#### Diagonal Dominance

A matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is said to be row diagonally dominant if

$$|a_{ii}| \ge \sum_{\substack{j=1\\j\neq i}}^{n} |a_{ij}|, \quad \forall i = 1, \dots, n$$

It is said to be column diagonally dominant if

$$|a_{ii}| \ge \sum_{\substack{j=1\\j\neq i}}^{n} |a_{ji}|, \quad \forall i = 1, \dots, n$$

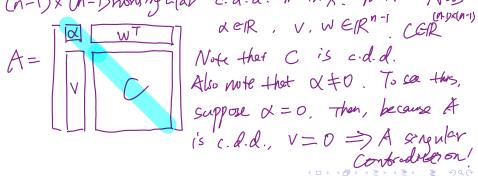
It is strictly row/column diagonally dominant if the above inequalities are strict

Diagonally dominant matrices may be singular (e.g.,  $\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$ )

# LU for Diagonally Dominant Matrices

If A is nonsingular and column diagonally dominant, then it has an LU decomposition  $\mathbf{A} = \mathbf{L}\mathbf{U}$  and  $|\ell_{ij}| \leq 1$  for all i, j.

Proof. By induction on n. The statement holds for n=1 clearly. Suppose the statement holds for any (n-1) x (n-1) monsing alar c.d.d. matrix. Partition A as



Let LU for Diagonally Dominant Matrices (cont'd)
$$A = \begin{bmatrix} x & w^{T} \\ v & C \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ x & I \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & R \end{bmatrix} \begin{bmatrix} x & w^{T} \\ 0 & R \end{bmatrix}$$

$$A = \begin{bmatrix} x & w^{T} \\ v & C \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ x & I \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & R \end{bmatrix} \begin{bmatrix} x & w^{T} \\ 0 & R \end{bmatrix}$$

$$A = \begin{bmatrix} x & w^{T} \\ 0 & R \end{bmatrix} \begin{bmatrix} x & w^{T} \\ 0 & R \end{bmatrix} \begin{bmatrix} x & w^{T} \\ 0 & R \end{bmatrix} \begin{bmatrix} x & w^{T} \\ 0 & R \end{bmatrix}$$

$$A = \begin{bmatrix} x & w^{T} \\ 0 & R \end{bmatrix} \begin{bmatrix} x &$$

LU for Diagonally Dominant Matrices (cont'd)

$$\leq |C_{jj}| - \left|\frac{w_j v_j}{\alpha}\right| \leq |C_{jj} - \frac{w_j v_j}{\alpha}| = |\hat{k}\hat{y}|$$

 $\Rightarrow$  B is  $(n-1) \times (n-1)$  nonsing for, c.d.d. Using the hypothesis, B has an LU decomposition  $B = L_1 U_1$  where all entries in  $L_1$  have absolute value  $\leq 1$ . Then, factorize A as  $A = \begin{bmatrix} 1 & 0 \\ A & L_1 \end{bmatrix} \begin{bmatrix} A & W^T \\ D & U_1 \end{bmatrix}$ 

$$A = \begin{bmatrix} V & L \\ \overline{Z} & L \end{bmatrix}$$

Muit lower

uppertriarela all the entires in a have

Sina A is c.d.d. absolute value = 1.

<ロ > < 回 > < 回 > < 巨 > < 巨 > 三 のQで

#### Positive Definite Matrices

X'A

A Matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is said to be

- positive definite if  $\mathbf{x}^T \mathbf{A} \mathbf{x} > 0$  for all **nonzero**  $\mathbf{x} \in \mathbb{R}^n$
- positive semi-definite if  $\mathbf{x}^T \mathbf{A} \mathbf{x} \ge 0$  for all  $\mathbf{x} \in \mathbb{R}^n$
- negative definite if  $\mathbf{x}^T \mathbf{A} \mathbf{x} < 0$  for all nonzero  $\mathbf{x} \in \mathbb{R}^n$
- negative semi-definite if  $\mathbf{x}^T \mathbf{A} \mathbf{x} \leq 0$  for all  $\mathbf{x} \in \mathbb{R}^n$
- indefinite if there exist  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$  s.t.  $(\mathbf{x}^T \mathbf{A} \mathbf{x})(\mathbf{y}^T \mathbf{A} \mathbf{y}) < 0$

**Properties**: For any positive definite  $\mathbf{A} \in \mathbb{R}^{n \times n}$ ,

• A is nonsingular

If  $X \in \mathbb{R}^{n \times q}$  has full column rank, then  $X^T A X \in \mathbb{R}^{q \times q}$  is positive definite

- All the principal submatrices are positive definite
- All the diagonal entries of A are positive
- A has an LU decomposition A = LU s.t. the diagonal entries of U are positive

