SinGAN: Learning a Generative Model from a Single Natural Image

Best paper of ICCV 2019

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2019. 11. 04 Mon

SinGAN: Learning a (Unconditional) Generative Model from a Single Natural Image (For General Image Manipulation)

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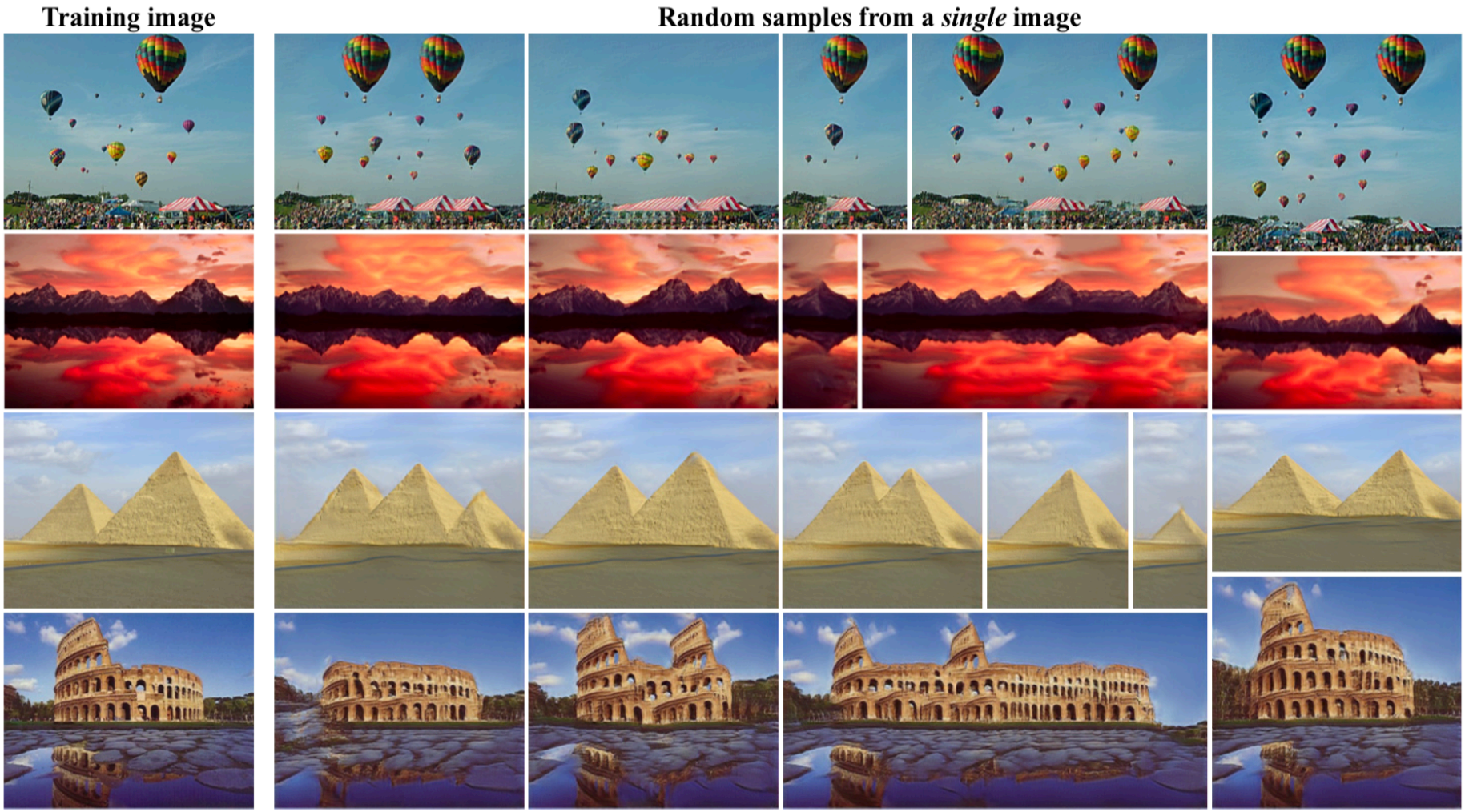
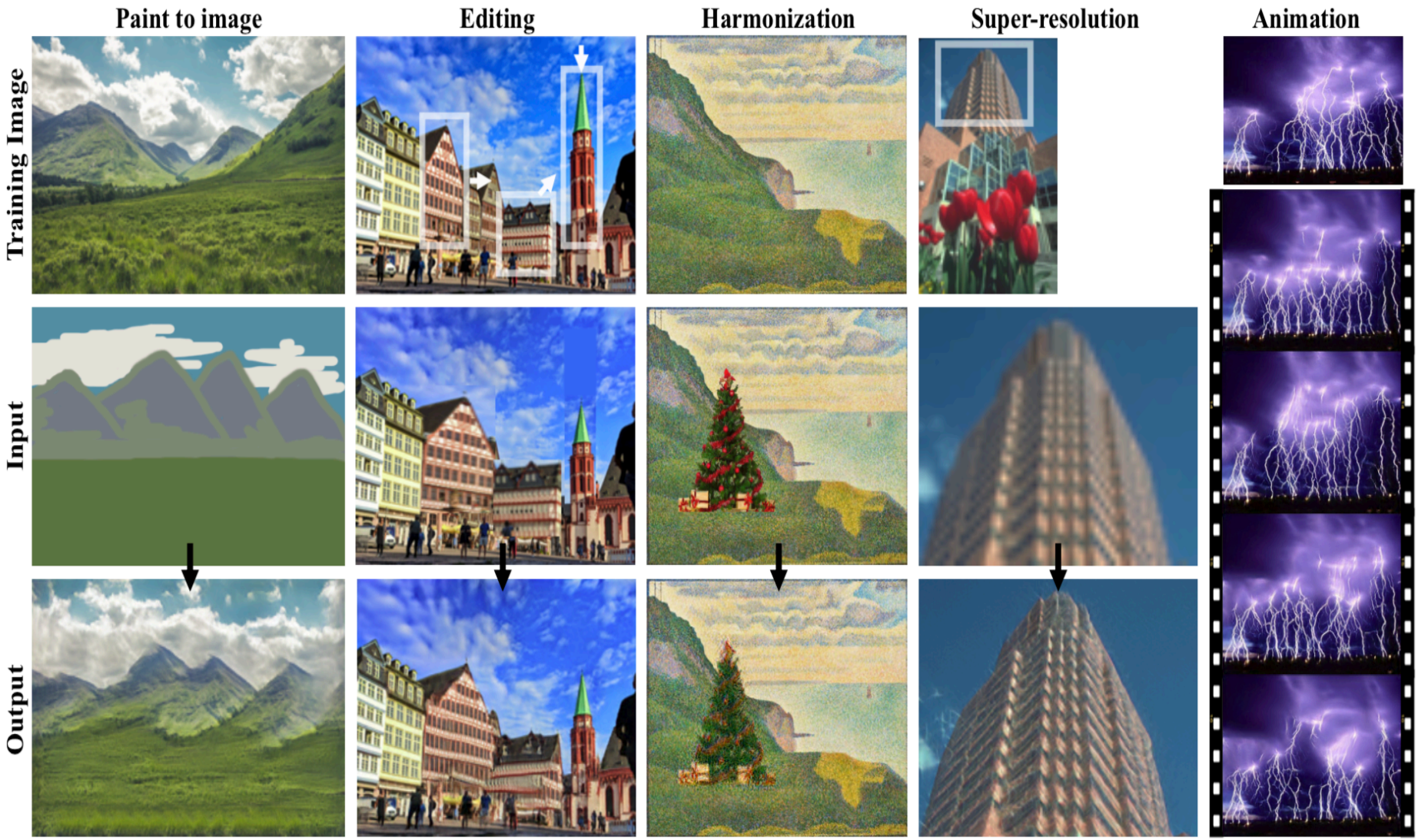
Results



