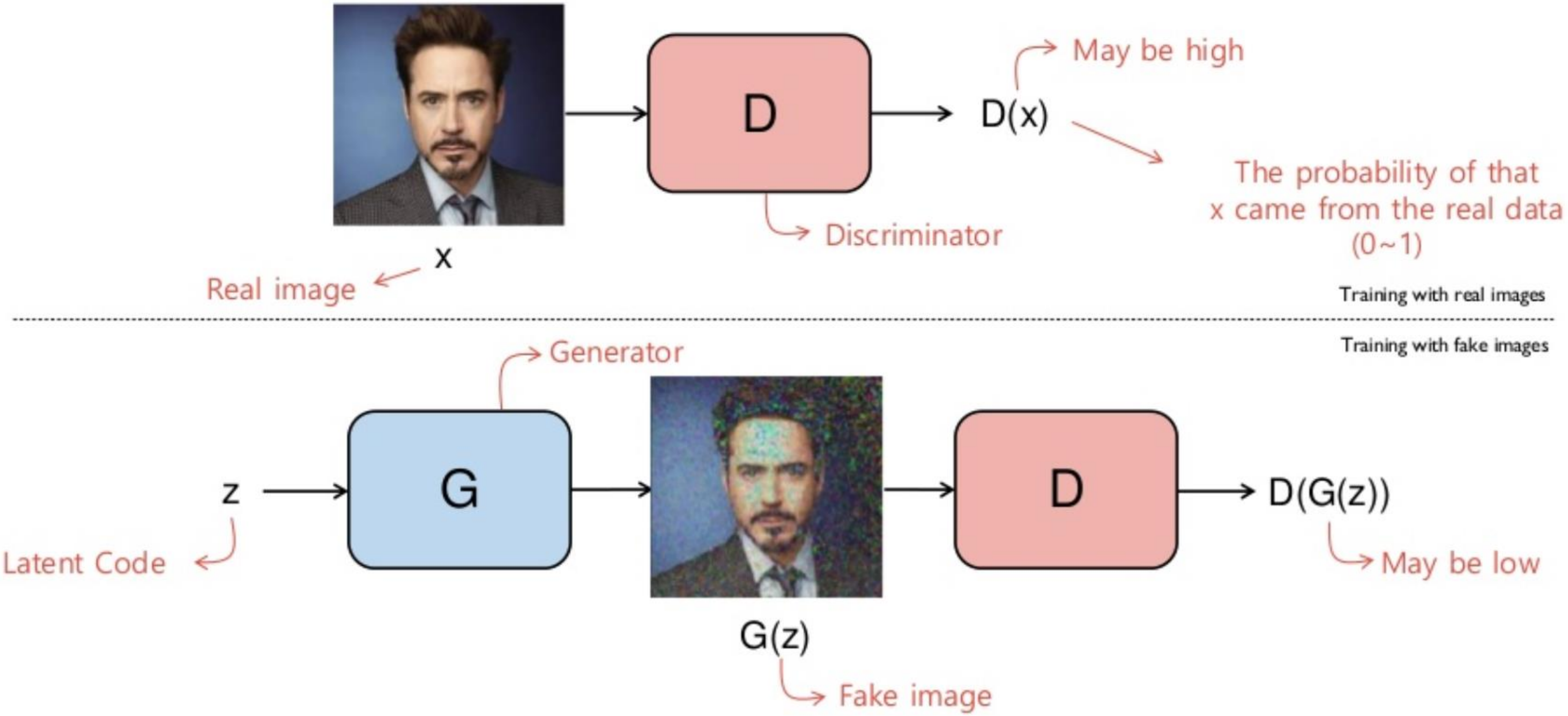
$$\boxed{H(D(G(z)),1)}$$

Generative Adversarial Networks (GAN)

- How to generate data?
  - Train through competition
  - Generator vs. Discriminator



Intuition for GAN



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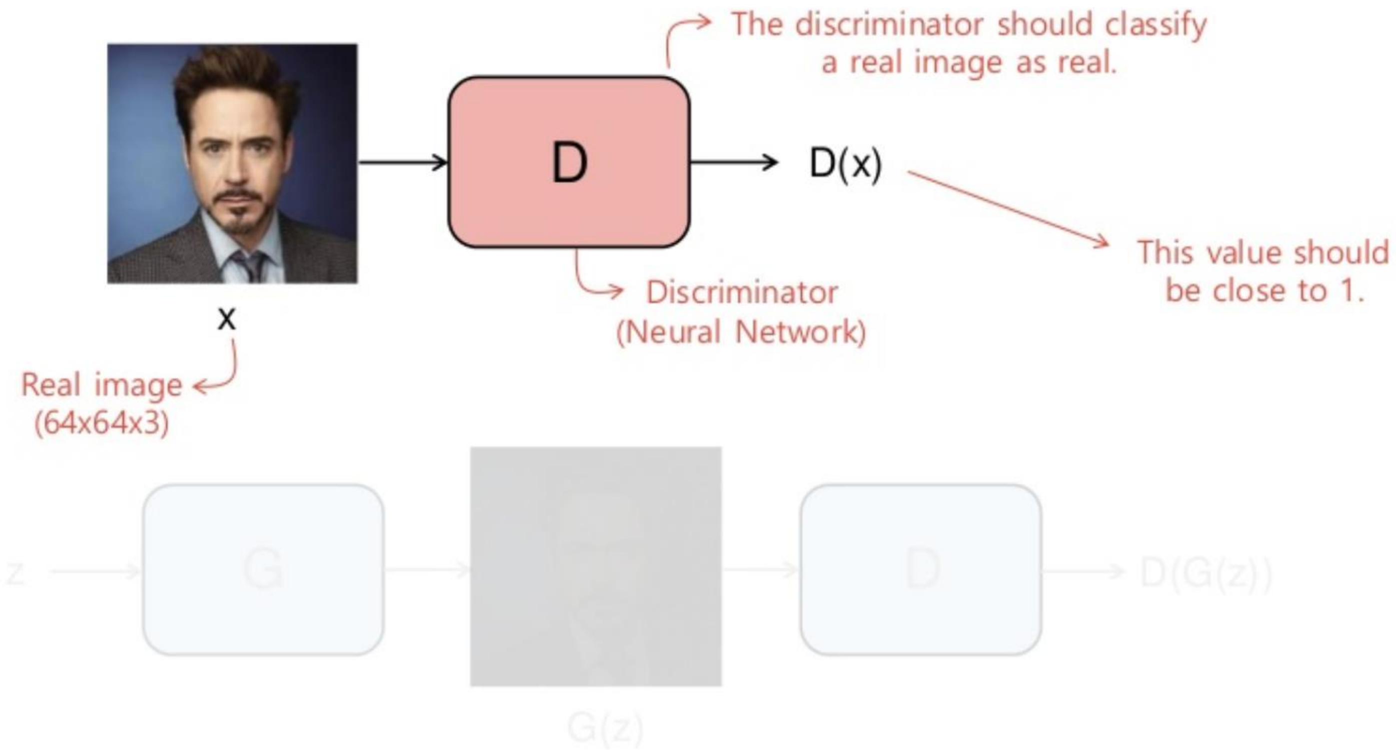
Discriminator Perspective



