Diffusion Models Beat GANs on Image Synthesis

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Introduction

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Introduction

- Only GAN can be conditional with class input

  → Conditional diffusion model

- GAN's benefit : trade off diversity and fidelity

  → bring it to diffusion models

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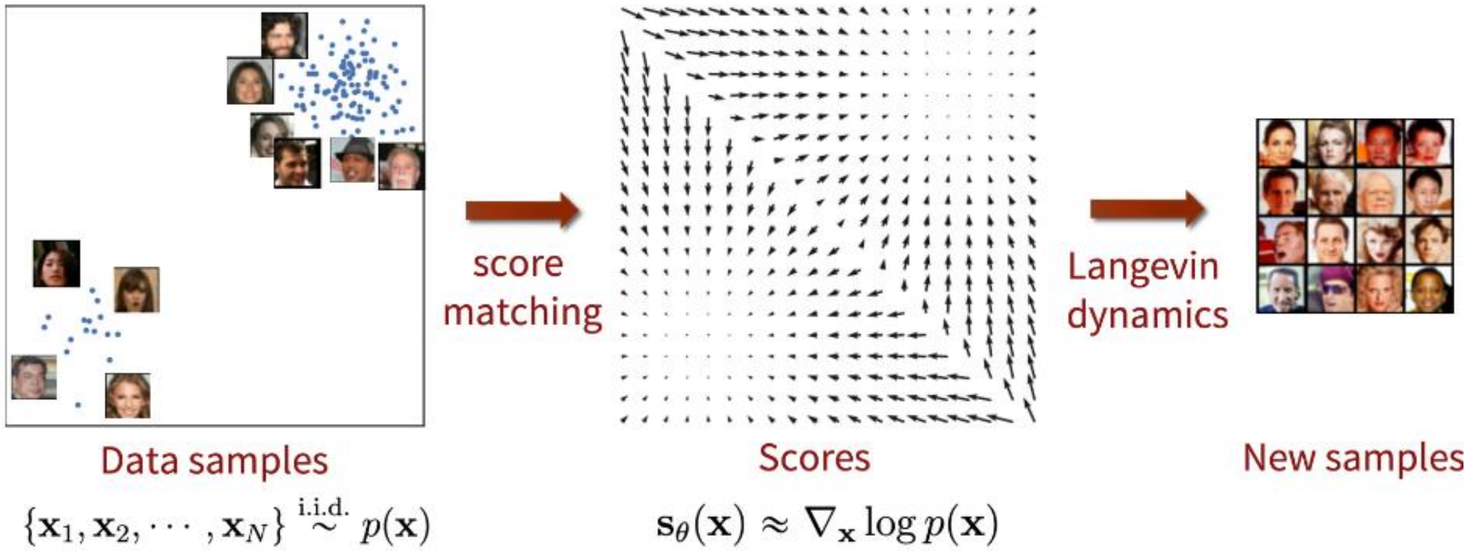
Background

