

# Dense Linear Algebra on Heterogeneous Platforms: State of the Art and Trends

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ComplexHPC Spring School 2013  
Heterogeneous computing - Impact on algorithms  
June 7th, 2013  
Uppsala University, Sweden



- 1 Setting the stage
- 2 Part 1: blocked algorithms
- 3 Part 2: multithreading, fork-join
- 4 Part 3: multihtreading, algorithms-by-blocks
- 5 Part 4: streaming

# Dense Linear Algebra

$$M = \begin{bmatrix} \times \\ \times \\ \times \\ \times \\ \times \\ \times \\ \times \\ \times \\ \times \\ \times \end{bmatrix}$$

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# Dense Linear Algebra

## Linear systems

$Ax = b$ ,  $AX = B$ , least squares, ...

## Eigenproblems

$Ax = \lambda x$ ,  $AX = BX\Lambda$ , SVD, ...

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## Support routines

factorizations, reductions, ...

# Dense Linear Algebra

## Matrix equations

$$AX + XB = C, A = \frac{A+A^{-1}}{2}, \dots$$

## Linear systems

$$Ax = b, AX = B, \text{least squares}, \dots$$

## Eigenproblems

$$Ax = \lambda x, AX = BX\Lambda, \text{SVD}, \dots$$

## Support routines

factorizations, reductions, ...

# Organization in layers

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BLAS

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## BLAS

BLAS-1:

$$y := y + \alpha x \quad x, y \in \mathbb{R}^n, \alpha \in R$$
$$dot := \alpha + x^T y$$

# Organization in layers

## BLAS

BLAS-2:       $y := y + Ax \quad A, L \in R^{n \times n}, x, y \in R^n$   
                 $y := L^{-1}x$

BLAS-1:       $y := y + \alpha x \quad x, y \in R^n, \alpha \in R$   
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**BLAS-3:**  $C := C + AB \quad A, B, C, L \in R^{n \times n}$   
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# Organization in layers

## LAPACK

$$LU = A, \quad LL^T = A, \quad QR = A, \quad Q^T T Q = A, \quad \dots$$

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# Organization in layers

other libraries

ScaLAPACK, Elemental, PETSc, ...

LAPACK

$$LU = A, \quad LL^T = A, \quad QR = A, \quad Q^T T Q = A, \quad \dots$$

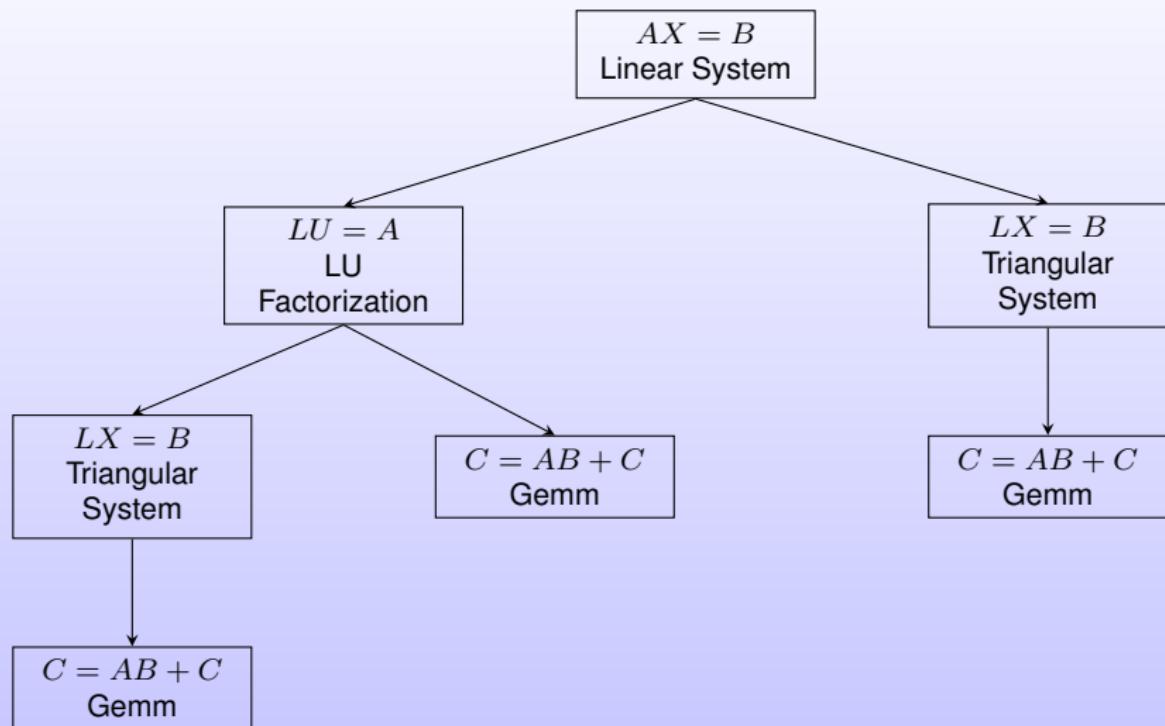
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# Example: $AX = B$ (full $A$ )



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BLAS	#FLOPS	Mem. refs.	Ratio
------	--------	------------	-------

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BLAS	#FLOPS	Mem. refs.	Ratio
Level 1	$2n$	$3n$	$2/3$

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BLAS-2:  $y := y + Ax \quad A \in R^{n \times n}, x, y \in R^n$

BLAS-1:  $y := y + \alpha x \quad x, y \in \mathbb{R}^n, \alpha \in R$

# Why BLAS-3? Why GEMM?

BLAS	#FLOPS	Mem. refs.	Ratio
Level 2	$2n^2$	$n^2$	2
Level 1	$2n$	$3n$	$2/3$

BLAS-2:  $y := y + Ax \quad A \in R^{n \times n}, x, y \in R^n$

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**Morale** *BLAS-3: The larger the problem the better, as long as it fits in memory.*  
*GEMM is the building block for all the other BLAS-3 kernels, and for LAPACK.*

