

# Balanced Conic Rectified Flow

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**VILAB**  
VISUAL INTELLIGENCE LAB



# Preliminaries: Flow matching for generative modeling



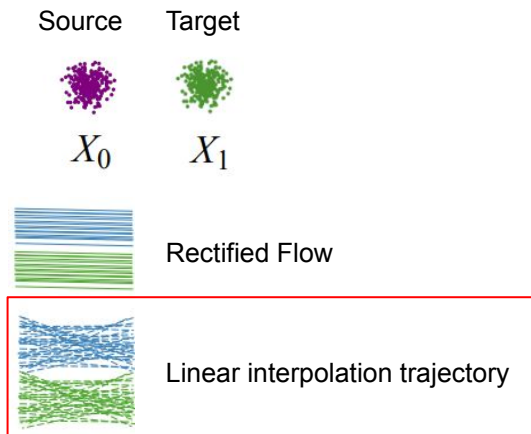
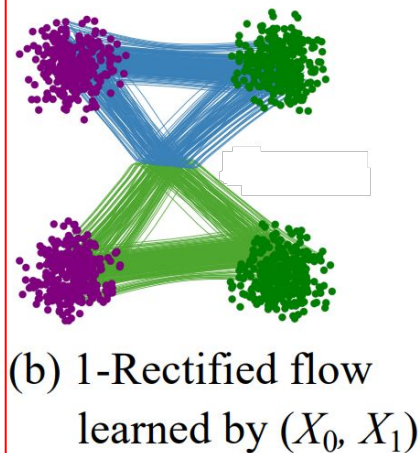
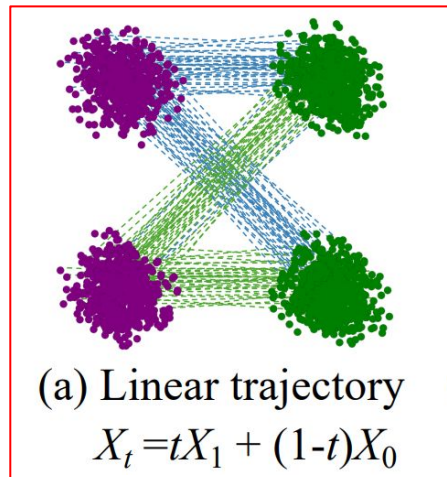
For time-dependent vector field,

$$v : [0, 1] \times \mathbb{R}^d \rightarrow \mathbb{R}^d$$

Vector field can construct time-dependent diffeomorphic map (flow)  $\phi : [0, 1] \times \mathbb{R}^d \rightarrow \mathbb{R}^d$  defined via the ordinary differential equations (ODE) such that,

$$\begin{aligned} \frac{d}{dt} \phi_t(x) &= v_t(\phi_t(x)) \\ \phi_0(x) &= x \end{aligned}$$

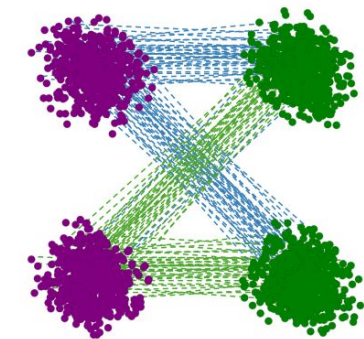
# Preliminaries : Rectified flow



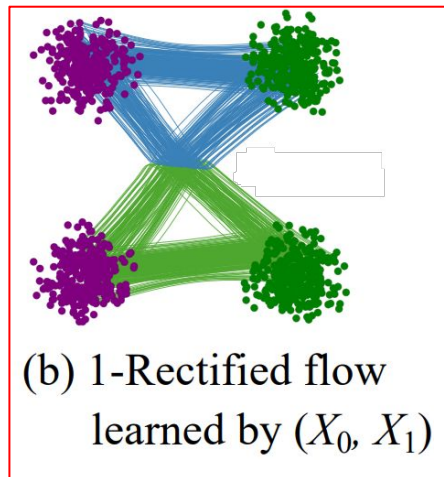
Consider the linear interpolation path between source and target

$$X_t = (1 - t)X_0 + tX_1 \text{ for } t \in [0, 1]$$

# Preliminaries : Rectified flow



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



(b) 1-Rectified flow  
learned by  $(X_0, X_1)$

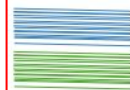
Source Target



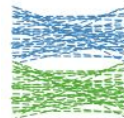
$X_0$



$X_1$



Rectified Flow



Linear interpolation trajectory

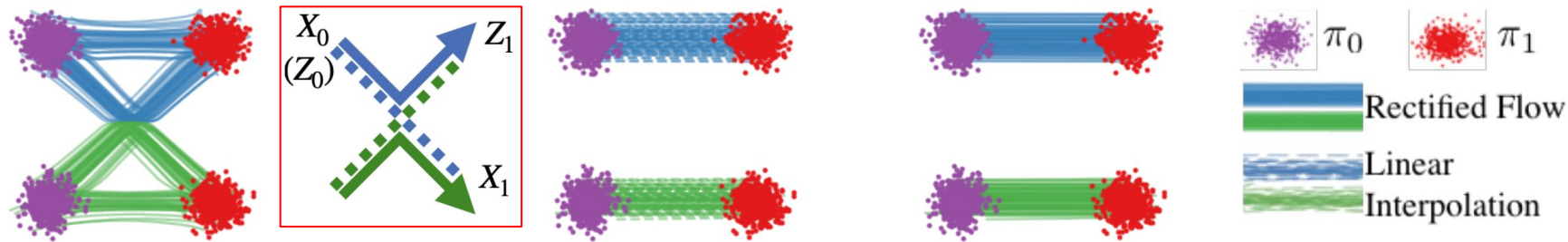
Use the time derivative of linear interpolation as supervision

$$\frac{dZ_t}{dt} = v_\theta(Z_t, t) := \frac{1}{t}(Z_t - \mathbb{E}[(X_1 - X_0)|X_t = Z_t])$$

Train the velocity field using an ODE neural network

$$\arg \min_{\theta} \mathbb{E} \left[ \left\| X_1 - X_0 - v(tX_1 + (1-t)X_0, t) \right\|^2 \right]$$

