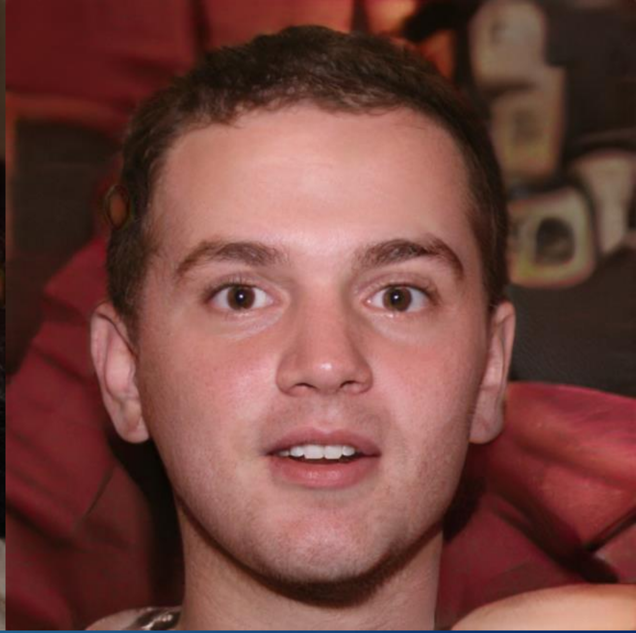
- I am not a neural network expert
- This is only intended for learning purpose (not refined nor applicable)
- The dataset used are conditionned
- We are going to see a limited set of neural network, so called CNN
- We don’t have much time for this presentation

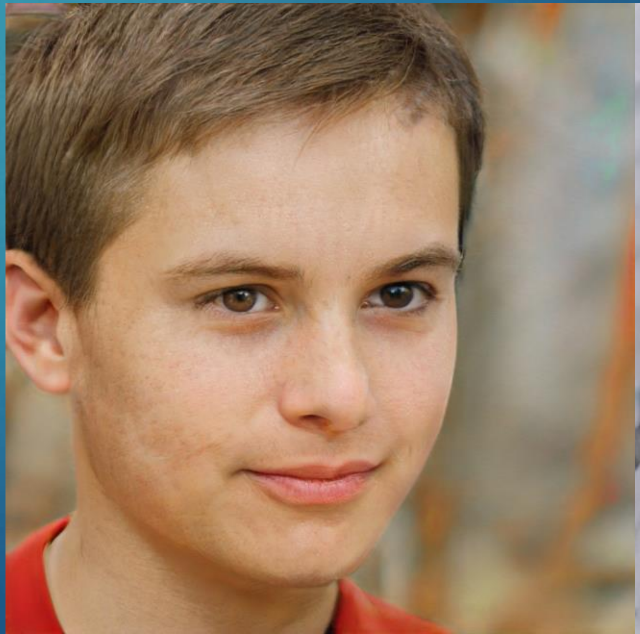
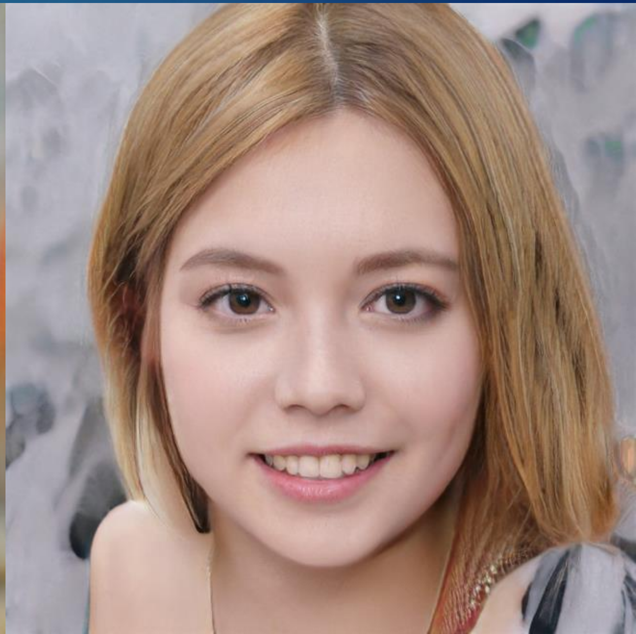
HTTPS://GITHUB.COM/HUBE12/NEURALNETWORK103

