


Joel Hancock

Diffusion Models

Generative AI Reading Group | 24/07/2024

 joel@menchelab.com

 www.menchelab.com

 [@menchelab](https://twitter.com/menchelab)

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1. Intro and Link to VAEs
 2. Learning to Reverse a Blurring Operation
 - a. General Principles
 - b. Specific Loss Function
 3. Multiplying by Other Priors
 - a. Why is this Good?
 - b. How do they do it?
 4. A Bit about Convolutional Layers
 5. What about the Link to Physics?

Comparison To VAEs

- lots of small VAE's stacked on top of one another.
- "Encoder" is not learned

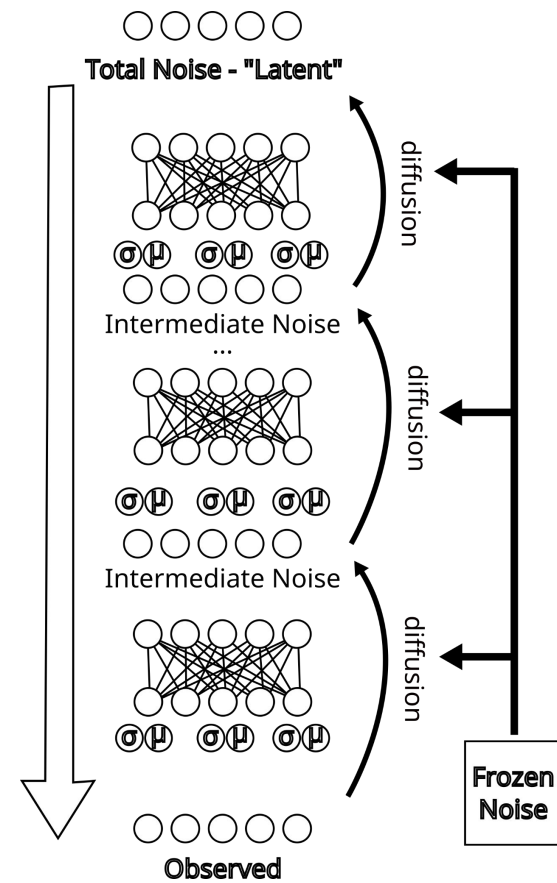
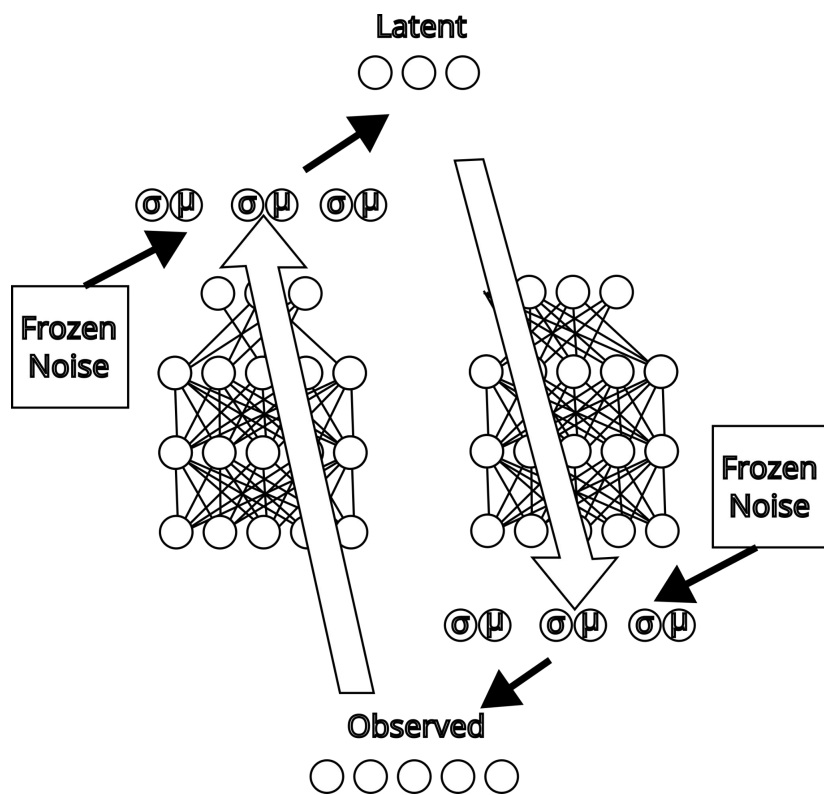
Con:

