SIMPLIFYING, STABILIZING & SCALING CONTINUOUS-TIME CONSISTENCY MODELS

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ABSTRACT

Consistency models (CMs) are a powerful class of diffusion-based generative models optimized for fast sampling. Most existing CMs are trained using discretized timesteps, which introduce additional hyperparameters and are prone to discretization errors. While continuous-time formulations can mitigate these issues, their success has been limited by training instability. To address this, we propose a simplified theoretical framework that unifies previous parameterizations of diffusion models and CMs, identifying the root causes of instability. Based on this analysis, we introduce key improvements in diffusion process parameterization, network architecture, and training objectives. These changes enable us to train continuous-time CMs at an unprecedented scale, reaching 1.5B parameters on ImageNet 512×512. Our proposed training algorithm, using only two sampling steps, achieves FID scores of 2.06 on CIFAR-10, 1.48 on ImageNet 64×64, and 1.88 on ImageNet 512×512, narrowing the gap in FID scores with the best existing diffusion models to within 10%.

1 INTRODUCTION

Diffusion models (Sohl-Dickstein et al., 2015; Song & Ermon, 2019; Ho et al., 2020; Song et al., 2021b) have revolutionized generative AI, achieving remarkable results in image (Rombach et al., 2022; Ramesh et al., 2022; Ho et al., 2022), 3D (Poole et al., 2022; Wang et al., 2024; Liu et al., 2023b), audio (Liu et al., 2023a; Evans et al., 2024), and video generation (Blattmann et al., 2023; Brooks et al., 2024). Despite their success, a significant drawback is their slow sampling speed, often requiring dozens to hundreds of steps to generate a single sample. Various diffusion distillation techniques have been proposed, including direct distillation (Luhman & Luhman, 2021; Zheng et al., 2023b), adversarial distillation (Wang et al., 2022; Sauer et al., 2023), progressive distillation (Salimans & Ho, 2022), and variational score distillation (VSD) (Wang et al., 2024; Yin et al., 2024b;a; Luo et al., 2024; Xie et al., 2024b; Salimans et al., 2024). However, these methods come with challenges: direct distillation incurs extensive computational cost due to the need for numerous diffusion model samples; adversarial distillation introduces complexities associated with GAN training; progressive distillation requires multiple training stages and is less effective for one or two-step generation; and VSD can produce overly smooth samples with limited diversity and struggles at high guidance levels.

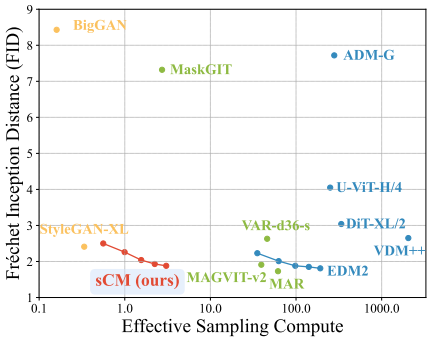


Figure 1: Sample quality vs. effective sampling compute (billion parameters × number of function evaluations during sampling). We compare the sample quality of different models on ImageNet 512×512, measured by FID (↓). Our 2-step sCM achieves sample quality comparable to the best previous generative models while using less than 10% of the effective sampling compute.

Consistency models (CMs) (Song et al., 2023; Song & Dhariwal, 2023) offer significant advantages in addressing these issues. They eliminate the need for supervision from diffusion model samples, avoiding the computational cost of generating synthetic datasets. CMs also bypass adversarial training, sidestepping its inherent difficulties. Aside from distillation, CMs can be trained from scratch with consistency training (CT), without relying on pre-trained diffusion models. Previous work (Song & Dhariwal, 2023; Geng et al., 2024; Luo et al., 2023; Xie et al., 2024a) has demonstrated the

Figure 2: Selected 2-step samples from a continuous-time consistency model trained on ImageNet 512×512.

effectiveness of CMs in few-step generation, especially in one or two steps. However, these results are all based on discrete-time CMs, which introduces discretization errors and requires careful scheduling of the timestep grid, potentially leading to suboptimal sample quality. In contrast, continuous-time CMs avoid these issues but have faced challenges with training instability (Song et al., 2023; Song & Dhariwal, 2023; Geng et al., 2024).

In this work, we introduce techniques to simplify, stabilize, and scale up the training of continuous-time CMs. Our first contribution is TrigFlow, a new formulation that unifies EDM (Karras et al., 2022; 2024) and Flow Matching (Peluchetti, 2022; Lipman et al., 2022; Liu et al., 2022; Albergo et al., 2023; Heitz et al., 2023), significantly simplifying the formulation of diffusion models, the associated probability flow ODE and CMs. Building on this foundation, we analyze the root causes of instability in CM training and propose a complete recipe for mitigation. Our approach includes improved time-conditioning and adaptive group normalization within the network architecture. Additionally, we re-formulate the training objective for continuous-time CMs, incorporating adaptive weighting and normalization of key terms, and progressive annealing for stable and scalable training.

With these improvements, we elevate the performance of consistency models in both consistency training and distillation, achieving comparable or better results compared to previous discrete-time formulations. Our models, referred to as sCMs, demonstrate success across various datasets and model sizes. We train sCMs on CIFAR-10, ImageNet 64×64, and ImageNet 512×512, reaching an unprecedented scale with 1.5 billion parameters—the largest CMs trained to date (samples in Figure 2). We show that sCMs scale effectively with increased compute, achieving better sample quality in a predictable way. Moreover, when measured against state-of-the-art diffusion models, which require significantly more sampling compute, sCMs narrow the FID gap to within 10% using two-step generation. In addition, we provide a rigorous justification for the advantages of continuous-

time CMs over discrete-time variants by demonstrating that sample quality improves as the gap between adjacent timesteps narrows to approach the continuous-time limit. Furthermore, we examine the differences between sCMs and VSD, finding that sCMs produce more diverse samples and are more compatible with guidance, whereas VSD tends to struggle at higher guidance levels.

2 PRELIMINARIES

2.1 DIFFUSION MODELS

Given a training dataset, let p_d denote its underlying data distribution and σ_d its standard deviation. Diffusion models generate samples by learning to reverse a noising process that progressively perturbs a data sample $\boldsymbol{x}_0 \sim p_d$ into a noisy version $\boldsymbol{x}_t = \alpha_t \boldsymbol{x}_0 + \sigma_t \boldsymbol{z}$, where $\boldsymbol{z} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})$ is standard Gaussian noise. This perturbation increases with $t \in [0, T]$, where larger t indicates greater noise.

We consider two recent formulations for diffusion models.

