

## Problem 1 — Sliced Score Matching (SSM)

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**Goal:** Show that

$$L_{\text{SSM}}(\theta) = \mathbb{E}_{x,v} [|v^\top S(x; \theta)|^2 + 2, v^\top \nabla_x (v^\top S(x; \theta))],$$

where  $S(x; \theta) = \nabla_x \log p(x; \theta)$

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### Definition

Start from the *sliced Fisher divergence* :

$$L_{\text{SSM}}(\theta) = \frac{1}{2} \mathbb{E}_{x,v} (v^\top \nabla_x \log p(x) - v^\top S(x; \theta))^2,$$

with  $v$  a random direction

### Expand & Drop Constants

$$L_{\text{SSM}} = \mathbb{E}_{x,v} \left[ \frac{1}{2} (v^\top S)^2 - (v^\top \nabla_x \log p)(v^\top S) \right].$$

First term of  $p(x)$  is constant  $\rightarrow$  omit

### Integration by Parts

$$\mathbb{E}_{x,v} [(v^\top \nabla_x \log p), g(x)] = -\mathbb{E}_{x,v} [v^\top \nabla_x g(x)],$$

where  $g(x) = v^\top S(x; \theta)$

Substitute:

$$L_{\text{SSM}} = \mathbb{E}_{x,v} \left[ \frac{1}{2} (v^\top S)^2 + v^\top \nabla_x (v^\top S) \right].$$

Multiply by 2 and ignore constants  $\rightarrow$  final form as in assignment.

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### References

- Hyvärinen (2005), *Score Matching*
  - Yang Song & S. Ermon (2019), *Sliced Score Matching* [arXiv:1905.07088](https://arxiv.org/abs/1905.07088)
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## Problem 2 — Stochastic Differential Equations (SDE)

### Definition

A stochastic differential equation describes dynamics under deterministic **drift** and stochastic **diffusion**:

$$dx_t = f(x_t, t)dt + G(x_t, t)dW_t, \quad x(0) = x_0.$$

- $x_t \in \mathbb{R}^d$ : state variable
- $f(x_t, t)$ : drift term
- $G(x_t, t)$ : diffusion matrix
- $W_t$ : standard Brownian motion

Itô form:

$$x_t = x_0 + \int_0^t f(x_s, s)ds + \int_0^t G(x_s, s)dW_s.$$

### Special cases

- \*Pure drift :  $dx_t = f(x_t, t)dt \rightarrow$  deterministic ODE
- \*Pure diffusion :  $dx_t = G(x_t, t)dW_t \rightarrow$  Brownian-like motion

### Wiener Process $W_t$

A standard Brownian motion satisfies:

1.  $W_0 = 0$
2. Stationary Gaussian increments  $W_{t+\Delta} - W_t \sim \mathcal{N}(0, \Delta I)$
3. Independent increments
4. Continuous paths with probability 1

**Moments:**

$$\mathbb{E}[W_t] = 0, \quad \text{Var}(W_t) = t$$

Noise  $h(t) = \frac{dW_t}{dt}$  is formally its derivative

### Euler–Maruyama Approximation

Partition  $([0, T])$  into  $(N)$  steps ( $\Delta t = T/N$ ):

$$X_{n+1} = X_n + f(X_n, t_n)\Delta t + G(X_n, t_n)\Delta W_n,$$

where  $\Delta W_n \sim \mathcal{N}(0, \Delta t, I)$

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## Problem 3 — Questions

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- How does the SSM approximation behave in high-dimensional manifolds?