# Part 1: Blocked algorithms

Simple example: Cholesky factorization

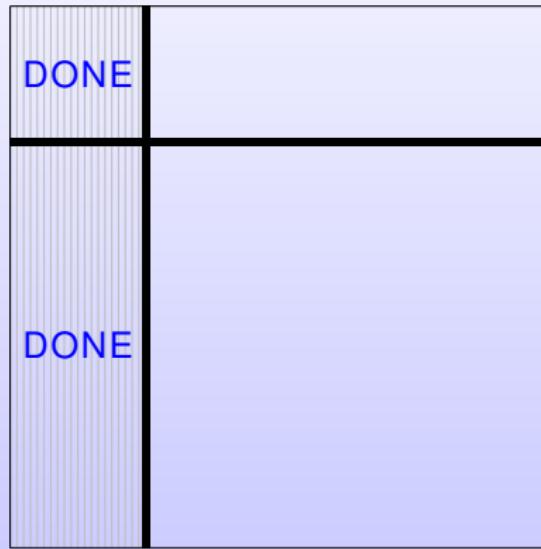
**Input:** Matrix  $A$ , symmetric and positive definite.

**Goal:** Determine  $L$  (lower triangular matrix) such that  $LL^T = A$

$$L = \left( \begin{array}{c|c} L_{TL} & \\ \hline L_{BL} & L_{BR} \end{array} \right) = ?$$

