

Generating Families of Practical Fast Matrix Multiplication Algorithms



Jianyu Huang, Leslie Rice,

Devin A. Matthews, Robert A. van de Geijn

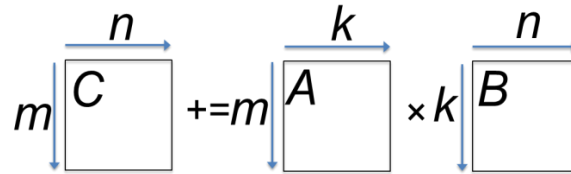
The University of Texas at Austin

Outline

- Background
 - High-performance GEMM
 - High-performance Strassen
- Fast Matrix Multiplication (FMM)
- Code Generation
- Performance Model
- Experiments
- Conclusion

High-performance matrix multiplication (GEMM)

State-of-the-art **GEMM** in **BLIS**



- BLAS-like Library Instantiation Software (**BLIS**) is a portable framework for instantiating BLAS-like dense linear algebra libraries.
 - ❑Field Van Zee, and Robert van de Geijn. “BLIS: A Framework for Rapidly Instantiating BLAS Functionality.” *ACM TOMS* 41.3 (2015): 14.
- BLIS provides a refactoring of **GotoBLAS** algorithm (best-known approach on CPU) to implement **GEMM**.
 - ❑Kazushige Goto, and Robert van de Geijn. “High-performance implementation of the level-3 BLAS.” *ACM TOMS* 35.1 (2008): 4.
 - ❑Kazushige Goto, and Robert van de Geijn. “Anatomy of high-performance matrix multiplication.” *ACM TOMS* 34.3 (2008): 12.
- GEMM implementation in BLIS has 6-layers of loops. The outer 5 loops are written in **C**. The inner-most loop (micro-kernel) is written in **assembly** for high performance.

GotoBLAS algorithm for GEMM in BLIS

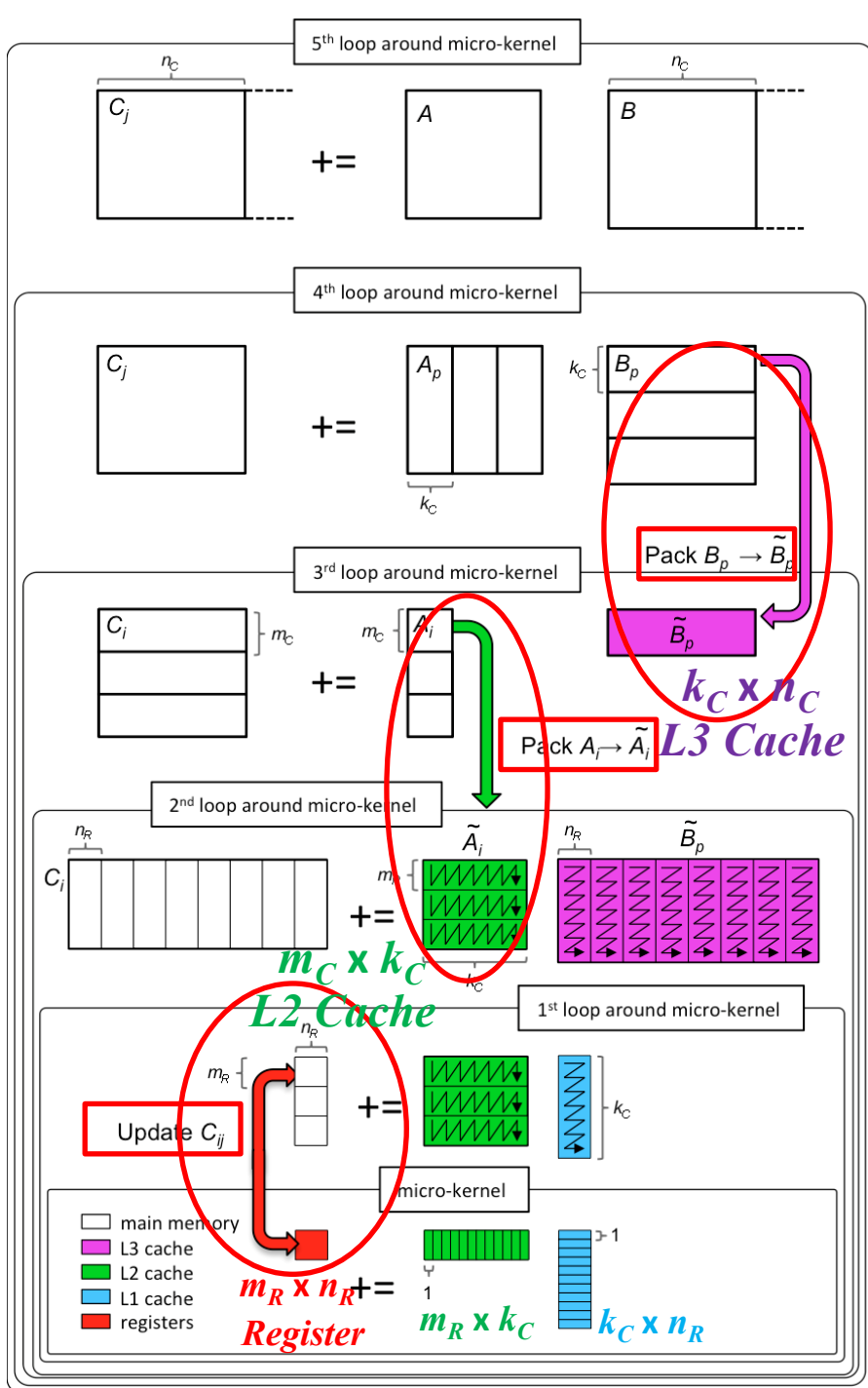
$$m \begin{matrix} \xrightarrow{n} \\ \downarrow m \end{matrix} C \quad += \quad m \begin{matrix} \xrightarrow{k} \\ \downarrow m \end{matrix} A \quad \times \quad k \begin{matrix} \xrightarrow{n} \\ \downarrow k \end{matrix} B$$

```

Loop 5  for  $j_c = 0 : n - 1$  steps of  $n_c$ 
         $\mathcal{J}_c = j_c : j_c + n_c - 1$ 
Loop 4  for  $p_c = 0 : k - 1$  steps of  $k_c$ 
         $\mathcal{P}_c = p_c : p_c + k_c - 1$ 
         $B(\mathcal{P}_c, \mathcal{J}_c) \rightarrow \tilde{B}_p$ 
Loop 3  for  $i_c = 0 : m - 1$  steps of  $m_c$ 
         $\mathcal{I}_c = i_c : i_c + m_c - 1$ 
         $A(\mathcal{I}_c, \mathcal{P}_c) \rightarrow \tilde{A}_i$ 
        // macro-kernel
Loop 2  for  $j_r = 0 : n_c - 1$  steps of  $n_r$ 
         $\mathcal{J}_r = j_r : j_r + n_r - 1$ 
Loop 1  for  $i_r = 0 : m_c - 1$  steps of  $m_r$ 
         $\mathcal{I}_r = i_r : i_r + m_r - 1$ 
        //micro-kernel
Loop 0  for  $p_r = 0 : p_c - 1$  steps of 1
         $C_c(\mathcal{I}_r, \mathcal{J}_r) += \tilde{A}_i(\mathcal{I}_r, p_r) \tilde{B}_p(p_r, \mathcal{J}_r)$ 
        endfor
    endfor
  endfor
endfor
endfor
endfor

```

*Field G. Van Zee, and Tyler M. Smith. "Implementing high-performance complex matrix multiplication via the 3m and 4m methods." In *ACM Transactions on Mathematical Software (TOMS)*, accepted.



