Towards the Efficient and Human Preference Aligned Diffusion Model-based Generation

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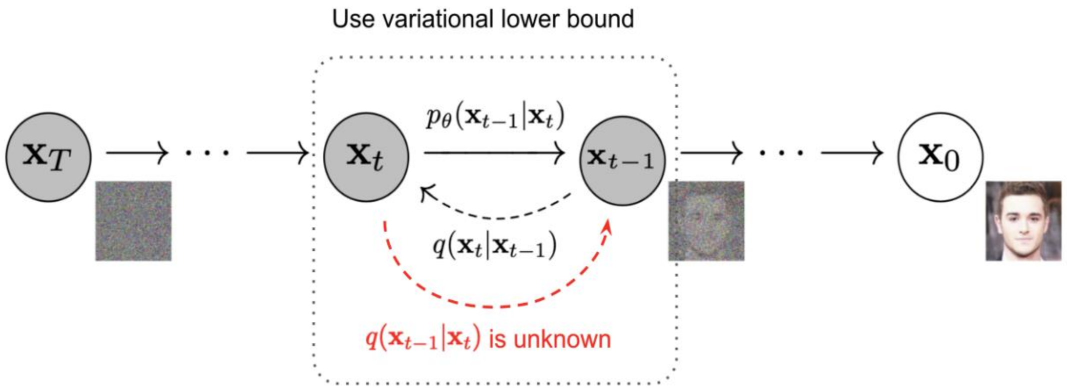
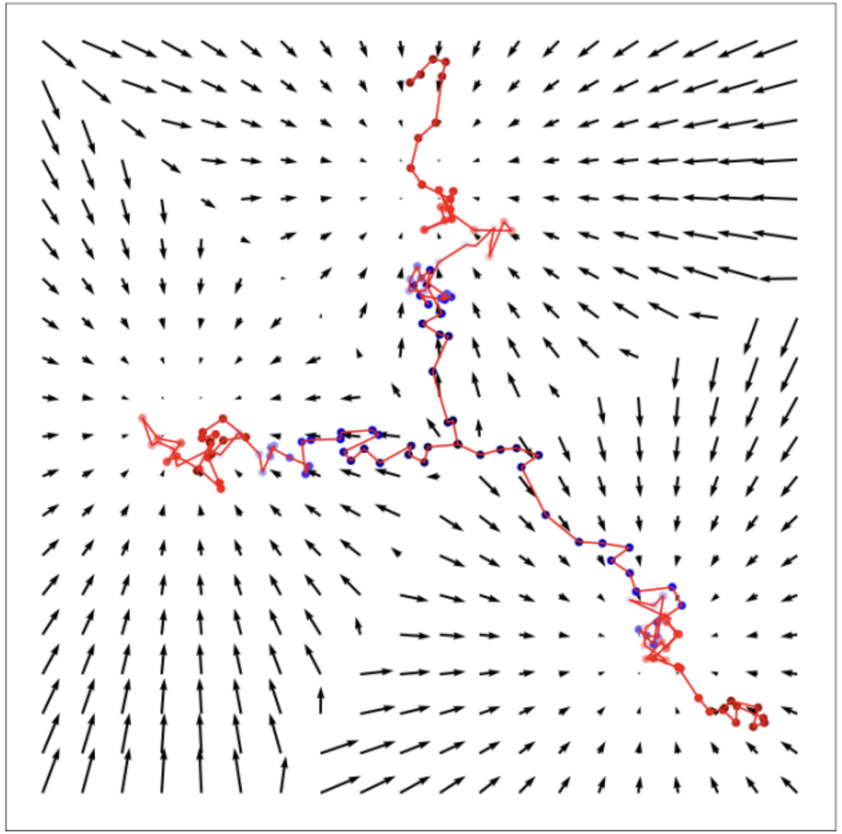
Diffusion Models: Markovian Perspective



- Assumption:
  - $$p(\boldsymbol{x}_{0:T}) = p(\boldsymbol{x}_T)\prod_{t=1}^{T} p_{\boldsymbol{\theta}}(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t)$$
- Forward Process:
  - $$q(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}) = \mathcal{N}(\boldsymbol{x}_t; \sqrt{\alpha_t}\boldsymbol{x}_{t-1}, (1-\alpha_t)\mathbf{I})$$
  - $$p(\boldsymbol{x}_T) = \mathcal{N}(\boldsymbol{x}_T; \mathbf{0}, \mathbf{I})$$
- Reverse Process:
  - $$q(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_t, \boldsymbol{x}_0) = \frac{q(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-1}, \boldsymbol{x}_0)q(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_0)}{q(\boldsymbol{x}_t \mid \boldsymbol{x}_0)}$$
  - Maximum Likelihood Estimation (MLE) is Equivalent to

$$\arg\min_{\boldsymbol{\theta}} \mathbb{E}_{t\sim U\{2,T\}}\left[\mathbb{E}_{q(\boldsymbol{x}_t|\boldsymbol{x}_0)}\left[D_{\mathrm{KL}}(q(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t, \boldsymbol{x}_0) \parallel p_{\boldsymbol{\theta}}(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t))\right]\right]$$

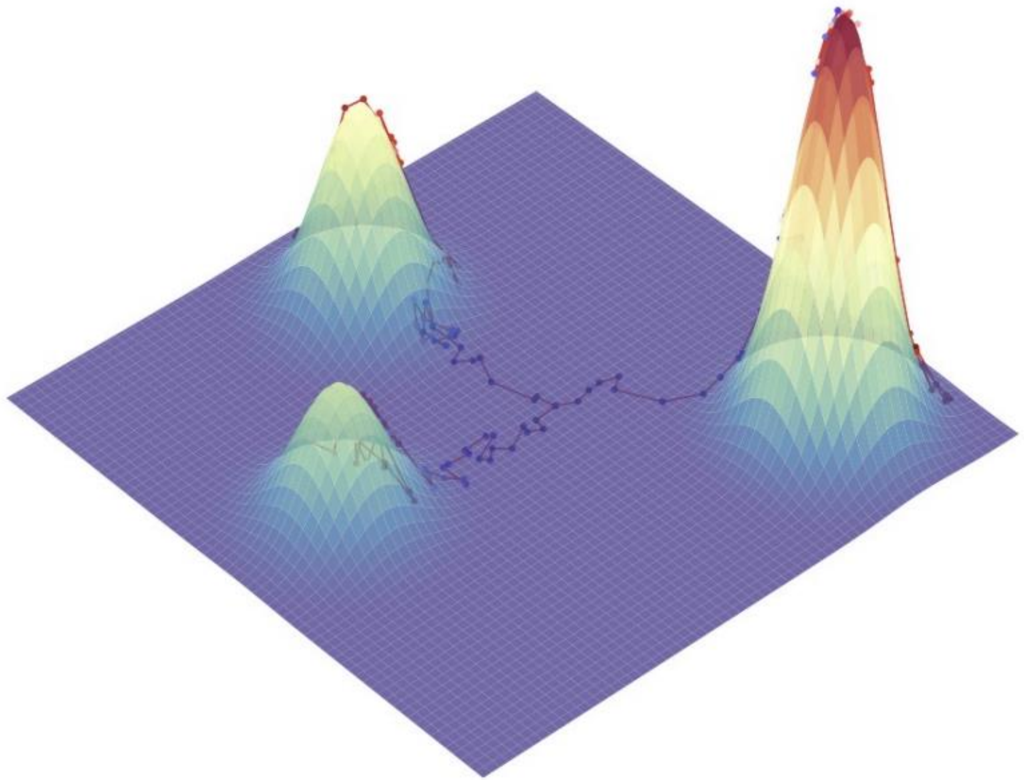
Vanilla Score Matching



- Energy-based model
  - $p_{\boldsymbol{\theta}}(\boldsymbol{x}) = \frac{1}{Z_{\boldsymbol{\theta}}} e^{-f_{\boldsymbol{\theta}}(\boldsymbol{x})}$
- Score-based model
  - $$\begin{aligned}\nabla_{\boldsymbol{x}} \log p_{\boldsymbol{\theta}}(\boldsymbol{x}) &= \nabla_{\boldsymbol{x}} \log\left(\frac{1}{Z_{\boldsymbol{\theta}}} e^{-f_{\boldsymbol{\theta}}(\boldsymbol{x})}\right) \\ &= \nabla_{\boldsymbol{x}} \log \frac{1}{Z_{\boldsymbol{\theta}}} + \nabla_{\boldsymbol{x}} \log e^{-f_{\boldsymbol{\theta}}(\boldsymbol{x})} \\ &= -\nabla_{\boldsymbol{x}} f_{\boldsymbol{\theta}}(\boldsymbol{x}) \\ &\approx \boldsymbol{s}_{\boldsymbol{\theta}}(\boldsymbol{x})\end{aligned}$$
- Score Matching

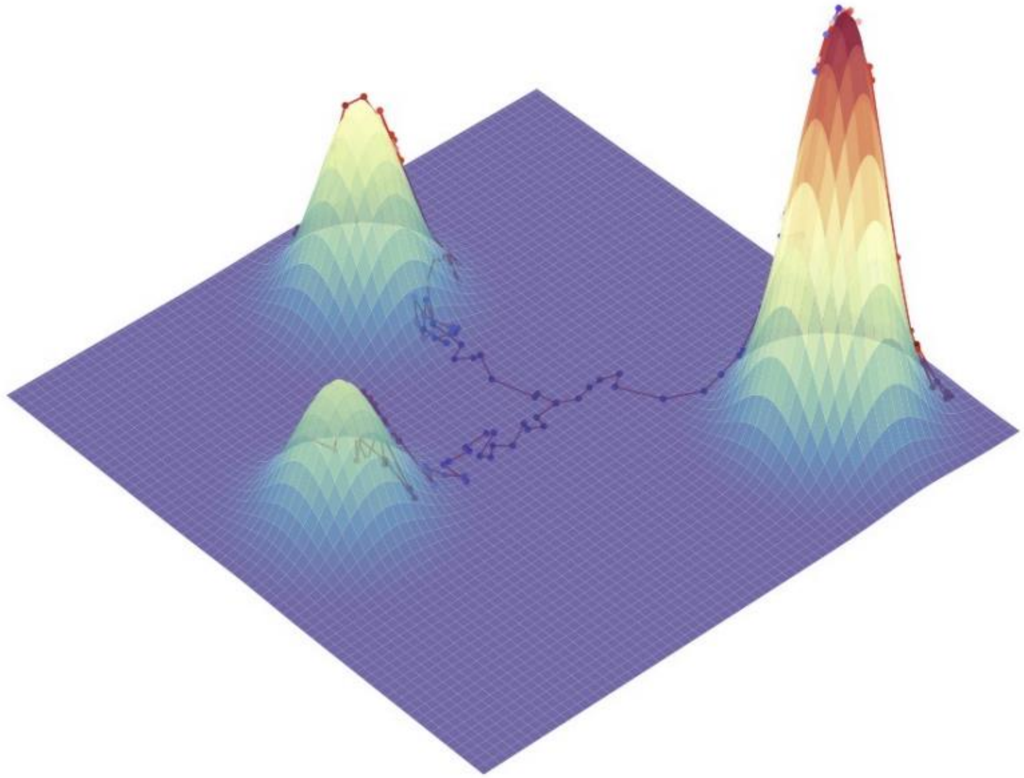
$$\mathbb{E}_{p(\boldsymbol{x})}\left[\|\boldsymbol{s}_{\boldsymbol{\theta}}(\boldsymbol{x}) - \nabla \log p(\boldsymbol{x})\|_2^2\right]$$

