

Generative Adversarial Networks

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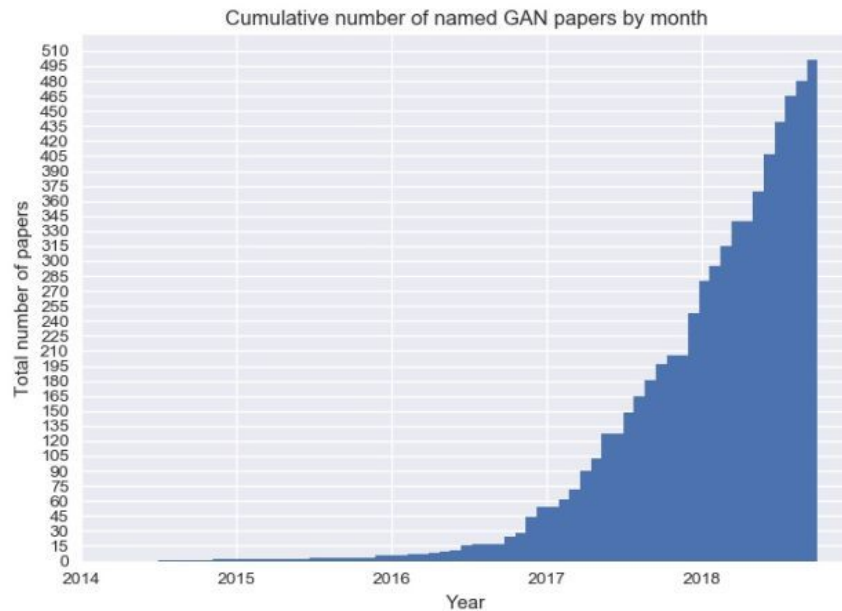
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Arsalan KHAWAJA, Mahmoud Badran.



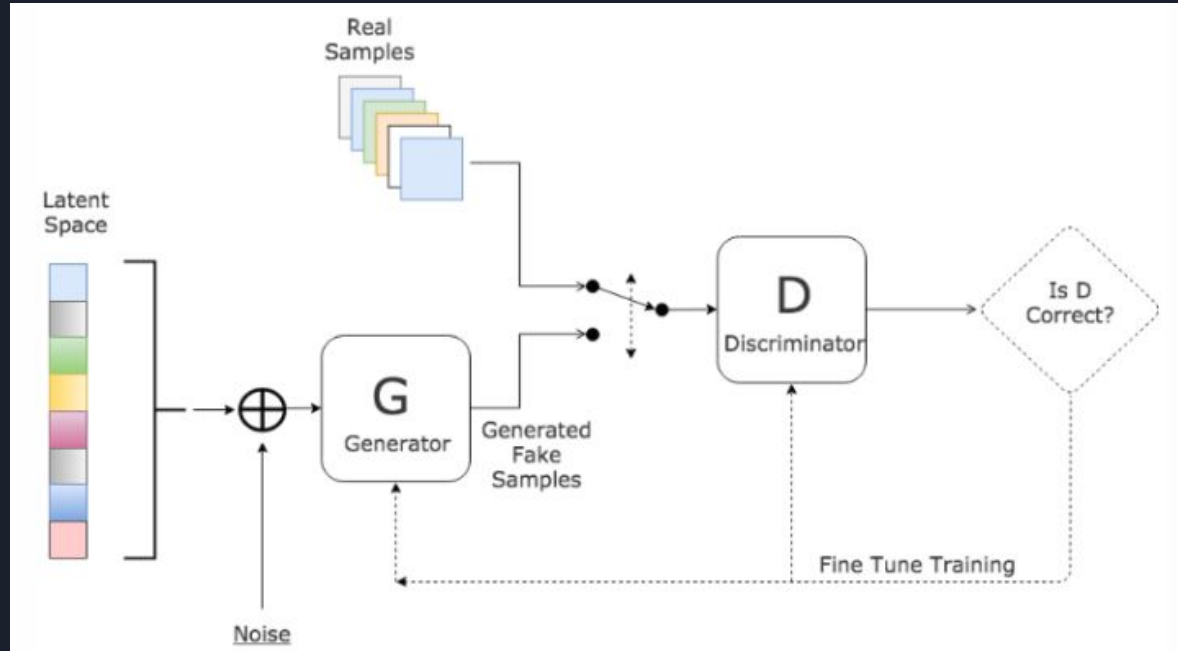
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Introduction

