

MeanFlowNFT: Bringing Forward-Process RL to Average-Velocity Generators

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Abstract. MeanFlow generators achieve fast few-step sampling by predicting average velocities over time intervals, making them attractive for efficient generation. Reinforcement learning (RL) has become a powerful way to align diffusion and flow models with human preferences and task-specific objectives. In particular, DiffusionNFT offers an efficient forward-process RL framework that does not require reverse-process trajectories or likelihood estimation. However, applying such RL methods to MeanFlow remains underexplored. DiffusionNFT optimizes instantaneous velocities, whereas MeanFlow samples with average velocities. To bridge this gap, we introduce **MeanFlowNFT**. Inspired by the MeanFlow identity, which bridges average and instantaneous velocities, we construct an induced instantaneous-velocity predictor. We apply the DiffusionNFT objective to this predictor, making reward optimization well-defined for MeanFlow. Sampling remains based on the average velocity, preserving MeanFlow’s fast few-step generation. We further prove that MeanFlowNFT inherits DiffusionNFT’s strict policy-improvement guarantee. Experiments on image and video generation show that MeanFlowNFT consistently improves baselines. Moreover, it outperforms prior state-of-the-art RL-tuned few-step generators on most metrics (6 of 8 on SD3.5-M), and can even surpass multi-step RL-tuned diffusion while using only a few sampling steps. For instance, on Wan2.1, 4-step MeanFlowNFT reaches a VBench score of 84.33, surpassing 50-step LongCat-Video RL (82.57).

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1 Introduction

Diffusion (Ho et al., 2020; Song et al., 2021a,b) and flow (Lipman et al., 2023; Liu et al., 2023) models are the dominant paradigm for high-quality image and video generation. However, they synthesize a sample by integrating an instantaneous velocity over many sequential steps (Podell et al., 2024; Seedream et al., 2025; Qin et al., 2025), which makes generation slow. MeanFlow (Geng et al., 2026a) removes this bottleneck by predicting the *average velocity* over a time interval rather than the instantaneous velocity, so that one or a few steps suffice. This few-step efficiency makes MeanFlow an increasingly practical deployment target.

“A sleek car keeps driving down a neon-lit cyberpunk street, its glowing red taillights trailing as the city lights streak past.”



(a) Wan2.1 1.3B (50 steps)



(b) LongCat-Video RL (50 steps)



(c) AnyFlow (4 steps)



(d) MeanFlowNFT (4 steps)

“a frosted donut with a bite out of it”



(a) Flow-GRPO (40 steps)



(b) DiffusionNFT (40 steps)



(c) AnyFlow (4 steps)



(d) MeanFlowNFT (4 steps)

Figure 1: Qualitative comparisons on Wan2.1 1.3B. Figure 2: Qualitative comparisons on SD3.5-M. Each row shows 3 frames sampled uniformly over time. More visual results are provided in Appendix G.

Reinforcement learning (RL) (Black et al., 2024; Fan et al., 2023; Wallace et al., 2024) from a scalar reward has become a standard tool for aligning such generative models with downstream objectives. For diffusion and flow models, the dominant recipe (Liu et al., 2026a; Xue et al., 2025) discretizes the reverse generative process and applies GRPO-style policy gradients (Guo et al., 2025), which require a stochastic policy and per-step likelihood estimation. DiffusionNFT (Zheng et al., 2026a) instead performs online RL *directly on the forward process*: it contrasts “positive” and “negative” generations (split by rewards) to form an implicit policy-improvement direction and folds rewards into a flow-matching objective. This makes training likelihood-free, solver-agnostic, and far more efficient than GRPO-based methods. However, RL for MeanFlow has received little attention. A key obstacle is that forward-process RL such as DiffusionNFT optimizes the *instantaneous* velocity, whereas MeanFlow samples with the *average* velocity. This raises a natural question:

Can we finetune a pretrained MeanFlow model with efficient forward-process RL to enable superior few-step generation?

In this paper, we answer this question affirmatively with **MeanFlowNFT**, the first forward-process RL framework for MeanFlow generators. Our starting point is the MeanFlow identity (Equation (3)), an intrinsic link between the average and instantaneous velocity. Through it, a MeanFlow network yields an *induced instantaneous-velocity predictor*, to which we apply the DiffusionNFT-style objective during RL training. This brings two benefits. As in DiffusionNFT, training is likelihood-free and stays on the forward noising process. It also decouples optimization from sampling, so inference still uses MeanFlow’s efficient few-step sampler. The objective never acts on the average velocity explicitly. Still, we prove in an idealized setting that the optimal induced predictor recovers DiffusionNFT’s improved policy and carries this improvement over to the average-velocity network. On the practical side, we approximate the total-derivative terms in the induced predictors by finite differences. The

trainable and reference predictors in our algorithm share the same estimate, computed along the forward-process conditional velocity. As a result, MeanFlowNFT delivers strong generation quality (Figures 1 and 2) while preserving MeanFlow’s few-step efficiency.

Our contributions are summarized as follows:

- We propose **MeanFlowNFT**, the first forward-process RL framework for MeanFlow generators: it applies the DiffusionNFT-style objective to an induced instantaneous-velocity predictor derived from the average-velocity network. This keeps training likelihood-free and leaves the efficient few-step sampler unchanged.
- We provide theoretical guarantees: in an idealized setting, the optimum of the induced predictor matches the DiffusionNFT improved-policy target, and this policy improvement provably carries over to MeanFlow’s average-velocity generator.
- Comprehensive experiments across text-to-image and text-to-video generation show that MeanFlowNFT consistently improves MeanFlow baselines and outperforms prior few-step methods. It even surpasses multi-step RL with far fewer sampling steps while scaling gracefully at test time.

2 Preliminaries

Throughout, $\mathbf{x}_t$ denotes a noised sample at time t and $\mathbf{c}$ a conditioning prompt. We write $\mathbf{u}$ for an average velocity (Geng et al., 2026a) and $\mathbf{v}$ for an instantaneous velocity field.

Notation. *Unless stated otherwise, all velocity fields and predictors are conditioned on $\mathbf{c}$, but we omit $\mathbf{c}$ from their arguments for notational brevity.*

2.1 Flow Matching

Flow Matching (Lipman et al., 2023; Liu et al., 2023) learns a probability-flow ODE that transports Gaussian noise to the data distribution $\pi(\mathbf{x}_0 \mid \mathbf{c})$. Given a schedule (α_t, σ_t) and writing $\dot{f}_t := df_t/dt$, the forward process is $\mathbf{x}_t = \alpha_t \mathbf{x}_0 + \sigma_t \boldsymbol{\epsilon}$, with $\mathbf{x}_0 \sim \pi(\cdot \mid \mathbf{c})$ and $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. Differentiating along a fixed pair $(\mathbf{x}_0, \boldsymbol{\epsilon})$ gives the *conditional velocity* $\mathbf{v}_t \triangleq \dot{\alpha}_t \mathbf{x}_0 + \dot{\sigma}_t \boldsymbol{\epsilon}$. For rectified flow (Liu et al., 2023), $\alpha_t = 1 - t$ and $\sigma_t = t$, so $\mathbf{v}_t = \boldsymbol{\epsilon} - \mathbf{x}_0$. Flow Matching trains a velocity predictor $\mathbf{v}_\theta(\mathbf{x}_t, t)$ by minimizing $\mathcal{L}_{\text{FM}}(\theta) = \mathbb{E}_{t, \mathbf{c}, \mathbf{x}_0 \sim \pi(\cdot \mid \mathbf{c}), \boldsymbol{\epsilon}} [w(t) \|\mathbf{v}_\theta(\mathbf{x}_t, t) - \mathbf{v}_t\|_2^2]$. Here $w(t)$ is a time-dependent loss weighting.

Although $\mathbf{v}_t$ is random given $\mathbf{x}_t$, the optimal predictor under this squared loss is the deterministic *marginal (instantaneous) velocity*

$$\mathbf{v}(\mathbf{x}_t, t) \triangleq \mathbb{E}[\mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}, t], \quad (1)$$

the conditional velocity averaged over the posterior of $(\mathbf{x}_0, \boldsymbol{\epsilon})$ given $\mathbf{x}_t$ (Lipman et al., 2023). At inference one integrates $d\mathbf{x}_t/dt = \mathbf{v}(\mathbf{x}_t, t)$ from noise to data using $\mathbf{v}_\theta \approx \mathbf{v}$, which typically requires many network evaluations.

2.2 MeanFlow

Flow Matching sampling is costly because integrating the generative ODE requires many instantaneous-velocity evaluations. MeanFlow (Geng et al., 2026a) instead learns a finite-interval flow map: predicting the average velocity from time t to an earlier time s lets sampling take large jumps rather

than many small steps. It considers the *average velocity* over an interval $[s, t]$ along the ODE induced by $\mathbf{v}$ (Equation (1)),

$$\mathbf{u}(\mathbf{x}_t, s, t) \triangleq \frac{1}{t-s} \int_s^t \mathbf{v}(\mathbf{x}_\tau, \tau) d\tau, \quad \frac{d\mathbf{x}_\tau}{d\tau} = \mathbf{v}(\mathbf{x}_\tau, \tau), \quad (2)$$

where the integral runs along the ODE trajectory from $\mathbf{x}_t$ to time s , so $\mathbf{u}$ depends on both endpoints (t, s) and recovers the instantaneous velocity as $s \rightarrow t$, $\lim_{s \rightarrow t} \mathbf{u}(\mathbf{x}_t, s, t) = \mathbf{v}(\mathbf{x}_t, t)$.

MeanFlow identity and training. Directly regressing $\mathbf{u}$ is impractical because Equation (2) contains a path integral. Differentiating the displacement form $(t-s)\mathbf{u} = \int_s^t \mathbf{v} d\tau$ with respect to t yields the exact *MeanFlow identity*

$$\mathbf{v}(\mathbf{x}_t, t) = \mathbf{u}(\mathbf{x}_t, s, t) + (t-s) \frac{d}{dt} \mathbf{u}(\mathbf{x}_t, s, t), \quad (3)$$

with total derivative $\frac{d}{dt} \mathbf{u} = \partial_t \mathbf{u} + (\partial_{\mathbf{x}} \mathbf{u}) \mathbf{v}$. Because the marginal velocity is the posterior mean of $\mathbf{v}_t$ (Equation (1)), replacing this intractable target with the conditional velocity $\mathbf{v}_t$ gives a trainable regression target. Specifically, a MeanFlow network $\mathbf{u}_\theta(\mathbf{x}_t, s, t)$ is trained by minimizing $\mathcal{L}_{\text{MF}}(\theta) = \mathbb{E}_{s,t,\mathbf{c},\mathbf{x}_0,\epsilon} [w(t) \|\mathbf{u}_\theta - \text{sg}(\mathbf{u}_{\text{tgt}})\|_2^2]$, with target $\mathbf{u}_{\text{tgt}} = \mathbf{v}_t - (t-s)(\partial_t \mathbf{u}_\theta + (\partial_{\mathbf{x}} \mathbf{u}_\theta) \mathbf{v}_t)$. The stop-gradient $\text{sg}(\cdot)$ is applied to the whole target, so no gradient backpropagates through the total derivative term. When $s = t$, the derivative correction term vanishes and $\mathcal{L}_{\text{MF}}$ reduces to $\mathcal{L}_{\text{FM}}$.

