



**POLITECNICO**  
MILANO 1863

# Computational Modeling for Materials Engineering

Deep Learning Application in Materials Engineering

## HANDS-ON SESSION 4: Generative Models

José Pablo Quesada Molina

[josepablo.quesada@polimi.it](mailto:josepablo.quesada@polimi.it)

# Agenda for today's class:

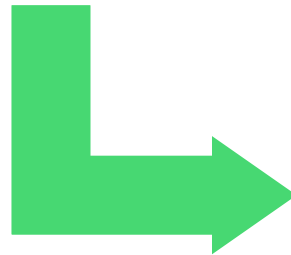
1

Brief overview of  
Generative Models



2

Code implementation  
example.



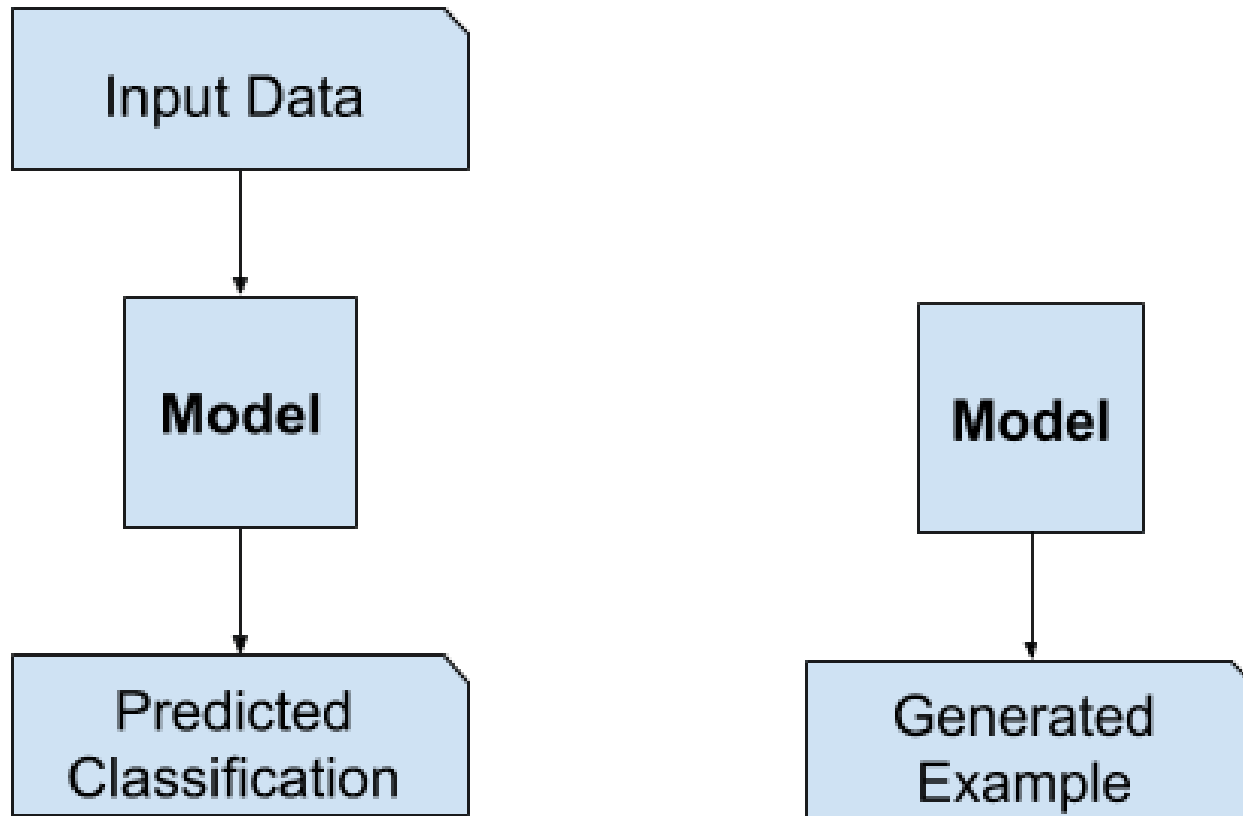
3

Review of the  
Project.

