



Parallel sparse linear algebra (1)

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Georgia Institute of Technology

CSE/CS 8803 PNA, Spring 2008

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Sources for today's material

- Mike Heath (UIUC)
- CS 267 (Yelick & Demmel, UCB)
- John Gilbert (UCSB)
- Xiaoye (Sherry) Li (LBNL)
- *Direct methods for sparse matrices*, by Duff, Erisman, and Reid



Review: Parallel dense linear algebra

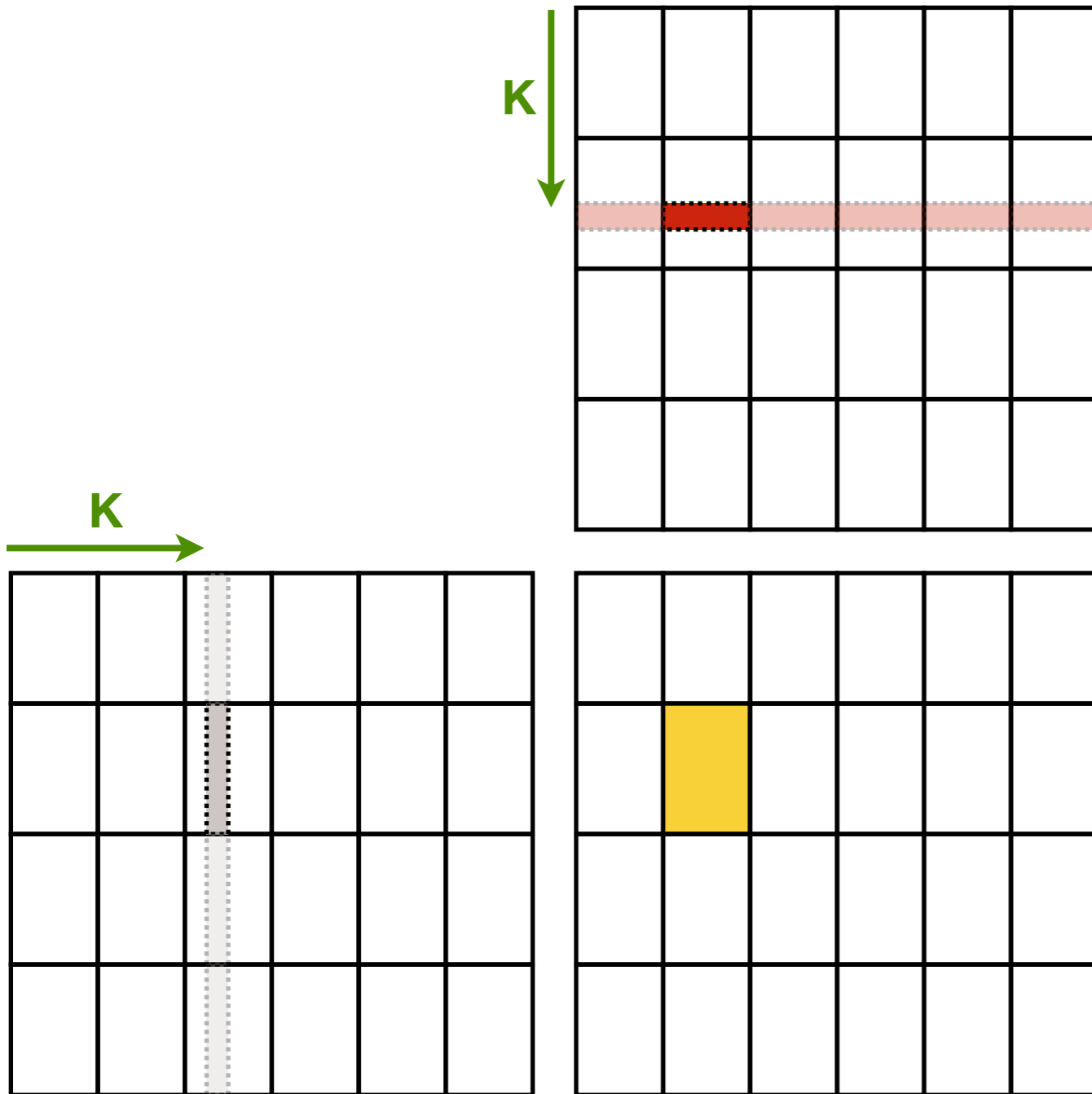
Equivalent formulations of matrix-matrix multiplication

Dot products

$$C = A \cdot B = \begin{pmatrix} \hat{a}_1^T \\ \vdots \\ \hat{a}_m^T \end{pmatrix} \cdot (b_1 \quad \cdots \quad b_n) = \begin{pmatrix} \hat{a}_1^T \cdot b_1 & \cdots & \hat{a}_1^T \cdot b_n \\ \vdots & & \vdots \\ \hat{a}_m^T \cdot b_1 & \cdots & \hat{a}_m^T \cdot b_n \end{pmatrix}$$
$$\implies c_{ij} = \hat{a}_i^T \cdot b_j$$

Outer products

$$C = A \cdot B = (a_1 \cdots a_k) \cdot \begin{pmatrix} \hat{b}_1^T \\ \vdots \\ \hat{b}_k^T \end{pmatrix} = a_1 \hat{b}_1^T + \cdots + a_k \hat{b}_k^T = \sum_k a_k \hat{b}_k^T$$



SUMMA:

for-all **K**:

Broadcast 

Broadcast 

$$\begin{array}{c}
 \text{yellow square} \\
 = \\
 \text{yellow square} + \text{vertical dashed line} * \text{red horizontal bar}
 \end{array}$$

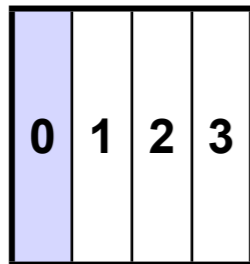


Possible data layouts for dense LU

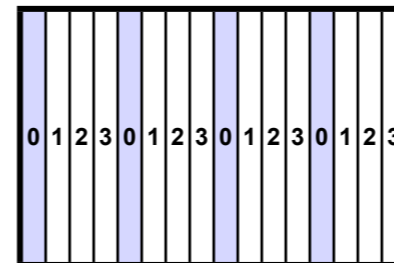


1-D column blocked

Bad load balance



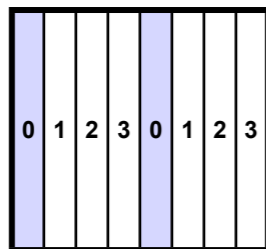
1-D column cyclic



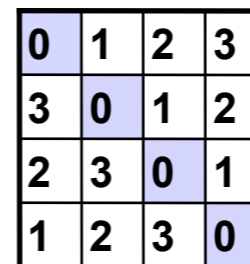
Can't easily use BLAS2/3

1-D column block cyclic

Factorization bottleneck



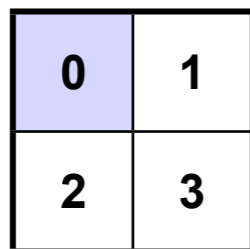
Block skewed



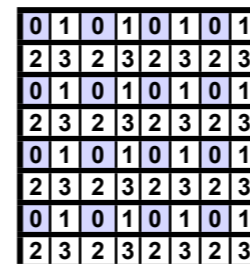
Complicated addressing

2-D row & col blocked

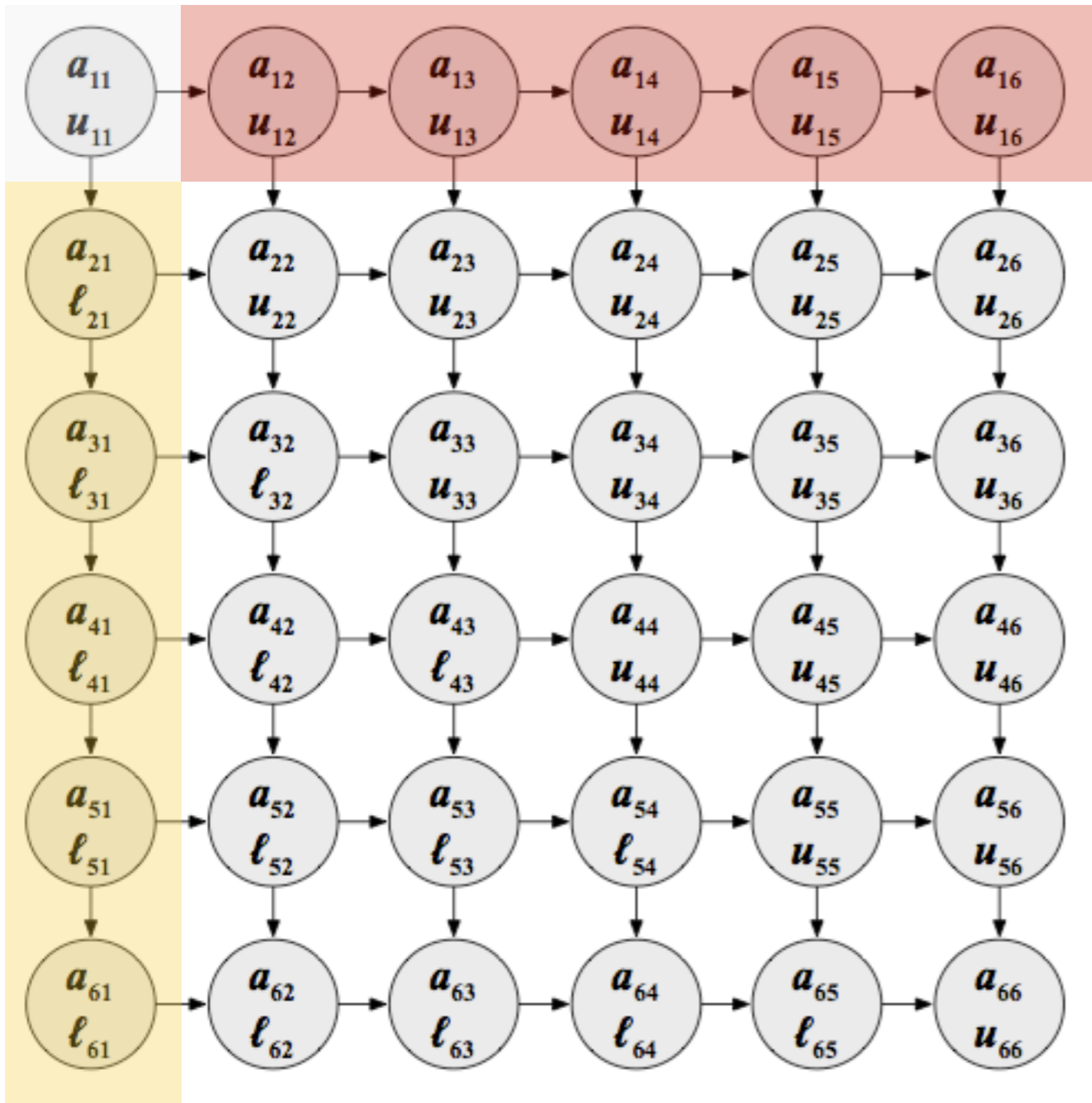
Bad load balance



2-D row & col block cyclic



Best option



$$\begin{aligned}
 l_{11} &= 1 \\
 u_{11} &= a_{11} \\
 \hat{u}_{12}^T &= \hat{a}_{12}^T \\
 l_{21} &= \frac{a_{21}}{a_{11}} \\
 L_{22}U_{22} &= A_{22} - l_{21}\hat{u}_{12}^T
 \end{aligned}$$





Partial pivoting to improve stability

$$A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

- Observation: GE as described fails on above matrix (divide by 0)
- **Partial pivoting:** At each elimination step, swap “top” row with row that has leading entry with largest magnitude