# Cholesky factorization

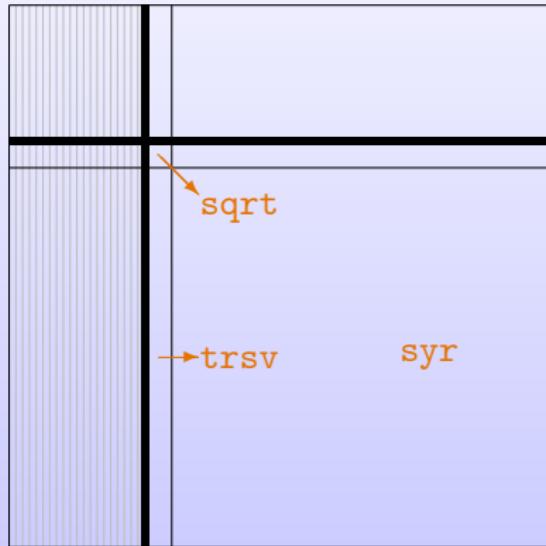
iteration  $i$



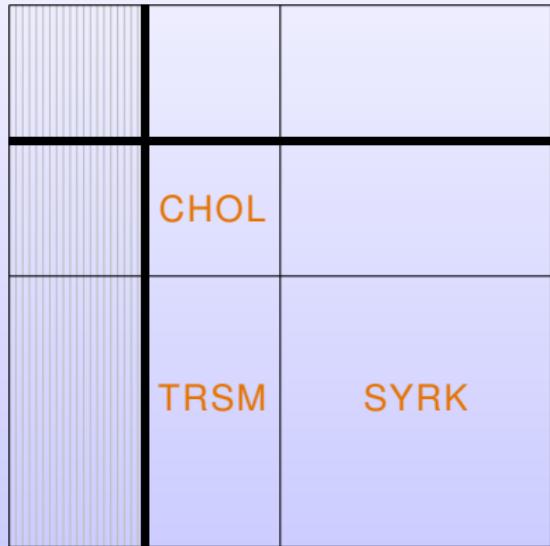
# Cholesky factorization

iteration  $i + 1$

unblocked algorithm



blocked algorithm



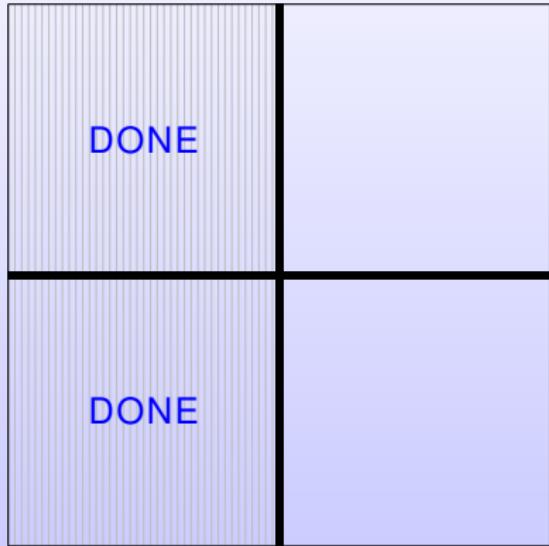
# Cholesky factorization

iteration  $i + 1$

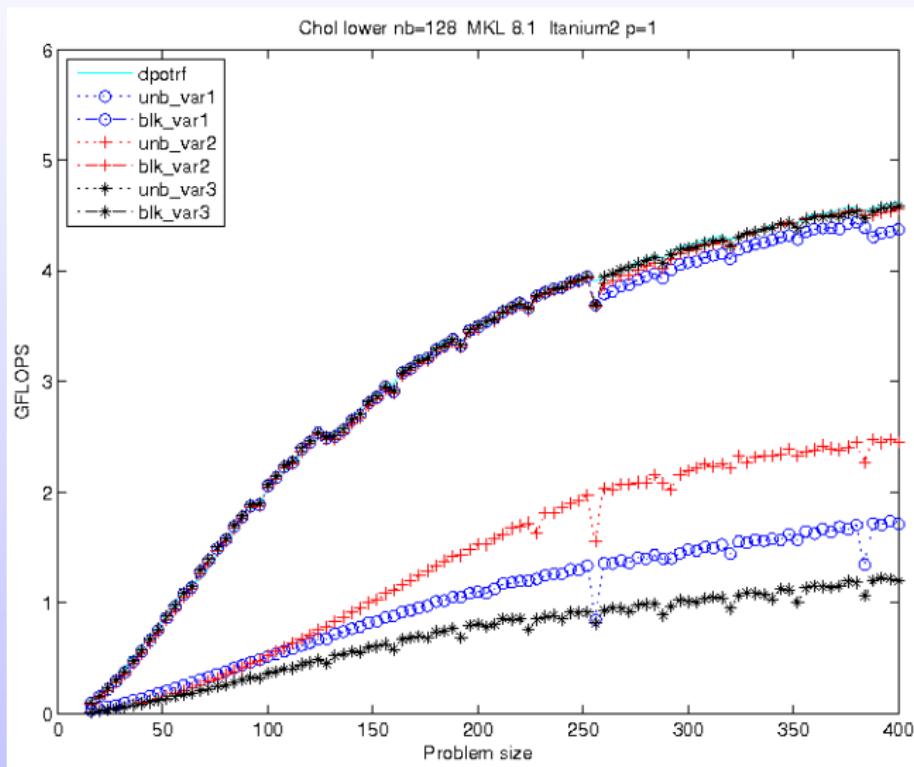
unblocked algorithm



blocked algorithm

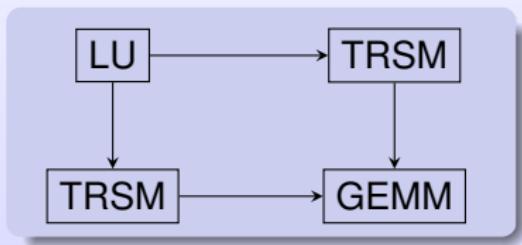
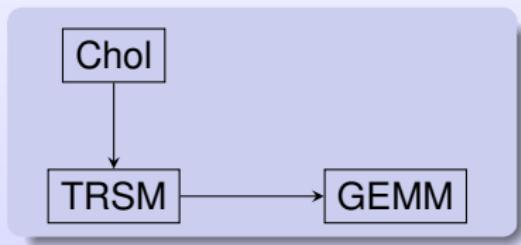


# Cholesky: unblocked vs. blocked algorithms



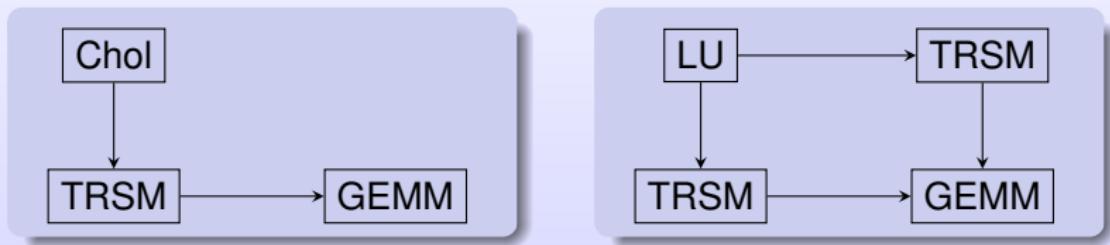
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- Solution #1: Multithreaded BLAS (+ vector instructions)



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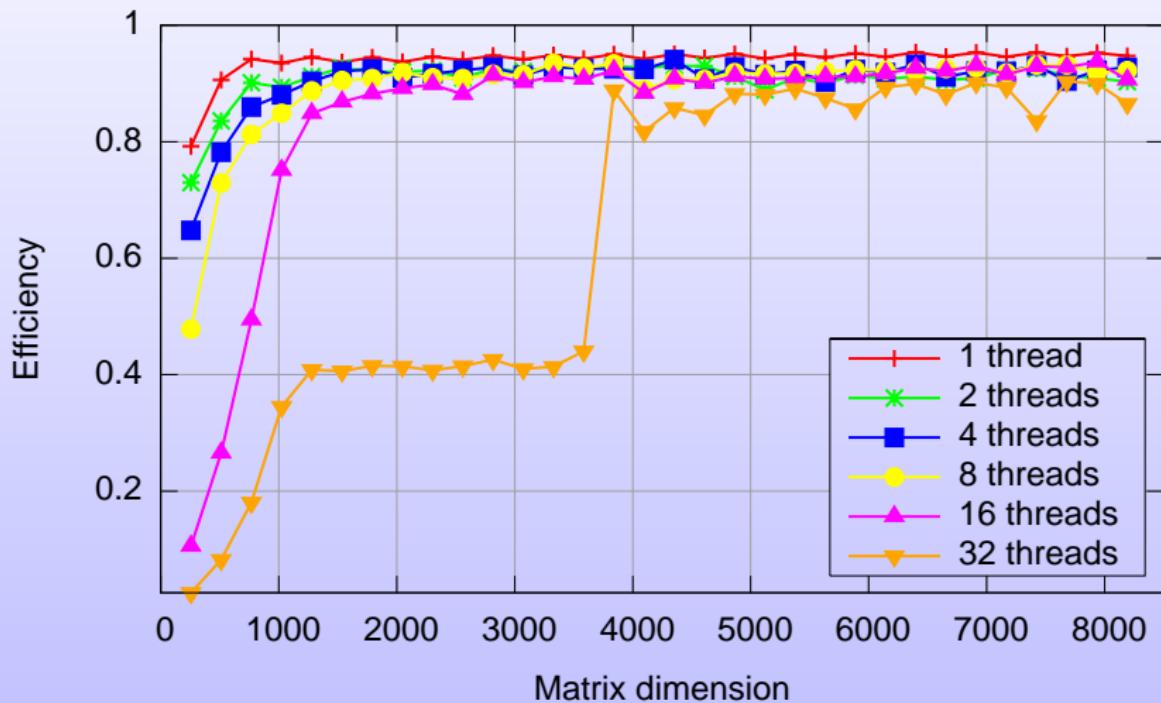


- Advantage: ease of use. Legacy code!
- Drawback: unnecessary synchronization points
- OpenBLAS, ATLAS, BLIS, old versions of MKL, ...

