Learning Process & Sampling Complexity of Diffusion Models

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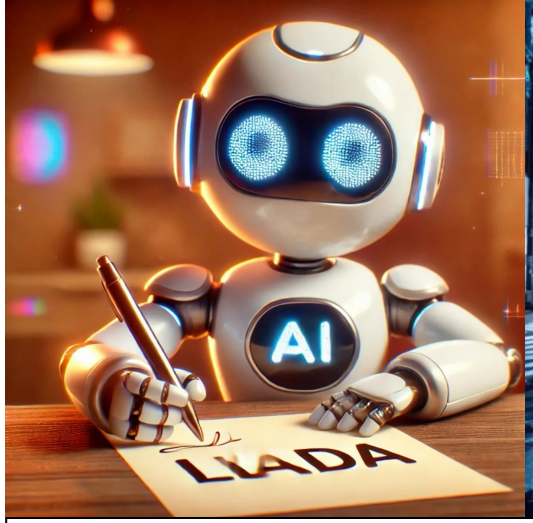
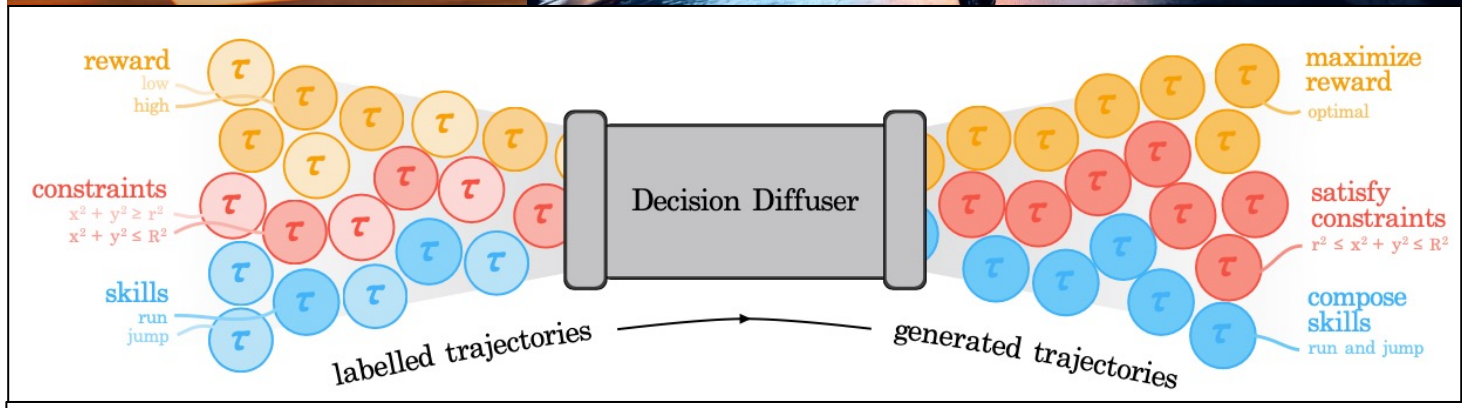
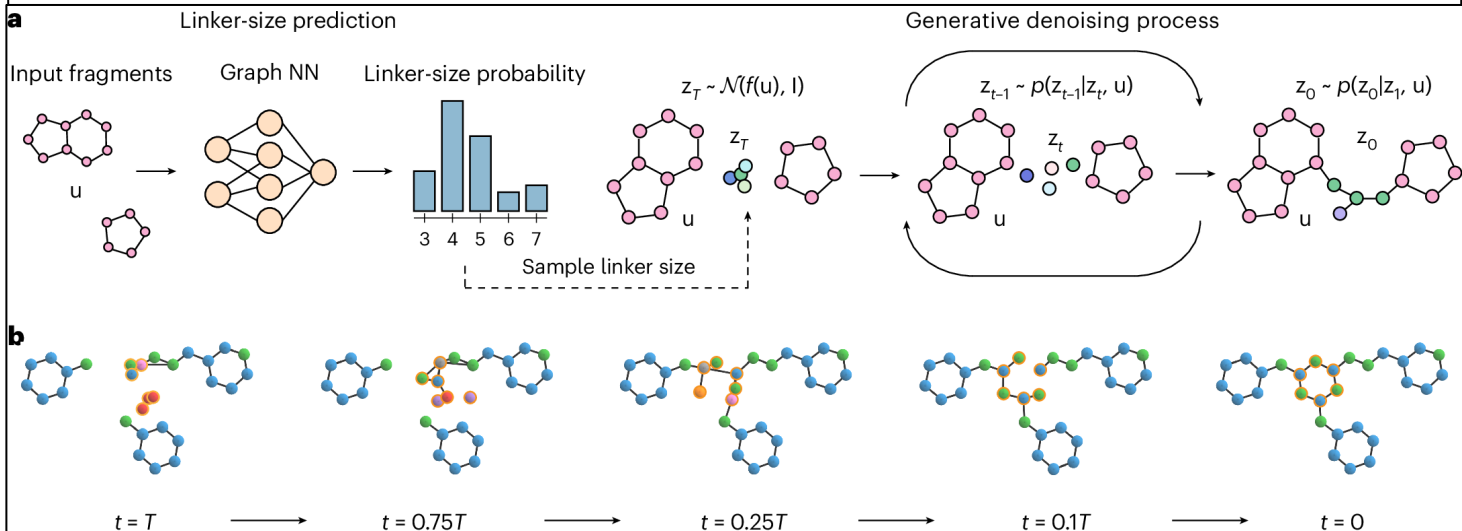
2026.03

Diffusion Models

- Vision: Sora, etc.
  - SOTA result: Image, 3D, video
- Language: LLaDA
- Multi-modal Models: MMaDA
- Reinforcement Learning
- AI4Science







[1] NZYZOHZLWL, Large Language Diffusion Models, ICLR 2025 DeLTa Workshop, Oral.
[2] YTLZSTW, Multimodal Large Diffusion Language Models, NeurIPS 2025.
[3] ADGTJA, Is Conditional Generative Modeling all you need for Decision Making?, ICLR 2023.
[4] ISVSSFWBC, Equivariant 3D-conditional diffusion model for molecular linker design, Nature Machine Intelligence 2024.

Theory Helps Training & Sampling

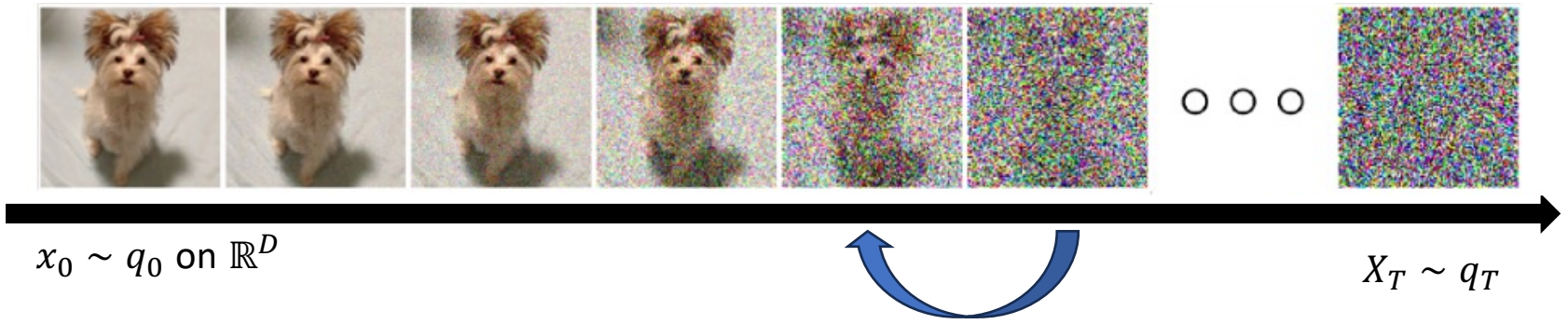
- Solid theoretical foundation helps efficient training & fast sampling:

- Theoretical SDE framework of diffusion family unifies training & sampling[1]
- New training paradigm with SOTA performance: Flow-matching[2]
- $10\times$ Faster sampling algorithm: DPM-Solvers series[3], Analytic-DPM[4]

[1] SDKKEP, Score-Based Generative Modeling through Stochastic Differential Equations, ICLR 2021.
[2] LG, Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow, ICLR 2023.
[3] LZBCLZ, Dpm-solver: A fast ode solver for diffusion probabilistic model sampling in around 10 steps, NeurIPS 2022.
[4] BLZZ, Analytic-DPM: an Analytic Estimate of the Optimal Reverse Variance in Diffusion Probabilistic Models, ICLR 2022.

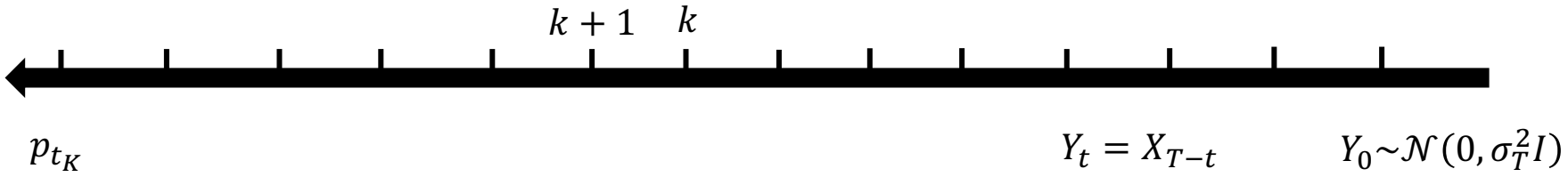
Paradigm of Multi-step Diffusion Models

Forward Process



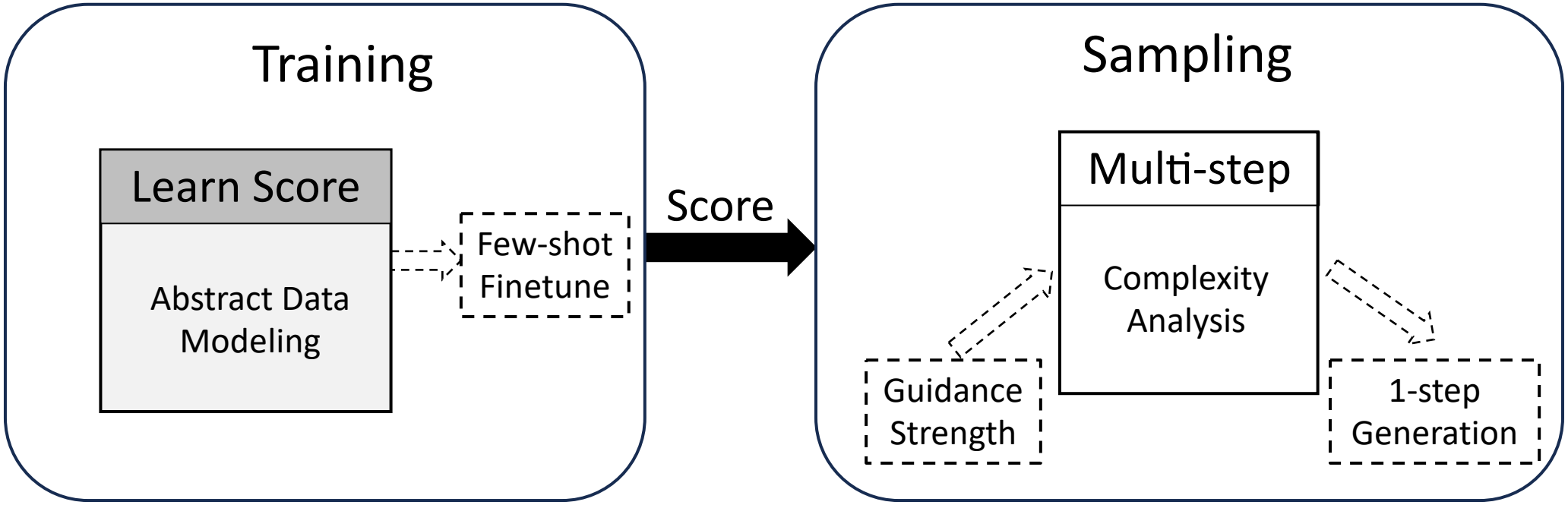
Core Problem 1: Training Process to Learn Denoising

