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THÈSE

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Auxiliary Tasks for the Conditioning of Generative Adversarial Networks

Tâches auxilliaires pour le conditionnement des réseaux antagonistes génératifs

Présentée et soutenue par

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Abstract

Résumé

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Acronyms

CGAN	Conditional Generative Adversarial Networks
CycleGAN	Cycle-Consistent Generative Adversarial Networks
ELBO	Evidence Lower Bound
FID	Fréchet Inception Distance
GAN	Generative Adversarial Networks
GMM	Gaussian Mixture Model
IS	Inception Score
JS	Jensen-Shannon (Divergence)
KL	Kullback-Leibler (Divergence)
MSE	Mean-Squared Error
ReLU	Rectified Linear Unit
VAE	Variational Auto-Encoder

Introduction

Context

Generic deep learning introduction, generic introduction to generative modeling (image generation, whichfaceisreal.com, etc...)

Introduction to applied conditional generative modeling : examples others than geology

Motivations

Geostatistical application : introduction and needs

- Tuneable (quality vs enforcement of the constraints)
- Pixel-precise
- Keeping diversity

Polarimetry application : introduction and needs

- Designing custom-made constraints for the problem
- Non-euclidian
- Compatible with domain transfer

Contributions

Outline

Chapter 1

Generative Adversarial Networks : Principles, strengths and limitations

Chapter abstract

In this chapter, we first propose an introduction to the problem of generative modeling and some solutions to tackle this problem. We then propose an overview of the Generative Adversarial Networks [1] framework, which is a recent method to train deep neural networks as generative models that is particularly adapted to the task of image generation. We will introduce some of its theoretical interpretations, as well as some of its variations and applications. We discuss the different limitations of this approach and expose a trilemma between the quality of the generated samples, their diversity and the conditioning of the model. We then discuss the recent advances that have been made to overcome some of these limitations and propose a taxonomy of these advances using the aforementioned trilemma. Finally, we discuss the evaluation of generative models and the difficulties of evaluating the intrinsic quality of a generated sample. We propose an overview of the different classical metrics and discuss their limitations.

Contents

1.1 Generative modeling

we will first propose an overview of generative modeling

Generative modeling with deep neural networks has been a challenging task due to the stochastic nature of sampling, which prevents the computation of gradient, thus preventing the training of a deep model with gradient descent. CR: TODO

1.1.1 Principles of generative modeling

Generative modeling is the task of learning the underlying distribution of a dataset in order to generate more samples from that distribution. In other words, it describes how data is generated in terms of a probabilistic model, a distribution from which the whole dataset could have been sampled with a high likelihood.

Indeed, whereas a discriminative model tries to fit a parametric model $p_\theta(y|x)$ to a conditional probability distribution $p(y|x)$ of labels $y \in \mathcal{Y}$ relatively to the data $x \sim p(x)$, a generative model aims to fit $p_\theta(x)$ to $p(x)$ the intrinsic distribution of the data and to provide a sampling mechanism on this distribution.

These two learning tasks, the discriminative (Equation. (1.1)) modeling and the generative modeling (Equation. (1.2)) can be formulated as a maximum log-likelihood estimation[**?**]

$$\theta^* = \arg\max_\theta \mathop{\mathbb{E}}_{x,y\sim p(y|x)} \log p_\theta(y|x) \qquad (1.1) \qquad\qquad \theta^* = \arg\max_\theta \mathop{\mathbb{E}}_{x\sim p(x)} \log p_\theta(x) \qquad (1.2)$$

An example of a simple generative model are Gaussian Mixture Models (GMM) . They consist in a sum of K Gaussian distributions $\mathcal{N}(\mu_k, \sigma_k^2), k \in 1..K$ which are all attributed a selection probability $p(z=k) = \pi_k$, so that $p(x|z=k) = \mathcal{N}(\mu_k, \sigma_k^2)$. The model is then formulated as

$$p_\theta(x) = \sum_z p(z)\, p_\theta(x|z) \ ,$$

with log-likelihood

$$\log \sum_{x\sim p(x)} p_\theta(x) = \sum_{x\sim p(x)} \log \sum_{k=1}^{k} \pi_k \mathcal{N}(x|\mu_k, \sigma_k^2) \ .$$

In the case of the GMMs, the Expectation-Maximization (EM) algorithm [2] can be used to find the parameters θ^* which, at convergence, maximizes the log-likelihood of the model. Once the model is trained, sampling a new data is done by picking a component k from the distribution $p(z)$, then drawing a sample from the Gaussian distribution $p(x|z=k) = \mathcal{N}(\mu_k^*, \sigma_k^{*2})$.

1.1.2 Latent variable models

Latent variable models and marginalization

For GMMs, sampling a new point consists in, once the Gaussian component has been selected, sampling a point on a normal distribution. This sampling can be done by using reparametrization: instead directly sampling $x \sim \mathcal{N}(\mu_k^*, \sigma_k^{*2})$, we can instead sample a latent variable $z \sim \mathcal{N}(0,1)$ and compute $x = G(z;\mu,\sigma) = \mu + z\sigma$. Such a model, that consists in a deterministic function $G : \mathcal{Z} \to \mathcal{X}$ with parameters θ applied to a random latent variable drawn from a fixed distribution $p(z)$ is a latent variable model.

