

Derivative



$f: \mathbb{R}^n \rightarrow \mathbb{R}^m \quad x \in \text{int dom}$

f is differentiable if there exists a matrix $Df(x) \in \mathbb{R}^{mn}$ such that

$$\lim_{\substack{z \in \text{dom} \\ z \rightarrow x}} \frac{\|f(z) - f(x) - Df(x)(z-x)\|_2}{\|z-x\|_2} = 0$$

$Df(x)$ is the derivative or Jacobian of f at x

First-order approximation

$$f(z) \approx f(x) + Df(x)(z-x)$$

$$Df(x)_{ij} = \frac{\partial f_i(x)}{\partial x_j}$$

$$\begin{bmatrix} \frac{\partial f_1(x)}{\partial x_1} \\ \frac{\partial f_1(x)}{\partial x_2} \\ \vdots \\ \frac{\partial f_m(x)}{\partial x_1} \\ \frac{\partial f_m(x)}{\partial x_2} \end{bmatrix} = \begin{bmatrix} \frac{\partial f_1(x)}{\partial x} \\ \frac{\partial f_2(x)}{\partial x} \\ \vdots \\ \frac{\partial f_m(x)}{\partial x} \end{bmatrix}$$

Log-determinant

$$f(X) = \log \det X \quad X \in S^n_+$$

let $z \in S^n_+$ be close to X , $\Delta X = z - X$

$$\begin{aligned} \log \det(z) &= \log \det(X + \Delta X) \\ &= \log \det[X^{\frac{1}{2}}(I + X^{-\frac{1}{2}}\Delta X X^{-\frac{1}{2}})X^{\frac{1}{2}}] \\ &= \log \det(X) + \log \det(I + X^{-\frac{1}{2}}\Delta X X^{-\frac{1}{2}}) \\ &= \log \det(X) + \sum_i \log(1 + \lambda_i) \quad \lambda_i \text{ is the } i\text{th eigenvalue of } X^{-\frac{1}{2}} \cdot \Delta X \cdot X^{-\frac{1}{2}} \end{aligned}$$

$$\begin{aligned} \log(1 + \lambda_i) &\approx \log(1) + \log'(1) \cdot \lambda_i \\ &= 0 + \frac{1}{1} \cdot \lambda_i \approx \lambda_i \quad \text{for small } \lambda_i \end{aligned}$$

$\therefore \Delta X$ is very small
 $\therefore \log(1 + \lambda_i) \approx \lambda_i$

$$\log \det(z) \approx \log \det(X) + \sum_i \lambda_i$$



$$\begin{aligned}
 &= \log \det(X) + \text{tr}(X^{-1} \cdot \Delta X \cdot X^{-1}) \\
 &= \log \det(X) + \text{tr}(X^{-1} \cdot \Delta X) \\
 &= \log \det(X) + \text{tr}[X^{-1}(Z-X)] \\
 &= \log \det(X) + \text{tr}[X^{-1}(Z-X)] \xrightarrow{\text{Standard form inner product}} \\
 \log \det(Z) \approx \log \det(X) + \text{tr}[X^{-1}(Z-X)]
 \end{aligned}$$

$$f(x) = \log \det(X) \quad X \in S_+^n \quad \nabla f(x) = X^{-1} = X'$$

Chain Rule

$$\begin{aligned}
 f: \mathbb{R}^n \rightarrow \mathbb{R}^m &\text{ is differentiable at } X \in \text{int dom } f \\
 g: \mathbb{R}^m \rightarrow \mathbb{R}^p &\text{ is differentiable at } f(x) \in \text{im dom } g \\
 h: \mathbb{R}^p \rightarrow \mathbb{R} & \quad h(x) = g(f(x))
 \end{aligned}$$

$$Dh(x) = Dg(f(x)) \cdot Df(x)$$

$$\begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & \cdots & \frac{\partial h_1}{\partial x_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial h_p}{\partial x_1} & \frac{\partial h_p}{\partial x_2} & \cdots & \frac{\partial h_p}{\partial x_m} \end{bmatrix} \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \frac{\partial f_m}{\partial x_2} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix} \begin{bmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} & \cdots & \frac{\partial g_1}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial g_p}{\partial x_1} & \frac{\partial g_p}{\partial x_2} & \cdots & \frac{\partial g_p}{\partial x_n} \end{bmatrix}$$

Composition with Affine function

$$\begin{aligned}
 f: \mathbb{R}^n \rightarrow \mathbb{R}^m &\text{ is differentiable} \\
 g: \mathbb{R}^p \rightarrow \mathbb{R}^m & \quad g(x) = f(Ax+b) \quad A \in \mathbb{R}^{mp}
 \end{aligned}$$

$$Dg(x) = Df(Ax+b) \cdot A = A^T \cdot \nabla f(Ax+b)$$

Line restriction

$$f: \mathbb{R}^n \rightarrow \mathbb{R} \quad x, v \in \mathbb{R}^n$$

$$\tilde{f}(t) = f(x+tv)$$

$$D\tilde{f}'(t) = \tilde{f}'(t) = \nabla f(x+tv)^T v$$

$\tilde{f}'(0)$ is the directional derivative of f at x in the direction v

$$\text{Eq. } f(x) = \log \sum_i \exp(a_i^T x + b_i)$$

$$g(y) = \log \sum_i \exp(y_i)$$

$$\nabla g(y) = \frac{1}{\sum_i \exp(y_i)} \cdot \left[\begin{matrix} \exp(y_1) \\ \vdots \\ \exp(y_n) \end{matrix} \right]$$