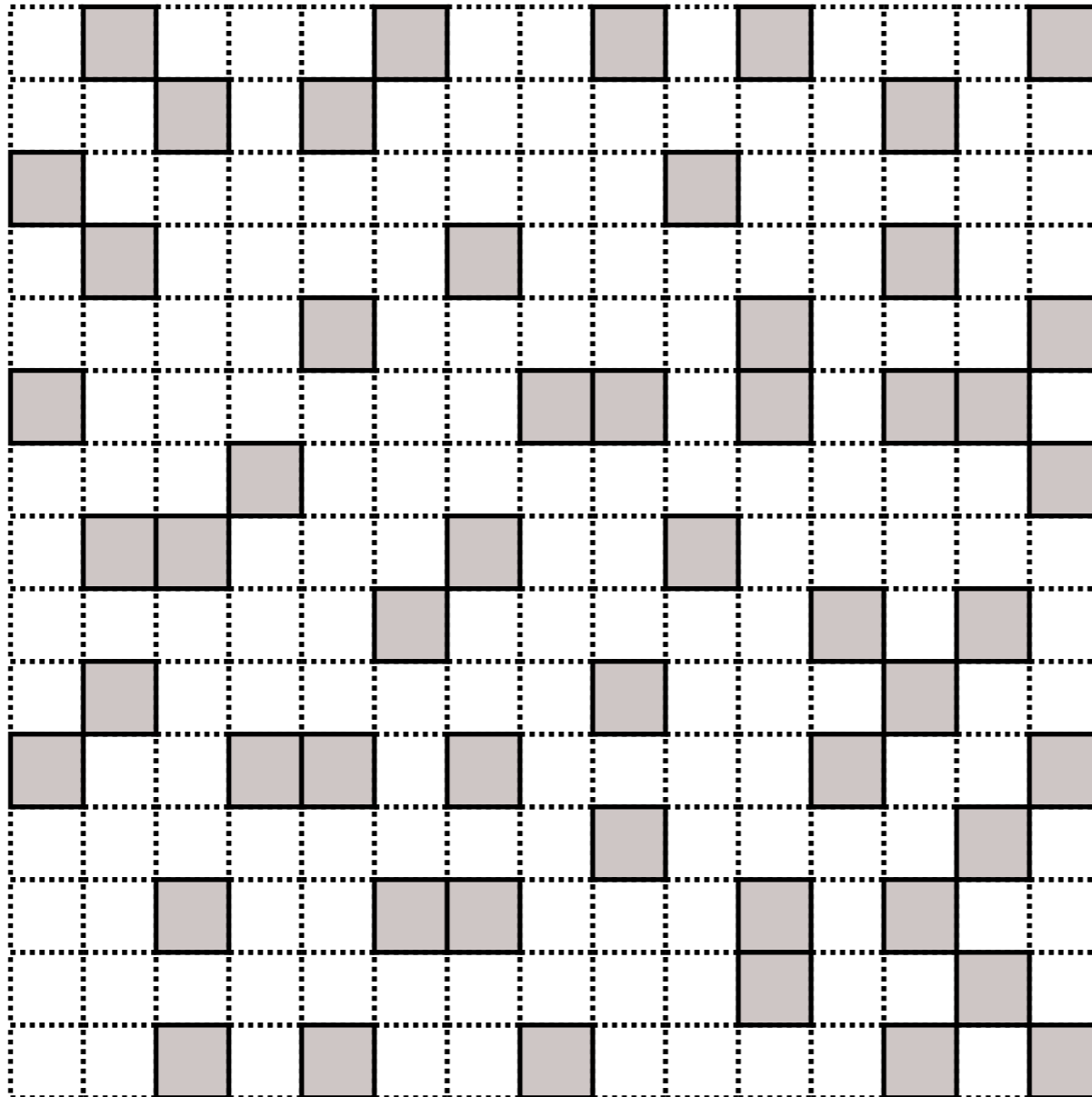


Sparse matrix-vector multiply

$$A^*x \rightarrow y$$

 x^T 

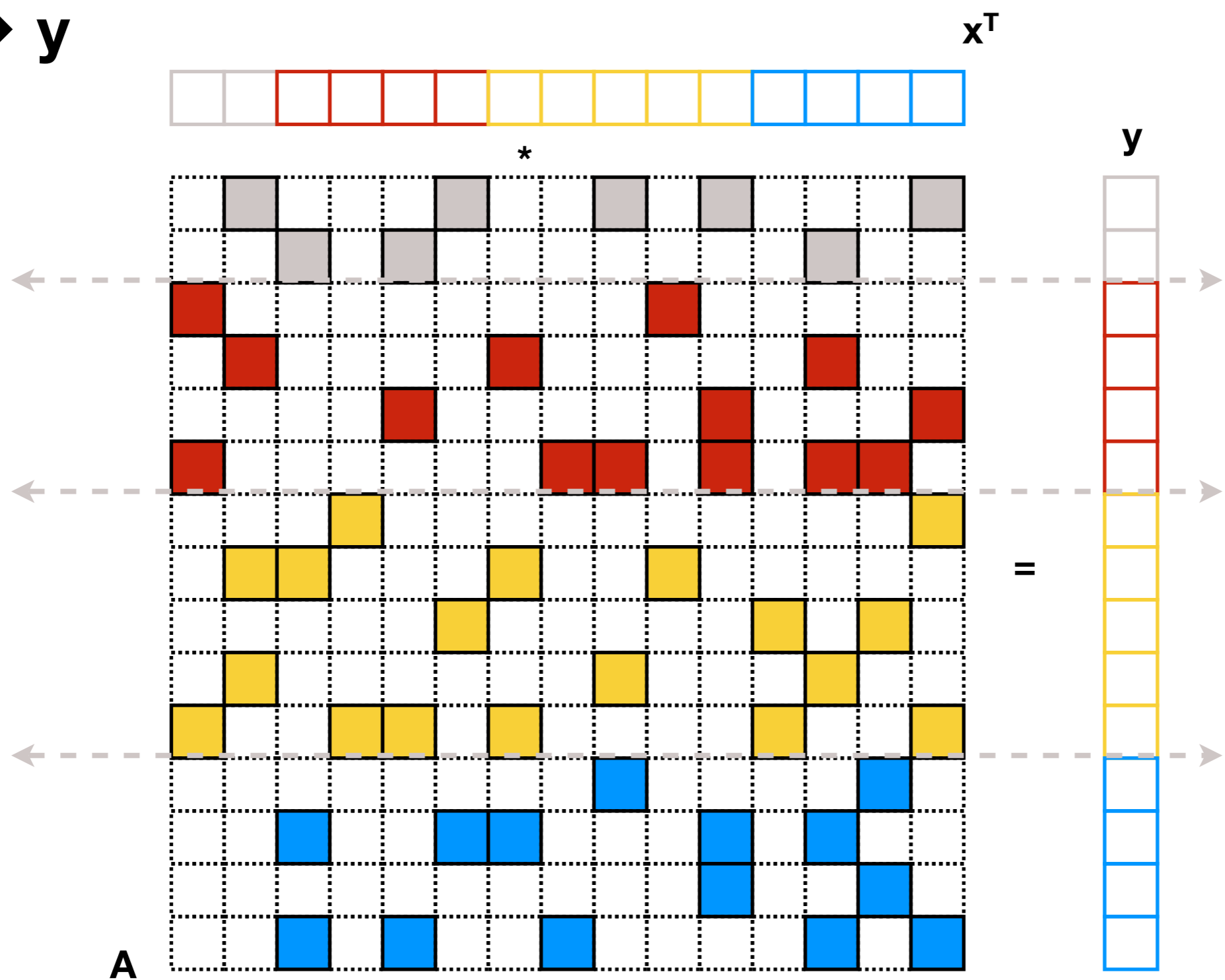
*

 y 

=

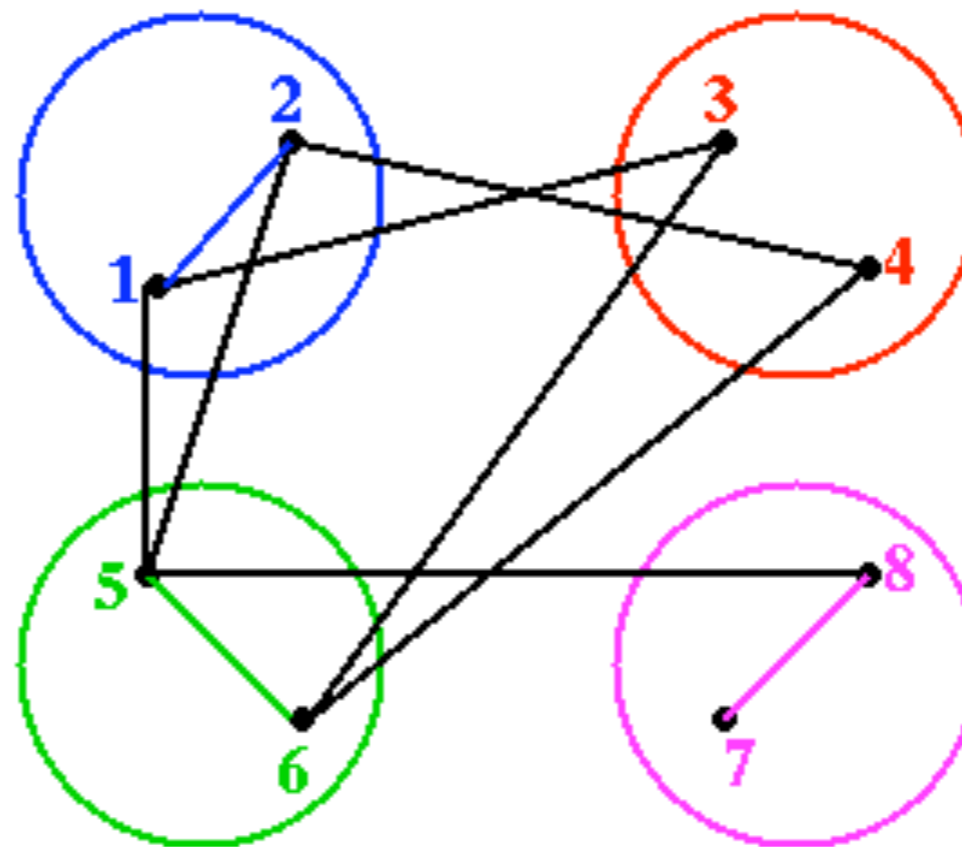
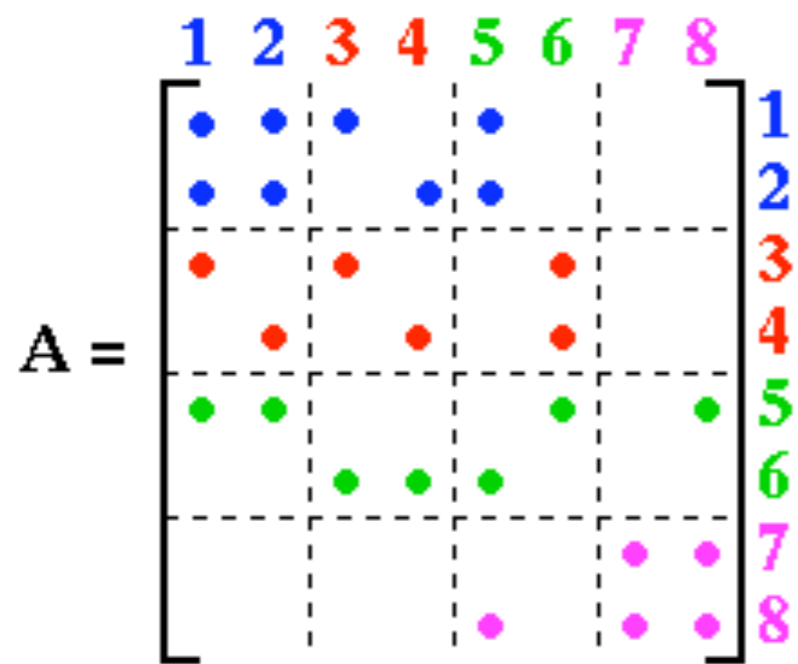
A

$$A^*x \rightarrow y$$





Partitioning a Sparse Symmetric Matrix





Parallelization options

- 1-D row vs. 1-D column vs. 2-D layouts?
 - Broadcasts vs. reductions
- Ideal matrix structure?
- Symmetry?

- Improving communication complexity
 - Distribution/mapping: Formulate as graph **partitioning** problem
 - Reduce communication volume: Row/column **reordering**



Sparse Gaussian elimination

Algorithms for 2-D (3-D) Poisson, $N=n^2$ ($=n^3$)

Algorithm	Serial	PRAM	Memory	# procs
Dense LU	N^3	N	N^2	N^2
<i>Band LU</i>	N^2 ($N^{7/3}$)	N	$N^{3/2}$ ($N^{5/3}$)	N ($N^{4/3}$)
Jacobi	N^2 ($N^{5/3}$)	N ($N^{2/3}$)	N	N
<i>Explicit inverse</i>	N^2	$\log N$	N^2	N^2
Conj. grad.	$N^{3/2}$ ($N^{4/3}$)	$N^{1/2(1/3)} \log N$	N	N
RB SOR	$N^{3/2}$ ($N^{4/3}$)	$N^{1/2}$ ($N^{1/3}$)	N	N
Sparse LU	$N^{3/2}$ (N^2)	$N^{1/2}$	$N \log N$ ($N^{4/3}$)	N
<i>FFT</i>	$N \log N$	$\log N$	N	N
Multigrid	N	$\log^2 N$	N	N
Lower bound	N	$\log N$	N	

PRAM = idealized parallel model with zero communication cost.

