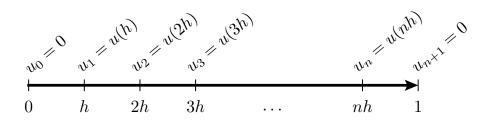
### Review

• Goal: solve for u(x) in the **boundary value problem** (BVP)

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

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



- $-\frac{\mathrm{d}^2 u}{\mathrm{d}x^2} \approx -\frac{u(x+h)-2u(x)+u(x-h)}{h^2}$  at these points (finite differences)
- get a linear equation at each point x = h, 2h, ..., nh; for n = 5,  $h = \frac{1}{6}$ :

$$\underbrace{\begin{bmatrix} 2 & -1 & & \\ -1 & 2 & -1 & \\ & -1 & 2 & -1 \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix}}_{\mathbf{x}} = \underbrace{\begin{bmatrix} h^2 f(h) \\ h^2 f(2h) \\ h^2 f(3h) \\ h^2 f(4h) \\ h^2 f(5h) \end{bmatrix}}_{\mathbf{b}}$$

• Compute the LU decomposition:

$$\begin{bmatrix} 2 & -1 & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{bmatrix} = \begin{bmatrix} 1 & & & \\ -\frac{1}{2} & 1 & & \\ & -\frac{2}{3} & 1 & \\ & & -\frac{3}{4} & 1 \\ & & & -\frac{4}{5} & 1 \end{bmatrix} \begin{bmatrix} 2 & -1 & & \\ & \frac{3}{2} & -1 & \\ & & \frac{4}{3} & -1 \\ & & & \frac{5}{4} & -1 \\ & & & & \frac{6}{5} \end{bmatrix}$$

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

#### LU decomposition vs matrix inverse

In many applications, we don't just solve Ax = b for a single b, but for many different b (think millions).

Note, for instance, that in our example of "steady-state temperature distribution in a bar" the matrix A is always the same (it only depends on the kind of problem), whereas the vector b models the external heat (and thus changes for each specific instance).

- That's why the LU decomposition saves us from repeating lots of computation in comparison with Gaussian elimination on  $\begin{bmatrix} A & b \end{bmatrix}$ .
- What about computing  $A^{-1}$ ?

We are going to see that this is a bad idea. (It usually is.)

**Example 1.** When using LU decomposition to solve Ax = b, we employ forward and backward substitution:

$$A oldsymbol{x} = oldsymbol{b}$$
  $\stackrel{A = L U}{\iff}$   $L oldsymbol{c} = oldsymbol{b}$  and  $U oldsymbol{x} = oldsymbol{c}$ 

Here, we have to solve, for each **b**,

$$\begin{bmatrix} 1 & & & \\ -\frac{1}{2} & 1 & & \\ & -\frac{2}{3} & 1 & \\ & & -\frac{3}{4} & 1 \\ & & & -\frac{4}{5} & 1 \end{bmatrix} \mathbf{c} = \mathbf{b}, \quad \begin{bmatrix} 2 & -1 & & \\ & \frac{3}{2} & -1 & \\ & & \frac{4}{3} & -1 \\ & & & \frac{5}{4} & -1 \\ & & & & \frac{6}{5} \end{bmatrix} \mathbf{x} = \mathbf{c}$$

by forward and backward substitution.

How many operations (additions and multiplications) are needed in the  $n \times n$  case?

2(n-1) for  $L\boldsymbol{c} = \boldsymbol{b}$ , and 1+2(n-1) for  $U\boldsymbol{x} = \boldsymbol{c}$ .

So, roughly, a total of 4n operations.

On the other hand,

$$A^{-1} = \frac{1}{6} \begin{bmatrix} 5 & 4 & 3 & 2 & 1 \\ 4 & 8 & 6 & 4 & 2 \\ 3 & 6 & 9 & 6 & 3 \\ 2 & 4 & 6 & 8 & 4 \\ 1 & 2 & 3 & 4 & 5 \end{bmatrix}$$

How many operations are needed to compute  $A^{-1}b$ ?