Few-step sampling. Since $\mathbf{u}$ is the exact average velocity over $[s, t]$, it obeys the exact displacement identity $\mathbf{x}_s = \mathbf{x}_t - (t-s)\mathbf{u}(\mathbf{x}_t, s, t)$. The MeanFlow sampler therefore updates

$$\mathbf{x}_{t_{i-1}} = \mathbf{x}_{t_i} - (t_i - t_{i-1}) \mathbf{u}_\theta(\mathbf{x}_{t_i}, t_{i-1}, t_i), \quad i = N, \dots, 1. \quad (4)$$

No instantaneous velocity is evaluated at inference, and a single step suffices in principle when $\mathbf{u}_\theta$ matches the true average velocity.

2.3 DiffusionNFT

DiffusionNFT (Zheng et al., 2026a) is an online diffusion RL method built on the forward-process Flow Matching objective rather than on policy gradients through a discretized reverse sampler.

Optimality partition. Let π^{old} be a frozen data-collection policy with marginal velocity $\mathbf{v}^{\text{old}}(\mathbf{x}_t, t)$. For each prompt $\mathbf{c}$ one samples K images $\mathbf{x}_0^{1:K} \sim \pi^{\text{old}}(\cdot | \mathbf{c})$ and scores each with a reward $r(\mathbf{x}_0, \mathbf{c}) \in [0, 1]$, read as the optimality probability $r(\mathbf{x}_0, \mathbf{c}) \triangleq p(\mathbf{o} = 1 | \mathbf{x}_0, \mathbf{c})$ in the RL-as-inference view (Levine, 2018). This induces positive and negative posteriors of π^{old} , $\pi^+ \propto r \pi^{\text{old}}$ and $\pi^- \propto (1-r) \pi^{\text{old}}$, normalized by $Z(\mathbf{c}) \triangleq \mathbb{E}_{\pi^{\text{old}}}[r]$ and $1 - Z(\mathbf{c})$, respectively. Under the objective $J(\pi) = \mathbb{E}_{\pi(\cdot|\mathbf{c})}[r]$, with $\pi \succ \pi'$ denoting $J(\pi) > J(\pi')$, one has $\pi^+ \succ \pi^{\text{old}} \succ \pi^-$ for any non-degenerate (non-constant) reward, so π^+ is a valid improved policy.

Reinforcement guidance. Rather than treating π^+ as an optimization *point* (rejection finetuning, which discards negatives), DiffusionNFT extracts an optimization *direction* from the triplet $(\pi^+, \pi^{\text{old}}, \pi^-)$. With

$$\alpha(\mathbf{x}_t, \mathbf{c}) \triangleq \frac{\pi_t^+(\mathbf{x}_t | \mathbf{c})}{\pi_t^{\text{old}}(\mathbf{x}_t | \mathbf{c})} Z(\mathbf{c}) = \mathbb{E}_{\pi^{\text{old}}}[r | \mathbf{x}_t, \mathbf{c}] \in [0, 1], \quad (5)$$

because $\mathbf{v}(\mathbf{x}_t, t)$ is a posterior mean (Equation (1)), the marginal-velocity decomposition $\mathbf{v}^{\text{old}}(\mathbf{x}_t, t) = \alpha \mathbf{v}^+(\mathbf{x}_t, t) + (1-\alpha) \mathbf{v}^-(\mathbf{x}_t, t)$ holds (Zheng et al., 2026a, Thm. 3.1), giving the shared *reinforcement*

guidance

$$\Delta(\mathbf{x}_t, \mathbf{c}, t) \triangleq \alpha(\mathbf{v}^+(\mathbf{x}_t, t) - \mathbf{v}^{\text{old}}(\mathbf{x}_t, t)) = (1 - \alpha)(\mathbf{v}^{\text{old}}(\mathbf{x}_t, t) - \mathbf{v}^-(\mathbf{x}_t, t)). \quad (6)$$

Guiding the reference model along Δ with strength $1/\beta$ defines the target $\mathbf{v}^*(\mathbf{x}_t, t) \triangleq \mathbf{v}^{\text{old}}(\mathbf{x}_t, t) + \frac{1}{\beta}\Delta$, which mirrors classifier-free guidance (Ho and Salimans, 2021) and recovers $\mathbf{v}^*(\mathbf{x}_t, t) = \mathbf{v}^+(\mathbf{x}_t, t)$ at $\beta = \alpha$.

Implicit parameterization. Instead of learning separate positive and negative models, DiffusionNFT uses the implicit parameterization $\mathbf{v}_\theta^+(\mathbf{x}_t, t) := (1 - \beta)\mathbf{v}^{\text{old}}(\mathbf{x}_t, t) + \beta\mathbf{v}_\theta(\mathbf{x}_t, t)$ and $\mathbf{v}_\theta^-(\mathbf{x}_t, t) := (1 + \beta)\mathbf{v}^{\text{old}}(\mathbf{x}_t, t) - \beta\mathbf{v}_\theta(\mathbf{x}_t, t)$, and optimizes the reward-weighted objective

$$\mathcal{L}_{\text{DNFT}}(\theta) = \mathbb{E}_{\substack{\mathbf{c}, \mathbf{x}_0 \sim \pi^{\text{old}}(\cdot|\mathbf{c}), \\ \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), t}} [r \|\mathbf{v}_\theta^+(\mathbf{x}_t, t) - \mathbf{v}_t\|_2^2 + (1 - r) \|\mathbf{v}_\theta^-(\mathbf{x}_t, t) - \mathbf{v}_t\|_2^2]. \quad (7)$$

At the exact optimum, Zheng et al. (2026a, Thm. 3.2) show $\mathbf{v}_{\theta^*}(\mathbf{x}_t, t) = \mathbf{v}^{\text{old}}(\mathbf{x}_t, t) + \frac{2}{\beta}\Delta$. In particular, when $\beta = 2\alpha$ the optimum coincides with $\mathbf{v}^+(\mathbf{x}_t, t)$, so the trained model itself realizes the positive policy improvement.

3 MeanFlow Reinforcement via Forward-Process RL

Here, we first build the proposed MeanFlowNFT (Section 3.1), which finetunes a MeanFlow generator with DiffusionNFT-style RL. Then, we analyze its closed-form induced optimum and policy-improvement guarantee (Section 3.2). Finally, we present the practical implementation (Section 3.3).

3.1 MeanFlowNFT

DiffusionNFT acts on the *instantaneous* velocity, while a MeanFlow network predicts the *average* velocity. Our key idea is to *keep the network in average-velocity space, but carry out optimization in instantaneous-velocity space*.

To achieve this, for any interval with $s \leq t$, we substitute $\mathbf{u}_\theta$ into the MeanFlow identity (Equation (3)) to build an *induced instantaneous-velocity predictor* $\mathbf{V}_\theta^1$,

$$\mathbf{V}_\theta(\mathbf{x}_t, s, t) \triangleq \mathbf{u}_\theta(\mathbf{x}_t, s, t) + (t - s) [\partial_t \mathbf{u}_\theta(\mathbf{x}_t, s, t) + (\partial_x \mathbf{u}_\theta)(\mathbf{x}_t, s, t) \hat{\mathbf{v}}_\theta(\mathbf{x}_t, t)]. \quad (8)$$

Here $\hat{\mathbf{v}}_\theta(\mathbf{x}_t, t) \triangleq \mathbf{u}_\theta(\mathbf{x}_t, t, t)$ is the network’s instantaneous velocity at time t , obtained by letting $s \rightarrow t$ as in Equation (2). Inside Equation (8), $\hat{\mathbf{v}}_\theta(\mathbf{x}_t, t)$ serves only as the direction that $\partial_x \mathbf{u}_\theta$ acts on, whereas $\mathbf{V}_\theta(\mathbf{x}_t, s, t)$ is the quantity we actually optimize. In the idealized setting, Equation (3) gives $\mathbf{V}_\theta(\mathbf{x}_t, s, t) = \hat{\mathbf{v}}_\theta(\mathbf{x}_t, t)$ for all $s \leq t$, so the induced velocity is identical across interval starts for fixed $(\mathbf{x}_t, \mathbf{c}, t)$. Yet $\mathbf{V}_\theta$ is constructed from the full-interval prediction $\mathbf{u}_\theta(\mathbf{x}_t, s, t)$, so optimizing it still reinforces the average velocity. In contrast, optimizing the single-time $\hat{\mathbf{v}}_\theta$, *i.e.*, using only the $s = t$ case of Equation (8), would reduce to plain Flow Matching (Liu et al., 2023) and lose MeanFlow’s average-velocity parameterization and few-step sampling. To keep the update on $\mathbf{u}_\theta(\mathbf{x}_t, s, t)$ and reduce costs, we wrap the total-derivative term of Equation (8) in a stop-gradient during optimization (*i.e.*, $\text{sg}(\partial_t \mathbf{u}_\theta + (\partial_x \mathbf{u}_\theta) \hat{\mathbf{v}}_\theta)$).

1. For clarity, lowercase $\mathbf{v}$ denotes marginal instantaneous velocities of policies (*e.g.*, $\mathbf{v}^+$ of π^+), while uppercase $\mathbf{V}$ denotes instantaneous predictors induced from MeanFlow average-velocity networks (*e.g.*, $\mathbf{V}_\theta$ induced by $\mathbf{u}_\theta$).

Now, we apply a DiffusionNFT-style objective to $\mathbf{V}_\theta$ to reinforce the underlying average velocity $\mathbf{u}_\theta(\mathbf{x}_t, s, t)$. Concretely, let $\mathbf{V}^{\text{old}}$ be the same construction applied to the frozen reference $\mathbf{u}^{\text{old}}$ ². We then define implicit “positive” and “negative” predictors in instantaneous-velocity space, $\mathbf{V}_\theta^+(\mathbf{x}_t, s, t) := (1 - \beta)\mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) + \beta\mathbf{V}_\theta(\mathbf{x}_t, s, t)$ and $\mathbf{V}_\theta^-(\mathbf{x}_t, s, t) := (1 + \beta)\mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) - \beta\mathbf{V}_\theta(\mathbf{x}_t, s, t)$. Mirroring Equation (7), we optimize the following objective

$$\mathcal{L}_{\text{MFNFT}}(\theta) = \mathbb{E}_{\substack{\mathbf{c}, \mathbf{x}_0 \sim \pi^{\text{old}}(\cdot|\mathbf{c}), \\ \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), s \leq t}} [r \|\mathbf{V}_\theta^+(\mathbf{x}_t, s, t) - \mathbf{v}_t\|_2^2 + (1 - r) \|\mathbf{V}_\theta^-(\mathbf{x}_t, s, t) - \mathbf{v}_t\|_2^2]. \quad (9)$$

Here π^{old} is the policy whose average velocity is $\mathbf{u}^{\text{old}}$, and $\mathbf{x}_0 \sim \pi^{\text{old}}$ means $\mathbf{x}_0$ is obtained by running the few-step MeanFlow sampler (Equation (4)) with $\mathbf{u}^{\text{old}}$. The reward r and the other symbols follow the same definitions as in DiffusionNFT (Section 2.3).

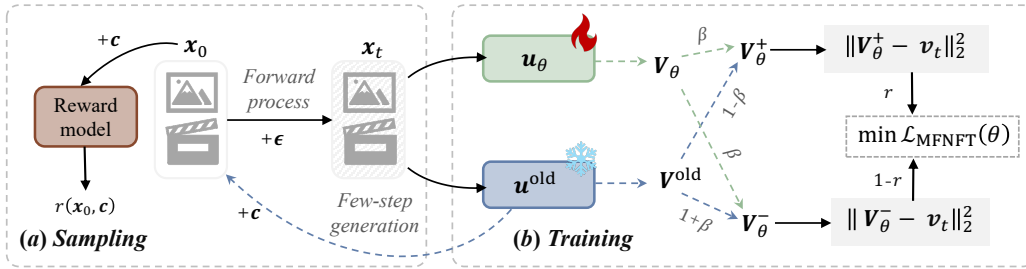


Figure 3: MeanFlowNFT keeps MeanFlow’s *average-velocity* parameterization (Equation (2)) and native few-step sampler (Equation (4)), while constructing an *induced instantaneous-velocity predictor* $\mathbf{V}_\theta$ for forward-process negative-aware finetuning optimization.

