MInDS @ MINES

Deep Learning

How Data Scientists become magicians

Generative Models

Generative models are ”general” models that learn the attributes that exist for each particular class in a data set.

A generative model can provide the probability of a data point $\mathbf{x}$ existing given that it is from class k, $p(\mathbf{x}|C_k)$.

Discriminative Models

Discriminative models are ”task-specific” models that learn the attributes that differentiate between different classes/groups.

A discriminative model provides the probability of a particular class k given a particular data point $\mathbf{x}$, $p(C_k|\mathbf{x})$.

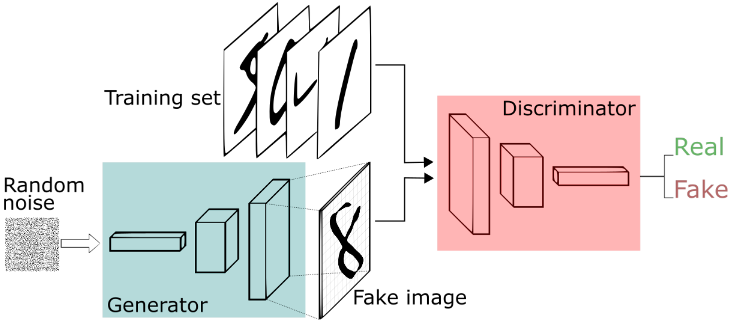
Generative vs Discriminative Models

- Generative: $p(\mathbf{x}|C_k)$
- Discriminative: $p(C_k|\mathbf{x})$

GANs

- **Generative** - generate samples of data similar to input
- **Adversarial** - train by competing against another model
- **Networks** - a neural network

GANs


Training set
Discriminator
Real
Fake
Random noise
Generator
Fake image

Binary Cross Entropy

$$H(p, q) = -(y \log p + (1 - y) \log(1 - p)),$$

where y is the indicator for the class and we assume that $1 - p = q$ since the data sample can only be one of the classes.

Discriminator Objective

$$\min_D -E_{x\sim p_{data}}[\log D(\mathbf{x})] - E_{z\sim p_z}[1 - \log D(G(\mathbf{z}))],$$
$$= \max_D E_{x\sim p_{data}}[\log D(\mathbf{x})] + E_{z\sim p_z}[1 - \log D(G(\mathbf{z}))].$$

Geenrator Objective

$$
\begin{aligned}
&\max_G -E_{x\sim p_{data}}[\log D(\mathbf{x})] - E_{z\sim p_z}[1-\log D(G(\mathbf{z}))],\\
&= \min_G E_{x\sim p_{data}}[\log D(\mathbf{x})] + E_{z\sim p_z}[1-\log D(G(\mathbf{z}))].
\end{aligned}
$$

Minmax Problem

$$\min_G \max_D E_{x \sim p_{data}}[\log D(\mathbf{x})] + E_{z \sim p_z}[1 - \log D(G(\mathbf{z}))].$$

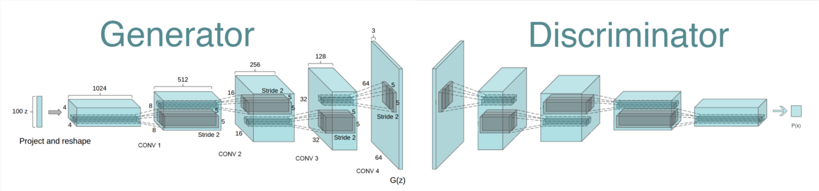
Mode Collapse

$$\min_G \max_D V(G, D) \neq \max_D \min_G V(G, D).$$

GAN Variations

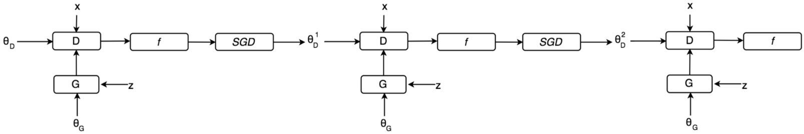
- Deep Convolutional GAN (DCGAN)
- Unrolled GAN
- Wasserstein GAN (WGAN)
- Conditional GAN (CGAN)

DCGAN



Generator
Discriminator
100 z
Project and reshape
1024
4
4
512
8
8
CONV 1
Stride 2
256
16
16
CONV 2
Stride 2
128
32
32
CONV 3
Stride 2
3
64
64
CONV 4
Stride 2
G(z)
P(x)

Unrolled GAN



Wasserstein GAN

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

CGAN

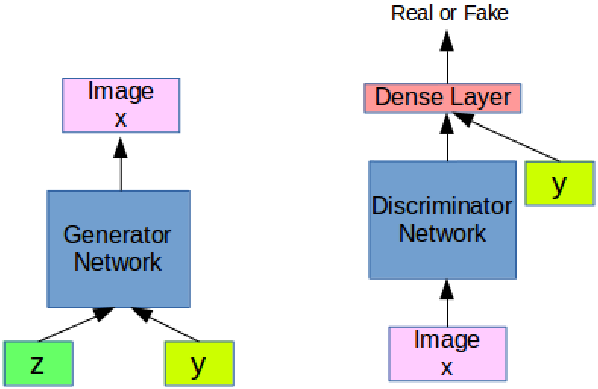


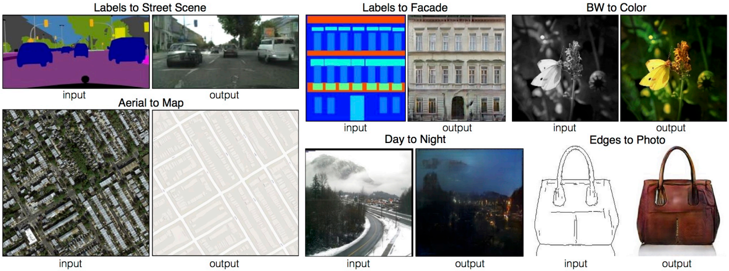
Image
x
Generator
Network
z
y
Real or Fake
Dense Layer
Discriminator
Network
y
Image
x

GAN Zoo

Example Applications of GANs

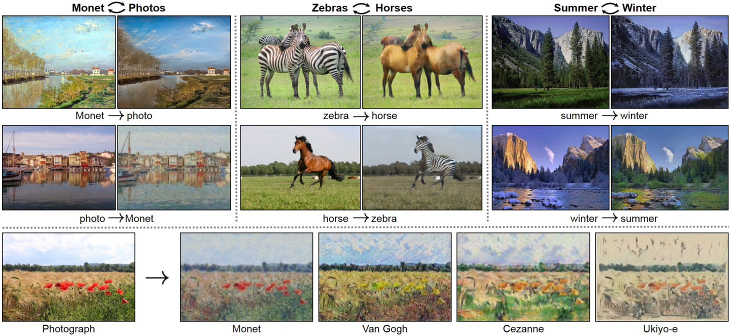
- Image style transfer
- Generating photos of nonexistent objects, animals or people
- Music composition
- Poetry / text authorship

Image Style Transfer



pix2pix

Image Style Transfer



CycleGAN

Photo Generation

Progressive Growing of GANs

MIT Nightmare

Questions