# Brief overview of Generative Models

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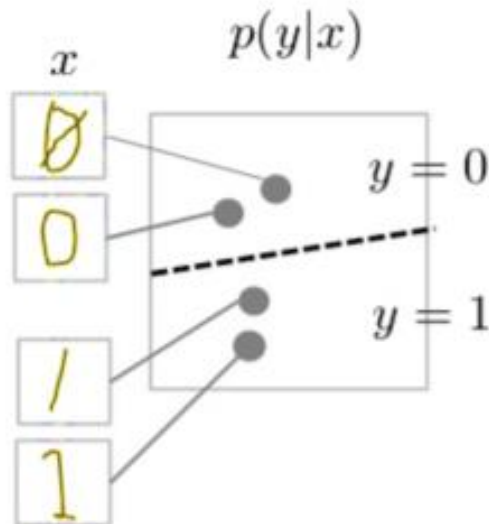
# Discriminative vs. Generative Modeling



<https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/>

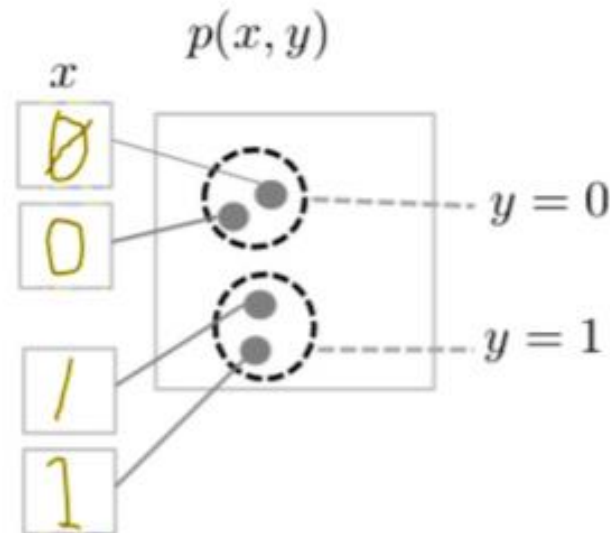
# Background: What is a Generative Model?

- Discriminative Model



- **Discriminative** models learn the boundary between classes

- Generative Model



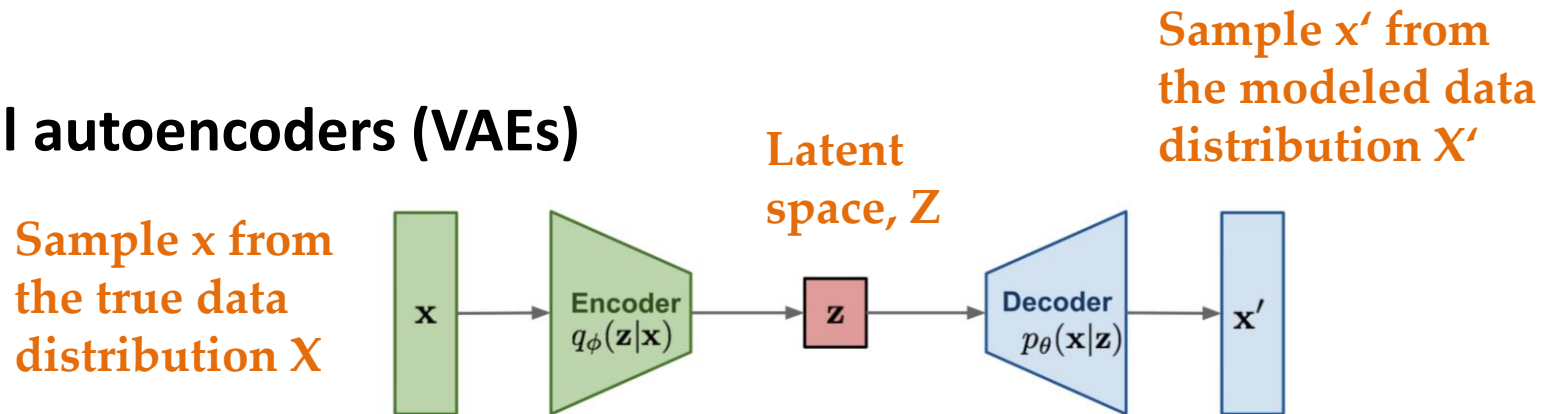
- **Generative** models model the distribution of individual classes

<https://developers.google.com/machine-learning/gan/generative>

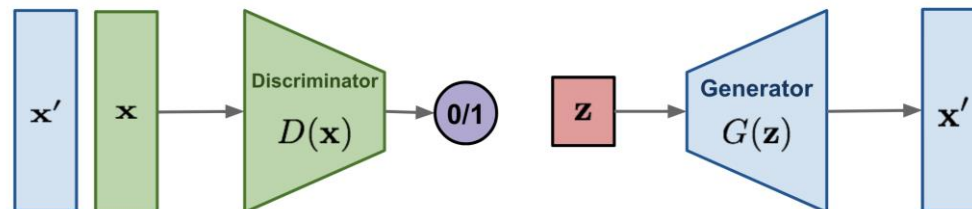
# Approaches to generative models

With the rise of deep learning, a new family of methods, called deep generative models (DGMs) is formed through the combination of **generative models** and **deep neural networks**. Popular DGMs include:

