Towards One-step Diffusion and Flow

From Consistency Model to Flow Map Models

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What Will We Cover Today?

- Recap Diffusion Models and Flow Matching
- **Consistency Models**
- Flow Maps Models: **Consistency Trajectory Models**, **MeanFlow**

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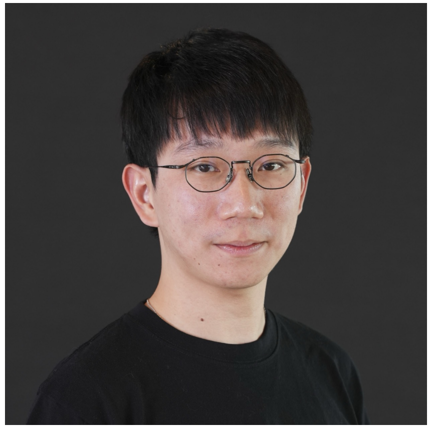

Chieh-Hsin (Jesse) Lai

Research Scientist at Sony AI

Kaiming He

Associate Professor at MIT

What is Generative Model Learning?

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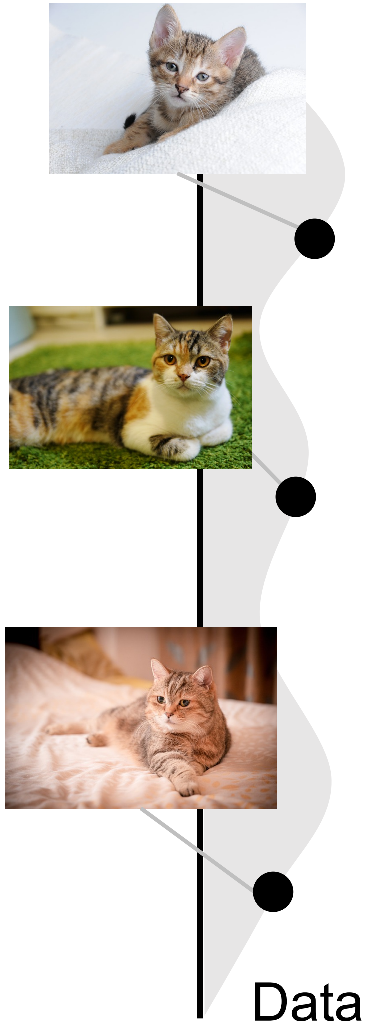
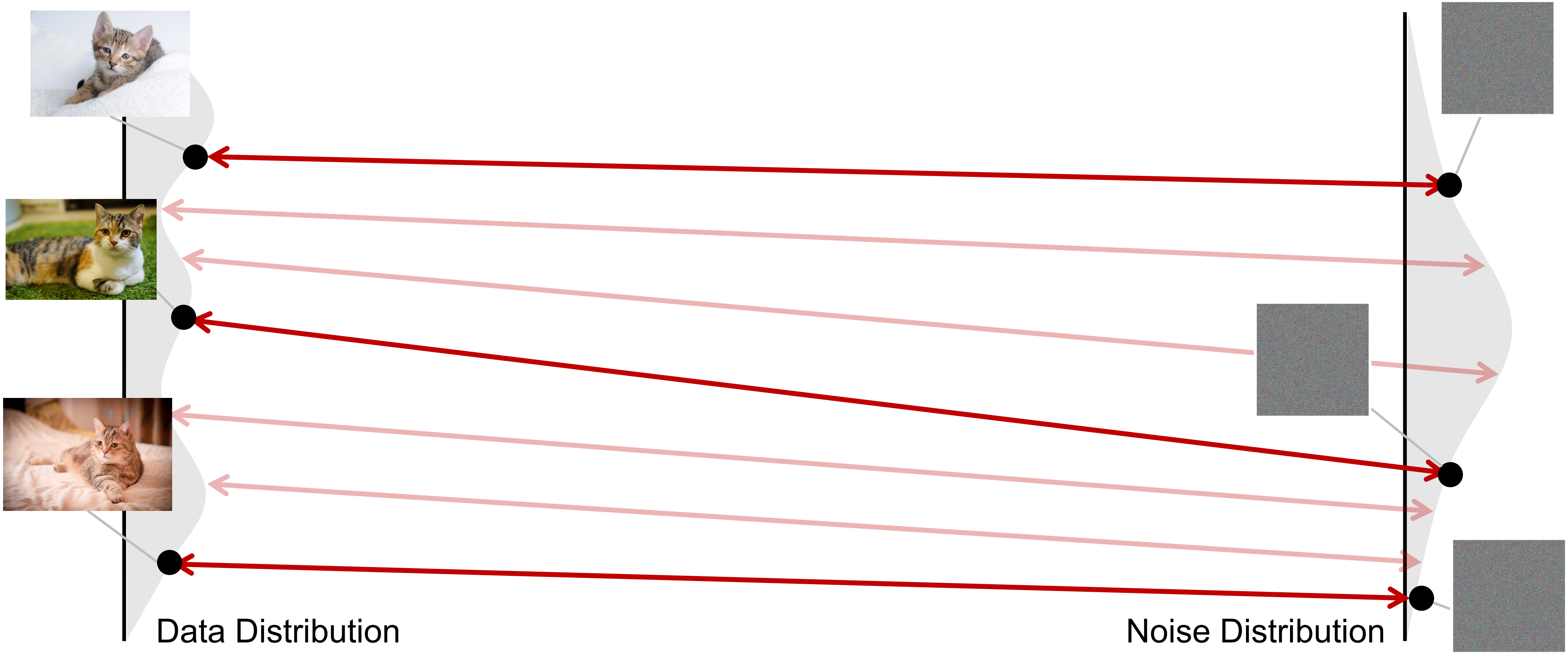
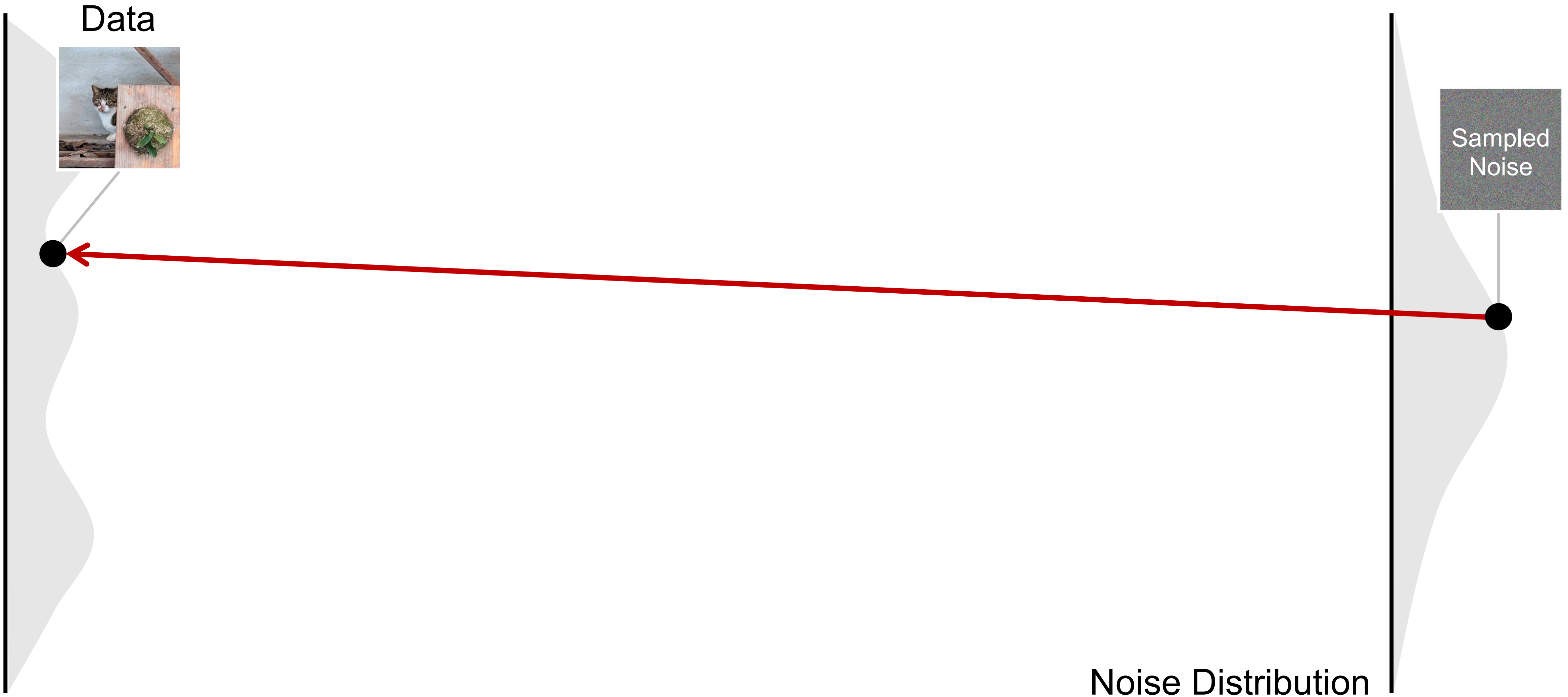


