

$$f(x) = x^2 \quad f(X) = X^2$$

$$f(X+E) = (X+E)^2 = \underbrace{X^2}_{f(X)} + \underbrace{XE + EX}_{L_{f,X}(E)} + \underbrace{E^2}_{o(\|E\|)}$$

Fréchet derivative
(linear operator $\mathbb{R}^{n \times n} \rightarrow \mathbb{R}^{n \times n}$)
 $\|E^2\| \leq \|E\|^2$

$$\Leftrightarrow \hat{L} \in \mathbb{R}^{n^2 \times n^2} : X^T \otimes I + I \otimes X \quad (\text{Jacobian of the map } \mathbb{R}^{n^2} \rightarrow \mathbb{R}^{n^2} \text{ vec } X \mapsto \text{vec } f(X))$$

$$L_{f+g, X} = L_{f, X} + L_{g, X}$$

$$L_{f \circ g, X} = L_{f, g(X)} \circ L_{g, X} \quad \hat{L}_{f, g(X)} \cdot \hat{L}_{g, X} \quad (\text{matrix product})$$

$$L_{f^{-1}, f(X)} = L_{f, X}^{-1} \quad (\hat{L}_{f, X})^{-1} \quad (\text{matrix inverse})$$

(because $I = L_{f \circ f^{-1}, X} = L_{f^{-1}, f(X)} \circ L_{f, X}$)

Ex: Let us take $g(y) = \sqrt{y}$ (principal square root, $y \in \mathbb{R}^+$, $\text{Re}(\sqrt{y}) > 0$)



$g(Y)$ for Y without eigenvalues in $\mathbb{R}^- = (-\infty, 0]$

$L_{g, Y}$ g is the inverse of $f(X) = X^2$

$$L_{g, Y} = (L_{f, X})^{-1}$$

$$F = L_{g, Y}(E)$$

$$L_{f, X}(F) = E$$

$$Y = X^2 = f(X)$$

$$X = \sqrt{Y} = g(Y)$$

$$XF + FX = E$$

(*)

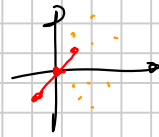
F is the solution of the Sylvester equation $XF + FX = E$

$$\sqrt{Y}F + F\sqrt{Y} = E$$

Condition for solvability of $(*)$: $\Lambda(X) \cap \Lambda(-X) = \emptyset$

$\Leftrightarrow X$ does not have two eigenvalues that are one the opposite of the other.

The eigenvalues of X are $g(\lambda)$, λ eigenvalues of Y , and our definition of g ensures that $\operatorname{Re} g(\lambda) > 0$ so there are no opposites.



$$\sqrt{Y} = X$$

$$\hat{L} = \left((\sqrt{Y})^T \otimes I + I \otimes \sqrt{Y} \right)^{-1} \quad \left(\text{consistent with scalar case: } \frac{d}{dy} \sqrt{y} = \left(2\sqrt{y} \right)^{-1} \right)$$

More complicated: Fréchet derivative of $\exp(x)$

$$\exp(X) = 1 + X + \frac{1}{2} X^2 + \frac{1}{3!} X^3 + \dots$$

$$\exp(X+E) = 1 + (X+E) + \frac{1}{2} (X+E)^2 + \frac{1}{3!} (X+E)^3 + \dots$$

$$= 1 + \underbrace{X+E}_{\sim} + \frac{1}{2} \left(\underbrace{X^2}_{\sim} + \underbrace{XE+EX}_{\sim} + \underbrace{E^2}_{\sim} \right) + \frac{1}{3!} \left(\underbrace{X^3}_{\sim} + \underbrace{X^2E+XEX+EX^2}_{\sim} + \underbrace{E^2X+EXE+XE^2+E^3}_{\sim} \right) + \dots$$

$$= \underbrace{\left(1 + X + \frac{1}{2} X^2 + \frac{1}{3!} X^3 + \dots \right)}_{\exp(X)} + \underbrace{\left(E + \frac{1}{2} (XE+EX) + \frac{1}{3!} (X^2E+XEX+EX^2) + \dots \right)}_{L_{\exp, X}} + o(\|E\|)$$

$$L_{\exp, X}(E) = E + \frac{1}{2} (XE+EX) + \frac{1}{3!} (X^2E+XEX+EX^2) + \frac{1}{4!} (X^3E+X^2EX+XEX^2+EX^3) + \dots$$