## Variational autoencoders (VAEs)



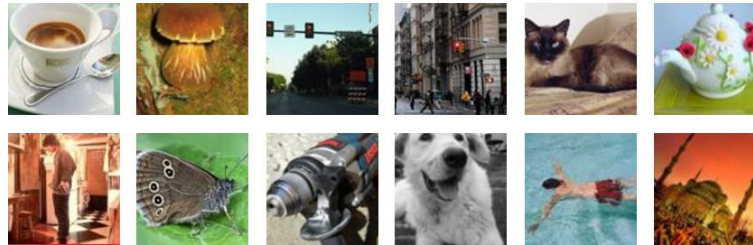
## Generative adversarial networks (GANs)



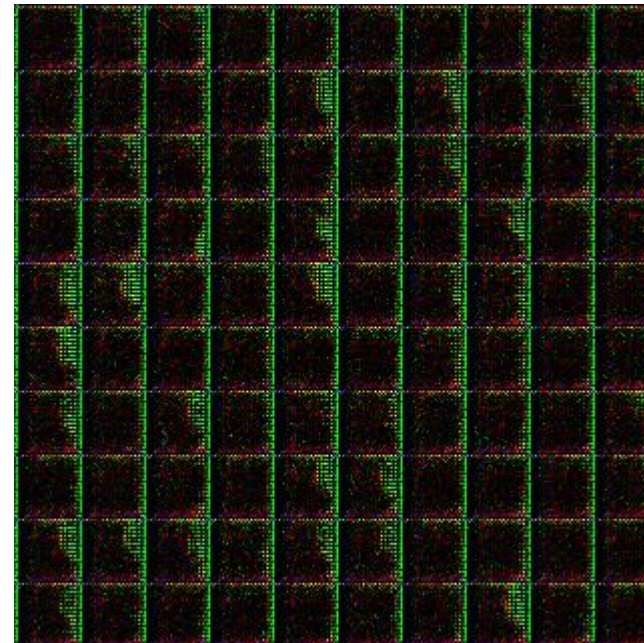


# DGMs: VAEs and GANs

ImageNet dataset



VAE learning to generate images

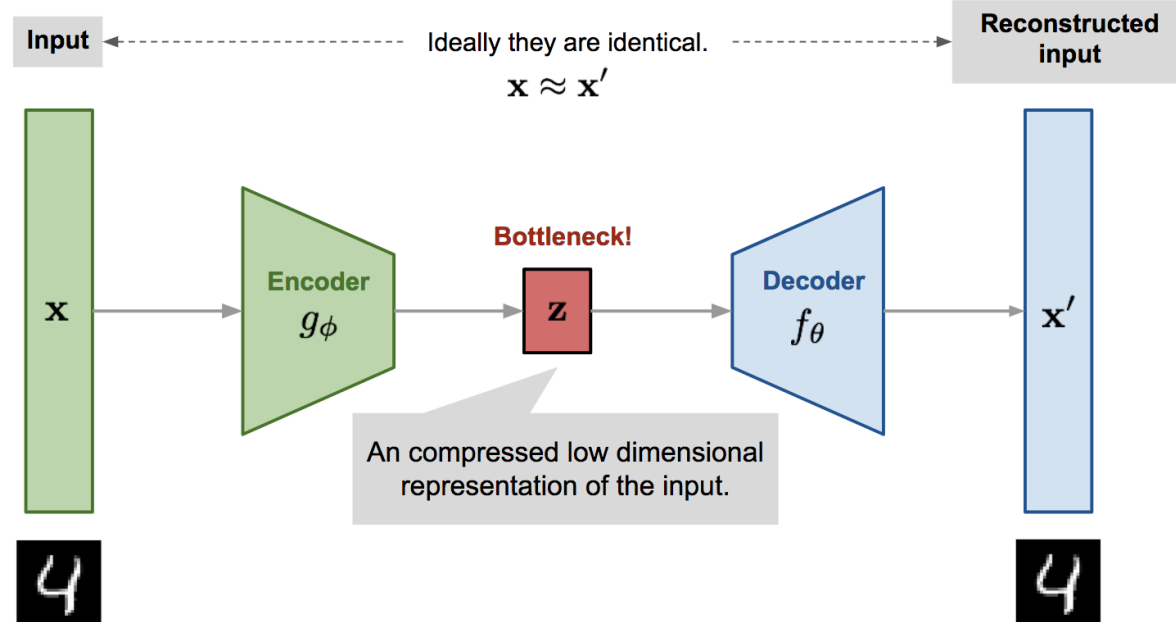


GAN learning to generate images

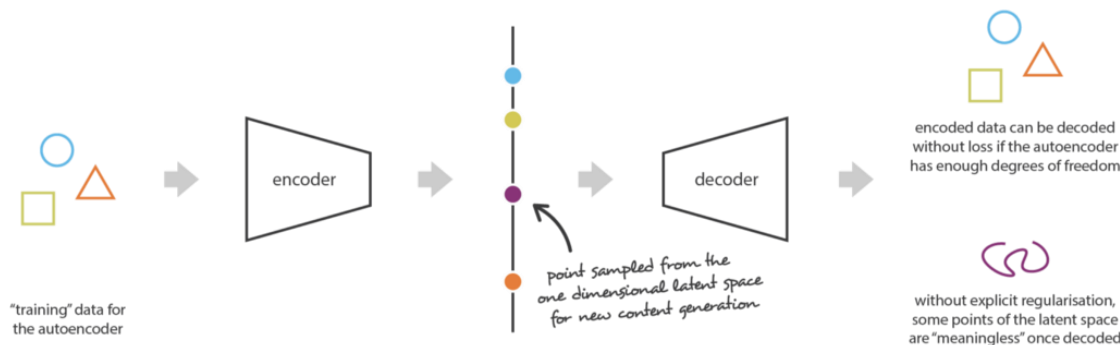
<https://openai.com/blog/generative-models/>

# Autoencoders and Variational Autoencoders

## Autoencoders



**Generative ?  
Irregular  
latent space !**

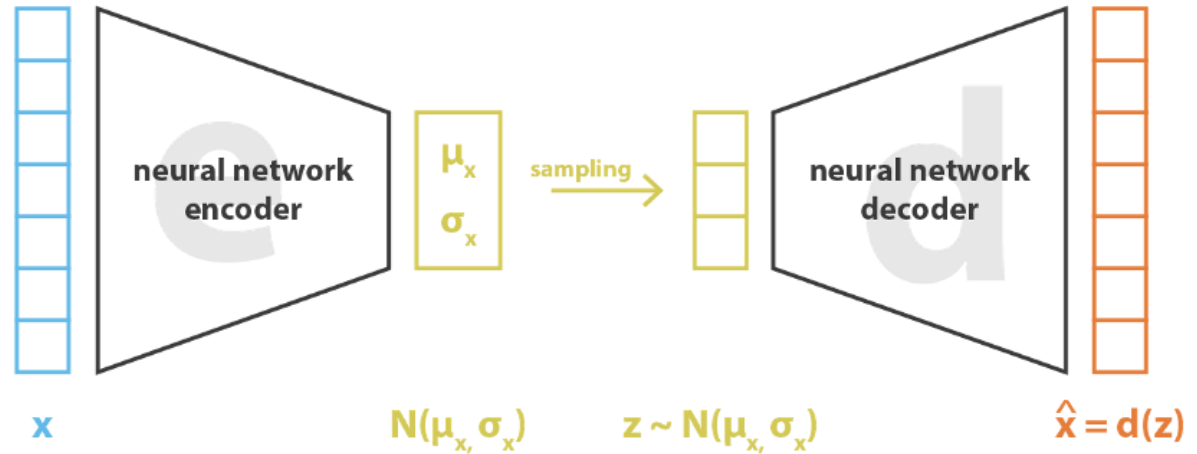