Data Distribution

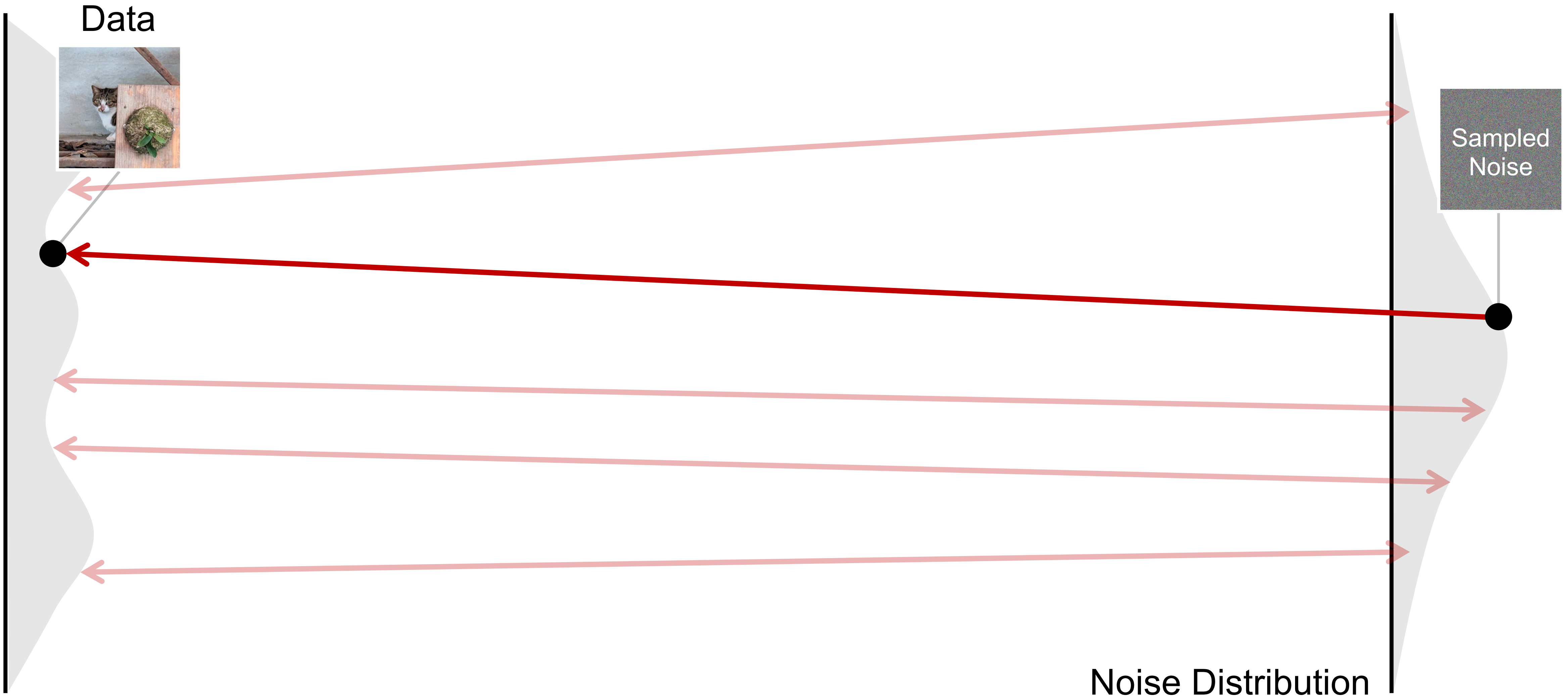
What is Generative Model Learning?



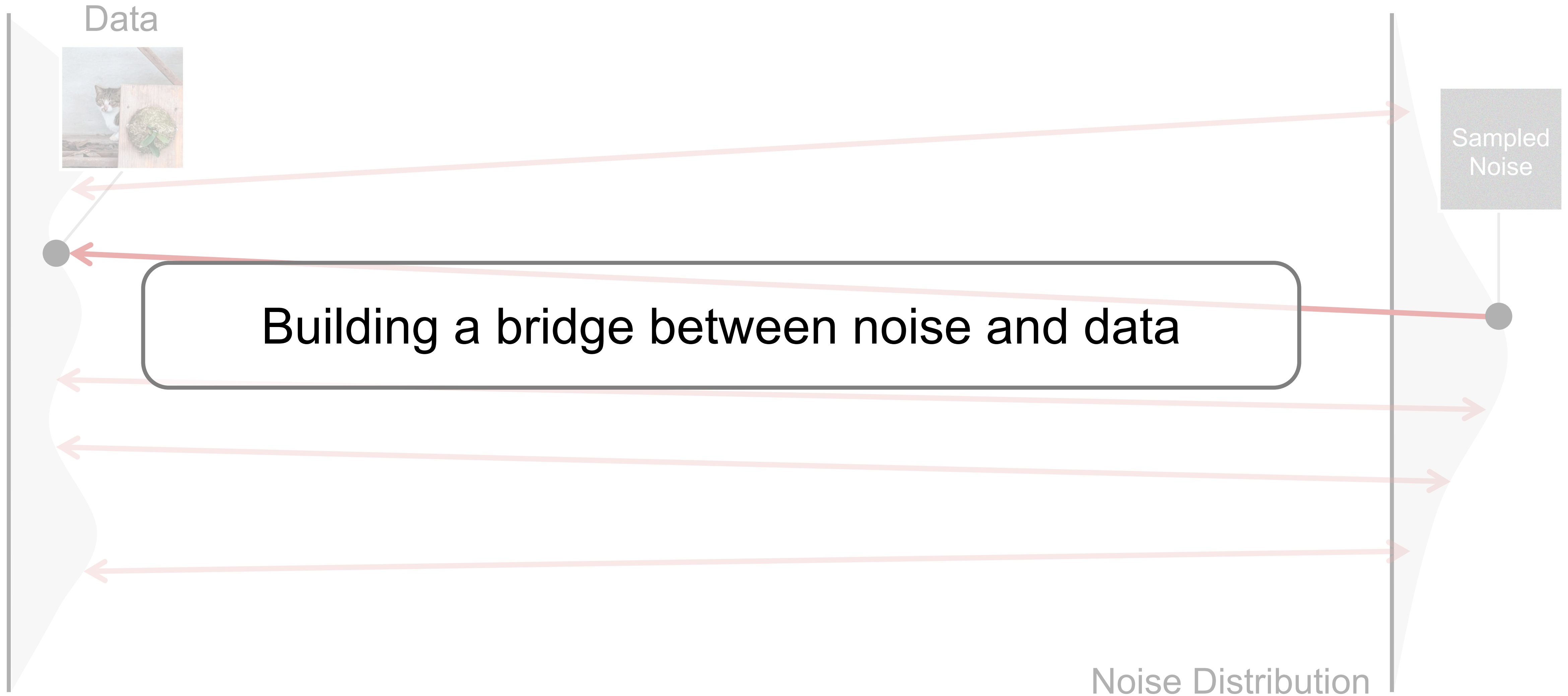
What is Generative Model Learning?



