SinGAN: Learning a Generative Model from a Single Natural Image

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April 1st, 2020

ICCV 2019
Seoul, Korea

What they did?

Generate realistic natural images using an unconditional GAN by only training **one image**

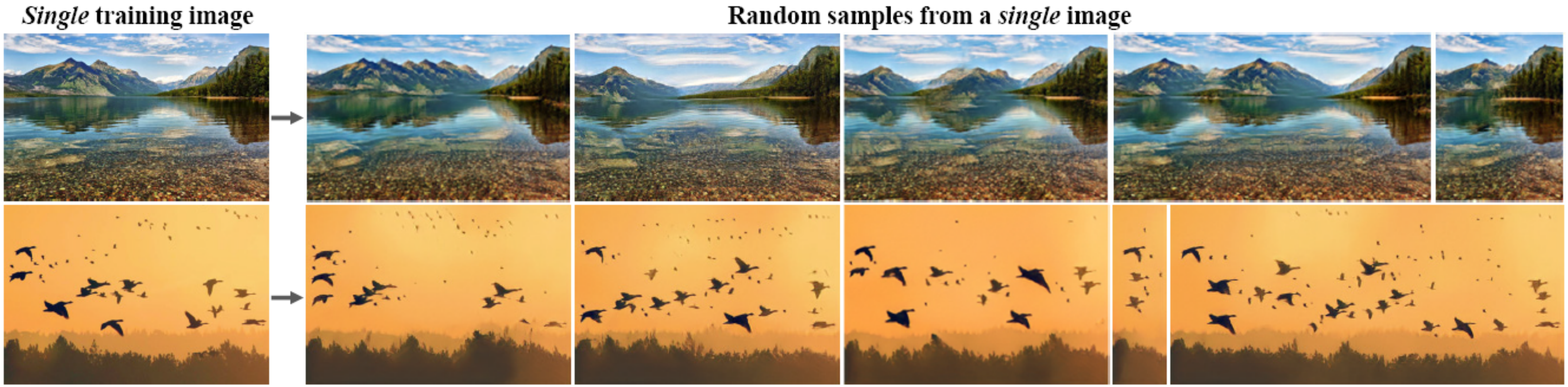
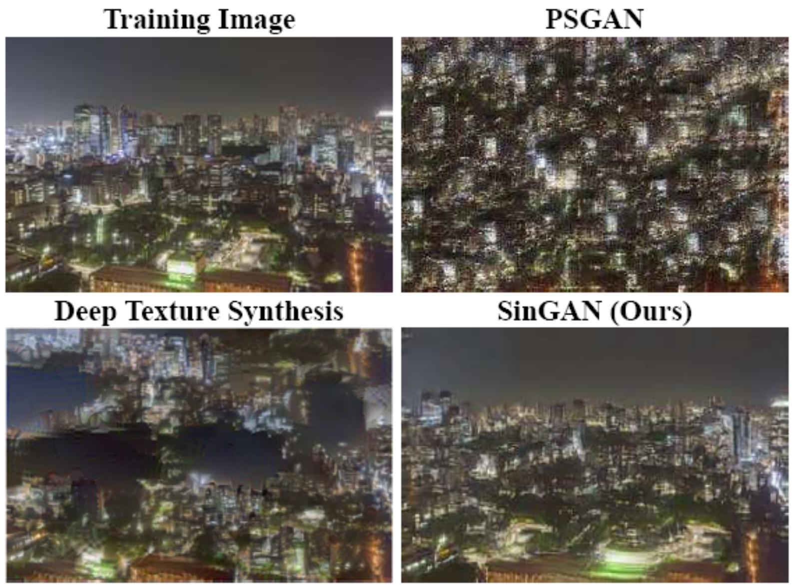


Figure 1: **Image generation learned from a single training image.** We propose *SinGAN*–a new unconditional generative model trained on a *single natural image*. Our model learns the image's patch statistics across multiple scales, using a dedicated multi-scale adversarial training scheme; it can then be used to generate new realistic image samples that preserve the original patch distribution while creating new object configurations and structures.

Why they conduct the experiment?