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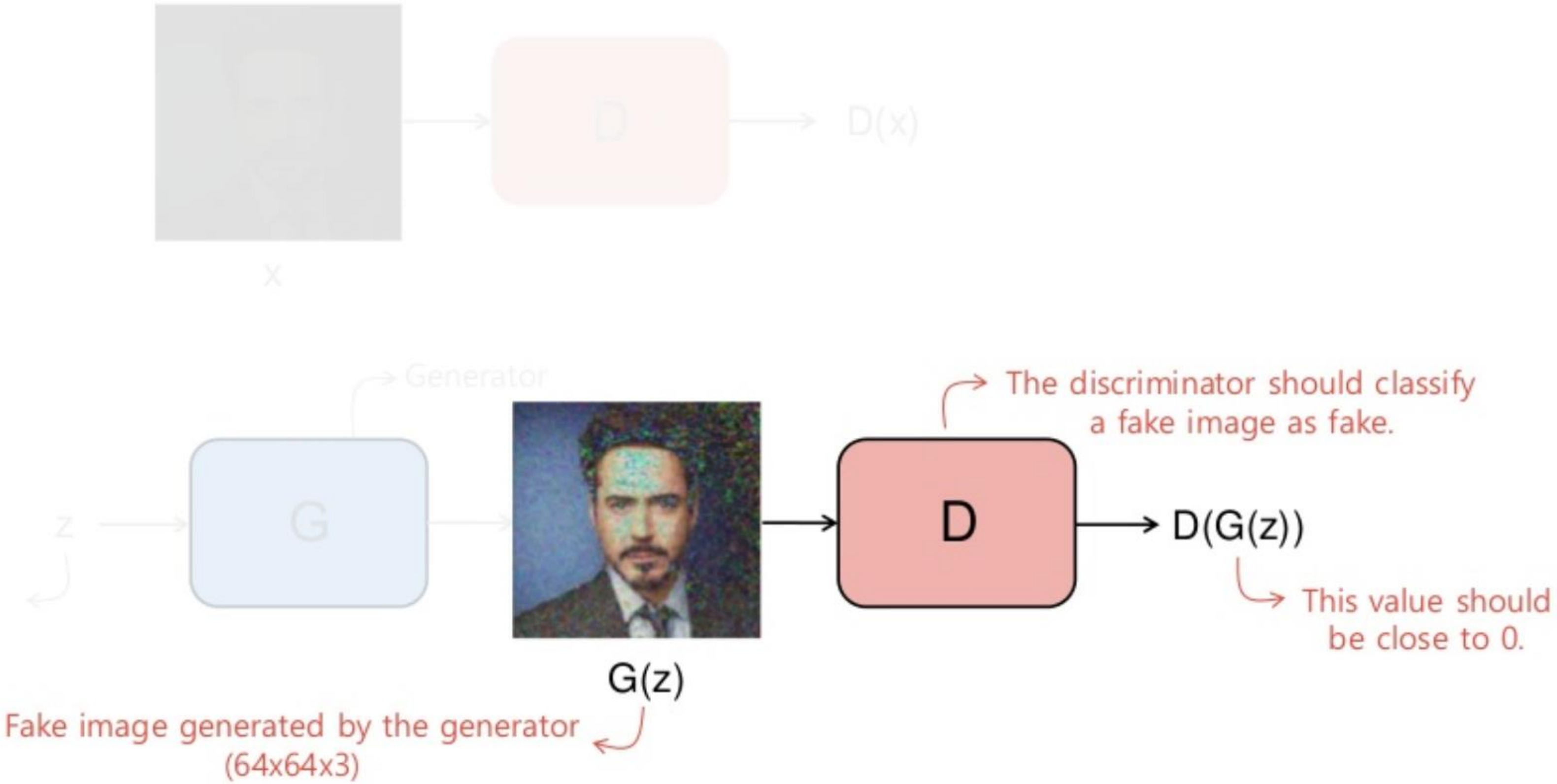
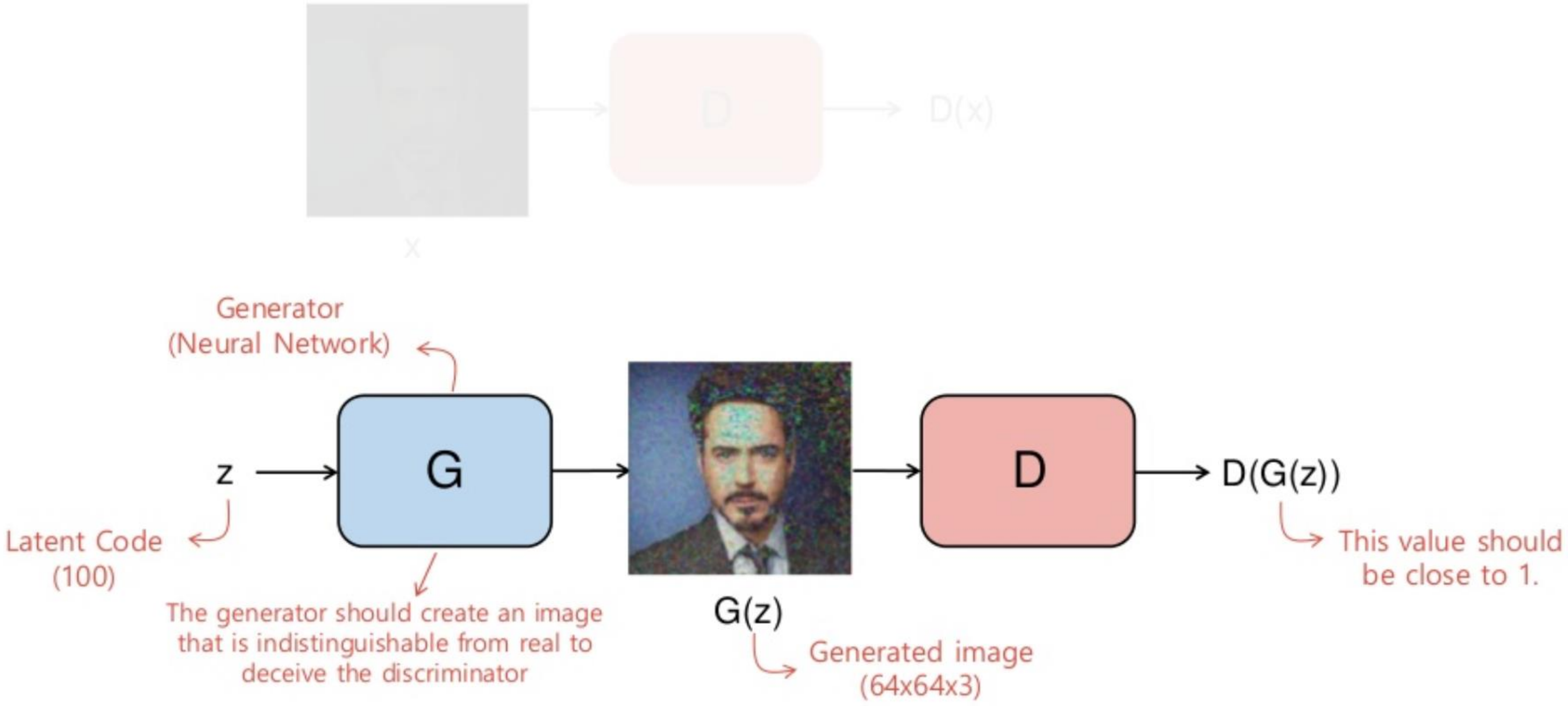
Discriminator Perspective

