

# SinGAN : Learning a Generative Model from a Single Natural Image

20201102

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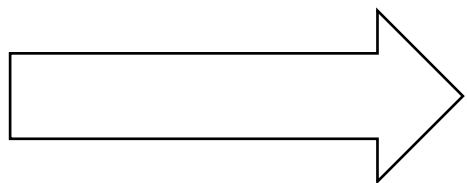
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# Intro

# SinGAN

## Intro

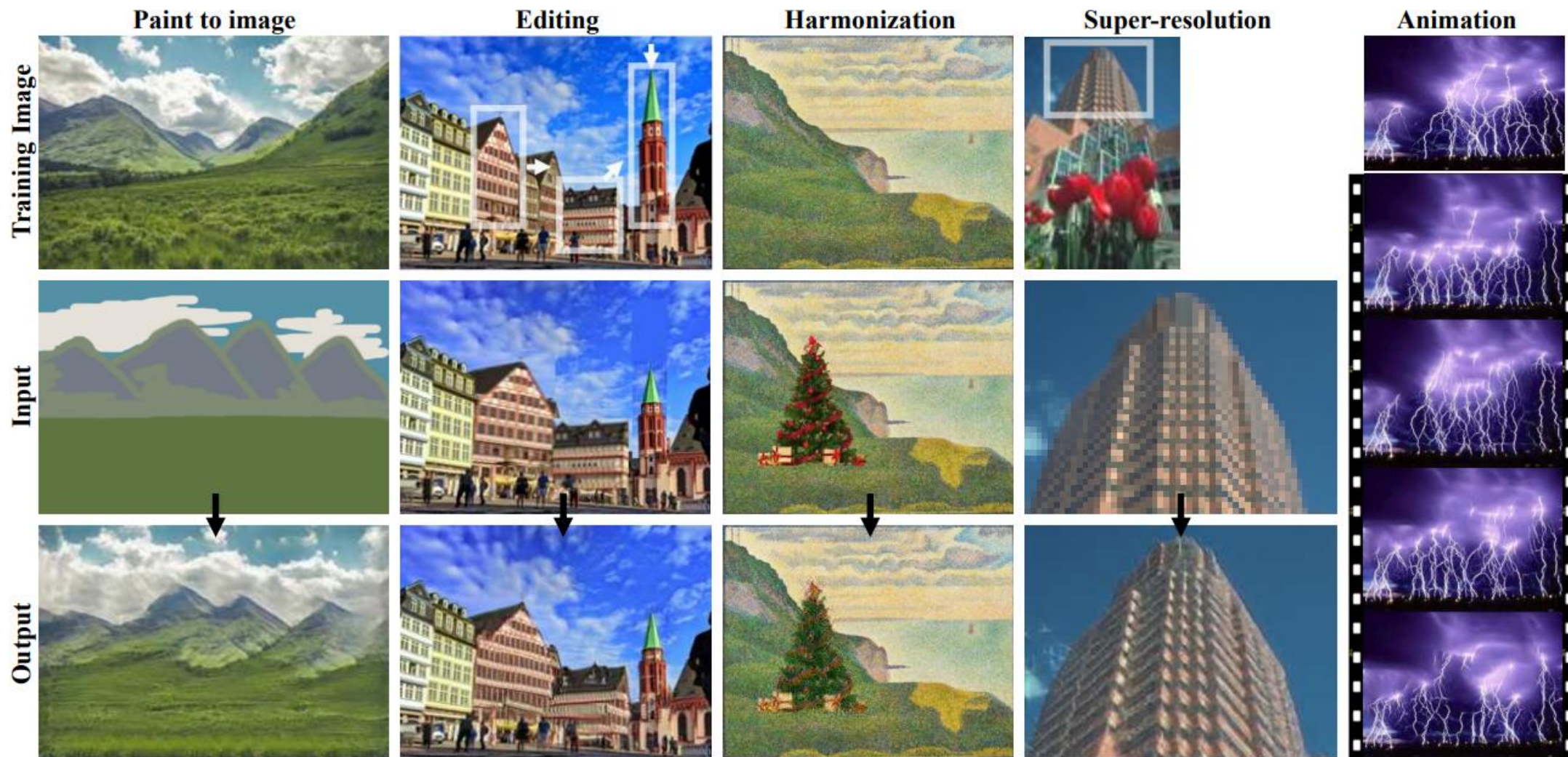
- 현재까지 대부분의 GAN모델은 특정 Domain ( 사람 얼굴, 침실 등 )에 한하여 Image를 생성했고, 많은 Data가 필요했다.
- 다양한 Class로 구성된 Dataset을 학습하는 것이 불가능 하였으며, Input 값에 조건을 걸어 주거나 Task ( Super Resolution, Inpainting 등 ) 를 한정하여 연구가 진행되었다.



적은 수의 Image만 가지고 (혹은 1장) GAN을 학습할 수 있을까?