# Preliminaries : Reflow process



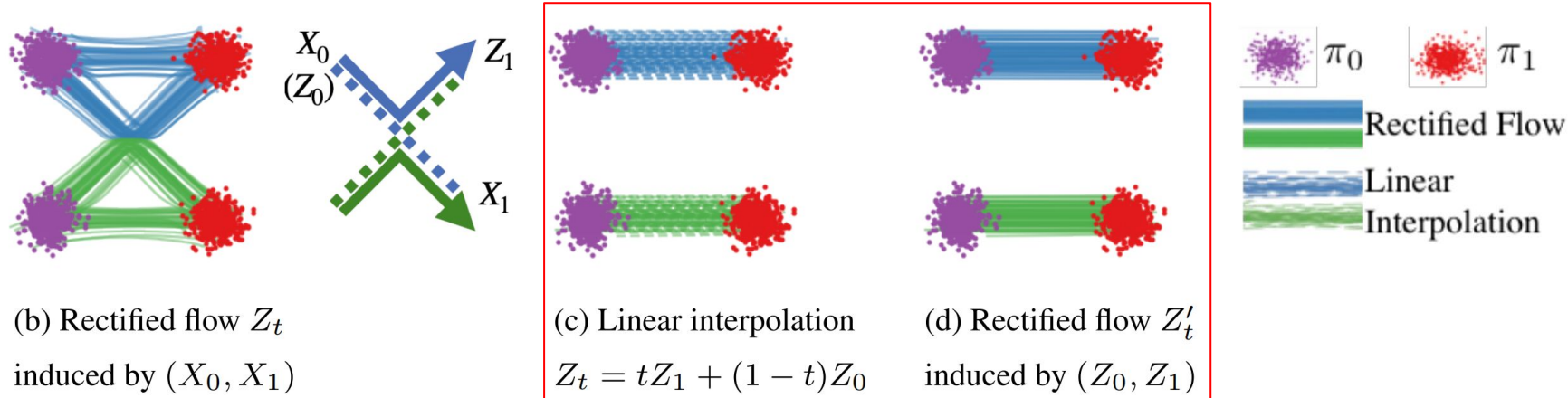
(b) Rectified flow  $Z_t$   
induced by  $(X_0, X_1)$

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

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

Generate Fake pairs  $(Z_{0,F}, Z_{1,F})$  using 1-Rectified models  $v_\theta$

# Preliminaries : Reflow process

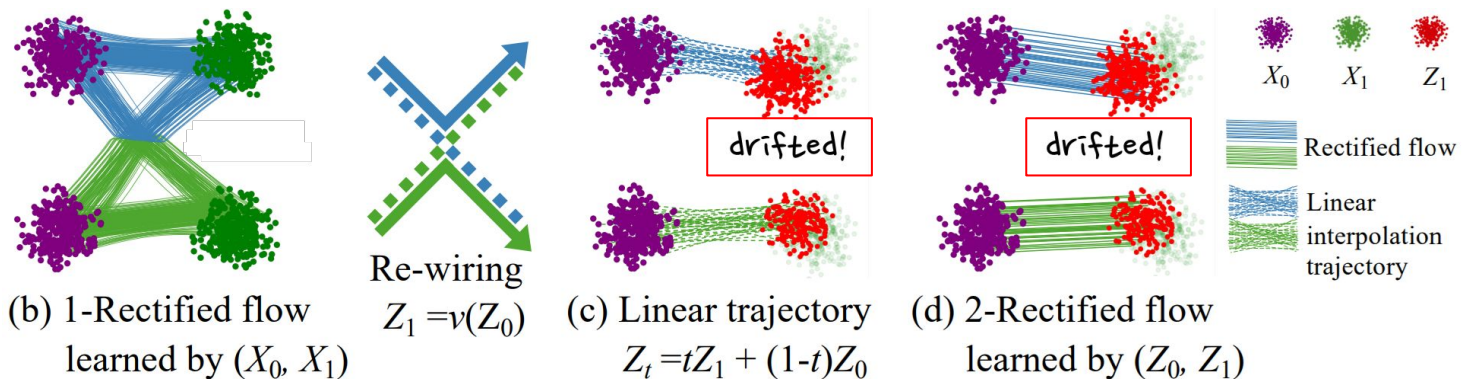


Generate Fake pairs  $(Z_{0,F}, Z_{1,F})$  using 1-Rectified models  $v_\theta$

Fine tuning with 1-Rectified models using fake pairs

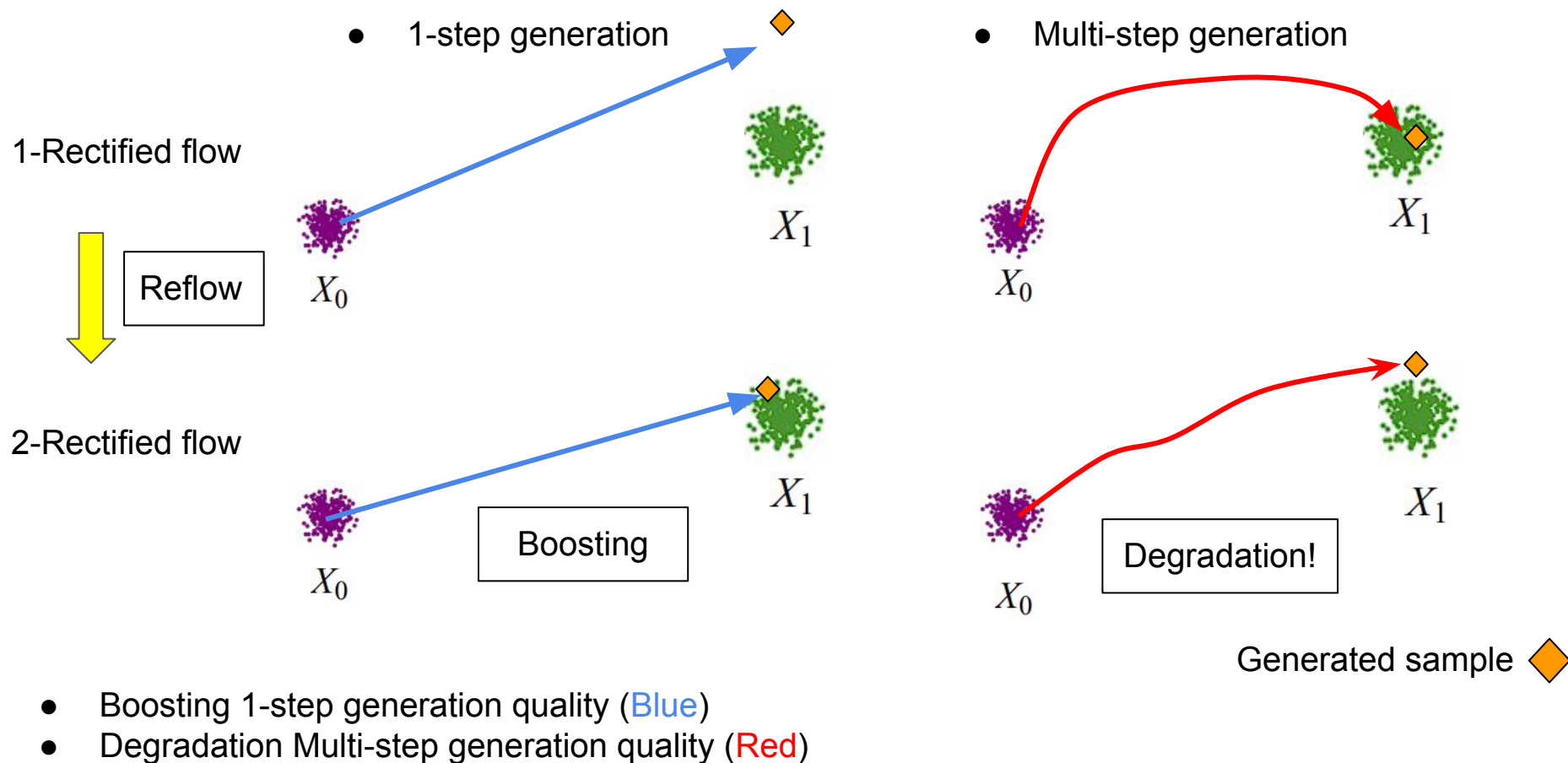
$$\arg \min_{\theta} \mathbb{E} \left[ \|Z_{1,F} - Z_{0,F} - v_\theta(tZ_{1,F} + (1 - t)Z_{0,F})\|^2 \right],$$

