

EASING TRAINING PROCESS OF RECTIFIED FLOW MODELS VIA LENGTHENING INTER-PATH DISTANCE

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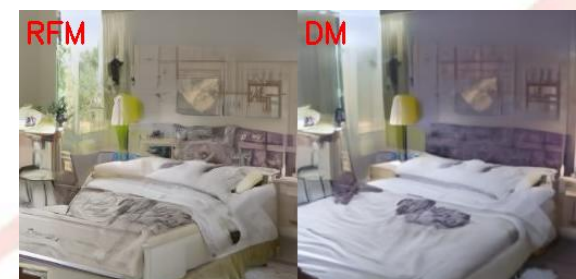
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Outlines

- Problem settings
- Our proposed method: DANSM
- Experiments

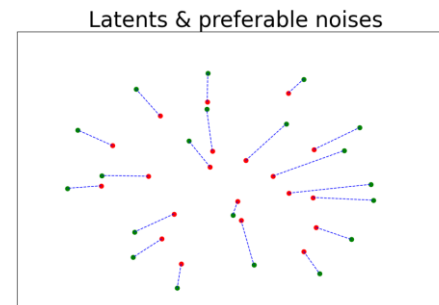
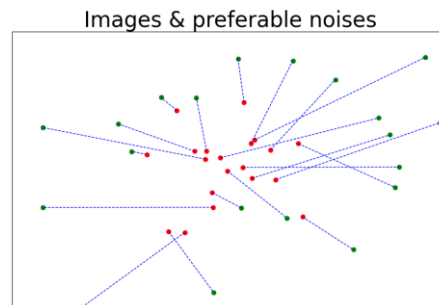
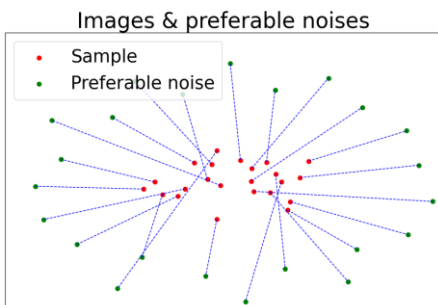
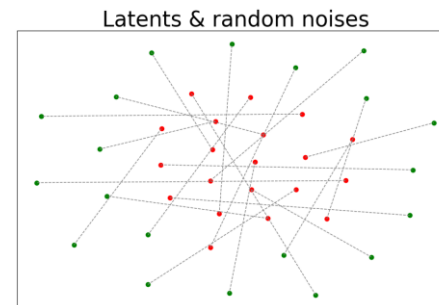
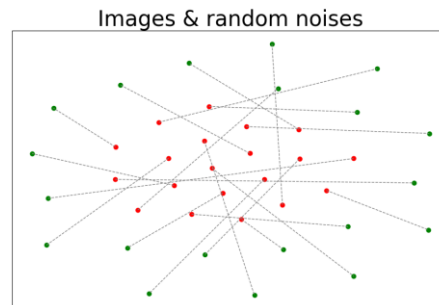
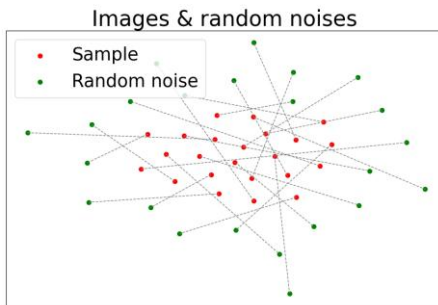
Problem settings

- Diffusion-based generative models
 - Diffusion models (DM)
 - Rectified flow models (RFM)
- Consistent model reproducibility
 - From the same noise, generate similar samples



Problem settings

- When converting a sample back to noise,
 - the resultant noise (referred to as **preferable noise**) differs from random noise.
 - The t-SNE visualization of random & preferable noises:



The preferable paths have less intersections

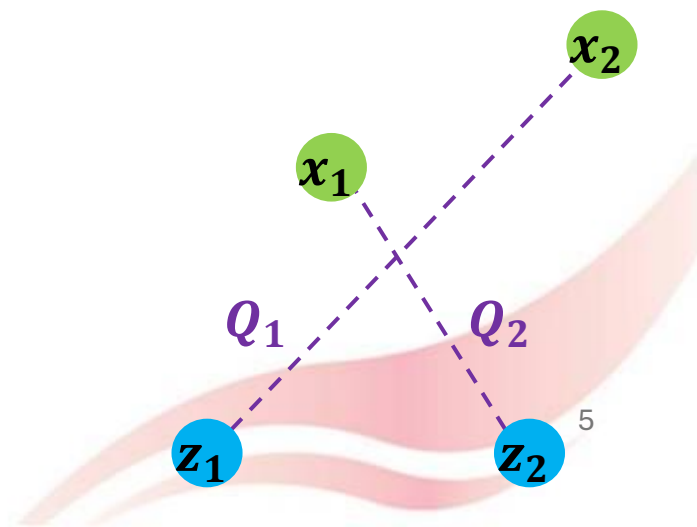
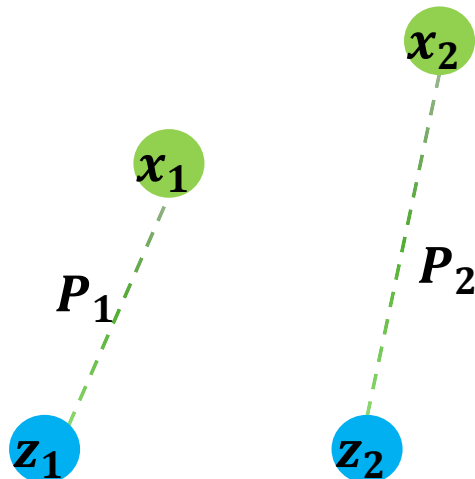
CIFAR-10 images

LSUN Bedroom images

Latents of LSUN Bedroom

Problem settings

- Preferable paths have:
 - **less** intersections in two-dimension visualization,
 - **larger** inter-path distance in high-dimension space.
- in RFM, the paths are straight lines
 - In training process, between 2 samples and 2 noises, which pairs (or paths) are better?



Problem settings

- Problem settings

- In \mathbb{R}^d space, n samples and n noises compose n paths. Let $\mathbf{p}_{i,j}$ be the path from the i -th noise to the j -th sample. We define n as the *match-size*. The objective is to maximize the inter-path distances among these n paths:

$$\max_{\sigma} \frac{2}{n(n-1)} \sum_{i=1}^n \sum_{k=i+1}^n \text{dist}(p_{i,\sigma(i)}, p_{k,\sigma(k)}) ,$$

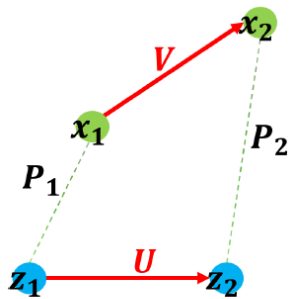
Too high complexity

where σ is a permutation of $\{1, 2, \dots, n\}$, and $\text{dist}(\cdot, \cdot)$ is the distance of two paths.

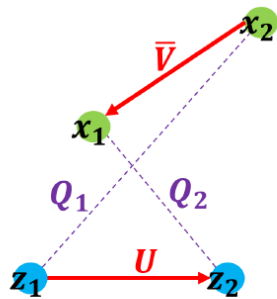
- This method is referred to as Distance-Aware Noise-Sample Matching (**DANSM**).

Our proposed method: DANSM

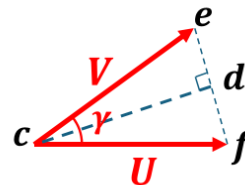
- We prove that inter-path distance and path length have **negative correlation**.