High-performance Strassen

***Jianyu Huang**, Tyler Smith, Greg Henry, and Robert van de Geijn. “Strassen’s Algorithm Reloaded.” In *SC’16*.

Strassen's Algorithm Reloaded

$$M_0 := (A_{00} + A_{11})(B_{00} + B_{11});$$

$$M_1 := (A_{10} + A_{11})B_{00};$$

$$M_2 := A_{00}(B_{01} - B_{11});$$

$$M_3 := A_{11}(B_{10} - B_{00});$$

$$M_4 := (A_{00} + A_{01})B_{11};$$

$$M_5 := (A_{10} - A_{00})(B_{00} + B_{01});$$

$$M_6 := (A_{01} - A_{11})(B_{10} + B_{11});$$

$$C_{00} += M_0 + M_3 - M_4 + M_6$$

$$C_{01} += M_2 + M_4$$

$$C_{10} += M_1 + M_3$$

$$C_{11} += M_0 - M_1 + M_2 + M_5$$



$$M_0 := (A_{00} + A_{11})(B_{00} + B_{11}); \quad C_{00} += M_0; \quad C_{11} += M_0;$$

$$M_1 := (A_{10} + A_{11})B_{00}; \quad C_{10} += M_1; \quad C_{11} -= M_1;$$

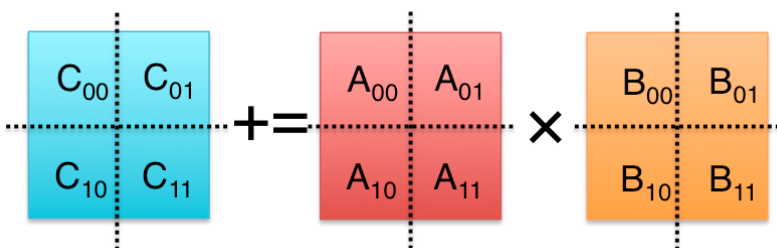
$$M_2 := A_{00}(B_{01} - B_{11}); \quad C_{01} += M_2; \quad C_{11} += M_2;$$

$$M_3 := A_{11}(B_{10} - B_{00}); \quad C_{00} += M_3; \quad C_{10} += M_3;$$

$$M_4 := (A_{00} + A_{01})B_{11}; \quad C_{01} += M_4; \quad C_{00} -= M_4;$$

$$M_5 := (A_{10} - A_{00})(B_{00} + B_{01}); \quad C_{11} += M_5;$$

$$M_6 := (A_{01} - A_{11})(B_{10} + B_{11}); \quad C_{00} += M_6;$$



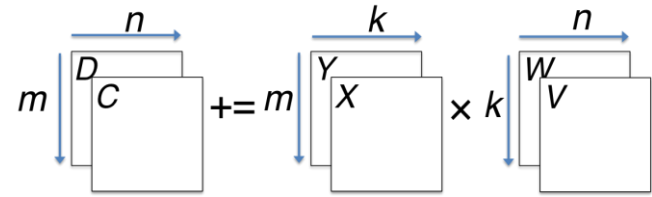
$$M := (X + Y)(V + W); \quad C += M; \quad D += M;$$

$$M := (X + \delta Y)(V + \varepsilon W); \quad C += \gamma_0 M; \quad D += \gamma_1 M;$$

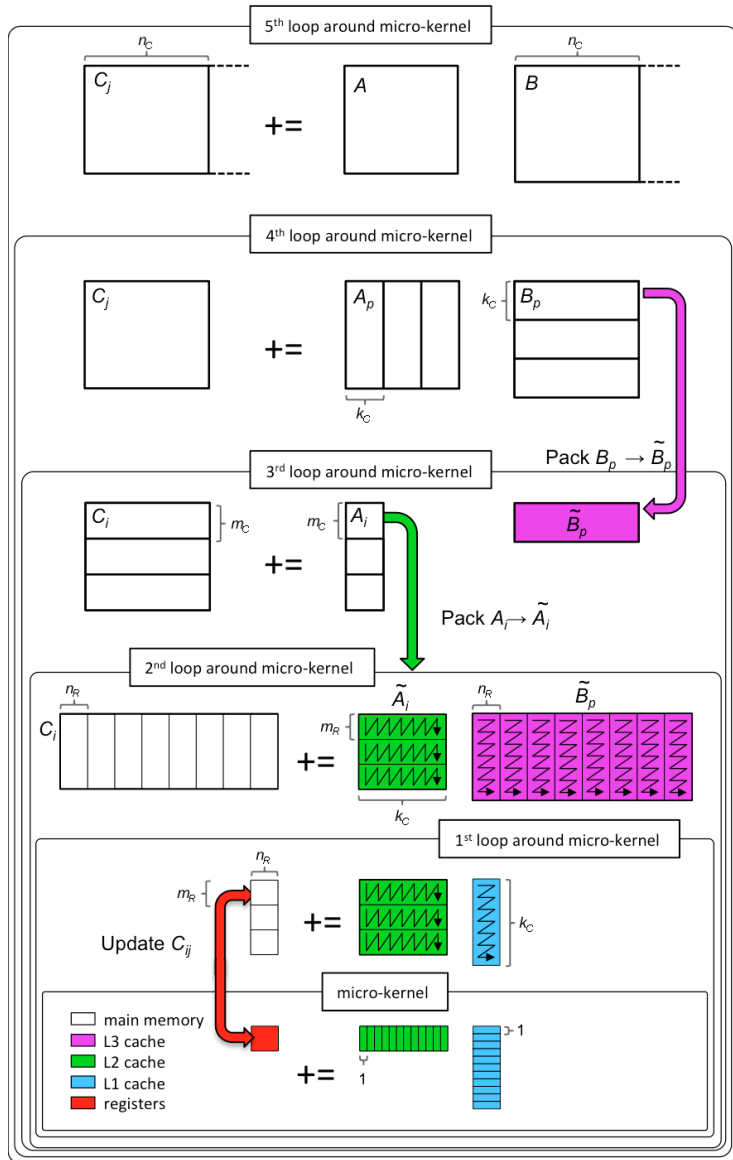
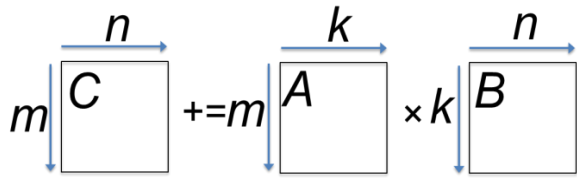
General operation for one-level Strassen:

$$\gamma_0, \gamma_1, \delta, \varepsilon \in \{-1, 0, 1\}.$$

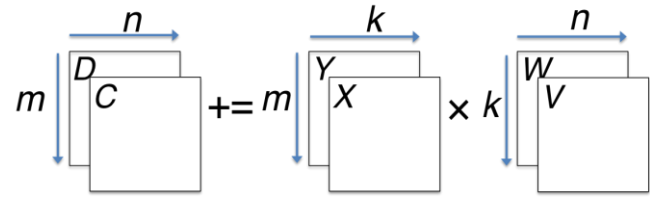
$M := (X + Y)(V + W); C += M; D += M;$



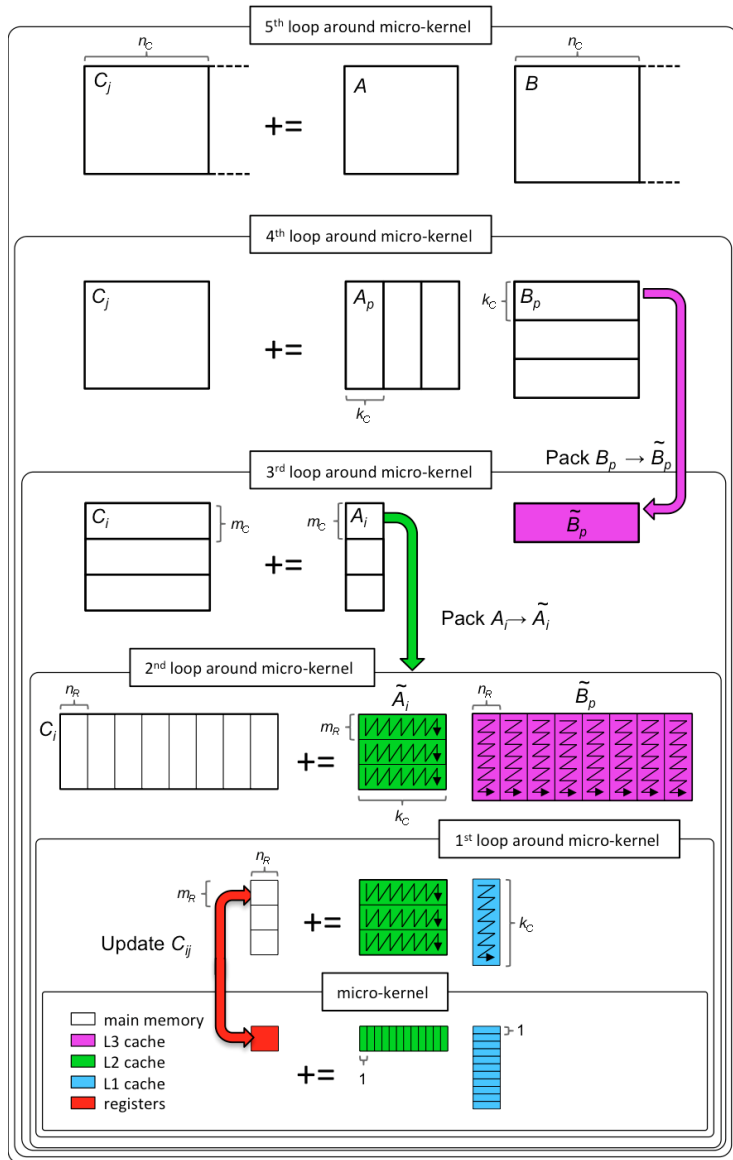
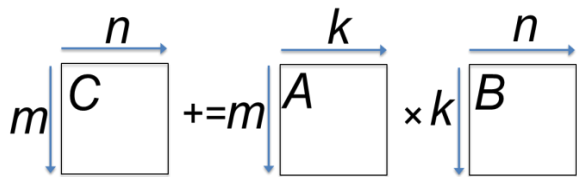
$$C += AB;$$