EDM (Karras et al., 2022; 2024). The noising process simply sets $\alpha_t = 1$ and $\sigma_t = t$, with the training objective given by $\mathbb{E}_{\boldsymbol{x}_0, \boldsymbol{z}, t}\left[w(t) \left\| \boldsymbol{f}_\theta^{\mathrm{DM}}(\boldsymbol{x}_t, t) - \boldsymbol{x}_0 \right\|_2^2\right]$, where $w(t)$ is a weighting function. The diffusion model is parameterized as $\boldsymbol{f}_\theta^{\mathrm{DM}}(\boldsymbol{x}_t, t) = c_{\mathrm{skip}}(t)\boldsymbol{x}_t + c_{\mathrm{out}}(t)\boldsymbol{F}_\theta(c_{\mathrm{in}}(t)\boldsymbol{x}_t, c_{\mathrm{noise}}(t))$, where $\boldsymbol{F}_\theta$ is a neural network with parameters θ, and c_{skip}, c_{out}, c_{in}, and c_{noise} are manually designed coefficients that ensure the training objective has the unit variance across timesteps at initialization. For sampling, EDM solves the *probability flow ODE (PF-ODE)* (Song et al., 2021b), defined by $\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} = [\boldsymbol{x}_t - \boldsymbol{f}_\theta^{\mathrm{DM}}(\boldsymbol{x}_t, t)]/t$, starting from $\boldsymbol{x}_T \sim \mathcal{N}(\boldsymbol{0}, T^2\boldsymbol{I})$ and stopping at $\boldsymbol{x}_0$.

Flow Matching. The noising process uses differentiable coefficients α_t and σ_t, with time derivatives denoted by α_t' and σ_t' (typically, $\alpha_t = 1 - t$ and $\sigma_t = t$). The training objective is given by $\mathbb{E}_{\boldsymbol{x}_0, \boldsymbol{z}, t}\left[w(t) \left\| \boldsymbol{F}_\theta(\boldsymbol{x}_t, t) - (\alpha_t' \boldsymbol{x}_0 + \sigma_t' \boldsymbol{z}) \right\|_2^2\right]$, where $w(t)$ is a weighting function and $\boldsymbol{F}_\theta$ is a neural network parameterized by θ. The sampling procedure begins at $t = 1$ with $\boldsymbol{x}_1 \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})$ and solves the probability flow ODE (PF-ODE), defined by $\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} = \boldsymbol{F}_\theta(\boldsymbol{x}_t, t)$, from $t = 1$ to $t = 0$.

2.2 CONSISTENCY MODELS

A consistency model (CM) (Song et al., 2023; Song & Dhariwal, 2023) is a neural network $\boldsymbol{f}_\theta(\boldsymbol{x}_t, t)$ trained to map the noisy input $\boldsymbol{x}_t$ directly to the corresponding clean data $\boldsymbol{x}_0$ in one step, by following the sampling trajectory of the PF-ODE starting at $\boldsymbol{x}_t$. A valid $\boldsymbol{f}_\theta$ must satisfy the *boundary condition*, $\boldsymbol{f}_\theta(\boldsymbol{x}, 0) \equiv \boldsymbol{x}$. One way to meet this condition is to parameterize the consistency model as $\boldsymbol{f}_\theta(\boldsymbol{x}_t, t) = c_{\mathrm{skip}}(t)\boldsymbol{x}_t + c_{\mathrm{out}}(t)\boldsymbol{F}_\theta(c_{\mathrm{in}}(t)\boldsymbol{x}_t, c_{\mathrm{noise}}(t))$ with $c_{\mathrm{skip}}(0) = 1$ and $c_{\mathrm{out}}(0) = 0$. CMs are trained to have consistent outputs at adjacent time steps. Depending on how nearby time steps are selected, there are two categories of consistency models, as described below.

Discrete-time CMs. The training objective is defined at two adjacent time steps with finite distance:

$$\mathbb{E}_{\boldsymbol{x}_t, t}\left[w(t) d(\boldsymbol{f}_\theta(\boldsymbol{x}_t, t), \boldsymbol{f}_{\theta^-}(\boldsymbol{x}_{t-\Delta t}, t - \Delta t))\right], \quad (1)$$

where θ^- denotes $\mathrm{stopgrad}(\theta)$, $w(t)$ is the weighting function, $\Delta t > 0$ is the distance between adjacent time steps, and $d(\cdot, \cdot)$ is a metric function; common choices are ℓ_2 loss $d(\boldsymbol{x}, \boldsymbol{y}) = \|\boldsymbol{x} - \boldsymbol{y}\|_2^2$, Pseudo-Huber loss $d(\boldsymbol{x}, \boldsymbol{y}) = \sqrt{\|\boldsymbol{x} - \boldsymbol{y}\|_2^2 + c^2} - c$ for $c > 0$ (Song & Dhariwal, 2023), and LPIPS loss (Zhang et al., 2018). Discrete-time CMs are sensitive to the choice of Δt, and therefore require manually designed annealing schedules (Song & Dhariwal, 2023; Geng et al., 2024) for fast convergence. The noisy sample $\boldsymbol{x}_{t-\Delta t}$ at the preceding time step $t - \Delta t$ is often obtained from $\boldsymbol{x}_t$

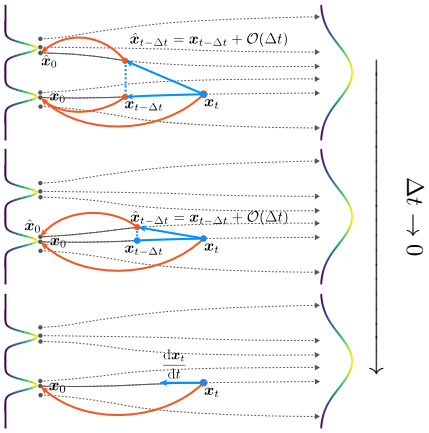


Figure 3: Discrete-time CMs (top & middle) vs. continuous-time CMs (bottom). Discrete-time CMs suffer from discretization errors from numerical ODE solvers, causing imprecise predictions during training. In contrast, continuous-time CMs stay on the ODE trajectory by following its tangent direction with infinitesimal steps.

by solving the PF-ODE with numerical ODE solvers using step size Δt, which can cause additional discretization errors.

