

CONSISTENT DISTRIBUTION MATCHING FOR DATA-FREE DIFFUSION DISTILLATION

Yuxiang Fu^{1,2} Qi Yan^{1,2} Zike Wu^{1,2} Yongxing Zhang^{1,2}

Purang Abolmaesumi¹ Lele Wang¹ Renjie Liao^{1,2,3}

¹University of British Columbia, ²Vector Institute for AI, ³Canada CIFAR AI Chair

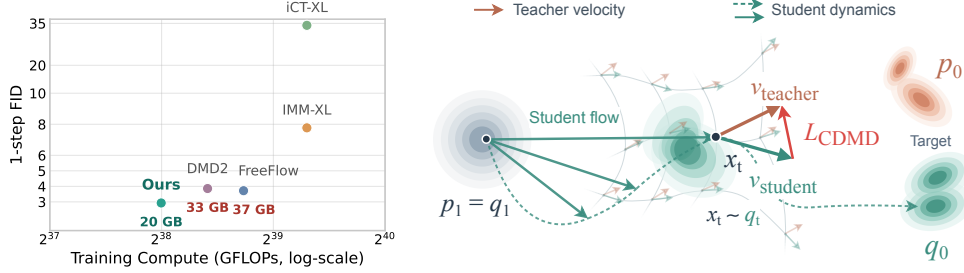


Figure 1: Left: compute versus one-step FID-50K on ImageNet 256×256 . The training memory below is measured with the same configuration on a single A100 80GB GPU. Right: Consistent Distribution Matching overview. Our method aligns the marginal probability paths of the teacher p_t and the student q_t without requiring curated distillation data or computationally intensive simulations.

ABSTRACT

Flow and diffusion models suffer from slow inference due to computationally expensive numerical integration. Distillation provides a promising way for a student model to learn from a teacher’s dynamics, enabling one-step or few-step generation. However, existing methods often depend on curated distillation datasets, costly teacher rollouts, or auxiliary proxy networks, which complicate model training and scaling. In this work, we propose Consistent Distribution Matching, a simulation-free and data-free distillation method for accelerating diffusion and flow models while preserving strong generative capacity. Our key insight is to unify sample generation and score estimation with one student network. Thus, our framework uses only **two** models, a frozen teacher and a trainable student, and optimizes **one** objective. We prove that minimizing our objective indicates Wasserstein convergence of the student flow-map pushforwards to the teacher marginals. On ImageNet 256×256 , our method attains an FID of **2.04** with a single function evaluation (1-NFE) and a 4-NFE FID of **1.37** within 40 epochs of training, surpassing the state-of-the-art distillation baselines without data. Our code code and model are available at <https://consistentdmd.github.io/>.

1 INTRODUCTION

Diffusion and flow-based generative models (Albergo et al., 2023; Lipman et al., 2023; Liu et al., 2023; Dhariwal & Nichol, 2021; Song et al., 2021; Karras et al., 2022; Ho et al., 2020; Rombach et al., 2022; Tong et al., 2025) have become a leading framework for high-fidelity image and video synthesis. By learning a continuous transport from a simple prior distribution to a complex data distribution, these models provide stable training and strong sample quality across a wide spectrum of generative tasks (Fu et al., 2025; Yan et al., 2023; Wu et al., 2023b; Li et al., 2025; Zhang et al., 2025; Yan et al., 2025; Yin et al., 2025). Despite these advantages, their inference cost remains non-trivial. The primary bottleneck lies in the iterative denoising procedure during inference. Generating a single sample requires numerically solving the differential equations governing the generative dynamics, which often involves hundreds of neural function evaluations.



Figure 2: Curated 1024×1024 samples produced by our 4-step CDMD generator distilled from SANA1.6B LORA (Xie et al., 2024a). Please zoom in for details.

To address this challenge, diffusion distillation (Geng et al., 2024; Song et al., 2023; Song & Dhariwal, 2023; Lu & Song, 2024; Meng et al., 2023; Frans et al., 2024; Sabour et al., 2025; Fu et al., 2025) provides a natural route to accelerate the generation with a new model. Given a powerful teacher diffuser, the student is trained to reproduce the teacher’s generative behavior while compressing the inference process in one or few steps. Existing distillation methods have made substantial progress, yet their training pipelines often introduce additional complexity. Some depend on heavy backward simulation (Liu et al., 2023; Zhao et al., 2026; Gu et al., 2023) of a teacher diffusion model, auxiliary fake score networks (Yin et al., 2024b;a; Xie et al., 2024b; Zhou et al., 2024; 2025d; Luo et al., 2025; Ge et al., 2026), adversarial objectives (Zhou et al., 2025d; Kim et al., 2023; Sauer et al., 2024; 2025), or multi-stage training (Lee et al., 2024). Although these components enable high-quality generation in few steps, they incur substantial memory overhead, impose an egregiously high optimization burden, and ultimately hinder the scalability of the distillation procedure.

Beyond this procedural complexity, reliance on external distillation data (Yin et al., 2024b;a; Peng et al., 2025; Song et al., 2023; Lu & Song, 2024; Meng et al., 2023; Zhou et al., 2024) introduces a fundamental source of mismatch between data and teacher probability path. Data-based methods construct intermediate states by noising real data samples, often drawn from a distillation dataset that differs from the data used to train the teacher. Consequently, these states may deviate from those actually visited by the teacher during generation, causing the student to be supervised on a surrogate state distribution, instead of along the teacher’s probability path. This mismatch of the supervision states (Tong et al., 2025) becomes pronounced when fine-tuning tilts the teacher’s distribution away from the original data (Xie et al., 2024b; Chen et al., 2025; Liu et al., 2025) or when the teacher adopts classifier-free guidance (Ho & Salimans, 2022) or autoguidance (Karras et al., 2024). In these settings, noising samples from the original data distribution provides progressively less faithful coverage of the states visited by the teacher. Moreover, when a teacher model is trained on proprietary data (Rombach et al., 2022; Wu et al., 2025; Seedream et al., 2025; Labs, 2025), constructing such a data-anchored supervision path may be infeasible. Direct supervision on teacher trajectories would address the mismatch, but obtaining such states requires backward simulation, thereby reintroducing the aforementioned computational burden. This trade-off motivates our central question: *can we distill a diffusion or flow teacher into a few-step student without external data, teacher rollouts, or auxiliary fake score models?*

We propose Consistent Distribution Matching Distillation (CDMD), a data-free and simulation-free framework for distilling diffusion and flow models using only a frozen teacher and a trainable student. Our framework aims to circumvent the distribution mismatch issues. Our central idea is to unify

sample generation and score estimation within a single flow map model, eliminating the need for a separately trained proxy network. The student predicts average velocities over arbitrary denoising time intervals, supporting generation in one or a few steps. We bootstrap intermediate training states from student predictions and analytic forward noising, avoiding real data and teacher rollouts while allowing the training distribution to evolve with the student.

Although these states do not necessarily coincide with those visited by the teacher during generation, our objective progressively aligns the corresponding student probability path with the teacher probability path. This enables the teacher to provide corrective velocity supervision directly on states relevant to the student’s generative dynamics. At these states, we regress the student velocity surrogate toward the teacher’s instantaneous velocity through a single objective. Moreover, as the states become noisier, they increasingly resemble the distributions encountered during teacher training, making the teacher’s velocity supervision more reliable. This trend is consistently observed across existing distribution matching baselines (Yin et al., 2024a;b). The quality of the supervision also improves as the student distribution moves closer to the teacher distribution.

We further establish a theoretical connection between local transport consistency and distribution matching. Under appropriate assumptions, minimizing population loss implies that the distributions induced by the student flow map converge to the teacher marginals in squared Wasserstein-2 distance averaged over time. Importantly, this result does not require the supervision states to be sampled from the teacher’s probability path. Next, the minimizer of our objective becomes the teacher average velocity. Overall, these results explain how local consistency can identify the teacher’s transport behavior and achieve distributional alignment without auxiliary score networks.

Our contributions are threefold:

1. We introduce Consistent Distribution Matching Distillation, a data-free and simulation-free distillation framework for diffusion and flow-based generative models. The method uses only a frozen teacher and a trainable student, avoiding external distillation data, teacher rollouts and auxiliary proxy networks.
2. We provide a distribution-matching analysis showing that minimizing the proposed CDMD objective leads to narrowing the gap between the teacher distribution and the student distribution under regularity assumptions. The analysis also identifies the teacher’s average velocity field as the unique global minimizer for our objective.
3. We analyze the variance of the JVP correction in the data-free setting and validate the analysis on synthetic datasets. These results clarify when the correction improves stability and when student-teacher path mismatch can degrade training. On ImageNet256×256, Consistent Distribution Matching Distillation achieves a 1-NFE FID of **2.04** and a 4-NFE FID of **1.37**, achieving state-of-the-art performance among data-free distillation methods. In the text-to-image comparison when training data is inaccessible, our method leads most preference and alignment metrics and FID.

2 BACKGROUND

Diffusion and Flow Matching. Let p_0 denote the data distribution and p_1 a prior distribution. For each $\mathbf{x}_0 \sim p_0$ and $\mathbf{x}_1 \sim p_1$, Flow Matching (FM) (Albergo et al., 2023; Lipman et al., 2023; Liu et al., 2023) defines a continuous flow path between $\mathbf{x}_0$ and $\mathbf{x}_1$ via an affine transformation $\mathbf{x}_t := \alpha_t \mathbf{x}_0 + \sigma_t \mathbf{x}_1$, $t \in [0, 1]$, where $\alpha_t, \sigma_t : [0, 1] \rightarrow [0, 1]$ are prescribed schedules. These schedules are smooth, monotone functions with the boundary conditions $\alpha_0 = \sigma_1 = 1, \alpha_1 = \sigma_0 = 0$. One standard approach constructs a path $\mathbf{x}_t = (1 - t)\mathbf{x}_0 + t\mathbf{x}_1$ between a noise sample $\mathbf{x}_1$ and a data sample $\mathbf{x}_0$, which induces a constant conditional velocity (Lipman et al., 2023; Tong et al., 2023): $\mathbf{v}_t(\mathbf{x}_t | \mathbf{x}_0, \mathbf{x}_1) = \frac{d\mathbf{x}_t}{dt} = \mathbf{x}_1 - \mathbf{x}_0$. By conditioning over all possible data and prior pairs $(\mathbf{x}_0, \mathbf{x}_1)$, we obtain a marginal probability path $\mathbf{x}_t \sim p_t$ and the corresponding target velocity field $\mathbf{v} : \mathbb{R}^D \times [0, 1] \rightarrow \mathbb{R}^D$,

$$\mathbf{v}(\mathbf{x}_t, t) := \mathbb{E}_{p(\mathbf{x}_0, \mathbf{x}_1 | \mathbf{x}_t)}[\mathbf{v}_t(\mathbf{x}_t | \mathbf{x}_0, \mathbf{x}_1)]. \quad (1)$$

Here $\mathbf{v}(\cdot, t)$ denotes the marginal velocity field at time t and Eq. (1) relates the marginal velocity field to the conditional velocity $\mathbf{v}_t$. Due to the intractability of the marginal velocity field $\mathbf{v}(\mathbf{x}_t, t)$, FM therefore learns a neural velocity field $\mathbf{v}_\theta(\cdot) : \mathbb{R}^D \times [0, 1] \rightarrow \mathbb{R}^D$ by minimizing the conditional FM

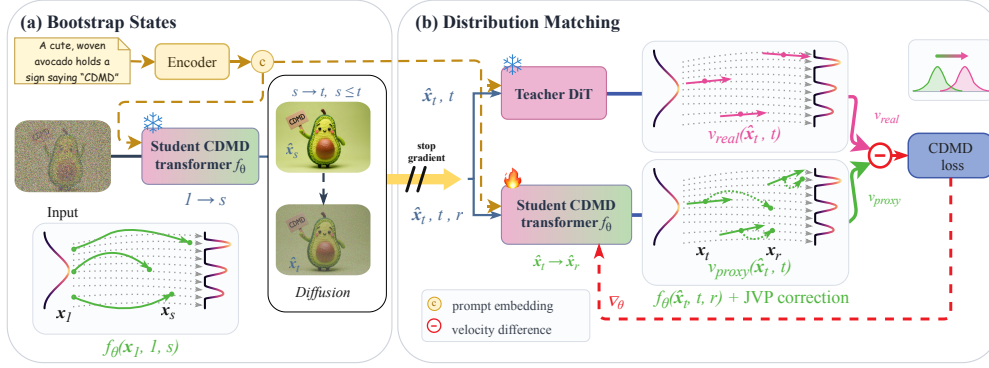


Figure 3: Overview of our Consistent Distribution Matching method. Panel (a) illustrates an effective data-free construction of $\hat{x}_t$. Note that s is the balancing time between student transition and forward path. In (b), we demonstrate how the student proxy velocity matches the target teacher velocity. t, r are the start and end time, respectively. Note that the teacher model is the only supervision source. We include the architectural detail of our CDMD transformer in the Appendix E.

(CFM) objective

$$\mathcal{L}_{\text{CFM}}(\theta) = \mathbb{E}_{\mathbf{x}_t, \mathbf{v}_t, t} [\|\mathbf{v}_\theta(\mathbf{x}_t, t) - \mathbf{v}_t(\mathbf{x}_t | \mathbf{x}_0, \mathbf{x}_1)\|_2^2], \quad (2)$$

for all $t \in [0, 1]$. The minimizer θ^* of Eq. (2) provably recovers the true marginal velocity field at optimum, *i.e.*, $\mathbf{v}_{\theta^*}(\mathbf{x}_t, t) = \mathbf{v}(\mathbf{x}_t, t)$ (Lipman et al., 2023; Tong et al., 2023). During inference, we solve an ordinary differential equation (ODE) $\frac{d\mathbf{x}_t}{dt} = \mathbf{v}_{\theta^*}(\mathbf{x}_t, t)$ via integration.

Score Distillation. Score distillation aligns the student distribution q_0 with the teacher distribution p_0 by minimizing their reverse KL divergence, *i.e.* $D_{\text{KL}}(q_0 \| p_0) = \mathbb{E}_{\hat{\mathbf{x}} \sim q_0} [\log q_0(\hat{\mathbf{x}}) - \log p_0(\hat{\mathbf{x}})]$. In practice, Distribution Matching Distillation (Yin et al., 2024a;b) (DMD) applies this objective to diffused distributions q_t and p_t . Given a generated sample $\hat{\mathbf{x}}_0 = G_\theta(\mathbf{z})$ from the student, DMD constructs $\hat{\mathbf{x}}_t = \alpha_t \hat{\mathbf{x}}_0 + \sigma_t \epsilon$ and updates the generator using

$$\nabla_\theta \mathcal{L}_{\text{SD}} = \mathbb{E}_t [\nabla_\theta D_{\text{KL}}(q_t \| p_t)] \approx \mathbb{E}_{\mathbf{z}, t, \epsilon} \left[w_t (s_{\text{fake}}(\hat{\mathbf{x}}_t, t) - s_{\text{real}}(\hat{\mathbf{x}}_t, t))^\top \left(\frac{\partial G_\theta(\mathbf{z})}{\partial \theta} \right) \right], \quad (3)$$

where $\mathbf{z}, \epsilon \sim \mathcal{N}(0, \mathbf{I})$, and w_t is an adaptive reweighting term. The frozen teacher provides the real score $s_{\text{real}} \approx \nabla_{\mathbf{x}} \log p_t$. In addition, an auxiliary network estimates the fake score $s_{\text{fake}} \approx \nabla_{\mathbf{x}} \log q_t$ through standard diffusion training, using student generated clean samples as targets. Following variational score distillation (Wang et al., 2023), this procedure alternates between updating the generator and training the fake score model with separate objectives. Similar to GANs (Huang et al., 2024; Brock et al., 2018; Kang et al., 2023; Sauer et al., 2025; 2022), this coupled two-player optimization makes DMD intrinsically difficult to train. Under the two-timescale update rule, the fake score model is updated substantially more often than the generator, consuming a large fraction of the training compute to track the generator’s evolving distribution, despite being discarded entirely at inference time. Although subsequent methods, including Score identity Distillation (SiD), FreeFlow, and SenseFlow (Zhou et al., 2024; Tong et al., 2025; Ge et al., 2026), improve the optimization and training objective, they still follow the same paradigm by devoting substantial computation to training an auxiliary fake score model. In particular, SiD extends reverse KL to Fisher divergence, *i.e.* $D_{\text{F}}(q_t \| p_t) = \mathbb{E}_{\hat{\mathbf{x}} \sim q_t} \|\nabla_{\hat{\mathbf{x}}} \log q_t(\hat{\mathbf{x}}) - \nabla_{\hat{\mathbf{x}}} \log p_t(\hat{\mathbf{x}})\|^2$.

3 CONSISTENT DISTRIBUTION MATCHING DISTILLATION

This section develops Consistent Distribution Matching Distillation as a distillation method without external data or teacher simulation, as illustrated in Fig. 3. We first motivate supervision on states bootstrapped from the student model. Beyond the tradition KL divergence, we develop Consistent Distribution Matching from a Fisher-divergence criterion using a velocity surrogate derived from the student network. Finally, we relate the resulting consistency residual to distribution matching under regularity assumptions.

