SLATE

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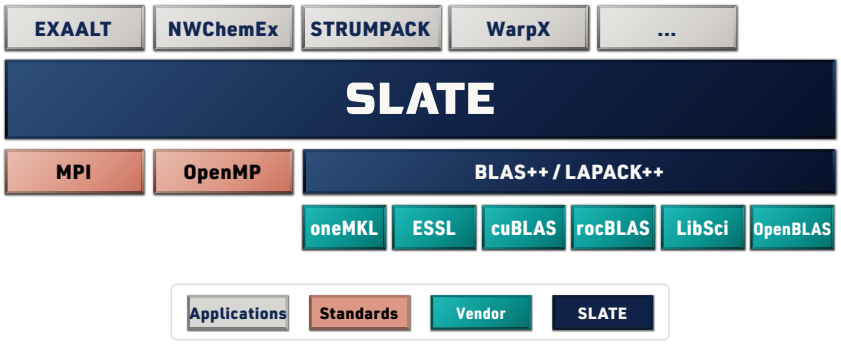
REPLACING ScaLAPACK

The objective of the Software for Linear Algebra Targeting Exascale (SLATE) project is to provide fundamental dense linear algebra capabilities to the US Department of Energy and to the high-performance computing (HPC) community at large. To this end, SLATE provides basic dense matrix operations (e.g., matrix multiplication, rank-k update, triangular solve), norms, linear systems solvers, least square solvers, and singular value and eigenvalue solvers. The ultimate objective of SLATE is to replace the venerable Scalable Linear Algebra PACKage (ScaLAPACK) library.



Primarily, SLATE aims to extract the full performance potential and maximum scalability from modern, many-node HPC machines with large numbers of cores and multiple hardware accelerators per node. For typical dense linear algebra workloads, this means getting close to the theoretical peak performance and scaling to the full size of the machine (i.e., thousands to tens of thousands of nodes). This is accomplished in a portable manner by relying on MPI, OpenMP, and C++ standards.

BLAS++ AND LAPACK++

Designed as independent libraries to be used separately from SLATE, these form a C++ interface and portability layer over both CPU Fortran BLAS and LAPACK, and GPU BLAS and LAPACK functionality in cuBLAS/cuSolver, rocBLAS/rocSolver, and oneMKL. The latest updates provide complete Level 1, 2, and 3 BLAS coverage on the GPU.

SLATE HIGHLIGHTS

Targets Modern Hardware

such as emerging exascale systems with heavyweight nodes containing multi-core CPUs and multiple GPU accelerators.

Guarantees Portability

by relying on standard computational components (e.g., vendor implementations of BLAS and LAPACK) and standard parallel programming technologies (e.g., MPI, OpenMP) or portable runtime systems (e.g., PaRSEC).

Provides Scalability

by employing proven techniques of dense linear algebra, such as the 2-D block cyclic data distribution, as well as modern parallel programming approaches, like dynamic scheduling and communication overlapping.

Ensures Maintainability

by employing useful facilities of the C++ language, such as templates and overloading of functions and operators, and focused on minimizing code bloat by relying on compact representations.

PAPERS AND WORKING NOTES

https://icl.utk.edu/slate/#papers

Gates, M., A. Abdelfattah, K. Akbudak, M. Al Farhan, R. Alomairy, D. Bielich, T. Burgess, S. Cayrols, N. Lindquist, D. Sukkari, and A. YarKhan
Evolution of the SLATE linear algebra library
The International Journal of High Performance Computing Applications, September 2024. DOI: 10.1177/10943420241286531

Sukkari, D., M. Gates, M. Al Farhan, H. Anzt, and J. Dongarra
Task-Based Polar Decomposition Using SLATE on Massively Parallel Systems with Hardware Accelerators
SC-W '23: Proceedings of the SC '23 Workshops of The International Conference on High Performance Computing, Network, Storage, and Analysis, Denver, CO, ACM, November 2023. DOI: 10.1145/3624062.3624248

Gates, M., A. YarKhan, D. Sukkari, K. Akbudak, S. Cayrols, D. Bielich, A. Abdelfattah, M. Al Farhan, and J. Dongarra
Portable and Efficient Dense Linear Algebra in the Beginning of the Exascale Era
In *2022 IEEE/ACM International Workshop on Performance, Portability and Productivity in HPC (P3HPC)*, pp. 36-46. IEEE, 2022.

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SLATE COVERAGE

BASIC LINEAR ALGEBRA ($C = AB$, ...)