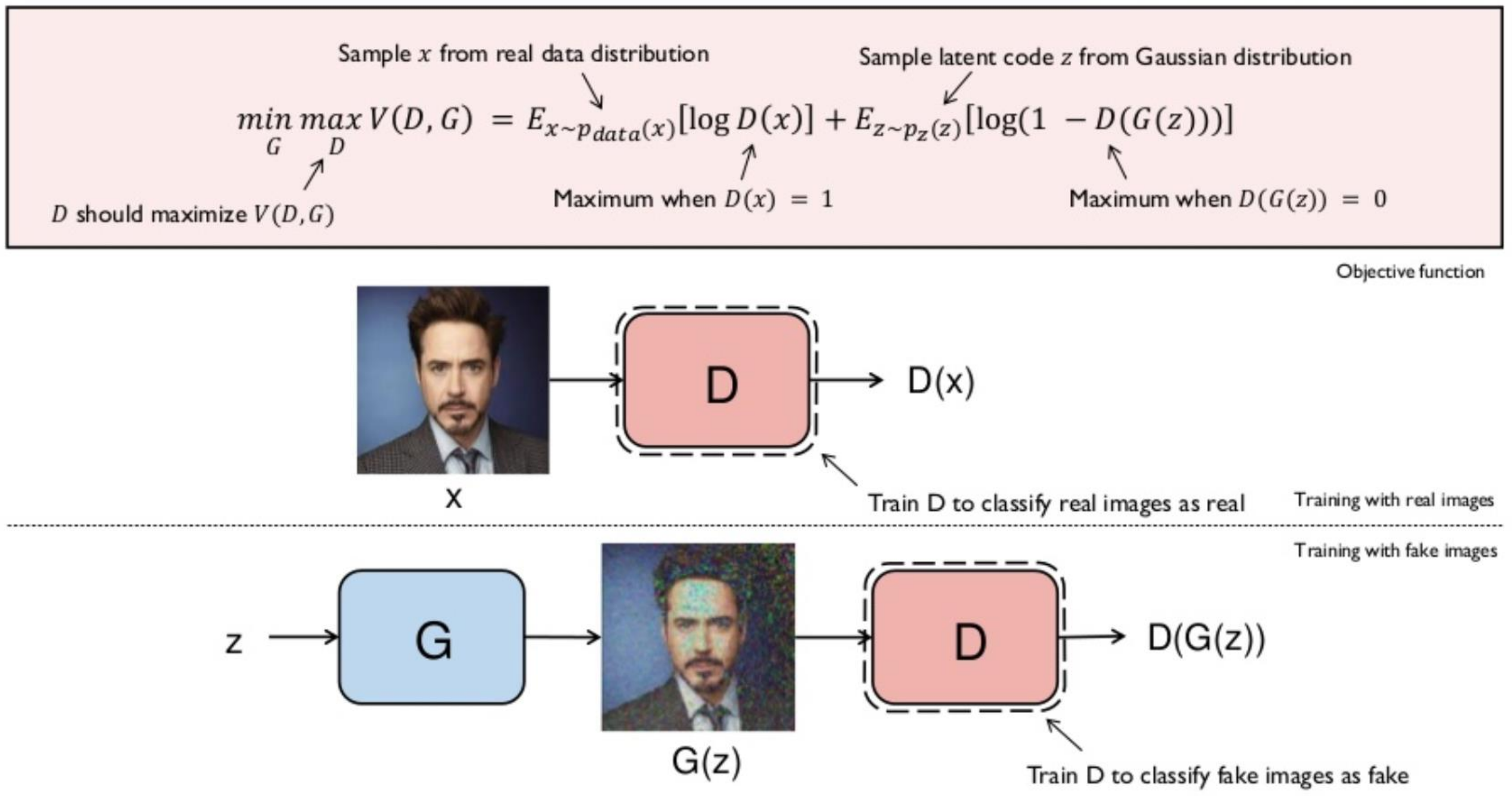


Generator Perspective



Objective Function of GAN

$$\text{loss} = -y \log h(x) - (1-y)\log(1-h(x))$$



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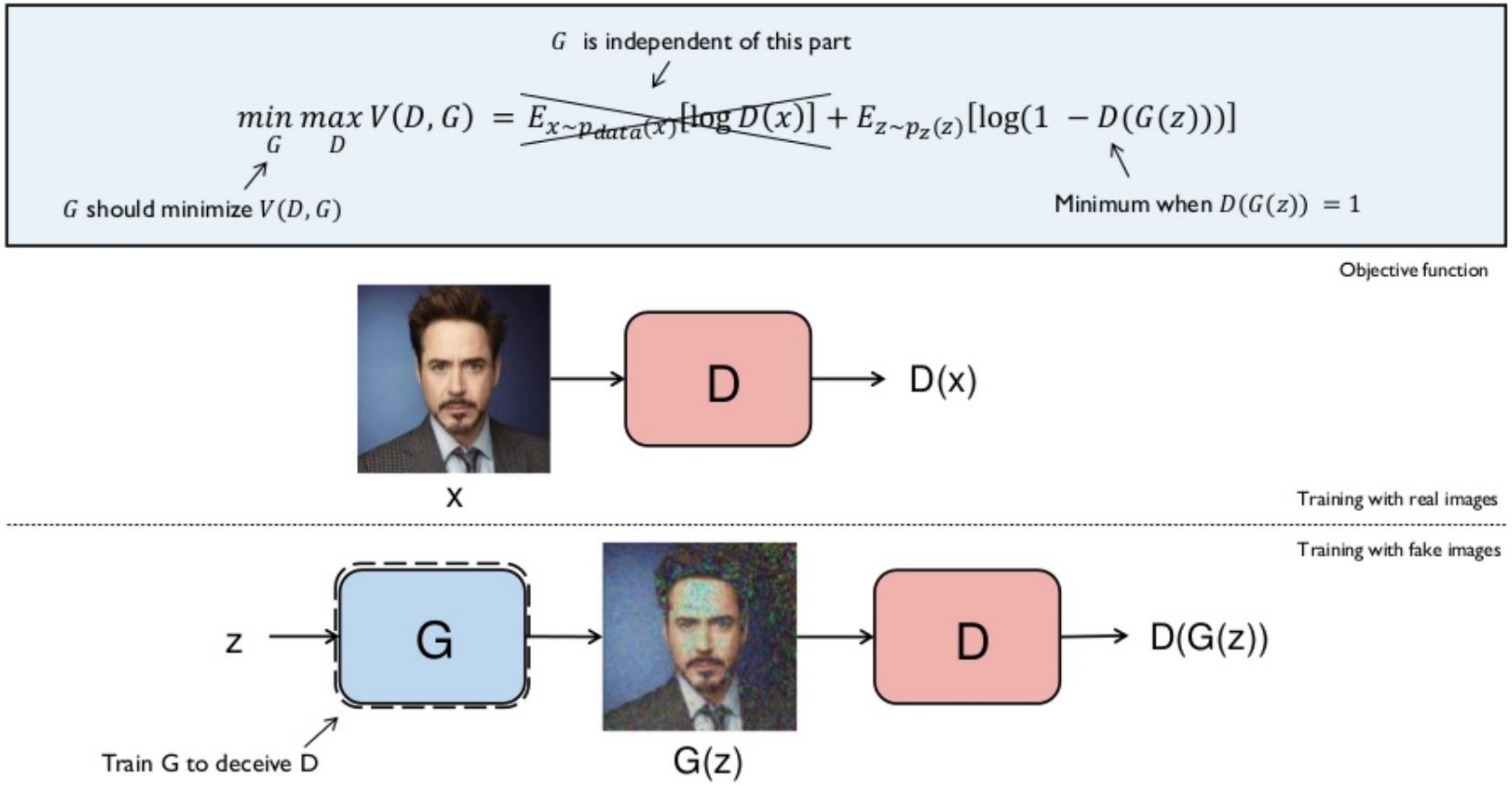
Objective Function of GAN



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Non-Saturating Game

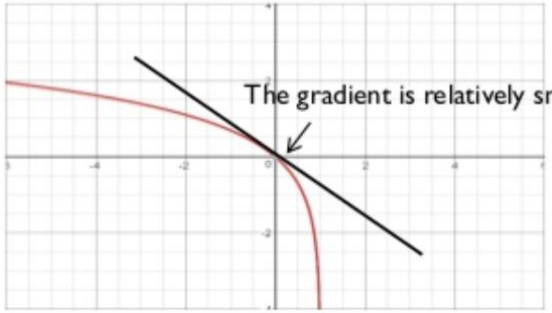
$$\min_G E_{z\sim p_z(z)}[\log(1 - D(G(z))]$$

Objective function of G

At the beginning of training, the discriminator can clearly classify the generated image as fake because the quality of the image is very low.

This means that D(G(z)) is almost zero at early stages of training.

Images created by the generator at the beginning of training



$$y = \log(1 - x)$$

Non-Saturating Game

$$\cancel{\min_{G} E_{z\sim p_z(z)}[\log(1 - D(G(z))]}$$

$$\downarrow \text{ Modification (heuristically motivated)}$$

$$\max_{G} E_{z\sim p_z(z)}[\log D(G(z))]$$

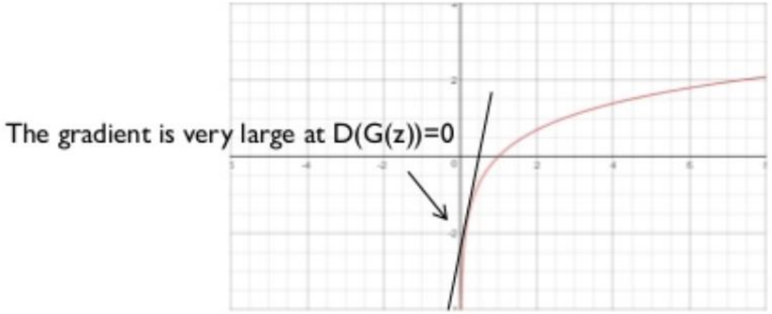
- Practical Usage

Use binary cross entropy loss function with fake label (1)

$$\min_{G} E_{z\sim p_z(z)}[-y \log D(G(z)) - (1-y)\log(1 - D(G(z))]$$

$$\downarrow \; y = 1$$

$$\min_{G} E_{z\sim p_z(z)}[-\log D\big(G(z)\big)]$$



$y = \log(x)$

Solving a MinMax Problem

Step 1: Fix G and perform a gradient step to

$$\max_D E_{x\sim p_{\text{data}}(x)}\left[\log D(x)\right] + E_{x\sim p_z(z)}\left[\log(1 - D(G(z)))\right]$$

Step 2: Fix D and perform a gradient step to

$$\max_G E_{x\sim p_z(z)}\left[\log D(G(z))\right]$$

OR

Step 1: Fix G and perform a gradient step to

$$\min_D E_{x\sim p_{\text{data}}(x)}\left[-\log D(x)\right] + E_{x\sim p_z(z)}\left[-\log(1 - D(G(z)))\right]$$

