

1. Show that the sliced score matching (SSM) loss can also be written as

$$L_{SSM} = \mathbb{E}_{x \sim p(x)} \mathbb{E}_{v \sim p(v)} [\|v^T S(x; \theta)\|^2 + 2v^T \nabla_x (v^T S(x; \theta))].$$

①

Let $S: \mathbb{R}^d \rightarrow \mathbb{R}^d$ be a continuously differentiable vector field (the score network output). Define the Implicit Score Matching (ISM) loss as: $L_{ISM}(\theta) = \mathbb{E}_{x \sim p(x)} [\|S(x; \theta)\|^2 + 2\nabla_x \cdot S(x; \theta)]$.

Let $\mathbf{z} \in \mathbb{R}^d$ be a random vector independent of x , satisfying $\mathbb{E}[\mathbf{z}] = 0$, $\mathbb{E}[\mathbf{z}\mathbf{z}^T] = \mathbf{I}_d$.

Then, $L_{ISM}(\theta) = \mathbb{E}_{x \sim p(x)} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} [\|\mathbf{z}^T S(x; \theta)\|^2 + 2\mathbf{z}^T \nabla_x (\mathbf{z}^T S(x; \theta))] = L_{SSM}(\theta)$.

(pf.)

1° Using Hutchinson's Trace Identity:

For any matrix $A \in \mathbb{R}^{d \times d}$, we have $\mathbb{E}_{\mathbf{z}} [\mathbf{z}^T A \mathbf{z}] = \mathbb{E}_{\mathbf{z}} [\text{tr}(\mathbf{z}^T A \mathbf{z})] = \mathbb{E}_{\mathbf{z}} [\text{tr}(A \mathbf{z} \mathbf{z}^T)] = \text{tr}(A)$.

This identity holds whenever $\mathbb{E}_{\mathbf{z}} [\mathbf{z}\mathbf{z}^T] = \mathbf{I}_d$, such as $\mathbf{z} \sim \mathcal{N}(0, \mathbf{I}_d)$.

2° By ① with $A = S(x) S(x)^T$,

then, $\|S(x)\|^2 = \text{tr}(S(x) S(x)^T) = \mathbb{E}_{\mathbf{z}} [\mathbf{z}^T S(x) S(x)^T \mathbf{z}] = \mathbb{E}_{\mathbf{z}} [\|\mathbf{z}^T S(x)\|^2] = \mathbb{E}_{\mathbf{z}} [\|\mathbf{z}^T S(x)\|^2]$ — ②

3° Let $J_S(x) = \nabla_x S(x) \in \mathbb{R}^{d \times d}$ denote the Jacobian matrix of S , then,

$\nabla_x (\mathbf{z}^T S(x)) = J_S(x)^T \mathbf{z}$, hence, $\mathbf{z}^T \nabla_x (\mathbf{z}^T S(x)) = \mathbf{z}^T J_S(x)^T \mathbf{z}$ — ③

Taking expectation, and applying ① again: $\mathbb{E}_{\mathbf{z}} [\mathbf{z}^T J_S(x)^T \mathbf{z}] = \text{tr}(J_S(x)^T) = \text{tr}(J_S(x)) = \nabla_x \cdot S(x)$.

4° Substituting ② & ③ into ISM definition, and apply Fubini's theorem:

$$L_{ISM}(\theta) = \mathbb{E}_x [\mathbb{E}_{\mathbf{z}} \|\mathbf{z}^T S(x; \theta)\|^2 + 2 \mathbb{E}_{\mathbf{z}} \mathbf{z}^T \nabla_x (\mathbf{z}^T S(x; \theta))] = \mathbb{E}_x \mathbb{E}_{\mathbf{z}} [\|\mathbf{z}^T S(x; \theta)\|^2 + 2 \mathbf{z}^T \nabla_x (\mathbf{z}^T S(x; \theta))]$$

This matches the definition of the sliced score matching loss:

$$L_{SSM}(\theta) = \mathbb{E}_{x \sim p(x)} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} [\|\mathbf{z}^T S(x; \theta)\|^2 + 2\mathbf{z}^T \nabla_x (\mathbf{z}^T S(x; \theta))]. \quad \square$$

2. Briefly explain SDE.

②

An SDE (stochastic differential equation) describes the continuous-time evolution of a random process influenced by both deterministic drift and random noise:

$dx_t = f(x_t, t)dt + g(x_t, t)dW_t$, where $f(x_t, t)$ is the drift term, $g(x_t, t)dW_t$ is the diffusion term, W_t is a Wiener process (Brownian motion).

Intuitively, the SDE says that the system moves deterministically according to f , but also experience continuous random perturbations determined by g .

3. Unanswered Questions

There are unanswered questions from the lecture, and there are likely more questions we haven't covered.

- Take a moment to think about these questions.
- Write down the ones you find important, confusing, or interesting.
- You do **not** need to answer them—just state them clearly.

- Q: ① How many random directions \mathbf{u} are typically needed in practice for SSM to be accurate?
- ② Are there better distributions for \mathbf{u} than Gaussian or Rademacher?