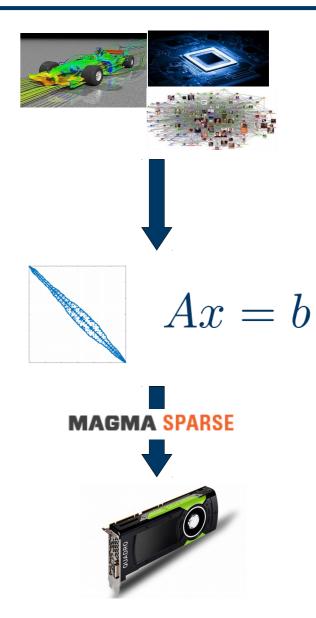


Flexible-Size Batched LU for Small Matrices and its Integration into Block-Jacobi Preconditioning

Hartwig Anzt, Jack Dongarra, Goran Flegar, Enrique S. Quintana-Ortí



- GPU-accelerated sparse linear algebra library
 - Focus: linear systems







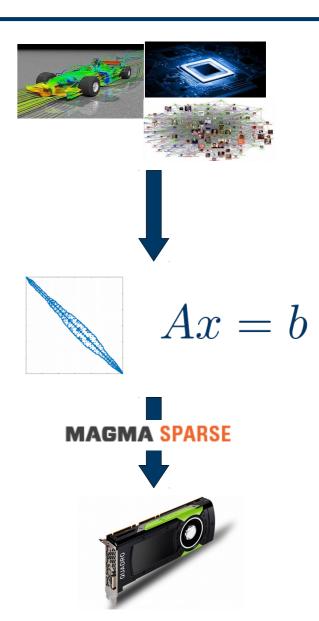


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 - Iterative, Krylov-subspace based linear solvers
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 - BLAS-1 operations









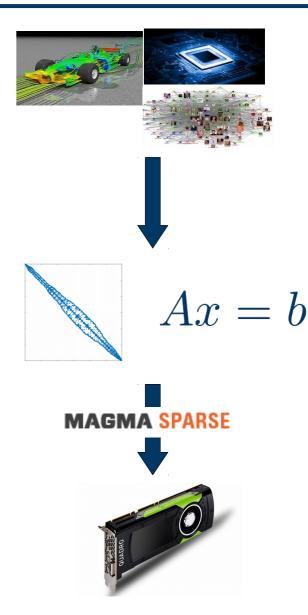


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 - accelerate each iteration of the solver









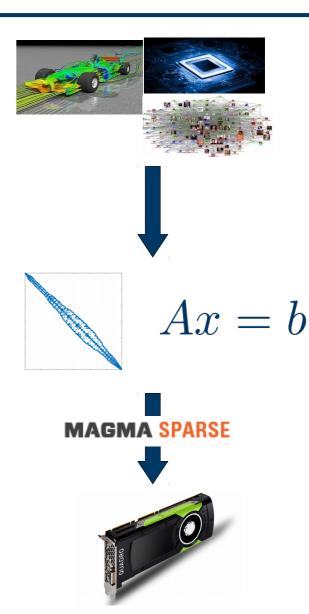


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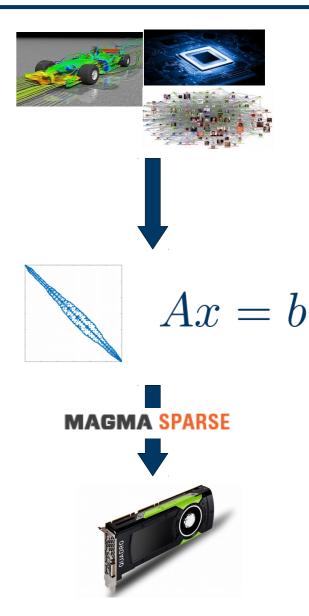


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Preconditioner application

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Do not compute the preconditioned system matrix explicitly!

Generate the preconditioner matrix, and store it in a form suitable for application

$$A \leadsto M$$

Preconditioner setup





$$z := Ax$$

$$u := M^{-1}z$$

Preconditioner application

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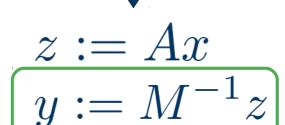


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Preconditioner setup

Preconditioner application

Trade-off:

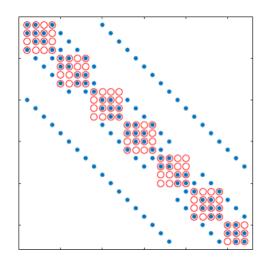
faster convergence, but more work per iteration



- Current focus: improve performance for problems with inherent block structure
 - Usually blocks are smaller than 30x30 (blocks can be of different sizes!)