- No one single latent space

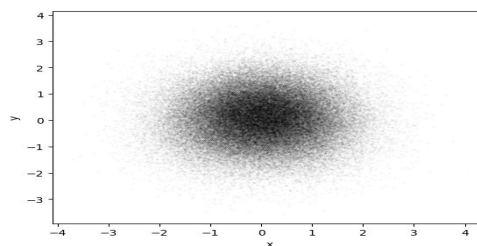
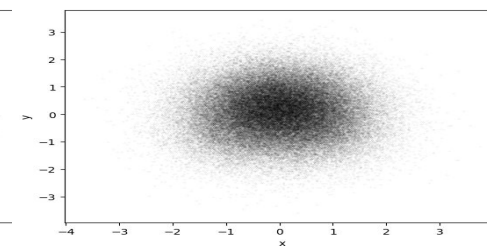
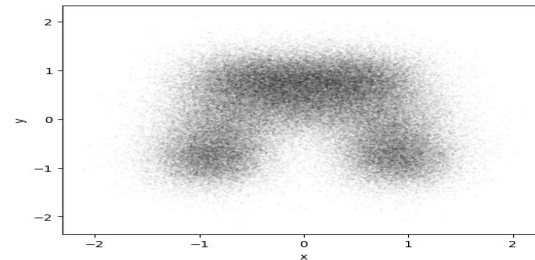
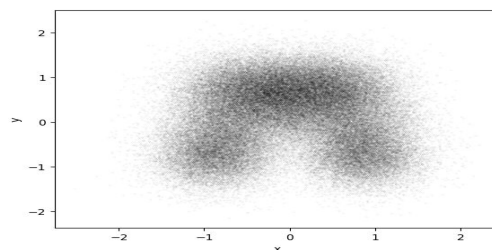
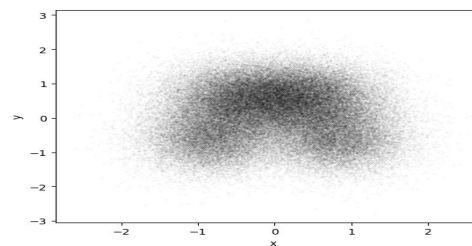
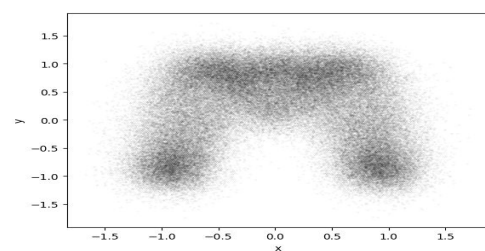
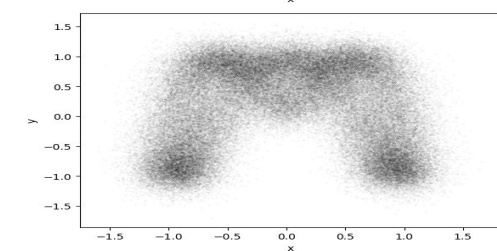
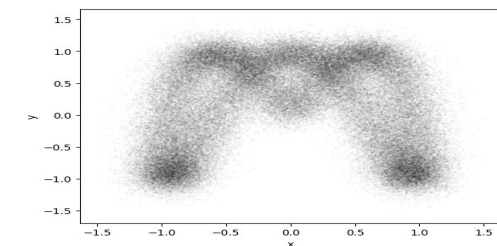
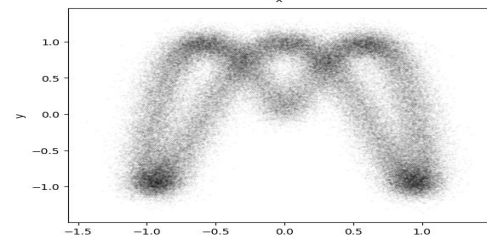
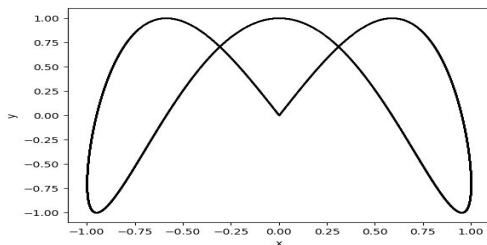
Pro:

- Target functions close to the identity, with very simple form.