Step 2: Fix D and perform a gradient step to

$$\min_G E_{x\sim p_z(z)}\left[-\log D(G(z))\right]$$

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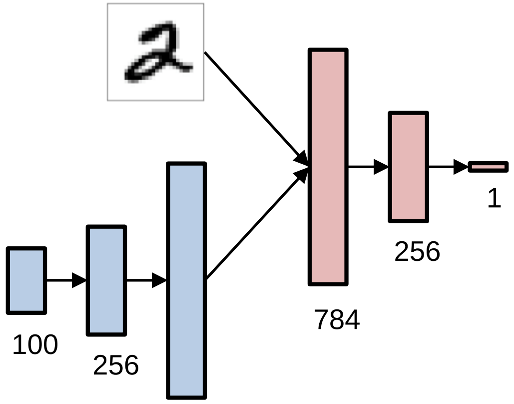
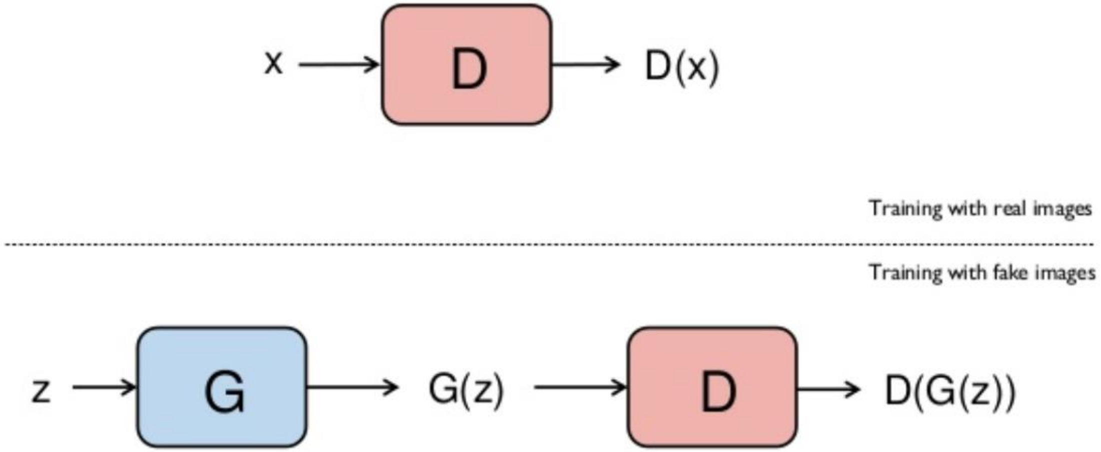
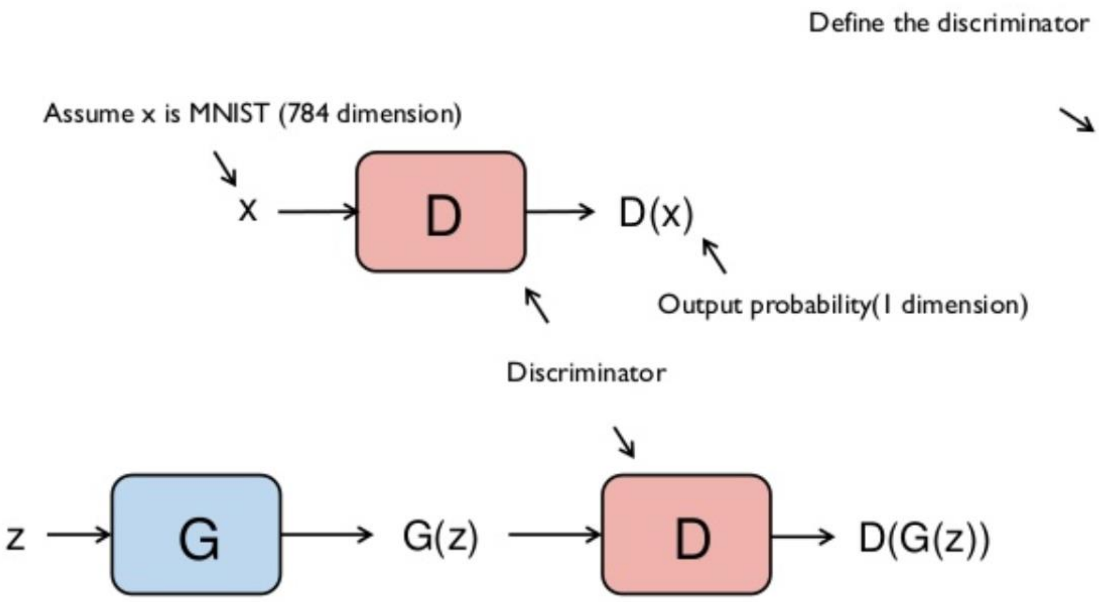
TensorFlow Implementation



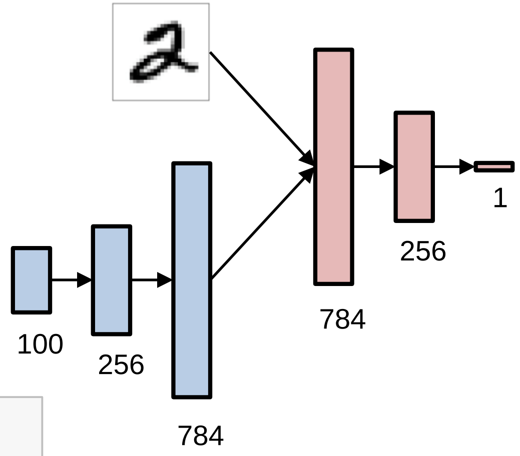


TensorFlow Implementation




```
n_D_input = 28*28
n_D_hidden = 256
n_D_output = 1

n_G_input = 100
n_G_hidden = 256
n_G_output = 28*28
```



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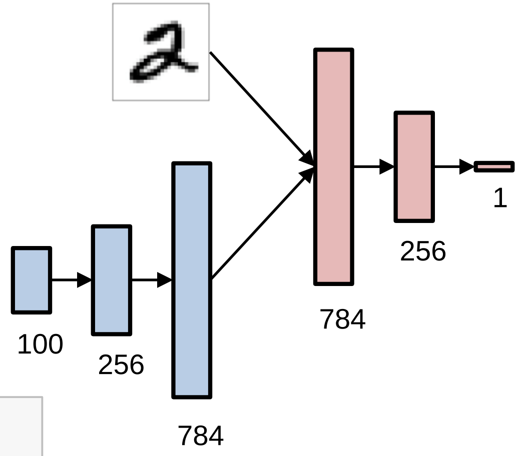
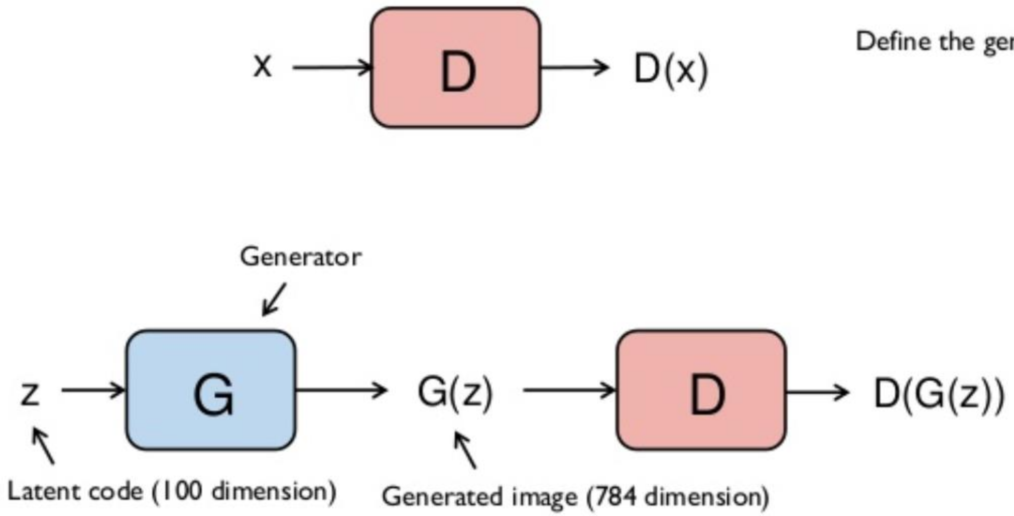
TensorFlow Implementation





Define the generator

```
n_D_input = 28*28
n_D_hidden = 256
n_D_output = 1

n_G_input = 100
n_G_hidden = 256
n_G_output = 28*28
```

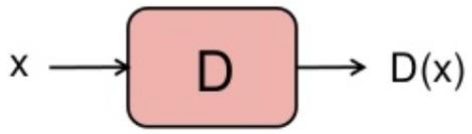
TensorFlow Implementation

Step 1: Fix G and perform a gradient step to

$$\min_D E_{x\sim p_{\text{data}}(x)}\left[-\log D(x)\right] + E_{x\sim p_z(z)}\left[-\log(1-D(G(z)))\right]$$