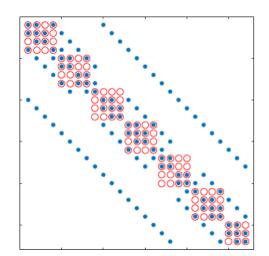
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- Block-Jacobi preconditioning
 - Use only diagonal blocks for approximation

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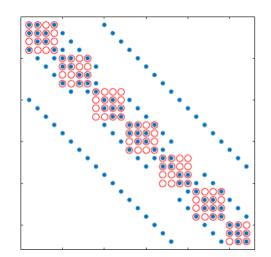
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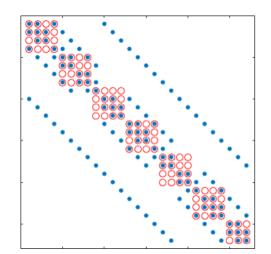
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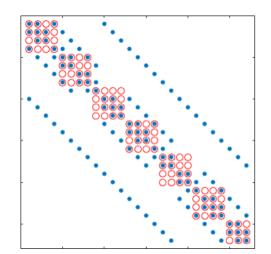
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$$U_i y_i = w_i$$

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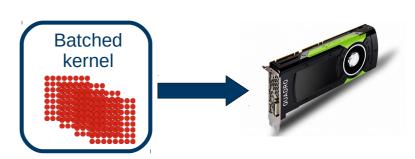
$$D_i y_i = z_i$$
 $D_i = L_i U_i$ Setup $U_i y_i = w_i$ Application $L_i w_i = z_i$

Solving 30-by-30 systems in sequence on a GPU with several thousand cores wastes computational resources!



Batched routines

Launch a single kernel which applies an operation to multiple independent data entities in parallel.

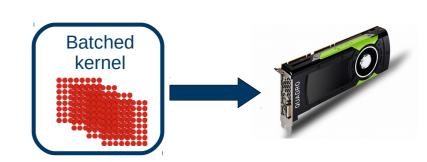


* Measured on NVIDIA P100



Batched routines

Launch a single kernel which applies an operation to multiple independent data entities in parallel.



- There is no standard BLAS & LAPACK interface
- Most implementations only support problems of equal sizes
- High performance libraries are not optimized for small blocks
 - cuBLAS batched trsv: ~25 Gflop/s *
 - MAGMA-sparse SpMV: 60 90 Gflop/s *

* Measured on NVIDIA P100



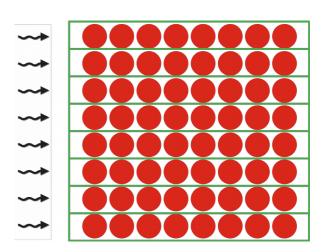
- Assign one warp to each problem
 - hardware SIMD unit, represented as a group of 32 threads in CUDA



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 - Able to support problems of size up to 32-by-32
 - keep the entire row in thread's registers
 - Communicate data between rows via warp-shuffles
 - Current implementation: use padding for problems of smaller sizes
 - Future work: multiple smaller problems per warp

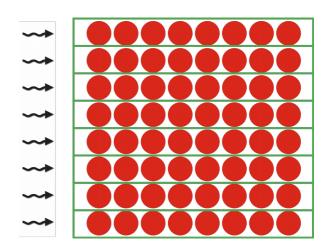




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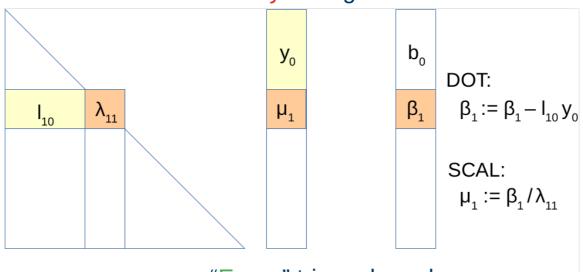
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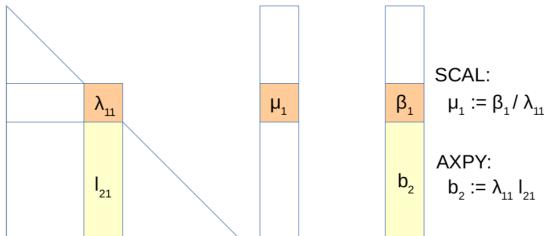
- Use implicit pivoting
 - Do not explicitly swap rows, "re-assign" the threads instead

- Use "eager" triangular solves
 - Cast solution vector updates in terms of axpy, not in terms of dot product!