Since more complex distributions does not necessarily provide a natural sampling mechanism, using a latent variable model allows to outsource the stochastic part of the sampling process from the learning process and only learn the function $G(z;\theta)$. More formally, instead of directly modeling $p(x)$, a latent variable model learns a deterministic mapping $p_G(x|z)$. From this mapping, the generative model can be obtain through marginalization

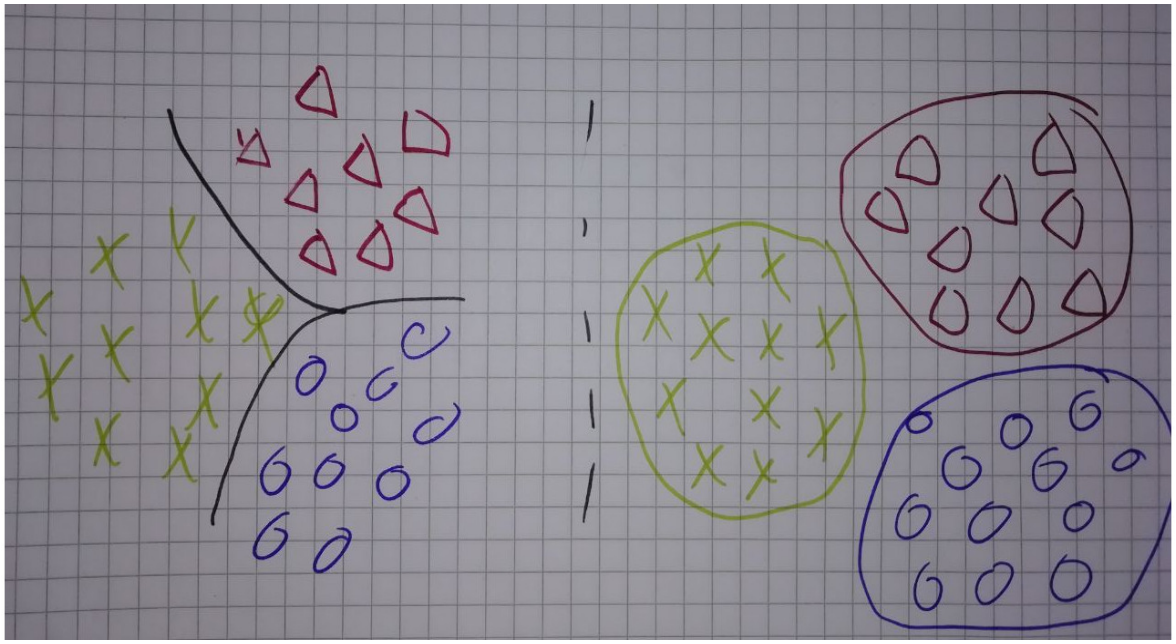


Figure 1.1: Left: Discriminative modeling, the model aims to find decision boundaries between classes. Right: Generative modeling, the model aims to learn the probability distribution of the data.

