

Review

- The **inverse** A^{-1} of a matrix A is, if it exists, characterized by

$$AA^{-1} = A^{-1}A = I_n.$$

- $\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$
- If A is invertible, then the system $Ax = b$ has the unique solution $x = A^{-1}b$.
- Gauss–Jordan method to compute A^{-1} :
 - bring to RREF $[A | I] \rightsquigarrow [I | A^{-1}]$
- $(A^{-1})^{-1} = A$
- $(A^T)^{-1} = (A^{-1})^T$
- $(AB)^{-1} = B^{-1}A^{-1}$

Why? Because $(B^{-1}A^{-1})(AB) = B^{-1}IB = B^{-1}B = I$

Further properties of matrix inverses

Theorem 1. Let A be an $n \times n$ matrix. Then the following statements are equivalent: (i.e., for a given A , they are either all true or all false)

- (a) A is invertible.
- (b) A is row equivalent to I_n .
- (c) A has n pivots. (Easy to check!)
- (d) For every b , the system $Ax = b$ has a unique solution.
Namely, $x = A^{-1}b$.
- (e) There is a matrix B such that $AB = I_n$. (A has a “right inverse”.)
- (f) There is a matrix C such that $CA = I_n$. (A has a “left inverse”.)

Note. Matrices that are not invertible are often called **singular**.

The book uses **singular** for $n \times n$ matrices that do not have n pivots. As we just saw, it doesn't make a difference.

Example 2. We now see at once that $A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$ is not invertible.

Why? Because it has only one pivot.

Application: finite differences

Let us apply linear algebra to the **boundary value problem** (BVP)

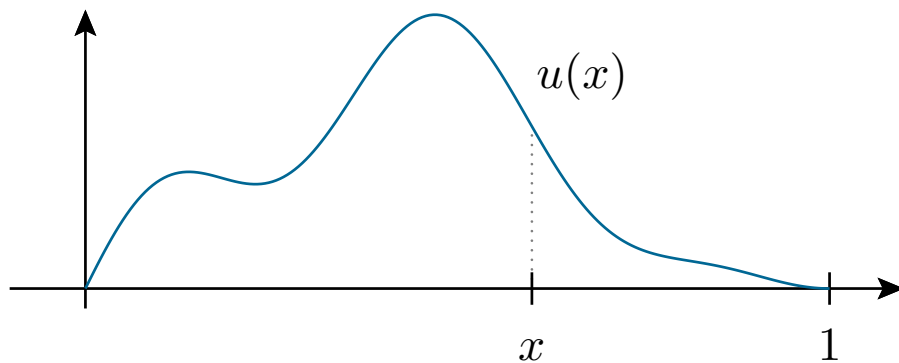
$$-\frac{d^2u}{dx^2} = f(x), \quad 0 \leq x \leq 1, \quad u(0) = u(1) = 0.$$

$f(x)$ is given, and the goal is to find $u(x)$.

Physical interpretation: models steady-state temperature distribution in a bar ($u(x)$ is temperature at point x) under influence of an external heat source $f(x)$ and with ends fixed at 0° (ice cube at the ends?).

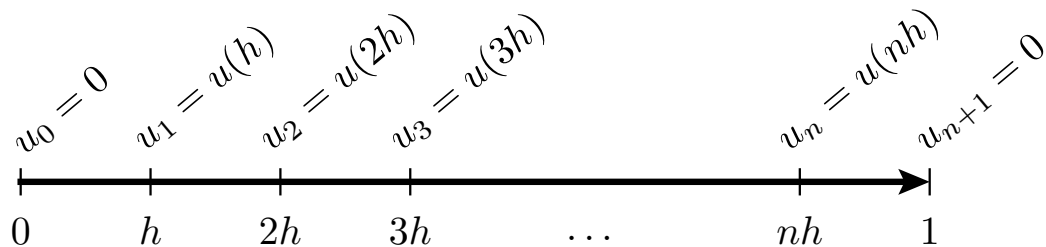
Remark 3. Note that this simple BVP can be solved by integrating $f(x)$ twice. We get two constants of integration, and so we see that the boundary condition $u(0) = u(1) = 0$ makes the solution $u(x)$ unique.