Results


Paint to image
Editing
Harmonization
Super-resolution
Animation
Training Image
Input
Output

1. Unconditional & from Single Image

2. Model Architecture

3. Training Methods and Details

4. Results and Evaluations

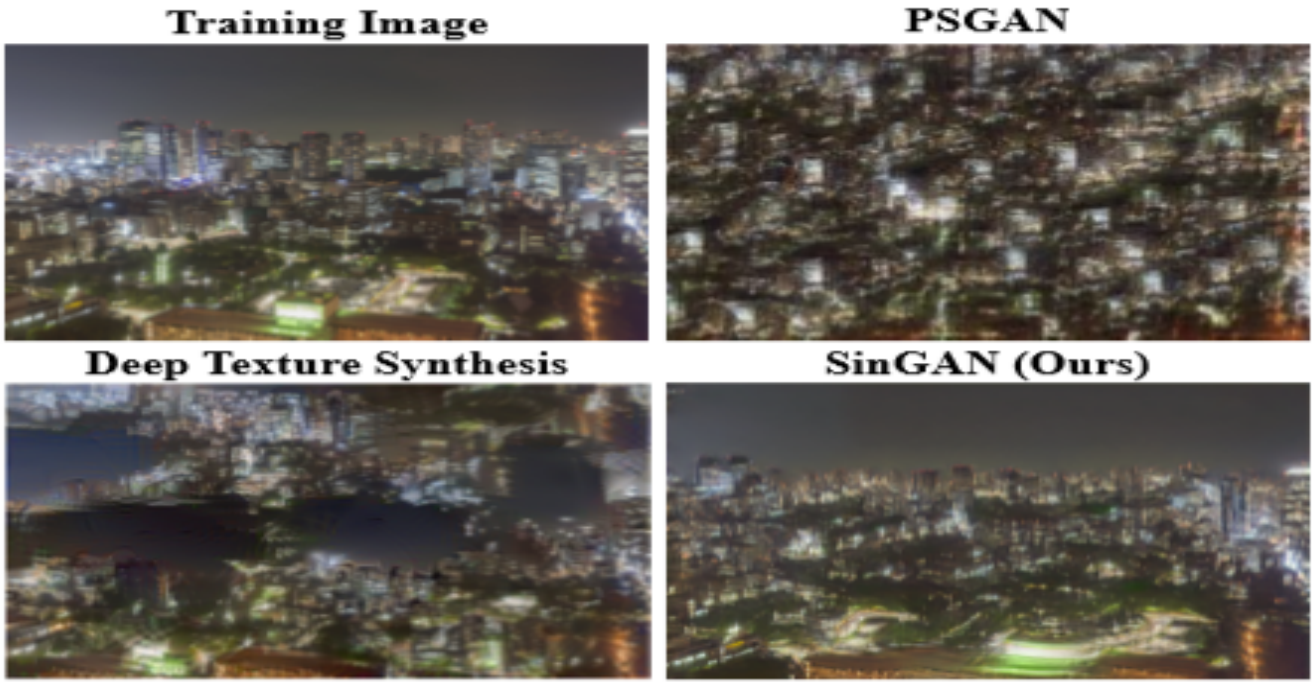
5. Various Applications

6. Conclusions

Unconditional Generative Model

- Generate Sample totally from random noise

- Does not restrained for texture generation
  - generate meaningful samples from non-texture images (real image)
  - generate complex textures or non-repetitive global structures and arrangement



From a Single Real Image

- Trained to capture the internal distribution of patches within the image

- Totally free from existence of dataset
  - regardless of paired or unpaired

- Does not designed for specific task(e.g. SR)
  - can be used for general image manipulation