Real Data Distribution



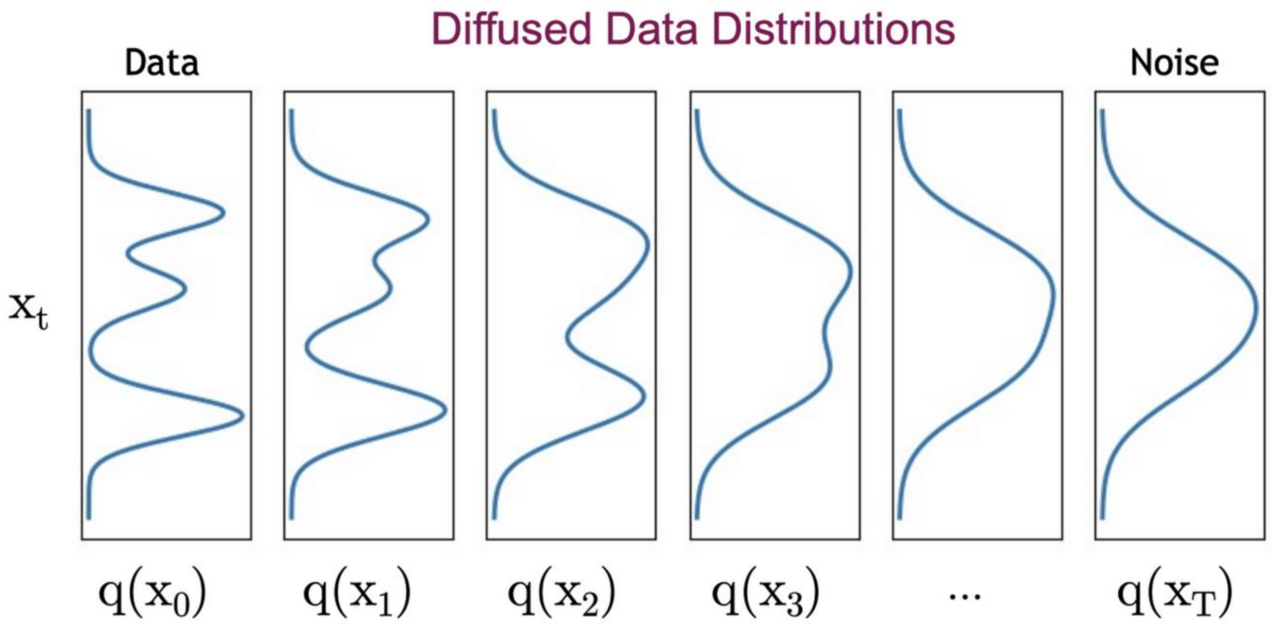
- Sparse
- Disconnected
- Non-overlapping modes

Vanilla Score Matching



- Limitations:
  - Poorly defined for real-world data
  - Inaccurate score estimation for low-density region
  - Poor sampling with large low-density region

Score-Based Generative Model



- Extending the distribution
  - $$p_{\sigma_t}(\boldsymbol{x}_t) = \int p(\boldsymbol{x})\mathcal{N}(\boldsymbol{x}_t; \boldsymbol{x}, \sigma_t^2\mathbf{I})d\boldsymbol{x}$$
- Score Matching for all noise levels
  - $$\arg\min_{\boldsymbol{\theta}} \sum_{t=1}^{T} \lambda(t)\mathbb{E}_{p_{\sigma_t}(\boldsymbol{x}_t)}\left[\|\boldsymbol{s}_{\boldsymbol{\theta}}(\boldsymbol{x}, t) - \nabla \log p_{\sigma_t}(\boldsymbol{x}_t)\|_2^2\right]$$

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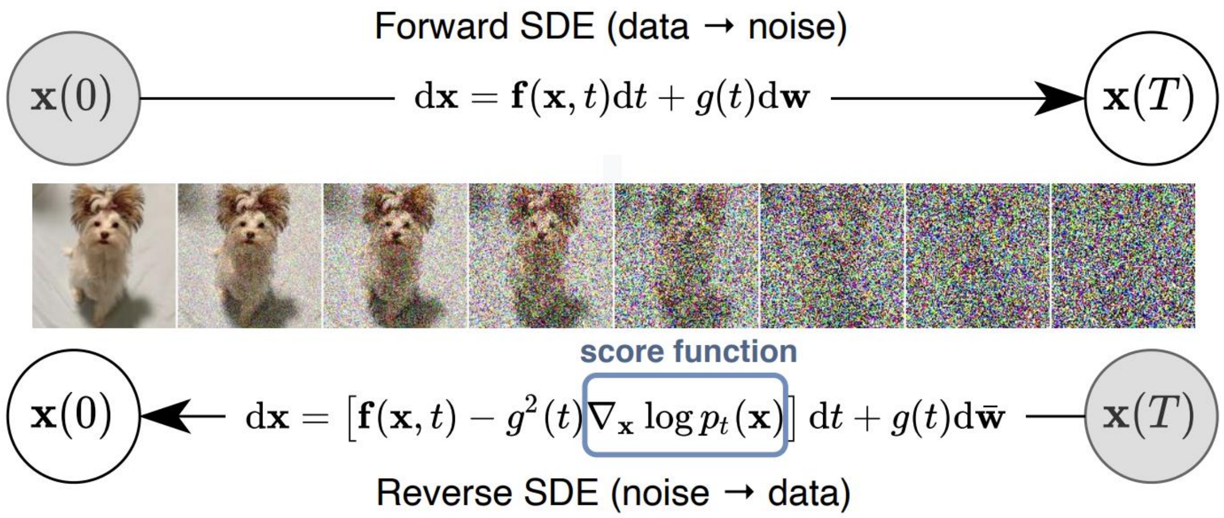
Score-Based Generative Model

- Limitations of vanilla score matching:
  - Poorly defined for real-world data
  - Inaccurate score estimation for low-density region
  - Poor sampling with large low-density region

- Advantages of score-based generative model
  - The support of a Gaussian noise distribution is the entire space.
  - Increase the area of each mode by adding noise.
  - Different modes are connected by adding noise.

https://miro.medium.com/v2/resize:fit:1400/1*gumPfXwQYkNnnlGxAGUlRA.png

Diffusion Models: Stochastic Differential Equation Perspective



The only unknown term is the score function.

Train a neural network through score matching!

Probability Flow ODE:

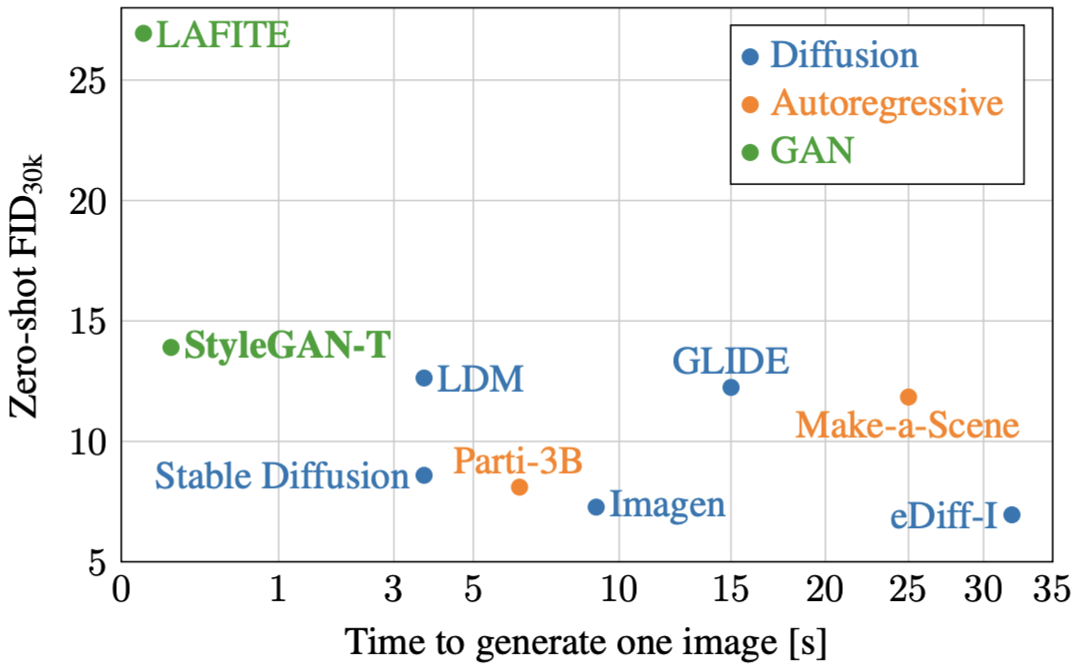
A deterministic reverse process

$$\mathrm{d}\mathbf{x} = \left[\mathbf{f}(\mathbf{x}, t) - \frac{1}{2} g(t)^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x})\right] \mathrm{d}t$$

Exact Solution form of PF-ODE

$$\boldsymbol{x}_t = \frac{\alpha_t}{\alpha_s}\boldsymbol{x}_s - \alpha_t \int_{\lambda_s}^{\lambda_t} e^{-\lambda} \hat{\boldsymbol{\epsilon}}_\theta(\hat{\boldsymbol{x}}_\lambda, \lambda)\mathrm{d}\lambda.$$

Diffusion Models: Slow Inference Speed



How to speed up the diffusion generation?

- Reducing the number of function evaluation (NFE).
  - Better Solvers.
  - Adversarial post-training.
  - Parallel Sampling.
  - Distillation.
    - Naïve distillation.
    - Guided distillation.
    - Score distillation.
    - Consistency distillation.
    - Rectification.

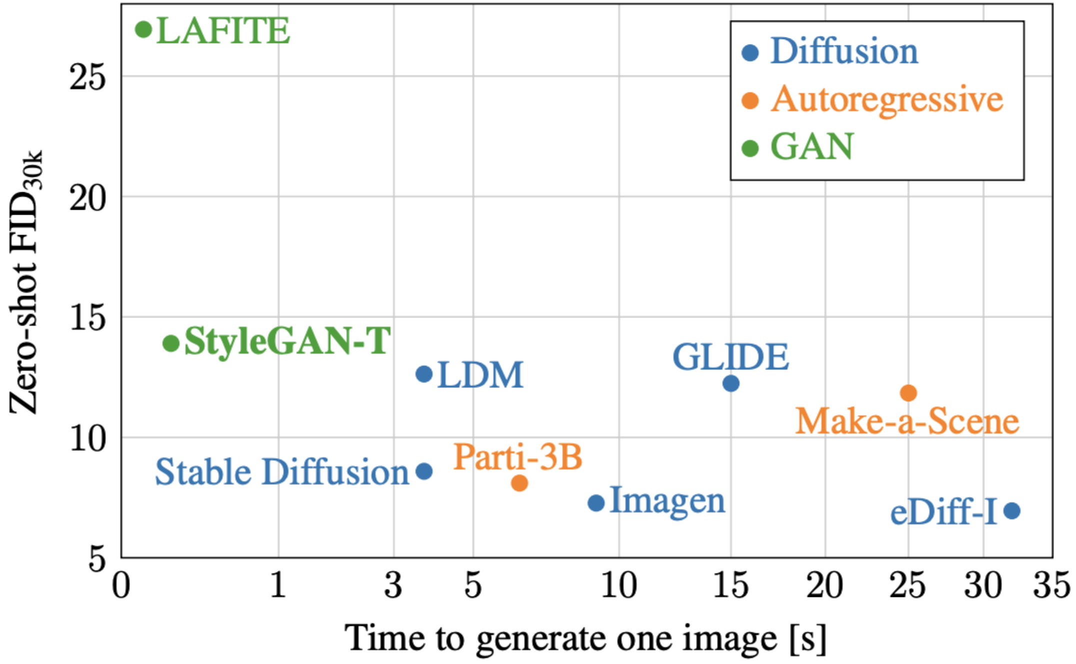
DPM-Solver

$$\boldsymbol{x}_{t_{i-1}\to t_i} = \frac{\alpha_{t_i}}{\alpha_{t_{i-1}}}\tilde{\boldsymbol{x}}_{t_{i-1}} - \alpha_{t_i}\int_{\lambda_{t_{i-1}}}^{\lambda_{t_i}} e^{-\lambda}\hat{\boldsymbol{\epsilon}}_\theta(\hat{\boldsymbol{x}}_\lambda, \lambda)\mathrm{d}\lambda.$$

$$\hat{\boldsymbol{\epsilon}}_\theta(\hat{\boldsymbol{x}}_\lambda, \lambda) = \sum_{n=0}^{k-1}\frac{(\lambda-\lambda_{t_{i-1}})^n}{n!}\hat{\boldsymbol{\epsilon}}_\theta^{(n)}(\hat{\boldsymbol{x}}_{\lambda_{t_{i-1}}}, \lambda_{t_{i-1}}) + \mathcal{O}((\lambda-\lambda_{t_{i-1}})^k),$$

$$\boldsymbol{x}_{t_{i-1}\to t_i} = \frac{\alpha_{t_i}}{\alpha_{t_{i-1}}}\tilde{\boldsymbol{x}}_{t_{i-1}} - \alpha_{t_i}\sum_{n=0}^{k-1}\hat{\boldsymbol{\epsilon}}_\theta^{(n)}(\hat{\boldsymbol{x}}_{\lambda_{t_{i-1}}}, \lambda_{t_{i-1}})\int_{\lambda_{t_{i-1}}}^{\lambda_{t_i}} e^{-\lambda}\frac{(\lambda-\lambda_{t_{i-1}})^n}{n!}\mathrm{d}\lambda + \mathcal{O}(h_i^{k+1}),$$