- Despite GANs have shown remarkable success in generating realistic images, capturing the **distribution of highly diverse datasets** with multiple object classes requires **conditioning the generation** on another input signal or training the model for a specific task
  - e.g. super-resolution, inpainting, retargeting
- These conditioning GAN models requires **large amount** of training dataset and can only be trained to implement a **single task**
- Current unconditional single image GANs do not generate meaningful samples when trained on non-texture images

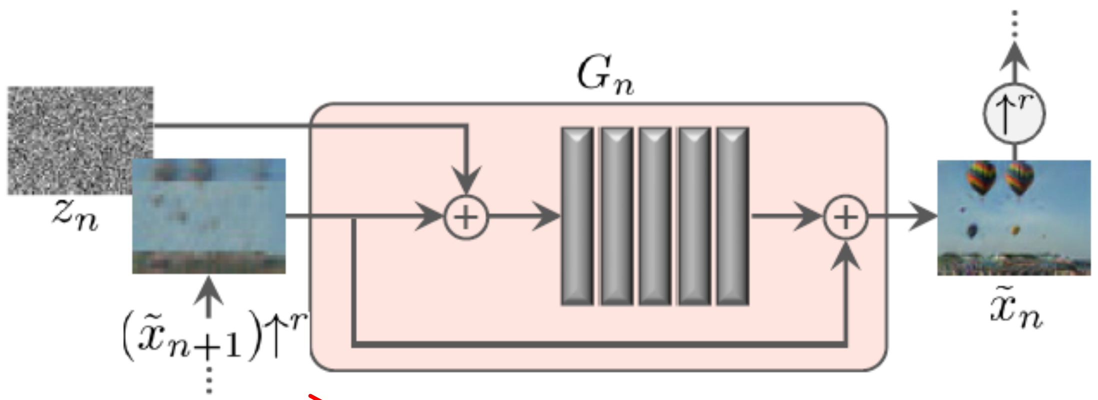


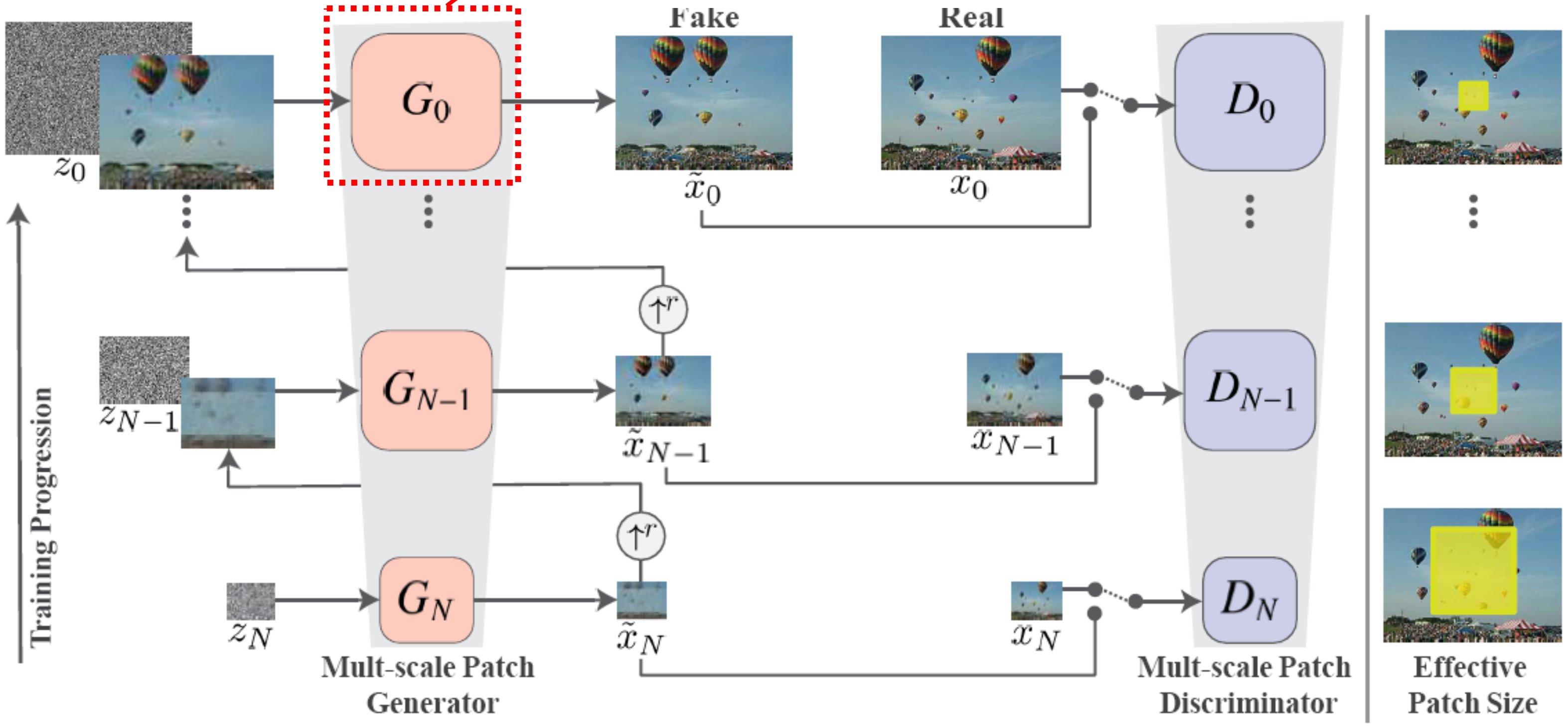
Their contributions