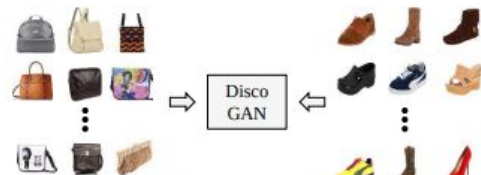


Introduction : basic principles



Introduction : types

- ❑ Deep Convolutional GANs (DCGANs)
- ❑ Conditional GANs (cGANs)
- ❑ StackGAN
- ❑ InfoGANs
- ❑ Wasserstein GANs(WGAN)
- ❑ Disco GANS
- ❑ etc...

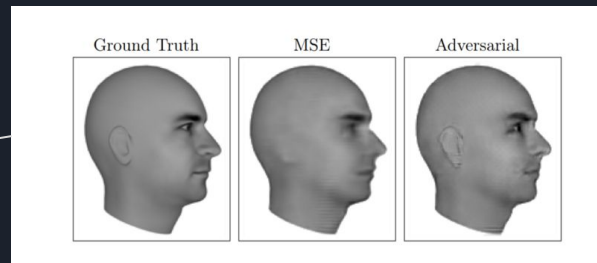


(a) Learning cross-domain relations **without any extra label**



Introduction : applications

➤ Predicting the next frame in a video :

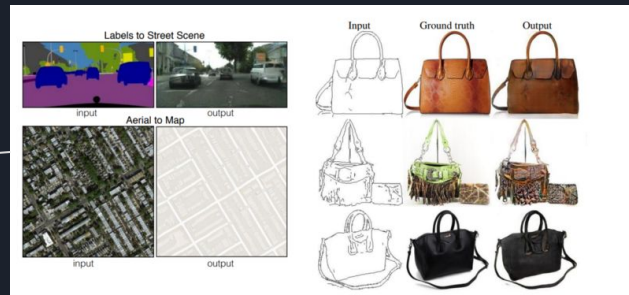


➤ Increasing Resolution of an image :



➤ Text-to-Image Generation

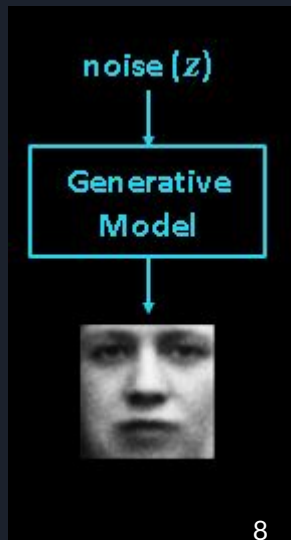
➤ Image to Image Translation :



Lets Explore GAN's

Generative Model

- How to make it generate different samples each time it is run?
 - input to model is noise
- Generative model as a neural network
 - computes $x=G(z|\theta)$
 - differentiable
 - does not have to be invertible
 - z typically has very high dimensionality (higher than x)



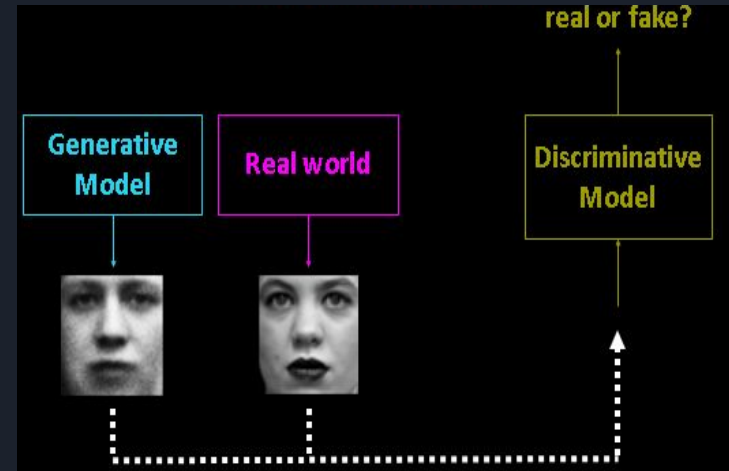
Discriminative Model

- Think of it as a critic
 - A good critic can tell real from fake
- Discriminative model is a neural net
- It is differentiable
- It computes $D(x)$, with value 1 if real, 0 if fake



