Direct Discriminative Optimization

Your Likelihood-Based Visual Generative Model is Secretly a GAN Discriminator

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ICML 2025 Spotlight

Issue of Maximum Likelihood Estimation

Diffusion Probabilistic Models (DPMs) and Autoregressive Models (ARs) based on **Maximum Likelihood Estimation (MLE)** have achieved dominance in both continuous and discrete data generation. Its

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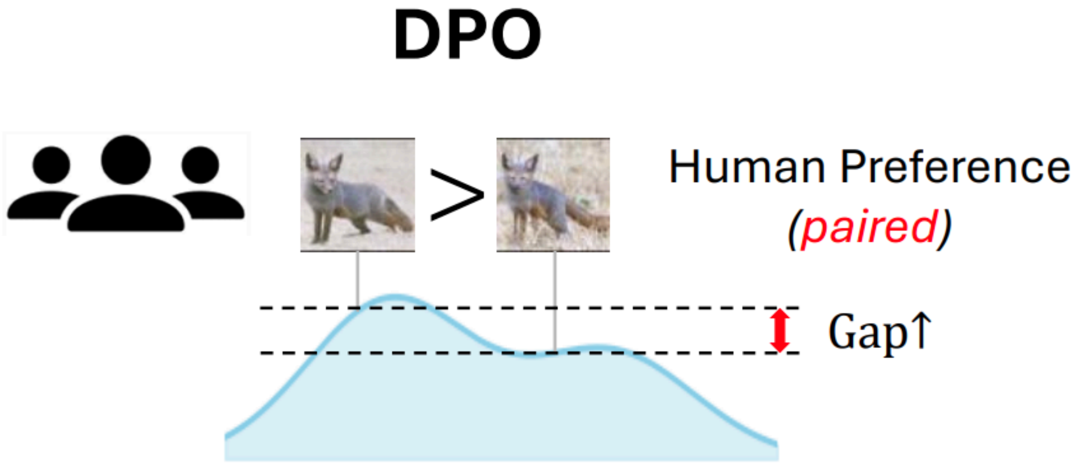
In order to solve this problem, introducing the adversarial loss of GANs is one of the solutions, but

- GANs need to construct additional discriminators for alternating optimization, which increases engineering complexity.
- The iterative sampling of DPMs and ARs makes it difficult to easily optimize through GANs.

Direct Preference Optimization (DPO)



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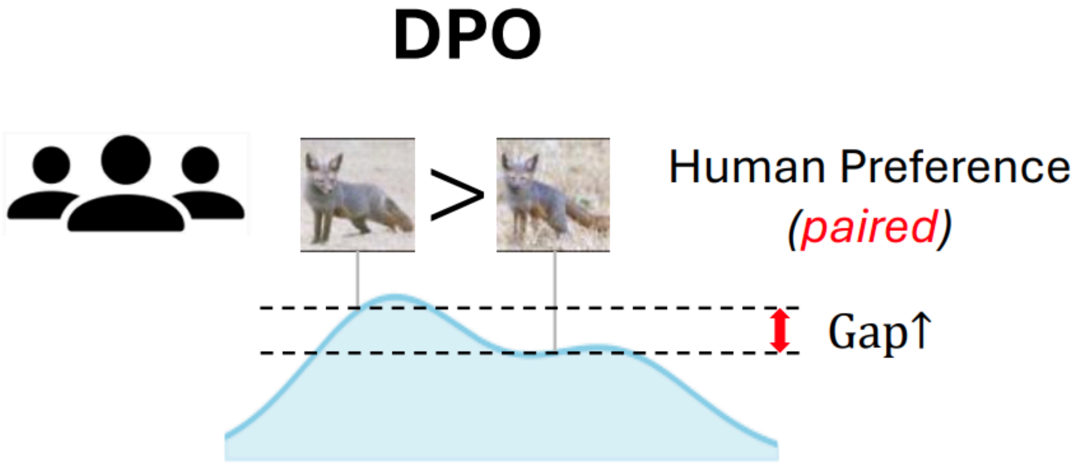