- The authors presented how to train an unconditional GAN model based on a single natural image
- It is shown that the **internal statistics of patches** within a single natural image typically **carry enough information** for learning a powerful generative model
- Once trained, their model can implement **multiple tasks**

How they did?

- Multi-scale architecture
- The model was trained sequentially





Same architecture
Same receptive field

Method in details

$$\tilde{x}_N = G_N(z_N)$$

$$\tilde{x}_n = G_n\left(z_n, (\tilde{x}_{n+1}) \uparrow^r\right), \qquad n < N$$

G_n :

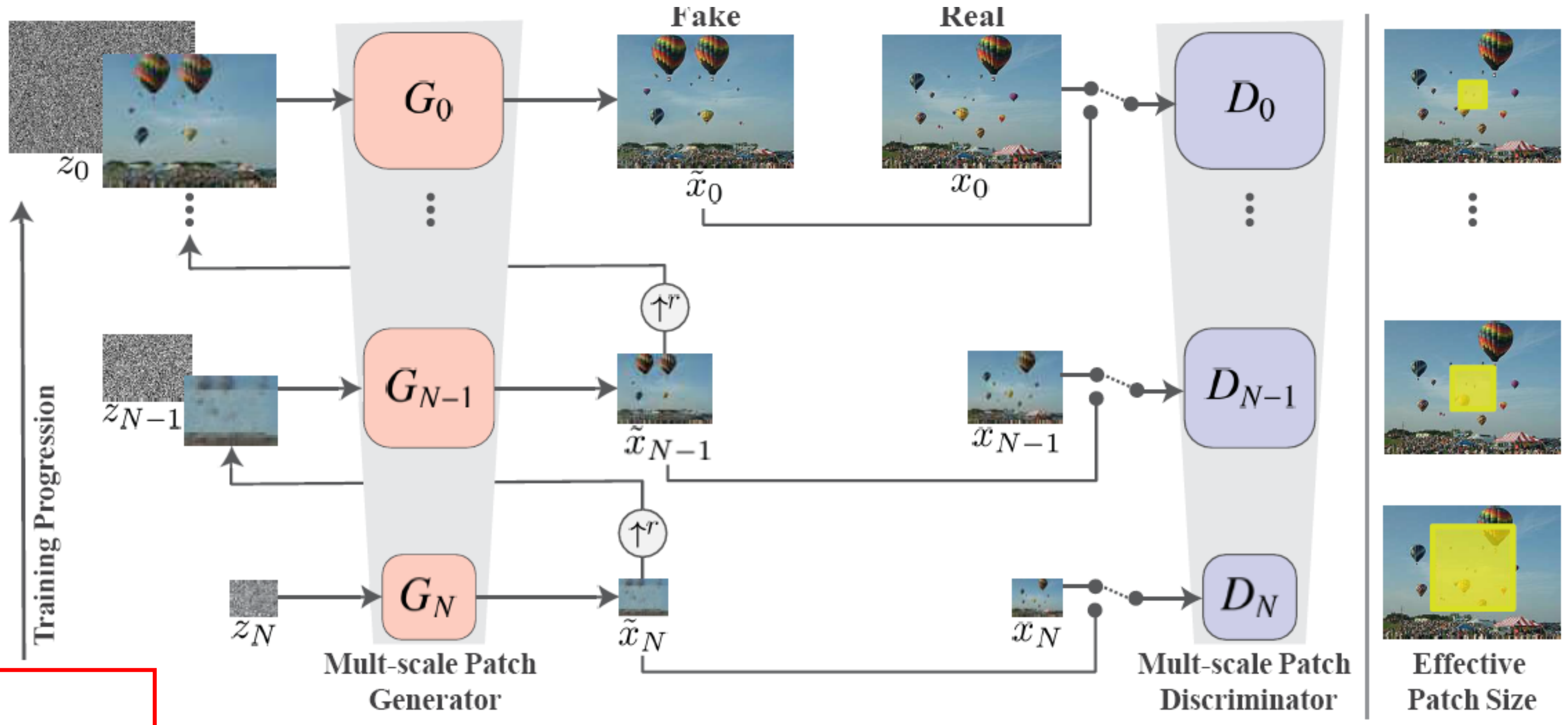
$$\tilde{x}_n = (\tilde{x}_{n+1}) \uparrow^r + \psi_n\left(z_n + (\tilde{x}_{n+1}) \uparrow^r\right)$$