Diffusion Models: Slow Inference Speed



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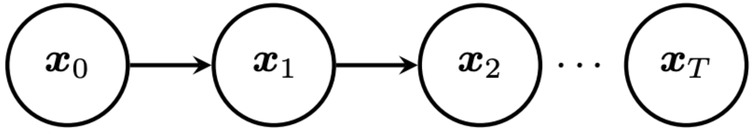
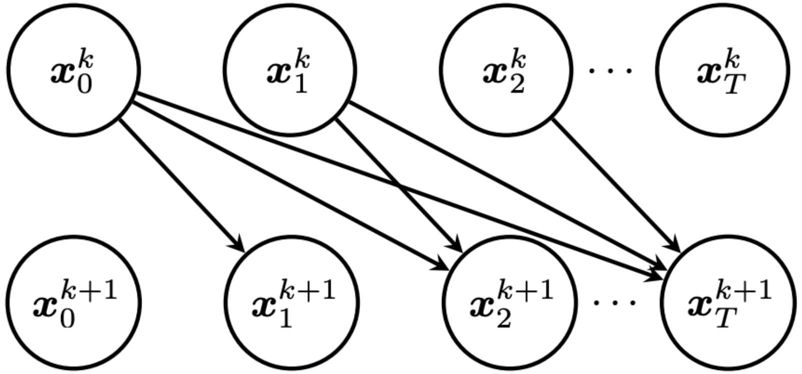
Picard Iteration





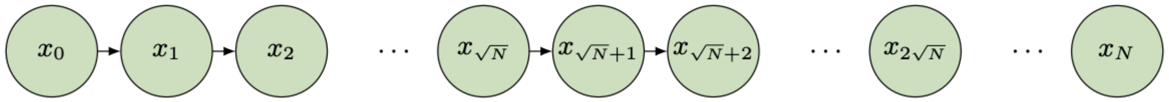
$$\boldsymbol{x}_t = \boldsymbol{x}_0 + \int_0^t s(\boldsymbol{x}_u, u) du.$$

$$\boldsymbol{x}_t^{k+1} = \boldsymbol{x}_0^k + \int_0^t s(\boldsymbol{x}_u^k, u) du.$$

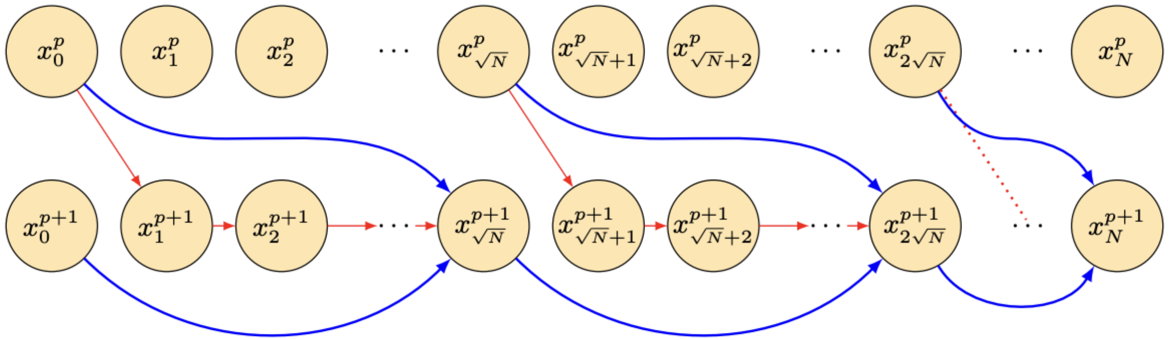
Lower Bound of Picard Iteration = Sequential Denoising

$$
\begin{aligned}
\boldsymbol{x}_{t+1}^{k+1} &= \boldsymbol{x}_0^k + \frac{1}{T}\sum_{i=0}^{t} s(\boldsymbol{x}_i^k, \frac{i}{T}) \\
&= \left(\boldsymbol{x}_0^k + \frac{1}{T}\sum_{i=0}^{t-1} s(\boldsymbol{x}_i^k, \frac{i}{T})\right) + \frac{1}{T}s(\boldsymbol{x}_t^k, \frac{t}{T}) \\
&= \boldsymbol{x}_t^{k+1} + \frac{1}{T}s(\boldsymbol{x}_t^k, \frac{t}{T}) \\
&= \boldsymbol{x}_t^{k+1} + \frac{1}{T}s(h_{t-1}(\ldots h_2(h_1(\boldsymbol{x}_0))), \frac{t}{T}) \\
&= \boldsymbol{x}_t^\star + \frac{1}{T}s(\boldsymbol{x}_t^\star, \frac{t}{T}) = \boldsymbol{x}_{t+1}^\star.
\end{aligned}
$$

Parareal Algorithm



(a) Sequential Sampling

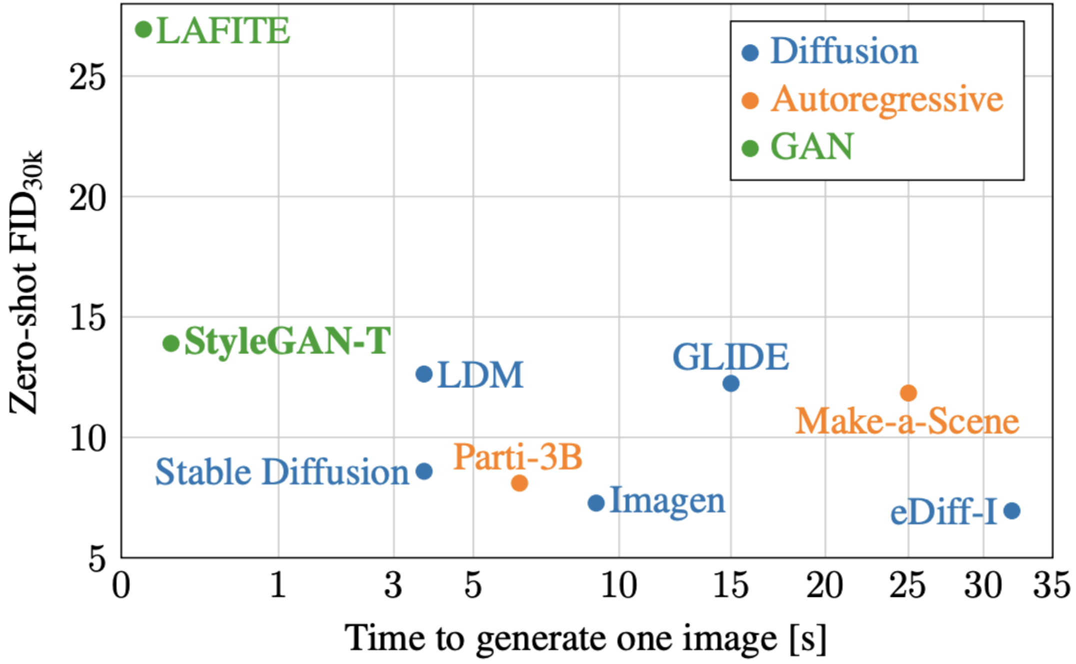


(b) SRDS

$$x_{i+1}^{p+1} = \boxed{\mathcal{F}\left(x_i^p, t_i, t_{i+1}\right)} + \left(\boxed{\mathcal{G}\left(x_i^{p+1}, t_i, t_{i+1}\right)} - \mathcal{G}\left(x_i^p, t_i, t_{i+1}\right)\right)$$

Fine Solver (Parallel) Coarse Solver (Sequential)

Diffusion Models: Slow Inference Speed



How to speed up the diffusion generation?

- Reducing the number of function evaluation (NFE).
  - Better Solvers.
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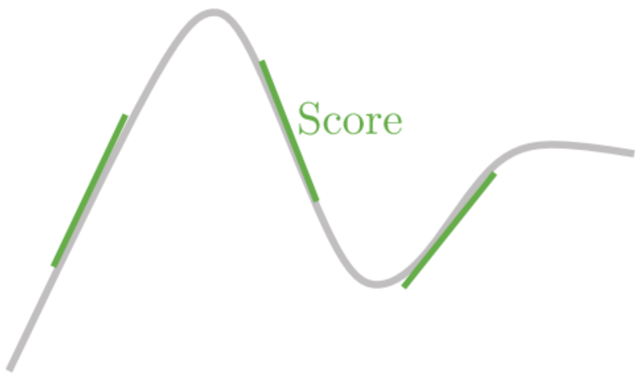
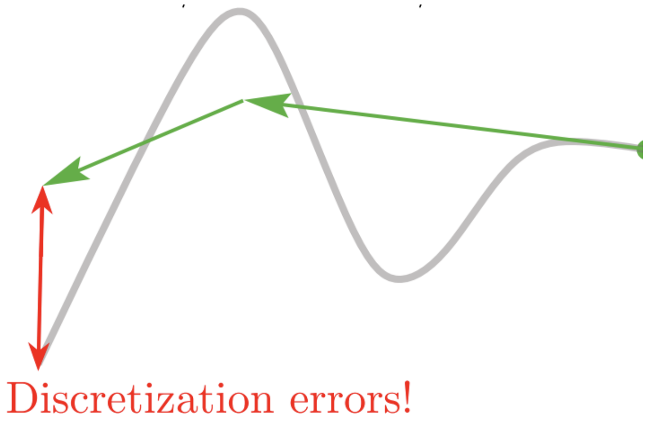
Understanding Diffusion Models from the PF-ODE path

We know the derivative w.r.t. time t.

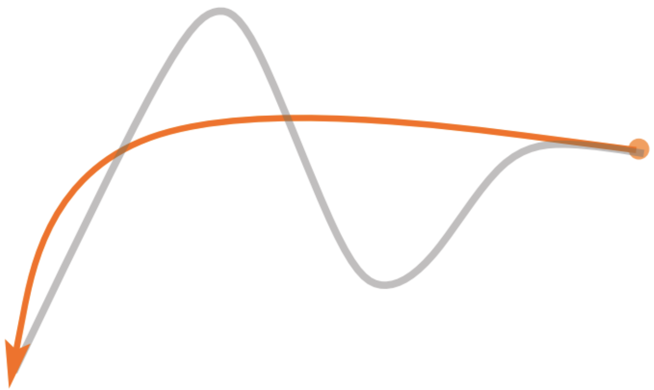
$$\mathrm{d}\mathbf{x} = \left[\mathbf{f}(\mathbf{x}, t) - \frac{1}{2} g(t)^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x})\right] \mathrm{d}t$$



PF-ODE

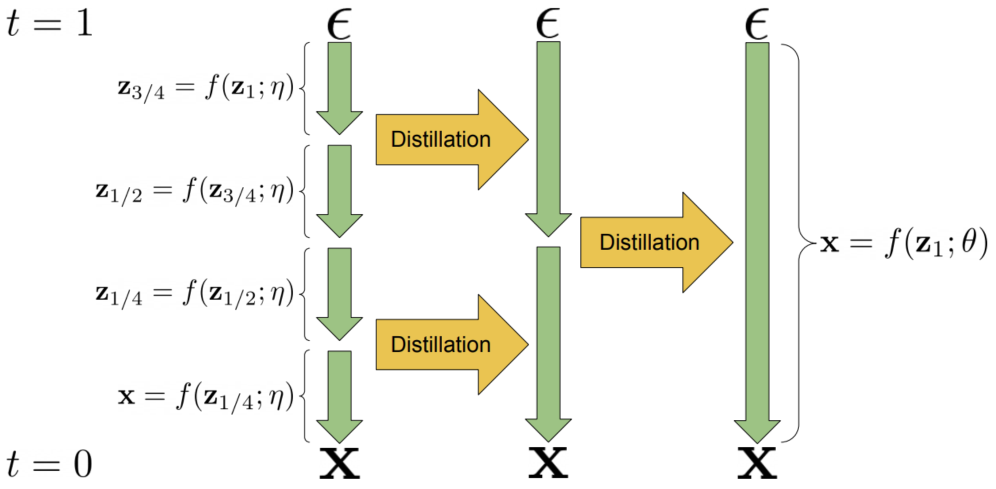


Discretized numerical solving.



Naïve distillation.