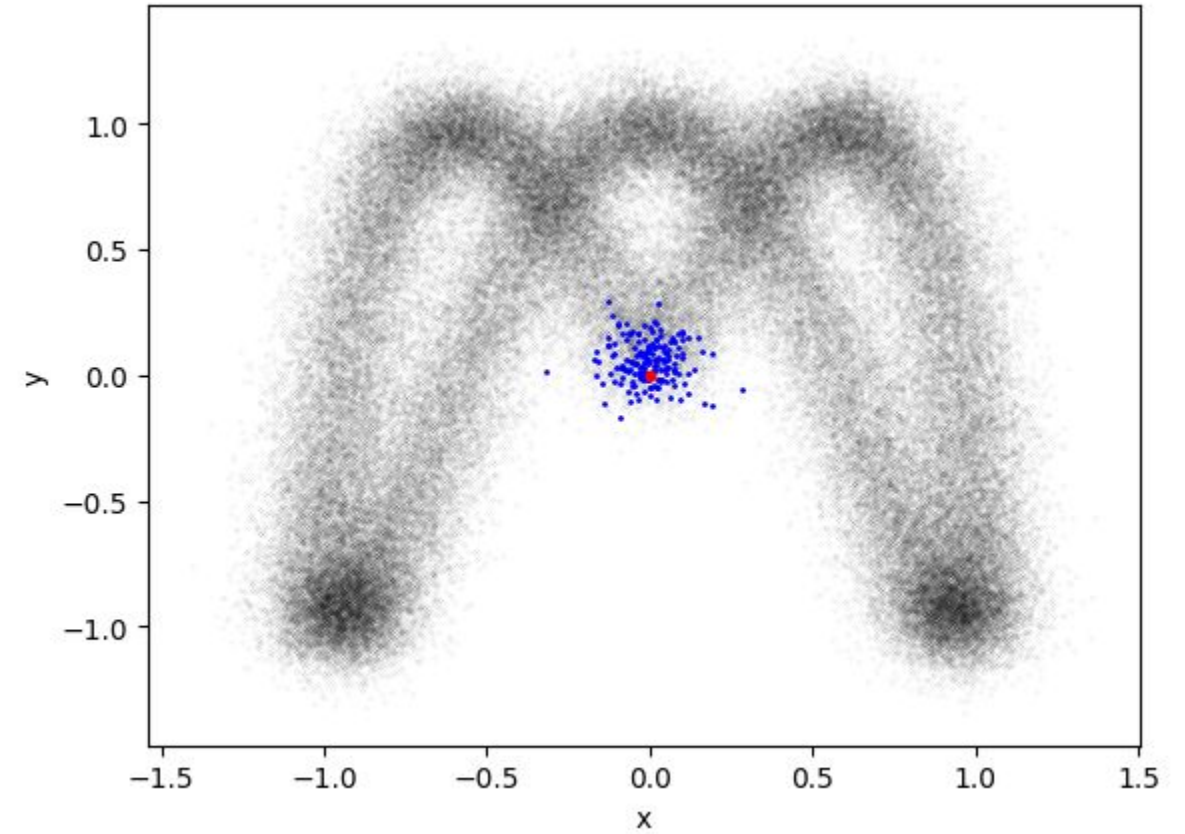
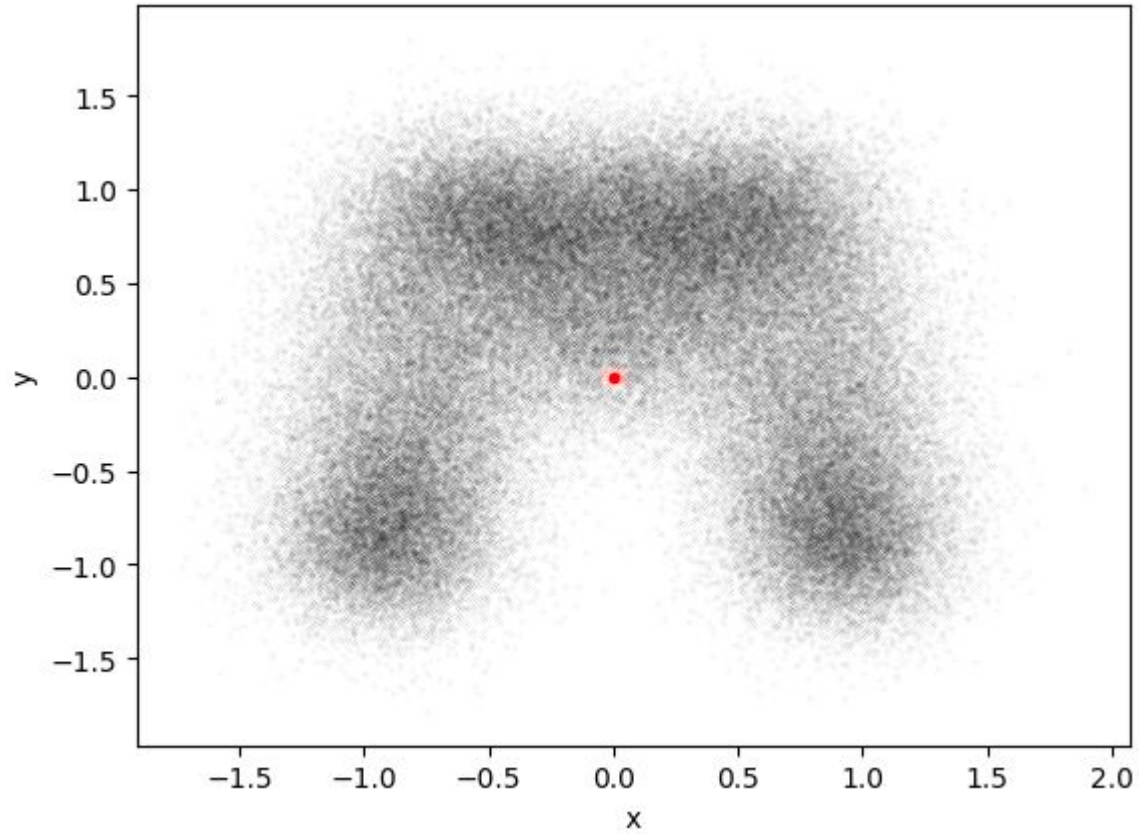
VAE versus Diffusion Model