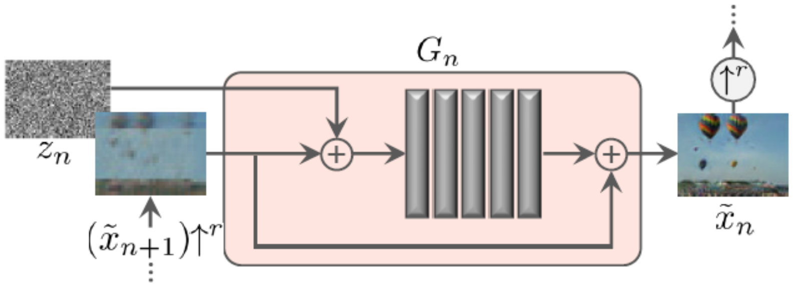
$$\min_{G_n} \max_{D_n} \mathcal{L}_{\text{adv}}(G_n, D_n) + \alpha \mathcal{L}_{\text{rec}}(G_n)$$

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

For n=N $\quad \mathcal{L}_{\text{rec}} = \|G_N(z^*) - x_N\|^2$

$$\{z^{\text{rec}}_N, z^{\text{rec}}_{N-1} \dots, z^{\text{rec}}_0\} = \{z^*, 0, \dots, 0\},$$