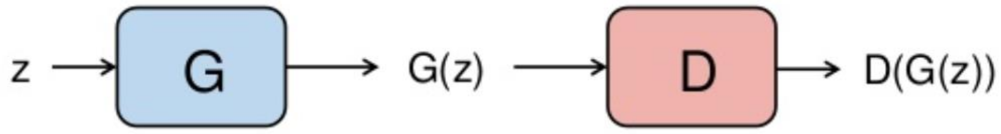
Step 2: Fix D and perform a gradient step to

$$\min_G E_{x\sim p_z(z)}\left[-\log D(G(z))\right]$$




```
D_loss = tf.reduce_mean(- tf.log(D_real) - tf.log(1 - D_fake))
G_loss = tf.reduce_mean(- tf.log(D_fake))
```

```
D_var_list = [weights['D1'], biases['D1'], weights['D2'], biases['D2']]
G_var_list = [weights['G1'], biases['G1'], weights['G2'], biases['G2']]
```




```
LR = 0.0002
D_optm = tf.train.AdamOptimizer(LR).minimize(D_loss, var_list = D_var_list)
G_optm = tf.train.AdamOptimizer(LR).minimize(G_loss, var_list = G_var_list)
```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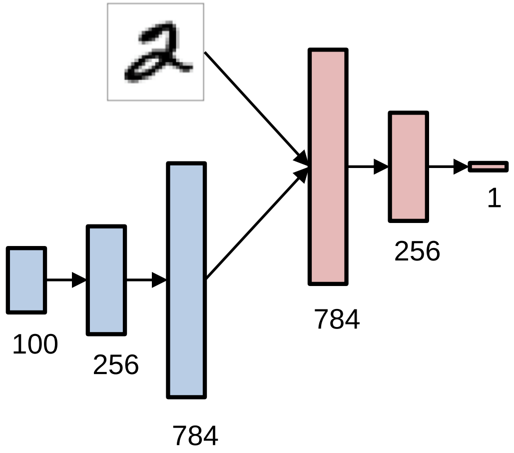
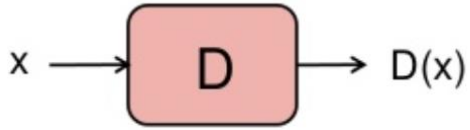
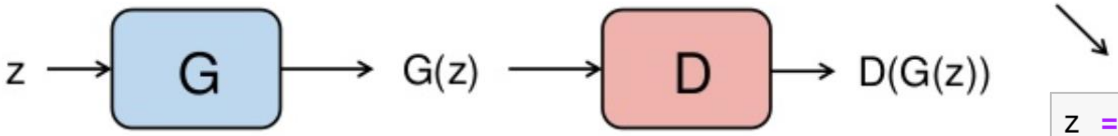
TensorFlow Implementation



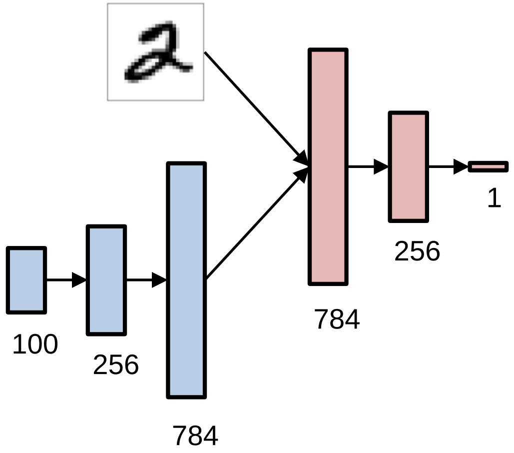


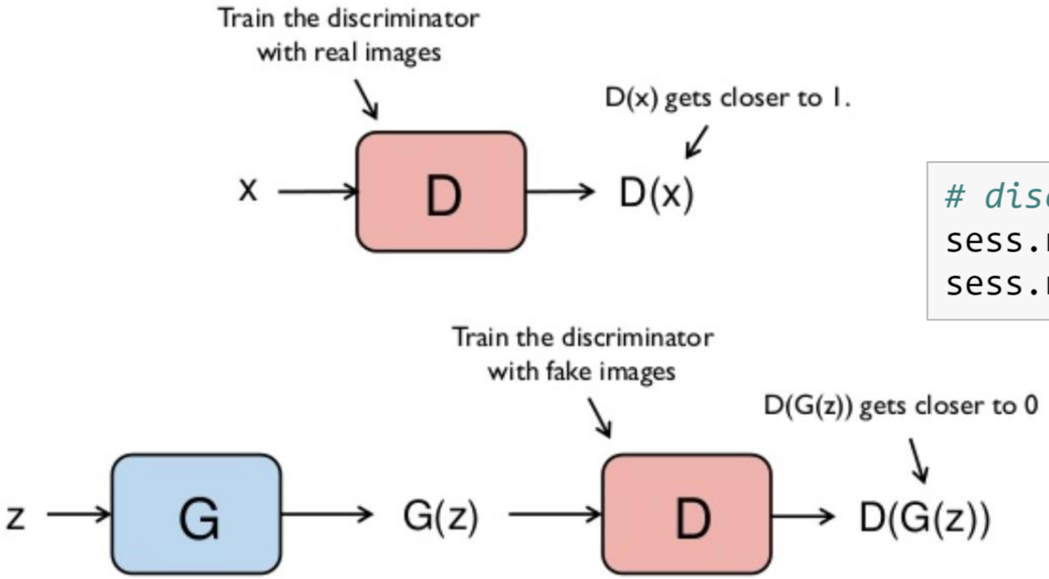
x is a tensor of shape (batch_size, 784).
z is a tensor of shape (batch_size, 100).




```
z = tf.placeholder(tf.float32, [None, n_G_input])
x = tf.placeholder(tf.float32, [None, n_D_input])
```

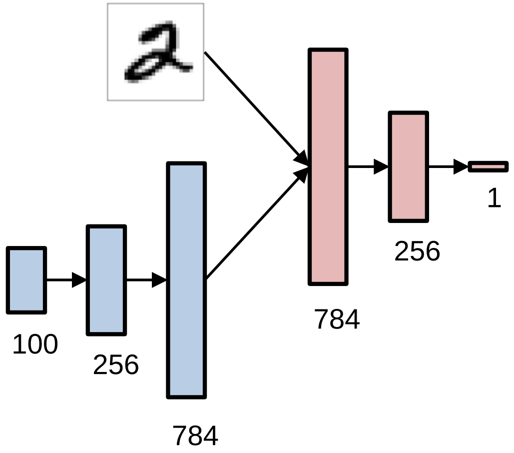
TensorFlow Implementation

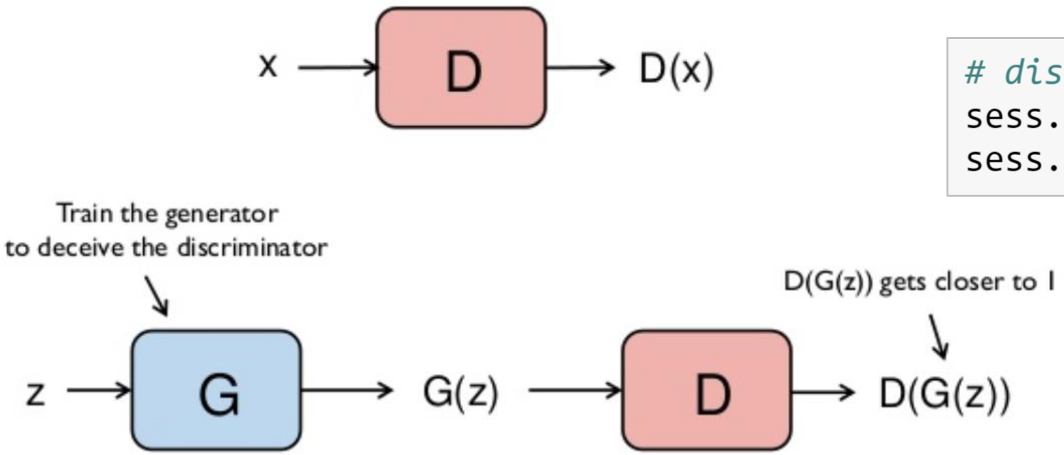





```
# discriminator and generator are separately trained
sess.run(D_optm, feed_dict = {x: train_x, z: noise})
sess.run(G_optm, feed_dict = {z: noise})
```

