Improving the Training of Rectified Flows

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Diffusion models are slow to sample from



Reverse denoising process (generative)

https://cvpr2022-tutorial-diffusion-models.github.io/

Rectified flows speed up sampling by learning straight trajectories.



Step 1: Independently sample noise-data pairs

Step 2: Linearly interpolate between noise-data pairs



Step 3: Learn an ODE that with crossing-free trajectories

Closed form ODE:

$$\frac{d\mathbf{z}_t}{dt} = \mathbf{v}_t(\mathbf{z}_t) := \frac{1}{t}(\mathbf{z}_t - \mathbb{E}[\mathbf{x}|\mathbf{x}_t = \mathbf{z}_t]).$$

Step 4: Generate noisedata pairs from new ODE

k-rectified flow = k rounds of repetition

 $\mathbb{E}[\mathbf{x}|\mathbf{x}_t]$ $\mathbb{E}[\mathbf{x}|\mathbf{x}_t]$ \mathbf{x}_t $p_{\mathbf{x}}^2$ $p_{\mathbf{z}}$ $p_{\mathbf{z}}$ $p_{\mathbf{z}}$ $p_{\mathbf{z}}$ $p_{\mathbf{x}}^{1}$ $p_{\mathbf{x}}^{\perp}$ $p_{\mathbf{x}}^{o}$ (a) Linear interpolation (b) Generative process (c) Linear interpolation (d) Generative process induced by p_{xz}^0 of 1-rectified flow induced by p_{xz}^1 of 2-rectified flow

k-rectified flow = k rounds of repetition

Step 4: Generate noisedata pairs from new ODE

Step 5: Repeat

How many rounds are enough?

Theoretically $k \rightarrow \infty$ gives straighttrajectories

Conventionally At least 3 rounds

Our claim:

Two rounds of Reflow are enough!

When do we get the straight ODE?

k-rectified flow ODE is straight iff the linear interpolation paths of (k-1)-rectified flow do not intersect.

Not a realistic Gaussian noise!

Cannot be mapped to a realistic horse image.

2-rectified flow++ is competitive with SOTA

FFHQ 64x64

AFHQ 64x64

ImageNet 64x64

One-step generated samples from our 2-rectified flow++.

In summary,

- The optimal 2-rectified flow is nearly straight.
 - This motivates new training techniques
- Our improved techniques make 2-rectified flow competitive to SOTA methods.
- It still retains and enhances the useful features of the neural ODE, such as multi-step iterative refinement and inversion from data to noise.

github.com/sangyun884/rfpp

