

## 16. Numerical integration

## Summary of the previous lecture

- Interpolation
- Find a function  $f(x)$  passing through points  $(x_i, y_i)$
- Lagrange interpolation
- Barycentric Lagrange interpolation

## Goals for today

- Numerical integration (“quadrature”)
- Approximating integrals
- Error analysis
- Conditioning

## Need for numerical integration

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- Hence numerical integration is of paramount importance

# Numerical integration problem

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- The problem is  $\mathcal{Y} = \Phi(\mathcal{X})$  with

$$\mathcal{X} = f; \quad \Phi = \int; \quad \mathcal{Y} = \int f$$



# Collaboration I

## Simplest versions of numerical integration

- 1 What does  $\int_a^b f$  represent geometrically?
- 2 What is the simplest approximation you could take?
- 3 How could you improve on that approximation?

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- As in Riemann integration
- Split  $[a, b]$  into  $N$  intervals (or **panels**) of length  $h = \frac{b-a}{N}$
- Take **nodes**  $x_k := a + k h$  (with  $x_0 = a$  and  $x_N = b$ )

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- So  $p(x) = \sum_k f(x_k) \mathbb{1}_{X_k}(x)$
- Where  $\mathbb{1}_{X_k}$  is **indicator function** of set  
 $= 1$  if  $x \in X_k$  and 0 if not

## Rectangular rule III

- Area  $A_k$  of  $k$ th rectangle is  $hf(x_k)$
- So  $I(f) \simeq A(f, h) := h \sum_k f(x_k)$



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- Weights  $w_k = h$  except  $w_N = 0$

## Collaboration II

How good is the rectangular rule?

Suppose we approximate  $I(f)$  with  $A(f, h)$ , approximating  $f$  with a piecewise constant function.

- 1 How can we measure how good the approximation is?
- 2 Which mathematical tool could you use to find how this varies?
- 3 What do you obtain?

## Error of rectangular rule

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- We want to calculate the **error**

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as a function of  $h$ , as  $h \rightarrow 0$

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- For small  $h$  the function is nearly constant in each  $X_k$
- Then it makes sense to model the function using a **Taylor expansion** around an end-point:

$$f(x) = f(x_k) + (x - x_k) f'(\xi_k) \quad \text{for } x \in X_k$$

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$$\leq M_k h$$

## Error of rectangular rule III

- Thus  $|f(x) - p(x)| \leq Mh$  for  $x$  in  $X_k$
- So  $E_k := |\int_{X_k} (f - p)| \leq \int_{X_k} Mh \leq Mh^2$

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- We have  $N \sim 1/h$  subintervals
- So global error in integral is  $E(f, h) = \sum_k E_k$

$$E(f, h) = \int_a^b [f(x) - p(x)] = \mathcal{O}(h)$$

## Collaboration III

### Improving the approximation

- 1 How can we get a better method?
- 2 How small an error do you expect?
- 3 Is there a way of minimising the error even more?

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- Try modelling the function with a piecewise-linear function instead of piecewise-constant
- Interpolate using Lagrange cardinal polynomials:
- $p_1(x) = \ell_0(x)f(a) + \ell_1(x)f(b)$

$$p_1(x) = \frac{x-b}{a-b} f(a) + \frac{x-a}{b-a} f(b)$$

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- $A_k$  is now the area of a **trapezium**:

$$A_k = \frac{h}{2}[f(x_k) + f(x_{k+1})]$$

- The total area is then

$$A(h) = h[\frac{1}{2}f(a) + f(x_1) + \cdots + f(x_{k-1}) + \frac{1}{2}f(b)]$$

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- Note:  $\int$  and this approximation are both **linear** operators

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$$f(x) = p_n(x) + \frac{f^{(n+1)}(\xi(x))}{(n+1)!} \pi_n(x)$$

where  $\pi_n(x) := \prod_{k=0}^n (x - x_k)$  – degree  $n + 1$

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- Note that the interpolation error = 0 at each node!

## Error for Newton–Cotes rules

- Integrating the interpolant gives

- $$\left| \int f - \int p_n \right| \leq \frac{M_{n+1}}{(n+1)!} \int |\pi_n|$$

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- E.g. trapezium rule has error  $\mathcal{O}(h^2)$

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- So  $\Delta I = I(\Delta f)$

## Conditioning II

- We have  $\Delta I = I(\Delta f)$
- So

$$|\Delta I| = \left| \int \Delta f \right| \leq \int |\Delta f| =: \|\Delta f\|_1$$

- The relative error is then

$$\left| \frac{\Delta I}{I} \right| \leq \frac{\|\Delta f\|_1}{|I|}$$

## Conditioning III

- So the relative condition number is

$$\kappa = \frac{|\Delta I|/|I|}{\|\Delta f\|/\|f\|} = \frac{\|f\|_1}{|I|}$$

- Hence

$$\kappa = \frac{\int_a^b |f(x)| dx}{\left| \int_a^b f(x) dx \right|}$$

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- We see that this is *ill-conditioned* when  $|f|$  is large but  $\int f$  is small
- I.e. when we integrate a **highly-oscillatory** function

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- Idea of adaptivity: Choose new nodes where it makes sense to do so
- I.e. where the function “behaves more badly”

## Higher dimensions

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- There are many more ways of dividing up 2D space

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- We can then carry out this integration *numerically*!
- Note that the result is independent of the parametrisation

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  - *Closed* curves are a particular case of importance in complex analysis
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- It turns out that the trapezium rule is surprisingly good for **periodic** functions like this

# Summary

- Numerical integration approximates definite integral
- Interpolate then integrate
- Degree  $n$  polynomial leads to  $\mathcal{O}(h^{n+1})$  error