Blurring/Soft Diffusion

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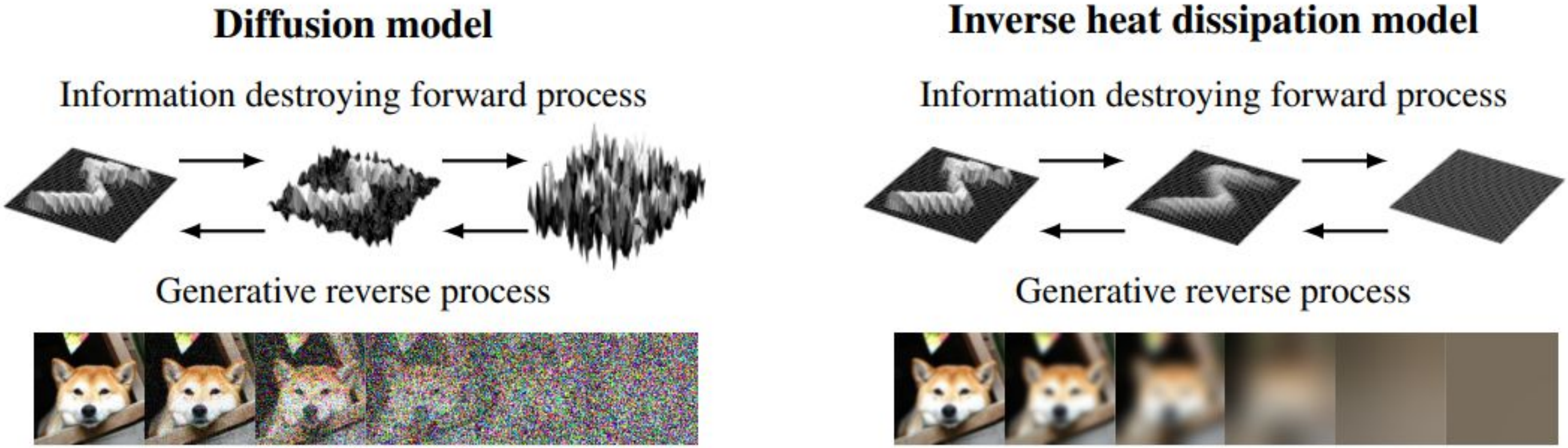
23 Sep 2022

Inverse Heat Dissipation Models (IHDM)



Severi Rissanen, Markus Heinonen, and Arno Solin. Generative modelling with inverse heat dissipation. CoRR, abs/2206.13397, 2022.

Inverse Heat Dissipation Models (IHDM)

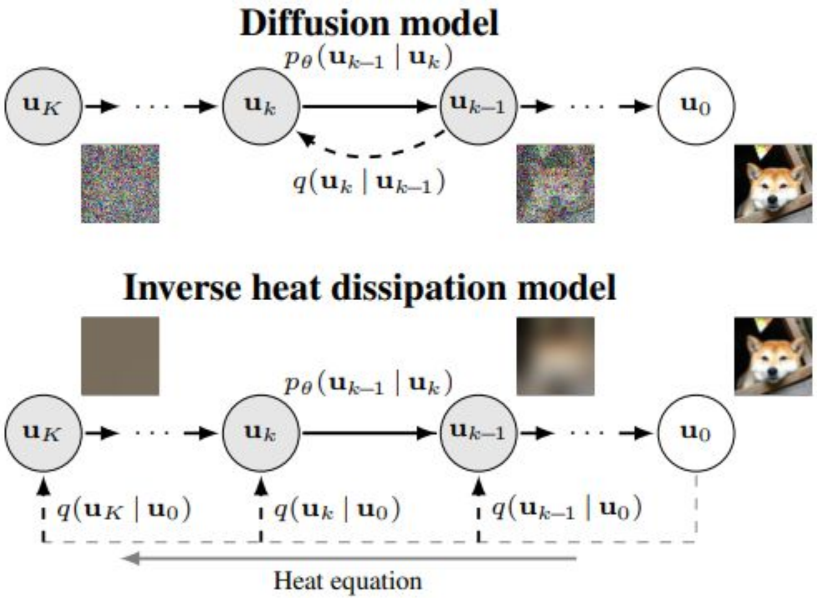
Forward process /
Inference distribution

$$q(\mathbf{u}_{1:K} \mid \mathbf{u}_0) = \prod_{k=1}^{K} q(\mathbf{u}_k \mid \mathbf{u}_0) = \prod_{k=1}^{K} \mathcal{N}(\mathbf{u}_k \mid \mathbf{F}(t_k)\, \mathbf{u}_0, \sigma^2 \mathbf{I}),$$