# Multithreaded BLAS

Xeon, 32 physical cores, MKL

Efficiency of GEMM



# Development of LA libraries

- New architecture / new architectural features

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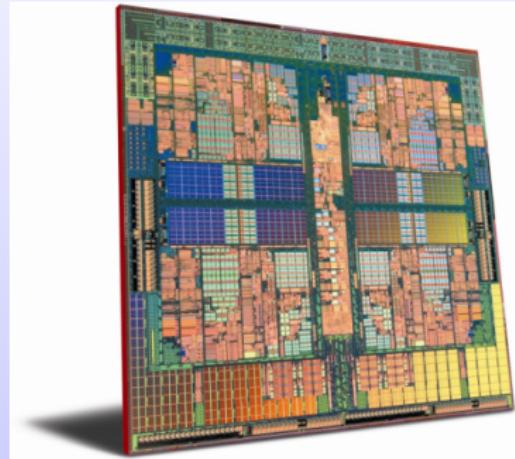
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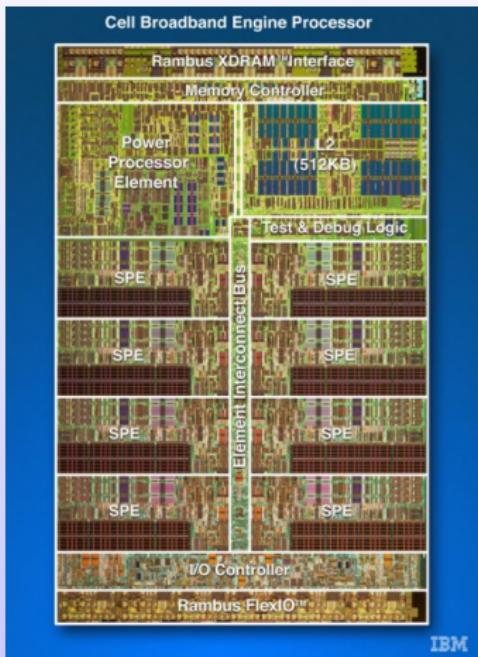
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- eigenproblems



- GEMM, mtBLAS
- HPL
  - 2005-7: **Blue Gene L**  
dual cores (PowerPC A2)
  - 2008-9: **Roadrunner**  
dual cores (Opteron)
  - 2009: **Jaguar**  
6-cores (Opteron)
  - 2010-11: **K Computer**  
8-cores SPARC64
  - ...
- libFLAME, PLASMA, MKL
- Eigensolvers: 2010



- GEMM: 99% [FFT]  
no BLAS
- HPL  
2008-9: **Roadrunner**  
>1 PetaFLOP  
6k \* (Opteron + 2 Cell)
- no libs
- 2009: discontinued
- Eigensolvers: –



- cuBLAS (\*)
- HPL 2010: **Tianhe-1A**  
2.5k dual-GPU (ATI Radeon)
- CULA (\*)
- libFLAME, MAGMA  
(multiGPU)
- Eigensolvers: 2010-11

# Present Intel Xeon Phi (MIC)



- GEMM (\*), MKL
- HPL (predicted)  
2013: **Tianhe-2**  
16k \* (2 Ivy Bridge + 3 Phi)

- -
- -
- -



- GEMM (\*), MKL
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- -
- -
- -

Also ARM, FPGAs, DSPs, ...

???

- heterogeneous architecture

# Back to the algorithms: Chol. fact

Fork-join  $\Rightarrow$  unnecessary synchronizations

CHOL	
TRSM	SYRK

Iteration 1

	CHOL	
TRSM		SYRK

Iteration 2

## Part 3: Parallelism? algorithms-by-blocks

- Idea: decompose the tasks
- Solution #2: dependent tasks + scheduling

$$\begin{matrix} A \\ \times \\ X \end{matrix} = \begin{matrix} B \end{matrix}$$

## Part 3: Parallelism? algorithms-by-blocks

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- Solution #2: dependent tasks + scheduling

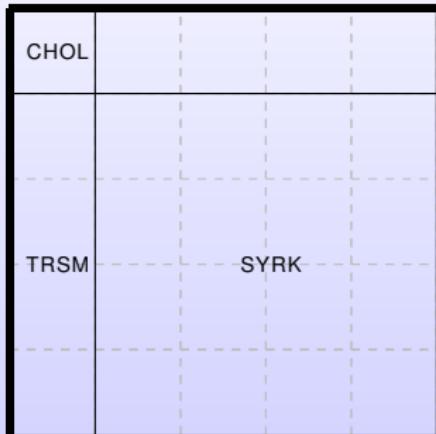
$$\begin{array}{c|c} \boxed{A} & X \\ \hline & \end{array} = \begin{array}{c} B \end{array}$$
$$\begin{array}{c|c} \boxed{A_0} & X \\ \hline A_1 & \\ \hline A_2 & \end{array} = \begin{array}{c} B_0 \\ \hline B_1 \\ \hline B_2 \end{array}$$

## Part 3: Parallelism? algorithms-by-blocks

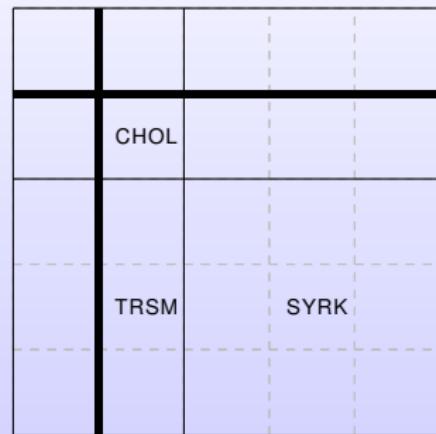
- Idea: decompose the tasks
- Solution #2: dependent tasks + scheduling

$$\begin{array}{c|c} \boxed{A} & X \\ \hline & \end{array} = \begin{array}{c} B \end{array}$$
$$\begin{array}{c|c} \boxed{A_0} & X \\ \hline A_1 & \\ \hline A_2 & \end{array} = \begin{array}{c|c} B_0 & \\ \hline B_1 & \\ \hline B_2 & \end{array}$$
$$A_0X = B_0$$
$$A_1X = B_1$$
$$A_2X = B_2$$

