



Improving the performance of direct solvers for sparse symmetric indefinite linear systems

Jonathan Hogg and Jennifer Scott
STFC Rutherford Appleton Laboratory

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Sparse indefinite system

Solve

$$Ax = b$$

with A large, sparse, symmetric and **indefinite**.

For example, systems arise in a number of important applications

$$\begin{pmatrix} H & B^T \\ B & \delta I \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} b \\ c \end{pmatrix}$$

(see next talk).

Direct method

- ▶ Compute explicit factorization

$$A = LDL^T$$

where L (unit) is lower triangular, D (block) diagonal.

- ▶ Complete solution by performing **triangular** solves.

Test examples

In this talk, we focus on **tough indefinite** systems only.

Examples from University of Florida Sparse Matrix Collection.

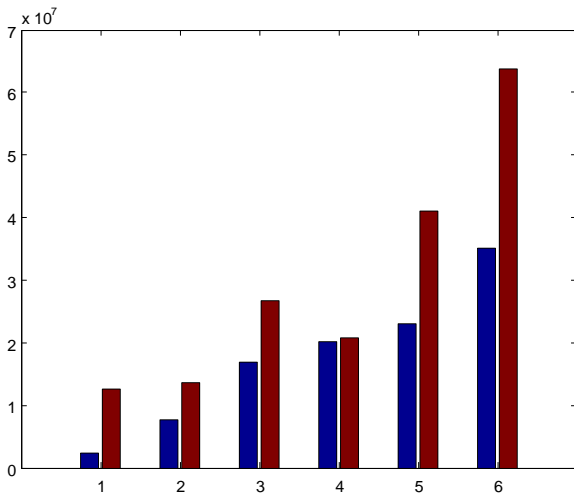
| Identifier | n | $\text{nz}(A)$ | $\text{nz}(L)$ | flops |
|---------------------------|---------|----------------|--------------------|-----------------------|
| 1. GHS_indef/ncvxqp1 | 12 111 | 73 963 | 1.68×10^6 | 7.28×10^8 |
| 2. GHS_indef/bratu3d | 27 792 | 173 796 | 6.28×10^6 | 4.42×10^9 |
| 3. GHS_indef/cont-300 | 180 895 | 988 195 | 1.17×10^7 | 2.96×10^9 |
| 4. GHS_indef/d_pretok | 182 730 | 1 641 672 | 1.46×10^7 | 5.06×10^9 |
| 5. TSOPF/TSOPF_FS_b300_c2 | 56 814 | 8 767 466 | 2.14×10^7 | 8.96×10^9 |
| 6. TSOPF/TSOPF_FS_b300_c3 | 84 414 | 13 135 930 | 3.31×10^7 | 1.43×10^{10} |

* $\text{nz}(L)$ and flops are for positive definite equivalent with nested dissection ordering

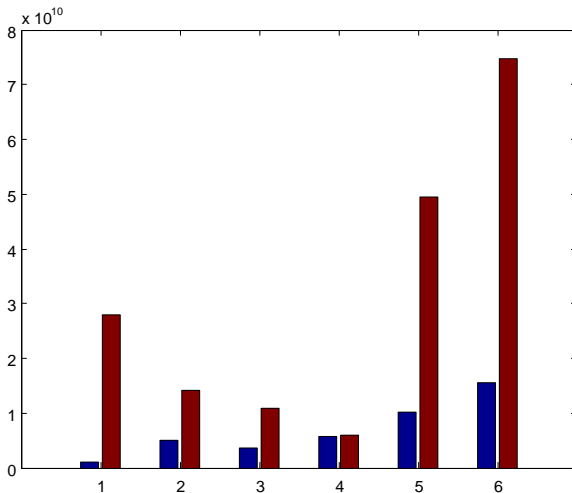
Let's look at the problem ...

- ▶ Run indefinite solver.
- ▶ Put large entries on diagonal and run positive definite solver.
- ▶ Compare the performance.

