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Contraintes physiques pour les réseaux génératifs et application à la synthèse et à la super-résolution de fonds nuageux

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Outline

- Goals

- Generative Adversarial Networks: principle and interest

- Application to clouds synthesis:

  Relevant prior physics information

  How to account for the different constraints in the loss ?

  Results

Goals

- Complete experimental databases to evaluate the performance of optronic sensors

- Keep the **same radiometric levels** and **cloud cover** but with different spatial distribution

- Use ice or liquid water content and thus not many training data

⇒ Input of radiative transfer code
⇒ Images for **different spectral bands**
different viewing angles

- Super-resolution with reversibility constraint

- **Keypoints**:

⇒ **Realistic cloud-edges**, as they are the main sources of false alarm for detecting targets on a cloudy sky

⇒ Be able to generate images larger than real input images, without mosaic effect

GANs: Principle and interest

Concept proposed in 2014 in the paper **Generative Adversarial Nets** by Ian J. Goodfellow and his colleagues at University of Montreal

“Generative Adversarial networks is the most interesting idea in the last ten years in machine learning” Yann LeCun

GANs are **deep neural network** architectures made of **two different networks**, contesting with each other by playing a zero-sum game

Two networks

- **Generator:** learns to generate plausible data from random noise (uniform, Gaussian…)
- **Discriminator**: learns to distinguish the generator's fake data from real data

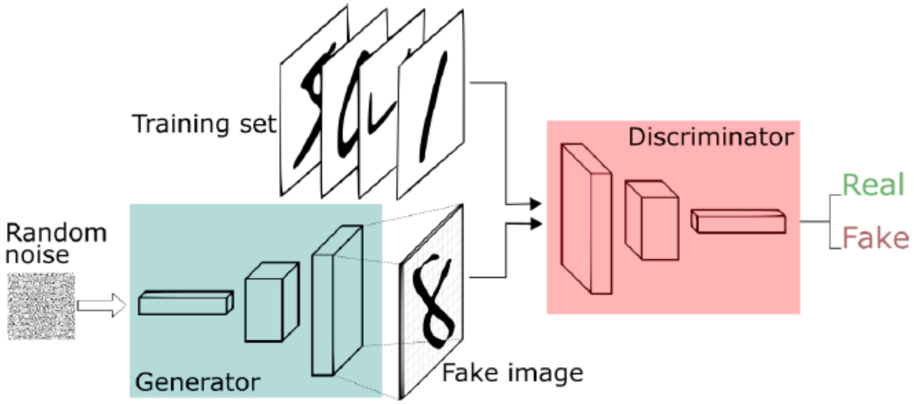
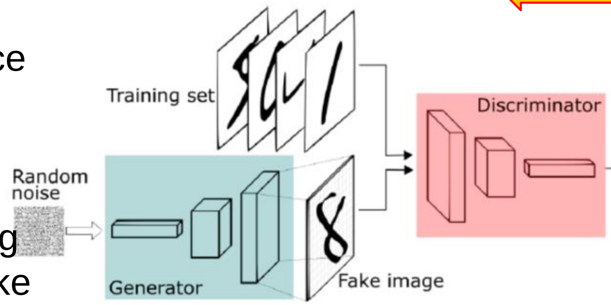


Illustration from https://2018.igem.org/Team:Vilnius-Lithuania-OG/Gan_Introduction

GANs: Principle and interest

Generator G:

- maps the noise to the data space
- implicitly defines the distribution $p_{model}(\ .,\theta)$
- G loss penalizes G for producing a sample that D classifies as fake
- G weights update through backpropagation from the discriminator loss through D and G



Backpropagation for D

Discriminator D:

- classifies real data + fake data from G
- D loss penalizes missclassifications
- D weights update through backpropagation from the discriminator loss through D

Backpropagation for G

Log loss function to optimize $\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))]$

Discriminator output for real data x

Discriminator output for generated fake data G(Z)