Source: Demmel (1997)

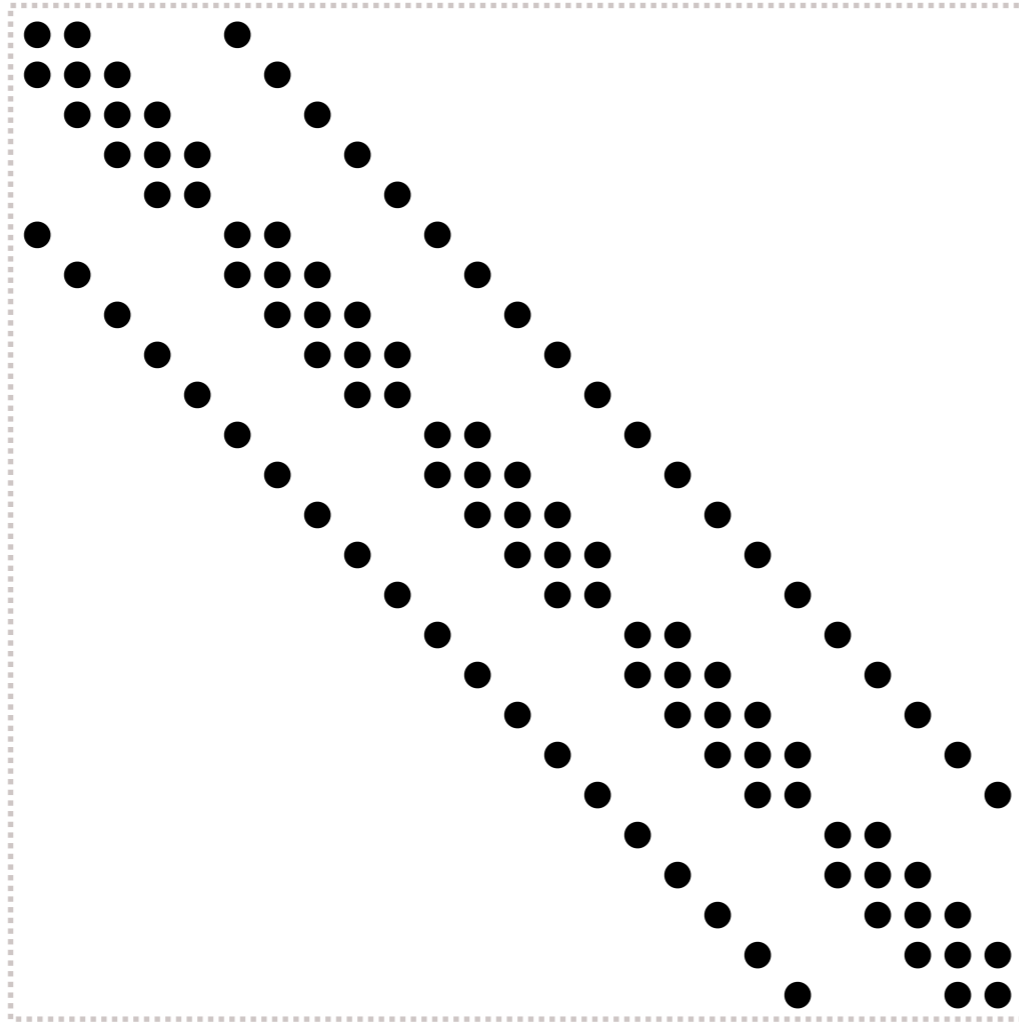
Recall: One step of GE

$$A = \begin{pmatrix} \alpha & w^T \\ v & B \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \frac{v}{\alpha} & I \end{pmatrix} \begin{pmatrix} \alpha & w^T \\ 0 & B - \frac{1}{\alpha}v \cdot w^T \end{pmatrix}$$

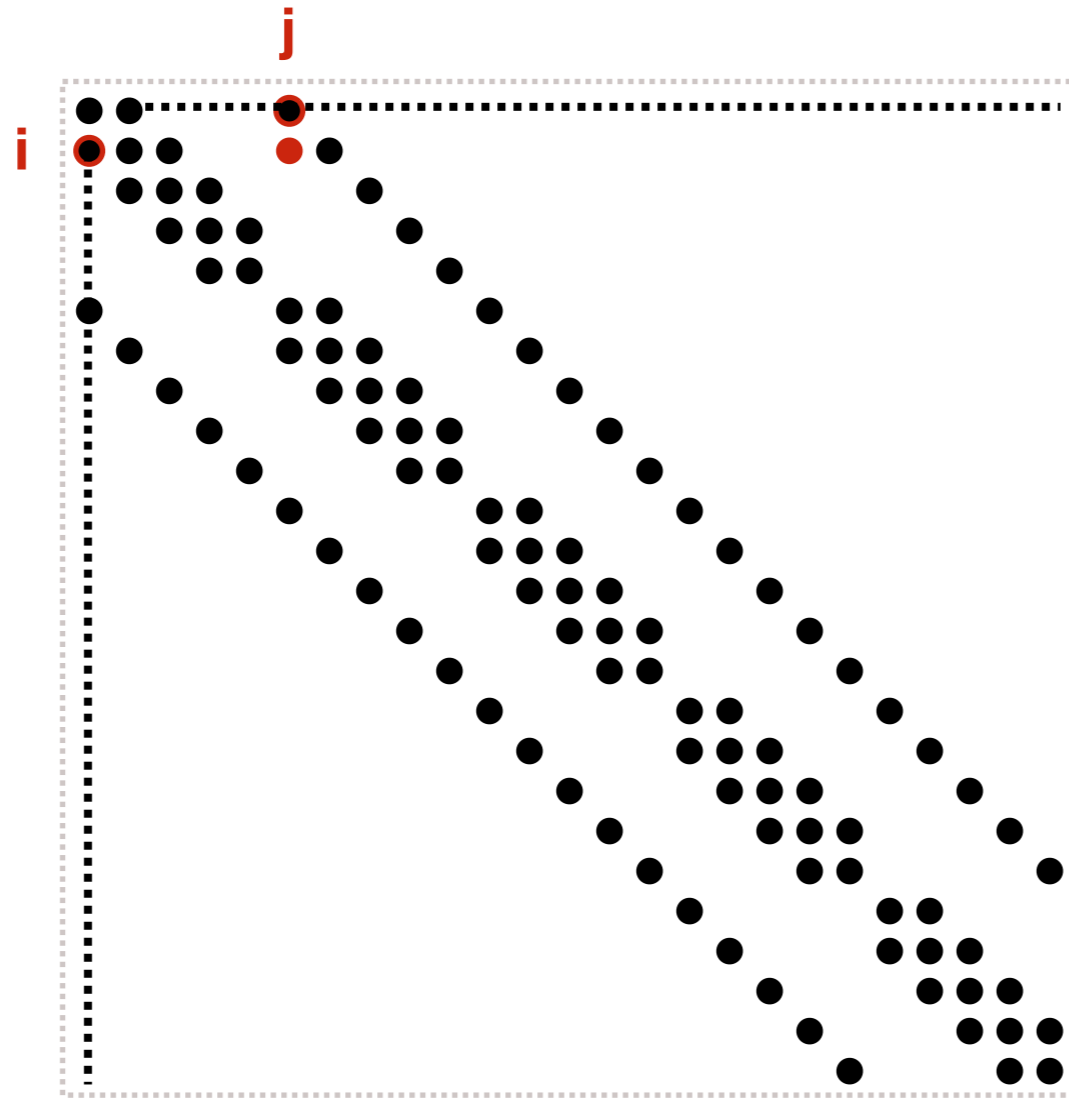
■ Question: What if A is **sparse**?

■ <http://crd.lbl.gov/~xiaoye/SuperLU/SparseDirectSurvey.pdf>

$$a_{ij} = a_{ij} - a_{ik} \cdot a_{kj}$$



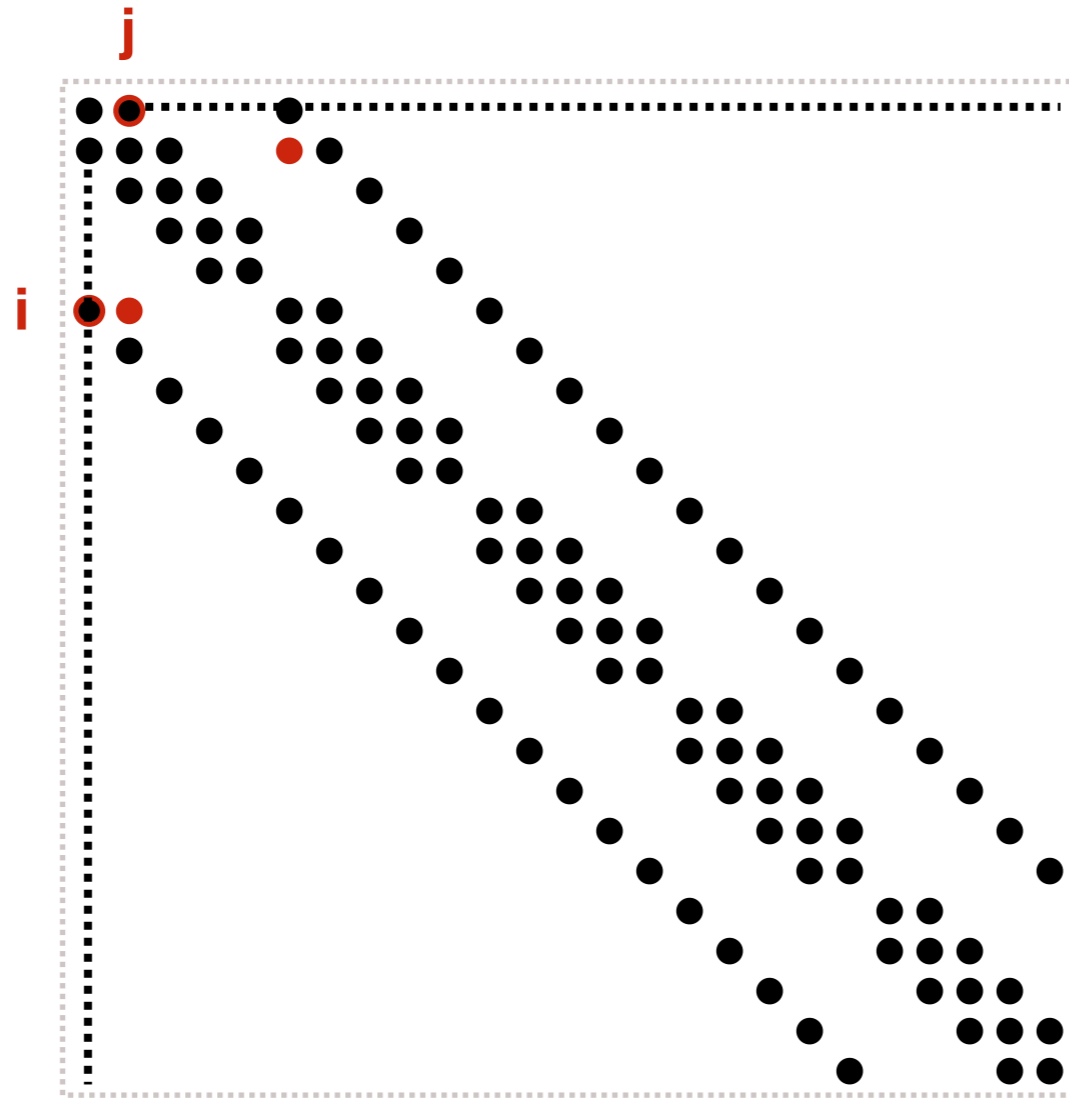
$$a_{ij} = a_{ij} - a_{ik} \cdot a_{kj}$$



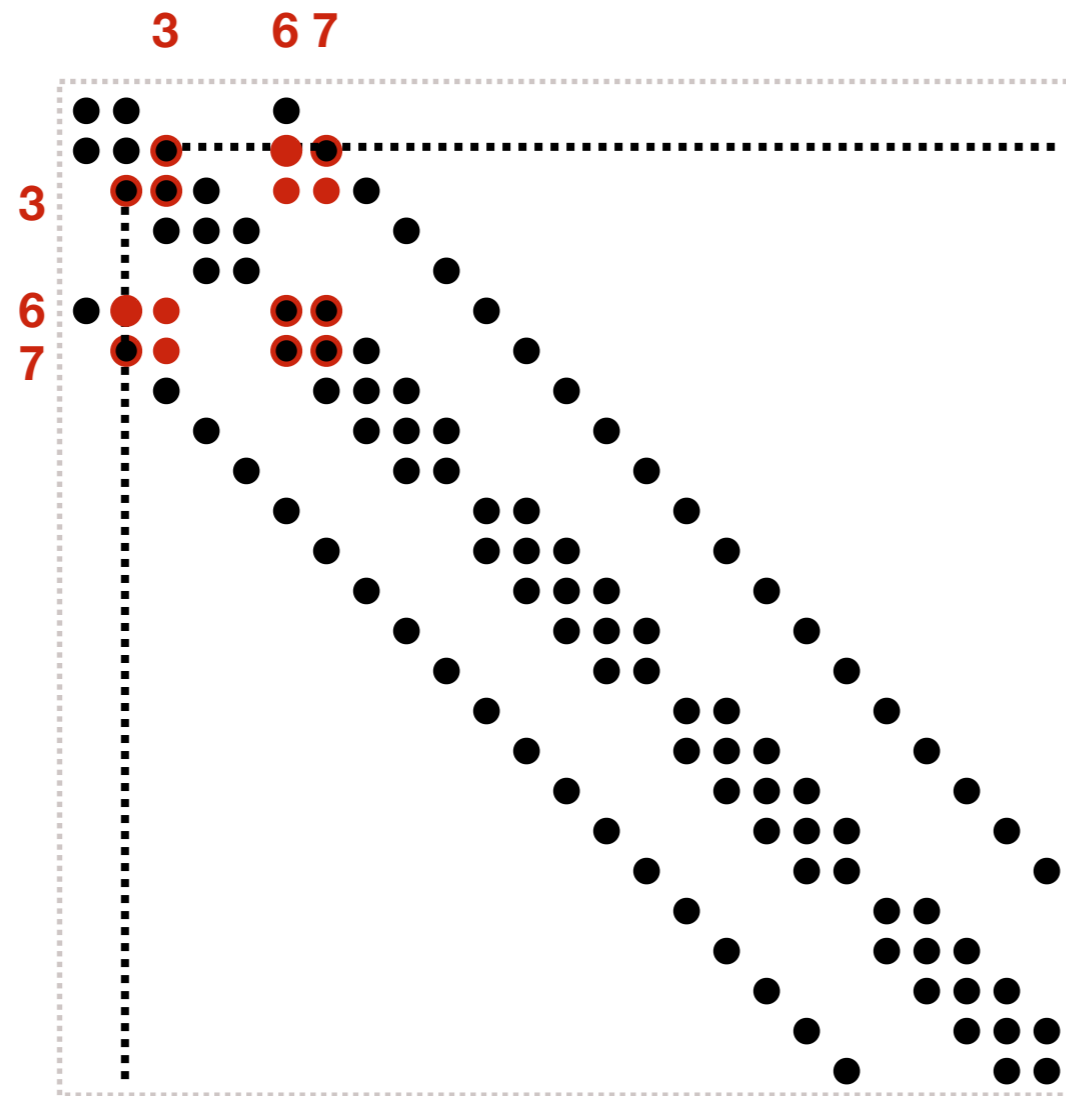
● = "fill-in"



