

Diffusion Schrödinger Bridge

29/06/2023

大纲


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Motivation

背景：

- 计算量
- 找到粒子在两个不同时间的分布下最可能的路径。

Methodology

 Trivial

-  Schrödinger Bridges (模型)
-  Score-Based Diffusions (模型)
-  Iterative Proportional Fitting (算法)
-  Diffusion Schrödinger Bridge (算法)

Methodology - Schrödinger Bridges

Schrödinger bridge 和 Static Schrödinger bridge

普通的Schrödinger Bridges

$$\pi^* = \arg \min \{ \text{KL}(\pi \mid p) : \pi \in \mathcal{P}_{N+1}, \pi_0 = p_{\text{data}}, \pi_N = p_{\text{prior}} \}$$

Methodology - Schrödinger Bridges

Static Schrödinger Bridge

$$\pi^{s,*} = \arg \min \{ \text{KL}(\pi^s \mid p_{0,N}) : \pi^s \in \mathcal{P}_2, \pi_0^s = p_{\text{data}}, \pi_N^s = p_{\text{prior}} \}$$

π 与 π^s 的主要差别在于:

- π 是 $N + 1$ 维 (关注了从 $0 \cdots N$ 时刻)
- π^s 是 2 维 (只关注 $0, N$ 时刻)

Methodology - Schrödinger Bridges

Link with optimal transport

Original:

$$\pi^{s,*} = \arg \min \{ \text{KL}(\pi^s \mid p_{0,N}) : \pi^s \in \mathcal{P}_2, \pi_0^s = p_{\text{data}}, \pi_N^s = p_{\text{prior}} \}$$

$$\pi^{s,*} = \arg \min \{ H(\pi^s, p_{0,N}) - H(\pi^s) : \pi^s \in \mathcal{P}_2, \pi_0^s = p_{\text{data}}, \pi_N^s = p_{\text{prior}} \}$$

$$\pi^{s,*} = \arg \min \{ -\mathbb{E}_{\pi^s}[p_{0,N}] - H(\pi^s) : \pi^s \in \mathcal{P}_2, \pi_0^s = p_{\text{data}}, \pi_N^s = p_{\text{prior}} \}$$

$$(\text{How?}) \pi^{s,*} = \arg \min \{ -\mathbb{E}_{\pi^s} [\log p_{N|0}(X_N \mid X_0)] - H(\pi^s) : \pi^s \in \mathcal{P}_2, \pi_0^s = p_{\text{data}}, \pi_N^s = p_{\text{prior}} \}$$

Methodology - Iterative Proportional Fitting (IPF)

这里的记号比较奇怪，和之前不太一样。上标代表的是当前的迭代次数，也就是说迭代n次代表n个“来回”：

$$\begin{aligned}\pi^{2n+1} &= \arg \min \left\{ \text{KL} \left(\pi \mid \pi^{2n} \right) : \pi \in \mathcal{P}_{N+1}, \pi_N = p_{\text{prior}} \right\} \\ \pi^{2n+2} &= \arg \min \left\{ \text{KL} \left(\pi \mid \pi^{2n+1} \right) : \pi \in \mathcal{P}_{N+1}, \pi_0 = p_{\text{data}} \right\}\end{aligned}$$

已知：

$$p^0(x_{0:N}) = p(x_{0:N})$$

向后更新：

$$q^n(x_{0:N}) = p_{\text{prior}}(x_N) \prod_{k=0}^{N-1} p_{k|k+1}^n(x_k \mid x_{k+1}), \text{ with } p_{k|k+1}^n(x_k \mid x_{k+1}) = \frac{p_{k+1|k}^n(x_{k+1} \mid x_k) p_k^n(x_k)}{p_{k+1}^n(x_{k+1})}$$

向前更新：

$$p^{n+1}(x_{0:N}) = p_{\text{data}}(x_0) \prod_{k=0}^{N-1} q_{k+1|k}^n(x_{k+1} \mid x_k), \text{ with } q_{k+1|k}^n(x_{k+1} \mid x_k) = \frac{q_{k|k+1}^n(x_k \mid x_{k+1}) q_{k+1}^n(x_{k+1})}{q_k^n(x_k)}$$

(Before)Methodology - Diffusion Schrödinger Bridge

有:

$$\begin{aligned}
 p_{k|k+1}(x_k | x_{k+1}) &= \frac{p_k(x_k) p_{k+1|k}(x_{k+1} | x_k)}{p_{k+1}(x_{k+1})} \\
 &= p_{k+1|k}(x_{k+1} | x_k) \frac{p_k(x_k)}{p_{k+1}(x_{k+1})} \\
 &= p_{k+1|k}(x_{k+1} | x_k) \exp[\log p_k(x_k) - \log p_{k+1}(x_{k+1})]
 \end{aligned} \tag{1}$$

和

$$\begin{aligned}
 p_{k+1|k}(x_{k+1} | x_k) &= \mathcal{N}(x_{k+1}; x_k + \gamma_{k+1} f(x_k), 2\gamma_{k+1} \mathbf{I}) \\
 &= \frac{1}{\sqrt{4\pi\gamma_{k+1}}} \exp\left(-\frac{(x_{k+1} - x_k - \gamma_{k+1} f(x_k))^2}{4\gamma_{k+1}}\right)
 \end{aligned} \tag{2}$$