# SinGAN

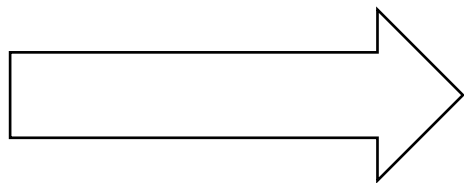
## Intro



# SinGAN

## Method

- SinGAN의 목표는 Single Training Image의 내부 분포를 배울 수 있는 Unconditional Generative Model을 형성하는 것

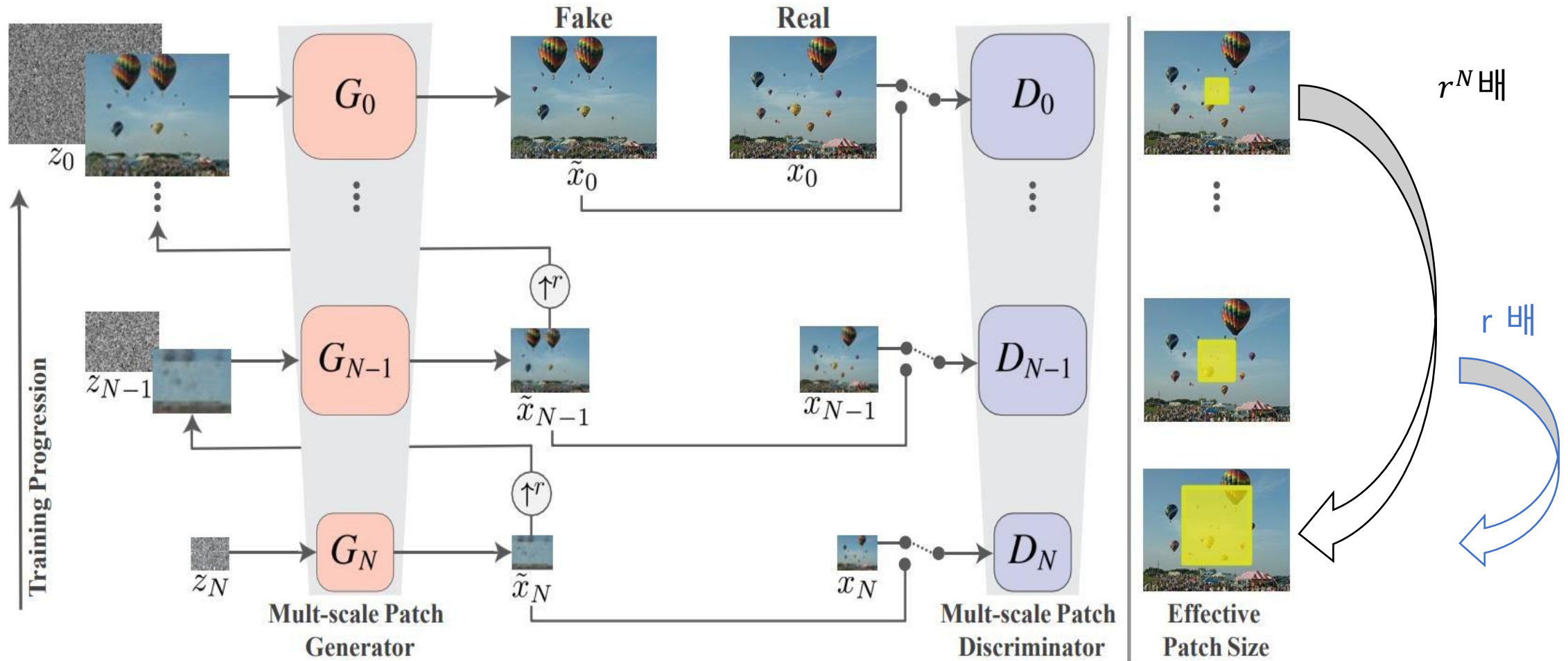


