

**COL100: Introduction to Computer Science**

# **12: Numerical methods**

# Conditioning and stability

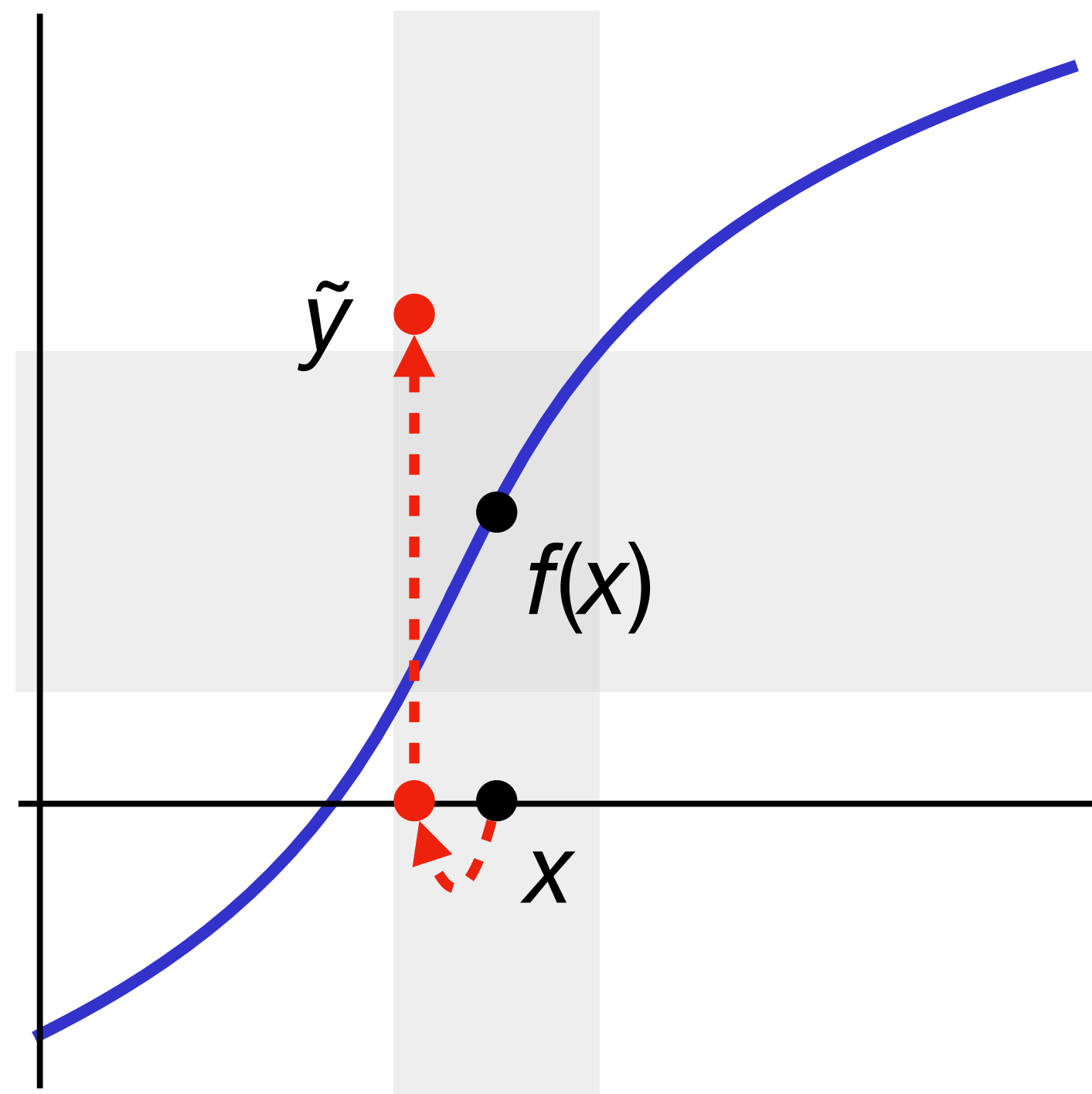
Given inaccurate inputs and inaccurate arithmetic, how accurate of an answer can we expect?