# Original Reflow process drift target distribution



- Since 1-Rectified Flow cannot perfectly match the target distribution, Reflow using only fake pairs becomes biased toward generated samples.

# Distribution drift degrades the quality of full-step generation

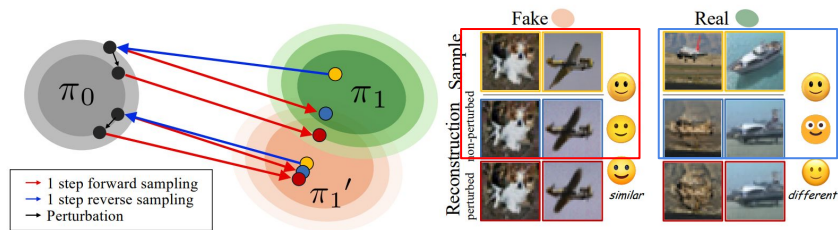




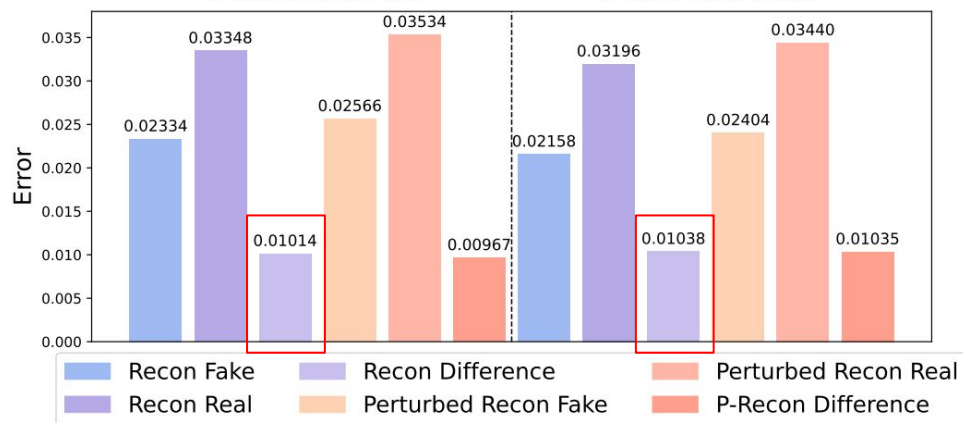
# Drift of target distribution in the original Reflow process

## Reconstruction Error

$$L_2^{\text{recon}}(X) = \mathbb{E}_{x \sim X} [\|x - v(v^{-1}(x))\|_2]$$



Recon and P-Recon Errors for 2,3-rectified flow

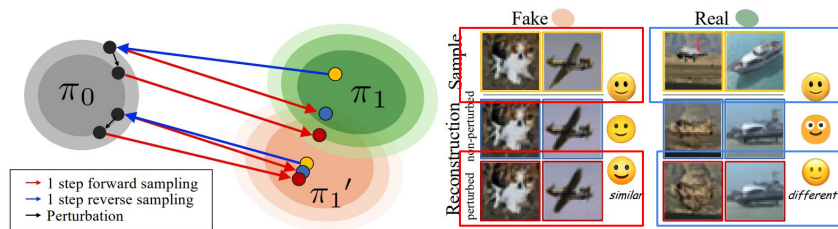


- Experimental results show a clear discrepancy in reconstruction and perturbed reconstruction errors between real and generated images

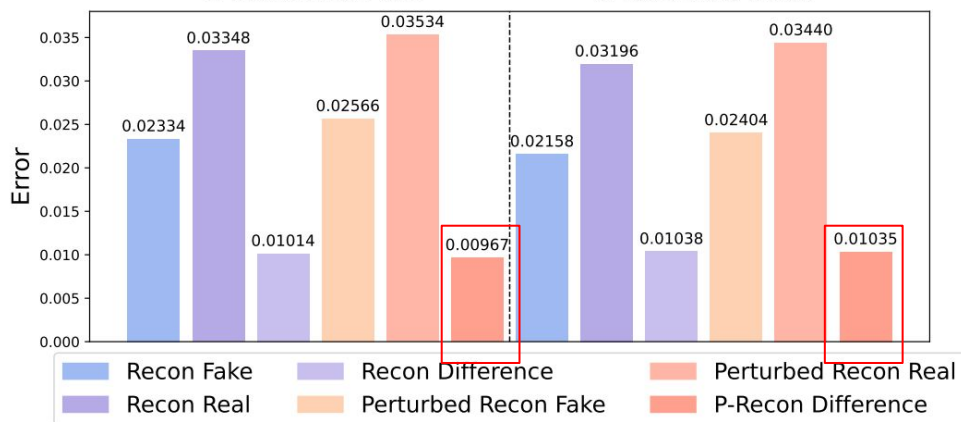
# Drift of target distribution in the original Reflow process

## Perturbed Reconstruction Error

$$L_2^{\text{p-recon}}(X, \varepsilon) = \mathbb{E}_{x \sim X, z \sim \pi_0} \|x - v(v^{-1}(x) + \varepsilon z)\|_2,$$



Recon and P-Recon Errors for 2,3-rectified flow



- Experimental results show a clear discrepancy in reconstruction and perturbed reconstruction errors between real and generated images