$\operatorname{vec}(AEB) = (B^T \otimes A) \operatorname{vec} E$

$$\hat{L} = I_{n^2 \times n^2} + \frac{1}{2} \left(1 \otimes X + X^T \otimes 1 \right) + \frac{1}{3!} \left(1 \otimes X^2 + X^T \otimes X + (X^2)^T \otimes 1 \right) + \dots$$

Theorem: Suppose $L_{f, X}$ exists. Then

$$f \left(\begin{bmatrix} X & E \\ 0 & X \end{bmatrix} \right) = \begin{bmatrix} f(X) & L_{f, X}(E) \\ 0 & f(X) \end{bmatrix}. \quad \hat{L} \cdot \operatorname{vec}(E)$$

$$E \in \mathbb{R}^{2n \times 2n}$$

(cfr. with automatic differentiation: $f \left(\begin{bmatrix} x & 1 \\ 0 & x \end{bmatrix} \right) = \begin{bmatrix} f(x) & f'(x) \\ 0 & f(x) \end{bmatrix}$)

Proof: let us evaluate $f\left(\begin{bmatrix} X+\varepsilon E & E \\ 0 & X \end{bmatrix}\right)$, then let $\varepsilon \rightarrow 0$

Let us find Z s.t.

$$\begin{bmatrix} 1 & -Z \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X+\varepsilon E & E \\ 0 & X \end{bmatrix} \begin{bmatrix} 1 & Z \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} X+\varepsilon E & 0 \\ 0 & X \end{bmatrix}$$

$$\text{LHS} = \begin{bmatrix} X+\varepsilon E & E-ZX \\ 0 & X \end{bmatrix} \begin{bmatrix} 1 & Z \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} X+\varepsilon E & \underbrace{(X+\varepsilon E)Z+E-ZX} \\ 0 & X \end{bmatrix}$$

holds iff Z solves Sylv. equation $(X+\varepsilon E)Z - ZX + E = 0$

One can check that $Z = -\frac{1}{\varepsilon}I$ works: $-\cancel{(X+\varepsilon E)}\frac{1}{\varepsilon} + \frac{1}{\varepsilon}\cancel{X+\varepsilon E} = 0 \quad \checkmark$

$$\begin{bmatrix} X+\varepsilon E & E \\ 0 & X \end{bmatrix} = \begin{bmatrix} 1 & Z \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X+\varepsilon E & 0 \\ 0 & X \end{bmatrix} \begin{bmatrix} 1 & -Z \\ 0 & 1 \end{bmatrix}$$

$$f\left(\begin{bmatrix} X+\varepsilon E & E \\ 0 & X \end{bmatrix}\right) = \begin{bmatrix} 1 & Z \\ 0 & 1 \end{bmatrix} \begin{bmatrix} f(X+\varepsilon E) & 0 \\ 0 & f(X) \end{bmatrix} \begin{bmatrix} 1 & -Z \\ 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & -\frac{1}{\varepsilon}I \\ 0 & 1 \end{bmatrix} \begin{bmatrix} f(X+\varepsilon E) & 0 \\ 0 & f(X) \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\varepsilon}I \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} f(X+\varepsilon E) & -\frac{1}{\varepsilon}f(X) \\ 0 & f(X) \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\varepsilon}I \\ 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} \underbrace{f(X+\varepsilon E)}_{f(X)} & \underbrace{\frac{1}{\varepsilon}f(X+\varepsilon E) - \frac{1}{\varepsilon}f(X)}_{L_{f,X}(E)} \\ 0 & f(X) \end{bmatrix} \quad \text{let } \varepsilon \rightarrow 0 \quad \checkmark$$