The Goal of Generative Model



The Goal of Generative Model



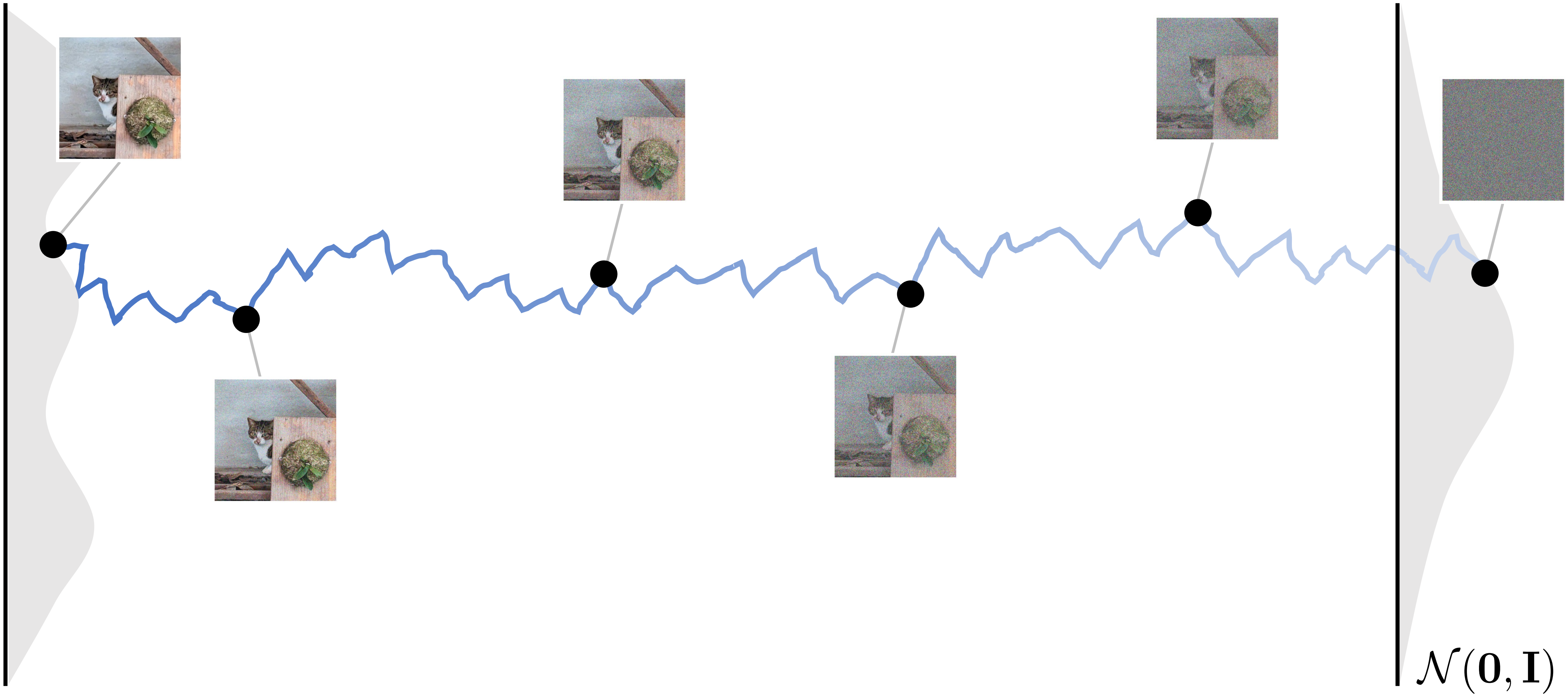
Building a bridge between noise and data

What is Diffusion Model?

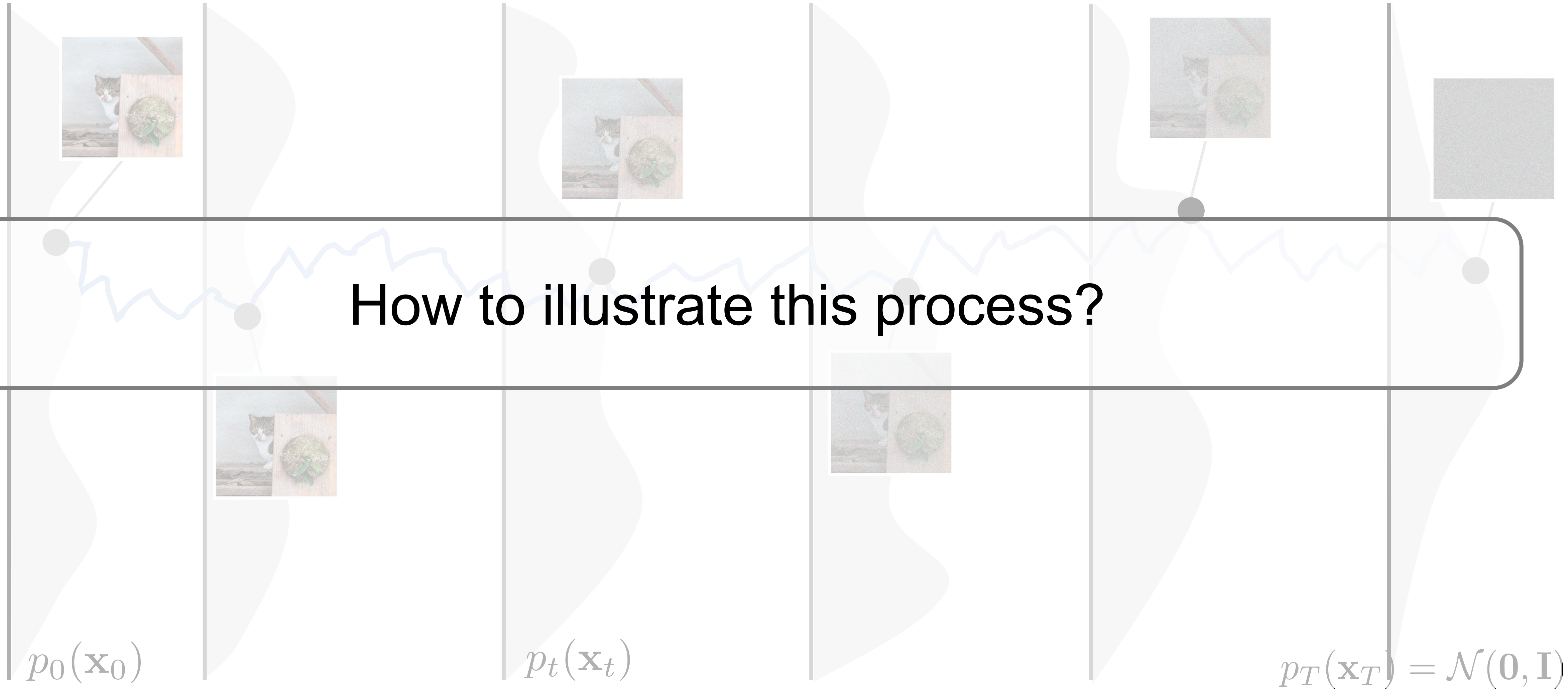
Forward Process: add noise step by step, from data to pure noise

Reverse Process: generate data from pure noise by denoising

Diffusion Models

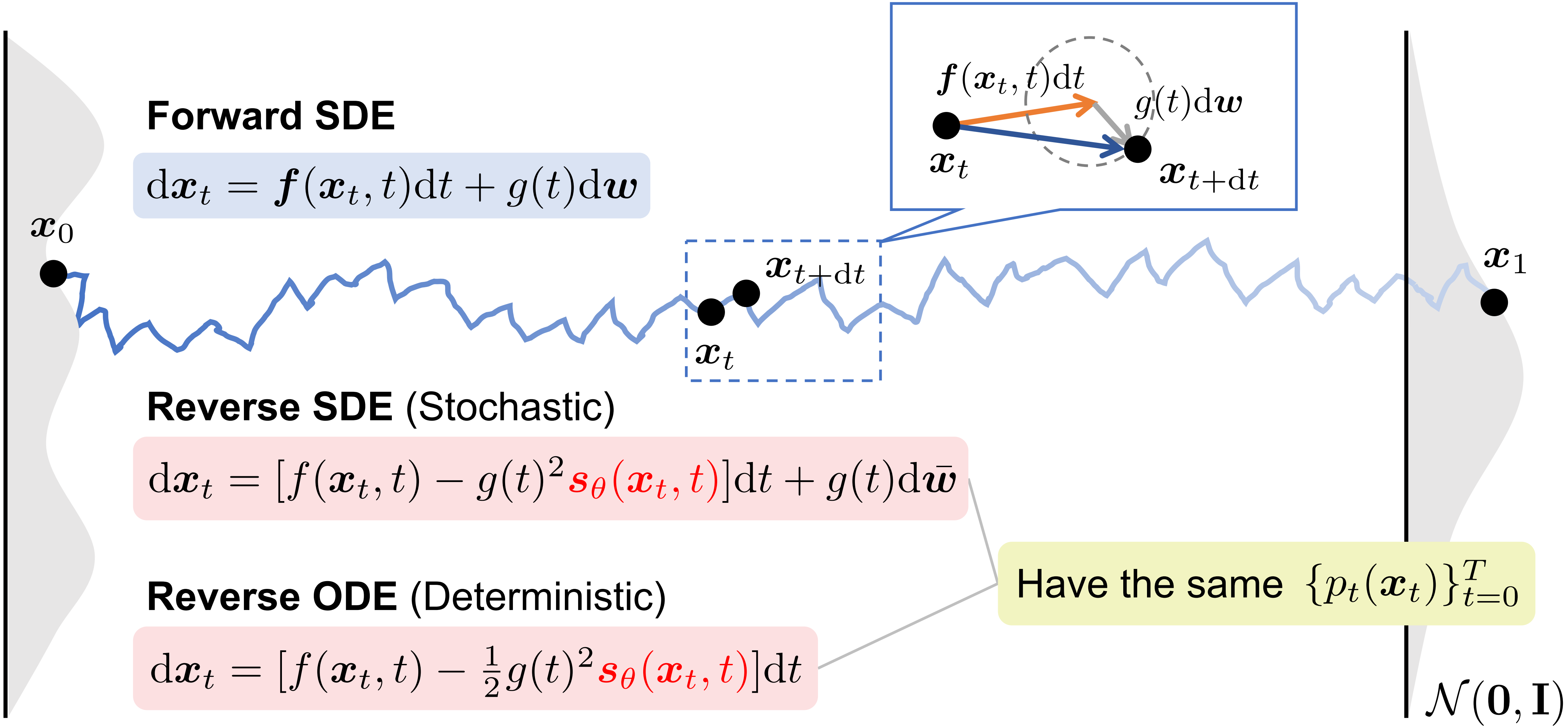


Diffusion Models



How to illustrate this process?