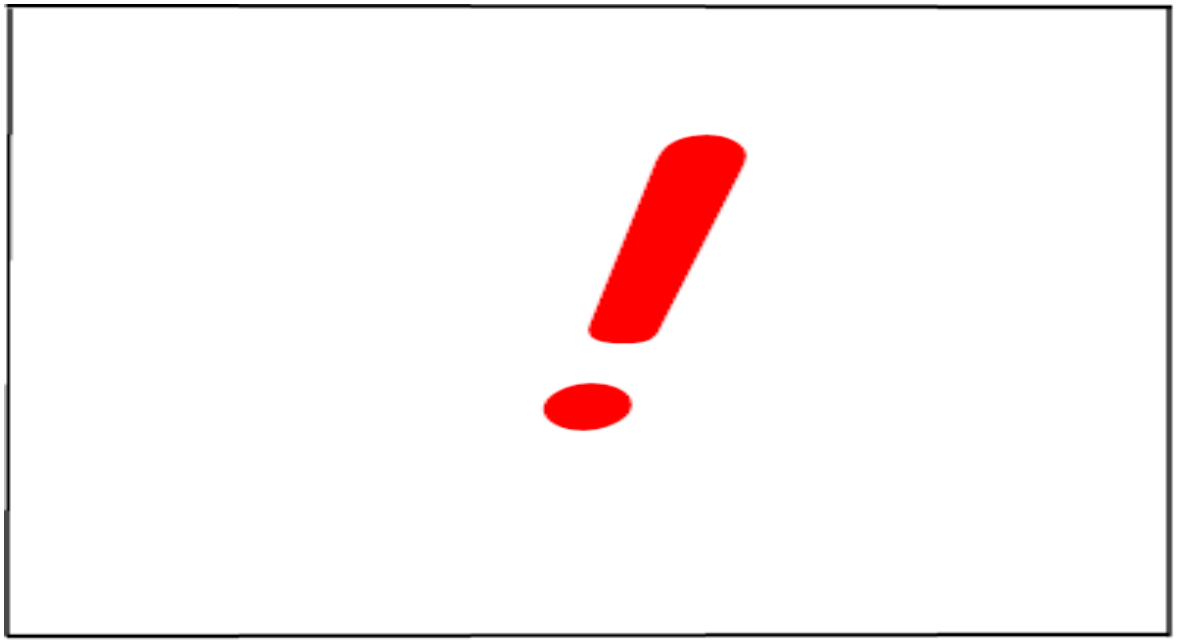


Figure 1.2: Latent variable model

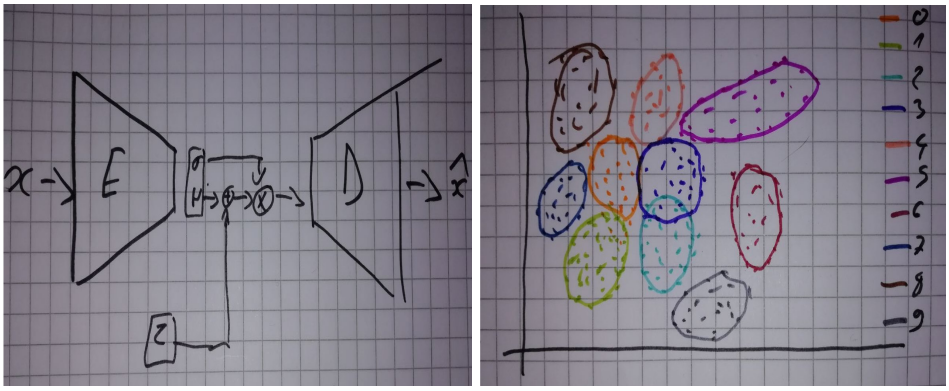


Figure 1.3: Left: the Variational auto-encoder global architecture. Right: the latent space of a VAE trained on the MNIST [4] dataset. We can observe a Gaussian component per class in the latent space,

$$p_{\mathrm{G}}(x) = \int_{\mathcal{Z}} p(z)\, p_{\mathrm{G}}(x|z)\, dz = \int_{\mathcal{Z}} p(z)\, p(x|\mathrm{G}(z;\theta))\, dz \ . \tag{1.3}$$

This marginalization allows for the use of an arbitrary flexible G. However, if G is non-linear, the actual evaluation of $p_{\mathrm{G}}(x)$ is very likely to be intractable due to the integral over $\mathcal{Z}$, which prevents the training of such a model as is.

While the marginal distribution $p_{\mathrm{G}}(x)$ cannot be explicitly computed for any function G, several solutions exist to overcome this problem and train deep generative models with latent variables anyways.

Variational auto-encoders

Variational Auto-Encoders (VAE)[3] are deep latent variable models which tackle the marginalization problem by approximating the integral using a variational approach. To this end, it both learns the distribution of the latent model $p_{\mathrm{G}}(x|z)$ as well as the distribution $q_{\mathrm{F}}(z|x)$. This is done with with two different neural networks, a decoder network $\mathrm{G} : \mathcal{Z} \to \mathcal{X}$ and an encoder network $\mathrm{F} : \mathcal{X} \to \mathcal{Z}$ and allows to compute the distribution $p(x)$ as

$$\log p_{\mathrm{G}}(x) - \mathrm{D}_{\mathrm{KL}}(q_{\mathrm{F}}(z|x)||p(z|x)) = \mathop{\mathbb{E}}_{z\sim q_{\mathrm{F}}(z|x)}\left[\log p_{\mathrm{G}}(x|z)\right] - \mathrm{D}_{\mathrm{KL}}(q_{\mathrm{F}}(zx)||p(z)) \ .$$

The KL terms evaluates the distance between the distribution $q_{\mathrm{F}}(z|x)$ learned by the encoder and real distribution $p(z|x)$, and since $p(z)$ is chosen Gaussian, this KL terms can be explicitly computed. The first term, is equivalent to the reconstruction error of an auto-encoder. Hence the model is trained by minimizing

$$\mathrm{L}_{\mathrm{VAE}}(\mathrm{F},\mathrm{G}) = \mathop{\mathbb{E}}_{z\sim q_{\mathrm{F}}(z|x)}\left[||x - \mathrm{G}(z)||_2^2\right] - \mathrm{D}_{\mathrm{KL}}(q_{\mathrm{F}}(z|x)||p(z))$$

However, since sampling $z \sim q_{\mathrm{F}}(z|x)$ is not differentiable, the VAE uses the so-called *reparametrization trick*, that is to have $\mathrm{F}(x)$ output the mean and the variance (μ_x, σ_x^2) of a normal distribution for a sample x, so that a $z' \sim \mathcal{N}(0,1)$ is sampled outside of the model and given as a parameter, thus allowing to compute $z = \mu_x + \sigma_x z'$, which is differentiable by considering z' a parameter.

Finally, generating a sample x with the trained model can be done by sampling a random vector $z \sim \mathcal{N}(0,1)$ and computing $x = \mathrm{G}(z)$.

Normalizing flows

Normalizing flow based techniques is a family of latent variable models that aim to tackle the marginalization problem by using the *change of variable formula*

$$p_{\mathrm{G}}(x) = p(z)\left|\det\left(\frac{\partial \mathrm{G}(z)}{\partial z^{\mathrm{T}}}\right)\right|^{-1} = p(\mathrm{G}^{-1}(x))\left|\det\left(\frac{\partial \mathrm{G}^{-1}(x)}{\partial x^{\mathrm{T}}}\right)\right| \ ,$$

with $z \sim p(z)$ a latent variable. This formulation has notable advantages such as explicitly allowing the computation of the exact inference. However, the model has to enforce some tough constraints: the input and output dimensions must be the same; G must be invertible; and computing the determinant of the Jacobian needs to be efficient and differentiable.

These constraints can be enforced through strong restrictions on the architecture of the model. By limiting the transformations to a set of invertible transformations with a tractable Jacobian determinant, the model remains invertible and the determinant of its Jacobian can be computed efficiently.