Background

Score-Matching

Score = Gradient of log(pdf)
$= \nabla_x logp(x)$



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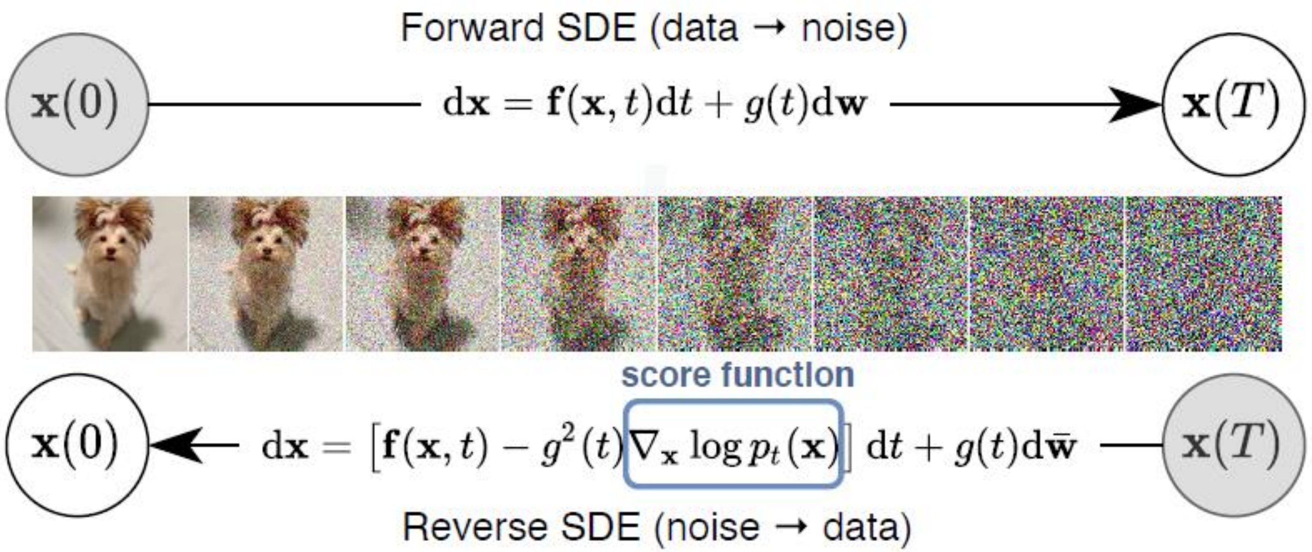
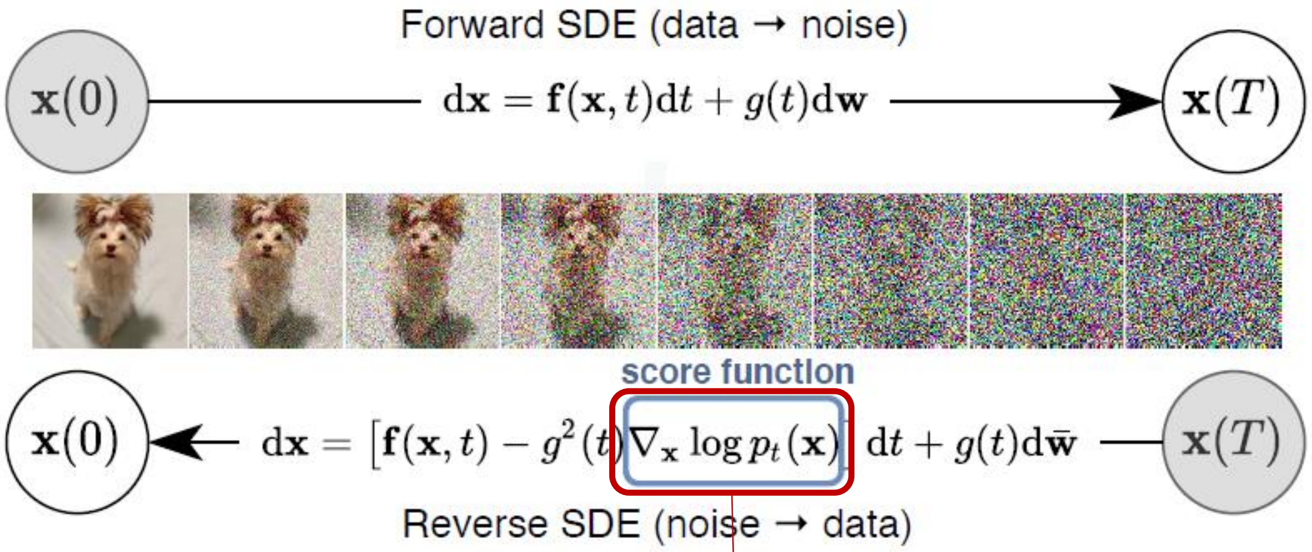
Background

