# Training Neural Samplers with Reverse Diffusive KL Divergence

Jiajun He<sup>1,\*</sup>, Wenlin Chen<sup>1,3,\*</sup>, Mingtian Zhang<sup>2,\*</sup>, David Barber<sup>2</sup>, José Miguel Hernández-Lobato<sup>1</sup>

<sup>1</sup>University of Cambridge, <sup>2</sup>University College London, <sup>3</sup>Max Planck Institute for Intelligent Systems \*Equal contribution

# AISTATS

https://arxiv.org/abs/2410.12456









# Background

Sampling from ur

 $p_d(x)$ 

- Bayesian posterio
- Boltzmann distrib
- Easy to evaluate,

Simiulation with

 $p_{ heta}(x)$ 

### **Our Method**

**Diffusive KL Divergence (DiKL)** 

### **DiKL Encourages Mode Coverage**



## Experiments





(a) Ground Truth







(a) Ground Truth

(b) KL



nnormalized density	Reverse
$= \exp(-E(x))/Z$	$\mathrm{KL}(p)$
or outions hard to sample	- Not def
a generative model	
$\approx p_d(x)$	- Mode c



### **DiKL Gradient Estimator**

$$abla_{ heta} ext{DiKL}_{k_t}(p_{ heta} || p_d) = 
abla_{ heta} ext{KL}(p_{ heta} * k_t || p_d * k_t)$$

$$= \int p_{ heta}(x_t) \left( 
abla_{x_t} \log p_{ heta}(x_t) - 
abla_{x_t} \log p_d(x_t) \right) \frac{\partial x_t}{\partial heta} dx_t,$$

 $\min_{\phi} \left\| \right\|$ 

- Estimating the noisy target score with mixed score identity (MSI)

 $\nabla_{x_t} \log p_d($ 



(b) R-KL SM



### (d) FAB







(c) FAB



(d) iDEM



(e) DiKL (ours)

**KL Minimization** 

$$egin{aligned} &||p_d) = \int (\log p_ heta(x) - \log p_d(x)) p_ heta(x) dx \ &= \int (\log p_ heta(x) + E(x)) p_ heta(x) dx + \log Z, \end{aligned}$$

fined for implicit model

$$p_{ heta}(x) = \int \delta(x - g_{ heta}(z)) p(z) dz.$$

- Mode collapse problem

- Estimating the noisy model score with denoising score matching (DSM)

$$s_{\phi}(x_t) - \nabla_{x_t} \log k(x_t|x) \|_2^2 k(x_t|x) p_{\theta}(x) dx dx_t$$

$$q(x_t) = \int (lpha_t(x + 
abla_x \log p_d(x)) - x_t) p_d(x|x_t) dx.$$