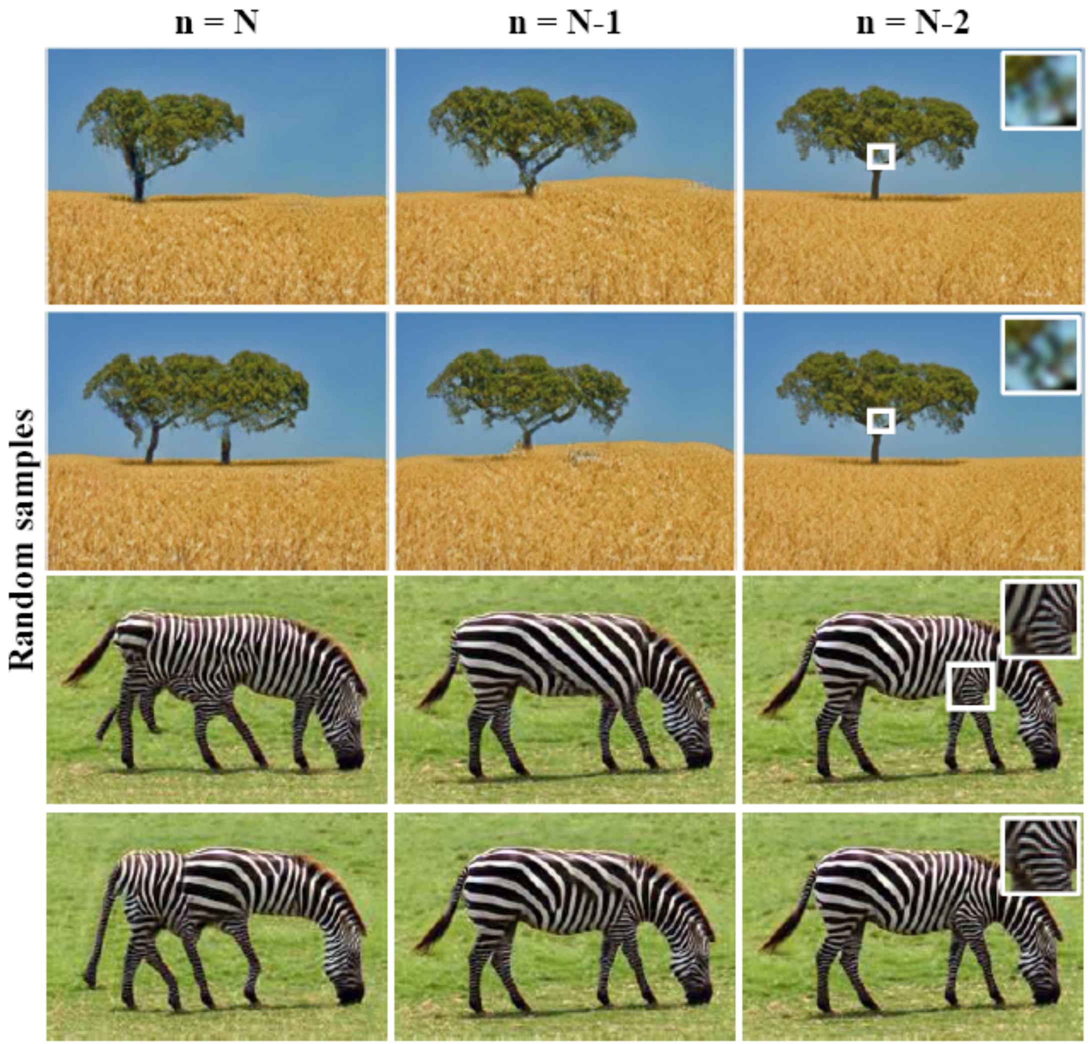


Method in details

- Receptive fields: 11 by 11
- Image size gradually increase by a factor $r \approx {}^{4}/_{3}$
- Image size in the coarsest level: 25 by 25

Result: Effect of scales at test time

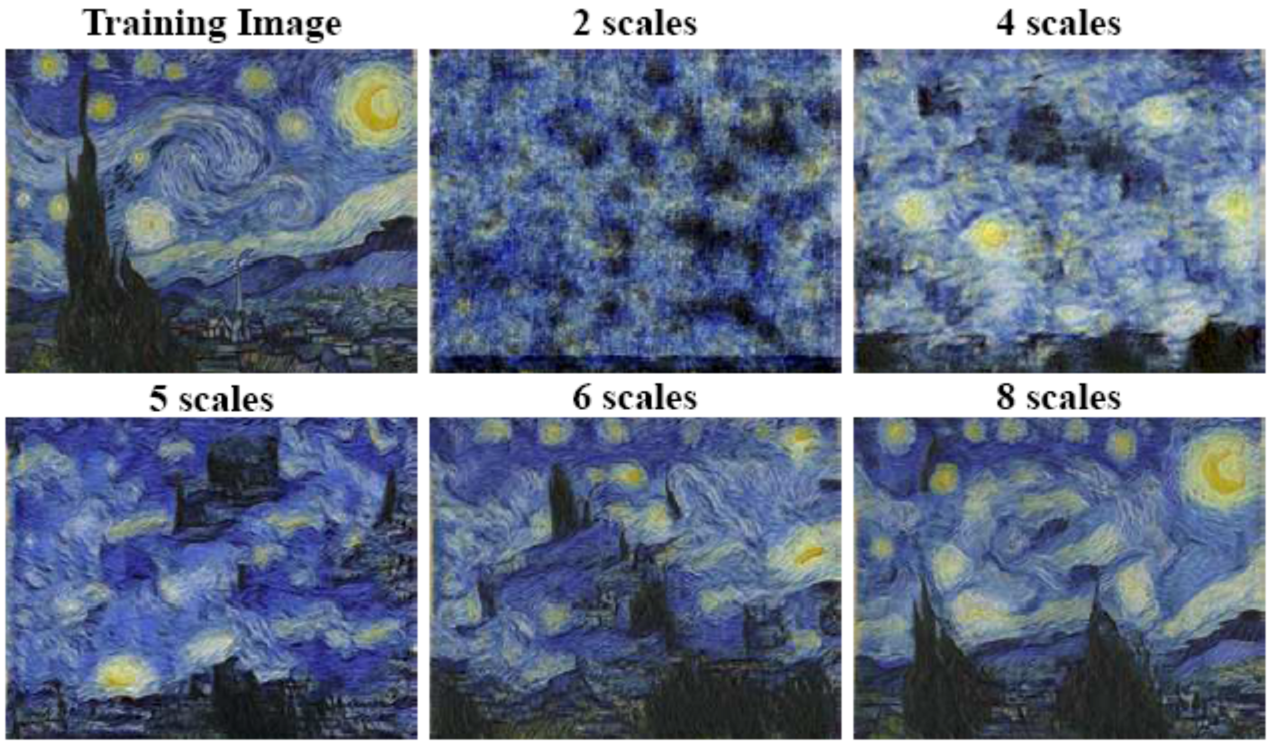
- During the testing, starting from different level