Image의 Global한 특징부터 Texture, Object의 세부적인 정보까지  
학습 필요

## Method

# SinGAN

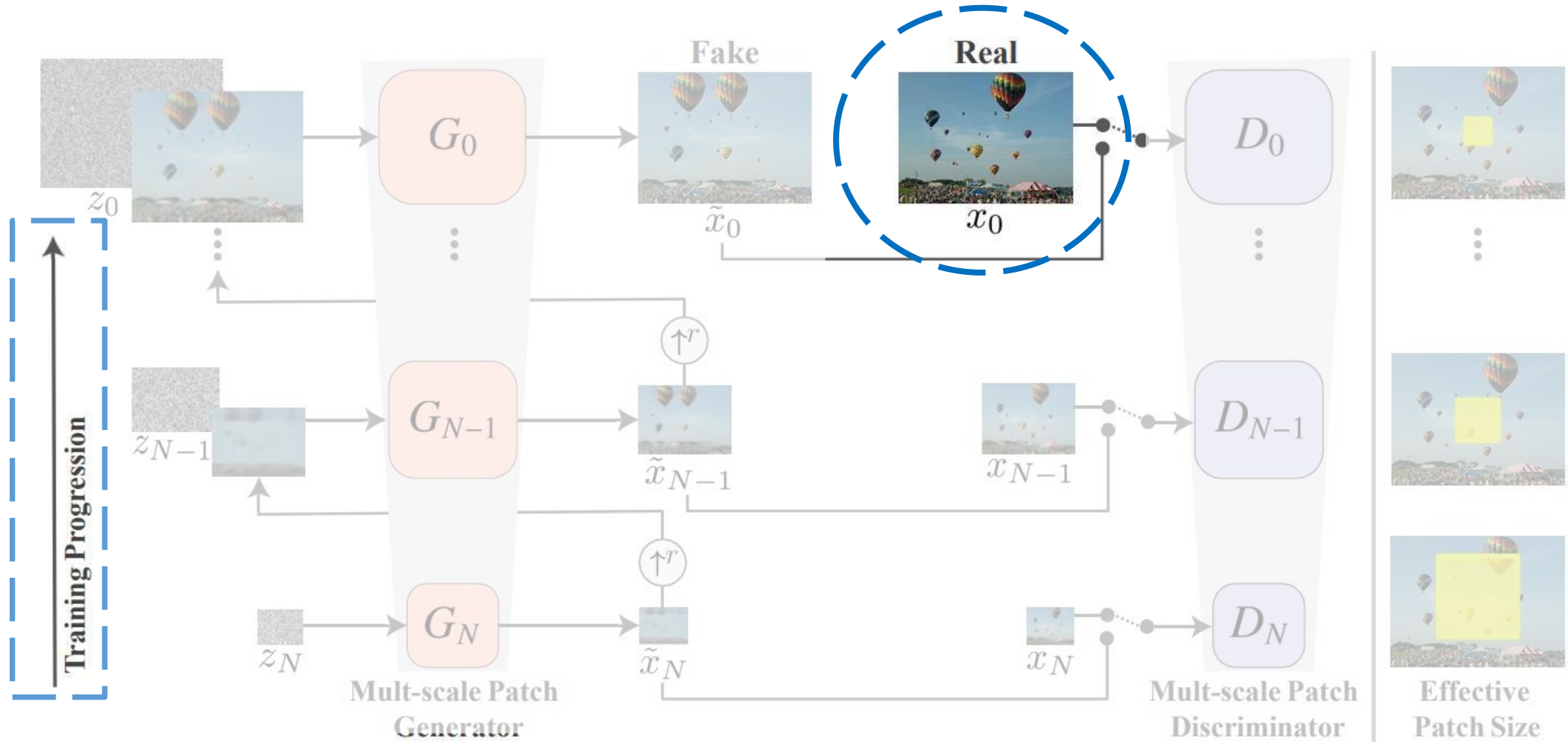
## Model





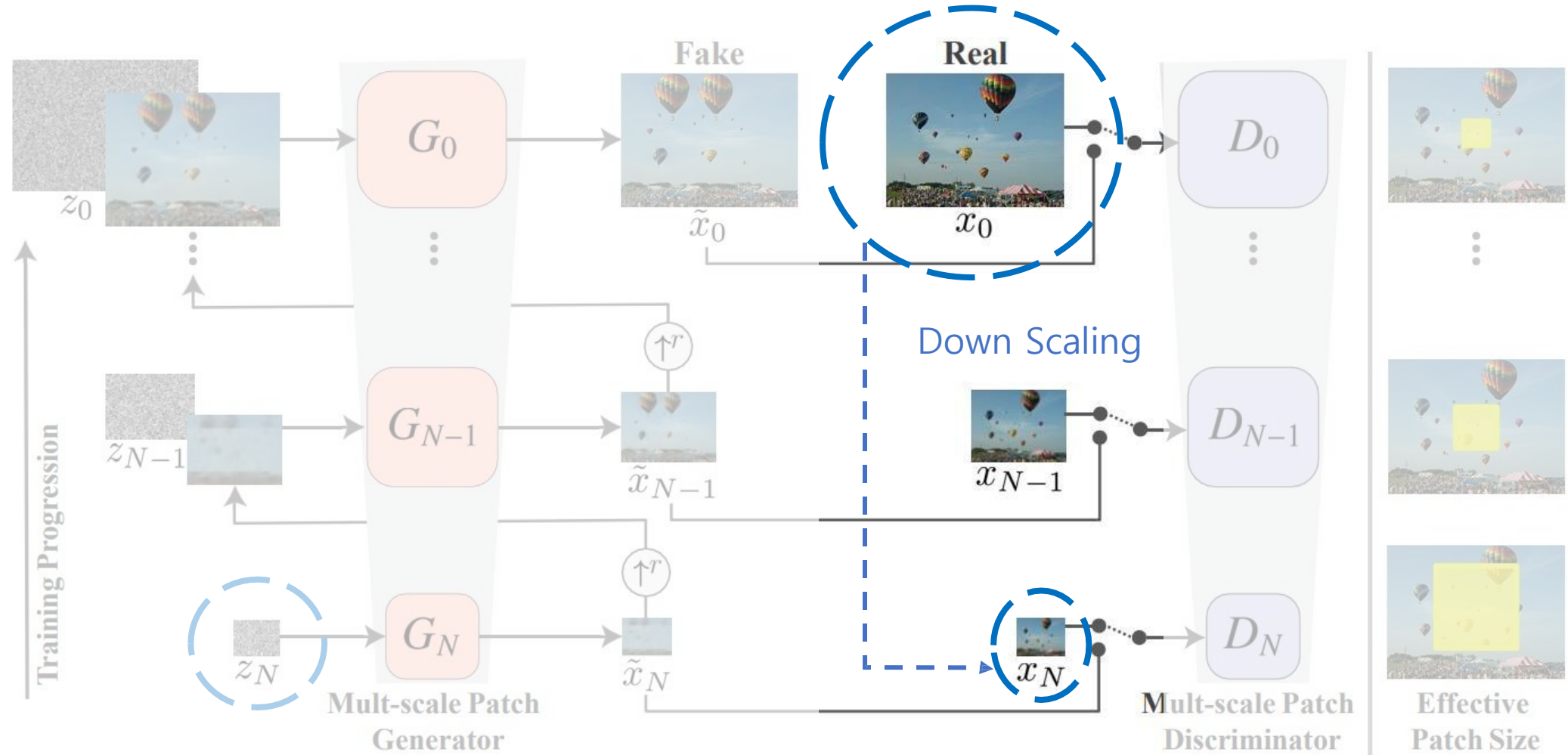
# SinGAN

Model



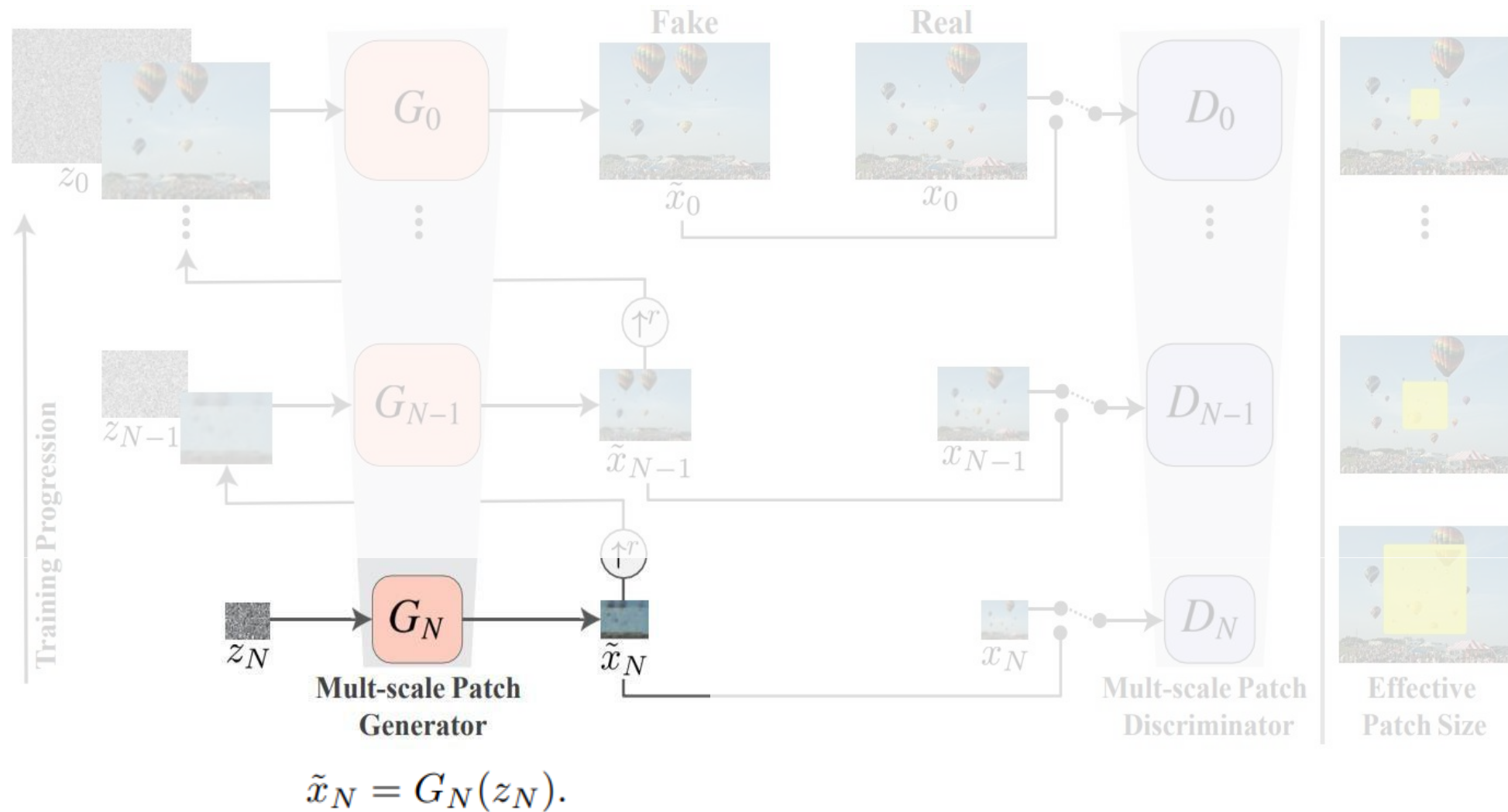
# SinGAN

Model



