

$$\gamma(e) = \limsup_{t \rightarrow \infty} \frac{1}{t} \log \|A(t)e\|$$

$$\log \det (A(t)e_k)$$

$$\dot{x}_t = A(\theta_t \omega) x_t$$

$$x_t = e^{\int_0^t A(\theta_s \omega) ds} x_0$$

Last time: * Oseledec's multiplicative ergodic theorem

* Gradient flow

* Proof of OMET

- Flipped lecture

M/W 26th, 28th

→ 26th (Flipped) } sign up poll
→ 28th (regular) } for time

Gradient flow

$$\frac{d\varphi^t(x)}{dt} = \underset{\substack{\uparrow \\ \text{differential}}}{df}(\varphi^t x)$$

→ $f: M \rightarrow \mathbb{R}$

Time-step maps

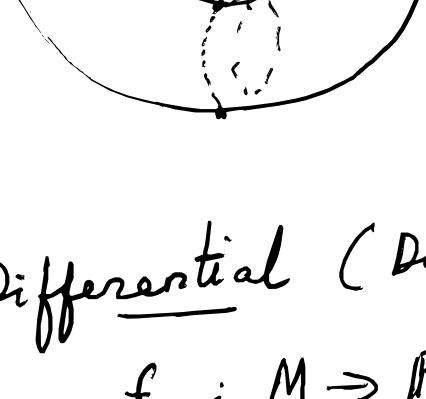
$$F^t(x) = x + \eta df(x)$$

η : time-step $\in \mathbb{R}^+$

Example:

$$x = (x_1, x_2, x_3)$$

$$f(x) = -x_3$$



→ Differential (Differential geometry)

$$f: M \rightarrow \mathbb{R} \quad f \in C^\infty(M)$$

$$df: M \rightarrow \mathbb{R}^d \quad (\text{scientific/ergo})$$

$$df_x: T_x M \rightarrow \mathbb{R}$$

Linear functional on tangent bundle.

$(df)_x \in T_x^* M$ (Dual of tangent bundle: cotangent bundle)

$$v \in T_x M$$

$$v(f)(x) = \lim_{\epsilon \rightarrow 0} \frac{f(x + \epsilon v(x)) - f(x)}{\epsilon}$$

$$= \langle df, v \rangle$$

(Defn applies to Riemannian manifolds)

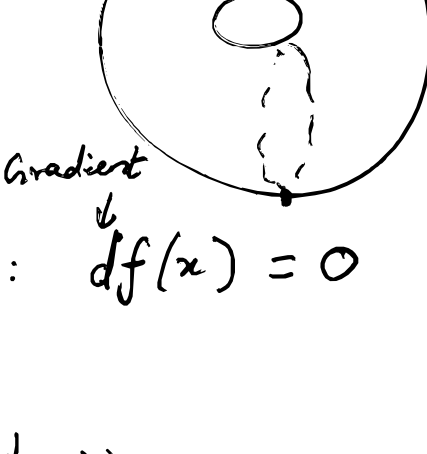
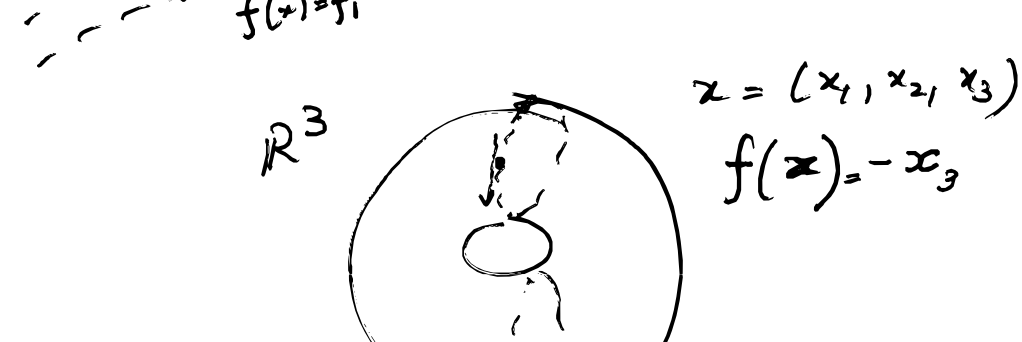
$$x = (x_1, x_2, \dots, x_d)$$

$$\nabla f_x = (\partial_{x_1} f, \partial_{x_2} f, \dots, \partial_{x_d} f) \in T_x^* M$$

$$v(f)(x) = \underset{\substack{\uparrow \\ T_x^* M}}{df_x} \cdot \underset{\substack{\uparrow \\ T_x M}}{v(x)}$$