	ScaLAPACK	SLATE
Level 1 PBLAS	✓	
Level 2 PBLAS	✓	partial
Level 3 PBLAS	✓	✓
Auxiliary routines (add, set, scale, ...)	✓	✓
Matrix norms	✓	✓
Test matrix generation	✓	✓

LINEAR SYSTEMS ($Ax = b$)

	ScaLAPACK	SLATE
LU (partial pivoting)	✓	✓
CALU (tournament pivoting)		panel on GPU
LU, band (pp)	✓	✓
LU (non-pivoting)		✓
LU Random Butterfly (RBT)		✓
LU BEAM solver		dev branch
Cholesky	✓	panel on GPU
Cholesky, band	✓	✓
Symmetric Indefinite (block Aasen)		CPU only
Mixed precision (single-double)		IR, GMRES-IR
Inverses (LU, Cholesky)	✓	✓
Condition estimate	✓	✓

LEAST SQUARES ($Ax \cong b$)

	ScaLAPACK	SLATE
QR	✓	panel on GPU
Cholesky QR		✓
LQ	✓	✓
Least squares solver	✓	QR, CholQR
PAQR (pivoting avoiding)		dev branch

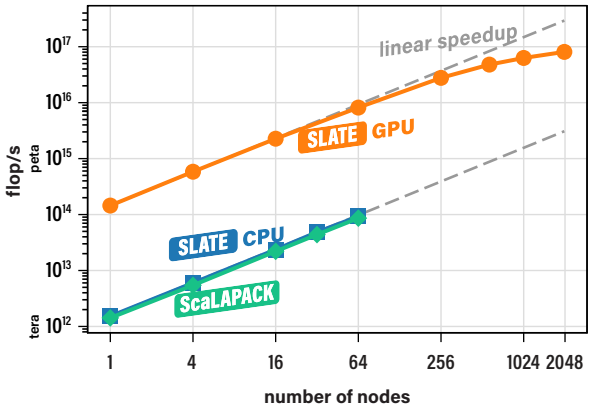
SVD, EIG, PD ($A = U\Sigma V^H$, $Ax = \lambda x$, $A = UH$)

	ScaLAPACK	SLATE
Singular value decomposition (SVD)	✓	values & vectors
Hermitian eigenvalue	✓	values & vectors
Generalized Hermitian eigenvalue	✓	values & vectors
Polar decomposition (QDWH)		dev branch
LOBPCG		dev branch
Non-symmetric eigenvalue		proposed

PERFORMANCE

The SLATE GPU-accelerated version attains up to 100× speedup over the CPU.
Weak scaling, from 1 to 2048 nodes, totaling 8 to 16384 AMD MI250X GPU GCDs. CPU-only runs were done from 1 to 64 nodes, totaling 56 to 3584 AMD EPYC CPU cores.

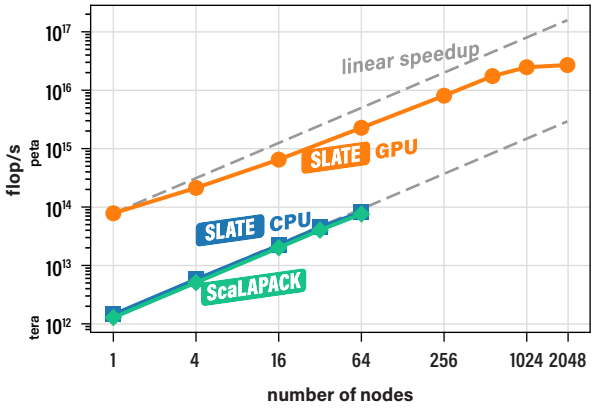
Weak scaling for matrix multiply (gemm)
on Frontier for a local problem size of 80,000 × 80,000 per node



SLATE on GPUs achieves 94.7× to 107.2× speedup compared to the CPU. Performance is falling off the linear speedup line for a larger number of nodes.

SLATE on CPUs is 7.2% to 10.5% faster than ScaLAPACK; the lines appear almost coincident at this scale. This closeness is expected since both are a significant fraction of the CPU peak. On 64 nodes, SLATE CPU gemm achieves 80.7% of peak at 92.6 Tflop/s, and ScaLAPACK achieves 75.2% of peak at 86.2 Tflop/s.

Weak scaling of Cholesky (potrf)
on Frontier for a local problem size of 140,000 × 140,000 per node



The SLATE GPU-accelerated version attains 60.8× speedup over the CPU on 1 node (8 GPU GCDs), falling to 29.9× on 64 nodes (512 GPU GCDs).

SLATE CPU is 6.8% to 13.4% faster than ScaLAPACK. These are not as fast as gemm; on 64 nodes, SLATE CPU Cholesky achieves 81.6 Tflop/s, 71% of peak, and ScaLAPACK achieves 76.4 Tflop/s, 66.6% of peak.

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