Score based Generative Model through SDE



Background

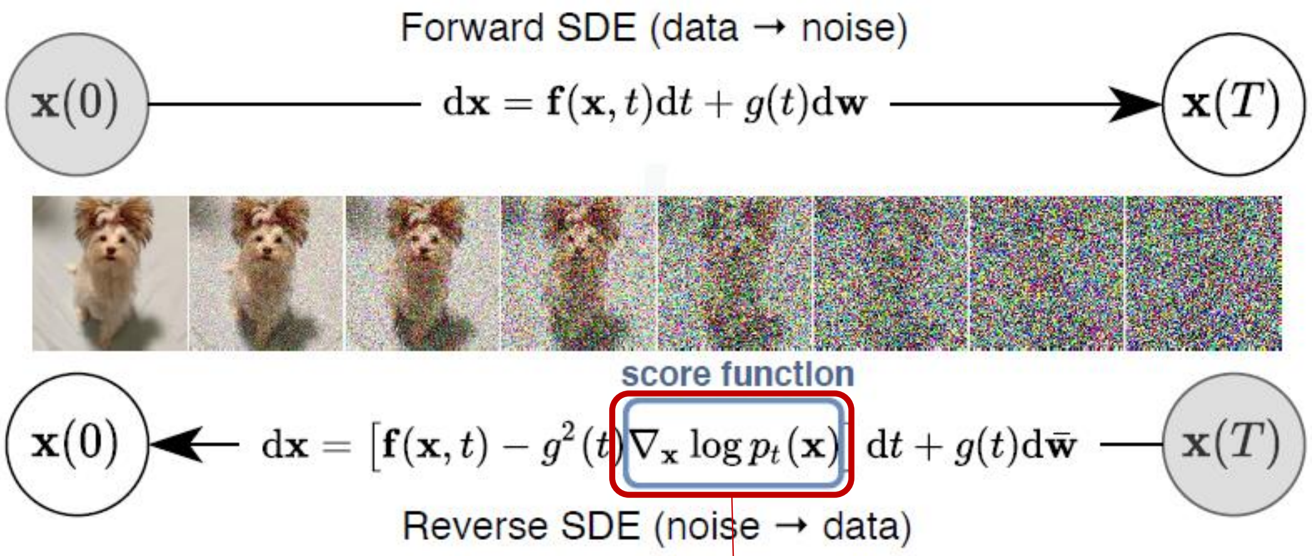
Classifier Guidance



Classifier Guidance $\boxed{\nabla_{x_t} \log(p_\theta(x_t|y))}$

Background

Classifier Guidance



Classifier Guidance $\boxed{\nabla_{x_t}\log(p_\theta(x_t|y))}$

class

+ discrete time

Classifier Guidance

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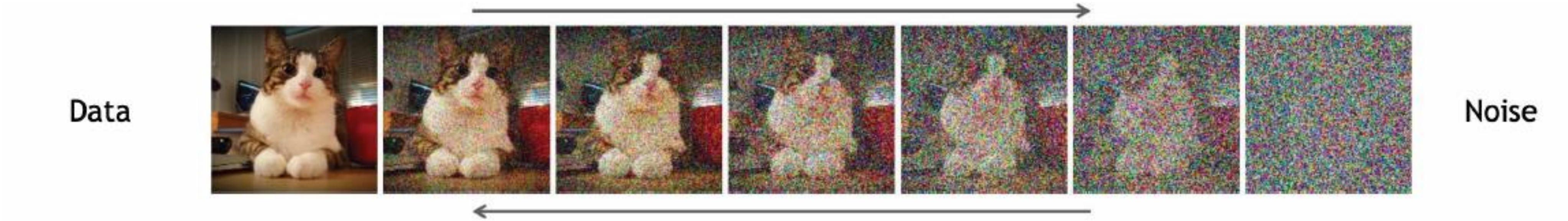
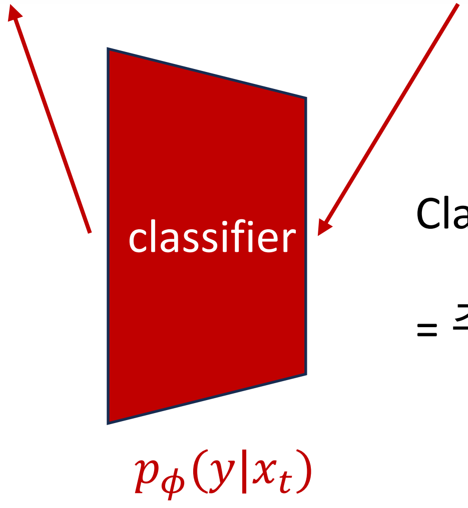
Classifier Guidance

