SinGAN: Learning a Generative Model from a Single Natural Image[1]

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[1] "SinGAN: Learning a Generative Model From a Single Natural Image" by Shaham, Dekel, and Michaeli

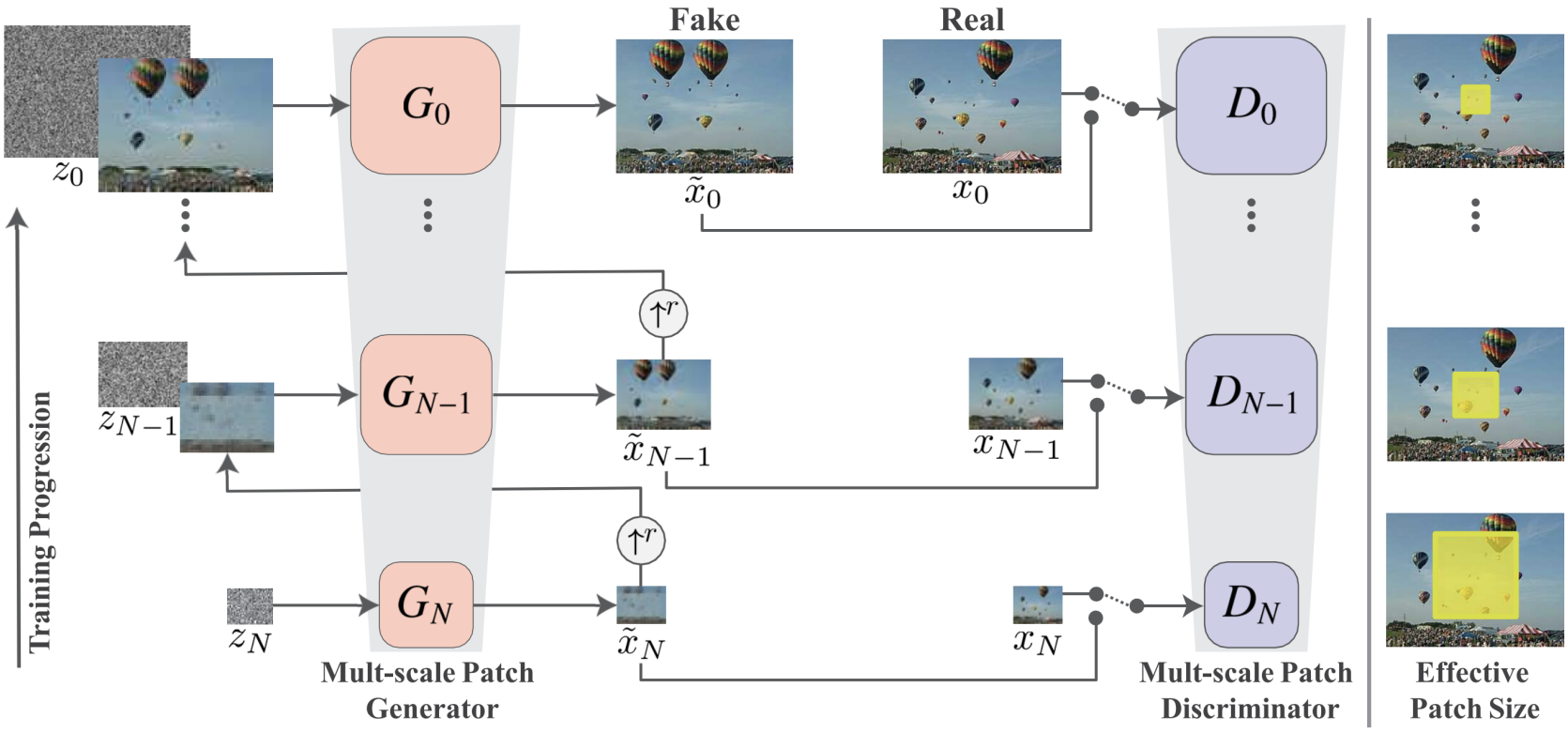
Overview

- **SinGAN** is a GAN model which is trained on a *single* image and can generate similar ones.
- It does so by using a Pyramid of GAN models, starting with a small resolution and gradually increasing it.
- Authors obtained *very* good results on other generative tasks: super-resolution, paint to image, editing, etc.