- Can generate more diverse samples
  - both photo-realism and diversity

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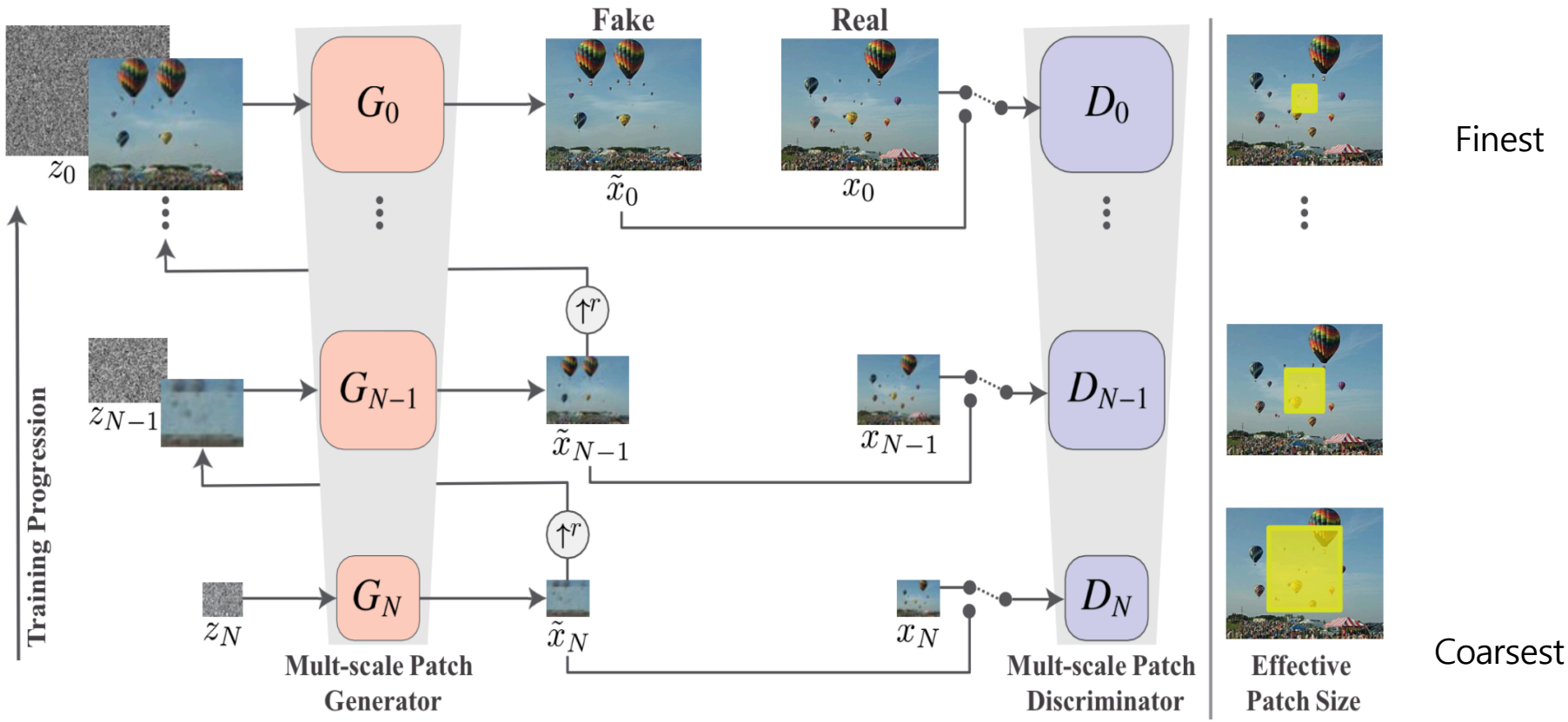
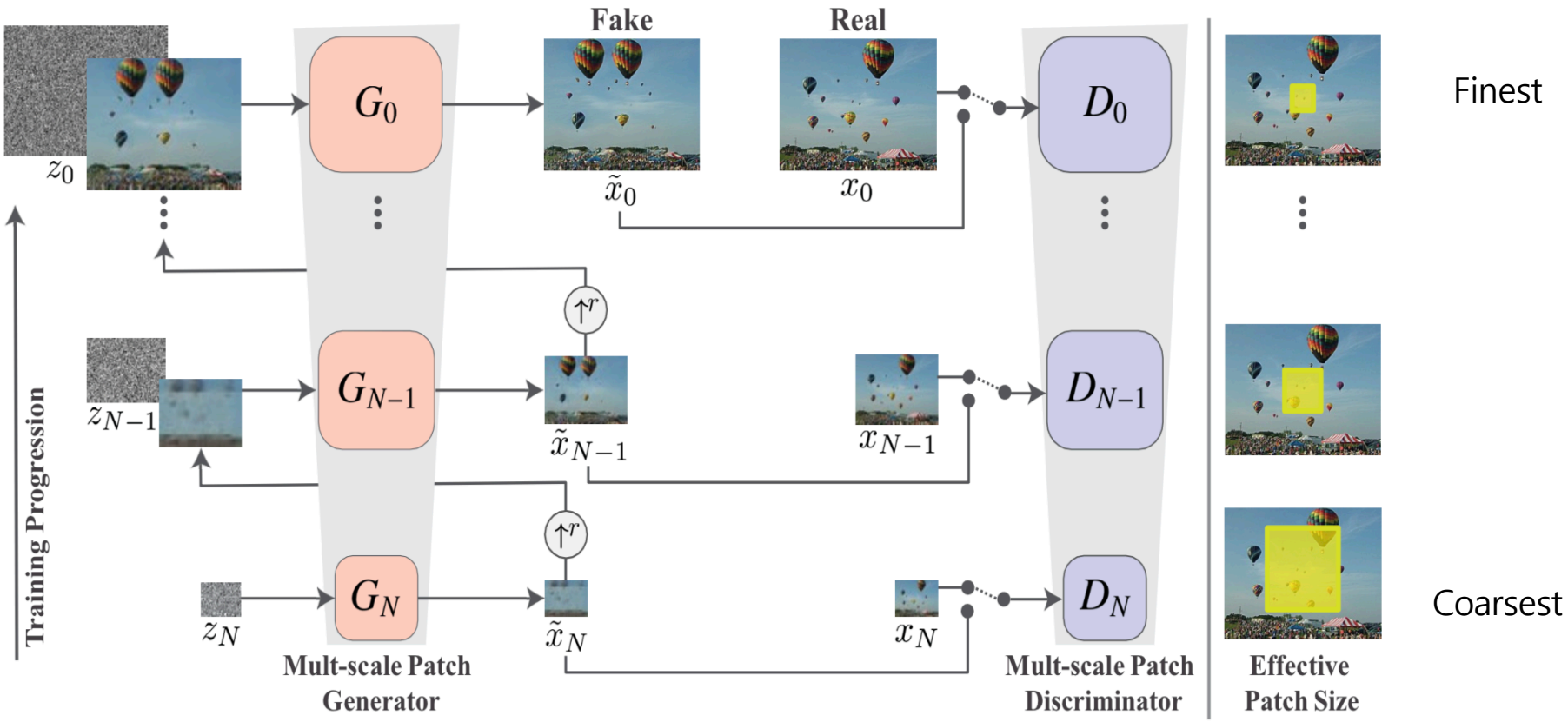
Model Architecture



- x_n is a downsampled version of x by a factor γ^n ($\gamma > 1$)
- Always set minimal dimension at coarsest scale 25px
- Set the number of scales, N s.t. scaling factor γ is as close as 4/3
- $N = int\left(\frac{\log\left(\frac{imageSize}{25}\right)}{\log(\gamma)}\right)$