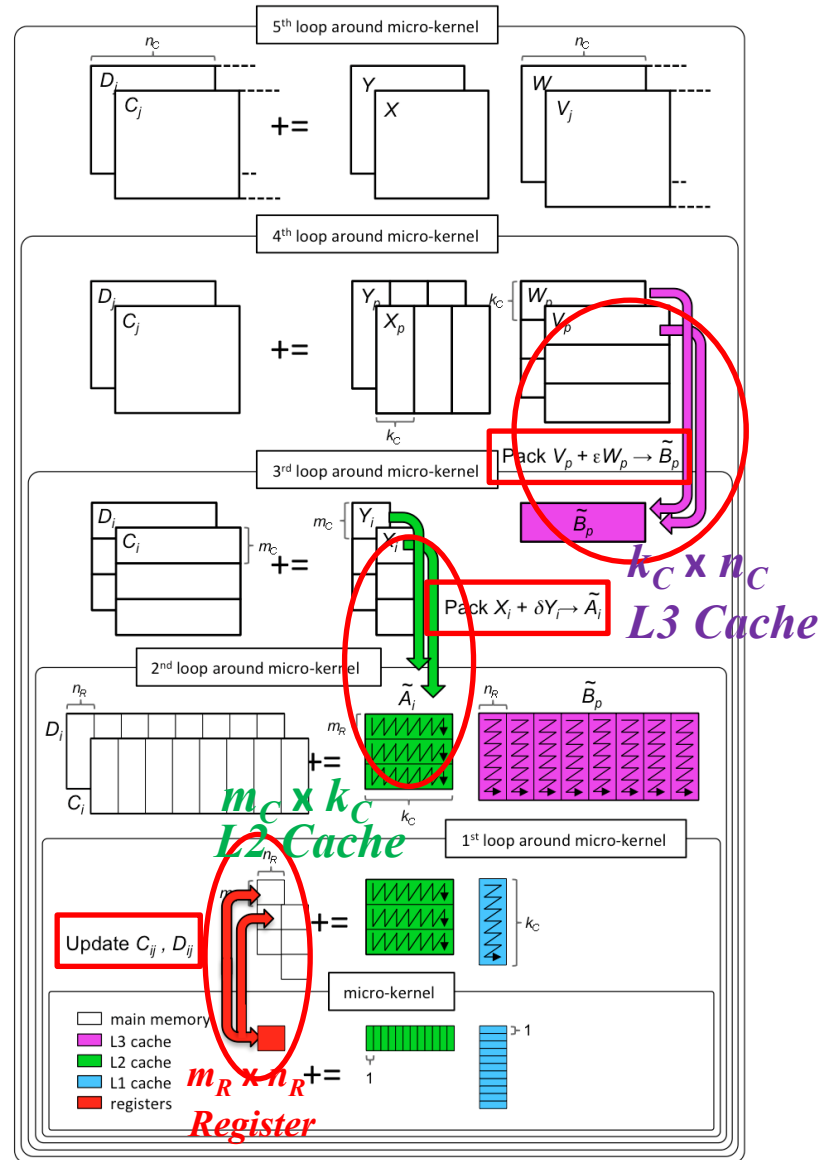
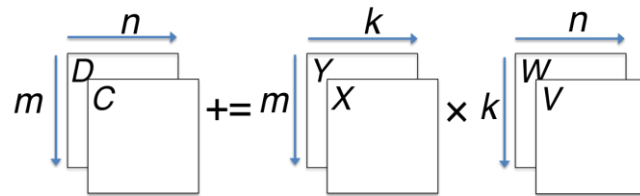
$$M := (X + Y)(V + W); C += M; D += M;$$



$$C += AB;$$



$$M := (X + Y)(V + W); C += M; D += M;$$



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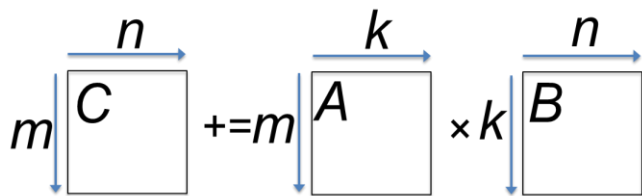
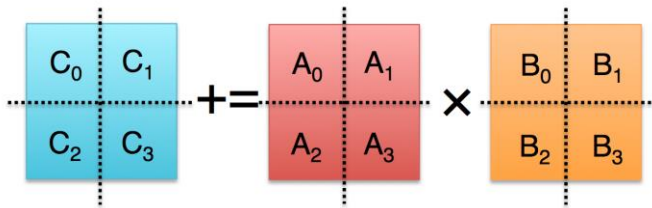
<2,2,2> Strassen's Algorithm

$$\begin{aligned}
 M_0 &:= (A_0 + A_3)(B_0 + B_3); & C_0 &+= M_0; & C_3 &+= M_0; \\
 M_1 &:= (A_2 + A_3)B_0; & C_2 &+= M_1; & C_3 &- = M_1; \\
 M_2 &:= A_0(B_1 - B_3); & C_1 &+= M_2; & C_3 &+= M_2; \\
 M_3 &:= A_3(B_2 - B_0); & C_0 &+= M_3; & C_2 &+= M_3; \\
 M_4 &:= (A_0 + A_1)B_3; & C_1 &+= M_4; & C_0 &- = M_4; \\
 M_5 &:= (A_2 - A_0)(B_0 + B_1); & C_3 &+= M_5; \\
 M_6 &:= (A_1 - A_3)(B_2 + B_3); & C_0 &+= M_6;
 \end{aligned}$$

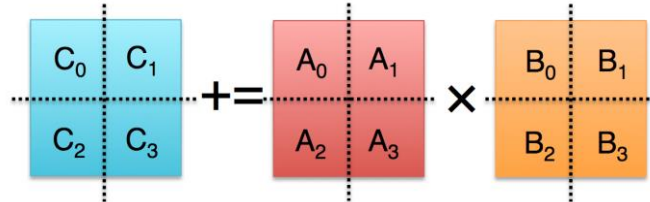
$$\mathbf{U} = \begin{bmatrix} 1 & 0 & 1 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 & -1 \end{bmatrix}$$

$$\mathbf{V} = \begin{bmatrix} 1 & 1 & 0 & -1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & -1 & 0 & 1 & 0 & 1 \end{bmatrix}$$

$$\mathbf{W} = \begin{bmatrix} 1 & 0 & 0 & 1 & -1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & -1 & 1 & 0 & 0 & 1 & 0 \end{bmatrix}$$