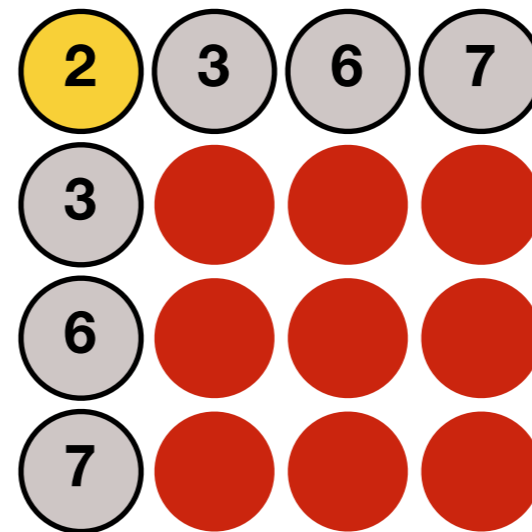
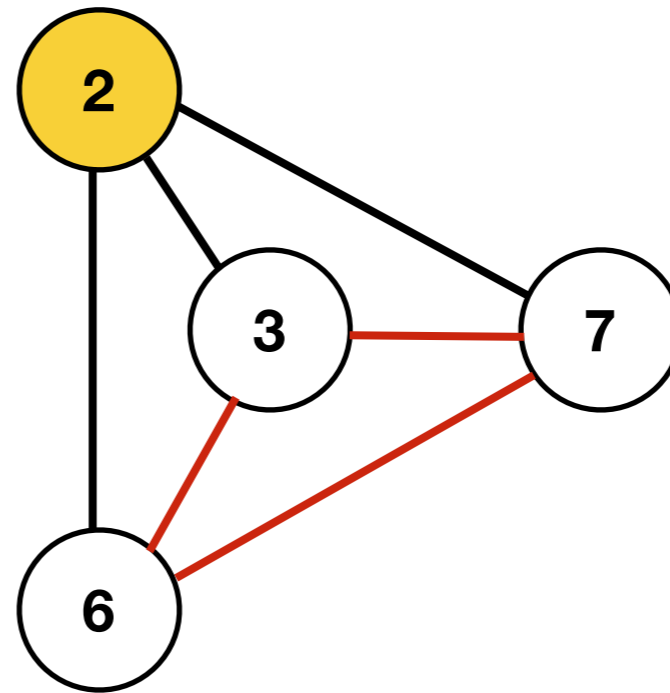
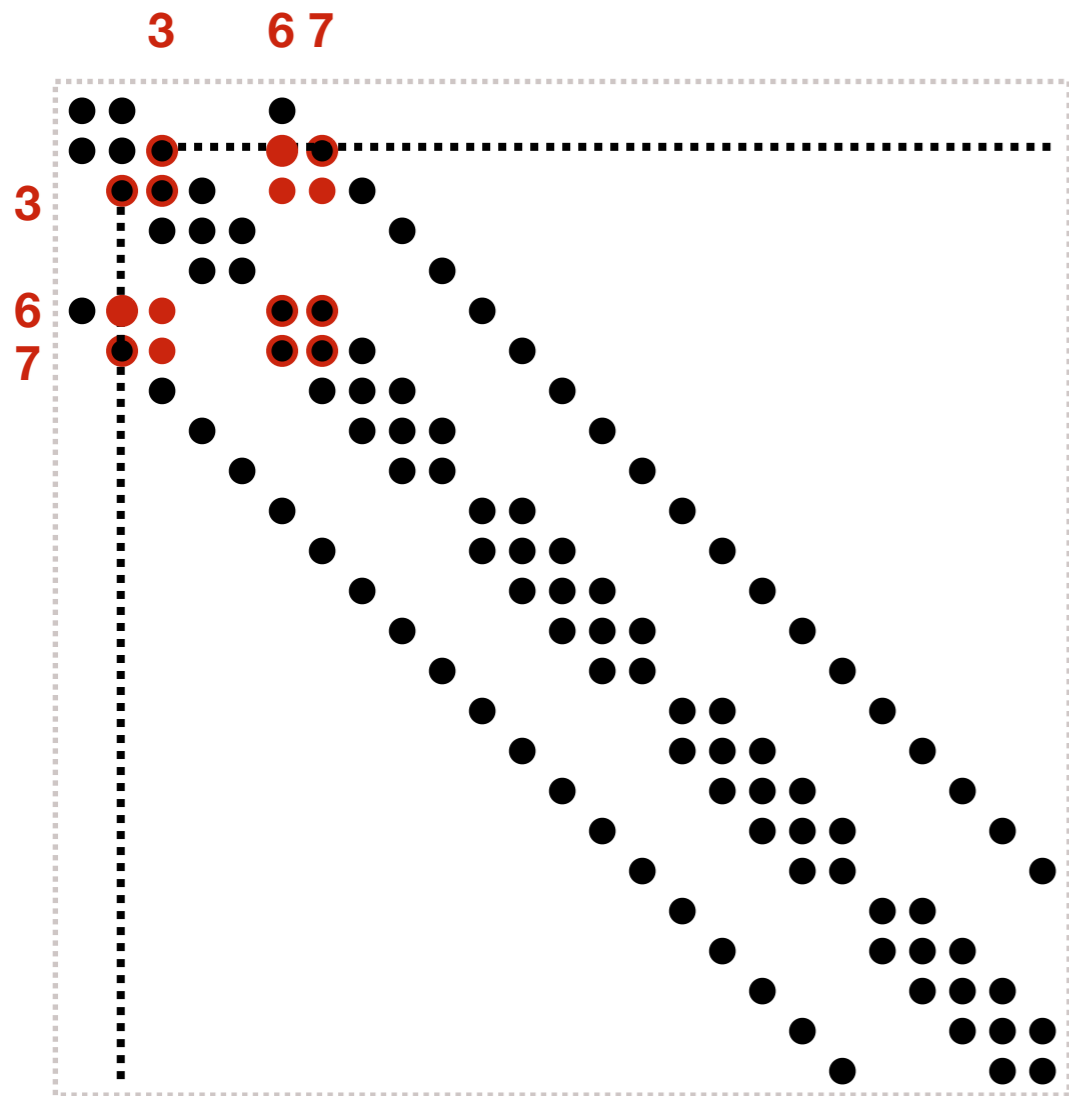
$$a_{ij} = a_{ij} - a_{ik} \cdot a_{kj}$$



$$a_{ij} = a_{ij} - a_{ik} \cdot a_{kj}$$



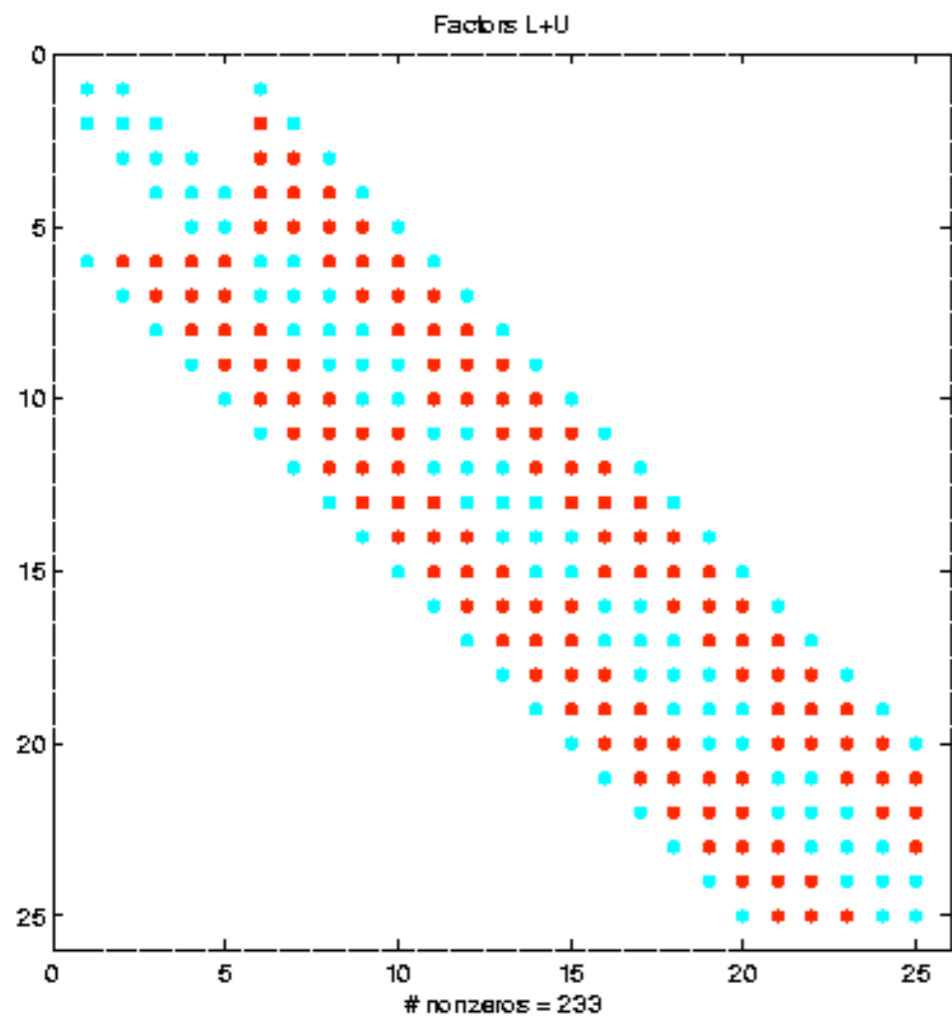
$$a_{ij} = a_{ij} - a_{ik} \cdot a_{kj}$$