Overview





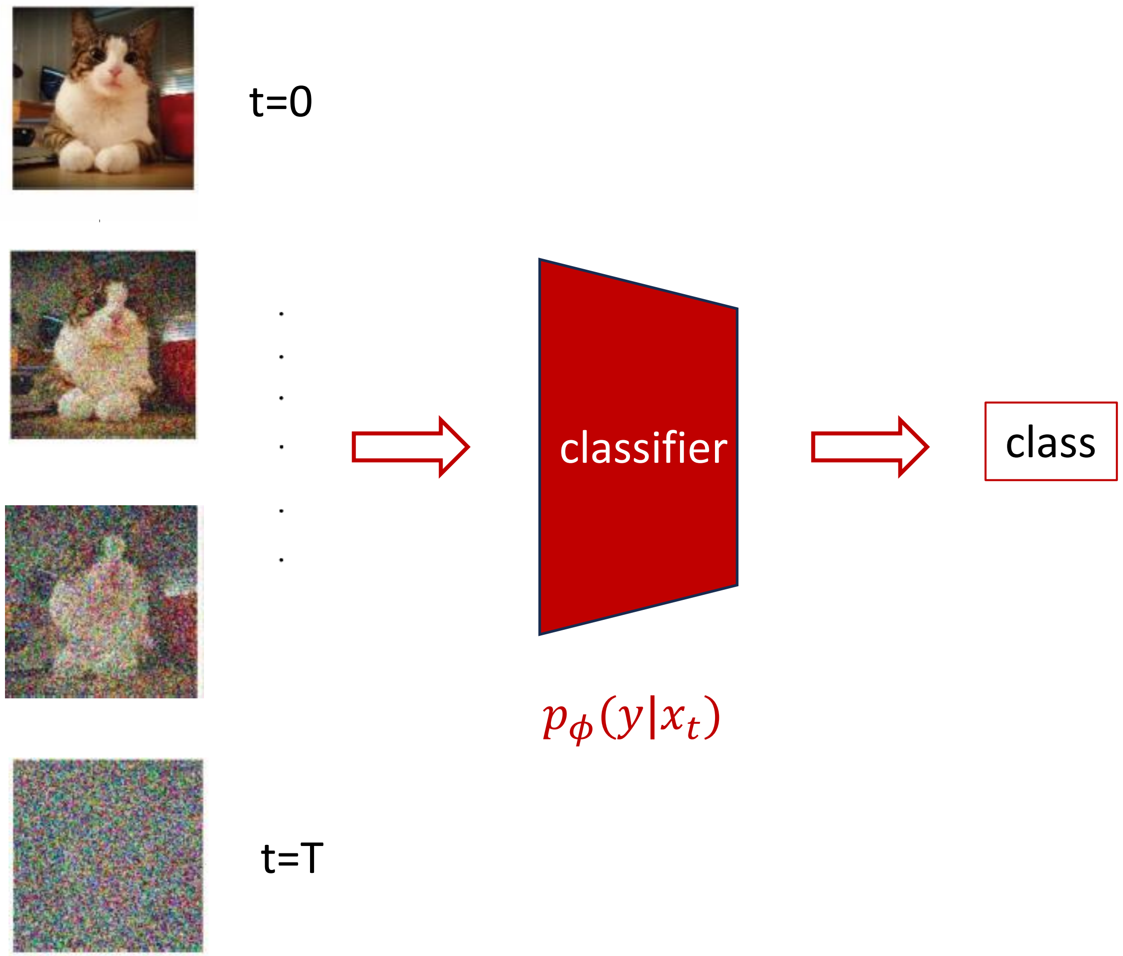
Classifier가 reverse process에 score 역할

= 주어진 class를 생성하도록 reconstruct 방향 조절

Classifier Guidance

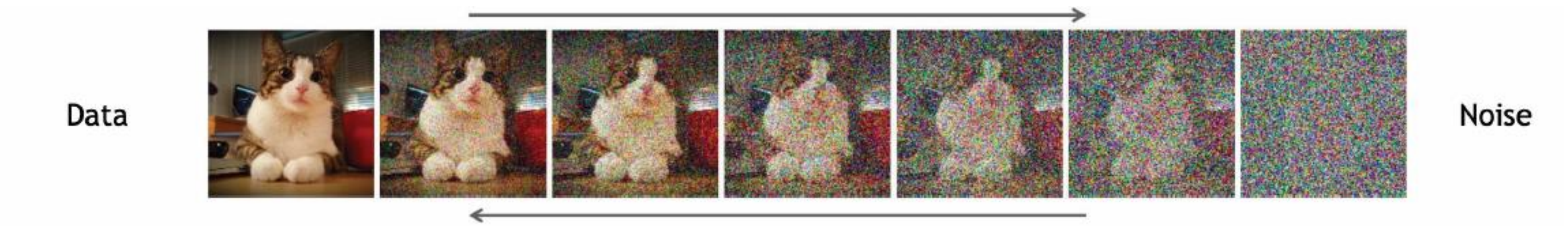
Training Classifier

- CNN based model
- Input noisy image
  with timestep embedding
- Predict class of given image