Theorem: if $f \in C^{2n-1}(U)$, then $L_{f,X}$ exists for all $X \in \mathbb{R}^{n \times n}$ with eigenvalues in U

Proof: If f is $2n-1$ -times diff'le, then we can evaluate $f\left(\begin{bmatrix} X & E \\ 0 & X \end{bmatrix}\right)$ for all matrices X with eigenvalues in U . \Rightarrow the directional derivative

$$\frac{1}{\varepsilon} (f(X+\varepsilon E) - f(X)) \text{ exists } \forall E \text{ and is continuous in } E \quad (\text{matrix functions are continuous!})$$

$\Rightarrow f$ is differentiable as a function $\mathbb{R}^{n^2} \rightarrow \mathbb{R}^{n^2}$ (from analysis II).

Relation between Jacobians and cond. number:

$$K_{\text{obs}, f, x} = \|J_{f, x}\| \quad (\text{induced matrix norm of Jacobian})$$

$$K_{\text{rel}, f, x} = \frac{\|J_{f, x}\| \cdot \|x\|}{\|f(x)\|}$$

In particular, for matrix functions.

$$K_{\text{obs}, f, x} = \|\hat{L}_{f, x}\| \quad \text{what norm though?}$$

When we vectorize, $\|X\|_F = \|\text{vec}(X)\|_2$ \leftarrow

$$\|X\|_2 = ??$$

$$\|X\|_\infty = ?? \quad (\text{they are norms in } \mathbb{R}^{n^2} \text{ but not "classical" ones})$$

$$\|X\|_1 = ??$$

With $\|X\|_F = \|\text{vec } X\|_2$,

$$K_{\text{obs}, f, x} = \|\hat{L}_{f, x}\|_2 \quad (\text{induced Euclidean norm of an } n^2 \times n^2 \text{ matrix})$$

$$= \sigma_{\max}(\hat{L}_{f, x}) = \rho(\hat{L}_{f, x}^T \hat{L}_{f, x})^{1/2}$$

(tells you the change in $\|f(x+E) - f(x)\|_F$ w.r.t. $\|E\|$)

$$\frac{\|f(x+E) - f(x)\|_F}{\|E\|_F} \leq \|\hat{L}_{f, x}\|_2 + o(1) \quad (\text{when } \|E\|_F \rightarrow 0)$$

$n^2 \times n^2$ (computing it costs $\mathcal{O}(n^5)$, unless one uses approximated methods)

Eigenvalues of Fréchet derivatives:

Let us assume f is a polynomial (interpolation!)

When we compute $f(x)$, we can replace $f(x)$ with $p(x)$ where p is an interpolating polynomial in the eigenvalues of x .

Is it still true that $L_{f, x} = L_{p, x}$?

In general no, but

$$f\left(\begin{bmatrix} x & E \\ 0 & x \end{bmatrix}\right) = \begin{bmatrix} f(x) & L_{f, x}(E) \\ 0 & f(x) \end{bmatrix}$$

if p

\rightarrow $\|$

interpolates f
in the eigenvalues
of X with

$$P\left(\begin{bmatrix} X & E \\ 0 & X \end{bmatrix}\right) = \begin{bmatrix} P(X) & L_{P,X}(E) \\ 0 & P(X) \end{bmatrix}$$

two multiplicities

As long as p, f coincide with enough derivatives, $L_{p,X} = L_{f,X}$

But let us assume that $p(x) = p_0 + x p_1 + x^2 p_2 + \dots + x^d p_d$

$$P(X+E) = p_0 I + p_1 (X+E) + p_2 (X+E)^2 + \dots + p_d (X+E)^d$$

$$= \underbrace{(p_0 I + p_1 X + \dots + p_d X^d)}_{P(X)} + \underbrace{p_1 E + p_2 (EX + XE) + \dots + p_d (X^{d-1} E + X^{d-2} EX + \dots + X^{d-1} E)}_{L_{P,X}(E)} + o(\|E\|)$$

$$\hat{L} = p_2 I + p_2 (X^T \otimes I + I \otimes X) + p_3 (X^{2T} \otimes I + X^T \otimes X + I \otimes X^2) + \dots$$