GAN

GENERATIVE ADVERSARIAL NETWORK

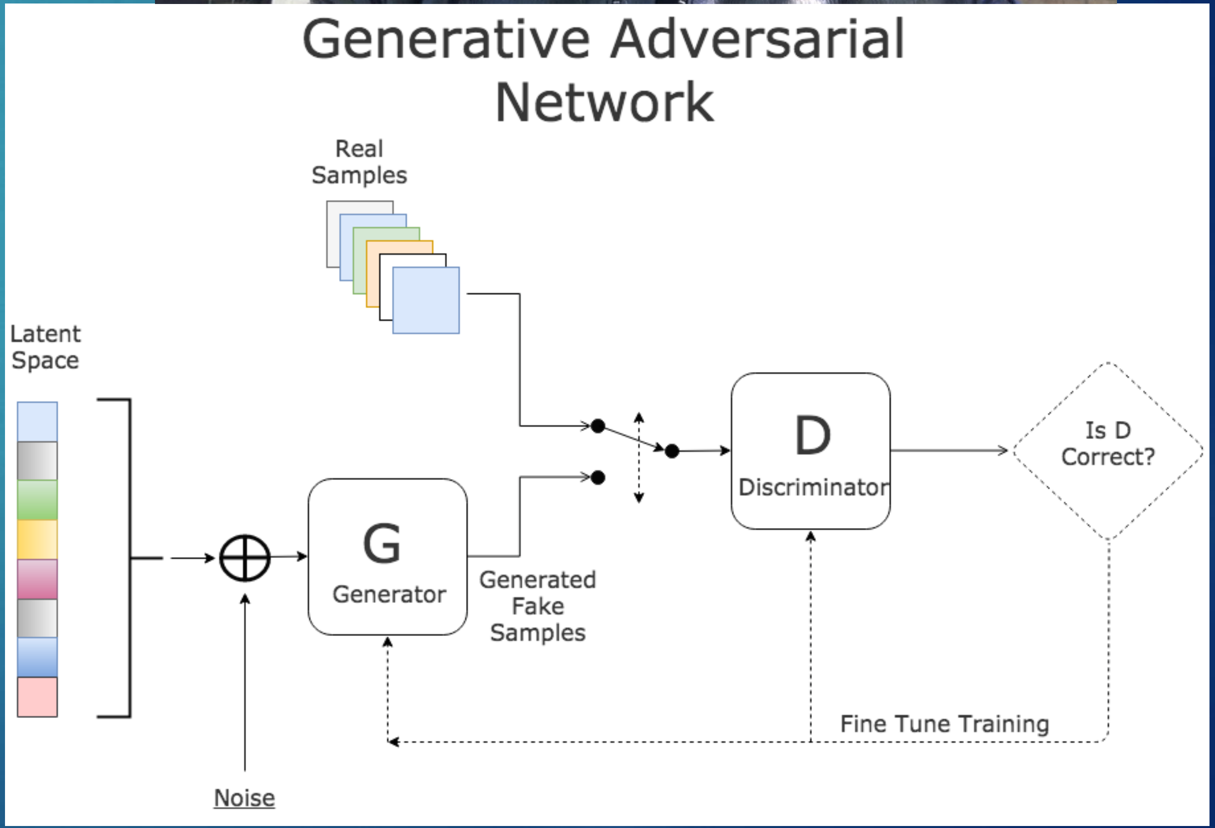



https://thispersondoesnotexist.com/

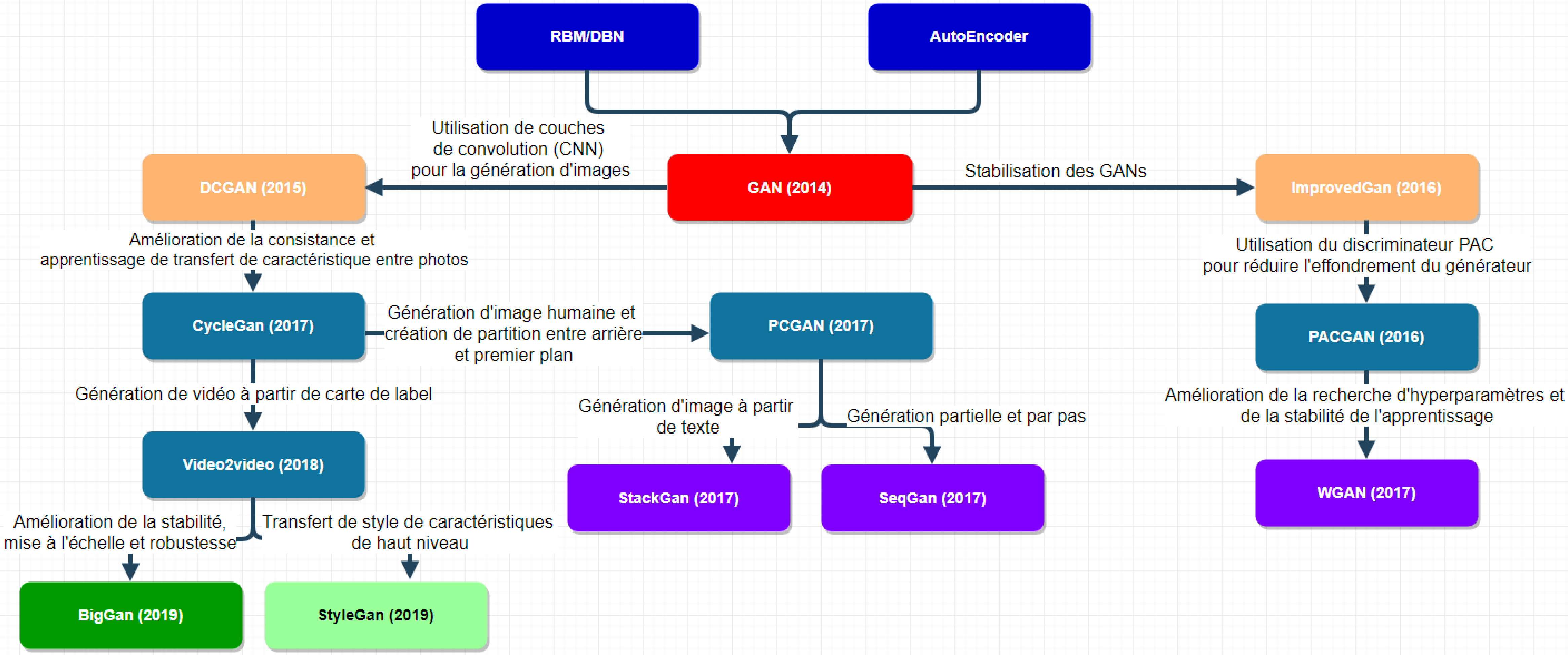



Qu’est ce qu’un GAN?

- En intelligence artificielle, les réseaux adverses génératifs (en anglais generative adversarial networks ou GANs) sont une classe d'algorithmes d'apprentissage non-supervisé. Ces algorithmes ont été introduits par Ian Goodfellow et al. 2014. Ils permettent de générer des images (et bien d’autres choses) avec un fort degré de réalisme.
- Un GAN est un modèle génératif où deux réseaux sont placés en compétition dans un scénario de théorie des jeux. Le premier réseau est le générateur, il génère un échantillon (ex. une image), tandis que son adversaire, le discriminateur essaie de détecter si un échantillon est réel ou bien s'il est le résultat du générateur. L'apprentissage peut être modélisé comme un jeu à somme nulle. (Nash Equilibrium)