Reverse Process

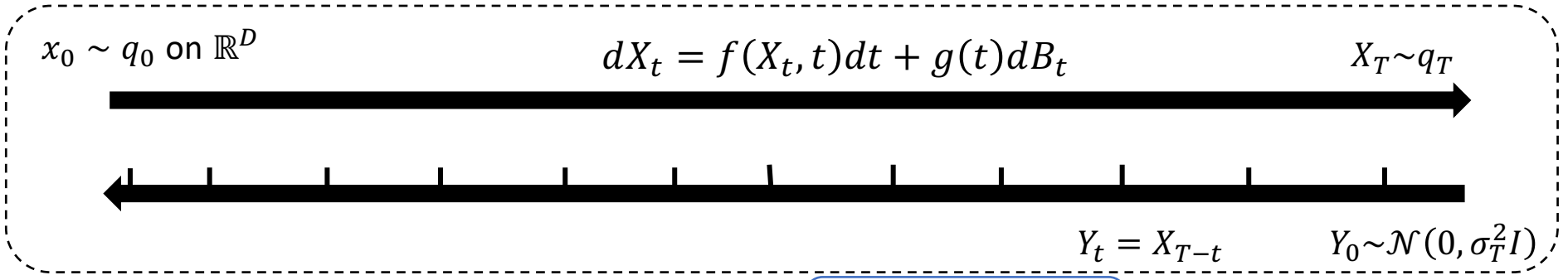


Core Problem 2: Sampling Complexity K

Overview


Training
Learn Score
Abstract Data Modeling
Few-shot Finetune
Score
Sampling
Multi-step
Complexity Analysis
Guidance Strength
1-step Generation

Mathematical Framework of Diffusion Models



score function

core to train DM unknown

- $dY_t = \left[-f(Y_t, T-t) + \frac{1+\eta^2}{2} g^2(T-t)\nabla \log q_{T-t}(Y_t)\right]dt + \eta g(T-t)dB_t, \eta \in [0,1]$

- Score matching training objective:

conditional distribution known

$$\min_{s \in \mathfrak{F}} \hat{\mathcal{L}}(s) = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{T-\delta}\int_{\delta}^{T} \mathbb{E}_{X_t|X_0=X_i} \left[\|\nabla \log q_t(X_t|X_0) - s(X_t, t)\|_2^2\right] dt$$

Learning Faces Curse of Dimension

- Minimiser $s_\theta \in \operatorname{argmin}_\Theta \hat{\mathcal{L}}(s)$ satisfies

  Estimation Error= $\frac{1}{T-\delta}\int_\delta^T \mathbb{E}_{q_t}\left[\|\nabla \log q_t(X_t) - s_\theta(X_t,t)\|_2^2\right] dt < O\left(n^{-2/D}\right)$

  covering number & concentration

  $D = 3\times256\times256 \approx 2\times10^5$

- Good training requires training data size $n = O(10^{10^5})$ Huge!!

- Efficient training needs utilizing data structure!

Data Structures: Existing Works

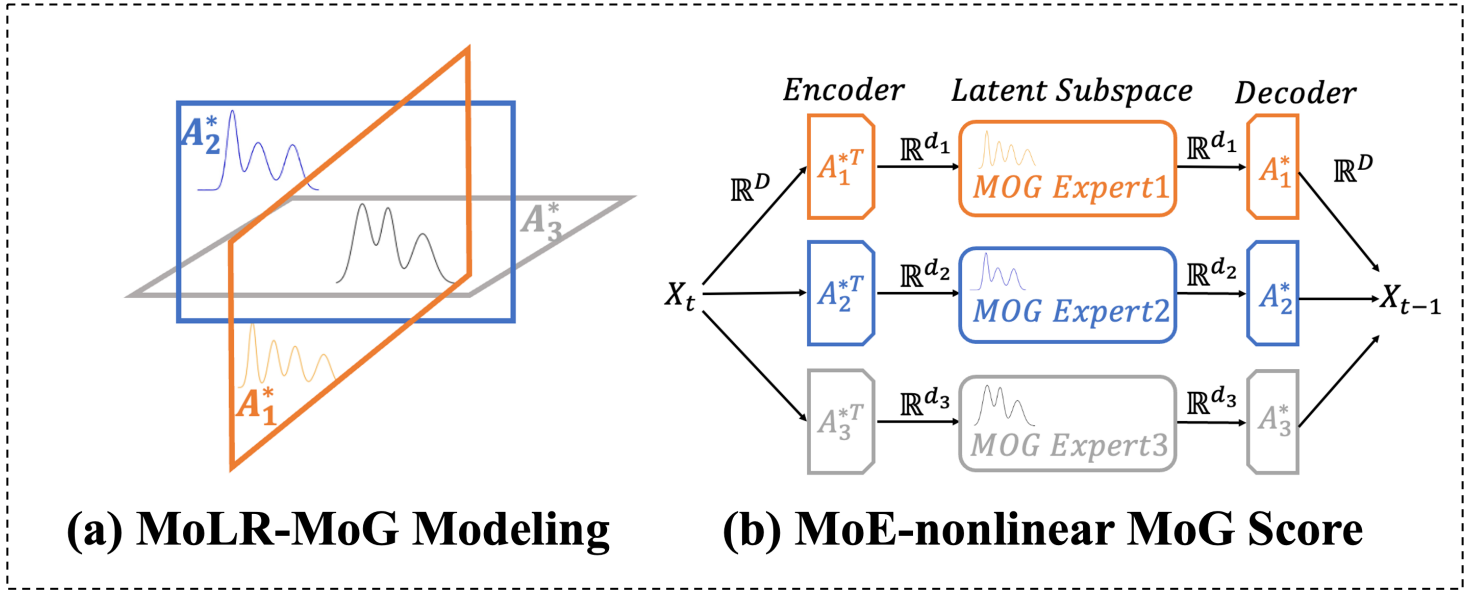
Manifold Modeling	Latent		# of Parameters	Estimation Error
Full Space [1]	General	X	$O(D^{D+1})$	$O\left(n^{-2/D}\right)$
Full Space [2]	Gaussian Mixture	$X \sim \sum_{m=1}^{M} \pi_m \mathcal{N}(\mu_m, \Sigma_m)$	$O(MD^2)$	$O(\frac{\sqrt{DM}}{\sqrt{n}})$
Low-dim Subspace [3]	General	$X = Az$, with $A \in \mathbb{R}^{D\times d}$	$O\left(Dd + d^{d+1}\right)$	$O(n^{-\frac{2}{d}})$
Multi-subspace	General	$X = \sum_{\ell=1}^{L} \pi_\ell A_\ell z_\ell$, with $A_\ell \in \mathbb{R}^{D\times d}$	$O\left(LDd + Ld^{d+1}\right)$	$O(\sqrt{L}n^{-\frac{2}{d}})$
Multi-subspace [4]	Gaussian	$X \sim \sum_{\ell=1}^{L} \pi_\ell \mathcal{N}\left(\cdot; 0, A_\ell A_\ell^\top\right)$	$O(LDd)$	$O(\frac{\sqrt{dL}}{\sqrt{n}} + \text{Const})$

[1] OAS, Diffusion Models are Minimax Optimal Distribution Estimators, ICML 2023.
[2] SCK, Learning mixtures of gaussians using the ddpm objective, NeurIPS 2023.
[3] CHZW, Score approximation, estimation and distribution recovery of diffusion models on low-dimensional data, ICML 2023.
[4] WZZCMQ. Diffusion models learn low-dimensional distributions via subspace clustering, NeurIPS 2024 M3L Workshop.

Multi-subspace Gaussian-Mixture-Model

- $X \sim \sum_{\ell=1}^{L} \pi_\ell \sum_{m=1}^{M} \pi_{\ell,m} \mathcal{N}\left(\cdot; A_\ell \mu_{\ell,m}, A_\ell \Sigma_{\ell,m} A_\ell^\top\right)$ Most general!
- Theorem. Its estimation error satisfies

$$\frac{1}{T-\delta}\int_{\delta}^{T} \mathbb{E}_{q_t}\left[\|\nabla \log q_t(X_t) - s_\theta(X_t, t)\|_2^2\right] dt < O\left(\frac{\sqrt{LM}\sqrt{dL}}{\sqrt{n}}\right)$$

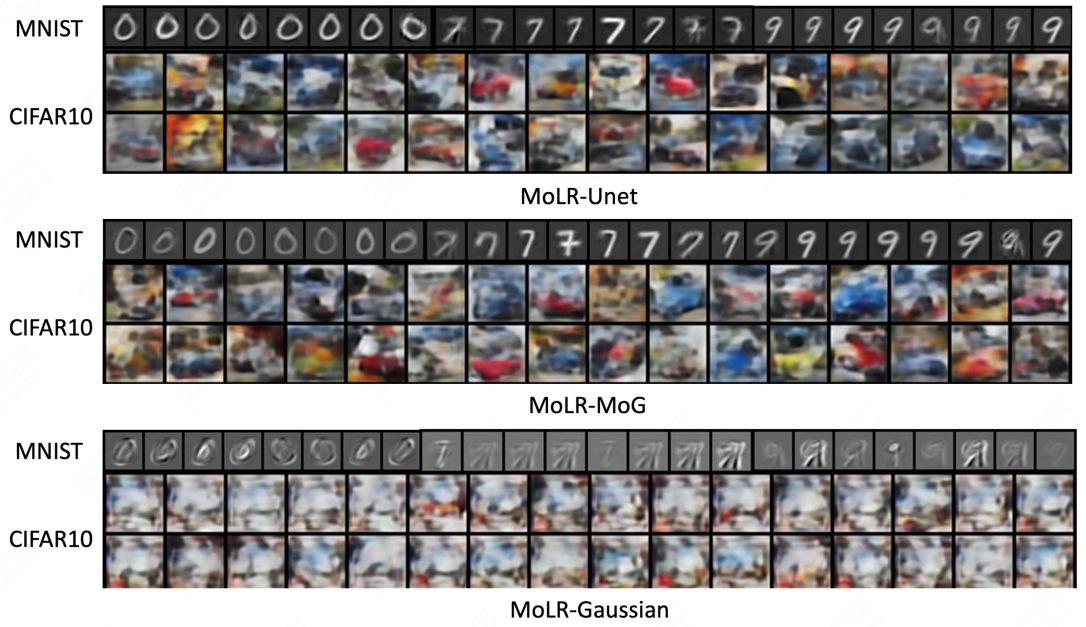


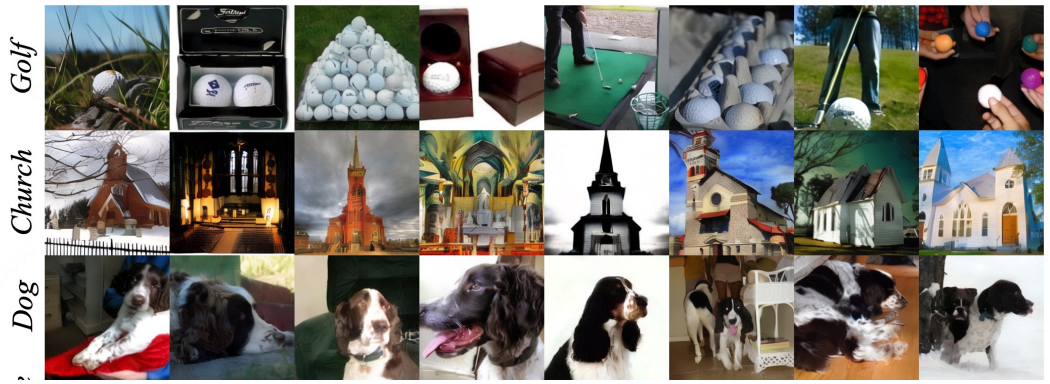
(a) MoLR-MoG Modeling **(b) MoE-nonlinear MoG Score**

