Simple and Fast Distillation of Diffusion Models

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[3] University at Buffalo, State University of New York

Reporter : Zhenyu Zhou

Preliminary

- **The Simplest Perspective on the Sampling of Diffusion Models**

[1] Song Y, Sohl-Dickstein J, Kingma D P, et al. Score-based generative modeling through stochastic differential equations[J]. arXiv preprint arXiv:2011.13456, 2020.
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Forward [1]:

$$\mathrm{d}\mathbf{x} = \mathbf{f}(\mathbf{x}, t)\mathrm{d}t + g(t)\mathrm{d}\mathbf{w}_t \tag{1}$$

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EDM formulation [2]: $$\mathrm{d}\mathbf{x} = -t\nabla_{\mathbf{x}} \log p_t(\mathbf{x})\mathrm{d}t \tag{3}$$

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Simplified formulation: $$\mathrm{d}\mathbf{x} = \boldsymbol{\epsilon}_\theta(\mathbf{x}, t)\mathrm{d}t \tag{5}$$

Sampling trajectory: $$\{\mathbf{x}_n\}_{n=0}^{N} \tag{6}$$

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Preliminary

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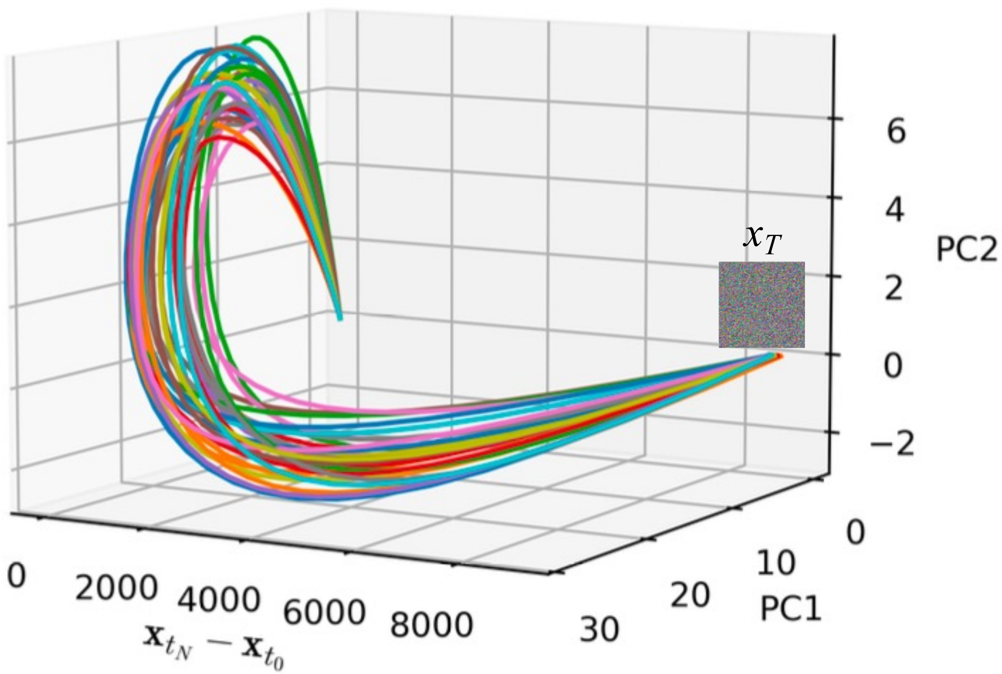

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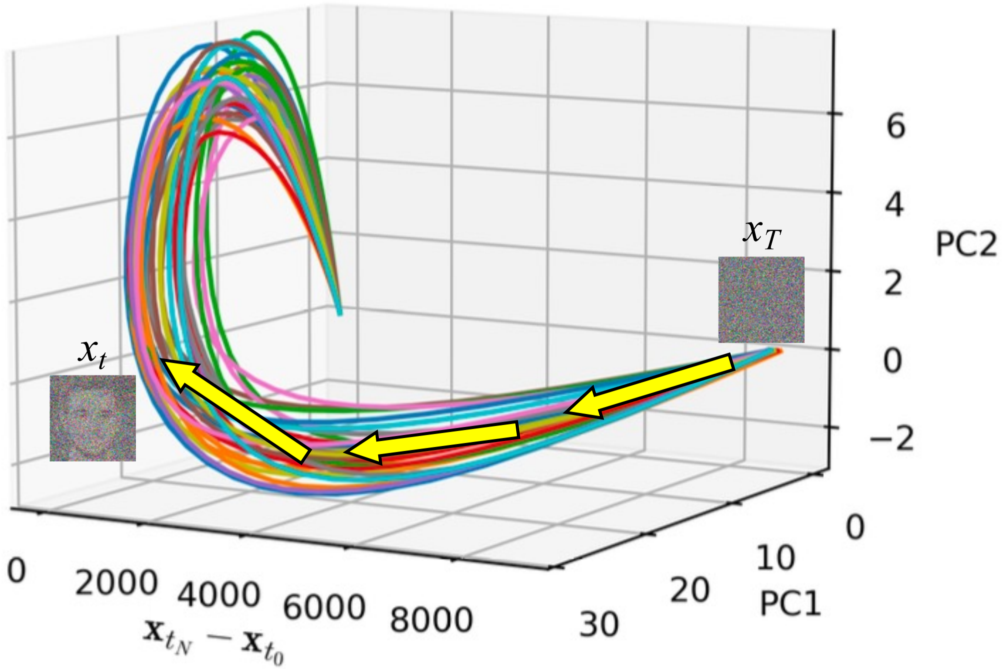