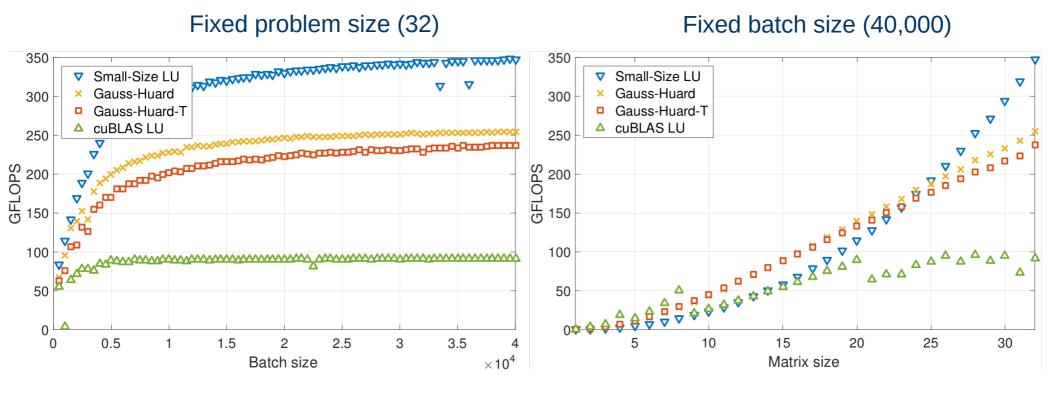


"Eager" triangular solve



LU decomposition performance

- Comparisson of MAGMA-sparse vs cuBLAS batched LU decomposition
- Gauss-Huard(-T) is a similar approach, using a different algorithm for decomposition/solves *

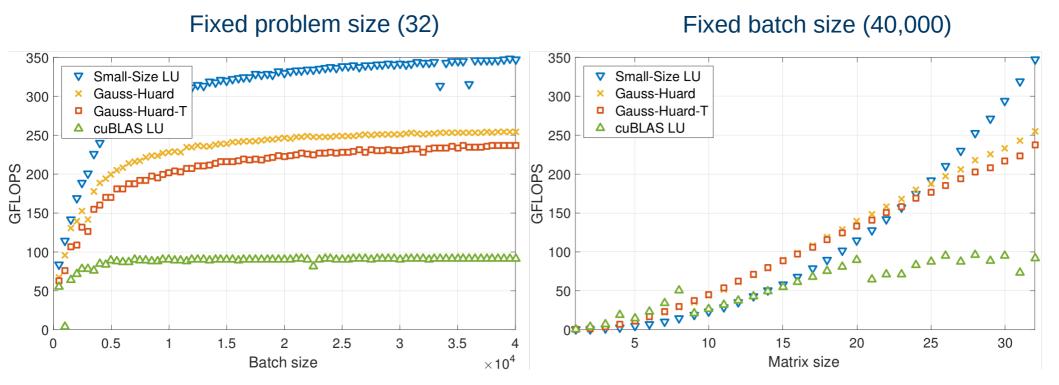


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MAGMA-sparse LU can also:

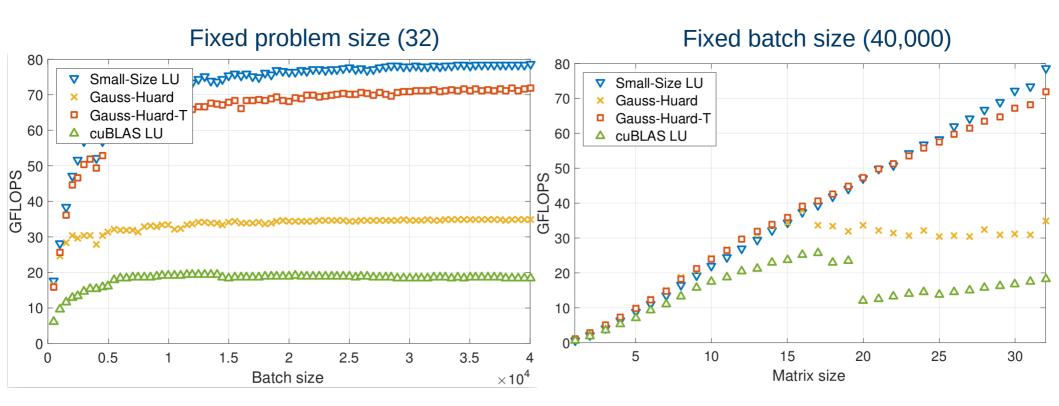
- Handle problems of different sizes
- Integrate diagonal block extraction and diagonal block decomposition into a single kernel

