MA3227 Numerical Analysis II

Lecture 3: Finite Differences in Two Dimensions

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Introduction

Consider Poisson's equation on $\Omega=(0,1)^2$, i.e. the problem of finding $u:[0,1]^2\to\mathbb{R}$ such that for all $(x_1,x_2)\in(0,1)^2$ we have

$$-\Delta u(x_1,x_2) = f(x_1,x_2),$$
 $u(0,x_2) = u(1,x_2) = u(x_1,0) = u(x_1,1) = 0.$

Finite difference discretisation works just like in 1D:

- ► Functions: $u(x_1, x_2) \rightarrow u[i_1, i_2] = u(\frac{i_1}{n+1}, \frac{i_2}{n+1})$
- Derivatives:

$$\frac{\partial^2 u}{\partial x_1^2} \left(\frac{i_1}{n+1}, \frac{i_2}{n+1} \right) \approx (n+1)^2 \left(u[i_1+1, i_2] - 2u[i_1, i_2] + u[i_1-1, i_2] \right),$$

$$\frac{\partial^2 u}{\partial x_1^2} \left(\frac{i_1}{n+1}, \frac{i_2}{n+1} \right) \approx (n+1)^2 \left(u[i_1, i_2+1] - 2u[i_1, i_2] + u[i_1, i_2-1] \right)$$

and thus

$$\Delta u(\frac{i_1}{n+1},\frac{i_2}{n+1}) \approx (n+1)^2 \left(u[i_1+1,i_2]+u[i_1,i_2+1]-4u[i_1,i_2]+u[i_1-1,i_2]+u[i_1,i_2-1]\right).$$

New issue: natural "layout" for point values $u[i_1, i_2]$ is a matrix, but for linear-algebra-purposes we would like $u[i_1, i_2]$ to be a vector.

Vectorisation of a matrix

Given $u \in \mathbb{R}^{n \times n}$, we define $\text{vec}(u) \in \mathbb{R}^{n^2}$ through

$$\text{vec}(u)[i_1 + n(i_2 - 1)] := u[i_1, i_2].$$

Example

vec(u) enumerates the entries of a 4 × 4 matrix u as follows:

1	5	9	13	
2	6	10	14	
3	7	11	15	•
4	8	12	16	

Remarks

- We write $\Delta_n^{(1)}$ and $\Delta_n^{(2)}$ to indicate the dimension of Δ_n .
- Vectorisation of u leads to a more complicated sparsity pattern for the finite-difference-discretised Laplacian matrix $\Delta_n^{(2)}$. See next slide.

Discussion

Solving Poisson's equation in 2D in principle works just like in 1D: assemble the linear system and solve.

However, there are a few technical complications:

- $ightharpoonup \Delta_n^{(2)}$ has n^4 entries, but only $\mathcal{O}(n^2)$ of these entries are nonzero. Exploiting this special sparsity property is crucial to stay within the memory limits of a typical laptop. Julia's SparseArrays package provides a data type which allows us to represent sparse matrices efficiently.
- ▶ The structure of $\Delta_n^{(2)}$ is quite complicated. Assembling this matrix is tricky unless we use the Kronecker product trick introduced on the next slide.

Kronecker product

Let a, b be vectors and A, B be matrices. We define

$$a \otimes b := \begin{pmatrix} a[1] \ b \\ \vdots \\ a[n] \ b \end{pmatrix}, \qquad A \otimes B := \begin{pmatrix} A[1,1] \ B & \cdots & A[1,n] \ B \\ \vdots & \ddots & \vdots \\ A[n,1] \ B & \cdots & A[n,n] \ B \end{pmatrix}.$$

Remarks

- ▶ $h = f \otimes g$ corresponds to the product $h(x_1, x_2) = g(x_1) f(x_2)$.
- Let I be the identity matrix. We have the correspondences

$$\begin{array}{cccc} \frac{\partial^2}{\partial x_1^2} & \longrightarrow & I \otimes \Delta_n^{(2)}, & & \frac{\partial^2}{\partial x_2^2} & \longrightarrow & \Delta_n^{(1)} \otimes I. \end{array}$$

Two-dimensional Laplacian

It follows from previous slide that the finite-difference discretisation of

$$\Delta = \frac{\partial^2}{\partial x_1^2} + \frac{\partial^2}{\partial x_2^2}$$

is given by

$$\Delta_n^{(2)} = \Delta_n^{(1)} \otimes I + I \otimes \Delta_n^{(1)}$$

Implementing $\Delta_n^{(2)}$ is straightforward with this formula. See laplacian_2d().

Convergence analysis for two-dimensional finite differences

The "stability & consistency \Rightarrow convergence" trick also works in 2D.

- ▶ Consistency can be shown using Taylor expansions just like in 1D.
- Stability of $\Delta_n^{(2)}$ requires us to study the eigenvalues of $\Delta_n^{(2)}$. These eigenvalues can be derived from the results on the next slide.

Lemma

$$(A \otimes B) (a \otimes b) = (Aa) \otimes (Bb)$$

Proof. Straightforward but tedious computations.

Eigenvalues and -vectors of 2D Laplacian

Let λ_k, u_k be eigenpairs of $\Delta_n^{(1)}$. Then, eigenpairs of $\Delta_n^{(2)}$ are

$$\lambda_{k_1,k_2} = \lambda_{k_1} + \lambda_{k_2}, \qquad u_{k_1,k_2} = u_{k_1} \otimes u_{k_2}.$$

Proof.
$$\Delta_{n}^{(2)} u_{k_{1},k_{2}} = \left(\Delta_{n}^{(1)} \otimes I + I \otimes \Delta_{n}^{(1)}\right) \left(u_{k_{1}} \otimes u_{k_{2}}\right)$$

$$= \left(\Delta_{n}^{(1)} u_{k_{1}}\right) \otimes u_{k_{2}} + u_{k_{1}} \otimes \left(\Delta_{n}^{(1)} u_{k_{2}}\right)$$

$$= \lambda_{k_{1}} u_{k_{1}} \otimes u_{k_{2}} + \lambda_{k_{2}} u_{k_{1}} \otimes u_{k_{2}}$$

$$= \left(\lambda_{k_{1}} + \lambda_{k_{2}}\right) u_{k_{1}} \otimes u_{k_{2}}$$

$$= \left(\lambda_{k_{1}} + \lambda_{k_{2}}\right) u_{k_{1},k_{2}}.$$

Stability of 2D Laplacian

It follows from results on previous slide that

$$|\lambda_{\mathsf{min}}| = |\lambda_{1,1}| = 2 \, |\lambda_1| = 2\pi^2 + \mathcal{O}\big(n^{-2}\big).$$

Hence, we have $\|(\Delta_n^{(2)})^{-1}\|_{2,n} = \mathcal{O}(1)$, i.e. 2D Laplacian is stable.

Convergence of 2D finite differences

Combining the consistency and stability result, we obtain

$$||u - u_n||_{n,2} = \mathcal{O}(n^{-2})$$

as in 1D.

Summary

- ► The structure of $\Delta_n^{(2)}$ is "tridiagonal + two far off-diagonals".
- ▶ Eigenpairs of $\Delta_n^{(2)}$ are given by

$$\lambda_{k_1,k_2} = \lambda_{k_1} + \lambda_{k_2}, \qquad u_{k_1,k_2} = u_{k_1} \otimes u_{k_2}$$

with λ_k , u_k the eigenpairs of $\Delta_n^{(1)}$.