<https://lilianweng.github.io/posts/2018-08-12-vae/>  
<https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73>



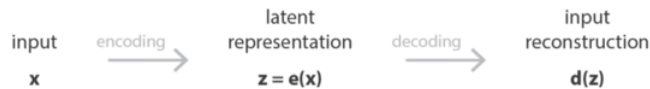
# Autoencoders and Variational Autoencoders

## Variational autoencoder



$$\text{loss} = ||x - \hat{x}||^2 + \text{KL}[N(\mu_x, \sigma_x), N(0, I)] = ||x - d(z)||^2 + \text{KL}[N(\mu_x, \sigma_x), N(0, I)]$$

simple  
autoencoders



variational  
autoencoders



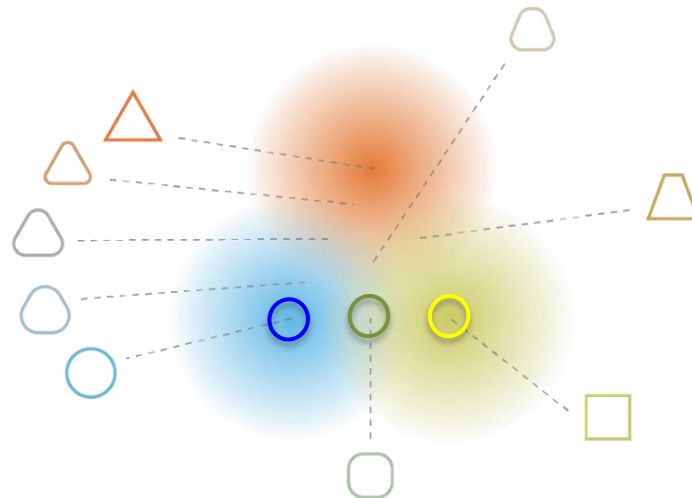
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# Autoencoders and Variational Autoencoders