# Drift of target distribution in the original Reflow process

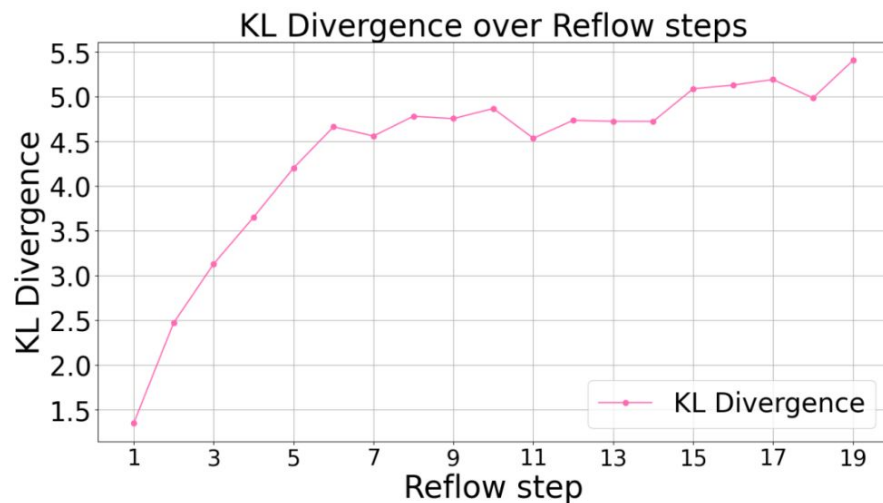
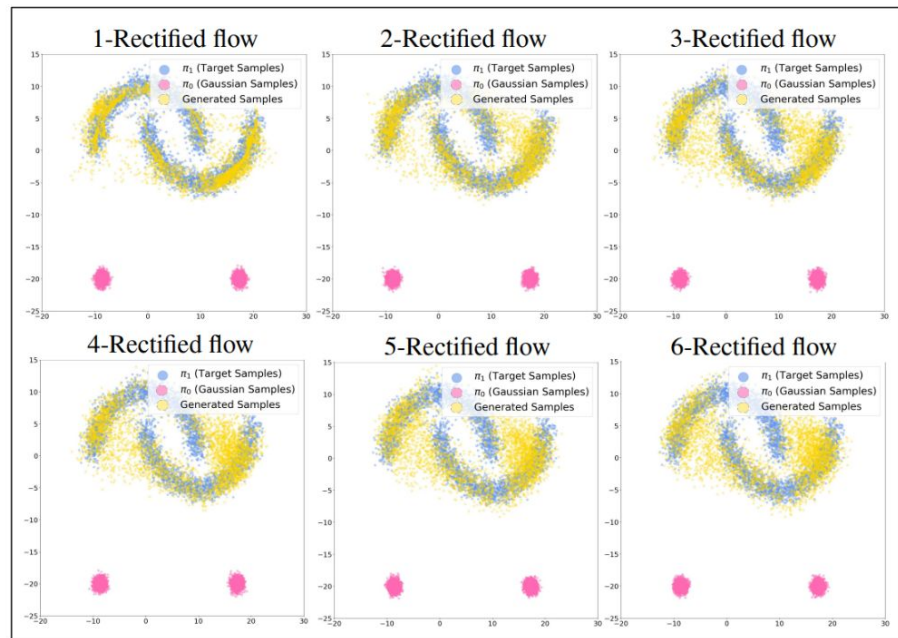
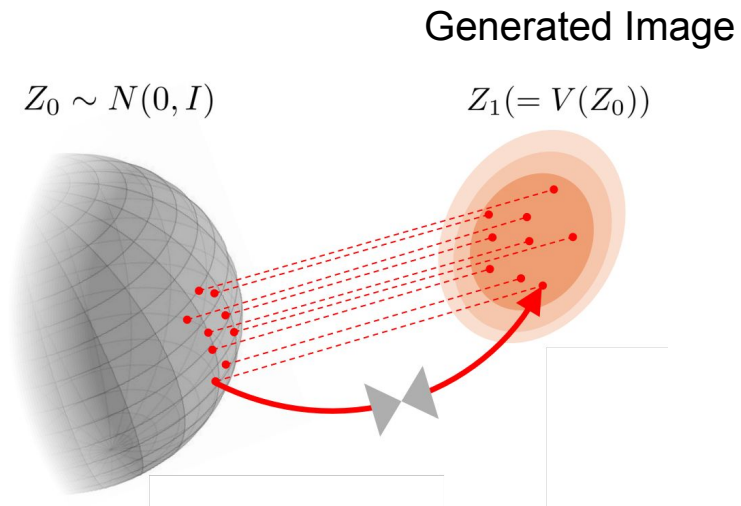


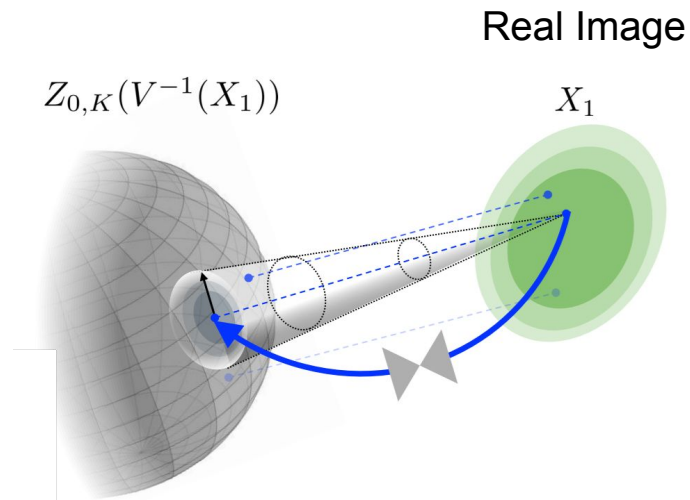
Figure 3: **(a)** As reflow steps increase, generated samples diverge from the target distribution. **(b)** This drift is further evidenced by the rising KL divergence from the real data distribution.

# Fake pair and Real Pair



- Fake Pair

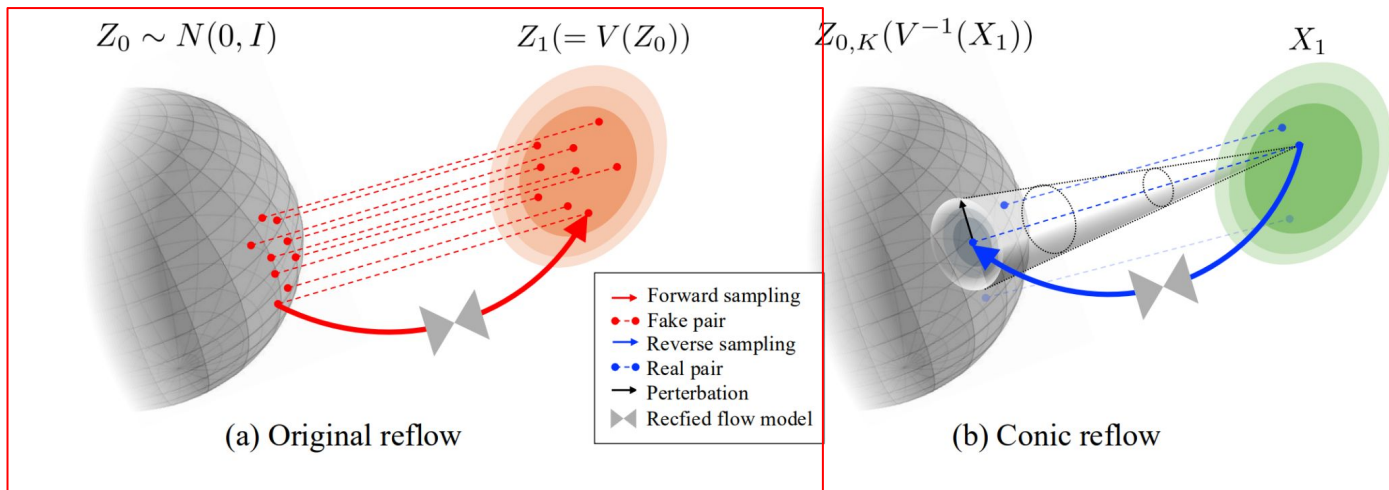
$$(Z_0, v_\theta(Z_0)) := (Z_{0,F}, Z_{1,F})$$



