ENM 360: Introduction to Data-driven Modeling

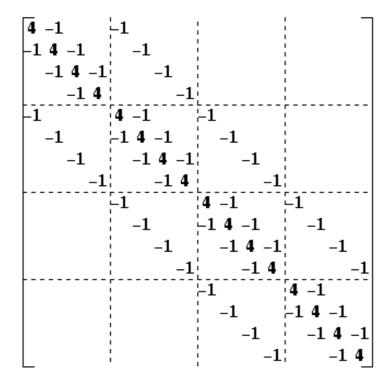
Lecture #3: Approximation of functions and data



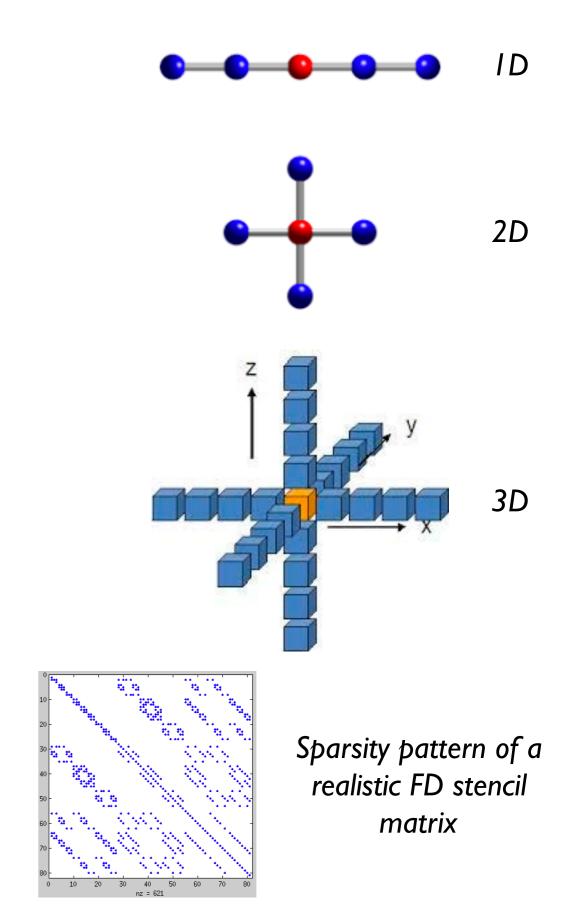
#### Numerical differentiation with finite differences

$$\mathbf{A} = \begin{bmatrix} -2 & 1 & & & & & \\ 1 & -2 & 1 & & & & \\ & 1 & -2 & 1 & & & \\ & & 1 & -2 & 1 & & \\ & & & 1 & -2 & 1 & \\ & & & \ddots & \ddots & \ddots \\ & & & & 1 & -2 \end{bmatrix}$$

Central difference stencil for second derivative approximation in 1D



Central difference stencil for second derivative approximation in 2D



For *continuous* periodic function f(x),  $f(x + 2\pi) = f(x)$ , represented by a Fourier series:

$$f(x) = \sum_{n = -\infty}^{\infty} \hat{f}_n e^{inx}$$

The differentiation of f(x) can then be evaluated by:

$$\frac{df(x)}{dx} = \sum_{n=-\infty}^{\infty} (in\hat{f}_n) e^{inx}$$
Fourier coefficient of  $f'(x)$ 

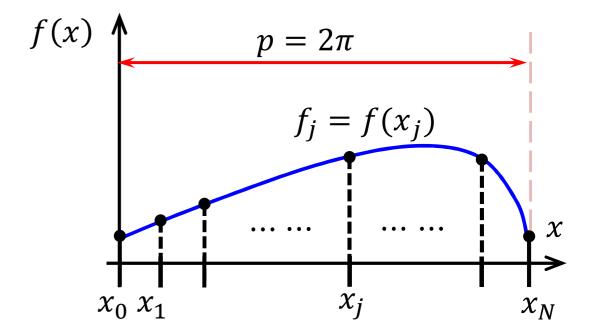
 $\therefore$  Once the coefficients of the Fourier series  $\hat{f}_n$  is obtained, the differentiation can be evaluated by summing the Fourier series with new coefficients  $(in\hat{f}_n)$ 

• Now, for discrete periodic function  $f_j$  defined at  $x_j$ , j=0,1,...,N-1:

$$f_j = \sum_{n = -\frac{N}{2}}^{\frac{N}{2} - 1} \hat{f}_n e^{inx_j} = \sum_{n = 0}^{N - 1} \hat{f}_n e^{inx_j}$$

where  $\hat{f}_n$  is the discrete Fourier transform:

$$\hat{f}_n = \frac{1}{N} \sum_{j=0}^{N-1} f(x_j) e^{-inx_j}$$



• Can the differentiation of f defined at  $x_j$ , i.e.,  $\frac{df}{dx}\Big|_j$  be evaluated by:

$$\left. \frac{df}{dx} \right|_{j} = \sum_{n=-\frac{N}{2}}^{\frac{N}{2}-1} (in)\hat{f}_{n} e^{inx_{j}}$$