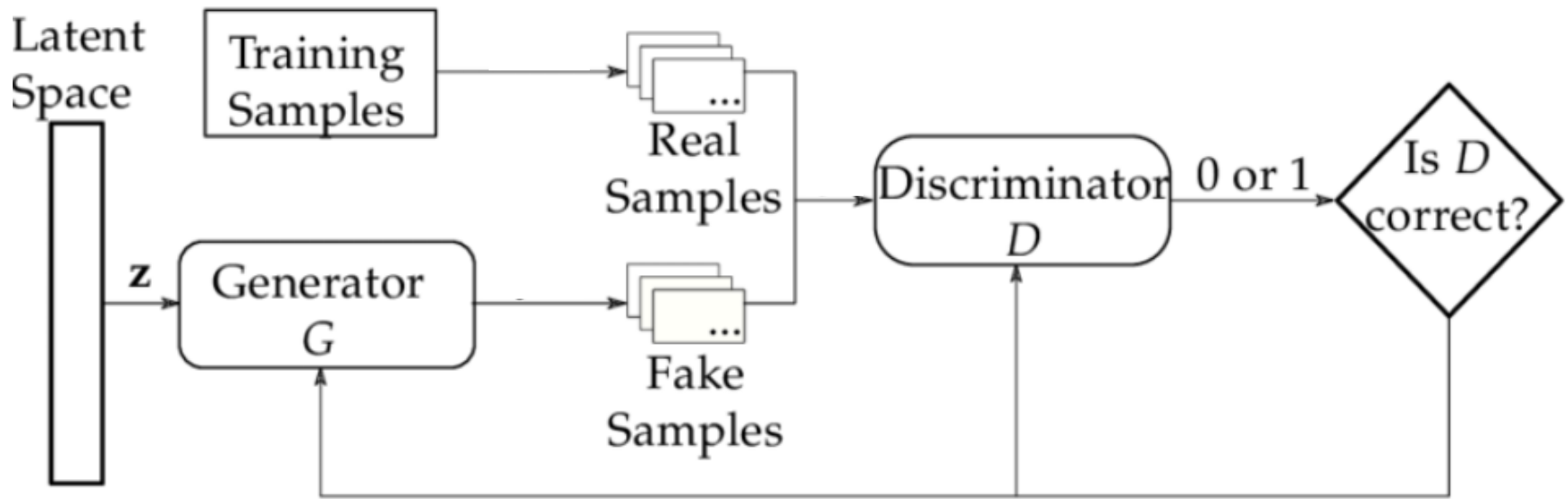


**Generative ?  
Regular  
latent space !**



<https://lilianweng.github.io/posts/2018-08-12-vae/>  
<https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73>