Minimax: Inner maximization by discriminator and outer minimization by generator

$\Rightarrow$ Alternate discriminator and generator optimization

End: when the generated images are not distinguishable from real images anymore

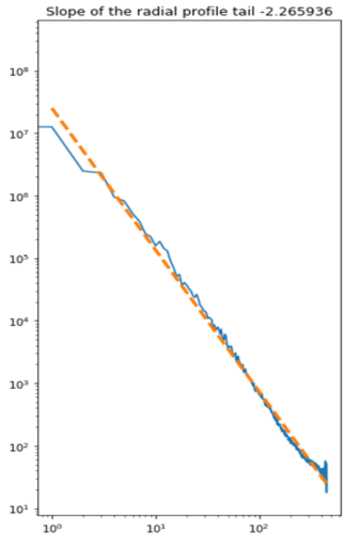
= Nash equilibrium

Can we account for prior information?

Q : **How can we decide if images simulated by GANs are realistic ?**

- Basic stats: μ, σ, skewness, kurtosis

- Stats for natural images: - **power spectrum** ~$1/f^p$ f spatial frequency



 - distribution of **difference between two adjacent pixels**

 in rows or columns = generalized Laplace distri $Ce^{-(\frac{x}{\beta})^{\alpha}}$

- Stats for cloud edges: quantiles of distribution of difference between two adjacent pixels in row or columns at cloud edges

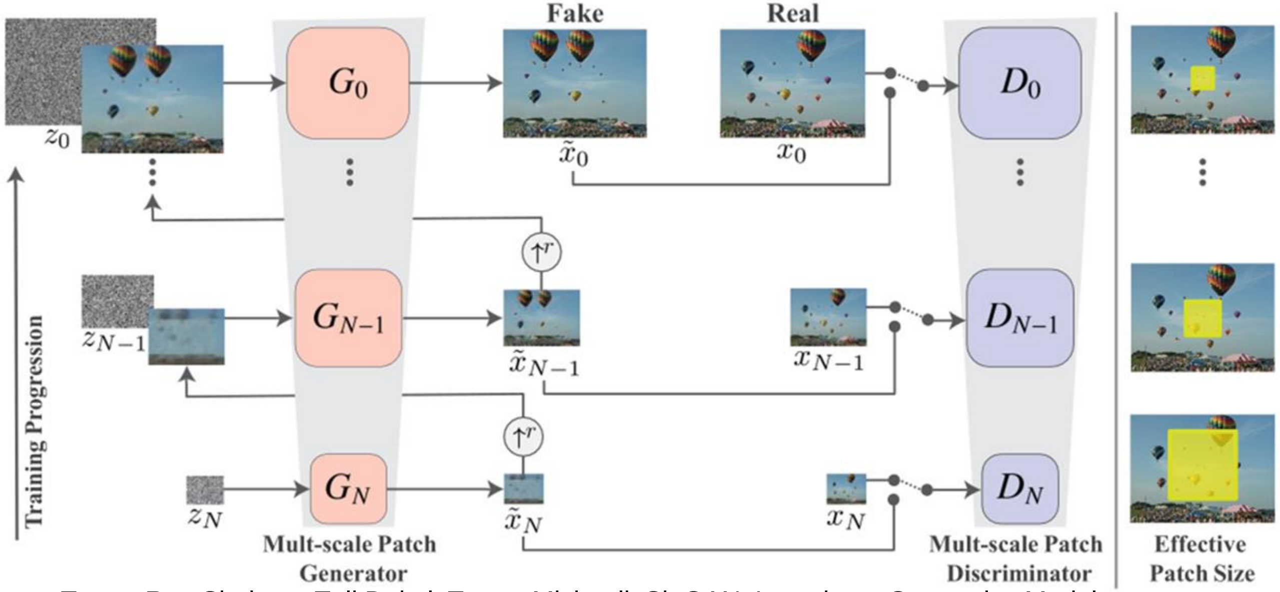
=> Take into account some of these criteria in the loss

Ongoing work – PhD P. Chatillon (dir. Y. Gousseau Télécom)

Goals:

- Add terms linked to relevant prior physics information in loss function
- Accounting for multiscale effects
- Super-resolution from low resolution images

First results using SinGAN:

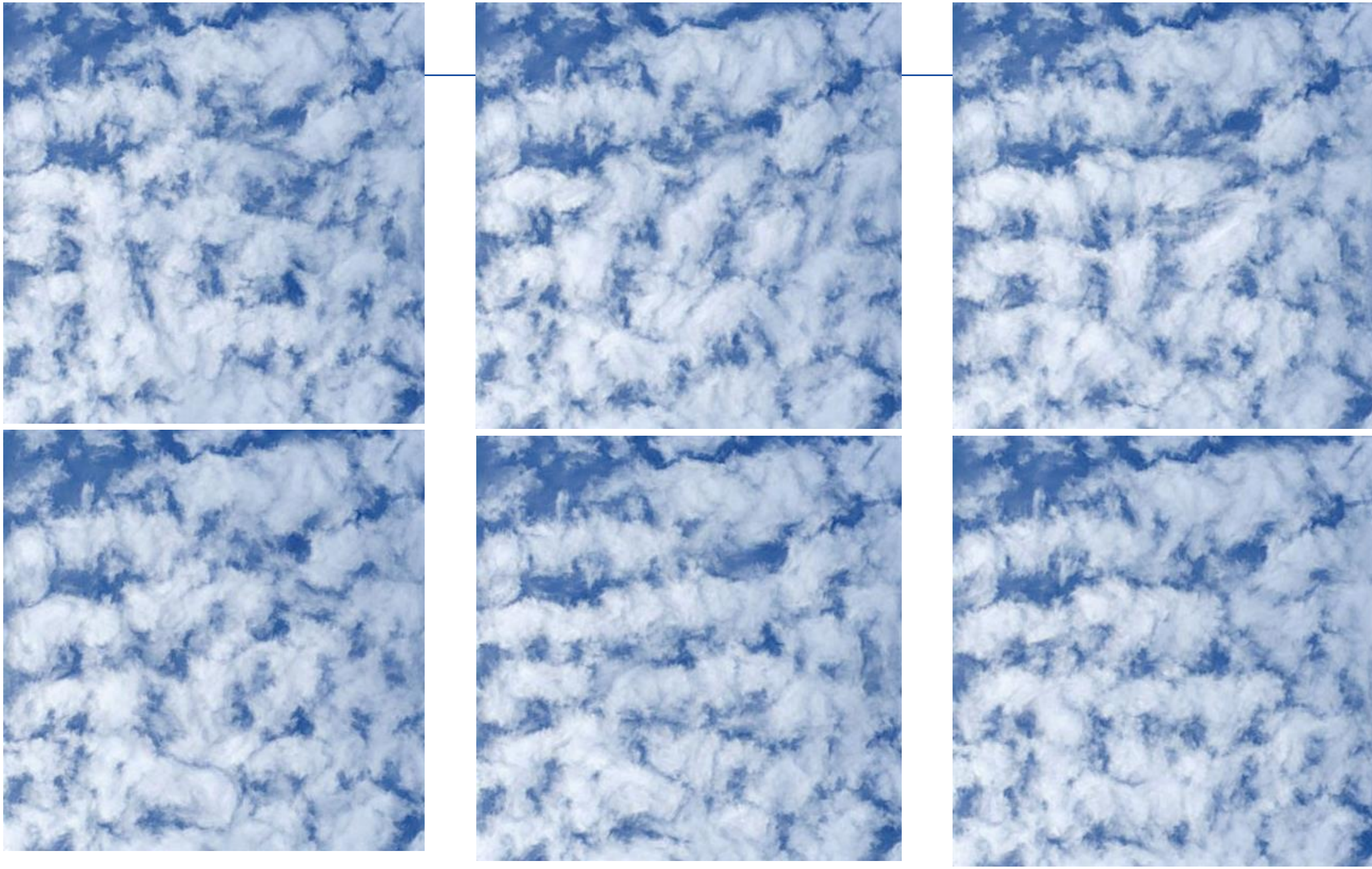


Tamar Rott Shaham, Tali Dekel, Tomer Michaeli: SinGAN: Learning a Generative Model from a Single Natural Image