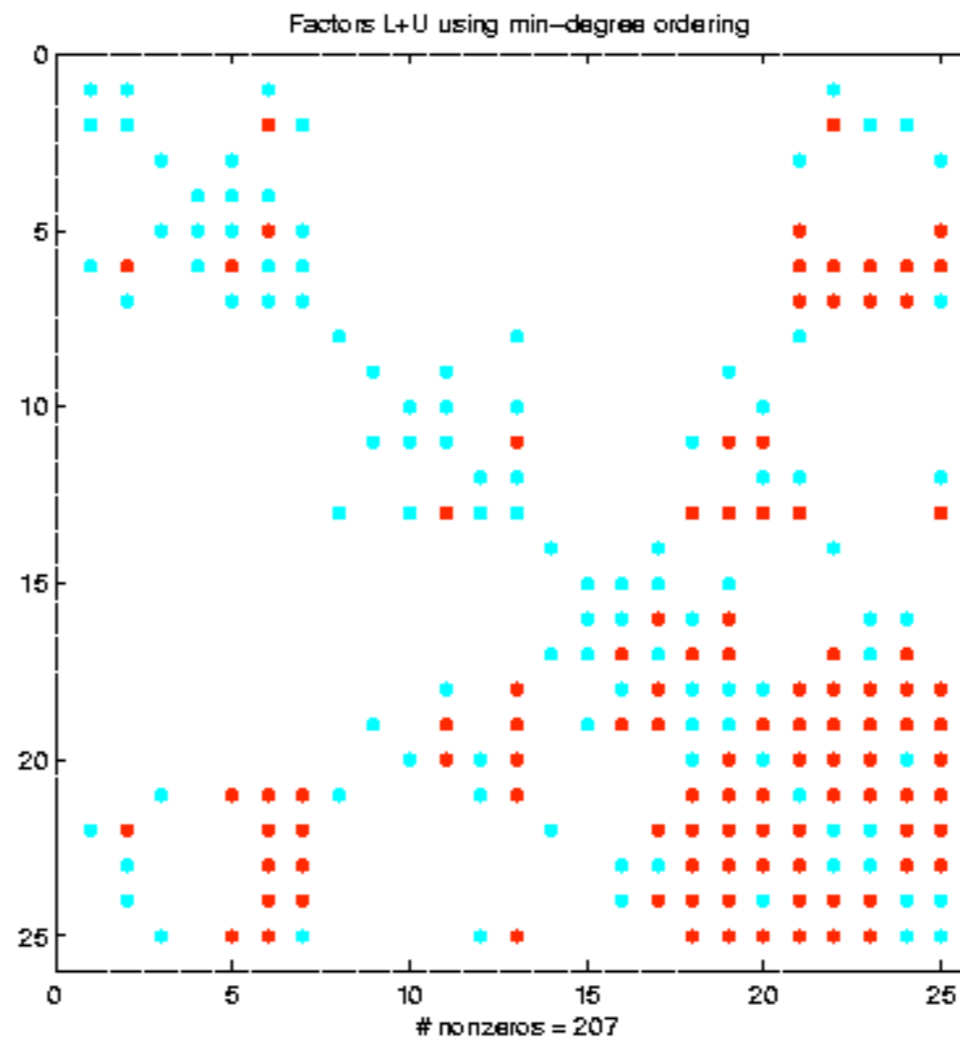
$$a_{ij} = a_{ij} - a_{ik} \cdot a_{kj}$$

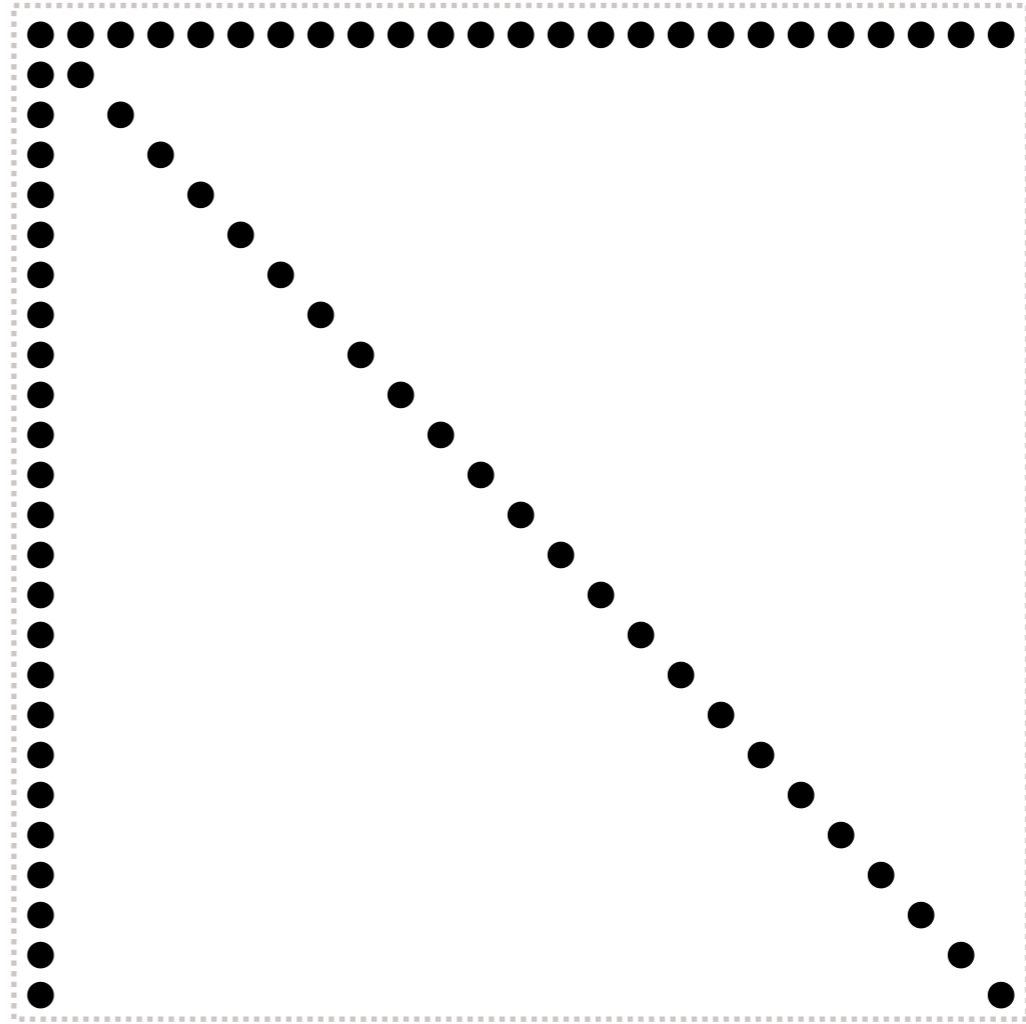
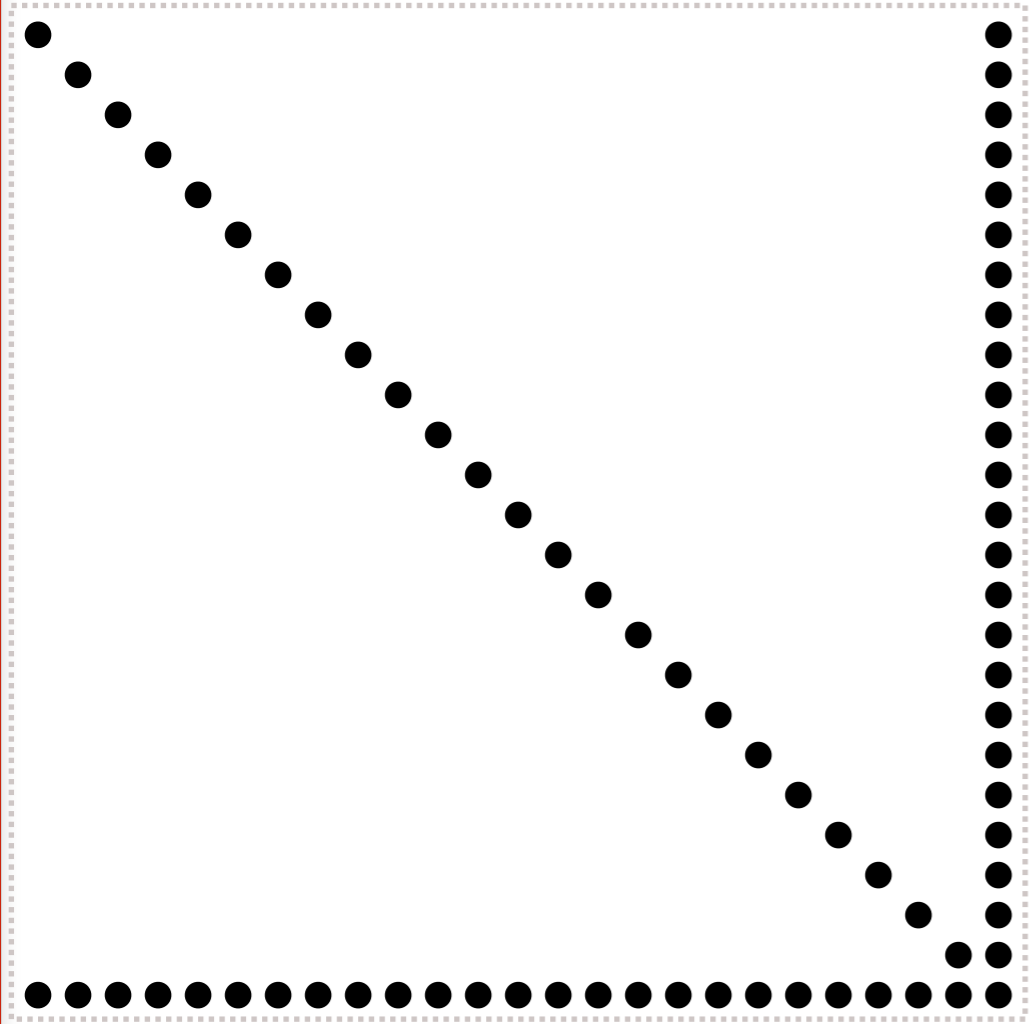


Total nnz = 233



Total nnz = 207







Dense vs. sparse LU

$$P_r A P_c = LU \quad \text{“Complete” pivoting}$$

- Dense
 - Choose P_r & P_c to **maintain stability**
 - Partial pivoting (P_r only) suffices in most cases
- Sparse
 - Permute to maintain stability and **preserve sparsity**
 - Dynamic pivoting causes dynamic structure updates



Algorithmic issues

- **Ordering** to minimize fill-in
 - *NP-complete* [Rose & Tarjan, '78; Yannakis '83 for symmetric case]
- **Predict** fill-in: Symbolic factorization step
- **Perform factorization** and triangular solves
 - Numerical factorization step
 - Usually dominates total run-time

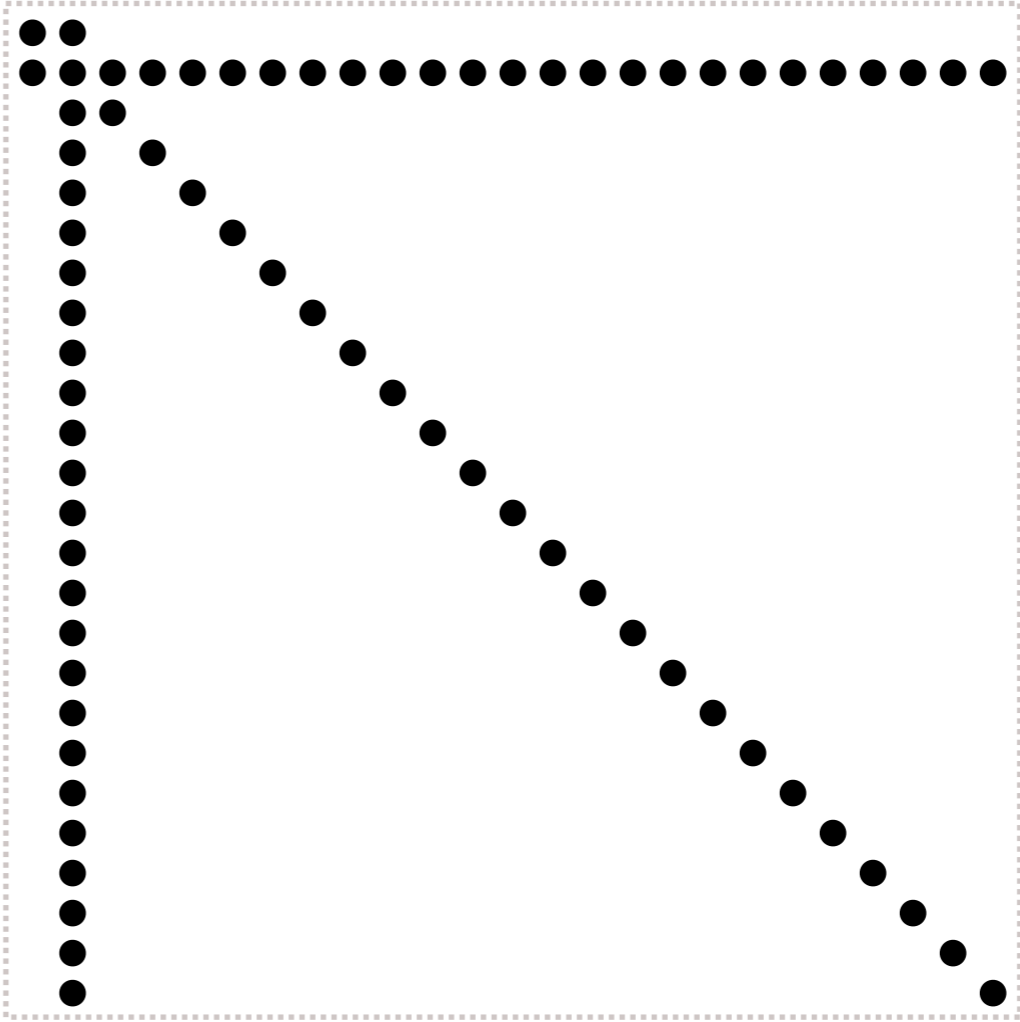
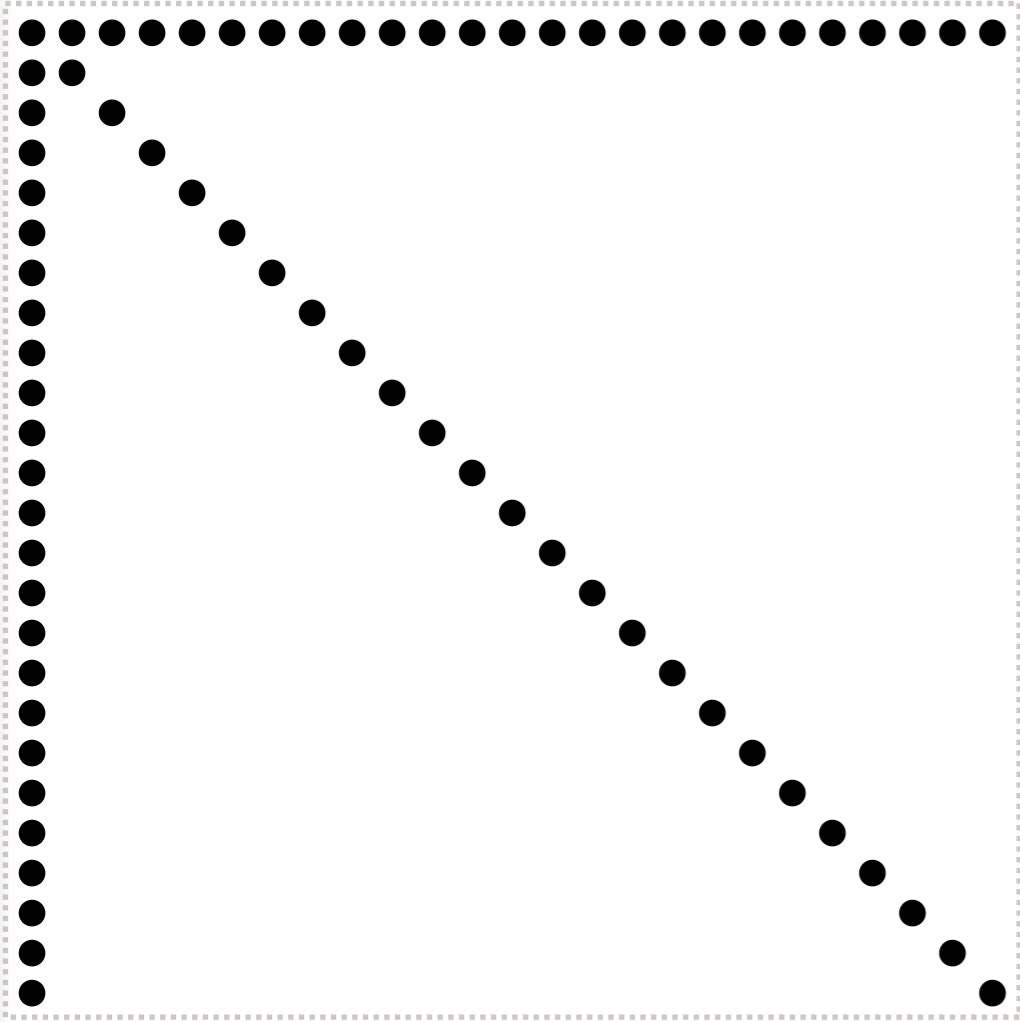
- Oh yeah, and do all this stuff in parallel