$\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$ Fast Matrix Multiplication (FMM)



$$C = \begin{pmatrix} C_0 & \cdots & C_{\tilde{n}-1} \\ \vdots & & \vdots \\ C_{(\tilde{m}-1)\tilde{n}} & \cdots & C_{\tilde{m}\tilde{n}-1} \end{pmatrix}, A = \begin{pmatrix} A_0 & \cdots & A_{\tilde{k}-1} \\ \vdots & & \vdots \\ A_{(\tilde{m}-1)\tilde{k}} & \cdots & A_{\tilde{m}\tilde{k}-1} \end{pmatrix}, B = \begin{pmatrix} B_0 & \cdots & B_{\tilde{n}-1} \\ \vdots & & \vdots \\ B_{(\tilde{k}-1)\tilde{n}} & \cdots & B_{\tilde{k}\tilde{n}-1} \end{pmatrix}$$

for $r = 0, \dots, R - 1$,

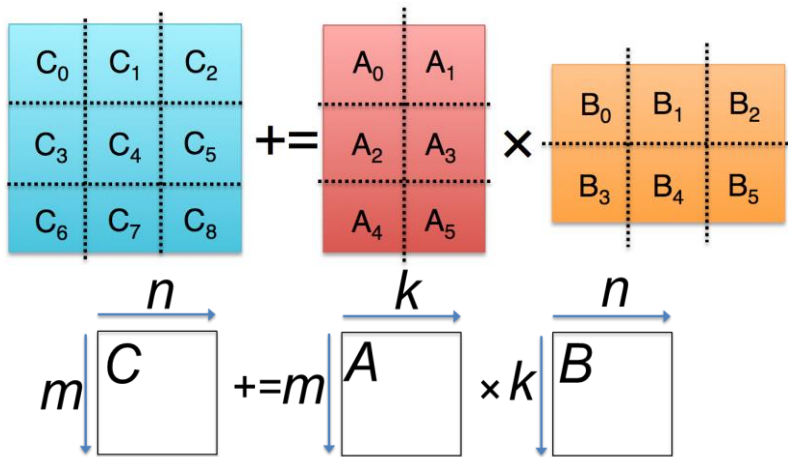
$$M_r := \left(\sum_{i=0}^{\tilde{m}\tilde{k}-1} u_{ir} A_i \right) \times \left(\sum_{j=0}^{\tilde{k}\tilde{n}-1} v_{jr} B_j \right);$$

$$C_p += w_{pr} M_r \quad (p = 0, \dots, \tilde{m}\tilde{n} - 1)$$

The set of coefficients that determine the $\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$ algorithm is denoted as $\llbracket U, V, W \rrbracket$.

<3,2,3> Fast Matrix Multiplication (FMM)

$$\begin{aligned}
 M_0 &:= (-A_1 + A_3 + A_5)(B_4 + B_5); & C_2 &-= M_0; \\
 M_1 &:= (-A_0 + A_2 + A_5)(B_0 - B_5); & C_2 &-= M_1; \quad C_7 &-= M_1; \\
 M_2 &:= (-A_0 + A_2)(-B_1 - B_4); & C_0 &-= M_2; \quad C_1 &+= M_2; \quad C_7 &+= M_2; \\
 M_3 &:= (A_2 - A_4 + A_5)(B_2 - B_3 + B_5); & C_2 &+= M_3; \quad C_5 &+= M_3; \quad C_6 &-= M_3; \\
 M_4 &:= (-A_0 + A_1 + A_2)(B_0 + B_1 + B_4); & C_0 &-= M_4; \quad C_1 &+= M_4; \quad C_4 &+= M_4; \\
 M_5 &:= (A_2)(B_0); & C_0 &+= M_5; \quad C_1 &-= M_5; \quad C_3 &+= M_5; \quad C_4 &-= M_5; \quad C_6 &+= M_5; \\
 M_6 &:= (-A_2 + A_3 + A_4 - A_5)(B_3 - B_5); & C_2 &-= M_6; \quad C_5 &-= M_6; \\
 M_7 &:= (A_3)(B_3); & C_2 &+= M_7; \quad C_3 &+= M_7; \quad C_5 &+= M_7; \\
 M_8 &:= (-A_0 + A_2 + A_4)(B_1 + B_2); & C_7 &+= M_8; \\
 M_9 &:= (-A_0 + A_1)(-B_0 - B_1); & C_1 &+= M_9; \quad C_4 &+= M_9; \\
 M_{10} &:= (A_5)(B_2 + B_5); & C_2 &+= M_{10}; \quad C_6 &+= M_{10}; \quad C_8 &+= M_{10}; \\
 M_{11} &:= (A_4 - A_5)(B_2); & C_2 &+= M_{11}; \quad C_5 &+= M_{11}; \quad C_7 &-= M_{11}; \quad C_8 &+= M_{11}; \\
 M_{12} &:= (A_1)(B_0 + B_1 + B_3 + B_4); & C_0 &+= M_{12}; \\
 M_{13} &:= (A_2 - A_4)(B_0 - B_2 + B_3 - B_5); & C_6 &-= M_{13}; \\
 M_{14} &:= (-A_0 + A_1 + A_2 - A_3)(B_5); & C_2 &-= M_{14}; \quad C_4 &-= M_{14};
 \end{aligned}$$



$$u = \begin{bmatrix} 0 & -1 & -1 & 0 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 0 & 0 & -1 \\ -1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & -1 \\ 1 & 1 & 0 & 1 & 0 & 0 & -1 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 \end{bmatrix}$$

$$v = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & -1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & -1 & 0 & 1 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 1 & -1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 & -1 & 0 & 0 & 0 & 1 & 0 & 0 & -1 & 0 \end{bmatrix}$$

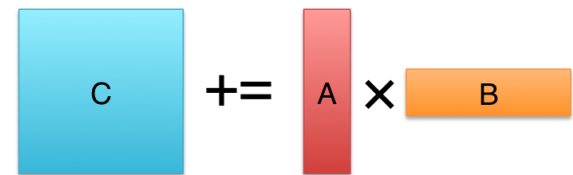
$$w = \begin{bmatrix} 0 & 0 & -1 & 0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & -1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & 0 & 1 & 0 & 0 & -1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 1 & 0 & 0 & -1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$	Ref. $\tilde{m}\tilde{k}\tilde{n}$ R	Speedup (%)				
		Theory	Practical #1		Practical #2	
			Ours	[1]	Ours	[1]
$\langle 2, 2, 2 \rangle$						
$\langle 2, 3, 2 \rangle$						
$\langle 2, 3, 4 \rangle$						
$\langle 2, 4, 3 \rangle$						
$\langle 2, 5, 2 \rangle$						
$\langle 3, 2, 2 \rangle$						
$\langle 3, 2, 3 \rangle$						
$\langle 3, 2, 4 \rangle$						
$\langle 3, 3, 2 \rangle$						
$\langle 3, 3, 3 \rangle$						
$\langle 3, 3, 6 \rangle$						
$\langle 3, 4, 2 \rangle$						
$\langle 3, 4, 3 \rangle$						
$\langle 3, 5, 3 \rangle$						
$\langle 3, 6, 3 \rangle$						
$\langle 4, 2, 2 \rangle$						
$\langle 4, 2, 3 \rangle$						
$\langle 4, 2, 4 \rangle$						
$\langle 4, 3, 2 \rangle$						
$\langle 4, 3, 3 \rangle$						
$\langle 4, 4, 2 \rangle$						
$\langle 5, 2, 2 \rangle$						
$\langle 6, 3, 3 \rangle$						