Directional derivative of f along v

$$df_x = \operatorname{argmax}_{v \in T_x M} \lim_{\epsilon \rightarrow 0} \frac{f(x + \epsilon v) - f(x)}{\epsilon}$$



$$x = (x_1, x_2, x_3)$$

$$f(x) = -x_3$$

Gradient

Fixed points: $df(x) = 0$

$$\frac{d\varphi^t(x)}{dt} = v(\varphi^t x)$$

$$= df(\varphi^t x)$$

$$\operatorname{eig}(dv(\varphi^t x^*))$$

$$= \operatorname{eig}(d^2 f(\varphi^t x^*))$$

↳ second derivative $\mathbb{R}^{d \times d}$

Example 2:

Optimization algorithms

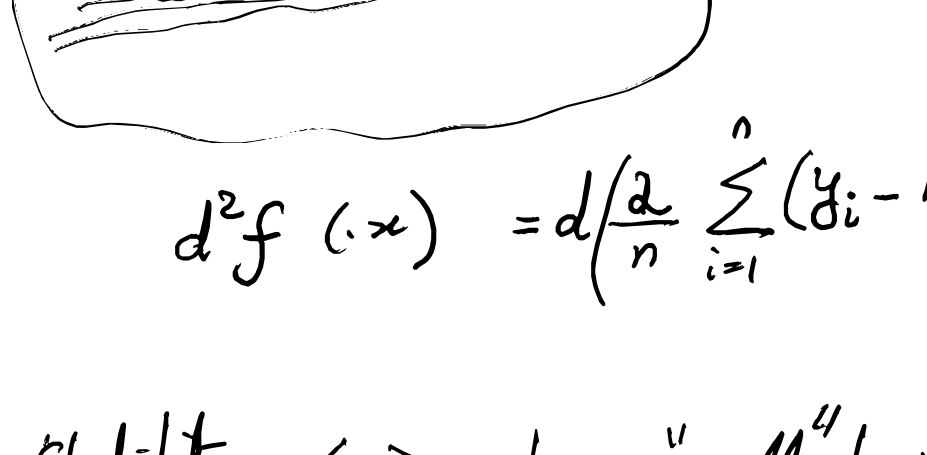
$$f(x) = \frac{1}{n} \sum_{i=1}^n \|y_i - h(z_i; x)\|^2$$

Loss function parameter

$h: NN$ z_i x : weights & biases

$$\bullet \frac{d\varphi^t(x)}{dt} = -df(\varphi^t x)$$

Generalization stability of fixed points



$$d^2 f(x) = d \left(\frac{2}{n} \sum_{i=1}^n (y_i - h(z_i; x)) \frac{dh(z_i; x)}{dx} \right)$$

Stability \iff how "well" h is learned

Asymptotically, gradient flows converge to fixed points

$$\text{For any } x \in M, \quad X_T := \{\varphi^t(x)\}_{t \geq 0}$$

$$\lim_{T \rightarrow \infty} X_T \subseteq \{\text{critical points of } f\}$$

Infinite-dimensional gradient flow

$$T^* = \operatorname{argmin}_{T \in \mathcal{T}} C(T_{\#} \mu, \nu)$$

cost

class of functions

ν : target measure

μ : known probab dist.