This time, we need roughly  $2n^2$  additions and multiplications.

## Conclusions

- Large matrices met in applications usually are not random but have some structure (such as band matrices).
- When solving linear equations, we do not (try to) compute  $A^{-1}$ .
  - It destroys structure in practical problems.
  - As a result, it can be orders of magnitude slower,
  - and require orders of magnitude more memory.
  - It is also numerically unstable.
  - LU decomposition can be adjusted to not have these drawbacks.

#### A practice problem

**Example 2.** Above we computed the LU decomposition for n = 5. For comparison, here are the details for computing the inverse when n = 3.

Do it for n = 5, and appreciate just how much computation has to be done.

Invert  $A = \begin{bmatrix} 2 & -1 \\ -1 & 2 & -1 \\ & -1 & 2 \end{bmatrix}$ .

Solution.

$$\begin{bmatrix} 2 & -1 & 0 & 1 & 0 & 0 \\ -1 & 2 & -1 & 0 & 1 & 0 \\ 0 & -1 & 2 & 0 & 0 & 1 \end{bmatrix} \begin{array}{c} R2 \rightarrow R2 + \frac{1}{2}R1 \begin{bmatrix} 2 & -1 & 0 & 1 & 0 & 0 \\ 0 & \frac{3}{2} & -1 & \frac{1}{2} & 1 & 0 \\ 0 & -1 & 2 & 0 & 0 & 1 \end{bmatrix}$$
$$R3 \rightarrow R3 + \frac{2}{3}R2 \begin{bmatrix} 2 & -1 & 0 & 1 & 0 & 0 \\ 0 & \frac{3}{2} & -1 & \frac{1}{2} & 1 & 0 \\ 0 & 0 & \frac{4}{3} & \frac{1}{3} & \frac{2}{3} & 1 \end{bmatrix}$$
$$R1 \rightarrow \frac{1}{2}R1 \begin{bmatrix} 1 & -\frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 \\ 0 & 1 & -\frac{2}{3} & \frac{1}{3} & \frac{2}{3} & 0 \\ 0 & 0 & 1 & \frac{1}{4} & \frac{1}{2} & \frac{3}{4} \end{bmatrix}$$
$$R2 \rightarrow \frac{2}{3}R2 R3 \rightarrow \frac{3}{4}R3 \begin{bmatrix} 1 & 0 & 0 & \frac{3}{4} & \frac{1}{2} & \frac{1}{4} \\ 0 & 1 & 0 & \frac{1}{2} & 1 & \frac{1}{2} \\ 0 & 0 & 1 & \frac{1}{4} & \frac{1}{2} & \frac{3}{4} \end{bmatrix}$$

Hence, 
$$\begin{bmatrix} 2 & -1 \\ -1 & 2 & -1 \\ & -1 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} \frac{3}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{2} & 1 & \frac{1}{2} \\ \frac{1}{4} & \frac{1}{2} & \frac{3}{4} \end{bmatrix}$$
.

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# Vector spaces and subspaces

We have already encountered **vectors** in  $\mathbb{R}^n$ . Now, we discuss the general concept of vectors.

In place of the space  $\mathbb{R}^n$ , we think of general **vector spaces**.

**Definition 3.** A vector space is a nonempty set V of elements, called vectors, which may be added and scaled (multiplied with real numbers).

The two operations of addition and scalar multiplication must satisfy the following axioms for all u, v, w in V, and all scalars c, d.

