

DERIVATIVES

i) Definition $\frac{df}{dx} \equiv f'(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$

Simplest thing to do. Take h "small" and estimate $f'(x)$ via finite difference

$$\frac{df}{dx} \approx \frac{f(x+h) - f(x)}{h}; \quad h > 0, h \text{ small.} \Rightarrow \text{forward difference}$$

②

$$\frac{df}{dx} \approx \frac{f(x) - f(x-h)}{h}; \quad h > 0, h \text{ small} \Rightarrow \text{backward difference}$$

ii) Problem: with difference, when h gets very small, you get large rounding errors.

•) Let's estimate the numerical error. Assume machine precision $\epsilon \approx 10^{-16}$

•) As usual, Taylor expand around x :

$$f(x+h) = f(x) + \frac{df}{dx} h + \frac{1}{2} \frac{d^2f}{dx^2} h^2 + O(h^3)$$

\Downarrow

$$\frac{df}{dx} = \underbrace{\frac{f(x+h) - f(x)}{h}}_{\text{Our numerical estimate}} - \underbrace{\frac{1}{2} h \frac{d^2f}{dx^2}}_{\text{Numerical error at leading order}} + \dots$$

Our numerical estimate

Numerical error at leading order

•) Therefore $|\mathcal{E}_1| = \left| \frac{f''(x)}{2} \right| h$ is the numerical error introduced by truncating the expansion.

•) But there is a rounding error in $f(x+h) - f(x)$ as well. We know that, if we evaluate $f(x)$, we have a rounding error on $f(x)$ which is $\mathcal{E}_r \approx C|f(x)|$. Since $f(x+h) \approx f(x)$ we get:

$$\begin{cases} \mathcal{E}_{r, f(x+h)} \approx C|f(x+h)| \\ \mathcal{E}_{r, f(x)} \approx C|f(x)| \end{cases}$$

Therefore the error on the difference is going to be $\lesssim 2C|f(x)|$ and the overall rounding error is then

$$|\mathcal{E}_2| \lesssim \frac{2C|f(x)|}{h}$$

Our conservative assumption on the total error is thus

$$\boxed{\mathcal{E}_{\text{der}} = |\mathcal{E}_1| + |\mathcal{E}_2| = \frac{h}{2} |f''(x)| + \frac{2C|f(x)|}{h}} \quad (*)$$

•) Note that, if we decrease h , $|\mathcal{E}_1|$ decreases but $|\mathcal{E}_2|$ increases at the same time! It is thus not true that arbitrarily small h minimizes the error

To minimize \mathcal{E}_{der} let us compute $\left[\frac{d\mathcal{E}_{\text{der}}}{dh} = 0 \right] \Rightarrow \frac{|f''|}{2} - \frac{2C}{h^2} |f| = 0$

Therefore $E_{\text{der}}^{\text{MIN}}$ is obtained for:

$$h = \left(4C \frac{|f'|}{|f''|} \right)^{\frac{1}{2}} \quad \text{this is the optimal choice} \quad (**)$$

Assuming $|f'(x)| \sim 1$ and $|f''(x)| \sim 1$ (not always true!), we get ($C \sim 10^{-16}$) an optimal choice of $|h| \sim 10^{-8}$

i) Replacing (**) into (v) we find a minimum error:

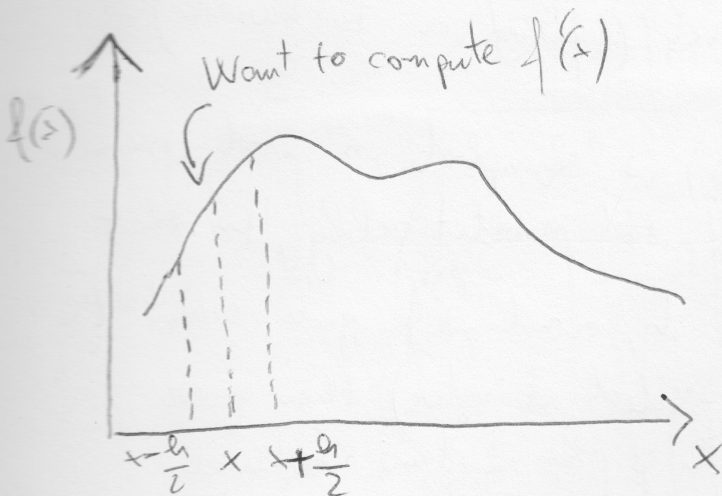
$$E_{\text{der}} \simeq \frac{2\sqrt{C}}{2} |f''|^{\frac{1}{2}} |f'|^{\frac{1}{2}} + \frac{2C}{2C^{\frac{1}{2}}} \frac{|f'|}{|f'|^{\frac{1}{2}}} |f''|^{\frac{1}{2}} \Rightarrow$$