Real-valued non-volume preserving (RealNVP) normalizing flows [**?**] uses affine coupling transformations, which transforms a variable x into y by partitioning it into (x_1, x_2) and computing $y_1 = x_1; y_2 = \exp(s_\theta(x_1)) \odot x_2 + m_\theta(x_1)$, where s_θ and m_θ are arbitrary scaling and translation parametric functions. These transformations can be inverted as $x_1 = y_1; x_2 = \exp(-s_\theta(y_1)) \odot (x_2 - m_\theta(x_1))$ and their Jacobian is triangular, which implies that computing its determinant can be done efficiently by computing the product of its diagonal terms. *Glow* [5] extended this set of transformations to 1×1 invertible convolutions as well as a variant of batch normalization.

1.2 Generative Adversarial Networks

Generative Adversarial Networks (GAN) [1] have been recently highlighted for their ability to generate photo-realistic images. By providing a simple framework for high-quality, high-dimensional generative modeling, they quickly found real-world applications ranging from the notorious "deepfakes" [6] to image super-resolution [**?**].

In this section, we will focus on the Generative Adversarial Networks framework, their training process and some of their variants, especially their conditional and domain-transfer variants.

We will then outline some limitations of this framework and propose a formulation of these limitations in the form of a trilemma between the intrinsic quality of the generated samples, their diversity and the quality of the conditioning of the model. With this tool, we propose a taxonomy of the recent GAN approaches and identify trends in these approaches.

1.2.1 The GAN framework

In the same fashion as the generative models mentioned in Subsection. 1.1.2, Generative Adversarial Networks aims to learn a parameterized mapping $p_{\mathrm{G}}(x|z)$ between a simple distribution $p(z)$ (usually normal or uniform) to the real data distribution $p(x)$. However, instead of trying to estimate the distribution through marginalization, it aims to directly minimize an estimation of a divergence between $p(x)$ and the mapped distribution $p_{\mathrm{G}}(x)$.

However, because divergences are usually intractable, GANs rely on a second learned function that will act as an adversary: the discriminator D. The discriminator is a binary classifier that aims to predict the probability that a sample x was sampled on the real distribution $p(x)$ or was generated from $z \sim p(z)$ and is trained by minimizing the binary cross-entropy. The objective of the generator G is then to fool the discriminator by maximizing the same binary cross-entropy. This training process is summed up as a mini-max game in Equation. (1.4)

$$\arg\min_{\mathrm{G}}\max_{\mathrm{D}} \mathrm{L}_{\mathrm{GAN}} = \arg\min_{\mathrm{G}}\max_{\mathrm{D}} \mathop{\mathbb{E}}_{x\sim p(x)}[\log \mathrm{D}(x)] + \mathop{\mathbb{E}}_{z\sim p(z)}[1 - \log \mathrm{D}(\mathrm{G}(z))] \ . \tag{1.4}$$

This mini-max game has, assuming infinite capacity for both G and D, a global optimum for $p(x) = p_{\mathrm{G}}(x)$, which can be proved as follows: the minimum of $f(x) = a\log(x) + b\log(1-x)$ is $\frac{a}{a+b}$, the discriminator that maximizes the criterion for a fixed G is given by

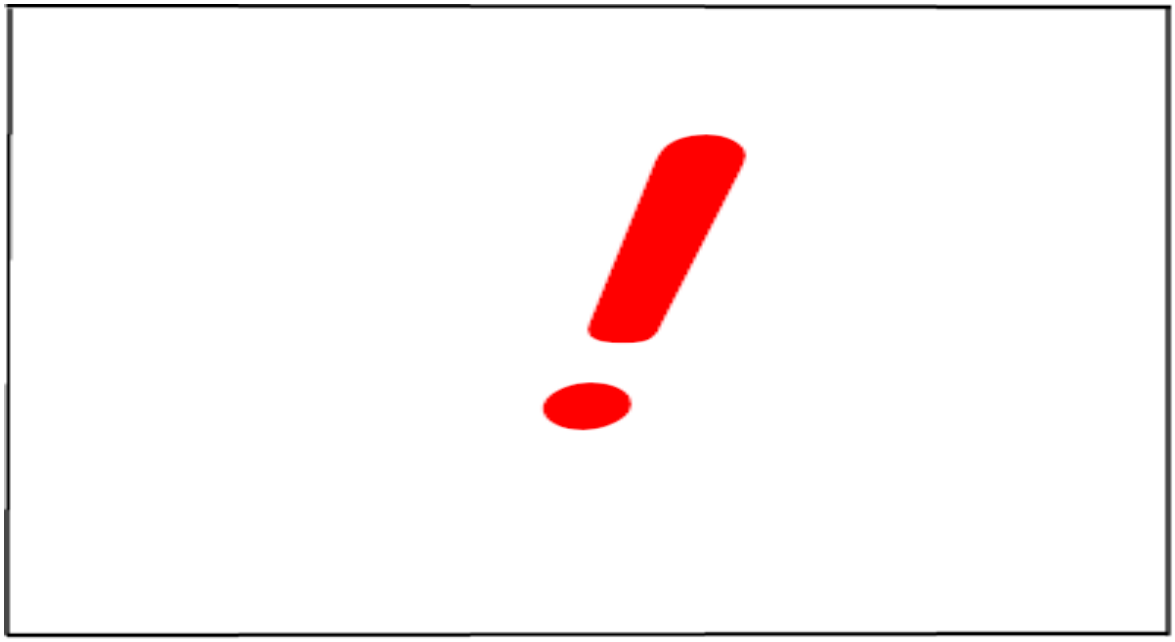


Figure 1.4: Generative Adversarial Networks framework

$$\mathrm{D}_{\mathrm{G}}^{*}(x) = \frac{p(x)}{p(x) + p_{\mathrm{G}}(x)} \ .$$

We can formulate a criterion C(G) by plugin this optimal discriminator in Equation. (1.4)