- Real Pair

$$(Z_{0,R}, X_1) := (v^{-1}(X_1), X_1)$$

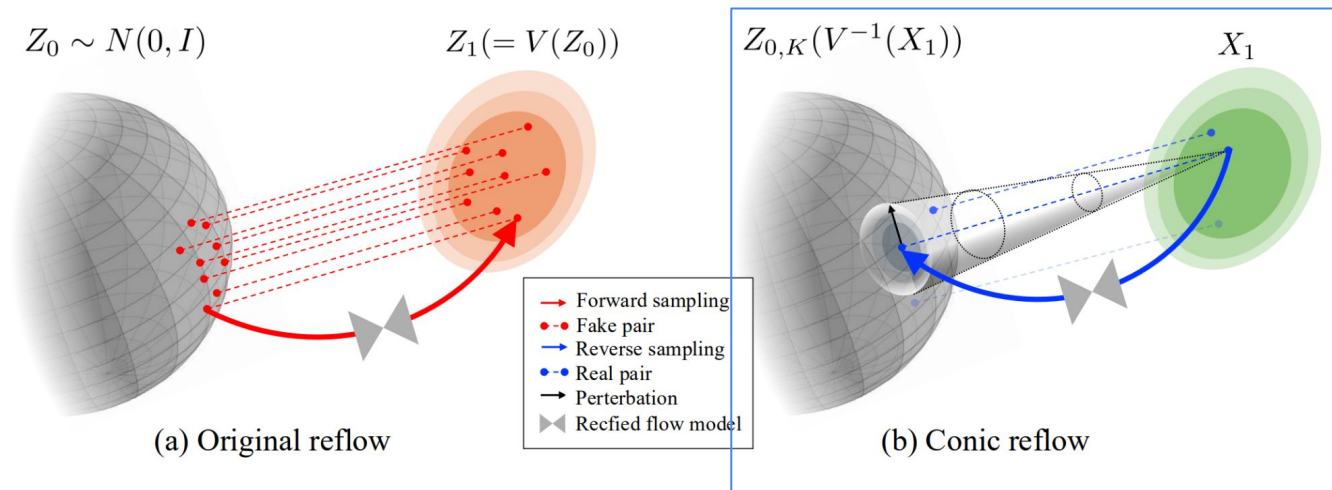
# Methods - Conic Reflow



Original reflow for Fake pairs

$$\arg \min_{\theta} \mathbb{E} [\|Z_{1,F} - Z_{0,F} - v_{\theta}(tZ_{1,F} + (1-t)Z_{0,F})\|^2]$$

# Methods - Conic Reflow



Perturbed based supervision for Real pairs

$$\hat{\theta} = \arg \min_{\theta} \int_0^1 \mathbb{E} \left[ w_t \left\| X_1 - \text{slerp}(Z_{0,R}, \epsilon, \zeta) - v_{\theta}(\text{Conic}(X_1, \epsilon, \zeta, t)) \right\|^2 \right] dt$$

where Conic operator defined as,

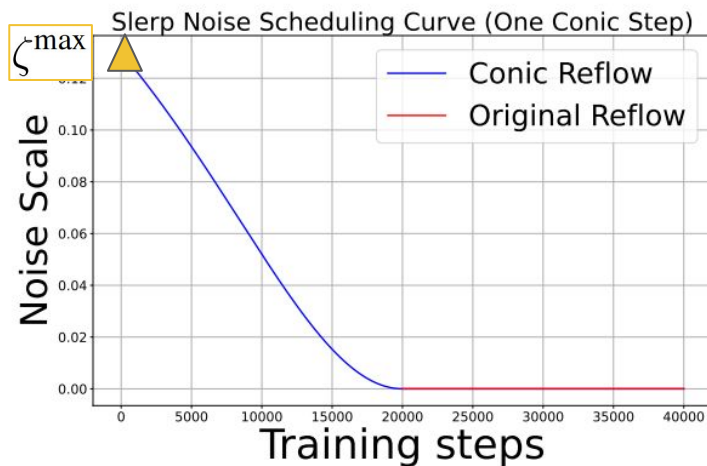
$$\text{Conic}(X_1, \epsilon, \zeta, t) = tX_1 + (1 - t)\text{slerp}(Z_{0,R}, \epsilon, \zeta), \quad \epsilon \sim \mathcal{N}(0, I), \quad \zeta: \text{Perturbation intensity via Slerp}$$

# Maximum perturbation intensity and noise schedule

Adaptively compute the maximum perturbation intensity

$$\zeta^{\max} := \max_{\zeta \in (0, 0.5]} \mathbb{E}_{\substack{x \sim X_1 \\ z \sim Z_{1,F}}} [\|v_{\theta}(\text{Slerp}(z_{0,R}, \epsilon, \zeta)) - x\|_2 - \|v_{\theta}(\text{Slerp}(z_{0,F}, \epsilon, \zeta)) - z\|_2]$$

where  $\epsilon \sim \mathcal{N}(0, I)$ , with  $z_{0,R} = v_{\theta}^{-1}(x)$  and  $z_{0,F} = v_{\theta}^{-1}(z_{1,F})$