Sequentially Adding Noise to a DataSet



Where did I Come From? Posterior Distributions



The Loss Term

$$= \underbrace{\mathbb{E}_{q(\mathbf{x}_1|\mathbf{x}_0)} [\log p_{\boldsymbol{\theta}}(\mathbf{x}_0|\mathbf{x}_1)]}_{\text{reconstruction term}} - \underbrace{D_{\text{KL}}(q(\mathbf{x}_T|\mathbf{x}_0) \parallel p(\mathbf{x}_T))}_{\text{prior matching term}} - \sum_{t=2}^T \underbrace{\mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [D_{\text{KL}}(q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) \parallel p_{\boldsymbol{\theta}}(\mathbf{x}_{t-1}|\mathbf{x}_t))]}_{\text{denoising matching term}}$$

This is why we have that extra conditioning Term

$$q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) = \frac{q(\mathbf{x}_t|\mathbf{x}_{t-1}, \mathbf{x}_0)q(\mathbf{x}_{t-1}|\mathbf{x}_0)}{q(\mathbf{x}_t|\mathbf{x}_0)} \quad (71)$$

$$= \frac{\mathcal{N}(\mathbf{x}_t; \sqrt{\alpha_t}\mathbf{x}_{t-1}, (1-\alpha_t)\mathbf{I})\mathcal{N}(\mathbf{x}_{t-1}; \sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0, (1-\bar{\alpha}_{t-1})\mathbf{I})}{\mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t}\mathbf{x}_0, (1-\bar{\alpha}_t)\mathbf{I})} \quad (72)$$

$$\propto \exp \left\{ - \left[\frac{(\mathbf{x}_t - \sqrt{\alpha_t}\mathbf{x}_{t-1})^2}{2(1-\alpha_t)} + \frac{(\mathbf{x}_{t-1} - \sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0)^2}{2(1-\bar{\alpha}_{t-1})} - \frac{(\mathbf{x}_t - \sqrt{\bar{\alpha}_t}\mathbf{x}_0)^2}{2(1-\bar{\alpha}_t)} \right] \right\} \quad (73)$$