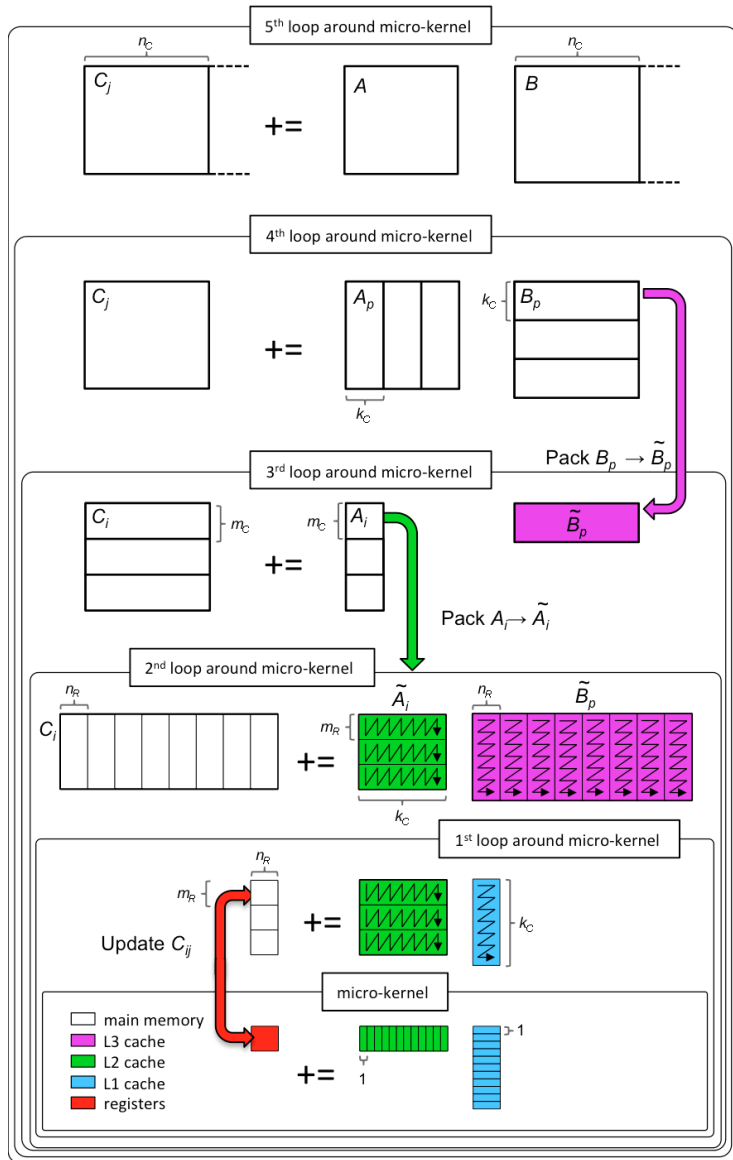
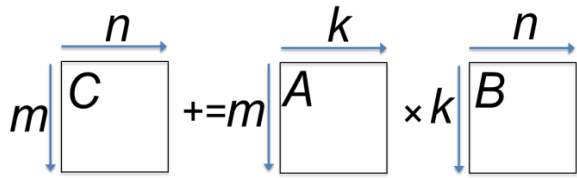
$\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$	Ref.	$\tilde{m}\tilde{k}\tilde{n}$	R	Speedup (%)				
				Theory	Practical #1		Practical #2	
					Ours	[1]	Ours	[1]
$\langle 2, 2, 2 \rangle$	[13]	8	7					
$\langle 2, 3, 2 \rangle$	[1]	12	11					
$\langle 2, 3, 4 \rangle$	[1]	24	20					
$\langle 2, 4, 3 \rangle$	[10]	24	20					
$\langle 2, 5, 2 \rangle$	[10]	20	18					
$\langle 3, 2, 2 \rangle$	[10]	12	11					
$\langle 3, 2, 3 \rangle$	[10]	18	15					
$\langle 3, 2, 4 \rangle$	[10]	24	20					
$\langle 3, 3, 2 \rangle$	[10]	18	15					
$\langle 3, 3, 3 \rangle$	[14]	27	23					
$\langle 3, 3, 6 \rangle$	[14]	54	40					
$\langle 3, 4, 2 \rangle$	[1]	24	20					
$\langle 3, 4, 3 \rangle$	[14]	36	29					
$\langle 3, 5, 3 \rangle$	[14]	45	36					
$\langle 3, 6, 3 \rangle$	[14]	54	40					
$\langle 4, 2, 2 \rangle$	[10]	16	14					
$\langle 4, 2, 3 \rangle$	[1]	24	20					
$\langle 4, 2, 4 \rangle$	[10]	32	26					
$\langle 4, 3, 2 \rangle$	[10]	24	20					
$\langle 4, 3, 3 \rangle$	[10]	36	29					
$\langle 4, 4, 2 \rangle$	[10]	32	26					
$\langle 5, 2, 2 \rangle$	[10]	20	18					
$\langle 6, 3, 3 \rangle$	[14]	54	40					

$\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$	Ref.	$\tilde{m}\tilde{k}\tilde{n}$	R	Speedup (%)				
				Theory	Practical #1		Practical #2	
					Ours	[1]	Ours	[1]
$\langle 2, 2, 2 \rangle$	[13]	8	7	14.3				
$\langle 2, 3, 2 \rangle$	[1]	12	11	9.1				
$\langle 2, 3, 4 \rangle$	[1]	24	20	20.0				
$\langle 2, 4, 3 \rangle$	[10]	24	20	20.0				
$\langle 2, 5, 2 \rangle$	[10]	20	18	11.1				
$\langle 3, 2, 2 \rangle$	[10]	12	11	9.1				
$\langle 3, 2, 3 \rangle$	[10]	18	15	20.0				
$\langle 3, 2, 4 \rangle$	[10]	24	20	20.0				
$\langle 3, 3, 2 \rangle$	[10]	18	15	20.0				
$\langle 3, 3, 3 \rangle$	[14]	27	23	17.4				
$\langle 3, 3, 6 \rangle$	[14]	54	40	35.0				
$\langle 3, 4, 2 \rangle$	[1]	24	20	20.0				
$\langle 3, 4, 3 \rangle$	[14]	36	29	24.1				
$\langle 3, 5, 3 \rangle$	[14]	45	36	25.0				
$\langle 3, 6, 3 \rangle$	[14]	54	40	35.0				
$\langle 4, 2, 2 \rangle$	[10]	16	14	14.3				
$\langle 4, 2, 3 \rangle$	[1]	24	20	20.0				
$\langle 4, 2, 4 \rangle$	[10]	32	26	23.1				
$\langle 4, 3, 2 \rangle$	[10]	24	20	20.0				
$\langle 4, 3, 3 \rangle$	[10]	36	29	24.1				
$\langle 4, 4, 2 \rangle$	[10]	32	26	23.1				
$\langle 5, 2, 2 \rangle$	[10]	20	18	11.1				
$\langle 6, 3, 3 \rangle$	[14]	54	40	35.0				