- Starting from finer scales enables to keep the global structure intact, while altering only finer image features

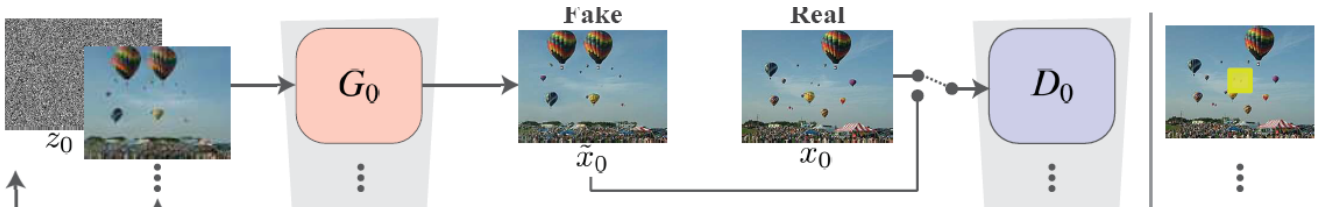
Result: Effect of scales during training

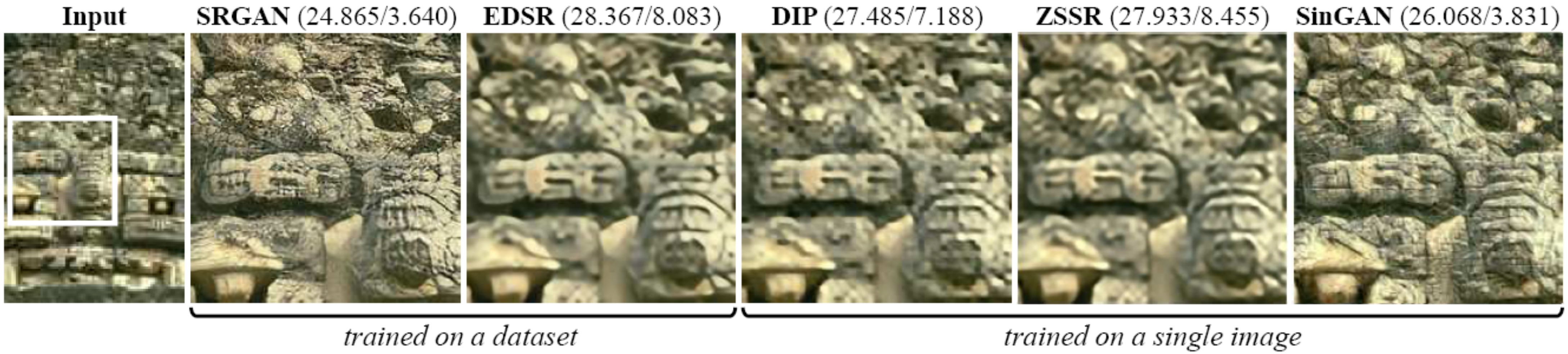
- As the number of scales increases, structures of larger support emerge, and the global object arrangement is better preserved