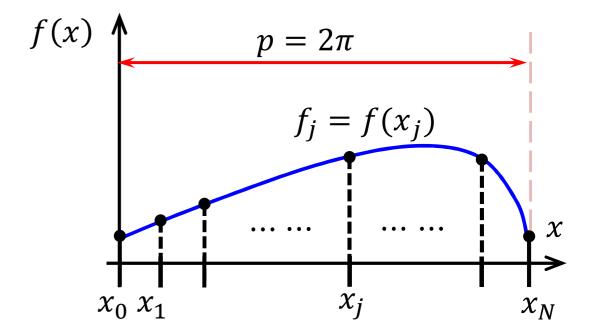
Similarly, 
$$\left. \frac{d^2 f}{dx^2} \right|_j = \sum_{n=-\frac{N}{2}}^{\frac{N}{2}-1} (in)^2 \hat{f}_n \ e^{inx_j} = -\sum_{n=-\frac{N}{2}}^{\frac{N}{2}-1} n^2 \hat{f}_n \ e^{inx_j}$$

• Now, for discrete periodic function  $f_j$  defined at  $x_j$ , j=0,1,...,N-1:

$$f_j = \sum_{n = -\frac{N}{2}}^{\frac{N}{2} - 1} \hat{f}_n e^{inx_j} = \sum_{n = 0}^{N - 1} \hat{f}_n e^{inx_j}$$

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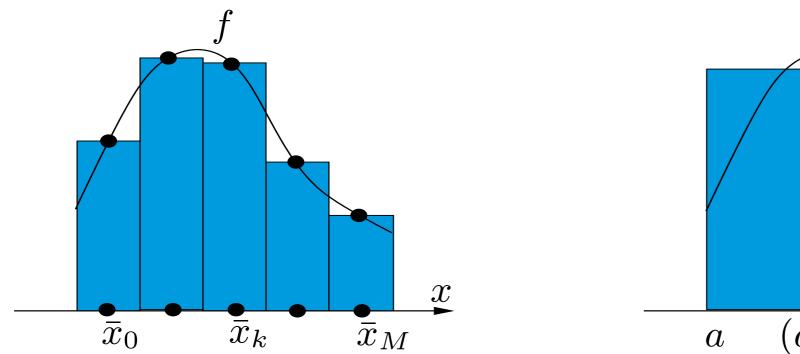
• Can the differentiation of f defined at  $x_j$ , i.e.,  $\frac{df}{dx}\Big|_j$  be evaluated by:

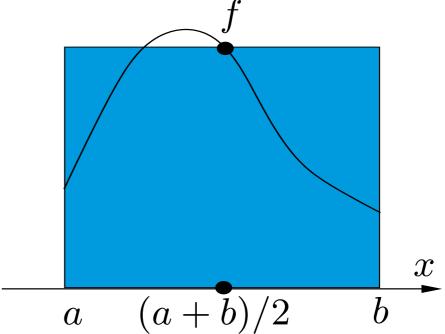
$$\left. \frac{df}{dx} \right|_{j} = \sum_{n=-\frac{N}{2}}^{\frac{N}{2}-1} (in)\hat{f}_{n} e^{inx_{j}}$$

Similarly, 
$$\left. \frac{d^2 f}{dx^2} \right|_j = \sum_{n=-\frac{N}{2}}^{\frac{N}{2}-1} (in)^2 \hat{f}_n \ e^{inx_j} = -\sum_{n=-\frac{N}{2}}^{\frac{N}{2}-1} n^2 \hat{f}_n \ e^{inx_j}$$

- The spectral derivative is much more accurate than any finite-difference schemes for *periodic functions*.
- The major cost involved is the use of fast Fourier transform.
- However, it is inaccurate and does not converge when the derivative is discontinuous.