In effect, MeanFlowNFT directly optimizes $\mathbf{V}_\theta$, and this improvement transfers to the average velocity $\mathbf{u}_\theta$. The overall pipeline is depicted in Figure 3, and it gives two key benefits. (i) Training depends only on the forward noising process: following DiffusionNFT, it is likelihood-free and never unrolls the reverse denoising process, in contrast to GRPO-style policy gradients (Liu et al., 2026a; Li et al., 2026a) that discretize the reverse sampler and estimate per-step likelihoods. (ii) It decouples optimization from sampling: while optimization acts in *instantaneous-velocity* space, inference and RL sampling still deploy the *average-velocity* $\mathbf{u}_\theta$ through its efficient few-step MeanFlow sampler.

3.2 Optimum and Policy Improvement

In this subsection, we provide theoretical guarantees for MeanFlowNFT in three steps: the idealized pointwise optimum in induced-predictor space (Proposition 3.1), its recovery of the improved policy’s marginal velocity (Corollary 3.2), and the transfer of this induced-velocity guarantee to the average-velocity network $\mathbf{u}_\theta$ (Theorem 3.4). All proofs are provided in Appendix C.

The objective Equation (9) matches the predictors $\mathbf{V}_\theta^\pm$ to the conditional velocity $\mathbf{v}_t$. Treating the induced prediction at each $(\mathbf{x}_t, \mathbf{c}, s, t)$ as an unconstrained value gives the following closed-form optimum.

2. Following DiffusionNFT (Zheng et al., 2026a), $\mathbf{u}^{\text{old}}$ is an exponential moving average (EMA) of $\mathbf{u}_\theta$.

Proposition 3.1 (Idealized pointwise optimum). *Conditioned on $(\mathbf{x}_t, \mathbf{c}, s, t)$, the idealized pointwise minimizer is*

$$\begin{aligned} \mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) &= \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) + \frac{2}{\beta} \hat{\Delta}(\mathbf{x}_t, \mathbf{c}, s, t), \\ \hat{\Delta}(\mathbf{x}_t, \mathbf{c}, s, t) &\triangleq \frac{1}{2} \mathbb{E}_{\pi^{\text{old}}} \left[(2r - 1)(\mathbf{v}_t - \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t)) \mid \mathbf{x}_t, \mathbf{c}, s, t \right]. \end{aligned} \quad (10)$$

The optimum mirrors the DiffusionNFT fixed point $\mathbf{v}_{\theta^*}(\mathbf{x}_t, t) = \mathbf{v}^{\text{old}}(\mathbf{x}_t, t) + \frac{2}{\beta} \Delta$ (Equation (6)), with the induced reference $\mathbf{V}^{\text{old}}$ and guidance $\hat{\Delta}$ in place of $\mathbf{v}^{\text{old}}$ and Δ .

Corollary 3.2 ($\mathbf{V}_{\theta^*}$ recovers the improved marginal velocity). *Setting the guidance strength to $\beta = 2\alpha(\mathbf{x}_t, \mathbf{c})$, Equation (10) collapses to*

$$\mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) = \mathbf{v}^+(\mathbf{x}_t, t) \quad (11)$$

for all $s \leq t$, the marginal instantaneous velocity of the improved policy π^+ .

This gives the DiffusionNFT improvement target in $\mathbf{V}$ -space. To transfer it to the deployed average velocity, we use the following consequence of the MeanFlow identity.

Lemma 3.3 (MeanFlow consistency). *Let $\mathbf{v}$ be an instantaneous velocity field. If $\mathbf{u}$ satisfies*

$$\mathbf{u}(\mathbf{x}_t, s, t) + (t - s) [\partial_t \mathbf{u}(\mathbf{x}_t, s, t) + (\partial_{\mathbf{x}} \mathbf{u})(\mathbf{x}_t, s, t) \mathbf{v}(\mathbf{x}_t, t)] = \mathbf{v}(\mathbf{x}_t, t) \quad (12)$$

for all $s \leq t$, then $\mathbf{u}$ is the exact average velocity of the ODE $\dot{\mathbf{x}}_\tau = \mathbf{v}(\mathbf{x}_\tau, \tau)$ over $[s, t]$.

Theorem 3.4 (MeanFlow policy improves). *In the setting of Corollary 3.2, if the induced optimum is attained for all intervals $s \leq t$, the optimal average velocity $\mathbf{u}_{\theta^*}$ is the exact average velocity of the ODE induced by $\mathbf{v}^+$. Therefore the MeanFlow policy induced by $\mathbf{u}_{\theta^*}$ coincides with π^+ , and consequently*

$$J(\pi_{\theta^*}) = J(\pi^+) > J(\pi^{\text{old}}).$$

Indeed, if $\mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) = \mathbf{v}^+(\mathbf{x}_t, t)$ for all $s \leq t$, then setting $s = t$ in Equation (8) removes the $(t - s)$ term and gives $\hat{\mathbf{v}}_{\theta^*}(\mathbf{x}_t, t) = \mathbf{u}_{\theta^*}(\mathbf{x}_t, t, t) = \mathbf{v}^+(\mathbf{x}_t, t)$. Substituting this identity back into Equation (8) shows that $\mathbf{u}_{\theta^*}$ satisfies Equation (12) with $\mathbf{v} = \mathbf{v}^+$. By Lemma 3.3, $\mathbf{u}_{\theta^*}$ is then the exact average velocity of the ODE induced by $\mathbf{v}^+$.

3.3 Practical implementation

Equation (8) provides the theoretical construction analyzed in Section 3.2. Guided by this construction, the practical implementation introduces the following design choices to reduce computational cost and improve training stability. Algorithm 1 summarizes the resulting MeanFlowNFT update.

Finite-difference derivative. The total-derivative term $\frac{d}{dt} \mathbf{u}_\theta = \partial_t \mathbf{u}_\theta + (\partial_{\mathbf{x}} \mathbf{u}_\theta) \hat{\mathbf{v}}_\theta$ in Equation (8) can be seen as a Jacobian-vector product (JVP)³. Computing this JVP with forward-mode automatic differentiation (`torch.func.jvp`) is expensive and not fully compatible with Fully Sharded Data

3. The Jacobian $[\partial_{\mathbf{x}} \mathbf{u}_\theta, \partial_s \mathbf{u}_\theta, \partial_t \mathbf{u}_\theta]$ stacks the first-order partial derivatives of $\mathbf{u}_\theta$, and its product with the direction $[\hat{\mathbf{v}}_\theta, 0, 1]$ recovers the total derivative $\partial_t \mathbf{u}_\theta + (\partial_{\mathbf{x}} \mathbf{u}_\theta) \hat{\mathbf{v}}_\theta$.

Algorithm 1 MeanFlowNFT (one update step)

Require: pretrained MeanFlow $\mathbf{u}_\theta$, frozen reference $\mathbf{u}^{\text{old}}$ (EMA of $\mathbf{u}_\theta$), reward r , guidance β

// Sampling

- 1: sample prompt $\mathbf{c}$; roll out $\mathbf{x}_0$ with $\mathbf{u}^{\text{old}}$; evaluate $r(\mathbf{x}_0, \mathbf{c}) \in [0, 1]$
- 2: sample an interval $s \leq t$, and $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
- 3: $\mathbf{x}_t \leftarrow \alpha_t \mathbf{x}_0 + \sigma_t \epsilon$; $\mathbf{v}_t \leftarrow \dot{\alpha}_t \mathbf{x}_0 + \dot{\sigma}_t \epsilon$

// Training

- 4: $\mathbf{x}_{t \pm \Delta t} \leftarrow \mathbf{x}_t \pm \Delta t \mathbf{v}_t$
- 5: $\mathbf{d} \leftarrow [\mathbf{u}^{\text{old}}(\mathbf{x}_{t+\Delta t}, s, t+\Delta t) - \mathbf{u}^{\text{old}}(\mathbf{x}_{t-\Delta t}, s, t-\Delta t)] / (2\Delta t)$
- 6: $\mathbf{V}_\theta \leftarrow \mathbf{u}_\theta(\mathbf{x}_t, s, t) + (t-s) \mathbf{d}$
- 7: $\mathbf{V}^{\text{old}} \leftarrow \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t) + (t-s) \mathbf{d}$
- 8: $\mathbf{V}_\theta^+ \leftarrow (1-\beta) \mathbf{V}^{\text{old}} + \beta \mathbf{V}_\theta$; $\mathbf{V}_\theta^- \leftarrow (1+\beta) \mathbf{V}^{\text{old}} - \beta \mathbf{V}_\theta$
- 9: $\mathcal{L}_{\text{MFNFT}} \leftarrow r \|\mathbf{V}_\theta^+ - \mathbf{v}_t\|_2^2 + (1-r) \|\mathbf{V}_\theta^- - \mathbf{v}_t\|_2^2$
- 10: update θ by $\nabla_\theta \mathcal{L}_{\text{MFNFT}}$

Parallel (FSDP) (Zhao et al., 2023) training. Following prior works (Nie et al., 2026; Gu et al., 2026), we instead approximate it by a central finite difference in t ,

$$\frac{d}{dt} \mathbf{u}_\theta(\mathbf{x}_t, s, t) \approx \frac{\mathbf{u}_\theta(\mathbf{x}_{t+\Delta t}, s, t+\Delta t) - \mathbf{u}_\theta(\mathbf{x}_{t-\Delta t}, s, t-\Delta t)}{2\Delta t}, \quad (13)$$

where $\mathbf{x}_{t \pm \Delta t} = \mathbf{x}_t \pm \Delta t \mathbf{v}_t$ displace $\mathbf{x}_t$ along the direction $\mathbf{v}_t$, instead of $\hat{\mathbf{v}}_\theta$ (justified below).

Shared total derivative. Following DiffusionNFT, we take $\mathbf{u}^{\text{old}}$ to be an EMA of $\mathbf{u}_\theta$, keeping the reference close to the trainable model during online training. Our objective, however, compares the induced predictors. If each predictor uses its own total derivative, their difference is

$$\mathbf{V}_\theta(\mathbf{x}_t, s, t) - \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) = \mathbf{u}_\theta(\mathbf{x}_t, s, t) - \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t) + (t-s) \left(\frac{d}{dt} \mathbf{u}_\theta - \frac{d}{dt} \mathbf{u}^{\text{old}} \right). \quad (14)$$

The EMA keeps the average-velocity difference $\mathbf{u}_\theta - \mathbf{u}^{\text{old}}$ small, but it does not control the difference between their derivatives. This additional term destabilizes $\mathbf{V}_\theta - \mathbf{V}^{\text{old}}$ and causes training to collapse (Figure 8). We therefore use the same derivative $\frac{d}{dt} \mathbf{u}^{\text{old}}$ for both predictors, so the derivative-difference term cancels exactly and leaves $\mathbf{V}_\theta(\mathbf{x}_t, s, t) - \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) = \mathbf{u}_\theta(\mathbf{x}_t, s, t) - \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t)$. This choice also saves computation because the finite-difference derivative is evaluated once for $\mathbf{u}^{\text{old}}$ rather than separately for both predictors.