Training Methodology: Basic Concept

- G tries to fool D
- D tries not to be fooled
- Models are trained simultaneously
- As G gets better, D has a more challenging task
- As D gets better, G has a more challenging task
- Ultimately, we don't care about the D
- Its role is to force G to work harder





Loss Function

- GAN can have **two** loss functions: one for generator training and one for discriminator training.
- In the paper that introduced GANs, the generator tries to minimize the function while the discriminator tries to maximize it, that's why the loss function is called **Minimax**



Loss Function for Discriminator

- Loss function for D
 - maximize the likelihood that model says 'real' to samples from the world and 'fake' to generated samples

$$\mathcal{L}_D = -\frac{1}{2}\mathbb{E}_{x \sim \text{world}} \ln D(x) - \frac{1}{2}\mathbb{E}_z \ln (1 - D(G(z)))$$



Loss Function for Generator

- What should the loss function be for G?
- $\mathcal{L}_G = -\mathcal{L}_D$
- But because first term doesn't matter for G

$$\mathcal{L}_D = \frac{1}{2} \mathbb{E}_z \ln (1 - D(G(z)))$$



Training

Because a GAN contains two separately trained networks, its training algorithm must address two complications:

- GANs must juggle two different kinds of training (generator and discriminator).
- GAN convergence is hard to identify.



Alternating Training

GAN training proceeds in alternating periods:

- The discriminator trains for one or more epochs.
- The generator trains for one or more epochs.
- Repeat steps 1 and 2 to continue to train the generator and discriminator networks.

Demonstration / Implementation of GAN

G Architecture

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 6272)	633472
leaky_re_lu (LeakyReLU)	(None, 6272)	0
reshape (Reshape)	(None, 7, 7, 128)	0
conv2d_transpose (Conv2DTran	(None, 14, 14, 128)	262272
leaky_re_lu_1 (LeakyReLU)	(None, 14, 14, 128)	0
conv2d_transpose_1 (Conv2DTr	(None, 28, 28, 128)	262272
leaky_re_lu_2 (LeakyReLU)	(None, 28, 28, 128)	0
conv2d (Conv2D)	(None, 28, 28, 1)	6273

Total params: 1,164,289

Trainable params: 1,164,289

Non-trainable params: 0

D Architecture

Model: "sequential"

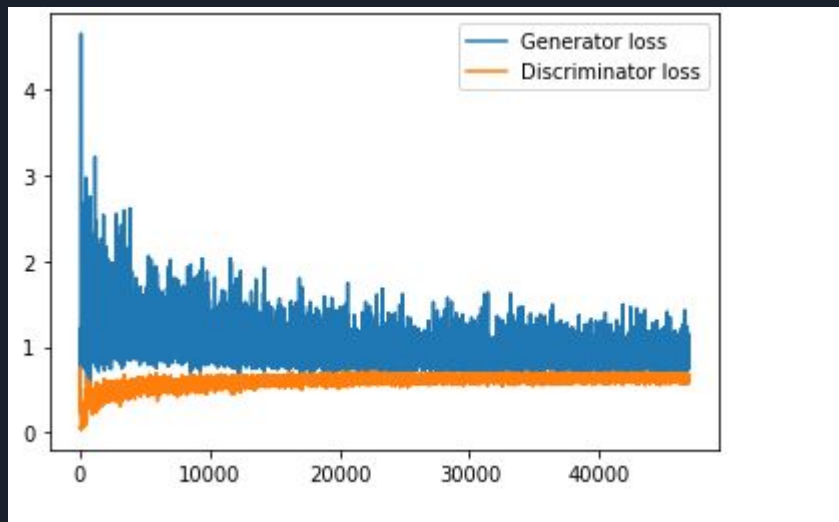
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 14, 14, 64)	640
leaky_re_lu (LeakyReLU)	(None, 14, 14, 64)	0
dropout (Dropout)	(None, 14, 14, 64)	0
conv2d_1 (Conv2D)	(None, 7, 7, 64)	36928
leaky_re_lu_1 (LeakyReLU)	(None, 7, 7, 64)	0
dropout_1 (Dropout)	(None, 7, 7, 64)	0
flatten (Flatten)	(None, 3136)	0
dense (Dense)	(None, 1)	3137