$$= \exp \left\{ - \frac{1}{2} \left[\frac{(\mathbf{x}_t - \sqrt{\alpha_t}\mathbf{x}_{t-1})^2}{1-\alpha_t} + \frac{(\mathbf{x}_{t-1} - \sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0)^2}{1-\bar{\alpha}_{t-1}} - \frac{(\mathbf{x}_t - \sqrt{\bar{\alpha}_t}\mathbf{x}_0)^2}{1-\bar{\alpha}_t} \right] \right\} \quad (74)$$

$$= \exp \left\{ - \frac{1}{2} \left[\frac{(-2\sqrt{\alpha_t}\mathbf{x}_t\mathbf{x}_{t-1} + \alpha_t\mathbf{x}_{t-1}^2)}{1-\alpha_t} + \frac{(\mathbf{x}_{t-1}^2 - 2\sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_{t-1}\mathbf{x}_0)}{1-\bar{\alpha}_{t-1}} + C(\mathbf{x}_t, \mathbf{x}_0) \right] \right\} \quad (75)$$

$$\propto \exp \left\{ - \frac{1}{2} \left[- \frac{2\sqrt{\alpha_t}\mathbf{x}_t\mathbf{x}_{t-1}}{1-\alpha_t} + \frac{\alpha_t\mathbf{x}_{t-1}^2}{1-\alpha_t} + \frac{\mathbf{x}_{t-1}^2}{1-\bar{\alpha}_{t-1}} - \frac{2\sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_{t-1}\mathbf{x}_0}{1-\bar{\alpha}_{t-1}} \right] \right\} \quad (76)$$

$$= \exp \left\{ - \frac{1}{2} \left[\left(\frac{\alpha_t}{1-\alpha_t} + \frac{1}{1-\bar{\alpha}_{t-1}} \right) \mathbf{x}_{t-1}^2 - 2 \left(\frac{\sqrt{\alpha_t}\mathbf{x}_t}{1-\alpha_t} + \frac{\sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0}{1-\bar{\alpha}_{t-1}} \right) \mathbf{x}_{t-1} \right] \right\} \quad (77)$$

$$= \exp \left\{ - \frac{1}{2} \left[\frac{\alpha_t(1-\bar{\alpha}_{t-1}) + 1 - \alpha_t}{(1-\alpha_t)(1-\bar{\alpha}_{t-1})} \mathbf{x}_{t-1}^2 - 2 \left(\frac{\sqrt{\alpha_t}\mathbf{x}_t}{1-\alpha_t} + \frac{\sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0}{1-\bar{\alpha}_{t-1}} \right) \mathbf{x}_{t-1} \right] \right\} \quad (78)$$

$$= \exp \left\{ - \frac{1}{2} \left[\frac{\alpha_t - \bar{\alpha}_t + 1 - \alpha_t}{(1-\alpha_t)(1-\bar{\alpha}_{t-1})} \mathbf{x}_{t-1}^2 - 2 \left(\frac{\sqrt{\alpha_t}\mathbf{x}_t}{1-\alpha_t} + \frac{\sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0}{1-\bar{\alpha}_{t-1}} \right) \mathbf{x}_{t-1} \right] \right\} \quad (79)$$

$$= \exp \left\{ - \frac{1}{2} \left[\frac{1 - \bar{\alpha}_t}{(1-\alpha_t)(1-\bar{\alpha}_{t-1})} \mathbf{x}_{t-1}^2 - 2 \left(\frac{\sqrt{\alpha_t}\mathbf{x}_t}{1-\alpha_t} + \frac{\sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0}{1-\bar{\alpha}_{t-1}} \right) \mathbf{x}_{t-1} \right] \right\} \quad (80)$$

$$= \exp \left\{ - \frac{1}{2} \left(\frac{1 - \bar{\alpha}_t}{(1-\alpha_t)(1-\bar{\alpha}_{t-1})} \right) \left[\mathbf{x}_{t-1}^2 - 2 \frac{\left(\frac{\sqrt{\alpha_t}\mathbf{x}_t}{1-\alpha_t} + \frac{\sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0}{1-\bar{\alpha}_{t-1}} \right)}{\frac{1-\bar{\alpha}_t}{(1-\alpha_t)(1-\bar{\alpha}_{t-1})}} \mathbf{x}_{t-1} \right] \right\} \quad (81)$$