Continuous-time CMs. When using $d(\boldsymbol{x}, \boldsymbol{y}) = \|\boldsymbol{x} - \boldsymbol{y}\|_2^2$ and taking the limit $\Delta t \to 0$, Song et al. (2023, *Remark 10*) show that the gradient of Eq. (1) with respect to θ converges to

$$\nabla_\theta \mathbb{E}_{\boldsymbol{x}_t, t}\left[w(t)\boldsymbol{f}_\theta^\top(\boldsymbol{x}_t, t)\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}(\boldsymbol{x}_t, t)}{\mathrm{d}t}\right], \tag{2}$$

where $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}(\boldsymbol{x}_t,t)}{\mathrm{d}t} = \nabla_{\boldsymbol{x}_t}\boldsymbol{f}_{\theta^-}(\boldsymbol{x}_t, t)\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} + \partial_t \boldsymbol{f}_{\theta^-}(\boldsymbol{x}_t, t)$ is the *tangent* of $\boldsymbol{f}_{\theta^-}$ at $(\boldsymbol{x}_t, t)$ along the trajectory of the PF-ODE $\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t}$. Notably, continuous-time CMs do not rely on ODE solvers, which avoids discretization errors and offers more accurate supervision signals during training. However, previous work (Song et al., 2023; Geng et al., 2024) found that training continuous-time CMs, or even discrete-time CMs with an extremely small Δt, suffers from severe instability in optimization. This greatly limits the empirical performance and adoption of continuous-time CMs.

Consistency Distillation and Consistency Training. Both discrete-time and continuous-time CMs can be trained using either *consistency distillation (CD)* or *consistency training (CT)*. In consistency distillation, a CM is trained by distilling knowledge from a pretrained diffusion model. This diffusion model provides the PF-ODE, which can be directly plugged into Eq. (2) for training continuous-time CMs. Furthermore, by numerically solving the PF-ODE to obtain $\boldsymbol{x}_{t-\Delta t}$ from $\boldsymbol{x}_t$, one can also train discrete-time CMs via Eq. (1). Consistency training (CT), by contrast, trains CMs from scratch without the need for pretrained diffusion models, which establishes CMs as a standalone family of generative models in their own right. Specifically, CT approximates $\boldsymbol{x}_{t-\Delta t}$ in discrete-time CMs as $\boldsymbol{x}_{t-\Delta t} = \alpha_{t-\Delta t}\boldsymbol{x}_0 + \sigma_{t-\Delta t}\boldsymbol{z}$, reusing the same data $\boldsymbol{x}_0$ and noise $\boldsymbol{z}$ when sampling $\boldsymbol{x}_t = \alpha_t \boldsymbol{x}_0 + \sigma_t \boldsymbol{z}$. In the continuous-time limit, as $\Delta t \to 0$, this approach yields an unbiased estimate of the PF-ODE $\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} \to \alpha_t'\boldsymbol{x}_0 + \sigma_t'\boldsymbol{z}$, leading to an unbiased estimate of Eq. (2) for training continuous-time CMs.

3 Simplifying Continuous-Time Consistency Models

Previous consistency models (CMs) adopt the model parameterization and diffusion process formulation in EDM (Karras et al., 2022). Specifically, the CM is parameterized as $\boldsymbol{f}_\theta(\boldsymbol{x}_t, t) = c_{\text{skip}}(t)\boldsymbol{x}_t + c_{\text{out}}(t)\boldsymbol{F}_\theta(c_{\text{in}}(t)\boldsymbol{x}_t, c_{\text{noise}}(t))$, where $\boldsymbol{F}_\theta$ is a neural network with parameters θ. The coefficients $c_{\text{skip}}(t)$, $c_{\text{out}}(t)$, $c_{\text{in}}(t)$ are fixed to ensure that the variance of the diffusion objective is equalized across all time steps at initialization, and $c_{\text{noise}}(t)$ is a transformation of t for better time conditioning. Since EDM diffusion process is variance-exploding (Song et al., 2021b), meaning that $\boldsymbol{x}_t = \boldsymbol{x}_0 + t\boldsymbol{z}$, we can derive that $c_{\text{skip}}(t) = \sigma_d^2/(t^2 + \sigma_d^2)$, $c_{\text{out}}(t) = \sigma_d \cdot t/\sqrt{\sigma_d^2 + t^2}$, and $c_{\text{in}}(t) = 1/\sqrt{t^2 + \sigma_d^2}$ (see Appendix B.6 in Karras et al. (2022)). Although these coefficients are important for training efficiency, their complex arithmetic relationships with t and σ_d complicate theoretical analyses of CMs.

To simplify EDM and subsequently CMs, we propose *TrigFlow*, a formulation of diffusion models that keep the EDM properties but satisfy $c_{\text{skip}}(t) = \cos(t)$, $c_{\text{out}}(t) = -\sigma_d \sin(t)$, and $c_{\text{in}}(t) \equiv 1/\sigma_d$ (proof in Appendix B). TrigFlow is a special case of flow matching (also known as stochastic interpolants or rectified flows) and v-prediction parameterization (Salimans & Ho, 2022). It closely resembles the trigonometric interpolant proposed by Albergo & Vanden-Eijnden (2023); Albergo et al. (2023); Ma et al. (2024), but is modified to account for σ_d, the standard deviation of the data distribution p_d. Since TrigFlow is a special case of flow matching and simultaneously satisfies EDM principles, it combines the advantages of both formulations while allowing the diffusion process, diffusion model parameterization, the PF-ODE, the diffusion training objective, and the CM parameterization to all have simple expressions, as provided below.

Diffusion Process. Given $\boldsymbol{x}_0 \sim p_d(\boldsymbol{x}_0)$ and $\boldsymbol{z} \sim \mathcal{N}(\boldsymbol{0}, \sigma_d^2\boldsymbol{I})$, the noisy sample is defined as $\boldsymbol{x}_t = \cos(t)\boldsymbol{x}_0 + \sin(t)\boldsymbol{z}$ for $t \in [0, \frac{\pi}{2}]$. As a special case, the prior sample $\boldsymbol{x}_{\frac{\pi}{2}} \sim \mathcal{N}(\boldsymbol{0}, \sigma_d^2\boldsymbol{I})$.

Diffusion Models and PF-ODE. We parameterize the diffusion model as $\boldsymbol{f}_\theta^{\text{DM}}(\boldsymbol{x}_t, t) = \boldsymbol{F}_\theta(\boldsymbol{x}_t/\sigma_d, c_{\text{noise}}(t))$, where $\boldsymbol{F}_\theta$ is a neural network with parameters θ, and $c_{\text{noise}}(t)$ is a transformation of t to facilitate time conditioning. The corresponding PF-ODE is given by

$$\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} = \sigma_d \boldsymbol{F}_\theta\left(\frac{\boldsymbol{x}_t}{\sigma_d}, c_{\text{noise}}(t)\right). \tag{3}$$

Diffusion Objective. In TrigFlow, the diffusion model is trained by minimizing

$$\mathcal{L}_{\text{Diff}}(\theta) = \mathbb{E}_{\boldsymbol{x}_0,\boldsymbol{z},t}\left[\left\|\sigma_d \boldsymbol{F}_\theta\left(\frac{\boldsymbol{x}_t}{\sigma_d}, c_{\text{noise}}\left(t\right)\right) - \boldsymbol{v}_t\right\|_2^2\right], \tag{4}$$

where $\boldsymbol{v}_t = \cos(t)\boldsymbol{z} - \sin(t)\boldsymbol{x}_0$ is the training target.