**Conditioning:** how sensitive the *problem* is to errors in *input*

**Stability:** how sensitive an *algorithm* is to errors in *computation*

# Stability

An algorithm is **stable** if error due to computation is not too large, relative to error due to input



$$\tilde{y} \approx f(\tilde{x}) \text{ and } \tilde{x} \approx x$$

“nearly\* the right answer  
to nearly\* the right question”

\*with relative error  $O(u)$

# Example: An unstable algorithm

Let  $f(x) = \sqrt{x + 1} - \sqrt{x}$ .

Verify that for large  $x$ , the condition number  $\approx 1/2$ .

Compute  $f(12345)$  with six decimal digits:

$$\begin{aligned} & f(12345) \\ &= \sqrt{12346} - \sqrt{12345} \\ &\approx 111.113 - 111.108 \\ &= 5 \times 10^{-3} \end{aligned}$$

Differs from correct answer  $4.50003... \times 10^{-3}$  by more than 10%!

# Example: An unstable algorithm

Rewrite function as  $f(x) = (\sqrt{x+1} + \sqrt{x})^{-1}$ .

Compute  $f(12345)$  again with six decimal digits:

$$\begin{aligned} & f(12345) \\ &= (\sqrt{12346} + \sqrt{12345})^{-1} \\ &\approx (111.113 + 111.108)^{-1} \\ &= 222.221^{-1} \\ &= 4.50002 \times 10^{-3} \end{aligned}$$

Now the result is correct to five digits.

# Example: Solving linear systems

$$\underbrace{\begin{bmatrix} 1.00 & 2.01 \\ 1.01 & 2.03 \end{bmatrix}}_A \underbrace{\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}}_x = \underbrace{\begin{bmatrix} 1.01 \\ 1.02 \end{bmatrix}}_b$$

**Problem:** Solve  $Ax = b$ , i.e. compute  $x = f(b) = A^{-1}b$ . Exact solution:  $x = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$

**Naive algorithm:** Compute  $A^{-1}$ , multiply with  $b$ . With 3 decimal digits,

$$\text{inv}(A) = \begin{bmatrix} -2.03 \times 10^4 & 2.01 \times 10^4 \\ 1.01 \times 10^4 & -1.00 \times 10^4 \end{bmatrix}, \quad \text{inv}(A) \odot b = \begin{bmatrix} 0.00 \\ 0.00 \end{bmatrix}$$

Instead, do Gaussian elimination on  $A$  and  $b$ , get  $\tilde{x} = \begin{bmatrix} 1.01 \\ 0.00 \end{bmatrix}$ . Why is this better?

# Exercise

- Given a large set of data  $x_1, x_2, \dots, x_n$ , there are two mathematically equivalent ways to compute the variance,

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2 \quad \text{where } \mu = \frac{1}{n} \sum_{i=1}^n x_i$$
$$= \frac{1}{n} \sum_{i=1}^n x_i^2 - \left( \frac{1}{n} \sum_{i=1}^n x_i \right)^2$$

Which one is more numerically stable? Construct a simple example with known  $\mu$  and  $\sigma^2$  where the difference in accuracy can be observed.

# Infinite series

How to compute  $e^\pi$  in the first place?

- $\pi \neq \text{math.pi} \in \mathbb{F} \dots$ rounding error
- Cannot sum infinitely many terms ...truncation error

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

**Exercise:** Let  $H(n) = 1 + 1/2 + 1/3 + \dots + 1/n$ . Why doesn't  $H(n)$  grow arbitrarily large when summed naively in floating-point arithmetic? How can you fix it?