$$= \exp \left\{ - \frac{1}{2} \left(\frac{1 - \bar{\alpha}_t}{(1-\alpha_t)(1-\bar{\alpha}_{t-1})} \right) \left[\mathbf{x}_{t-1}^2 - 2 \frac{\left(\frac{\sqrt{\alpha_t}\mathbf{x}_t}{1-\alpha_t} + \frac{\sqrt{\bar{\alpha}_{t-1}}\mathbf{x}_0}{1-\bar{\alpha}_{t-1}} \right) (1-\alpha_t)(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t} \mathbf{x}_{t-1} \right] \right\} \quad (82)$$

$$= \exp \left\{ - \frac{1}{2} \left(\frac{1}{\frac{(1-\alpha_t)(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t}} \right) \left[\mathbf{x}_{t-1}^2 - 2 \frac{\sqrt{\alpha_t}(1-\bar{\alpha}_{t-1})\mathbf{x}_t + \sqrt{\bar{\alpha}_{t-1}}(1-\alpha_t)\mathbf{x}_0}{1-\bar{\alpha}_t} \mathbf{x}_{t-1} \right] \right\} \quad (83)$$

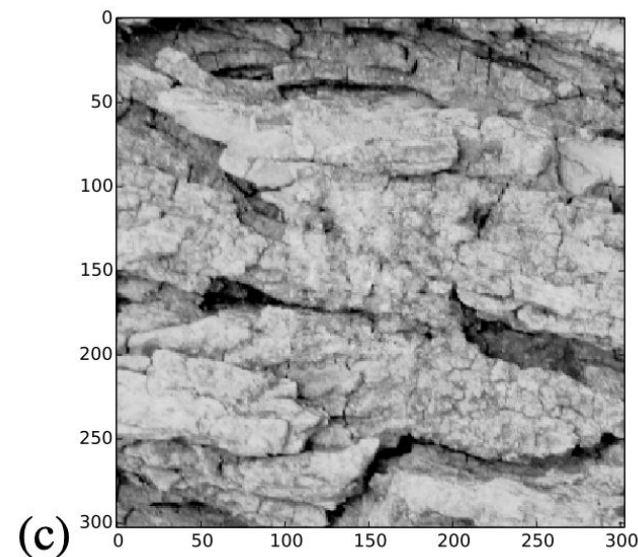
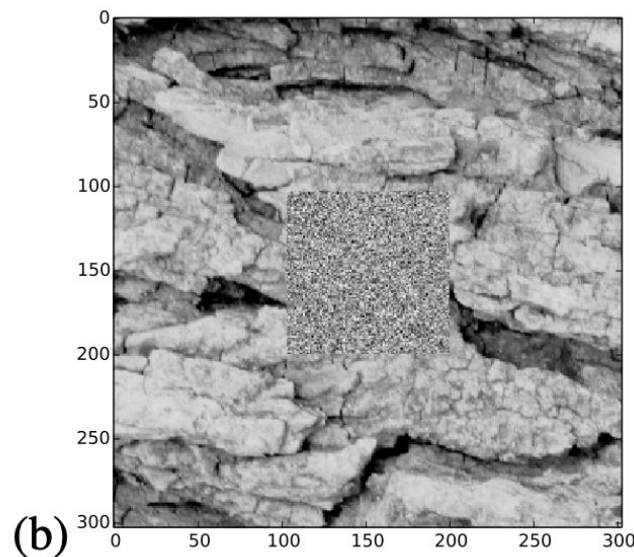
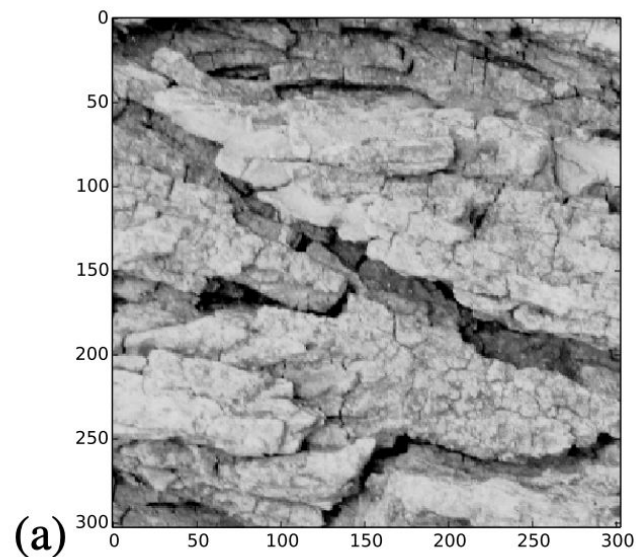
$$\propto \mathcal{N}(\mathbf{x}_{t-1}; \underbrace{\frac{\sqrt{\alpha_t}(1-\bar{\alpha}_{t-1})\mathbf{x}_t + \sqrt{\bar{\alpha}_{t-1}}(1-\alpha_t)\mathbf{x}_0}{1-\bar{\alpha}_t}}_{\mu_q(\mathbf{x}_t, \mathbf{x}_0)}, \underbrace{\frac{(1-\alpha_t)(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t}}_{\Sigma_q(t)} \mathbf{I}) \quad (84)$$