Consistency Models. As mentioned in Sec. 2.2, a valid CM must satisfy the boundary condition $\boldsymbol{f}_\theta(\boldsymbol{x}, 0) \equiv \boldsymbol{x}$. To enforce this condition, we parameterize the CM as the single-step solution of the PF-ODE in Eq. (3) using the first-order ODE solver (see Appendix B.1 for derivations). Specifically, CMs in TrigFlow take the form of

$$\boldsymbol{f}_\theta(\boldsymbol{x}_t, t) = \cos(t)\boldsymbol{x}_t - \sin(t)\sigma_d \boldsymbol{F}_\theta\left(\frac{\boldsymbol{x}_t}{\sigma_d}, c_{\text{noise}}(t)\right), \tag{5}$$

where $c_{\text{noise}}(t)$ is a time transformation for which we defer the discussion to Sec. 4.1.

4 Stabilizing Continuous-time Consistency Models

Training continuous-time CMs has been highly unstable (Song et al., 2023; Geng et al., 2024). As a result, they perform significantly worse compared to discrete-time CMs in prior works. To address this issue, we build upon the TrigFlow framework and introduce several theoretically motivated improvements to stabilize continuous-time CMs, with a focus on parameterization, network architecture, and training objectives.

4.1 Parameterization and Network Architecture

Key to the training of continuous-time CMs is Eq. (2), which depends on the tangent function $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}(\boldsymbol{x}_t,t)}{\mathrm{d}t}$. Under the TrigFlow formulation, this tangent function is given by

$$\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}(\boldsymbol{x}_t,t)}{\mathrm{d}t} = -\cos(t)\left(\sigma_d \boldsymbol{F}_{\theta^-}\left(\frac{\boldsymbol{x}_t}{\sigma_d}, t\right) - \frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t}\right) - \sin(t)\left(\boldsymbol{x}_t + \sigma_d \frac{\mathrm{d}\boldsymbol{F}_{\theta^-}\left(\frac{\boldsymbol{x}_t}{\sigma_d}, t\right)}{\mathrm{d}t}\right), \tag{6}$$

where $\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t}$ represents the PF-ODE, which is either estimated using a pretrained diffusion model in consistency distillation, or using an unbiased estimator calculated from noise and clean samples in consistency training.

To stabilize training, it is necessary to ensure the tangent function in Eq. (6) is stable across different time steps. Empirically, we found that $\sigma_d \boldsymbol{F}_{\theta^-}$, the PF-ODE $\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t}$, and the noisy sample $\boldsymbol{x}_t$ are all relatively stable. The only term left in the tangent function now is $\sin(t)\frac{\mathrm{d}\boldsymbol{F}_{\theta^-}}{\mathrm{d}t} = \sin(t)\nabla_{\boldsymbol{x}_t}\boldsymbol{F}_{\theta^-}\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} + \sin(t)\partial_t \boldsymbol{F}_{\theta^-}$. After further analysis, we found $\nabla_{\boldsymbol{x}_t}\boldsymbol{F}_{\theta^-}\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t}$ is typically well-conditioned, so instability originates from the time-derivative $\sin(t)\partial_t \boldsymbol{F}_{\theta^-}$, which can be decomposed according to

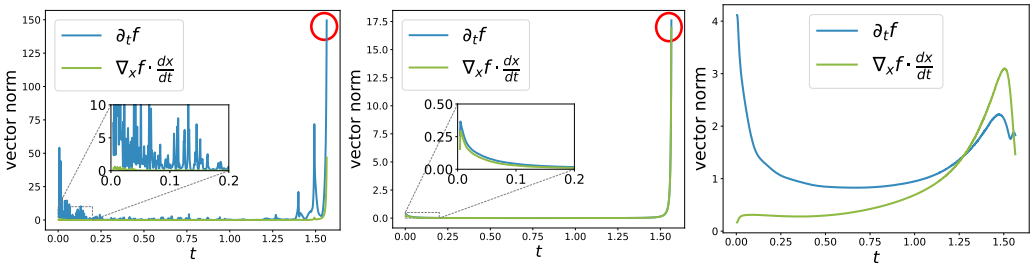
$$\sin(t)\partial_t \boldsymbol{F}_{\theta^-} = \sin(t)\frac{\partial c_{\text{noise}}(t)}{\partial t} \cdot \frac{\partial \text{emb}(c_{\text{noise}})}{\partial c_{\text{noise}}} \cdot \frac{\partial \boldsymbol{F}_{\theta^-}}{\partial \text{emb}(c_{\text{noise}})}, \tag{7}$$

where $\text{emb}(\cdot)$ refers to the time embeddings, typically in the form of either positional embeddings (Ho et al., 2020; Vaswani, 2017) or Fourier embeddings (Song et al., 2021b; Tancik et al., 2020) in the literature of diffusion models and CMs.

Below we describe improvements to stabilize each component from Eq. (7) in turns.

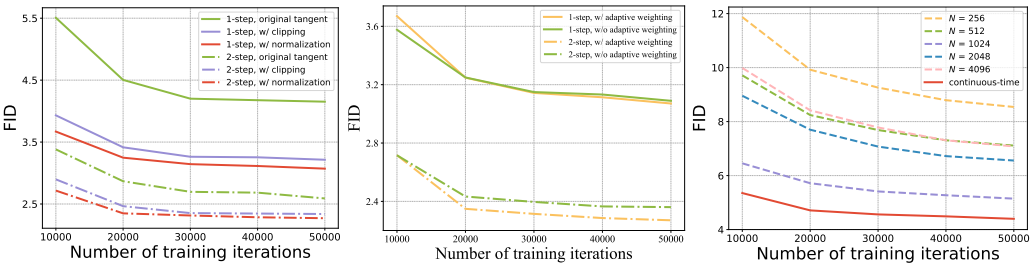
Identity Time Transformation ($c_{\text{noise}}(t) = t$). Most existing CMs use the EDM formulation, which can be directly translated to the TrigFlow formulation as described in Appendix B.2. In particular, the time transformation becomes $c_{\text{noise}}(t) \propto \log(\sigma_d \tan t)$. Straightforward derivation shows that with this $c_{\text{noise}}(t)$, $\sin(t) \cdot \partial_t c_{\text{noise}}(t) = 1/\cos(t)$ blows up whenever $t \to \frac{\pi}{2}$. To mitigate numerical instability, we propose to use $c_{\text{noise}}(t) = t$ as the default time transformation.