Of course, in the real applications the BVP would be harder. Also, $f(x)$ might only be known at some points, so we cannot use calculus to integrate it.



We will approximate this problem as follows:

- replace $u(x)$ by its values at equally spaced points in $[0, 1]$



- approximate $\frac{d^2u}{dx^2}$ at these points (**finite differences**)
- replace differential equation with linear equation at each point
- solve linear problem using Gaussian elimination

Finite differences

Finite differences for first derivative:

$$\begin{aligned}\frac{du}{dx} &\approx \frac{\Delta u}{\Delta x} = \frac{u(x+h) - u(x)}{h} \\ &\stackrel{\text{or}}{=} \frac{u(x) - u(x-h)}{h} \\ &\stackrel{\text{or}}{=} \frac{u(x+h) - u(x-h)}{2h} \\ &\text{symmetric and most accurate}\end{aligned}$$

Note. Recall that you can always use L'Hospital's rule to determine the limit of such quantities (especially more complicated ones) as $h \rightarrow 0$.

Finite difference for second derivative:

$$\begin{aligned}\frac{d^2u}{dx^2} &\approx \frac{u(x+h) - 2u(x) + u(x-h)}{h^2} \\ &\text{the only symmetric choice involving only } u(x), u(x \pm h)\end{aligned}$$

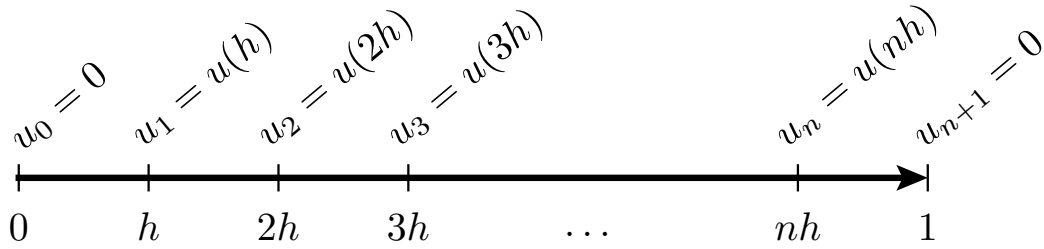
Question 4. Why does this approximate $\frac{d^2u}{dx^2}$ as $h \rightarrow 0$?

Solution.

$$\begin{aligned}\frac{d^2u}{dx^2} &\approx \frac{\frac{du}{dx}(x+h) - \frac{du}{dx}(x)}{h} \\ &\approx \frac{\frac{u(x+h) - u(x)}{h} - \frac{u(x) - u(x-h)}{h}}{h} \\ &\approx \frac{u(x+h) - 2u(x) + u(x-h)}{h^2}\end{aligned}$$

Setting up the linear equations

$$-\frac{d^2u}{dx^2} = f(x), \quad 0 \leq x \leq 1, \quad u(0) = u(1) = 0.$$



Using $-\frac{d^2u}{dx^2} \approx -\frac{u(x+h) - 2u(x) + u(x-h)}{h^2}$, we get:

$$\begin{aligned} \text{at } x = h: \quad & -\frac{u(2h) - 2u(h) + u(0)}{h^2} = f(h) \\ \implies \quad & 2u_1 - u_2 = h^2 f(h) \end{aligned} \tag{1}$$

$$\begin{aligned} \text{at } x = 2h: \quad & -\frac{u(3h) - 2u(2h) + u(h)}{h^2} = f(2h) \\ \implies \quad & -u_1 + 2u_2 - u_3 = h^2 f(2h) \end{aligned} \tag{2}$$

$$\begin{aligned} \text{at } x = 3h: \quad & \\ \implies \quad & -u_2 + 2u_3 - u_4 = h^2 f(3h) \end{aligned} \tag{3}$$

