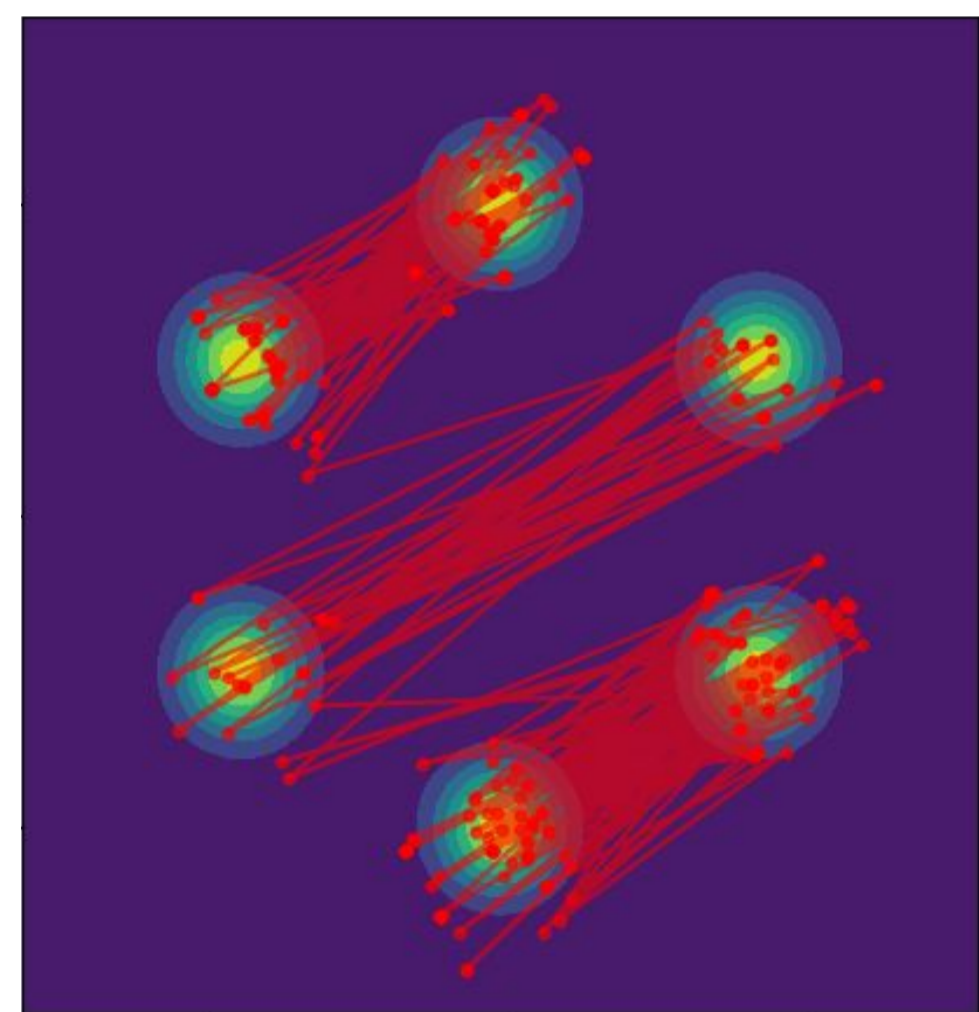
