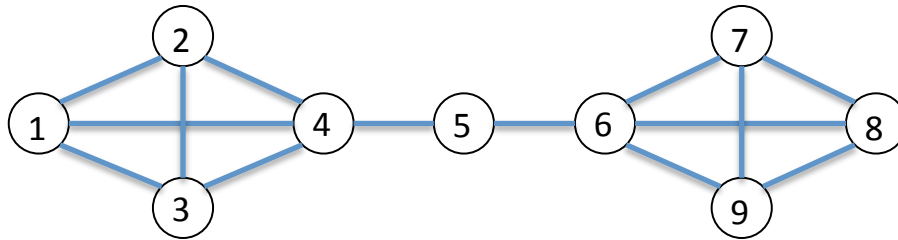


Minimum degree ordering

- In the matrix graph, choose the node with least edges connected to it.
- A tree graph will be ordered correctly.
- It is a local strategy; no guarantee it will produce the least amount of total fill.

Counter example:



The given order produces no fill.

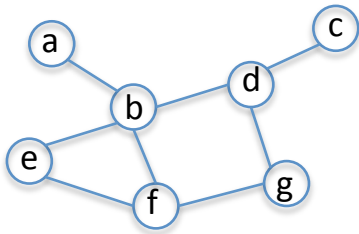
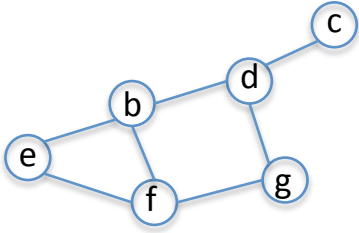
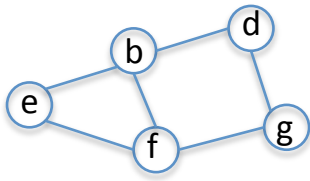
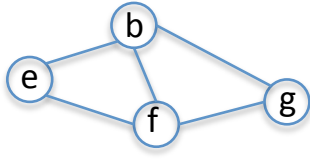
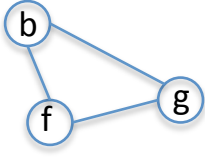


Minimum degree ordering will start with node 5.

Produces fill at the first step -> not optimal

Tie-breaking

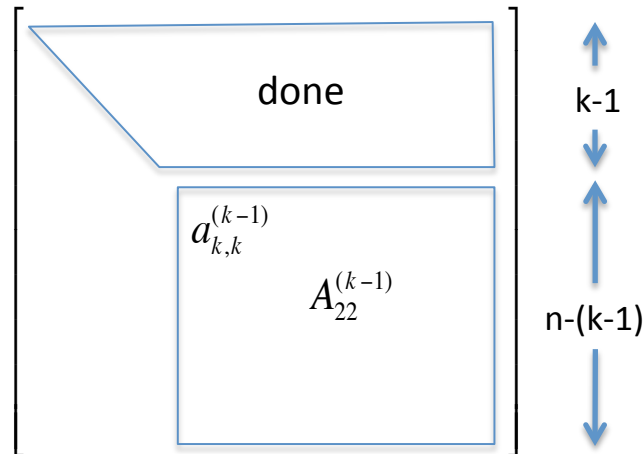
- 1) Select the node that had the smallest node number in the original order.
- 2) RCM preordering -> min. deg.
Tie broken by selecting earlier RCM ordered node.

Example

<u>k</u>	<u>Elimination graph $G(A^{(k-1)})$</u>	<u>node</u>	<u>min deg</u>
1		a	1
2		c	1
3		d	2
4		e	2
5		b	2
6		f	1
7		g	0

Stability of factorization

- Problem arises: 1) zero pivot: $a_{kk}^{(k-1)} = 0$, or 2) small pivot: $a_{kk}^{(k-1)} \approx 0$
- Pivoting



Complete: search the largest element in A_{22} .

Partial: search the largest element in col k .

$$\text{swap} \begin{matrix} \longrightarrow \\ \longrightarrow \end{matrix} \begin{bmatrix} a_{kk} \\ a_{k^*k} \end{bmatrix}$$

- Modified LU factorization: $PA = LU$, P = permutation obtained from swapping during partial pivoting.
- Pivoting is stable but bad news for sparse matrices \rightarrow destroy sparsity
- Several conditions on A will ensure pivoting is not necessary.

Theorem: Suppose A is SPD. Then during GE, $a_{kk}^{(k-1)} > 0$.

Pf: For $n = 1$, obviously true. In general, use inductive argument.

Write

$$A = \begin{bmatrix} a_{11} & v^T \\ v & A_{22} \end{bmatrix}$$

Since A is SPD, $a_{11} > 0$.

Eliminate v using a_{11} as pivot:

$$\begin{bmatrix} a_{11} & v^T \\ v & A_{22} \end{bmatrix} \xrightarrow{\text{GE}} \begin{bmatrix} a_{11} & v^T \\ & A_{22} - \frac{v}{a_{11}} v^T \end{bmatrix}$$

Let $A_{22}^{(1)} = A_{22} - vv^T/a_{11}$. Note $A_{22}^{(1)}$ is symmetric.

Want to show $A_{22}^{(1)}$ is SPD.

Let x in \mathbb{R}^{n-1} , $x \neq 0$. Consider y defined as

$$y = \begin{bmatrix} -\frac{x^T v}{a_{11}} \\ x \end{bmatrix} \in \mathbb{R}^n$$

A SPD $\Rightarrow y^T A y > 0$

i.e.

$$\begin{aligned} 0 &< \begin{bmatrix} -\frac{x^T v}{a_{11}} & x^T \end{bmatrix} \begin{bmatrix} a_{11} & v^T \\ v & A_{22} \end{bmatrix} \begin{bmatrix} -\frac{x^T v}{a_{11}} \\ x \end{bmatrix} \\ &= \begin{bmatrix} 0 & x^T A_{22} - \frac{x^T v v^T}{a_{11}} \end{bmatrix} \begin{bmatrix} -\frac{x^T v}{a_{11}} \\ x \end{bmatrix} \\ &= x^T A_{22} x - \frac{1}{a_{11}} x^T (v v^T) x \\ &= x^T (A_{22} - \frac{v v^T}{a_{11}}) x = x^T A_{22}^{(1)} x \end{aligned}$$

Thus $A_{22}^{(1)}$ is SPD $\Rightarrow a_{22}^{(1)} > 0 \Rightarrow$ pivot is positive.

Continuing this process, one can show that

$$a_{kk}^{(k-1)} > 0 \quad \forall k$$

Other matrices that pivoting is not necessary:

- Row diagonally dominant

$$\text{i.e.} \quad |a_{k,k}| > \sum_{j \neq k} |a_{k,j}| \quad k = 1, \dots, n$$

- Column diagonally dominant

$$\text{i.e.} \quad |a_{k,k}| > \sum_{i \neq k} |a_{i,k}| \quad k = 1, \dots, n$$

Image Denoising

- Images are treated as 2D functions:

$$u_{i,j} = \text{pixel value at row } i, \text{ col } j$$

- Inverse problem: Given

1) the observed image: $u^0 = u^* + n$ (n = noise)

2) estimate of variance of noise:

$$\|n\|^2 = \sigma^2 \quad \sigma = \text{known parameter}$$

find an approximation to the original image u^*

PDE approach

min “fluctuation of pixel values”

subject to “noise constraint level”

- The objective function is to get rid of noise
- The constraint is necessary so that you don't get an image of constant pixel values

i.e. $\|u - u^0\|^2 \approx \sigma^2 = \|u^* - u^0\|^2$

The noise level of u^0 is the same w.r.t u and w.r.t. u^*

- Ill-posed problem: many images u satisfy the same constraint.
- Need a selection criterion -> regularization

Regularization models

Noise level constraint optimization problem:

$$\begin{aligned} & \min_u R(u) \\ \text{subject to } & \|u - u^0\|^2 = \sigma^2 \end{aligned}$$

Equivalently:

$$\min_u f(u) \equiv \alpha R(u) + \|u - u^0\|^2$$

α measures tradeoff between fit and regularity

- If $\alpha \approx 0$, $u \approx u^0$
- If $\alpha \approx \infty$, $u \approx \text{constant}$

What is $R(u)$? The idea is to min the fluctuation of u