Exploiting Batched Operation in Applications

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Workshop on Batched, Reproducible, and Reduced Precision BLAS GATech

Feb 25, 2017



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- Motivations
- Real Scientific Applications
- Cholesky-based Matrix Computations
- Climate/Weather Prediction Application

S KBLAS

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- Motivations
- Real Scientific Applications
- 3 Cholesky-based Matrix Computations
- Climate/Weather Prediction Application
- 5 KBLAS

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Motivations

- Covariance Matrix Problems
 - Ubiquitous in computational science and engineering
 - Symmetric, positive-definite matrix structure
 - (Apparently) Dense matrices
 - Often data-sparse
 - Decay of parameter correlations with distance
 - Hierarchically of low rank
 - Convergence big data / HPC
- Sparse direct and iterative solvers
 - Schur complement
 - Preconditioning

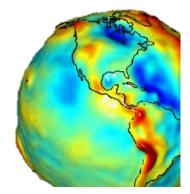
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Geospatial Statistics

 Multivariate large spatial data sets in climate/weather modeling to improve prediction



$$\ell(\boldsymbol{\theta}) = -\frac{1}{2}\mathbf{Z}^T \Sigma^{-1}(\boldsymbol{\theta}) \mathbf{Z} - \frac{1}{2} \log|\Sigma(\boldsymbol{\theta})|$$

(a) Problem Definition.

(b) Temperature prediction.

Figure: Climate/weather modeling.

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Computational Ground-Based Astronomy

 Enhancing the observed image quality using MOAO by filtering out the noise coming from the adaptive optics instrumentation and the atmospheric turbulence.



$$R = C_{tm}.C_{mm}^{-1} \ C_{ee} = C_{tt} - C_{tm}R^{t} - RC_{tm}^{t} + RC_{mm}R^{t}$$

(a) Problem Definition.

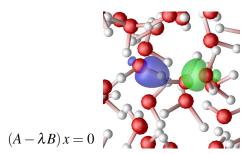
(b) The E-ELT.

Figure: Finding new galaxies.

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Computing the Eigenspectrum for Symmetric Hierarchical Low Rank Matrix

 Structural and vibrational analysis to problems in computational physics and chemistry like electronic and band structure calculations



(a) Problem (b) Electronic structure. Definition.

Figure: Design of new materials.

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Matrix Form

The Cholesky factorization of an $N \times N$ real symmetric, positive-definite matrix A has the form

$$A = LL^T$$
,

where L is an $N \times N$ real lower triangular matrix with positive diagonal elements.

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LAPACK Block Algorithms

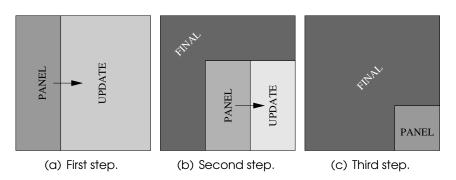


Figure: Block Algorithms.

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PLASMA Tile Algorithms

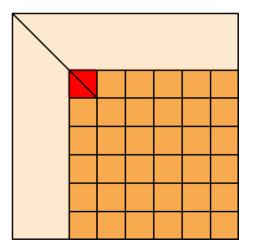


Figure: Tile Algorithms.

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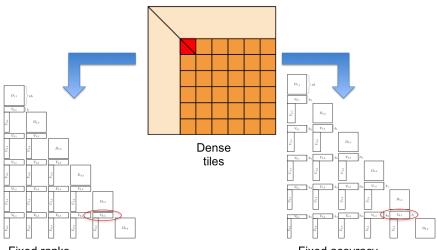
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Computational Statistics for Climate/Weather Prediction Applications

- Applications from climate and weather science often deal with a very large number of measurements regularly or irregularly located in geographical region.
- In geospatial statistics, these data are usually modeled as a realization from Gaussian spatial random field.
- This translates into evaluating the log-likelihood function, involving a large dense (but data-sparse) covariance matrix.

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Dense Linear Algebra Renaissance

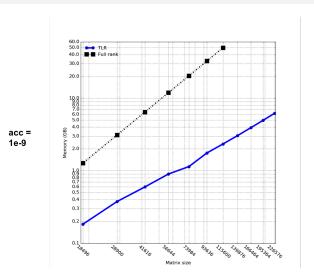


Fixed ranks
Preconditioners
Performance oriented

Fixed accuracy Variable ranks Dense/Sparse Direct Solvers

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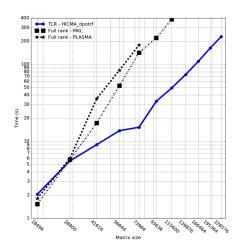
Tile Low Rank Cholesky: Memory Footprint



