

2D Poisson equation

Dirichlet BV problem

Dirichlet problem for the 2D Poisson equation

Let $u(x)$ is defined for $x = (x_1, x_2) \in G = [0, 1] \times [0, 1]$.

$$\frac{\partial^2 u}{\partial x_1^2} + \frac{\partial^2 u}{\partial x_2^2} = f(x) \quad (1)$$

Boundary conditions

$$u(x) = \mu(x) \quad \text{for } x \in \Gamma$$

Grids and grid functions

Consider a 2D grid

$$\Omega_h = \{x_{kl} = (x_1^k, x_2^l)\}$$

with

$$x_1^k = h_1 k, \quad k = 0, \dots, K \quad (h_1 K = 1)$$

$$x_2^l = h_2 l, \quad l = 0, \dots, L \quad (h_2 L = 1)$$

Call ω_h the set of internal nodes and γ_h the set of boundary nodes.

Define a *grid function* $y_{kl} \equiv y(x_1^k, x_2^l)$.

The five-point stencil

Using the five-point stencil

Eq.(1) generates at $x_{kl} \in \omega_h$

$$\frac{y_{k+1,l} - 2y_{kl} + y_{k-1,l}}{h_1^2} + \frac{y_{k,l+1} - 2y_{kl} + y_{k,l-1}}{h_2^2} = f_{kl} \quad (2)$$

and

$$y_{kl} = \mu(x_{kl}) \quad \text{for } x_{kl} \in \gamma_h$$

The scheme approximates Eq. (1) with $O(h_1^2 + h_2^2)$.

The matrix form of the FDE

Rewrite the FDE (2) in the matrix form.

Define the flat index

$$j = k(L + 1) + l$$

$$y_j \equiv y_{kl} \quad \text{with} \quad k = 0, 1, \dots, K \quad l = 0, 1, \dots, L$$

The matrix form of the FDE

$$\frac{y_{k+1,l} - 2y_{kl} + y_{k-1,l}}{h_1^2} + \frac{y_{k,l+1} - 2y_{kl} + y_{k,l-1}}{h_2^2} = f_{kl}$$

Indices:

$$(k, l \pm 1) \Rightarrow k(L+1) + (l \pm 1) = j \pm 1$$

$$(k \pm 1, l) \Rightarrow (k \pm 1)(L+1) + l = j \pm (L+1)$$

$$\frac{y_{j+L+1} - 2y_j + y_{j-(L+1)}}{h_1^2} + \frac{y_{j+1} - 2y_j + y_{j-1}}{h_2^2} = f_j$$

The matrix form of the FDE

Taking, for simplicity, $\mu(x) = 0$,

$$\mathbf{A}\mathbf{y} = \mathbf{f}$$

with \mathbf{A} being “tridiagonal with fringes” of $(L - 1) \times (L - 1)$ blocks

The matrix form of the FDE

- ▶ The size of the \mathbf{A} matrix is $O(L^2) = O(h^{-2})$
- ▶ Each row of \mathbf{A} has at most five $\neq 0$ elements, the sparsity is

$$\sim 5/L^2 = O(h^{-2})$$

- ▶ Direct solve with e.g. Gauss elimination requires

$$O((L^2)^3) = O(L^6)$$

flops.

\implies Need a sparse solver.

Iterative methods for the 2D Poisson equation

Iterative methods, recap

The canonic form of the two-step iterative methods (a.k.a. *relaxation*)

$$\mathbf{P} \frac{\mathbf{x}^{(n+1)} - \mathbf{x}^{(n)}}{\tau} + \mathbf{A}\mathbf{x}^{(n)} = \mathbf{b}$$

$$\mathbf{A}\mathbf{x} = \mathbf{b} \quad \longrightarrow \quad \mathbf{A} = \mathbf{L} + \mathbf{D} + \mathbf{U}$$

lower diagonal upper

Iterative methods, recap

► Jacobi iteration: $\mathbf{D}\mathbf{x}^{(n+1)} + (\mathbf{L} + \mathbf{U})\mathbf{x}^{(n)} = \mathbf{b}$

► Seidel iteration: $\mathbf{D}\mathbf{x}^{(n+1)} + \mathbf{L}\mathbf{x}^{(n+1)} + \mathbf{U}\mathbf{x}^{(n)} = \mathbf{b}$

Jacobi method for the 2D Poisson equation

Take $\mu(x) = 0$ for clarity.

$$\frac{y_{k+1,l}^n - 2y_{kl}^{n+1} + y_{k-1,l}^n}{h_1^2} + \frac{y_{k,l+1}^n - 2y_{kl}^{n+1} + y_{k,l-1}^n}{h_2^2} = f_{kl}, \quad x_{kl} \in \omega_h$$

$$y_{kl}^n = 0, \quad x_{kl} \in \gamma_h$$

Here $n = 0, 1, \dots$

The convergence rate is $O(h^{-2})$.