(Before)Methodology - Diffusion Schrödinger Bridge

使用泰勒展开: 我们对 $\log p_{k+1}$ 在 $x_k \approx x_{k+1}$ 处进行泰勒展开。泰勒展开是:

$$\log p_{k+1}(x_{k+1}) \approx \log p_{k+1}(x_k) + \frac{x_{k+1} - x_k}{1!} \nabla \log p_{k+1}(x_k)$$

代入泰勒展开: 将泰勒展开代入原始公式后并化简:

$$\begin{aligned} p_{k|k+1}(x_k | x_{k+1}) &\approx p_{k+1|k}(x_{k+1} | x_k) \exp [\log p_k(x_k) - \log p_{k+1}(x_k) - (x_{k+1} - x_k) \nabla \log p_{k+1}(x_k)] \\ &= p_{k+1|k}(x_{k+1} | x_k) \exp [-2(x_{k+1} - x_k) \nabla \log p_{k+1}(x_k)] \end{aligned}$$

∴ 算不动了

$$= \mathcal{N}(x_k; x_{k+1} - \gamma_{k+1} f(x_{k+1}) + 2\gamma_{k+1} \nabla \log p_{k+1}(x_{k+1}), 2\gamma_{k+1} \mathbf{I})$$

Methodology - Diffusion Schrödinger Bridge

对于第n次迭代, 首先向前:

$$p_{k+1|k}^n(x_{k+1} | x_k) = \mathcal{N}(x_{k+1}; x_k + \gamma_{k+1} f_k^n(x_k), 2\gamma_{k+1} \mathbf{I})$$

with, $p^0 = p$ and $f_k^0 = f$

然后, 向后:

$$q_{k|k+1}^n(x_k | x_{k+1}) = p_{k+1|k}^n(x_{k+1} | x_k) \exp [\log p_k^n(x_k) - \log p_{k+1}^n(x_{k+1})]$$

$$\approx \mathcal{N}(x_k; x_{k+1} + \gamma_{k+1} b_{k+1}^n(x_{k+1}), 2\gamma_{k+1} \mathbf{I}),$$

where $b_{k+1}^n(x_{k+1}) = -f_k^n(x_{k+1}) + 2\nabla \log p_{k+1}^n(x_{k+1})$

Methodology - Diffusion Schrödinger Bridge

现在我们要优化的目标就是：

$$q_{k|k+1}^n(x_k | x_{k+1}) = \mathcal{N}(x_k; B_{k+1}^n(x_{k+1}), 2\gamma_{k+1}\mathbf{I}), p_{k+1|k}^n(x_{k+1} | x_k) = \mathcal{N}(x_{k+1}; F_k^n(x_k), 2\gamma_{k+1}\mathbf{I})$$

因此：

$$B_{k+1}^n = \arg \min_{B \in L^2(\mathbb{R}^d, \mathbb{R}^d)} \mathbb{E}_{p_{k,k+1}^n} \left[\| B(X_{k+1}) - (X_{k+1} + F_k^n(X_k) - F_k^n(X_{k+1})) \|^2 \right]$$

$$F_k^{n+1} = \arg \min_{F \in L^2(\mathbb{R}^d, \mathbb{R}^d)} \mathbb{E}_{q_{k,k+1}^n} \left[\| F(X_k) - (X_k + B_{k+1}^n(X_{k+1}) - B_{k+1}^n(X_k)) \|^2 \right]$$

Methodology - Diffusion Schrödinger Bridge

每个iteration需要计算两次

Schrödinger Bridge (DSB) and is summarized in Algorithm 1 for an illustration.

Algorithm 1 Diffusion Schrödinger Bridge

```
1: for  $n \in \{0, \dots, L\}$  do
2:   while not converged do
3:     Sample  $\{X_k^j\}_{k,j=0}^{N,M}$ , where  $X_0^j \sim p_{\text{data}}$ , and
        $X_{k+1}^j = F_{\alpha^n}(k, X_k^j) + \sqrt{2\gamma_{k+1}}Z_{k+1}^j$ 
4:     Compute  $\hat{\ell}_n^b(\beta^n)$  approximating (12)
5:      $\beta^n \leftarrow \text{Gradient Step}(\hat{\ell}_n^b(\beta^n))$ 
6:   end while
7:   while not converged do
8:     Sample  $\{X_k^j\}_{k,j=0}^{N,M}$ , where  $X_N^j \sim p_{\text{prior}}$ , and
        $X_{k-1}^j = B_{\beta^n}(k, X_k^j) + \sqrt{2\gamma_k}\tilde{Z}_k^j$ 
9:     Compute  $\hat{\ell}_{n+1}^f(\alpha^{n+1})$  approximating (13)
10:     $\alpha^{n+1} \leftarrow \text{Gradient Step}(\hat{\ell}_{n+1}^f(\alpha^{n+1}))$ 
11:   end while
12: end for
13: Output:  $(\alpha^{L+1}, \beta^L)$ 
```

3.4 Convergence of Iterative Proportional Fitting

Train

Loss function

$$\hat{\ell}_{n,I}^b(\beta) = M^{-1} \sum_{(k,y) \in I} \left\| B_{\beta}(k+1, X_{k+1}^j) - \left(X_{k+1}^j + F_k^n(X_{k+1}^j) - F_k^n(X_k^j) \right) \right\|^2$$

$$\hat{\ell}_{n+1,I}^j(\alpha) = M^{-1} \sum_{(k,y) \in I} \left\| F_{\alpha}(k, X_k^j) - \left(X_k^j + B_{k+1}^n(X_{k+1}^j) - B_{k+1}^n(X_k^j) \right) \right\|^2$$