Un bref historique

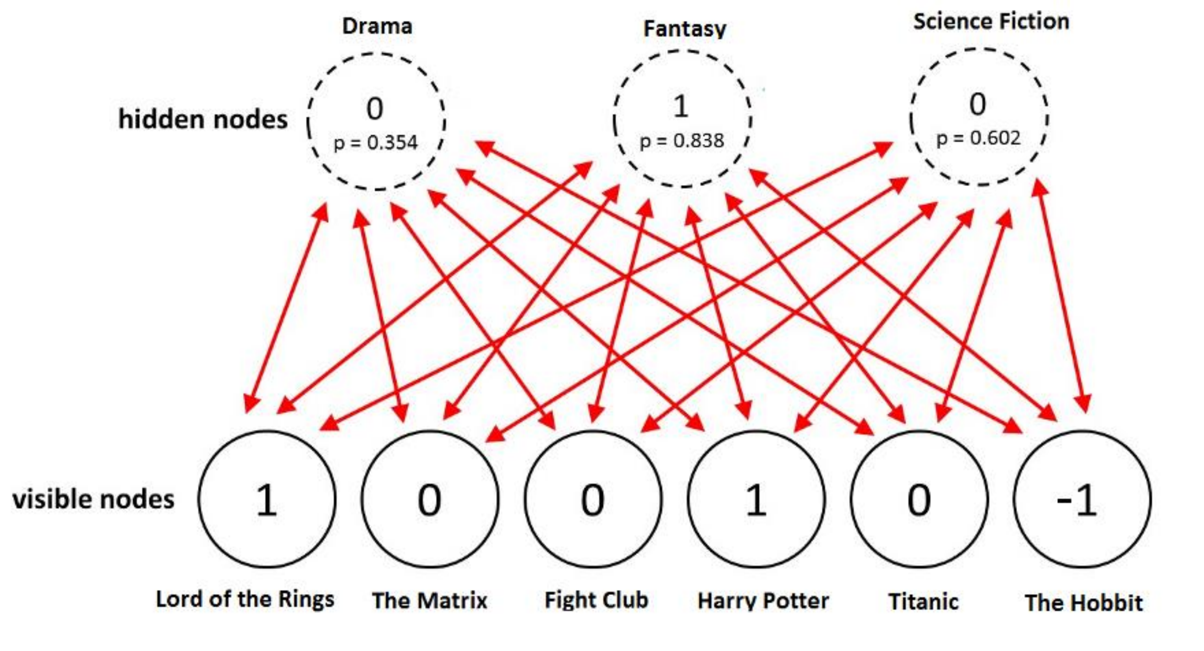


RBM:
Restricted Boltzmann Machine

$$E = -\left(\sum_{i,j} w_{ij}\, x_i\, h_j + \sum_i b_i\, x_i + \sum_j c_j h_j\right)$$

$$\frac{\partial\left[-\log(p(x^{(t)})\right]}{\partial\theta} = \mathbb{E}_h\left[\frac{\partial E(x^{(t)},h)}{\partial\theta}|x^{(t)}\right] - \mathbb{E}_{x,y}\left[\frac{\partial E(x,h)}{\partial\theta}\right]$$

$$\mathbb{E}_h\left[\frac{\partial E(x^{(t)},h)}{\partial W_{ij}}|x^{(t)}\right] = -h(x^{(t)}) * {x^{(t)}}^{\mathsf{T}}$$