$$T_{\#} \mu = \mu \circ T^{-1}$$

$$\mu: M_1 \rightarrow \mathbb{R}^+$$

$$\nu: M_2 \rightarrow \mathbb{R}^+$$

$$T: M_1 \rightarrow M_2$$

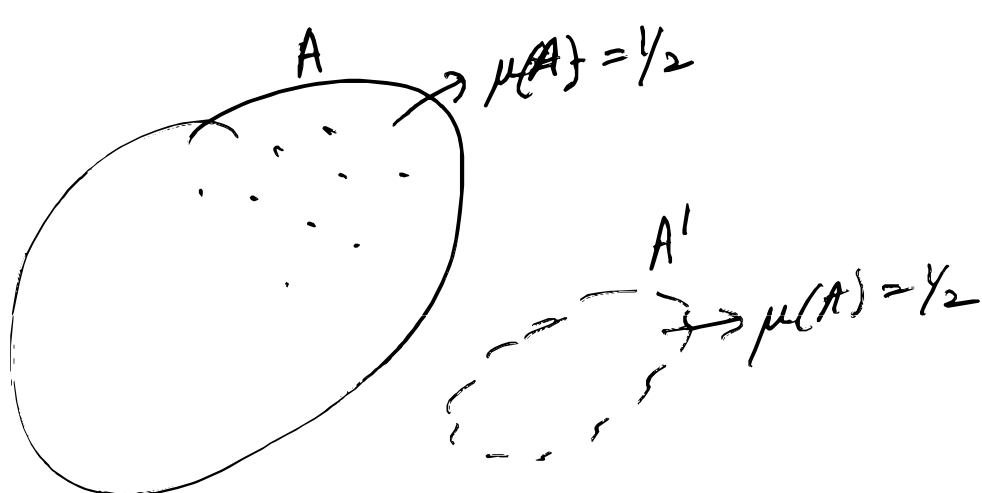
$$\frac{d}{dt} \varphi^t(T) = \underset{\substack{\uparrow \\ \text{Wasserstein}}}{dc}(T_{\#} \mu, \nu)$$

OMET

→ Ergodic theory: long-time behavior of dynamics \Leftrightarrow ensemble/statistical behavior

→ We say that μ is an ergodic distribution for φ if any φ -invariant set has measure 0 or 1.

- A is invariant if $\varphi^{-1}(A) = A$



→ $f \in C^0(M)$, and μ is ergodic for φ , then

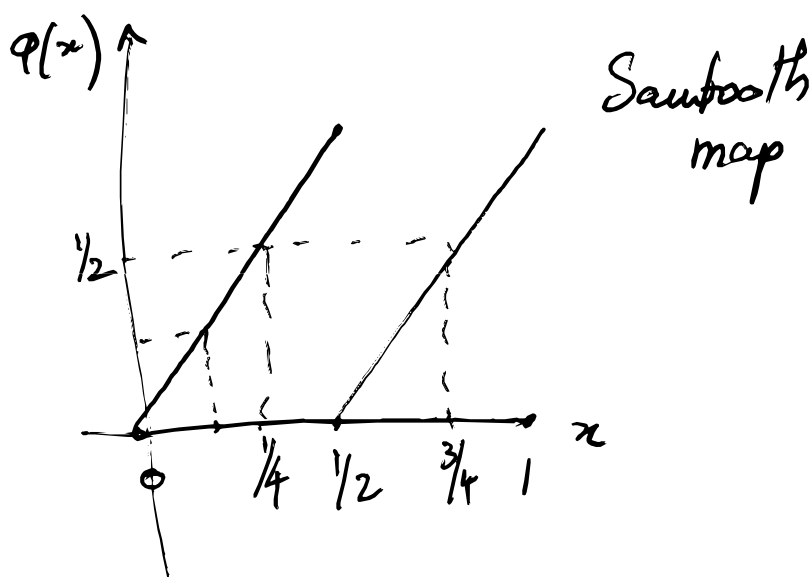
$$\frac{1}{T} \sum_{t=0}^{T-1} f \circ \varphi^t(x) \xrightarrow{T \rightarrow \infty} \int f(x) d\mu(x)$$

for μ a.e.

Example

Chaotic system

$$\varphi(x) = 2x \mod 1 \quad \mathbb{R}/\mathbb{Z}$$



Uniform measure on $[0, 1]$.

- $x = \text{rand}()$ → Not Simulating almost every point according to Uniform measure
- 2^{63} : dyadic

$$\frac{1}{T} \sum_{t \leq T} \varphi^t x \xrightarrow{T \rightarrow \infty} \int_0^1 x dx = \frac{1}{2}$$

$$\left(\int f(x) d\mu(x) = \sum_{i=1}^N f(x_i) \mu(x_i) \right)$$

$$\rightarrow \frac{1}{10}, \frac{2}{10} = \frac{1}{5}, \frac{2}{5}, \frac{4}{5}, \frac{8}{5} - 1 = \frac{3}{5}, \frac{1}{5}, \frac{2}{5}, \frac{4}{5}, \frac{3}{5},$$

$$\frac{1}{4} \left(\frac{1}{5} + \frac{2}{5} + \frac{4}{5} + \frac{3}{5} \right) = \frac{2}{4}$$