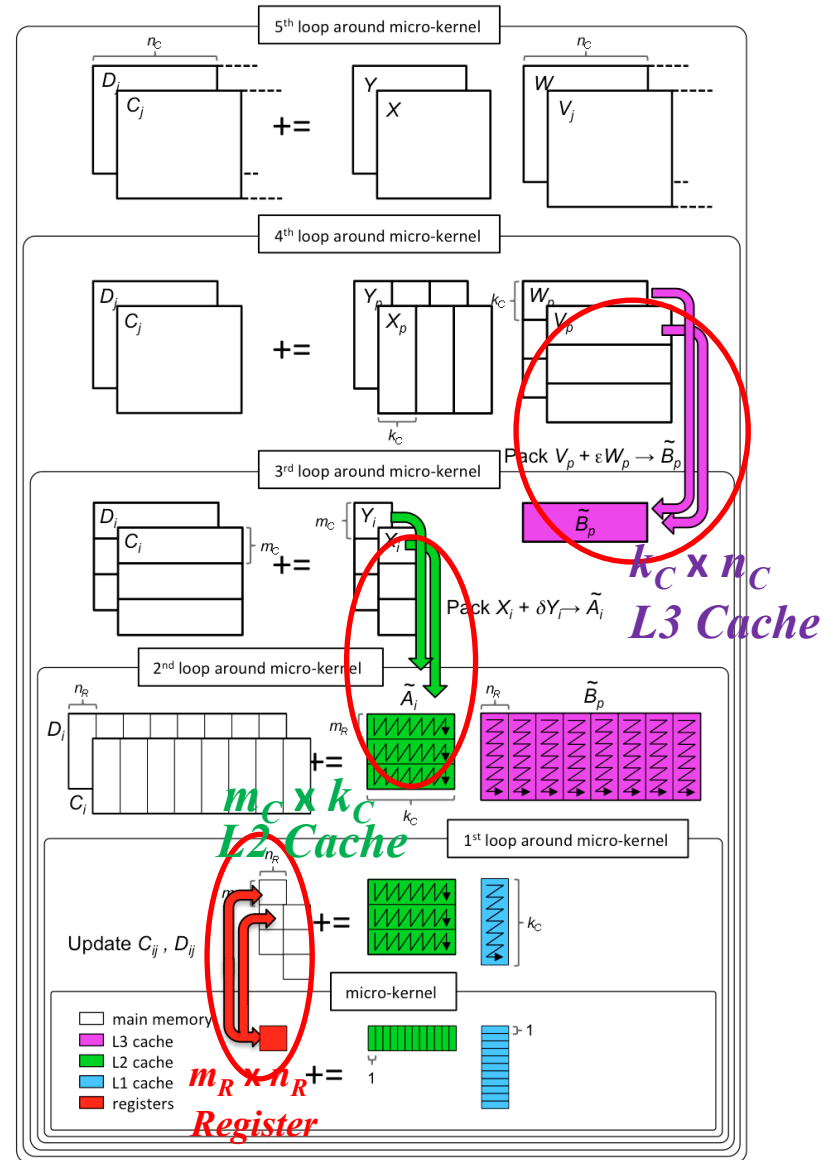
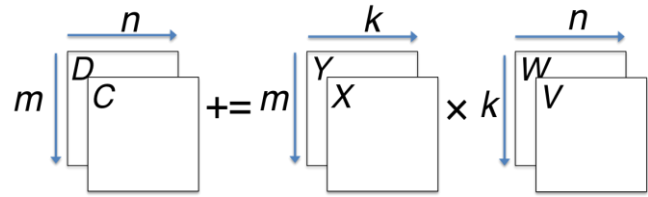
$\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$	Ref. $\tilde{m}\tilde{k}\tilde{n}$ R			Speedup (%)				
				Theory	Practical #1		Practical #2	
					Ours	[1]	Ours	[1]
$\langle 2, 2, 2 \rangle$	[13]	8	7	14.3	11.9	-3.0		
$\langle 2, 3, 2 \rangle$	[1]	12	11	9.1	5.5	-13.1		
$\langle 2, 3, 4 \rangle$	[1]	24	20	20.0	11.9	-8.0		
$\langle 2, 4, 3 \rangle$	[10]	24	20	20.0	4.8	-15.3		
$\langle 2, 5, 2 \rangle$	[10]	20	18	11.1	1.5	-23.1		
$\langle 3, 2, 2 \rangle$	[10]	12	11	9.1	7.1	-6.6		
$\langle 3, 2, 3 \rangle$	[10]	18	15	20.0	14.1	-0.7		
$\langle 3, 2, 4 \rangle$	[10]	24	20	20.0	11.9	-1.8		
$\langle 3, 3, 2 \rangle$	[10]	18	15	20.0	11.4	-8.1		
$\langle 3, 3, 3 \rangle$	[14]	27	23	17.4	8.6	-9.3		
$\langle 3, 3, 6 \rangle$	[14]	54	40	35.0	-34.0	-41.6		
$\langle 3, 4, 2 \rangle$	[1]	24	20	20.0	4.9	-15.7		
$\langle 3, 4, 3 \rangle$	[14]	36	29	24.1	8.4	-12.6		
$\langle 3, 5, 3 \rangle$	[14]	45	36	25.0	5.2	-20.6		
$\langle 3, 6, 3 \rangle$	[14]	54	40	35.0	-21.6	-64.5		
$\langle 4, 2, 2 \rangle$	[10]	16	14	14.3	9.4	-4.7		
$\langle 4, 2, 3 \rangle$	[1]	24	20	20.0	12.1	-2.3		
$\langle 4, 2, 4 \rangle$	[10]	32	26	23.1	10.4	-2.7		
$\langle 4, 3, 2 \rangle$	[10]	24	20	20.0	11.3	-7.8		
$\langle 4, 3, 3 \rangle$	[10]	36	29	24.1	8.1	-8.4		
$\langle 4, 4, 2 \rangle$	[10]	32	26	23.1	-4.2	-18.4		
$\langle 5, 2, 2 \rangle$	[10]	20	18	11.1	7.0	-6.7		
$\langle 6, 3, 3 \rangle$	[14]	54	40	35.0	-33.4	-42.2		



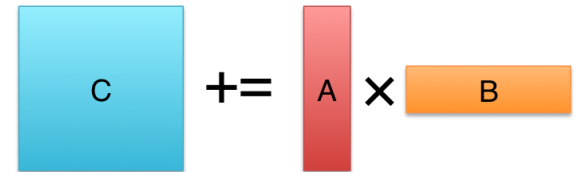
$$C += AB;$$



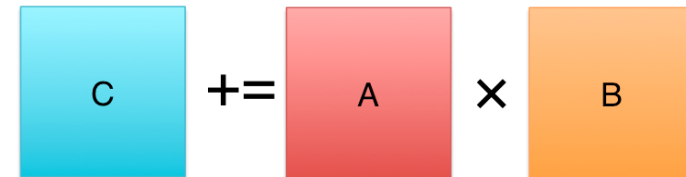
$$M := (X + Y)(V + W); C += M; D += M;$$



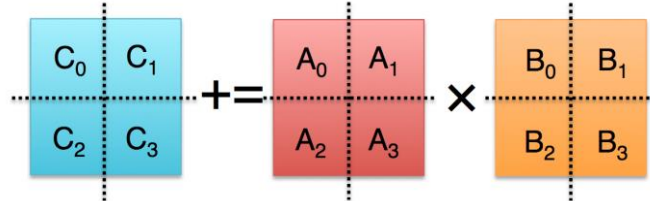
$\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$	Ref. $\tilde{m}\tilde{k}\tilde{n}$ R			Speedup (%)				
				Theory	Practical #1		Practical #2	
					Ours	[1]	Ours	[1]
$\langle 2, 2, 2 \rangle$	[13]	8	7	14.3	11.9	-3.0		
$\langle 2, 3, 2 \rangle$	[1]	12	11	9.1	5.5	-13.1		
$\langle 2, 3, 4 \rangle$	[1]	24	20	20.0	11.9	-8.0		
$\langle 2, 4, 3 \rangle$	[10]	24	20	20.0	4.8	-15.3		
$\langle 2, 5, 2 \rangle$	[10]	20	18	11.1	1.5	-23.1		
$\langle 3, 2, 2 \rangle$	[10]	12	11	9.1	7.1	-6.6		
$\langle 3, 2, 3 \rangle$	[10]	18	15	20.0	14.1	-0.7		
$\langle 3, 2, 4 \rangle$	[10]	24	20	20.0	11.9	-1.8		
$\langle 3, 3, 2 \rangle$	[10]	18	15	20.0	11.4	-8.1		
$\langle 3, 3, 3 \rangle$	[14]	27	23	17.4	8.6	-9.3		
$\langle 3, 3, 6 \rangle$	[14]	54	40	35.0	-34.0	-41.6		
$\langle 3, 4, 2 \rangle$	[1]	24	20	20.0	4.9	-15.7		
$\langle 3, 4, 3 \rangle$	[14]	36	29	24.1	8.4	-12.6		
$\langle 3, 5, 3 \rangle$	[14]	45	36	25.0	5.2	-20.6		
$\langle 3, 6, 3 \rangle$	[14]	54	40	35.0	-21.6	-64.5		
$\langle 4, 2, 2 \rangle$	[10]	16	14	14.3	9.4	-4.7		
$\langle 4, 2, 3 \rangle$	[1]	24	20	20.0	12.1	-2.3		
$\langle 4, 2, 4 \rangle$	[10]	32	26	23.1	10.4	-2.7		
$\langle 4, 3, 2 \rangle$	[10]	24	20	20.0	11.3	-7.8		
$\langle 4, 3, 3 \rangle$	[10]	36	29	24.1	8.1	-8.4		
$\langle 4, 4, 2 \rangle$	[10]	32	26	23.1	-4.2	-18.4		
$\langle 5, 2, 2 \rangle$	[10]	20	18	11.1	7.0	-6.7		
$\langle 6, 3, 3 \rangle$	[14]	54	40	35.0	-33.4	-42.2		