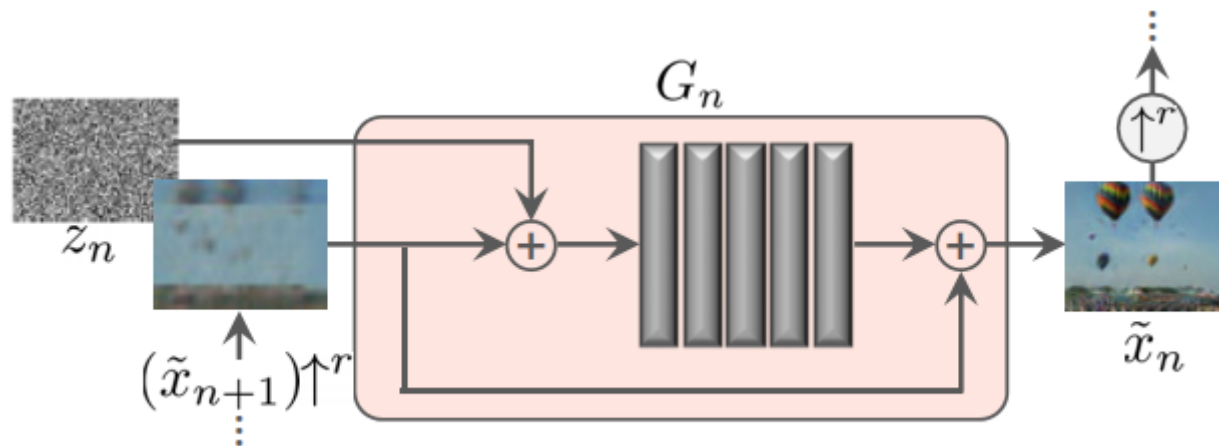
# SinGAN

## Model



# SinGAN

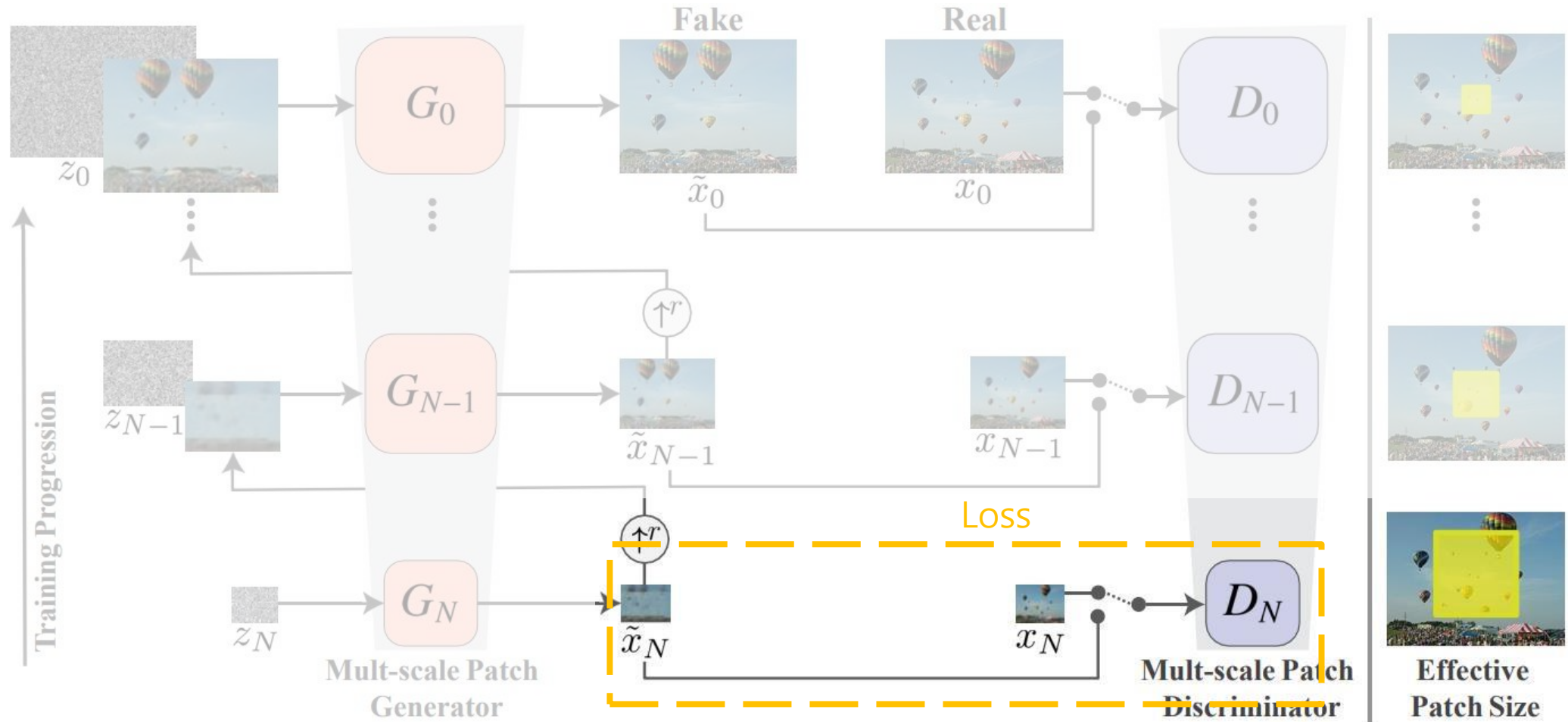
## Model



- 3x3 Conv-BatchNorm-LeakyReLU 를 5번 반복한 간단한 Fully-Convolutional 구조
- 제일 Coarse한 Generator는 32개의 Kernel을 사용하였고, 4개의 Scale이 증가할 때마다 Kernel 수를 2배로 증가