# Storage by blocks



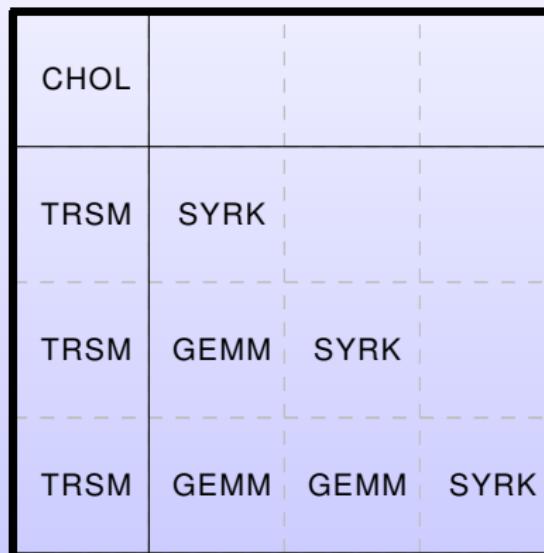
Iteration 1



Iteration 2

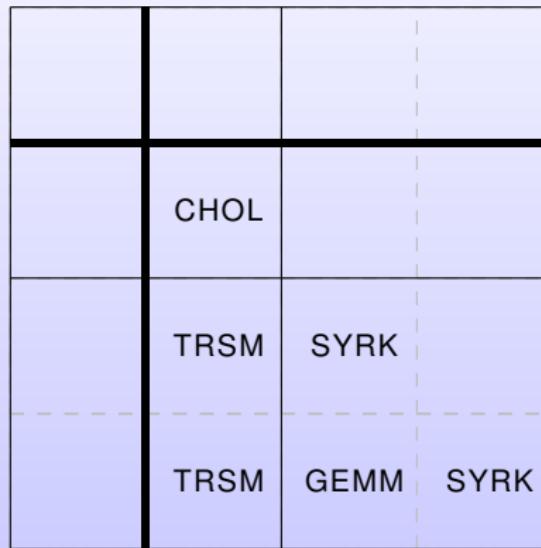
# Creating tasks

Iteration 1



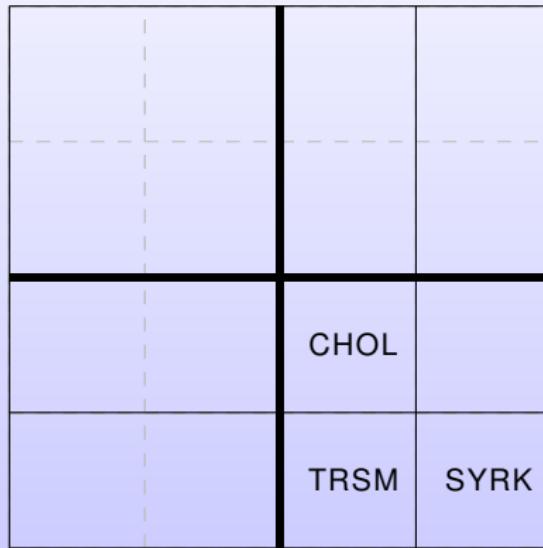
# Creating tasks

Iteration 2



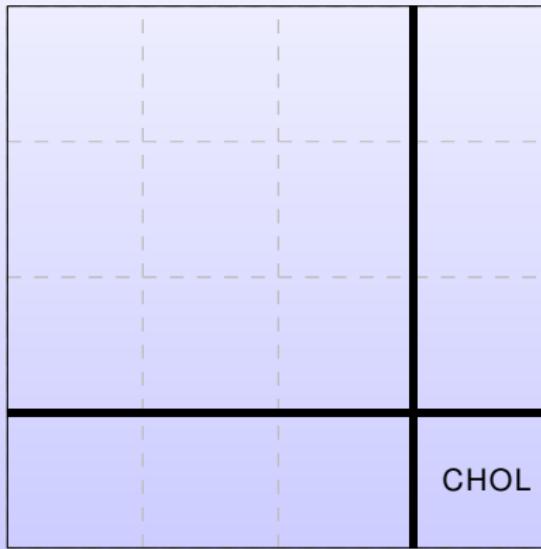
# Creating tasks

Iteration 3

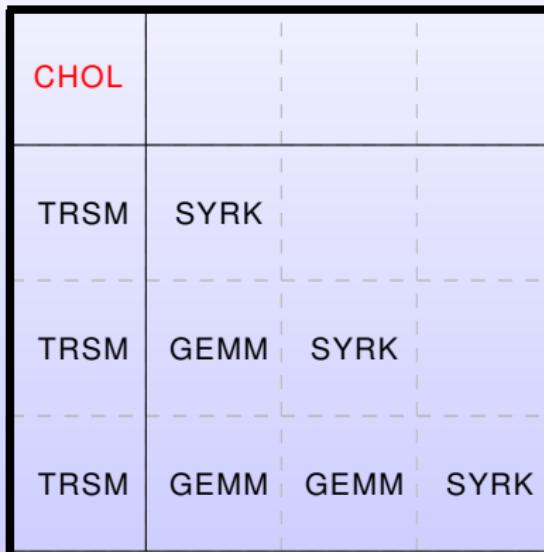


# Creating tasks

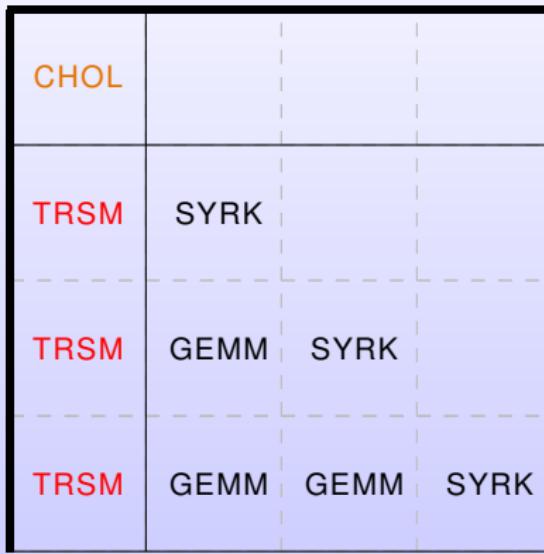
Iteration 4



# Dependencies



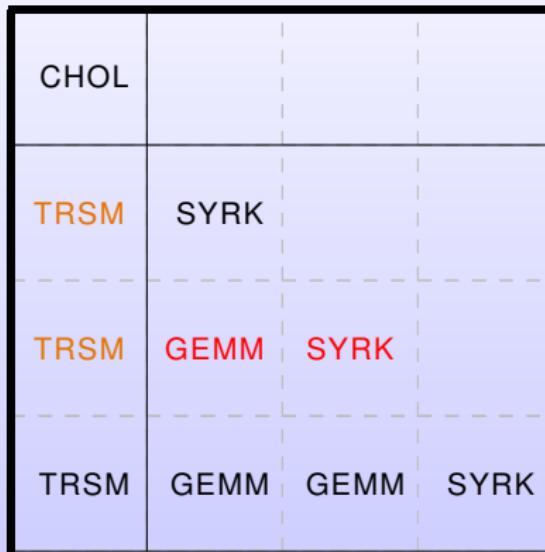