SinGAN in short

- Take an image and downsample it several times to obtain a sequence $x_0 > x_1 > ... > x_N$ of its downsampled versions.
- Initialize N GANs $(G_0, D_0), ..., (G_N, D_N)$, where (G_n, D_n) operate on image resolution of x_n.
- On each level n, generator takes an image $\tilde{x}_{n-1}$ from the previous level and produces an image for the next level: $\tilde{x}_n = G_n(z_n, \tilde{x}_{n-1})$.
- In addition to an adversarial loss, we also use a reconstruction loss to reconstruct original image.

Architecture



- On each level, we take noise z_n and image from the previous level $\tilde{x}_{n+1}$ and generate image $\tilde{x}_n = G_n(z_n, \tilde{x}_{n+1})$.
- Discriminator D_n works on patches instead of the full image scale.

Architectural details

- Given noise z_n and upsampled previous image $\tilde{x}_{n+1}^{\uparrow}$, generator G_n predicts only "missing details" which we should add to an image, i.e. we do not predict the image from scratch.
- To incorporate noise, we just some it up: $z_n + \tilde{x}_{n+1}^{\uparrow}$ (this forces G_n not to discard it)

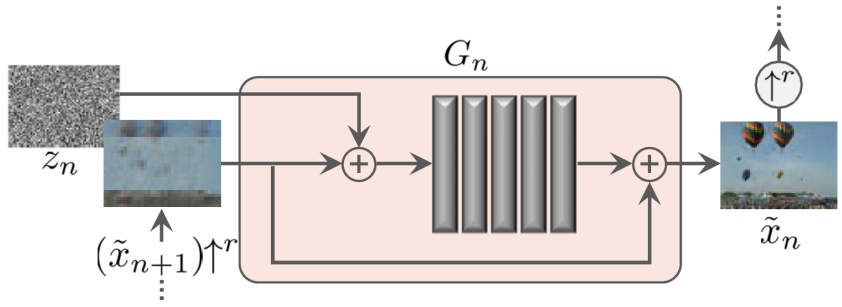


Figure: Generator architecture

- Discriminator D_n operates on patches of images instead of their full scales
- G_n, D_n are kept simple so not to overfit.

Training details

- The whole architecture is trained sequentially, i.e. once the (G_n, D_n) is trained, it is kept fixed.
- Adversarial loss:
  - Adversarial loss $\mathcal{L}_{\text{adv}}$ is WGAN-GP loss
  - They used PatchGAN (or "markovian discriminator"), which predicts scores for image patches independently and the final score for an image is an average of individual patch scores.
- Reconstruction loss:
  - We want to ensure that our model can produce an original image for some noise vector.
  - Pick "golden" noise vectors $z_N^{\text{rec}}, z_{N-1}^{\text{rec}}, ..., z_0^{\text{rec}}$ to be $z^*, 0, ..., 0$, where z^* is random and fixed.
  - Force G_n to produce original (downsampled) image x_n from the given noise z_n^{rec} and previous reconstruction $\tilde{x}_{n+1}^{\text{rec}}$ by optimizing:

$$\mathcal{L}_{\text{rec}} = \| G_n(0, (\tilde{x}_{n+1}^{\text{rec}})^{\uparrow}) - x_n \|^2 \tag{1}$$

- Total loss:

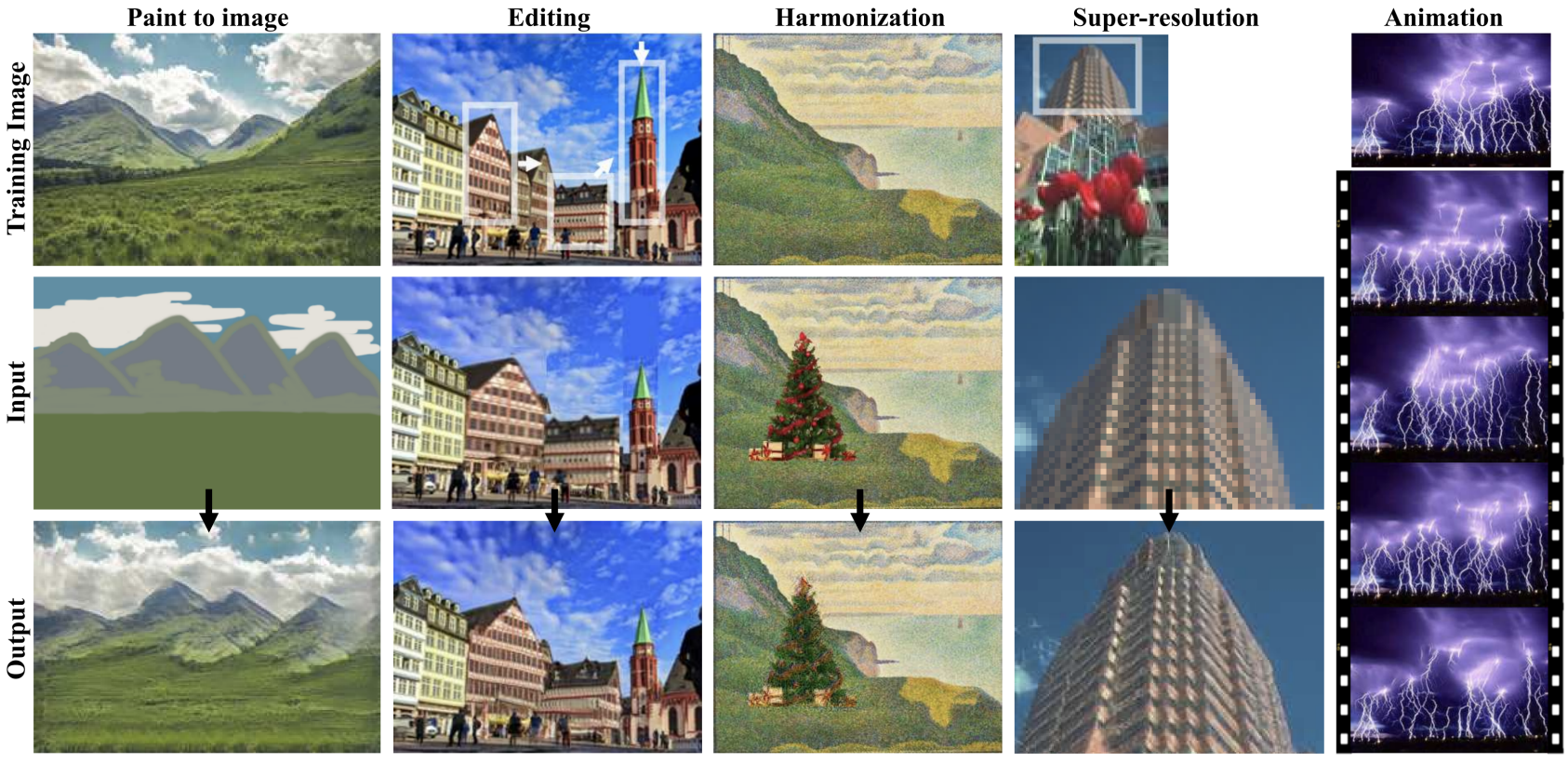
$$\min_{G_n} \max_{D_n} \mathcal{L}_{\text{adv}}(G_n, D_n) + \alpha \mathcal{L}_{\text{rec}}(G_n) \tag{2}$$