The perturbation intensity progressively decrease during training

$$\zeta(t') := \zeta^{\max} \cdot \frac{2t'^2}{1+t'^2}, \quad t' \in [0, 1]$$



# Comparison with baselines

Method	NFE ( $\downarrow$ )	IS ( $\uparrow$ )	FID ( $\downarrow$ )
<b>One-Step Generation (Euler solver, N=1)</b>			
1-Rectified Flow	1	1.13 (9.08)	378 (6.18)
<i>2-Rectified Flow</i>			
Original (+Distill)	1	8.08 (9.01)	12.21 (4.85)
<b>Ours (+Distill)</b>	1	<b>8.79 (9.11)</b>	<b>5.98 (4.16)</b>
Rf++ <sup>†</sup> [24]	1	8.87	4.43
Rf++ <sup>†</sup> ( <b>+ours</b> )	1	8.87	<b>4.22</b>
<i>3-Rectified Flow</i>			
Original (+Distill)	1	8.47 (8.79)	8.15 (5.21)
<b>Ours (+Distill)</b>	1	<b>8.84 (8.96)</b>	<b>5.48 (4.68)</b>
<b>Full Simulation (Runge–Kutta (RK45), Adaptive N)</b>			
1-Rectified Flow	127	<b>9.60</b>	<b>2.58</b>
<i>2-Rectified Flow</i>			
Original	110	9.24	3.36
<b>Ours</b>	104	<b>9.30</b>	<b>3.24</b>
<i>3-Rectified Flow</i>			
Original	104	9.01	3.96
<b>Ours</b>	98	<b>9.14</b>	<b>3.70</b>

Table 1: One-step and full-simulation comparison of 2,3 Rectified Flows on CIFAR-10.

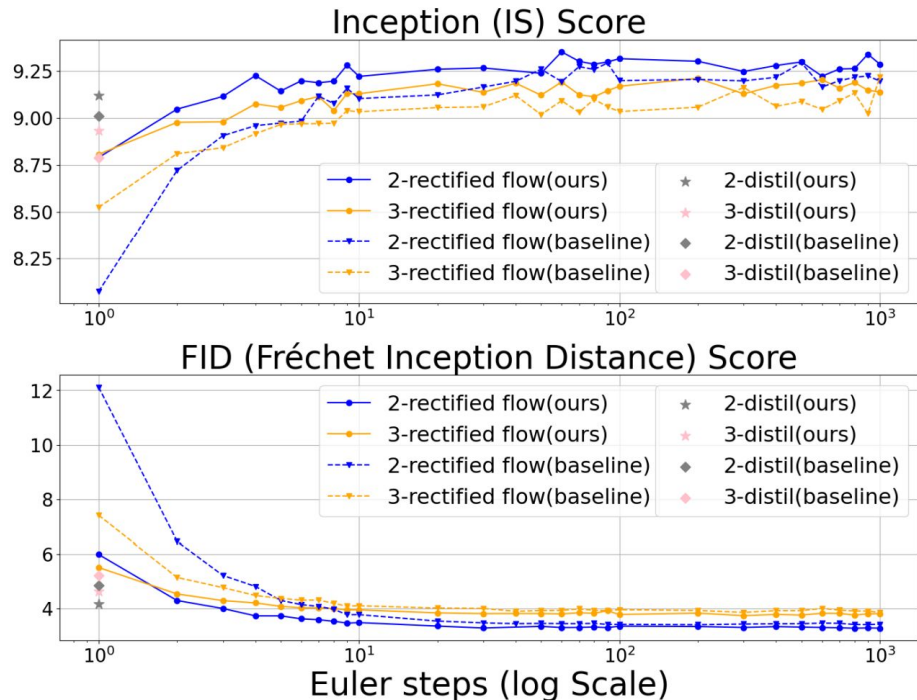
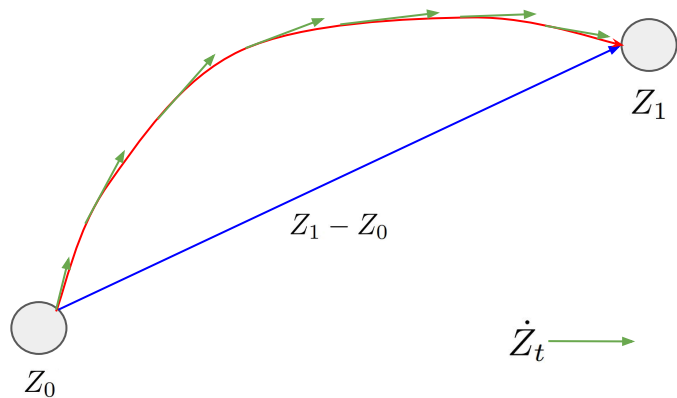


Figure 6: CIFAR-10 generation quality across Euler steps.



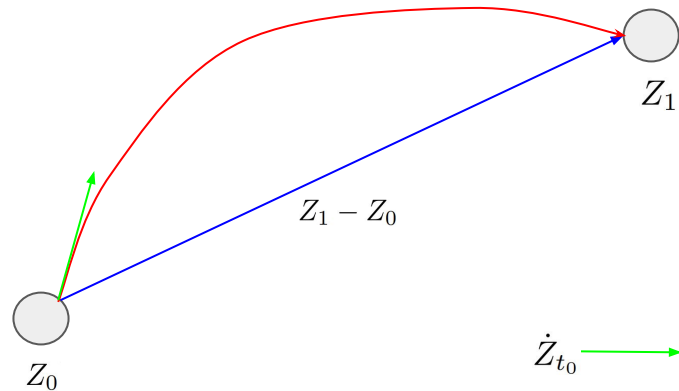
# Curvature and Initial Velocity Delta (IVD)