$$\nabla f(x) = \frac{1}{\sum_i \exp(y_i)} \cdot A^T \cdot \left[\begin{matrix} \exp(y_1) \\ \vdots \\ \exp(y_n) \end{matrix} \right]$$

$$\text{Eq. } f(x) = \log \det(F_0 + x_1 F_1 + \dots + x_n F_n) \quad F_i \in S^n$$

$$\text{dom } f = \{x \mid F_0 + x_1 F_1 + \dots + x_n F_n > 0\}$$

$$\frac{\partial f}{\partial x_i} = \text{tr}(F_i^T \nabla \log \det(F)) = \text{tr}(F_i^T F^{-T}) = \text{tr}(F^T F_i)$$

$$\text{where } F = F_0 + x_1 F_1 + \dots + x_n F_n$$

Second Derivative



$f: \mathbb{R}^n \rightarrow \mathbb{R}$

The second derivative / Hessian matrix at $x \in \text{dom } f$

$$\nabla^2 f(x)_{ij} = \frac{\partial^2 f(x)}{\partial x_i \partial x_j}$$

Second-order approximation

$$\hat{f}(z) \approx f(x) + \nabla f(x)^T(z-x) + \frac{1}{2} (z-x)^T \nabla^2 f(x) (z-x)$$

$$\lim_{z \in \text{dom } f, z \rightarrow x} \frac{|\hat{f}(z) - f(z)|}{\|z - x\|_2} = 0$$

$$D \nabla f(x) = \nabla^2 f(x)$$

Eg. $f: S^n \rightarrow \mathbb{R}$ $f(x) = \log \det(x)$ $\text{dom } f = S^n_{++}$
 $\nabla f(x) = X^{-1}$ for $z \in S^n_{++}$ near x $z = x + \Delta x$

$$\begin{aligned}
 Z^{-1} &= (X + \Delta X)^{-1} \\
 &= (X^{-1} (I + X^{-1} \Delta X X^{-1}) X^{-1})^{-1} \\
 &= X^{-1} \cdot (I + X^{-1} \Delta X X^{-1})^{-1} \cdot X^{-1} \\
 &\approx X^{-1} \cdot (I - X^{-1} \Delta X X^{-1}) \cdot X^{-1} \\
 &= X^{-1} - X^{-1} \Delta X X^{-1}
 \end{aligned}$$

$(I + A)^{-1} \approx I - A$ first-order approximation

// TODO:

chain rule

composition with scalar function.

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$g: \mathbb{R} \rightarrow \mathbb{R} \quad h(x) = g(f(x))$$

$$\nabla h(x) = g'(f(x)) \cdot \nabla f(x)$$

$$[g'] \cdot [\nabla f(x)]$$

$$\nabla^2 h(x) = g'(f(x)) \cdot \nabla^2 f(x) + g''(f(x)) \cdot \nabla f(x) \cdot \nabla f(x)^T$$

$$[\frac{dg}{df}] \cdot \begin{bmatrix} \frac{\partial f}{\partial x_1} & \cdots & \frac{\partial f}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f}{\partial x_1} & \cdots & \frac{\partial f}{\partial x_n} \end{bmatrix}$$

$$+ [g''(f(x))] \cdot \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix} \begin{bmatrix} dx \\ \vdots \\ dx \end{bmatrix}$$

$$\begin{aligned} dx^T \cdot \nabla h(x) \cdot dx &= \left[\frac{dg}{df} \right] \cdot [dx] + [g''(f(x))] \cdot [dx] \cdot \begin{bmatrix} df \\ \vdots \\ df \end{bmatrix} \\ &= \frac{dg}{df} \cdot df + g''(f(x)) \cdot df \cdot df \end{aligned}$$

composition with affine function

$$f: \mathbb{R}^m \rightarrow \mathbb{R}$$

$$g(x) = f(Ax+b) \quad A \in \mathbb{R}^{mn} \quad b \in \mathbb{R}^m \quad h(x) = Ax+b$$

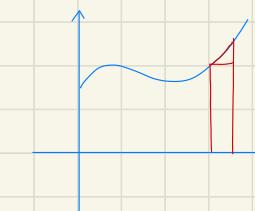
$$\nabla g(x) = A^T \cdot \nabla f(Ax+b)$$

$$\begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\nabla g(x) = \begin{bmatrix} A^T \\ \vdots \\ A^T \end{bmatrix} \nabla f(x)$$

$$\nabla^2 g(x) = A^T \nabla^2 f(Ax+b) A \quad m \times n \quad \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix} \begin{bmatrix} dx \\ \vdots \\ dx \end{bmatrix}$$

$$\begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix} \begin{bmatrix} dx \\ \vdots \\ dx \end{bmatrix}$$



$$\begin{aligned} &dx^T \left[A^T \nabla^2 f(Ax+b) A \right] dx \\ &= (A^T dx)^T \nabla^2 f(Ax+b) \cdot (A^T dx) \\ &= dx^T \cdot \nabla^2 f(Ax+b) \cdot dx \end{aligned}$$