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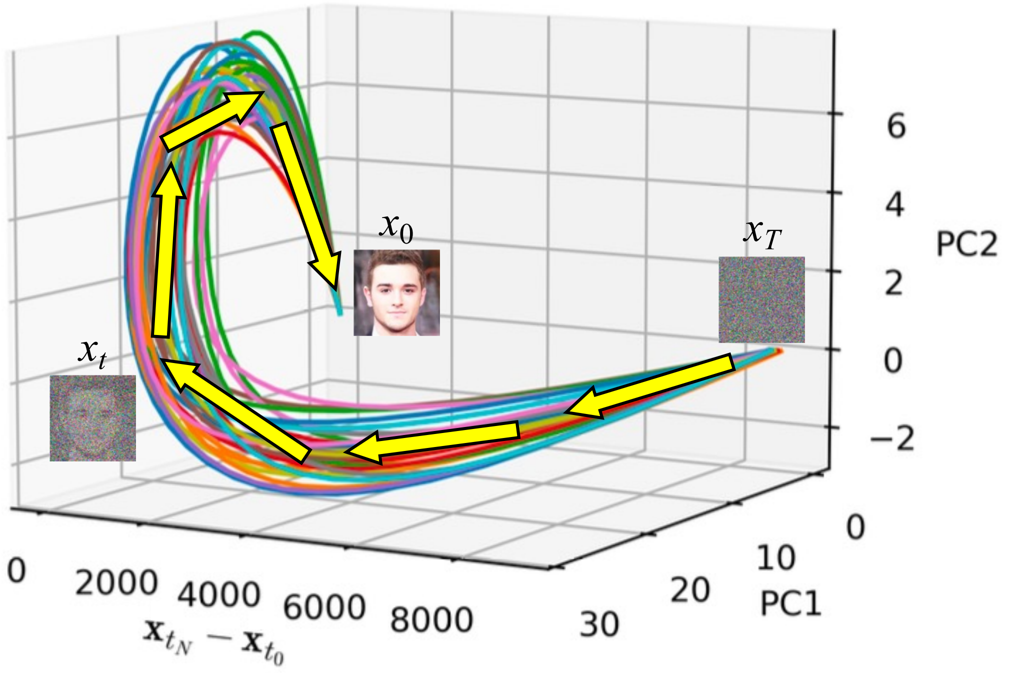

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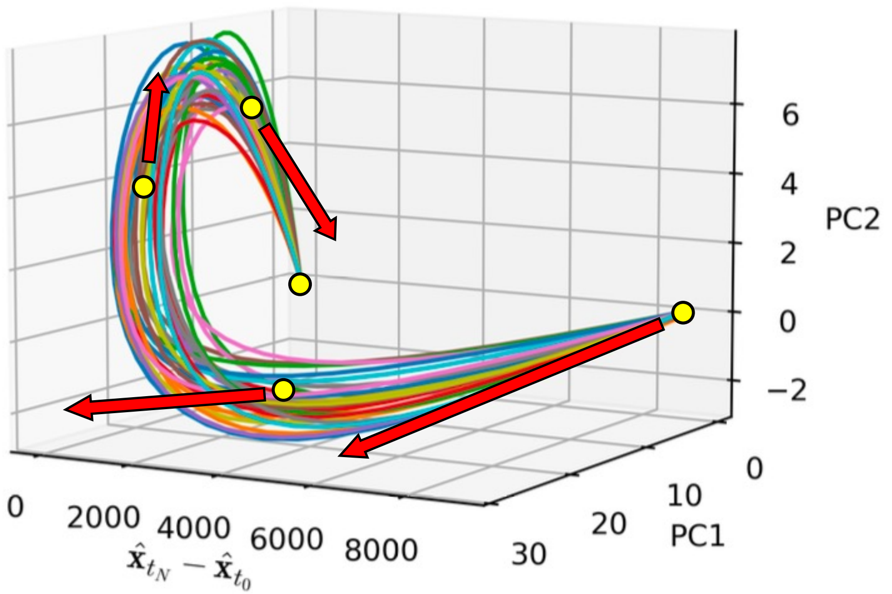
Motivation

Progressive Distillation [4]



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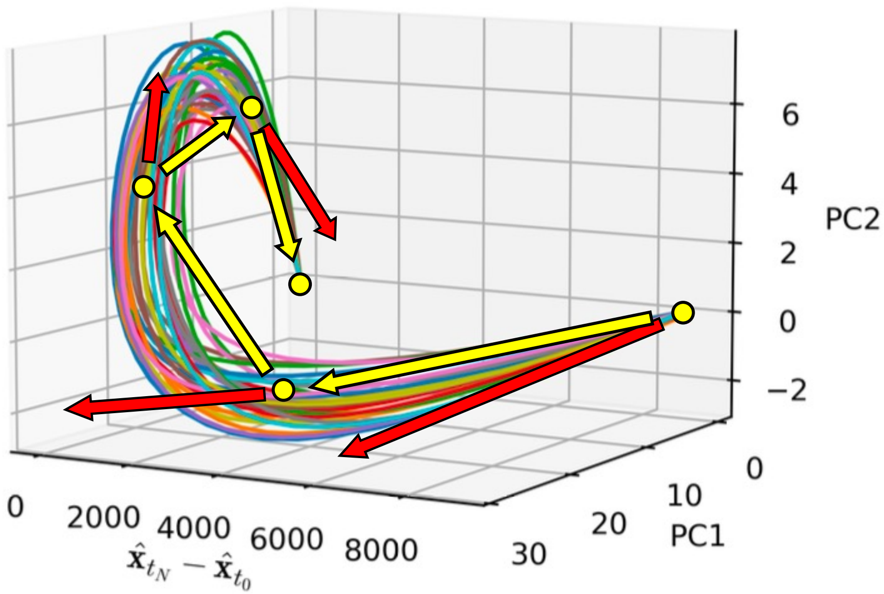