Conditional-velocity direction. The idealized direction $\hat{\mathbf{v}}_\theta(\mathbf{x}_t, t) = \mathbf{u}_\theta(\mathbf{x}_t, t, t)$ in Equation (8) requires an extra network evaluation. We instead reuse the forward-process conditional velocity $\mathbf{v}_t = \dot{\alpha}_t \mathbf{x}_0 + \dot{\sigma}_t \epsilon$, which is already available at no extra cost. In practice, it is used to compute the displaced points $\mathbf{x}_{t \pm \Delta t}$ in Equation (13). This choice is decisive: tying the direction to the shifting $\hat{\mathbf{v}}_\theta$ collapses training, whereas $\mathbf{v}_t$ stays stable (Figure 9).

4 Experiments

4.1 Implementation Details

Models. We validate MeanFlowNFT on both image and video generation. For image generation, we use Stable Diffusion 3.5-Medium (SD3.5-M) (Esser et al., 2024) at 512×512 for training and

1024×1024 for evaluation following DiffusionNFT (Zheng et al., 2026a). For video generation, we use Wan2.1 1.3B (Wan et al., 2025) at 480p with 81 frames. In each case, the MeanFlow policy is obtained by distilling the base model with AnyFlow (Gu et al., 2026). For video generation, we directly adopt the publicly released AnyFlow checkpoint. Following DiffusionNFT (Zheng et al., 2026a), the entire pipeline is *CFG-free* (Ho and Salimans, 2021). At inference, the model is deployed with its native MeanFlow few-step sampler with different sampling steps.

Rewards. For image RL, we train with CLIPScore (Hessel et al., 2021), PickScore (Kirstain et al., 2023), and HPSv2 (Wu et al., 2023) on PickScore prompt set. For video RL, we train with HPSv3-general and HPSv3-percentile (Ma et al., 2025) together with the motion-quality (MQ) and text-alignment (TA) scores of VideoAlign (Liu et al., 2026b), following the reward setup of LongCat-Video (Team et al., 2025). Here, the training prompts are those used by DanceGRPO (Xue et al., 2025). More details are deferred to the Appendix D.

Training. We finetune with LoRA (Hu et al., 2022) (rank 32, scaling factor 64) applied to all linear layers in the attention blocks. We set the guidance strength to $\beta=0.1$ and update $\mathbf{u}^{\text{old}}$ with the same EMA schedule in DiffusionNFT (Zheng et al., 2026a), $\eta_i = \min(0.001 i, 0.5)$ (i denotes the i^{th} update step), and weight the Kullback–Leibler (KL) regularization term by 10^{-4} . Optimization uses AdamW (Loshchilov and Hutter, 2019) with a constant learning rate of 3×10^{-6} . For each prompt, we adopt the generator with 4 steps to collect rollouts. For SD3.5-M we use a group size of 24 with 48 groups per update on 8 NVIDIA H20 GPUs. For Wan2.1 we use a group size of 16 with 8 groups per epoch on 32 NVIDIA H20 GPUs.

Evaluation. For images, we report ImageReward (Xu et al., 2023), CLIPScore, Aesthetic Score (Schuhmann, 2022), PickScore, HPSv2, HPSv3 (Ma et al., 2025), GenEval2 (Kamath et al., 2025), and OCR (Liu et al., 2026a). We evaluate HPSv3 and OCR following Liu et al. (2026a); Xue et al. (2025), adopt the official setting for GenEval2, and compute the remaining metrics on DrawBench (Saharia et al., 2022). For video, we report VBench (Huang et al., 2024) together with the four video training metrics on a held-out set of 256 prompts that are excluded from training.

4.2 Main Results

Image generation. Table 1 reports the quantitative comparison on SD3.5-M. Among all few-step models, MeanFlowNFT attains the best results on 6 of the 8 metrics. It clearly outperforms the few-step distillation baselines DMD (Yin et al., 2024b), CDM (Liu et al., 2026c), and AnyFlow (Gu et al., 2026), and also beats the recent few-step RL methods R_{dm} (Fan et al., 2026) and RTDMD (Huang et al., 2026) on most metrics (*e.g.*, OCR 0.65 *vs.* 0.30 against RTDMD). Remarkably, with only 4 sampling steps MeanFlowNFT already matches or exceeds the 40-step forward-process RL method DiffusionNFT (Zheng et al., 2026a) on several reward metrics (ImageReward 1.45 *vs.* 1.41, CLIPScore 0.297 *vs.* 0.289, *etc.*) at $10\times$ fewer function evaluations. Qualitatively (Figures 13 to 15), MeanFlowNFT produces more faithful samples with fewer reward-hacking artifacts, such as over-saturated colors and implausible object scales, than DiffusionNFT and RTDMD.

Additionally, we apply DiffusionNFT directly to few-step generators. AnyFlow trains an average-velocity network, while DMD and CDM are trained by distribution matching (Yin et al., 2024b) rather than flow matching. In each case the network does not predict the instantaneous velocity as a posterior mean, so the linearity behind DiffusionNFT’s improvement guarantee is absent and

Table 1: Main results on SD3.5-M for image generation with 1024×1024 resolution. Among few-step models, **bold** and underline denote the best and second-best results.

Method	ImageReward $\uparrow$	CLIPScore $\uparrow$	Aesthetic $\uparrow$	PickScore $\uparrow$	HPSv2 $\uparrow$	HPSv3 $\uparrow$	GenEval2 $\uparrow$	OCR $\uparrow$
<i>Multi-step models (40 steps)</i>								
SD3.5-M (w/o CFG)	-0.4770	0.2391	5.1514	20.6587	0.2109	3.4601	0.1171	0.1439
+ DiffusionNFT	1.4066	0.2889	5.9647	23.6440	0.3236	13.5959	0.2613	0.9098
SD3.5-M (w/ CFG)	0.9253	0.2880	5.3811	22.4638	0.2822	11.2489	0.2038	0.5449
+ Flow-GRPO	1.0193	0.2912	5.2843	22.4783	0.2657	9.8059	0.2638	0.6282
<i>Few-step models (4 steps)</i>								
DMD	0.9241	0.2841	5.5055	22.2807	0.2874	11.7156	0.2042	0.3996
CDM	1.0307	0.2819	5.5721	22.4160	0.2976	12.5190	0.2020	0.3225
AnyFlow	1.1125	0.2886	5.4203	22.4789	0.2969	12.0691	0.1896	0.4520
RTDMD	1.2315	0.2775	6.1290	<u>23.2825</u>	<u>0.3265</u>	13.9253	0.2042	0.2965
R_{dm}	0.7236	0.2720	5.7537	22.0748	0.2759	11.2115	0.1619	0.3759
DMD + DiffusionNFT	0.7158	0.2843	5.3784	21.9571	0.2708	9.6985	0.2249	0.4865
CDM + DiffusionNFT	0.1455	0.2745	4.8335	21.3849	0.2143	-3.2834	0.2103	0.3303
AnyFlow + DiffusionNFT	<u>1.2394</u>	<u>0.2915</u>	<u>5.9489</u>	23.0876	0.2919	12.1378	<u>0.2335</u>	<u>0.5948</u>
MeanFlowNFT (Ours)	1.4504	0.2967	5.9275	23.5019	0.3269	<u>13.8826</u>	0.2375	0.6534

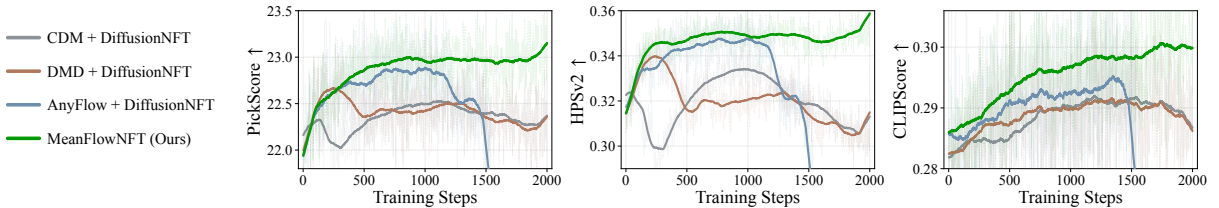


Figure 4: Training reward curves of MeanFlowNFT compared with the baselines on SD3.5-M.

no policy improvement can be derived (Appendix B). As a result, AnyFlow+DiffusionNFT⁴ and DMD/CDM+DiffusionNFT fall far short of MeanFlowNFT and train very unstably, collapsing early (Figure 4). For instance, CDM+DiffusionNFT diverges within 400 steps.

Video generation. Table 2 further evaluates MeanFlowNFT on video generation with Wan2.1 1.3B. Since there is currently no open-source few-step video-generation RL baseline, we compare with few-step distillation methods (rCM (Zheng et al., 2026b), DMD (Yin et al., 2024b), SC-DMD (Ge et al., 2026)⁵, AnyFlow (Gu et al., 2026)) and the 50-step flow-matching RL baseline LongCat-Video RL (Team et al., 2025)⁶. With only 4 sampling steps, MeanFlowNFT obtains the best few-step results on 5 of the 7 reported metrics and improves over AnyFlow on VBench total, HPSv3, and motion quality. It also outperforms LongCat-Video RL on all reported metrics with far fewer function evaluations, confirming its applicability to video MeanFlow models.

Test-time scaling. Since $\mathbf{u}_\theta$ approximates the average velocity over any interval $[s, t]$, MeanFlowNFT supports any-step inference via the sampler of Equation (4), sweeping the number of steps $N \in \{2, 4, 8, 16, 32\}$. MeanFlowNFT exhibits the same test-time scaling trend as AnyFlow (Gu et al., 2026): most metrics improve as N increases (Figure 5). More notably, MeanFlowNFT is noticeably

4. AnyFlow+DiffusionNFT plugs the average velocities $\mathbf{u}^{\text{old}}$ and $\mathbf{u}_\theta$ into Equation (7) in place of the instantaneous velocities $\mathbf{v}^{\text{old}}$ and $\mathbf{v}_\theta$, and optimizes it exactly as DiffusionNFT does.

5. We use the numbers reported in the SC-DMD paper.

6. <https://huggingface.co/lightx2v/Wan2.1-T2V-1.3B-longcat-step1500>

Table 2: Main results on Wan2.1 1.3B for video generation. We report VBench scores and four metrics on 256 held-out prompts (HPSv3-G/HPSv3-P: HPSv3 general/percentile; MQ/TA: VideoAlign motion-quality/text-alignment). Among few-step models, **bold** and underline denote the best and second-best results.

Method	VBench			256 held-out prompts			
	Total↑	Quality↑	Semantic↑	HPSv3-G↑	HPSv3-P↑	MQ↑	TA↑
<i>Multi-step models (50 steps)</i>							
Wan2.1 1.3B (w/ CFG)	82.94	84.69	75.97	3.9099	8.2868	0.8684	1.2255
+ LongCat-Video RL	82.57	84.44	75.10	4.7099	9.2730	0.5493	1.6321
<i>Few-step models (4 steps)</i>							
rCM	82.43	84.58	73.82	3.9660	8.7198	0.2740	1.6290
DMD	82.64	84.65	74.57	3.8598	8.7955	0.1810	1.6845
SC-DMD	83.36	84.76	77.77	—	—	—	—
AnyFlow	<u>83.71</u>	<u>85.36</u>	77.11	<u>6.0536</u>	<u>10.450</u>	<u>0.7504</u>	1.7356
MeanFlowNFT (Ours)	84.33	85.99	<u>77.68</u>	6.5959	10.793	0.9535	<u>1.7235</u>

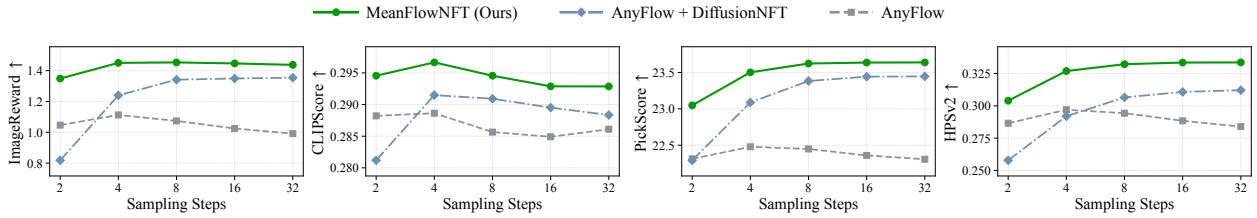


Figure 5: Quantitative results of test-time scaling for MeanFlow-based methods on SD3.5-M. More results for Wan2.1 1.3B and SD3.5-M can be found in Appendix E.

more step-consistent than AnyFlow, with samples that vary far less across N in both layout and content (Figures 6 and 7). As a more accurate average-velocity estimation yields more N -invariant sampling, this consistency indicates that our RL improves AnyFlow.

