

Estimation of the Condition Number of a Square Matrix with Hager's Method

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Abstract

The condition number of a matrix quantifies how accurately the solution to $Ax = b$ is computed. More specifically, it equals the maximum by which a relative error in the right-hand side b can be magnified into the relative accuracy of the solution. In this study we examine Hager's method for estimating the condition number of a matrix when using the one-norm and infinity norm.

Background Information

Conditioning

Consider solving a linear system of equation

$$Ax = b$$

In reality, the input is not accurate, so what we actually solve maybe the equation below

$$A(x + \delta x) = b + \delta b$$

We want to explore how the relative error on b can effect the relative error on x

$$\frac{\|\delta x\|}{\|x\|} \leq \kappa(A, b, \delta b) \frac{\|\delta b\|}{\|b\|}$$

Definitions

1 Vector norm: For vector

$v = (v_0, v_1 \dots v_{n-1})^T$ define l_p norm as

$$\|v\|_p = \left(\sum_{i=0}^{n-1} (v_i)^p \right)^{1/p}$$

2 Matrix norm: For matrix $A_{m \times n}$, define p norm of a matrix as

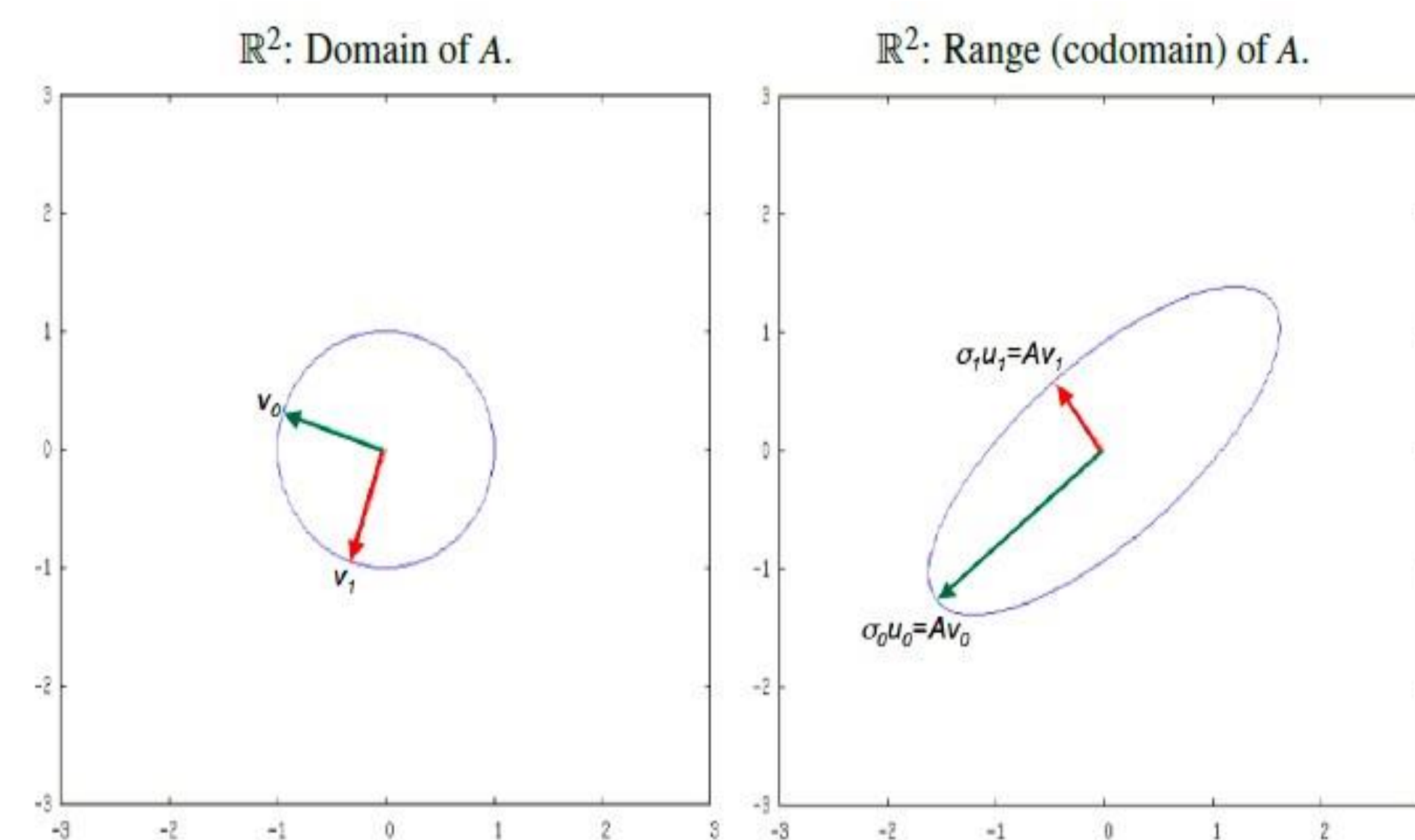
$$\|A\|_p = \max \frac{\|Ax\|_p}{\|x\|_p}$$