Score-based Diffusion Models [Song+ ICLR'21]



Forward SDE

$$\mathrm{d}\boldsymbol{x}_t = \boldsymbol{f}(\boldsymbol{x}_t, t)\mathrm{d}t + g(t)\mathrm{d}\boldsymbol{w}$$

Reverse SDE (Stochastic)

$$\mathrm{d}\boldsymbol{x}_t = [\boldsymbol{f}(\boldsymbol{x}_t, t) - g(t)^2 \boldsymbol{s}_\theta(\boldsymbol{x}_t, t)]\mathrm{d}t + g(t)\mathrm{d}\bar{\boldsymbol{w}}$$

Reverse ODE (Deterministic)

$$\mathrm{d}\boldsymbol{x}_t = [\boldsymbol{f}(\boldsymbol{x}_t, t) - \tfrac{1}{2} g(t)^2 \boldsymbol{s}_\theta(\boldsymbol{x}_t, t)]\mathrm{d}t$$

Have the same $\{p_t(\boldsymbol{x}_t)\}_{t=0}^T$

Diffusion Model vs Flow Matching

- Score-based Diffusion Model

$$\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} = f(\boldsymbol{x}_t, t) - \frac{1}{2} g(t)^2 \boldsymbol{s}_\theta(\boldsymbol{x}_t, t)$$

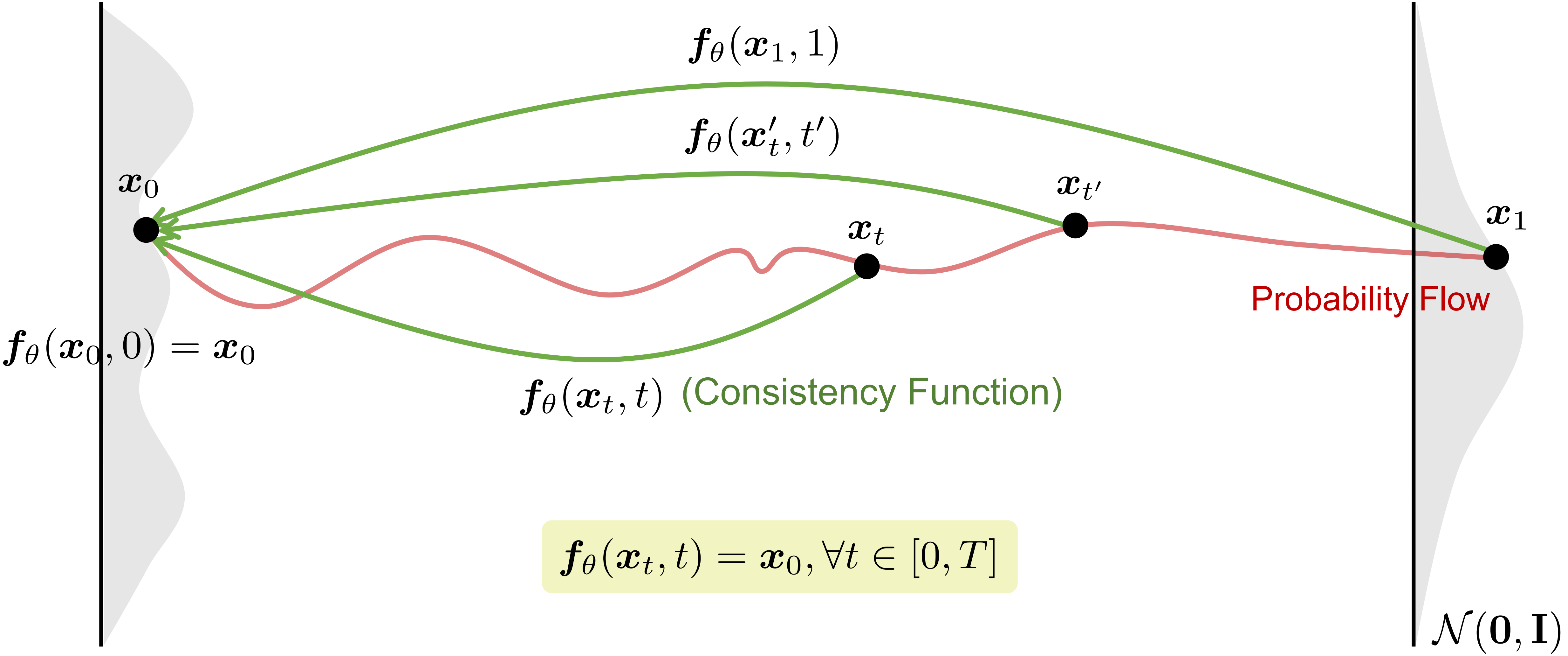
$$\mathcal{L}_{\mathrm{SM}}(\theta) = \mathbb{E}_{\boldsymbol{x}_0, \boldsymbol{x}_t | \boldsymbol{x}_0} \| \boldsymbol{s}_\theta(\boldsymbol{x}_t, t) - \underset{\substack{\wr\wr \\ \nabla_{\boldsymbol{x}_t} \log p_t(\boldsymbol{x}_t | \boldsymbol{x}_0)}}{\nabla_{\boldsymbol{x}_t} \log p_t(\boldsymbol{x}_t)} \|_2^2$$

- Flow Matching

$$\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} = \boldsymbol{v}_\theta(\boldsymbol{x}_t, t)$$

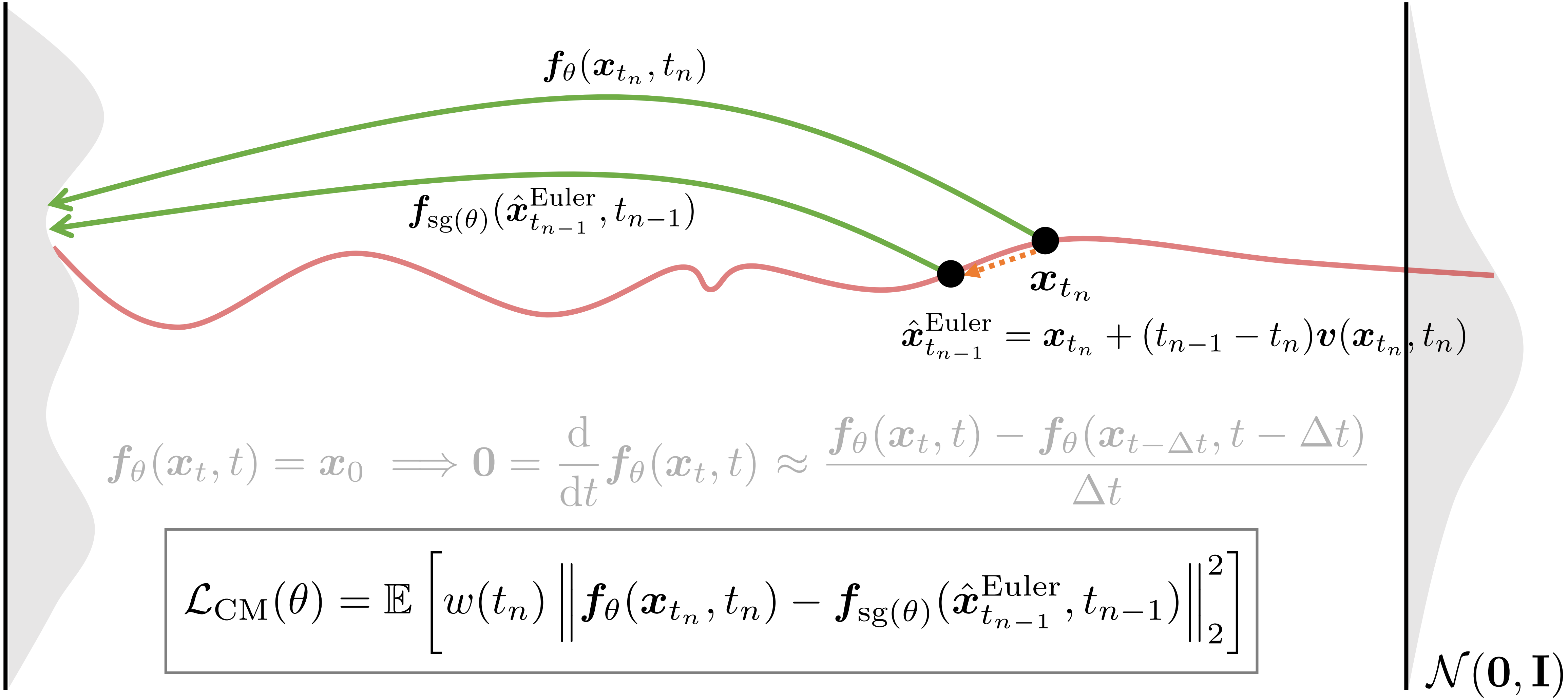
$$\mathcal{L}_{\mathrm{FM}}(\theta) = \mathbb{E}_{\boldsymbol{x}_0, \boldsymbol{x}_t | \boldsymbol{x}_0} \| \boldsymbol{v}_\theta(\boldsymbol{x}_t, t) - \boldsymbol{v}_t \|_2^2$$