- YLJCL, Multi-Subspace Multi-Modal Modeling for Diffusion Models: Estimation, Convergence and Mixture of Experts (ICLR 2026)

Much Smaller Model w/ Good Performance

Latent	# of Parameters	Estimation Error	MNIST Acc/ Performance	CIFAR10 Acc/ Performance
General	$O(LDd + Ld^{d+1})$	$O(\sqrt{L}n^{-\frac{2}{d}})$	0.96 √	0.86 √
GMM	$O(LDd + Ld^2)$	$O\left(\frac{\sqrt{LM}\sqrt{dL}}{\sqrt{n}}\right)$	0.89 √	0.85 √
Gaussian	$O(LDd)$	$O(\frac{\sqrt{dL}}{\sqrt{n}} +$ Const)	0.08 ×	0.25 ×





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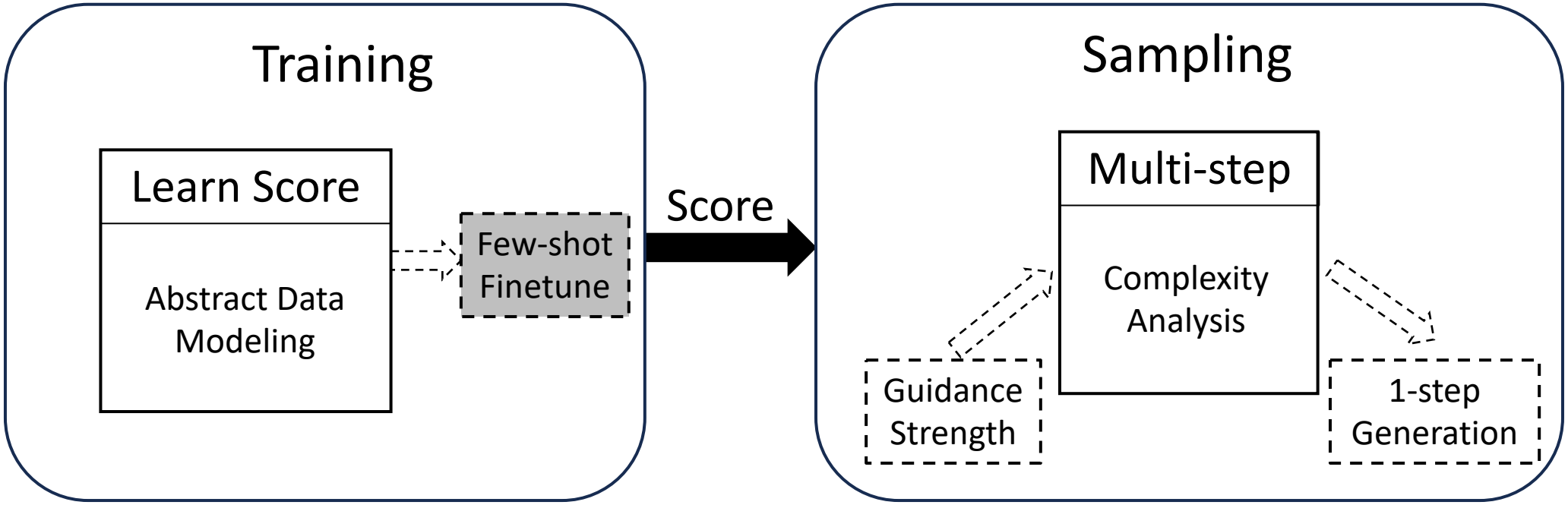
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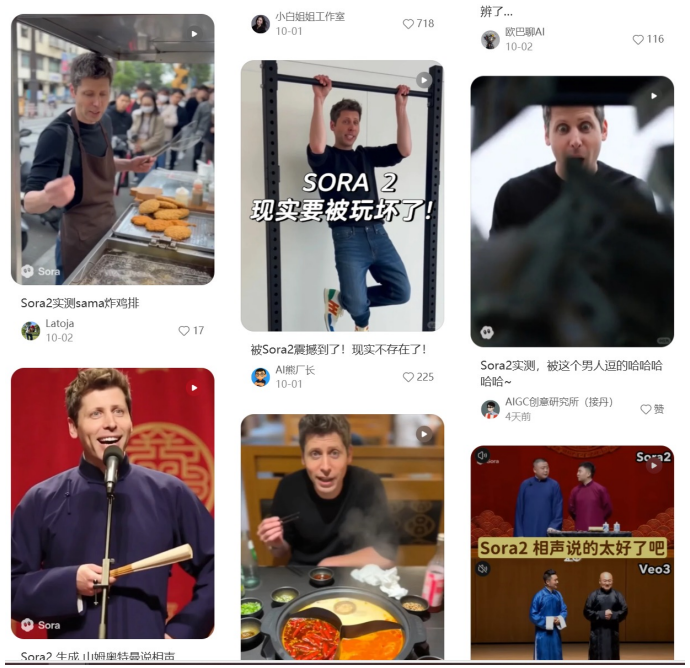
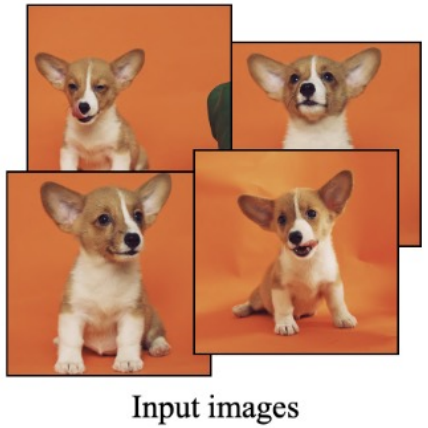




Few-shot Fine-tuning is key to the customized creation

but no theory supports effective information sharing

Few-shot Fine-tuning

- Pretrain w/ large source data (2.3 Billion): $\{X_{\mathrm{s},i}\}_{i=1}^{n_{\mathrm{s}}} \sim q_0^{\mathrm{s}}$ on $\mathbb{R}^D$
- $\min_{s \in \text{Source } \mathfrak{P}} \hat{\mathcal{L}}_{\mathrm{s}}(s) = \frac{1}{n_{\mathrm{s}}} \sum_{i=1}^{n_{\mathrm{s}}} \frac{1}{T-\delta} \int_{\delta}^{T} \mathbb{E}_{X_t|X_0=X_{s,i}} [\|\nabla \log q_t^{S}(X_t|X_0) - s(X_t,t)\|_2^2] \, dt$

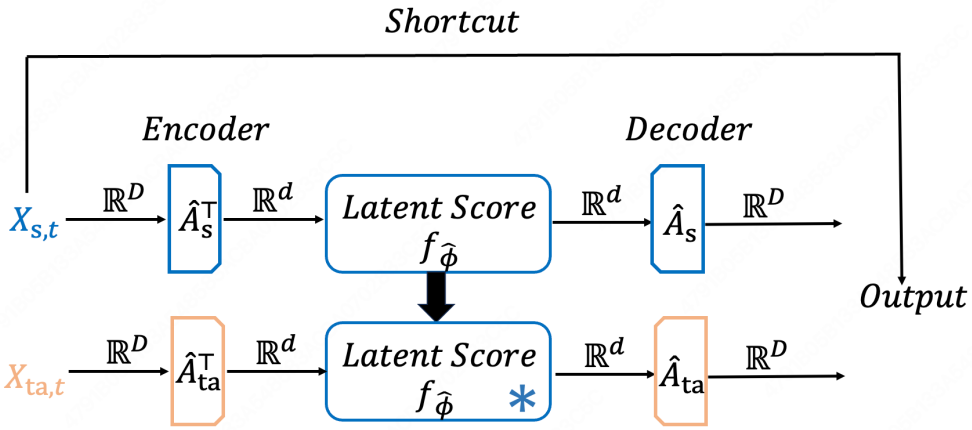
  e.g. 882M
- Estimation error $O(n_{\mathrm{s}}^{-\frac{2}{d}})$ — Tolerable!

- Fine-tune with limited target data (~10 images): $\{X_{\mathrm{ta},i}\}_{i=1}^{n_{\mathrm{ta}}} \sim q_0^{\mathrm{ta}}$
- $\min_{s \in \text{Target } \mathfrak{P}} \hat{\mathcal{L}}_{\mathrm{ta}}(s) = \frac{1}{n_{\mathrm{ta}}} \sum_{i=1}^{n_{\mathrm{ta}}} \frac{1}{T-\delta} \int_{\delta}^{T} \mathbb{E}_{X_t|X_0=X_{\mathrm{ta},i}} [\|\nabla \log q_t^{\mathrm{ta}}(X_t|X_0) - s(X_t,t)\|_2^2] \, dt$

  e.g. 1.5M 0.17%
- Estimation error $O(n_{\mathrm{ta}}^{-\frac{2}{d}})$ — Meaningless!