$\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$	Ref. $\tilde{m}\tilde{k}\tilde{n}$ R			Speedup (%)				
				Theory	Practical #1		Practical #2	
					Ours	[1]	Ours	[1]
$\langle 2, 2, 2 \rangle$	[13]	8	7	14.3	11.9	-3.0	13.1	13.1
$\langle 2, 3, 2 \rangle$	[1]	12	11	9.1	5.5	-13.1	7.7	7.7
$\langle 2, 3, 4 \rangle$	[1]	24	20	20.0	11.9	-8.0	16.3	17.0
$\langle 2, 4, 3 \rangle$	[10]	24	20	20.0	4.8	-15.3	14.9	16.6
$\langle 2, 5, 2 \rangle$	[10]	20	18	11.1	1.5	-23.1	8.6	8.3
$\langle 3, 2, 2 \rangle$	[10]	12	11	9.1	7.1	-6.6	7.2	7.5
$\langle 3, 2, 3 \rangle$	[10]	18	15	20.0	14.1	-0.7	17.2	16.8
$\langle 3, 2, 4 \rangle$	[10]	24	20	20.0	11.9	-1.8	16.1	17.0
$\langle 3, 3, 2 \rangle$	[10]	18	15	20.0	11.4	-8.1	17.3	16.5
$\langle 3, 3, 3 \rangle$	[14]	27	23	17.4	8.6	-9.3	14.4	14.7
$\langle 3, 3, 6 \rangle$	[14]	54	40	35.0	-34.0	-41.6	24.2	20.1
$\langle 3, 4, 2 \rangle$	[1]	24	20	20.0	4.9	-15.7	16.0	16.8
$\langle 3, 4, 3 \rangle$	[14]	36	29	24.1	8.4	-12.6	18.1	20.1
$\langle 3, 5, 3 \rangle$	[14]	45	36	25.0	5.2	-20.6	19.1	18.9
$\langle 3, 6, 3 \rangle$	[14]	54	40	35.0	-21.6	-64.5	19.5	17.8
$\langle 4, 2, 2 \rangle$	[10]	16	14	14.3	9.4	-4.7	11.9	12.2
$\langle 4, 2, 3 \rangle$	[1]	24	20	20.0	12.1	-2.3	15.9	17.3
$\langle 4, 2, 4 \rangle$	[10]	32	26	23.1	10.4	-2.7	18.4	19.1
$\langle 4, 3, 2 \rangle$	[10]	24	20	20.0	11.3	-7.8	16.8	15.7
$\langle 4, 3, 3 \rangle$	[10]	36	29	24.1	8.1	-8.4	19.8	20.0
$\langle 4, 4, 2 \rangle$	[10]	32	26	23.1	-4.2	-18.4	17.1	18.5
$\langle 5, 2, 2 \rangle$	[10]	20	18	11.1	7.0	-6.7	8.2	8.5
$\langle 6, 3, 3 \rangle$	[14]	54	40	35.0	-33.4	-42.2	24.0	20.2



One-level Fast Matrix Multiplication (FMM)



$$C = \begin{pmatrix} C_0 & \cdots & C_{\tilde{n}-1} \\ \vdots & & \vdots \\ C_{(\tilde{m}-1)\tilde{n}} & \cdots & C_{\tilde{m}\tilde{n}-1} \end{pmatrix}, A = \begin{pmatrix} A_0 & \cdots & A_{\tilde{k}-1} \\ \vdots & & \vdots \\ A_{(\tilde{m}-1)\tilde{k}} & \cdots & A_{\tilde{m}\tilde{k}-1} \end{pmatrix}, B = \begin{pmatrix} B_0 & \cdots & B_{\tilde{n}-1} \\ \vdots & & \vdots \\ B_{(\tilde{k}-1)\tilde{n}} & \cdots & B_{\tilde{k}\tilde{n}-1} \end{pmatrix}$$

for $r = 0, \dots, R - 1$,

$$M_r := \left(\sum_{i=0}^{\tilde{m}\tilde{k}-1} u_{ir} A_i \right) \times \left(\sum_{j=0}^{\tilde{k}\tilde{n}-1} v_{jr} B_j \right);$$

$$C_p += w_{pr} M_r \quad (p = 0, \dots, \tilde{m}\tilde{n} - 1)$$

The set of coefficients that determine the $\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$ algorithm is denoted as $\llbracket U, V, W \rrbracket$.

Two-level Fast Matrix Multiplication (FMM)

$$C = \left(\begin{array}{c|c|c} C_0 & \cdots & C_{\tilde{n}-1} \\ \hline \vdots & & \vdots \\ \hline C_{(\tilde{m}-1)\tilde{n}} & \cdots & C_{\tilde{m}\tilde{n}-1} \end{array} \right), A = \left(\begin{array}{c|c|c} A_0 & \cdots & A_{\tilde{k}-1} \\ \hline \vdots & & \vdots \\ \hline A_{(\tilde{m}-1)\tilde{k}} & \cdots & A_{\tilde{m}\tilde{k}-1} \end{array} \right), B = \left(\begin{array}{c|c|c} B_0 & \cdots & B_{\tilde{n}-1} \\ \hline \vdots & & \vdots \\ \hline B_{(\tilde{k}-1)\tilde{n}} & \cdots & B_{\tilde{k}\tilde{n}-1} \end{array} \right)$$

The set of coefficients of a two-level $\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$ and $\langle \tilde{m}', \tilde{k}', \tilde{n}' \rangle$ FMM algorithm can be denoted as .

Kronecker Product

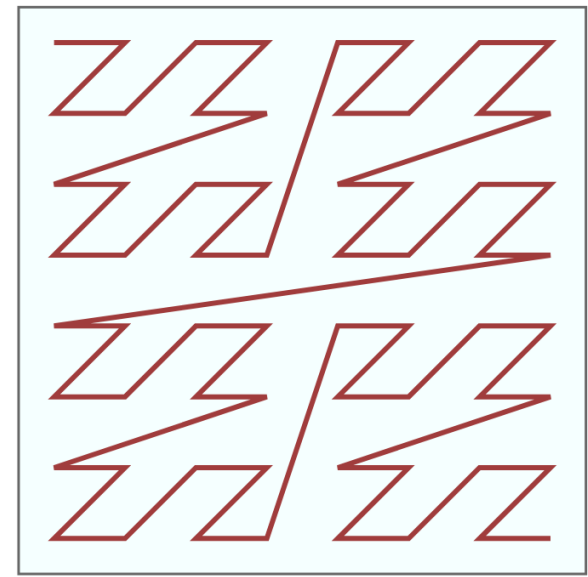
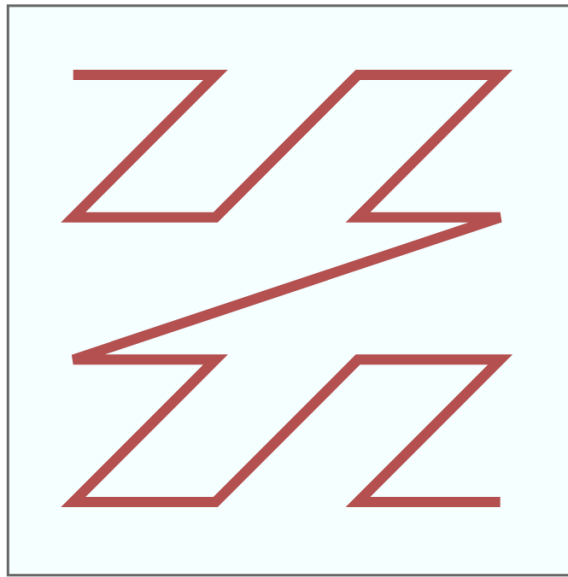
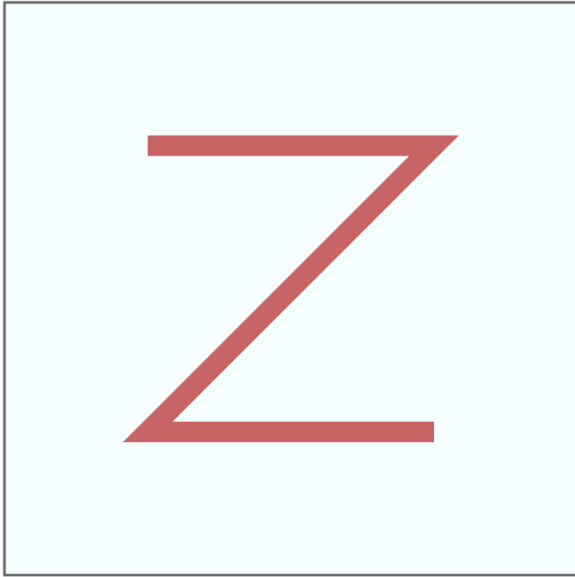
$$\begin{array}{ccc}
 X \otimes Y = & \begin{pmatrix} x_{0,0} Y & \cdots & x_{0,n-1} Y \\ \vdots & \ddots & \vdots \\ x_{m-1,0} Y & \cdots & x_{m-1,n-1} Y \end{pmatrix} \\
 \begin{array}{c} \downarrow \\ m \times n \end{array} & \begin{array}{c} \downarrow \\ p \times q \end{array} & \begin{array}{c} \downarrow \\ (mp) \times (nq) \end{array}
 \end{array}$$