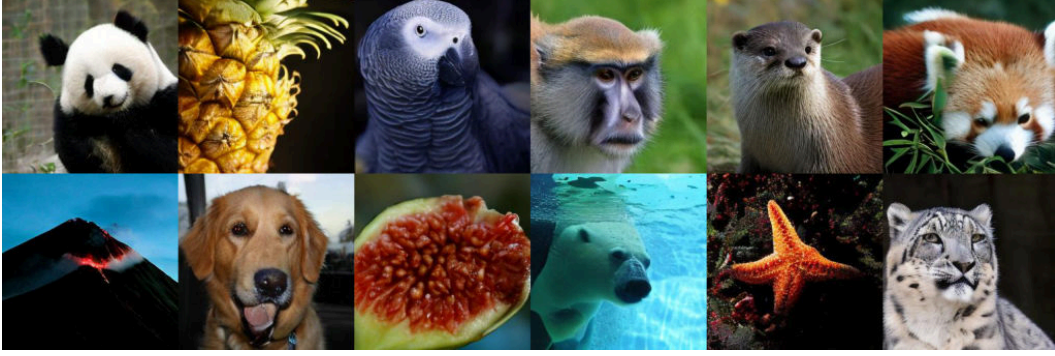


Figure 4: Uncurated qualitative Results on ImageNet 256×256 dataset. Samples are generated by our CDMD method with **one** NFE conditioned on the class labels.

3.1 MINIMAL DESIGN ON DATA-FREE DISTILLATION

Current distillation methods require either online training with external data or expensive offline generation of teacher samples. In the former setting, training states are drawn from a forward FM path $\hat{p}_t$, while the teacher follows its own probability path p_t . Since $\hat{p}_t \neq p_t$ in general, the student is supervised on a mismatched state distribution. Training directly on p_t avoids this mismatch, but sampling intermediate teacher states requires simulating the teacher dynamics, introducing substantial computational overhead.

Unifying proxy model and student generator. Motivated by SiD (Zhou et al., 2024), we therefore adopt a data-free construction based on the student rollout. However, evaluating this objective typically introduces an auxiliary model to estimate the student’s marginal velocity, which violates our design principle of involving only the teacher and student. To eliminate this extra model, the student must be capable of both generating clean samples and providing a surrogate for its own marginal velocity within a unified framework.

We recast the Fisher-divergence objective in velocity form under the FM framework¹:

$$\mathcal{L}_{\text{VD}}(\theta) = \mathbb{E}_t [w_t D_F(q_t \| p_t)] = \mathbb{E}_{t, \mathbf{z}, \epsilon} \left[\bar{w}_t \|\mathbf{v}_{\text{fake}}(\hat{\mathbf{x}}_t, t) - \mathbf{v}_{\text{real}}(\hat{\mathbf{x}}_t, t)\|_2^2 \right], \quad (4)$$

where $\bar{w}_t = (1-t)^2 t^{-2} w_t$ is a weighting function for $0 < t < 1$. Consequently, the problem reduces to jointly modeling global one-step generation and local instantaneous velocity. This calls for a model that maps between arbitrary times along an ODE trajectory by representing the integrated velocity, *i.e.* a flow map model (Albergo & Vanden-Eijnden, 2023; Boffi et al., 2024; Geng et al., 2025a;b; Zhang et al., 2026; Lee et al., 2026; Sabour et al., 2025). We therefore opt to model the average velocity field. Define the average velocity $\mathbf{u} : \mathbb{R}^D \times [0, 1] \times [0, 1] \rightarrow \mathbb{R}^D$, for $0 \leq r < t \leq 1$, as $\mathbf{u}(\mathbf{x}_t, t, r) := \frac{\mathbf{x}_t - \mathbf{x}_r}{t - r} = \frac{1}{t - r} \int_r^t \mathbf{v}(\mathbf{x}_\tau, \tau) d\tau$.

If r is independent of t , we recover the instantaneous velocity along the underlying ODE trajectory by differentiating this definition with respect to t . This identity motivates replacing the auxiliary proxy model with a velocity surrogate derived from the student itself. In particular, one-step generation and the velocity surrogate take the forms $G_\theta(\mathbf{z}) = \mathbf{z} - \mathbf{u}_\theta(\mathbf{z}, 1, 0)$, $\mathbf{v}_{\text{fake}}(\mathbf{x}_t, t) \approx \mathbf{u}_\theta(\mathbf{x}_t, t, r) + (t - r) \frac{d}{dt} \mathbf{u}_\theta(\mathbf{x}_t, t, r)$, respectively, where we unify the proxy model and the generator with $\mathbf{u}_\theta(\mathbf{x}_t, t, r)$. For the surrogate, the total derivative is evaluated in the teacher’s velocity direction, holding r fixed. Note that the average-velocity quotient is undefined at $r = t$. Hence, we define its continuous extension as $\mathbf{u}(\mathbf{x}_t, t, t) := \lim_{r \rightarrow t} \mathbf{u}(\mathbf{x}_t, t, r) = \mathbf{v}(\mathbf{x}_t, t)$, assuming the underlying velocity is continuous.

One advantage of modeling average velocity is that we can recover instantaneous velocity from its definition. The same parameterization also allows us to generate a clean sample in one forward

¹We show the equivalence between the score and velocity formulations of reverse KL in the Appendix C.3, allowing us to use the velocity formulation directly. The same applies for Fisher divergence. The precise form depends on the parameterization of the diffusion or flow-based model.

pass. Thus, a single student network provides both one-step generation and instantaneous velocity modeling in tandem, eliminating the auxiliary network. Substituting the one-step generation and the velocity surrogate into Eq. (4) yields the following surrogate for the Fisher-divergence objective:

$$\mathcal{L}_{\text{VD}}(\theta) \approx \mathbb{E}_{t,r,z,\varepsilon} \left[\bar{w}_t \left\| \left[\mathbf{u}_\theta(\hat{\mathbf{x}}_t, t, r) + (t-r) \frac{d}{dt} \mathbf{u}_\theta(\hat{\mathbf{x}}_t, t, r) \right] - \mathbf{v}_{\text{real}}(\hat{\mathbf{x}}_t, t) \right\|_2^2 \right]. \quad (5)$$

This substitution is exact when the velocity surrogate coincides with the marginal velocity of q_t .

Training objective. In the absence of external data, the central question becomes how to construct the intermediate noisy state $\mathbf{x}_t$. Our construction is motivated by two desiderata. First, we aim to perform distillation without access to real training data, requiring the intermediate states to be generated from the student dynamic path. Second, to keep the procedure simulation-free, each intermediate state involves only a single evaluation of the student model. Let $\mathbf{f}_\theta(\mathbf{x}_t, t, r) := \mathbf{x}_t - (t-r)\mathbf{u}_\theta(\mathbf{x}_t, t, r)$ be the endpoint of the student transport, given initial state at time t and terminal time r . Leveraging the closed-form forward noising path, we therefore construct the target $\hat{\mathbf{x}}_t$ by first denoising the prior sample $\mathbf{z} \sim p_1$ to an earlier time s , followed by analytically renoising the resulting state from s to t :

$$\hat{\mathbf{x}}_t = \frac{1-t}{1-s} \mathbf{f}_\theta(\mathbf{z}, 1, s) + \frac{t-s}{1-s} \varepsilon \quad \mathbf{z}, \varepsilon \sim p_1, \quad 0 \leq s \leq t < 1. \quad (6)$$

The two extremes of s recover familiar constructions. At $s = t$, the state lies on the student path, $\hat{\mathbf{x}}_t = \mathbf{f}_\theta(\mathbf{z}, 1, t)$. At $s = 0$, it is a noised one-step student sample, $\hat{\mathbf{x}}_t = (1-t)\hat{\mathbf{x}}_0 + t\varepsilon$, as in score distillation. We denote the resulting law of $\hat{\mathbf{x}}_t$ by q_t^θ and refer to it as the student probability path. As the student approaches the teacher, q_t^θ moves toward the teacher path and supplies more informative supervision states. We train the student with

$$\mathcal{L}_{\text{CDMD}}(\theta) := \mathbb{E}_{t,r,\hat{\mathbf{x}}_t \sim q_t^\theta} \left\| \mathbf{u}_\theta(\hat{\mathbf{x}}_t, t, r) + (t-r) \cdot \text{sg} \left[\frac{d}{dt} \mathbf{u}_\theta(\hat{\mathbf{x}}_t, t, r) \right] - \mathbf{v}(\hat{\mathbf{x}}_t, t) \right\|^2, \quad (7)$$

where sg is the stop-gradient operator, and we overload this notation $\overset{\text{sg}}{\sim}$ to indicate the sampled state is detached from the computation graph. The total derivative $\frac{d}{dt} \mathbf{u}_\theta = D_{\hat{\mathbf{x}}_t} \mathbf{u}_\theta \frac{d\hat{\mathbf{x}}_t}{dt} + \partial_t \mathbf{u}_\theta = \text{JVP}(\mathbf{u}_\theta; (\frac{d\hat{\mathbf{x}}_t}{dt}, 1, 0))$ is computed by one Jacobian-vector product (JVP) in the forward mode. We study the choice of the tangent $\frac{d\hat{\mathbf{x}}_t}{dt}$ in Sec. 3.2. Detaching the JVP prevents higher-order gradients through the total derivative, which stabilizes training. Our objective uses the consistency residual motivated by Eq. (5), aiming to reduce the Fisher divergence between student and teacher distributions.

Let $p_t := (\mathbf{f}(\cdot, 1, t))_{\#} p_1$ be the teacher marginal, i.e., the law of $\mathbf{f}(\mathbf{z}, 1, t)$ with $\mathbf{z} \sim p_1$. Let the consistency residual of our CDMD objective be $\mathcal{R}_\theta(\mathbf{x}_t, t, r) := \mathbf{u}_\theta(\mathbf{x}_t, t, r) + (t-r) \cdot \frac{d}{dt} \mathbf{u}_\theta(\mathbf{x}_t, t, r) - \mathbf{v}(\mathbf{x}_t, t)$. Theorem 3.1 compares the teacher joint law $\mathbf{P}$ with the training law $\mathbf{Q}_\theta$ of $(r, t, \hat{\mathbf{x}}_t)$. Part (a) shows that if $\mathbf{P}$ is contiguous with respect to $(\mathbf{Q}_\theta)_n$, then $\mathcal{L}_{\text{CDMD}}(\theta_n) \rightarrow 0$ implies that the W_2 distance between the student pushforwards and the teacher marginals, averaged over r , also goes to zero. Part (b) shows that if $\mathbf{P}$ and $\mathbf{Q}_\theta$ are mutually absolutely continuous on denoising intervals, then every global minimizer recovers the teacher average velocity. Student-bootstrapped states are therefore a principled substitute for teacher rollouts, provided the student path stays close to the teacher path. The detailed theorem and proof are in Appendix A.

Theorem 3.1 (Distributional consistency and identification (simplified)). *Let p_t denote the teacher marginals and ν the reference-time law on $[0, 1)$. Under the respective regularity, coverage, and integrability assumptions detailed in Appendix A:*

- (a) *For any parameter sequence (θ_n) , vanishing population loss $\mathcal{L}_{\text{CDMD}}(\theta_n) \rightarrow 0$ implies $\int_{[0,1)} W_2^2((\mathbf{f}_{\theta_n}(\cdot, 1, r))_{\#} p_1, p_r) \nu(dr) \rightarrow 0$.*
- (b) *If an admissible student can represent the teacher average velocity $\mathbf{u}$, the minimum population loss is zero, and every global minimizer recovers $\mathbf{u}$ almost surely under its training distribution.*

Sampling. Once $\mathbf{u}_\theta$ is learned, the corresponding flow map is recovered by $\mathbf{f}_\theta(\mathbf{x}_t, t, r) = \mathbf{x}_t - (t-r)\mathbf{u}_\theta(\mathbf{x}_t, t, r)$. In particular, one-step generation over the full interval $(r, t) = (0, 1)$ is given by $\hat{\mathbf{x}}_0 = \mathbf{f}_\theta(\mathbf{x}_1, 1, 0) = \mathbf{x}_1 - \mathbf{u}_\theta(\mathbf{x}_1, 1, 0)$, where $\mathbf{x}_1 \sim p_1$. Few-step sampling can be obtained by

Table 1: **Data-free distillation on class-conditional ImageNet256×256 dataset.** **Left:** Comparison using LightningDiT-XL/2 as the teacher. **Right:** Comparison using SiT-XL/2 and SiT-XL/2+VA-REPA as teachers. All numbers are reported with CFG when applicable, and ×2 in NFE indicates that CFG doubles the number of function evaluations at inference time. † denotes results reproduced by us on ImageNet256×256, while * denotes methods adapted by us to the data-free setting. Bold and underlined values indicate the best and second-best results, respectively.

Method	NFE	FID↓	IS↑	Method	NFE	FID↓	IS↑
Teacher Diffusion / Flow Models				Data-free Distillation			
SiT-XL/2 (Ma et al., 2024)	250×2	2.06	277.5	<i>Teacher: SiT-XL/2 (FID = 2.06)</i>			
SiT-XL/2+VA-REPA (Yang et al., 2026)	250×2	1.31	309.7	DMD2† (Yin et al., 2024a)	1	3.93	273.2
LightningDiT (Yao et al., 2025)	250×2	1.35	295.3	FreeFlow w.o. DMD	1	14.5	182.4
Data-free Distillation				FreeFlow (Tong et al., 2025)	1	4.13	268.7
<i>Teacher: LightningDiT-XL/2 (FID = 1.35)</i>				MeanFlow* (Geng et al., 2025a)	1	4.07	251.5
FreeFlow (Tong et al., 2025)	1	4.28	264.9		1	<u>3.47</u>	251.4
DMD2† (Yin et al., 2024a)	1	3.43	317.2	Ours	2	2.87	<u>271.0</u>
MFD† (Zhao et al., 2026)	1	6.67	281.6	<i>Teacher: SiT-XL/2+VA-REPA (FID = 1.31)</i>			
MeanFlow* (Geng et al., 2025a)	1	4.19	213.8	DMD2† (Yin et al., 2024a)	1	3.86	239.1
sCM* (Lu & Song, 2024)	1	4.21	266.9	FreeFlow w.o. DMD	1	15.4	171.3
FACM* (Peng et al., 2025)	1	2.15	303.8	FreeFlow (Tong et al., 2025)	1	3.72	266.4
	2	1.79	319.6	MeanFlow* (Geng et al., 2025a)	1	4.47	214.5
	1	2.04	294.3		1	<u>2.93</u>	286.4
Ours	2	<u>1.62</u>	<u>317.3</u>	Ours	2	2.60	<u>272.8</u>
	4	1.37	306.9				

applying the same map over a sequence of consecutive intervals. Therefore, this parameterization $\mathbf{u}_\theta(\mathbf{x}_t, t, r)$ naturally enables inference-time scaling, as shown by the ablation in Fig. 6.

Tab. 4 shows that CDMD uniquely combines data-free and simulation-free distillation with only two models and a single optimizer, avoiding both adversarial training and the external real data required by GAN objectives (Huang et al., 2024; Zhou et al., 2025d; Sauer et al., 2025).

3.2 VARIANCE OF THE JVP CORRECTION

The detached JVP correction in $\mathcal{L}_{\text{CDMD}}$ is sensitive to the tangent direction used to evaluate it. In our notation, this direction is the input direction $(d\hat{\mathbf{x}}_t/dt, 1, 0)$ of the JVP, rather than the derivative vector $(\partial_{\mathbf{x}}\mathbf{u}_\theta, \partial_t\mathbf{u}_\theta, \partial_r\mathbf{u}_\theta)$ itself. Hence, in the data-free setting, where supervision is obtained only from the teacher on student-generated states, the choice of $d\hat{\mathbf{x}}_t/dt$ directly affects the stochasticity and bias of the detached target. For any realization of $d\hat{\mathbf{x}}_t/dt$, we define the corresponding JVP correction $\mathcal{G}_\theta(\hat{\mathbf{x}}_t, t, r; \frac{d\hat{\mathbf{x}}_t}{dt}) := \text{JVP}(\mathbf{u}_\theta; (\frac{d\hat{\mathbf{x}}_t}{dt}, 1, 0))$.

To diagnose the stochasticity of the correction under data-free supervision, we first define the cross-centered projected JVP second moment

$$\mathcal{M}_{\text{JVP}}^{q,p}\left(\frac{d\hat{\mathbf{x}}_t}{dt}; t, r\right) := \mathbb{E}_{\hat{\mathbf{x}}_t \sim q_t^\theta} \left[\left\| \mathcal{G}_\theta\left(\hat{\mathbf{x}}_t, t, r; \frac{d\hat{\mathbf{x}}_t}{dt}\right) - \mathbb{E}_{\mathbf{x}_t \sim p_t} \left[\mathcal{G}_\theta\left(\mathbf{x}_t, t, r; \frac{d\mathbf{x}_t}{dt}\right) \right] \right\|^2 \right].$$

This term measures the deviation of the JVP correction computed on student-generated states from the average correction on the target path. It captures both the intrinsic fluctuation of the correction under q_t^θ and the distributional mean shift between q_t^θ and p_t . Note the intrinsic JVP variance is recovered as the special case $\mathcal{V}_{\text{JVP}} = \mathcal{M}_{\text{JVP}}^{q,q}$, and the decomposition can be found in Appendix B. We evaluate these statistics for the term $d\hat{\mathbf{x}}_t/dt$ with three viable options, i.e. $d\hat{\mathbf{x}}_t/dt \in \{v(\hat{\mathbf{x}}_t, t), \mathbf{u}_\theta(\hat{\mathbf{x}}_t, t, t), \mathbf{u}_\theta(\mathbf{z}, 1, 0)\}$. The first two terms are the teacher velocity and the student limiting velocity, while the last term is commonly known as the conditional velocity field $\mathbf{x}_1 - \hat{\mathbf{x}}_0$. We find that using $v(\hat{\mathbf{x}}_t, t)$ works best, shown in Fig. 5 (c) the on synthetic dataset.

