

$$y = F(x)$$

$$F: \mathcal{X} \longrightarrow \mathcal{Y}$$

$$x \longrightarrow y = F(x)$$

## Functional Evaluation

$$\mathcal{X} : \mathbb{R}, \quad \mathcal{Y} : \mathbb{R}$$

$F$ : continuous func.

$$y = F(x)$$

Sum of two numbers:

$$\mathcal{X} : \mathbb{R}^2, \quad \mathcal{Y} : \mathbb{R} \quad : F: \text{sum of numbers.}$$

$$x = (a, b) \quad F(x) = F((a, b)) = a+b$$

## Computation of derivative

$$\mathcal{X} : C^1([a, b]) \quad \mathcal{Y} : \mathbb{R}$$

$F$ : evaluation of first derivative in  $x_0 \in [a, b]$

$$y = F(x) := \underbrace{x'(x_0)}_{\text{function}}$$

## Only well posed problems

$$1) \nexists x \in \mathcal{X}, \exists! y \in \mathcal{Y} \text{ st. } F(x) = y$$

$$2) \exists k \text{ (condition number) s.t. } \forall x, \hat{x} \in \mathcal{X}$$

$$\|F(x) - F(\hat{x})\|_{\mathcal{Y}} \leq k \|x - \hat{x}\|_{\mathcal{X}}$$

# $\mathbb{X}, \mathbb{Y}$ Real Vector Spaces (Normed)

RVS: collection of objects for which it makes sense  
 "V" to "sum" and "scale"

$$+ : V \times V \longrightarrow V$$

$$(u, v) \longrightarrow w = u + v$$

$$\cdot : V \times \underline{\mathbb{R}} \longrightarrow V$$

$$\forall u, v \in V, \forall \alpha, \beta \in \mathbb{R}$$

$$\alpha u + \beta v = w \in V$$

$\mathbb{R}^2$

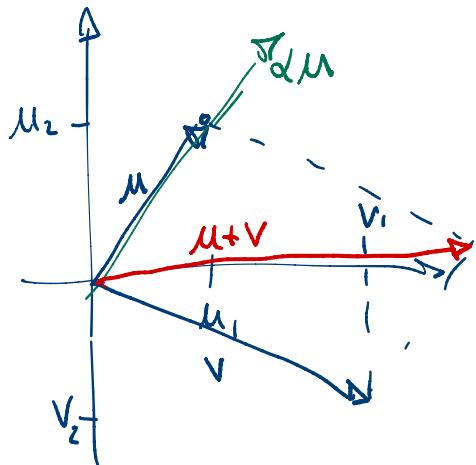
$C^0([a, b])$

$$u = (u_1, u_2)$$

$$v = (v_1, v_2)$$

$$u+v = (u_1+v_1, u_2+v_2)$$

$$\alpha u = (\alpha u_1, \alpha u_2)$$

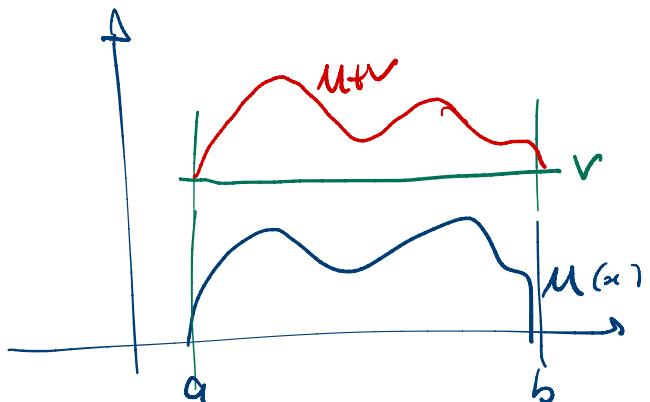


$$u : [a, b] \longrightarrow \mathbb{R}$$

$$v : [a, b] \longrightarrow \mathbb{R}$$

$$w = u+v : [a, b] \longrightarrow \mathbb{R}$$

$$\alpha \longrightarrow u(\alpha) + v(\alpha)$$



# Norms on Real Vector Spaces

a function  $\|\cdot\| : V \rightarrow \mathbb{R}_0^+$

$$1) \|u\| > 0 \quad \forall u \in V$$

$$2) \|u+v\| \leq \|u\| + \|v\| \quad \text{Triangle Inequality}$$

$$3) \|\alpha u\| = |\alpha| \|u\|$$

$$\text{optional } 4) \|u\| = 0 \iff u = 0$$

without ④ it is a semi-norm

$\ell_p$  norms on  $\mathbb{R}^n$

$L_p$  norms on  $S \subset \mathbb{R}^d$

$\|\cdot\|_*$  operational norms induced by  $\|\cdot\|_V$

$$\mathbb{R}^n: \quad \ell_p \text{ norm} \quad \|u\|_p := \left( \sum_{i=1}^n |u_i|^p \right)^{\frac{1}{p}}$$