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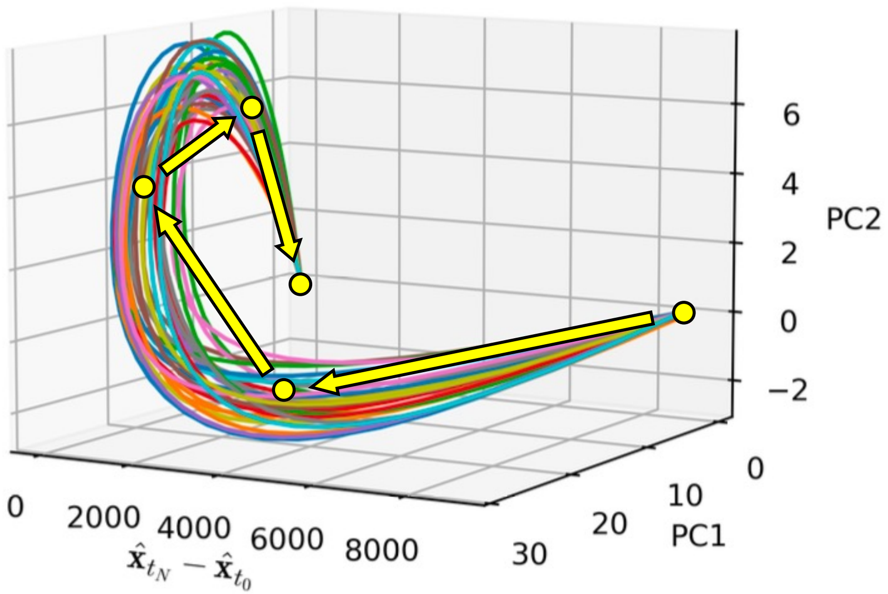

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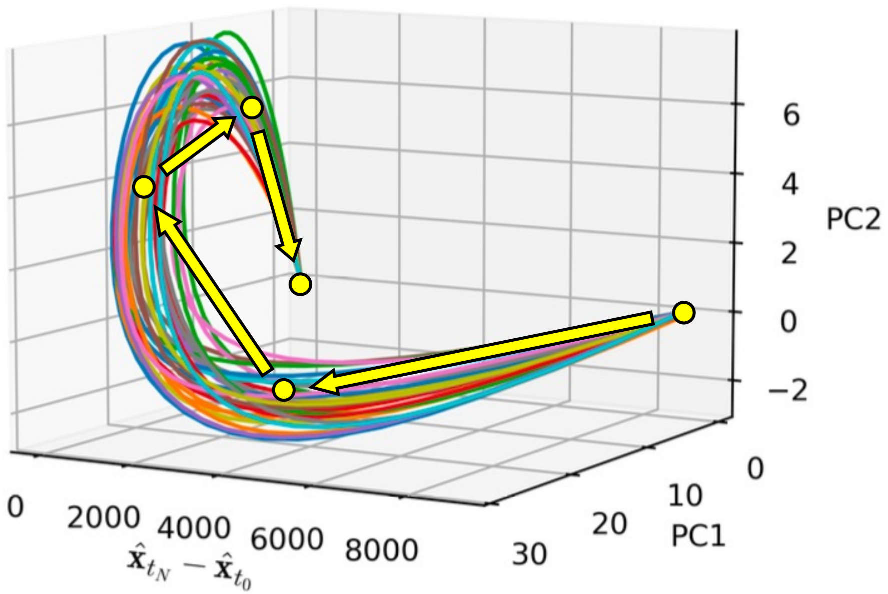

- **Problem: Time-consuming**
  - ➢ The mismatch between fine-tuning and sampling steps:
    Wasted training efforts
  - ➢ The complex optimization objectives:
    LPIPS loss, adversarial training, regularization…

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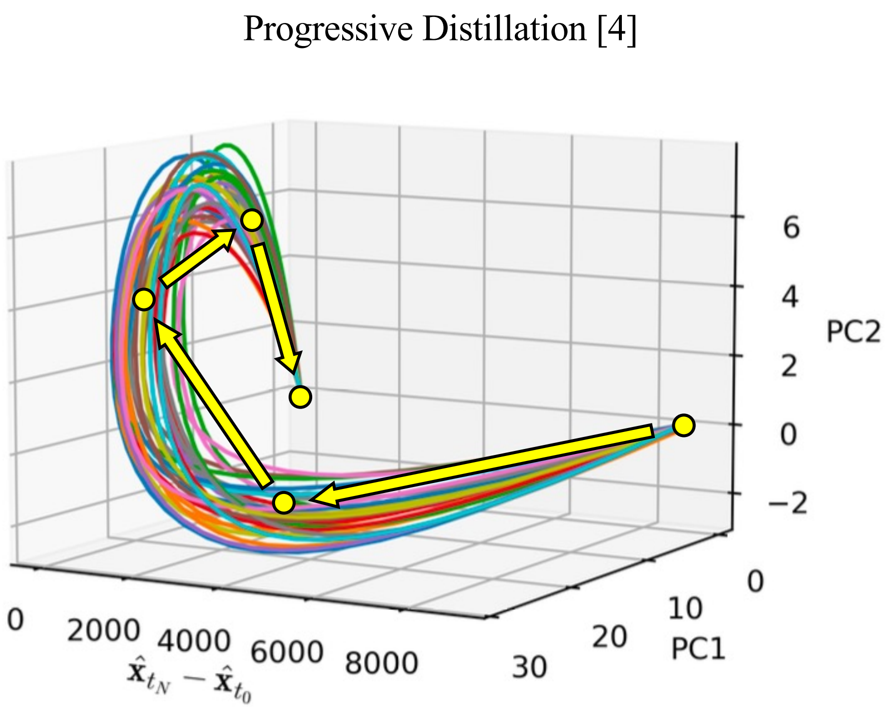

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- **Our Goal**
  - ➢ Simple distillation: simplified pipeline
  - ➢ Fast distillation: accelerated training