4 EXPERIMENTS

Below we test CDMD on a synthetic 2D benchmark, class-conditional ImageNet 256×256, and text-to-image generation with SANA-1.6B. We then ablate guidance, the training-state distribution, and the number of sampling steps.

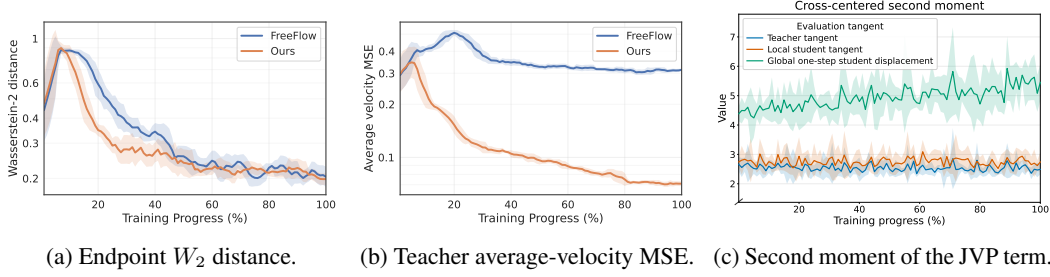


Figure 5: **Endpoint matching does not imply transport matching.** Results on the 2D spiral dataset, where the teacher is the exact velocity field. (a) CDMD and FreeFlow reach similar endpoint distances to the target, showing comparable marginal matching ability. (b) CDMD learns the true teacher average velocity accurately, while FreeFlow has a higher error. (c) Among the three tangent choices in Sec. 3.2, the teacher tangent provides the lowest and most stable JVP second moment.

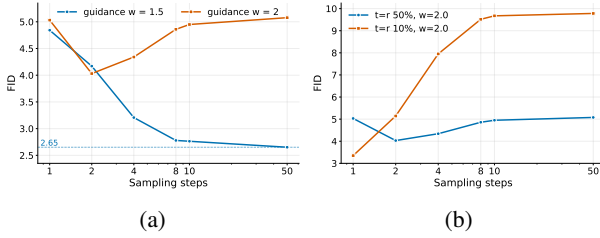


Figure 6: **Multi-step gains depend on guidance and on the fraction of $t=r$ pairs.** (a) FID ($\downarrow$) against sampling steps for two guidance scales. (b) FID ($\downarrow$) against sampling steps for two $t=r$ ratios at $w = 2.0$.

m	Peak step	FID $\downarrow$	IS $\uparrow$
0	41K	3.62	251.5
0.25	43K	3.67	239.9
0.50	41K	3.41	254.8
0.75	44K	3.51	261.4
0.875	42K	3.57	262.7
1.00	44K	3.84	259.6

Table 2: **Mixing both noisy state types beats either alone.** 1-NFE results at the best checkpoint for each mixing ratio m , trained for 50K iterations.

Setup. On ImageNet 256×256 , we distill three teachers: SiT-XL/2 (Ma et al., 2024), SiT-XL/2 trained with VA-REPA (Yang et al., 2026), and LightningDiT-XL/2 with a VA-VAE autoencoder (Yao et al., 2025). The student uses the teacher architecture, with extra embeddings for r and w (Appendix D). We report FID-50K and IS. All baselines use the same training budget and the same evaluation pipeline. For text-to-image, we follow the protocol of MFD (Zhao et al., 2026) with a SANA-1.6B teacher (Xie et al., 2024a). Full hyperparameters are listed in Tab. 5.

Synthetic benchmark. We first use a 2D spiral, where both the target distribution and the ground-truth average velocity are known. The exact velocity field serves as the teacher. This removes the effect of a learned teacher checkpoint and of image metrics. We track two quantities during training (Fig. 5). First, CDMD and FreeFlow reduce the endpoint W_2 distance at the same rate. Endpoint matching therefore cannot distinguish the two methods. Second, only CDMD keeps reducing the teacher average-velocity MSE, while FreeFlow plateaus at a much higher value. This suggests that *matching the endpoint marginal does not imply learning the teacher transport map*. The full metrics in Tab. 6 show the same pattern. Marginal Wasserstein scores are tied, but CDMD has lower coupled endpoint error and lower teacher average-velocity error. Appendix D provides the full setup. In Fig. 5 (c), we observe that JVP yields the most stable behavior when computed in the teacher direction, even on student-bootstrapped states.

ImageNet 256×256 . Tab. 1 groups data-free methods by teacher under matched training budgets. CDMD achieves the best 1-NFE FID across all three teachers: 3.47 with SiT-XL/2, 2.93 with SiT-XL/2+VA-REPA, and 2.04 with LightningDiT-XL/2. It also benefits more from stronger teachers: replacing SiT-XL/2 with VA-REPA improves CDMD by 0.54 FID, compared with 0.41 for FreeFlow and 0.07 for DMD2, while MeanFlow degrades. Without retraining, the same student further improves with additional NFes, reaching FIDs of 2.60 with VA-REPA and 1.62 with LightningDiT-XL/2 at 2 NFes, and 1.37 at 4 NFes, close to the teacher’s 1.35. We omit FreeFlow without DMD in the LightningDiT block because it fails to converge within the training budget. Baselines marked with $\star$ are one-step methods that we adapt to the data-free setting. Specifically, we construct training states by noising clean samples from the current student generator, corresponding to the $s = 0$ case of CDMD. Notice that, these adaptations remain worse comparing to CDMD.

Table 3: **CDMD leads on aesthetics, preference, and FID at 4 NFEs.** Text-to-image generation with SANA-1.6B (Xie et al., 2024a). Baseline numbers follow (Zhao et al., 2026). Bold marks the best result among learned 4-NFE methods. † denotes methods reproduced by us. FID is computed against the COCO-5K 2017 validation set (Lin et al., 2014).

Model	NFE ↓	Aesthetic ↑	PS ↑	HPSv2 ↑	IR ↑	CLIPScore ↑	FID ↓
SANA teacher (Xie et al., 2024a)	20	6.335	0.2021	0.2417	0.8363	30.717	30.39
SANA teacher (Xie et al., 2024a)	4	5.976	0.1872	0.2173	-0.1008	28.251	35.65
SenseFlow (Ge et al., 2026)	4	6.482	0.1998	0.2445	0.7925	29.321	–
AYF (Sabour et al., 2025)	4	6.231	0.1963	0.2298	0.7022	29.176	–
Diff-Instruct (Luo et al., 2023b)	4	6.453	0.1985	0.2434	0.7677	29.393	–
Consistency Distillation† (Song et al., 2023)	4	6.248	0.1906	0.2263	0.6743	28.890	54.38
DMD2† (Yin et al., 2024a)	4	6.489	0.2006	0.2439	0.8042	29.103	32.34
MFD† (Zhao et al., 2026)	4	6.541	0.2002	0.2442	0.8483	29.430	28.77
CDMD (ours)	4	6.906	0.2011	0.2387	0.8864	28.992	27.83

Inference-time scaling. FreeFlow (Tong et al., 2025) is anchored to the prior. Its student only takes noise at $t = 1$, so it cannot be applied over sub-intervals. In contrast, CDMD learns $u_\theta(x_t, t, r)$ for any interval, so extra steps are available at inference time. Fig. 6 (a) shows that the benefit depends on guidance. With $w = 1.5$, FID keeps improving with more steps and approaches the dashed reference. With $w = 2.0$, FID is best at very few steps and worsens as steps increase. This suggests that strong guidance helps one-step generation but amplifies the student–teacher mismatch over multi-step sampling. Fig. 11 in the appendix shows that the gain from extra steps also depends on the sampler.

Training-state construction. Alg. 1 samples $m \in [0, 1]$ to linearly interpolate the two states in Eq. (6): larger m emphasizes one-step student samples, while smaller m emphasizes shared-noise interval states. Tab. 2 shows that intermediate values work best, with the lowest FID at $m = 0.5$ and highest IS at $m = 0.875$, while convergence speed remains similar. Fig. 6b shows a related trade-off for the fraction of $t = r$ pairs: 10% improves 1-NFE FID but degrades multi-step sampling, whereas 50% yields more stable few-step performance. This suggests that sufficient exposure to local intervals is important for multi-step sampling.

Text-to-image generation. We distill SANA-1.6B (Xie et al., 2024a), a flow-matching text-to-image model. The teacher and student are initialized from the same checkpoint. We follow the protocol of MFD (Zhao et al., 2026), training and evaluating on LAION-Aesthetics 6.5+ (Schuhmann et al., 2022). We report Aesthetic Score, PickScore (Kirstain et al., 2023), HPSv2 (Wu et al., 2023a), ImageReward (Xu et al., 2023), CLIPScore (Hessel et al., 2021), and FID against COCO-5k 2017 (Lin et al., 2014).

Tab. 3 gives three findings. First, among learned 4-NFE methods, CDMD has the best Aesthetic Score, PickScore (PS), and ImageReward (IR). Its FID of 27.83 is also below MFD’s 28.77. Second, CDMD beats the teacher run at 4 NFEs on all six metrics, and it beats the 20-NFE teacher on Aesthetic Score, IR, and FID. Third, CDMD trails on HPSv2 and CLIPScore, where four and five of the six baselines score higher, respectively. These results show that CDMD works in one large-scale text-to-image setting. They do not establish statistical superiority. CDMD is also cheap to train. It uses about 7 GPU hours, compared with 22 for Diff-Instruct, 25 for MFD, and 30 for DMD2 (Tab. 7). Only consistency distillation is cheaper (~ 4 GPU hours), yet it scores lower on all five point metrics. All costs are measured on one NVIDIA RTX PRO 6000 GPU, the same setup as the baseline measurements of MFD (Zhao et al., 2026).

5 RELATED WORK

Trajectory Distillation. Distillation accelerates diffusion sampling by training students to reproduce the teacher’s dynamics in fewer steps. Knowledge distillation (Zheng et al., 2023) learns a direct mapping from noise to data, while progressive distillation (Salimans & Ho, 2022; Meng et al., 2023) repeatedly halves the number of sampling steps. Consistency models (Lu & Song, 2024; Song & Dhariwal, 2023; Song et al., 2023; Luo et al., 2023a) map states along the same ODE trajectory to a shared clean sample. Flow map distillation (Boffi et al., 2025; Geng et al., 2025a;b; Sabour et al., 2025; Lee et al., 2026) extends this idea to transitions between arbitrary times along a trajectory. BOOT (Gu et al., 2023), π -Flow (Chen et al., 2025), and rectified flow (Liu et al., 2023) explore

ways to reduce reliance on real training data. For methods that require teacher reference trajectories, generating them during training or precomputing them can limit scalability as tasks become more complex. Our method avoids numerically integrating the teacher during training. Compared with FreeFlow (Tong et al., 2025), which anchors its flow map at noise, our model supports transitions from arbitrary input states and times.

6 CONCLUSION

We presented CDMD, a data-free and simulation-free framework for distilling pretrained diffusion and flow-based teachers into efficient one-step or few-step flow map students. Our method eliminates the need for external distillation data, teacher rollouts, backward simulation, and auxiliary proxy networks by training on a student-induced distribution with a single objective. Motivated by the velocity form Theoretically, we showed that, under regularity assumptions, minimizing our CDMD objective leads to convergence of student sampling distributions to teacher distributions in Wasserstein distance, averaged over reference times, and every global minimizer recovers the teacher average velocity on sampled states. Empirically, CDMD achieves state-of-the-art ImageNet256 $\times$ 256 generation quality among data-free distillation methods and further benefits from inference-time scaling through its parameterization. Our method also achieves the best overall performance in text-to-image generation, leading on both preference and alignment metrics as well as image-quality metrics. These results suggest that strong data-free distillation can be achieved with a simpler two-model training pipeline, while preserving the flexibility of multi-step sampling. Future work includes improving the stability of the JVP term, developing initialization strategies when no model weights are available, and extending the framework to large-scale generative tasks where data scarcity problem dominates.

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APPENDIX CONTENTS

A	Proofs	17
B	More on the Variance of the Target	20
C	Relationship with Prior Methods	21
C.1	FreeFlow	21
C.2	Flow Maps	22
C.3	Equivalence with Original DMD Updates	23
D	Implementation Details	25
D.1	Class-conditional ImageNet	25
D.2	Synthetic 2D Benchmarks	27
D.3	Text-to-image Dataset	28
E	Ablation on Endpoint Conditioning	29
F	Ablation on Inference-time Scaling	30
F.1	Sampler Comparison with the SiT-XL/2+VA-REPA Teacher	30
F.2	Inference-time Scaling with the LightningDiT-XL/2 Teacher	31
G	CDMD with Guidance	31
H	Limitations and Broader Impact	33
I	Image Prompts	33
J	Qualitative Samples	35

A PROOFS

Theorem A.1 (Distributional consistency and identification). *Assume the characteristic regularity conditions in Appendix A. Let p_t be the teacher marginal probability path, ν a probability law on $[0, 1]$. Define $P(dr, dt, d\mathbf{x}) := \nu(dr) \frac{\mathbf{1}_{\{r < t < 1\}}}{1-r} dt p_t(d\mathbf{x})$, to be the joint state measure and let Q_θ be the training state measure of the student model on $(r, t, \hat{\mathbf{x}}_t)$.*

(a) *Consider a sequence (θ_n) . Suppose P is contiguous with respect to (Q_{θ_n}) and $(\|\mathcal{R}_{\theta_n}\|^2)$ is uniformly integrable under P . Then $\mathcal{L}_{\text{CDMD}}(\theta_n) = \mathbb{E}_{Q_{\theta_n}} \|\mathcal{R}_{\theta_n}\|^2 \rightarrow 0$ implies*

$$\int_{[0,1]} W_2^2((f_{\theta_n}(\cdot, 1, r))_{\#} p_1, p_r) \nu(dr) \rightarrow 0.$$

where

$$\mathcal{R}_\theta(\mathbf{x}_t, t, r) := \mathbf{u}_\theta(\mathbf{x}_t, t, r) + (t - r) \cdot \frac{d}{dt} \mathbf{u}_\theta(\mathbf{x}_t, t, r) - \mathbf{v}(\hat{\mathbf{x}}_t, t).$$

(b) *Suppose an admissible student represents the teacher average velocity $\mathbf{u}$ as a differentiable field on the teacher-flow domain used by the sampler. For every global minimizer $\bar{\theta}$, assume $P \ll Q_{\bar{\theta}}, Q_{\bar{\theta}}|_{\{r < t\}} \ll P$. Then the minimum population loss is zero, and every global minimizer satisfies $\mathbf{u}_{\bar{\theta}}(\mathbf{x}, t, r) = \mathbf{u}(\mathbf{x}, t, r)$ and is unique $Q_{\bar{\theta}}$ -almost surely.*

Characteristic regularity. Throughout parts (a) and (b), assume that the teacher flow is measurable and that, for p_1 -almost every $\mathbf{x}_1$, the trajectory $t \mapsto \mathbf{x}_t$ is absolutely continuous on $[0, 1]$ and satisfies $\frac{d}{dt} \mathbf{x}_t = \mathbf{v}(\mathbf{x}_t, t)$ almost everywhere. For every admissible parameter θ , assume that $\mathbf{u}_\theta(\mathbf{x}, t, r)$ is jointly measurable and continuously differentiable in $(\mathbf{x}, t)$ for each fixed r and $t > r$. In addition, for $\nu \otimes p_1$ -almost every $(r, \mathbf{x}_1)$, assume that

$$k_{\theta,r}(t) := (t - r) \mathbf{u}_\theta(\mathbf{x}_t, t, r), \quad t \in (r, 1], \quad (8)$$

extends to an absolutely continuous function on $[r, 1]$ with $k_{\theta,r}(r) = 0$. These assumptions apply to every θ_n in part (a) and every admissible field considered in part (b). We also assume $p_r \in \mathcal{P}_2(\mathbb{R}^D)$ for ν -almost every r .

Proof. (a) Let $\mathbf{x}_1 \sim p_1$ and let $\mathbf{x}_t = f(\mathbf{x}_1, 1, t)$ denote the corresponding teacher trajectory. Then $\mathbf{x}_t \sim p_t$ and $\frac{d}{dt} \mathbf{x}_t = \mathbf{v}(\mathbf{x}_t, t)$ for almost every t . Throughout the proof, r is held fixed when differentiating in t . More precisely, the residual is the function

$$\mathcal{R}_\theta(\mathbf{x}, t, r) := \mathbf{u}_\theta(\mathbf{x}, t, r) - \mathbf{v}(\mathbf{x}, t) + (t - r) (\partial_t \mathbf{u}_\theta(\mathbf{x}, t, r) + D_{\mathbf{x}} \mathbf{u}_\theta(\mathbf{x}, t, r) \mathbf{v}(\mathbf{x}, t)).$$

Along a teacher trajectory, the expression in parentheses equals $\frac{d}{dt} \mathbf{u}_\theta(\mathbf{x}_t, t, r)$. At a student-sampled state $\hat{\mathbf{x}}_t$, the same residual is evaluated at $\mathbf{x} = \hat{\mathbf{x}}_t$; the derivative still uses the teacher velocity $\mathbf{v}(\hat{\mathbf{x}}_t, t)$.