Application: super-resolution

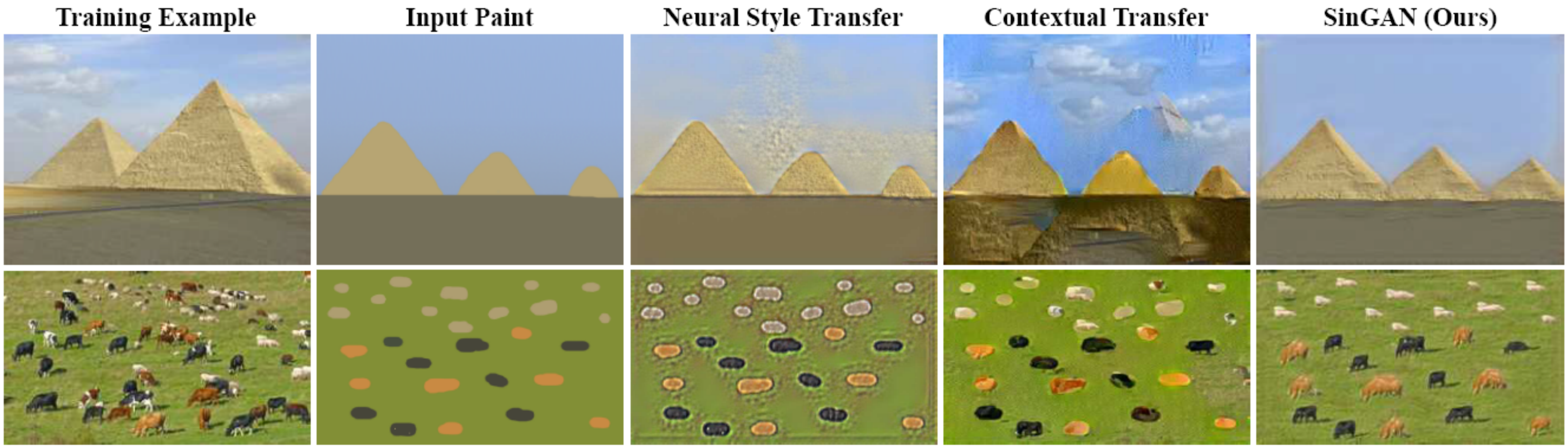
During the testing, upsample the LR image by a factor of *r* and inject it to the last generator, G_0. We repeat this procedure several times to obtain the final high-res output





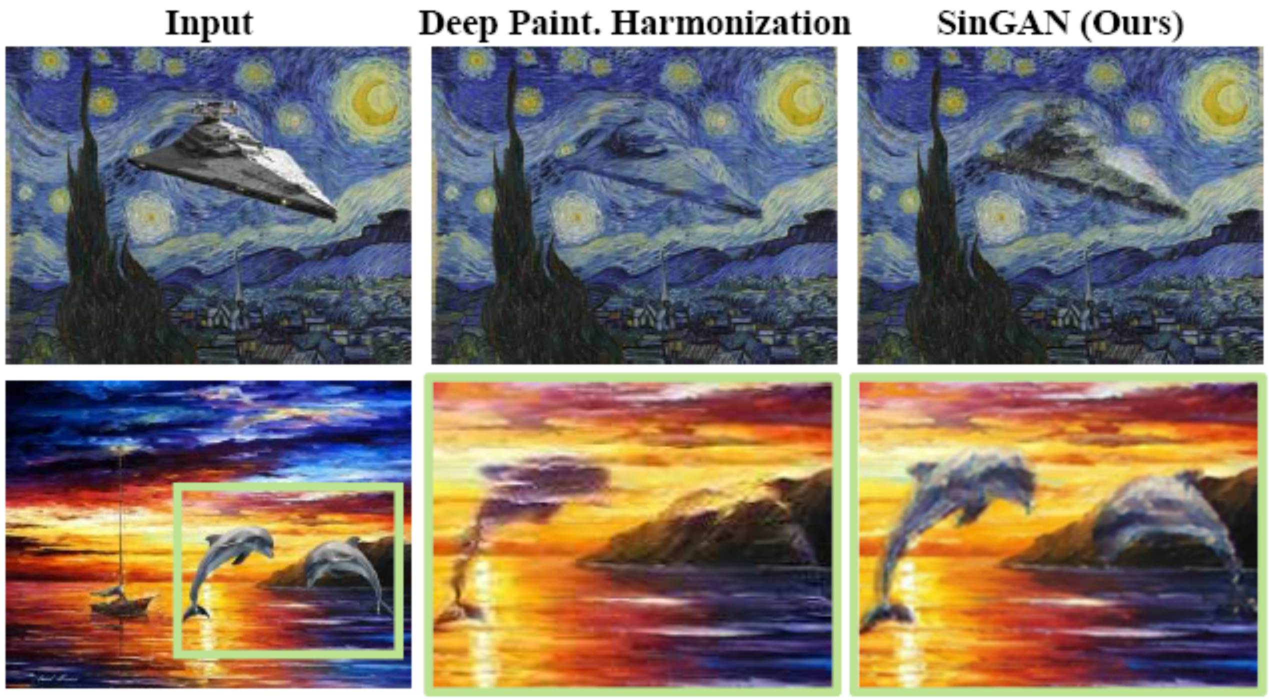
Application: Paint-to-image

Downsampling the clipart image and feeding it into one of the coarse scales (e.g. N-1 or N-2)