# Finite differences

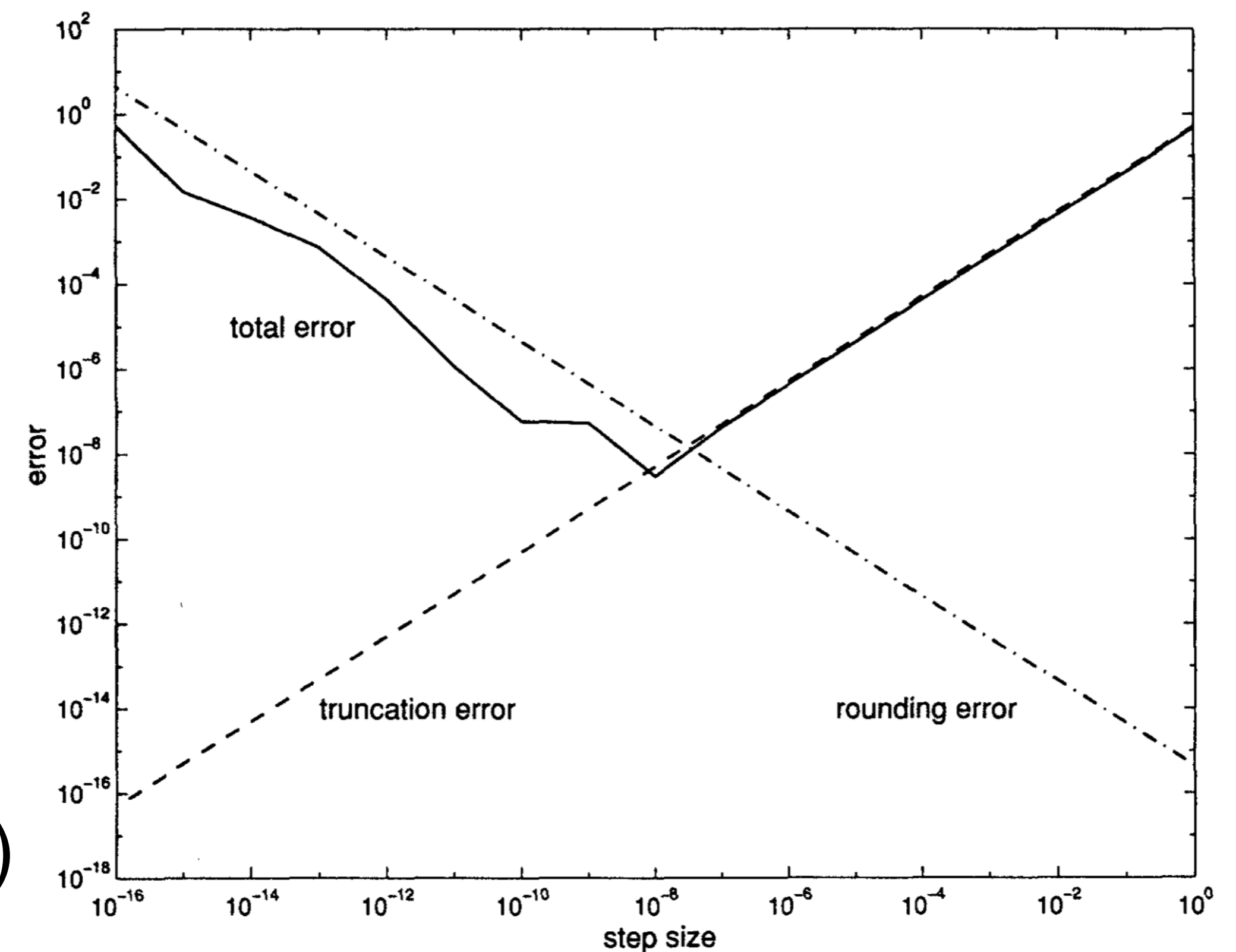
Given an black-box function  $f$ , how to compute (or approximate)  $f'(x)$ ?