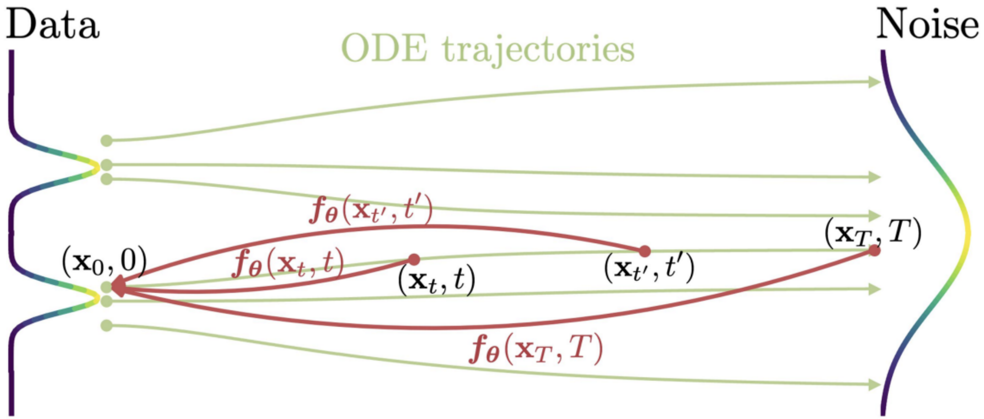
Distillation Techniques: Progressive Distillation



Algorithm 2 Progressive distillation

Require: Trained teacher model $\hat{\mathbf{x}}_\eta(\mathbf{z}_t)$
Require: Data set $\mathcal{D}$
Require: Loss weight function $w()$
Require: Student sampling steps N
for K iterations **do**
 $\theta \leftarrow \eta$ ▷ Init student from teacher
 while not converged **do**
  $\mathbf{x} \sim \mathcal{D}$
  $t = i/N, \quad i \sim Cat[1, 2, \ldots, N]$
  $\epsilon \sim N(0, I)$
  $\mathbf{z}_t = \alpha_t \mathbf{x} + \sigma_t \epsilon$
  `# 2 steps of DDIM with teacher`
  $t' = t - 0.5/N, \quad t'' = t - 1/N$
  $\mathbf{z}_{t'} = \alpha_{t'} \hat{\mathbf{x}}_\eta(\mathbf{z}_t) + \frac{\sigma_{t'}}{\sigma_t}(\mathbf{z}_t - \alpha_t \hat{\mathbf{x}}_\eta(\mathbf{z}_t))$
  $\mathbf{z}_{t''} = \alpha_{t''} \hat{\mathbf{x}}_\eta(\mathbf{z}_{t'}) + \frac{\sigma_{t''}}{\sigma_{t'}}(\mathbf{z}_{t'} - \alpha_{t'} \hat{\mathbf{x}}_\eta(\mathbf{z}_{t'}))$
  $\tilde{\mathbf{x}} = \frac{\mathbf{z}_{t''} - (\sigma_{t''}/\sigma_t)\mathbf{z}_t}{\alpha_{t''} - (\sigma_{t''}/\sigma_t)\alpha_t}$ ▷ Teacher $\hat{\mathbf{x}}$ target
  $\lambda_t = \log[\alpha_t^2/\sigma_t^2]$
  $L_\theta = w(\lambda_t)\|\tilde{\mathbf{x}} - \hat{\mathbf{x}}_\theta(\mathbf{z}_t)\|_2^2$
  $\theta \leftarrow \theta - \gamma \nabla_\theta L_\theta$
 end while
 $\eta \leftarrow \theta$ ▷ Student becomes next teacher
 $N \leftarrow N/2$ ▷ Halve number of sampling steps
end for

Distillation Techniques: Consistency Distillation



Algorithm 2 Consistency Distillation (CD)

Input: dataset $\mathcal{D}$, initial model parameter $\boldsymbol{\theta}$, learning rate η, ODE solver $\Phi(\cdot,\cdot;\boldsymbol{\phi})$, $d(\cdot,\cdot)$, $\lambda(\cdot)$, and μ

$\boldsymbol{\theta}^- \leftarrow \boldsymbol{\theta}$

repeat

Sample $\mathbf{x} \sim \mathcal{D}$ and $n \sim \mathcal{U}[\![1, N-1]\!]$

Sample $\mathbf{x}_{t_{n+1}} \sim \mathcal{N}(\mathbf{x}; t_{n+1}^2 \boldsymbol{I})$

$\hat{\mathbf{x}}_{t_n}^{\boldsymbol{\phi}} \leftarrow \mathbf{x}_{t_{n+1}} + (t_n - t_{n+1})\Phi(\mathbf{x}_{t_{n+1}}, t_{n+1}; \boldsymbol{\phi})$

$\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\theta}^-; \boldsymbol{\phi}) \leftarrow$

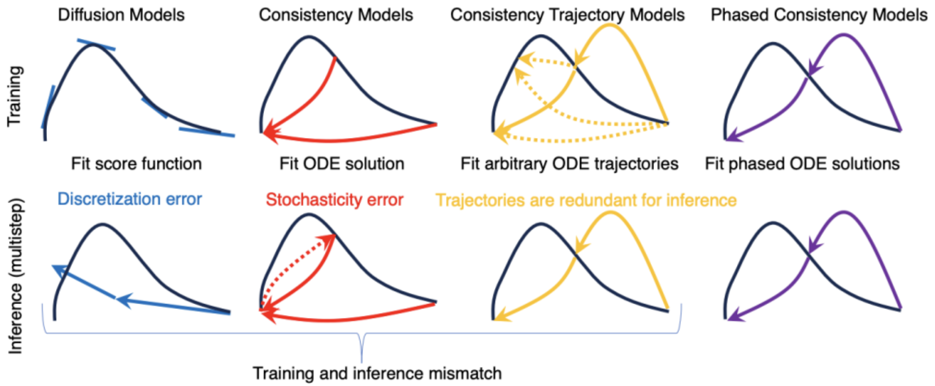
$\lambda(t_n) d(\boldsymbol{f_\theta}(\mathbf{x}_{t_{n+1}}, t_{n+1}), \boldsymbol{f}_{\boldsymbol{\theta}^-}(\hat{\mathbf{x}}_{t_n}^{\boldsymbol{\phi}}, t_n))$

$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \nabla_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\theta}^-; \boldsymbol{\phi})$

$\boldsymbol{\theta}^- \leftarrow \text{stopgrad}(\mu \boldsymbol{\theta}^- + (1-\mu)\boldsymbol{\theta})$

until convergence

Distillation Techniques: Phased Consistency Distillation



Algorithm 1 Phased Consistency Distillation with CFG-augmented ODE solver (PCD)

Input: dataset $\mathcal{D}$, initial model parameter $\boldsymbol{\theta}$, learning rate η, ODE solver $\Psi(\cdot,\cdot,\cdot,\cdot)$, distance metric $d(\cdot,\cdot)$, EMA rate μ, noise schedule α_t, σ_t, guidance scale $[w_{\min}, w_{\max}]$, number of ODE step k, discretized timesteps $t_0 = \epsilon < t_1 < t_2 < \cdots < t_N = T$, edge timesteps $s_0 = t_0 < s_1 < s_2 < \cdots < s_M = t_N \in \{t_i\}_{i=0}^N$ to split the ODE trajectory into M sub-trajectories.

Training data : $\mathcal{D}_{\mathbf{x}} = \{(\mathbf{x}, \boldsymbol{c})\}$

$\boldsymbol{\theta}^- \leftarrow \boldsymbol{\theta}$

repeat

  Sample $(\boldsymbol{z}, \boldsymbol{c}) \sim \mathcal{D}_z$, $n \sim \mathcal{U}[0, N-k]$ and $\omega \sim [\omega_{\min}, \omega_{\max}]$

  Sample $\mathbf{x}_{t_{n+k}} \sim \mathcal{N}(\alpha_{t_{n+k}} \boldsymbol{z}; \sigma_{t_{n+k}}^2 \mathbf{I})$

  Determine $[s_m, s_{m+1}]$ given n

  $\mathbf{x}_{t_n}^{\phi} \leftarrow (1+\omega)\Psi(\mathbf{x}_{t_{n+k}}, t_{n+k}, t_n, \boldsymbol{c}) - \omega\Psi(\mathbf{x}_{t_{n+k}}, t_{n+k}, t_n, \varnothing)$

  $\tilde{\mathbf{x}}_{s_m} = \boldsymbol{f}_{\boldsymbol{\theta}}^m(\mathbf{x}_{t_{n+k}}, t_{n+k}, \boldsymbol{c})$ and $\hat{\mathbf{x}}_{s_m} = \boldsymbol{f}_{\boldsymbol{\theta}^-}(\mathbf{x}_{t_n}^{\phi}, t_n, \boldsymbol{c})$

  Obtain $\tilde{\mathbf{x}}_s$ and $\hat{\mathbf{x}}_s$ through adding noise to $\tilde{\mathbf{x}}_{s_m}$ and $\hat{\mathbf{x}}_{s_m}$

  $\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\theta}^-) = d(\tilde{\mathbf{x}}_{s_m}, \hat{\mathbf{x}}_{s_m}) + \lambda(\mathrm{ReLU}(1 + \tilde{\mathbf{x}}_s) + \mathrm{ReLU}(1 - \hat{\mathbf{x}}_s))$

  $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \nabla_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\theta}^-)$

  $\boldsymbol{\theta}^- \leftarrow \mathrm{stopgrad}(\mu \boldsymbol{\theta}^- + (1-\mu)\boldsymbol{\theta})$

until convergence

Application: AnimateLCM

- AnimateLCM support
  - NOTE: You will need to use `autoselect` or `lcm` or `lcm[100_ots]` beta_schedule. To use fully with LCM, be sure to use appropriate LCM lora, use the `lcm` sampler_name in KSampler nodes, and lower cfg to somewhere around 1.0 to 2.0. Don't forget to decrease steps (minimum = ~4 steps), since LCM converges faster (less steps). Increase step count to increase detail as desired.
- AnimateLCM-I2V support, big thanks to Fu-Yun Wang for providing me the original diffusers code he created during his work on the paper
  - NOTE: Requires same settings as described for AnimateLCM above. Requires `Apply AnimateLCM-I2V Model` Gen2 node usage so that `ref_latent` can be provided; use `Scale Ref Image and VAE Encode` node to preprocess input images. While this was intended as an img2video model, I found it works best for vid2vid purposes with `ref_drift=0.0`, and to use it for only at least 1 step before switching over to other models via chaining with toher Apply AnimateDiff Model (Adv.) nodes. The `apply_ref_when_disabled` can be set to True to allow the img_encoder to do its thing even when the `end_percent` is reached. AnimateLCM-I2V is also extremely useful for maintaining coherence at higher resolutions (with ControlNet and SD LoRAs active, I could easily upscale from 512x512 source to 1024x1024 in a single pass). TODO: add examples

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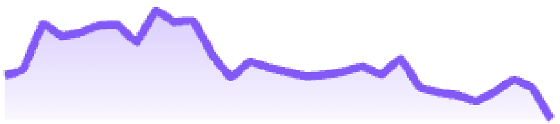
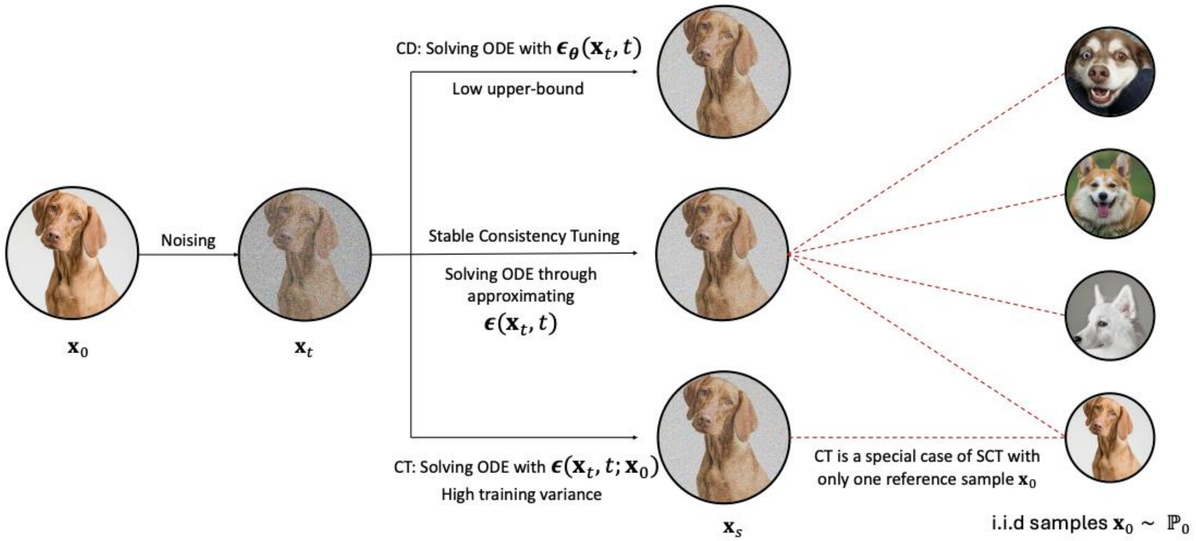


Application: AnimateLCM

Consistency Training



$$h_\theta(\mathbf{x}_t, t) \xleftarrow{\text{fit}} r + h_{\theta^-}(\mathbf{x}_r, r)$$

Bootstrapping

$$r \approx \epsilon_\phi(\mathbf{x}_t, t) \int_{\lambda_t}^{\lambda_r} e^{-\lambda} \mathrm{d}\lambda + \mathcal{O}((\lambda_r - \lambda_t)^2)$$

Consistency Distillation

$$r \approx \epsilon(\mathbf{x}_t, t; \mathbf{x}_0) \int_{\lambda_t}^{\lambda_r} e^{-\lambda} \mathrm{d}\lambda + \mathcal{O}((\lambda_r - \lambda_t)^2)$$