Consistency Models (CM) [Song+ ICML'23]



$$\boldsymbol{f}_\theta(\boldsymbol{x}_t, t) = \boldsymbol{x}_0, \forall t \in [0, T]$$

Consistency Models (CM) [Song+ ICML'23]



$$\boldsymbol{f}_\theta(\boldsymbol{x}_t, t) = \boldsymbol{x}_0 \implies \mathbf{0} = \frac{\mathrm{d}}{\mathrm{d}t}\boldsymbol{f}_\theta(\boldsymbol{x}_t, t) \approx \frac{\boldsymbol{f}_\theta(\boldsymbol{x}_t, t) - \boldsymbol{f}_\theta(\boldsymbol{x}_{t-\Delta t}, t - \Delta t)}{\Delta t}$$

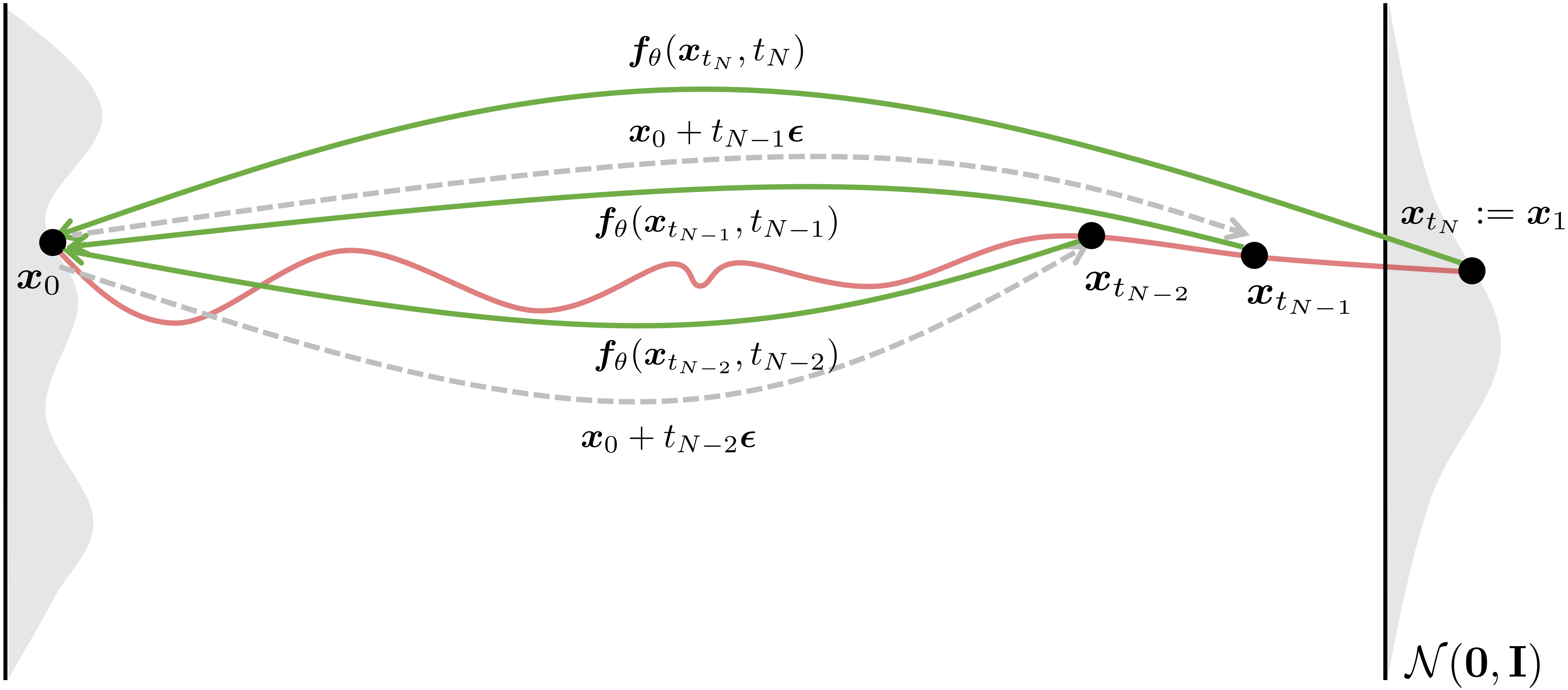
$$\boxed{\mathcal{L}_{\mathrm{CM}}(\theta) = \mathbb{E}\left[w(t_n)\left\|\boldsymbol{f}_\theta(\boldsymbol{x}_{t_n}, t_n) - \boldsymbol{f}_{\mathrm{sg}(\theta)}(\hat{\boldsymbol{x}}^{\mathrm{Euler}}_{t_{n-1}}, t_{n-1})\right\|_2^2\right]}$$

Consistency Models (CM) [Song+ ICML'23]

- **Consistency Distillation (CD)**
  - Pretrained Diffusion: $\boldsymbol{v}(\boldsymbol{x}_t, t) = -t\boldsymbol{s}_\phi(\boldsymbol{x}_t, t)$
  - Pretrained Flow: $\boldsymbol{v}(\boldsymbol{x}_t, t) = \boldsymbol{v}_\phi(\boldsymbol{x}_t, t)$

Slow Convergence !!

Sampling with CM



CM Experiments

Table 1: Sample quality on CIFAR-10. *Methods that require synthetic data construction for distillation.

