Beyond Blur

A Fluid Perspective on Generative Diffusion Models

Background Our forward pass formulates image corruption via a physically motivated PDE that couples directional advection with isotropic diffusion and Gaussian noise,

$$\frac{\partial u}{\partial t} + \underbrace{\nabla \cdot (\mathbf{v} u)}_{\text{advection}} = \underbrace{\nabla \cdot (\alpha \nabla u)}_{\text{diffusion}} + \underbrace{\dot{Q}(t)}_{\text{reaction}} .$$

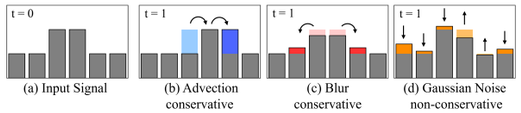

Figure 1: Corruption process: (a) input image, (b) advection and (c) blur "redistribute" the intensities but preserve the total "mass", i.e., pixel-intensity sum (conservative). (d) Gaussian noise adds or subtracts "mass" (non-conservative).

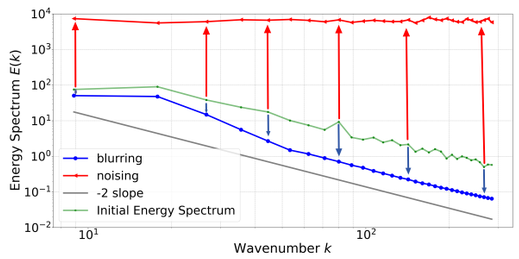

Figure 2: Comparison of the Energy Spectrum of an image subjected to different corruption processes.

Overview of the NN training pipeline

In our method we do *not* inject noise directly into the PDE itself in order to keep the process conservative.

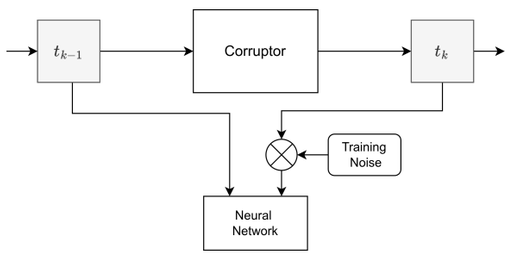

Figure 3: The image corruptor applies the advection–diffusion operator during each of the discrete time steps. The NN is trained on pairs of images destroyed up to the prescribed time, as dictated by the scheduler.

Generative model that integrates the **advection** (shift) term along **blurring** (averaging) and a random **reaction** (Gaussian noise)

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Visual comparison of different forward processes

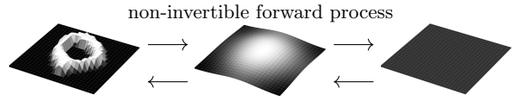
Standard diffusion model

non-invertible forward process

generative reverse process

Inverse heat dissipation model (IHD)

non-invertible forward process



generative reverse process

Advection diffusion model (Our)

non-invertible forward process

generative reverse process

Results To quantify the ratio of advective transport to diffusion rate, we use a dimensionless Peclet number $Pe = VL/\alpha$. The baseline values refer to purely blurring approach at $Pe = 0$.

Table 1: Evaluation metrics for different Peclet numbers on FFHQ 128×128 dataset.

Pe	FID↓	P↑	R↑	D↑	C↑
0 (IHD)	55.87	0.798	0.109	0.762	0.482
0.02	56.57	0.797	0.102	0.806	0.491
0.04	51.44	0.815	0.115	0.921	0.539
0.06	36.64	0.826	0.243	1.040	0.665
0.08	37.41	0.817	0.247	1.043	0.662
0.10	42.88	0.764	0.187	0.854	0.556
0.12	48.62	0.688	0.183	0.683	0.510

Conclusions The advection term improves the quality (FID) of generated images compared to the baseline approach (blurring only).