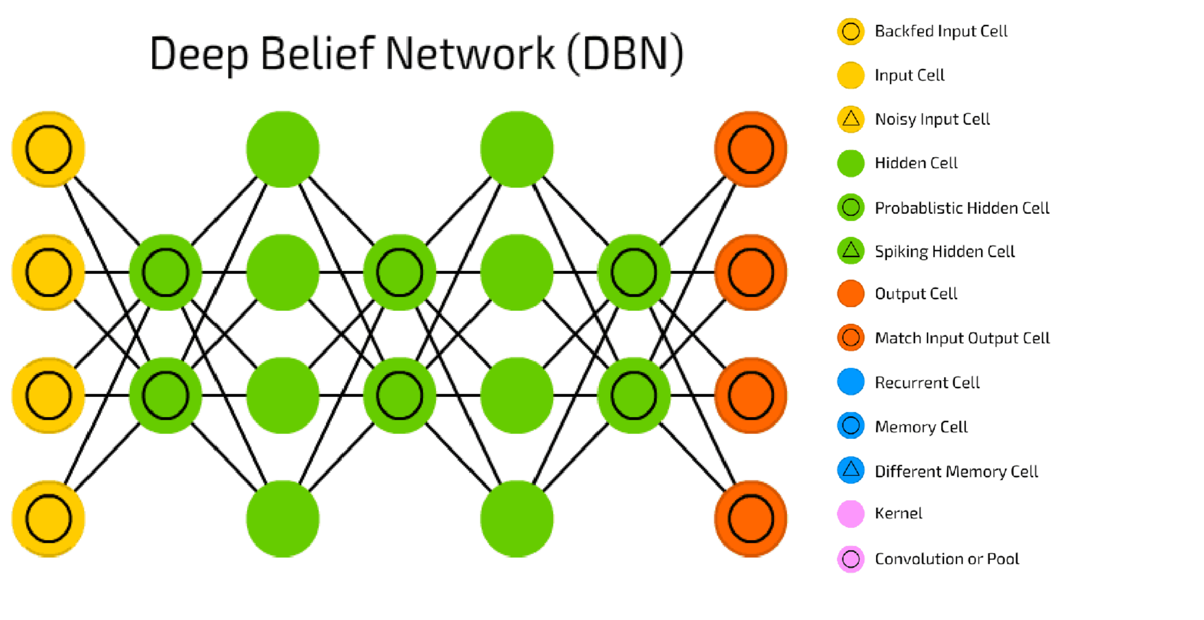
Elle est couramment utilisée pour avoir une estimation de la distribution probabiliste d'un jeu de données

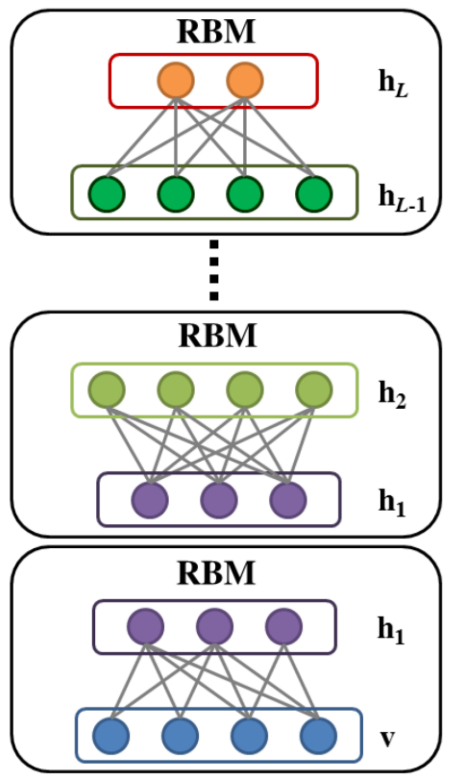
$$P(x_i, h_j) = \exp(-E(x_i, h_j))/Z$$

colab https://colab.research.google.com/github/hube12/NeuralNetwork103/blob/master/Notebook/RBM.ipynb