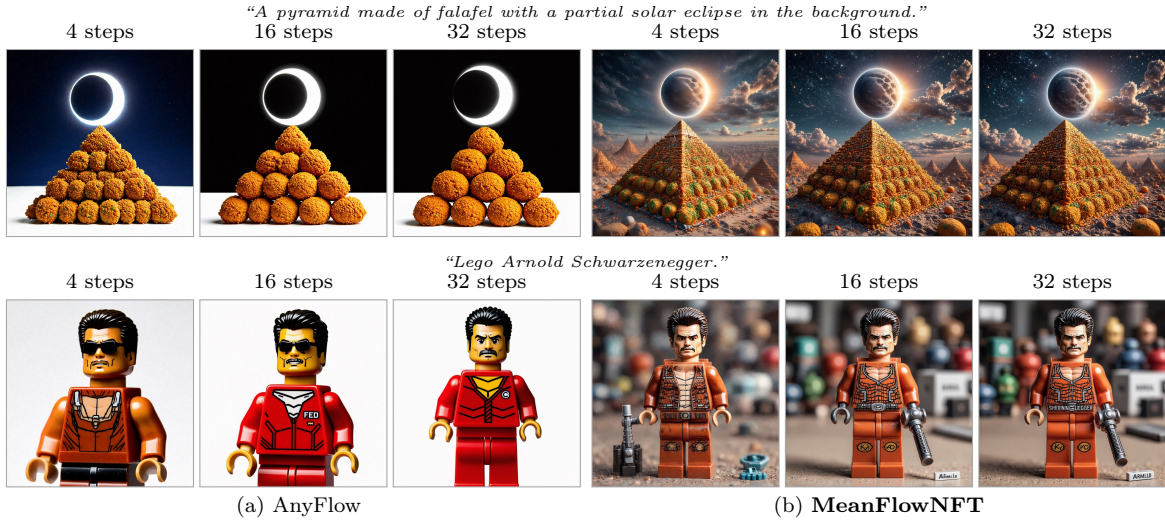


Figure 6: Qualitative results of test-time scaling on SD3.5-M.

“A Mongol warrior in bright red-and-gold armor gallops on horseback, drawing a bow and firing an arrow across the open plain.”



Figure 7: Qualitative results of test-time scaling on Wan2.1 1.3B.

4.3 Analysis

We further analyze several design choices in MeanFlowNFT on SD3.5-M.

Effect of shared $\frac{d}{dt}\mathbf{u}^{\text{old}}$. We examine whether the trainable and reference predictors should share a single derivative term $\frac{d}{dt}\mathbf{u}^{\text{old}}$ or form one each, and find sharing essential for stability. With a shared derivative, reward rises smoothly and monotonically across PickScore, HPSv2, and CLIPScore, whereas forming the two derivatives independently lets reward rise briefly before collapsing (Figure 8a). The induced deviation $\|\mathbf{V}_\theta - \mathbf{V}^{\text{old}}\|_2^2$ exposes the mechanism, which grows by orders of magnitude without sharing (Figure 8b). The gap between the two predictors is then governed by the uncontrolled derivative-difference term rather than the EMA-bounded $\mathbf{u}_\theta - \mathbf{u}^{\text{old}}$ signal (Section 3.3). This reference drift is what destabilizes training, and sharing eliminates it exactly.

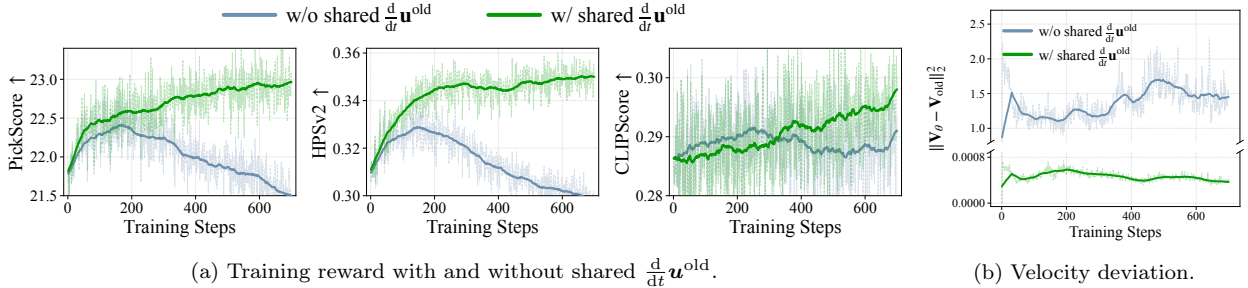


Figure 8: Effect of sharing the derivative term $\frac{d}{dt}\mathbf{u}^{\text{old}}$ between $\mathbf{V}^{\text{old}}$ and $\mathbf{V}_\theta$ on SD3.5-M.

Direction for $\mathbf{x}_{t\pm\Delta t}$. We compare the two directions that can drive $\mathbf{x}_{t\pm\Delta t}$ in the finite-difference derivative (Section 3.3): $\hat{\mathbf{v}}_\theta = \mathbf{u}_\theta(\mathbf{x}_t, t, t)$ (Equation (8)), and the model-free conditional velocity $\mathbf{v}_t = \dot{\alpha}_t \mathbf{x}_0 + \dot{\sigma}_t \epsilon$ (Algorithm 1). Using $\mathbf{v}_t$ improves reward steadily across all three metrics, whereas anchoring the direction to the trainable $\hat{\mathbf{v}}_\theta$ peaks early and then degrades (Figure 9). As $\mathbf{v}_t$ is model-free and saves an additional network evaluation, we adopt it by default.

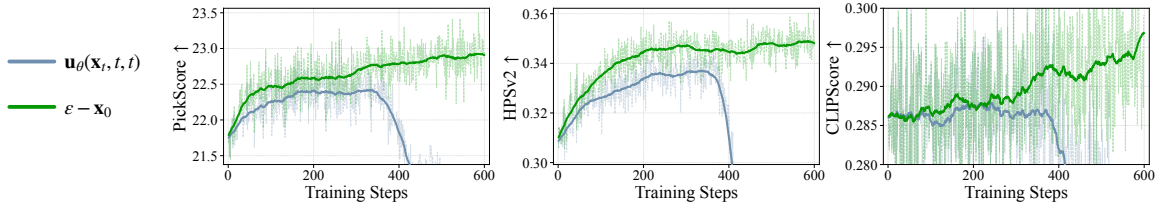


Figure 9: Training reward curves for MeanFlowNFT with different choices of direction for $\mathbf{x}_{t\pm\Delta t}$.

Training only on $s=t$ pairs. MeanFlow training mixes two kinds of pairs. Zero-length pairs ($s=t$) supervise the instantaneous velocity $\mathbf{u}_\theta(\mathbf{x}_t, t, t)$, as in standard flow matching. Finite-interval pairs ($s<t$) supervise the average velocity behind few-step sampling. Training only on $s=t$ pairs keeps just the instantaneous velocity and drops this average velocity. The 4-step training rollouts then degrade, so the reward briefly rises and collapses. In contrast, our default keeps both pair types throughout training and improves stably (Figure 10).

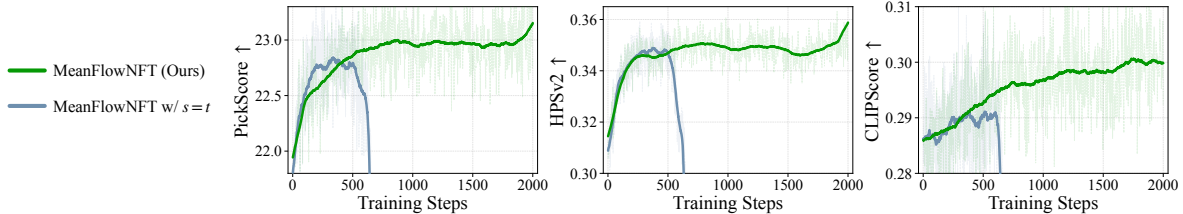


Figure 10: Training reward curves for MeanFlowNFT and a variant trained only on $s=t$ pairs, *i.e.*, only the instantaneous velocity $\mathbf{u}_\theta(\mathbf{x}_t, t, t)$.

5 Conclusion

In this work, we presented MeanFlowNFT, the first forward-process RL method tailored for MeanFlow models. MeanFlow predicts an average velocity, but the DiffusionNFT framework we build on works with the instantaneous velocity. To bridge this gap, we use the MeanFlow identity to optimize the reward on the instantaneous velocity while keeping the average-velocity network for fast sampling. We prove that, in an idealized setting, this reaches DiffusionNFT’s improved policy and carries the gain to the average-velocity model. Experiments show that MeanFlowNFT consistently improves MeanFlow baselines and can even surpass multi-step RL with only a few sampling steps.

6 Limitations and Future Work

In terms of limitations, we only explore DiffusionNFT-style forward-process RL on MeanFlow. We do not study other forward-process objectives, such as RAM (Bergmeister et al., 2026) and AWM (Xue et al., 2026). Since these methods also act on the instantaneous velocity and rely on a frozen reference, we expect our induced instantaneous-velocity construction and practical implementation to carry over to them. Additionally, we consider only MeanFlow, one instance of the broader family of flow-map models. These models learn a direct map between two time points, so one or a few steps replace iterative sampling. MeanFlow realizes this by predicting the average velocity over an interval, while other instances include shortcut models (Frans et al., 2025), consistency trajectory models (Kim et al., 2024), *etc.* Because the induced-predictor construction in Equation (8) is not specific to MeanFlow, we believe our approach can also extend to them. In short, both directions lie outside the scope of this paper, and we leave them to future work.

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Appendix A. Related Work

Diffusion and flow models. Diffusion (Ho et al., 2020; Song et al., 2021b,a) and flow models (Liu et al., 2023; Lipman et al., 2023) have become the dominant paradigm for high-quality image and video generation. Diffusion models synthesize data by learning to reverse a fixed noising process, and latent diffusion (Rombach et al., 2022) runs this process in a compressed latent space for efficiency. Transformer backbones improve scalability (Peebles and Xie, 2023; Ma et al., 2024), and scaling rectified-flow transformers enables high-resolution synthesis (Esser et al., 2024). Flow matching (Lipman et al., 2023) and rectified flow (Liu et al., 2023) recast generation as regressing a velocity field that transports noise to data. Building on these formulations, large text-to-image (Podell et al., 2024; Labs, 2024; Qin et al., 2025; Seedream et al., 2025) and text-to-video (Wan et al., 2025; Team et al., 2025) systems reach strong visual quality.