Let ν be the reference-time probability law on $[0, 1]$, and define the teacher joint measure by

$$P(dr, dt, d\mathbf{x}) := \nu(dr) \frac{\mathbf{1}_{\{r < t < 1\}}}{1-r} dt p_t(d\mathbf{x}).$$

Let Q_{θ_n} denote the actual joint sampling law of $(r, t, \hat{\mathbf{x}}_t)$ used in the population loss, and write

$$G_n(r, t, \mathbf{x}) := \|\mathcal{R}_{\theta_n}(\mathbf{x}, t, r)\|^2, \quad \mathcal{L}_{\text{CDMD}}(\theta_n) = \mathbb{E}_{Q_{\theta_n}} G_n.$$

If the sampler includes $r = t$, the residual there is defined directly as $\mathcal{R}_\theta(\mathbf{x}, t, t) = \mathbf{u}_\theta(\mathbf{x}, t, t) - \mathbf{v}(\mathbf{x}, t)$.

We first relate the residual along teacher trajectories to the transport error. For $\nu \otimes p_1$ -almost every $(r, \mathbf{x}_1)$, define

$$\Delta_{\theta_n}(\mathbf{x}_t, t, r) := \mathbf{u}_{\theta_n}(\mathbf{x}_t, t, r) - \mathbf{u}(\mathbf{x}_t, t, r).$$

The teacher average velocity satisfies

$$(t - r) \mathbf{u}(\mathbf{x}_t, t, r) = \mathbf{x}_t - \mathbf{x}_r.$$

Differentiating this identity and subtracting it from the student residual gives, for almost every $t \in (r, 1)$,

$$\begin{aligned}\mathcal{R}_{\theta_n}(\mathbf{x}_t, t, r) &= \Delta_{\theta_n}(\mathbf{x}_t, t, r) + (t - r) \frac{d}{dt} \Delta_{\theta_n}(\mathbf{x}_t, t, r) \\ &= \frac{d}{dt} [(t - r) \Delta_{\theta_n}(\mathbf{x}_t, t, r)].\end{aligned}$$

Since

$$(t - r) \Delta_{\theta_n}(\mathbf{x}_t, t, r) = k_{\theta_n, r}(t) - (\mathbf{x}_t - \mathbf{x}_r),$$

the characteristic assumptions imply that this function extends absolutely continuously to $[r, 1]$ with value zero at $t = r$. The fundamental theorem of calculus therefore gives

$$(1 - r) \Delta_{\theta_n}(\mathbf{x}_1, 1, r) = \int_r^1 \mathcal{R}_{\theta_n}(\mathbf{x}_t, t, r) dt.$$

Using the definitions of the student and teacher maps, we obtain

$$\begin{aligned}\mathbf{f}_{\theta_n}(\mathbf{x}_1, 1, r) - \mathbf{f}(\mathbf{x}_1, 1, r) &= -(1 - r) \Delta_{\theta_n}(\mathbf{x}_1, 1, r) \\ &= - \int_r^1 \mathcal{R}_{\theta_n}(\mathbf{x}_t, t, r) dt.\end{aligned}$$

By Jensen's inequality for the uniform probability measure on $[r, 1]$,

$$\|\mathbf{f}_{\theta_n}(\mathbf{x}_1, 1, r) - \mathbf{f}(\mathbf{x}_1, 1, r)\|^2 \leq (1 - r) \int_r^1 \|\mathcal{R}_{\theta_n}(\mathbf{x}_t, t, r)\|^2 dt.$$

Note that $\mathbf{f}_{\theta_n}(\mathbf{x}_1, 1, r) \sim (\mathbf{f}_{\theta_n}(\cdot, 1, r))_{\#} p_1$ and $\mathbf{f}(\mathbf{x}_1, 1, r) = \mathbf{x}_r \sim p_r$. Coupling these outputs through the same $\mathbf{x}_1$, and using Tonelli's theorem, yields

$$\begin{aligned}W_2^2((\mathbf{f}_{\theta_n}(\cdot, 1, r))_{\#} p_1, p_r) &\leq \mathbb{E}_{\mathbf{x}_1 \sim p_1} \|\mathbf{f}_{\theta_n}(\mathbf{x}_1, 1, r) - \mathbf{f}(\mathbf{x}_1, 1, r)\|^2 \\ &\leq (1 - r) \int_r^1 \mathbb{E}_{\mathbf{x}_t \sim p_t} \|\mathcal{R}_{\theta_n}(\mathbf{x}_t, t, r)\|^2 dt.\end{aligned}$$

Uniform integrability implies $\mathbb{E}_{\mathbb{P}} G_n < \infty$, so the last bound is finite for ν -almost every r . Together with $p_r \in \mathcal{P}_2(\mathbb{R}^D)$, this also ensures that the student pushforward has finite second moment for such r . Integrating over r gives

$$\begin{aligned}&\int_{[0,1]} W_2^2((\mathbf{f}_{\theta_n}(\cdot, 1, r))_{\#} p_1, p_r) \nu(dr) \\ &\leq \int_{[0,1]} (1 - r) \int_r^1 \mathbb{E}_{\mathbf{x}_t \sim p_t} \|\mathcal{R}_{\theta_n}(\mathbf{x}_t, t, r)\|^2 dt \nu(dr) \\ &= \mathbb{E}_{\mathbb{P}} [(1 - r)^2 G_n] \leq \mathbb{E}_{\mathbb{P}} G_n.\end{aligned}\tag{9}$$

It remains to show that $\mathbb{E}_{\mathbb{P}} G_n \rightarrow 0$. For every $\varepsilon > 0$, Markov's inequality gives

$$\mathbb{Q}_{\theta_n}(G_n > \varepsilon) \leq \frac{\mathcal{L}_{\text{CDMD}}(\theta_n)}{\varepsilon} \rightarrow 0.$$

By contiguity, applied to the measurable sets $\{G_n > \varepsilon\}$, we also have $\mathbb{P}(G_n > \varepsilon) \rightarrow 0$. For every $M > \varepsilon$, splitting the expectation gives

$$\mathbb{E}_{\mathbb{P}} G_n \leq \varepsilon + M \mathbb{P}(G_n > \varepsilon) + \mathbb{E}_{\mathbb{P}} [G_n \mathbf{1}_{\{G_n > M\}}].$$

Taking $\limsup_{n \rightarrow \infty}$, then letting $M \rightarrow \infty$ using uniform integrability, and finally letting $\varepsilon \downarrow 0$, proves $\mathbb{E}_{\mathbb{P}} G_n \rightarrow 0$. Substituting this convergence into Eq. (9) proves the desired result.

- (b) In this part, we use the same residual $\mathcal{R}_\theta$ as in part (a). Since stop-gradient operators leave its numerical value unchanged, our population loss is

$$\mathcal{L}_{\text{CDMD}}(\theta) = \mathbb{E}_{(r,t,\hat{x}_t) \sim \mathcal{Q}_\theta} \|\mathcal{R}_\theta(\hat{x}_t, t, r)\|^2. \quad (10)$$

We first show that zero residual and the characteristic boundary condition uniquely determine the field values along a teacher trajectory. Fix an admissible field $\mathbf{u}^*$, and choose $(r, \mathbf{x}_1)$ from the full-measure set on which its characteristic regularity conditions hold. Let $\mathbf{x}_t = \mathbf{f}(\mathbf{x}_1, 1, t)$ denote the corresponding teacher trajectory. Suppose that $\mathbf{u}^*$ has zero residual for almost every $t \in (r, 1)$. Then

$$\begin{aligned} 0 &= \mathbf{u}^*(\mathbf{x}_t, t, r) + (t-r) \frac{d}{dt} \mathbf{u}^*(\mathbf{x}_t, t, r) - \frac{d\mathbf{x}_t}{dt} \\ &= \frac{d}{dt} [(t-r) \mathbf{u}^*(\mathbf{x}_t, t, r) - (\mathbf{x}_t - \mathbf{x}_r)] \end{aligned}$$

for almost every $t \in (r, 1)$. By characteristic regularity, the expression in brackets is absolutely continuous on $[r, 1]$. Therefore,

$$(t-r) \mathbf{u}^*(\mathbf{x}_t, t, r) - (\mathbf{x}_t - \mathbf{x}_r) = C, \quad r < t \leq 1, \quad (11)$$

where $C \in \mathbb{R}^D$ is independent of t . We then show that $C = 0$. The characteristic boundary condition and continuity of the teacher trajectory give

$$\lim_{t \downarrow r} (t-r) \mathbf{u}^*(\mathbf{x}_t, t, r) = 0, \quad \lim_{t \downarrow r} (\mathbf{x}_t - \mathbf{x}_r) = 0. \quad (12)$$

Taking $t \downarrow r$ in Eq. (11) therefore gives $C = 0$. It follows that

$$\mathbf{u}^*(\mathbf{x}_t, t, r) = \frac{\mathbf{x}_t - \mathbf{x}_r}{t-r} = \mathbf{u}(\mathbf{x}_t, t, r), \quad r < t \leq 1. \quad (13)$$

Here we used the teacher identity $(t-r) \mathbf{u}(\mathbf{x}_t, t, r) = \mathbf{x}_t - \mathbf{x}_r$.

We now consider the population loss. By the realizability assumption in part (b), there exists an admissible parameter θ^T representing the teacher average velocity and satisfying

$$\mathcal{R}_{\theta^T} = 0 \quad \mathcal{Q}_{\theta^T}\text{-almost surely.} \quad (14)$$

Consequently, $\mathcal{L}_{\text{CDMD}}(\theta^T) = 0$. Since the loss is nonnegative, its global minimum is zero and θ^T is a global minimizer.

Now suppose $\bar{\theta}$ is another global minimizer. We have

$$0 = \mathcal{L}_{\text{CDMD}}(\bar{\theta}) = \mathbb{E}_{\mathcal{Q}_{\bar{\theta}}} \|\mathcal{R}_{\bar{\theta}}\|^2. \quad (15)$$

Nonnegativity implies that $\mathcal{R}_{\bar{\theta}} = 0$ $\mathcal{Q}_{\bar{\theta}}$ -almost surely. By the coverage assumption $\mathcal{P} \ll \mathcal{Q}_{\bar{\theta}}$, the residual also vanishes $\mathcal{P}$ -almost surely. The definition of $\mathcal{P}$ and Tonelli's theorem therefore give

$$\mathbb{E}_{\mathbf{x}_1 \sim p_1} \int_r^1 \|\mathcal{R}_{\bar{\theta}}(\mathbf{x}_t, t, r)\|^2 dt = 0 \quad \text{for } \nu\text{-almost every } r. \quad (16)$$

Hence, for $\nu \otimes p_1$ -almost every $(r, \mathbf{x}_1)$, the residual vanishes for almost every $t \in (r, 1)$. Applying the uniqueness argument above with $\mathbf{u}^* = \mathbf{u}_{\bar{\theta}}$ yields $\mathbf{u}_{\bar{\theta}}(\mathbf{x}_t, t, r) = \mathbf{u}(\mathbf{x}_t, t, r)$ for every $r < t \leq 1$ along these trajectories, and consequently $\mathbf{u}_{\bar{\theta}} = \mathbf{u}$ $\mathcal{P}$ -almost surely.

Finally, the reverse coverage assumption $\mathcal{Q}_{\bar{\theta}}|_{\{r < t\}} \ll \mathcal{P}$ transfers this equality to the off-diagonal training law. On any sampled diagonal, zero residual gives $\mathbf{u}_{\bar{\theta}}(\mathbf{x}, t, t) = \mathbf{v}(\mathbf{x}, t) = \mathbf{u}(\mathbf{x}, t, t)$ directly. Therefore, the teacher average velocity is realized by a global minimizer, and every global minimizer satisfies

$$\mathbf{u}_{\bar{\theta}}(\mathbf{x}, t, r) = \mathbf{u}(\mathbf{x}, t, r) \quad \mathcal{Q}_{\bar{\theta}}\text{-almost surely,} \quad (17)$$

as desired. $\square$

B MORE ON THE VARIANCE OF THE TARGET

Sec. 3.2 compares three candidate tangents $d\hat{\mathbf{x}}_t/dt$ for the JVP in the detached correction: $\mathbf{v}(\hat{\mathbf{x}}_t, t)$, $\mathbf{u}_\theta(\hat{\mathbf{x}}_t, t, t)$, and $\mathbf{u}_\theta(\mathbf{z}, 1, 0)$. This section defines the statistics used to compare them; Fig. 9 in Appendix D.2 reports them on the checkerboard and spiral datasets. The first uses the teacher tangent, the second uses the local student tangent, and the third uses the global one-step student displacement.

In practice, for a minibatch $\{\hat{\mathbf{x}}_t^{(i)}, t^{(i)}, r^{(i)}\}_{i=1}^B$, we estimate

$$\hat{\mathcal{V}}_{\text{JVP}} = \frac{1}{B} \sum_{i=1}^B \left\| \mathcal{G}_\theta^{(i)} - \bar{\mathcal{G}}_\theta \right\|^2, \quad \bar{\mathcal{G}}_\theta = \frac{1}{B} \sum_{i=1}^B \mathcal{G}_\theta^{(i)},$$

where

$$\mathcal{G}_\theta^{(i)} = \mathcal{G}_\theta \left(\hat{\mathbf{x}}_t^{(i)}, t^{(i)}, r^{(i)}; \frac{d\hat{\mathbf{x}}_t^{(i)}}{dt} \right).$$

Similarly, the ground-truth projected error is

$$\hat{\mathcal{D}}_{\text{JVP}} = \frac{1}{B} \sum_{i=1}^B \left\| \mathcal{G}_\theta^{(i)} - \mathcal{G}_{\theta, \text{T}}^{(i)} \right\|^2,$$

where

$$\mathcal{G}_{\theta, \text{T}}^{(i)} = \mathcal{G}_\theta \left(\hat{\mathbf{x}}_t^{(i)}, t^{(i)}, r^{(i)}; \mathbf{v}(\hat{\mathbf{x}}_t^{(i)}, t^{(i)}) \right).$$

The projected variance measures the stability of the detached correction, while the ground-truth projected error measures its deviation from the teacher-consistent tangent.

To diagnose whether the JVP correction on student-generated states is aligned with the correction on the target path, we also consider a cross-centered projected JVP quantity. For a fixed tangent realization $d\hat{\mathbf{x}}_t/dt$, define

$$\mathcal{G}_\theta \left(\hat{\mathbf{x}}_t, t, r; \frac{d\hat{\mathbf{x}}_t}{dt} \right) := \text{JVP} \left(\mathbf{u}_\theta; \left(\frac{d\hat{\mathbf{x}}_t}{dt}, 1, 0 \right) \right).$$

Let

$$\mu_q \left(\frac{d\hat{\mathbf{x}}_t}{dt}; t, r \right) := \mathbb{E}_{\hat{\mathbf{x}}_t \sim q_t^\theta} \left[\mathcal{G}_\theta \left(\hat{\mathbf{x}}_t, t, r; \frac{d\hat{\mathbf{x}}_t}{dt} \right) \right]$$

and

$$\mu_p \left(\frac{d\mathbf{x}_t}{dt}; t, r \right) := \mathbb{E}_{\mathbf{x}_t \sim p_t} \left[\mathcal{G}_\theta \left(\mathbf{x}_t, t, r; \frac{d\mathbf{x}_t}{dt} \right) \right].$$

Here, μ_q is the mean JVP correction on student-generated states, while μ_p is the mean JVP correction on the target path. We define the cross-centered projected JVP second moment as

$$\mathcal{M}_{\text{JVP}}^{q,p} \left(\frac{d\hat{\mathbf{x}}_t}{dt}; t, r \right) := \mathbb{E}_{\hat{\mathbf{x}}_t \sim q_t^\theta} \left[\left\| \mathcal{G}_\theta \left(\hat{\mathbf{x}}_t, t, r; \frac{d\hat{\mathbf{x}}_t}{dt} \right) - \mu_p \left(\frac{d\mathbf{x}_t}{dt}; t, r \right) \right\|^2 \right].$$

This quantity is not a variance under a single distribution. Instead, it decomposes as

$$\mathcal{M}_{\text{JVP}}^{q,p} \left(\frac{d\hat{\mathbf{x}}_t}{dt}; t, r \right) = \mathcal{V}_{\text{JVP}}^q \left(\frac{d\hat{\mathbf{x}}_t}{dt}; t, r \right) + \left\| \mu_q \left(\frac{d\hat{\mathbf{x}}_t}{dt}; t, r \right) - \mu_p \left(\frac{d\mathbf{x}_t}{dt}; t, r \right) \right\|^2,$$

where

$$\mathcal{V}_{\text{JVP}}^q \left(\frac{d\hat{\mathbf{x}}_t}{dt}; t, r \right) := \mathbb{E}_{\hat{\mathbf{x}}_t \sim q_t^\theta} \left[\left\| \mathcal{G}_\theta \left(\hat{\mathbf{x}}_t, t, r; \frac{d\hat{\mathbf{x}}_t}{dt} \right) - \mu_q \left(\frac{d\hat{\mathbf{x}}_t}{dt}; t, r \right) \right\|^2 \right].$$

Therefore, $\mathcal{M}_{\text{JVP}}^{q,p}$ measures both the intrinsic stochasticity of the JVP correction on student-generated states and the mismatch between the average correction under q_t^θ and the average correction under the target path p_t .