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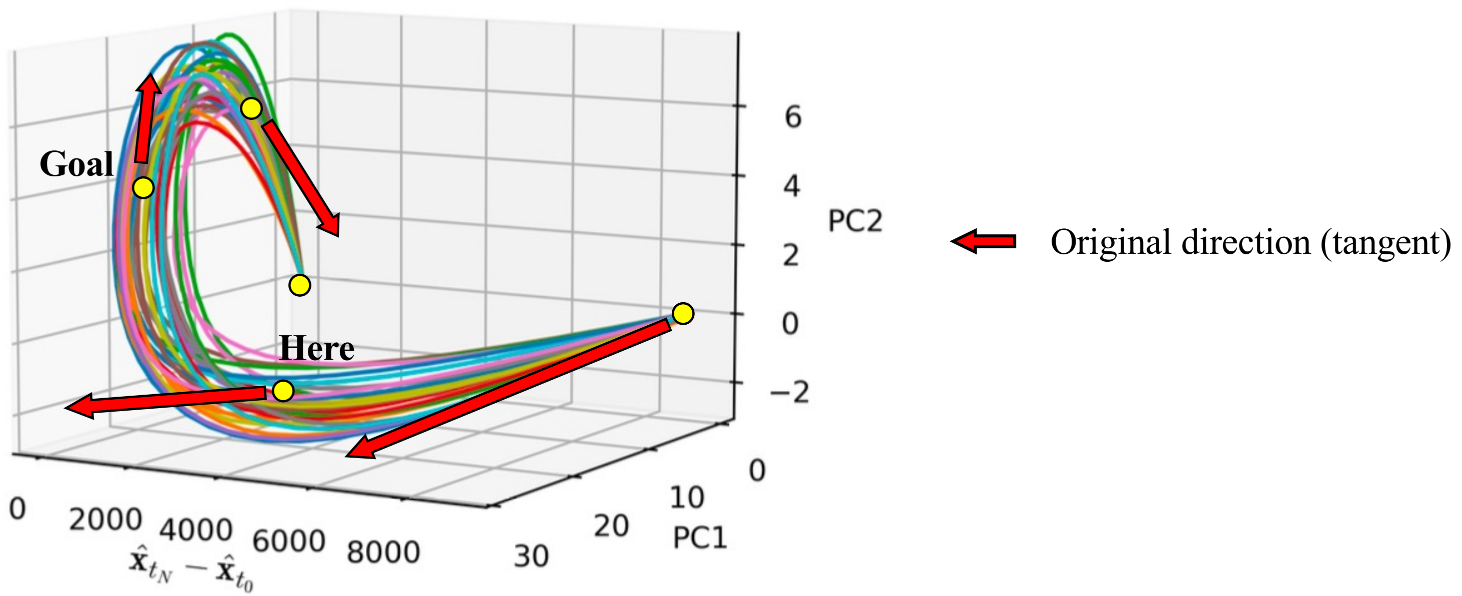
- **The Mutual Enhancement of Fine-tuning at Different Timestamps**



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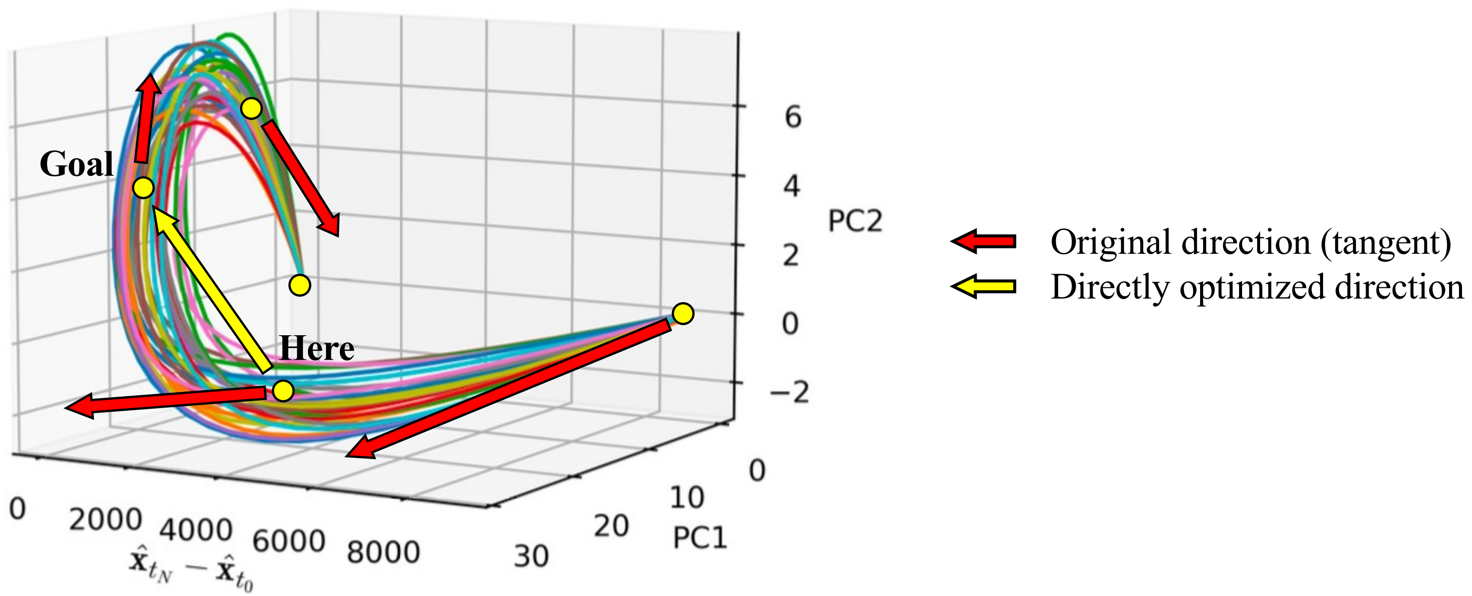