TensorFlow Implementation

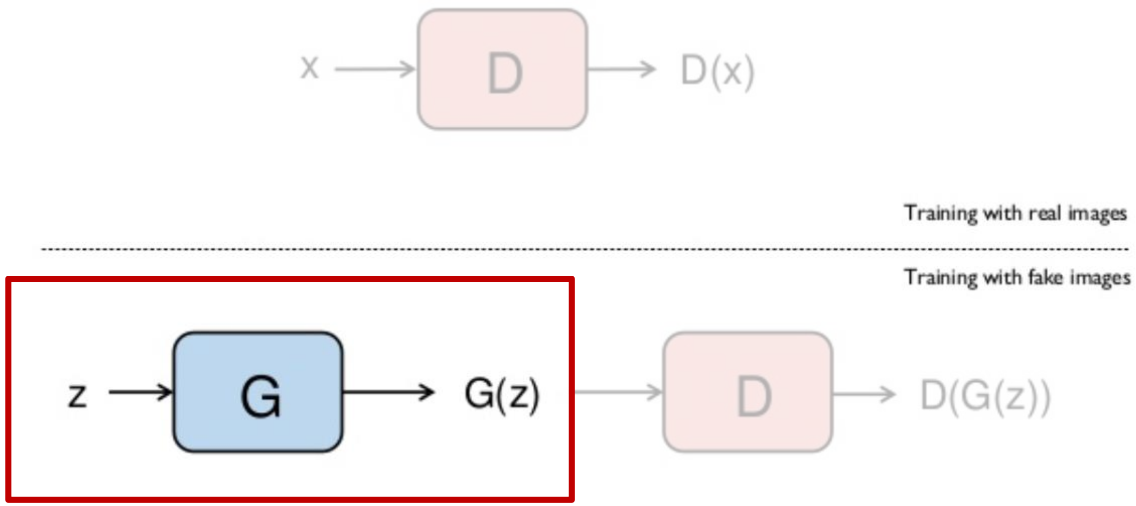


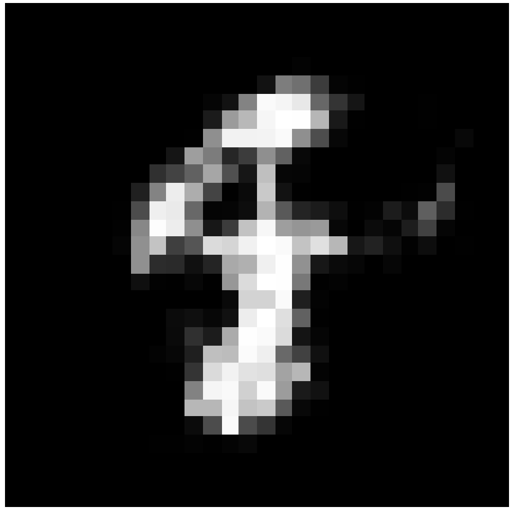



```
# discriminator and generator are separately trained
sess.run(D_optm, feed_dict = {x: train_x, z: noise})
sess.run(G_optm, feed_dict = {z: noise})
```

After Training

- After training, use generator network to generate new data





```
noise = make_noise(n_batch, n_G_input)
G_img = sess.run(G_output, feed_dict = {z: noise})
```