$$\begin{aligned}
\mathrm{C}(\mathrm{G}) &= \max_{\mathrm{D}} \mathrm{L}_{\mathrm{GAN}}(\mathrm{D},\mathrm{G}) \\
&= \mathop{\mathbb{E}}_{x\sim p(x)}\left[\log \mathrm{D}^{*}(x)\right] + \mathop{\mathbb{E}}_{z\sim \mathrm{P}_z}\left[1-\log \mathrm{D}^{*}(\mathrm{G}(z))\right] = \mathop{\mathbb{E}}_{x\sim p(x)}\left[\log \mathrm{D}^{*}(x)\right] + \mathop{\mathbb{E}}_{x\sim p_{\mathrm{G}}(x)}\left[1-\log \mathrm{D}^{*}(x)\right] \\
&= \mathop{\mathbb{E}}_{x\sim p(x)}\left[\log \frac{p(x)}{p(x)+p_{\mathrm{G}}(x)}\right] + \mathop{\mathbb{E}}_{x\sim p_{\mathrm{G}}(x)}\left[1-\log \frac{p_{\mathrm{G}}(x)}{p(x)+p_{\mathrm{G}}(x)}\right] \ .
\end{aligned}$$

Up to additive and multiplicative constants, the criterion C(G) can be reformulated as

$$\mathrm{C}(\mathrm{G}) = \mathrm{D}_{\mathrm{KL}}\left(\left|\left|\right.\right.() p(x)\middle|\middle|\frac{p(x)+p_{\mathrm{G}}(x)}{2}\right) + \mathrm{D}_{\mathrm{KL}}\left(\left|\left|\right.\right.() p_{\mathrm{G}}(x)\middle|\middle|\frac{p(x)+p_{\mathrm{G}}(x)}{2}\right) = 2\cdot \mathrm{JSD}\left(\left|\left|\right.\right.() p(x)\middle|\middle| p_{\mathrm{G}}(x)\right) \ .$$

When the discriminator is trained to convergence, minimizing the criterion $\mathrm{C}(\mathrm{G}) = \mathrm{L}_{\mathrm{GAN}}(\mathrm{D}^{*},\mathrm{G})$ is equivalent to minimizing the Jensen-Shannon (JS) divergence between $p(x)$ and $p_{\mathrm{G}}(x)$. The GAN training process then consists in alternatively updating the discriminator and the generator via gradient ascent/descent. A summary of this process is presented in Algorithm. 1.

1.2.2 Conditional modeling with CGANs

While classical generative models such as GANs try to unconditionally approximate the real-data distribution $p(x)$, a conditional generative model aim to learn a model of the conditional distribution $p(x|y)$, where $y \in \mathscr{Y}$ is a label of any kind.

Several extensions of the GAN framework allow for conditional modeling. First introduced, Conditional GANs (CGANs)[1][7] simply adds the label y as an input for both the discriminator and the generator. The new optimization problem that results from this change is summed-up in Equation. (1.5) as follows

Algorithm 1 The GAN training algorithm

Require: $\mathscr{D}_{\mathrm{X}}$ the real dataset, G the generator model, and D the discriminator model
  repeat
    sample a mini-batch $\{x_i\}_{i=1}^m$ from $\mathscr{D}_{\mathrm{X}}$
    sample a mini-batch $\{z_i\}_{i=1}^m$ from $p(z)$
    update D by stochastic gradient ascent of
      $\sum_{i=1}^m \log(\mathrm{D}(x_i)) + \log(1-\mathrm{D}(\mathrm{G}(z_i)))$
    sample a a mini-batch $\{z_j\}_{j=1}^n$ from distribution $p(z)$;
    update G by stochastic gradient descent of
      $\sum_{j=1}^n \log(1-\mathrm{D}(\mathrm{G}(z_j)))$
  until a stopping condition is met

$$\arg\min_{\mathrm{G}}\max_{\mathrm{D}} \mathrm{L}_{\mathrm{CGAN}} = \arg\min_{\mathrm{G}}\max_{\mathrm{D}} \mathop{\mathbb{E}}_{x,y\sim p(x,y)} [\log \mathrm{D}(x,y)] + \mathop{\mathbb{E}}_{\substack{y\sim p(y)\\ z\sim p(z)}} [1-\log \mathrm{D}(\mathrm{G}(y,z),y)] \tag{1.5}$$

While this approach is trivially simple to implement, it relies entirely on the discriminator to use the label. Other approaches try to learn the conditional distribution by adding an explicit loss term to the optimization problem, such as Auxillary Classifier GAN (ACGAN) [8]. This approach aims to learn a conditional generative model with discrete labels by adding another output to the discriminator that acts as a classifier. The model is then trained by having both the generator and the discriminator minimize the categorical cross-entropy between the real and predicted labels.