Positional Time Embeddings. For general time embeddings in the form of $\text{emb}(c) = \sin(s \cdot 2\pi\omega \cdot c + \phi)$, we have $\partial_c \text{emb}(c) = s \cdot 2\pi\omega \cos(s \cdot 2\pi\omega \cdot c + \phi)$. With larger Fourier scale s, this derivative



EDM, Fourier scale = 16.0 | EDM, positional embedding | TrigFlow, positional embedding

Figure 4: **Stability of different formulations.** We show the norms of both terms in $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t} = \nabla_{\boldsymbol{x}} \boldsymbol{f}_{\theta^-} \cdot \frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} + \partial_t \boldsymbol{f}_{\theta^-}$ for diffusion models trained with the EDM ($c_{\text{noise}}(t) = \log(\sigma_d \tan(t))$) and TrigFlow ($c_{\text{noise}}(t) = t$) formulations using different time embeddings. We observe that large Fourier scales in Fourier embeddings cause instabilities. In addition, the EDM formulation suffers from numerical issues when $t \to \frac{\pi}{2}$, while TrigFlow (using positional embeddings) has stable partial derivatives for both $\boldsymbol{x}_t$ and t.



(a) Tangent Normalization | (b) Adaptive Weighting | (c) Discrete vs. Continuous

Figure 5: **Comparing different training objectives for consistency distillation.** The diffusion models are EDM2 (Karras et al., 2024) pretrained on ImageNet 512×512. (a) 1-step and 2-step sampling of continuous-time CMs trained by using raw tangents $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$, clipped tangents $\text{clip}(\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}, -1, 1)$ and normalized tangents $(\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t})/(\|\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}\| + 0.1)$. (b) Quality of 1-step and 2-step samples from continuous-time CMs trained w/ and w/o adaptive weighting, both are w/ tangent normalization. (c) Quality of 1-step samples from continuous-time CMs vs. discrete-time CMs using varying number of time steps (N), trained using all techniques in Sec. 4.

has greater magnitudes and oscillates more vibrantly, causing worse instability. To avoid this, we use positional embeddings, which amounts to $s \approx 0.02$ in Fourier embeddings. This analysis provides a principled explanation for the observations in Song & Dhariwal (2023).

Adaptive Double Normalization. Song & Dhariwal (2023) found that the AdaGN layer (Dhariwal & Nichol, 2021), defined as $\boldsymbol{y} = \text{norm}(\boldsymbol{x}) \odot \boldsymbol{s}(t) + \boldsymbol{b}(t)$, negatively causes CM training to diverge. Our modification is *adaptive double normalization*, defined as $\boldsymbol{y} = \text{norm}(\boldsymbol{x}) \odot \text{pnorm}(\boldsymbol{s}(t)) + \text{pnorm}(\boldsymbol{b}(t))$, where $\text{pnorm}(\cdot)$ denotes pixel normalization (Karras, 2017). Empirically we find it retains the expressive power of AdaGN for diffusion training but removes its instability in CM training.

As shown in Figure 4, we visualize how our techniques stabilize the time-derivates for CMs trained on CIFAR-10. Empirically, we find that these improvements help stabilize the training dynamics of CMs without hurting diffusion model training (see Appendix G).

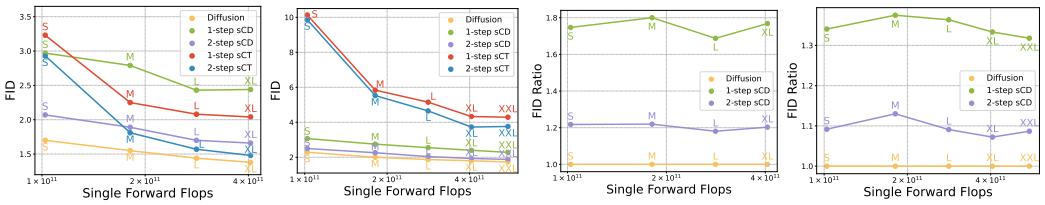
4.2 Training Objectives

Using the TrigFlow formulation in Sec. 3 and techniques proposed in Sec. 4.1, the gradient of continuous-time CM training in Eq. (2) becomes

$$\nabla_\theta \mathbb{E}_{\boldsymbol{x}_t, t}\left[-w(t)\sigma_d \sin(t) \boldsymbol{F}_\theta^\top \left(\frac{\boldsymbol{x}_t}{\sigma_d}, t \right) \frac{\mathrm{d}\boldsymbol{f}_{\theta^-}(\boldsymbol{x}_t, t)}{\mathrm{d}t} \right].$$

Below we propose additional techniques to explicitly control this gradient for improved stability.

Tangent Normalization. As discussed in Sec. 4.1, most gradient variance in CM training comes from the tangent function $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$. We propose to explicitly normalize the tangent function by replacing $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$ with $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}/(\|\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}\| + c)$, where we empirically set $c = 0.1$. Alternatively, we can clip the



ImageNet 64× 64 ImageNet 512× 512 ImageNet 64× 64 ImageNet 512× 512

(a) FID (↓) as a function of single forward flops. (b) FID ratio (↓) as a function of single forward flops.

Figure 6: **sCD scales commensurately with teacher diffusion models**. We plot the (a) FID and (b) FID ratio against the teacher diffusion model (at the same model size) on ImageNet 64×64 and 512×512. sCD scales better than sCT, and has a *constant offset* in the FID ratio across all model sizes, implying that sCD has the same scaling property of the teacher diffusion model. Furthermore, the offset diminishes with more sampling steps.

tangent within $[-1, 1]$, which also caps its variance. Our results in Figure 5(a) demonstrate that either normalization or clipping leads to substantial improvements for the training of continuous-time CMs.

Adaptive Weighting. Previous works (Song & Dhariwal, 2023; Geng et al., 2024) design weighting functions $w(t)$ manually for CM training, which can be suboptimal for different data distributions and network architectures. Following EDM2 (Karras et al., 2024), we propose to train an adaptive weighting function alongside the CM, which not only eases the burden of hyperparameter tuning but also outperforms manually designed weighting functions with better empirical performance and negligible training overhead. Key to our approach is the observation that $\nabla_\theta \mathbb{E}[\boldsymbol{F}_\theta^\top \boldsymbol{y}] = \frac{1}{2}\nabla_\theta \mathbb{E}[\|\boldsymbol{F}_\theta - \boldsymbol{F}_{\theta^-} + \boldsymbol{y}\|_2^2]$, where $\boldsymbol{y}$ is an arbitrary vector independent of θ. When training continuous-time CMs using Eq. (2), we have $\boldsymbol{y} = -w(t)\sigma_d \sin(t)\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$. This observation allows us to convert Eq. (2) into the gradient of an MSE objective. We can therefore use the same approach in Karras et al. (2024) to train an adaptive weighting function that minimizes the variance of MSE losses across time steps (details in Appendix D). In practice, we find that integrating a prior weighting $w(t) = \frac{1}{\sigma_d \tan(t)}$ further reduces training variance. By incorporating the prior weighting, we train both the network $\boldsymbol{F}_\theta$ and the adaptive weighting function $w_\phi(t)$ by minimizing

$$\mathcal{L}_{\text{sCM}}(\theta, \phi) := \mathbb{E}_{\boldsymbol{x}_t, t}\left[\frac{e^{w_\phi(t)}}{D}\left\|\boldsymbol{F}_\theta\left(\frac{\boldsymbol{x}_t}{\sigma_d}, t\right) - \boldsymbol{F}_{\theta^-}\left(\frac{\boldsymbol{x}_t}{\sigma_d}, t\right) - \cos(t)\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}(\boldsymbol{x}_t, t)}{\mathrm{d}t}\right\|_2^2 - w_\phi(t)\right], \quad (8)$$