(a) 
$$\boldsymbol{u} + \boldsymbol{v}$$
 is in V

(b)  $\boldsymbol{u} + \boldsymbol{v} = \boldsymbol{v} + \boldsymbol{u}$ 

(c) (u+v)+w=u+(v+w)

- (d) there is a vector (called the **zero vector**) **0** in V such that u + 0 = u for all u in V
- (e) there is a vector  $-\boldsymbol{u}$  such that  $\boldsymbol{u} + (-\boldsymbol{u}) = \boldsymbol{0}$
- (f)  $c\boldsymbol{u}$  is in V

(g) 
$$c(\boldsymbol{u}+\boldsymbol{v})=c\boldsymbol{u}+c\boldsymbol{v}$$

(h) 
$$(c+d)\boldsymbol{u} = c\boldsymbol{u} + d\boldsymbol{u}$$

- (i)  $(cd)\boldsymbol{u} = c(d\boldsymbol{u})$
- (j) 1u = u

tl;dr — A **vector space** is a collection of vectors which can be added and scaled (without leaving the space!); subject to the usual rules you would hope for.

namely: associativity, commutativity, distributivity

**Example 4.** Convince yourself that  $M_{2\times 2} = \left\{ \begin{bmatrix} a & b \\ c & d \end{bmatrix} : a, b, c, d \text{ in } \mathbb{R} \right\}$  is a vector space.

**Solution.** In this context, the zero vector is  $\mathbf{0} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$ . Addition is componentwise:

$$\left[\begin{array}{cc}a&b\\c&d\end{array}\right] + \left[\begin{array}{cc}e&f\\g&h\end{array}\right] = \left[\begin{array}{cc}a+e&b+f\\c+g&d+h\end{array}\right]$$

Scaling is componentwise:

$$r \left[ \begin{array}{cc} a & b \\ c & d \end{array} \right] = \left[ \begin{array}{cc} ra & rb \\ rc & rd \end{array} \right]$$

Addition and scaling satisfy the axioms of a vector space because they are defined component-wise and because ordinary addition and multiplication are associative, commutative, distributive and what not.

Important note: we do not use matrix multiplication here!

*Note:* as a vector space,  $M_{2\times 2}$  behaves precisely like  $\mathbb{R}^4$ ; we could translate between the two via

$$\left[\begin{array}{cc}a&b\\c&d\end{array}\right]\longleftrightarrow \left[\begin{array}{cc}a\\b\\c\\d\end{array}\right]$$

A fancy person would say that these two vector spaces are **isomorphic**.

**Example 5.** Let  $\mathbb{P}_n$  be the set of all polynomials of degree at most  $n \ge 0$ . Is  $\mathbb{P}_n$  a vector space?

**Solution.** Members of  $\mathbb{P}_n$  are of the form

$$p(t) = a_0 + a_1 t + \ldots + a_n t^n,$$

where  $a_0, a_1, ..., a_n$  are in  $\mathbb{R}$  and t is a variable.

 $\mathbb{P}_n$  is a vector space.

Adding two polynomials:

$$[a_0 + a_1t + \dots + a_nt^n] + [b_0 + b_1t + \dots + b_nt^n]$$
  
=  $[(a_0 + b_0) + (a_1 + b_1)t + \dots + (a_n + b_n)t^n]$ 

So addition works "component-wise" again. Scaling a polynomial:

$$r[a_0 + a_1t + \dots + a_nt^n] = [(ra_0) + (ra_1)t + \dots + (ra_n)t^n]$$

Scaling works "component-wise" as well.

Again: the vector space axioms are satisfied because addition and scaling are defined component-wise.

As in the previous example, we see that  $\mathbb{P}_n$  is isomorphic to  $\mathbb{R}^{n+1}$ :

$$a_0 + a_1 t + \ldots + a_n t^n \quad \longleftrightarrow \quad \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix}$$

Armin Straub astraub@illinois.edu **Example 6.** Let V be the set of all polynomials of degree exactly 3. Is V a vector space?

**Solution.** No, because V does not contain the zero polynomial p(t) = 0.

Every vector space has to have a zero vector; this is an easy necessary (but not sufficient) criterion when thinking about whether a set is a vector space.

More generally, the sum of elements in V might not be in V:

$$[1+4t^2+t^3]+[2-t+t^2-t^3]=[3-t+5t^2]$$