Bidirectional Consistency Models

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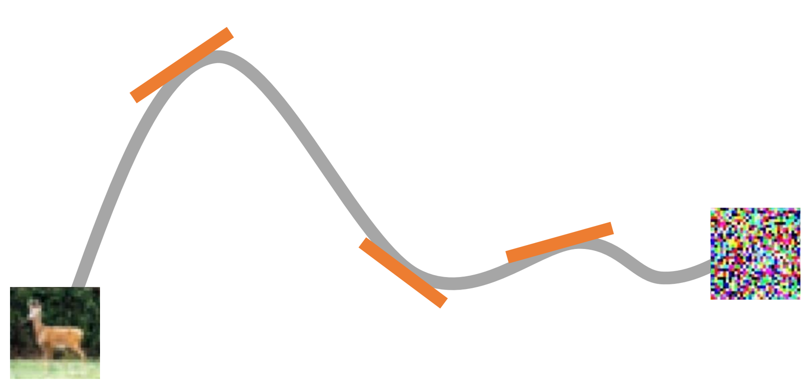
TL;DR: We extend consistency models to Bidirectional Consistency Models for fast sampling and its inversion.

Motivation

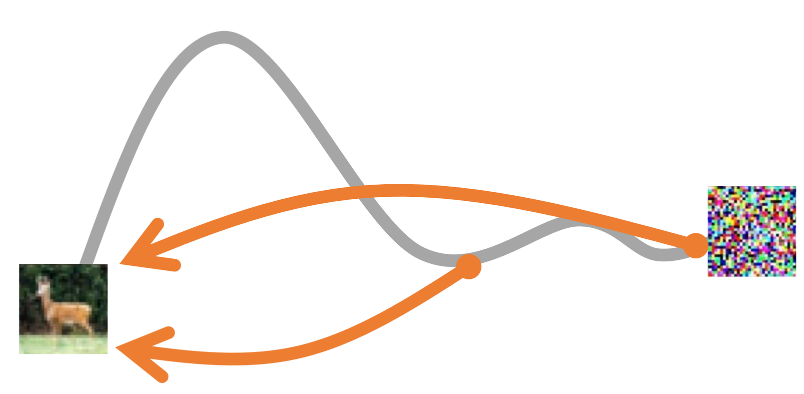
- Diffusion models requires **hundreds of NFEs** for high-quality samples; consistency models (CMs) only requires **1-2 NFE**;
- (ODE-based) diffusion models can map noise ⟷ image
- Consistency models only support noise ⟶ image

Backgrounds

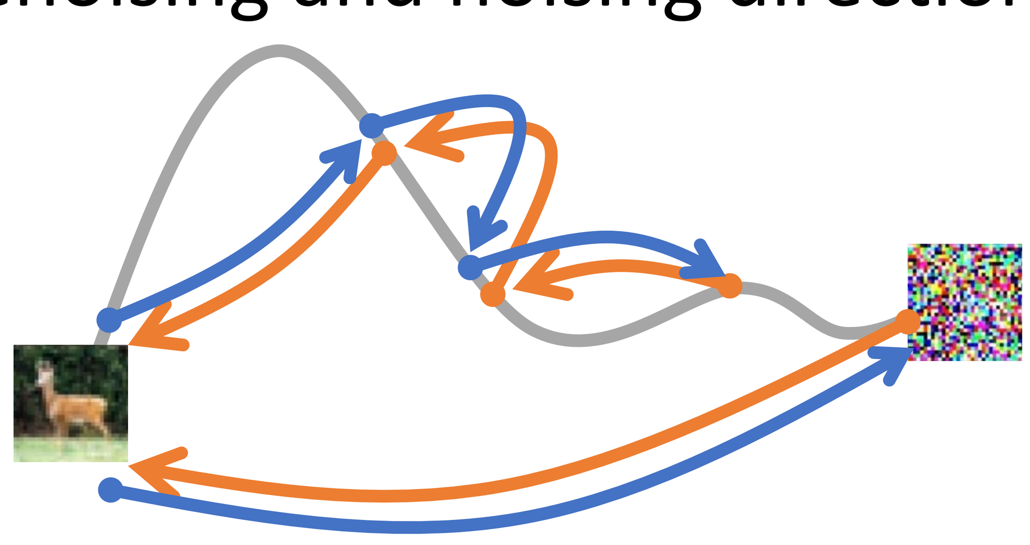
Diffusion Models estimate **scores** along the PF ODE:



Consistency Models estimates **starting points** of the PF ODE:



Bidirectional Consistency Models estimates **the points on the entire PF ODE** towards both denoising and noising directions:



Methods

- We train a network $f_\theta(x, t_1, t_2)$ mapping x from time step t_1 to t_2;
- Given training image x, Gaussian noise z, and random time steps t, t', we calculate:
  1. Target image:
     $$x_0 \leftarrow f_{\mathrm{sg}(\theta)}(x + tz, t, 0)$$
  2. Estimator of x_0:
     $$x_0{}' \leftarrow f_\theta(x + (t+\delta)z, t+\delta, 0)$$
  3. Estimator of $x_{t'}$:
     $$x_{t'} \leftarrow f_\theta(x + tz, t, t')$$
  4. New estimator of x_0:
     $$x_0{}'' \leftarrow f_{\mathrm{sg}(\theta)}(x_{t'}, t', 0)$$
- We minimize $d(x_0, x_0')$ and $d(x_0, x_0'')$ together:

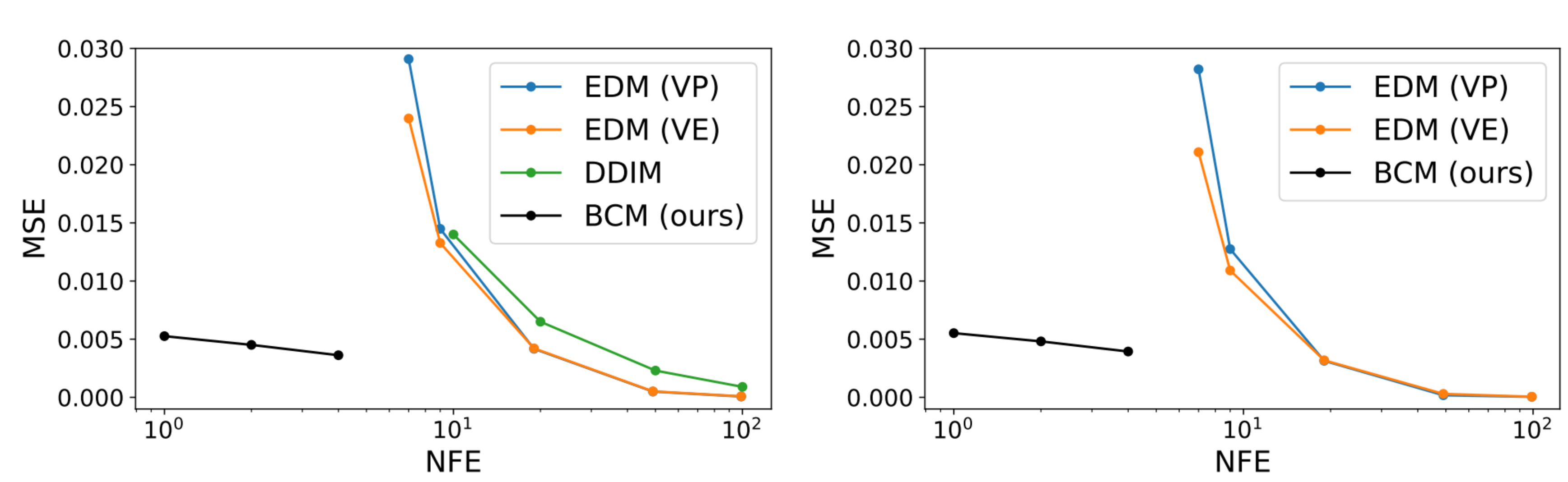
$$\ell = \underbrace{\frac{1}{\delta} d(x_0, x_0')}_{\text{Consistency training loss}} + \underbrace{\frac{1}{|t - t'|} d(x_0, x_0'')}_{\text{'soft' trajectory constraint}}$$

Results

- In terms of sampling, BCM achieves competitive FID compared to CMs:

Methods	NFE	FID
iCT	1	2.83
	2	2.46
iCT-deep	1	2.51
	2	2.24
BCM	1	3.10
	2	2.39
	3	2.50
	4	2.29
BCM-deep	1	2.64
	2	2.36
	3	2.19
	4	2.07

- In terms of inversion, BCM achieves lower reconstruction error with fewer NFE:



- Interpolate between two real images: