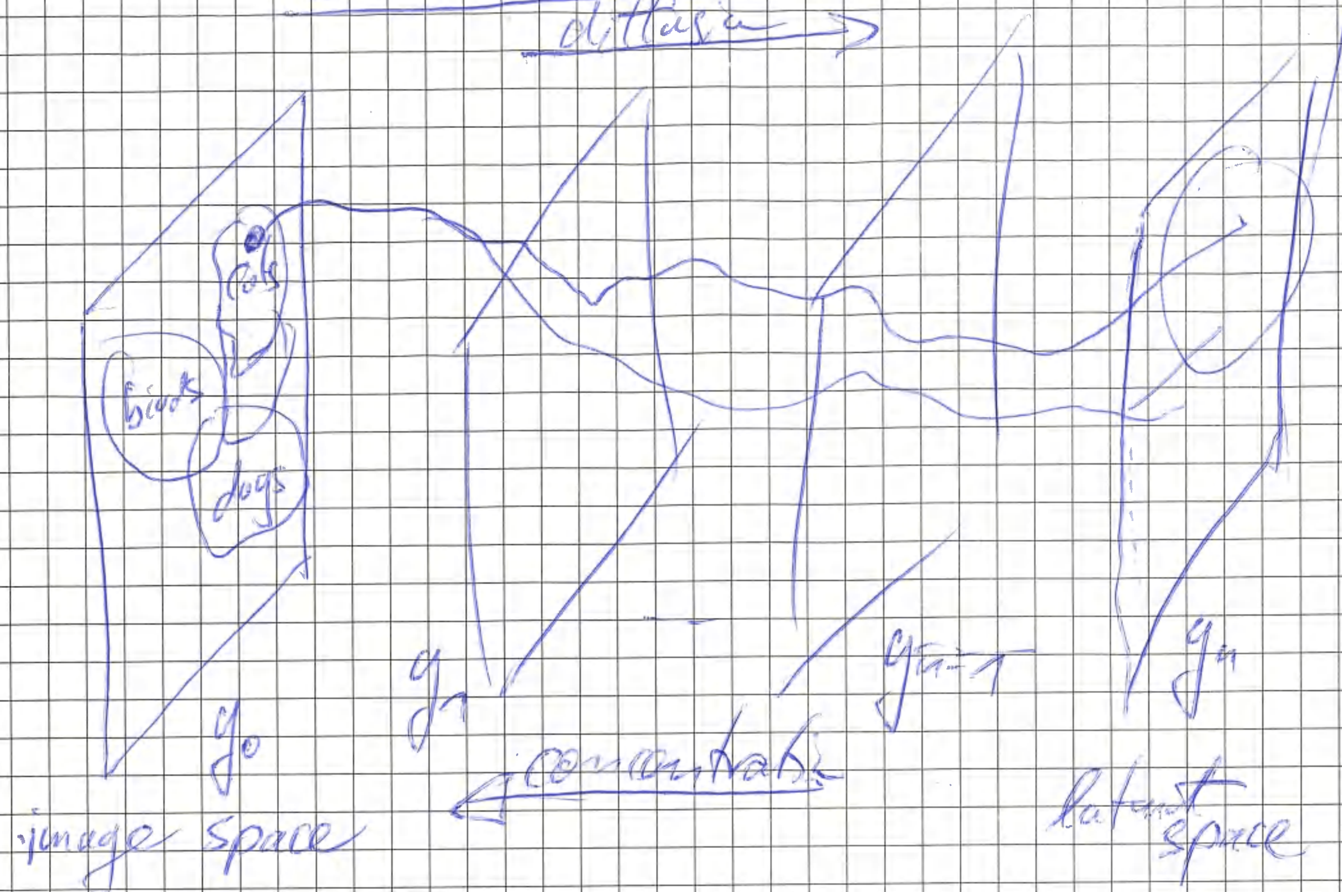
Stable diffusion



forwards: $y = (y_0, \dots, y_n)$

$$y_{i+1} = y_i + \varepsilon \xi_i \, , \quad P(\xi_i | y_i) = \mathcal{N}(\xi_i, \mathbb{1})$$

$$P(y) = P(y_n | y_{n-1}) \cdots P(y_1 | y_0) P(y_0)$$ ← data distr

n large enough $\Rightarrow P(y_n) \approx \mathcal{N}(y_n, \mathbb{1})$

backwards

output of time reversal pair trained network

$$y_i = y_{i+1} - \varepsilon \xi_i (y_{i+1})$$

$$\delta(y_{n-1} - y_n + \varepsilon \xi(y_n))$$

$$P(y) = \underbrace{P(y_0|y_1)}_{\delta(y_0 - y_1 + \varepsilon \xi(y_1))} \cdots P(y_{n-1}|y_n) \mathcal{N}(y_n, \mathbb{1})$$

$$Z(J) = \int \mathcal{D}y \, e^{J^t y} \, P(y)$$

$$= \int \mathcal{D}y \, e^{J^t y} \, \delta(y - G(y)) \, \mathcal{G}(y_u, \mathbb{1})$$

$$\propto \int \mathcal{D}y \int \mathcal{D}\beta \exp\left[J^t y + i\beta^t (y - G(y)) - \frac{y_u^t y_u}{2} \right]$$

Conditional stable diffusion

d = data constraint to be fulfilled

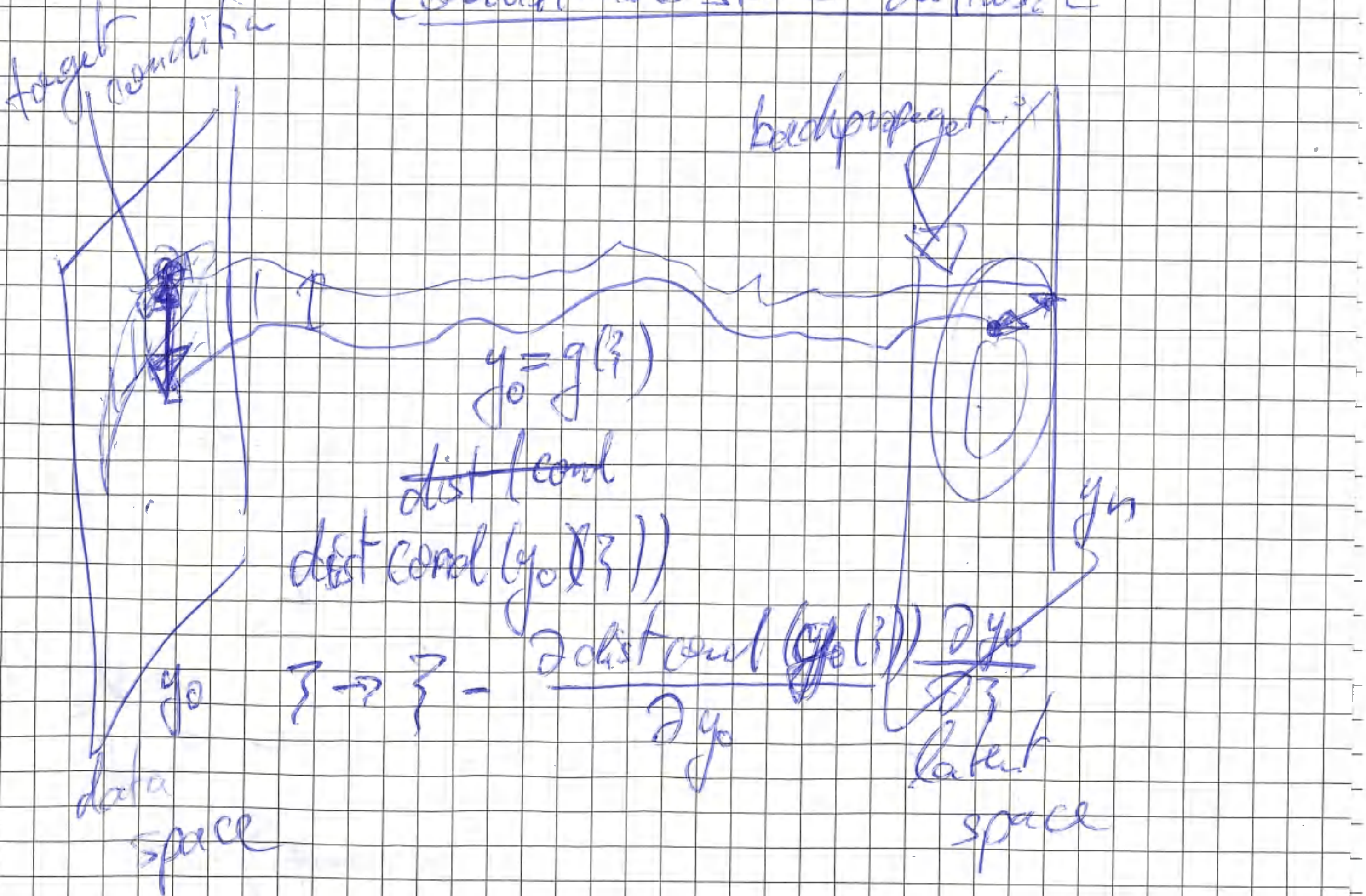
$\mathcal{P}(d|y_0)$ = likelihood expressing fulfillment

$$\mathcal{P}(y_0|d) \propto \mathcal{P}(d|y_0)\,\mathcal{P}(y_0)$$
$$= \int \mathcal{D}\xi \; \mathcal{P}(d|y_0 = g(\xi))\, \mathcal{G}(\xi, \mathbb{1})$$

$$\mathcal{H}(y_0|d) \widehat{=} \frac{1}{2}\xi^\dagger \xi + \mathcal{H}(d|y_0 = g(\xi))$$

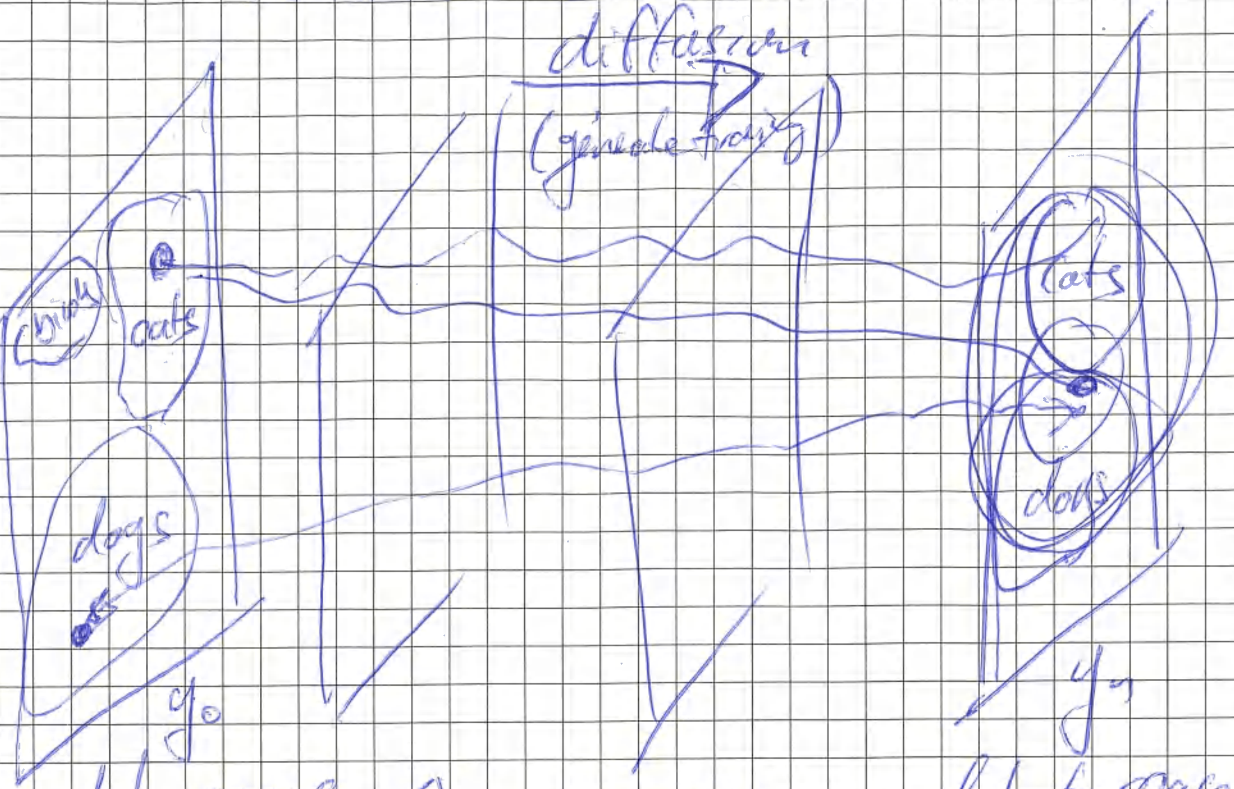
usage of MGVI/geoVI for stable diffusion sampling?