Information-sharing Model Design

- Empirical works share most parameters and fine-tune key parameters
- Assumption. Data admit linear structure $X_s = A_s z, X_{ta} = A_{ta} z, z \in \mathbb{R}^d$ and share latent space/score q_t^{Latent}

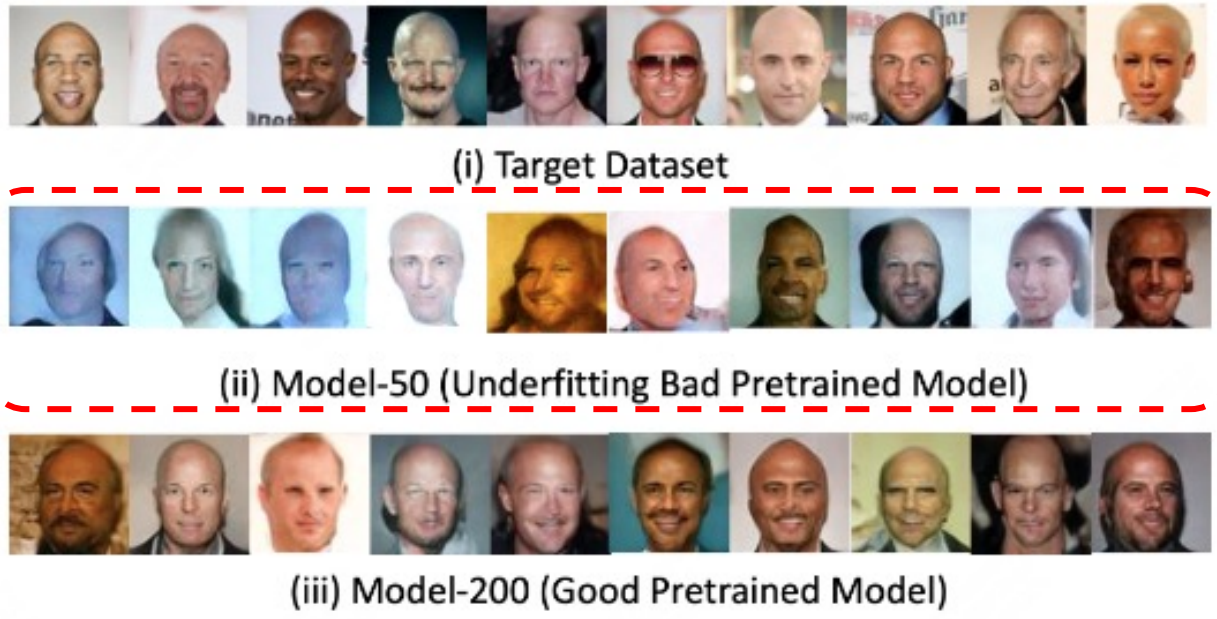


- Then the score function is

$$\nabla \log q_t^{\text{ta}}(X) = A_{\text{ta}} \nabla \log q_t^{\text{Latent}}\left(A_{\text{ta}}^\top X\right) - \frac{1}{\sigma_t^2}\left(I_D - A_{\text{ta}} A_{\text{ta}}^\top\right) X$$

Shared Latent Score

Bad Latent Leads to Large Estimation Error



Strange Generation!!

Large Gap!

- Theorem. W/ bad latent

$$\frac{1}{T-\delta}\int_{\delta}^{T} \mathbb{E}_{q_t^{\mathrm{ta}}}\left[\|\nabla \log q_t^{\mathrm{ta}}(X_t) - s_\theta(X_t, t)\|_2^2\right] dt \geq \mathrm{Const}$$

- YLJCL, Evaluating the Role of Great Pre-trained Diffusion Models in Few-shot Phase: Warm-up and Acceleration (ICLR 2026 DeLTa Workshop)

Bad Latent Suffers Bad Local Minima

Prompt cat but results in dog figure

Bad latent fails to fit target feature!

- Theorem. W/ bad latent, $\exists\ s_\theta^{\text{few-shot}} \neq s_{\theta^*}^{\text{few-shot}}$ s.t. $\frac{\partial s_\theta^{\text{few-shot}}}{\partial \theta} \approx 0$

Good Latent Secures Efficiency

- Theorem. The estimation error of few-shot diffusion model is

$$\frac{1}{T-\delta}\int_{\delta}^{T}\mathbb{E}_{q_t^{\mathrm{ta}}}\left[\left\|\nabla \log q_t^{\mathrm{ta}}(X_t)-s_{\hat{A}_{\mathrm{ta}},\hat{\phi}}(X_t,t)\right\|_2^2\right]dt \le O\left(n_{\mathrm{ta}}^{-\frac{1}{2}}+n_s^{-\frac{2}{d}}\right)$$

Guarantee good latent

- $O\left(n_{\mathrm{ta}}^{-\frac{1}{2}}\right)$ explains why $5-8$ images are enough for few-shot fine-tuning

Table 1: The requirement of n_{ta} in popular datasets. We use latent dimension in Pope et al. (2021).

Dataset	CIFAR-10	CIFAR-100	CelebA	MS-COCO	ImageNet
Dataset Size	6×10^4	6×10^4	2×10^5	3.3×10^5	1.2×10^6
Latent Dimension	25	22	24	37	43
The Requirement of n_{ta}	6	8	8	5	5

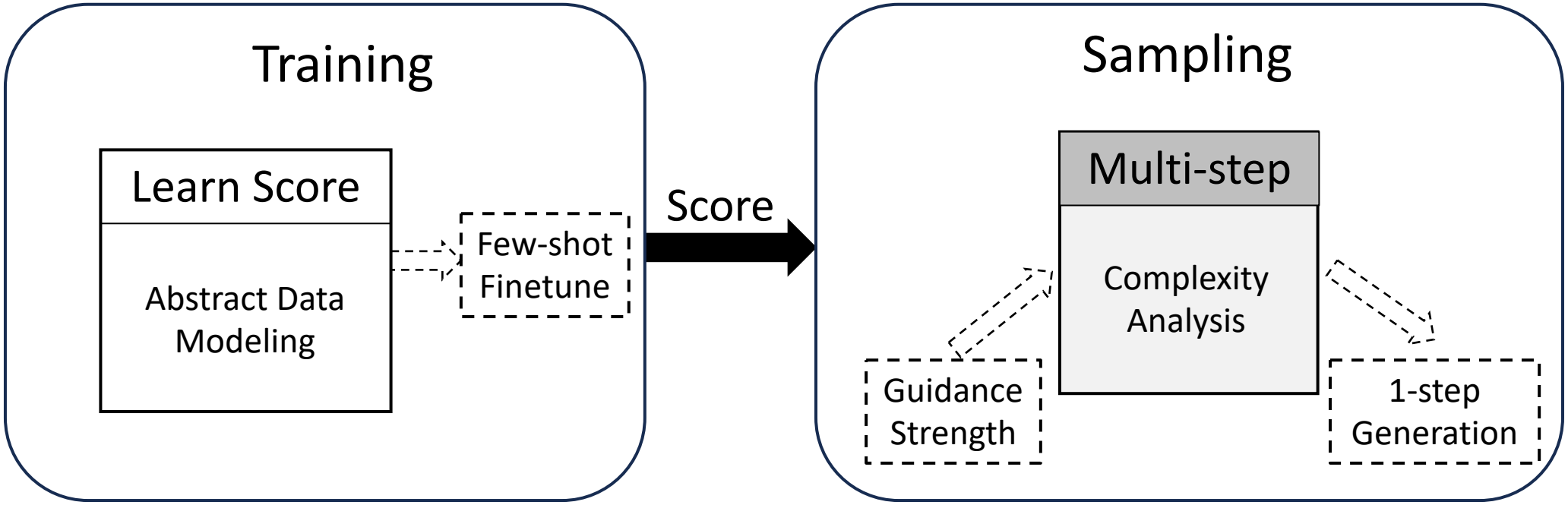
- YHCJWL, Few-shot diffusion models escape the curse of dimensionality. NeurIPS 2024.

Good Latent Leads to Good Landscape

- Theorem. With a good shared latent, the landscape of the few-shot optimization is κ-strongly convex w/ convergence rate

$$\left\| \hat{A}_{\text{ta}}^{(i)} \hat{A}_{\text{ta}}^{(i)\top} - A_{\text{ta}} A_{\text{ta}}^{\top} \right\|_F \leq \left(\frac{\kappa - 1}{\kappa + 1} \right)^i \|A_{\text{ta}}\|_F \left\| \hat{A}_{\text{ta}}^{(0)} - A_{\text{ta}} \right\|_F$$

Overview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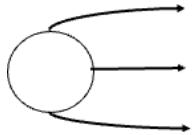
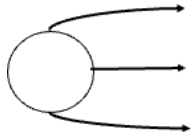
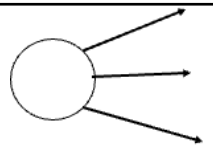
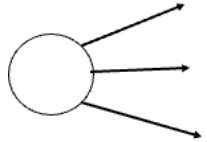
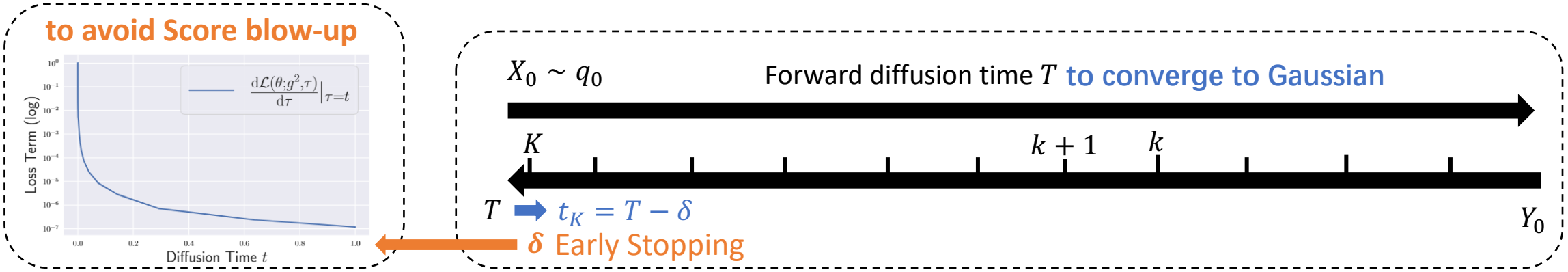
Common Forward Processes

$$dX_t = f(X_t, t)dt + g(t)dB_t \qquad T$$

		Trajectory	Forward Distribution	
Variance Preserving (VP) [1]	$f(X_t, t) = -\frac{1}{2}X_t$ $g(t) = 1$		$\mathcal{N}(0, I_D)$	stability.ai Midjourney
Variance Exploding (VE–SMLD) [2]	$f(X_t, t) = 0$ $g(t) = \sqrt{2}$		$\mathcal{N}(0, TI_D)$	Stanford University
Variance Exploding (VE–EDM) [3]	$f(X_t, t) = 0$ $g(t) = \sqrt{2t}$		$\mathcal{N}(0, T^2 I_D)$	
Rectified Flow (RF) [4]	$X_t = (1-t)X_0 + tZ$ $t \in [0,1]$		$\mathcal{N}(0, I_D)$	

[1] HJA, Denoising diffusion probabilistic models, NeurIPS 2020.
[2] SE, Generative modeling by estimating gradients of the data distribution, NeurIPS 2019.
[3] KAAL, Elucidating the Design Space of Diffusion-Based Generative Models, NeurIPS 2022.
[4] LG, Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow, ICLR 2023.