Classifier Guidance

Conditional Sampling for DDPM



x_t $\quad\quad$ x_{t+1}

$$\boxed{p_{\theta,\phi}(x_t|x_{t+1}, y)}$$

Classifier Guidance

Conditional Sampling for DDPM

$$\boxed{p_{\theta,\phi}(x_t|x_{t+1},y)} = Z\underbrace{p_\theta(x_t|x_{t+1})}_{\text{noise}}\underbrace{p_\phi(y|x_t)}_{\text{classifier}}$$

noise

$$p_\theta(x_t|x_{t+1}) = \mathcal{N}(\mu,\Sigma)$$
$$\log p_\theta(x_t|x_{t+1}) = -\frac{1}{2}(x_t-\mu)^T\Sigma^{-1}(x_t-\mu)+C$$

classifier

$$\log p_\phi(y|x_t) \approx \log p_\phi(y|x_t)|_{x_t=\mu} + (x_t-\mu)\nabla_{x_t}\log p_\phi(y|x_t)|_{x_t=\mu}$$
$$= (x_t-\mu)g + C_1$$

$g = \nabla_{x_t}\log p_\phi(y|x_t)$: Score of Classifier

$$\log(p_\theta(x_t|x_{t+1})p_\phi(y|x_t)) \approx -\frac{1}{2}(x_t-\mu)^T\Sigma^{-1}(x_t-\mu)+(x_t-\mu)g+C_2$$
$$= -\frac{1}{2}(x_t-\mu-\Sigma g)^T\Sigma^{-1}(x_t-\mu-\Sigma g)+C_3$$
$$= \log p(z) + C_4, z\sim\mathcal{N}(\mu+\Sigma g,\Sigma)$$

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Classifier Guidance

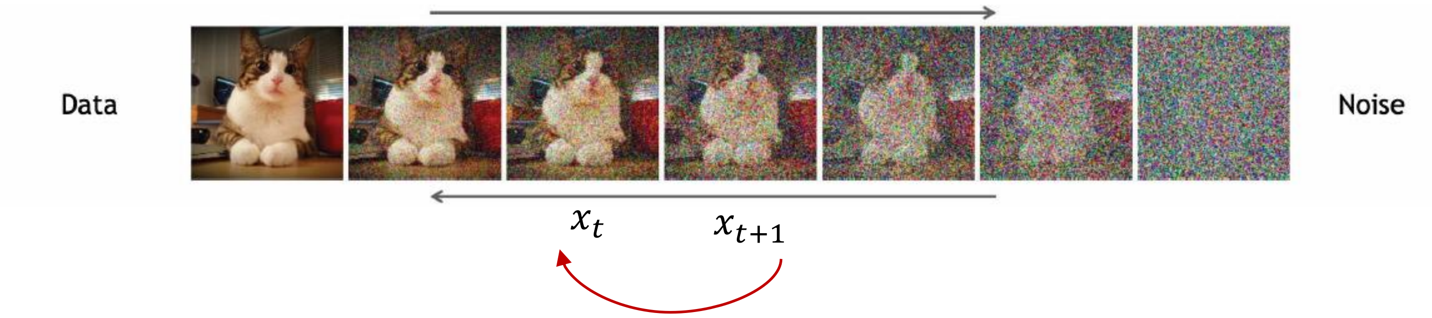
Conditional Sampling for DDPM

$$\boxed{\log(p_\theta(x_t|x_{t+1})p_\phi(y|x_t)) = \log p(z) + C_4, z \sim \mathcal{N}(\mu + \Sigma g, \Sigma)}$$

$$g = \nabla_{x_t} \log p_\phi(y|x_t)$$

Algorithm 1 Classifier guided diffusion sampling, given a diffusion model $(\mu_\theta(x_t), \Sigma_\theta(x_t))$, classifier $p_\phi(y|x_t)$, and gradient scale s.

Input: class label y, gradient scale s
$x_T \leftarrow$ sample from $\mathcal{N}(0, \mathbf{I})$
for all t from T to 1 **do**
  $\mu, \Sigma \leftarrow \mu_\theta(x_t), \Sigma_\theta(x_t)$
  $x_{t-1} \leftarrow$ sample from $\mathcal{N}(\mu + s\Sigma\, \nabla_{x_t} \log p_\phi(y|x_t), \Sigma)$
end for
return x_0



Classifier Guidance

Conditional Sampling for DDIM

- Stochastic diffusion process cannot be applied to deterministic sampling methods like DDIM.

$$
\begin{aligned}
\nabla_{x_t} \log(p_\theta(x_t) p_\phi(y|x_t)) &= \nabla_{x_t} \log p_\theta(x_t) + \nabla_{x_t} \log p_\phi(y|x_t) \\
&= -\frac{1}{\sqrt{1-\bar{\alpha}_t}} \underbrace{\epsilon_\theta(x_t)}_{\text{Noise prediction model}} + \underbrace{\nabla_{x_t} \log p_\phi(y|x_t)}_{\text{Score of classifier}}
\end{aligned}
$$

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Classifier Guidance

Conditional Sampling for DDIM

Algorithm 2 Classifier guided DDIM sampling, given a diffusion model $\epsilon_\theta(x_t)$, classifier $p_\phi(y|x_t)$, and gradient scale s.