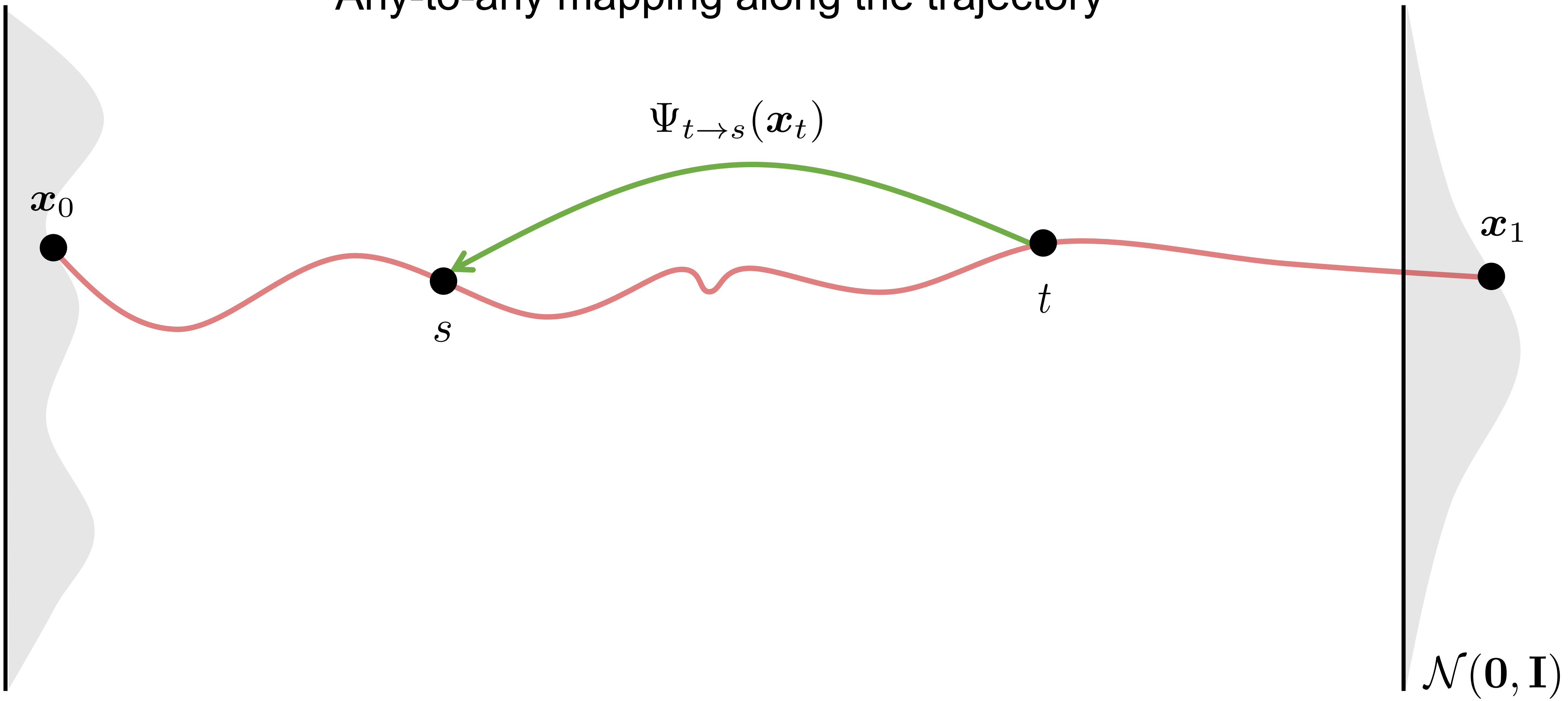
METHOD	NFE (↓)	FID (↓)	IS (↑)
Diffusion + Samplers			
DDIM (Song et al., 2020)	50	4.67	
DDIM (Song et al., 2020)	20	6.84	
DDIM (Song et al., 2020)	10	8.23	
DPM-solver-2 (Lu et al., 2022)	10	5.94	
DPM-solver-fast (Lu et al., 2022)	10	4.70	
3-DEIS (Zhang & Chen, 2022)	10	**4.17**	
Diffusion + Distillation			
Knowledge Distillation* (Luhman & Luhman, 2021)	1	9.36	
DFNO* (Zheng et al., 2022)	1	4.12	
1-Rectified Flow (+distill)* (Liu et al., 2022)	1	6.18	9.08
2-Rectified Flow (+distill)* (Liu et al., 2022)	1	4.85	9.01
3-Rectified Flow (+distill)* (Liu et al., 2022)	1	5.21	8.79
PD (Salimans & Ho, 2022)	1	8.34	8.69
CD	1	**3.55**	**9.48**
PD (Salimans & Ho, 2022)	2	5.58	9.05
CD	2	**2.93**	**9.75**
Direct Generation			
BigGAN (Brock et al., 2019)	1	14.7	9.22
Diffusion GAN (Xiao et al., 2022)	1	14.6	8.93
AutoGAN (Gong et al., 2019)	1	12.4	8.55
E2GAN (Tian et al., 2020)	1	11.3	8.51
ViTGAN (Lee et al., 2021)	1	6.66	9.30
TransGAN (Jiang et al., 2021)	1	9.26	9.05
StyleGAN2-ADA (Karras et al., 2020)	1	2.92	**9.83**
StyleGAN-XL (Sauer et al., 2022)	1	**1.85**	
Score SDE (Song et al., 2021)	2000	2.20	**9.89**
DDPM (Ho et al., 2020)	1000	3.17	9.46
LSGM (Vahdat et al., 2021)	147	2.10	
PFGM (Xu et al., 2022)	110	2.35	9.68
EDM (Karras et al., 2022)	35	**2.04**	9.84
1-Rectified Flow (Liu et al., 2022)	1	378	1.13
Glow (Kingma & Dhariwal, 2018)	1	48.9	3.92
Residual Flow (Chen et al., 2019)	1	46.4	
GLFlow (Xiao et al., 2019)	1	44.6	
DenseFlow (Grcić et al., 2021)	1	34.9	
DC-VAE (Parmar et al., 2021)	1	17.9	8.20
CT	1	**8.70**	**8.49**
CT	2	**5.83**	**8.85**

Table 2: Sample quality on ImageNet 64×64, and LSUN Bedroom & Cat 256×256. †Distillation techniques.

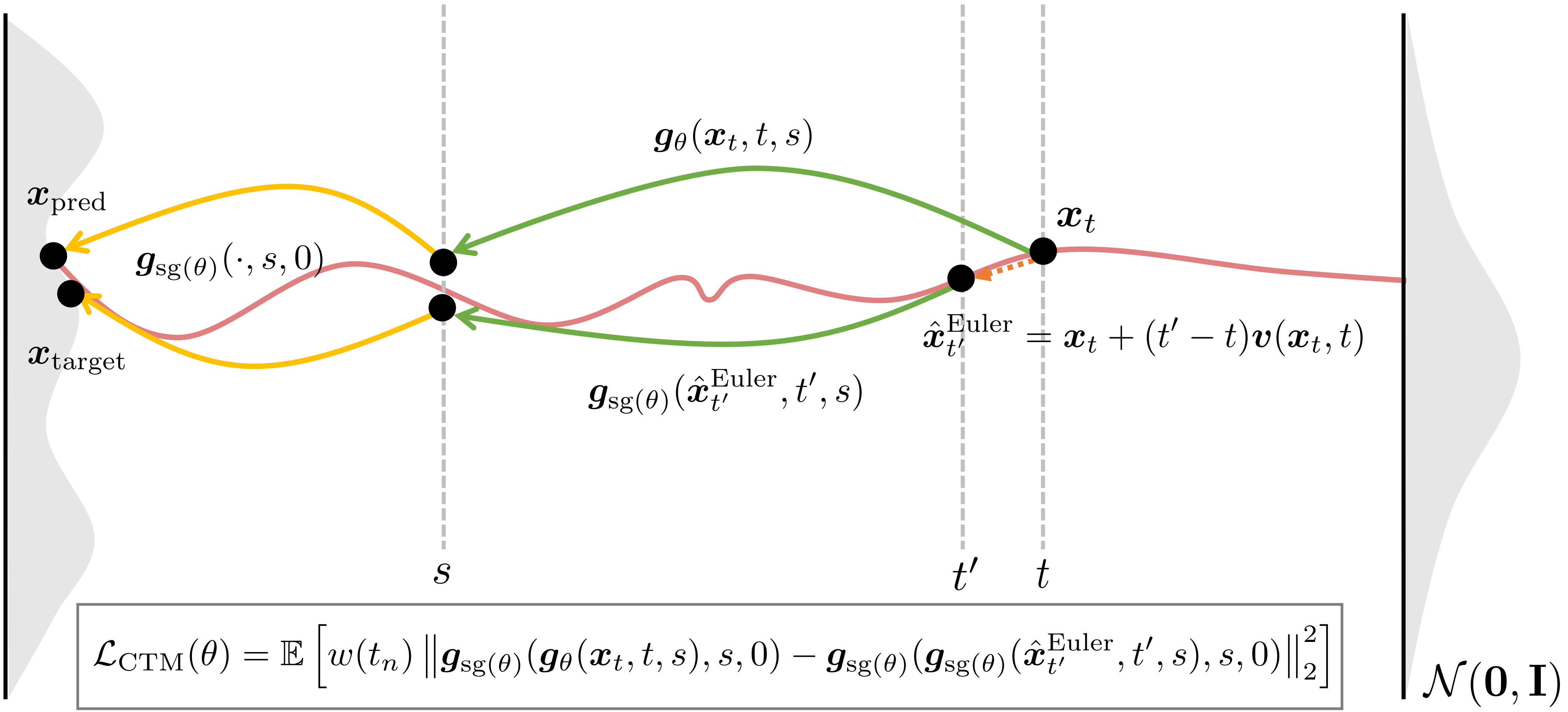
METHOD	NFE (↓)	FID (↓)	Prec. (↑)	Rec. (↑)
ImageNet 64 × 64				
PD† (Salimans & Ho, 2022)	1	15.39	0.59	0.62
DFNO† (Zheng et al., 2022)	1	8.35		
CD†	1	6.20	0.68	0.63
PD† (Salimans & Ho, 2022)	2	8.95	0.63	**0.65**
CD†	2	**4.70**	**0.69**	0.64
ADM (Dhariwal & Nichol, 2021)	250	**2.07**	0.74	0.63
EDM (Karras et al., 2022)	79	2.44	0.71	**0.67**
BigGAN-deep (Brock et al., 2019)	1	4.06	**0.79**	0.48
CT	1	13.0	0.71	0.47
CT	2	11.1	0.69	0.56
LSUN Bedroom 256 × 256				
PD† (Salimans & Ho, 2022)	1	16.92	0.47	0.27
PD† (Salimans & Ho, 2022)	2	8.47	0.56	**0.39**
CD†	1	7.80	0.66	0.34
CD†	2	**5.22**	**0.68**	**0.39**
DDPM (Ho et al., 2020)	1000	4.89	0.60	0.45
ADM (Dhariwal & Nichol, 2021)	1000	**1.90**	0.66	**0.51**
EDM (Karras et al., 2022)	79	3.57	0.66	0.45
PGGAN (Karras et al., 2018)	1	8.34		
PG-SWGAN (Wu et al., 2019)	1	8.0		
TDPM (GAN) (Zheng et al., 2023)	1	5.24		
StyleGAN2 (Karras et al., 2020)	1	2.35	0.59	0.48
CT	1	16.0	0.60	0.17
CT	2	7.85	**0.68**	0.33
LSUN Cat 256 × 256				
PD† (Salimans & Ho, 2022)	1	29.6	0.51	0.25
PD† (Salimans & Ho, 2022)	2	15.5	0.59	0.36
CD†	1	11.0	0.65	0.36
CD†	2	**8.84**	**0.66**	**0.40**
DDPM (Ho et al., 2020)	1000	17.1	0.53	0.48
ADM (Dhariwal & Nichol, 2021)	1000	**5.57**	0.63	**0.52**
EDM (Karras et al., 2022)	79	6.69	**0.70**	0.43
PGGAN (Karras et al., 2018)	1	37.5		
StyleGAN2 (Karras et al., 2020)	1	7.25	0.58	0.43
CT	1	20.7	0.56	0.23
CT	2	11.7	0.63	0.36