Table 4: Comparison of representative distillation methods. Some methods that can be trained from scratch, we consider their distillation variants, as our focus is exclusively on the distillation task. Among the compared methods, our method is the only approach that is simultaneously data-free and simulation-free while requiring only two models and a single optimizer. $\dagger$ indicates that the property may vary depending on the training setup. $\star$ indicates that these models can also be trained from scratch, whereas we only consider the distillation setting here.

Method	# Models	# Opts	Data-Free	Simulation-Free	GAN
BOOT (Gu et al., 2023)	2	1	✓	✗	✗
DMD2 (Yin et al., 2024a)	3	2	✓ $\dagger$	✓ $\dagger$	✓ $\dagger$
SiD-LSG (Zhou et al., 2025c)	3	2	✓	✓	✗
SiDA (Zhou et al., 2025d)	3	2	✗	✓	✓
FreeFlow (Tong et al., 2025)	3	2	✓	✓	✗
CTM (Kim et al., 2023)	3	2	✗	✓	✓
FACM (Peng et al., 2025)	2	1	✗	✓	✗
MF(Geng et al., 2025a)/CM(Lu & Song, 2024; Song et al., 2023)/IMM(Zhou et al., 2025a)	2 $\star$	1	✗	✓	✗ $\dagger$
CDMD (Ours)	2	1	✓	✓	✗

C RELATIONSHIP WITH PRIOR METHODS

Tab. 4 compares representative distillation methods by the number of networks and optimizers they need, and by whether they require real data, trajectory simulation, or an adversarial objective. DMD2, SiD-LSG, SiDA, FreeFlow, and CTM train a third auxiliary network, either a fake-score model or a discriminator, with a second optimizer. BOOT is data-free but simulates trajectories during training. FACM and the flow map models (MF, CM, IMM) use only two networks and one optimizer, but they construct noisy states from real data. CDMD is the only method in the table that is both data-free and simulation-free while keeping only the teacher, the student, and a single optimizer. The subsections below relate CDMD to FreeFlow, flow maps, and DMD in more detail.

C.1 FREEFLOW

FreeFlow (Tong et al., 2025) observed that many existing distillation methods can suffer from *Teacher-Data Mismatch*: the student is trained on intermediate states sampled from data-noising distributions $\tilde{p}_t$, whereas the teacher follows its own generative distributions

$$\hat{p}_t := (\mathbf{f}(\cdot, 1, t))_{\#} p_1, \quad (18)$$

where $(\mathbf{f}(\cdot, 1, t))_{\#} p_1$ denotes the pushforward of p_1 under the teacher flow map $z \mapsto \mathbf{f}(z, 1, t)$; equivalently, if $z \sim p_1$, then $\mathbf{f}(z, 1, t) \sim \hat{p}_t$. This mismatch becomes problematic when the teacher distribution differs from the available data distribution, *e.g.*, due to generalization, guidance, post-training, or unavailable proprietary training data. FreeFlow (Tong et al., 2025) circumvents this issue by sampling only from the prior, since the noising process and the teacher generative process are guaranteed to coincide at $t = 1$, *i.e.*, $\tilde{p}_1 = \hat{p}_1 = p_1$.

In particular, FreeFlow (Tong et al., 2025) adopts a prior-anchored framework, which can be viewed as the converse of consistency models (Lu & Song, 2024; Song et al., 2023; Luo et al., 2023a). Let $z \sim p_1$ and define the target time $r = 1 - \delta$, where $\delta \in [0, 1]$ is the duration of a single reverse-time transition from the prior time 1 to the target time r . Intuitively, FreeFlow learns to predict intermediate states directly from noise, rather than matching intermediate states obtained from the data-noising process. Using our notation, $\mathbf{u}_{\theta}(z, 1, r)$ denotes the average velocity associated with this prior-anchored transition, with $\delta = 1 - r$. The student flow map from time 1 to time r is written as

$$\hat{\mathbf{x}}_r = \mathbf{f}_{\theta}(z, 1, r) = z - (1 - r)\mathbf{u}_{\theta}(z, 1, r), \quad r \in [0, 1]. \quad (19)$$

Differentiating with respect to the jump duration δ gives

$$\partial_{\delta} \mathbf{f}_{\theta}(z, 1, 1 - \delta) = \mathbf{u}_{\theta}(z, 1, r) - (1 - r) \partial_r \mathbf{u}_{\theta}(z, 1, r), \quad r = 1 - \delta. \quad (20)$$

Matching this generating velocity to the teacher velocity evaluated at the student-predicted state yields the FreeFlow prediction objective with only teacher and student involved

$$\mathcal{L}_{\text{FreeFlow w.o. DMD}}(\theta) = \mathbb{E}_{\mathbf{z} \sim p_1, r} \left[\left\| \mathbf{u}_\theta(\mathbf{z}, 1, r) + \text{sg}(\mathbf{v}(\hat{\mathbf{x}}_r, r) - (1-r) \partial_r \mathbf{u}_\theta(\mathbf{z}, 1, r)) \right\|_2^2 \right], \quad (21)$$

where $\text{sg}(\cdot)$ denotes stop-gradient. This stems from Eq. (26) by setting $t = 1$.

Since this prediction objective is self-referential, approximation errors in $\mathbf{f}_\theta$ may accumulate along the generated trajectory. FreeFlow therefore introduces an additional correction term that aligns the noising velocity induced by the student-generated distribution with the teacher velocity. This correction is closely related to the variational score distillation objective (Wang et al., 2023). If $\mathbf{v}_N(\hat{\mathbf{x}}_r, r)$ denotes the marginal noising velocity induced by the student-generated distribution $\hat{p}_0$, the correction signal aligns $\mathbf{v}_N$ with the teacher velocity through the surrogate gradient

$$\nabla_\theta \mathcal{L}_{\text{FreeFlow-VSD}}(\theta) = \nabla_\theta \mathbb{E}_{\mathbf{z}, \varepsilon, r} \left[\mathbf{u}_\theta(\mathbf{z}, 1, 0)^\top \text{sg}(\mathbf{v}_N(\hat{\mathbf{x}}_r, r) - \mathbf{v}(\hat{\mathbf{x}}_r, r)) \right], \quad (22)$$

where $\hat{\mathbf{x}}_r$ is obtained by first generating $\hat{\mathbf{x}}_0 = \mathbf{z} - \mathbf{u}_\theta(\mathbf{z}, 1, 0)$ with $\mathbf{z} \sim p_1$ and then applying the noising process,

$$\hat{\mathbf{x}}_r = (1-r) \cdot \hat{\mathbf{x}}_0 + r \cdot \varepsilon = (1-r)(\mathbf{z} - \mathbf{u}_\theta(\mathbf{z}, 1, 0)) + r\varepsilon, \quad \varepsilon \sim p_1, \quad r \in [0, 1]. \quad (23)$$

In practice, $\mathbf{v}_N$ is estimated by an auxiliary proxy FM model trained on student-generated samples, using either fine-tuning or LoRA adaptation. FreeFlow thus combines a trajectory-consistency prediction term with a distribution-level correction term, while requiring only prior samples from p_1 . This prior-anchored formulation introduces a trade-off: it simplifies distillation by avoiding supervision over arbitrary timestep pairs, but confines training to trajectories initialized at $t = 1$. As a result, the student is optimized primarily as a one-step noise-to-data sampler, rather than as a general flow map capable of modeling denoising transitions between arbitrary timesteps (t, r) with $t > r$. Consequently, it reduces training complexity at the cost of limiting inference-time scaling and not naturally preserving the multi-step scaling behavior of the original flow model.

In the notation of FreeFlow (Tong et al., 2025), $\mathbf{F}_\theta$ denotes the forward-time velocity, whereas our $\mathbf{u}(\cdot)$ denotes the corresponding backward-time velocity. Therefore, the two are related by $\mathbf{F}_\theta = -\mathbf{u}(\cdot)$. Beyond this notational difference, FreeFlow relies on pseudo-gradients propagated through student-generated trajectories, typically over intervals such as $[0, 1]$ or $[t, 1]$. Consequently, its updates depend on the quality of the intermediate student states $\hat{\mathbf{x}}_t$, which may introduce additional sensitivity during training. In contrast, our method avoids this rollout dependence by providing supervision directly on arbitrary local intervals $[r, t]$. This enables training across the denoising process without explicitly simulating intermediate student trajectories.

C.2 FLOW MAPS

For a ground-truth velocity field $\mathbf{v}(\mathbf{x}_t, t)$, there exists a flow map (Albergo & Vanden-Eijnden, 2023; Boffi et al., 2024) $\mathbf{f} : \mathbb{R}^D \times [0, 1] \times [0, 1] \rightarrow \mathbb{R}^D$ that maps a state at time $t \in [0, 1]$ to its corresponding state at time $r \in [0, 1]$. Throughout this work, we primarily consider the backward map, *i.e.* a denoiser, with $0 \leq r \leq t \leq 1$ for simplicity. More precisely, the flow map defines the ODE trajectory following $\mathbf{v}(\mathbf{x}_\tau, \tau)$ for all $\tau \in [r, t]$, *i.e.*,

$$\mathbf{f}(\mathbf{x}_t, t, r) := \mathbf{x}_t + \int_t^r \mathbf{v}(\mathbf{x}_\tau, \tau) \, d\tau. \quad (24)$$

When $r < t$, the integral is taken in the backward direction and $\mathbf{f}(\mathbf{x}_t, t, r)$ returns the state at the earlier time r . In practice, sampling is carried out by numerically integrating the learned ODE using standard solvers such as Euler’s method.

By viewing the marginal $\mathbf{v}(\mathbf{x}_t, t)$ as the instantaneous velocity field, MeanFlow and its variants (Geng et al., 2025a;b; Zhang et al., 2026) construct an average velocity field between times $0 \leq r < t \leq 1$ as

$$\mathbf{u}(\mathbf{x}_t, t, r) := \frac{\mathbf{x}_t - \mathbf{f}(\mathbf{x}_t, t, r)}{t - r} = \frac{1}{t - r} \int_r^t \mathbf{v}(\mathbf{x}_\tau, \tau) \, d\tau,$$

where $\mathbf{f}(\mathbf{x}_t, t, r)$ denotes the flow map from time t to time r so that these one-step models can be trained from scratch. Equivalently, we have

$$\int_r^t \mathbf{v}(\mathbf{x}_\tau, \tau) \, d\tau = (t - r) \cdot \mathbf{u}(\mathbf{x}_t, t, r). \quad (25)$$

Note that the flow map can also be recovered from the average velocity field via $\mathbf{f}(\mathbf{x}_t, t, r) = \mathbf{x}_t - (t - r)\mathbf{u}(\mathbf{x}_t, t, r)$. We define $\mathbf{u}(\mathbf{x}_t, t, t) := \lim_{r \rightarrow t} \mathbf{u}(\mathbf{x}_t, t, r) = \mathbf{v}(\mathbf{x}_t, t)$, where we assume the limit exists and is equal to the velocity field at time t . Now, differentiating both sides of Eq. (25) with respect to t yields

$$\mathbf{v}(\mathbf{x}_t, t) = \mathbf{u}(\mathbf{x}_t, t, r) + (t - r) \cdot \frac{d}{dt} \mathbf{u}(\mathbf{x}_t, t, r), \quad (26)$$

where r is held fixed and d/dt denotes the total derivative along the ODE trajectory $t \mapsto \mathbf{x}_t$. Motivated by the equation above, improved MeanFlow (Geng et al., 2025b) parameterizes the student average velocity field with a neural network $\mathbf{u}_\theta(\mathbf{x}_t, t, r)$ and defines the corrected prediction $\mathbf{v}_\theta(\mathbf{x}_t, t, r) := \mathbf{u}_\theta(\mathbf{x}_t, t, r) + (t - r) \cdot \frac{d}{dt} \mathbf{u}_\theta(\mathbf{x}_t, t, r)$.

By design, matching this corrected prediction to the instantaneous velocity yields an objective analogous to the standard CFM objective:

$$\mathcal{L}_{\text{FlowMap}}(\theta) := \mathbb{E}_{\mathbf{x}_t, t, r} \left[\|\mathbf{v}_\theta(\mathbf{x}_t, t, r) - \mathbf{v}(\mathbf{x}_t, t)\|_2^2 \right]. \quad (27)$$

C.3 EQUIVALENCE WITH ORIGINAL DMD UPDATES

We show that the velocity-form distribution matching gradient used in the main text is equivalent to the original DMD update up to a time-dependent scalar weight. The difference is only a choice of parametrization: DMD is commonly written in score- or denoiser-prediction form, whereas our presentation writes the same update in velocity form.

Let the student clean sample be

$$\hat{\mathbf{x}}_0 = \mathbf{f}_\theta(\mathbf{z}, 1, 0), \quad \mathbf{z} \sim p_1,$$

and let the perturbed sample be generated by the affine forward path

$$\hat{\mathbf{x}}_t = \alpha_t \hat{\mathbf{x}}_0 + \sigma_t \varepsilon, \quad \varepsilon \sim p_1, \quad t \in [0, 1].$$

We use Gaussian perturbation noise ε independent of $\mathbf{z}$, and hence independent of $\hat{\mathbf{x}}_0 = \mathbf{f}_\theta(\mathbf{z}, 1, 0)$. This independence is required for the denoising identity below. Let q_t denote the marginal distribution of $\hat{\mathbf{x}}_t$ induced by the student, and let p_t denote the corresponding teacher marginal.

For a generic clean distribution p_0 , let $\tilde{p}_t$ denote the perturbed marginal induced by

$$\mathbf{x}_t = \alpha_t \mathbf{x}_0 + \sigma_t \varepsilon, \quad \mathbf{x}_0 \sim p_0, \quad \varepsilon \sim p_1.$$

Let

$$s_{\tilde{p}}(\mathbf{x}_t, t) := \nabla_{\mathbf{x}_t} \log \tilde{p}_t(\mathbf{x}_t)$$

be the score of the perturbed marginal, and let

$$\mu_{\tilde{p}}(\mathbf{x}_t, t) := \mathbb{E}_{\tilde{p}}[\mathbf{x}_0 \mid \mathbf{x}_t]$$

be the optimal clean estimator. The standard denoising identity gives

$$s_{\tilde{p}}(\mathbf{x}_t, t) = \frac{\alpha_t \mu_{\tilde{p}}(\mathbf{x}_t, t) - \mathbf{x}_t}{\sigma_t^2}. \quad (28)$$

Indeed,

$$\nabla_{\mathbf{x}_t} \tilde{p}_t(\mathbf{x}_t) = \int -\frac{\mathbf{x}_t - \alpha_t \mathbf{x}_0}{\sigma_t^2} q(\mathbf{x}_t \mid \mathbf{x}_0) p_0(\mathbf{x}_0) d\mathbf{x}_0,$$

and dividing by $\tilde{p}_t(\mathbf{x}_t)$ yields Eq. (28).

Now define the marginal velocity field associated with $\tilde{p}_t$ as

$$\mathbf{v}_{\tilde{p}}(\mathbf{x}_t, t) := \mathbb{E}_{\tilde{p}}[\dot{\alpha}_t \mathbf{x}_0 + \dot{\sigma}_t \varepsilon \mid \mathbf{x}_t].$$

Since

$$\mathbb{E}[\varepsilon \mid \mathbf{x}_t] = \frac{\mathbf{x}_t - \alpha_t \mu_{\tilde{p}}(\mathbf{x}_t, t)}{\sigma_t},$$

we obtain

$$\mathbf{v}_{\bar{p}}(\mathbf{x}_t, t) = \dot{\alpha}_t \boldsymbol{\mu}_{\bar{p}}(\mathbf{x}_t, t) + \dot{\sigma}_t \frac{\mathbf{x}_t - \alpha_t \boldsymbol{\mu}_{\bar{p}}(\mathbf{x}_t, t)}{\sigma_t} \quad (29)$$

$$= \frac{\dot{\sigma}_t}{\sigma_t} \mathbf{x}_t + \left(\dot{\alpha}_t - \frac{\alpha_t \dot{\sigma}_t}{\sigma_t} \right) \boldsymbol{\mu}_{\bar{p}}(\mathbf{x}_t, t). \quad (30)$$

Substituting Eq. (28), i.e.

$$\boldsymbol{\mu}_{\bar{p}}(\mathbf{x}_t, t) = \frac{\mathbf{x}_t + \sigma_t^2 s_{\bar{p}}(\mathbf{x}_t, t)}{\alpha_t},$$

gives

$$\mathbf{v}_{\bar{p}}(\mathbf{x}_t, t) = a_t \mathbf{x}_t + b_t s_{\bar{p}}(\mathbf{x}_t, t), \quad (31)$$

where

$$a_t = \frac{\dot{\sigma}_t}{\sigma_t} + \frac{1}{\alpha_t} \left(\dot{\alpha}_t - \frac{\alpha_t \dot{\sigma}_t}{\sigma_t} \right), \quad b_t = \frac{\sigma_t^2}{\alpha_t} \left(\dot{\alpha}_t - \frac{\alpha_t \dot{\sigma}_t}{\sigma_t} \right).$$

The term $a_t \mathbf{x}_t$ is independent of the perturbed marginal. Therefore, for the fake and real marginals,

$$\mathbf{v}_{\text{fake}}(\mathbf{x}_t, t) - \mathbf{v}_{\text{real}}(\mathbf{x}_t, t) = b_t (s_{\text{fake}}(\mathbf{x}_t, t) - s_{\text{real}}(\mathbf{x}_t, t)). \quad (32)$$

Thus the score difference used by DMD and the velocity difference used in our presentation are equivalent up to the scalar b_t .