Sampling Complexity: Objective



- Objective:

  With accurate score $\|\nabla \log q_t(X) - s_\theta(X,t)\|_2^2 \leq \epsilon_{\text{score}}^2$

  Minimize sample complexity K s.t.

$$\mathrm{KL}\left(p_{t_K}, q_\delta\right) \leq \epsilon_{\mathrm{KL}}^2 \text{ and } W_2^2(q_0, q_\delta) \leq \epsilon_{W_2}^2$$

Sample Complexity: General Guarantee for Reverse SDE

- Theorem. Sample complexity can be divided by

Convergence of Forward Process

Discretization

$$\mathrm{KL}(p_{t_K}, q_\delta) \le \mathrm{KL}(\mathcal{N}(0, \sigma_T^2), q_T) + \sum_{k=0}^{K-1} \mathbb{E}_{q_{t_k}(x)} \mathrm{KL}\left(p_{t_{k+1}|t_k}(\cdot\,|x), q_{t_{k+1}|t_k}(\cdot\,|x)\right)$$

$$\le D^2 m_T / \sigma_T^2 + D^2 (T/\delta)^{\frac{1}{a}} / K \le \tilde{O}\left(\epsilon_{\mathrm{KL}}^2\right)$$

- Then the sample complexity requires $K = O(D^2 (T/\delta)^{\frac{1}{a}} / \epsilon_{\mathrm{KL}}^2)$ where δ satisfies

$$\mathrm{W}_2^2(q_0, q_\delta) \le \sigma_\delta^2 \le \epsilon_{W_2}^2$$

Sample Complexities

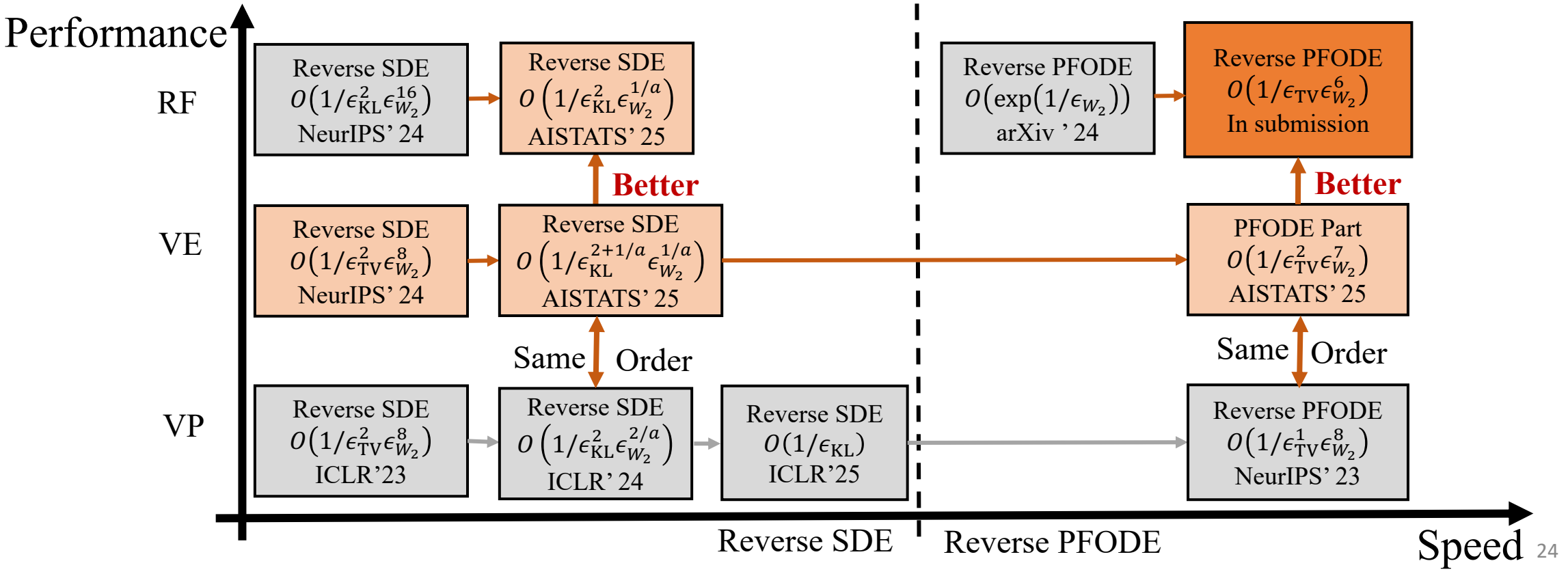
	m_T	σ_T^2	$\boldsymbol{T}$: $\mathrm{KL}(\mathcal{N}(0,\sigma_T^2), q_T) \le \frac{m_T}{\sigma_T^2} \le \epsilon_{\mathrm{KL}}^2$	σ_δ^2	$\boldsymbol{\delta}$: $\mathrm{W}_2^2(q_0, q_\delta) \le \sigma_\delta^2 \le \epsilon_{W_2}^2$	$\boldsymbol{K}$: $O(D^2(T/\delta)^{\frac{1}{a}}/\epsilon_{\mathrm{KL}}^2)$
VP	e^{-T}	$1-e^{-2T}$	$\log(1/\epsilon_{\mathrm{KL}})$✓	δ	$\epsilon_{W_2}^2$ ×	$O\left(D^2/\epsilon_{\mathrm{KL}}^2\epsilon_{W_2}^{2/a}\right)$
VE (SMLD)	1	T	$1/\epsilon_{\mathrm{KL}}^2$ ×	δ	$\epsilon_{W_2}^2$ ×	$O\left(D^2/\epsilon_{\mathrm{KL}}^{2+2/a}\epsilon_{W_2}^{2/a}\right)$
VE (EDM)	1	T^2	$1/\epsilon_{\mathrm{KL}}$ ×	δ^2	ϵ_{W_2} ✓	$O\left(D^2/\epsilon_{\mathrm{KL}}^{2+1/a}\epsilon_{W_2}^{1/a}\right)$
RF	1	1	1✓	δ^2	ϵ_{W_2} ✓	$O\left(D^2/\epsilon_{\mathrm{KL}}^2\epsilon_{W_2}^{1/a}\right)$

- VP better in T and VE (EDM) better in δ
- RF better in both T and δ and thus has a better complexity

Results Extend to PRODE

[1] YWJL, Leveraging drift to improve sample complexity of variance exploding diffusion models. NeurIPS 2024.
[2] YJL, The Polynomial Iteration Complexity for Variance Exploding Diffusion Models: Elucidating SDE and ODE Samplers. AISTATS 2025.
[3] YZJCL, Elucidating Rectified Flow with Deterministic Sampler: Polynomial Discretization Complexity for Multi and One-step Models. Arxiv.

- Reverse SDE generate diverse samples while PFODE generate fast



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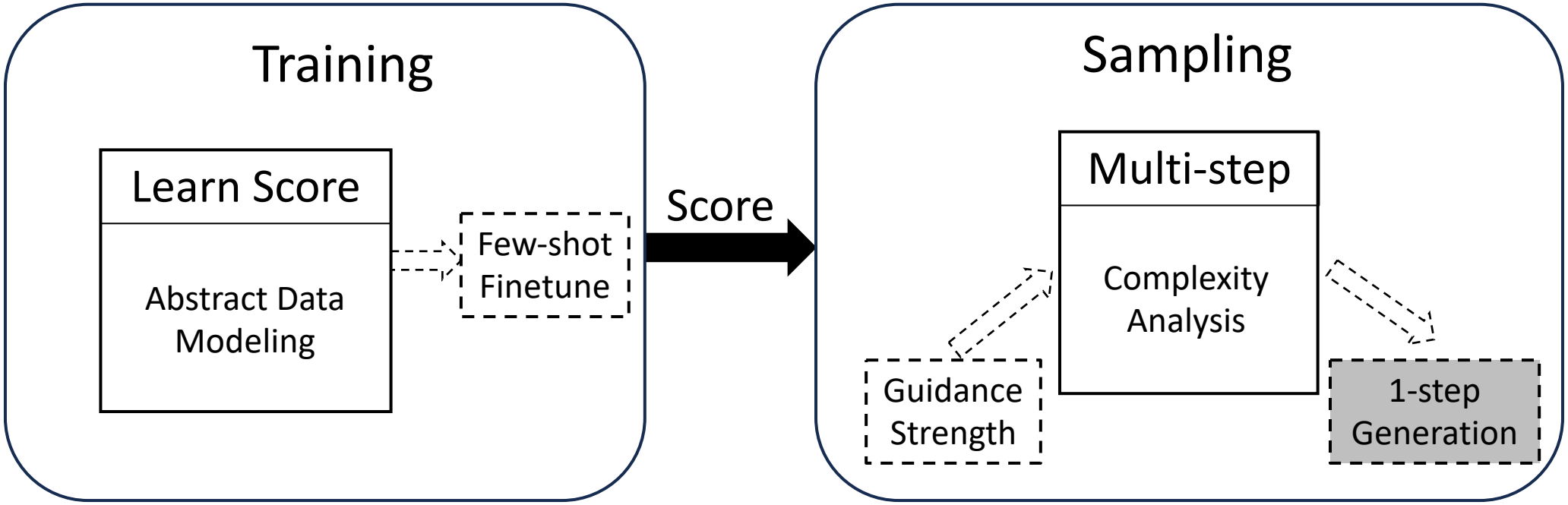
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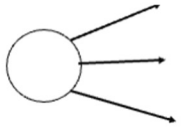
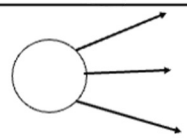
Linear Trajectory & PFODE Achieve 1-step Generation

- PFODE generate deterministically compared to reverse SDE

- VE-EDM and RF have linear trajectory

Variance Exploding (VE–EDM) [3]	$f(X_t, t) = 0$ $g(t) = \sqrt{2t}$	
Rectified Flow (RF) [4]	$X_t = (1-t)X_0 + tZ$ $t \in [0,1]$	

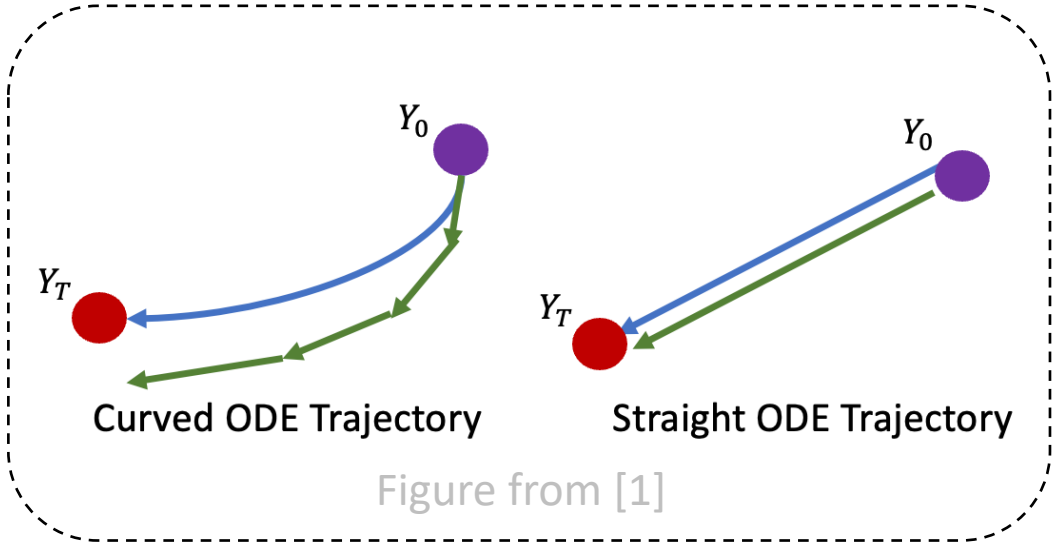


Figure from [1]

[1] LZMPL, InstaFlow: One Step is Enough for High-Quality Diffusion-Based Text-to-Image Generation, ICLR 2024.