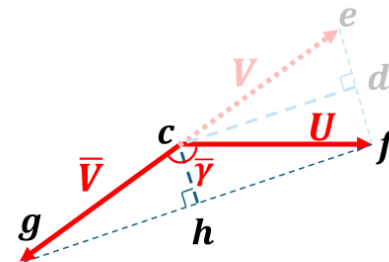
(a) Case 1



(b) Case 2



(c) Distance in case 1



(d) Distance in case 2

$$\begin{aligned}
 \cos \gamma &= \frac{\|U\|^2 + \|V\|^2 - \|U - V\|^2}{2\|U\| \cdot \|V\|} \\
 &= \frac{\|Q_1\|^2 + \|Q_2\|^2 - (\|P_1\|^2 + \|P_2\|^2)}{2\|U\| \cdot \|V\|} \\
 &= -\cos \bar{\gamma}
 \end{aligned}$$

Our proposed method: DANSM

- Surrogate method
 - Instead of lengthening inter-path distance, we **shorten** the path length:

$$\min_{\sigma} \frac{1}{n} \sum_{i=1}^n \|p_{i,\sigma(i)}\|$$

Lower complexity than previous:

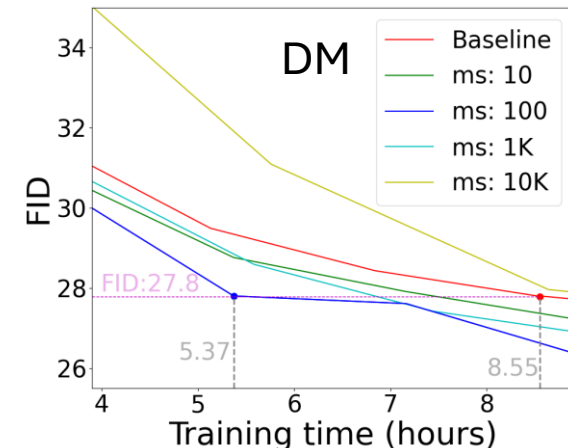
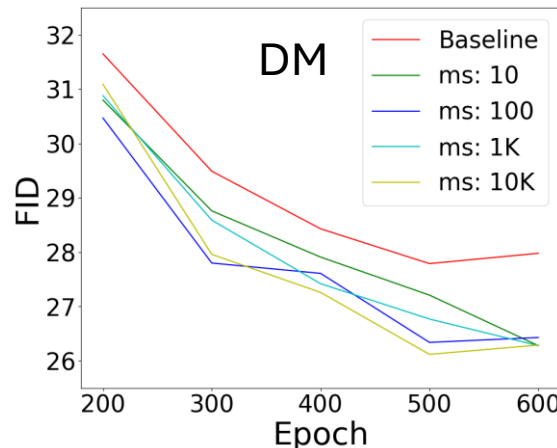
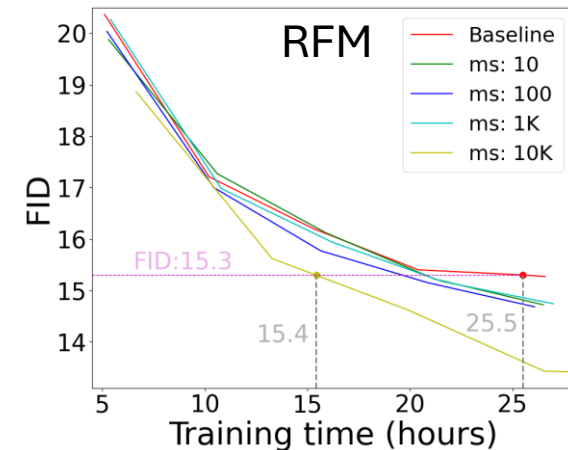
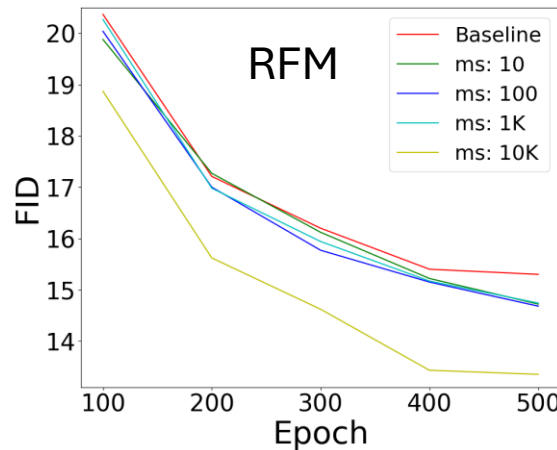
$$\max_{\sigma} \frac{2}{n(n-1)} \sum_{i=1}^n \sum_{k=i+1}^n \text{dist}(p_{i,\sigma(i)}, p_{k,\sigma(k)})$$