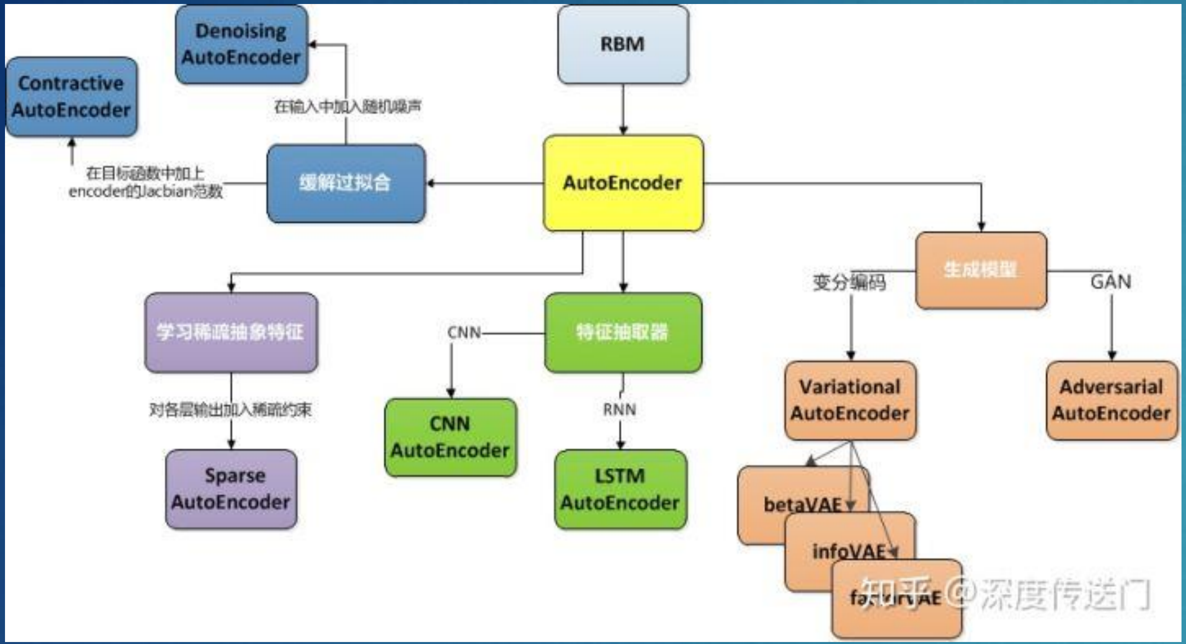
DBN:
Deep Belief Network

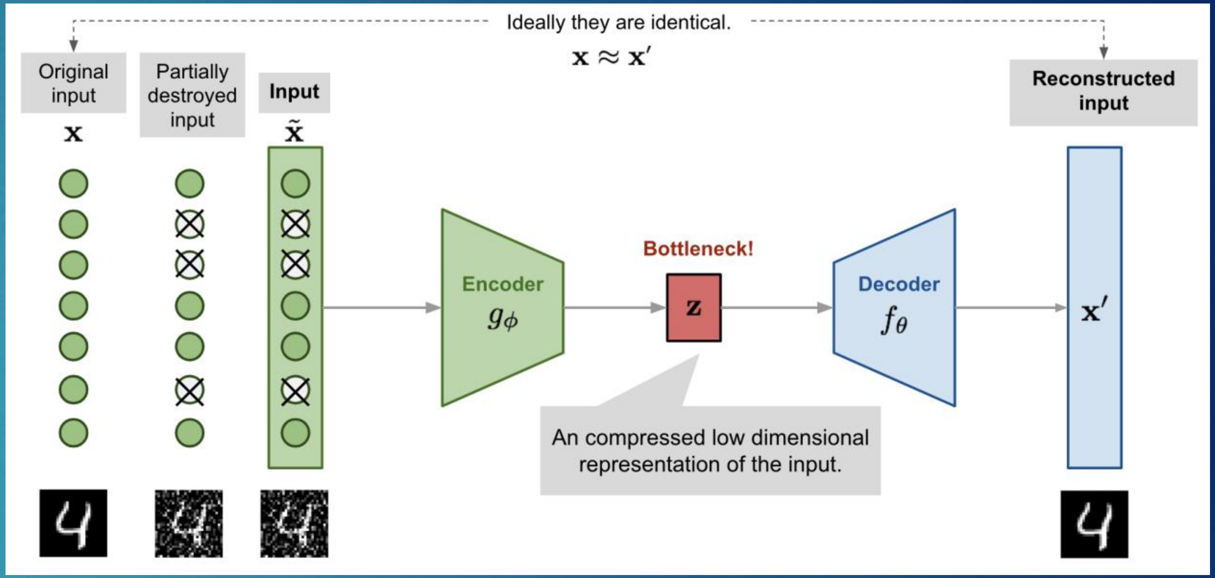
- Ce reseau est composé de plusieurs couches caches (ici de RBM) avec des connections entre couches mais pas entre les neurons de chaque couche, cela permet de reconstruire l'entrée ou alors de classifier