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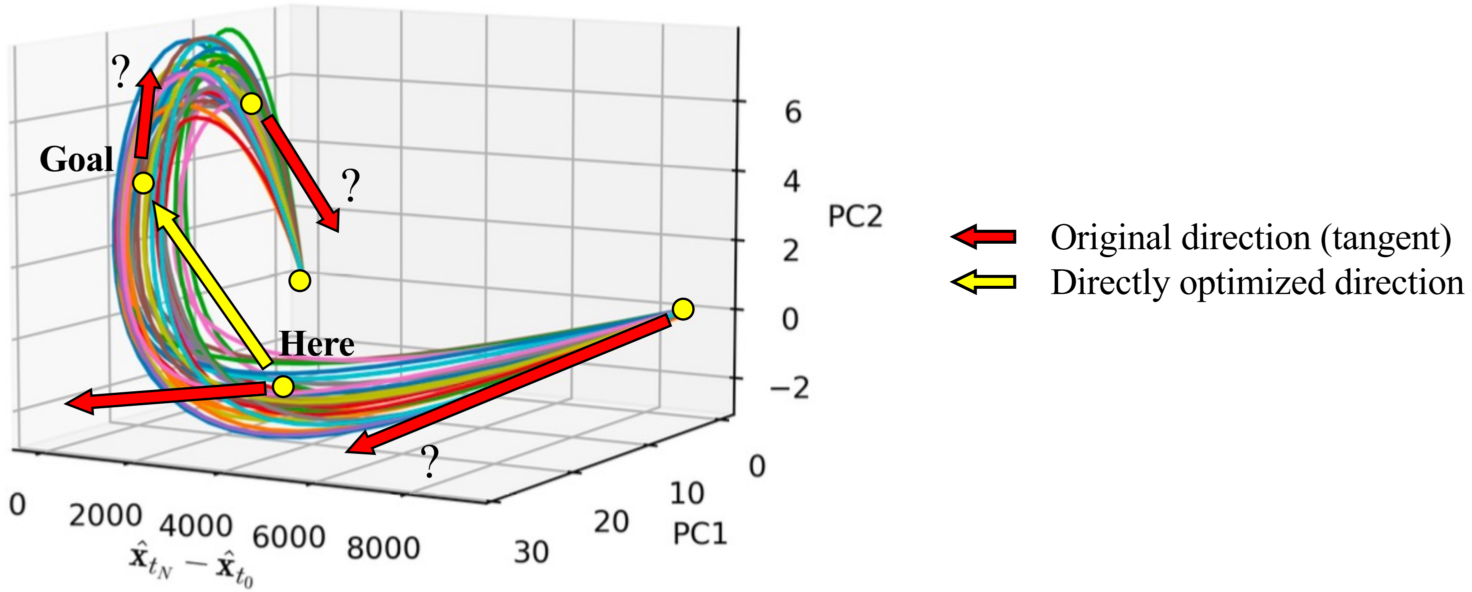

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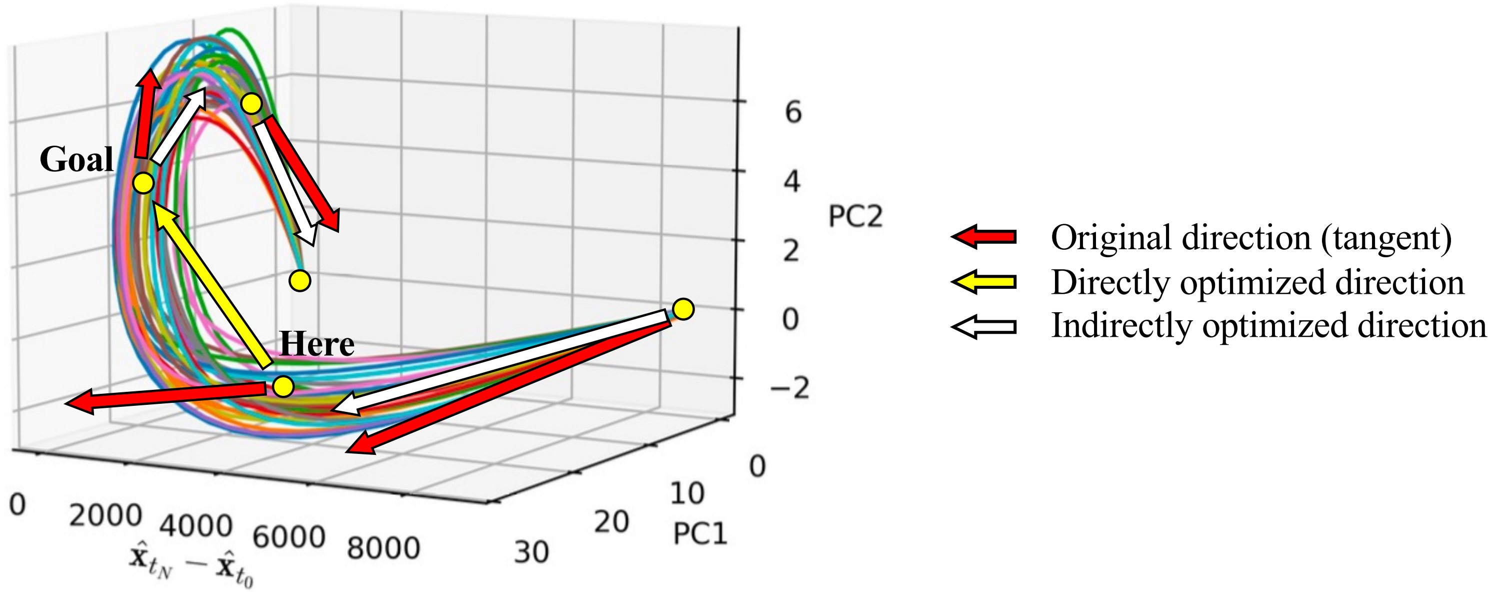