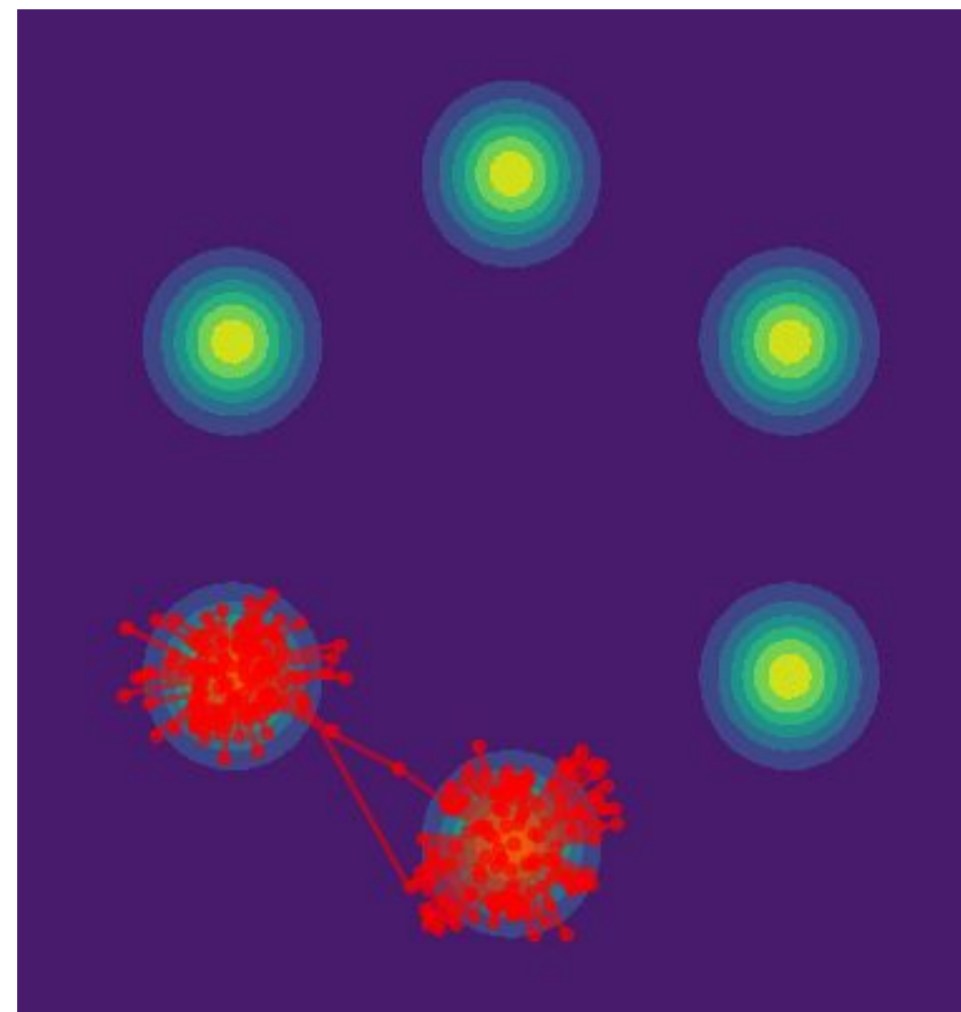