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$$\begin{aligned} \text{at } x = nh: \quad & -\frac{u((n+1)h) - 2u(nh) + u((n-1)h)}{h^2} = f(nh) \\ \implies \quad & -u_{n-1} + 2u_n = h^2 f(nh) \end{aligned} \tag{n}$$

Example 5. In the case of six divisions ($n = 5$, $h = \frac{1}{6}$), we get:

$$\underbrace{\begin{bmatrix} 2 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{bmatrix}}_A \underbrace{\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix}}_x = \underbrace{\begin{bmatrix} h^2 f(h) \\ h^2 f(2h) \\ h^2 f(3h) \\ h^2 f(4h) \\ h^2 f(5h) \end{bmatrix}}_b$$

Such a matrix is called a **band matrix**. As we will see next, such matrices always have a particularly simple LU decomposition.

Gaussian elimination:

$$\begin{array}{c}
 \left[\begin{array}{cccc} 2 & -1 & & \\ -1 & 2 & -1 & \\ & -1 & 2 & -1 \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{array} \right] \\
 \\
 \begin{array}{c}
 R2 \rightarrow R2 + \frac{1}{2}R1 \\
 \left[\begin{array}{cccc} 1 & & & \\ \frac{1}{2} & 1 & & \\ & & 1 & \\ & & & 1 \end{array} \right] \\
 \\
 R3 \rightarrow R3 + \frac{2}{3}R2 \\
 \left[\begin{array}{cccc} 1 & & & \\ \frac{1}{2} & 1 & & \\ \frac{2}{3} & & 1 & \\ & & & 1 \end{array} \right] \\
 \\
 R4 \rightarrow R4 + \frac{3}{4}R3 \\
 \left[\begin{array}{cccc} 1 & & & \\ \frac{1}{2} & 1 & & \\ \frac{2}{3} & & 1 & \\ \frac{3}{4} & & & 1 \end{array} \right] \\
 \\
 R5 \rightarrow R5 + \frac{4}{5}R4 \\
 \left[\begin{array}{cccc} 1 & & & \\ \frac{1}{2} & 1 & & \\ \frac{2}{3} & & 1 & \\ \frac{3}{4} & & & 1 \\ \frac{4}{5} & & & & 1 \end{array} \right]
 \end{array}
 \end{array}
 \begin{array}{c}
 \left[\begin{array}{cccc} 2 & -1 & & \\ 0 & \frac{3}{2} & -1 & \\ & -1 & 2 & -1 \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{array} \right] \\
 \\
 \left[\begin{array}{cccc} 2 & -1 & & \\ 0 & \frac{3}{2} & -1 & \\ & 0 & \frac{4}{3} & -1 \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{array} \right] \\
 \\
 \left[\begin{array}{cccc} 2 & -1 & & \\ 0 & \frac{3}{2} & -1 & \\ & 0 & \frac{4}{3} & -1 \\ & & 0 & \frac{5}{4} & -1 \\ & & & -1 & 2 \end{array} \right] \\
 \\
 \left[\begin{array}{cccc} 2 & -1 & & \\ 0 & \frac{3}{2} & -1 & \\ & 0 & \frac{4}{3} & -1 \\ & & 0 & \frac{5}{4} & -1 \\ & & & 0 & \frac{6}{5} \end{array} \right]
 \end{array}
 \end{array}$$

In conclusion, we have the LU decomposition:

$$\left[\begin{array}{cccc} 2 & -1 & & \\ -1 & 2 & -1 & \\ & -1 & 2 & -1 \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{array} \right] = \left[\begin{array}{cccc} 1 & & & \\ -\frac{1}{2} & 1 & & \\ & -\frac{2}{3} & 1 & \\ & & -\frac{3}{4} & 1 \\ & & & -\frac{4}{5} & 1 \end{array} \right] \left[\begin{array}{cccc} 2 & -1 & & \\ & \frac{3}{2} & -1 & \\ & & \frac{4}{3} & -1 \\ & & & \frac{5}{4} & -1 \\ & & & & \frac{6}{5} \end{array} \right]$$

That's how the LU decomposition of band matrices always looks like.