# SinGAN

Model



# SinGAN

## Model

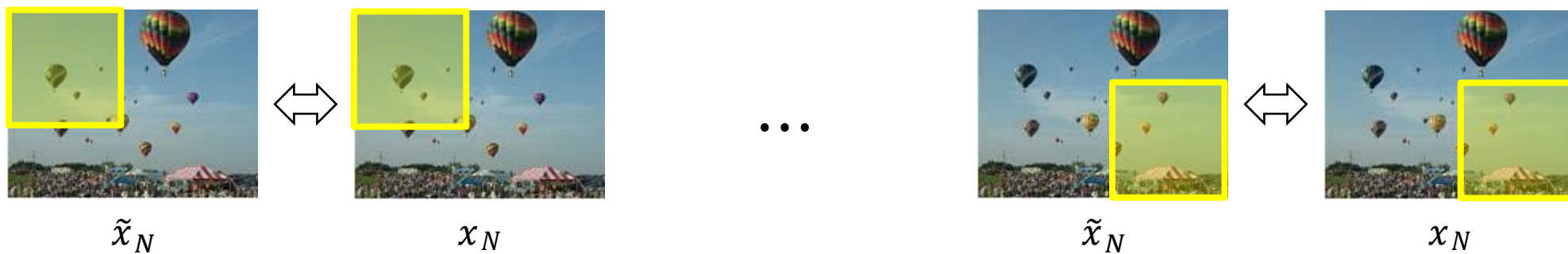
$$\min_{G_n} \max_{D_n} \mathcal{L}_{\text{adv}}(G_n, D_n) + \alpha \mathcal{L}_{\text{rec}}(G_n).$$

- Loss Function은 Adversarial Loss와 Reconstruction Loss로 구성

# SinGAN

Model

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



- Adversarial Loss는 PatchGAN 원리를 이용
- 영역별 구체적인 정보를 학습하기 위해 사용
- 한 부분의 데이터를 알아내기 위해 이웃하고 있는 데이터들의 관계를 파악하여 판단
- $L_{adv}(\cdot)$  : WGAN - GP