- Paired Data

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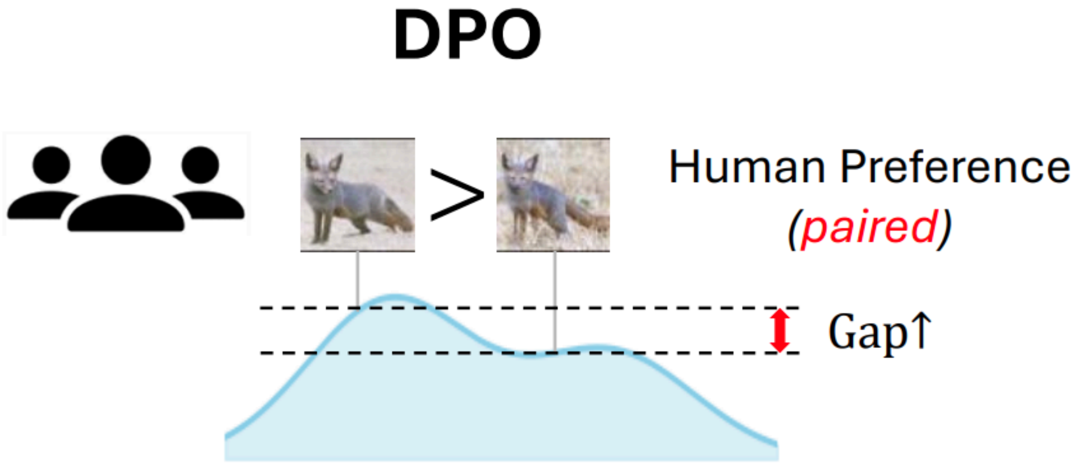

- Paired Data
- Human-Annotated

preferred/non-preferred

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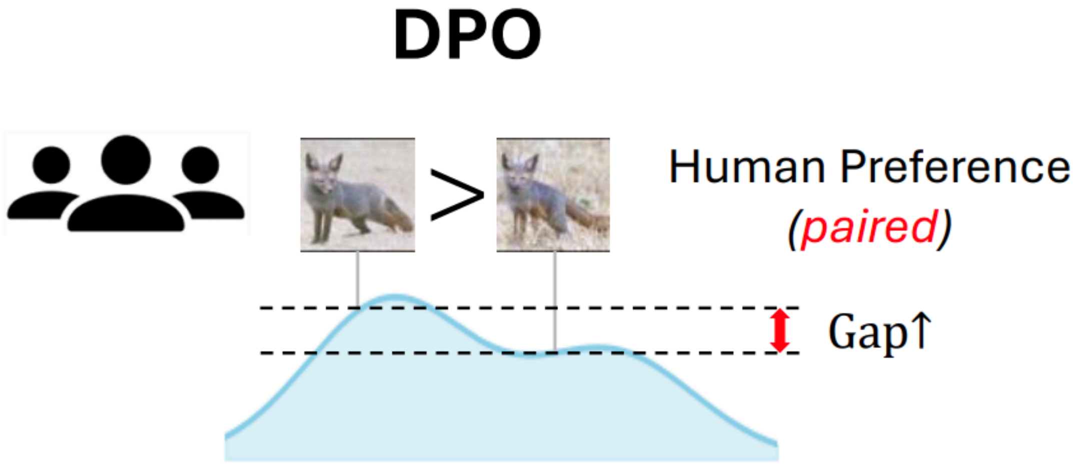