Aim at learning internal stats of patches at different scales within a single image

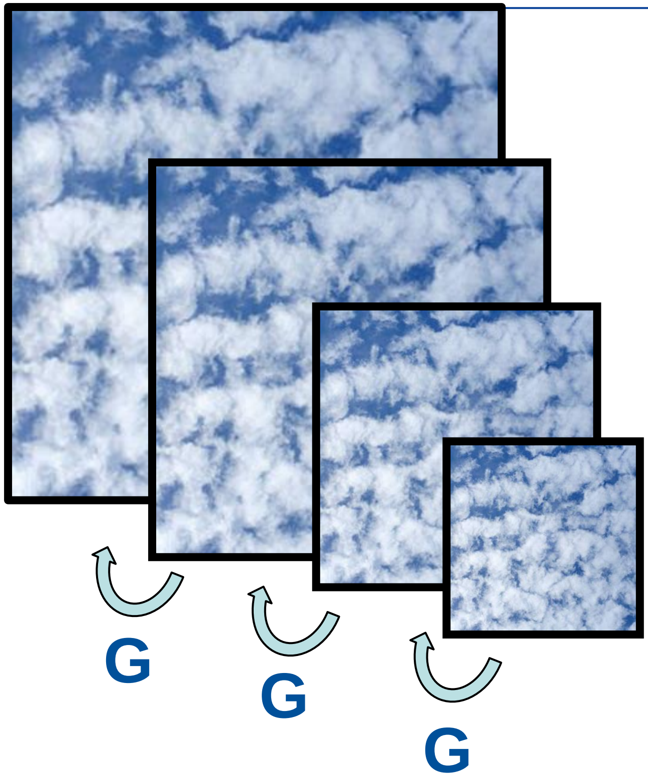
Trained in a coarse-to-fine fashion

Examples of generation with Singan



➢ **Copy on image borders**

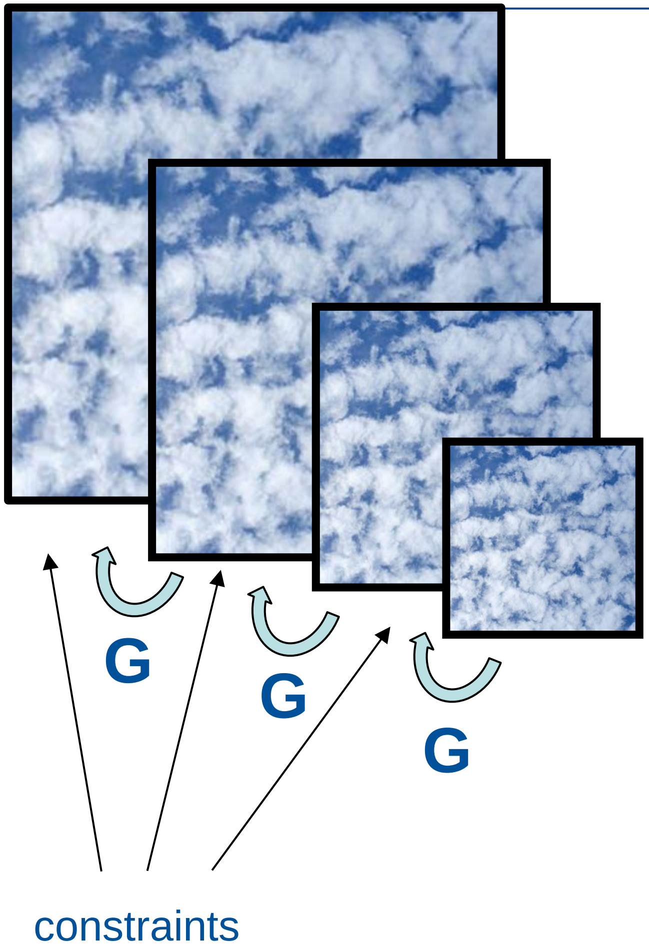
‘Super-resolution’ with SinGAN



- Use the same generator for every scale

Use the learned generator to create higher resolution