Total params: 40,705

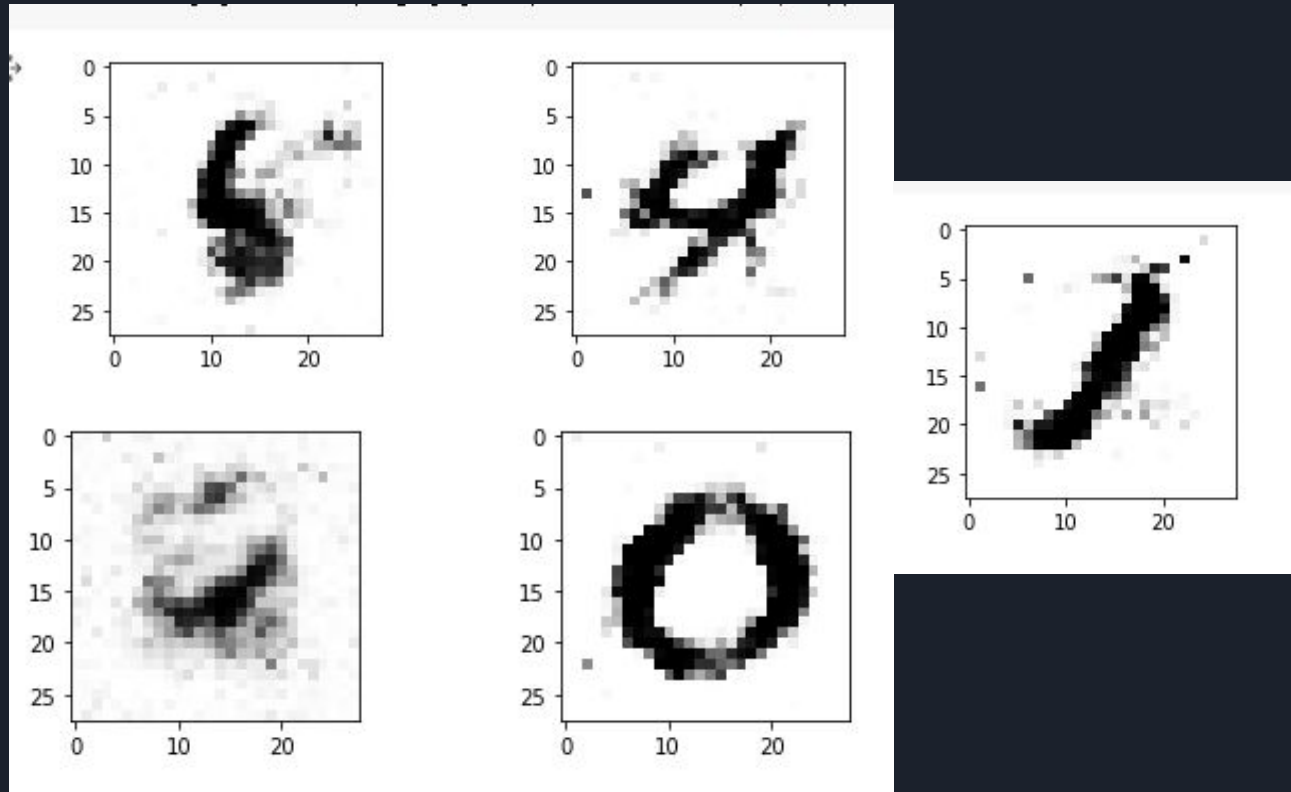
Trainable params: 40,705

Non-trainable params: 0

Loss



Generated images (MNIST)