Few-step generation. Because iterative sampling is slow, many methods distill pretrained diffusion or flow models into few-step generators, including progressive distillation (Salimans and Ho, 2022), consistency models (Song et al., 2023; Luo et al., 2023a), distribution matching distillation (Yin et al., 2024b,a; Luo et al., 2023b), and adversarial distillation (Sauer et al., 2024b,a). A closely related line learns *flow maps*, long-range transport operators that move samples directly between two time points instead of integrating an instantaneous velocity (Frans et al., 2025; Kim et al., 2024). In particular, MeanFlow (Geng et al., 2026a,b) parameterizes the average velocity over a time interval, so one evaluation advances a sample across it and enables one or few-step generation. AnyFlow (Gu et al., 2026) and transition matching (Nie et al., 2026) distill such flow maps. Our work builds on this average-velocity parameterization.

Reinforcement learning for diffusion models. Reinforcement learning is now a standard tool for aligning diffusion and flow models with human preferences and task rewards. Existing approaches rely on policy gradients (Black et al., 2024; Fan et al., 2023), reward-weighted training (Lee et al., 2023), preference optimization (Wallace et al., 2024), or reward backpropagation (Xu et al., 2023; Wang et al., 2026). A dominant recent recipe discretizes the reverse sampling process into a Markov decision process and applies GRPO-style policy gradients (Guo et al., 2025; Liu et al., 2026a; Xue et al., 2025; Li et al., 2026a; He et al., 2026), which need a stochastic policy and per-step likelihood estimation. A complementary line runs reinforcement learning on the forward process, recasting reward optimization as a regression objective on analytically noised samples and thereby avoiding reverse rollouts and likelihoods. It includes advantage weighted matching (Xue et al., 2026), DiffusionNFT (Zheng et al., 2026a), and reinforce adjoint matching (Bergmeister et al., 2026). MeanFlowNFT follows this forward-process line.

Reinforcement learning for few-step generation. A growing line of work brings reinforcement learning to few-step generators. Most methods reinforce distribution-matching distillation, either by combining a reward objective with the matching loss (Jiang et al., 2026; Chen et al., 2026; Fan et al., 2026; Dong et al., 2026) or by reward-tilting the target distribution (Huang et al., 2026). Others post-train distilled few-step generators with surrogate reward learning (Luo et al., 2026) or pairwise sample objectives (Miao et al., 2025). Overall, reinforcement learning for flow-map generators remains underexplored. We study it through forward-process RL, bringing the DiffusionNFT (Zheng et al., 2026a) paradigm to MeanFlow. The concurrent Flow-Map GRPO (Li et al., 2026b) introduces path-preserving stochastic flow-map transitions during RL training and applies GRPO with stochastic rollouts and per-step likelihood ratios. MeanFlowNFT instead uses analytically noised forward-process samples and a likelihood-free regression objective.

Appendix B. Why Direct Plug-Ins Lack DiffusionNFT’s Guarantee

This section explains why the direct DiffusionNFT plug-ins for AnyFlow, DMD, and CDM in Section 4.2 do not inherit the policy improvement guarantee of DiffusionNFT. The issue is the meaning of the network output rather than the number of reverse sampling steps.

Output required by DiffusionNFT. The idealized DiffusionNFT analysis assumes that the optimized output is the marginal instantaneous velocity

$$\mathbf{v}^q(\mathbf{x}_t, t) = \mathbb{E}_{\pi^q}[\mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}, t], \quad \mathbf{v}_t = \dot{\alpha}_t \mathbf{x}_0 + \dot{\sigma}_t \boldsymbol{\epsilon}, \quad q \in \{\text{old}, +, -\}.$$

The map from $(\mathbf{x}_0, \boldsymbol{\epsilon})$ to $\mathbf{v}_t$ is identical for all three policies. Reward reweighting changes the posterior distribution of $(\mathbf{x}_0, \boldsymbol{\epsilon})$ but leaves this map unchanged. At fixed $(\mathbf{x}_t, \mathbf{c}, t)$, the definition $\pi^+ \propto r\pi^{\text{old}}$ gives $\mathbb{E}_{\pi^{\text{old}}}[r\mathbf{v}_t] = \alpha\mathbf{v}^+$. The definition $\pi^- \propto (1-r)\pi^{\text{old}}$ similarly gives $\mathbb{E}_{\pi^{\text{old}}}[(1-r)\mathbf{v}_t] = (1-\alpha)\mathbf{v}^-$. All expectations here are conditioned on the fixed tuple, and we write α for $\alpha(\mathbf{x}_t, \mathbf{c})$ in Equation (5). Adding these identities and using $r + (1-r) = 1$ gives $\mathbf{v}^{\text{old}} = \alpha\mathbf{v}^+ + (1-\alpha)\mathbf{v}^-$. This decomposition yields the guidance Δ in Equation (6) (Zheng et al., 2026a, Thm. 3.1). DiffusionNFT then minimizes Equation (7) over an instantaneous velocity predictor. Its pointwise optimum is $\mathbf{v}_{\theta^*} = \mathbf{v}^{\text{old}} + \frac{2}{\beta}\Delta$ (Zheng et al., 2026a, Thm. 3.2). At points where $\alpha > 0$, substituting $\beta = 2\alpha$ and $\Delta = \alpha(\mathbf{v}^+ - \mathbf{v}^{\text{old}})$ gives $\mathbf{v}_{\theta^*} = \mathbf{v}^+$. The guarantee therefore uses both the posterior mean identity above and the fact that the optimized output is an instantaneous velocity. Reusing the same loss for another output quantity preserves the algebraic form but not this policy interpretation.

Direct substitution of AnyFlow outputs. AnyFlow (Gu et al., 2026) is a MeanFlow network that predicts the interval average velocity $\mathbf{u}$ in Equation (2), rather than the marginal instantaneous

velocity $\mathbf{v}$ in Equation (1). The AnyFlow+DiffusionNFT baseline replaces $\mathbf{v}_\theta$ and $\mathbf{v}^{\text{old}}$ in Equation (7) with $\mathbf{u}_\theta$ and $\mathbf{u}^{\text{old}}$. It keeps the regression target $\mathbf{v}_t$. Fix $(\mathbf{x}_t, \mathbf{c}, s, t)$ and regard $\mathbf{u}_\theta(\mathbf{x}_t, s, t)$ as a free output value. The resulting conditional objective is

$$\begin{aligned} \ell(\mathbf{u}_\theta(\mathbf{x}_t, s, t)) &= \mathbb{E}_{\pi^{\text{old}}} \left[r \|\mathbf{u}^{\text{old}} + \beta(\mathbf{u}_\theta - \mathbf{u}^{\text{old}}) - \mathbf{v}_t\|_2^2 \right. \\ &\quad \left. + (1-r) \|\mathbf{u}^{\text{old}} - \beta(\mathbf{u}_\theta - \mathbf{u}^{\text{old}}) - \mathbf{v}_t\|_2^2 \mid \mathbf{x}_t, \mathbf{c}, s, t \right], \end{aligned}$$

where every average velocity in the display is evaluated at $(\mathbf{x}_t, s, t)$. The interval sampler makes s independent of $(\mathbf{x}_0, \epsilon, r)$ given $(\mathbf{c}, t)$. Conditioning on s therefore leaves the required posterior moments unchanged.

Differentiating the conditional objective with respect to its output gives

$$\frac{1}{2\beta} \nabla_{\mathbf{u}_\theta} \ell = \beta(\mathbf{u}_\theta(\mathbf{x}_t, s, t) - \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t)) - \mathbb{E}_{\pi^{\text{old}}} \left[(2r-1)(\mathbf{v}_t - \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t)) \mid \mathbf{x}_t, \mathbf{c}, s, t \right].$$

For $\beta > 0$, the objective is strictly convex in this output value. Its unique minimizer sets the displayed gradient to zero. The conditional residual can be written as

$$\begin{aligned} &\mathbb{E}_{\pi^{\text{old}}} \left[(2r-1)(\mathbf{v}_t - \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t)) \mid \mathbf{x}_t, \mathbf{c}, s, t \right] \\ &= 2\mathbb{E}_{\pi^{\text{old}}} [r\mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}, t] - \mathbb{E}_{\pi^{\text{old}}} [\mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}, t] - (2\alpha-1)\mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t) \\ &= 2\alpha\mathbf{v}^+(\mathbf{x}_t, t) - \mathbf{v}^{\text{old}}(\mathbf{x}_t, t) - (2\alpha-1)\mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t) \\ &= 2\Delta(\mathbf{x}_t, \mathbf{c}, t) + (2\alpha-1)(\mathbf{v}^{\text{old}}(\mathbf{x}_t, t) - \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t)). \end{aligned}$$

Denoting the unique minimizer by $\mathbf{u}^\dagger(\mathbf{x}_t, s, t)$ and substituting the residual into the zero gradient condition gives

$$\begin{aligned} \mathbf{u}^\dagger(\mathbf{x}_t, s, t) &= \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t) + \frac{2}{\beta} \Delta(\mathbf{x}_t, \mathbf{c}, t) + \frac{2\alpha-1}{\beta} (\mathbf{v}^{\text{old}}(\mathbf{x}_t, t) - \mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t)) \\ &\stackrel{\beta=2\alpha}{=} \mathbf{v}^+(\mathbf{x}_t, t) + \frac{\mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t) - \mathbf{v}^{\text{old}}(\mathbf{x}_t, t)}{2\alpha}, \quad \alpha > 0. \end{aligned} \tag{15}$$

The last equality uses $\Delta = \alpha(\mathbf{v}^+ - \mathbf{v}^{\text{old}})$ from Equation (6) and collects the terms involving $\mathbf{u}^{\text{old}}$ and $\mathbf{v}^{\text{old}}$. Let $\mathbf{u}^+(\mathbf{x}_t, s, t)$ denote the exact average velocity induced by $\mathbf{v}^+$ over $[s, t]$. This is the desired output, whereas Equation (15) gives

$$\mathbf{u}^\dagger(\mathbf{x}_t, s, t) - \mathbf{u}^+(\mathbf{x}_t, s, t) = \mathbf{v}^+(\mathbf{x}_t, t) - \mathbf{u}^+(\mathbf{x}_t, s, t) + \frac{\mathbf{u}^{\text{old}}(\mathbf{x}_t, s, t) - \mathbf{v}^{\text{old}}(\mathbf{x}_t, t)}{2\alpha}.$$

Both terms vanish when s approaches t . For a finite interval, the DiffusionNFT identities do not force them to cancel. The direct objective therefore does not guarantee $\mathbf{u}^\dagger(\mathbf{x}_t, s, t) = \mathbf{u}^+(\mathbf{x}_t, s, t)$.

Direct substitution of DMD and CDM outputs. DMD (Yin et al., 2024b) and CDM (Liu et al., 2026c) are trained with distribution matching. Their distribution matching terms compare the generated and target marginal distributions after averaging over latent noise. Matching these distributions does not identify a unique generator map at each fixed $(\mathbf{x}_t, \mathbf{c}, t)$. Both methods include additional regression or alignment terms, but these terms do not regress the network output against the forward conditional target $\mathbf{v}_t$. Consequently, even when the output is parameterized as a velocity, their objectives do not establish that the network output equals the posterior mean $\mathbb{E}[\mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}, t]$ required by DiffusionNFT. The posterior decomposition therefore does not apply to the outputs inserted into Equation (7). As a result, DiffusionNFT’s regression analysis cannot identify the optimum of the substituted objective with $\mathbf{v}^+$. Its Theorems 3.1 and 3.2 do not establish that DMD+DiffusionNFT or CDM+DiffusionNFT realizes π^+ .

Appendix C. Proofs for MeanFlowNFT

This appendix restates and proves each result of Section 3.2.