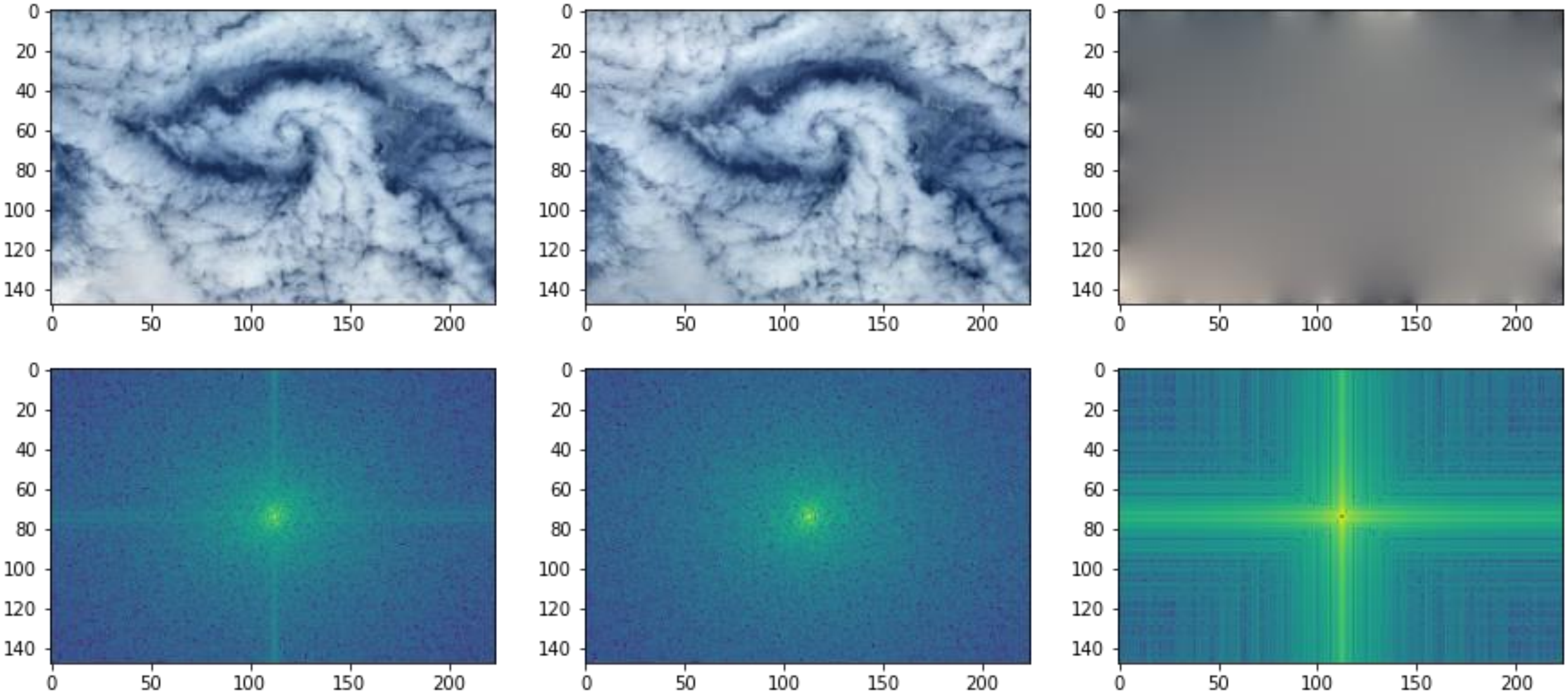
Physical constraints



- Spectrum
- Histogram
- Reversibility

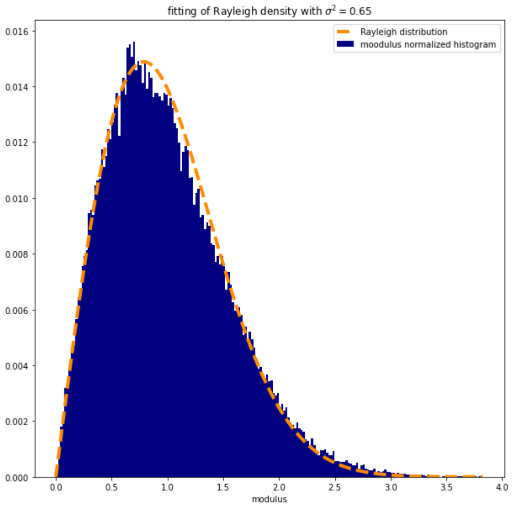
Spectrum constraint

- L. Moisan, Per plus smooth decomposition



Spectrum constraint

- Mean modulus decreases in $\dfrac{1}{||\xi||^p}$



- For $||\xi|| = cst$, $\hat{f}(||\xi||)$ follows a Rayleigh distribution