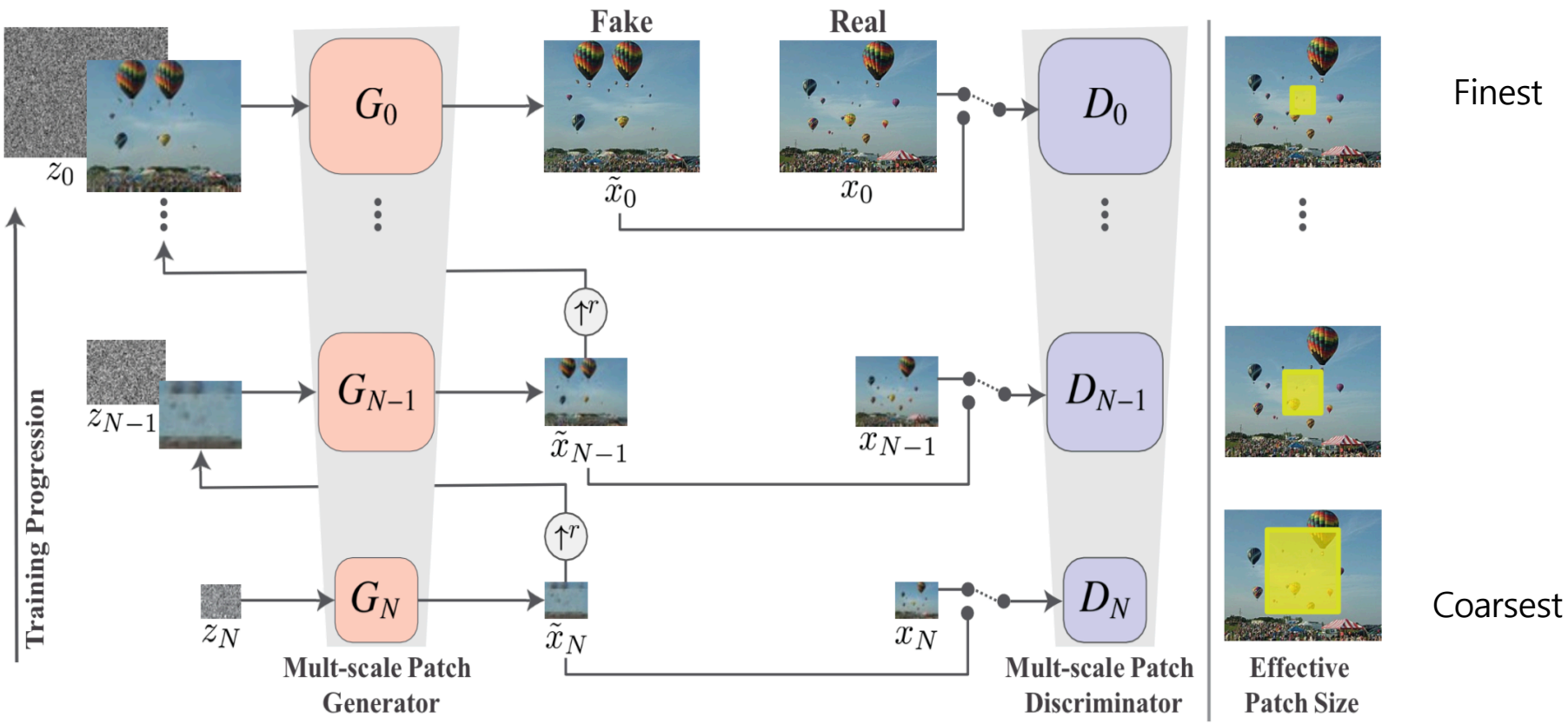
Model Architecture



$$\tilde{x}_N = G_N(z_N). \qquad n = N,$$

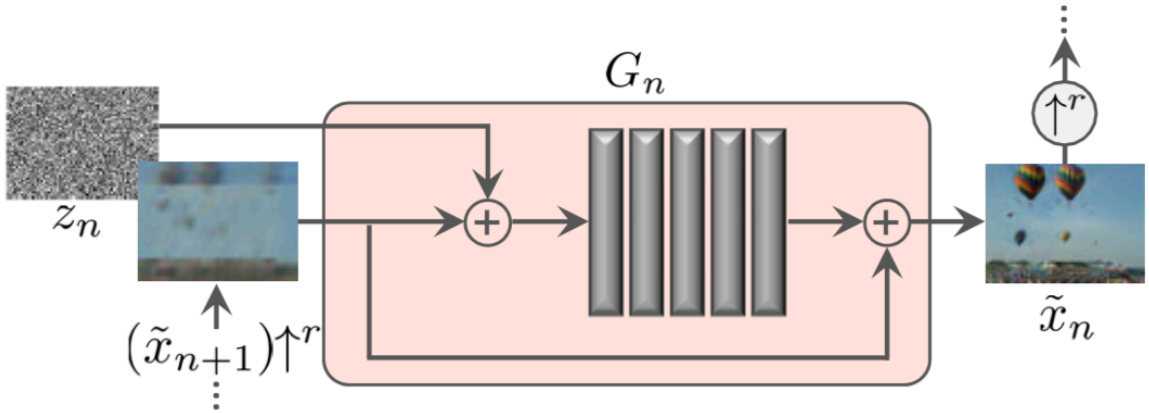
$$\tilde{x}_n = G_n\left(z_n, \left(\tilde{x}_{n+1}\right)\uparrow^r\right), \qquad n < N.$$

Model Architecture



- Train to capture the internal distribution of patches within the image
- Finer scale adds details that are not generated for previous scale
- All the generators have a similar architecture, only filters differs a little.

Model Architecture



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

- ψ_n is a fully conv net with 5 conv-blocks of Conv(3X)-BN-LeakyRelu.
- The role of the conv layer is to generate the missing details.
- Because they are fully convolutional, can generate images of arbitrary size and aspect ratio at test time.
- Light weight : takes only 30 minutes for one 1080Ti for an image of 256 X 256 size

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Training Methods

Objective Function for Nth GAN

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

Training Details

- Sequentially train multi-scale architecture, from the coarsest scale to the finest one.
- Once each GAN is trained, it is kept fixed.
- At each scale, the weights of the generator and discriminator are initialized to those from the previous trained scale.
- Train each scale for 2000 iterations. In each iteration, alternate between 3 gradient steps for the generator and 3 gradient steps for the discriminator

Objective Function for nth GAN

Adversarial Loss Term

$$L = \underbrace{\mathop{\mathbb{E}}_{\tilde{\boldsymbol{x}} \sim \mathbb{P}_g} [D(\tilde{\boldsymbol{x}})] - \mathop{\mathbb{E}}_{\boldsymbol{x} \sim \mathbb{P}_r} [D(\boldsymbol{x})]}_{\text{Original critic loss}} + \underbrace{\lambda \mathop{\mathbb{E}}_{\hat{\boldsymbol{x}} \sim \mathbb{P}_{\hat{\boldsymbol{x}}}} \left[(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1)^2 \right]}_{\text{Our gradient penalty}} .$$

- WGAN – GP (Wasserstein with Gradient Penalty)
  - set lambda as 0.1
- Patch GAN

Reconstruction Loss Term

$$\begin{aligned} \text{for } n < N, \quad & \mathcal{L}_{\text{rec}} = \|G_n(0, (\tilde{x}_{n+1}^{\text{rec}}) \uparrow^r) - x_n\|^2, \\ n = N, \quad & \mathcal{L}_{\text{rec}} = \|G_N(z^*) - x_N\|^2. \end{aligned}$$

$$\{z_N^{\text{rec}}, z_{N-1}^{\text{rec}} \ldots, z_0^{\text{rec}}\} = \{z^*, 0, \ldots, 0\}$$

- set alpha as 10

More Optimization Details

- Adam optimizer with a lr 0.0005 (decreased by a factor of 0.1 after 1600 iterations) and $\beta 1 = 0.5$, $\beta 2 = 0.999$.
- The generator's last conv-block activation at each scale is Tanh instead of ReLU.
- The descriminator's last conv-block at each scale includes neither normalization nor activation.
- Leaky Relu with slope 0.2 for negative values.