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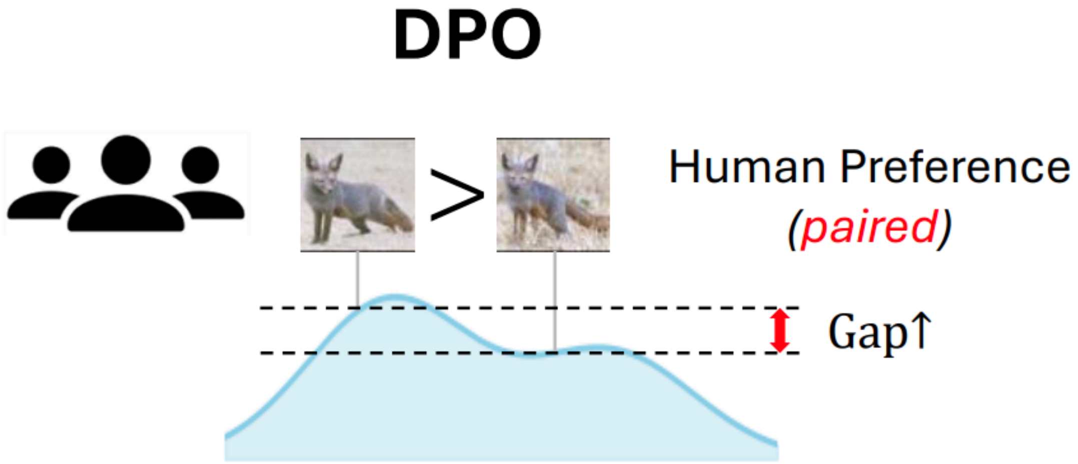

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Optimizing the reward function

$$p(y_w \succ y_l|x) := \frac{e^{r(x,y_w)}}{e^{r(x,y_l)} + e^{r(x,y_w)}} = \sigma(r(x,y_w) - r(x,y_l))$$

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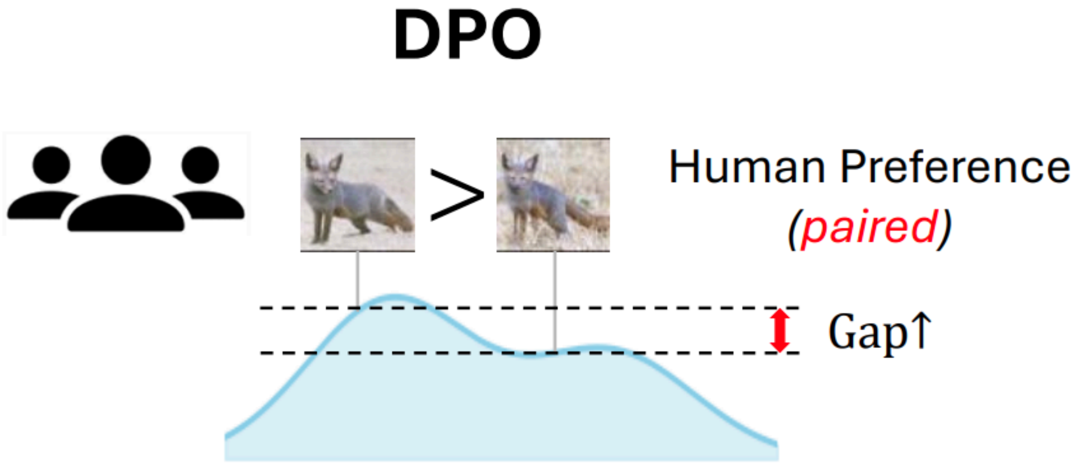

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Your Likelihood-Based Generative Model is Secretly a Discriminator

$$\mathcal{L}^{\text{DPO}}(\theta) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}} \log\sigma\left(\beta\log\frac{\pi_\theta(y_w|x)}{\pi_{\theta_{\text{ref}}}(y_w|x)} - \beta\log\frac{\pi_\theta(y_l|x)}{\pi_{\theta_{\text{ref}}}(y_l|x)}\right)$$

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Direct Preference Optimization

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Direct Preference Optimization	>>	**Direct Discriminative Optimization**
▪ Paired Data		▪ Real Data / Generated Data
▪ Preferred / Non-preferred		▪ Truth / Fake