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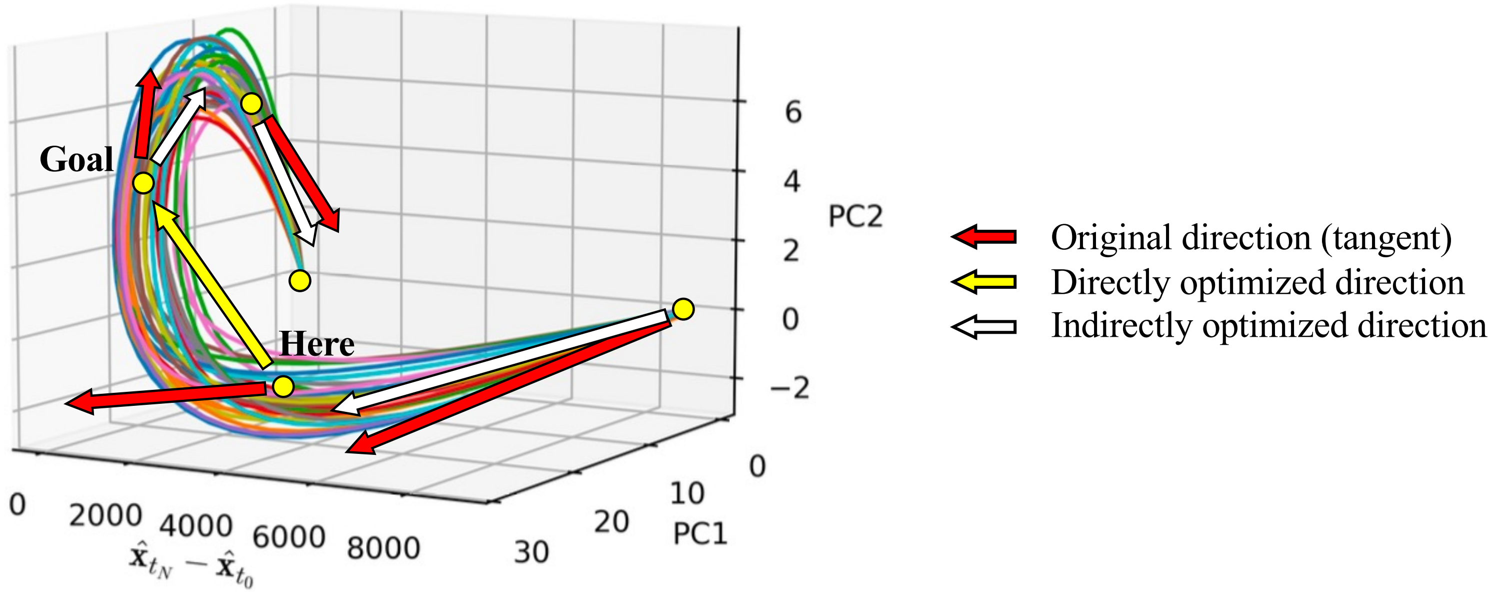

No need to fine-tune on a fine-grained timestamps

Method Overview

- **Ingredient 1: From Local Optimization to Global Optimization**

Algorithm 1 Trajectory Distillation

repeat
  Sample $\mathbf{x}_0$ from the dataset
  Sample $n \sim \mathcal{U}(0, N-1)$
  Sample $\mathbf{x}_{n+1} \sim \mathcal{N}(\mathbf{x}_0; t_{n+1}^2 \mathbf{I})$
  $\mathbf{x}_n^{\psi} \leftarrow \text{Euler}(\mathbf{x}_{n+1}, t_{n+1}, t_n, 1; \psi)$
  $\tilde{\mathbf{x}}_n \leftarrow \text{Solver}(\mathbf{x}_{n+1}, t_{n+1}, t_n, K; \theta)$
  $\mathcal{L}(\psi) \leftarrow d(\mathbf{x}_n^{\psi}, \tilde{\mathbf{x}}_n)$
  $\psi \leftarrow \psi - \eta \nabla_{\psi} \mathcal{L}(\psi)$
until convergence

Algorithm 2 SFD (ours)

repeat
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  - Enable the teacher to sample more efficiently by multi-step solvers
  - Enable the student to fix accumulated errors

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  - DPM++(3M) > DPM(2S) > Heun > DDIM (Euler)

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  - Use analytical first step (AFS) to save one sampling step

- **Ingredient 4: Loss Metric:** L1 > Pseudo-Huber > LPIPS > L2

Method	Teacher	$t_{\min}$	AFS	Loss	FID
Vanilla	Heun	0.002	N/A	L2	46.84
Vanilla	DPM(2S)	0.002	N/A	L2	16.69
SFD	Heun	0.002	False	L2	20.88
SFD	DPM(2S)	0.002	False	L2	12.50
SFD	DPM++(3M)	0.002	False	L2	11.65
SFD	DPM++(3M)	0.006	False	L2	10.93
SFD	DPM++(3M)	0.002	True	L2	7.17
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Consistent settings can be applied to various datasets