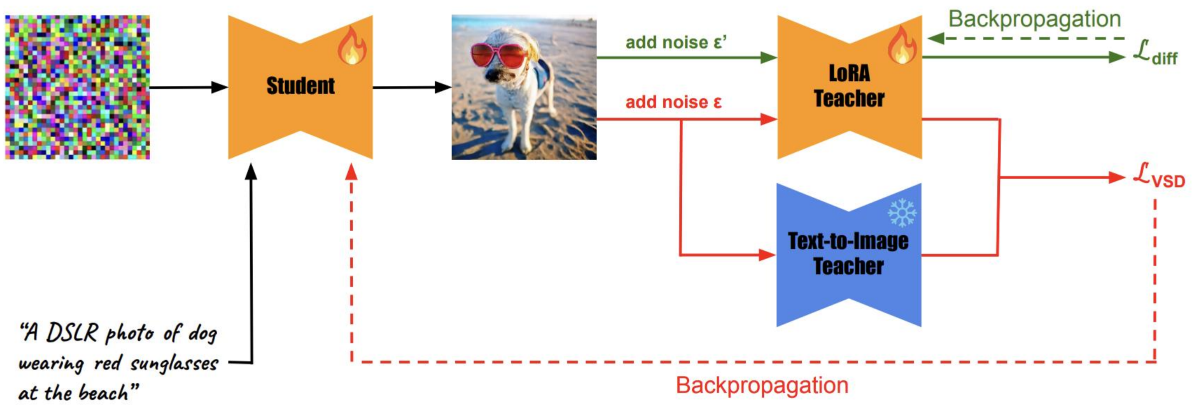
Consistency Training

Ground Truth of Score Estimation: Stable Consistency Tuning

$$
\begin{aligned}
\nabla_{\mathbf{x}_t} \log \mathbb{P}_t(\mathbf{x}_t \mid \boldsymbol{c}) &= \mathbb{E}_{\mathbb{P}(\mathbf{x}_0 \mid \mathbf{x}_t, \boldsymbol{c})}\left[\nabla_{\mathbf{x}_t} \log \mathbb{P}_t(\mathbf{x}_t \mid \mathbf{x}_0, \boldsymbol{c})\right] \\
&= \mathbb{E}_{\mathbb{P}(\mathbf{x}_0 \mid \boldsymbol{c})}\left[\frac{\mathbb{P}(\mathbf{x}_0 \mid \mathbf{x}_t, \boldsymbol{c})}{\mathbb{P}(\mathbf{x}_0 \mid \boldsymbol{c})} \nabla_{\mathbf{x}_t} \log \mathbb{P}_t(\mathbf{x}_t \mid \mathbf{x}_0, \boldsymbol{c})\right] \\
&= \mathbb{E}_{\mathbb{P}(\mathbf{x}_0 \mid \boldsymbol{c})}\left[\frac{\mathbb{P}(\mathbf{x}_t \mid \mathbf{x}_0, \boldsymbol{c})}{\mathbb{P}(\mathbf{x}_t \mid \boldsymbol{c})} \nabla_{\mathbf{x}_t} \log \mathbb{P}_t(\mathbf{x}_t \mid \mathbf{x}_0, \boldsymbol{c})\right] \\
&= \mathbb{E}_{\mathbb{P}(\mathbf{x}_0 \mid \boldsymbol{c})}\left[\frac{\mathbb{P}(\mathbf{x}_t \mid \mathbf{x}_0)}{\mathbb{P}(\mathbf{x}_t \mid \boldsymbol{c})} \nabla_{\mathbf{x}_t} \log \mathbb{P}_t(\mathbf{x}_t \mid \mathbf{x}_0)\right] \\
&\approx \frac{1}{n} \sum_{\{\mathbf{x}_0^{(i)}\} \sim \mathbb{P}(\mathbf{x}_0 \mid c)}^{i=0,\ldots n-1} \frac{\mathbb{P}(\mathbf{x}_t \mid \mathbf{x}_0^{(i)})}{\mathbb{P}(\mathbf{x}_t \mid \boldsymbol{c})} \nabla_{\mathbf{x}_t} \log \mathbb{P}_t(\mathbf{x}_t \mid \mathbf{x}_0^{(i)}) \\
&\approx \frac{1}{n} \sum_{\{\mathbf{x}_0^{(i)}\} \sim \mathbb{P}(\mathbf{x}_0 \mid c)}^{i=0,\ldots n-1} \frac{\mathbb{P}(\mathbf{x}_t \mid \mathbf{x}_0^{(i)})}{\sum_{\mathbf{x}_0^{(j)} \in \{\mathbf{x}_0^{(i)}\}} \mathbb{P}(\mathbf{x}_t \mid \mathbf{x}_0^{(j)}, \boldsymbol{c})} \nabla_{\mathbf{x}_t} \log \mathbb{P}_t(\mathbf{x}_t \mid \mathbf{x}_0^{(i)}) \\
&= \frac{1}{n} \sum_{\{\mathbf{x}_0^{(i)}\} \sim \mathbb{P}(\mathbf{x}_0 \mid c)}^{i=0,\ldots n-1} \frac{\mathbb{P}(\mathbf{x}_t \mid \mathbf{x}_0^{(i)})}{\sum_{\mathbf{x}_0^{(j)} \in \{\mathbf{x}_0^{(i)}\}} \mathbb{P}(\mathbf{x}_t \mid \mathbf{x}_0^{(j)})} \nabla_{\mathbf{x}_t} \log \mathbb{P}_t(\mathbf{x}_t \mid \mathbf{x}_0^{(i)})
\end{aligned}
$$

Distillation Techniques: Score Distillation

$$\nabla_\theta \mathcal{L}_{\text{VSD}}(\theta) \triangleq \mathbb{E}_{t,\boldsymbol{\epsilon},c}\left[\omega(t)\left(\boldsymbol{\epsilon}_{\text{pretrain}}(\boldsymbol{x}_t, t, y^c) - \boldsymbol{\epsilon}_\phi(\boldsymbol{x}_t, t, c, y)\right)\frac{\partial \boldsymbol{g}(\theta, c)}{\partial \theta}\right]$$



Algorithm 1 SwiftBrush Distillation

Require: a pretrained text-to-image teacher ϵ_ψ, a LoRA teacher ϵ_ϕ, a student model f_θ, two learning rates η_1 and η_2, a weighting function ω, a prompts dataset Y, the maximum number of time steps T and the noise schedule $\{(\alpha_t, \sigma_t)\}_{t=1}^{T}$ of the teacher model
Initialize: $\phi \leftarrow \psi, \theta \leftarrow \psi$
while not converged **do**
  Sample input noise $z \sim \mathcal{N}(0, I)$
  Sample text caption input $y \sim Y$
  Compute student output $\hat{x}_0 = f_\theta(z, y)$
  Sample timestep $t \sim \mathcal{U}(0.02T, 0.98T)$
  Sample added noise $\epsilon \sim \mathcal{N}(0, I)$
  Compute noisy sample $\hat{x}_t = \alpha_t \hat{x}_0 + \sigma_t \epsilon$
  $\theta \leftarrow \theta - \eta_1 \left[\omega(t)\left(\epsilon_\psi(\hat{x}_t, t, y) - \epsilon_\phi(\hat{x}_t, t, y)\right)\frac{\partial \hat{x}_0}{\partial \theta}\right]$
  Sample timestep $t' \sim \mathcal{U}(0, T)$
  Sample added noise $\epsilon' \sim \mathcal{N}(0, I)$
  Compute noisy sample $\hat{x}_{t'} = \alpha_{t'} \hat{x}_0 + \sigma_{t'} \epsilon'$
  $\phi \leftarrow \phi - \eta_2 \nabla_\phi \|\epsilon_\phi(\hat{x}_{t'}, t', y) - \epsilon'\|^2$
end while
return trained student model f_θ

Distillation Techniques: Score Distillation

$$\mathcal{L}(\theta) = \mathcal{D}^{[0,T]}(p_\theta, q) = \int_{t=0}^{T} w(t)\mathbb{E}_{\boldsymbol{x}_t \sim \pi_t}\left[\mathbf{d}\left(\boldsymbol{s}_{p_{\theta,t}}(\boldsymbol{x}_t) - \boldsymbol{s}_{q_t}(\boldsymbol{x}_t)\right)\right]\mathrm{d}t,$$

Generator $g_\theta : p_z \to p_{\boldsymbol{\theta}}$, $p_{\theta,t} = p_\theta * \mathcal{N}(0, I)$, $s_{\theta,t}(\mathbf{x}_t) = \nabla_{\mathbf{x}_t} \log p_{\theta,t}(\mathbf{x}_t)$

impossible to compute $\frac{d}{\theta} s_{\theta,t}(\mathbf{x}_t)$

Score Divergence Gradient Theorem

$$\mathcal{L}(\theta) = \mathcal{D}^{[0,T]}(p_\theta, q) = \int_{t=0}^{T} w(t)\mathbb{E}_{\boldsymbol{x}_t \sim \pi_t}\left[\mathbf{d}(\boldsymbol{s}_{p_{\theta,t}}(\boldsymbol{x}_t) - \boldsymbol{s}_{q_t}(\boldsymbol{x}_t))\right]\mathrm{d}t,$$

$$\mathbb{E}_{\boldsymbol{x}_t \sim p_{\mathrm{sg}[\theta],t}}\left[\mathbf{d}'(\boldsymbol{s}_{p_{\theta,t}}(\boldsymbol{x}_t) - \boldsymbol{s}_{q_t}(\boldsymbol{x}_t))\frac{\partial}{\partial\theta}\boldsymbol{s}_{p_{\theta,t}(\boldsymbol{x}_t)}\right] \tag{3.6}$$

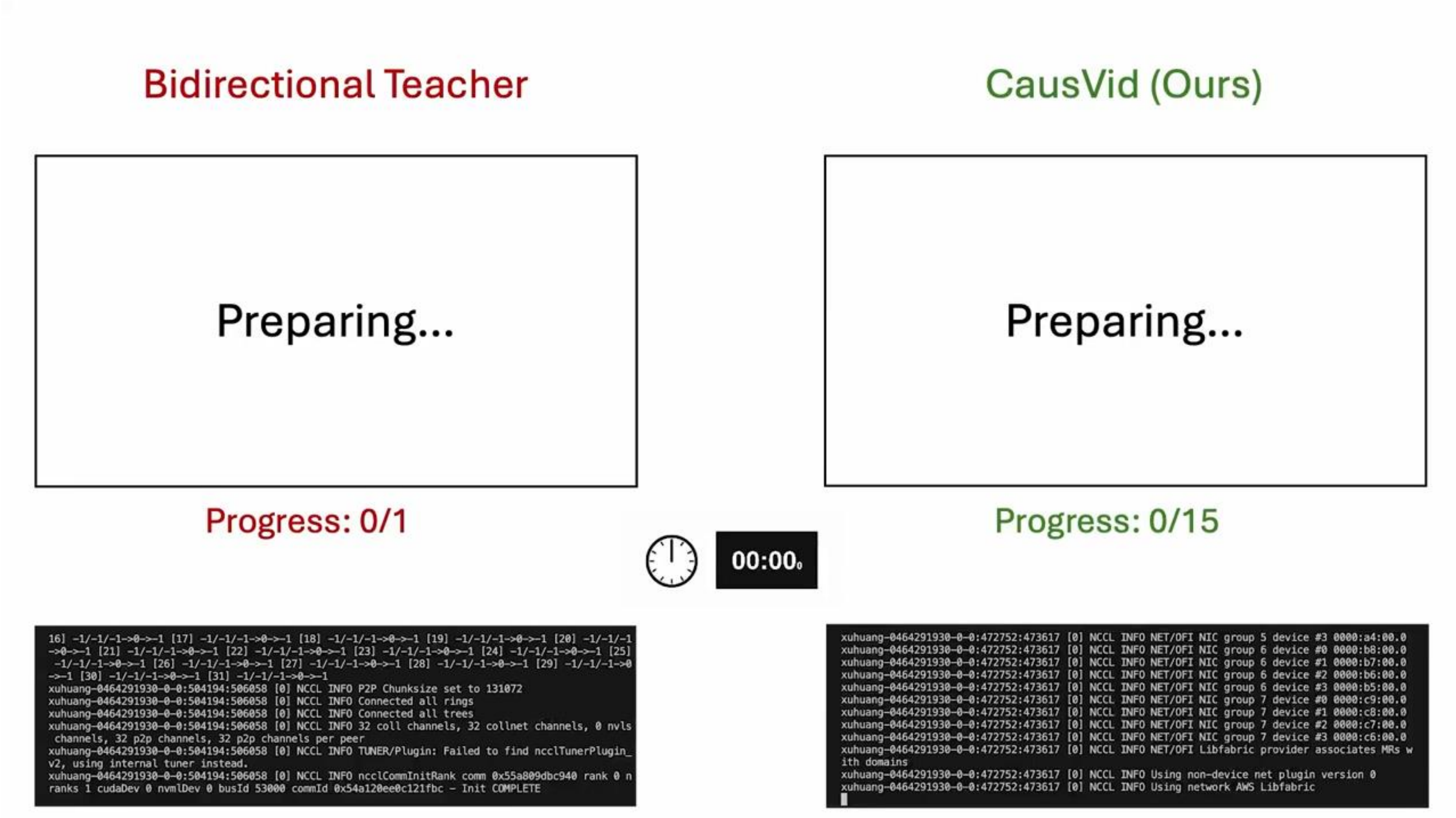
$$= -\frac{\partial}{\partial\theta}\mathbb{E}_{\substack{\boldsymbol{x}_0 \sim p_{\theta,0}, \\ \boldsymbol{x}_t|\boldsymbol{x}_0 \sim q_t(\boldsymbol{x}_t|\boldsymbol{x}_0)}}\left[\left\{\mathbf{d}'(\boldsymbol{s}_{p_{\mathrm{sg}[\theta],t}}(\boldsymbol{x}_t) - \boldsymbol{s}_{q_t}(\boldsymbol{x}_t))\right\}^T \left\{\boldsymbol{s}_{p_{\mathrm{sg}[\theta],t}}(\boldsymbol{x}_t) - \nabla_{\boldsymbol{x}_t}\log q_t(\boldsymbol{x}_t|\boldsymbol{x}_0)\right\}\right].$$