It's not so hard to Gradient Descend on a KL-Divergence

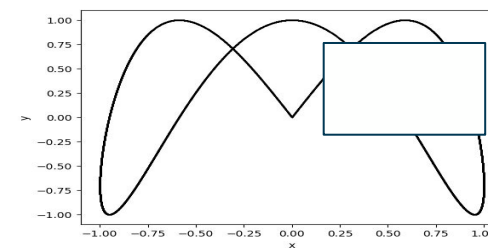
$$D_{\text{KL}}(\mathcal{N}(\mathbf{x}; \boldsymbol{\mu}_x, \boldsymbol{\Sigma}_x) \parallel \mathcal{N}(\mathbf{y}; \boldsymbol{\mu}_y, \boldsymbol{\Sigma}_y)) = \frac{1}{2} \left[\log \frac{|\boldsymbol{\Sigma}_y|}{|\boldsymbol{\Sigma}_x|} - d + \text{tr}(\boldsymbol{\Sigma}_y^{-1} \boldsymbol{\Sigma}_x) + (\boldsymbol{\mu}_y - \boldsymbol{\mu}_x)^T \boldsymbol{\Sigma}_y^{-1} (\boldsymbol{\mu}_y - \boldsymbol{\mu}_x) \right] \quad (86)$$

We actually have a deterministic formula to gradient descend on!
No need for re-parametrization trick here!