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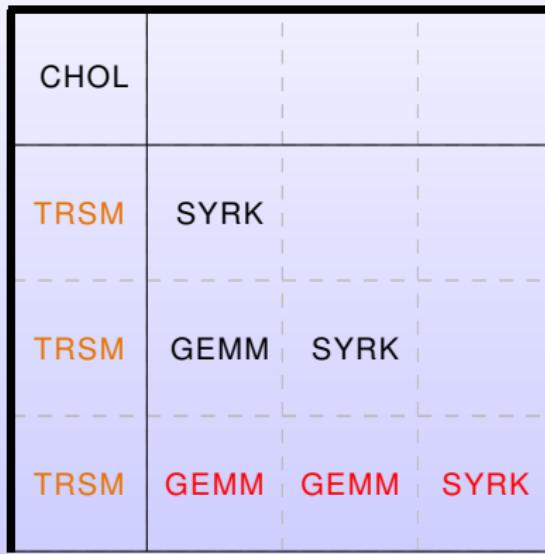
# Dependencies

CHOL			
TRSM	SYRK		
TRSM	GEMM	SYRK	
TRSM	GEMM	GEMM	SYRK

# Dependencies

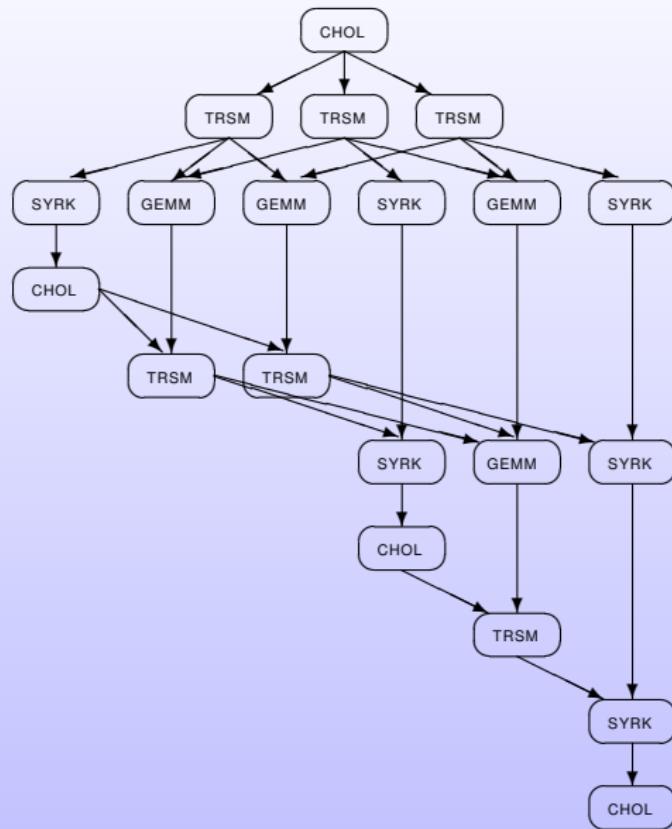


# Dependencies



# DAG - Dependencies

4 × 4-tile matrix



# Task Execution

4 × 4-tile matrix

Stage	Scheduled Tasks			
1	CHOL			
2	TRSM	TRSM	TRSM	TRSM
3	SYRK	GEMM	SYRK	GEMM
4	GEMM	SYRK	GEMM	GEMM
5	GEMM	SYRK	CHOL	
6	TRSM	TRSM	TRSM	
7	SYRK	GEMM	SYRK	GEMM
8	GEMM	SYRK	CHOL	
9	TRSM	TRSM		
10	SYRK	GEMM	SYRK	
11	CHOL			
12	TRSM			
13	SYRK			
14	CHOL			