Simplify

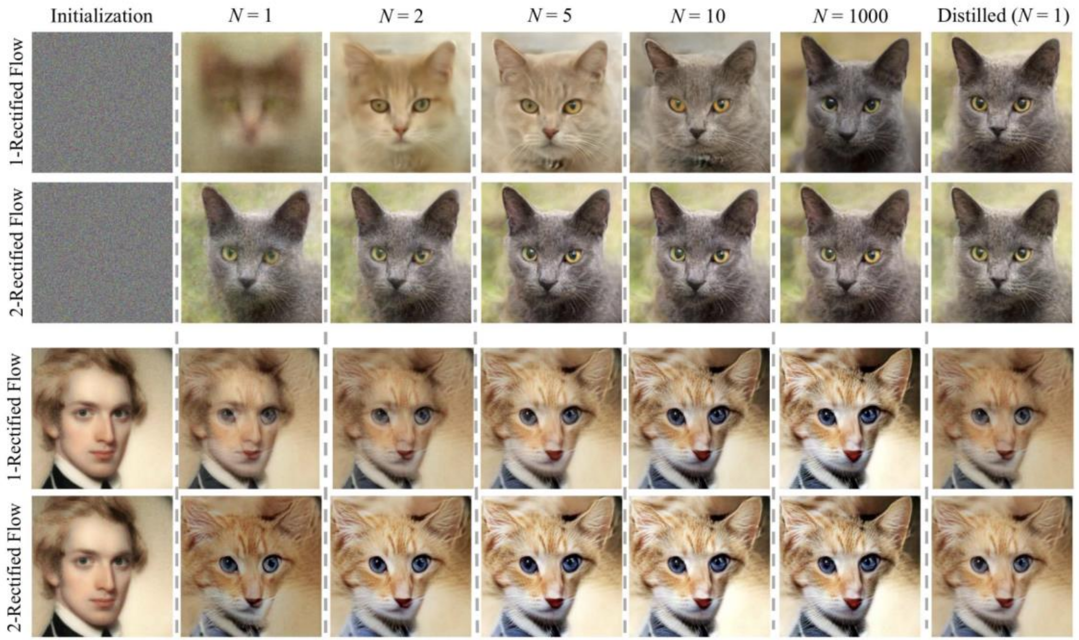
$$\boldsymbol{d}_\psi(\boldsymbol{x}_t, t) - \boldsymbol{x}_0$$

Ignore

Application: Casual Vid



Distillation Techniques: Rectified Flow



Advantages:

- High-quality few-step generation.
- Flexibility on inference steps.
- Simple forms.

Distillation Techniques: Rectified Flow

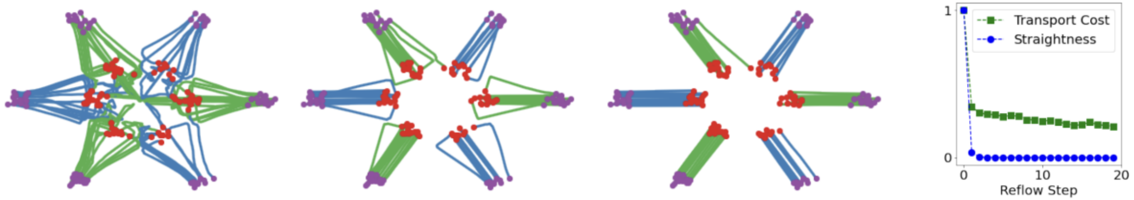
- Linear interpolation.

$$X_t = tX_1 + (1-t)X_0$$

- v-prediction.

$$\mathrm{d}X_t = (X_1 - X_0)\mathrm{d}t$$

- Rectification (Reflow).

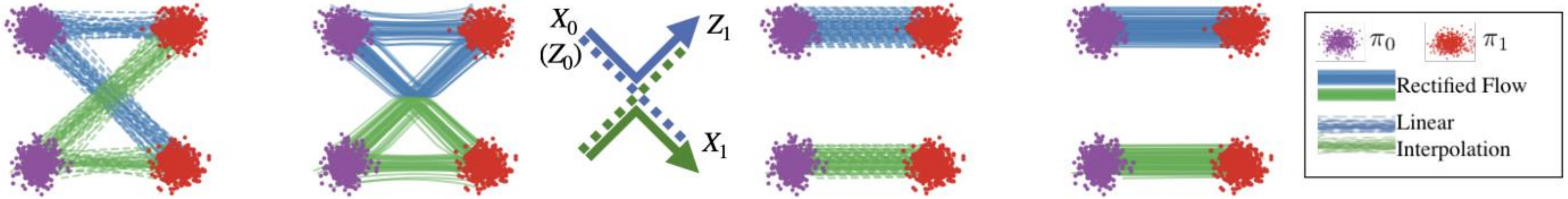


(a)The 1st rectified flow $\boldsymbol{Z}^1$ $\boldsymbol{Z}^1 = \texttt{RectFlow}((X_0, X_1))$

(b) Reflow $\boldsymbol{Z}^2$ $\boldsymbol{Z}^2 = \texttt{RectFlow}((Z_0^1, Z_1^1))$

(c) Reflow $\boldsymbol{Z}^3$ $\boldsymbol{Z}^3 = \texttt{RectFlow}((Z_0^2, Z_1^2))$

(d) Transport cost, Straightness



(a) Linear interpolation $X_t = tX_1 + (1-t)X_0$

(b) Rectified flow Z_t induced by (X_0, X_1)

(c) Linear interpolation $Z_t = tZ_1 + (1-t)Z_0$

(d) Rectified flow Z'_t induced by (Z_0, Z_1)

Diffusion Models: A (relative) Unified Perspective

$$\mathbf{x}_t = \alpha_t \mathbf{x}_0 + \sigma_t \boldsymbol{\epsilon}$$

- DDPM (Variance Preserving) $\sigma_t = \sqrt{1 - \alpha_t^2}$
- EDM (Variance Exploding) $\alpha_t = 1 \quad \sigma_{\max} = 80$
- Rectified Flow (Flow Matching) $\alpha_t = t \quad \sigma_t = 1 - t$
- Sub-VP $\sigma_t = 1 - \alpha_t^2$

The Magic of Rectified Flow: Retraining with Matched Noise-Sample Pairs

Algorithm 1 Flow Matching $\boldsymbol{v}$-Prediction

Input:
Sample $\mathbf{x}_0$ from the data distribution
Sample time t from a predefined schedule or uniformly from $[0, 1]$
Sample noise $\boldsymbol{\epsilon}$ from normal distribution
Compute $\mathbf{x}_t$: $\mathbf{x}_t = (1 - t) \cdot \mathbf{x}_0 + t \cdot \boldsymbol{\epsilon}$
Predict velocity $\hat{\boldsymbol{v}}$ using the model: $\hat{\boldsymbol{v}} = \text{Model}(\mathbf{x}_t, t)$
Compute loss: $\mathcal{L} = \|\hat{\boldsymbol{v}} - (\mathbf{x}_0 - \boldsymbol{\epsilon})\|_2^2$
Backpropagate and update parameters

Algorithm 3 Rectified Flow $\boldsymbol{v}$-Prediction

Input: noise-data pair $(\boldsymbol{\epsilon}, \hat{\mathbf{x}}_0)$
~~Sample $\mathbf{x}_0$ from the data distribution~~
Sample time t from a predefined schedule or uniformly from $[0, 1]$
~~Sample noise $\boldsymbol{\epsilon}$ from normal distribution~~
Compute $\mathbf{x}_t$: $\mathbf{x}_t = (1 - t) \cdot \hat{\mathbf{x}}_0 + t \cdot \boldsymbol{\epsilon}$
Predict velocity $\hat{\boldsymbol{v}}$ using the model: $\hat{\boldsymbol{v}} = \text{Model}(\mathbf{x}_t, t)$
Compute loss: $\mathcal{L} = \|\hat{\boldsymbol{v}} - (\hat{\mathbf{x}}_0 - \boldsymbol{\epsilon})\|_2^2$
Backpropagate and update parameters

Rectified Flow Training Is a Subset of Diffusion Training

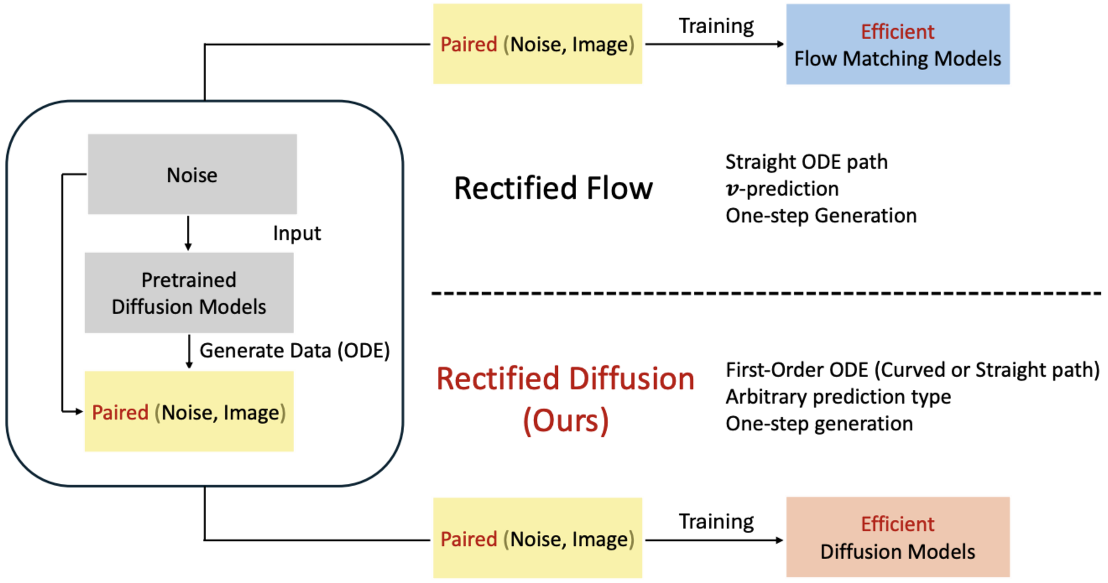
Algorithm 1 Flow Matching $\boldsymbol{v}$-Prediction

Input:
Sample $\mathbf{x}_0$ from the data distribution
Sample time t from a predefined schedule or uniformly from $[0, 1]$
Sample noise $\boldsymbol{\epsilon}$ from normal distribution
Compute $\mathbf{x}_t$: $\mathbf{x}_t = (1 - t) \cdot \mathbf{x}_0 + t \cdot \boldsymbol{\epsilon}$
Predict velocity $\hat{\boldsymbol{v}}$ using the model: $\hat{\boldsymbol{v}} = \text{Model}(\mathbf{x}_t, t)$
Compute loss: $\mathcal{L} = \|\hat{\boldsymbol{v}} - (\mathbf{x}_0 - \boldsymbol{\epsilon})\|_2^2$
Backpropagate and update parameters

Algorithm 2 Diffusion Training $\boldsymbol{\epsilon}$-Prediction

Input: α_t, σ_t
Sample $\mathbf{x}_0$ from the data distribution
Sample time t from a predefined schedule or uniformly from $[0, 1]$
Sample noise $\boldsymbol{\epsilon}$ from normal distribution
Compute $\mathbf{x}_t$: $\mathbf{x}_t = \alpha_t \cdot \mathbf{x}_0 + \sigma_t \cdot \boldsymbol{\epsilon}$
Predict noise $\hat{\boldsymbol{\epsilon}}$ using the model: $\hat{\boldsymbol{\epsilon}} = \text{Model}(\mathbf{x}_t, t)$
Compute loss: $\mathcal{L} = \|\hat{\boldsymbol{\epsilon}} - \boldsymbol{\epsilon}\|_2^2$
Backpropagate and update parameters

