

ExaNLA Survey Response Report

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Submission Details

Library Name: PLASMA
Version: 25.5.27
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Organization: MIT Lincoln Lab

Selected NLA Operations

1. Symmetric/Hermitian Eigenvalue Problems
2. Matrix-Matrix Multiplication (GEMM)
3. Cholesky Factorization

1. Codes Information

Basic information about your application/simulation codes.

Library Name:
PLASMA

Current Version:
25.5.27

Contact Information:
Not specified

Name:
Piotr

Email:
luszczek@icl.utk.edu

Organization:
MIT Lincoln Lab

Application Domain:
Not specified

What is the primary application domain of your codes?:
Other: Numerical Linear Algebra

Materials Science:
Not specified

What are the main functionalities of your code?:
Not specified

If you selected "Other", please specify::
Not specified

Climate/Weather Modeling:
Not specified

What are the main functionalities of your code?:
Not specified

If you selected "Other", please specify::
Not specified

Fluid Dynamics:
Not specified

What are the main functionalities of your code?:
Not specified

If you selected "Other", please specify::
Not specified

Other Domain Functions:
Not specified

What are the main functionalities of your code?:
Linear systems, least squares, eigenvalue pairs and singular triplets

Use Case Information:
Not specified

Does your codes have multiple distinct use cases?:
Yes, multiple distinct use cases

Which use case are you describing in this submission?:
linear system solve

Library Description:
The PLASMA library solves linear systems, least squares problems, and also computes either eigenvalue pairs or singular triplets. The majority of BLAS functionality is also provided.

2. Matrix-Matrix Multiplication (GEMM)

Matrix-Matrix Multiplication (GEMM):
Yes

Matrix Properties:
Not specified

Matrix Structure:
Dense matrices, Banded matrices, Triangular matrices, Tall-and-skinny matrices

Matrix Distribution:
Not specified

Matrix Storage Format:
Dense (column-major/row-major), Multiple formats (conversion as needed), Other: tile block

Which types of matrix multiplications do you perform?:
Standard multiplication (AB), Scaled multiplication ($\pm AB$), A Full GEMM ($\pm AB + {}^2C$), Transpose multiplication ($A @ B$, $AB @$) multiplication ($A^\dagger B$, AB^\dagger)

Typical Dimensions:
Not specified

Matrix Size Range:
Very Large (10,000 - 100,000)

Typical Matrix Shapes:
Square matrices ($m \approx n \approx k$), Tall-skinny matrices ($m \gg n$), Wide-short matrices (m small, $n \gg k$), Block-outer product (k small, m and n large), Block-inner product (m and n small, k large), General rectangular (no dominant pattern), Varies significantly by operation

Batch Size:
Not applicable

Distributed-Memory NLA Library Usage:

Not specified

General Distributed Memory Libraries (CPU/GPU):

Custom distributed implementation

Special/Advanced Implementations:

Fused operations (e.g., GEMM + bias, GEMM + activation, or custom fused kernels)

Are there any NLA libraries you are interested in using (but have not yet adopted)?:

Not specified

Future Requirements:

Not specified

Desired Features:

Better mixed precision support, Auto-tuning capabilities

Benchmarking Requirements:

Not specified

Benchmark Input Types:

Synthetic / random matrices

Can You Provide Data or Mini-apps?:

Yes, both matrices and mini-apps

Scaling Requirements:

Both strong and weak scaling needed

Working Precision:

Single precision (32-bit), Double precision (64-bit), Mixed precision (e.g., FP32 multiplication with FP64 accumulation)

3. Cholesky Factorization

Cholesky Factorization ($A = LL^T$):

Yes

Diagonal Dominance:

Strictly diagonally dominant

Condition Number:

Varies widely / Not known

Matrix Properties and Structure:

Dense

Matrix Distribution:

Not specified

Matrix Storage Format:

Dense (column-major/row-major), Other: tile block

Matrix Dimensions:

Very large (100,000 – 1,000,000)

Factorization Tolerance:

Machine precision

Working Precision:

Double precision (64-bit), Single precision (32-bit)

Workload Characteristics:

Not specified

Computation Pattern: capability or capacity:

Large-scale single factorizations (e.g., one large matrix at a time, using significant computational resources)

Distributed-Memory Dense NLA Library Usage:
Not specified

Currently Used Libraries:
Not specified

Interested in Using, but not currently using:
Not specified

Specialized Libraries (Sparse/Structured/Hierarchical):
Not specified

Currently Used Libraries:
Not specified

Interested in Using, but not currently using:
Not specified

Benchmarking Requirements:
Not specified

Benchmark Input Types:
Synthetic / random matrices

Can You Provide Data or Mini-apps?:
Yes, both matrices and mini-apps

Scaling Requirements:
Both strong and weak scaling needed

4. Standard Eigenvalue Problems ($Ax = \lambda x$)

Symmetric/Hermitian

Primary Use Cases:
Kohn–Sham equations (standard DFT), GW quasiparticle calculations, Bethe–Salpeter equation (Tamm-Dancoff approximation), Tight-binding models

Matrix Properties and Structure:
Dense

Matrix Properties:
Not specified

Matrix Distribution:
Not specified

Matrix Storage Format:
Dense (column-major/row-major), Other: tile block

Positive definiteness:
Varies depending on the problem

Eigenvalue distribution:
Varies

Problem Scale:
Very Large (100,000 - 1,000,000)

Computation Requirements:
Not specified

Percentage of eigenvalues:
Varies

What to compute:
Varies

Eigenvalue location:
Varies

Required tolerance/precision:

Not specified

Residual tolerance type:

Absolute residual ($\|Ax - x\|$)

Absolute residual tolerance:

Machine precision

Relative residual tolerance:

Not specified

Hybrid residual tolerance:

Not specified

Orthogonality tolerance:

Machine precision

Working Precision:

Single precision (32-bit), Double precision (64-bit)

Workload Characteristics:

Not specified

Computation Pattern: capability or capacity:

Large-scale single problems (e.g., one large matrix at a time, using significant computational resources)

Distributed-Memory NLA Library Usage:

Not specified

Distributed-Memory Dense Linear Algebra:

Not specified

Iterative Eigensolvers:

Not specified

High-Level & Interface Libraries:

Not specified

Are there any NLA libraries you are interested in using (but have not yet adopted)?:

Not specified

Benchmarking Requirements:

Not specified

Benchmark Input Types:

Synthetic / random matrices

Can You Provide Data or Mini-apps?:

Yes, both matrices and mini-apps

Scaling Requirements:

Both strong and weak scaling needed

5. Generalized Eigenvalue Problems ($Ax = \lambda Bx$)

Symmetric/Hermitian A, SPD B

Matrix Structure:

A is dense, B is dense

Reduction to Standard Eigenproblem (using B):

Not specified

Reduction to Standard Eigenproblem:

Yes, always

Reduction Method:

Cholesky factorization of B ($B = LL^T$ or $B = L^*L$)

Matrix Properties:

Not specified

Eigenvalue distribution:

Varies

Problem Scale:

Very Large (100,000 - 1,000,000)

Computation Requirements:

Not specified

Percentage of eigenvalues:

Varies

What to compute:

Varies

Eigenvalue location:

Varies

Required tolerance/precision:

Not specified

Residual tolerance type:

Absolute residual ($\|Ax - x\|$)

Absolute residual tolerance:

Machine precision

Relative residual tolerance:

Not specified

Hybrid residual tolerance:

Not specified

Orthogonality tolerance:

Machine precision

Working Precision:

Single precision (32-bit), Double precision (64-bit)

Workload Characteristics:

Not specified

Computation Pattern: capability or capacity:

Asynchronous/background processing (can wait for solutions)

Distributed-Memory NLA Library Usage:

Not specified

Distributed-Memory Dense Linear Algebra:

Not specified

Iterative Eigensolvers:

Not specified

High-Level & Interface Libraries:

Not specified

Are there any NLA libraries you are interested in using (but have not yet adopted)?:

Not specified

Benchmarking Requirements:

Not specified

Benchmark Input Types:

Synthetic / random matrices

Can You Provide Data or Mini-apps?:

Yes, both matrices and mini-apps

Scaling Requirements:

Both strong and weak scaling needed