Problem: how to *learn to sample* with better mixing and ESS?

Ai-Sampler



Hamiltonian Monte Carlo



- Markov kernel instead of independent proposal
- Use adversarial loss instead of hand-crafted
 - Derived from detailed-balance condition
- Use time-reversible dynamics as deterministic map

The Markov kernel:

$$t_D(x'|x) = \delta(x' - RL_\theta(x))r[D(x)] + \delta(x' - x)(1 - r[D(x)]).$$

$$D^*(x) =$$

$$= \arg \min \int p(x)r[D_{\phi, RL_\theta}(x)] \log r[D_{\phi, RL_\theta}(x)] dx$$

$$= \log \frac{p(RL_\theta)}{p(x)} J_x^{RL_\theta(x)}.$$

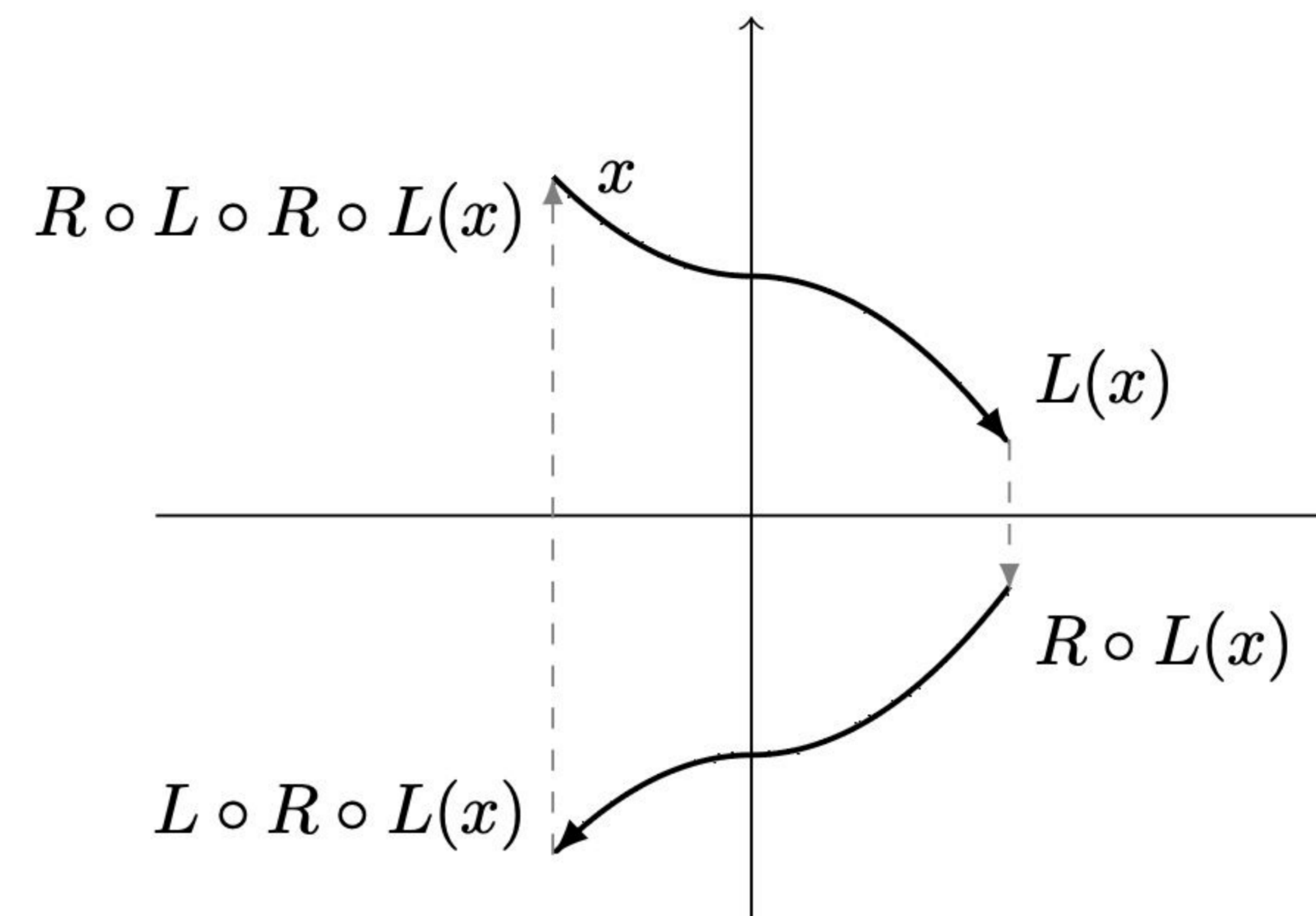
For such discriminator $TV^2[p; t_{D^*} \circ p] = 0$

Our adversarial objective:

$$\max_{\theta} A_{\theta} = \max_{\theta} \mathbb{E}_{p(x)} (r[D_{\phi, RL_\theta}(x)]), \text{ with fixed } \phi$$

$$\min_{\phi} \mathbb{E}_{p(x)} (r[D_{\phi, RL_\theta}(x)] \log r[D_{\phi, RL_\theta}(x)]), \text{ with fixed } \theta.$$

How to parametrize the discriminator?