1-Step Mapping Function from Multi-step

- For PFODE reverse process of multi-step diffusion models

$$\mathrm{d}Y_t = v(Y_t, t)\mathrm{d}t, Y_0 \sim q_T$$

the corresponding 1-step mapping function (by integral) is

$$f(Y_t, t) = Y_{T-\delta} = X_\delta \approx X_0, \forall t \in [0, T-\delta]$$

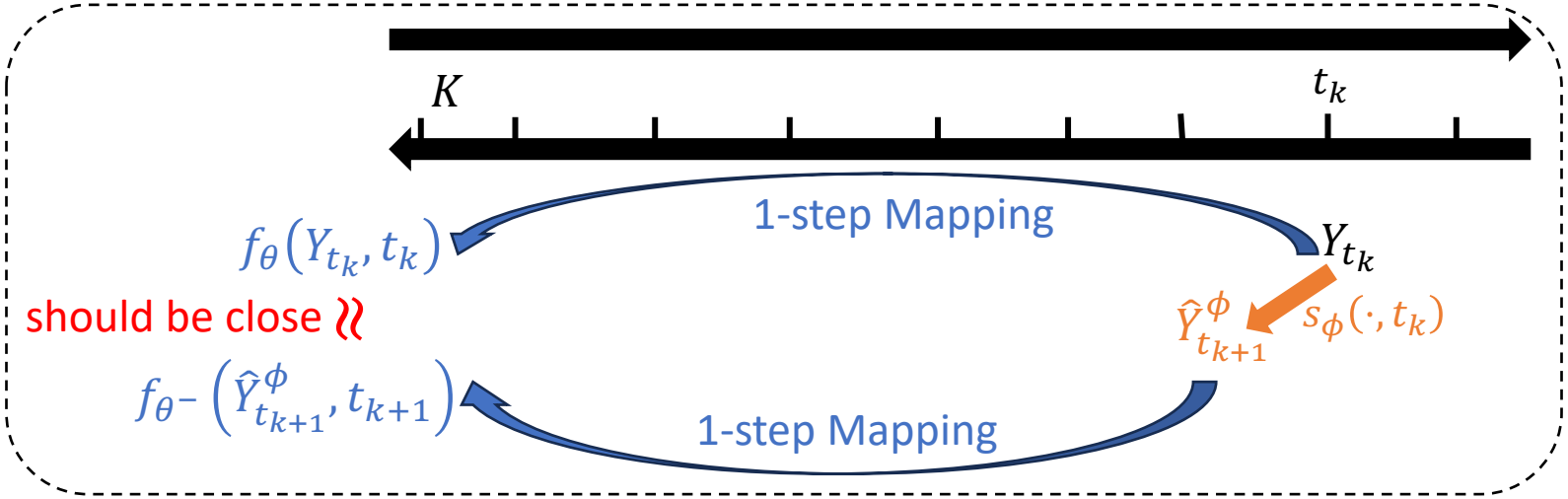
to avoid Score blow-up

- Use NN $f_\theta(Y_t, t)$ to approximate 1-step mapping function f

What is a Good Optimization Objective?

- Consistency distillation to learn good 1-step mapping [1]

$$\mathcal{L}_{\mathrm{CD}}^{K}(\boldsymbol{\theta}, \boldsymbol{\theta}^{-}; \boldsymbol{\phi}) := \mathbb{E}_{X_0}\left[\mathbb{E}_{Y_{t_k}|X_0}\left\|\boldsymbol{f}_{\boldsymbol{\theta}}(Y_{t_k}, t_k) - \boldsymbol{f}_{\boldsymbol{\theta}^{-}}\left(\hat{Y}^{\phi}_{t_{k+1}}, t_{k+1}\right)\right\|_2^2\right]$$



- Minimize K s.t. $W_2^2(f_\theta(\mathcal{N}(0, \sigma_T^2 I_d), 0; K), q_0) \leq \epsilon_{W_2}^2$

[1] SDCS, Consistency Models, ICML 2023.

Similar Balance

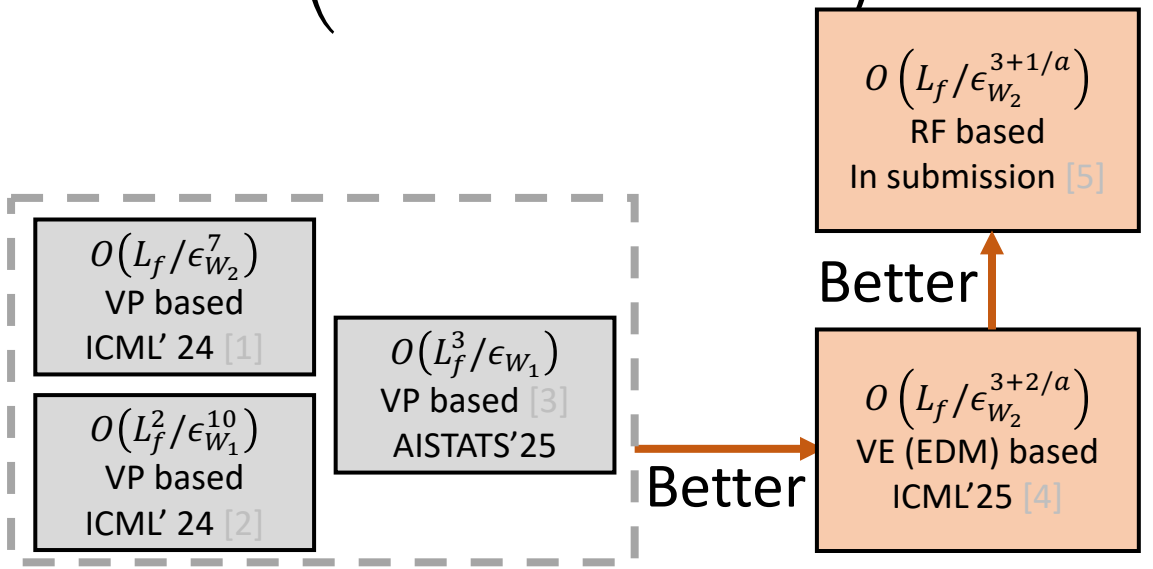
[1] LCF, Sampling is as easy as keeping the consistency: convergence guarantee for consistency models , ICML 2024
[2] DCWY, Theory of consistency diffusion models: Distribution estimation meets fast sampling, ICML 2024
[3] LHW, Towards a mathematical theory for consistency training in diffusion models, AISTATS 2025
[4] YJVL, Improved Discretization Complexity Analysis of Consistency Models: Variance Exploding Forward Process and Decay Discretization Scheme, ICML 2025
[5] YZJCL, Elucidating Rectified Flow with Deterministic Sampler: Polynomial Discretization Complexity for Multi and One-step Models, Arxiv.

- Theorem. For 1-step generation models,

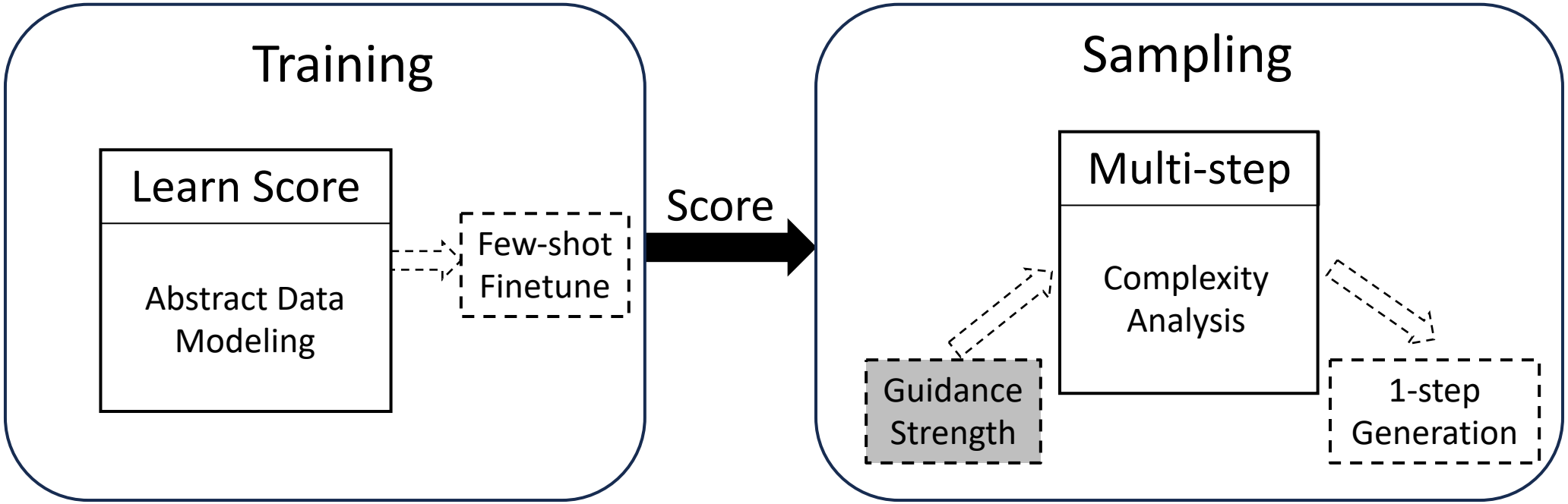
$$W_2^2\left(f_\theta\left(\mathcal{N}(0,\sigma_T^2 I_d), T-\delta\right), q_0\right) \le \frac{m_T}{\sigma_T^2} + \frac{L_f^2 (T/\delta)^{\frac{2}{a}}}{K^2\delta^4} + \sigma_\delta^2 \le \epsilon_{W_2}^2$$

- Then it requires discretization complexity $K = O\left(L_f (T/\delta)^{\frac{1}{a}} / \left(\delta^2 \epsilon_{W_2}\right)\right)$

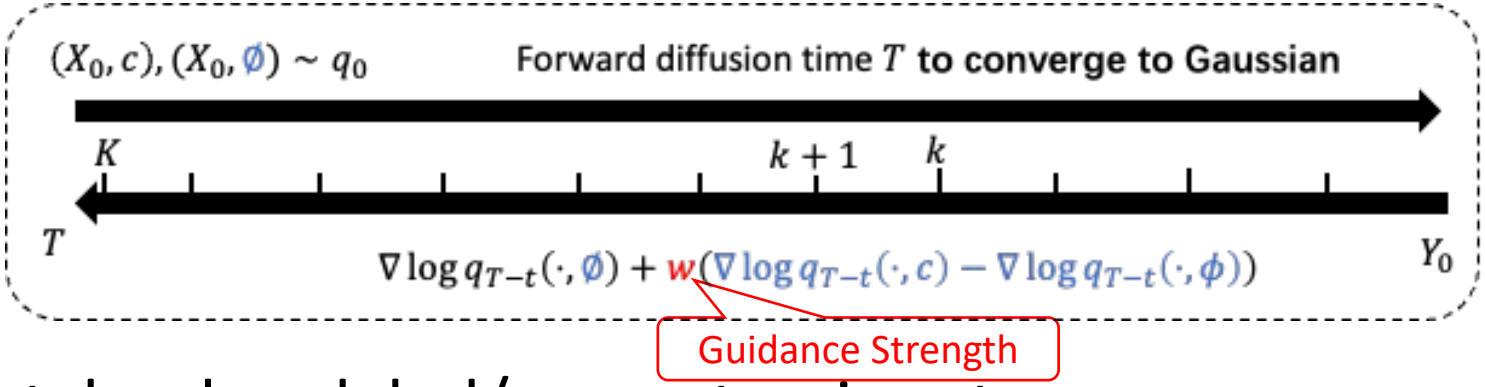
	T: $\frac{m_T}{\sigma_T^2} \le \epsilon_{W_2}^2$	δ: $\sigma_\delta^2 \le \epsilon_{W_2}^2$	K: $O(L_f(T/\delta)^{\frac{1}{a}}/(\delta^2\epsilon_{W_2}))$
VP	$\log(1/\epsilon_{W_2})$√	$\epsilon_{W_2}^2$ ×	$O\left(L_f/\epsilon_{W_2}^{5+2/a}\right)$
VE (EDM)	$1/\epsilon_{W_2}$ ×	ϵ_{W_2} √	$O\left(L_f/\epsilon_{W_2}^{3+2/a}\right)$
RF	1√	ϵ_{W_2} √	$O\left(L_f/\epsilon_{W_2}^{3+1/a}\right)$