- Curvature



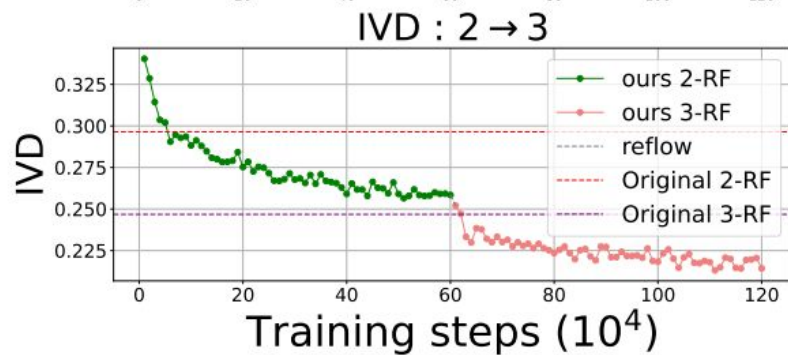
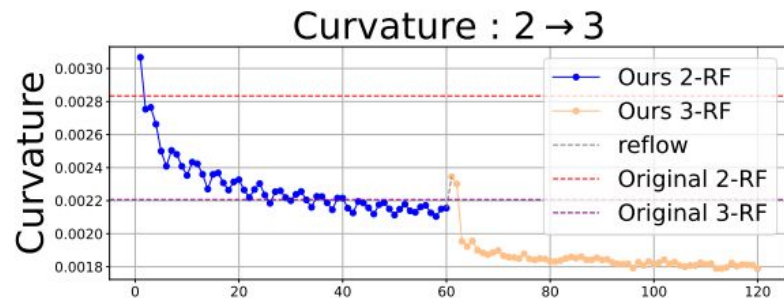
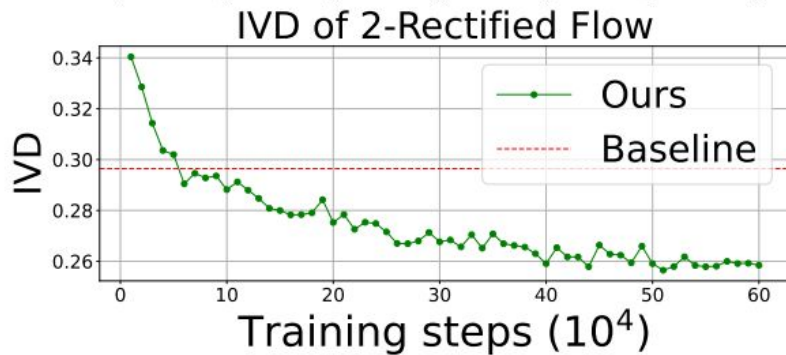
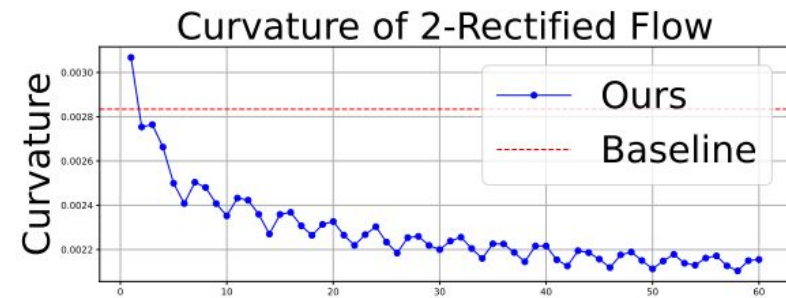
$$S(\mathbf{Z}) = \int_0^1 \mathbb{E} \left[ \left\| (Z_1 - Z_0) - \dot{Z}_t \right\|^2 \right] dt$$

- Initial Velocity Delta (IVD)



$$IVD(\mathbf{Z}, t_0) = \mathbb{E} \left[ \left\| (Z_1 - Z_0) - \dot{Z}_{t_0} \right\|^2 \right]$$

# Straightness and Initial Velocity Delta (IVD)



Our methods reduces rap between real and fake image during reflow process

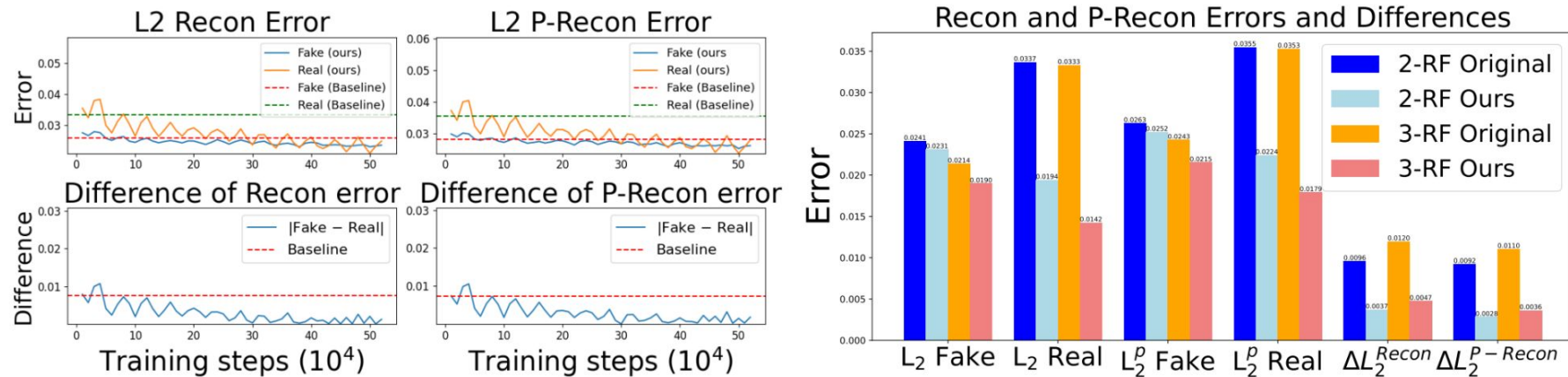
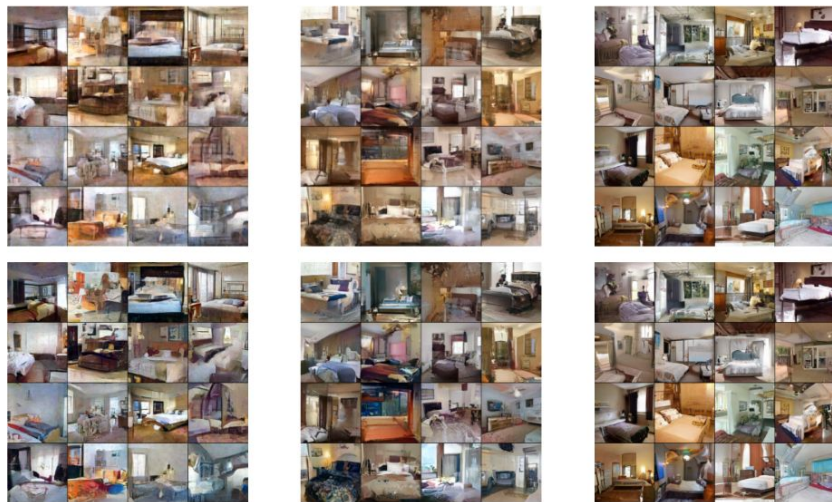


Figure 7: Reconstruction and perturbed reconstruction error across training iterations.