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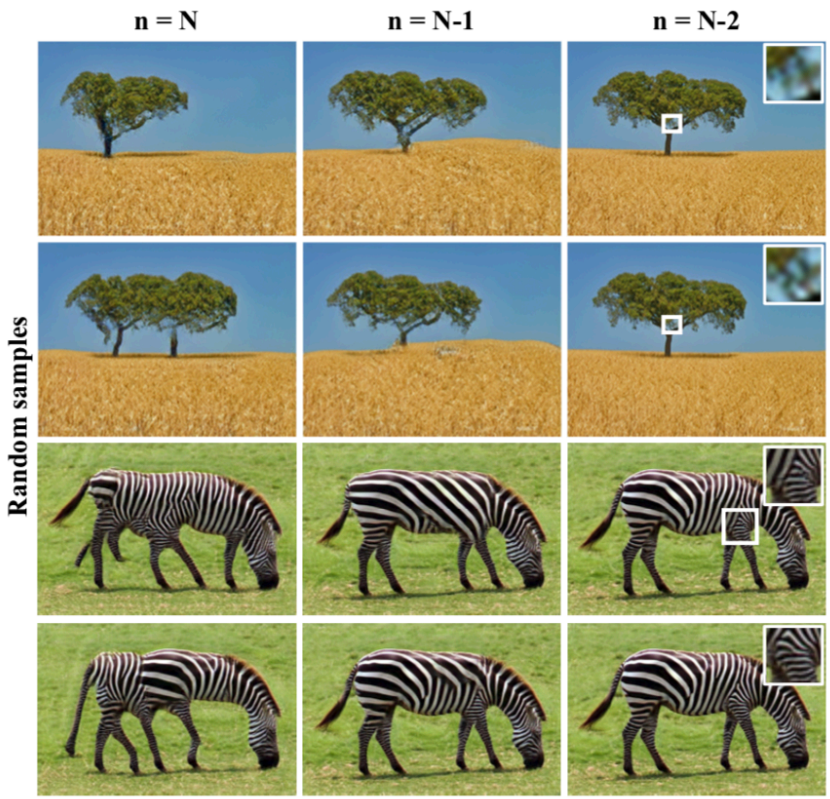
Effects of Scales at Test Time



Starting from coarsest scale(n = N)

- large variability in the global structure
- in case of large object, can lead to unrealistic samples

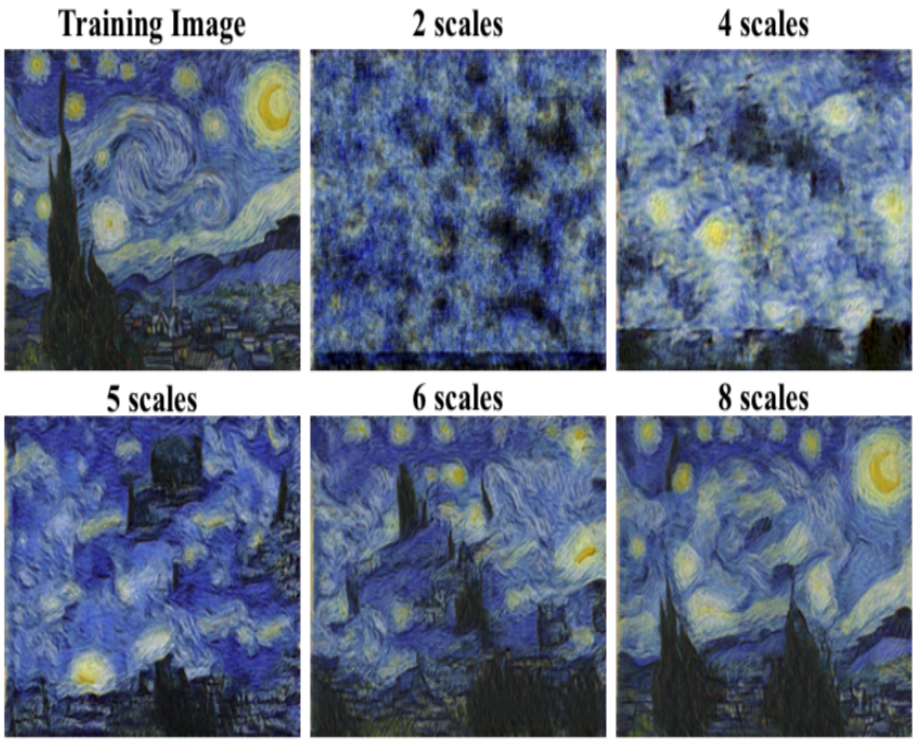
Starting from finer scale(n = N-1, N-2)

- keep the global structure intact
- alter only finer image features

Set noise, $Z = \{z_N^{rec}, \dots, z_{n+1}^{rec}, \mathrm{z_n}, \dots, \mathrm{z_0}\}$

Multi-Scale architecture can control the amount of variability, by choosing the scale from which to start at test time

Effects of Scales at Training Time



With a small number of scales

- can only capture fine textures.