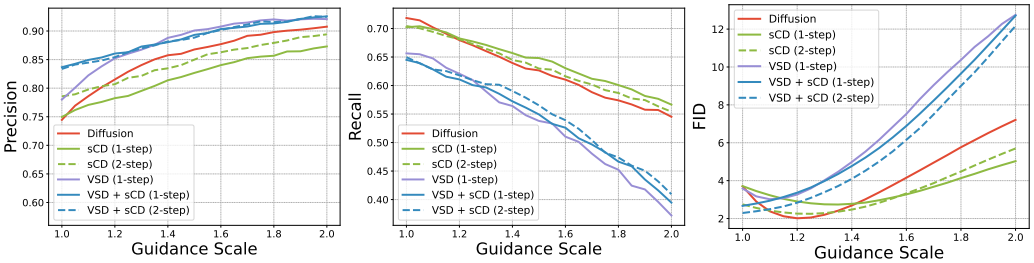
where D is the dimensionality of $\boldsymbol{x}_0$, and we sample $\tan(t)$ from a log-Normal proposal distribution (Karras et al., 2022), that is, $e^{\sigma_d \tan(t)} \sim \mathcal{N}(P_{\text{mean}}, P_{\text{std}}^2)$ (details in Appendix G).

Diffusion Finetuning and Tangent Warmup. For consistency distillation, we find that finetuning the CM from a pretrained diffusion model can speed up convergence, which is consistent with Song et al. (2023); Geng et al. (2024). Recall that in Eq. (6), the tangent $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$ can be decomposed into two parts: the first term $\cos(t)(\sigma_d \boldsymbol{F}_{\theta^-} - \frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t})$ is relatively stable, whereas the second term $\sin(t)(\boldsymbol{x}_t + \sigma_d \frac{\mathrm{d}\boldsymbol{F}_{\theta^-}}{\mathrm{d}t})$ may cause instability. We introduce an optional technique named as *tangent warmup* by replacing the coefficient $\sin(t)$ with $r \cdot \sin(t)$, where r linearly increases from 0 to 1 over the first 10k training iterations. We find that the tangent normalization does not affect sample quality but may reduce some gradient spikes during training.

With all techniques in place, the stability of both discrete-time and continuous-time CM training substantially improves. We provide detailed algorithms for discrete-time CMs in Appendix E, and train continuous-time CMs and discrete-time CMs with the same setting. As demonstrated in Figure 5(c), increasing the number of discretization steps N in discrete-time CMs improves sample quality by reducing discretization errors, but degrades once N becomes too large (after $N > 1024$) to suffer from numerical precision issues. By contrast, continuous-time CMs significantly outperform discrete-time CMs across all N's which provides strong justification for choosing continuous-time CMs over discrete-time counterparts. We call our model **sCM** (s for *simple, stable, and scalable*), and provide detailed pseudo-code for sCM training in Appendix A.

5 Scaling up Continuous-Time Consistency Models

Below we test all the improvements proposed in previous sections by training large-scale sCMs on a variety of challenging datasets.



(a) Precision score (↑) (b) Recall score (↑) (c) FID score (↓)

Figure 7: **sCD has higher diversity compared to VSD**: Sample quality comparison of the EDM2 (Karras et al., 2024) diffusion model, VSD (Wang et al., 2024; Yin et al., 2024b), sCD, and the combination of VSD and sCD, across varying guidance scales. All models are of EDM2-M size and trained on ImageNet 512×512.

Table 1: Sample quality on unconditional CIFAR-10 and class-conditional ImageNet 64× 64.

Unconditional CIFAR-10

METHOD	NFE (↓)	FID (↓)
Diffusion models & Fast Samplers		
Score SDE (deep) (Song et al., 2021b)	2000	2.20
EDM (Karras et al., 2022)	35	2.01
Flow Matching (Lipman et al., 2022)	142	6.35
OT-CFM (Tong et al., 2023)	1000	3.57
DPM-Solver (Lu et al., 2022a)	10	4.70
DPM-Solver++ (Lu et al., 2022b)	10	2.91
DPM-Solver-v3 (Zheng et al., 2023c)	10	2.51
Joint Training		
Diffusion GAN (Xiao et al., 2022)	4	3.75
Diffusion StyleGAN (Wang et al., 2022)	1	3.19
StyleGAN-XL (Sauer et al., 2022)	1	1.52
CTM (Kim et al., 2023)	1	**1.87**
Diff-Instruct (Luo et al., 2024)	1	4.53
DMD (Yin et al., 2024b)	1	3.77
SiD (Zhou et al., 2024)	1	1.92
Diffusion Distillation		
DFNO (LPIPS) (Zheng et al., 2023b)	1	3.78
2-Rectified Flow (Liu et al., 2022)	1	4.85
PID (LPIPS) (Tee et al., 2024)	1	3.92
Consistency-FM (Yang et al., 2024)	2	5.34
PD (Salimans & Ho, 2022)	1	8.34
	2	5.58
TRACT (Berthelot et al., 2023)	1	3.78
	2	3.32
CD (LPIPS) (Song et al., 2023)	1	**3.55**
	2	2.93
sCD (ours)	1	3.66
	2	**2.52**
Consistency Training		
iCT (Song & Dhariwal, 2023)	1	2.83
	2	2.46
iCT-deep (Song & Dhariwal, 2023)	1	**2.51**
	2	2.24
ECT (Geng et al., 2024)	1	3.60
	2	2.11
sCT (ours)	1	2.85
	2	**2.06**