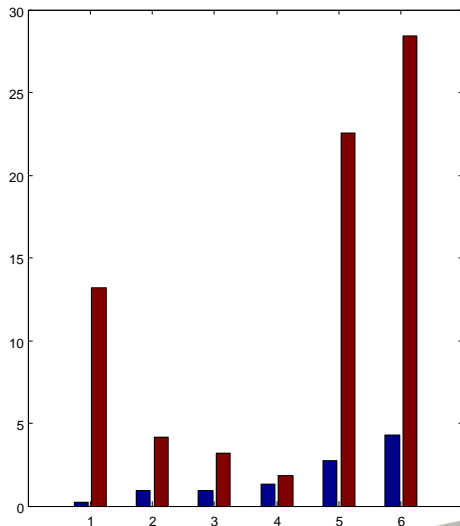
Positive definite versus indefinite $nz(L)$



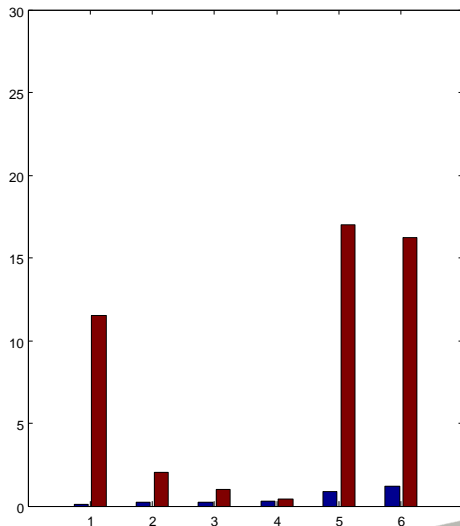
Positive definite versus indefinite flops



Positive definite versus indefinite time (serial)



Positive definite versus indefinite time (8 cores)



Why the differences?

- ▶ May not be able to use pivot sequence in supplied order.
- ▶ Rejected pivots \Rightarrow more flops and denser factors.
- ▶ Extra data movement.
- ▶ Less scope for parallelism.

Our aim: improve indefinite performance without **compromising stability** or the computation of the inertia.

Note: indefinite solver designed on assumption of few rejected pivots so we need to **reduce rejected pivots**.

The heart of a direct solver

Elimination (pivot) order **pre-selected** to reduce fill in.

At each stage of factorization, the solver works with **dense** $m \times m$ submatrix ($m \ll n$)

$$\begin{pmatrix} F_1 & F_2^T \\ F_2 & E \end{pmatrix}.$$

Only rows/columns of F_1 are ready for elimination.

- ▶ Factorization: $F_1 = L_1 D L_1^T$
- ▶ Solve: $L_2 = F_2 L_1^{-1}$. (L_1, L_2) are computed columns of L .
- ▶ Update: $E \leftarrow E - L_2 (L_2 D)^T$ (BLAS 3).

Achieving good solver performance

Key is efficiency of partial **dense** factorizations.

In positive-definite case:

- ▶ Pivots can be selected from **diagonal** of F_1 in turn ... allows data structures to be **fixed** before factorization commences (simplifies code and reduces data movement).
- ▶ Factorization of F_1 can begin **before** all updates to F_2 have been made (improves scope for parallelism ... work with block tasks).

Indefinite case

For good performance want to use the supplied pivot sequence.

But

- ▶ Zero (or small) diagonal entries cannot be used as pivots.
- ▶ Necessary to incorporate **numerical pivoting**.
- ▶ 1×1 and 2×2 pivots needed to retain symmetry.
- ▶ Standard approach: threshold partial pivoting.

Threshold partial pivoting

Involves checking that the candidate pivot is 'large' compared to the other entries in its column(s).

Test for 1×1 pivot:

$$|a_{q+1,q+1}| > u \max_{q+1 < i \leq n} |a_{i,q+1}|.$$

Corresponding test for 2×2 pivot:

$$\left| \begin{pmatrix} a_{q+1,q+1} & a_{q+1,q+2} \\ a_{q+1,q+2} & a_{q+2,q+2} \end{pmatrix}^{-1} \right| \begin{pmatrix} \max_{q+2 < i \leq n} |a_{i,q+1}| \\ \max_{q+2 < i \leq n} |a_{i,q+2}| \end{pmatrix} < \begin{pmatrix} u^{-1} \\ u^{-1} \end{pmatrix}.$$

Threshold partial pivoting

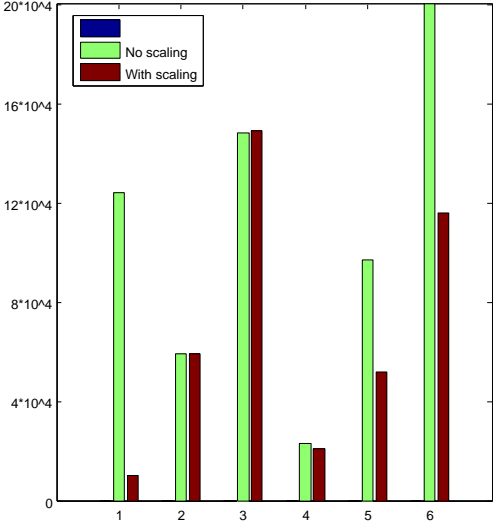
- ▶ u is threshold parameter, typical default value 0.01. This was used in our earlier tests.
- ▶ Larger u favours stability; smaller u means fewer rejects.
- ▶ If a pivot fails test, may have to be delayed until later in factorization. **This is what we want to avoid.**

How can we reduce delays?