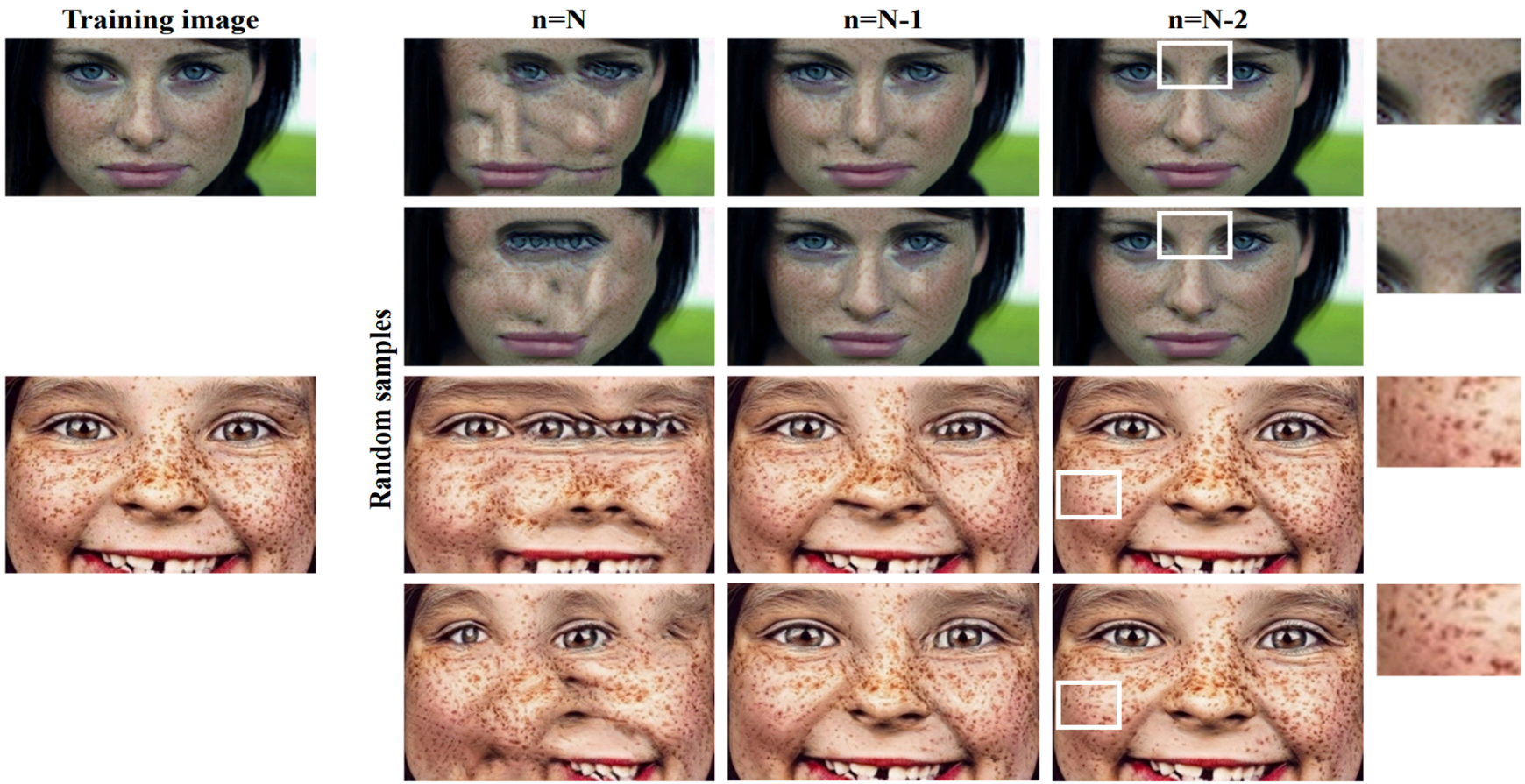
As a number of scales increase

- can capture larger structures and global arrangement of objects

With a small number of scales, the effective receptive field at coarsest level is smaller, allowing to capture only fine features

Failure Case

- SinGAN may produce unrealistic results when the global structure of the image is of high importance
- but, can avoid this by starting the generation process at a finer scale.



Quantitative Evaluation

Amazon Mechanical Turk (AMT)

- real / fake

1st Scale	Diversity	Survey	Confusion
N	0.5	paired	$21.45\% \pm 1.5\%$
		unpaired	$42.9\% \pm 0.9\%$
$N-1$	0.35	paired	$30.45\% \pm 1.5\%$
		unpaired	$47.04\% \pm 0.8\%$

Single Image Frechet Inception Distance (SIFID)

- feature distance at the output of the conv layer just before the second pooling layer

1st Scale	SIFID	Survey	SIFID/AMT Correlation
N	0.09	paired	-0.55
		unpaired	-0.22
$N-1$	0.05	paired	-0.56
		unpaired	-0.34

Quantitative Evaluation

AMT Survey Images

Real Image

Fake Image(low diversity)

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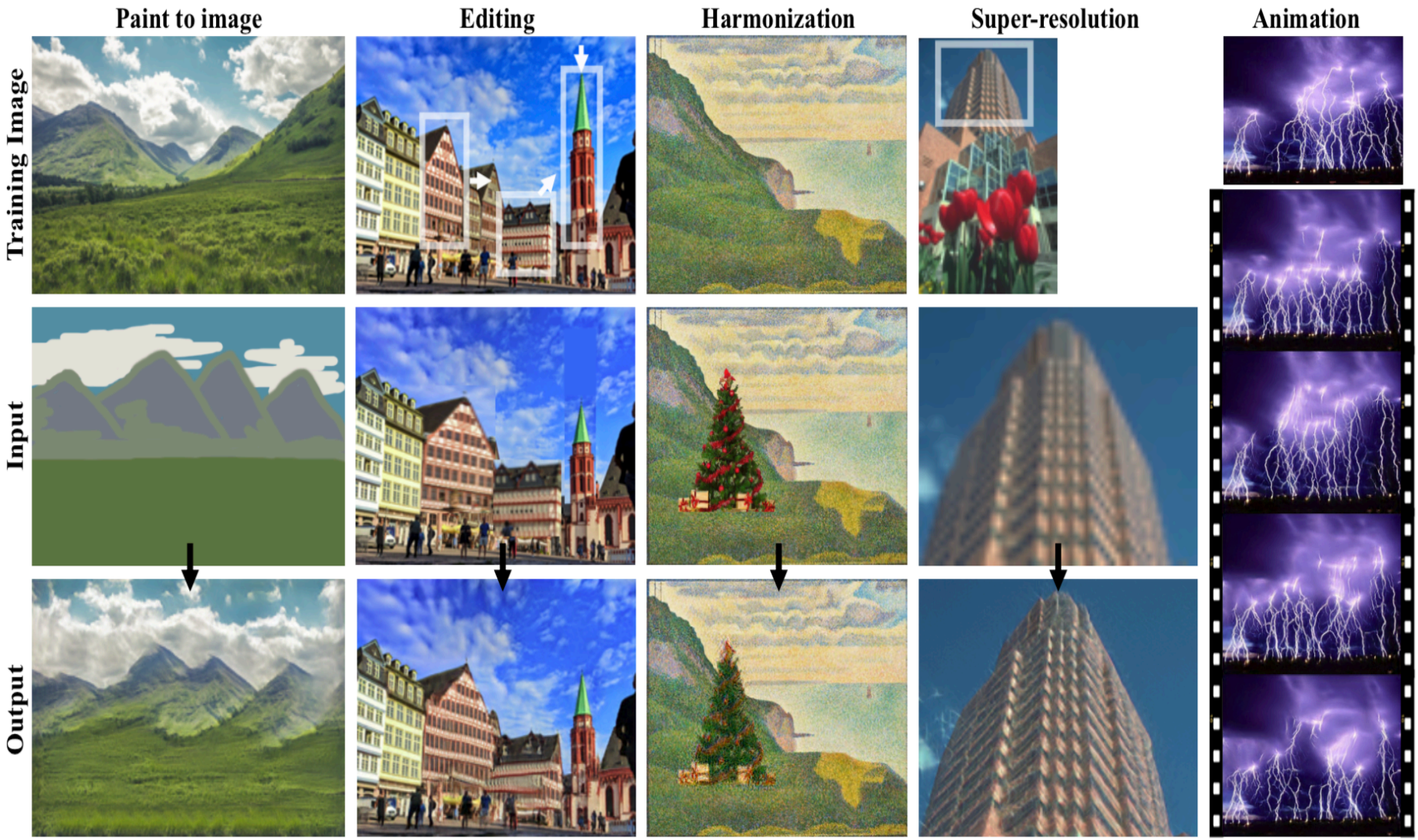
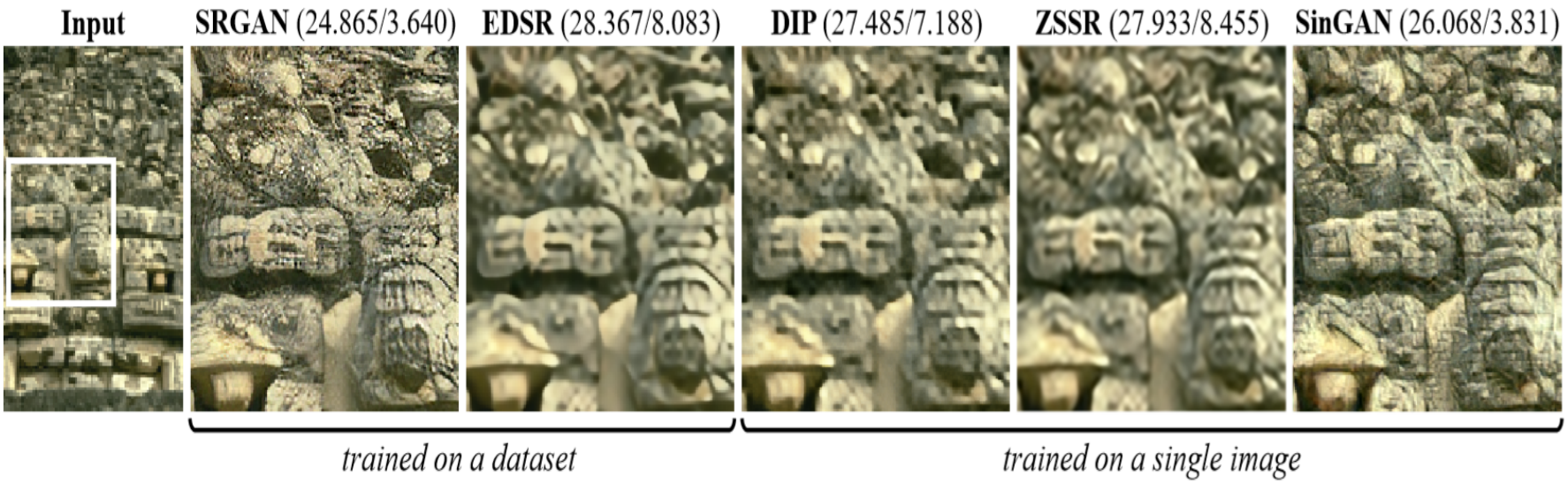
Various Applications