Direct Discriminative Optimization

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Practical Implementation

Generalized Objective with Extra Coeffecients

To address gradient vanishing and numerical precision issues.

$$\begin{aligned}\mathcal{L}_{\alpha,\beta}(\theta) = &-\mathbb{E}_{p_{\mathrm{data}}(\mathrm{x})}\left[\log\sigma\left(\beta\log\frac{p_\theta(\mathrm{x})}{p_{\theta_{\mathrm{ref}}}(\mathrm{x})}\right)\right]\\ &-\alpha\mathbb{E}_{p_{\theta_{\mathrm{ref}}(\mathrm{x})}}\left[\log\left(1-\sigma\left(\beta\log\frac{p_\theta(\mathrm{x})}{p_{\theta_{\mathrm{ref}}}(\mathrm{x})}\right)\right)\right],\ \alpha\in[0.5,50]\text{ and }\beta\in[0.01,0.1]\end{aligned}$$

Direct Discriminative Optimization

Practical Implementation

Handling Compute-Intensive Likelihood

$$\log \frac{p_\theta(\mathbf{x})}{p_{\theta_{\text{ref}}}(\mathbf{x})} \approx \mathbb{E}_{t,\epsilon}\left[\Delta_{\mathbf{x}_t,t,\epsilon}\right]$$

where $\mathbf{x}_t = \alpha_t \mathbf{x} + \sigma_t \epsilon,\ \ \epsilon \sim \mathcal{N}(0, I)$ and
$\Delta_{\mathbf{x}_t,t,\epsilon} = -w(t)\left(\|\epsilon_\theta(\mathbf{x}_t, t) - \epsilon\|_2^2 - \|\epsilon_{\theta_{\text{ref}}}(\mathbf{x}_t, t) - \epsilon\|_2^2\right)$

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Apply Jensen's inequalit: $\psi(\mathbb{E}[X]) \leq \mathbb{E}[\psi(X)]$, if ψ is a convex function e.g. $-\log \sigma(\cdot)$.

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$$\begin{aligned}
&\mathcal{L}(\theta) \\
&\approx -\mathbb{E}_{p_{\mathrm{data}}(\mathrm{x})} \log \sigma\left(\mathbb{E}_{t,\epsilon}[\Delta]\right) - \mathbb{E}_{p_{\theta\mathrm{ref}}(\mathrm{x})} \log\left(1 - \sigma\left(\mathbb{E}_{t,\epsilon}[\Delta]\right)\right) \\
&\le \underbrace{-\mathbb{E}_{t,\epsilon}\left[\mathbb{E}_{p_{\mathrm{data}}(\mathrm{x})} \log \sigma(\Delta) + \mathbb{E}_{p_{\theta_{\mathrm{ref}}}(\mathrm{x})} \log(1 - \sigma(\Delta))\right]}_{\text{upper bound}}
\end{aligned}$$

Direct Discriminative Optimization

Amazing Feature: Multi-Round Refinement via Self-Play

$$\text{Round } n: \quad \ldots \quad \rightarrow \quad \underbrace{p_{\theta^*_{n-1}}}_{\text{Reference}} \quad \rightarrow \quad \underbrace{\sigma\left(\beta \log \frac{p_{\theta_n}}{p_{\theta^*_{n-1}}}\right)}_{\text{Discriminator}}$$

$$\text{Round } n+1: \quad \rightarrow \quad \underbrace{p_{\theta^*_{n}}}_{\text{Reference}} \quad \rightarrow \quad \ldots$$