$$\dots + p_d (I \otimes X^{d-1} + X^T \otimes X^{d-2} + X^{2T} \otimes X^{d-3} + \dots + (X^{d-1})^T \otimes I)$$

$$\hat{L} = \sum_{k=1}^d P_k \sum_{h=1}^k (X^{k-h})^T \otimes X^{h-1}$$

$$\begin{aligned} X^T &= Q_1 T_1 Q_1^* \\ X &= Q_2 T_2 Q_2^* \end{aligned}$$

Schur forms

$$= \sum_k P_k \sum_h \underbrace{Q_1 T_1^{k-h} Q_1^*}_{\text{Unitary}} \otimes \underbrace{Q_2 T_2^{h-1} Q_2^*}_{\text{Unitary}} =$$

$$= \underbrace{(Q_1 \otimes Q_2)}_{\text{Unitary}} \left(\sum_k P_k \sum_h \underbrace{T_1^{k-h} \otimes T_2^{h-1}}_{\text{triangular}} \right) \underbrace{(Q_1 \otimes Q_2)^*}_{\text{Unitary}^*}$$

is a Schur form of $\hat{L}_{f,X}$

$$T_1^{k-h} \otimes T_2^{h-1} = \begin{bmatrix} t_{11}^{k-h} t_{22}^{h-1} & & & \\ & \ddots & & \\ & & t_{22}^{k-h} t_{22}^{h-1} & \\ & & & \ddots \\ & & & & t_{mm}^{k-h} t_{22}^{h-1} \end{bmatrix}$$

$$\begin{aligned} \text{diag}(T_1) &= \\ \text{diag}(T_2) &= \\ &= \lambda_1, \lambda_2, \dots, \lambda_n \\ &= \text{eigenvalues of } X \end{aligned}$$

The diagonal contains

$$\sum_{k=0}^d P_k \sum_{h=1}^k t_{ii}^{k-h} t_{jj}^{h-1} = \sum_{k=0}^d P_k \sum_{h=1}^k \lambda_i^{k-h} \lambda_j^{h-1} \quad \text{for all } i, j = 1, \dots, n$$

$$= \sum_{k=0}^d p_k \frac{\lambda_i^k - \lambda_j^k}{\lambda_i - \lambda_j} = \frac{1}{\lambda_i - \lambda_j} (p(\lambda_i) - p(\lambda_j))$$

$$= \frac{f(\lambda_i) - f(\lambda_j)}{\lambda_i - \lambda_j}$$

Th: if X has eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$, the eigenvalues of $L_{f,X}$

are

$$f[\lambda_i, \lambda_j] = \begin{cases} \frac{f(\lambda_i) - f(\lambda_j)}{\lambda_i - \lambda_j} & \text{if } \lambda_i \neq \lambda_j \\ f'(\lambda_i) & \text{if } \lambda_i = \lambda_j \end{cases} \quad \text{for all } i, j = 1, 2, \dots, n$$

(Proved above)

By proceeding analogously with an eigendecomposition:

If $X = V \cdot \Lambda \cdot V^{-1}$ is diagonalizable, then

$$\hat{L}_{f,X} = (V^T \otimes V) \text{diag} \left(f[\lambda_i, \lambda_j] \mid_{i,j=1..n} \right) (V^T \otimes V)^{-1}$$

$$\|\hat{L}_{f,X}\| = \underbrace{\|V^T\| \cdot \|V\|}_{\textcircled{1}} \cdot \max_{i,j} |f[\lambda_i, \lambda_j]| \cdot \underbrace{\|V^{-T}\| \cdot \|V^{-1}\|}_{\textcircled{1}}$$

$$= \textcircled{1} K(V)^2 \cdot \max_{i,j} |f[\lambda_i, \lambda_j]|$$

Computing a matrix function may be ill-conditioned because either

① diagonalizing X is ill-conditioned, or

② $|f[\lambda_i, \lambda_j]|$ is large for some eigenvalues

When does ② happen for

A. $f(x) = \exp(x)$?

B. $f(x) = \sqrt{x}$?