Consider the reverse-KL objective over perturbed marginals,

$$\mathcal{L}_{\text{rKL}}(\boldsymbol{\theta}) = \mathbb{E}_t [D_{\text{KL}}(q_t \| p_t)].$$

The DMD pathwise gradient has the form

$$\nabla_{\boldsymbol{\theta}} \mathcal{L}_{\text{rKL}}(\boldsymbol{\theta}) = \mathbb{E}_{t, \mathbf{z}, \boldsymbol{\varepsilon}} \left[(s_{\text{fake}}(\hat{\mathbf{x}}_t, t) - s_{\text{real}}(\hat{\mathbf{x}}_t, t))^\top \frac{\partial \hat{\mathbf{x}}_t}{\partial \boldsymbol{\theta}} \right]. \quad (33)$$

Using Eq. (32), we can rewrite this as

$$\nabla_{\boldsymbol{\theta}} \mathcal{L}_{\text{rKL}}(\boldsymbol{\theta}) = \mathbb{E}_{t, \mathbf{z}, \boldsymbol{\varepsilon}} \left[\frac{1}{b_t} (\mathbf{v}_{\text{fake}}(\hat{\mathbf{x}}_t, t) - \mathbf{v}_{\text{real}}(\hat{\mathbf{x}}_t, t))^\top \frac{\partial \hat{\mathbf{x}}_t}{\partial \boldsymbol{\theta}} \right]. \quad (34)$$

The scalar $1/b_t$ depends only on the noise schedule and can be absorbed into the time-dependent weighting function. Therefore,

$$\nabla_{\boldsymbol{\theta}} \mathcal{L}_{\text{rKL}}(\boldsymbol{\theta}) \propto \mathbb{E}_{t, \mathbf{z}, \boldsymbol{\varepsilon}} \left[w_t (\mathbf{v}_{\text{fake}}(\hat{\mathbf{x}}_t, t) - \mathbf{v}_{\text{real}}(\hat{\mathbf{x}}_t, t))^\top \frac{\partial \hat{\mathbf{x}}_t}{\partial \boldsymbol{\theta}} \right], \quad (35)$$

which is the velocity-form gradient used in the main text.

For the linear interpolation path $\alpha_t = 1 - t$ and $\sigma_t = t$, we have

$$\mathbf{v}_{\bar{p}}(\mathbf{x}_t, t) = \mathbb{E}[\boldsymbol{\varepsilon} - \mathbf{x}_0 \mid \mathbf{x}_t],$$

and Eq. (32) becomes

$$\mathbf{v}_{\text{fake}}(\mathbf{x}_t, t) - \mathbf{v}_{\text{real}}(\mathbf{x}_t, t) = -\frac{t}{1-t} (s_{\text{fake}}(\mathbf{x}_t, t) - s_{\text{real}}(\mathbf{x}_t, t)). \quad (36)$$

Hence, under the linear schedule, the two gradients differ only by the scalar factor $(t-1)t^{-1}$, which is absorbed into w_t and depends on the sign convention for velocity definition.

Finally, we show that the fake velocity model trained in the main text is equivalent to the fake score model in DMD. Original DMD trains a fake denoiser by

$$\mathcal{L}_{\text{denoise}}(\boldsymbol{\phi}; \boldsymbol{\theta}) = \mathbb{E}_{t, \mathbf{z}, \boldsymbol{\varepsilon}} \left[\|\boldsymbol{\mu}_{\boldsymbol{\phi}}(\hat{\mathbf{x}}_t, t) - \hat{\mathbf{x}}_0\|_2^2 \right],$$

with the generator $\boldsymbol{\theta}$ frozen. The population minimizer is $\boldsymbol{\mu}_{\boldsymbol{\phi}}^*(\mathbf{x}_t, t) = \mathbb{E}[\hat{\mathbf{x}}_0 \mid \hat{\mathbf{x}}_t]$. Equivalently, if we parameterize the fake critic as a velocity field and train it with the flow-matching objective

$$\mathcal{L}_{\text{fake}}(\boldsymbol{\phi}; \boldsymbol{\theta}) = \mathbb{E}_{t, \mathbf{z}, \boldsymbol{\varepsilon}} \left[\|\mathbf{v}_{\boldsymbol{\phi}}(\hat{\mathbf{x}}_t, t) - (\dot{\alpha}_t \hat{\mathbf{x}}_0 + \dot{\sigma}_t \boldsymbol{\varepsilon})\|_2^2 \right],$$

then its population minimizer is $\mathbf{v}_{\boldsymbol{\phi}}^*(\mathbf{x}_t, t) = \mathbb{E}[\dot{\alpha}_t \hat{\mathbf{x}}_0 + \dot{\sigma}_t \boldsymbol{\varepsilon} \mid \hat{\mathbf{x}}_t] = \mathbf{v}_{\text{fake}}(\mathbf{x}_t, t)$.

According to Eq. (31), $\boldsymbol{\mu}_{\boldsymbol{\phi}}^*$, s_{fake} , and $\mathbf{v}_{\text{fake}}$ are related by deterministic affine transformations at each time t . Therefore, training a fake velocity model by the flow-matching objective is equivalent to training the fake score model used in DMD, up to parametrization. Consequently, the velocity-form update in Eq. (35) optimizes the same distribution matching objective as the original DMD update.

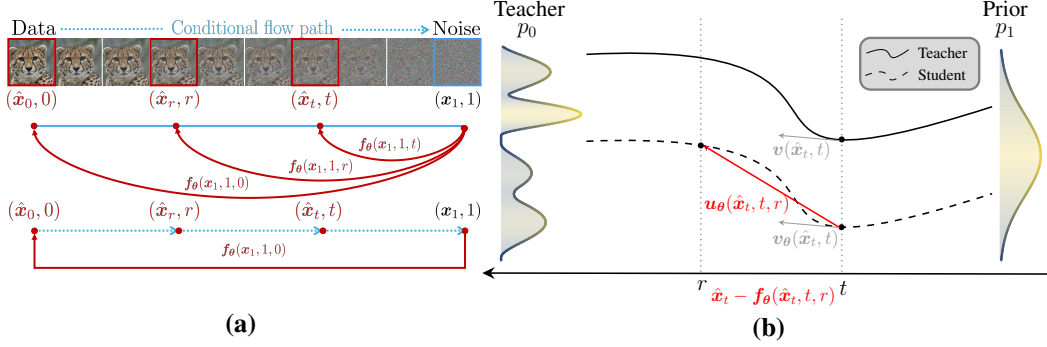


Figure 7: Overview of our method. Panel (a) illustrates two data-free constructions of $\hat{x}_t$ shown by the red curves. In (b), we demonstrate how the student velocity matches the target teacher velocity. Note that teacher velocity is the only supervision signal.

D IMPLEMENTATION DETAILS

This section gives the training, architecture, and evaluation details for class-conditional ImageNet (Appendix D.1), the analytic 2D benchmarks behind Fig. 5 (Appendix D.2), and the SANA-1.6B text-to-image setting (Appendix D.3).

D.1 CLASS-CONDITIONAL IMAGENET

Training-state construction. Fig. 7(a) shows the two data-free constructions of $\hat{x}_t$ in Eq. (6). In the upper construction ($s = t$), the student jumps from the prior sample x_1 directly to each intermediate time, e.g., $\hat{x}_t = f_\theta(x_1, 1, t)$, so the training state lies on the student path. In the lower construction ($s = 0$), the student first produces a clean sample $\hat{x}_0 = f_\theta(x_1, 1, 0)$, which is then re-noised along the conditional flow path with fresh Gaussian noise. Each construction costs one student evaluation and no teacher rollout. Fig. 7(b) shows the supervision on such a state: the student average velocity $u_\theta(\hat{x}_t, t, r)$ defines the jump $\hat{x}_t - f_\theta(\hat{x}_t, t, r)$ over $[r, t]$, and its corrected velocity is regressed onto the teacher velocity $v(\hat{x}_t, t)$. In Alg. 1, z_1 and z_2 are the $s = 0$ and $s = t$ states, respectively. They are mixed with ratio m (Tab. 2) and detached before the teacher is queried.

Training. The backbone architectures follow SiT, which is based on DiT (Peebles & Xie, 2023) with adaLN-Zero (Peebles & Xie, 2023) for conditioning. To condition the student model on the additional variables, we use a two-layer SiLU-activated MLP whose hidden dimension matches the model’s hidden dimension. We add new embeddings for r and w , and adopt adaLN-Zero for conditioning. The resulting conditioning signal is fed to each transformer block. No further architectural changes are necessary for stable and effective training. Note that SiT teacher and SiT+VA-REPA have different configurations on what the time in FM represents. SiT adopts the convention when $x_1 \sim p_{\text{data}}$, $x_0 \sim p_{\text{prior}}$ which is the opposite of the notion we adopt in this paper. Our convention on FM time aligns with SiT+VA-REPA (Yang et al., 2026) or SiT+REPA (Yu et al., 2024) in their implementation. Our training algorithm strictly follows 1. In addition, we use Flash-Attention to reduce GPU memory usage and accelerate training. Plus, we customize the Flash-Attention kernel to support JVP computation, following sCM (Lu & Song, 2024).

All models are trained using the PyTorch framework. The detailed training hyperparameters are provided in Tab. 5.

Architecture. Inspired by DMF (Lee et al., 2026), we investigate delaying endpoint conditioning to the later DiT blocks, as illustrated in Fig. 13. It is important to note that our architecture also differs from DMF (Lee et al., 2026): rather than decoupling the t and r signals, we preserve the original time-conditioning branch throughout the network and inject the additional endpoint signal only into the later DiT blocks. We find this design to be more effective for data-free distillation. Empirically, we find that decoupling strategy from DMF can accelerate FID convergence during early training, but does not improve the final performance and can occasionally degrade it. We thereby

Table 5: Training hyperparameters and model configuration. The listed distributions are the initial proposals. ‡: Teacher CFG is 1.75 for $t \in [0.125, 1]$ and 1 otherwise. The Lightning-DiT run uses post-hoc EMA for evaluation. The listed decay is the configured student EMA decay. We do not apply student guidance and flexible guidance approaches (Geng et al., 2025b) to Lightning-DiT-XL/2 teacher.

<i>Task</i>			
teacher model	SiT-XL/2+VA-REPA	SiT-XL/2	Lightning-DiT-XL/2
resolution	256×256	256×256	256×256
General			
iterations	100K	100K	100K
batch size	1024	1024	1024
optimizer	Adam	Adam	AdamW
optimizer betas	(0.9, 0.99)	(0.9, 0.99)	(0.9, 0.999)
optimizer eps	1×10^{-8}	1×10^{-8}	1×10^{-8}
weight decay	0.0	0.0	0.0
dropout	0.0	0.0	0.0
learning rate	3×10^{-5}	3×10^{-5}	1×10^{-4}
EMA decay	0.9995	0.9995	0.999
Network			
params (M)		683	
depth		28	
endpoint conditioning depth	0	0	10
hidden dim		1152	
heads		16	
patch size		2×2	
change from teacher		additional input for r and w	
Training			
t sampling	LogitNormal($-0.4, 1.0$)	LogitNormal($0.4, 1.0$)	LogitNormal($-0.4, 1.6$)
r sampling	LogitNormal($-0.4, 1.0$)	LogitNormal($0.4, 1.0$)	LogitNormal($1.2, 1.6$)
% of $r = t$	10%		50%
α sampling	$\mathcal{U}[0, 0.875]$		N/A
Class dropout	10%		0%
teacher CFG w	$[1, 2]$		$1.75^\ddagger$
m ratio		0.5	

ablate both the form of the conditioning signal and the layer at which endpoint-related information is introduced in the data-free setting. Our results show that conditioning on the interval $t - r$, as in MeanFlow, consistently performs best. Moreover, for our 28-block student, injecting this signal from an intermediate block performs much better than injecting it in every block, with the best FID at block 8 under a 25K-iteration budget (Tab. 8); our full LightningDiT-XL/2 run uses block 10 (Tab. 5). Appendix E discusses this ablation in detail. Importantly, the original timestep t remains available to all DiT blocks, while the additional $t - r$ conditioning is introduced only from block 10 onward. This design therefore differs from DMF: rather than fully decoupling the timestep and endpoint signals, we retain global conditioning on t and selectively inject the interval signal into later layers.

Evaluation. For evaluation, we use the same PyTorch sampling and evaluation pipeline for all reported models to ensure a consistent comparison with baseline methods. Unless otherwise specified, we evaluate the 256×256 class-conditional ImageNet generation performance of the student model distilled from the SiT-XL/2+VA-REPA teacher. Because the model is trained with teacher guidance strengths sampled from $w \sim \mathcal{U}(1, 2)$, we sweep the guidance strength within this range at evaluation time and report the best-performing setting. The final results are reported in Tab. 1. For completeness, Tab. 9 lists ImageNet 256×256 results of representative 1-NFE and multi-NFE diffusion/flow models trained from scratch, GANs, autoregressive/masking models, and data-based distillation methods. These methods use real training data and different training budgets, so they serve as reference points rather than as baselines for the data-free comparison in Tab. 1.

Table 6: Convergence-state evaluation results on the analytic 2D spiral benchmark.

Method	$W_2 \downarrow$	GT avg.-velocity MSE $\downarrow$	$t = 1$ endpoint MSE $\downarrow$
FreeFlow	0.190	0.317	0.0316
Ours	0.190	0.070	0.0040

For the SiT-XL/2 teacher setting, we currently specify only the corresponding t and r sampling distributions, as shown in Tab. 5. The remaining settings and evaluation results are left empty until stable training outcomes are obtained.

D.2 SYNTHETIC 2D BENCHMARKS

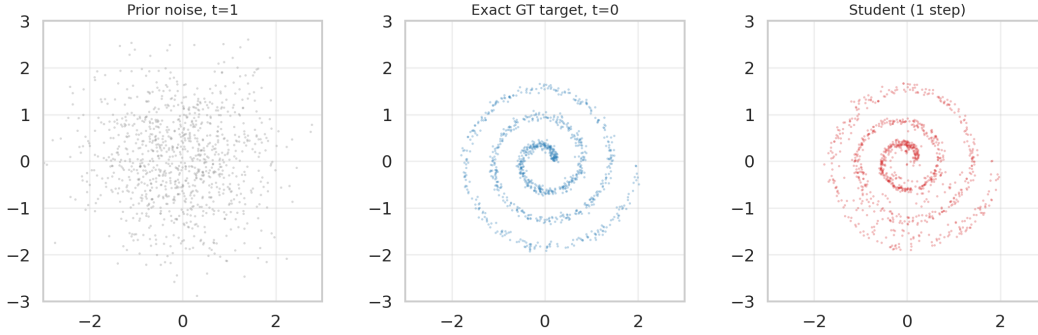
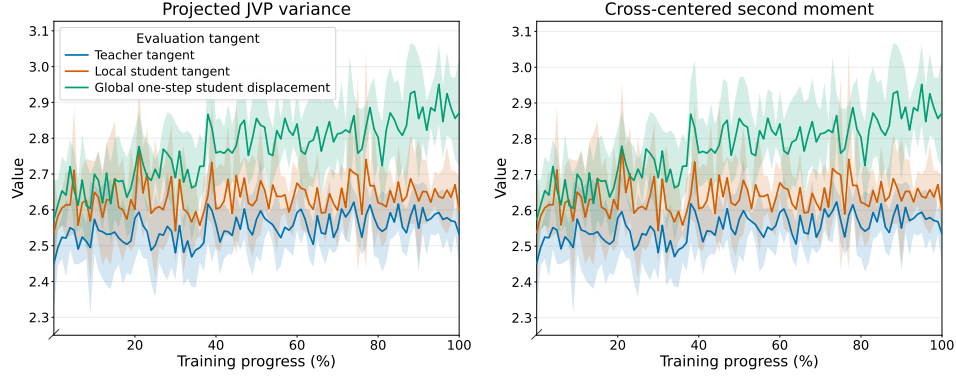


Figure 8: **Analytic 2D spiral benchmark.** Left: Gaussian prior noise at $t = 1$. Middle: exact ground-truth spiral target at $t = 0$. Right: one-step student samples after distillation.

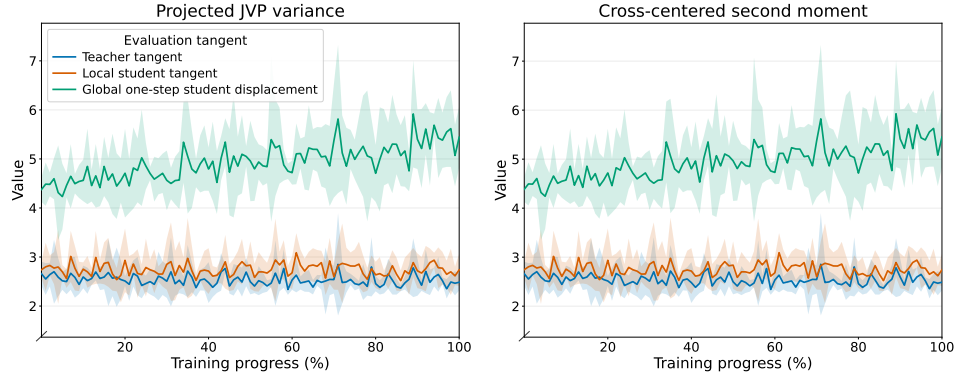
We evaluate on an analytic 2D spiral benchmark, where the teacher velocity field and target distribution are available in closed form, without relying on a learned teacher checkpoint. As shown in Fig. 8, samples are transported from a Gaussian prior at $t = 1$ to a spiral target distribution at $t = 0$. This controlled low-dimensional setting allows us to evaluate not only the terminal marginal distribution but also the learned transport behavior.