Ordering: Markowitz criterion ('57)

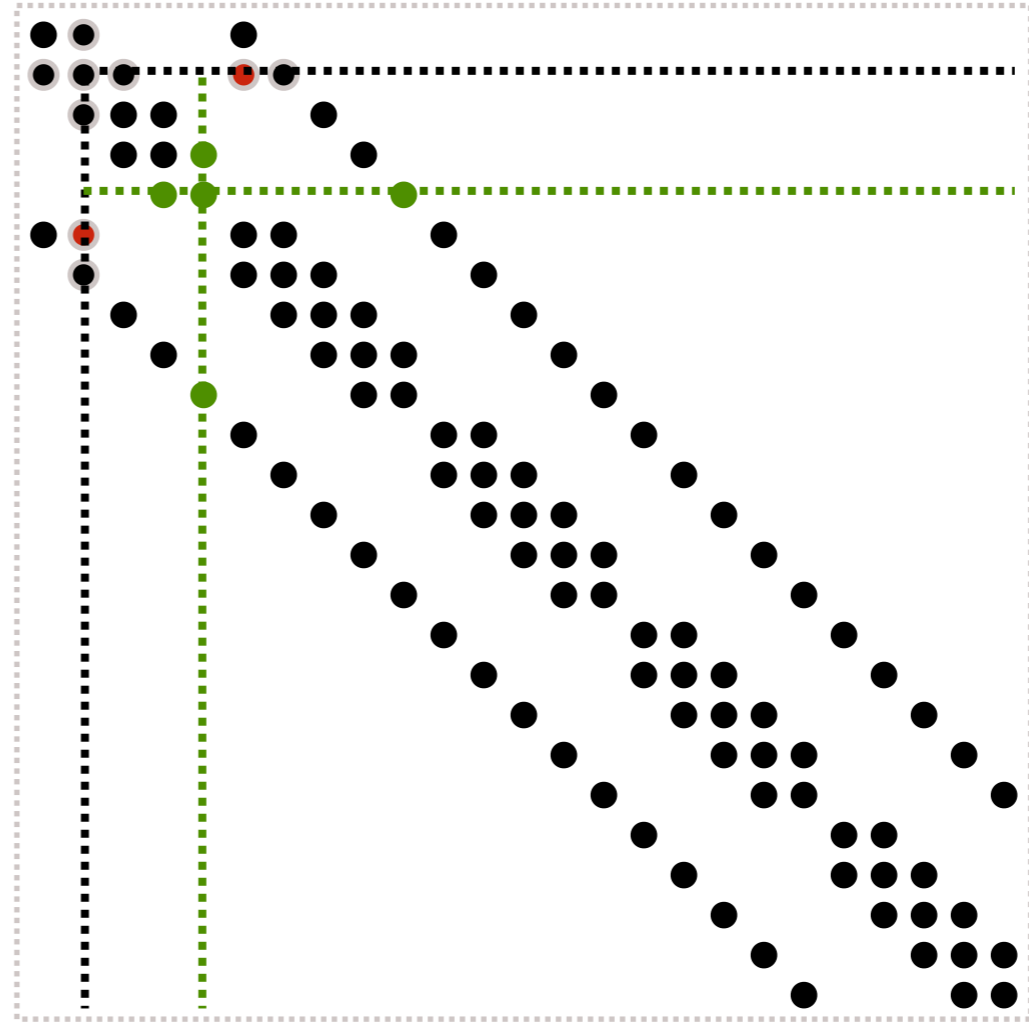
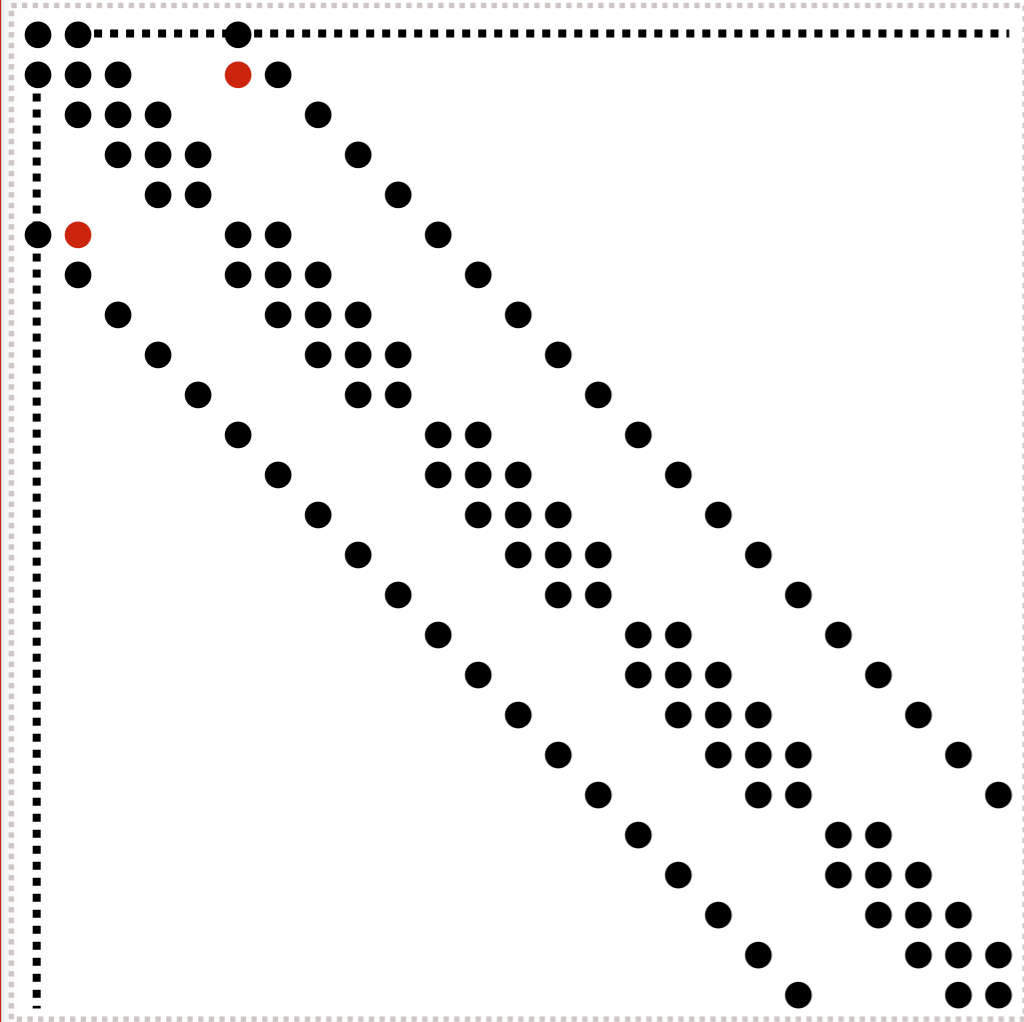
- At elimination stage k :
 - Let $r_i^{(k)} = \text{nnz}(\text{row } i)$, $c_j^{(k)} = \text{nnz}(\text{col } j)$, in uneliminated submatrix
 - Choose pivot entry a_{ij} (*i.e.*, swap row & col) that minimizes:

$$(r_i^{(k)} - 1) \times (c_j^{(k)} - 1)$$

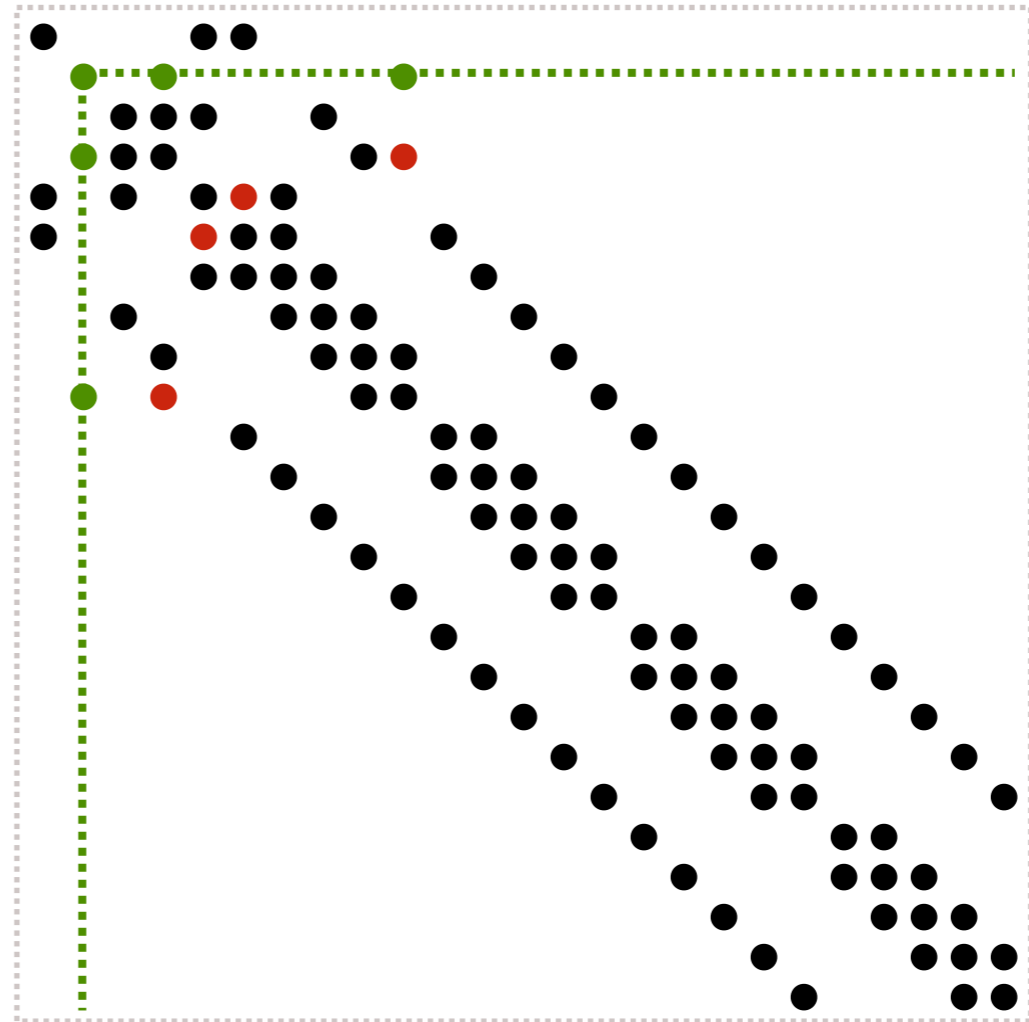
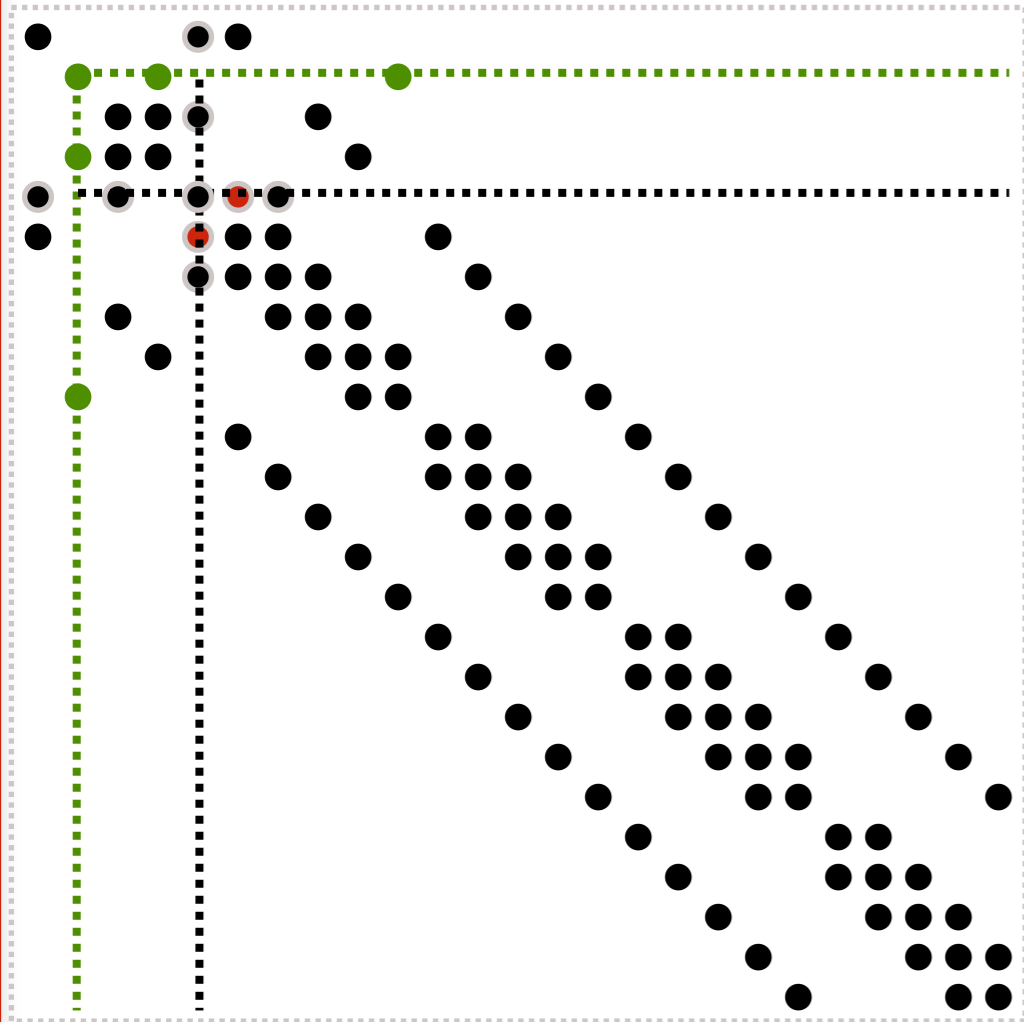
- Don't forget about numerical values, too! (*E.g.*, threshold)



$$a_{ij} = a_{ij} - a_{ik} \cdot a_{kj}$$



$$a_{ij} = a_{ij} - a_{ik} \cdot a_{kj}$$





Markowitz criterion

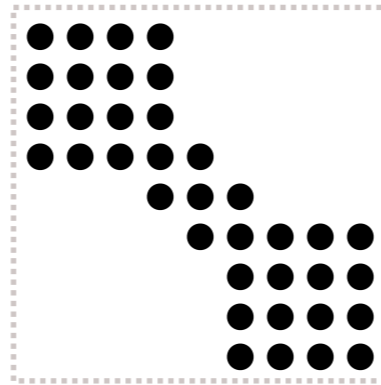
- Generally effective, but has high cost (scan entire uneliminated submatrix)



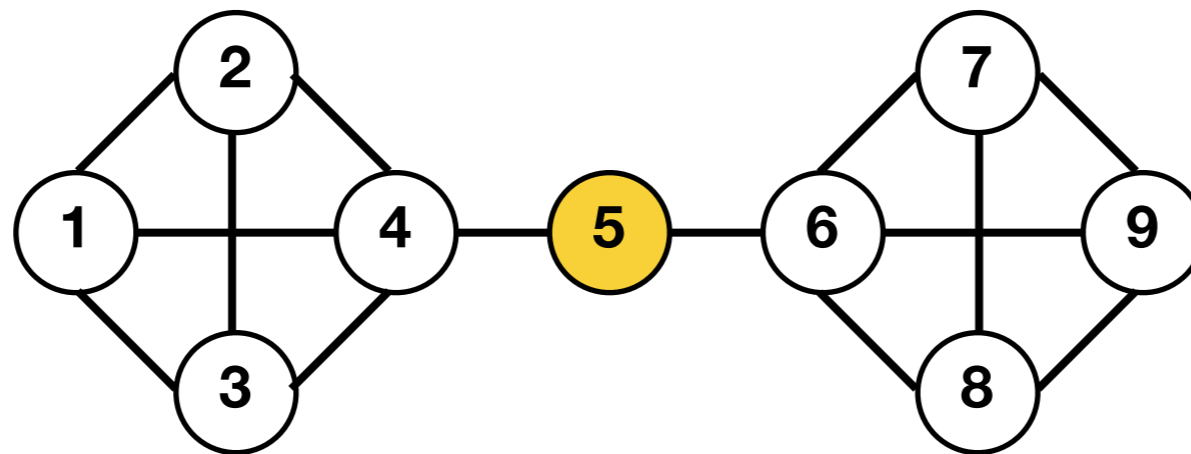
Minimum degree orderings (Tinney & Walker, '67)

- Suppose A is symmetric positive definite
 - Symmetric: Only need to look at $r_i^{(k)}$
 - Positive definite: Don't need to pivot
- Greedy algorithm: At each elimination, pick node with fewest edges
- For unsymmetric matrix, apply to $\text{pattern}(A^T A)$ or $\text{pattern}(A + A^T)$

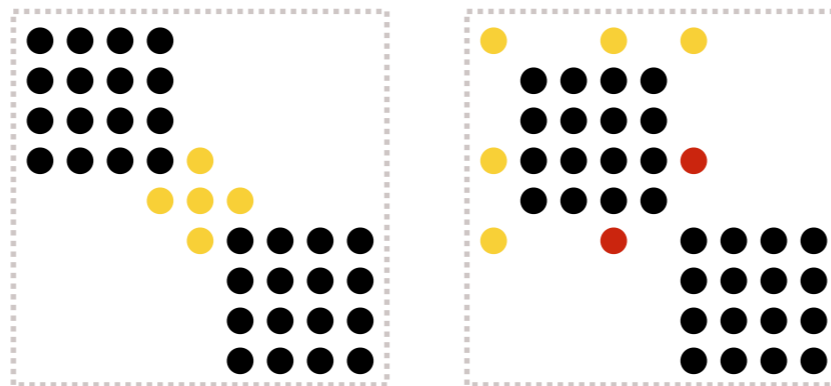
No fill in natural ordering:



Min-degree node: 5



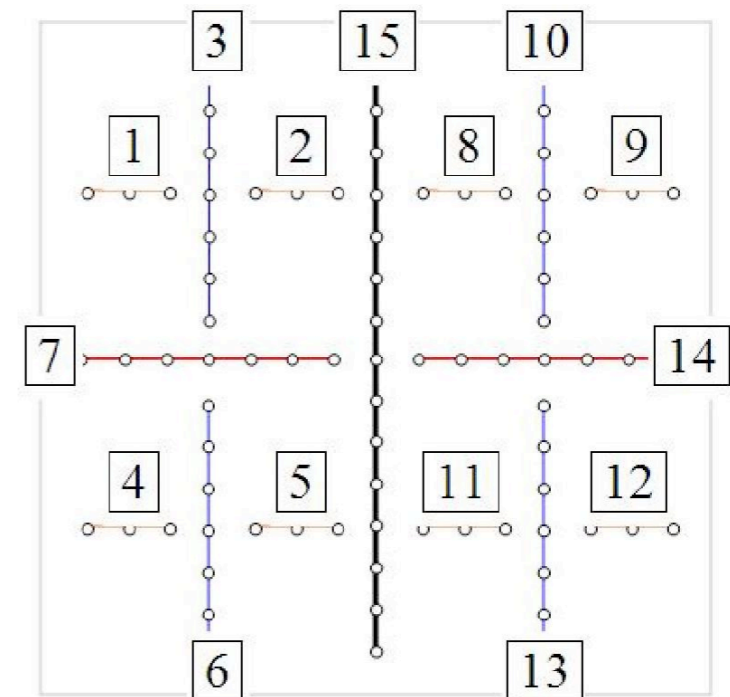
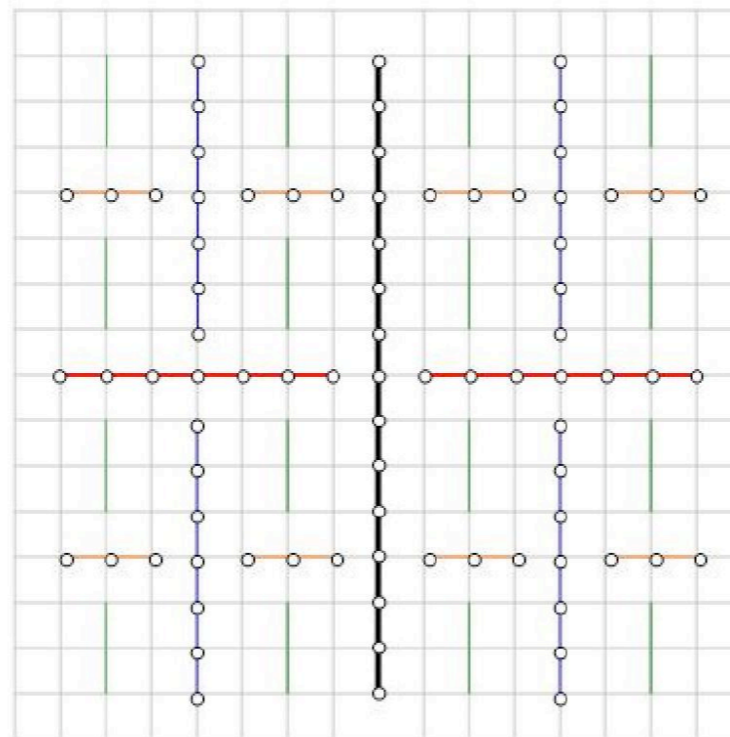
Choosing 5 leads to fill-in:

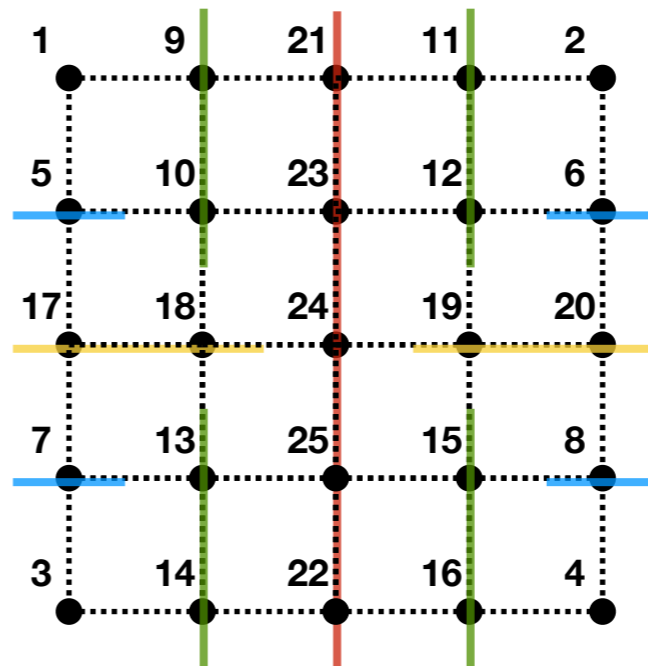
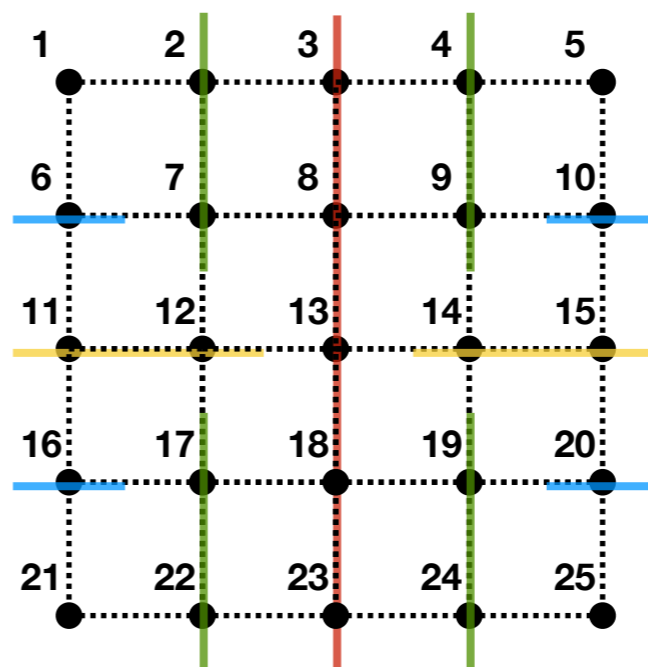
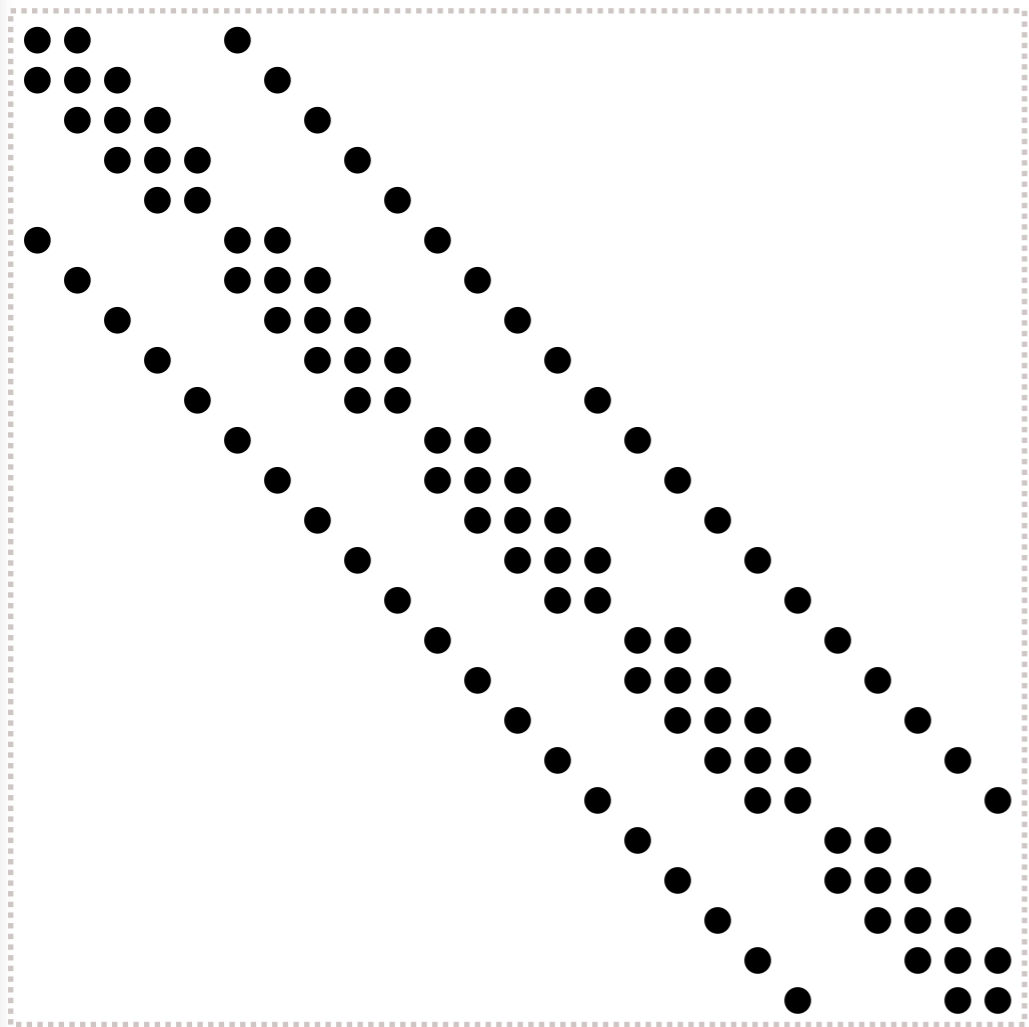


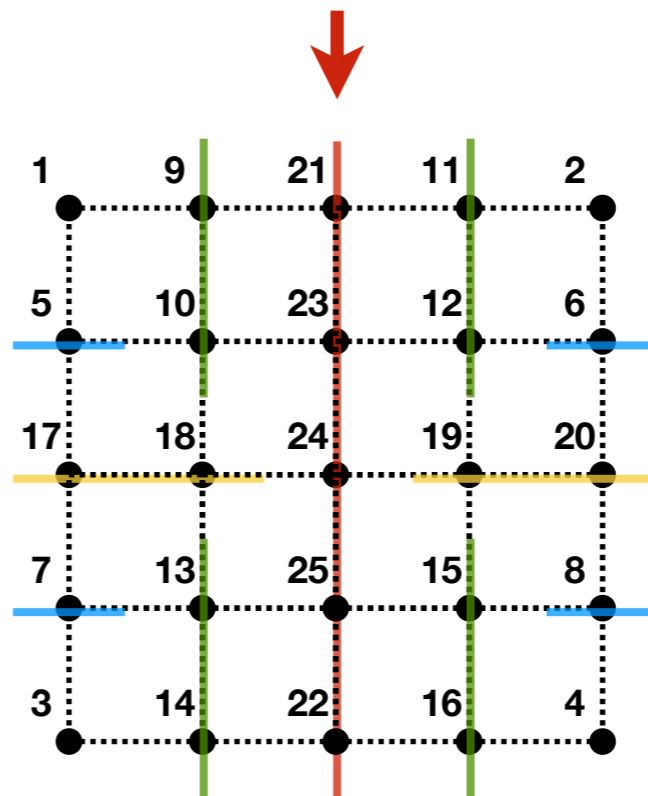
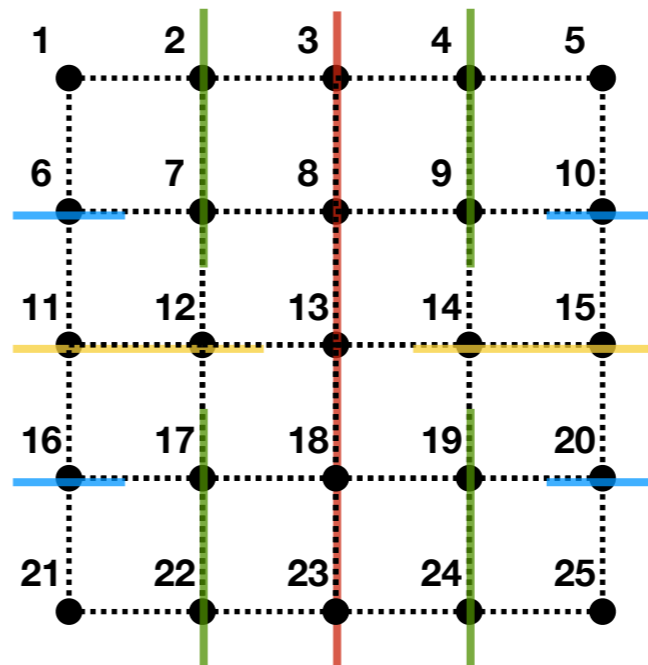
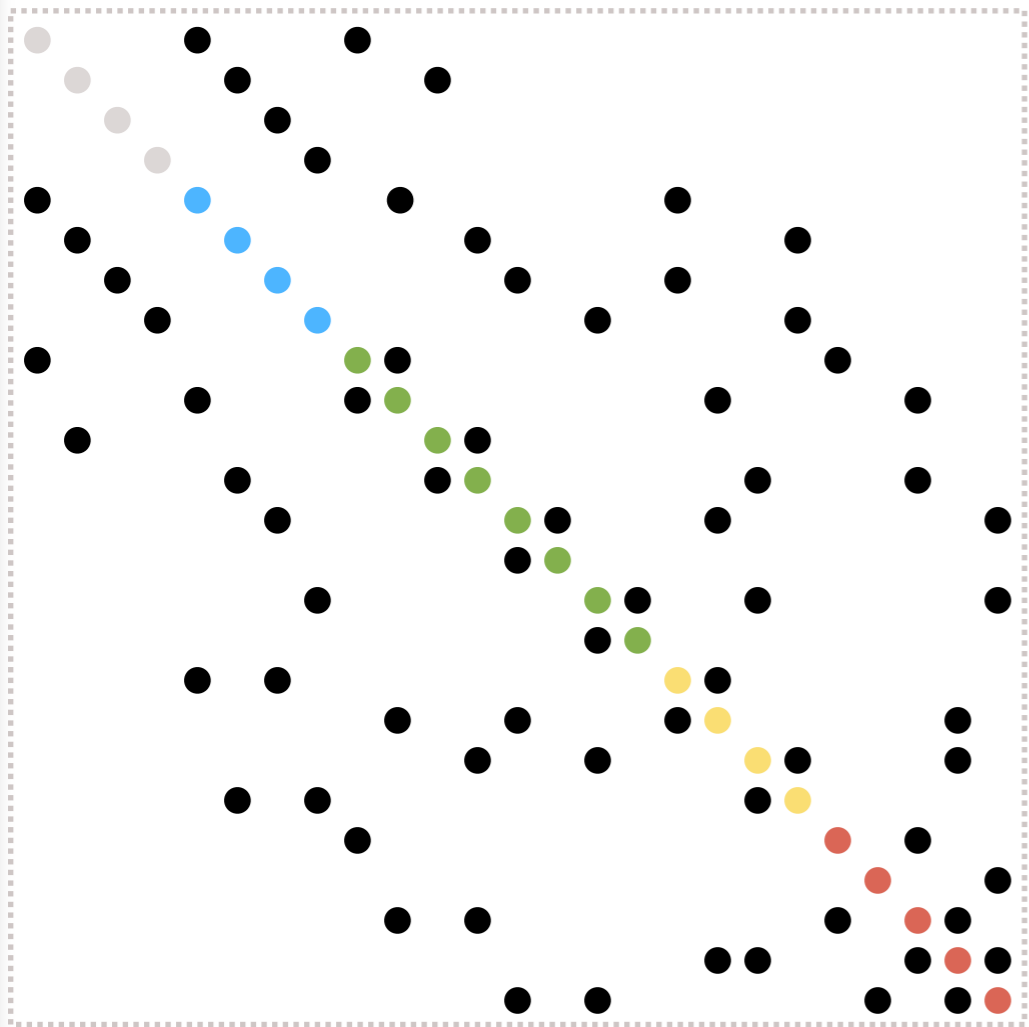


Nested dissection orderings (George '73)

- Originally introduced for the model problem (e.g., 5-point stencil for Poisson)
- Find a **separator** ... **number** it *last* ... **recurse**









Nested dissection orderings

- Given an $n \times n$ grid graph, fill-in is $O(n^2 \log n)$ & flops are $O(n^3)$ [George '73]



Finding good separators

- Multilevel schemes
 - Chaco [Hendrickson & Leland '94]
 - Metis [Karypis & Kumar '95]
- Spectral bisection [Simon, *et al.* '90+]
- Geometric and spectral bisection [Chan, Gilbert, & Teng '94]



Administrivia



Administrative stuff

- **New room** (dumpier, but cozier?): College of Computing Building **(CCB) 101**
- **Accounts**: Apparently, you already have them
- Front-end login node: **ccil.cc.gatech.edu** (CoC Unix account)
 - We “own” **warp43—warp56**
 - Some docs (**MPI**): <http://www-static.cc.gatech.edu/projects/ihpcl/mpi.html>
 - **Sign-up** for mailing list: <https://mailman.cc.gatech.edu/mailman/listinfo/ihpc-lab>



Homework 1:

Parallel conjugate gradients

- Implement a parallel solver for $Ax = b$ (serial C version provided)
 - Evaluate on three matrices: 27-pt stencil, and two application matrices
 - “Simplified:” No preconditioning
 - **Bonus:** Reorder, precondition
- Performance models to understand scalability of your implementation
 - Make measurements
 - Build predictive models
- Collaboration encouraged: Compare programming models or platforms



“In conclusion...”



Backup slides



Landscape of $Ax=b$ solvers

	Iterative $y' = Ay$	Direct $A = LU$	
General A	GMRES, BiCGStab, ...	Pivoting LU	↑ More general ↓
$A = A^T$	Conjugate gradient, ...	Cholesky	
	← Less storage (if sparse) →		More robust

Source: Gilbert (UCSB)