$$\|u\|_\infty := \max_i |u_i|$$

$$S \subset \mathbb{R}^d \quad L_p \text{ norms} \quad \|u\|_p := \left( \int_S |u|^p \right)^{\frac{1}{p}}$$

$$\|u\|_\infty := (\text{ess}) \sup_{x \in S} |u(x)|$$

$\|\cdot\|_*$  induced by vector space norm  $\|\cdot\|_V$  on  $V$  and  $\|\cdot\|_W$

$$A: V \rightarrow W \quad \|A\|_* := \sup_{0 \neq x \in V} \frac{\|A(x)\|_W}{\|x\|_V}$$

$\ell_p$  norm of Matrices in  $\mathbb{R}^{n \times m}$

$$A : \mathbb{R}^m \rightarrow \mathbb{R}^n$$

$$A \xrightarrow{x \in \mathbb{R}^m} \underset{\substack{A \in \mathbb{R}^{n \times m} \\ x \in \mathbb{R}^m}}{A \cdot x} = \underline{y} \in \mathbb{R}^n$$

$$\|A\|_p := \sup_{0 \neq x \in \mathbb{R}^n} \frac{\|Ax\|_p}{\|x\|_p} = \|A\|_* \text{ induced by } \|\cdot\|_p \text{ on } \mathbb{R}^n$$

$$A \in \mathbb{R}^{n \times m} \quad A(x) = y \quad \sum_{j=1}^m A_{ij} x_j = y_i$$

$$A \in L(\mathbb{R}^m, \mathbb{R}^n)$$

$$\|\cdot\|_* \text{ norm on } L(\mathbb{R}^m, \mathbb{R}^n) \equiv \mathbb{R}^{n \times m}$$

well posed problems

$$1) \quad \forall x \in \underline{\mathcal{X}}, \exists! y \in \underline{\mathcal{Y}} \text{ s.t. } F(x) = y$$

Normed Vector Space      Normed Vector Space

$$2) \quad \exists k \text{ (condition number)} \text{ s.t. } \forall x, \hat{x} \in \underline{\mathcal{X}}$$

$$\|F(x) - F(\hat{x})\| \underset{\mathcal{Y}}{\equiv} \underset{\mathcal{X}}{\equiv} k_{\text{Abs}} \|x - \hat{x}\|$$

$$3) \quad \begin{array}{l} \text{Relative cond. number (only if } x \neq 0, F(x) \neq 0) \\ \text{Krel st. } \forall x, \hat{x} \end{array}$$

$$\frac{\|F(x) - F(\hat{x})\|_Y}{\|F(x)\|_Y} \leq \frac{K_{rel}}{\frac{\|x - \hat{x}\|_X}{\|x\|_X}}$$

A problem is well posed if  $K_{rel/abs}$  is "small"

Example : sum of two numbers: (e, norm)

$$X: \mathbb{R}^2 \quad Y: \mathbb{R}$$

$$x \in \mathbb{R}^2 \rightarrow \|x\|_1 := |x_1| + |x_2| \quad \|y\|_1 = |y|$$

$$\frac{\|F(x) - F(\hat{x})\|_1}{\|F(x)\|_1} = \frac{|x_1 - \hat{x}_1 + x_2 - \hat{x}_2|}{|x_1 + x_2|}$$

$$\frac{\|x - \hat{x}\|_1}{\|x\|_1} = \frac{|x_1 - \hat{x}_1| + |x_2 - \hat{x}_2|}{|x_1| + |x_2|}$$

$$\Delta y, \quad \Delta x \quad \Delta x = x - \hat{x} \quad \Delta y = F(x) - F(\hat{x})$$

Find  $k_{abs}$ :  $\exists k_{abs} \mid \forall x_1, x_2, \quad |\Delta y| \leq k \|\Delta x\| ?$

$$|\Delta y| \leq k \|\Delta x\| \leq k(|\Delta x_1| + |\Delta x_2|)$$

Assume that  $\Delta x \neq 0$

$$\frac{|\Delta g|}{|\Delta x|} \leq \kappa$$

$$\frac{|\Delta x_1 + \Delta x_2|}{|\Delta x_1| + |\Delta x_2|} \leq \frac{|\Delta x_1| + |\Delta x_2|}{|\Delta x_1| + |\Delta x_2|} \leq 1$$