For an R-reversible flow, the density ratio between image and preimage is symmetric:

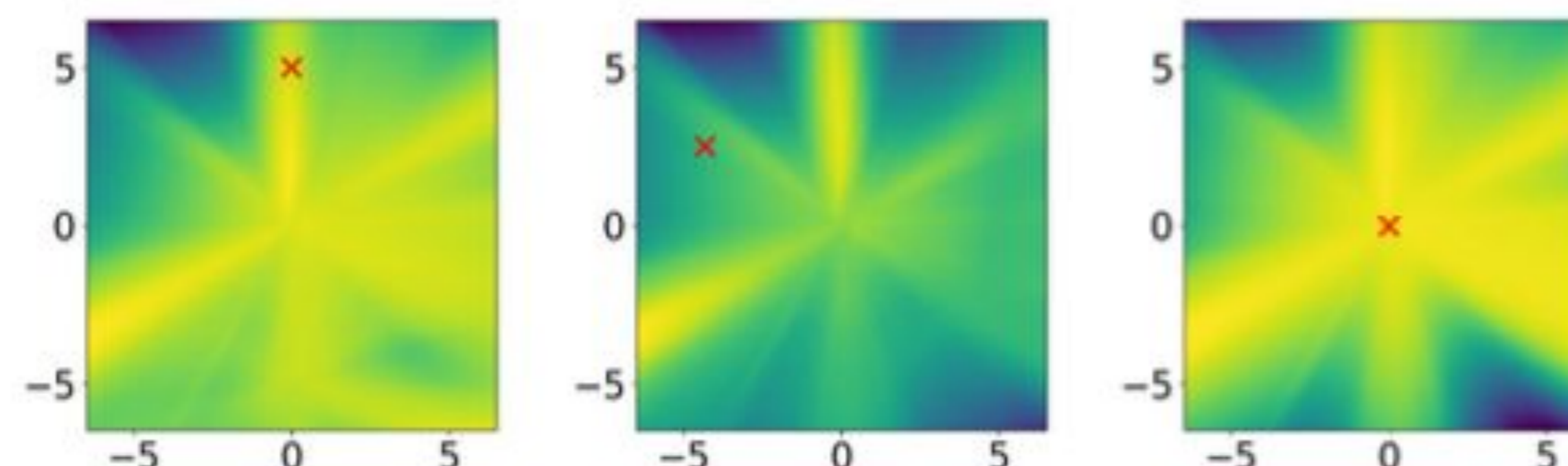
$$\lambda(x) = \log \frac{p(RLx)}{p(x)} J_x^{RL} = -\log \frac{p(RLRLx)}{p(RLx)} J_{RLx}^{RL} = -\lambda(RLx)$$

Equivariance with respect to:

$$\rho_{2n} : C_2 \rightarrow GL(\mathbb{R}^{2n} \oplus \mathbb{R}^{2n}), \rho_{2n}(g) = \begin{bmatrix} 0 & I_{2n} \\ I_{2n} & 0 \end{bmatrix}$$

This induces a constraint on linear layers:

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} 0 & I_{2n} \\ I_{2n} & 0 \end{bmatrix} \begin{bmatrix} RL(x) \\ x \end{bmatrix} = \begin{bmatrix} 0 & I_{2s} \\ I_{2s} & 0 \end{bmatrix} \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} RL(x) \\ x \end{bmatrix}$$



How to parametrize an R-reversible map?

Theorem 4.1. (Valperga et al., 2022) Let $L : \mathbb{R}^D \rightarrow \mathbb{R}^D$ be an R-reversible diffeomorphism², with R being a linear involution. Then, there exists a unique diffeomorphism $g : \mathbb{R}^D \rightarrow \mathbb{R}^D$, such that $L = R \circ g^{-1} \circ R \circ g$. If L is symplectic, then g can be chosen symplectic.