Proposition 3.1 (Idealized pointwise optimum). *Conditioned on $(\mathbf{x}_t, \mathbf{c}, s, t)$, the idealized pointwise minimizer is*

$$\begin{aligned}\mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) &= \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) + \frac{2}{\beta} \widehat{\Delta}(\mathbf{x}_t, \mathbf{c}, s, t), \\ \widehat{\Delta}(\mathbf{x}_t, \mathbf{c}, s, t) &\triangleq \frac{1}{2} \mathbb{E}_{\pi^{\text{old}}} \left[(2r - 1)(\mathbf{v}_t - \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t)) \mid \mathbf{x}_t, \mathbf{c}, s, t \right].\end{aligned}$$

Proof Fix $(\mathbf{x}_t, \mathbf{c}, s, t)$. Under Equation (8), the induced predictor $\mathbf{V}_{\theta}(\mathbf{x}_t, s, t)$ is a deterministic function of the conditioned variables for fixed θ . Its value is therefore shared by all posterior draws $(\mathbf{x}_0, \epsilon)$ consistent with the same $\mathbf{x}_t$, and the idealized pointwise optimum can be obtained by minimizing $\mathbb{E}_{\pi^{\text{old}}}[\ell \mid \mathbf{x}_t, \mathbf{c}, s, t]$ over the value $\mathbf{V}_{\theta}(\mathbf{x}_t, s, t)$. By the definitions of $\mathbf{V}_{\theta}^{\pm}$, the per-sample integrand of Equation (9) is

$$\begin{aligned}\ell(\mathbf{V}_{\theta}(\mathbf{x}_t, s, t)) &= r \|(1 - \beta)\mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) + \beta\mathbf{V}_{\theta}(\mathbf{x}_t, s, t) - \mathbf{v}_t\|_2^2 \\ &\quad + (1 - r) \|(1 + \beta)\mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) - \beta\mathbf{V}_{\theta}(\mathbf{x}_t, s, t) - \mathbf{v}_t\|_2^2.\end{aligned}$$

Dividing the gradient by 2β and collecting terms gives

$$\frac{1}{2\beta} \nabla_{\mathbf{V}_{\theta}} \ell = \beta(\mathbf{V}_{\theta}(\mathbf{x}_t, s, t) - \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t)) + (2r - 1)(\mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) - \mathbf{v}_t).$$

Since this is a strictly convex quadratic in $\mathbf{V}_{\theta}(\mathbf{x}_t, s, t)$ for $\beta > 0$, the stationarity condition $\mathbb{E}_{\pi^{\text{old}}}[\nabla_{\mathbf{V}_{\theta}} \ell \mid \mathbf{x}_t, \mathbf{c}, s, t] = 0$ yields

$$\begin{aligned}\beta(\mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) - \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t)) &= \mathbb{E}_{\pi^{\text{old}}} \left[(2r - 1)(\mathbf{v}_t - \mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t)) \mid \mathbf{x}_t, \mathbf{c}, s, t \right] \\ &= 2\widehat{\Delta}(\mathbf{x}_t, \mathbf{c}, s, t),\end{aligned}$$

which is exactly Equation (10). ■

Corollary 3.2 ($\mathbf{V}_{\theta^*}$ recovers the improved marginal velocity). *Setting the guidance strength to $\beta = 2\alpha(\mathbf{x}_t, \mathbf{c})$, Equation (10) collapses to*

$$\mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) = \mathbf{v}^+(\mathbf{x}_t, t)$$

for all $s \leq t$, the marginal instantaneous velocity of the improved policy π^+ .

Proof Since $\mathbf{u}^{\text{old}}$ is the MeanFlow average velocity of π^{old} , its MeanFlow-induced instantaneous velocity is

$$\widehat{\mathbf{v}}^{\text{old}}(\mathbf{x}_t, t) = \mathbf{u}^{\text{old}}(\mathbf{x}_t, t, t) = \mathbf{v}^{\text{old}}(\mathbf{x}_t, t).$$

Applying the MeanFlow identity to this exact reference therefore gives $\mathbf{V}^{\text{old}}(\mathbf{x}_t, s, t) = \mathbf{v}^{\text{old}}(\mathbf{x}_t, t)$ for all $s \leq t$. Thus $\mathbf{V}^{\text{old}}$ is a deterministic function of $(\mathbf{x}_t, \mathbf{c}, t)$ and may be pulled out of the conditional expectation. Then

$$\begin{aligned}\widehat{\Delta} &= \frac{1}{2} \mathbb{E}_{\pi^{\text{old}}} \left[(2r - 1)(\mathbf{v}_t - \mathbf{v}^{\text{old}}(\mathbf{x}_t, t)) \mid \mathbf{x}_t, \mathbf{c}, s, t \right] \\ &= \mathbb{E}_{\pi^{\text{old}}} [r \mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}] - \frac{1}{2} \mathbb{E}_{\pi^{\text{old}}} [\mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}] - \frac{1}{2} \mathbb{E}_{\pi^{\text{old}}} [2r - 1 \mid \mathbf{x}_t, \mathbf{c}] \mathbf{v}^{\text{old}}(\mathbf{x}_t, t).\end{aligned}$$

Writing $\alpha = \mathbb{E}_{\pi^{\text{old}}}[r \mid \mathbf{x}_t, \mathbf{c}]$ and using the posterior-mean identities $\mathbb{E}_{\pi^{\text{old}}}[\mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}] = \mathbf{v}^{\text{old}}(\mathbf{x}_t, t)$ (Equation (1)) and $\mathbb{E}_{\pi^{\text{old}}}[r \mathbf{v}_t \mid \mathbf{x}_t, \mathbf{c}] = \alpha \mathbf{v}^+(\mathbf{x}_t, t)$, the last display becomes

$$\hat{\Delta} = \alpha \mathbf{v}^+(\mathbf{x}_t, t) - \frac{1}{2} \mathbf{v}^{\text{old}}(\mathbf{x}_t, t) - \frac{1}{2} (2\alpha - 1) \mathbf{v}^{\text{old}}(\mathbf{x}_t, t) = \alpha (\mathbf{v}^+(\mathbf{x}_t, t) - \mathbf{v}^{\text{old}}(\mathbf{x}_t, t)) = \Delta,$$

the DiffusionNFT reinforcement guidance in Equation (6). Substituting this into Equation (10) and using $\beta = 2\alpha$ gives, for all $s \leq t$,

$$\mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) = \mathbf{v}^{\text{old}}(\mathbf{x}_t, t) + \frac{2}{2\alpha} \alpha (\mathbf{v}^+(\mathbf{x}_t, t) - \mathbf{v}^{\text{old}}(\mathbf{x}_t, t)) = \mathbf{v}^+(\mathbf{x}_t, t),$$

as claimed. ■

Lemma 3.3 (MeanFlow consistency). *Let $\mathbf{v}$ be an instantaneous velocity field. If $\mathbf{u}$ satisfies*

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

for all $s \leq t$, then $\mathbf{u}$ is the exact average velocity of the ODE $\dot{\mathbf{x}}_\tau = \mathbf{v}(\mathbf{x}_\tau, \tau)$ over $[s, t]$.

Proof Fix $s < t$ and a trajectory $\{\mathbf{x}_\tau\}_{\tau \in [s, t]}$ of the velocity field $\mathbf{v}$ with endpoint $\mathbf{x}_t$ at time t , i.e., $\dot{\mathbf{x}}_\tau = \mathbf{v}(\mathbf{x}_\tau, \tau)$. Define $G(\tau) = (\tau - s) \mathbf{u}(\mathbf{x}_\tau, s, \tau)$. Differentiating along the trajectory,

$$\begin{aligned} G'(\tau) &= \mathbf{u}(\mathbf{x}_\tau, s, \tau) + (\tau - s) [\partial_t \mathbf{u}(\mathbf{x}_\tau, s, \tau) + (\partial_{\mathbf{x}} \mathbf{u})(\mathbf{x}_\tau, s, \tau) \dot{\mathbf{x}}_\tau] \\ &= \mathbf{u}(\mathbf{x}_\tau, s, \tau) + (\tau - s) [\partial_t \mathbf{u}(\mathbf{x}_\tau, s, \tau) + (\partial_{\mathbf{x}} \mathbf{u})(\mathbf{x}_\tau, s, \tau) \mathbf{v}(\mathbf{x}_\tau, \tau)] \\ &= \mathbf{v}(\mathbf{x}_\tau, \tau), \end{aligned}$$

where the last equality uses Equation (12) at time τ . Since $G(s) = 0$, integrating from s to t gives

$$(t - s) \mathbf{u}(\mathbf{x}_t, s, t) = \int_s^t \mathbf{v}(\mathbf{x}_\tau, \tau) d\tau.$$

This is precisely the average velocity of the ODE induced by $\mathbf{v}$ over $[s, t]$. ■

Theorem 3.4 (The deployed MeanFlow policy improves). *In the setting of Corollary 3.2, if the induced optimum is attained for all intervals $s \leq t$, the optimal average velocity $\mathbf{u}_{\theta^*}$ is the exact average velocity of the ODE induced by $\mathbf{v}^+$. Therefore the MeanFlow policy induced by $\mathbf{u}_{\theta^*}$ coincides with π^+ , and consequently*

$$J(\pi_{\theta^*}) = J(\pi^+) > J(\pi^{\text{old}}).$$

Proof By the premise, the optimum in Corollary 3.2 is attained for all intervals $s \leq t$, so

$$\mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) = \mathbf{v}^+(\mathbf{x}_t, t).$$

Taking $s = t$ in Equation (8), the correction term vanishes and hence

$$\hat{\mathbf{v}}_{\theta^*}(\mathbf{x}_t, t) = \mathbf{u}_{\theta^*}(\mathbf{x}_t, t, t) = \mathbf{V}_{\theta^*}(\mathbf{x}_t, t, t) = \mathbf{v}^+(\mathbf{x}_t, t).$$

Substituting this identity back into Equation (8) and using $\mathbf{V}_{\theta^*}(\mathbf{x}_t, s, t) = \mathbf{v}^+(\mathbf{x}_t, t)$ yields

$$\mathbf{u}_{\theta^*}(\mathbf{x}_t, s, t) + (t - s) [\partial_t \mathbf{u}_{\theta^*}(\mathbf{x}_t, s, t) + (\partial_{\mathbf{x}} \mathbf{u}_{\theta^*})(\mathbf{x}_t, s, t) \mathbf{v}^+(\mathbf{x}_t, t)] = \mathbf{v}^+(\mathbf{x}_t, t),$$

which is Equation (12) with $\mathbf{v} = \mathbf{v}^+$. By Lemma 3.3, $\mathbf{u}_{\theta^*}$ is the exact average velocity of the ODE induced by $\mathbf{v}^+$. Since $\mathbf{v}^+$ is the marginal instantaneous velocity of the positive policy π^+ , this ODE has marginals corresponding to π^+ , so the exact MeanFlow update driven by $\mathbf{u}_{\theta^*}$ samples from π^+ . Consequently $J(\pi_{\theta^*}) = J(\pi^+) > J(\pi^{\text{old}})$ for any non-degenerate reward. ■

Appendix D. More Implementation Details

This appendix provides more implementation details for MeanFlowNFT.

Reward. For image training, we follow the multi-reward setup of DiffusionNFT (Zheng et al., 2026a), using equally weighted CLIPScore, PickScore, and HPSv2 as reward signals on the PickScore prompt set. For video training, we follow the multi-reward setup of LongCat-Video (Team et al., 2025). The HPSv3-general reward evaluates visual quality by scoring each frame with the generic prompt “A high-quality image” and averaging over all frames. The HPSv3-percentile reward instead uses the video caption as the text prompt and averages the top 30% frame scores, reducing the effect of occasional low scores caused by temporal content changes. These two HPSv3 rewards are combined with the VideoAlign motion-quality and text-alignment rewards described in Section 4.1.