Conditional stable diffusion



Stable Diffusion

diffusion
(generate training)



dataspace ⟵ concentration ⟶ latent space

train anti-diffusion steps

$$y_i = y_{i-1} + \varepsilon \xi_{i-1}$$ diffusion, $P(\xi_{i-1} | y_{i-1})$

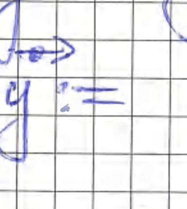
$$\vec{y} := \frac{y_i - y_{i-1}}{\varepsilon} = \xi$$ $= g(\xi_{i-1}, i)$

$$y_{i-1} = y_i - \varepsilon \xi_{i-1}(y_i)$$ concentration

$$\overleftarrow{y} = \frac{y_{i-1} - y_i}{\varepsilon} = -\xi(y)$$ train network on this

$$g(y_i, i) = \xi_{i-1}$$

this is an approx!

 overlap has no unique origin.

$$y = \underbrace{(y_0, \ldots, y_n)}_{\text{or } (\Delta y, \vec{1})} \qquad \approx \frac{1}{N}\sum_{i=1}^{N} \delta(y_0 - d_i) \quad \text{today}$$

$$P(y) = P(y_n | y_{n-1}) \ldots P(y_1|y_0) P(y_0) \qquad \text{forward view}$$

$$\approx \underbrace{P(y_0|y_1)} \ldots P(y_{n-1}|y_n) \underbrace{P(y_n)} \qquad \text{backward view}$$

$$\approx \delta(y_0 - f(y_1)) - \delta(y_{n-1} - f(y_n)) g(y_n, \mathbb{1})$$

$$Z(J) = \int \mathcal{D}y \, e^{J^t y} P(y)$$

forward view

$$\approx \int \mathcal{D}y \, e^{J^t y} \exp\left[\underset{\uparrow \Sigma_i}{-\frac{(y_i - y_{i-1})^2}{2\varepsilon^2}}\right] \frac{1}{N}\sum_{i=1}^{N} \delta(y_0 - d_i)$$

$$= \int \mathcal{D}y \, e^{J^t y} \delta(y_0 - f_1(y_1)) - \delta(y_{n-1} - f_n(y_n)) g(y_n, \mathbb{1})$$

backward view

$$= \int \mathcal{D}y \, e^{J^t y} \delta(f_1^{-1}(y_0) - y_1) \left|\frac{\partial f_1^{-1}}{\partial y_0}\right| \ldots$$

$$\left|\frac{\partial f_n^{-1}}{\partial y_{n-1}}\right| \delta(f_n^{-1}(y_{n-1}) - y_n) \, g(y_n, \mathbb{1})$$

$$Z(J) = \underbrace{\int \mathcal{D}y \int \mathcal{D}\beta}_{\text{bosonic}} \underbrace{\int \mathcal{D}\chi \int \mathcal{D}\bar{\chi}}_{\text{fermionic}} \exp\Big\{ J^{\dagger} y$$

$$+ \sum_{n} \beta_n \left(f_n^{-1}(y_{n+1}) - y_n \right) + \bar{\chi}_n \frac{\partial f_n^{-1}(y_{n+1})}{\partial y_{n+1}} \chi_{n+1} + \frac{y_n^2}{2} \Big\}$$

$$\cancel{i\beta^{\dagger}(f^{-1}(y) - y)}$$

$$\ln Z = \sum \text{all connected diagrams}$$

(including Fermions)