

Transpose matrices

A $m \times n$ matrix. The transpose A^T is an $n \times m$ matrix with

$$(A^T)_{ij} = (A)_{ji}$$

Example $A = \begin{bmatrix} 2 & 1 & 4 \\ 0 & 0 & 3 \end{bmatrix}$ $A^T = \begin{bmatrix} 2 & 0 \\ 1 & 0 \\ 4 & 3 \end{bmatrix}$

Useful facts • $(A^T)^T = A$

• (upper triangular)^T = (lower triangular)

• $(A+B)^T = A^T + B^T$

• $(AB)^T = B^T A^T$

• $(A^{-1})^T = (A^T)^{-1}$ ← check:

$$AA^{-1} = I$$

$$(AA^{-1})^T = I^T = I$$

"

$$(A^{-1})^T A^T = I \Rightarrow (A^{-1})^T \text{ is inverse for } A^T$$

Symmetric matrices

A matrix is symmetric if $A^T = A$

Examples I $[3]$ $\begin{bmatrix} 1 & 0 & -1 \\ 0 & 2 & 0 \\ -1 & 0 & 3 \end{bmatrix}$

Fact if A is symmetric, and A^{-1} exists, then A^{-1} is symmetric.

Proof A symmetric $\Rightarrow A^T = A$

so $(A^T)^{-1} = A^{-1}$

"
 $(A^{-1})^T$

so $(A^{-1})^T = A^{-1}$ □.

Symmetric products

Fact: let R be an $(m \times n)$ matrix then $R^T R$ is a square symmetric matrix.

Proof $R^T R = m \times m$.
 $(R^T R)^T = R^T (R^T)^T = R^T R \Rightarrow$ symmetric \square .

Example $[1 \ 2 \ 0] \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix} = [5]$ $\begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix} [1 \ 2 \ 0] = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 4 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

Fact suppose A is symmetric ($A = A^T$) and $A = LDU$ with no row swaps then $U = L^T$, so $A = LDL^T$. This is the symmetric factorization.

Proof $A = LDU$
 $A^T = U^T D^T L^T = U^T D L^T$, but U, L unique $\Rightarrow L = U^T \square$.

Special matrices and applications

example solve $-\frac{d^2 u}{dx^2} = f(x)$ $0 \leq x \leq 1$

solution: a function $u(x)$

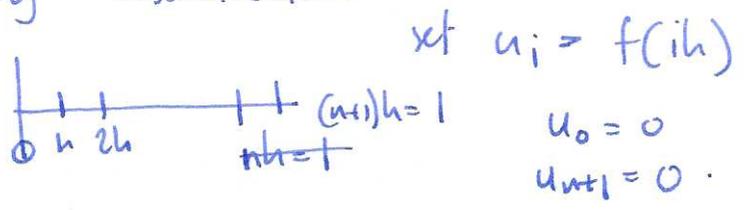
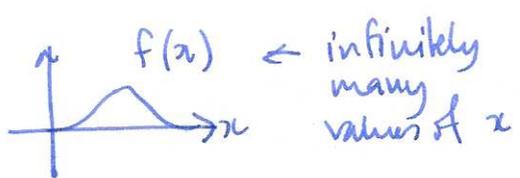
note: if $u(x)$ is a solution $u(x) + C + Dx$ is also a solution.

e.g. if $f(x) = 0$, then $u(x) = C + Dx$ is a solution.

boundary conditions $u(0) = 0, u(1) = 0 \rightsquigarrow$ determines C, D .

application: temperature distribution in a rod with heat source $f(x)$.

aim: find approximate solution by discretization.



approximate derivative $\frac{\Delta u}{\Delta x} = \frac{u(x+h) - u(x)}{h}$

symmetric version : $\frac{du}{dx} \approx \frac{\Delta u}{\Delta x} = \frac{u(x+h) - u(x-h)}{2h}$

approx 2nd derivative $\frac{d^2 u}{dx^2} = \frac{u(x+h) - 2u(x) + u(x-h)}{h^2}$

$-\frac{d^2 u}{dx^2} = f(x)$: $-\frac{u_{j+1} - 2u_j + u_{j-1}}{h^2} = f(jh)$

example $h = \frac{1}{6}$

$$A = \begin{bmatrix} 2 & -1 & & & & \\ -1 & 2 & -1 & & & \\ & -1 & 2 & -1 & & \\ & & -1 & 2 & -1 & \\ & & & -1 & 2 & -1 \\ & & & & -1 & 2 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_6 \end{bmatrix} = h^2 \begin{bmatrix} f(h) \\ f(2h) \\ \vdots \\ f(5h) \end{bmatrix}$$

- properties :
- tridiagonal (sparse)
 - symmetric $A = A^T$
 - positive definite \Rightarrow all pivots are positive.
- $A = LDL^T$

Elimination

$\textcircled{2} - \frac{1}{2}\textcircled{1}$

$$\begin{bmatrix} 2 & -1 & & & & \\ 0 & 3/2 & -1 & & & \\ & -1 & 2 & -1 & & \\ & & -1 & 2 & -1 & \\ & & & 1 & 2 & \end{bmatrix} \text{ etc.}$$

obtain

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

L D L^T

det(A) = det(D) = $\frac{2}{1} \cdot \frac{3}{2} \cdot \frac{4}{3} \cdot \frac{5}{4} \cdot \frac{6}{5} = 6$. complexity $O(n)$.

