### Topic and contents

## **UNSW**, School of Mathematics and Statistics

MATH2089 - Numerical Methods

Week 04 – Structured Linear Systems and Sparse Matrices



Structured Systems of Linear Equations

- Symmetric matrices
- Positive definite matrices

- Banded matrices
- Fill-in
- Tridiagonal matrices
- Sparse matrices

- MATLAB M-files
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- spex1.m

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west.m

Structured Systems of Linear Equations Symmetric matrices

### Symmetric matrices - examples

Example (Symmetric matrices)

Are the following matrices symmetric?

$$A = \begin{pmatrix} 5 & -7 & -6 \\ -7 & 13 & 2 \\ -6 & 2 & 20 \end{pmatrix}, \qquad B = \begin{pmatrix} 5 & -7 & -6 \\ -7 & 13 & 2 \\ -5 & 2 & 20 \end{pmatrix}$$

#### Solution

A is symmetric (why?), B is not symmetric (why?)

Example  $(A^TA)$ 

Show that for any  $A \in \mathbb{R}^{m \times n}$ , the matrix  $B = A^T A$  is symmetric.

#### Solution

The transpose satisfies  $(UV)^T = V^TU^T$  and  $(U^T)^T = U$ . Thus

$$B^{T} = (A^{T}A)^{T} = A^{T}(A^{T})^{T} = A^{T}A = B,$$

so  $B = A^T A$  is symmetric.

Structured Systems of Linear Equations Symmetric matrices

### Symmetric Matrices

Definition (Symmetric, Skew-symmetric matrices)

- A is symmetric  $\iff A^T = A$
- A is skew-symmetric  $\iff A^T = -A$
- ullet A symmetric or skew-symmetric  $\Longrightarrow A$  square,  $A \in \mathbb{R}^{n \times n}$
- A symmetric  $\iff a_{ij} = a_{ji}$  for all  $i, j = 1, \dots, n$
- A symmetric  $\Longrightarrow$  storage n(n+1)/2 elements
- A skew-symmetric  $\iff a_{ij} = -a_{ij}$  for all  $i, j = 1, \dots, n$
- A skew-symmetric  $\implies a_{ii} = 0$  for all  $i = 1, \dots, n$

#### Example (Testing for symmetry)

Give Matlab commands to determine if A is symmetric

#### Solution

See function M-file chksym.m

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### Positive definite matrices

Definition (Positive-definite matrices)

Symmetric matrix  $A \in \mathbb{R}^{n \times n}$  is

- positive definite  $\iff \mathbf{x}^T A \mathbf{x} > 0$  for all  $\mathbf{x} \in \mathbb{R}^n$ ,  $\mathbf{x} \neq \mathbf{0}$
- positive semi-definite  $\iff \mathbf{x}^T A \mathbf{x} > 0$  for all  $\mathbf{x} \in \mathbb{R}^n$
- A is positive definite  $\iff$  eigenvalues  $\lambda_i(A) > 0$  for all  $i = 1, \dots, n$
- A positive definite  $\iff$  Cholesky factorization  $A = R^T R$  exists
  - R upper triangular,  $R_{ii} > 0, i = 1, \ldots, n$
  - MATLAB R = chol(A) or [R, p] = chol(A)
  - No pivoting required for numerical stability
  - Flops: Cholesky  $\frac{n^3}{2} + O(n^2)$  versus  $LU \frac{2n^3}{2} + O(n^2)$
- ullet  $A^TA$  symmetric positive semi-definite for any  $A\in\mathbb{R}^{m imes n}$

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Structured Systems of Linear Equations Positive definite matrices

### Positive definite matrices - examples

Example (Positive definite matrices)

Consider the matrices

$$A = \begin{pmatrix} 5 & -7 & -6 \\ -7 & 13 & 2 \\ -6 & 2 & 20 \end{pmatrix}, \ B = \begin{pmatrix} 6 & -7 & -6 \\ -7 & 14 & 2 \\ -6 & 2 & 21 \end{pmatrix}, \ C = \begin{pmatrix} 4 & -7 & -6 \\ -7 & 13 & 2 \\ -6 & 2 & 20 \end{pmatrix}.$$

Calculate. in MATLAB.