Overview

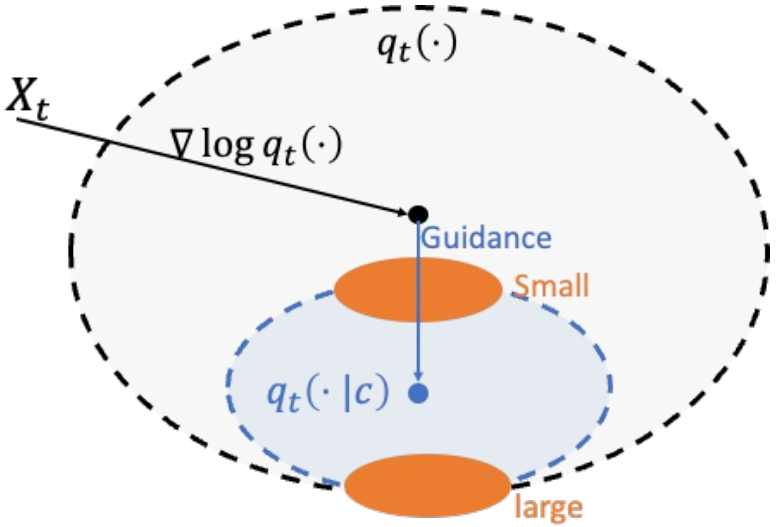

Training
Learn Score
Abstract Data Modeling
Few-shot Finetune
Score
Sampling
Multi-step
Complexity Analysis
Guidance Strength
1-step Generation

Guidance



- Generation tasks usually take class-label/prompt as input
- Learn $\nabla \log q_t(\cdot\,|c)$ directly mainly apply to discrete/independent c
- For continuous c, $\nabla \log q_t(\cdot\,|c) = \nabla \log q_t(\cdot) + \nabla \log q_t(c|\,\cdot)$
- Use $\nabla \log q_t(\cdot, \emptyset) + w(\nabla \log q_t(\cdot, c) - \nabla \log q_t(\cdot, \emptyset))$ as guided score

Classfier-free Guidance (CFG)



- Small guidance ⟶ Bad alignment
- Large guidance ⟶ OOD & Modal Collapse

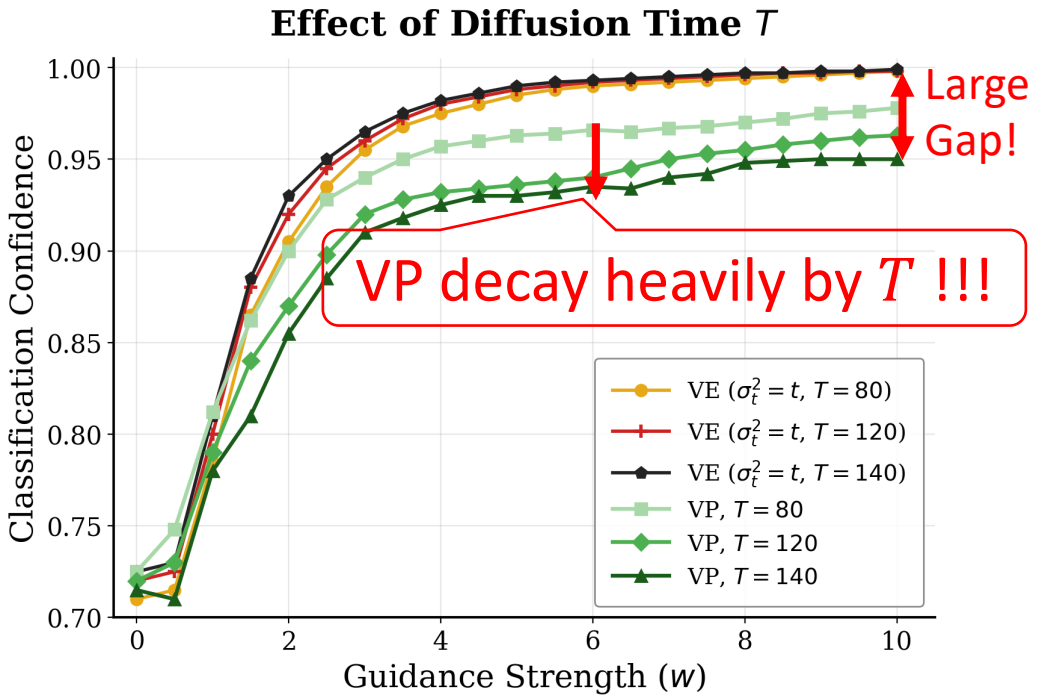
What is the influence of guidance strength?

Measurement: Classficiation Confidence

- $\mathbb{P}(c|X)$ is the classification confidence
- Ideally $\mathbb{P}(c|X) = 1$ if X belongs to class c

- Compare VP vs VE w/ 3GMM
- Assume accurate score function
- VP is much worse than VE

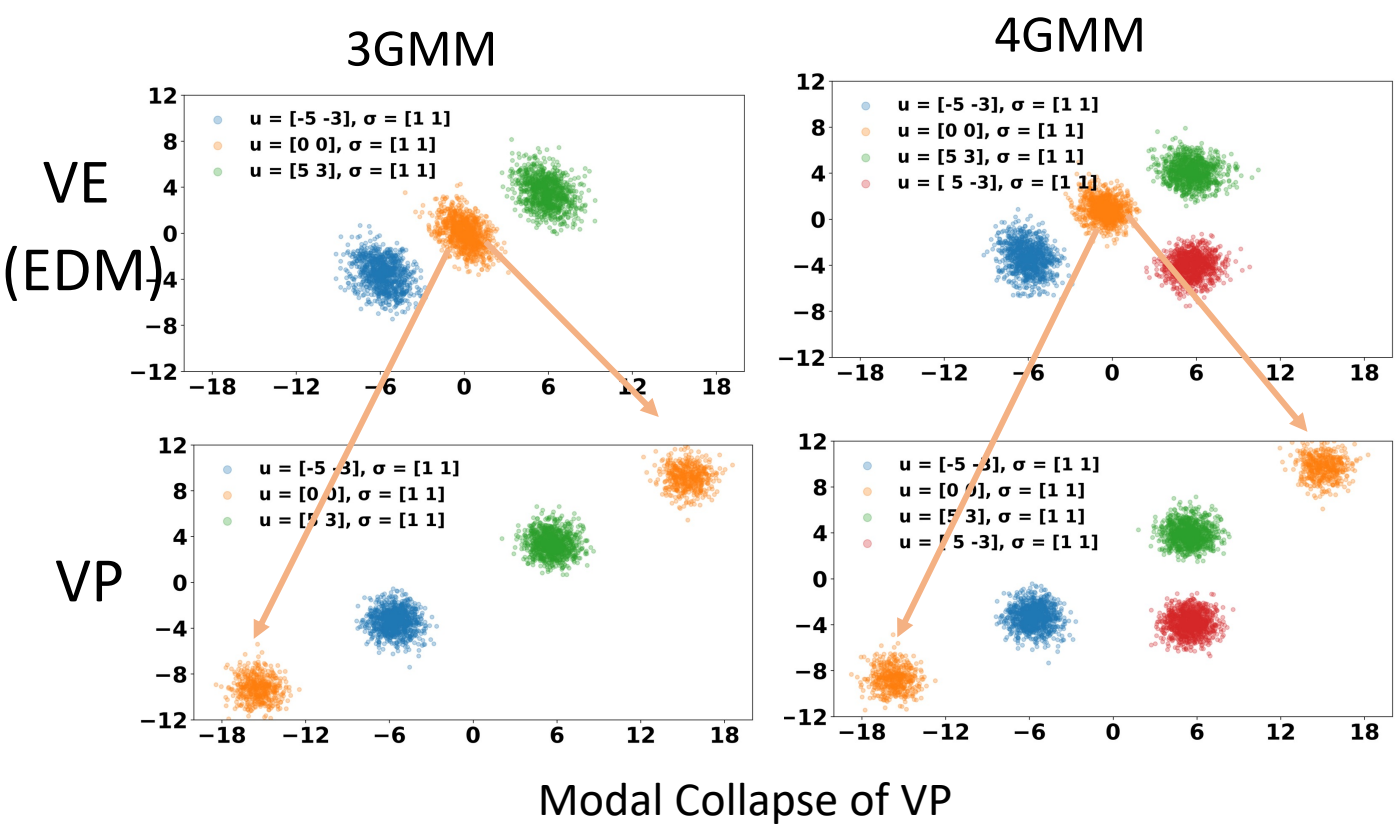
Forward Process	Classification Confidence
VP	$1 - \eta^{-e^{-T}}(\log \eta)^2$
VE-EDM	$1 - \eta^{-1}(\log \eta)^2$



[1] WCLWW, Theoretical insights for diffusion guidance: A case study for Gaussian mixture models, ICML 2024

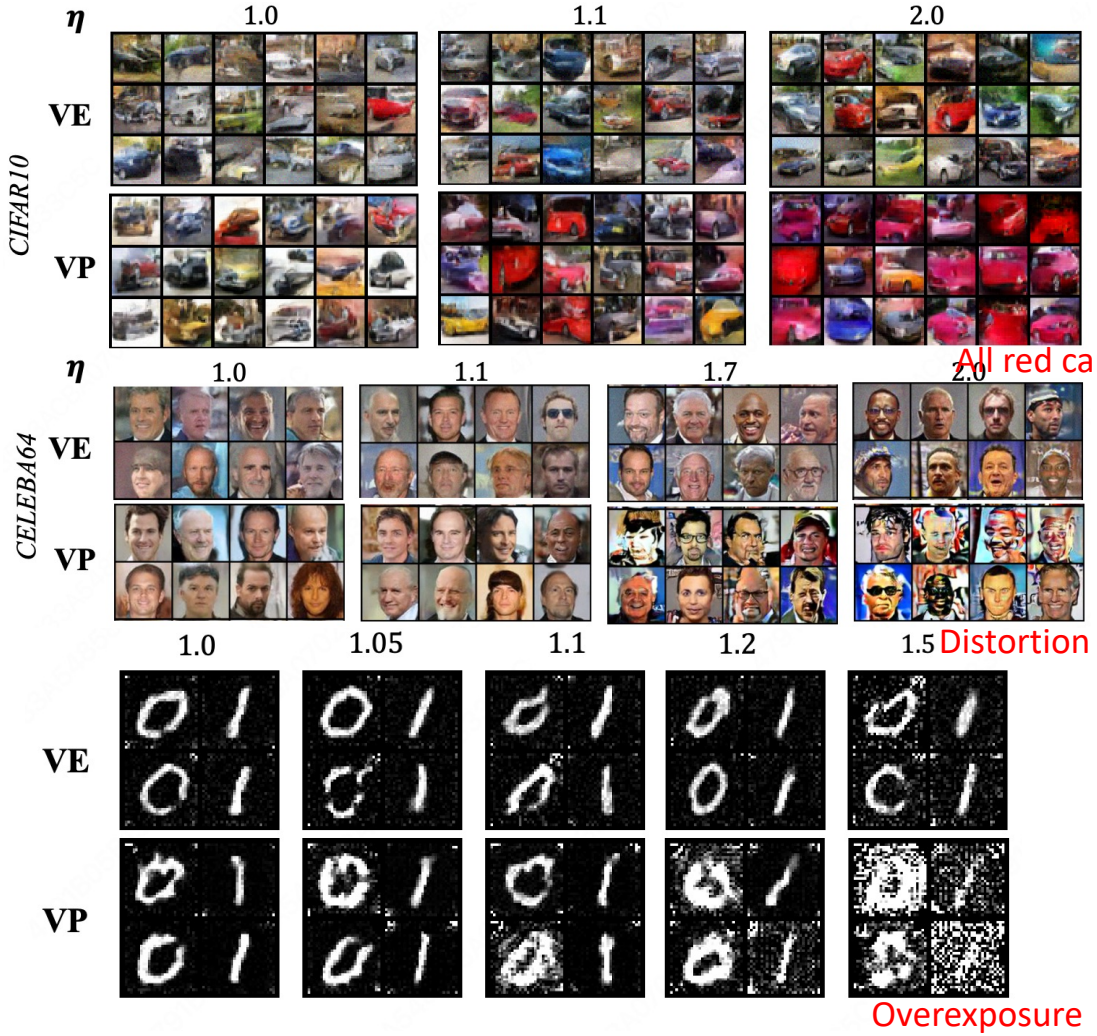
[2] YCJCL, Elucidating Guidance in Variance Exploding Diffusion Models: Fast Convergence and Better Diversity (ICLR 2026 DeLTa Workshop)