# Generative Adversarial Network (GAN)



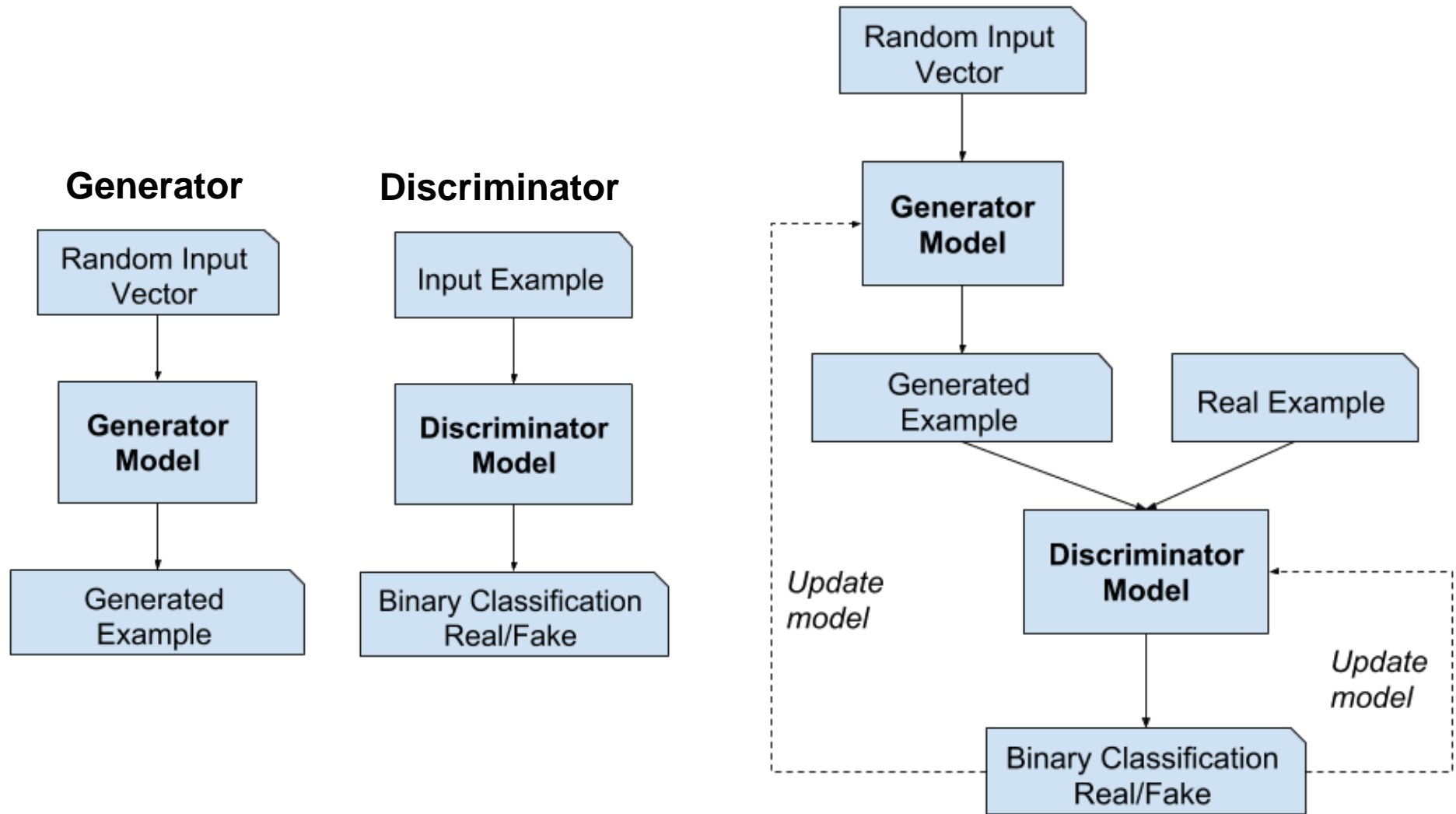
$$\min_G \max_D L(D, G) = \underbrace{\mathbb{E}_{x \sim p_r(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]}_{\max}$$

$\uparrow$   $D: \text{real} \mid \text{real}$ 
 $\downarrow$   $D: \text{fake} \mid \text{real}$