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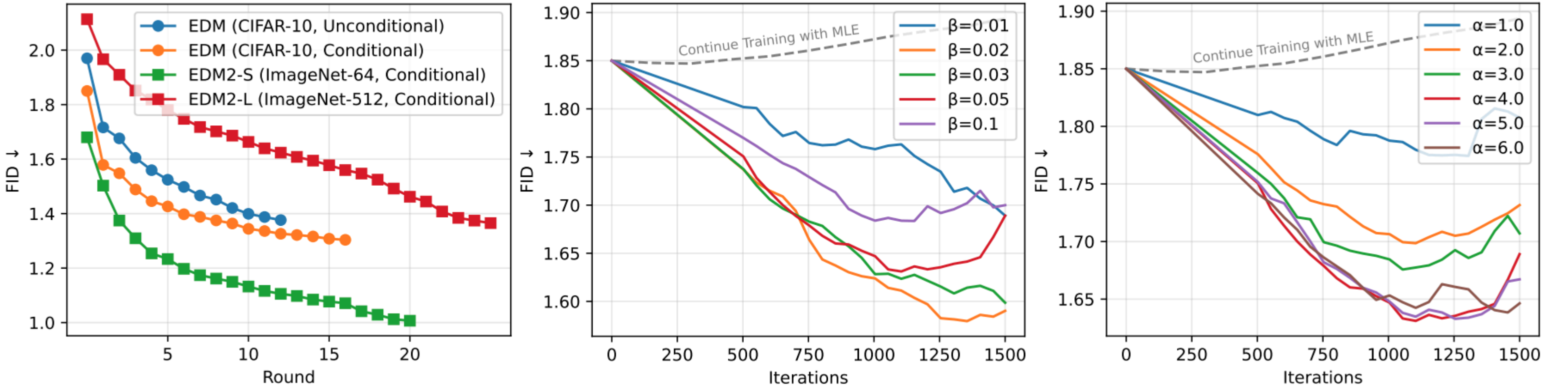