1.2.3 Domain-transfer with GANs

Domain-transfer is the task of learning a mapping $p(x|y)$ between two high-dimensional distributions $p(x)$ and $p(y)$ that maintains semantic information, for example changing the color palette of an image while keeping the same objects at the same position. CGANs already learn to model the conditional distribution $p(x|y)$, and adding a way to enforce the consistency of the semantic information enables domain-transfer.

Pix2Pix [9] implemented this approach explicitly by using paired samples $(x,y) \sim p(x|y)$ forcing the generator to minimize the ℓ_1 reconstruction term between x and $\mathrm{G}(y,z)$ (Equation. (**??**)).

$$\arg\min_{\mathrm{G}}\max_{\mathrm{D}} \mathrm{L}_{p2p} = \arg\min_{\mathrm{G}}\max_{\mathrm{D}} \mathrm{L}_{\mathrm{CGAN}}(\mathrm{D},\mathrm{G}) + \lambda \mathop{\mathbb{E}}_{\substack{x\sim p(x)\\ y\sim p(y)\\ z\sim p(z)}} ||x-\mathrm{G}(y,z)||_1 \tag{1.6}$$

However, this kind of approaches rely on paired data which can be very hard to obtain, especially in the case of natural images. When trying for example to transfer images of zebras to images of horses, you need a dataset of very similar zebras and horses in the exact same position for the ℓ_1 term to work.

This problem of paired data was solved by CycleGAN [10] using cycle-consistency. Instead of training a single model G with reconstruction between x and $\mathrm{G}(y,z)$, the CycleGAN approach train two domain-transfer models simultaneously: G_{YX} and G_{XY} that map samples from $p(y)$ onto $p(x)$ and $p(x)$ onto $p(y)$, respectively. This allows to compute the ℓ_1 reconstruction errors $||x - \mathrm{G}_{\mathrm{YX}}(\mathrm{G}_{\mathrm{XY}}(x))||_1$ and $||y - \mathrm{G}_{\mathrm{XY}}(\mathrm{G}_{\mathrm{YX}}(y))||_1$, thus completely removing the need for paired data (x,y). The training of the two models in done an adversarial setup, with two discriminators D_{X} and D_{Y}, and is summed up as an optimization problem in Equation. (1.7)

$$\begin{aligned}\arg\min_{\mathrm{G_{XY}},\mathrm{G_{YX}}}\max_{\mathrm{D_X},\mathrm{D_Y}} \mathrm{L}_{CycGAN} = \arg\min_{\mathrm{G_{XY}},\mathrm{G_{YX}}}\max_{\mathrm{D_X},\mathrm{D_Y}} &\mathrm{L}_{\mathrm{GAN}}(\mathrm{D_X},\mathrm{G_{YX}}) + \mathrm{L}_{\mathrm{GAN}}(\mathrm{D_Y},\mathrm{G_{XY}})\\ &+ \lambda \mathop{\mathbb{E}}_{x\sim p(x)} ||x-\mathrm{G_{YX}}(\mathrm{G_{XY}}(x))||_1 + \lambda \mathop{\mathbb{E}}_{y\sim p(y)} ||y-\mathrm{G_{XY}}(\mathrm{G_{YX}}(y))||_1\end{aligned} \tag{1.7}$$

The CycleGAN training process then consists in alternatively updating the two discriminator and the two generators via gradient ascent/descent. A summary of this process is presented in Algorithm. 2.

Algorithm 2 CycleGAN training algorithm

Require: $\mathcal{X}$ and $\mathcal{Y}$ two unpaired datasets, G_{XY} and G_{YX} the mapping networks, D_X and D_Y the discrimination models, m the mini-batch size

repeat

sample a mini-batch $\{x_i\}_{i=1}^m$ from $\mathcal{X}$

sample a mini-batch $\{y_i\}_{i=1}^m$ from $\mathcal{Y}$

update D_X by stochastic gradient descent of

$\sum_{i=1}^m (D_X(x_i)-1)^2 + (D_X(G_{YX}(y_i)))^2$

update D_Y by stochastic gradient descent of

$\sum_{i=1}^m (D_Y(y_i)-1)^2 + (D_Y(G_{XY}(x_i)))^2$

sample a mini-batch $\{x_i\}_{i=1}^m$ from X

sample a mini-batch $\{y_i\}_{i=1}^m$ from Y

update G_{XY} by stochastic gradient descent of

$\sum_{i=1}^n (D_Y(G_{XY}(x_i))-1)^2 + \lambda(||x_i - G_{YX}(G_{XY}(x_i))||_1$

$+||y_i - G_{XY}(G_{YX}(y_i))||_1)$

update G_{YX} by stochastic gradient descent of

$\sum_{i=1}^n (D_X(G_{YX}(y_i))-1)^2 + \lambda(||x_i - G_{YX}(G_{XY}(x_i))||_1$

$+||y_i - G_{XY}(G_{YX}(y_i))||_1)$

until a stopping condition is met

1.3 Limitations

While GANs have shown strong advantages over the classical generative modeling methods, such as generating sharper samples, they still exhibit limitations, namely: the instability of the training process; the diversity of the generated samples, the problem of *mode-collapse*; and finally the problems due to conditioning.

The instability of the GAN training process has first been conjectured to be caused by the bad quality of the gradients obtained when G generates bad samples, which makes D strongly reject these samples and therefore saturating the loss. The first solution proposed [1] was to slightly change the generator's loss function from $\log(1-D(G(z)))$ to $-\log(D(G(z)))$, which helped considerably to avoid failures of the training process and was then widely used

While this loss term converges to the same minimum as the original loss term, it however no longer correspond to a JSD

CR: Image quality : Incremental enhancement through architecture, more data, ...

Instability, catastrophic forgetting and the mode collapse problem

Trade-off image quality/diversity : Explanation through the loss term and distribution coverage

Black-box approach to conditioning, no tuning possible, no interpretability

1.4 The GAN Zoo

1.4.1 A taxonomy of GANs

Enorme nombre de variantes de GANs

Taxonomie des approches GANs (pour s'éviter une liste des différents GANs)

Schéma pour définir les grandes familles de GAN (évoquer les AmbientGAN / UNIR)

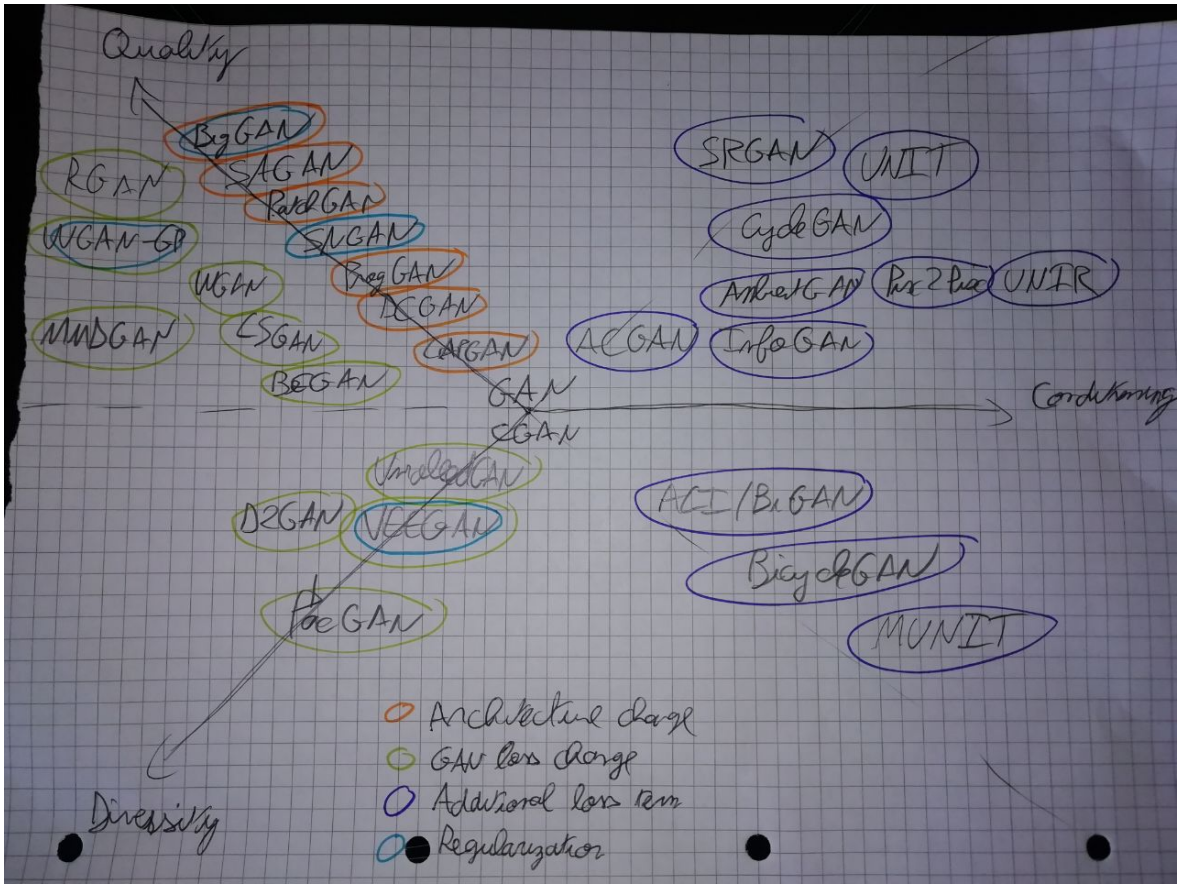


Figure 1.5: Classifications of some advances in GANs on the trilemma

1.4.2 Architecture variants

1.4.3 Divergence variants

Table des loss alternatives (f-divergences + transport optimal)

1.4.4 Task-specific losses

1.5 A note on the evaluation of generative models

No good adhoc methods

Image quality : Inception distance + Fréchet inception distance, advantages

Conditioning : Direct evaluation (pixel-wise), Classifier accuracy, Projections (PCA, t-SNE)

Limitations of those metrics : need a pre-trained model

Chapter 2

Reconstruction as an Auxiliary Task for Generative Modeling

Chapter abstract

In this chapter, we propose an approach for conditioning a GAN model to reconstuct images from a very sparse set of randomly-positioned pixels known beforehand. This approach, based on a Maximum A Posteriori estimation, takes the form of an explicit auxiliary reconstruction task which adds to the GAN objective as an additional loss term. Complemented with the PacGAN variant for training GANs, this approach enables the generation of diverse samples from a sparse pixel map. As opposed to the more classical Conditional GAN approach, this auxiliary task is interpretable and a hyperparameter allows to control the importance of the conditioning in the learning process. We evaluate our approach on the classical MNIST, FashionMNIST and CIFAR10 datasets, as well as a custom-made texture dataset. Finally, we apply this approach to a task of geostatistical simulation.

Contents

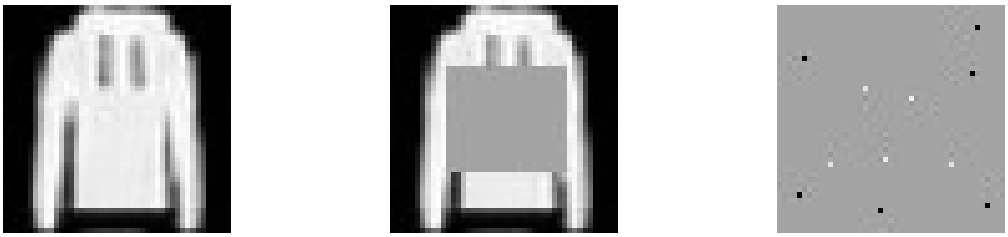
2.1 Image Reconstruction with Generative Models

Image reconstruction is the task of completing an image from a very small subset of the pixels. Such source data can usually be found in domains where the measurement process is very noisy or where measurements are expensive. This task differs from image inpainting since the source data is usually unstructured and very scarce, as in this chapter we will consider randomly scattered measurements of less than a percent of the image. While our discussion focus on image reconstruction, it is noteworthy to mention that this applies to other kinds of signals.

The task of image reconstruction is challenging since very few information is available for use. To overcome this lack of information, generative models such as GANs leverage on existing datasets to learn the distribution of the real images. By conditioning the learned distribution, a GAN could learn to generate an image while enforcing the constraint that the pixels known beforehand must remain similar in the generated image.

Similarly as in the GAN setup, we denote by $\mathrm{X} \in \mathscr{X}$ a random variable and x its realization. Let p_{X} be the distribution of X over $\mathscr{X}$ and $p_{\mathrm{X}}(x)$ be its evaluation at x. Similarly $p_{\mathrm{X}|\mathrm{Y}}$ represents the distribution of X conditioned on the random variable $\mathrm{Y} \in \mathscr{Y}$.

We denote by $x \in \mathscr{X} = [-1,1]^{n \times p \times c}$ (see Figure 2.1a) an image sampled from an unknown distribution p_{X} and a sparse matrix $y \in \mathscr{Y} = [-1,1]^{n \times p \times c}$ (Figure 2.1c) as the given constrained pixels.



(a) Original Image (b) Inpainting Input (c) Constraint Map

Figure 2.1: Difference between regular inpainting (2.1b) and the problem undertaken in this work (2.1c) on a real sample (2.1a).

(a) Original Image (b) Constraints (c) Generated Image (d) Satisfied Consts.

Figure 2.2: Generation of a sample during training. We first sample an image from a training set (2.2a) and we sample the constraints (2.2b) from it. Then our GAN generates a sample (2.2c). The constraints with squared error smaller than $\epsilon = 0.1$ are deemed satisfied and shown by green pixels in (2.2d) while the red pixels are unsatisfied.

The problem then consists in finding a generative model G with inputs z (a random vector sampled from a known distribution p_Z over the space $\mathcal{Z}$) and constrained pixel values $y \in [-1,1]^{n \times p \times c}$ that maps the distribution p_Z onto the conditional distribution $p_{X|Y}$ of the real images given the constraints y (see Figure 2.2).

CR: Related works : CGAN, AmbientGAN, UNIR, Compressed Sensing with Meta-Learning
Limitations of these models

2.2 Conditional generation as a Maximum A Posteriori estimation

Approche de l'article NeuCom :

Formulation as a Maximum A Posteriori Estimation, assumptions (normal error)
Construction of the loss term using bayes rule and least squares
PacGAN for keeping the diversity

2.3 Experimental evaluation and application to underground soil generation

Datasets : MNIST/FashionMNIST/CelebA/Texture

Evaluation : MSE/FID; Epoch selection criterion
Architectures : Appendix ? DCGAN + SGAN (encoder-decoder)
Results : visible trade-off, good fidelity overall
Application to hydro-geology : subsurface dataset
Evaluation : MSE/HOG+LBP

2.4 Conclusion

Objective reached : tuneable loss, pixel-wise, keeping diversity

Applications in hydro-geology : papier Eric

Future works : other distributions (modelling error using Laplacian, beta or Poisson distributions)

Chapter 3

Conditioning generation with multiple task-specific constraints

Chapter abstract

content...

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3.1 Introduction

Formulation as a constrained optimization problem
- Reformulation of CycleGAN as a constrained optimization problem
- Relaxation of the constraints
- Ici, expérimenter sur des datasets artificiels ?

3.2 Proximal method for non-Euclidean output space

Travail sur le proximal ?
- Envelope theorem application

3.3 Application to RGB to Polarimetric domain transfer

Introduction to polarimetry-specific physical constraints (briefly, no need to write a physics essay)
- Reformulation as constraints on the output space
- Relaxations : L_2 term + rectified term
- Dataset, Evaluation
- Experiments and results

3.4 Conclusion

Relaxation of the constraints works even when a lot of constraints are applied
- The application to the polarimetric dataset works
- Future works : using adapted metrics for the non-euclidean outspace X

Chapter 4

Conclusion and Perspectives

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Appendix A

Publications

Appendix B

Experiment details for the Pixel-Wise Conditionned GAN

Appendix C

Experiment details for the Polarimetric CycleGAN