# SPD Inverse: Chol+Inv+GEMM

$5 \times 5$ -tile matrix

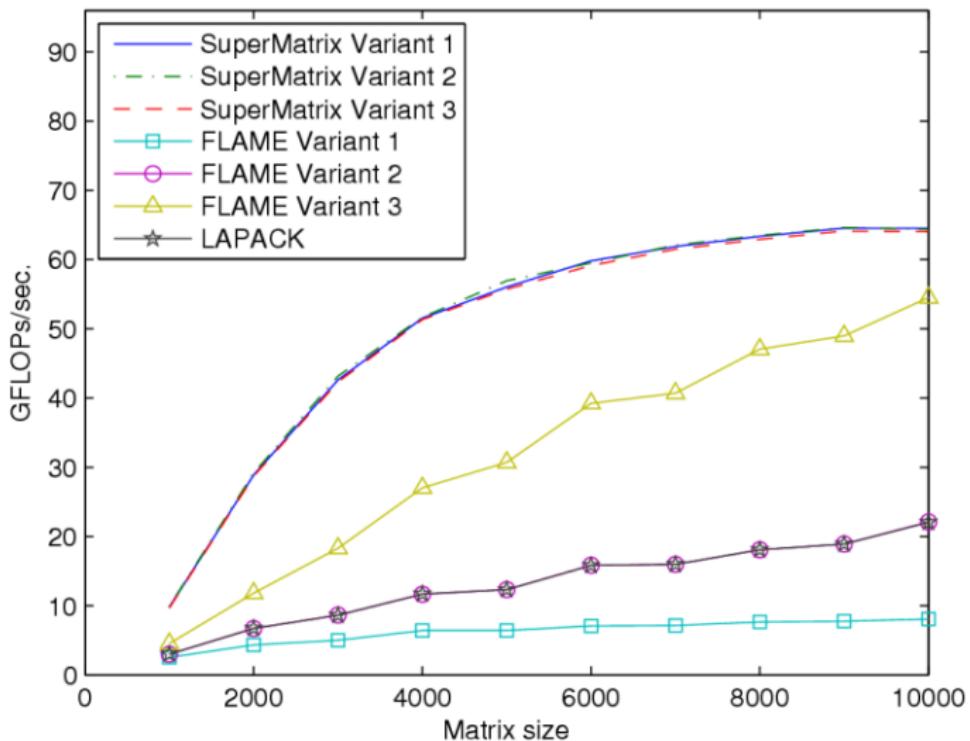
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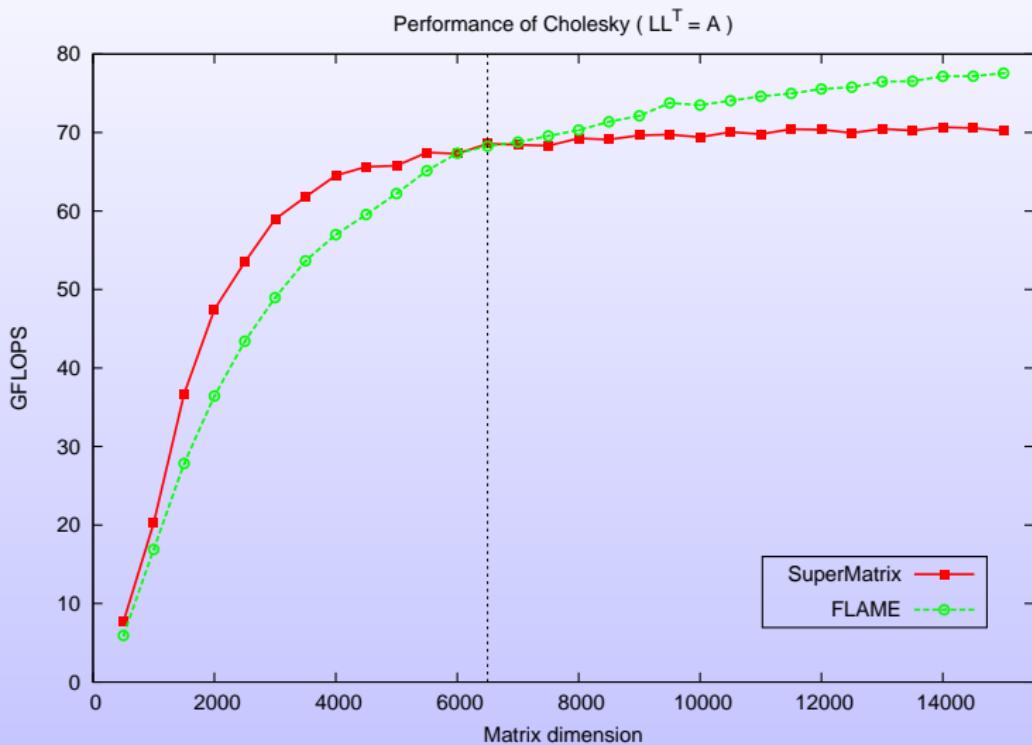
Stage	Scheduled Tasks			
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2	TRSM	TRSM	TRSM	TRSM
3	SYRK	GEMM	SYRK	GEMM
4	GEMM	SYRK	GEMM	GEMM
5	GEMM	SYRK	CHOL	TRSM
6	TRSM	TRSM	TRSM	TRSM
7	TRSM	TRSM	TRINV	SYRK
8	GEMM	SYRK	GEMM	GEMM
9	SYRK	TTMM	CHOL	TRSM
10	TRSM	TRSM	TRSM	TRSM
11	GEMM	GEMM	GEMM	SYRK
12	GEMM	SYRK	TRSM	CHOL
13	TRSM	TRSM	TRINV	SYRK
14	TRSM	GEMM	GEMM	GEMM
15	GEMM	TRMM	SYRK	TRSM
16	TRSM	TTMM	CHOL	TRSM
17	SYRK	TRINV	GEMM	SYRK
18	GEMM	GEMM	GEMM	TRMM
19	TRMM	TRSM	TRSM	TRSM
20	TRSM	TRSM	TRSM	TRSM
21	TTMM	SYRK	GEMM	SYRK
22	TRINV	GEMM	GEMM	TRINV
23	SYRK	SYRK	GEMM	SYRK
24	TRMM	GEMM	TRMM	GEMM
25	TRMM	SYRK	GEMM	GEMM
26	TTMM	GEMM	TRMM	TRMM
27	SYRK	TRMM		
28	TRMM			
29	TTMM			

# Blocked vs. By-blocks

Chol lower Itanium2 p=16 MKL



# Blocked vs. By-blocks: crossover



## Multithreaded BLAS vs. Algorithms-by-blocks

No absolute winner: crossover!

- ✓ Ease of use
- ✗ Synchronization
- ✓ Out of order execution
- ✓ Parallelism dictated by data dependencies
- ✗ Plateaux

libFLAME, MKL, PLASMA, ...