# SinGAN

## Model

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

- Reconstruction Loss에는 L2 Norm Loss 사용
- Global 한 정보를 얻기 위해 사용

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

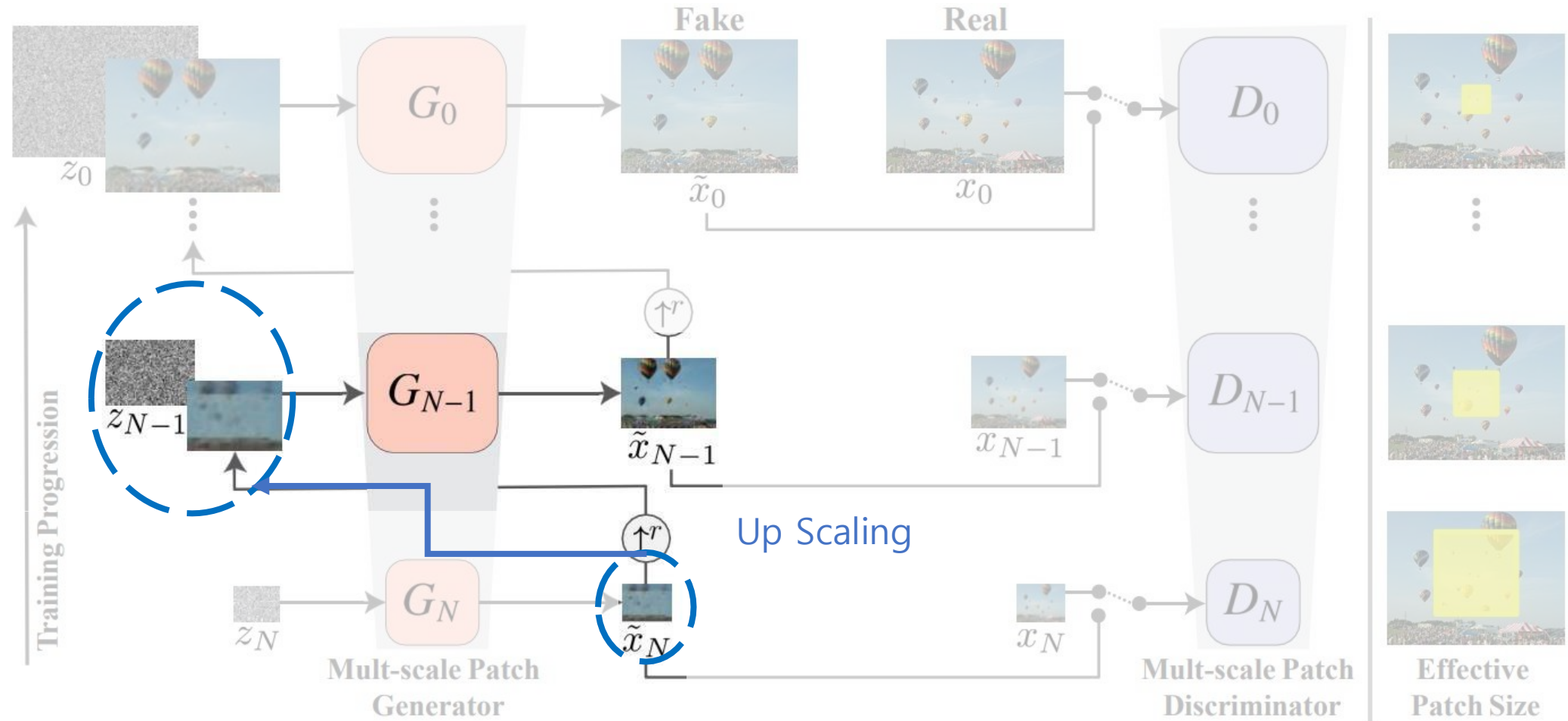
$$\text{for } n < N, \quad \mathcal{L}_{\text{rec}} = \|G_n(0, (\tilde{x}_{n+1}^{\text{rec}}) \uparrow^r) - x_n\|^2$$