(a) FID-Round

(b) $\alpha = 4.0$

(c) $\beta = 0.05$

Experiment

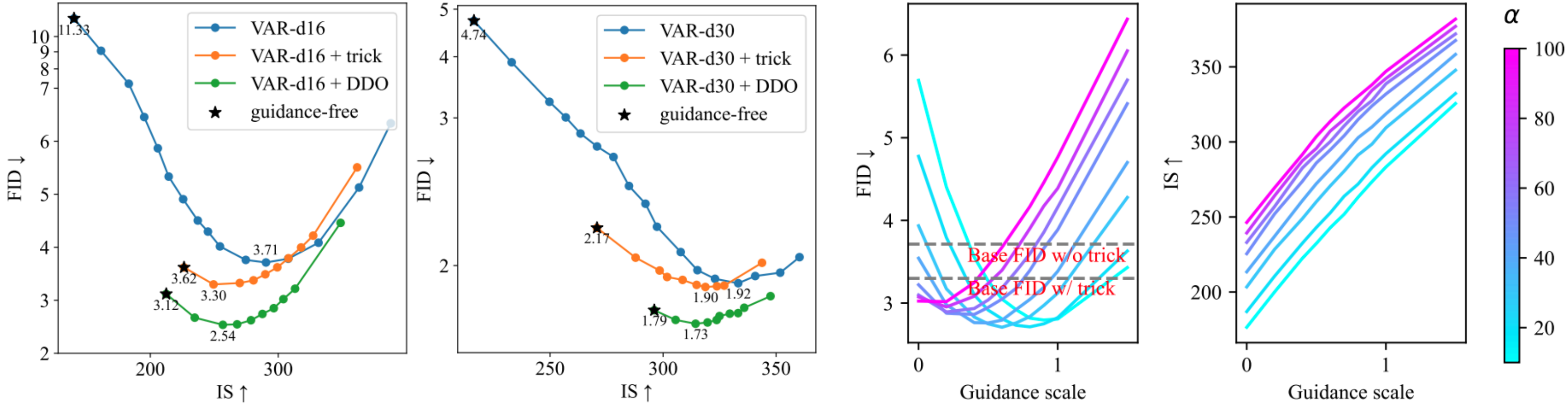
ImageNet 64x64

Type	Model	#Params	NFE	FID↓
GAN	StyleGAN-XL (Sauer et al., 2022)	135M	1	1.51
	R3GAN (Huang et al., 2025)	104M	1	2.09
	CTM (Kim et al., 2023b)	324M	1	1.92
	DMD2 (Yin et al., 2024)	296M	1	1.28
	PaGoDA (Kim et al., 2024)	296M	1	1.21
	SiD^{2}A (Zhou et al., 2024b)	296M	1	1.11
Diffusion	iDDPM (Nichol & Dhariwal, 2021)	270M	250	2.92
	ADM (Dhariwal & Nichol, 2021)	296M	250	2.07
	RIN (Jabri et al., 2022)	281M	1000	1.23
	EDM (Karras et al., 2022)	296M	511	1.36
	VDM++ (Kingma & Gao, 2024)	296M	511	1.43
	DisCo-Diff (Xu et al., 2024)	-	623	1.22
	EDM2-S (Karras et al., 2024b)	280M	63	1.58
	+ CFG (Ho & Salimans, 2021)	560M	126	1.48
	+ AG (Karras et al., 2024a)	405M	126	1.01
	EDM2-M	498M	63	1.43
	EDM2-L	777M	63	1.33
	EDM2-XL	1.1B	63	1.33
Ours	EDM2-S (retested)	280M	63	1.60
	+ DDO	280M	63	**0.97**

ImageNet 512x512

Type	Model	w/o G			w/ G
		#Params	NFE	FID↓	FID↓
GAN	BigGAN-deep (Brock, 2018)	112M	1	8.43	-
	StyleGAN-XL (Sauer et al., 2022)	168M	1	2.41	-
	SiD^{2}A (Zhou et al., 2024b)	1.5B	1	1.37	-
Diffusion	ADM (Dhariwal & Nichol, 2021)	559M	250	23.24	7.72†
	ADM-U	731M	500	9.96	3.85†
	DiT-XL/2 (Peebles & Xie, 2023)	675M	250	12.03	3.04
	SiT-XL (Ma et al., 2024)	675M	250	-	2.62
	+ REPA (Yu et al., 2024b)	675M	250	-	2.08
	RIN (Jabri et al., 2022)	410M	1000	3.95	-
	U-ViT, L (Hoogeboom et al., 2023)	2B	512	3.54	3.02
	VDM++ (Kingma & Gao, 2024)	2B	512	2.99	2.65
	USiT-2B (Chen et al., 2024b)	2B	-	2.90	1.72
	EDM2-XS (Karras et al., 2024b)	125M	63	3.53	2.91
	EDM2-S	280M	63	2.56	2.23
	+ AG				1.34‡
	EDM2-L	777M	63	2.06	1.88
	EDM2-XXL	1.5B	63	1.91	1.81
	+ AG				1.25‡
Masked	MaskGIT (Chang et al., 2022)	227M	12	7.32	-
	MAGVIT-v2 (Yu et al., 2023)	307M	64	3.07	1.91
	MAR-L (Li et al., 2024)	481M	1024	2.74	1.73
AR	VAR-d36-s (Tian et al., 2024)	2.3B	10	-	2.63
Ours	EDM2-L (retested)	777M	63	1.96	1.77
	+ DDO	777M	63	**1.26**	**1.21**‡
	+ DPM-Solver-v3 (Zheng et al., 2023a)	777M	25	1.29	**1.21**‡

Experiment



(a) VAR-d16 (b) VAR-d30 (c) FID and IS w.r.t. guidance scale w

Figure 7. Illustrations of DDO on autoregressive models. (a)(b) FID-IS trade-off curves and (c) the impact of α under $\beta = 0.02$.

Conclusions

Advantages

- Hight efficiency and effectiveness.
- No additional redundant structure required.

Weaknesses

- The need for hyperparameter searching.
- It takes time to iteratively sample fake samples as training data.

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  Maybe it can be combined with a single-step generation method, e.g. Consistency Models [Song et al., 2023; Song et al., 2023; Lu et al., 2025]

END