Conditioning the Prior

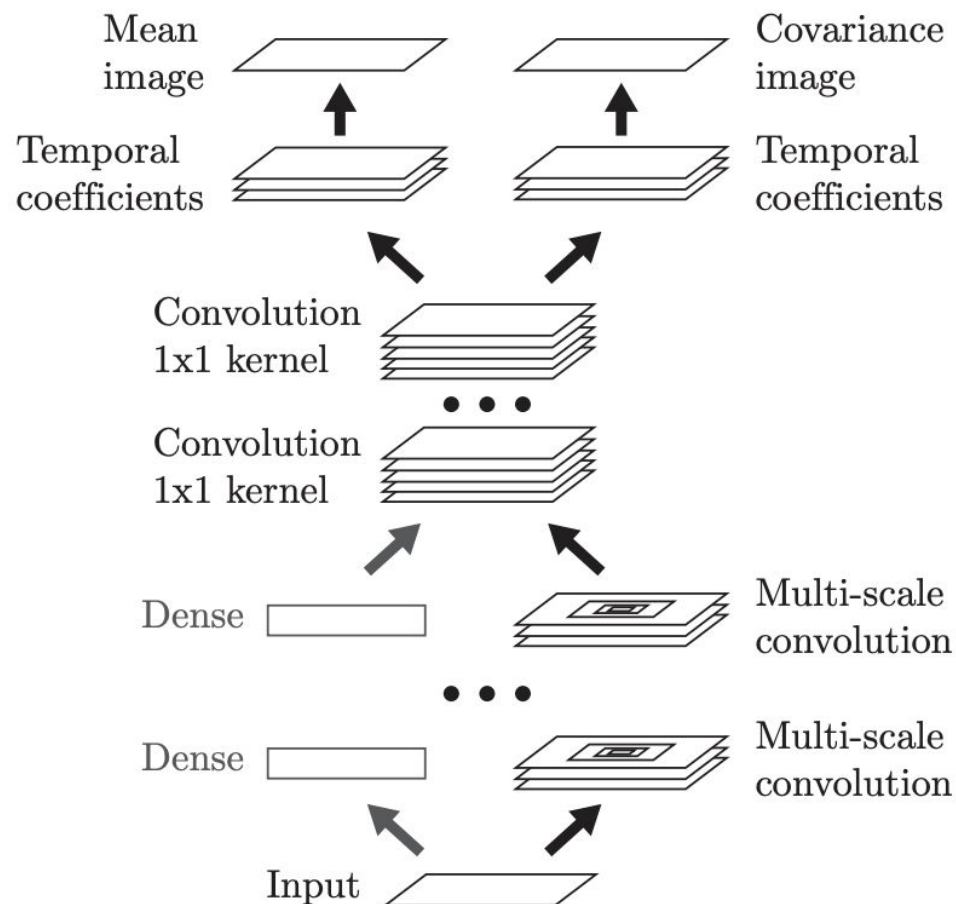


$$\tilde{p}(\mathbf{x}^{(t-1)}|\mathbf{x}^{(t)}) = \left| \mathcal{N}\left(x^{(t-1)}; \mathbf{f}_\mu(\mathbf{x}^{(t)}, t) + \mathbf{f}_\Sigma(\mathbf{x}^{(t)}, t) \frac{\partial \log r(\mathbf{x}^{(t-1)'})}{\partial \mathbf{x}^{(t-1)'}} \right) \right|_{\mathbf{x}^{(t-1)'} = \mathbf{f}_\mu(\mathbf{x}^{(t)}, t)}, \mathbf{f}_\Sigma(\mathbf{x}^{(t)}, t)$$



A Bit about Convolutional Layers

- Naturally, simply diffusing per-pixel is not really enough
- They need some kind of convolution and pooling
- So the real model for the image generation is more complex



Connection to Physics

- Honestly pretty obscure
- Jarzynski's Inequality
 - Exponential of Work is Exponential of Free Energy Change

Sources

Original paper

<https://arxiv.org/pdf/1503.03585>

Excellent explanation (h/t Moritz)

<https://arxiv.org/pdf/2208.11970>

Discussion

Shall we go over the fundamentals?

- Entropy?
- KL-Divergence?
- Bayes Theorem?
- What does "Variational" Mean in This context?

ELBO Re-prise

$$\log p(\mathbf{x}) = \log p(\mathbf{x}) \int q_{\phi}(\mathbf{z}|\mathbf{x}) d\mathbf{z} \quad (\text{Multiply by } 1 = \int q_{\phi}(\mathbf{z}|\mathbf{x}) d\mathbf{z}) \quad (9)$$

$$= \int q_{\phi}(\mathbf{z}|\mathbf{x}) (\log p(\mathbf{x})) d\mathbf{z} \quad (\text{Bring evidence into integral}) \quad (10)$$

$$= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} [\log p(\mathbf{x})] \quad (\text{Definition of Expectation}) \quad (11)$$

$$= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{p(\mathbf{z}|\mathbf{x})} \right] \quad (\text{Apply Equation 2}) \quad (12)$$

$$= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z}) q_{\phi}(\mathbf{z}|\mathbf{x})}{p(\mathbf{z}|\mathbf{x}) q_{\phi}(\mathbf{z}|\mathbf{x})} \right] \quad (\text{Multiply by } 1 = \frac{q_{\phi}(\mathbf{z}|\mathbf{x})}{q_{\phi}(\mathbf{z}|\mathbf{x})}) \quad (13)$$

$$= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q_{\phi}(\mathbf{z}|\mathbf{x})} \right] + \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} \left[\log \frac{q_{\phi}(\mathbf{z}|\mathbf{x})}{p(\mathbf{z}|\mathbf{x})} \right] \quad (\text{Split the Expectation}) \quad (14)$$

$$= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q_{\phi}(\mathbf{z}|\mathbf{x})} \right] + D_{\text{KL}}(q_{\phi}(\mathbf{z}|\mathbf{x}) \parallel p(\mathbf{z}|\mathbf{x})) \quad (\text{Definition of KL Divergence}) \quad (15)$$



Team Jörg Menche

Anna Hakobyan
Celine Sin
Christiane Hütter
Daniel Malzl
Felix Müller
Joel Hancock
Julia Pazmandi
Loan Vulliard
Martin Chiettoni
Michael Caldera
Pisanu “Ize” Buphamalai
Salvo D Lombardo
Sebastian Pirch

Contact

✉ your mail address

🌐 www.menchelab.com

🐦 [@menchelab.com](https://twitter.com/menchelab.com)