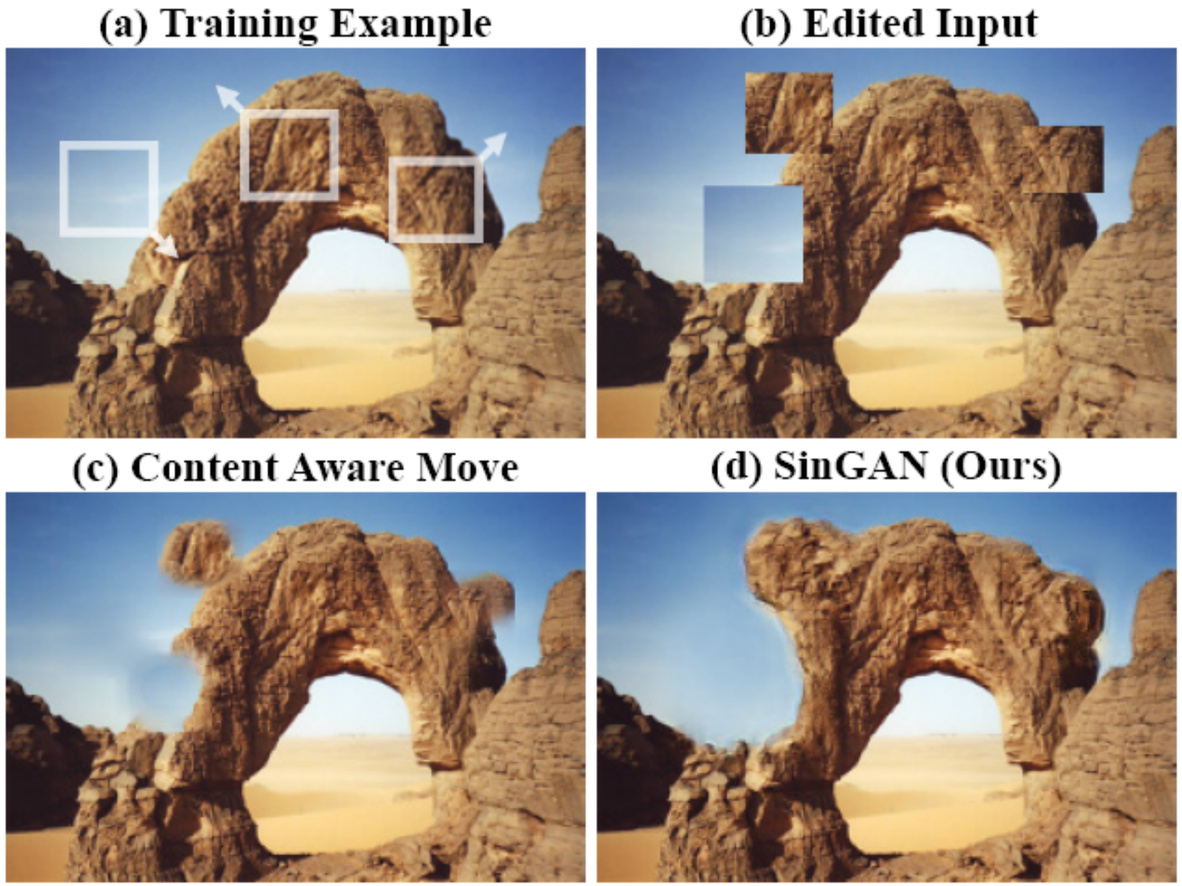
Application: Harmonization

Train the model on the background image, and inject a downsampled version of the naively pasted composite at test time



Application: Editing

Injecting a downsampled version of the composite into one of the coarse scales



More resources

https://www.youtube.com/watch?v=OvZVxqUmE3g
Start from 1:23:20