X'AX QUARACTIC

13 s.t. Z<sup>T</sup>(X<sup>T</sup>AX)Z ≤ 1

 $(X_{\overline{z}})^T \bigwedge^{X} (X_{\overline{z}}) \leq$ 

fis p.d. >XZ=

full columna

### Positive Definite Matrices (cont'd)

Given  $\mathbf{A} \in \mathbb{R}^{n \times n}$ , define its symmetric part as

$$T = \frac{A + A^T}{2}$$
 Symmetric

and its skew-symmetric part as

$$S = \frac{A - A^T}{2}$$

Clearly,

$$\mathbf{A} = \frac{\mathbf{T} + \mathbf{S}}{2}$$

A is positive definite if and only if T is positive definite (That's why one mostly considers symmetric positive definite matrices)

$$\chi^T A \chi \stackrel{\text{scalar}}{=} (\chi^T A \chi)^T = \chi^T A^T \chi$$

$$\chi^T A \chi = \frac{1}{2} \chi^T A \chi + \frac{1}{2} \chi^T A^T \chi = \chi^T \frac{A + A^T}{2} \chi = \chi^T \int_{-\infty}^{\infty} \chi^T A \chi = \chi^T A \chi =$$

# Cholesky Decomposition for Positive Definite Matrices

Given a positive definite  $\mathbf{A} \in \mathbb{S}^n$ , there exists a unique lower triangular matrix  $\mathbf{G} \in \mathbb{R}^{n \times n}$  with positive diagonal entries such that

• Can be computed in  $O(n^3/3)$  (similar to LDL), no pivoting, numerically very stable

#### **Banded Systems**

A matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$  has upper bandwidth q if  $a_{ij} = 0 \ \forall j > i + q$  and lower bandwidth p if  $a_{ij} = 0 \ \forall i > j + p$ 

**Example**:  $\mathbf{A} \in \mathbb{R}^{5 \times 5}$  has upper bandwidth q = 1 and lower bandwidth p = 2

$$\mathbf{A} = \begin{bmatrix} \times & \times & 0 & 0 & 0 \\ \times & \times & \times & 0 & 0 \\ \times & \times & \times & \times & 0 \\ 0 & \times & \times & \times & \times \\ 0 & 0 & \times & \times & \times \end{bmatrix}$$

The triangular factors in **LU**,  $\mathbf{GG}^T$ , and  $\mathbf{LDL}^T$  are also banded  $\Longrightarrow$  save a lot of computations

## Banded LU Decomposition

#### **Theorem**

Suppose  $\mathbf{A} \in \mathbb{R}^{n \times n}$  has an LU decomposition  $\mathbf{A} = \mathbf{LU}$  and has upper bandwidth q and lower bandwidth p. Then,  $\mathbf{U}$  has upper bandwidth q and  $\mathbf{L}$  has lower bandwidth p.

Proof. By induction on 
$$n$$
. Recall that
$$A = \begin{bmatrix} \alpha & w^T \\ v & C \end{bmatrix} = \begin{bmatrix} v & J_{n-1} \\ \overline{\alpha} & J_{n-1} \end{bmatrix} \begin{bmatrix} 0 & C - \frac{vw^T}{\alpha} \end{bmatrix} \begin{bmatrix} \alpha & w^T \\ 0 & J_{n-1} \end{bmatrix}$$
Since  $A$  is banded. only  $w(1:g)$  in  $w$  and  $v(1:p)$  in  $v$  are nanzero. Thus,  $C - \frac{vw^T}{\alpha}$  has upper bandwidth  $q$  and lower bandwidth  $p$ .

Let  $C - \frac{vw^T}{\alpha} = L_1U_1$  be its  $LV$  decomposition.

From the hypothesis on  $n-1$  and the spansity of  $w, v$ ,
$$L = \begin{bmatrix} 1 & 0 \\ v & L_1 \end{bmatrix} \quad V = \begin{bmatrix} \alpha & w^T \\ 0 & V \end{bmatrix}$$
 is the  $LV$  decomposition.

## Band LU Decomposition (cont'd)

Suppose  $\mathbf{A} = \mathbf{L}\mathbf{U}$  exists and  $\mathbf{A}$  has upper bandwidth q and lower bandwidth p

```
for k=1:n-1
    for i=k+1:min(k+p,n)
        A(i,k)=A(i,k)/A(k,k)
    end
    for j=k+1:min(k+q,n)
        for i=k+1:min(k+p,n)
             A(i,j)=A(i,j)-A(i,k)*A(k,j)
    end
    end
end
```

Complexity: O(2npq) flops, much smaller than  $O(2n^3/3)$  when  $n \gg p, q$ 

#### Solving Band Triangular Systems

Solving Ax = b, where A = LU exists and

**L** is unit lower triangular with lower bandwidth *p* 

 ${f U}$  is **nonsingular** upper triangular with upper bandwidth q

1. Solve Lz = b for z using band forward substitution

Complexity:  $O(2np) \ll O(n^2)$  if  $p \ll n$ 

## Solving Band Triangular Systems (cont'd)

2. Solve  $\mathbf{U}\mathbf{x} = \mathbf{z}$  for  $\mathbf{x}$  using band backward substitution

Complexity:  $O(2nq) \ll O(n^2)$  if  $q \ll n$ 

Read Chapter 4 of textbook for more on special linear systems and their decompositions

## Solving Band Triangular Systems (cont'd)

2. Solve  $\mathbf{U}\mathbf{x} = \mathbf{z}$  for  $\mathbf{x}$  using band backward substitution

Complexity:  $O(2nq) \ll O(n^2)$  if  $q \ll n$ 

Read Chapter 4 of textbook for more on special linear systems and their decompositions