Conclusion

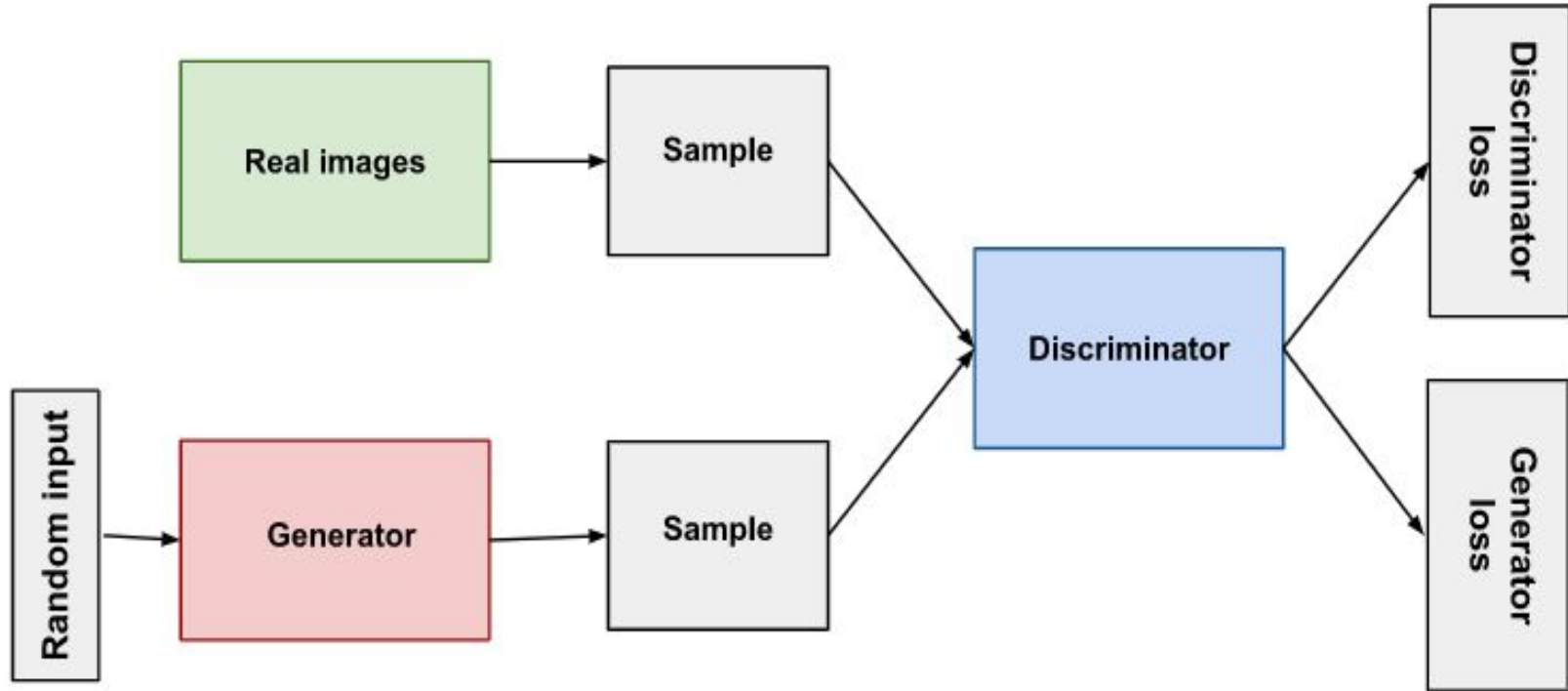
- ❑ Mode collapse: the generator produces limited varieties of samples,
- ❑ Diminished gradient: the discriminator gets too successful that the gradients vanish and the generator learns nothing,
- ❑ Non-convergence: the model parameters oscillate, destabilize and never converge,



Conclusion

- ❑ Unbalance between the generator and discriminator causes overfitting.
- ❑ Highly sensitive to hyperparameters.

Executive Summary of GAN's



Thank you~