# GAN Architecture

## Generator

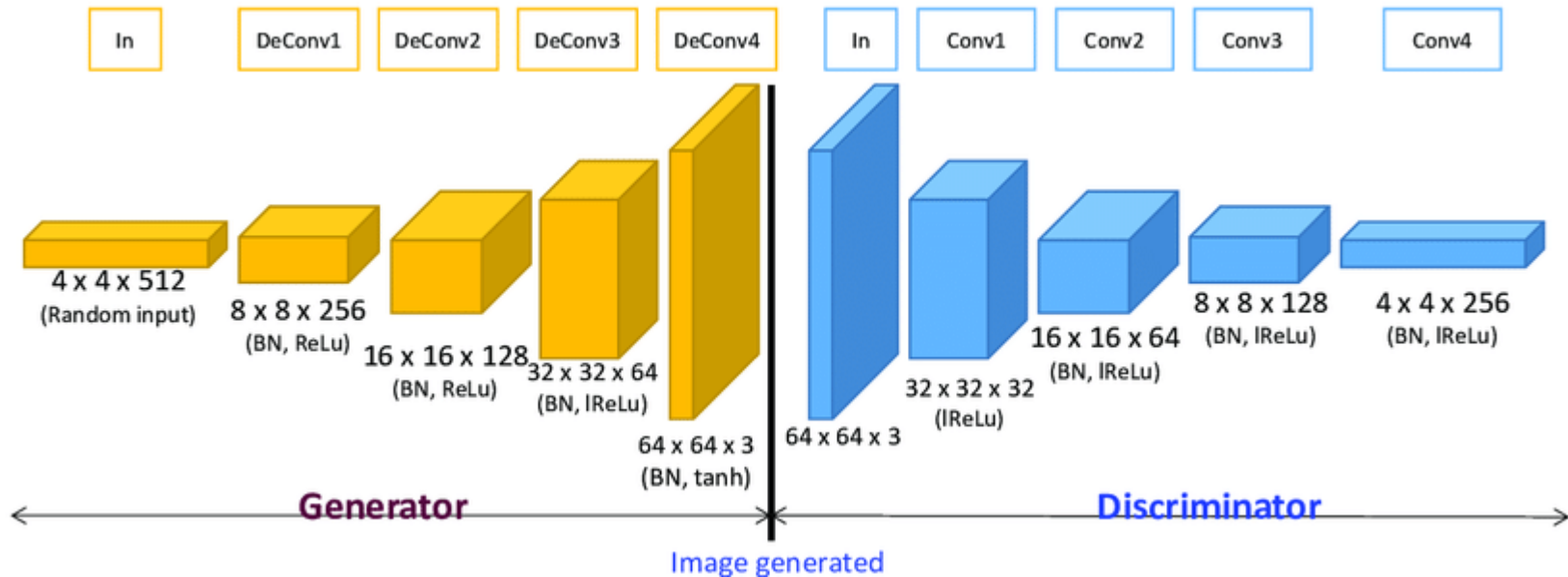
## Discriminator



<https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/>

# (some) Types of GAN

## 1. Deep Convolutional GAN (DCGAN)



Uses convolutional and convolutional-transpose (sometimes called Deconvolution) layers in the discriminator and generator, respectively

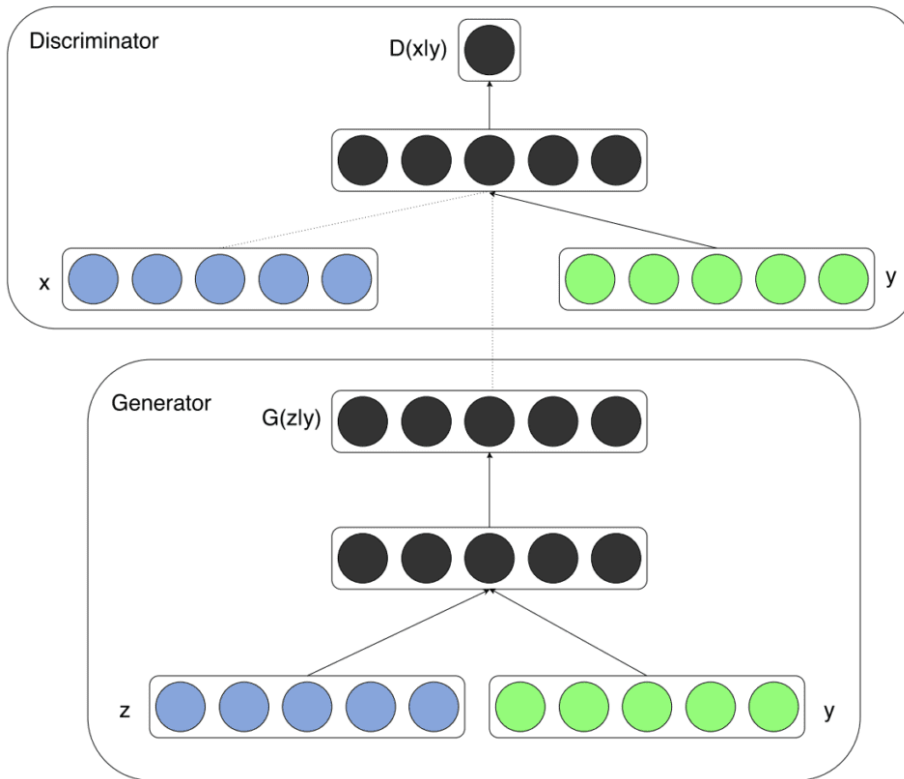
<https://machinelearningmastery.com/how-to-develop-a-conditional-generative-adversarial-network-from-scratch/>



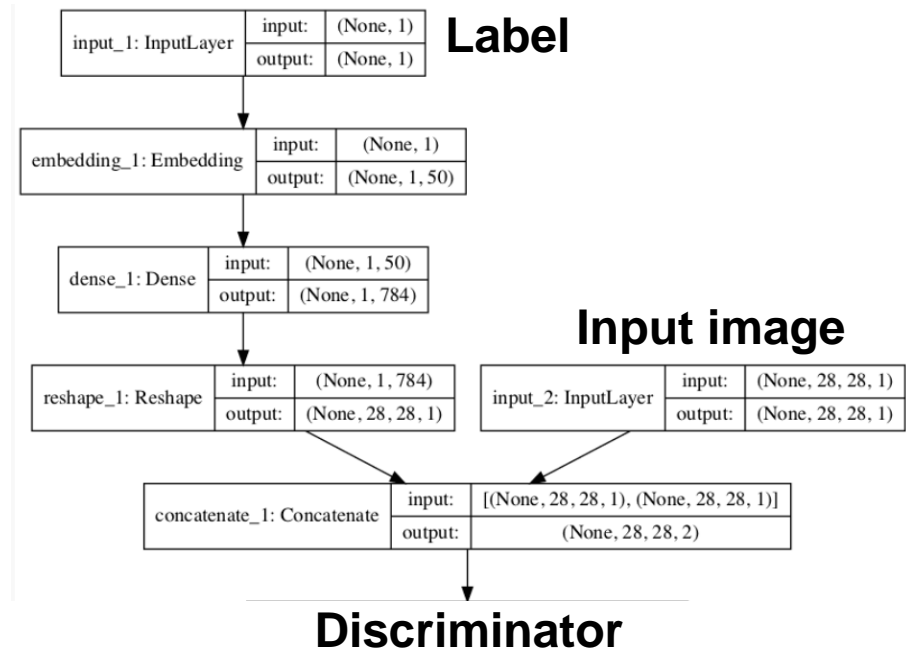
# (some) Types of GAN

## 2. Conditional Deep Convolutional GAN (cDCGAN)

Both the generator and discriminator are **conditioned** on some extra information i.e. labels.