Rectified Diffusion: Extending Rectified Flow to General Diffusion Models



Algorithm 4 Rectified Diffusion ϵ-Prediction

Input: noise-data pair $(\epsilon, \hat{\mathbf{x}}_0)$, α_t, σ_t

~~Sample $\mathbf{x}_0$ from the data distribution~~

Sample time t from a predefined schedule or uniformly from $[0, 1]$

~~Sample noise ϵ from normal distribution~~

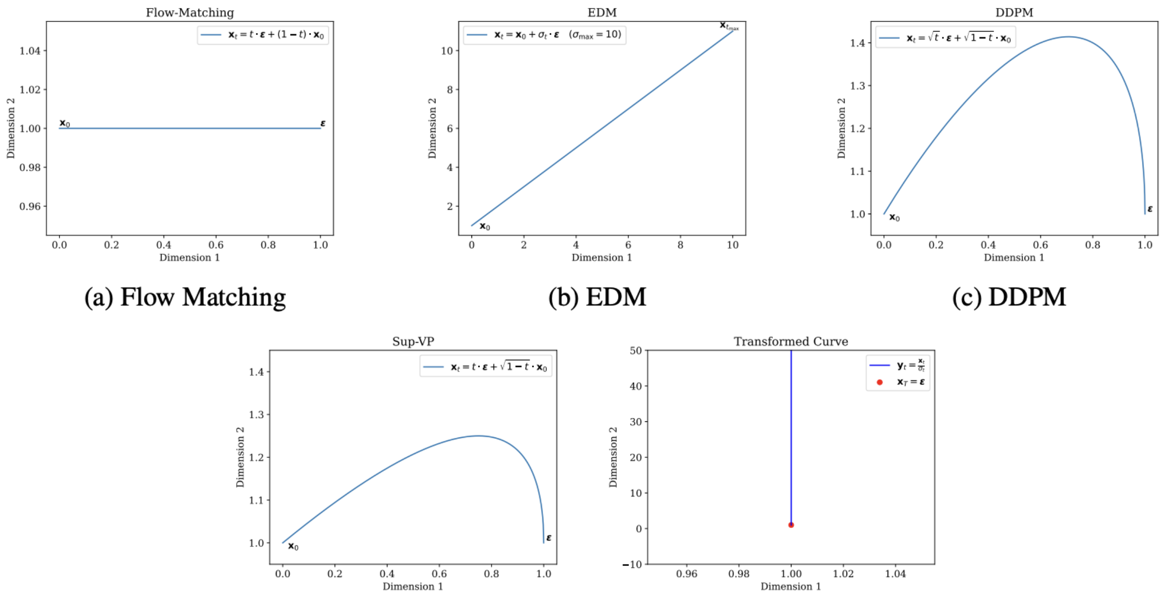
Compute $\mathbf{x}_t$: $\mathbf{x}_t = \alpha_t \cdot \hat{\mathbf{x}}_0 + \sigma_t \cdot \epsilon$

Predict noise $\hat{\epsilon}$ using the model: $\hat{\epsilon} = \text{Model}(\mathbf{x}_t, t)$

Compute loss: $\mathcal{L} = \|\hat{\epsilon} - \epsilon\|_2^2$

Backpropagate and update parameters

Rectified Diffusion: the Essential Training Target Is First-Order Approximated ODE



(a) Flow Matching (b) EDM (c) DDPM

(d) Sub-VP (e) Transformed

Important points of first-order approximated ODE:

- It has the same form of predefined diffusion forms.

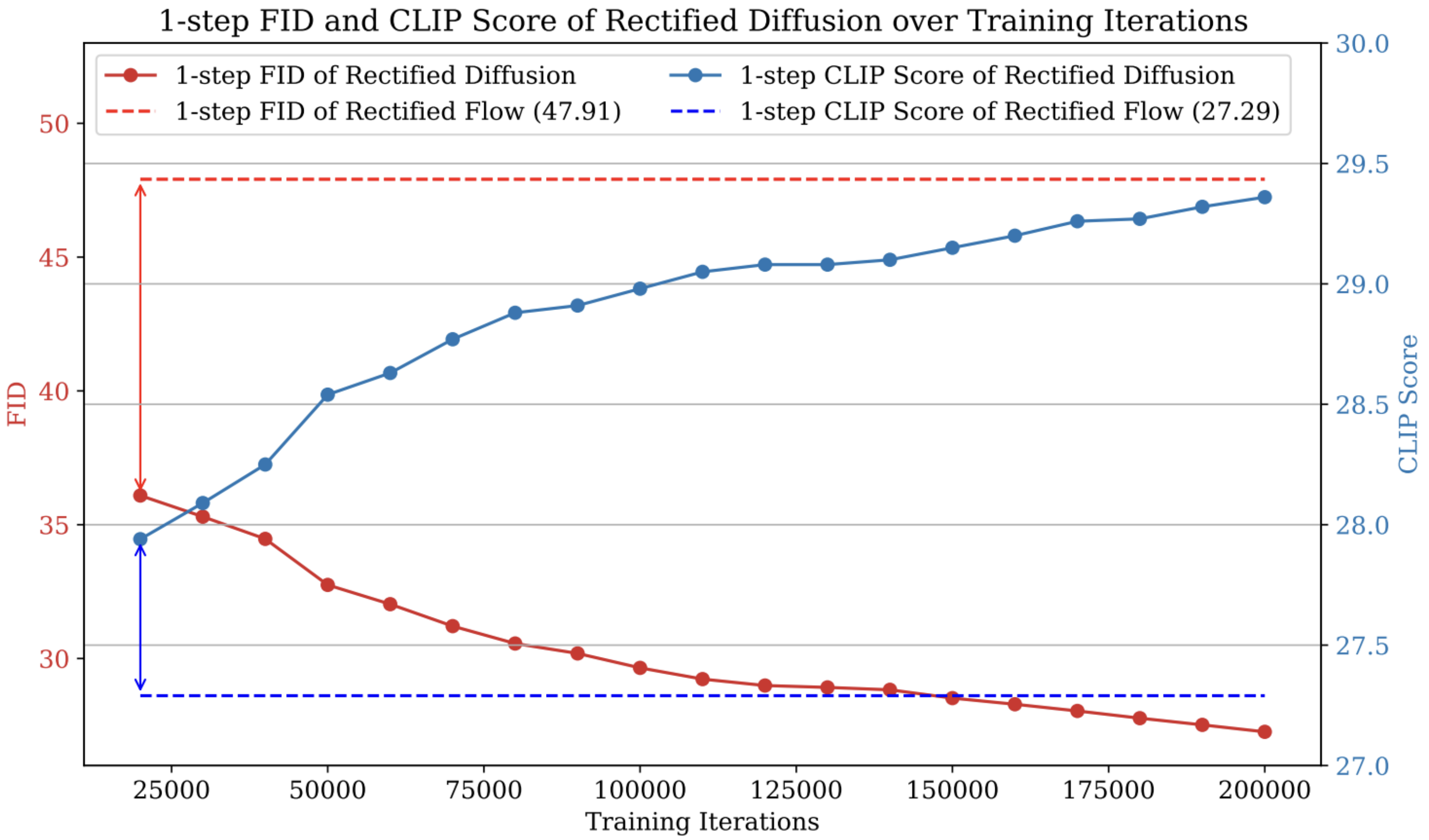
$$\mathbf{x}_t = \alpha_t \mathbf{x}_0 + \sigma_t \boldsymbol{\epsilon}$$

- It can be inherently curved.

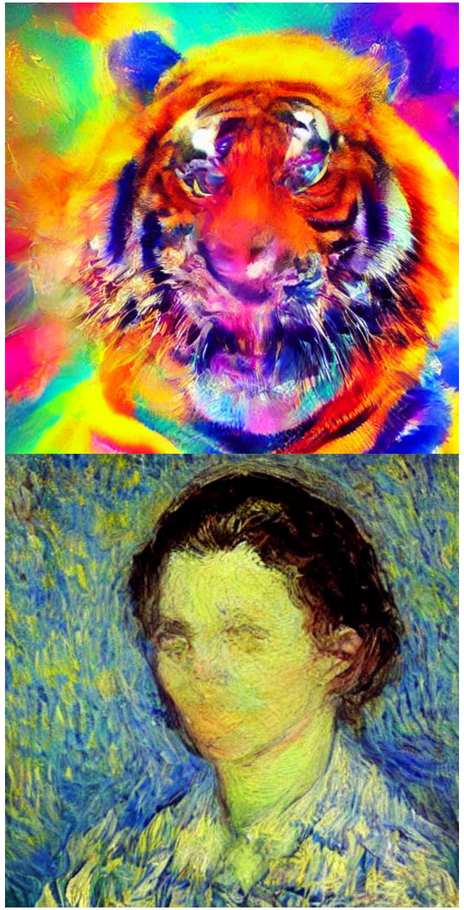
- It can be transformed into straight lines with timestep dependent scaling.

$$\mathbf{y}_t = \frac{\alpha_t}{\sigma_t} \mathbf{x}_0 + \boldsymbol{\epsilon}$$

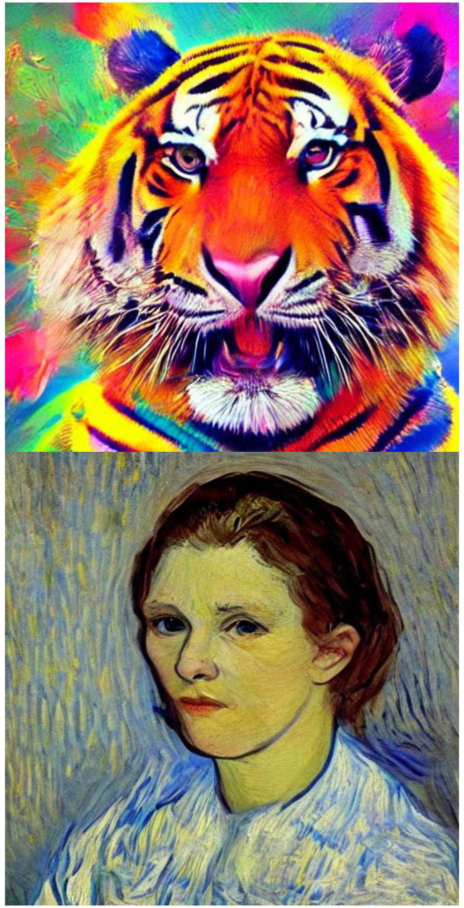
Rectified Diffusion Vs Rectified Flow



Rectified Diffusion Vs Rectified Flow

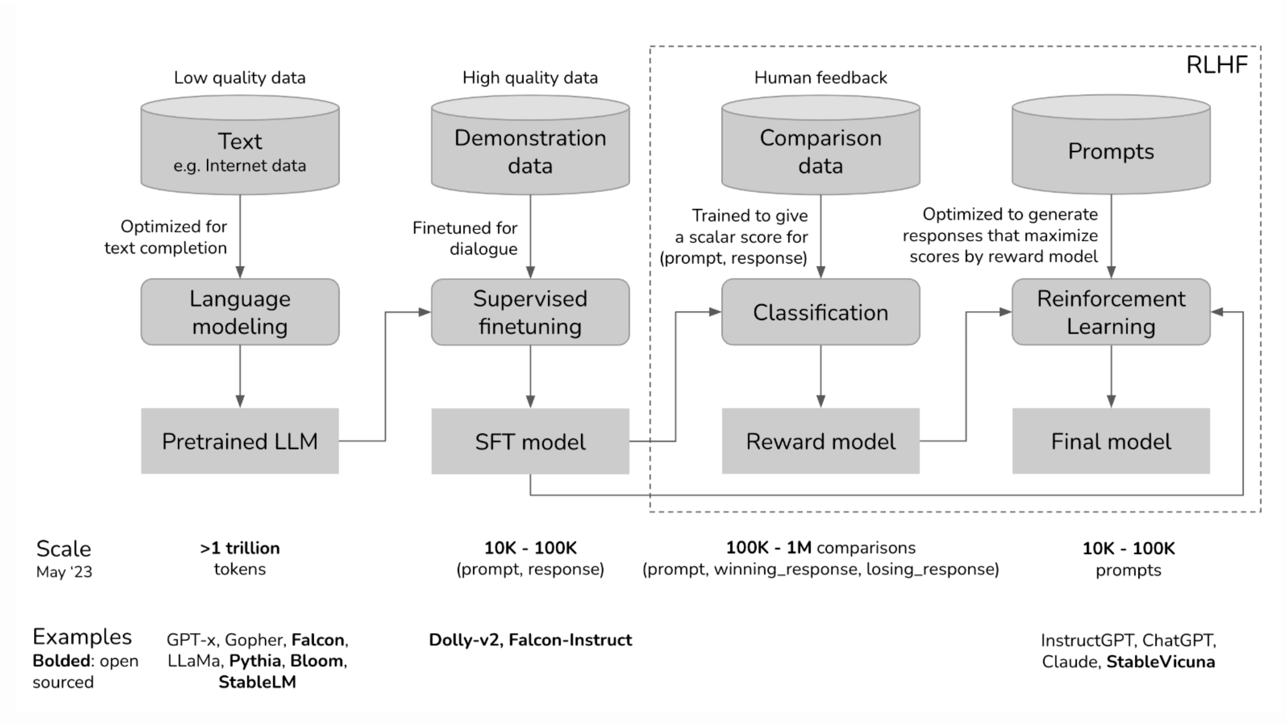


Rectified-Flow



Rectified-Diffusion

Human Preference Learning



Three ways for Preference Optimization:

- Differential Reward
- Reinforcement Learning
- Direct Preference Optimization

https://huyenchip.com/2023/05/02/rlhf.html

Reinforcement Learning

The generation process of generative models can be seen as Markov decision process (MDP)

- Large language models.
  - Token-by-token prediction.
  - Each token sampling can be seen as an action following the implicitly defined policy.
  - All the generated tokens can be seen as state.
  - Reward Models: LLMs.