- We force the modulus to follow this distribution on every circle $||\xi|| = cst$, by 1D optimal transportation

Histogram constraint

- Sliced optimal transport => I_{hist}
- Projection onto I_{hist}

Reversibility constraint

- Consistency with blurring and subsampling

- Retained option: gradient descent on

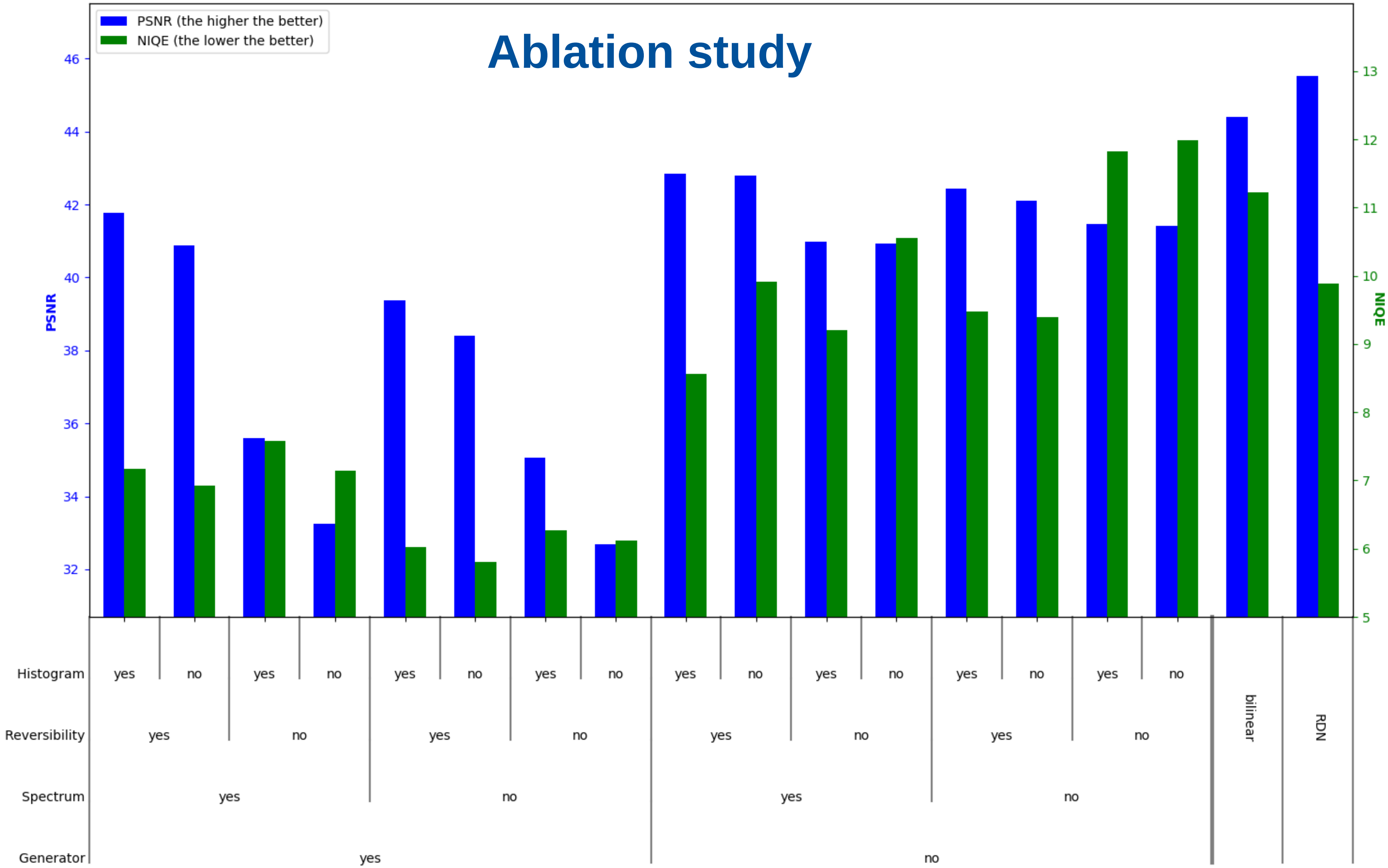
$$\mathcal{L}_{rev} = \frac{1}{2}||Q_r(I_{HR} * g) - I_{LR}||^2$$ with respect to I_{HR}