Class-Conditional ImageNet 64×64

METHOD	NFE (↓)	FID (↓)
Diffusion models & Fast Samplers		
ADM (Dhariwal & Nichol, 2021)	250	2.07
RIN (Jabri et al., 2022)	1000	1.23
DPM-Solver (Lu et al., 2022a)	20	3.42
EDM (Heun) (Karras et al., 2022)	79	2.44
EDM2 (Heun) (Karras et al., 2024)	63	1.33
Joint Training		
StyleGAN-XL (Sauer et al., 2022)	1	1.52
Diff-Instruct (Luo et al., 2024)	1	5.57
EMD (Xie et al., 2024b)	1	2.20
DMD (Yin et al., 2024b)	1	2.62
DMD2 (Yin et al., 2024a)	1	**1.28**
SiD (Zhou et al., 2024)	1	1.52
CTM (Kim et al., 2023)	1	1.92
	2	1.73
Moment Matching (Salimans et al., 2024)	1	3.00
	2	3.86
Diffusion Distillation		
DFNO (LPIPS) (Zheng et al., 2023b)	1	7.83
PID (LPIPS) (Tee et al., 2024)	1	9.49
TRACT (Berthelot et al., 2023)	1	7.43
	2	4.97
PD (Salimans & Ho, 2022)	1	10.70
(reimpl. from Heek et al. (2024))	2	4.70
CD (LPIPS) (Song et al., 2023)	1	6.20
	2	4.70
MultiStep-CD (Heek et al., 2024)	1	3.20
	2	1.90
sCD (ours)	1	**2.44**
	2	**1.66**
Consistency Training		
iCT (Song & Dhariwal, 2023)	1	4.02
	2	3.20
iCT-deep (Song & Dhariwal, 2023)	1	3.25
	2	2.77
ECT (Geng et al., 2024)	1	2.49
	2	1.67
sCT (ours)	1	**2.04**
	2	**1.48**

5.1 Tangent Computation in Large-Scale Models

The common setting for training large-scale diffusion models includes using half-precision (FP16) and Flash Attention (Dao et al., 2022; Dao, 2023). As training continuous-time CMs requires computing the tangent $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$ accurately, we need to improve numerical precision and also support memory-efficient attention computation, as detailed below.

JVP Rearrangement. Computing $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$ involves calculating $\frac{\mathrm{d}\boldsymbol{F}_{\theta^-}}{\mathrm{d}t} = \nabla_{\boldsymbol{x}_t}\boldsymbol{F}_{\theta^-} \cdot \frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t} + \partial_t \boldsymbol{F}_{\theta^-}$, which can be efficiently obtained via the Jacobian-vector product (JVP) for $\boldsymbol{F}_{\theta^-}(\frac{\cdot}{\sigma_d}, \cdot)$ with the input

Table 2: Sample quality on class-conditional ImageNet 512× 512. †Our reimplemented teacher diffusion model based on EDM2 (Karras et al., 2024) but with modifications in Sec. 4.1.

METHOD	NFE (↓)	FID (↓)	#Params
Diffusion models			
ADM-G (Dhariwal & Nichol, 2021)	250×2	7.72	559M
RIN (Jabri et al., 2022)	1000	3.95	320M
U-ViT-H/4 (Bao et al., 2023)	250×2	4.05	501M
DiT-XL/2 (Peebles & Xie, 2023)	250×2	3.04	675M
SimDiff (Hoogeboom et al., 2023)	512×2	3.02	2B
VDM++ (Kingma & Gao, 2024)	512×2	2.65	2B
DiffiT (Hatamizadeh et al., 2023)	250×2	2.67	561M
DiMR-XL/3R (Liu et al., 2024)	250×2	2.89	525M
DiffuSSM-XL (Yan et al., 2024)	250×2	3.41	673M
DiM-H (Teng et al., 2024)	250×2	3.78	860M
U-DiT (Tian et al., 2024b)	250	15.39	204M
SiT-XL (Ma et al., 2024)	250×2	2.62	675M
Large-DiT (Alpha-VLLM, 2024)	250×2	2.52	3B
MaskDiT (Zheng et al., 2023a)	79×2	2.50	736M
DiS-H/2 (Fei et al., 2024a)	250×2	2.88	900M
DRWKV-H/2 (Fei et al., 2024b)	250×2	2.95	779M
EDM2-S (Karras et al., 2024)	63×2	2.23	280M
EDM2-M (Karras et al., 2024)	63×2	2.01	498M
EDM2-L (Karras et al., 2024)	63×2	1.88	778M
EDM2-XL (Karras et al., 2024)	63×2	1.85	1.1B
EDM2-XXL (Karras et al., 2024)	63×2	**1.81**	1.5B
GANs & Masked Models			
BigGAN (Brock, 2018)	1	8.43	160M
StyleGAN-XL (Sauer et al., 2022)	1×2	2.41	168M
VQGAN (Esser et al., 2021)	1024	26.52	227M
MaskGIT (Chang et al., 2022)	12	7.32	227M
MAGVIT-v2 (Yu et al., 2023)	64×2	1.91	307M
MAR (Li et al., 2024)	64×2	**1.73**	481M
VAR-$d36$-s (Tian et al., 2024a)	10×2	2.63	2.3B

METHOD	NFE (↓)	FID (↓)	#Params
†Teacher Diffusion Model			
EDM2-S (Karras et al., 2024)	63×2	2.29	280M
EDM2-M (Karras et al., 2024)	63×2	2.00	498M
EDM2-L (Karras et al., 2024)	63×2	1.87	778M
EDM2-XL (Karras et al., 2024)	63×2	1.80	1.1B
EDM2-XXL (Karras et al., 2024)	63×2	1.73	1.5B
Consistency Training (sCT, ours)			
sCT-S (ours)	1	10.13	280M
	2	9.86	280M
sCT-M (ours)	1	5.84	498M
	2	5.53	498M
sCT-L (ours)	1	5.15	778M
	2	4.65	778M
sCT-XL (ours)	1	4.33	1.1B
	2	3.73	1.1B
sCT-XXL (ours)	1	4.29	1.5B
	2	3.76	1.5B
Consistency Distillation (sCD, ours)			
sCD-S	1	3.07	280M
	2	2.50	280M
sCD-M	1	2.75	498M
	2	2.26	498M
sCD-L	1	2.55	778M
	2	2.04	778M
sCD-XL	1	2.40	1.1B
	2	1.93	1.1B
sCD-XXL	1	**2.28**	1.5B
	2	**1.88**	1.5B

vector $(\boldsymbol{x}_t, t)$ and the tangent vector $(\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t}, 1)$. However, we empirically find that the tangent may overflow in intermediate layers when t is near 0 or $\frac{\pi}{2}$. To improve numerical precision, we propose to rearrange the computation of the tangent. Specifically, since the objective in Eq. (8) contains $\cos(t)\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$ and $\frac{\mathrm{d}\boldsymbol{f}_{\theta^-}}{\mathrm{d}t}$ is proportional to $\sin(t)\frac{\mathrm{d}\boldsymbol{F}_{\theta^-}}{\mathrm{d}t}$, we can compute the JVP as:

$$\cos(t)\sin(t)\frac{\mathrm{d}\boldsymbol{F}_{\theta^-}}{\mathrm{d}t} = \left(\nabla_{\frac{\boldsymbol{x}_t}{\sigma_d}}\boldsymbol{F}_{\theta^-}\right)\cdot\left(\cos(t)\sin(t)\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t}\right) + \partial_t\boldsymbol{F}_{\theta^-}\cdot(\cos(t)\sin(t)\sigma_d),$$

which is the JVP for $\boldsymbol{F}_{\theta^-}(\cdot,\cdot)$ with the input $(\frac{\boldsymbol{x}_t}{\sigma_d}, t)$ and the tangent $(\cos(t)\sin(t)\frac{\mathrm{d}\boldsymbol{x}_t}{\mathrm{d}t}, \cos(t)\sin(t)\sigma_d)$. This rearrangement greatly alleviates the overflow issues in the intermediate layers, resulting in more stable training in FP16.

JVP of Flash Attention. Flash Attention (Dao et al., 2022; Dao, 2023) is widely used for attention computation in large-scale model training, providing both GPU memory savings and faster training. However, Flash Attention does not compute the Jacobian-vector product (JVP). To fill this gap, we propose a similar algorithm (detailed in Appendix F) that efficiently computes both softmax self-attention and its JVP in a single forward pass in the style of Flash Attention, significantly reducing GPU memory usage for JVP computation in attention layers.

5.2 Experiments

To test our improvements, we employ both consistency training (referred to as **sCT**) and consistency distillation (referred to as **sCD**) to train and scale continuous-time CMs on CIFAR-10 (Krizhevsky, 2009), ImageNet 64×64 and ImageNet 512×512 (Deng et al., 2009). We benchmark the sample quality using FID (Heusel et al., 2017). We follow the settings of Score SDE (Song et al., 2021b) on CIFAR10 and EDM2 (Karras et al., 2024) on both ImageNet 64×64 and ImageNet 512×512, while changing the parameterization and architecture according to Section 4.1. We adopt the method proposed by Song et al. (2023) for two-step sampling of both sCT and sCD, using a fixed intermediate time step $t = 1.1$. For sCD models on ImageNet 512×512, since the teacher diffusion model relies on classifier-free guidance (CFG) (Ho & Salimans, 2021), we incorporate an additional input s into the model $\boldsymbol{F}_\theta$ to represent the guidance scale (Meng et al., 2023). We train the model with sCD

by uniformly sampling $s \in [1, 2]$ and applying the corresponding CFG to the teacher model during distillation (more details are provided in Appendix G). For sCT models, we do not test CFG since it is incompatible with consistency training.

Training compute of sCM. We use the same batch size as the teacher diffusion model across all datasets. The effective compute per training iteration of sCD is approximately twice that of the teacher model. We observe that the quality of two-step samples from sCD converges rapidly, achieving results comparable to the teacher diffusion model using less than 20% of the teacher training compute. In practice, we can obtain high-quality samples after only 20k finetuning iterations with sCD.

Benchmarks. In Tables 1 and 2, we compare our results with previous methods by benchmarking the FIDs and the number of function evaluations (NFEs). First, sCM outperforms all previous few-step methods that do not rely on joint training with another network and is on par with, or even exceeds, the best results achieved with adversarial training. Notably, the 1-step FID of sCD-XXL on ImageNet 512×512 surpasses that of StyleGAN-XL (Sauer et al., 2022) and VAR (Tian et al., 2024a). Furthermore, the two-step FID of sCD-XXL outperforms all generative models except diffusion and is comparable with the best diffusion models that require 63 sequential steps. Second, the two-step sCM model significantly narrows the FID gap with the teacher diffusion model to within 10%, achieving FIDs of 2.06 on CIFAR-10 (compared to the teacher FID of 2.01), 1.48 on ImageNet 64×64 (teacher FID of 1.33), and 1.88 on ImageNet 512×512 (teacher FID of 1.73). Additionally, we observe that sCT is more effective at smaller scales but suffers from increased variance at larger scales, while sCD shows consistent performance across both small and large scales.

Scaling study. Based on our improved training techniques, we successfully scale continuous-time CMs without training instability. We train various sizes of sCMs using EDM2 configurations (S, M, L, XL, XXL) on ImageNet 64×64 and 512×512, and evaluate FID under optimal guidance scales, as shown in Fig. 6. First, as model FLOPs increase, both sCT and sCD show improved sample quality, showing that both methods benefit from scaling. Second, compared to sCD, sCT is more compute efficient at smaller resolutions but less efficient at larger resolutions. Third, sCD scales predictably for a given dataset, maintaining a consistent relative difference in FIDs across model sizes. This suggests that the FID of sCD decreases at the same rate as the teacher diffusion model, and therefore *sCD is as scalable as the teacher diffusion model*. As the FID of the teacher diffusion model decreases with scaling, the *absolute* difference in FID between sCD and the teacher model also diminishes. Finally, the relative difference in FIDs decreases with more sampling steps, and the sample quality of the two-step sCD becomes on par with that of the teacher diffusion model.

Comparison with VSD. Variational score distillation (VSD) (Wang et al., 2024; Yin et al., 2024b) and its multi-step generalization (Xie et al., 2024b; Salimans et al., 2024) represent another diffusion distillation technique that has demonstrated scalability on high-resolution images (Yin et al., 2024a). We apply one-step VSD from time T to 0 to finetune a teacher diffusion model using the EDM2-M configuration and tune both the weighting functions and proposal distributions for fair comparisons. As shown in Figure 7, we compare sCD, VSD, a combination of sCD and VSD (by simply adding the two losses), and the teacher diffusion model by sweeping over the guidance scale. We observe that VSD has artifacts similar to those from applying large guidance scales in diffusion models: it increases fidelity (as evidenced by higher precision scores) while decreasing diversity (as shown by lower recall scores). This effect becomes more pronounced with increased guidance scales, ultimately causing severe mode collapse. In contrast, the precision and recall scores from two-step sCD are comparable with those of the teacher diffusion model, resulting in better FID scores than VSD.

6 Conclusion

Our improved formulations, architectures, and training objectives have simplified and stabilized the training of continuous-time consistency models, enabling smooth scaling up to 1.5 billion parameters on ImageNet 512×512. We ablated the impact of TrigFlow formulation, tangent normalization, and adaptive weighting, confirming their effectiveness. Combining these improvements, our method demonstrated predictable scalability across datasets and model sizes, outperforming other few-step sampling approaches at large scales. Notably, we narrowed the FID gap with the teacher model to within 10% using two-step generation, compared to state-of-the-art diffusion models that require significantly more sampling steps.

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