Applications

Super Resolution

- Increase the resolution of an input image by a factor s.
- Set reconstruction loss weight α to 100 and scale factor $\gamma = \sqrt[k]{s}$ for some $k \in \mathbb{N}$
- Train model on low-resolution image(LR)
- At test time, upsample LR images by γ and inject it to the last generator, G_0
- repeat this procedure k times



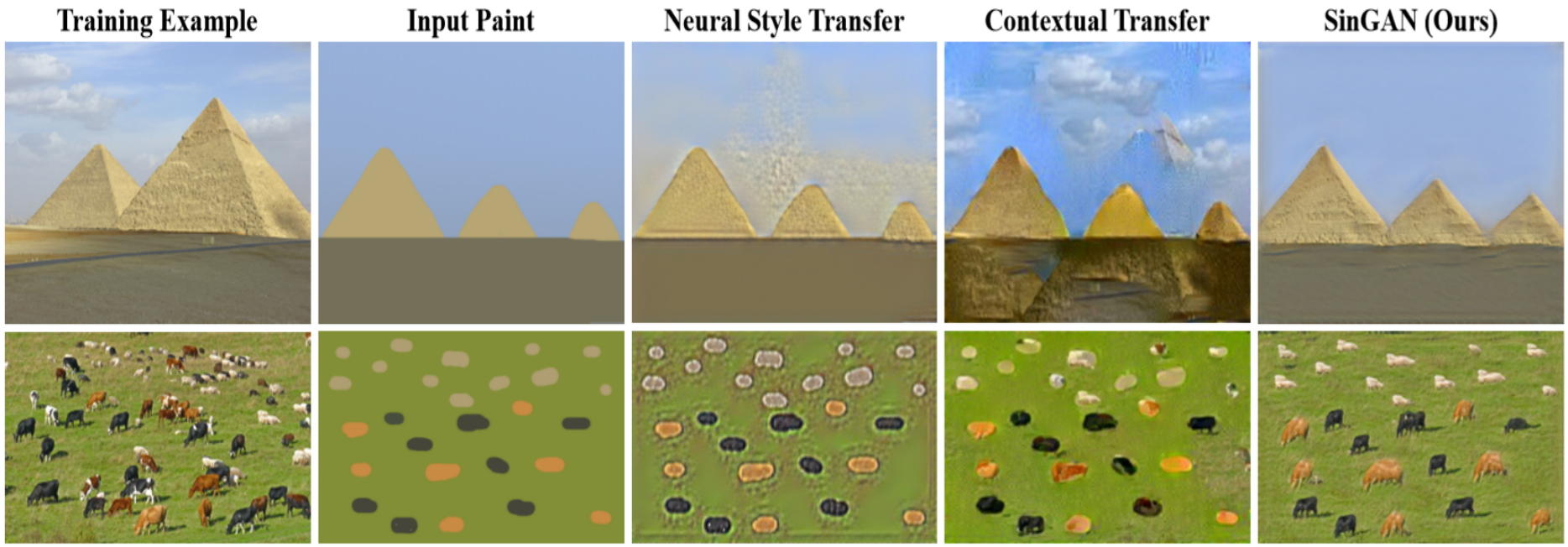
Applications

Super Resolution

Applications

Paint-to-Image

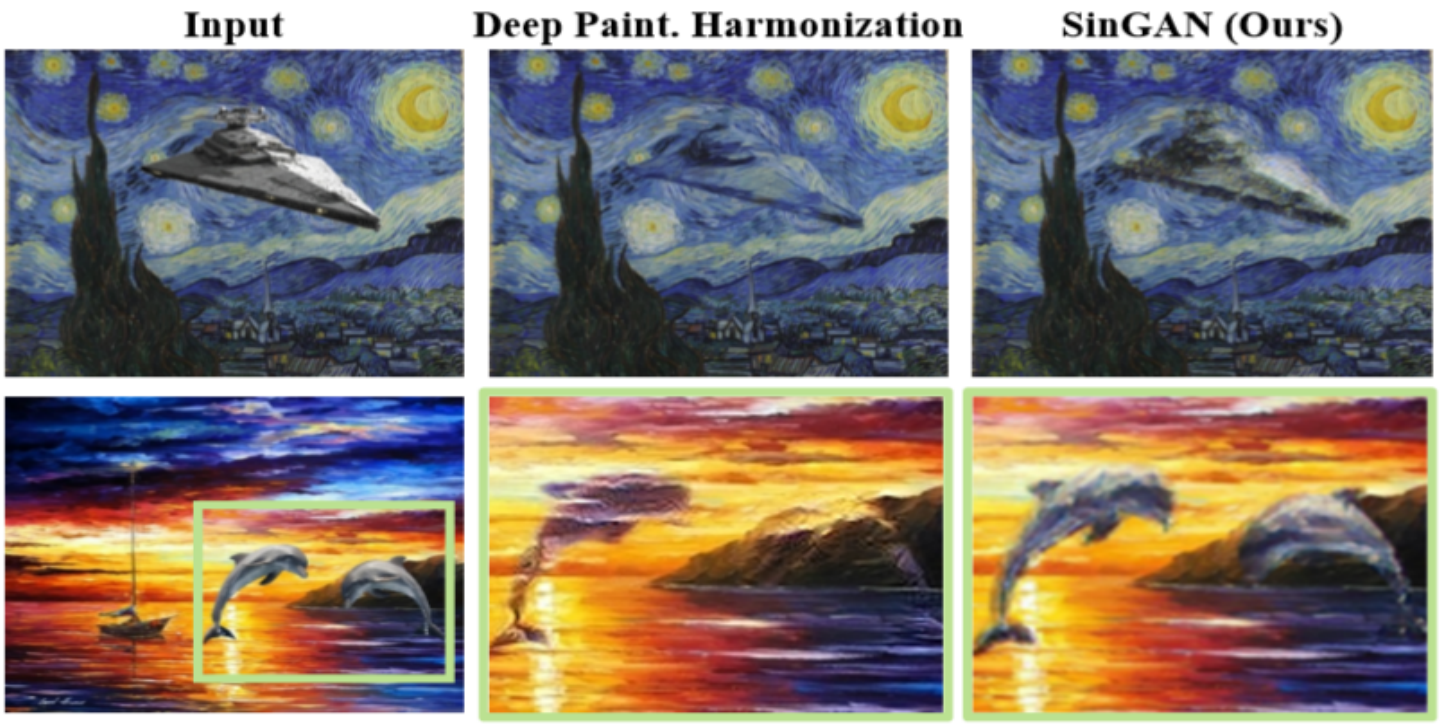
- Transfer a clipart into a photo-realistic image
- train as usual, background image
- downsample the clipart image and feed it into one of the coarse scales



Applications

Harmonization

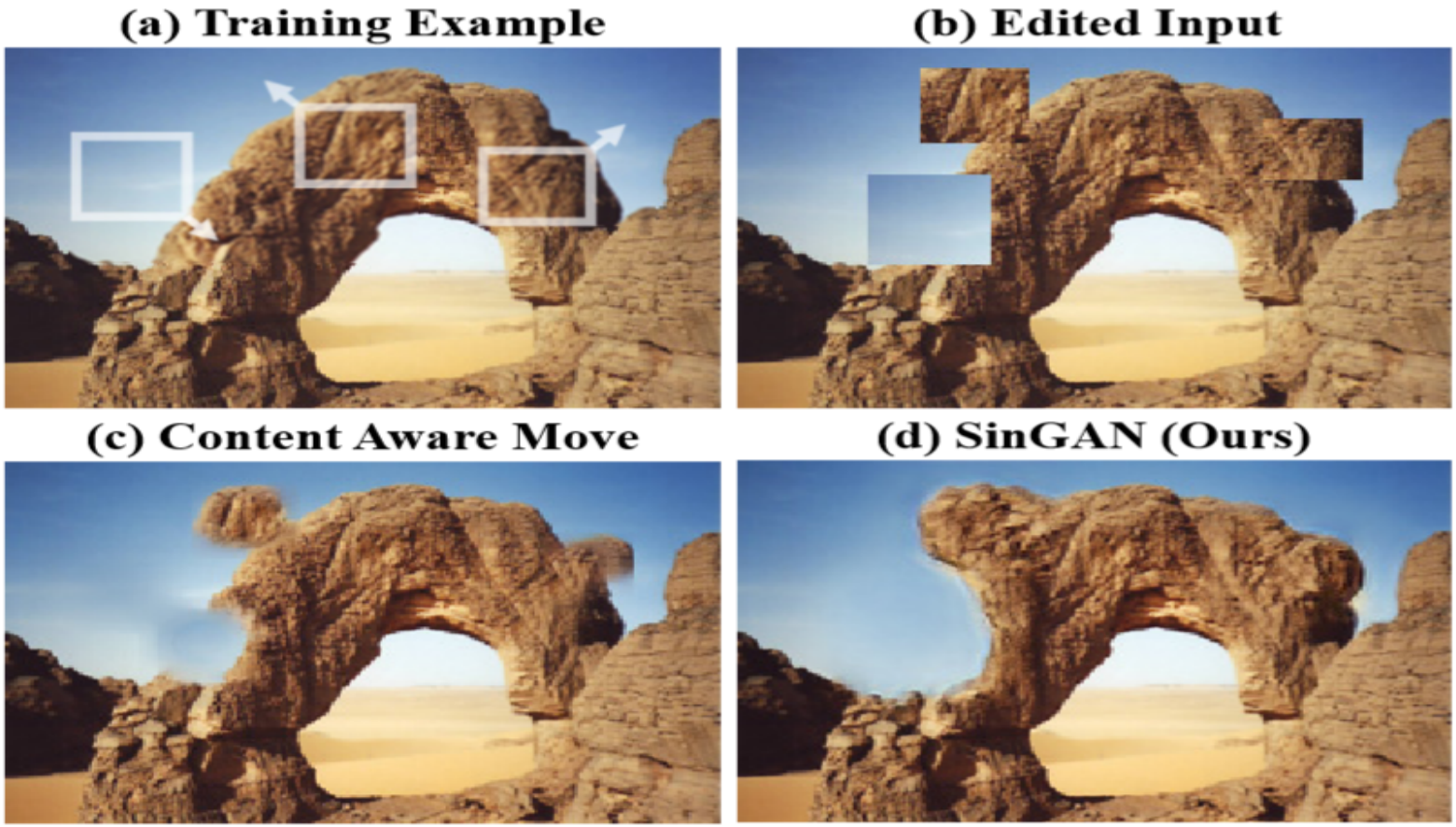
- Realistically blend a pasted object with a background image
- train as usual, background image
- downsample the composite and feed it into one of the coarse scales
- combine the generated image with the original background.



Applications

Editing

- Produce a seamless composite in which image regions have been copied and pasted in other locations



Applications

Single Image Animation

- Create a short video clip with realistic object motion, from a single input image
- Using SinGAN, can travel along the manifold of all appearances of the object
- Realistic effect is achieved by a random walk in z-space

https://www.youtube.com/watch?v=xk8bWLZk4DU&feature=youtu.be

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Conclusion

- unconditional generative model that can be learned from a single natural image
- contains a pyramid of fully convolutional GANs, each responsible for learning the patch distribution at a different scale of the image.
- generated samples are high quality and SinGAN can be used in a wide range of image manipulation tasks.
- Internal learning is inherently limited in terms of semantic diversity compared to externally trained generation methods.
- For example, if the training image contains a single dog, SinGAN will not generate samples of different dog breeds.

(My) Implementation

Paint to Image

Harmonization

https://github.com/bocharm/sinGAN

Q & A

감사합니다.