# High resolution dataset (Lsun-Bedroom 256x256)



Euler 1-step

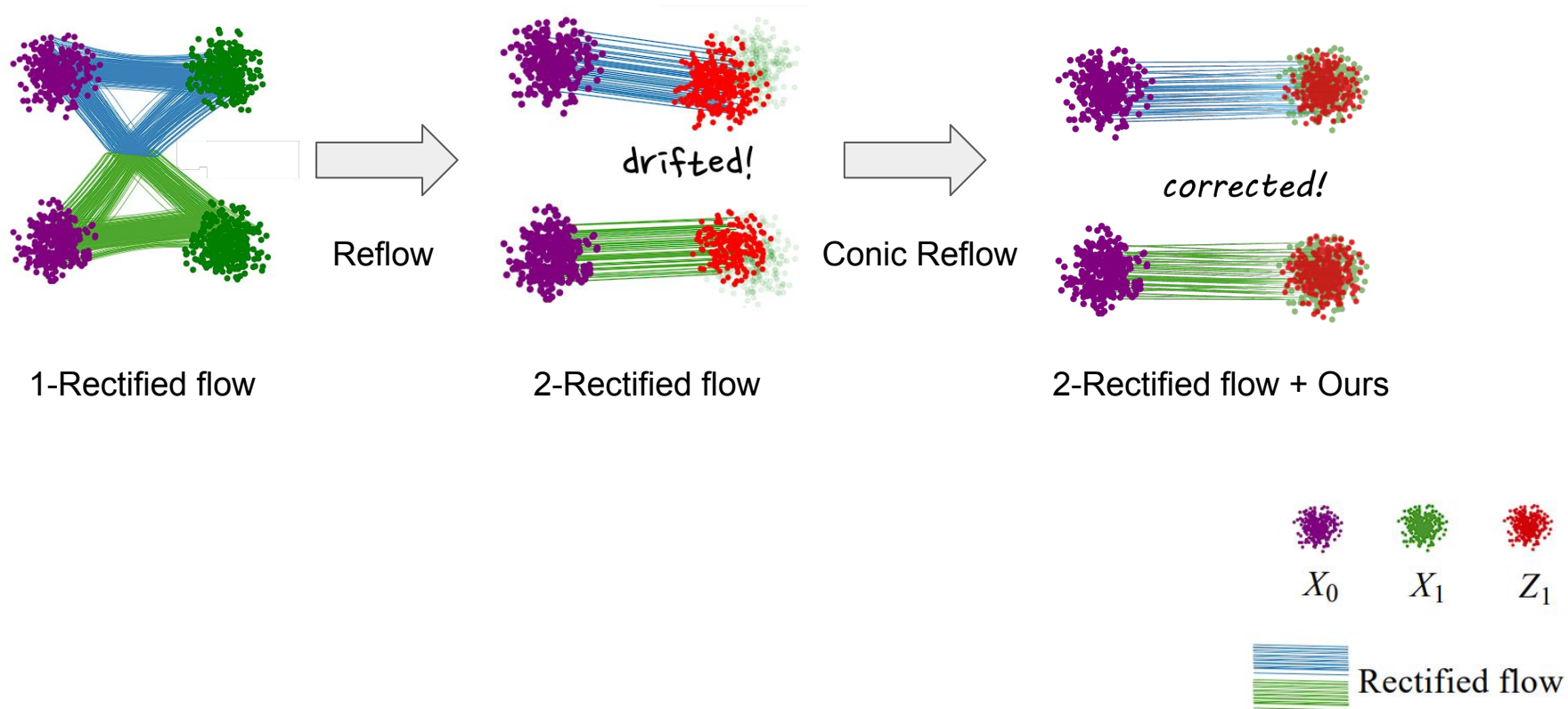
Euler 2-step

RK - 45

Solver	FID (Original/Ours)	Precision	Recall
1-step Euler	139.98 / <b>26.54</b>	0.0290 / <b>0.4822</b>	0.0220 / <b>0.2274</b>
RK	24.76 / <b>24.14</b>	0.4525 / <b>0.4703</b>	0.2386 / <b>0.2388</b>
IVD, Recon, P-Recon error (Fake/Real)			
	IVD	$L_2^{recon}$	$L_2^{p-recon}$
Original	1.1790	0.0822 / 0.1147	0.0820 / 0.1146
Ours	<b>0.9103</b>	<b>0.0487 / 0.0405</b>	<b>0.0486 / 0.0407</b>
	$\Delta L_2^{recon}$	$\Delta L_2^{p-recon}$	
Original	0.0325	0.0326	
Ours	<b>0.0083</b>	<b>0.0079</b>	

Figure 8: Visual and quantitative comparison on LSUN. **Left:** 2-row layout showing original (**top**) and ours (**bottom**) for each solver (1-step, 2-step, RK). **Right:** evaluation metrics.

# Our method realigns the drift in 2-Rectified Flow



# Our method realigns the drift in 2-Rectified Flow

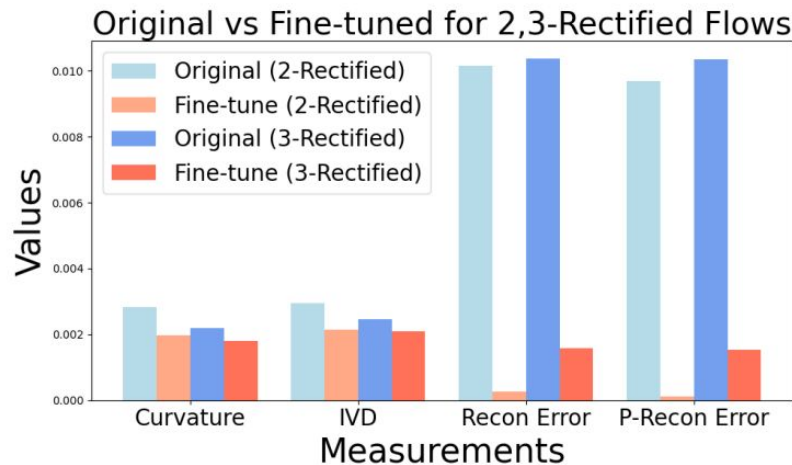
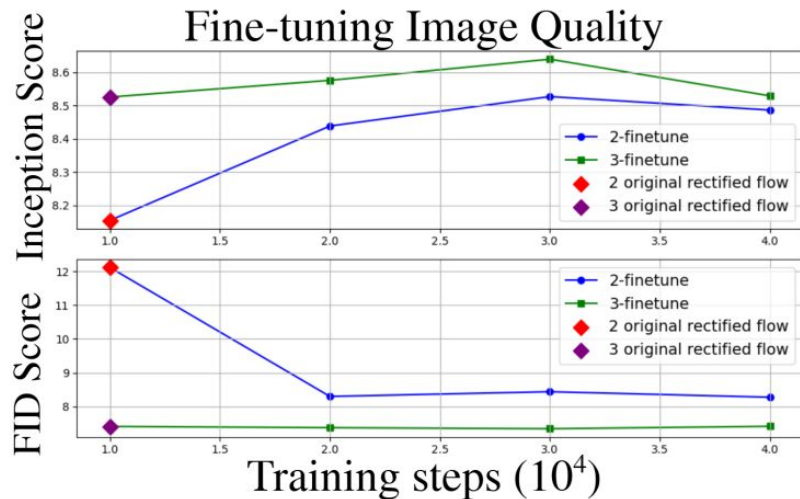


Figure A2: (a) Comparison of image quality between the original rectified model and our fine-tuned model across training steps (**left**). (b) Comparison of measurements for original and fine-tuned models for 2- and 3-rectified flows (**right**).

# Balanced Conic Rectified flow

- Mitigated distribution drift of the target distribution during Reflow process
- Achieves better generation quality than the original Reflow process even with a small number of fake pairs.
- Produces a straighter solution trajectory than original 2-Rectified flow.