Theorem:

For any matrix A , we have

$$\|A\|_1 = \|A^T\|_\infty$$

Condition Number



$\|A\|$ Maximum Magnification

$\frac{1}{\|A^{-1}\|}$ Inverse of the Minimal Magnification

The ratio :the effect of small change at rhs has on the lhs

We define the **condition number** as

$$\kappa(A) = \|A\| * \|A^{-1}\|$$

Methodology and Algorithm

Motivations

- (1) Computing Inverse matrix expensive $O(n^3)$
- (2) LAPACK require Pass in 1-norm when computing Condition Number

```
SUBROUTINE DGECON( NORM, N, A, LDA, ANORM, RCOND, WORK, IWORK, INFO )
```

Condition Number function header in LAPACK

- (3) GOTO Considered Harmful

```
$      GO TO 20  
CALL DRSCL( N, SCALE, WORK, 1 )  
END IF  
GO TO 10  
END IF
```

GOTO In LAPACK Routine

Algorithm for Computing L_1 norm

Input: Matrix A , dimension n

(0) Compute $\|A\|_1 = \max \sum_{i=1}^n \|A_{ij}\|_1$

(1) Pick the vector $x = \frac{1}{n} (1, 1, 1 \dots 1)^T$

(2) Factor $A = LU$

(3) Solve $Lb = x$ and $Uy = b$

(4) Set $v = \text{sign}(A^{-1}x) = \text{sign}(y)$

(5) Solve $U'd = y$ and $L'g = d$

(6) If $\|g_\infty\| < g^T x$, then estimate as
 $\text{est}(\|A^{-1}\|_1) = \|A^{-1}x\|_1$