Both methods use the same one-step student architecture and evaluation protocol. We compare our training objective directly against the FreeFlow objective. The converged-state results in Table 6 show that matching the terminal marginal alone is insufficient to characterize distillation quality: although both methods achieve essentially the same final W_2 score, our objective learns a substantially more accurate average velocity field and a better coupled transport map. Concretely, CDMD reduces the error to the ground-truth average velocity from 0.317 to 0.070 and the coupled $t = 1$ endpoint error from 0.0316 to 0.0040, while both methods reach $W_2 = 0.190$. In addition to the spiral, we use a 2D checkerboard target with the same protocol for the JVP diagnostics below.

Figure 9 compares the projected JVP variance $\mathcal{V}_{\text{JVP}}$ and the cross-centered second moment $\mathcal{M}_{\text{JVP}}^{q,p}$ for the three candidate tangent directions on the 2D checkerboard (Figure 9a) and spiral (Figure 9b) datasets. Across both datasets, evaluating the JVP along the teacher tangent, $d\hat{x}_t/dt = v(\hat{x}_t, t)$, consistently yields the smallest and most stable correction statistics throughout training. The local student tangent, $u_\theta(\hat{x}_t, t, t)$, results in a modest increase in both quantities, whereas the global one-step student displacement, $u_\theta(z, 1, 0)$, exhibits substantially larger variability and an increasing trend over training. This difference is particularly pronounced on the spiral dataset, where the global displacement remains well separated from the two state-local tangent choices. Moreover, the projected variance and cross-centered second moment exhibit nearly identical trends and rankings, suggesting that the cross-distribution contribution is relatively small in these experiments and that the observed differences are primarily driven by the intrinsic stochasticity of the JVP correction. These results support using the teacher velocity $v(\hat{x}_t, t)$ as the JVP input direction when constructing the detached correction target.



(a) Results on the 2D checkerboard dataset.



(b) Results on the 2D spiral dataset.

Figure 9: Effect of the JVP tangent direction on the stochasticity of the detached correction. We compare three candidate JVP input directions on the checkerboard dataset in **a** and the spiral dataset in **b**: the teacher tangent $v(\hat{x}_t, t)$, the local student tangent $u_\theta(\hat{x}_t, t, t)$, and the global one-step student displacement $u_\theta(z, 1, 0)$. For each dataset, the left panel reports the projected JVP variance $\mathcal{V}_{\text{JVP}}$, while the right panel reports the cross-centered second moment $\mathcal{M}_{\text{JVP}}^{q,p}$. Across both datasets, the teacher tangent produces the smallest and most stable statistics, whereas the global one-step displacement produces the largest variability, particularly on the spiral dataset.

D.3 TEXT-TO-IMAGE DATASET

To adapt our method on text-to-image dataset at a larger scale, some aspects need to be altered. First, we need to anchor on the teacher trajectory to prevent drifting effect. Similar to the baselines, we use 4 step during our inference. To control the noise added during training, we adopt the TDM (Luo et al., 2025) method in our data-free setting. Every time we construct the intermediate states we start with the nearest earlier teacher checkpoint and we add noise according to the forward path. We decrease the variance of our target which leads to a better final performance. Fig. 10 illustrates this construction. The student generator first moves the prior sample backward along a coarse schedule, $x_1 \rightarrow \hat{x}_s \rightarrow \hat{x}_r \rightarrow \hat{x}_0$, and caches every intermediate state. A training state at time t is then obtained by re-noising the nearest cached state that is cleaner than t along the forward conditional path: $\hat{x}_0$ for $t \in [0, r)$, $\hat{x}_r$ for $t \in [r, s)$, and $\hat{x}_s$ for $t \in [s, 1]$. Each re-noising step therefore covers a short interval, so the training states stay close to the 4-step trajectory used at inference. In this case, we observe more diversified background and better detailed being preserved from the teacher model. With the same hardware and matching configuration, our CDMD requires approximately 7 GPU hours and 18 GB of peak memory (Tab. 7). Its cost is higher than CD but lower than the reported costs of Diff-Instruct, DMD2, and MFD. Note that our method performs significantly better than CD according to Table 3.

Table 7: **Training cost on SANA-1.6B.** Approximate wall-clock cost and peak memory on one NVIDIA RTX PRO 6000 GPU.

Method	GPU hours	Peak memory (GB)
Diff-Instruct (VSD) (Luo et al., 2023b)	~22	~20
Consistency Distillation (CD) (Song et al., 2023)	~4	~15
DMD2 (Yin et al., 2024a)	~30	~50
MFD (Zhao et al., 2026)	~25	~20
CDMD (ours)	~7	~18

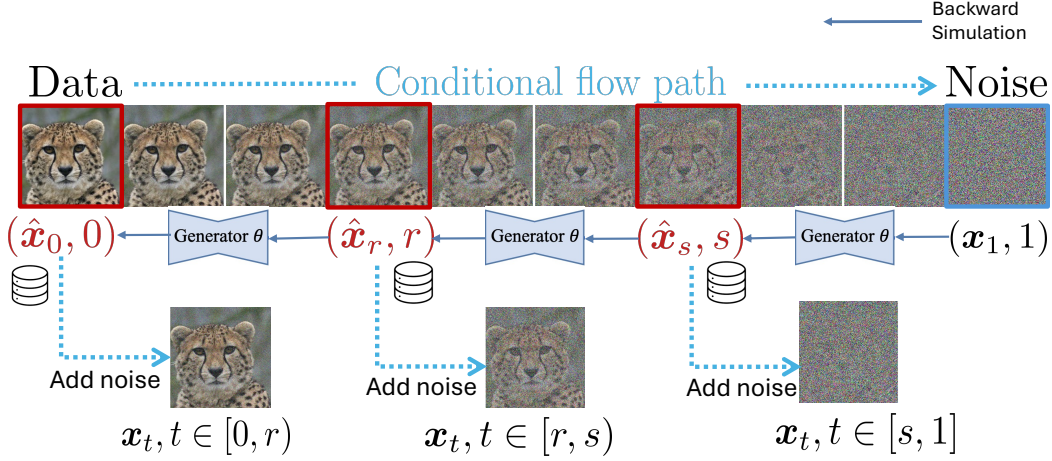


Figure 10: CDMD on Text to Image pipeline. The student generator θ simulates the prior sample backward to cached states $\hat{x}_s$, $\hat{x}_r$, and $\hat{x}_0$. Training states x_t are obtained by adding noise to the nearest cached state that is cleaner than t .

E ABLATION ON ENDPOINT CONDITIONING

Fig. 13 compares how three transformer designs receive time information. (a) The DiT teacher predicts the instantaneous velocity and conditions every block on the embeddings of t and the class label y through adaLN-Zero. (b) The MeanFlow transformer predicts the average velocity and adds an embedding of the second time variable to the same signal, so every block sees both time variables. (c) The CDMD transformer keeps the teacher conditioning for the all blocks and adds the endpoint embedding, implemented as the gap $t - r$, only to the last $L - D$ blocks and the final layer.

Tab. 8 varies D for the $L = 28$ student under a fixed budget of 25K iterations. At depth D , the first D blocks see only the teacher conditioning, and $D = 0$ conditions every block on $(t - r)$, as in MeanFlow. Conditioning every block on the gap ($D = 0$) gives an FID of 17.60, far worse than any delayed variant. Delaying the signal by five blocks already lowers FID to 2.80. All depths from 5 to 20 reach FID at most 2.80 and IS above 273, and $D = 8$ performs best with FID 2.21 and IS 284.46. Delaying the signal too far ($D = 25$) raises FID to 3.84, since only three blocks remain to separate different intervals that start from the same (x_t, t) .

We interpret this effect through teacher capacity. The first D blocks receive exactly the conditioning of the teacher, so they can reproduce the teacher features for the instantaneous velocity at (x_t, t) , which every interval $[r, t]$ shares. The endpoint signal then only modulates the later blocks, which turn these shared features into the average velocity of a specific interval. With $D = 0$, every block must handle both time variables from the start, and the student spends capacity on the endpoint before it reproduces the teacher. This matches our finding on the t and r schedule in Appendix F.2: the conditioning depth and the fraction of $t = r$ pairs both control how much of the student stays dedicated to the teacher velocity, and preserving this teacher capacity is what keeps the distilled student close to the teacher.

Algorithm 1 CDMD data-free algorithm: training.

```

t, r = sample_t_r()
m = sample_m()
e, e' = randn()

x = fn(e, 1, 0)          # fn(z, t, r): student flow map
z1 = (1 - t) * x + t * e'
z2 = fn(e, 1, t)
z = m * z1 + (1 - m) * z2
z_sg = stopgrad(z)

vt = gn(z_sg, t)         # gn(z, t): teacher velocity
Vt = fc(z_sg, t, r)      # fc: corrected velocity on fn
error = Vt - stopgrad(vt)
loss = metric(error)

```

Depth	FID ↓	IS ↑
0	17.60	154.19
5	2.80	276.35
8	2.21	284.46
10	2.47	277.19
15	2.68	273.75
20	2.65	280.04
25	3.84	259.32

Table 8 Effect of the DiT block depth at which the gap ($t - r$) is injected as a conditioning signal on final performance, under a fixed training budget of 25K iterations.

Table 9: Reference results on class-conditional ImageNet256×256. Left: Representative 1-NFE and multi-NFE diffusion/flow models. **Right:** Representative GANs and autoregressive/masking models. All numbers are reported with CFG when applicable, and ×2 in NFE indicates that CFG doubles the number of function evaluations at inference time.

Method	# Params	NFE	FID↓	Method	# Params	NFE	FID↓
<i>1-NFE Diffusion / Flow from Scratch</i>				<i>GANs</i>			
Shortcut-XL/2 (Frans et al., 2024)	675M	1	10.60	BigGAN (Brock et al., 2018)	112M	1	6.95
IMM-XL/2 (Zhou et al., 2025a)	675M	1×2	7.77	GigaGAN (Kang et al., 2023)	569M	1	3.45
MeanFlow-XL/2 (Geng et al., 2025a)	676M	1	3.43	StyleGAN-XL (Sauer et al., 2022)	166M	1	2.30
TVM (Zhou et al., 2025b)	678M	1	3.29	<i>Autoregressive / Masking</i>			
SoFlow-XL/2 (Luo et al., 2026)	675M	1	2.96	MaskGIT (Chang et al., 2022)	227M	8	6.18
DMF-XL/2 (Lee et al., 2026)	675M	1	2.16	RQ-Transformer (Lee et al., 2022)	3.8B	256×2	3.80
iMF-XL/2 (Geng et al., 2025b)	675M	1	1.72	STARFlow (Gu et al., 2025)	1.4B	1024×2	2.40
<i>Multi-NFE Diffusion / Flow</i>				LlamaGen-3B (Sun et al., 2024)	3.1B	256×2	2.18
ADM-G (Dhariwal & Nichol, 2021)	554M	250×2	4.59	VAR-d30 (Tian et al., 2024)	2B	10×2	1.92
LDM-4-G (Rombach et al., 2022)	400M	250×2	3.60	MAR-H (Li et al., 2024)	943M	256×2	1.55
DiT-XL/2 (Peebles & Xie, 2023)	675M	250×2	2.27	RAR-XXL (Yu et al., 2025)	1.5B	256×2	1.48
SiT-XL/2 (Ma et al., 2024)	675M	250×2	2.06	<i>Data-based Distillation</i>			
SiT-XL/2+REPA (Yu et al., 2024)	675M	250×2	1.42	<i>Teacher: SiT-XL/2 (FID = 2.06)</i>			
SiD2 (Hoogeboom et al., 2025)	—	512×2	1.38	SDEI (Liu & Yue, 2025)	675M	8	2.46
DDT-XL/2 (Wang et al., 2025)	675M	250×2	1.26	FACM (Peng et al., 2025)	675M	2	2.07
LightningDiT (Yao et al., 2025)	675M	250	2.05	<i>Teacher: SiT-XL/2+REPA (FID = 1.37)</i>			
		250×2	1.35	π-Flow (Chen et al., 2025)	675M	1	2.85
SiT-XL/2+REPA-E (Leng et al., 2025)	675M	250	1.69			2	1.97
		250×2	1.12				

F ABLATION ON INFERENCE-TIME SCALING

F.1 SAMPLER COMPARISON WITH THE SiT-XL/2+VA-REPA TEACHER

We further study inference-time scaling by comparing Euler, Heun, and DDIM samplers under different classifier-free guidance scales. Figure 11 reports FID as a function of the number of sampling steps for $w = 1.5$ and $w = 2.0$. In some literatures (Lee et al., 2026; Song et al., 2023), DDIM method has also been referred as the Restart sampler.

The ablation suggests that increasing the inference-time sampling budget does not automatically improve our distilled model. DDIM gives the strongest low-step performance in both guidance settings and remains especially stable from one to four steps. Euler is competitive at one or two steps for $w = 1.5$, but its FID increases as more steps are used and then plateaus. Heun is the least stable in the low-step regime: it exhibits a sharp FID spike at two steps and only recovers after additional steps. The effect is more pronounced under stronger guidance, where both Euler and Heun drift to noticeably worse FID than DDIM as the sampling budget grows.

These results give useful guidance for scaling inference time in our model. The interval-conditioned parameterization supports multi-step sampling, but the benefit depends strongly on the sampler and guidance scale. In this setting, DDIM is the most reliable choice for converting extra inference steps into stable sample quality, while higher-order updates can amplify student-teacher mismatch at small step counts. We attribute this behavior primarily to these two factors. First, our training schedule assigns substantial probability mass to intervals with $t \neq r$, which may make the learned update less compatible with aggressive higher-order extrapolation at inference time. Second, the quality of the teacher, particularly its performance without CFG, has a pronounced effect on the distilled model. Empirically, we observe that differences in teacher performance without CFG translate into differences in the final student performance. Note that this student is trained with $t = r$ for only 10% of the pairs (Tab. 5). Appendix F.2 tests the first factor with a student trained with $t = r$ for 50% of the pairs.

F.2 INFERENCE-TIME SCALING WITH THE LIGHTNINGDiT-XL/2 TEACHER

Fig. 12 repeats the inference-time scaling study for the student distilled from LightningDiT-XL/2. We sample the same student with Euler and DDIM from 1 to 64 steps without retraining. Unlike the SiT-XL/2+VA-REPA student in Fig. 11, the Euler FID decreases from 2.04 at 1 step to 1.62 at 2 steps and 1.37 at 4 steps (Tab. 1), and reaches its minimum at 8 steps. From 8 to 64 steps, the Euler FID stays nearly flat and close to the teacher reference instead of drifting upward. The Euler IS rises from about 294 at 1 step to about 320 at 16 steps and then saturates. Additional steps thus refine the samples, as they do for the teacher FM model, and never cause the large degradation of the 10% $t = r$ student.

The main difference between the two students is the training schedule. The LightningDiT student samples $t = r$ for 50% of the pairs, whereas the SiT-XL/2+VA-REPA student in Fig. 11 uses 10% (Tab. 5). On $t = r$ pairs, the objective reduces to $\|\mathbf{u}_\theta(\hat{\mathbf{x}}_t, t, t) - \mathbf{v}(\hat{\mathbf{x}}_t, t)\|^2$, so the student directly learns the teacher instantaneous velocity, which governs small sampling steps. This result matches Fig. 6b in the main text, where raising the fraction of $t = r$ pairs from 10% to 50% substantially reduces the multi-step degradation (FID about 5.1 instead of 9.8 at 50 steps). Since the same behavior appears with a different teacher, the stability is a property of the t and r schedule rather than of a particular teacher: keeping $t = r$ for 50% of the pairs is enough to preserve the multi-step behavior of the teacher as the number of sampling steps increases, while still giving the best 1-NFE FID in Tab. 1.

DDIM behaves differently. Its FID is close to Euler at 1 and 2 steps but rises steadily after 4 steps and exceeds 5 at 64 steps, while its IS grows monotonically to above 420. Rising IS together with rising FID indicates that DDIM increasingly trades sample diversity for class fidelity as the number of steps grows. For this student, Euler is therefore the preferred sampler for inference-time scaling.

G CDMD WITH GUIDANCE

Classifier-free guidance (CFG) (Ho & Salimans, 2022) is significant to class-conditional image generation because it facilitates conditional generation by extrapolating from unconditional to conditional predictions. Since the most pre-trained diffusion baselines are evaluated with CFG, we formulate our distillation objective to match the guided teacher dynamics rather than the unguided velocity field alone. Let $\mathbf{v}(\mathbf{x}_t, t \mid \mathbf{c})$ and $\mathbf{v}(\mathbf{x}_t, t \mid \emptyset)$ denote the conditional and unconditional teacher velocity fields, respectively. For a guidance scale $w \geq 1$, the guided velocity field is defined as $\mathbf{v}^{\text{cfg}}(\mathbf{x}_t, t \mid \mathbf{c}) = (1 - w) \mathbf{v}(\mathbf{x}_t, t \mid \emptyset) + w \mathbf{v}(\mathbf{x}_t, t \mid \mathbf{c})$.