$$E_{\text{der}} = \left[C |f'(x)| |f''(x)| \right]^{\frac{1}{2}}$$

If $|f'| \sim 1$ and $|f''| \sim 1$, we are always limited to $E \sim 10^{-8}$, that is 8-digits precision in the derivative.

iii) To improve precision, use central differences

$$\frac{df}{dx} \simeq \frac{f\left(x + \frac{h}{2}\right) - f\left(x - \frac{h}{2}\right)}{h}$$



•) You can show as exercise that $f'(x) = \frac{f(x+\frac{h}{2}) - f(x-\frac{h}{2})}{h} - \frac{1}{24} h^2 f'''(x) + \dots$

(just Taylor expand ^{both} $f(x+\frac{h}{2})$, $f(x-\frac{h}{2})$ and rearrange terms suitably)

Therefore now ε is $O(h^2)$ (before it was $O(h)$).

We still have some rounding error of course, hence

$$|\varepsilon| \stackrel{\text{central deriv.}}{=} \frac{2C|f|}{h} + \frac{h^2}{24} |f'''(x)|$$

•) The optimal h becomes

$$h = \left(\frac{24C|f|}{|f'''(x)|} \right)^{\frac{1}{3}}$$

If $f(x) \sim 1$, $f'''(x) \sim 1$ and $C \sim 10^{-16}$, we now get

$$h \sim 10^{-5}$$

•) The corresponding error is

$$\varepsilon = \left(\frac{9}{8} C^2 |f(x)|^2 |f'''(x)| \right)^{\frac{1}{3}}$$

For $f \sim 1$, $f''' \sim 1$, $C \sim 10^{-16}$ we get $\varepsilon \sim 10^{-10}$. About 100 times better than the 1-side derivatives (forward or backward)

•) Note that, very often, your $f(x)$ is sampled in fixed points from data and cannot be computed analytically. In that case you don't get to choose h , and, if you want to take the central difference (2-sided derivative) then your interval will be $2h$, where h is the distance between consecutive points in the sample

iv) We often need to compute second derivatives: $f''(x)$. Of course, we do that by finite difference, ~~not~~ starting from first derivative. We use central, 2-sided scheme for everything:

$$f''(x) \approx \frac{f'(x + \frac{h}{2}) - f'(x - \frac{h}{2})}{h}$$

$$f'(x + \frac{h}{2}) \approx \frac{f(x+h) - f(x)}{h}; \quad f'(x - \frac{h}{2}) = \frac{-f(x-h) + f(x)}{h}$$

Combining everything:

$$f''(x) \approx \frac{1}{h} \left[\frac{f(x+h) - f(x)}{h} - \frac{f(x) - f(x-h)}{h} \right] = \frac{1}{h} \frac{f(x+h) - 2f(x) + f(x-h)}{h}$$

Therefore:
$$f''(x) \approx \frac{f(x+h) - 2f(x) + f(x-h)}{h^2}$$

•) With the usual Taylor expansions (for $f(x+h)$ and $f(x-h)$) we can estimate ϵ and the optimal choice of h .

$$\epsilon = \frac{4C|f|}{h^2} + \frac{h^2}{12} |f'''|$$

$$h = \left(\frac{48C|f|}{|f''|} \right)^{\frac{1}{4}} \quad (h \approx 10^{-4})$$

$$\epsilon_{\text{MIN}} = \left(\frac{4}{3} C|f| |f'''| \right)^{\frac{1}{2}} \quad (\epsilon_{\text{MIN}} \approx 10^{-8})$$

We get similar accuracy as 1-sided 1st derivative evaluation.