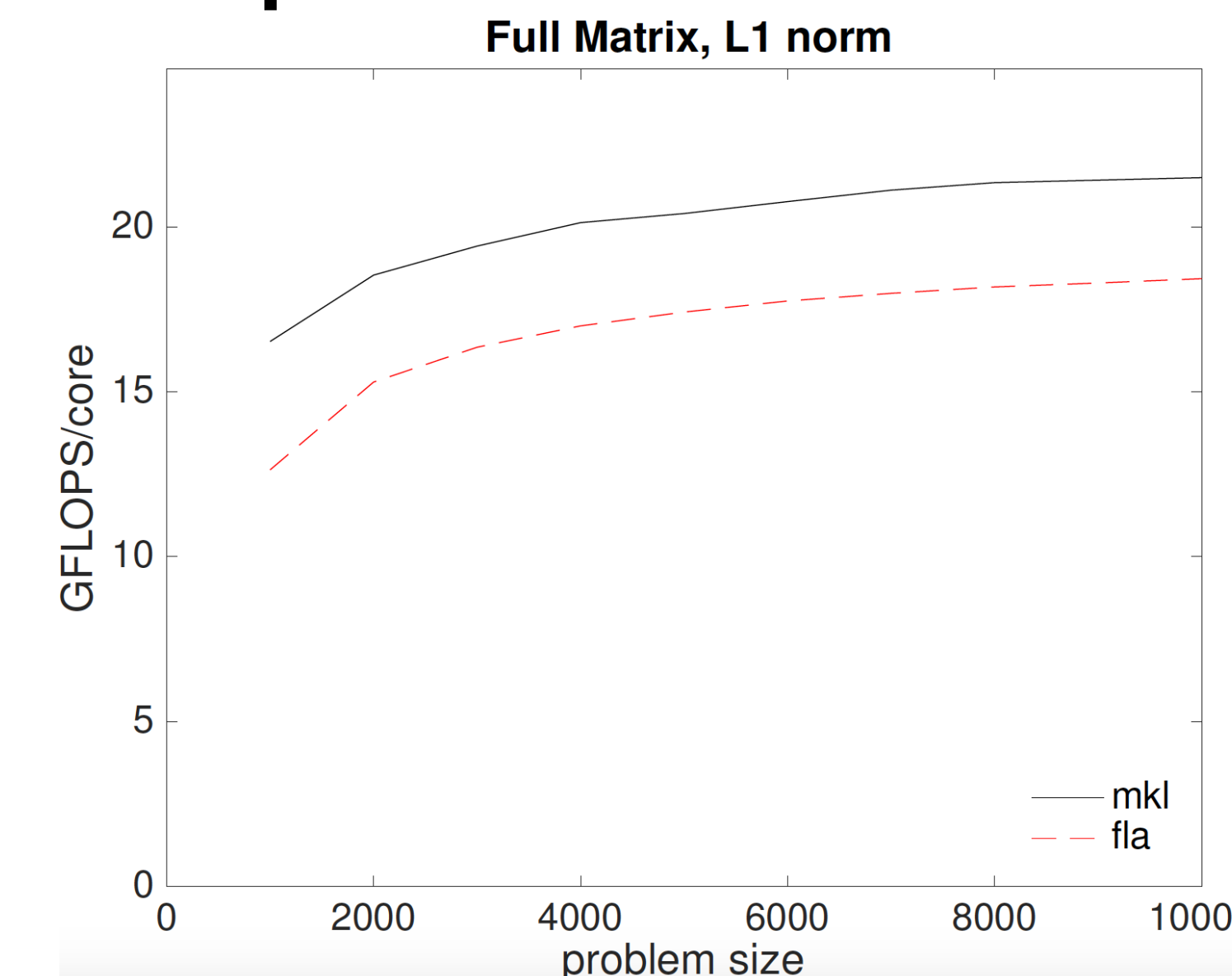
(7) else set $x = e_j$ where $g_j = g_\infty$ and repeat from (3)