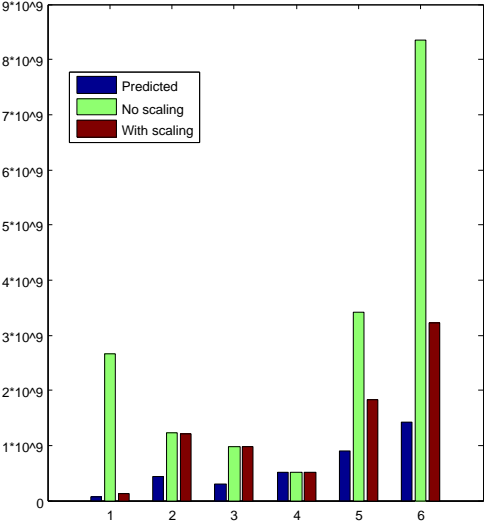
First remedy: scaling

- ▶ In particular, use symmetrized version of MC64 (Duff and Koster, Duff and Pralet), which is based on maximum weighted matchings.
- ▶ Entries in scaled matrix **SAS** that are in the matching have absolute value 1 while rest have absolute value ≤ 1 .

Effect of scaling on delayed pivots



Effect of scaling on flops

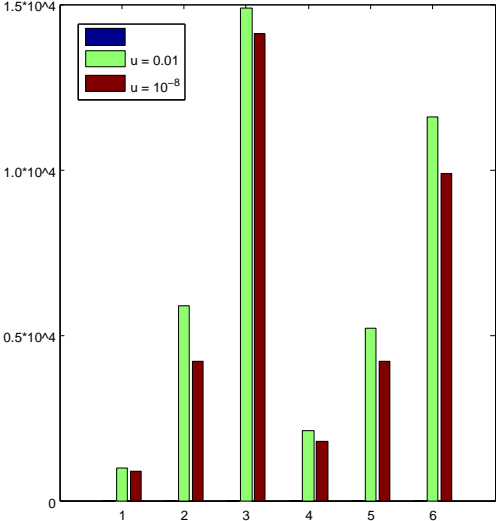


Next remedy: small u

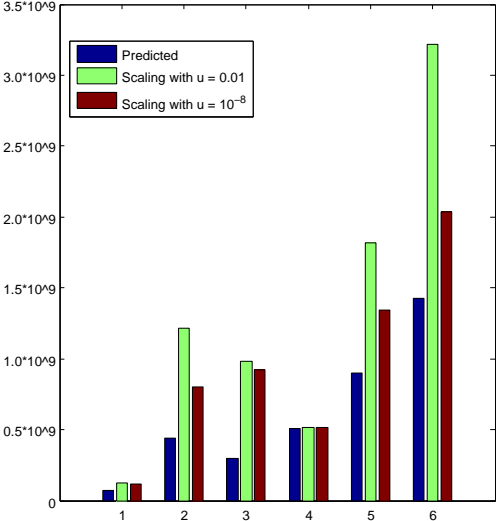
- ▶ Use a smaller threshold u to weaken stability test.
- ▶ If necessary, use iterative refinement or FGMRES to recover accuracy.
- ▶ If u too small, entries of L can become unbounded.
- ▶ Here we use $u = 10^{-8}$.

Note: in this and all other experiments, we prescale.

Effect of small u on delayed pivots



Effect of small u on flops



Story so far:

- ▶ Good scaling can really help.
- ▶ Small u may also help ... but may need additional solves.

So what else?

Try preselecting 2×2 pivots?

An approach that does this is **MA47** (Duff and Reid):
sparse indefinite solver that uses structured 2×2 pivots.

Experiments show can work really well for matrices of form

$$\begin{pmatrix} 0 & B^T \\ B & 0 \end{pmatrix}$$

but more generally leads to **much denser** factors
(without eliminating delayed pivots).

What else? Constraint ordering

Proposed (Bridson) for systems of form

$$\begin{pmatrix} H & B^T \\ B & C \end{pmatrix}$$

with H symmetric positive definite, B rectangular, and C symmetric positive semi-definite.

Only order a C -node after its H -node neighbours have been ordered.