- Implementation
 - Hungarian algorithm has a time complexity of $O(n^3)$.
 - We adopt a **greedy algorithm** with complexity of $O(n^2)$, achieving similar performance.

Experiments

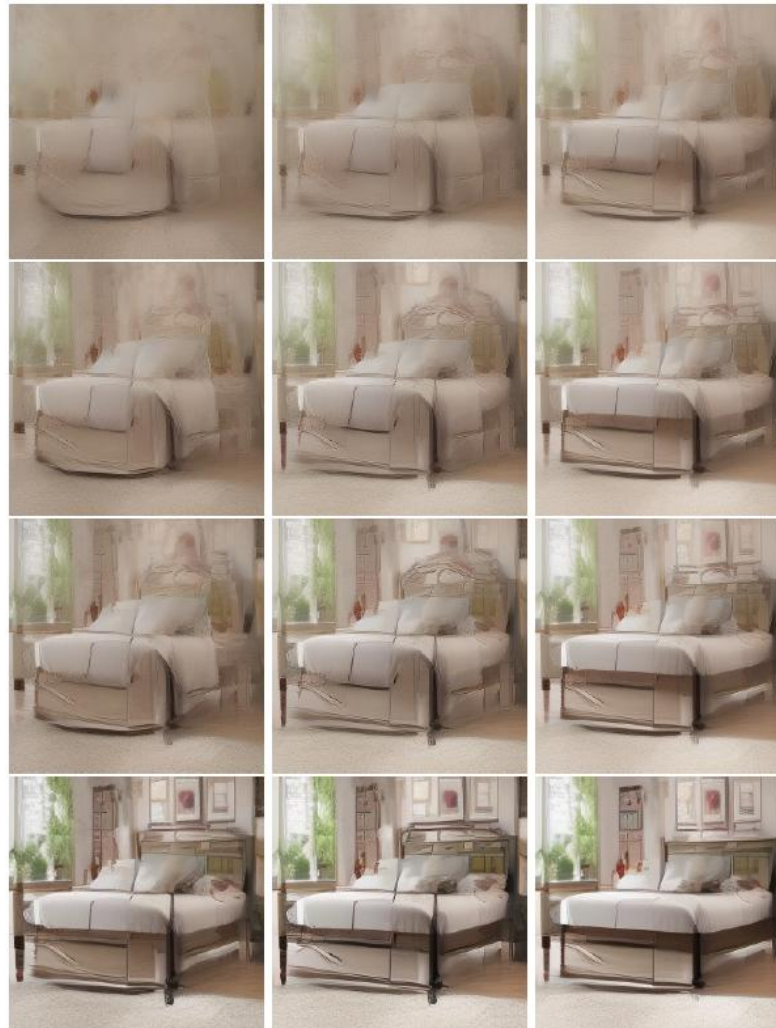
- FID comparison
 - *ms*: match-size
 - match-size n : optimize the noise-sample pairs between n noises and n samples.

Training time includes
DANSM overhead



Experiments

- Visualization
 - Samples by
 - 3 steps
 - 4 steps
 - 5 steps
 - 10 steps



Baseline

ms:100

ms:10K



Baseline ms:100 ms:1K

Thanks