- Diffusion models.
  - Step-by-step prediction.
  - Each step can be seen as an action following the implicitly defined policy.
  - Last denoised results can be seen as state.
  - Reward models: VLMs or CLIP.

Direct Preference Optimization

$$\max_{\pi} \mathbb{E}_{x\sim\mathcal{D}, y\sim\pi}\left[r(x,y)\right] - \beta\mathbb{D}_{\mathrm{KL}}\left[\pi(y|x)||\pi_{\mathrm{ref}}(y|x)\right]$$

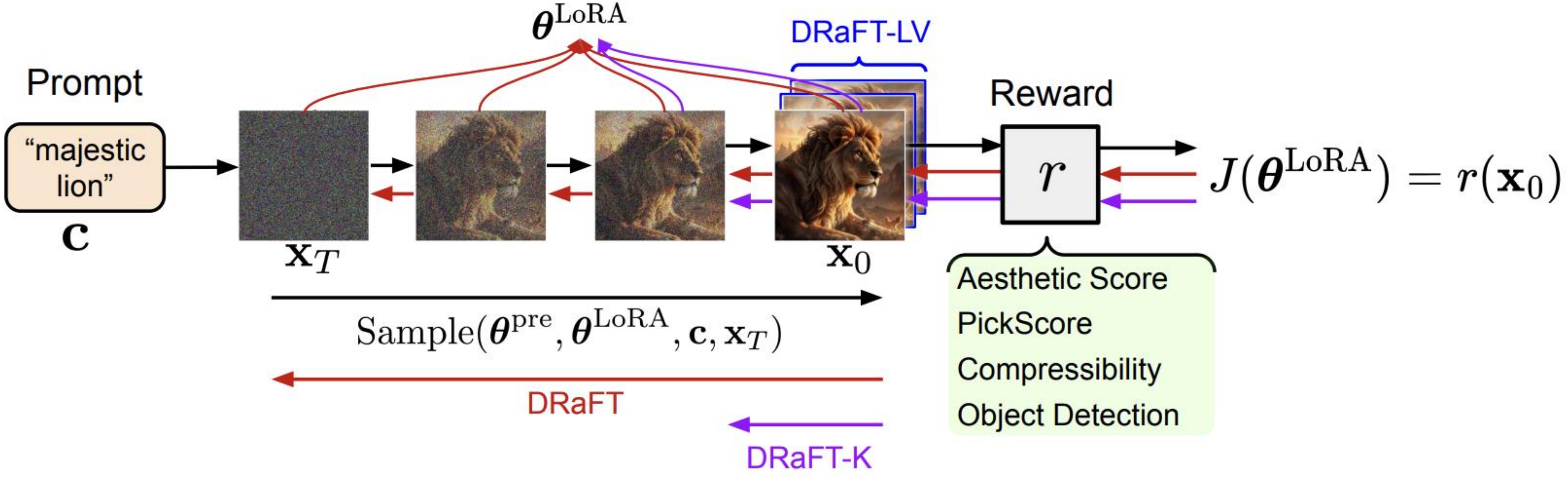
$$\pi(y|x) = \pi^*(y|x) = \frac{1}{Z(x)}\pi_{\mathrm{ref}}(y|x)\exp\left(\frac{1}{\beta}r(x,y)\right)$$

$$r^*(x,y) = \beta\log\frac{\pi^*(y|x)}{\pi_{\mathrm{ref}}(y|x)} + \beta\log Z(x)$$

Direct Preference Optimization

$$
\begin{aligned}
p^*(y_1 \succ y_2|x) &= \frac{\exp\left(\beta \log \frac{\pi^*(y_1|x)}{\pi_{\text{ref}}(y_1|x)} + \beta \log Z(x)\right)}{\exp\left(\beta \log \frac{\pi^*(y_1|x)}{\pi_{\text{ref}}(y_1|x)} + \beta \log Z(x)\right) + \exp\left(\beta \log \frac{\pi^*(y_2|x)}{\pi_{\text{ref}}(y_2|x)} + \beta \log Z(x)\right)} \\
&= \frac{1}{1 + \exp\left(\beta \log \frac{\pi^*(y_2|x)}{\pi_{\text{ref}}(y_2|x)} - \beta \log \frac{\pi^*(y_1|x)}{\pi_{\text{ref}}(y_1|x)}\right)} \\
&= \sigma\left(\beta \log \frac{\pi^*(y_1|x)}{\pi_{\text{ref}}(y_1|x)} - \beta \log \frac{\pi^*(y_2|x)}{\pi_{\text{ref}}(y_2|x)}\right).
\end{aligned}
$$

Differential Reward



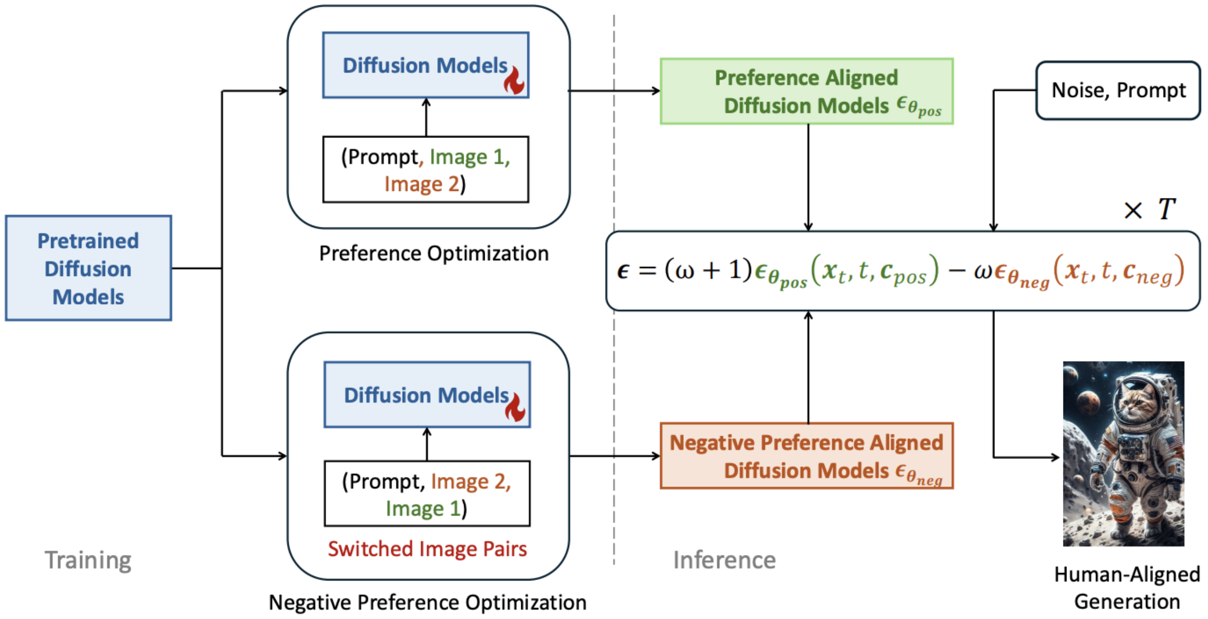
Classifier-free guidance

$$\nabla_{\boldsymbol{x}_t} \log \mathbb{P}_{\boldsymbol{\theta}}(\boldsymbol{x}_t|\boldsymbol{c};t) + \nabla_{\boldsymbol{x}_t} \log \left[\frac{\mathbb{P}_{\boldsymbol{\theta}}(\boldsymbol{x}_t|\boldsymbol{c};t)}{\mathbb{P}_{\boldsymbol{\theta}}(\boldsymbol{x}_t|\boldsymbol{c}';t)}\right]^{\omega}$$

$$\boldsymbol{\epsilon}_{\boldsymbol{\theta}}^{\omega} = (\omega+1)\boldsymbol{\epsilon}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, \boldsymbol{c}, t) - \omega\boldsymbol{\epsilon}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, \boldsymbol{c}', t)$$

$$\boldsymbol{\epsilon}_{\boldsymbol{\theta}}^{\omega} = (\omega+1)\boldsymbol{\epsilon}_{\boldsymbol{\theta}_{pos}}(\boldsymbol{x}_t, \boldsymbol{c}, t) - \omega\boldsymbol{\epsilon}_{\boldsymbol{\theta}_{neg}}(\boldsymbol{x}_t, \boldsymbol{c}', t)$$

Diffusion Negative Preference Optimization



$$\nabla_{\boldsymbol{x}_t} \log \mathbb{P}_{\boldsymbol{\theta}}(\boldsymbol{x}_t|\boldsymbol{c};t) + \nabla_{\boldsymbol{x}_t} \log \left[\frac{\mathbb{P}_{\boldsymbol{\theta}}(\boldsymbol{x}_t|\boldsymbol{c};t)}{\mathbb{P}_{\boldsymbol{\theta}}(\boldsymbol{x}_t|\boldsymbol{c}';t)}\right]^{\omega}$$

$$\boldsymbol{\epsilon}_{\boldsymbol{\theta}}^{\omega} = (\omega + 1)\boldsymbol{\epsilon}_{\boldsymbol{\theta}_{pos}}(\boldsymbol{x}_t, \boldsymbol{c}, t) - \omega\boldsymbol{\epsilon}_{\boldsymbol{\theta}_{neg}}(\boldsymbol{x}_t, \boldsymbol{c}', t)$$

To train Diffusion-NPO, we only need one line code.

Diffusion Negative Preference Optimization

We only need one line code for Negative Preference Optimization

- Reinforcement learning or differential reward
  - Negating the output of reward model

$$R_{\text{NPO}}(\mathbf{x}, \boldsymbol{c}) = 1 - R(\mathbf{x}, \boldsymbol{c})$$

- Direct preference optimization
  - Switch the order of preference annotations

$$r = (\mathbf{x}_0, \mathbf{x}_1, \boldsymbol{c})$$

$$r_{\text{NPO}} = (\mathbf{x}_1, \mathbf{x}_0, \boldsymbol{c})$$

Diffusion Negative Preference Optimization

Diffusion Negative Preference Optimization

References

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[2] Denoising Diffusion Implicit Models.
[3] Score-Based Generative Modeling through Stochastic Differential Equations.
[4] Flow Matching for Generative Modeling.
[5] Elucidating the Design Space of Diffusion-Based Generative Models.
[6] DPM-Solver: A Fast ODE Solver for Diffusion Probabilistic Model Sampling in Around 10 Steps.
[7] Discrete Flow Matching.
[8] Consistency Models.
[9] Consistency Models Made Easy.
[10] Latent Consistency Models: Synthesizing High-Resolution Images with Few-step Inference.
[11] Phased Consistency Model.
[12] Multistep Consistency Models.
[13] PeRFlow: Piecewise Rectified Flow as Universal Plug-and-Play Accelerator.
[14] Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow.
[15] InstaFlow: One Step is Enough for High-Quality Diffusion-Based Text-to-Image Generation.
[16] StyleGAN-T: Unlocking the Power of GANs for Fast Large-Scale Text-to-Image Synthesis.
[17] Stable Consistency Tuning: Understanding and Improving Consistency Models.
[18] SwiftBrush : One-Step Text-to-Image Diffusion Model with Variational Score Distillation.
[19] One-step Diffusion with Distribution Matching Distillation.
[20] Progressive Distillation for Fast Sampling of Diffusion Models

Our Works

[1] Stable Consistency Tuning: Understanding and Improving Consistency Models.

[2] Rectified Diffusion: Straightness Is Not Your Need in Rectified Flow.

[3] Phased Consistency Model.

[4] AnimateLCM: Computation-Efficient Personalized Style Video Generation without Personalized Video Data.

[5] Diffusion-NPO: Negative Preference Optimization for Better Preference Aligned Generation of Diffusion Models

Thank you!

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