- $\bullet$  S1 = A'==A, S2 = A' A, S3 = norm(A'-A,1)
- $\bigcirc$  The eigenvalues of A.
- The Cholesky factorization using [R, p] = chol(A)

Is A positive definite? Is A symmetric? Repeat for the matrices B and C.

MATLAB pdex1.m

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Structured Systems of Linear Equations Banded matrices

### Banded matrices

Definition (Banded matrices)

 $A \in \mathbb{R}^{m \times n}$  has

- upper bandwidth  $m_u \iff a_{ij} = 0 \quad \forall i > i + m_u$
- lower bandwidth  $m_l \iff a_{ij} = 0 \quad \forall i > j + m_l$
- total bandwidth  $m_l + m_u + 1$
- L lower triangular  $\iff$  upper bandwidth  $m_u = 0$
- U upper triangular  $\iff$  lower bandwidth  $m_l = 0$
- D diagonal  $\iff$  lower bandwidth  $m_l = 0$ , upper bandwidth  $m_u = 0$
- MATLAB spy plots: pattern of non-zero elements in matrix

Proposition (Factorization of banded matrices)

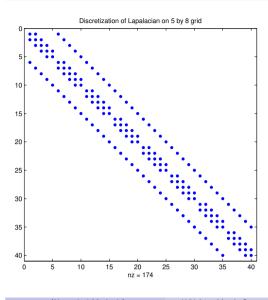
Banded matrix A, lower bandwidth  $m_l$  and upper bandwidth  $m_u \Longrightarrow$ LU factorization of A: L lower bandwidth  $m_l$ , U upper bandwidth  $m_u$ 

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Structured Systems of Linear Equations Banded matrices

#### Structured Systems of Linear Equations Banded matrices

## Banded matrix - Example



#### Example

Spy plot: non-zero elements in A: give size, upper, lower and total bandwidth, number of non-zero elements

#### Solution

- $size(A) = [40 \ 40]$
- Upper bandwidth  $m_u = 5$
- Lower bandwidth  $m_l = 5$
- Bandwidth 11
- nnz(A) = 174

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### Fill-in

### Definition (Fill-in)

Fill-in: creation of non-zero elements where original elements were zero

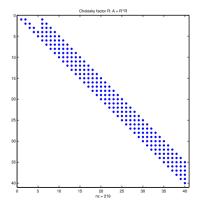
• Row operations can cause fill-in

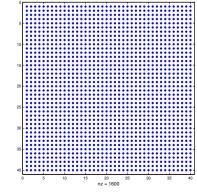
Matrix multiplication can cause fill-in

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### Banded matrices - fill-in

- Banded matrix: fill-in during factorization only occurs within bands
- Inverse  $A^{-1}$  can get lot of fill-in  $\Longrightarrow$  avoid explicitly calculating  $A^{-1}$





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## Diagonals

### Definition (Diagonals)

Diagonal k of  $A \in \mathbb{R}^{m \times n} \iff a_{ij} : j - i = k$ 

- Diagonal  $0 \iff i-i=0 \iff i=j$  main diagonal
- Diagonal  $1 \iff j-i=1 \iff j=i+1$  super-diagonal
- Diagonal  $-1 \iff j-i=-1 \iff j=i-1$  sub-diagonal
- MATLAB command diag

Example (MATLAB diag command)

Give the results of

 $u = [2 \ 1 \ 0 \ -1 \ 2];$ A = diag(u), B = diag(u,1), C = diag(u,-1) $X = [11 \ 12 \ 13; \ 21 \ 22 \ 23; \ 31 \ 32 \ 33]$ diag(X), diag(diag(X))