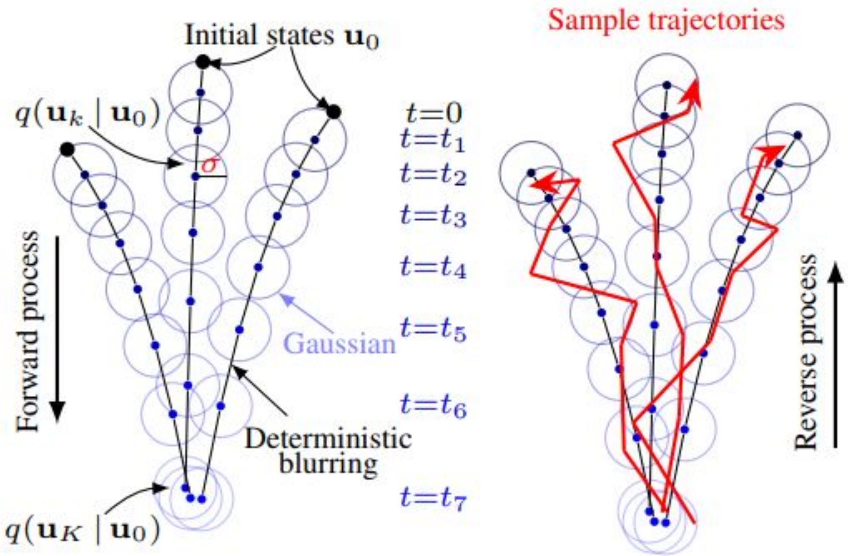
Reverse process /
Generative model

$$p_\theta(\mathbf{u}_{0:K}) = p(\mathbf{u}_K) \prod_{k=1}^{K} p_\theta(\mathbf{u}_{k-1} \mid \mathbf{u}_k),$$

Inverse Heat Dissipation Models (IHDM)



(a) Graphical models



(b) Illustration of the parameter σ and joining of forward process paths, enabling branching in the reverse

Inverse Heat Dissipation Models (IHDM)

- DDPM:

$$\mathbb{E}_q\Bigg[\underbrace{D_{\mathrm{KL}}(q(\mathbf{x}_T|\mathbf{x}_0) \parallel p(\mathbf{x}_T))}_{L_T} + \sum_{t>1} \underbrace{D_{\mathrm{KL}}(q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) \parallel p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t))}_{L_{t-1}} \underbrace{- \log p_\theta(\mathbf{x}_0|\mathbf{x}_1)}_{L_0}\Bigg]$$

- IHDM:

$$\mathbb{E}_q\Bigg[\underbrace{\mathrm{D}_{\mathrm{KL}}[q(\mathbf{u}_K \mid \mathbf{u}_0) \parallel p(\mathbf{u}_K)]}_{L_K} + \sum_{k=2}^{K} \underbrace{\mathrm{D}_{\mathrm{KL}}[q(\mathbf{u}_{k-1} \mid \mathbf{u}_0) \parallel p_\theta(\mathbf{u}_{k-1} \mid \mathbf{u}_k)]}_{L_{k-1}} \underbrace{- \log p_\theta(\mathbf{u}_0 \mid \mathbf{u}_1)}_{L_0}\Bigg],$$

Variational Diffusion Models

$$q(\boldsymbol{z}_t|\boldsymbol{x}) = \mathcal{N}(\boldsymbol{z}_t|\alpha_t \boldsymbol{x}, \sigma_t^2 \mathbf{I}),$$

$$q(\boldsymbol{z}_t|\boldsymbol{z}_s) = \mathcal{N}(\boldsymbol{z}_t|\alpha_{t|s} \boldsymbol{z}_s, \sigma_{t|s}^2 \mathbf{I}),$$

where $0 \leq s < t$:

$\alpha_{t|s} = \alpha_t / \alpha_s$ and $\sigma_{t|s}^2 = \sigma_t^2 - \alpha_{t|s}^2 \sigma_s^2$.

$$q(\boldsymbol{z}_s|\boldsymbol{z}_t, \boldsymbol{x}) = \mathcal{N}(\boldsymbol{z}_s|\boldsymbol{\mu}_{t \to s}, \sigma_{t \to s}^2 \mathbf{I}),$$

$$\sigma_{t \to s}^2 = \left(\frac{1}{\sigma_s^2} + \frac{\alpha_{t|s}^2}{\sigma_{t|s}^2} \right)^{-1} \text{ and } \boldsymbol{\mu}_{t \to s} = \sigma_{t \to s}^2 \left(\frac{\alpha_{t|s}}{\sigma_{t|s}^2} \boldsymbol{z}_t + \frac{\alpha_s}{\sigma_s^2} \boldsymbol{x} \right)$$

$$p(\boldsymbol{z}_s|\boldsymbol{z}_t) = q(\boldsymbol{z}_s|\boldsymbol{z}_t, \hat{\boldsymbol{x}}(\boldsymbol{z}_t)),$$

Diederik P. Kingma, Tim Salimans, Ben Poole, and Jonathan Ho. Variational diffusion models. CoRR, abs/2107.00630, 2021.

Blurring Diffusion Models

$$q(\boldsymbol{z}_t|\boldsymbol{x}) = \mathcal{N}(\boldsymbol{z}_t|\mathbf{A}_t\boldsymbol{x}, \sigma^2\mathbf{I}) \quad \text{where } \mathbf{A}_t = \mathbf{V}\mathbf{D}_t\mathbf{V}^{\mathrm{T}} \quad \mathbf{D}_t = \exp(-\boldsymbol{\Lambda}\tau_t)$$

$$q(\boldsymbol{u}_t|\boldsymbol{u}_0) = \mathcal{N}(\boldsymbol{u}_t|\boldsymbol{d}_t \cdot \boldsymbol{u}_0, \sigma^2\mathbf{I}) \qquad \boldsymbol{u}_0 = \mathbf{V}^{\mathrm{T}}\boldsymbol{x} \qquad \boldsymbol{d}_t = \exp(-\boldsymbol{\lambda}\tau_t)$$

$$q(\boldsymbol{u}_t|\boldsymbol{u}_s) = \mathcal{N}(\boldsymbol{u}|\boldsymbol{\alpha}_{t|s}\boldsymbol{u}_s, \boldsymbol{\sigma}^2_{t|s})$$