Training. For SD3.5-M, we first construct the MeanFlow policy with the two-stage AnyFlow recipe (Gu et al., 2026). The first stage is flow-map pretraining for 6000 steps on precomputed latent-prompt pairs. It uses AnyFlow’s three-mode endpoint sampling: 50% of samples take $s = t$ for standard flow matching, 25% take $s = 0$ for endpoint consistency, and the remaining samples draw $s \sim \mathcal{U}(0, t)$. Following AnyFlow (Gu et al., 2026), we use the reverse-CFG fusion with scale 4.5, so the resulting policy can be sampled CFG-free. The second stage performs on-policy AnyFlow distillation for 12000 steps, initialized from the stage-one LoRA checkpoint, with sampling steps drawn from $\{2, 4, 8, 16, 40\}$.

MeanFlowNFT is then applied on top of the trained AnyFlow policy. We run RL finetuning for 2000 steps on SD3.5-M and 1600 steps on Wan2.1, where the video run starts from the publicly released AnyFlow-Wan checkpoint. Both runs use CFG-free 4-step rollouts, equally weighted reward dimensions, $\beta = 0.1$, KL weight 10^{-4} , AdamW with learning rate 3×10^{-6} , and fresh training-time (s, t) pairs sampled from the same three-mode AnyFlow schedule. For video, following LongCat-Video, we compute a group-normalized relative advantage for each reward dimension independently, and then average the normalized advantages for the RL update.

Evaluation. Besides the evaluation protocol described in Section 4.1, we evaluate videos with the official VBench suite following AnyFlow (Gu et al., 2026). Specifically, we compute all 16 VBench dimensions and report their aggregated Total, Quality, and Semantic scores in Table 2, with the full per-dimension breakdown in Tables 3 and 4. All evaluations, including the image benchmarks, are run on 8 NVIDIA H20 GPUs.

Appendix E. Additional Test-time Scaling Results

Figure 11 reports the remaining evaluation metrics for the test-time scaling study of Figure 5, on SD3.5-M, and Figure 12 reports the corresponding results on Wan2.1 1.3B. MeanFlowNFT retains AnyFlow’s any-step scaling behavior while consistently delivering stronger generation quality.

Appendix F. VBench Full Results

In this section, we report the per-dimension VBench breakdown for the Wan2.1 1.3B video-generation experiment of Table 2, split across Tables 3 and 4 for readability.

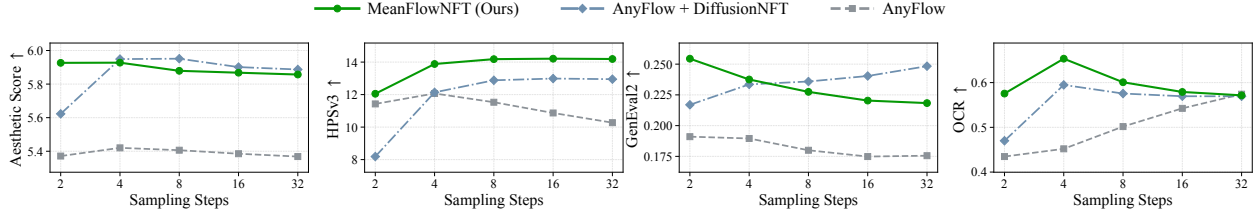


Figure 11: Additional quantitative results of MeanFlowNFT test-time scaling on SD3.5-M.

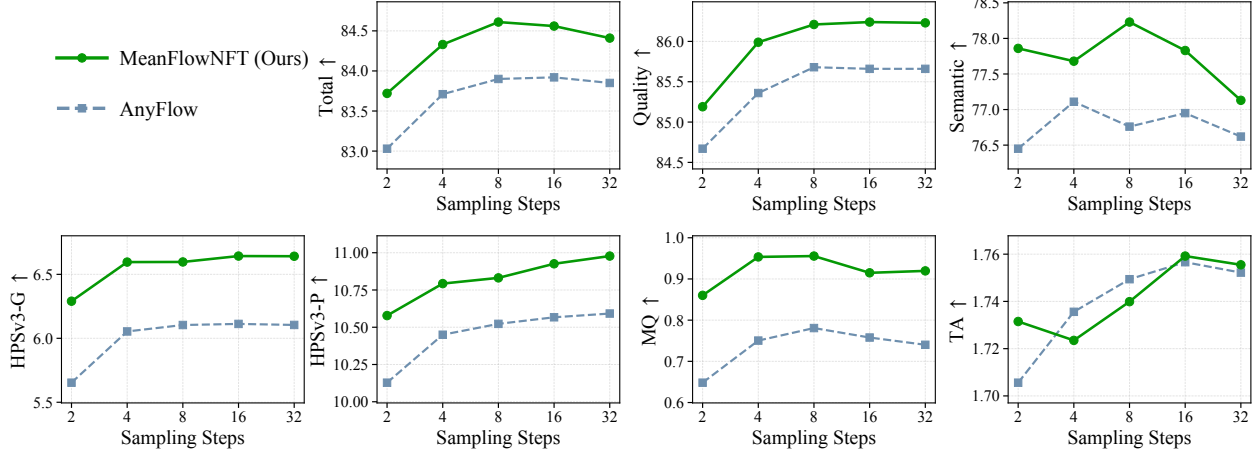


Figure 12: Quantitative results of MeanFlowNFT test-time scaling on Wan2.1 1.3B. Total, Quality, and Semantic are VBench scores, while the remaining metrics (HPSv3-G/HPSv3-P and MQ/TA) are evaluated on the 256 held-out prompts.

Table 3: Full VBench per-dimension results on Wan2.1 1.3B (part 1 of 2). Among few-step models, **bold** and underline denote the best and second-best results.

Method	Dynamic Degree↑	Temporal Flickering↑	Human Action↑	Overall Consistency↑	Multiple Objects↑	Color↑	Appearance Style↑	Scene↑
<i>Multi-step models (50 steps)</i>								
Wan2.1 1.3B (w/ CFG)	65.56	99.32	93.80	25.47	74.36	89.43	21.32	44.91
+ LongCat-Video RL	52.78	99.12	92.00	25.43	75.90	87.23	21.19	39.55
<i>Few-step models (4 steps)</i>								
rCM	88.89	97.28	91.20	24.72	71.42	88.12	20.59	41.82
DMD	<u>88.61</u>	97.37	<u>94.00</u>	24.90	76.16	86.00	20.19	39.52
AnyFlow	58.89	<u>98.83</u>	93.20	25.17	<u>82.48</u>	<u>88.42</u>	<u>20.81</u>	43.71
MeanFlowNFT (Ours)	59.45	99.44	94.40	<u>25.09</u>	84.79	89.21	21.08	<u>43.41</u>

Appendix G. More Qualitative Results

This section provides additional qualitative comparisons for both image and video generation. The image examples compare MeanFlowNFT with multi-step/few-step RL methods, few-step distillation baselines, and directly applying DiffusionNFT to few-step generators. The video examples further compare against Wan2.1, LongCat-Video RL, and few-step video distillation baselines. Across these

Table 4: Full VBench per-dimension results on Wan2.1 1.3B (part 2 of 2). Among few-step models, **bold** and underline denote the best and second-best results.

Method	Object Class↑	Spatial Relationship↑	Aesthetic Quality↑	Motion Smoothness↑	Temporal Style↑	Imaging Quality↑	Subject Consistency↑	Background Consistency↑
<i>Multi-step models (50 steps)</i>								
Wan2.1 1.3B (w/ CFG)	90.98	71.87	65.95	98.76	23.33	67.42	94.98	96.63
+ LongCat-Video RL	89.68	75.56	67.07	98.87	23.08	70.08	96.38	96.27
<i>Few-step models (4 steps)</i>								
rCM	88.78	71.80	65.27	97.89	22.67	<u>68.95</u>	94.04	93.96
DMD	87.71	76.88	65.86	97.88	<u>23.04</u>	68.03	94.41	94.16
AnyFlow	<u>90.28</u>	81.96	70.00	<u>98.61</u>	22.77	69.57	<u>97.89</u>	<u>96.55</u>
MeanFlowNFT (Ours)	90.49	<u>81.36</u>	<u>69.53</u>	99.22	23.06	68.82	98.44	97.07

examples, MeanFlowNFT produces more faithful and visually coherent results, while preserving strong quality across different sampling steps.



Figure 13: Text-to-image comparison on SD3.5-M. Here “+NFT” abbreviates “+DiffusionNFT”.



Figure 14: Text-to-image comparison on SD3.5-M. Here “+NFT” abbreviates “+DiffusionNFT”.



Figure 15: Text-to-image comparison on SD3.5-M. Here “+NFT” abbreviates “+DiffusionNFT”.

"An armored superhero in a metallic suit plunges headfirst from the night sky, shot cinematically against glowing dusk clouds."

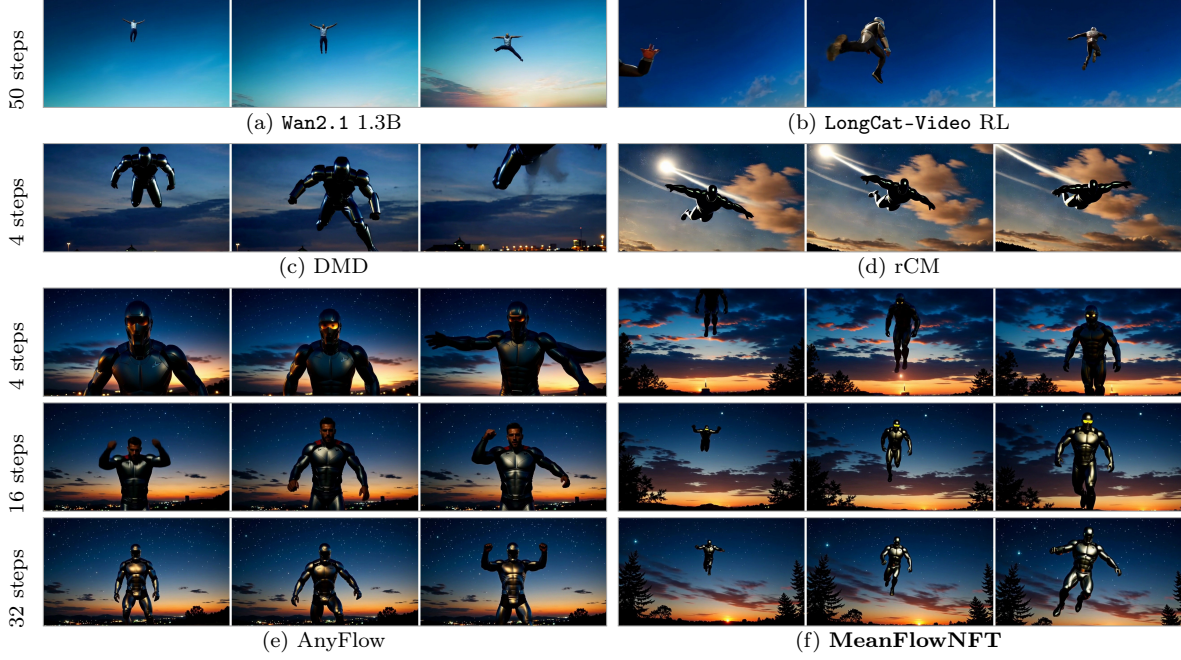


Figure 16: Text-to-video comparison on Wan2.1 1.3B.

"A thick steak with a rich, seared Maillard crust sizzles on a flaming grill, sparks and fire rising from the grates."



Figure 17: Text-to-video comparison on Wan2.1 1.3B.



Figure 18: Text-to-video comparison on Wan2.1 1.3B.