Advantages: able to use modified Cholesky code with no delays (although stability not guaranteed, works in practice).

But: too restrictive so that generally **much denser factors** and **more flops** (can require order of magnitude more flops).

So what else? Matching orderings

Aim: permute large off-diagonal entries a_{ij} close to diagonal so that 2×2 block

$$\begin{pmatrix} a_{ii} & a_{ij} \\ a_{ij} & a_{jj} \end{pmatrix}$$

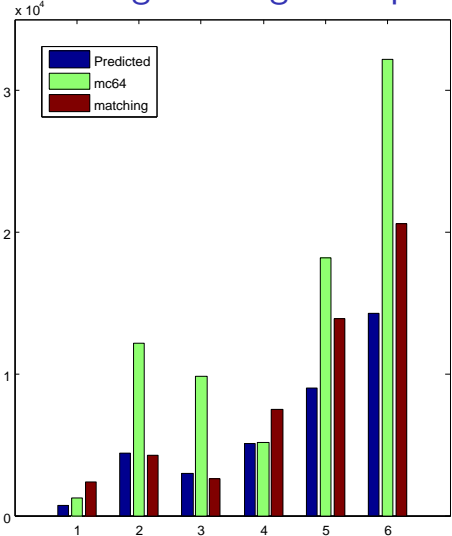
is potentially good 2×2 candidate pivot.

Use cycle structure of permutation associated with **unsymmetric maximum weighted matching** \mathcal{M} to obtain such a permutation

(Duff and Gilbert, also Duff and Pralet, Schenk *et. al.*).

Combines **scaling with ordering** in single step.

Effect of matching ordering on flops



Effect of matching ordering

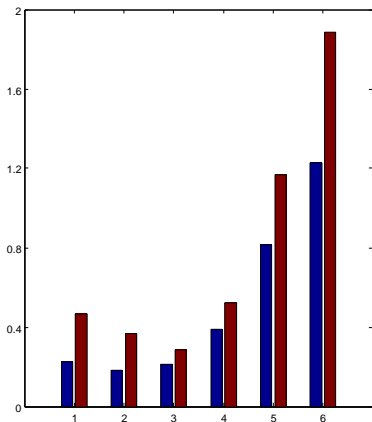
- ▶ Predicted values in last plot were for default ordering.
- ▶ Predicted values for matching ordering are typically 50 to 100% greater.

But for the matching ordering, (almost) **no delays** and, most importantly,

predicted flops (and $nz(L)$) \approx actual flops (and $nz(L)$)

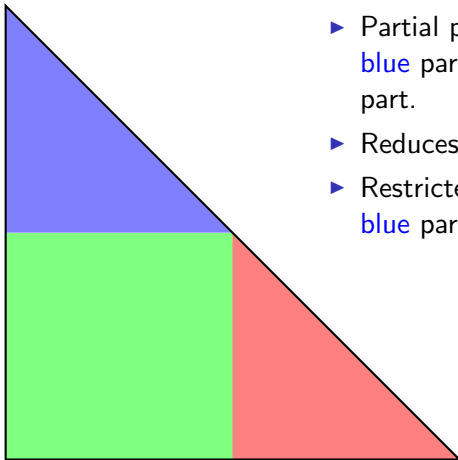
- ▶ Also, matching ordering **stable** (single step of refinement sufficient with $u = 0.01$ and 10^{-8}).

Positive definite versus indefinite time (matching ordering)



Difference now is down to pivot searches that restrict parallelism.

Restricted pivoting



- ▶ Partial pivoting — when factorizing **blue** part, takes into account **green** part.
- ▶ Reduces scope for parallelism.
- ▶ Restricted pivoting: just pivot within **blue** part.

Restricted pivoting

- ▶ Found that used just with scaling can lead to numerical instability (accuracy not recovered by refinement).
- ▶ If combined with matching ordering, works well for many problems
- ▶ **But** does not give stable factorization in all cases so **not** recommended for black box solver (note: it is used within PARDISO).



Concluding remarks

- ▶ Strategies explored to reduce delayed pivots and hence improve performance of direct solvers for tough (non-singular) indefinite problems.
- ▶ Robust approach: matching ordering (used with scaling), combined with threshold partial pivoting.
- ▶ **But matching is expensive so only use on tough problems.**
- ▶ Still requires access to whole pivot column and so scope for parallelism less than in positive-definite case.
- ▶ For many problems can get away with cheaper strategies but for a robust solver, matching is a good fall back strategy.

More details, further suggestions and lots of results available in technical report [RAL-TR-2012-009](#).

Thank you!

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