Diversity/Modal Collapse of VP w/ large guidance



Modal Collapse of VP

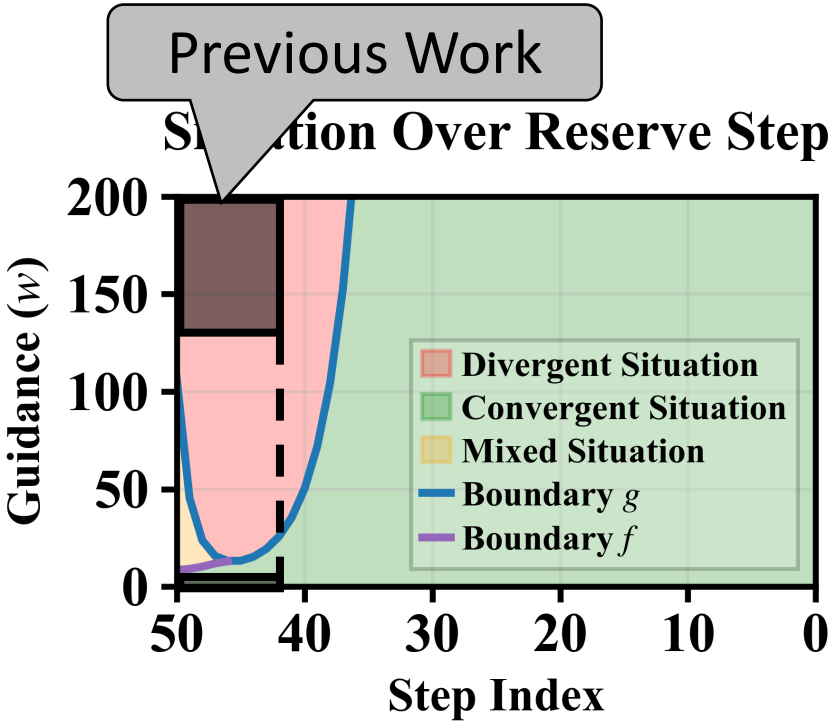
What happens?



Full Guidance Characterization of VP for GMM

- 3GMM and target central 0 mode

- 3-situation full characterization:
  - Convergent situation: Closer to center 0
  - Divergent situation: Farther from center 0
  - Mixed: Could be both

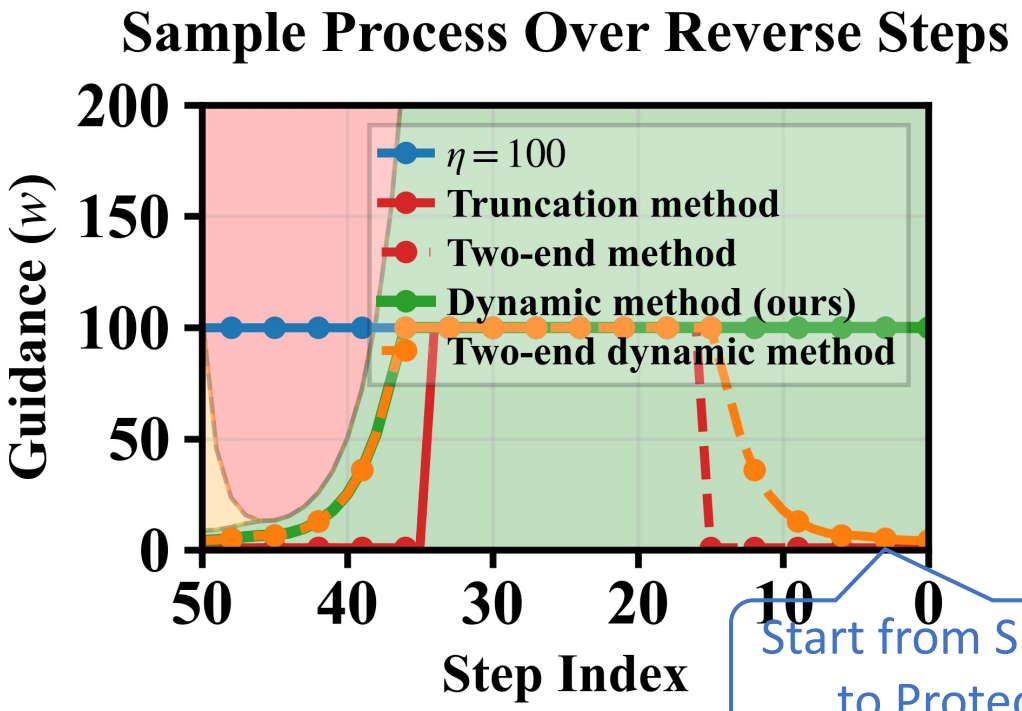


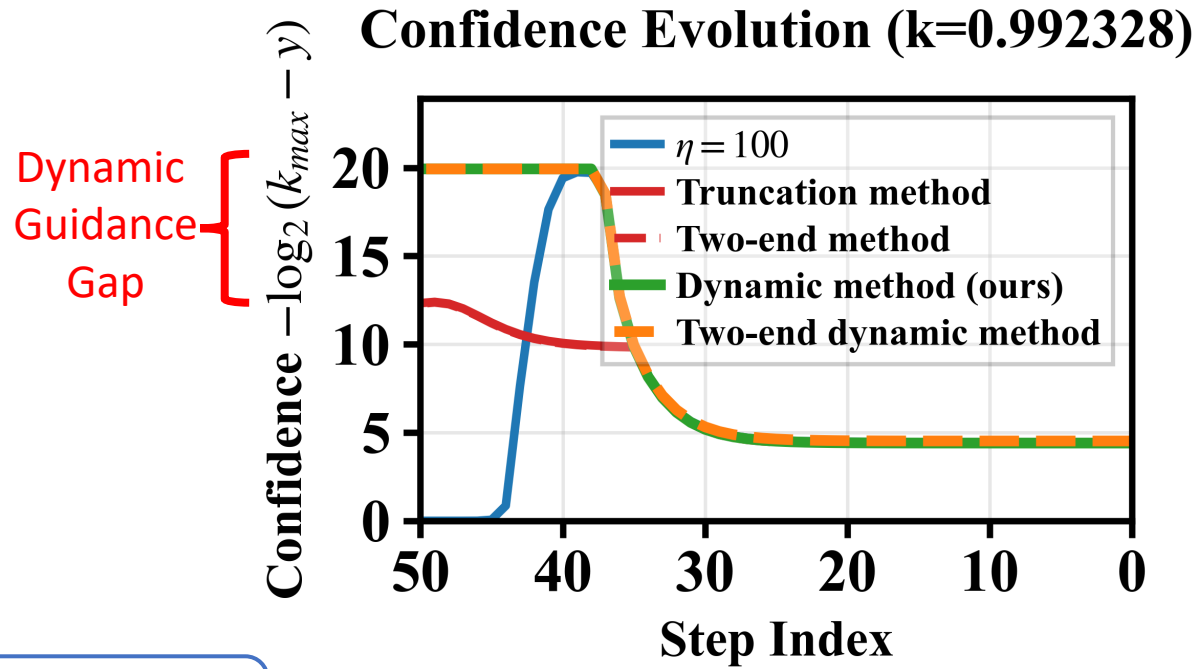
[1] WCLWW, Theoretical insights for diffusion guidance: A case study for Gaussian mixture models, ICML 2024

[2] CYJCL, Three-Phase Dynamics of Classifier-Free Guidance: Rigorous Analysis and Design Principle via Gaussian Mixture Models (In submission)

Schedule of Guidance Strength

- Safe-region guidance leads to high classification confidence
- Dynamic/larger guidance better than truncation method





Start from Small Guidance to Protect Diversity

- CYJCL, Three-Phase Dynamics of Classifier-Free Guidance: Rigorous Analysis and Design Principle via Gaussian Mixture Models (In submission)

Conclusions

- Pretraining: Efficient Multi-manifold MoG Model
  - Empirical: Much less parameters with good enough performance
  - Theoretical: Estimation error escape the curse of dimensionality
- Fine-tuning: Good Sharing Latent Guarantees Few-shot Efficiency
  - Model the sharing scheme between pretraining and few-shot fine-tuning
- Sampling: Complexity for Multi-step Diffusion Models
  - Unified framework for sampling complexities of VP, VE, RF models
  - Guidance: VE has faster convergence and better diversity compared to VP
- Discretization: Complexity of 1-step Models in Training Phase
  - Support good performances of RF models

Future Work – Continuous Diffusion 1

- Pretraining Phase
  - SOTA Results with Multi-manifold MoG Modeling and Fewer Parameters
  - Global Optimization Guarantee and Generalization Mechanism
- Few-shot Fine-tuning Phase
  - Multi-task Meta-learning and Few-shot Fine-tuning Framework and Analysis
- Post-Training Phase
  - Efficient Post-Training GRPO Algorithm with Theoretical Guarantee for Image/Video/3D Generation
- Learning Process of 1-Step Generative Models
  - With the simplified MoG latent of Multi Subspace MoG modeling, better training and SOTA Results

Future Work – Continuous Diffusion 2

- Conditional Sampling
  - Property Analysis for the RF-based Method
  - Dynamic Guidance Schedule for Conditional Generation with Text and Data Information
- Learning Process of 1-Step Generative Models
  - With the simplified MoG latent of Multi Subspace MoG modeling, better training and SOTA Results

Future Work – Discrete Diffusion/dLLM

- Pretraining Phase
  - Pretraining with Text Data Structure (such as Chain MRF, Tree Structure)
  - Estimation Error with Data Structure to Escape the Curse of Dimensionality
  - Analysis for Fundamental Difference between continuous and discrete dLLM
- dLLM Agent: Parallel Decoding Mechanism Leads to Higher Efficient but Less Stable Tool Call
  - AR Distill SFT
  - Tree Based Step-by-Step GPRO Post Training Algorithm

Thanks!

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Questions?