Solution (MATLAB M-file diagex1.m)

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Structured Systems of Linear Equations Tridiagonal matrices

### Tridiagonal matrices

Definition (Tridiagonal matrix)

A tridiagonal  $\iff$  upper bandwidth  $m_u = 1$  and lower bandwidth  $m_l = 1$ 

Tridiagonal matrix

$$A = \begin{bmatrix} b_1 & c_1 & 0 & \cdots & 0 & 0 \\ a_2 & b_2 & c_2 & 0 & \cdots & 0 \\ 0 & a_3 & b_3 & c_3 & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & a_{n-1} & b_{n-1} & c_{n-1} \\ 0 & 0 & \cdots & 0 & a_n & b_n \end{bmatrix}$$

- Storage n + 2(n 1) = 3n 2 elements
- Thomas algorithm
  - Gaussian elimination/ back-substitution exploiting structure
  - MATLAB function M-file tridiag.m
  - 8n + O(1) flops

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Thomas algorithm

test\_thomas.m

```
\Rightarrow a = [-2 -1 \ 0 \ 1]:
>> b = [1 2 2 4 1];
>> c = [6 4 8 6];
\Rightarrow d = [8 16 32 32 8];
>> x = tridiag(a,b,c,d)
>> x = x
 -28 6 -13 8 0
```

$$\begin{bmatrix} 1 & 6 & 0 & 0 & 0 \\ -2 & 2 & 4 & 0 & 0 \\ 0 & -1 & 2 & 8 & 0 \\ 0 & 0 & 0 & 4 & 6 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} 8 \\ 16 \\ 32 \\ 32 \\ 8 \end{bmatrix}$$

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### Sparse matrices

#### Definition (Sparse matrix)

- A sparse  $\iff$  zero elements in A can be exploited to improve efficiency (storage, time)
- Sparsity of  $A \in \mathbb{R}^{m \times n}$  is number of non-zero elements in A divided by total number of elements (mn) in A (express as %)

### Example (Sparsity)

Give the sparsity of  $A \in \mathbb{R}^{n \times n}$  where A is diagonal, tridiagonal, triangular

#### Solution

- Diagonal matrix: sparsity =  $100n/n^2 \approx 100/n\%$
- Tridiagonal matrix: sparsity =  $100(3n-2)/n^2 \approx 300/n\%$
- Triangular matrix: sparsity =  $100n(n+1)/(2n^2) \approx 50\%$

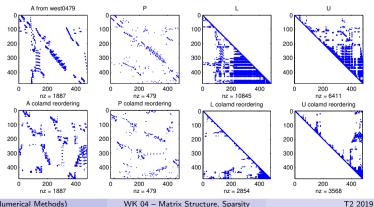
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### Reordering to reduce fill-in

- Chemical Engineering plant simulation:
  - http://math.nist.gov/MatrixMarket/data/Harwell-Boeing/chemwest/chemwest.html
- Column reordering: q = colamd(A);  $x = A(:,q) \setminus b$
- Symmetric reordering: p = symrcm(A);  $y = A(p,p) \setminus b(p)$
- MATLAB M-file west.m



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#### 

# Sparse matrices – storage

- A sparse  $\Longrightarrow$  only store non-zero elements of A
  - Row index i, column index j, element  $a_{ij}$
  - More efficient, more complicated sparse storage schemes
- MATLAB M-file spex1.m
  - number of non-zero elements nnz(A)
  - sparsity 100\*nnz(A)/numel(A)
  - sparse, full commands
  - speye
  - sparse diagonals spdiags
- Fill-in during matrix operations
  - Reorder rows and columns to reduce fill-in
  - Conflict with reordering for numerical stability, except Cholesky
  - A symmetric apply same reordering to rows, columns
  - MATLAB functions amd, colamd, symamd, symrcm

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