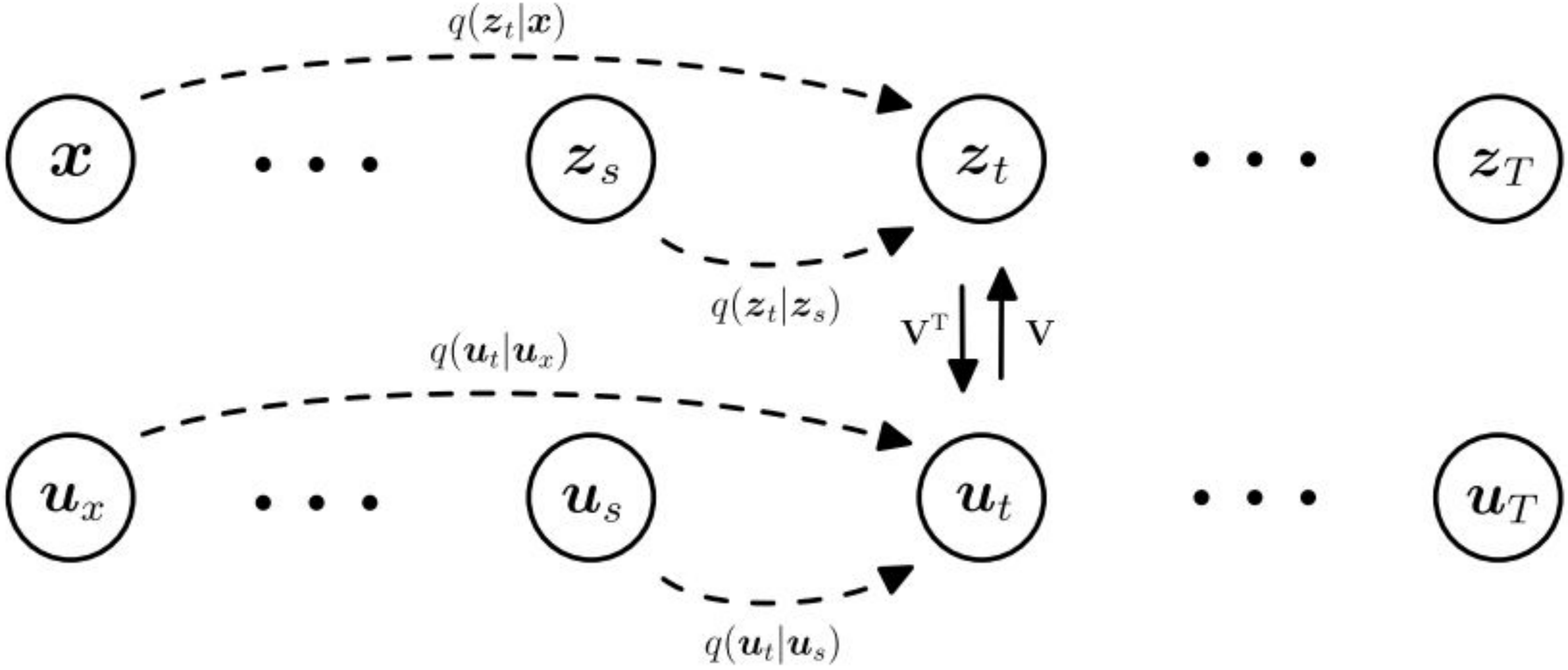
$$\boldsymbol{\alpha}_{t|s} = \boldsymbol{d}_t/\boldsymbol{d}_s \quad \text{and} \quad \boldsymbol{\sigma}^2_{t|s} = (1 - (\boldsymbol{d}_t/\boldsymbol{d}_s)^2)\sigma^2$$

$$q(\boldsymbol{u}_s|\boldsymbol{u}_t, \boldsymbol{x}) = \mathcal{N}(\boldsymbol{u}_s|\boldsymbol{\mu}_{t\to s}, \boldsymbol{\sigma}^2_{t\to s}),$$

$$p(\boldsymbol{u}_s|\boldsymbol{u}_t) = q(\boldsymbol{u}_s|\boldsymbol{u}_t, \hat{\boldsymbol{u}}_x) = \mathcal{N}(\boldsymbol{u}_s|\hat{\boldsymbol{\mu}}_{t\to s}, \boldsymbol{\sigma}_{t\to s})$$

Hoogeboom E., Salimans T. Blurring Diffusion Models //arXiv preprint arXiv:2209.05557. – 2022.

Blurring Diffusion Models



Soft Diffusion: Score Matching for General Corruptions

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Abstract

We define a broader family of corruption processes that generalizes previously known diffusion models. To reverse these general diffusions, we propose a new objective called Soft Score Matching that provably learns the score function for any linear corruption process and yields state of the art results for CelebA. Soft Score Matching incorporates the degradation process in the network and trains the model to predict a clean image that after corruption matches the diffused observation. We show that our objective learns the gradient of the likelihood under suitable regularity conditions for the family of corruption processes. We further develop a principled way to select the corruption levels for general diffusion processes and a novel sampling method that we call Momentum Sampler. We evaluate our framework with the corruption being Gaussian Blur and low magnitude additive noise. Our method achieves state-of-the-art FID score 1.85 on CelebA-64, outperforming all previous linear diffusion models. We also show significant computational benefits compared to vanilla denoising diffusion.

Daras G. et al. Soft Diffusion: Score Matching for General Corruptions //arXiv preprint arXiv:2209.05442. – 2022.

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