## Numerical integration: The midpoint rule



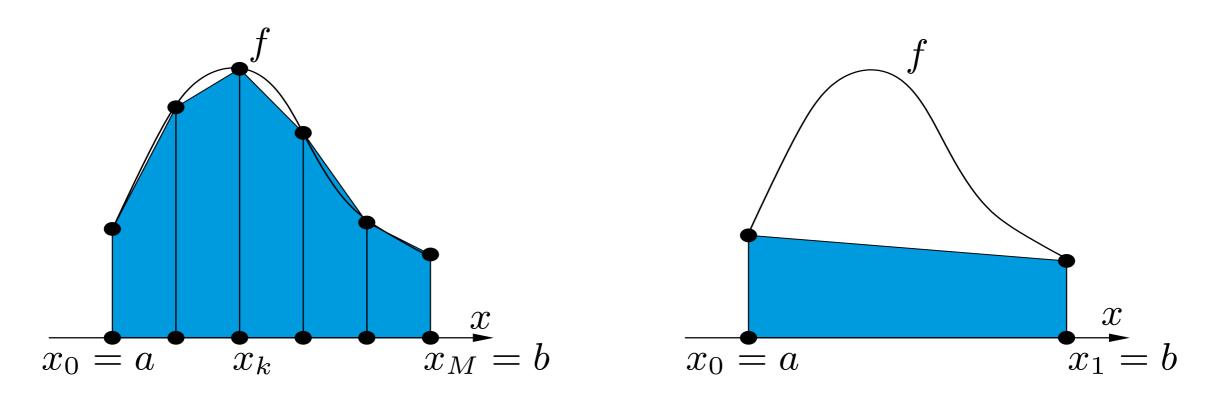


**Fig. 4.3.** The composite midpoint formula (left); the midpoint formula (right)

$$I_{mp}^c(f) = H \sum_{k=1}^{M} f(\bar{x}_k)$$

$$I_{mp}(f) = (b-a)f[(a+b)/2]$$

## Numerical integration: The trapezoidal rule



**Fig. 4.4.** Composite trapezoidal formula (left); trapezoidal formula (right)

$$I_t^c(f) = \frac{H}{2} \sum_{k=1}^{M} [f(x_k) + f(x_{k-1})]$$

$$= \frac{H}{2} [f(a) + f(b)] + H \sum_{k=1}^{M-1} f(x_k)$$

$$I_t(f) = \frac{b-a}{2} [f(a) + f(b)]$$

## Numerical integration: Simpson's rule

$$I_s(f) = \frac{b-a}{6} \left[ f(a) + 4f((a+b)/2) + f(b) \right]$$

Simpson's formula

$$I_s^c(f) = \frac{H}{6} \sum_{k=1}^{M} \left[ f(x_{k-1}) + 4f(\bar{x}_k) + f(x_k) \right]$$

The composite Simpson's rule

## Gauss-Legendre quadrature

$$I_s(f) = \sum_{j=1}^n w_j f(x_j)$$
  $w_j$  weights  $x_j$  nodes

$\underline{\hspace{1cm}}$	$x_j$	$w_{j}$
1	$\{\pm 1/\sqrt{3}\}$	{1}
2	$\left\{\pm\sqrt{15}/5,0\right\}$	$\{5/9, 8/9\}$
3	$\{\pm (1/35)\sqrt{525 - 70\sqrt{30}},$	$\{(1/36)(18+\sqrt{30}),$
	$\pm (1/35)\sqrt{525+70\sqrt{30}}$	$(1/36)(18 - \sqrt{30})$
4	$\left\{0, \pm (1/21)\sqrt{245 - 14\sqrt{70}}\right\}$	$\{128/225, (1/900)(322+13\sqrt{70})$
	$\pm (1/21)\sqrt{245 + 14\sqrt{70}}$	$(1/900)(322 - 13\sqrt{70})$

**Table 4.1.** Nodes and weights for some quadrature formulae of Gauss-Legendre on the interval (-1,1). Weights corresponding to symmetric couples of nodes are reported only once

## Monte Carlo approximation

$$\mathbb{E}_{x \sim p(x)}[f(x)] = \int f(x)p(x)dx \approx \frac{1}{n} \sum_{i=1}^{n} f(x_i),$$

where  $x_i$  are drawn iid from p(x)

# Monte Carlo approximation

#### Example: estimating $\pi$ by Monte Carlo integration

MC approximation can be used for many applications, not just statistical ones. Suppose we want to estimate  $\pi$ . We know that the area of a circle with radius r is  $\pi r^2$ , but it is also equal to the following definite integral:

$$I = \int_{-r}^{r} \int_{-r}^{r} \mathbb{I}(x^2 + y^2 \le r^2) dx dy \tag{2.99}$$

Hence  $\pi = I/(r^2)$ . Let us approximate this by Monte Carlo integration. Let  $f(x,y) = \mathbb{I}(x^2 + y^2 \le r^2)$  be an indicator function that is 1 for points inside the circle, and 0 outside, and let p(x) and p(y) be uniform distributions on [-r, r], so p(x) = p(y) = 1/(2r). Then

$$I = (2r)(2r) \int \int f(x,y)p(x)p(y)dxdy$$

$$= 4r^{2} \int \int f(x,y)p(x)p(y)dxdy$$

$$\approx 4r^{2} \frac{1}{S} \sum_{i=1}^{S} f(x_{s},y_{s})$$
(2.100)
(2.101)
(2.102)

We find  $\hat{\pi} = 3.1416$  with standard error 0.09 (see Section 2.7.3 for a discussion of standard errors). We can plot the points that are accepted/ rejected as in Figure 2.19.