Round off error

Example $A = \begin{bmatrix} 1 & 1 \\ 1 & 1.0001 \end{bmatrix}$ $B = \begin{bmatrix} 0.0001 & 1 \\ 1 & 1 \end{bmatrix}$

ill conditioned well conditioned

A: $u + v = 2$ $u + v = 2$
 $u + 1.0001v = 2$ $u + 1.0001v = 2.0001$

solution $u = 2$ $u = 1$
 $v = 0$ $v = 1$

naive elimination on B $\begin{bmatrix} 0.0001 & 1 \\ 1 & 1 \end{bmatrix} \xrightarrow{2} \begin{bmatrix} 0.0001 & 1 \\ 0 & -9999 \end{bmatrix}$

round off in back substitution, get $v = 1, u = 0$
 correct result: $v = 0.9999, u = 1$.

moral: small pivots bad!

solution: for best numerical results swap rows to get largest pivot
 this is called: elimination with partial pivoting.

Vector spaces and subspaces

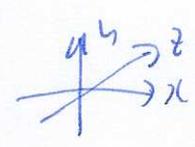
Examples \mathbb{R}^n

\mathbb{R} : numbers.

\mathbb{R}^2 : $\langle x, y \rangle$

\mathbb{R}^3 : $\langle x, y, z \rangle$

\mathbb{R}^n : $\langle x_1, x_2, x_3, \dots, x_n \rangle$



key properties: linear combinations, i.e. we can add vectors and take scalar multiples.

Properties V vector space $x, y, z \in V, c_1, c_2 \in \mathbb{R}$.

addition: $x + y = y + x$ commutes

$x + (y + z) = (x + y) + z$ associative

$0 + x = x + 0 = x$ zero vector

$x + (-x) = 0$ inverse (additive)

scalar multiplication: $1x = x$ identity

$$(c_1 c_2)x = c_1(c_2 x)$$

$$c(x + y) = cx + cy$$
 distribution

$$(c_1 + c_2)x = c_1 x + c_2 x$$
 distribution

Examples \mathbb{R}^∞

(x_1, x_2, \dots)

$(0, 0, 0, \dots)$

$(1, 1, 1, \dots)$

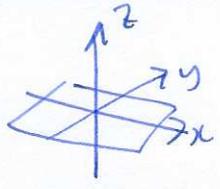
• collections of 3×2 matrices. $\begin{bmatrix} \vdots & \vdots \\ \vdots & \vdots \\ \vdots & \vdots \end{bmatrix}$

$$A+B \quad 0 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

space of functions $f(x)$ on $[0, 1]$ $f(x) + g(x)$ $cf(x)$ zero: $f(x) = 0$

subspaces

$xy\text{-plane} \subseteq \mathbb{R}^3$



example

Defn: A subspace of a vector space is a non-empty subset that satisfies the requirements for a vector space: linear combinations stay in the subspace. i.e. if $x, y \in \text{subspace}$ then $x+y \in \text{subspace}$
 $\alpha \in \text{subspace}$ then $c\alpha \in \text{subspace}$.

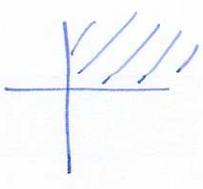
Notation we say the subspace is closed under addition and scalar multiplication

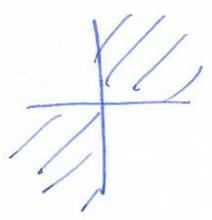
Observation $0 \cdot x = 0$ vector, so every subspace contains the zero vector.

- the smallest subspace is $\{0\}$ zero vector
- the largest subspace of V is all of V .

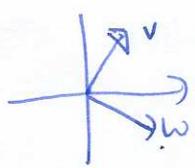
Examples

① all vectors in \mathbb{R}^2 with non-negative components $\langle x, y \rangle$ $x \geq 0$
 $y \geq 0$

 not a subspace (satisfies addition but not scalar mult)

② 1st and 3rd quadrants  (satisfies scalar mult, but not addition).

③ $V = 3 \times 3$ matrices subspaces: lower triangular matrices
symmetric matrices.

④  $A = \{ \lambda v \mid \lambda \in \mathbb{R} \}$ is a subspace.
 $B = \{ \lambda w \mid \lambda \in \mathbb{R} \}$ π
 $A \cup B$ not a subspace in general.