AutoEncoder



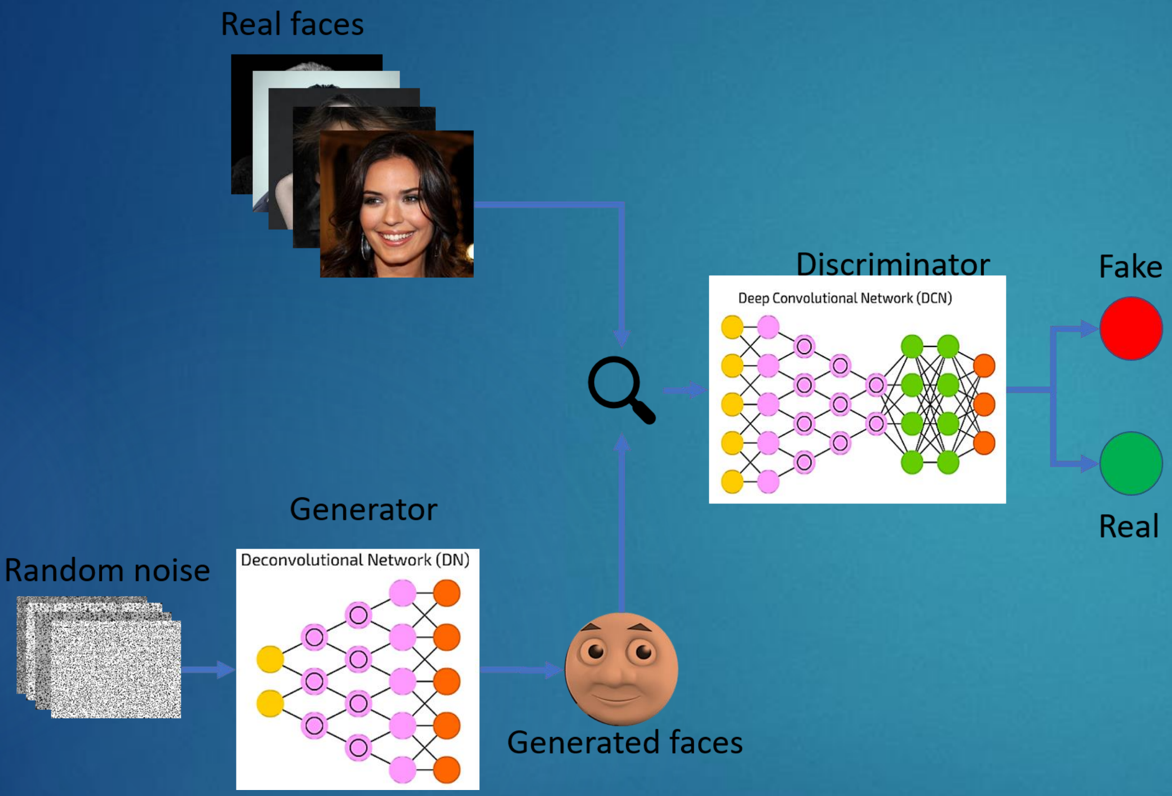


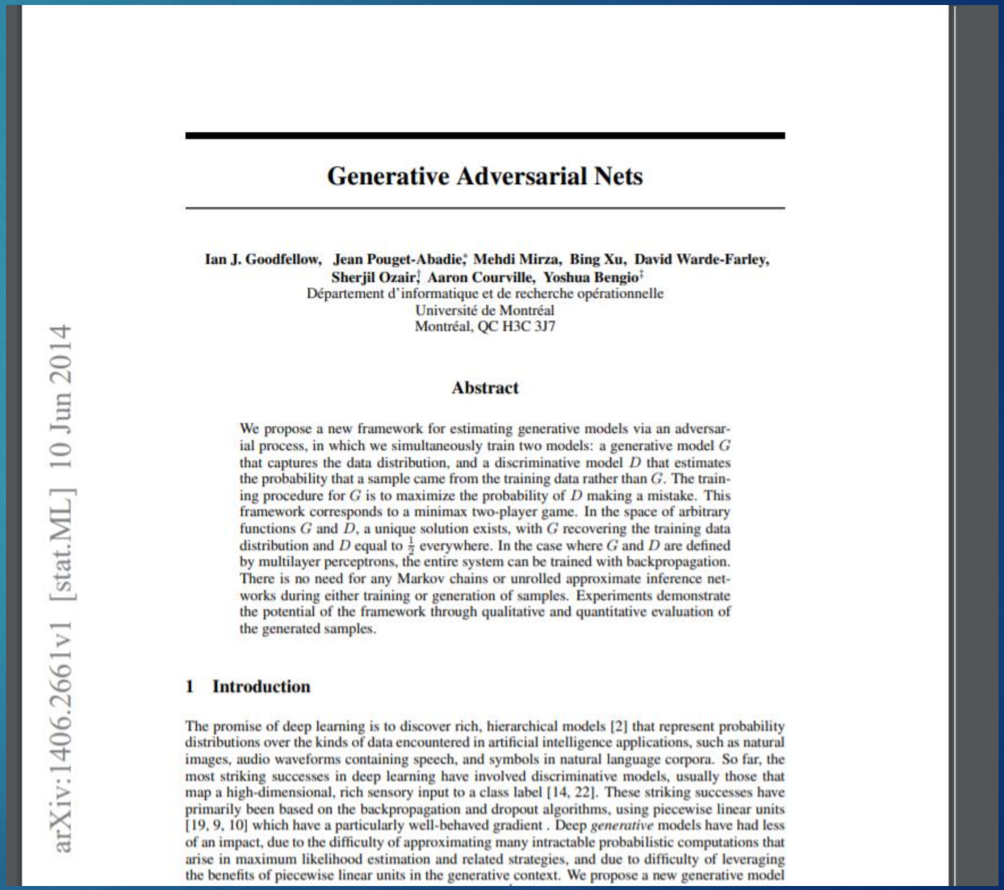
Voir hube12/NeuralNetwork102 (prochain week-end)

GAN (2014)

https://github.com/T-Almeida/GAN-study

https://arxiv.org/abs/1406.2661





arXiv:1406.2661v1 [stat.ML] 10 Jun 2014

Generative Adversarial Nets

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Abstract

We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to $\frac{1}{2}$ everywhere. In the case where G and D are defined by multilayer perceptrons, the entire system can be trained with backpropagation. There is no need for any Markov chains or unrolled approximate inference networks during either training or generation of samples. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated samples.

1 Introduction

The promise of deep learning is to discover rich, hierarchical models [2] that represent probability distributions over the kinds of data encountered in artificial intelligence applications, such as natural images, audio waveforms containing speech, and symbols in natural language corpora. So far, the most striking successes in deep learning have involved discriminative models, usually those that map a high-dimensional, rich sensory input to a class label [14, 22]. These striking successes have primarily been based on the backpropagation and dropout algorithms, using piecewise linear units [19, 9, 10] which have a particularly well-behaved gradient . Deep *generative* models have had less of an impact, due to the difficulty of approximating many intractable probabilistic computations that arise in maximum likelihood estimation and related strategies, and due to difficulty of leveraging the benefits of piecewise linear units in the generative context. We propose a new generative model

S’amuser avec StyleGan

https://github.com/hube12/NeuralNetwork103/blob/master/Notebook/StyleGAN.ipynb

colab