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Triangular solve performance

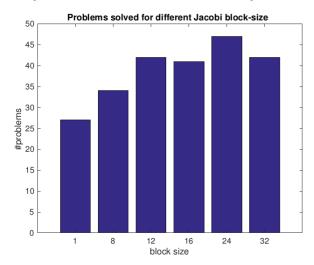
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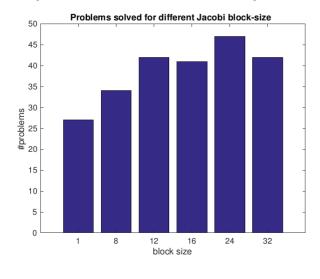
Complete solver runtime

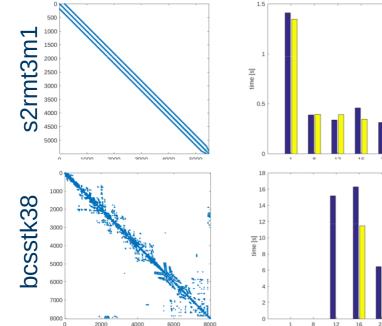
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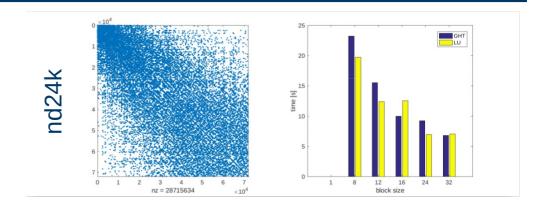


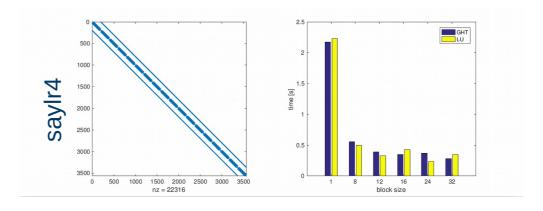
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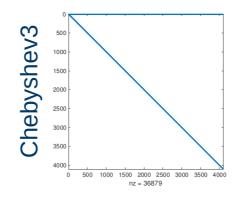
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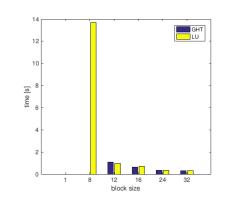












"Solving many small problems in sequence on manycore hardware wastes computational resources! We can design batched routines which apply the same operation on a set of independent data entities."

Workshop on batched BLAS*

Effort to standardize the batched BLAS interface





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- Can we design a single routine that can handle both 8-by-8 and 500-by-500 matrices?
- Or should we have more routines?

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- Batched gemm proposal has 16 input arguments!
- Global synchronization between two batched calls.

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Instead provide BLAS which operates on a part of memory/core hierarchy?

- E.g. block, warp, thread level BLAS for CUDA.
- Let users build their own batched routines from these building blocks.

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Thank you! Questions?

All functionalities are part of the MAGMA-sparse project.

MAGMA SPARSE

ROUTINES BiCG, BiCGSTAB, Block-Asynchronous Jacobi, CG,

CGS, GMRES, IDR, Iterative refinement, LOBPCG,

LSQR, QMR, TFQMR

PRECONDITIONERS ILU / IC, Jacobi, ParlLU, ParlLUT, Block Jacobi, ISAI

KERNELS SpMV, SpMM

DATA FORMATS CSR, ELL, SELL-P, CSR5, HYB

http://icl.cs.utk.edu/magma/



github.com/gflegar/talks/icpp 2017

This research is based on a cooperation between Hartwig Anzt, Jack Dongarra (University of Tennessee), Goran Flegar and Enrique S. Quintana-Ortí (Universidad Jaume I).