Flow Map

Any-to-any mapping along the trajectory



Consistency Trajectory Models (CTM) [Kim+ ICLR'24]



$$\mathcal{L}_{\text{CTM}}(\theta) = \mathbb{E}\left[w(t_n)\left\|\boldsymbol{g}_{\text{sg}(\theta)}(\boldsymbol{g}_\theta(\boldsymbol{x}_t, t, s), s, 0) - \boldsymbol{g}_{\text{sg}(\theta)}(\boldsymbol{g}_{\text{sg}(\theta)}(\hat{\boldsymbol{x}}_{t'}^{\text{Euler}}, t', s), s, 0)\right\|_2^2\right]$$

CTM Losses

- **DM Loss:** When *t* an *s* are very close, the gradients from the CTM loss become weak, leading to slow learning. Incorporating the DM loss provides a stronger local training signal and stabilizes optimization.
- **GAN Loss:** CTM and DSM losses can yield overly smooth outputs; therefore, an adversarial term can be added to encourage sharper and more realistic samples by aligning the generator distribution with the data distribution.
- **Total Loss:** $\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CTM}} + \lambda_{\text{DM}}\mathcal{L}_{\text{DM}} + \lambda_{\text{GAN}}\mathcal{L}_{\text{GAN}}$

CTM Experiments

Table 1: Performance comparisons on CIFAR-10[9].

Model	NFE	Unconditional		Conditional
		FID↓	NLL↓	FID↓
GAN Models				
BigGAN (Brock et al., 2018)	1	8.51	✗	-
StyleGAN-Ada (Karras et al., 2020)	1	2.92	✗	2.42
StyleGAN-D2D (Kang et al., 2021)	1	-	✗	2.26
StyleGAN-XL (Sauer et al., 2022)	1	-	✗	1.85
Diffusion Models – Score-based Sampling				
DDPM (Ho et al., 2020)	1000	3.17	3.75	-
DDIM (Song et al., 2020a)	100	4.16	-	-
	10	13.36	[illegible]	-
Score SDE (Song et al., 2020a)	[illegible]	[illegible]	[illegible]	[illegible]
VDM (Kingma et al., 2021)	1000	7.41	2.49	-
LSGM (Vahdat et al., 2021)	138	2.10	3.43	-
EDM (Karras et al., 2022)	35	2.01	2.56	1.82
Diffusion Models – Distillation Sampling				
KD (Luhman & Luhman, 2021)	1	9.36	✗	-
DFNO (Zheng et al., 2023)	1	3.78	✗	-
2-Rectified Flow (Liu et al., 2022)	1	4.85	✗	-
PD (Salimans & Ho, 2021)	1	9.12	✗	-
CD (official report) (Song et al., 2023)	1	3.55	✗	-
CD (retrained)	1	10.53	✗	-
CD + GAN (Lu et al., 2023)	1	2.65	✗	-
CTM (ours)	1	1.98	**2.43**	1.73
PD (Salimans & Ho, 2021)	2	4.51	-	-
CD (Song et al., 2023)	2	2.93	-	-
CTM (ours)	2	**1.87**	**2.43**	**1.63**
Models without Pre-trained DM – Direct Generation				
CT	1	8.70	✗	-
CTM (ours)	1	2.39	-	-

Table 2: Performance comparisons on ImageNet 64 × 64.

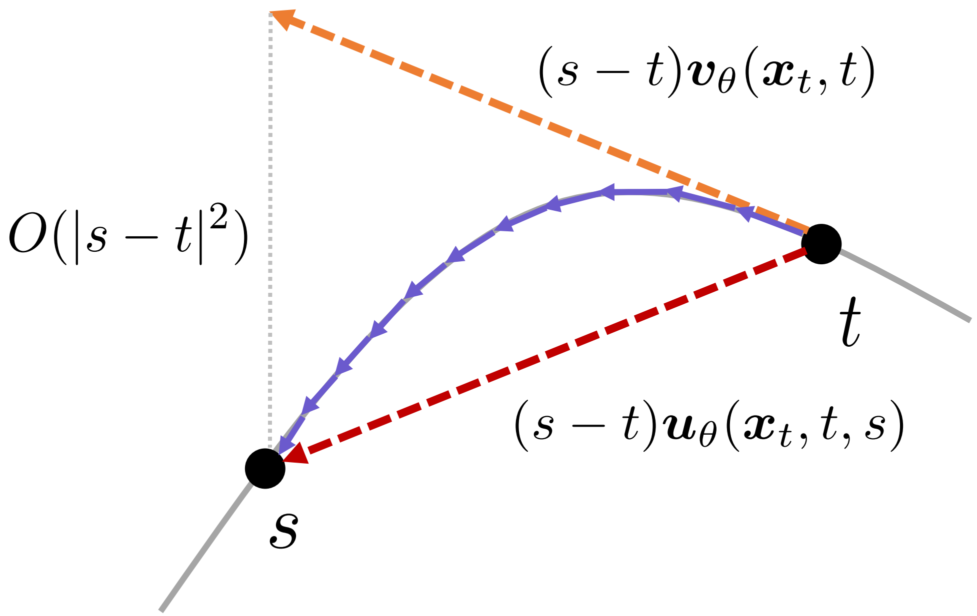
Model	NFE	FID↓	IS↑	Rec↑
Validation Data		1.41	64.10	0.67
ADM (Dhariwal & Nichol, 2021)	250	2.07	-	0.63
EDM (Karras et al., 2022)	79	2.44	48.88	**0.67**
BigGAN-deep (Brock et al., 2018)	1	4.06	-	0.48
StyleGAN-XL (Sauer et al., 2022)	1	2.09	**82.35**	0.52
Diffusion Models – Distillation Sampling				
PD (Salimans & Ho, 2021)	1	15.39	-	0.62
BOOT (Gu et al., 2023)	1	16.3	-	0.36
CD (Song et al., 2023)	1	[illegible]	[illegible]	[illegible]
CTM (ours)	1	[illegible]	[illegible]	[illegible]
PD (Salimans & Ho, 2021)	2	8.95	-	0.65
CD (Song et al., 2023)	2	4.70	-	0.64
CTM (ours)	2	**1.73**	64.29	0.57

Is there a more efficient and simplified training strategy?

