

HW8

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1.

Handwritten derivation for the Evidence Lower Bound (ELBO) in a Variational Autoencoder (VAE):

$$\begin{aligned} 1. \quad \tilde{L}_{SSM} &= E_{x,v} [v^T s^*(x) - v^T S(x; \theta)]^2 \\ &= E_{x,v} [(v^T s^*)^2] - 2E_{x,v} [v^T s^* v^T S] + E_{x,v} [(v^T S)^2] \quad \text{--- ①} \\ \text{let } g(x) &= v^T S(x; \theta) \\ \because p(x) \nabla_x (\log p(x)) &= \nabla_x p(x) \\ E_x [v^T s^*(x) g(x)] &= \int v^T \nabla_x p(x) g(x) dx = - \int p(x) v^T \nabla_x g(x) dx = -E_x [v^T \nabla_x g(x)] \\ \Rightarrow E_{x,v} [v^T s^* v^T S] &= -E_{x,v} [v^T \nabla_x (v^T S)] \quad \text{--- ②} \\ \text{②} \rightarrow \text{①} \Rightarrow L_{SSM} &= E_{x \sim p(x)} E_{v \sim p(v)} [(v^T S(x; \theta))^2 + 2v^T \nabla_x (v^T S(x; \theta))] \end{aligned}$$

2.

SDE 描述含隨機擾動的連續時間動態：

$$dX_t = f(X_t, t) dt + g(X_t, t) dW_t$$

其中 f 為漂移 (drift)、 g 為擴散 (diffusion/噪聲強度)、 W_t 為布朗運動。對應的密度 $p_t(x)$ 依 Fokker-Planck 方程 演化。

在擴散模型中：前向 SDE 逐步向資料加噪，使 p_0 走向高斯 p_T ；反向時間的 reverse SDE

$$dX_t = [f(X_t, t) - g(X_t, t)^2 \nabla_x \log p_t(X_t)] dt + g(X_t, t) d\bar{W}_t$$

利用 score 把分佈推回資料分佈，據此從噪聲逐步生成樣本。

3.

How does the Ito integral differ conceptually from the standard Riemann integral, and why can't we define it in the usual way?