Akbudak et al., accepted at ISC'17

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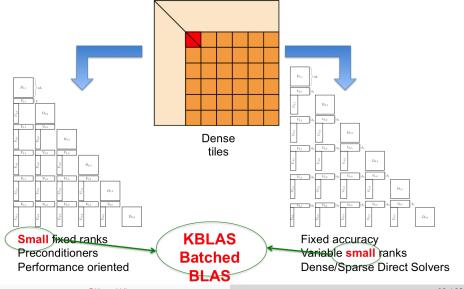
Tile Low Rank Cholesky: Time to Solution



Akbudak et al., accepted at ISC'17

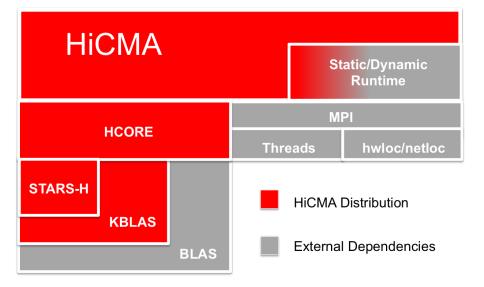
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Dense Linear Algebra Renaissance



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HiCMA Software Stack



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Recursive formulation

- Usually used for Level 2 BLAS algorithms (e.g., panel factorization)
- Increase data locality
- Run at the cache level speed
- Again, not new and literature is quite rich: Kågström et. al (1998), Goto et. al (2008), etc.
- And it does pay off for Level 3 BLAS too!

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Triangular matrix-matrix multiplication (TRMM)

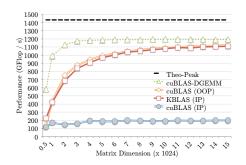


Figure: Performance comparisons of KBLAS DTRMM against IP and OOP cuBLAS DTRMM running on NVIDIA K40 GPU.

A. Charara, H. Ltaief and D. Keyes, Best Papers, EuroPar, 2016. Integrated in CUDA 8.0

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Triangular Solves (TRSM)

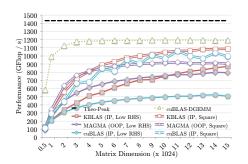


Figure: Performance comparisons of KBLAS IP DTRSM against cuBLAS IP DTRSM and MAGMA OOP TRSM running on NVIDIA K40 GPU, with square and low RHS matrices.

A. Charara, H. Ltaief and D. Keyes, Best Papers, EuroPar, 2016.
Integrated in CUDA 8.0

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Advanced Batched BLAS Operations: HBLAS

Context:

- Very small sizes!
- Batch operation executions at each level of the tree
- Currently fixed sizes (need to handle variable sizes)
- Recursive formulation, stressing register usage
- Convert into batch of large GEMMs
- Minimize data transfer
- Enhance data locality
- Increase arithmetic intensity
- State-of-the-art implementations not well optimized for this scope or not supported

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Advanced Batched BLAS Operations: HBLAS

HBLAS Matrix computations:

- Level 3 BLAS: SYRK, TRMM, TRSM
- Factorizations: POTRF
- Solves: POTRS, POSV, POTRI, POTI

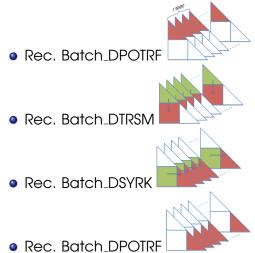
HBLAS Matrix compression:

- Batch QR factorizations
- Batch SVD

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Advanced Batched BLAS Operations: HBLAS

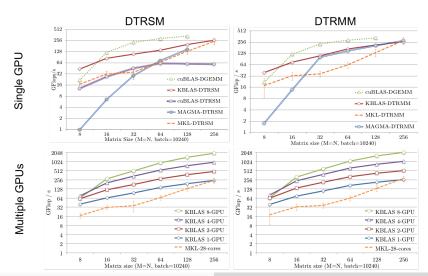
Batches of Batched



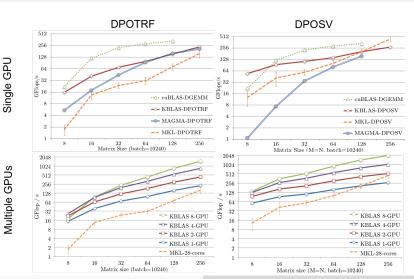
Profiling shows 76% of time is spent in batch DGEMM (MAGMABLAS).

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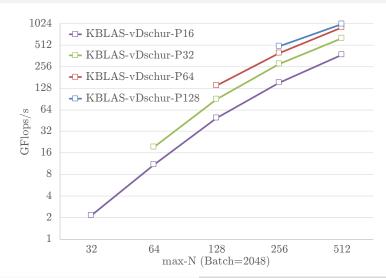
Performance Results: Batched Level 3 BLAS on NVIDIA K40 GPUs



Performance Results: Batched Solves on NVIDIA K40 GPUs



Performance Results: Batched Schur Complement on NVIDIA K40 GPUs



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Students/Collaborators/Support

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- Intel Parallel Computing Center
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