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

- Taylor series  $\Rightarrow$  truncation error =  $O(h)$
- But rounding error =  $O(u/h)$

Total error is minimized at  $h = O(u^{1/2})$

**Exercise:** Show that  $(f(x+h) - f(x-h))/(2h)$  has  $O(h^2)$  truncation error, allowing  $h = O(u^{2/3})$



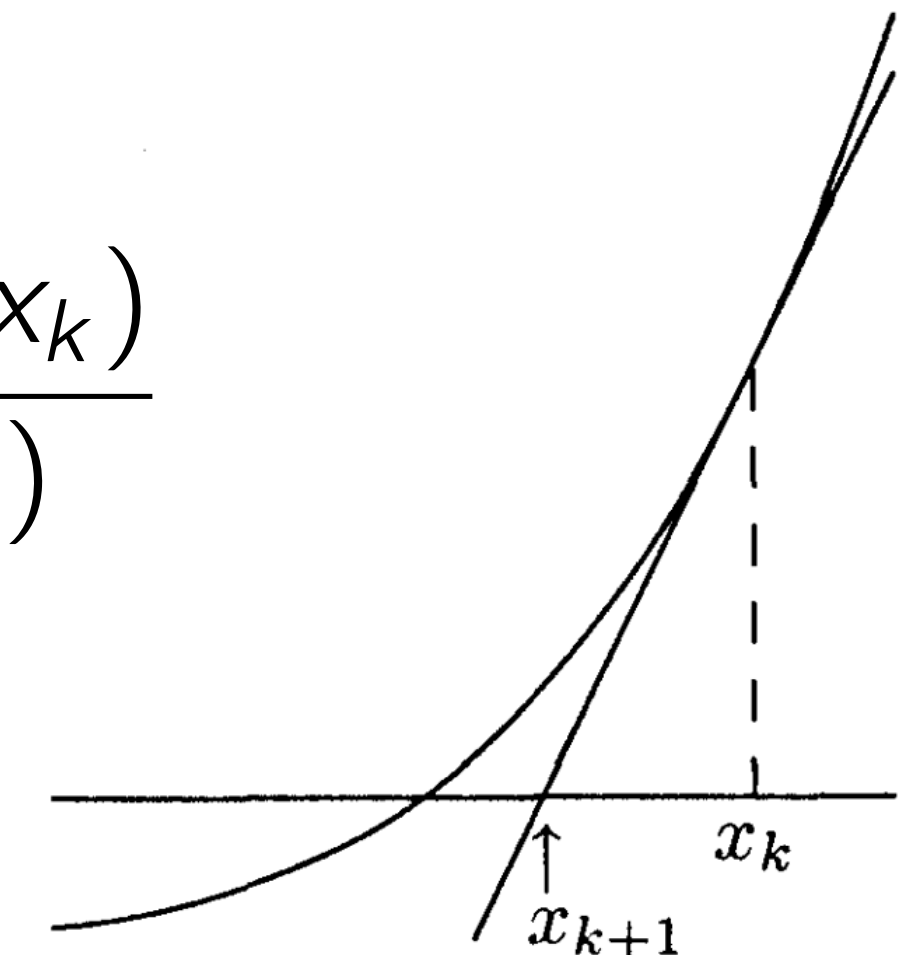
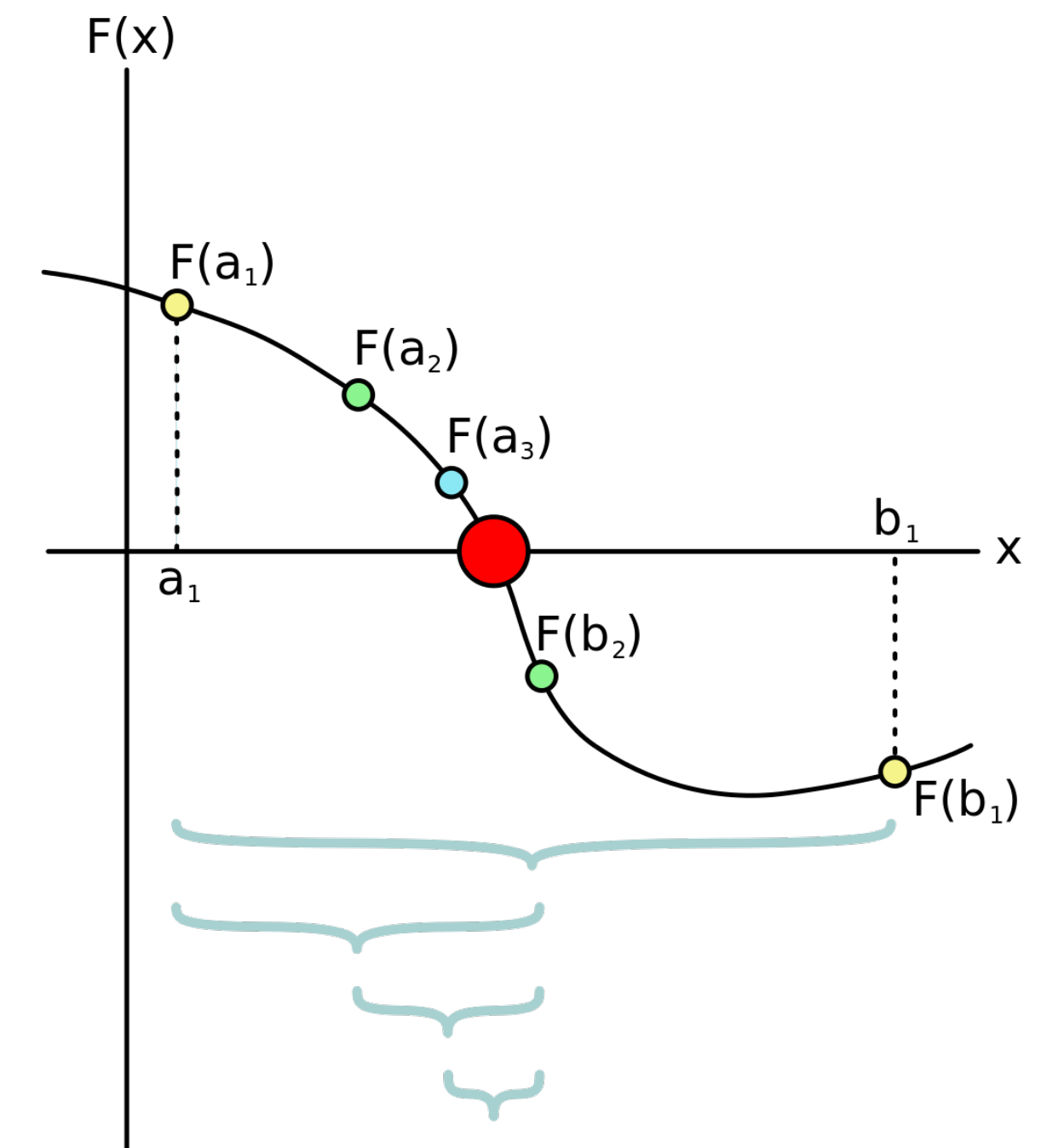
# Root finding

Given  $f : \mathbb{R} \rightarrow \mathbb{R}$  and  $y \in \mathbb{R}$ , find  $x^* \in \mathbb{R}$  such that  $f(x^*) = y$ .

- If  $f$  continuous and given **bracket**  $[a, b]$  s.t.  $f(a) < y < f(b)$ , apply **bisection** (analogous to binary search in array)
  - Error bound  $|b-a|$  decreases by  $1/2$  on each iteration
- If  $f$  differentiable, **Newton's method**

$$f(x_{k+1}) \approx f(x_k) + (x_{k+1} - x_k)f'(x_k) \implies x_{k+1} = x_k + \frac{y - f(x_k)}{f'(x_k)}$$

- Error decreases as  $|x_{k+1} - x^*| = O(|x_k - x^*|^2)$   
 ...if  $f'(x^*) \neq 0$  and  $x_k$  is close to  $x^*$ !



# Afterwards

- Read the notes on floating-point numbers and numerical computation, Sec. 1.5.2 onwards
- Derive Newton's method for computing  $\sqrt{y}$  by solving  $x^2 = y$ , and compare with the Babylonian method  $x_{k+1} = \frac{1}{2} (x_k + y/x_k)$ .