MeanFlow: Average Velocity

- What we want: $$\boldsymbol{x}_s = \boldsymbol{x}_t + \int_t^s \boldsymbol{v}_\theta(\boldsymbol{x}_\tau, \tau)\mathrm{d}\tau$$
- But we do: $$\boldsymbol{x}_s = \boldsymbol{x}_t + (s-t)\cancel{\boldsymbol{v}_\theta(\boldsymbol{x}_\tau, \tau) + O(|s-t|^2)}$$

$$\boldsymbol{u}_\theta(\boldsymbol{x}_t, t, s) \approx \frac{1}{s-t}\int_t^s \boldsymbol{v}_t(\boldsymbol{x}_\tau, \tau)\mathrm{d}\tau$$



MeanFlow Identity

Differential

$$\boxed{\boldsymbol{u}(\boldsymbol{x}_t, t, s) = \frac{1}{s-t}\int_t^s \boldsymbol{v}(\boldsymbol{x}_\tau, \tau)\mathrm{d}\tau}$$

$$\frac{\mathrm{d}}{\mathrm{d}t}(s-t)\boldsymbol{u}(\boldsymbol{x}_t, t, s) = \frac{\mathrm{d}}{\mathrm{d}t}\int_t^s \boldsymbol{v}(\boldsymbol{x}_\tau, \tau)\mathrm{d}\tau$$

$$-\boldsymbol{u}(\boldsymbol{x}_t, t, s) + (s-t)\frac{\mathrm{d}}{\mathrm{d}t}\boldsymbol{u}(\boldsymbol{x}_t, t, s) = -\boldsymbol{v}(\boldsymbol{x}_t, t)$$

$$\boxed{\boldsymbol{u}(\boldsymbol{x}_t, t, s) = \boldsymbol{v}(\boldsymbol{x}_t, t) + (s-t)\frac{\mathrm{d}}{\mathrm{d}t}\boldsymbol{u}(\boldsymbol{x}_t, t, s)}$$

Integral

MeanFlow: Time Derivative

$$\frac{\mathrm{d}}{\mathrm{d}t}\boldsymbol{u}(\boldsymbol{x}_t, t, s) = \frac{\partial \boldsymbol{u}}{\partial \boldsymbol{x}_t} \cdot \frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} + \frac{\partial \boldsymbol{u}}{\partial t} \cdot \frac{\mathrm{d}t}{\mathrm{d}t} + \frac{\partial \boldsymbol{u}}{\partial s} \cdot \frac{\mathrm{d}s}{\mathrm{d}t}$$

$$= \boldsymbol{v}_t(\boldsymbol{x}_t, t)\partial_{\boldsymbol{x}_t}\boldsymbol{u} + \partial_t \boldsymbol{u}$$

$$= \left[\frac{\partial \boldsymbol{u}(\boldsymbol{x}_t, t, s)}{\partial(\boldsymbol{x}_t, t, s)}\right] \begin{bmatrix}\boldsymbol{v}_t(\boldsymbol{x}_t, t) & 1 & 0\end{bmatrix}^\top$$ (Jacobian-Vector Product)

$$\boldsymbol{u}(\boldsymbol{x}_t, t, s) = \boldsymbol{v}_t(\boldsymbol{x}_t, t) + (s - t)(\boldsymbol{v}(\boldsymbol{x}_t, t)\partial_{\boldsymbol{x}_t}\boldsymbol{u} + \partial_t \boldsymbol{u})$$

MeanFlow: Training Objective

$$\mathcal{L}_{\mathrm{MF}}(\theta) = \mathbb{E}\left[\left\|\boldsymbol{u}_\theta(\boldsymbol{x}_t, t, s) - \boldsymbol{u}_{\mathrm{target}}\right\|_2^2\right]$$

$$\Downarrow$$

$$\boldsymbol{u}_{\mathrm{target}}(\boldsymbol{x}_t, t, s) = \boldsymbol{v}_t(\boldsymbol{x}_t, t) + (s - t)\big(\boldsymbol{v}(\boldsymbol{x}_t, t)\partial_{\boldsymbol{x}_t}\boldsymbol{u}_{\mathrm{sg}(\theta)} + \partial_t \boldsymbol{u}_{\mathrm{sg}(\theta)}\big)$$

MeanFlow: Sampling

- Multi-step Sampling

$$\boldsymbol{x}_{t_i} = \boldsymbol{x}_{t_{i+1}} + (t_i - t_{i+1})\boldsymbol{u}_\theta(\boldsymbol{x}_{t_{i+1}}, t_{i+1}, t_i)$$

- One-step Sampling

$$\boldsymbol{x}_0 = \boldsymbol{x}_1 + \boldsymbol{u}_\theta(\boldsymbol{x}_1, 1, 0)$$

MeanFlow Experiments

Result on ImageNet-256 x 256

method	params	NFE	FID
1-NFE diffusion/flow from scratch			
iCT-XL/2 [43]†	675M	1	34.24
Shortcut-XL/2 [13]	675M	1	10.60
MeanFlow-B/2	131M	1	6.17
MeanFlow-M/2	308M	1	5.01
MeanFlow-L/2	459M	1	3.84
MeanFlow-XL/2	676M	1	**3.43**
2-NFE diffusion/flow from scratch			
iCT-XL/2 [43]†	675M	2	20.30
iMM-XL/2 [52]	675M	1×2	7.77
MeanFlow-XL/2	676M	2	2.93
MeanFlow-XL/2+	676M	2	**2.20**

method	params	NFE	FID
GANs			
BigGAN [5]	112M	1	6.95
GigaGAN [21]	569M	1	3.45
StyleGAN-XL [40]	166M	1	2.30
autoregressive/masking			
AR w/ VQGAN [10]	227M	1024	26.52
MaskGIT [6]	227M	8	6.18
VAR-*d*30 [47]	2B	10×2	1.92
MAR-H [27]	943M	256×2	1.55
diffusion/flow			
ADM [8]	554M	250×2	10.94
LDM-4-G [37]	400M	250×2	3.60
SimDiff [20]	2B	512×2	2.77
DiT-XL/2 [34]	675M	250×2	2.27
SiT-XL/2 [33]	675M	250×2	2.06
SiT-XL/2+REPA [51]	675M	250×2	**1.42**

Summary

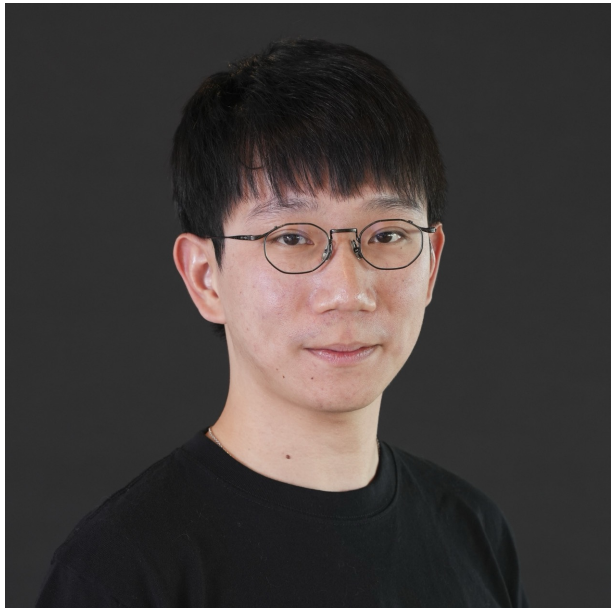
- Consistency Models formulate diffusion in a one-step manner and support both distillation and direct training.
- Consistency Trajectory Models extend Consistency Models by learning the flow map along the trajectory and introducing multiple loss terms to improve generation quality.
- MeanFlow introduces integral-based velocity averaging to further improve sample quality and stability, moving us closer to fast and high-fidelity generative models.

Further Follow-up

- **Consistency Models**
  - Consistency Model (CM)
  - Improved Consistency Training (iCT)
  - Easy Consistency Model (ECM)
  - Simple/stable/scalable Consistency Model (sCM)
- **Flow Maps Models**
  - Consistency Trajectory Model (CTM)
  - Shortcut Model
  - MeanFlow (MF)
  - Improved MeanFlow (iMF)
  - Consistency Mid-Training (CMT)

Recommended Reading

Some concepts and insights in these slides are inspired by Jesse



[Chieh-Hsin (Jesse) Lai]

Research Scientist at Sony AI

The Principles of Diffusion Models

From Origins to Advances

Chieh-Hsin Lai
Sony AI

Yang Song
OpenAI

Dongjun Kim
Stanford University

Yuki Mitsufuji
Sony Corporation, Sony AI

Stefano Ermon
Stanford University

Thank you