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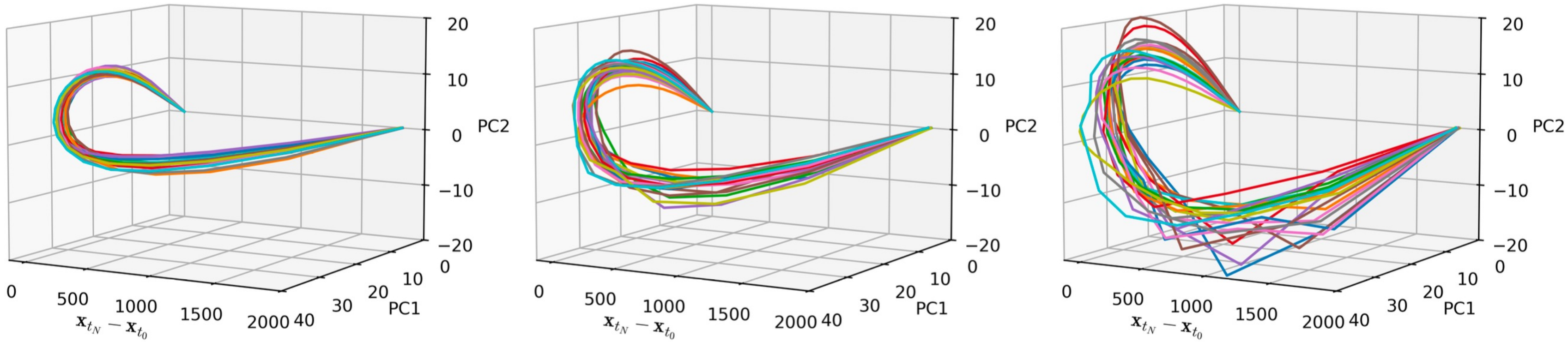
- **Distillation under Classifier-free Guidance**
  - Classifier-free guidance: $\tilde{\boldsymbol{\epsilon}}_\theta(\mathbf{x}, t, c) = \omega \boldsymbol{\epsilon}_\theta(\mathbf{x}, t, c) + (1-\omega)\boldsymbol{\epsilon}_\theta(\mathbf{x}, t, c=\varnothing)$
  - Distill with guidance scale of 1 and sampling with any guidance scale



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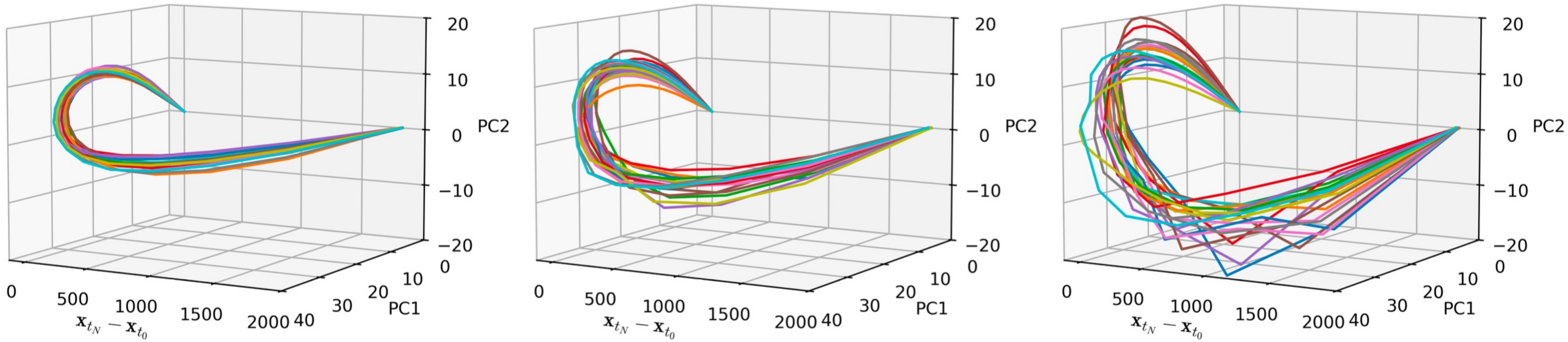

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- **Second-stage Distillation for One-NFE Sampling**

Experiments: Main Results

Table 2: Results on CIFAR10 32 $\times$ 32.

Method	NFE	FID	Training time (A100 hours)
Solver-based Methods			
DDIM [44]	10	15.69	0
	50	2.91	0
DPM++(3M) [28]	5	24.97	0
	10	3.00	0
AMED-Plugin [58]	5	6.61	$\sim$ 0.08
	10	2.48	$\sim$ 0.11
GITS [4]	5	8.38	$<$ 0.01
	10	2.49	$\sim$ 0.01
Diffusion Distillation			
PD [41]	1	9.12	$\sim$ 195
	2	4.51	$\sim$ 171
Guided PD [32]	1	8.34	$\sim$ 146
	2	4.48	$\sim$ 128
	4	3.18	$\sim$ 119
CD [46]	1	3.55	$\sim$ 1156
	2	2.93	$\sim$ 1156
CTM [15]	1	1.98	$\sim$ 83
CTM [15] w/o GAN loss	1	$>$ 5	$\sim$ 60
SFD (ours) (second-stage)	1	5.83	4.88
SFD (ours)	2	4.53	0.64
	3	3.58	0.92
	4	3.24	1.17
	5	3.06	1.42
SFD-v (ours)	2	4.28	4.26
	3	3.50	
	4	3.18	
	5	2.95	

Table 3: Results on ImageNet 64 $\times$ 64.

Method	NFE	FID	Training time (A100 hours)
Solver-based Methods			
DDIM [44]	10	16.72	0
	50	4.09	0
DPM++(3M) [28]	5	25.49	0
	10	5.67	0
AMED-Plugin [58]	5	13.83	$\sim$ 0.18
	10	5.01	$\sim$ 0.32
GITS [4]	5	10.79	$<$ 0.02
	10	4.48	$\sim$ 0.02
Diffusion Distillation			
PD [41]	1	15.39	$<$ 5533
	2	8.95	$<$ 4611
Guided PD [32]	1	22.74	$<$ 5533
	2	9.75	$<$ 4611
	4	4.14	$<$ 4150
CD [46]	1	6.20	$<$ 7867
	2	4.70	$<$ 7867
CTM [15]	1	2.06	$<$ 902
	2	1.90	$<$ 902
SFD (ours) (second-stage)	1	12.89	6.86
SFD	2	10.25	3.34
	3	6.35	4.63
	4	4.99	5.98
	5	4.33	7.11
SFD-v (ours)	2	9.47	23.62
	3	5.78	
	4	4.72	
	5	4.21	