Image manipulation with SinGANs

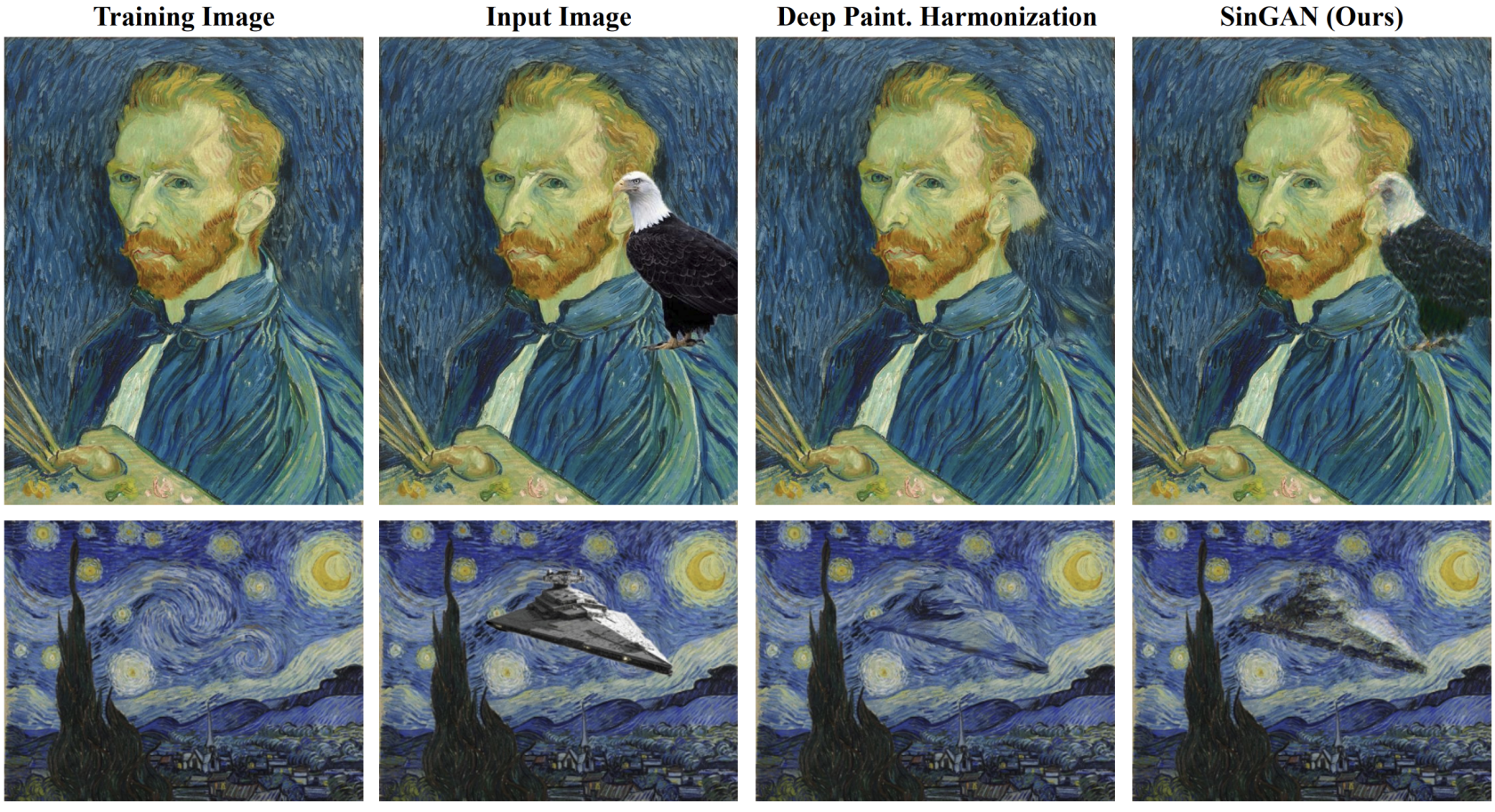
SinGAN gives a straightforward way to do different image manipulations after training *without any additional tuning*:

- Super-resolution: just apply G_0 several times to a low-resolution image.
- Paint to image (create an image from a clip art): downscale clip-art image to the coarsest scale and feed it to G_N.
- Harmonization (blend a pasted object with a background): downscale the image to a factor $n \approx 3$ and feed it to G_n.
- Editing (replace image regions): same as for harmonization.

Image manipulation samples



Harmonization samples



Conclusion

- Good quantitive results on standard metrics and human evaluation
- A possibility to train a good GAN model from a single image gives a lot of opportunities.
- Previous works on single-image GANs were only about producing texture
- Good results on image manipulation
- Ablation study is missing
- How will we benefit from using several images?