Example to encode and incorporate the class labels into the discriminator input



<https://machinelearningmastery.com/how-to-develop-a-conditional-generative-adversarial-network-from-scratch/>

# (some) Types of GAN

## Deep Convolutional GAN (DCGAN)



## Conditional Deep Convolutional GAN (cDCGAN)

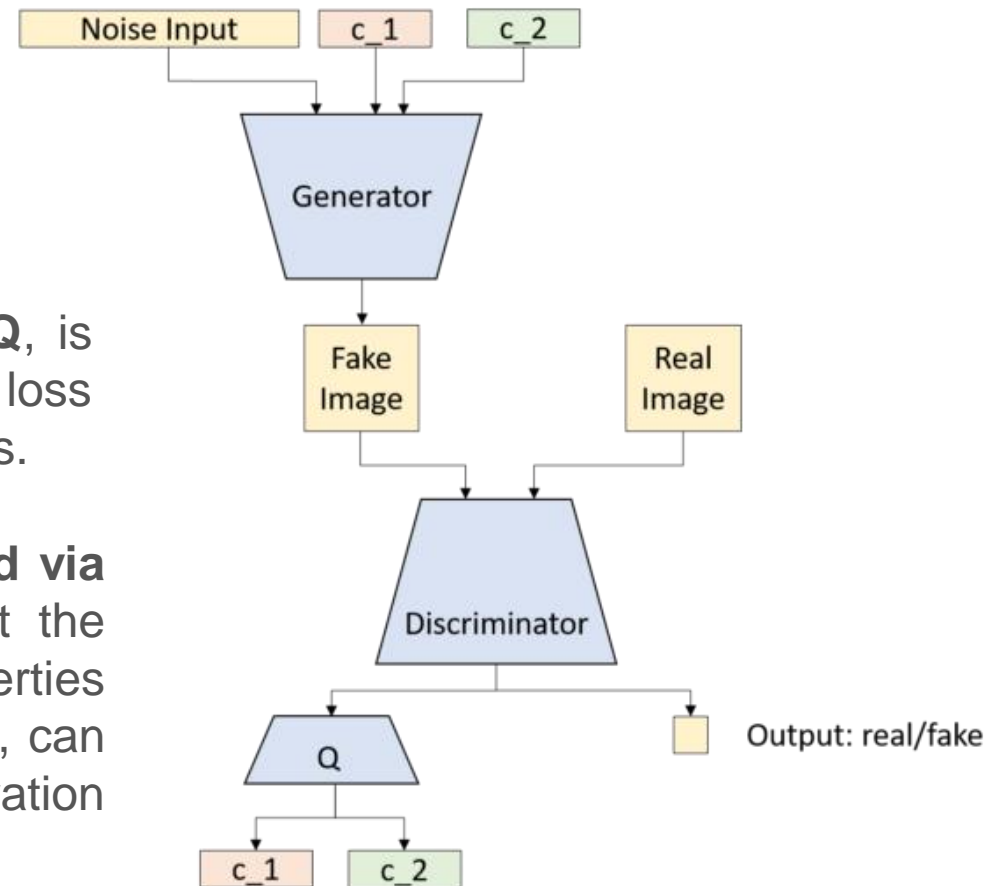


<https://machinelearningmastery.com/how-to-develop-a-conditional-generative-adversarial-network-from-scratch/>

# (some) Types of GAN

## 3. Information Maximizing GAN (InfoGAN)

- **Control variables** (categorical and continuous) are added as input to the generator, along with the point in latent space
- **An auxiliary network denoted as Q**, is trained via Mutual Information loss function to predict the control variables.
- **The generator model is regularized via mutual information loss** such that the control variables capture salient properties of the generated images and, in turn, can be used to control the image generation process



<https://towardsdatascience.com/build-infogan-from-scratch-f20ee85cba03>

<https://machinelearningmastery.com/how-to-develop-an-information-maximizing-generative-adversarial-network-infogan-in-keras/>

# Code implementation example



<https://github.com/josepabloquesadamolina/CMME2022/tree/main/Session%204>

# Review of the Project.



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<https://github.com/josepabloquesadamolina/CMME2022/tree/main/Project>