Some results:

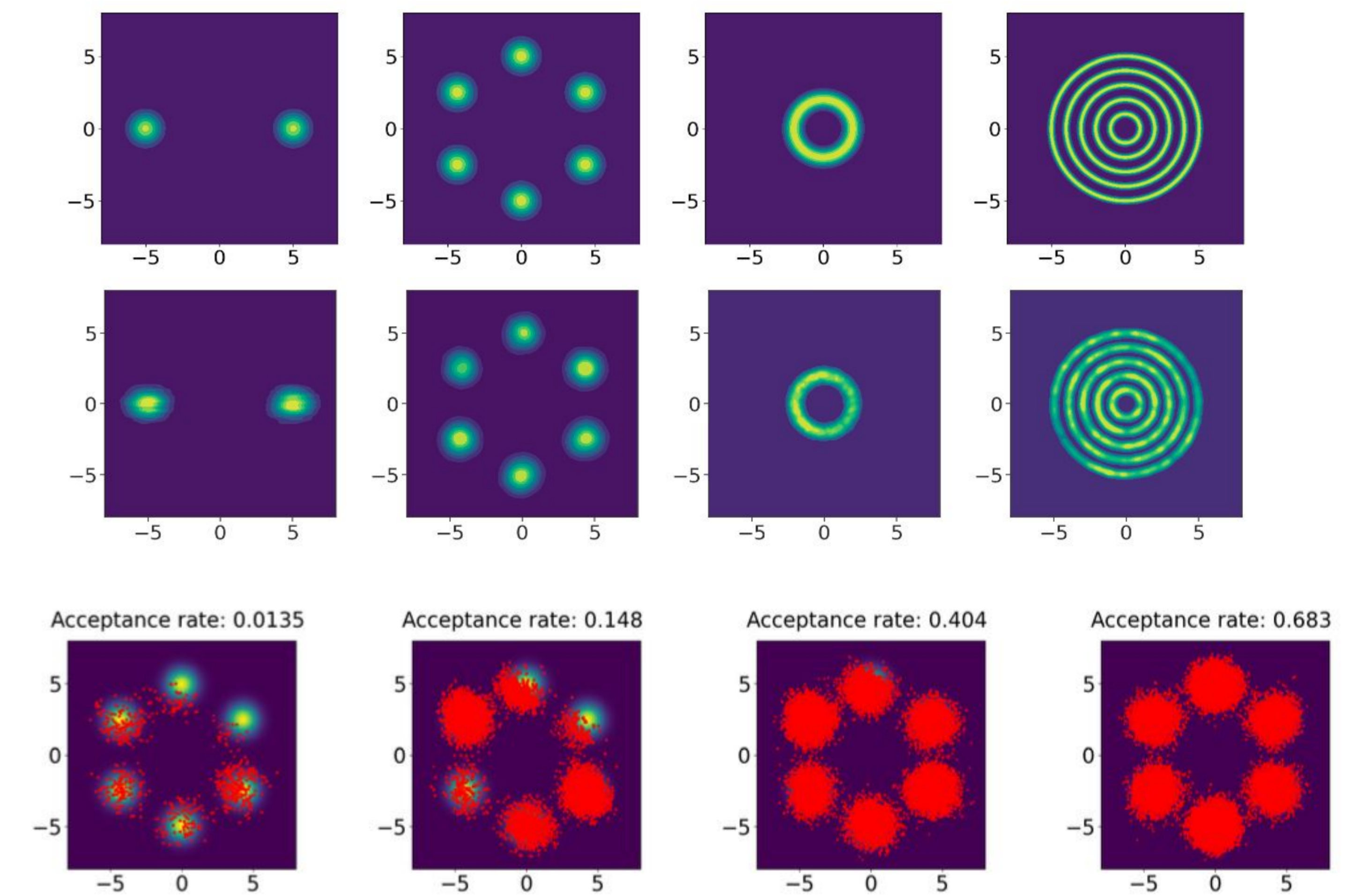


Figure 7. Adversarial objective and acceptance rate during training. Sample quality increasing during training.

Density	ESS		
	HMC	A-NICE-MC	Ai-sampler (ours)
mog2	0.8	355.4	1000.0
mog6	2.4	320.0	1000.0
ring	981.3	1000.0	378.0
ring5	256.6	155.57	396.5

Density	ESS/s	
	HMC	Ai-sampler (ours)
mog2	0.4	1052.6
mog6	0.98	1041.7
ring	2725.8	402.1
ring5	333.2	434.7