(8) $\kappa(A) = \|A\| * \|A^{-1}\|$

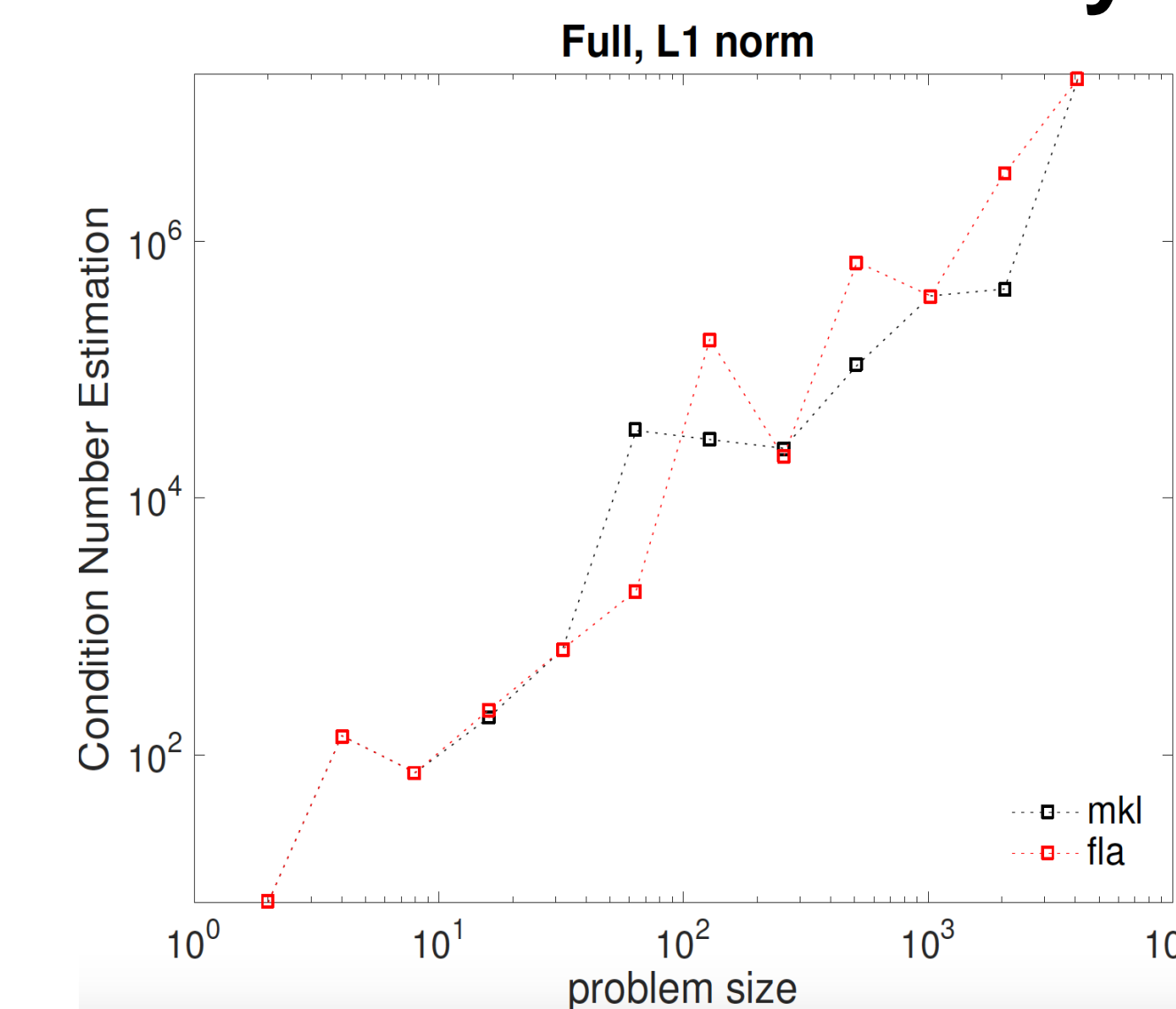
Performance and Accuracy

All data coming from TACC Stampede System (Intel® Xeon® CPU E5-2680, Sandy Bridge, 23.76 GFLOPS peak for single-core, 21.6 GFLOPS/core peak for multi-core) processor using Intel C compiler version 15.0.2 with optimization flag -O2.