In addition, we can reinforce this signal by incorporating student guidance with scale $\alpha \geq 0$ during training to support 1-NFE sampling (Geng et al., 2025a). Compared with standard CFG sampling, which evaluates both conditional and unconditional branches at each solver step and therefore doubles the NFE count, this training-time guided target lets the distilled student absorb part of the conditional guidance signal before inference. Specifically, we define the enhanced guided velocity field as follows:

$$\mathbf{v}^{\text{cfg}++}(\mathbf{x}_t, t \mid \mathbf{c}) = \mathbf{v}^{\text{cfg}}(\mathbf{x}_t, t \mid \mathbf{c}) + \alpha \left(\mathbf{u}_\theta(\mathbf{x}_t, t, t \mid \mathbf{c}) - \mathbf{u}_\theta(\mathbf{x}_t, t, t \mid \emptyset) \right), \quad (37)$$

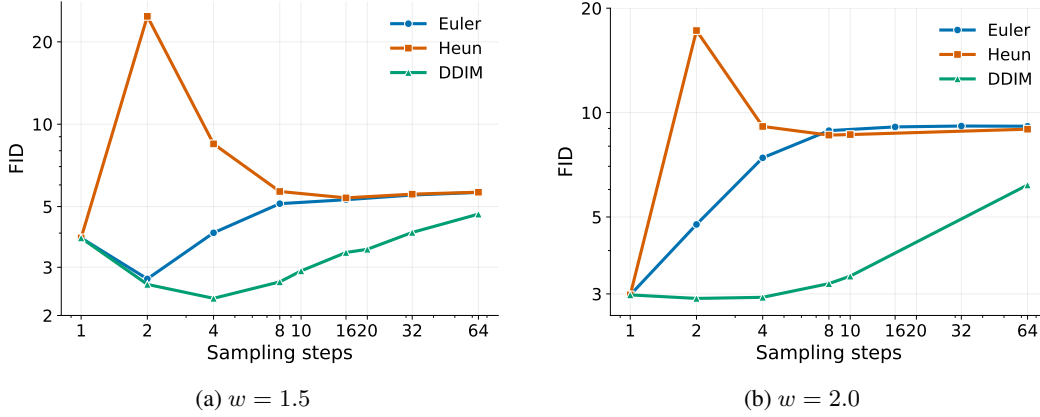


Figure 11: Sampler comparison for inference-time scaling under classifier-free guidance scales $w = 1.5$ and $w = 2.0$. The student network is trained with SiT+VA-REPA teacher. We report FID across different numbers of sampling steps for Euler, Heun, and DDIM. DDIM gives the most stable low-step behavior, while Heun shows a sharp degradation at two steps and Euler becomes less favorable as the sampling budget increases.

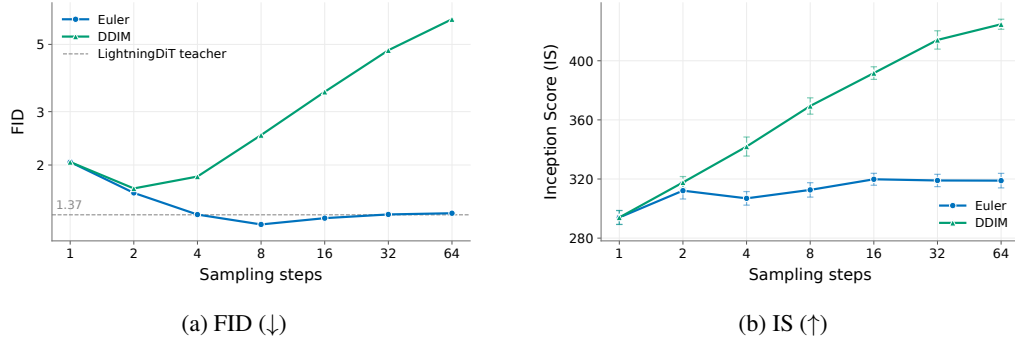


Figure 12: **Inference-time scaling with the LightningDiT-XL/2 teacher.** (a) FID and (b) IS against the number of sampling steps for Euler and DDIM, using the same distilled student trained with $t = r$ for 50% of the pairs. Euler sampling improves up to 8 steps and stays close to the teacher reference (dashed) up to 64 steps, preserving the multi-step behavior of the teacher. DDIM raises IS but degrades FID beyond 4 steps.

where $\mathbf{u}_\theta(\mathbf{x}_t, t, t \mid \mathbf{c})$ approximates the ground-truth instantaneous marginal velocity field under condition $\mathbf{c}$. This additional term further amplifies the conditional signal while retaining the stabilizing effect of the unconditional component. Following the flexible guidance in iMF (Geng et al., 2025b), we allow the network to condition on the guidance term.

Guidance and tangent choice. The teacher velocity enters the objective twice: as the regression target and as the tangent in the JVP. We find that using the CFG velocity $\mathbf{v}^{\text{cfg}}(\mathbf{x}_t, t \mid \mathbf{c})$ as the tangent and $\mathbf{v}^{\text{cfg}++}(\mathbf{x}_t, t \mid \mathbf{c})$ as the target performs best. Fig. 14 shows that the best w depends on both the teacher checkpoint and the EMA rate. Moderate w gives the best FID in most settings, while large w or strong EMA smoothing degrades it. For the SiT-XL/2+VA-REPA teacher, all three EMA settings reach their lowest FID at $w \in [1.8, 1.9]$. The student without EMA attains the lowest FID-50K of about 2.93, whereas an EMA decay of 0.9999 raises the minimum to about 3.38. For the SiT-XL/2 teacher, the optimum shifts to $w \approx 2.0$, and the student without EMA again performs best at about 3.47. We also observe that student guidance is difficult to tune with Lightning-DiT as the teacher, so we set $\alpha = 0$. It occasionally yields a very high IS with exaggerated class features.

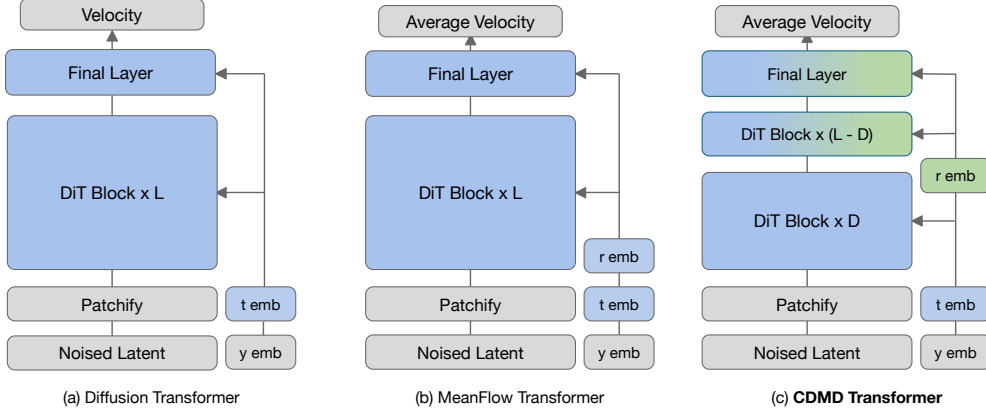


Figure 13: High level comparison of Diffusion Transformer architectures. (a) The DiT teacher conditions every block on t and y . (b) MeanFlow conditions every block on both time variables. (c) CDMD keeps the teacher conditioning in **all** the blocks and injects the endpoint embedding only into the last $L - D$ blocks and the final layer (Tab. 8).

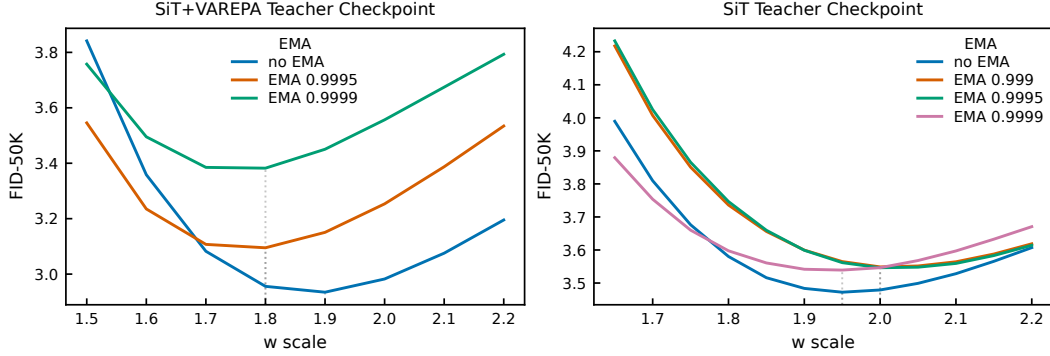


Figure 14: FID-50K versus classifier-free guidance scale w condition for students distilled from two teacher checkpoints. Left: SiT+VAREPA teacher checkpoint. Right: SiT teacher checkpoint. Different curves compare various EMA settings. Note that we do not condition on guidance scale when we distill from Lightning-DiT teacher model.

H LIMITATIONS AND BROADER IMPACT

A key limitation of the current formulation is the absence of meaningful constraints on the total derivative term $\frac{d}{dt} \mathbf{u}(\mathbf{x}_t, t, r) = \mathbf{v}(\mathbf{x}_t, t) D_{\mathbf{x}_t} \mathbf{u} + \partial_t \mathbf{u}$. To date, this component has not been rigorously analyzed. In prior work, it is typically detached from the computational graph and excluded from backpropagation, effectively treating it as a constant. However, empirical observations reveal that its norm is large and fluctuates substantially throughout training, suggesting that this simplification may be problematic. A plausible direction for regularization is to leverage a well-trained reference velocity field $\mathbf{v}(\mathbf{x}_t, t)$, encouraging the derivative term to exhibit similar, more stable behavior. In practice, not only is the dataset private, but the teacher model weights are also inaccessible. Hence, we cannot initialize the student model with the teacher model weights, which is a common practice in distillation work. This makes training more challenging and less stable. Moreover, we speculate that for different tasks, the way we bootstrapped our x_t is of great importance. This can substantially influence the learning dynamics and overall effectiveness of distillation.

I IMAGE PROMPTS

We list the text prompts used for the 4-step SANA-1.6B samples in Fig. 2.

-
1. **Tram:** watercolor of Istanbul rainy night with the tramway
 2. **Portrait:** portrait photo of a girl, photograph, highly detailed face, depth of field
 3. **Neon bear:** a bear riding a skateboard, 4k, high resolution, with a Neon sign at the back saying "CDMD"
 4. **Warrior:** Artstation Assassin S Creed Iv Black Flag Concept Art Martin Deschambault
 5. **Shiba Inu:** a shiba inu wearing a beret and black turtleneck
 6. **Llama:** A photo of llama wearing sunglasses standing on the deck of a spaceship with the Earth in the background.
 7. **Pirate ship:** Pirate ship trapped in a cosmic maelstrom nebula, rendered in cosmic beach whirlpool engine, volumetric lighting, spectacular, ambient lights, light pollution, cinematic atmosphere, art nouveau style, illustration art artwork by SenseiJaye, intricate detail, 2k
 8. **Astronaut:** Astronaut in a jungle, cold color palette, muted colors, detailed, 4k
 9. **Autumn river:** Fascinating autumn forest scene with a river and foliage.
 10. **Capybara:** a capybara made of voxels sitting in a grass field

J QUALITATIVE SAMPLES

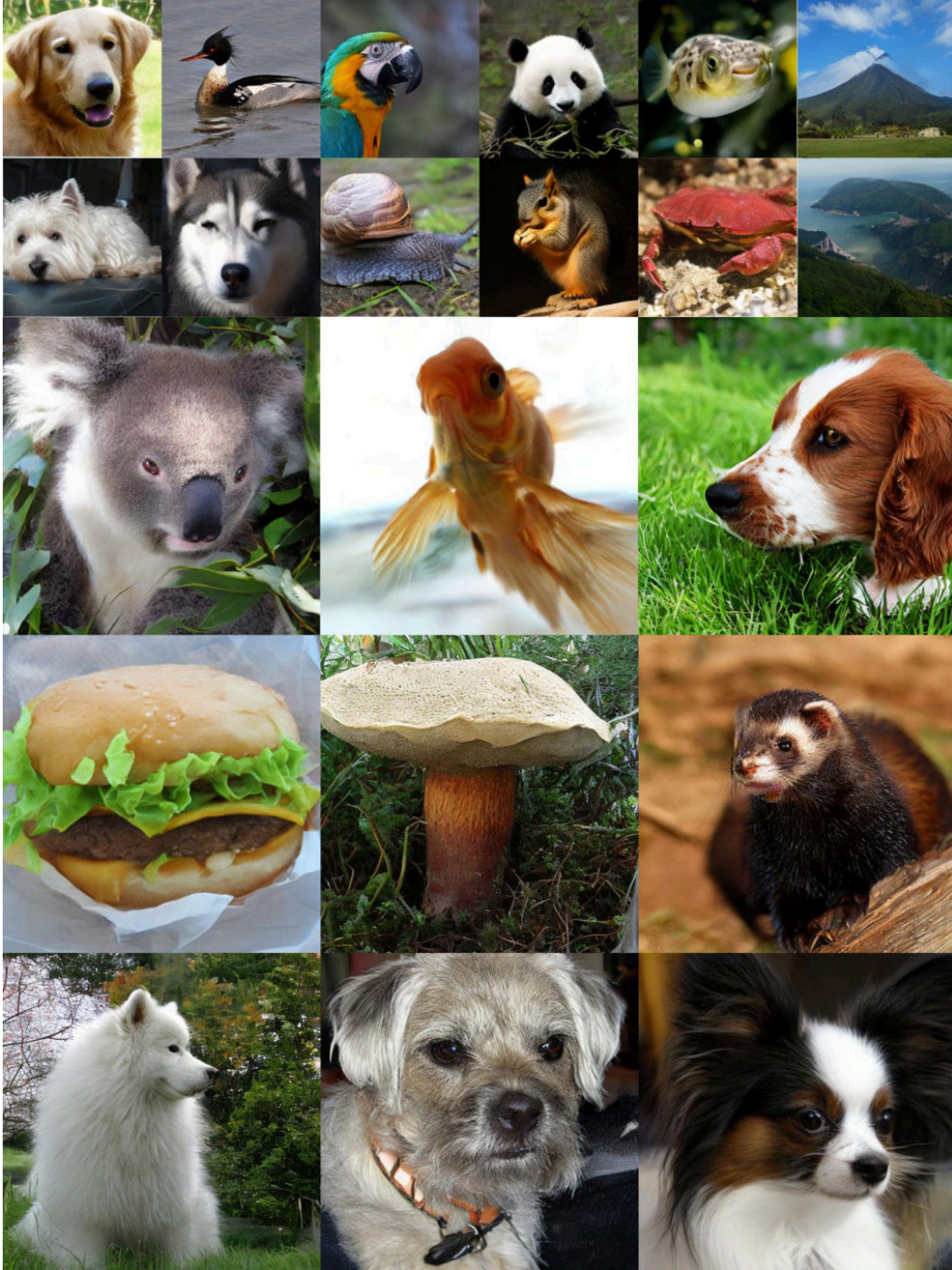


Figure 15: Qualitative results on ImageNet 256×256 and 512×512 datasets with 1-NFE sampling. Note that we sample the class index randomly.



(a) 1-step



(b) 2-step Euler



(c) 2-step DDIM



(d) 4-step Euler



(e) 4-step DDIM

Figure 16: **Uncurated** samples generated from CDMD with LightningDiT-XL/2 with class id 22: bald eagle.



(a) 1-step



(b) 2-step Euler



(c) 2-step DDIM



(d) 4-step Euler



(e) 4-step DDIM

Figure 17: **Uncurated** samples generated from CDMD with LightningDiT-XL/2 with class id 207: golden retriever.



(a) 1-step



(b) 2-step Euler



(c) 2-step DDIM



(d) 4-step Euler



(e) 4-step DDIM

Figure 18: **Uncurated** samples generated from CDMD with LightningDiT-XL/2 with class id 279: Arctic fox.



(a) 1-step



(b) 2-step Euler



(c) 2-step DDIM



(d) 4-step Euler



(e) 4-step DDIM

Figure 19: **Uncurated** samples generated from CDMD with LightningDiT-XL/2 with class id 387: lesser panda.



(a) 1-step



(b) 2-step Euler



(c) 2-step DDIM



(d) 4-step Euler



(e) 4-step DDIM

Figure 20: **Uncrated** samples generated from CDMD with LightningDiT-XL/2 with class id 780: schooner.



(a) 1-step



(b) 2-step Euler



(c) 2-step DDIM



(d) 4-step Euler



(e) 4-step DDIM

Figure 21: **Uncurated** samples generated from CDMD with LightningDiT-XL/2 with class id 933: cheeseburger.



(a) 1-step



(b) 2-step Euler



(c) 2-step DDIM



(d) 4-step Euler



(e) 4-step DDIM

Figure 22: **Uncurated** samples generated from CDMD with LightningDiT-XL/2 with class id 974: geyser.