

§3.2 Finite difference approximations

We showed. $\delta f = f(x + \delta x) - f(x) = f'(x) \delta x + o(\|\delta x\|)$.

1. Finite difference approximations

$f(x + \delta x) - f(x)$ fwd difference

$f(x) - f(x - \delta x)$ backward difference

← have no relation with fwd differentiation

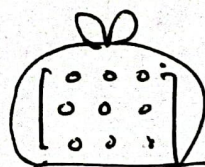
Example. $f(A) = A^2$.

$$\frac{\|\text{approx} - \text{exact}\|}{\|\text{exact}\|} := \text{relative error.}$$

where $\|\cdot\|$ is a norm, like that in the vector case.

2. Norm of a matrix - the simplest one

$$\|x\| = \sqrt{x^T x} = \sqrt{\sum_i x_i^2} \quad (L_2 \text{ norm}).$$

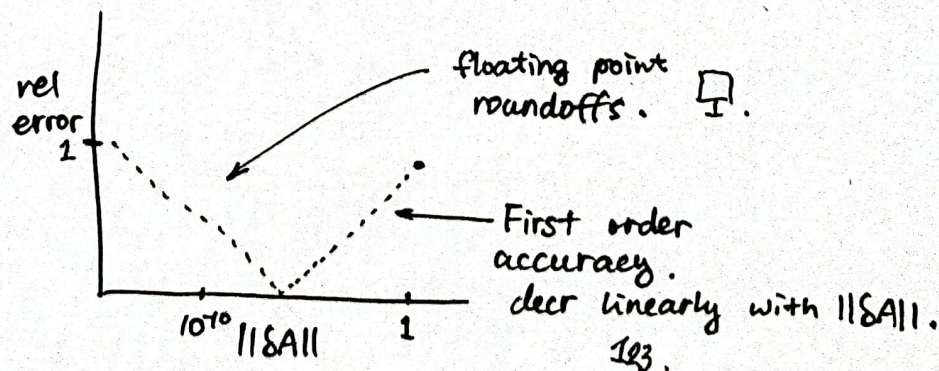


big bag of n

(Generalized dot product is $B \cdot A = \text{tr}(B^T A)$).

3. Accuracy of finite differences

- plot (relative error - $\|\delta A\|$) in log-log scale.



What's the ~~ratio~~ portion of the?

- Order of accuracy.

using Taylor Series, getting x^2 order accuracy.

$$f(x+\delta x) = f(x) + f'(x)\delta x + \frac{f''(x)}{2!}\delta x^2 + \dots$$

\downarrow
 $O(\|\delta x\|^2)$.

higher-order terms

$$\text{Then our rel. error} = \frac{\|f(x+\delta x) - f(x) - f'(x)\delta x\|}{\|f'(x)\delta x\|}$$

grab off

$$= \frac{(\text{terms prop. to } \|\delta x\|^2) + O(\|\delta x\|^2)}{\text{proportional to } \|\delta x\|}$$

$$= (\text{terms proportional to } \|\delta x\|) + O(\|\delta x\|).$$

truncation error (why it is linear).

- Roundoff error. When δx is too small,

$f(x+\delta x) - f(x)$ get rounded off to 0. round to 0.

i.e. $\sin(x)$ at $x=1$, $f'(x) = \frac{f(x+\delta x) - f(x)}{\delta x} + O(\delta x)$.

3. Rule of thumb for finite difference

The number of significant digits stored by pc is expred by machine epsilon ϵ .

ϵ is the sz of last significant digit of x .

choose half of significant digits.

$$\|\delta x\| \approx \sqrt{\epsilon} \|x\|.$$

if x is of order ~ 1 , δx should be of order $\sqrt{\epsilon} = 10^{-8}$.