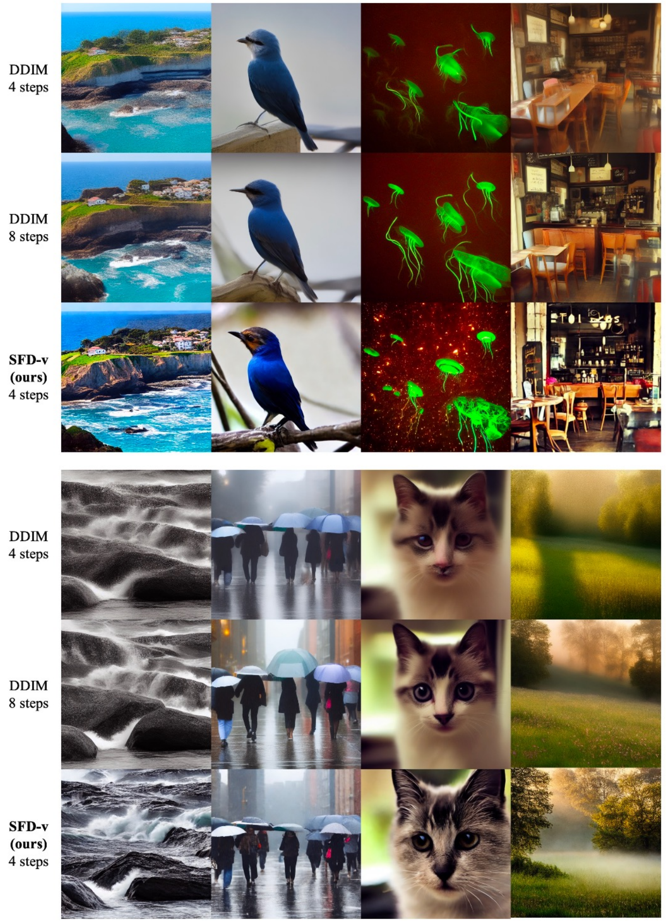
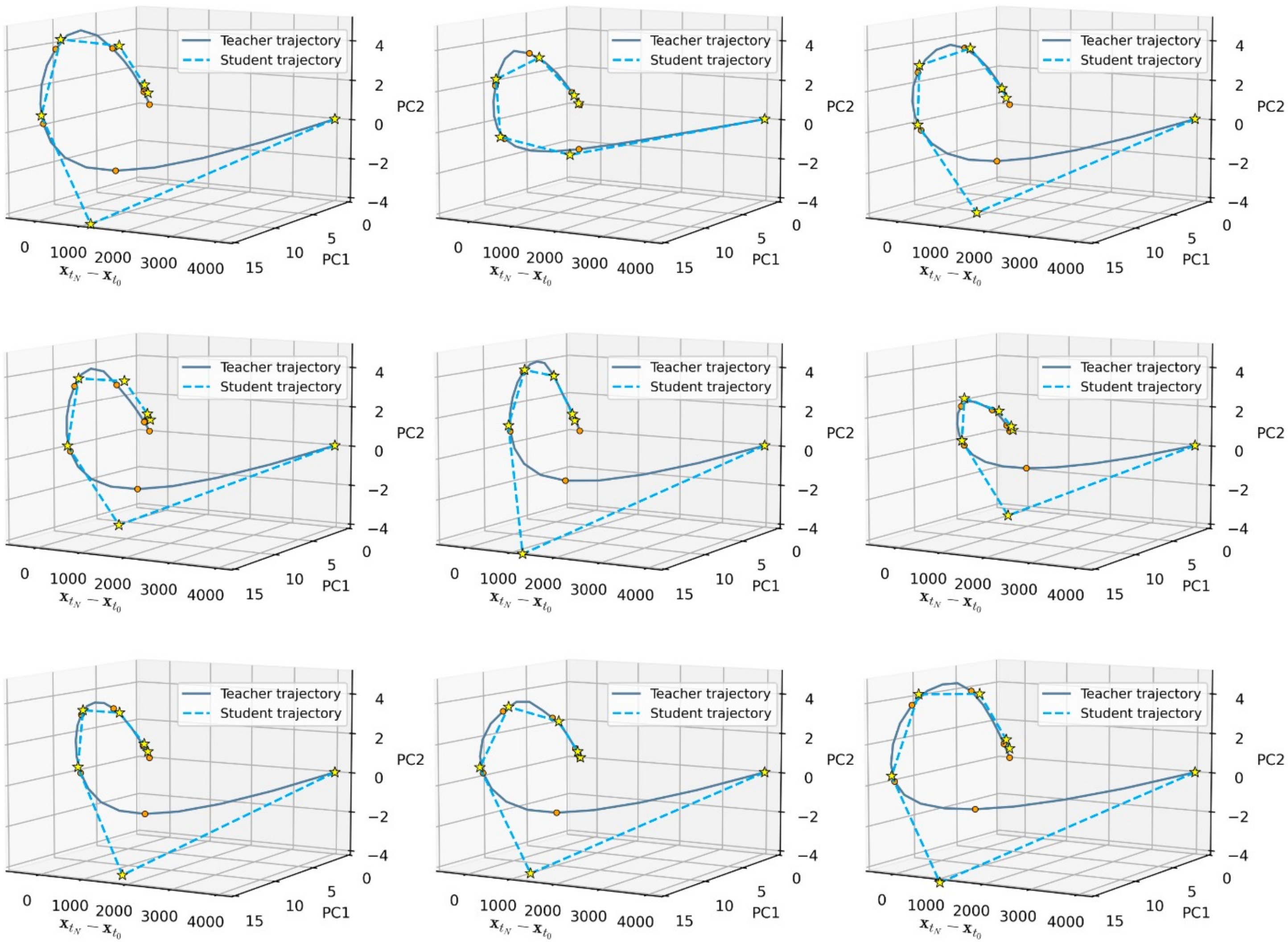


Figure 12: Qualitative results generated by Stable Diffusion v1.5 [41].

Experiments: Visualization



Thanks for watching !