Heterogeneous systems  $\leftrightarrow$  schedulers

## Part 4: Streaming

The entire problem does not fit even in main memory

**Example**     $b := (X^T M^{-1} X)^{-1} X^T M^{-1} y$

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The entire problem does not fit even in main memory

**Example**  $b := (X^T M^{-1} X)^{-1} X^T M^{-1} y$

Linear regression with non-independent outcomes

### Inputs

- $M \in \mathcal{R}^{n \times n}$ ,  $SPD(M)$ ,  $n \in [10^3, \dots, 10^4]$
- $X \in \mathcal{R}^{n \times p}$ ,  $p \in [1, \dots, 20]$ , full rank
- $y \in \mathcal{R}^n$

### Output

- $b \in \mathcal{R}^p$

**\*Sequence of thousands of problems\***

# Algorithm

$$LL^T = M$$

$$X := L^{-1}X$$

$$S := X^T X$$

$$GG^T = S$$

$$y := L^{-1}y$$

$$b := X^T y$$

$$b := G^{-1}b$$

$$b := G^{-T}b$$

# Algorithm – bottleneck?

$$LL^T = M$$

$X := L^{-1}X$  → to accelerator (TRSM)

$$S := X^T X$$

$$GG^T = S$$

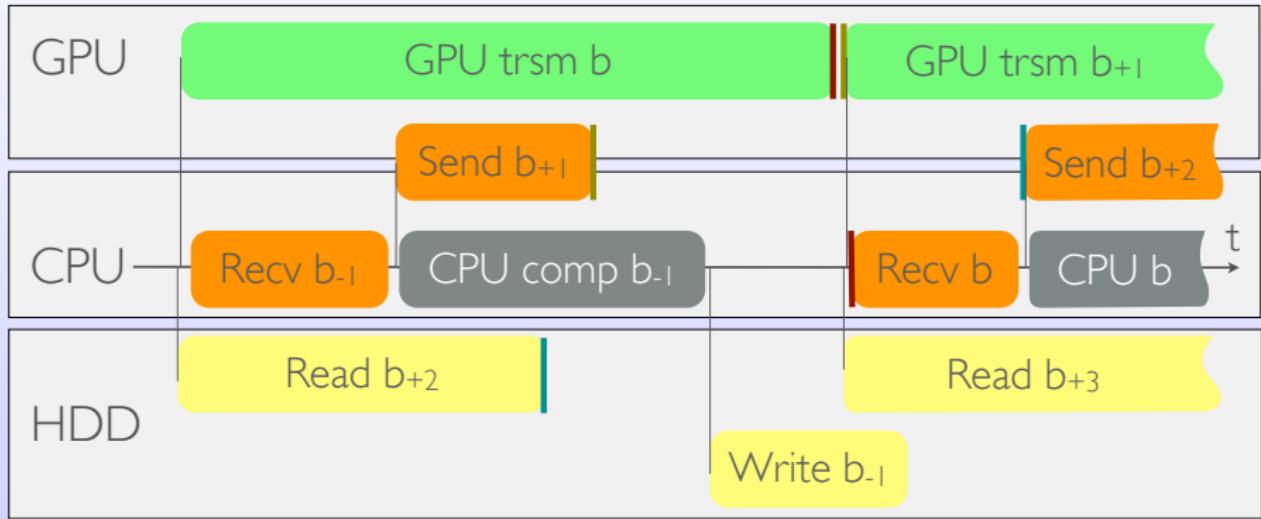
$$y := L^{-1}y$$

$$b := X^T y$$

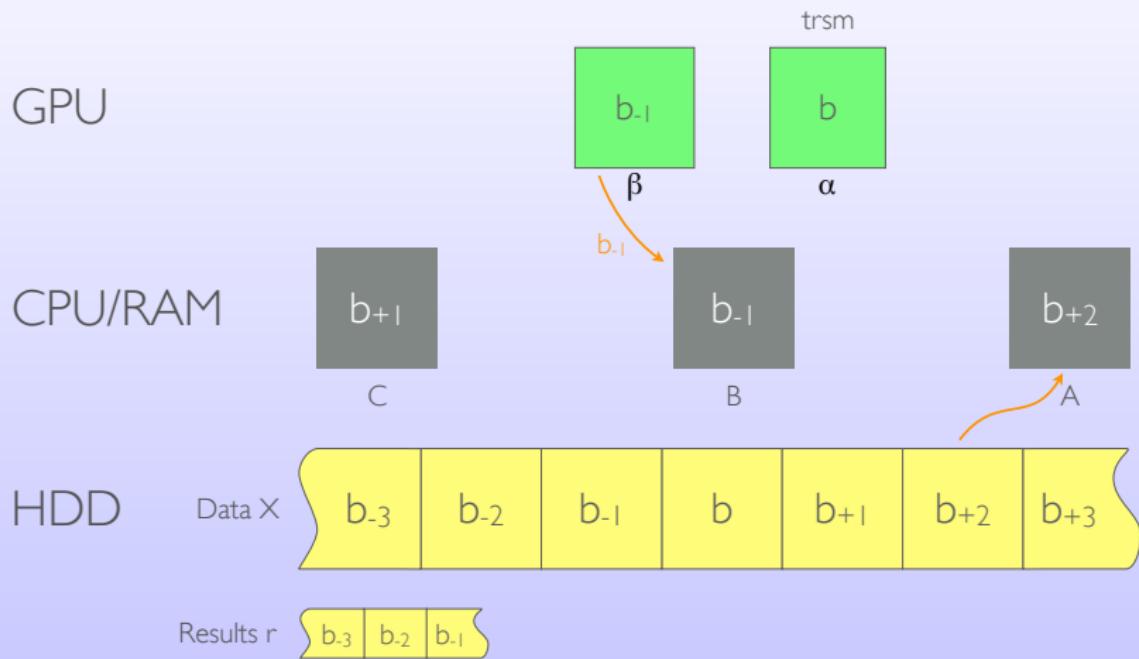
$$b := G^{-1}b$$

$$b := G^{-T} b$$

# double+triple buffering



# double+triple buffering



# Summary

- Dense linear algebra: it's matter of layers  
GEMM = foundations, THE building block
- Irrespective of the architecture, need for highly optimized BLAS
- How to use threads/cores?  
Multithreaded BLAS vs. algorithms-by-blocks
- Large/many problems but limited memory  $\Rightarrow$  streaming

# References

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