Input: class label y, gradient scale s
$x_T \leftarrow$ sample from $\mathcal{N}(0, \mathbf{I})$
for all t from T to 1 **do**
  $\hat{\epsilon} \leftarrow \epsilon_\theta(x_t) - \sqrt{1-\bar{\alpha}_t}\,\nabla_{x_t} \log p_\phi(y|x_t)$
  $x_{t-1} \leftarrow \sqrt{\bar{\alpha}_{t-1}}\left(\frac{x_t - \sqrt{1-\bar{\alpha}_t}\hat{\epsilon}}{\sqrt{\bar{\alpha}_t}}\right) + \sqrt{1-\bar{\alpha}_{t-1}}\hat{\epsilon}$
end for
return x_0

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Classifier Guidance

Scaling Classifier Gradients

trade off

Conditional	Guidance	Scale	FID	sFID	IS	Precision	Recall
✗	✗		26.21	**6.35**	39.70	0.61	0.63
✗	✓	1.0	33.03	6.99	32.92	0.56	**0.65**
✗	✓	10.0	**12.00**	10.40	**95.41**	**0.76**	0.44
✓	✗		10.94	6.02	100.98	0.69	**0.63**
✓	✓	1.0	**4.59**	**5.25**	186.70	0.82	0.52
✓	✓	10.0	9.11	10.93	**283.92**	**0.88**	0.32

Table 4: Effect of classifier guidance on sample quality. Both conditional and unconditional models were trained for 2M iterations on ImageNet 256×256 with batch size 256.

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Classifier Guidance

Scaling Classifier Gradients

Figure 3: Samples from an unconditional diffusion model with classifier guidance to condition on the class "Pembroke Welsh corgi". Using classifier scale 1.0 (left; FID: 33.0) does not produce convincing samples in this class, whereas classifier scale 10.0 (right; FID: 12.0) produces much more class-consistent images.

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Result

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Result

SOTA image Synthesis

Figure 6: Samples from BigGAN-deep with truncation 1.0 (FID 6.95, left) vs samples from our diffusion model with guidance (FID 4.59, middle) and samples from the training set (right).

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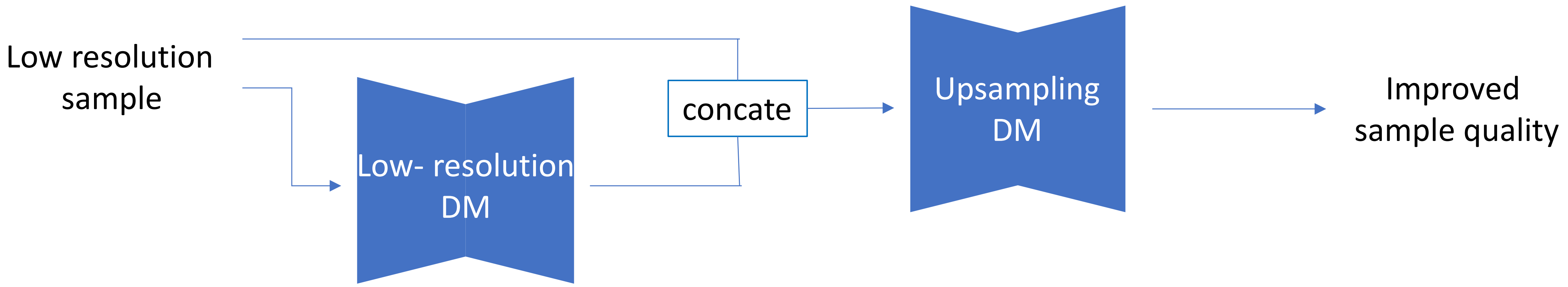
Result

Comparision to Upsampling



Limitation

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Limitation

- Slower than GAN at sampling time
  (multiple denoising step)

- Limited to labeled dataset

  → no effective strategy for trading off diversity and fidelity

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