Examples: original

Bilinear

Our method

Ablation study



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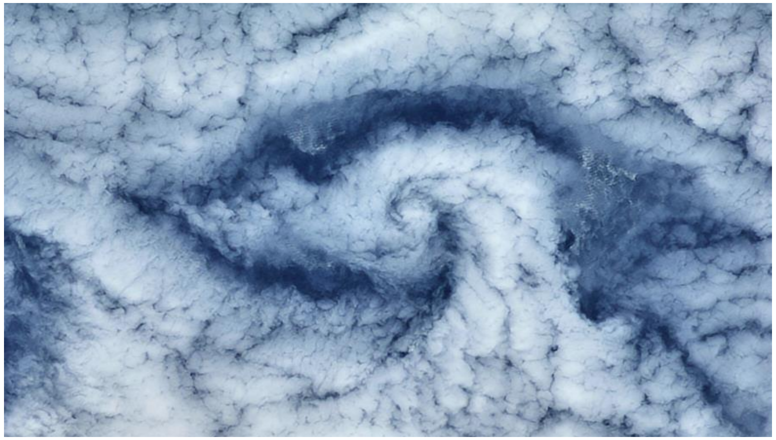
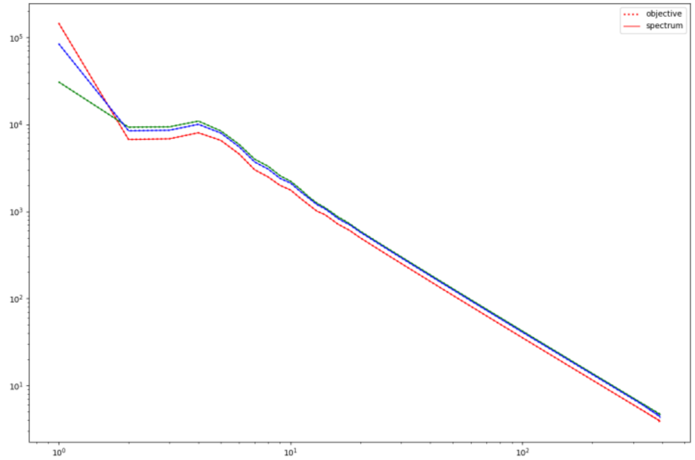
Generation with this procedure





Conclusion

- Promising first results for clouds synthesis and super-resolution

Next steps:

- Other architectures and frameworks
- Benchmark ≠ networks: SinGAN, non stationary GAN, multiscale Gatys (High resolution neural texture synthesis with long range constraints, arXiv:2008.01808)
- 3D, multispectral…