Seidel iteration in components

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2m} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \end{pmatrix}$$

$$a_{11}x_1^{(n+1)} + a_{12}x_2^{(n)} + a_{13}x_3^{(n)} + \cdots + a_{1m}x_m^{(n)} = b_1$$

$$a_{22}x_2^{(n+1)} + a_{21}x_1^{(n+1)} + a_{23}x_3^{(n)} + \cdots + a_{2m}x_m^{(n)} = b_2$$

...

At each iteration, sweep down the system of equations; at each step use $\mathbf{x}^{(n+1)}$ -s from previous steps: for $x_i^{(n+1)}$ use $x_1^{(n+1)} \cdots x_{i-1}^{(n+1)}$ (Jacobi iteration uses $x_1^{(n)} \cdots x_{i-1}^{(n)}$)

Seidel method for the 2D Poisson equation

Take $\mu(x) = 0$ for clarity.

$$\frac{y_{k+1,l}^n - 2y_{kl}^{n+1} + y_{k-1,l}^{n+1}}{h_1^2} + \frac{y_{k,l+1}^n - 2y_{kl}^{n+1} + y_{k,l-1}^{n+1}}{h_2^2} = f_{kl}, \quad x_{kl} \in \omega_h$$

$$y_{kl}^{n+1} = 0, \quad x_{kl} \in \gamma_h$$

Here $n = 0, 1, \dots$

The convergence rate is $O(h^{-2})$.

Relaxation methods

- ▶ Seidel iteration converges faster than Jacobi's (symmetric \mathbf{A})
- ▶ The convergence rate is still $O(h^{-2})$
- ▶ S.O.R. and/or Chebyshev iterations: can push to $O(h^{-1})$
- ▶ More specialized methods: can push to $O(h^{-1/2})$

see, e.g. Part III Chap 5 in S.G.

Spectral approach to the 2D Poisson FDE

1D fast Fourier transform + tridiagonal solve

Dirichlet problem for 2D Poisson equation

Consider

$$\frac{y_{k+1,l} - 2y_{kl} + y_{k-1,l}}{h_1^2} + \frac{y_{k,l+1} - 2y_{kl} + y_{k,l-1}}{h_2^2} = f_{kl} \quad (3)$$
$$y_{kl} = 0 \quad \text{for } x_{kl} \in \gamma_h$$

Here

$$\Omega_h = \{x_{kl} = (x_1^k, x_2^l) : \quad x_1^k = h_1 k, x_2^l = h_2 l$$
$$k = 0, 1, \dots, N_1, \quad l = 0, 1, \dots, N_2$$
$$N_\alpha h_\alpha = a_\alpha, \alpha = 1, 2\}$$

1D eigenvalue problem

Consider the 1D eigenvalue problem

$$\frac{g(l+1) - 2g(l) + g(l-1)}{h_2^2} + \lambda g(l) = 0$$

$$g(0) = g(N_2) = 0$$

$l = 1, 2, \dots, N_2 - 1$ and $l_2 N_2 = a_2$. Here $g(l) \equiv g(x_2^l)$ for brevity.

1D eigenvalue problem

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The eigenvalues and eigenfunctions are

$$g_s(l) = \sqrt{\frac{2}{a_2}} \sin \frac{\pi s x_2^l}{a_2}$$
$$\lambda_s = \frac{4}{h_2^2} \sin^2 \frac{\pi s h_2}{2a_2}, \quad s = 1, \dots, N_2 - 1$$

Fourier expansion over the x_2 -eigenfunctions

At a fixed value of k , $0 < k < N_1$, expand

$$y_{kl} = \sum_{s=1}^{N_2-1} c_s(k) g_s(l)$$

$$f_{kl} = \sum_{s=1}^{N_2-1} \hat{f}_s(k) g_s(l)$$

NB: for each value of k , there are $N_2 - 1$ coefficients $c_s(k)$.

The Fourier coefficients of f_{kl} are $\hat{f}_s(k) = h_2 \sum_{l=1}^{N_2-1} f_{kl} g_s(l)$

Fourier expansion over the x_2 -eigenfunctions

Substitute the expansions into the FDE, use the completeness of the eigensystem:

$$\frac{c_s(k+1) - 2c_s(k) + c_s(k-1))}{h_1^2} - \lambda_s c_s(k) = \hat{f}_s(k)$$

$$c_s(0) = c_s(N_1) = 0$$

$$k = 1, 2, \dots, N_1 - 1.$$

This is a tridiagonal system *at each value of s* .

The spectral algorithm

1. Compute the Fourier coefficients of the r.h.s., $\hat{f}_s(k)$.

For each $k, s = 1, \dots, N_2 - 1$. Using the discrete FFT, the complexity is $O(N_2 \ln N_2)$ per k value; the total complexity is $O(N_1 N_2 \ln N_2)$

2. Solve for $c_s(k)$.

For each $s, s = 1, \dots, N_1 - 1$, use a tridiagonal solver. The total complexity is $O(N_1 N_2)$

3. Restore y_{kl} via

$$y_{kl} = \sum_{s=1}^{N_2-1} c_s(k) g_s(l)$$

With FFT, the complexity is $O(N_1 N_2 \ln N_2)$