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



# SinGAN

Model



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

## Result

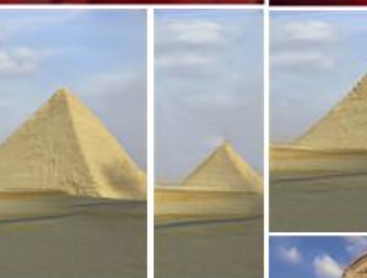
# SinGAN

Result

Training image



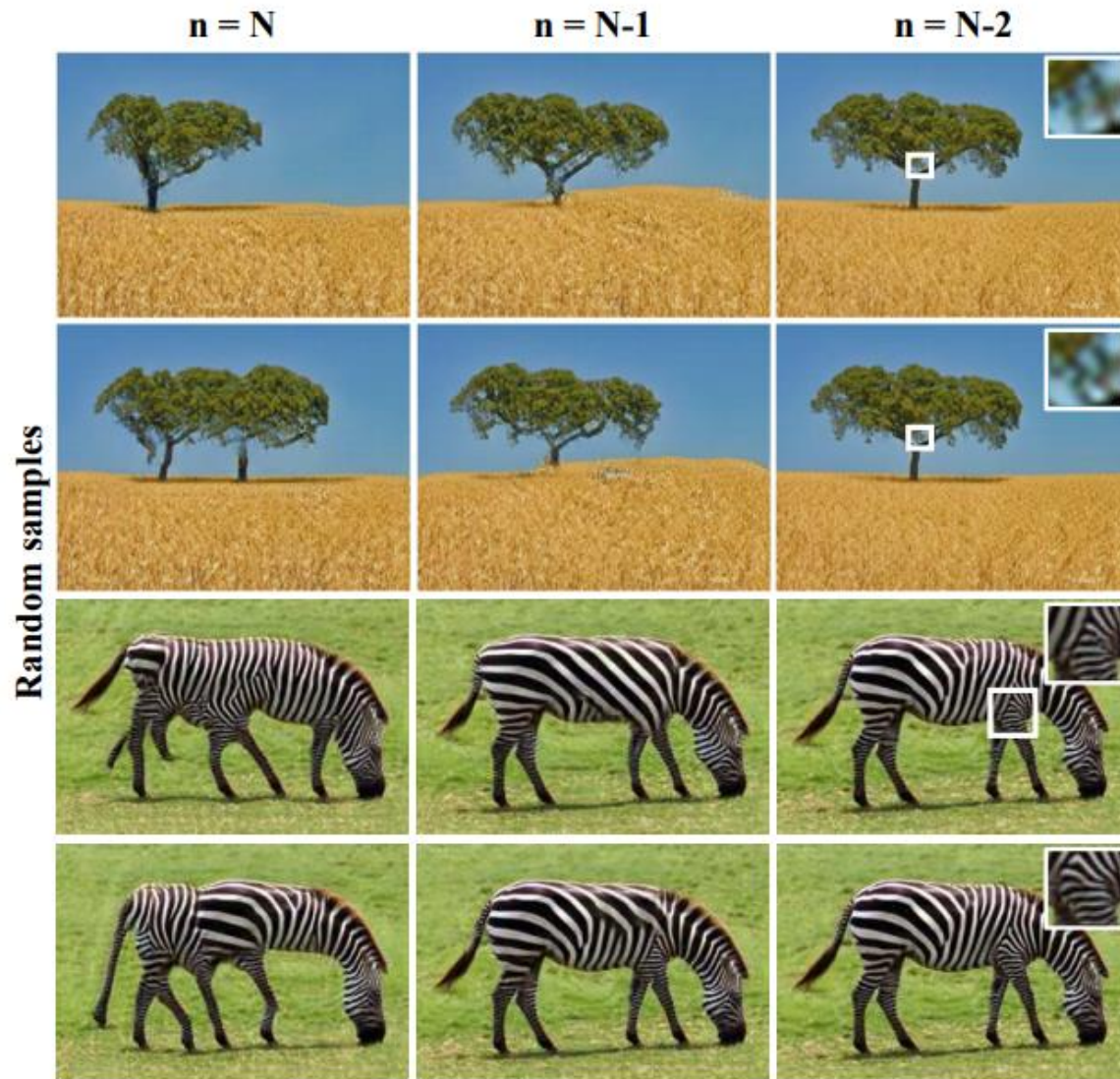
Random samples from a *single* image





# SinGAN

## Result

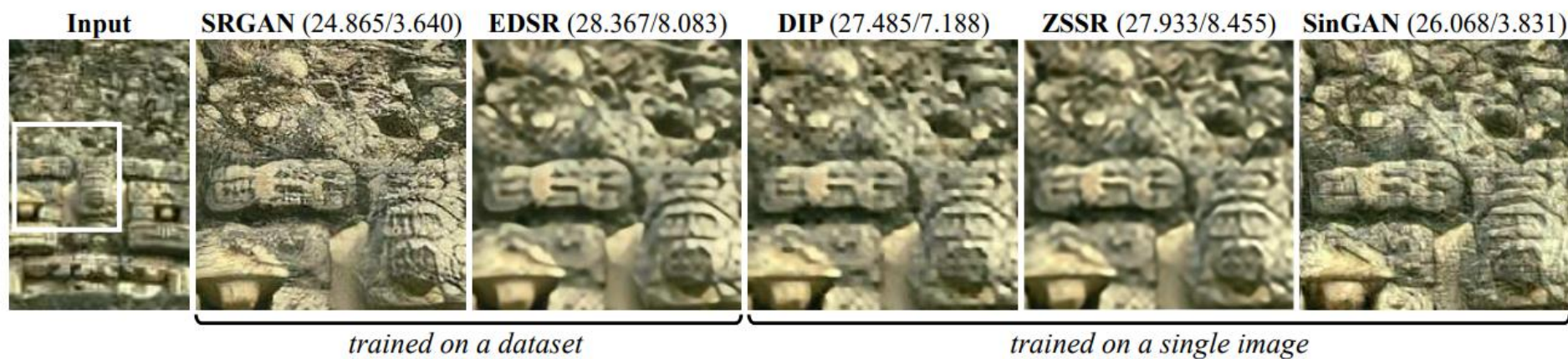


1st Scale	Diversity	Survey	Confusion
$N$	0.5	paired unpaired	$21.45\% \pm 1.5\%$ $42.9\% \pm 0.9\%$
$N - 1$	0.35	paired unpaired	$30.45\% \pm 1.5\%$ $47.04\% \pm 0.8\%$

- Unpaired : Fake Image와 GT를 동시에 보여주지 않고 1초간격으로 보여줌
- Paired : Fake Image와 GT를 동시에 보여줌

# SinGAN

## Result



	External methods		Internal methods		
	SRGAN	EDSR	DIP	ZSSR	SinGAN
RMSE	16.34	12.29	13.82	13.08	16.22
NIQE	3.41	6.50	6.35	7.13	3.71

## Reference

# SinGAN

## Method

- [https://openaccess.thecvf.com/content\\_ICCV\\_2019/papers/Shaham\\_SinGAN\\_Learning\\_a\\_Generative\\_Model\\_From\\_a\\_Single\\_Natural\\_Image\\_ICCV\\_2019\\_paper.pdf](https://openaccess.thecvf.com/content_ICCV_2019/papers/Shaham_SinGAN_Learning_a_Generative_Model_From_a_Single_Natural_Image_ICCV_2019_paper.pdf)
- [https://hoya012.github.io/blog/ICCV-2019\\_review\\_2/](https://hoya012.github.io/blog/ICCV-2019_review_2/)
- <https://www.youtube.com/watch?v=-f8sz8AExdc>