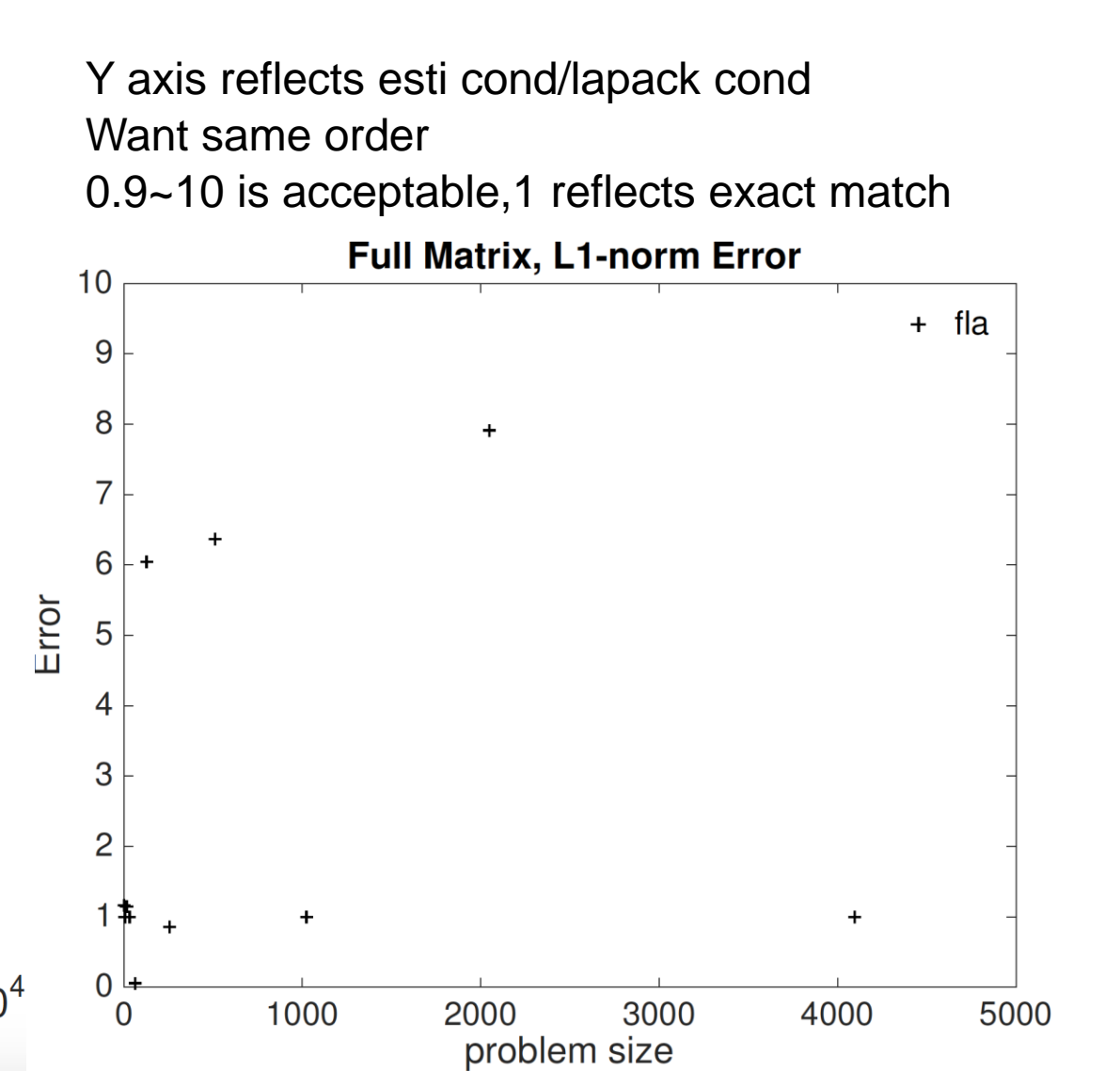
Full Square Matrix Performance



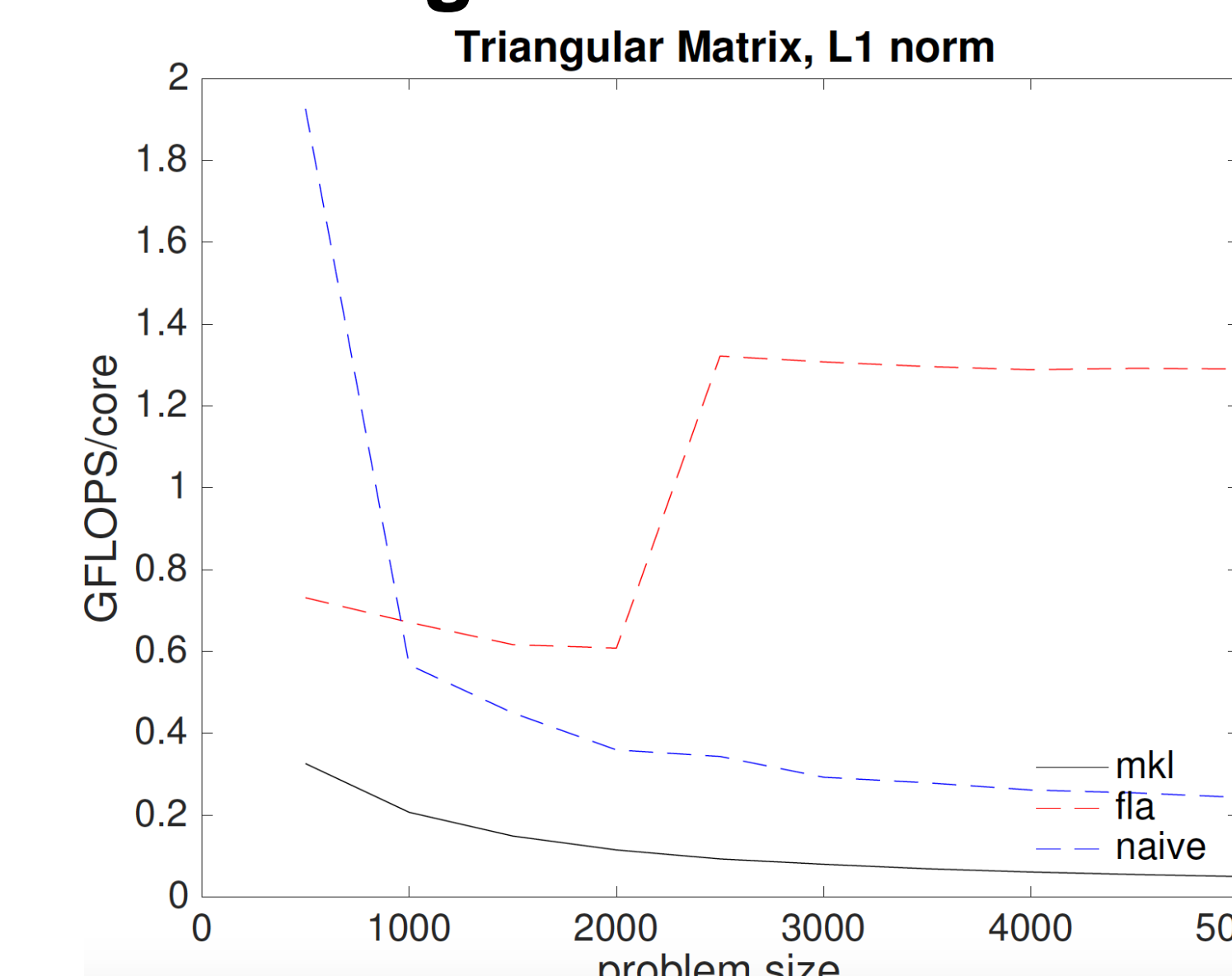
Full Matrix Accuracy



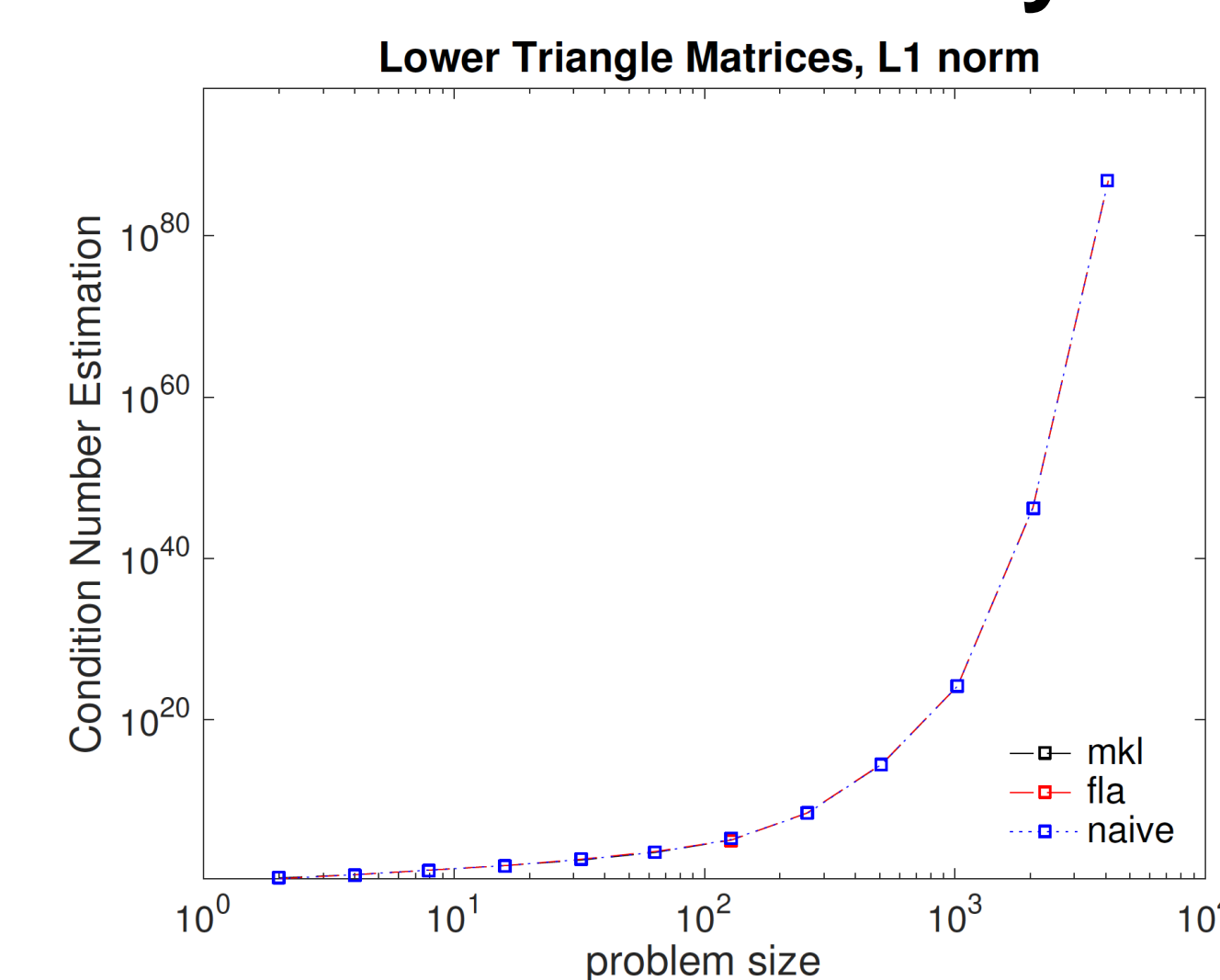
Error



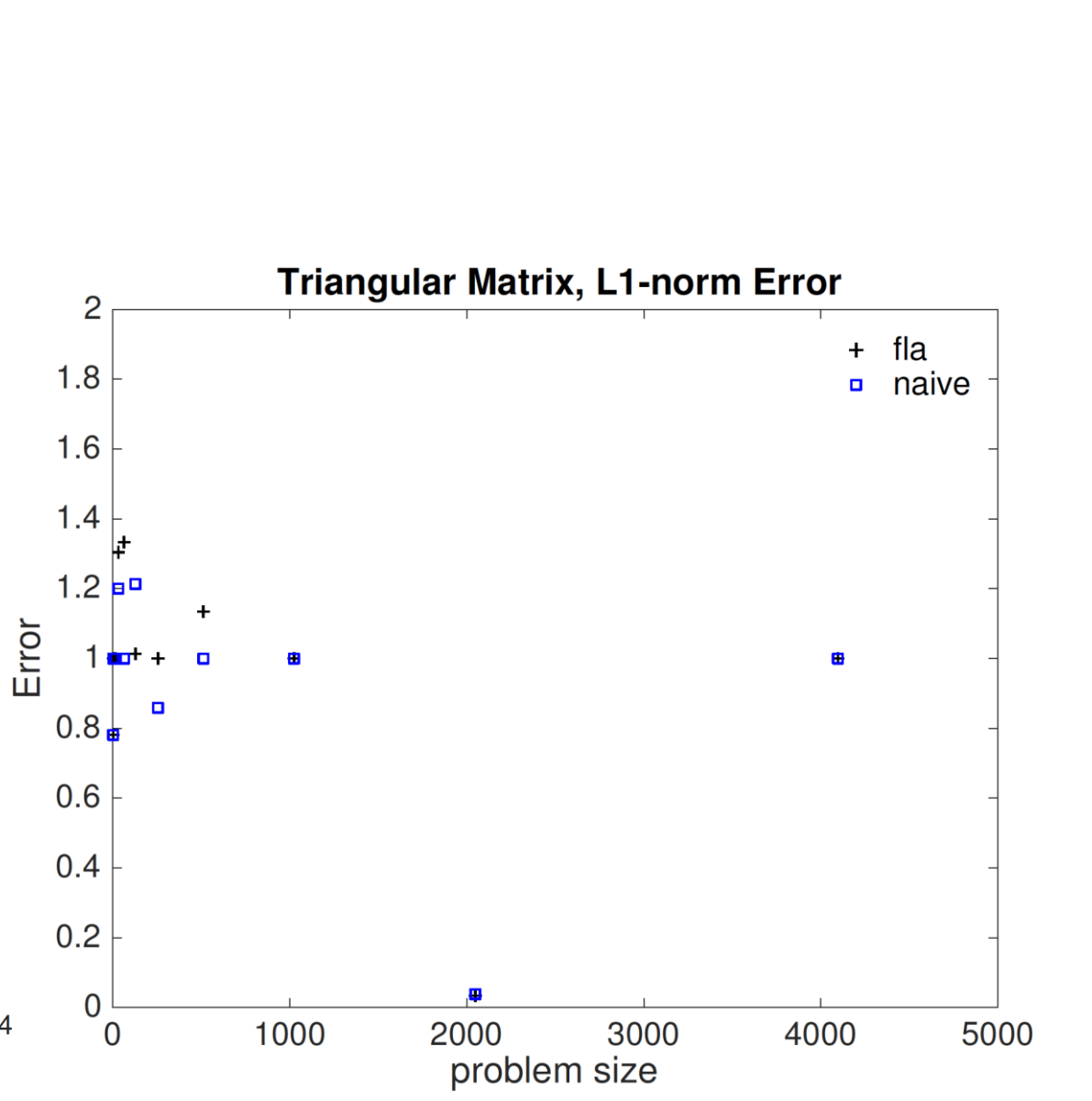
Lower Triangular Matrix Performance



Lower Triangular Matrix Accuracy



Error



Conclusion

Performance

Full Matrices

MKL Better than FLA

Triangular Matrices

Naïve C extremely good when small

FLA good in general.

MKL generally stable

Accuracy

Full Matrices

FLA estimates good

Triangular Matrices

Generally good with bad on one of them

Future Work

- 1 Extend to complex matrices
- 2 Extend to full matrices of C implementation
- 3 Find the condition number under l_2 norm
- 4 Deal with both overflow and underflow

Reference

<https://github.com/flame/blis>

<https://github.com/flame/libflame>

<http://www.netlib.no/netlib/lapack/double/dgecon.f>

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