$\kappa_{\text{abs}} = 1$

~~for~~ local s.t.

$$\underbrace{\frac{|\Delta y|}{|\Delta x|}, \frac{|x|}{|y|}}_{\leq 1} \leq \underbrace{\frac{|x|}{|y|}}_{\leq \kappa_{\text{rel}}}$$

because

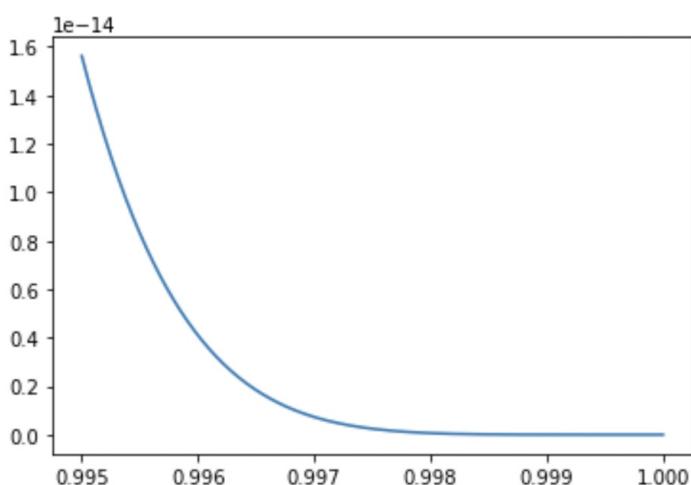
$$\frac{|x|}{|y|} = \frac{|x_1| + |x_2|}{|x_1 + x_2|}$$

can be  
as large  
as we  
want

Example

$$\underbrace{(1-x)^6}_{\text{in } [1-\epsilon, 1]}$$

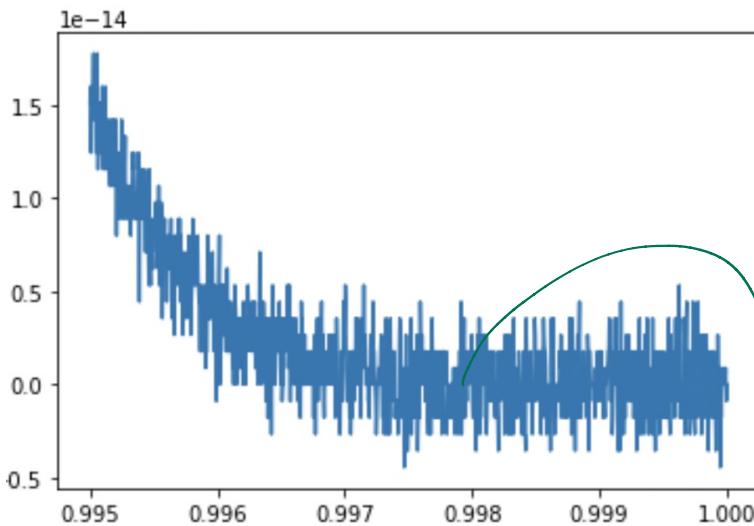
$\epsilon$  is small.



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x = linspace(.995, 1, 1029)
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y = (x-1)**6
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$$y = x^{**6} - 6*x^{**5} + 15*x^{**4} - 20*x^{**3} + 15*x^{**2} - 6*x + 1$$



$x - \hat{x}$  = floating point errors  
(rounding errors)

If  $x_1 = -(x_2 + \varepsilon)$  with  $\varepsilon$  "small"

$$\rightarrow \frac{|x|}{|y|} = \frac{|x_2 + \varepsilon| + |x_2|}{|-x_2 - \varepsilon + x_2|} \leq \frac{2|x_2| + |\varepsilon|}{|\varepsilon|}$$

if  $x_2$  not close to zero then

$$\frac{|x|}{|y|} \leq \frac{2|x_2|}{|\varepsilon|} + 1$$

$$\frac{|\Delta y|}{|y|} \cdot \frac{|x|}{|\Delta x|} \leq k_{rel}$$

$$\frac{|\Delta y|}{|\Delta x|} \cdot \frac{|x|}{|y|} \leq \underline{k_{rel}}$$