https://www.slideshare.net/NaverEngineering/1-gangenerative-adversarial-network

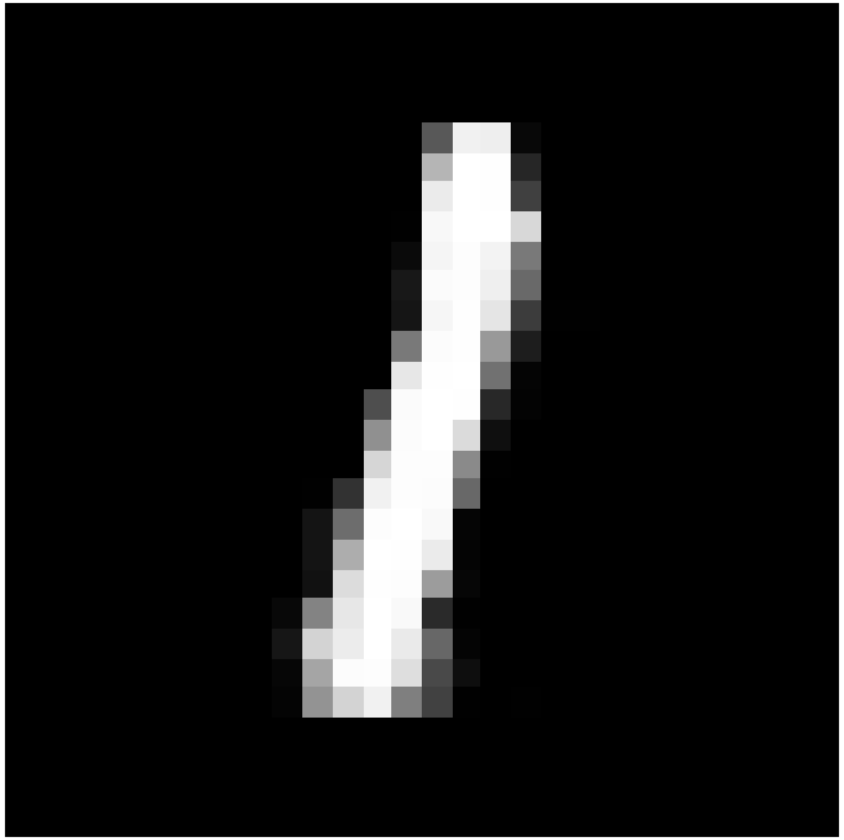
GAN Samples

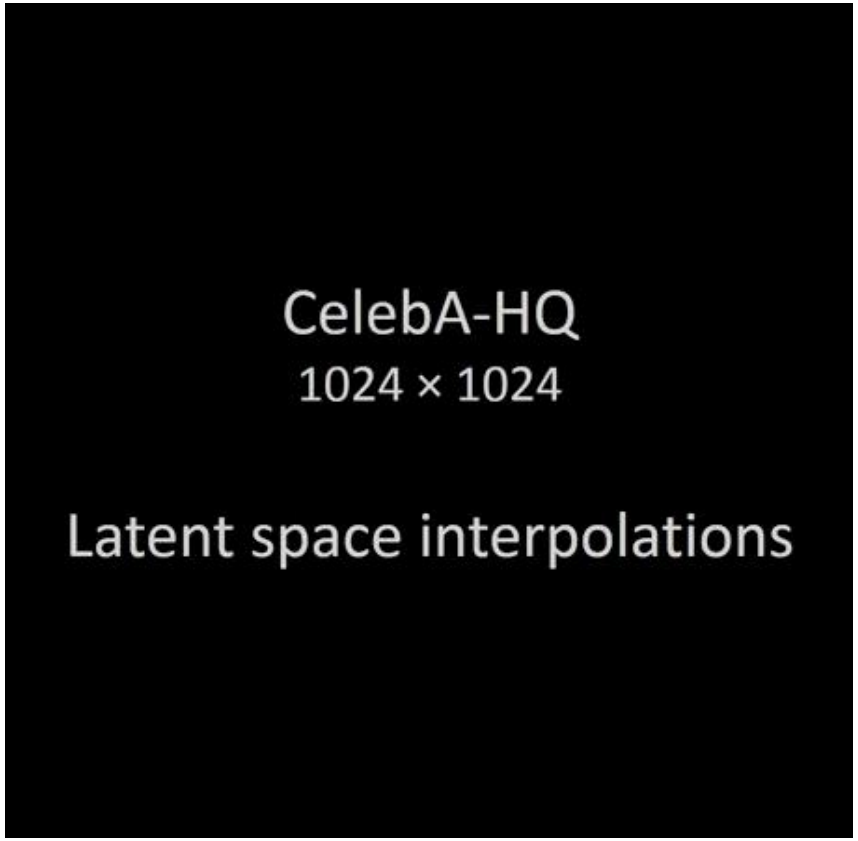
2009

2015

2018

GAN Samples





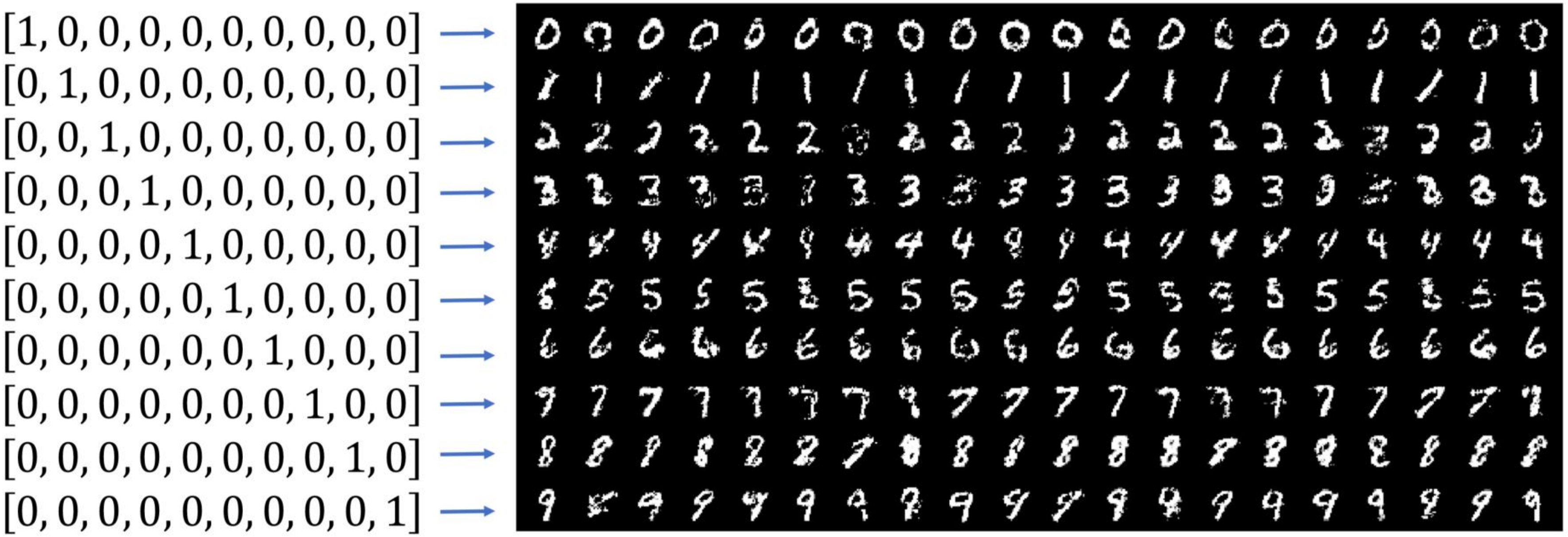
Conditional GAN

- In an unconditioned generative model, there is no control on modes of the data being generated.

- In the Conditional GAN (CGAN), the generator learns to generate a fake sample with a specific condition or characteristics (such as a label associated with an image or more detailed tag) rather than a generic sample from unknown noise distribution.

Conditional GAN

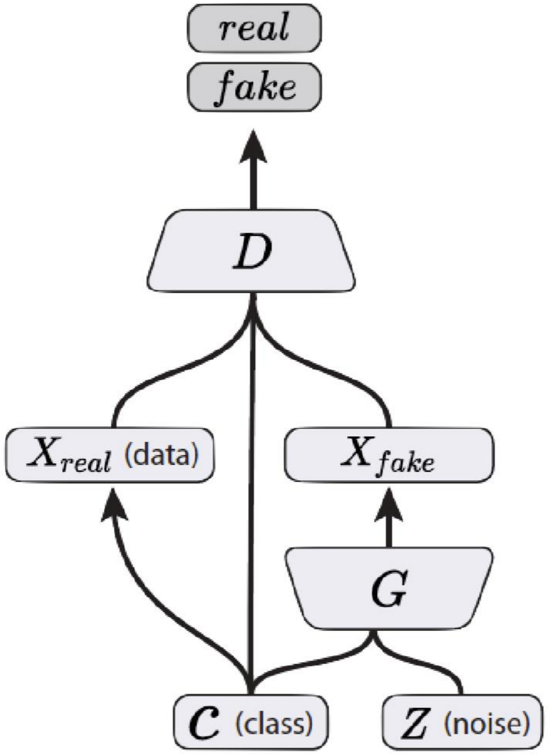
- MNIST digits generated conditioned on their class label



Conditional GAN

- Simple modification to the original GAN framework that conditions the model on additional information for better multi-modal learning

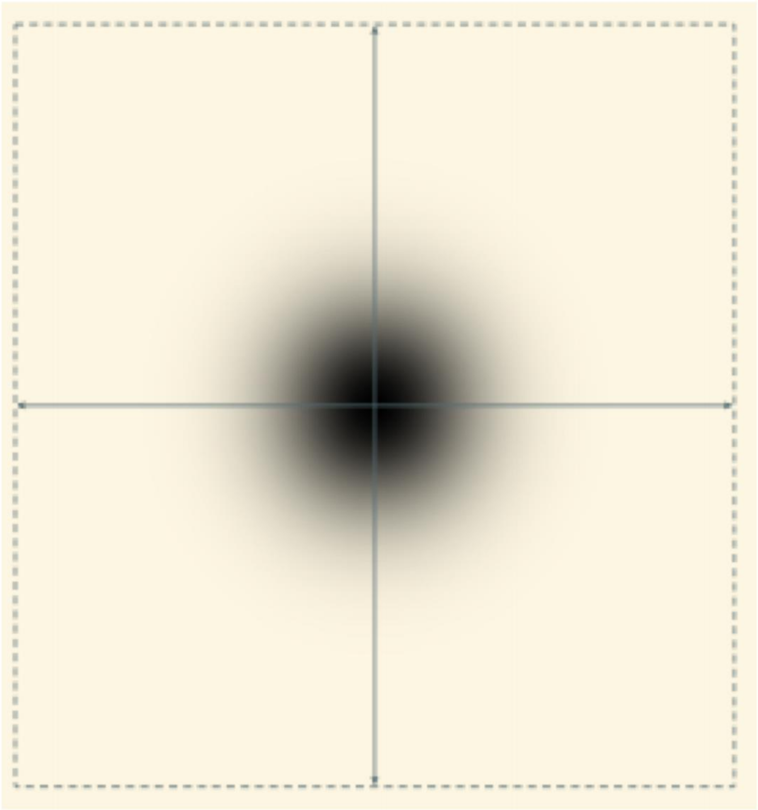
- Many practical applications of GANs when we have explicit supervision available



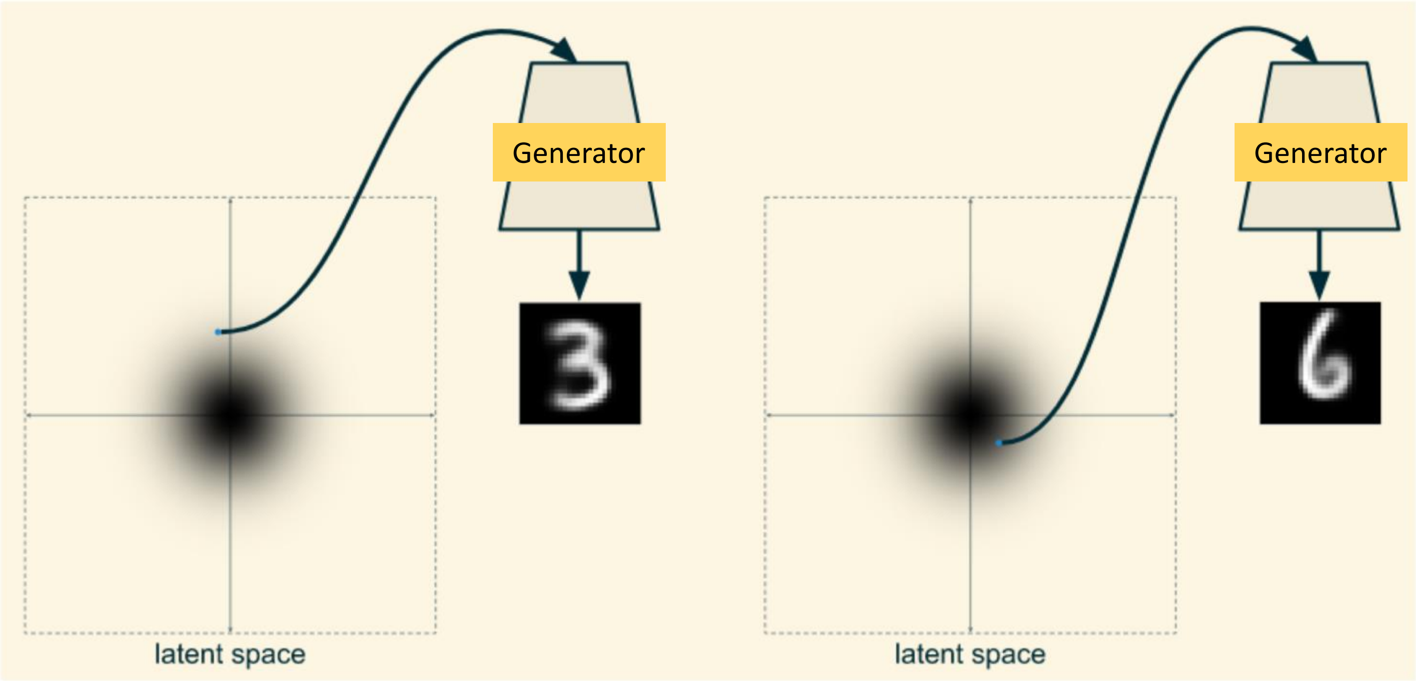
Conditional GAN
(Mirza & Osindero, 2014)

Normal Distribution of MNIST

- A standard normal distribution
- This is how we would like points corresponding to MNIST digit images to be distributed in the latent space

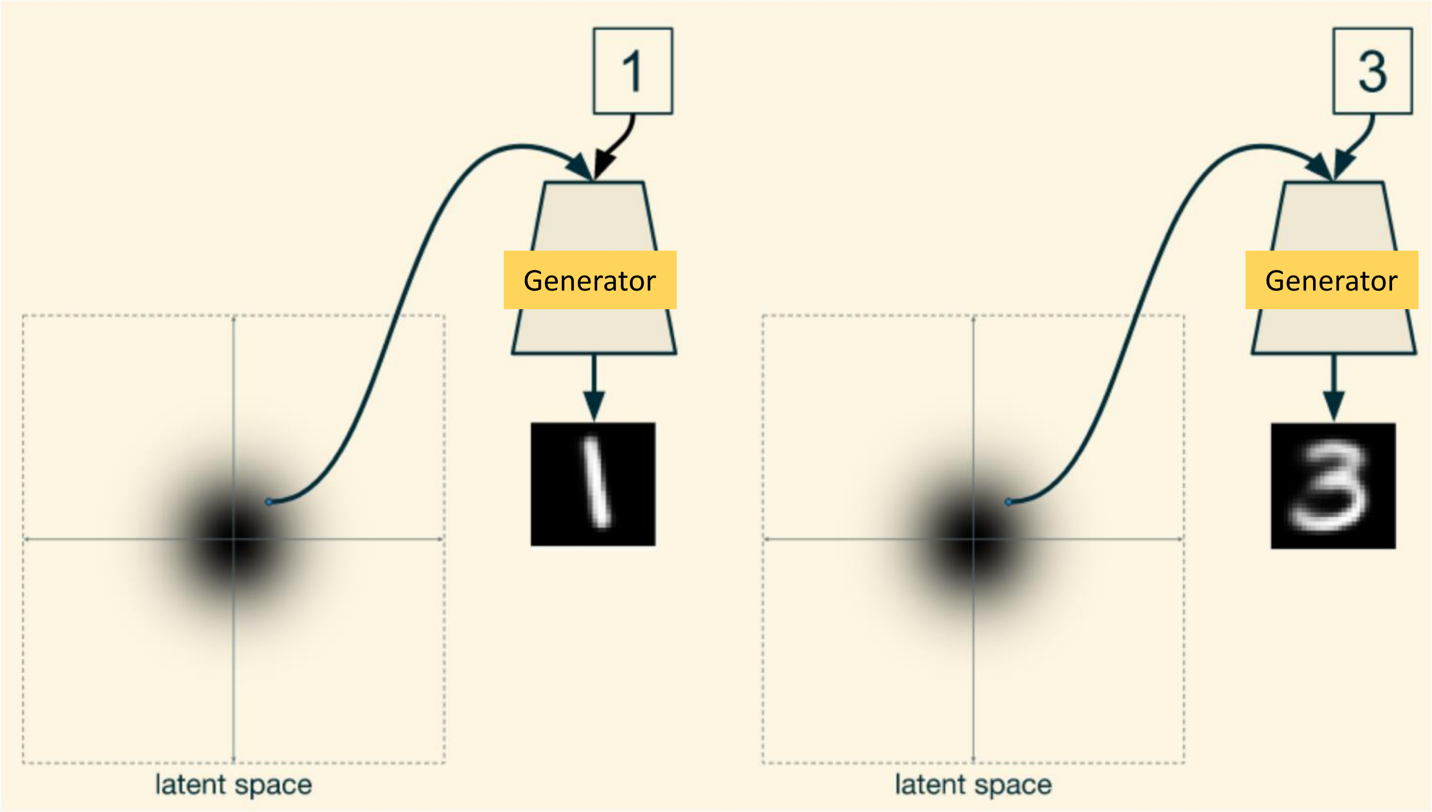


Generator at GAN



Generator at Conditional GAN

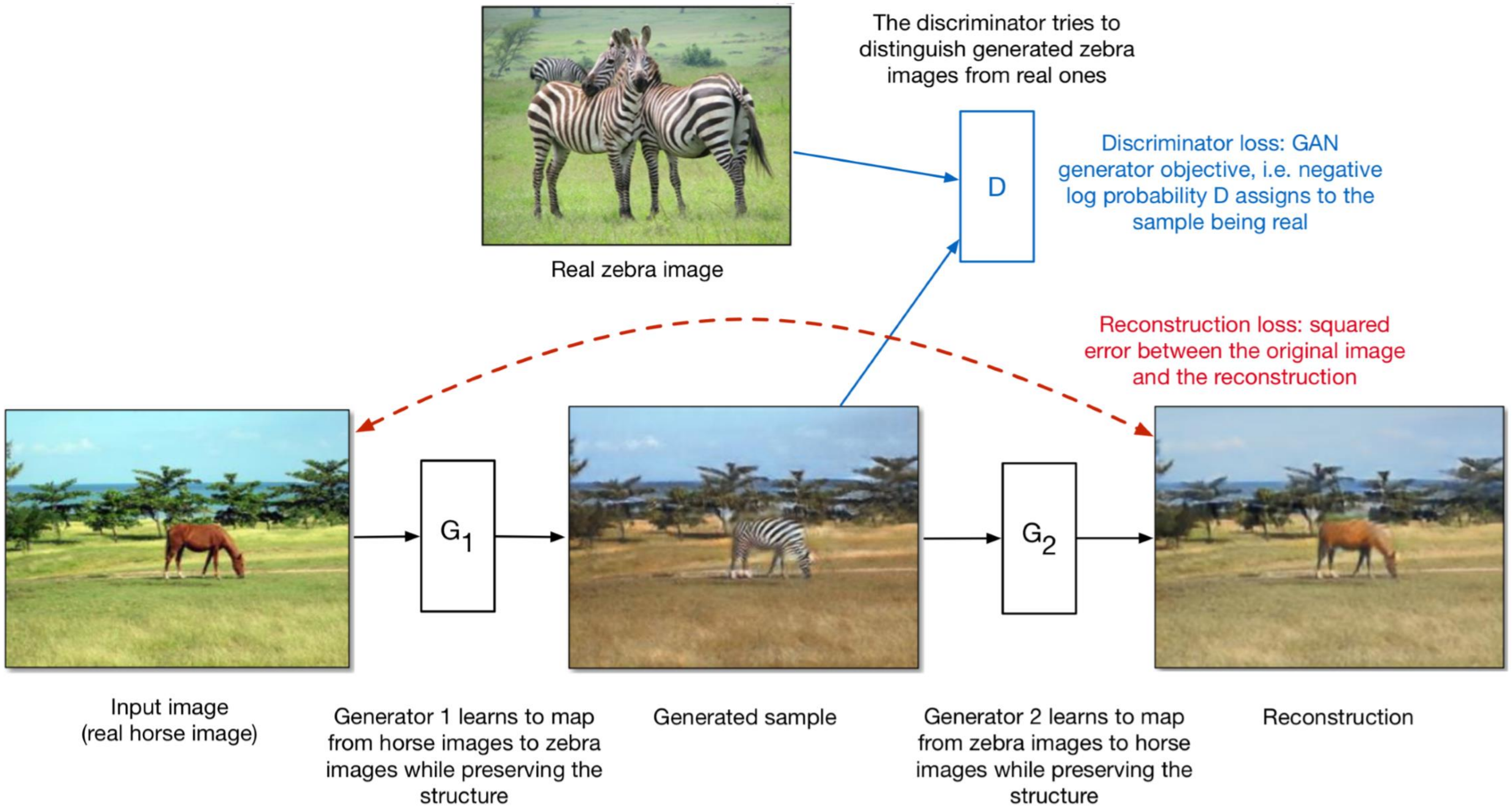
- Feed a random point in latent space and desired number.
- Even if the same latent point is used for two different numbers, the process will work correctly since the latent space only encodes features such as stroke width or angle



CycleGAN by UC Berkeley (2016)

https://github.com/junyanz/CycleGAN

CycleGAN



Total loss = discriminator loss + reconstruction loss

Source: Prof. Roger Grosse at U of Toronto