$$\begin{bmatrix} a_{1,1} & a_{1,2} \\ a_{2,1} & a_{2,2} \end{bmatrix} \otimes \begin{bmatrix} b_{1,1} & b_{1,2} \\ b_{2,1} & b_{2,2} \end{bmatrix} = \begin{bmatrix} a_{1,1} \begin{bmatrix} b_{1,1} & b_{1,2} \\ b_{2,1} & b_{2,2} \end{bmatrix} & a_{1,2} \begin{bmatrix} b_{1,1} & b_{1,2} \\ b_{2,1} & b_{2,2} \end{bmatrix} \\ a_{2,1} \begin{bmatrix} b_{1,1} & b_{1,2} \\ b_{2,1} & b_{2,2} \end{bmatrix} & a_{2,2} \begin{bmatrix} b_{1,1} & b_{1,2} \\ b_{2,1} & b_{2,2} \end{bmatrix} \end{bmatrix} = \begin{bmatrix} a_{1,1}b_{1,1} & a_{1,1}b_{1,2} & a_{1,2}b_{1,1} & a_{1,2}b_{1,2} \\ a_{1,1}b_{2,1} & a_{1,1}b_{2,2} & a_{1,2}b_{2,1} & a_{1,2}b_{2,2} \\ a_{2,1}b_{1,1} & a_{2,1}b_{1,2} & a_{2,2}b_{1,1} & a_{2,2}b_{1,2} \\ a_{2,1}b_{2,1} & a_{2,1}b_{2,2} & a_{2,2}b_{2,1} & a_{2,2}b_{2,2} \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \otimes \begin{bmatrix} 0 & 5 \\ 6 & 7 \end{bmatrix} = \begin{bmatrix} 1 \cdot 0 & 1 \cdot 5 & 2 \cdot 0 & 2 \cdot 5 \\ 1 \cdot 6 & 1 \cdot 7 & 2 \cdot 6 & 2 \cdot 7 \\ 3 \cdot 0 & 3 \cdot 5 & 4 \cdot 0 & 4 \cdot 5 \\ 3 \cdot 6 & 3 \cdot 7 & 4 \cdot 6 & 4 \cdot 7 \end{bmatrix} = \begin{bmatrix} 0 & 5 & 0 & 10 \\ 6 & 7 & 12 & 14 \\ 0 & 15 & 0 & 20 \\ 18 & 21 & 24 & 28 \end{bmatrix}$$

- https://en.wikipedia.org/wiki/Kronecker_product.
- https://en.wikipedia.org/wiki/Tensor_product

Morton-like Ordering



$$\left(\begin{array}{cc|cc|cc|cc} 0 & 1 & 4 & 5 & 16 & 17 & 20 & 21 \\ \hline 2 & 3 & 6 & 7 & 18 & 19 & 22 & 23 \\ \hline 8 & 9 & 12 & 13 & 24 & 25 & 28 & 29 \\ \hline 10 & 11 & 14 & 15 & 26 & 27 & 30 & 31 \\ \hline 32 & 33 & 36 & 37 & 48 & 49 & 52 & 53 \\ \hline 34 & 35 & 38 & 39 & 50 & 51 & 54 & 55 \\ \hline 40 & 41 & 44 & 45 & 56 & 57 & 60 & 61 \\ \hline 42 & 43 & 46 & 47 & 58 & 59 & 62 & 63 \end{array} \right)$$

Two-level Fast Matrix Multiplication

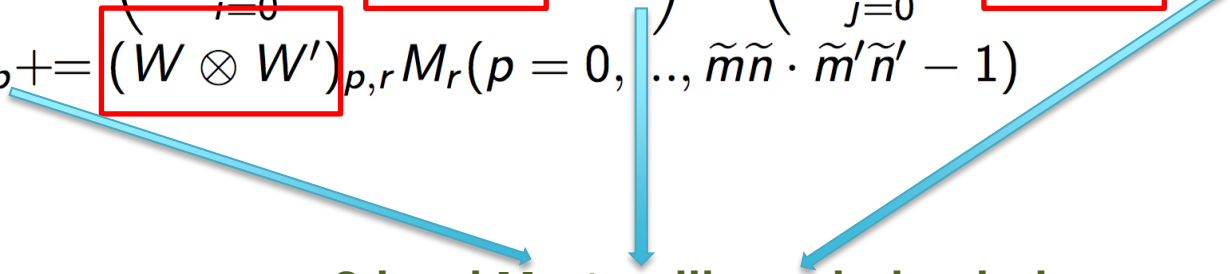
$$C = \left(\begin{array}{c|c|c} C_0 & \cdots & C_{\tilde{n}-1} \\ \hline \vdots & & \vdots \\ \hline C_{(\tilde{m}-1)\tilde{n}} & \cdots & C_{\tilde{m}\tilde{n}-1} \end{array} \right), A = \left(\begin{array}{c|c|c} A_0 & \cdots & A_{\tilde{k}-1} \\ \hline \vdots & & \vdots \\ \hline A_{(\tilde{m}-1)\tilde{k}} & \cdots & A_{\tilde{m}\tilde{k}-1} \end{array} \right), B = \left(\begin{array}{c|c|c} B_0 & \cdots & B_{\tilde{n}-1} \\ \hline \vdots & & \vdots \\ \hline B_{(\tilde{k}-1)\tilde{n}} & \cdots & B_{\tilde{k}\tilde{n}-1} \end{array} \right)$$

The set of coefficients of a two-level $\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$ and $\langle \tilde{m}', \tilde{k}', \tilde{n}' \rangle$ FMM algorithm can be denoted as $\llbracket U \text{?} U', V \text{?} V', W \text{?} W' \rrbracket$.

Two-level Fast Matrix Multiplication

for $r = 0, \dots, R \cdot R' - 1$,

$$M_r := \left(\sum_{i=0}^{\tilde{m}\tilde{k} \cdot \tilde{m}'\tilde{k}' - 1} (U \otimes U')_{i,r} A_i \right) \times \left(\sum_{j=0}^{\tilde{k}\tilde{n} \cdot \tilde{k}'\tilde{n}' - 1} (V \otimes V')_{j,r} B_j \right);$$

$$C_p += (W \otimes W')_{p,r} M_r (p = 0, \dots, \tilde{m}\tilde{n} \cdot \tilde{m}'\tilde{n}' - 1)$$


2-level Morton-like ordering index

The set of coefficients of a two-level $\langle \tilde{m}, \tilde{k}, \tilde{n} \rangle$ and $\langle \tilde{m}', \tilde{k}', \tilde{n}' \rangle$ FMM algorithm can be denoted as $\llbracket U \otimes U', V \otimes V', W \otimes W' \rrbracket$.

Two-level <2,2,2> Strassen Algorithm

$$\begin{aligned}
 M_0 &:= (A_0 + A_{12} + A_3 + A_{15})(B_0 + B_{12} + B_3 + B_{15}); \\
 M_1 &:= (A_2 + A_{14} + A_3 + A_{15})(B_0 + B_{12}); \\
 M_2 &:= (A_0 + A_{12})(B_1 + B_{13} + B_3 + B_{15}); \\
 M_3 &:= (A_3 + A_{15})(B_2 + B_{14} + B_0 + B_{12}); \\
 M_4 &:= (A_0 + A_{12} + A_1 + A_{13})(B_3 + B_{15}); \\
 M_5 &:= (A_2 + A_{14} + A_0 + A_{12})(B_0 + B_{12} + B_1 + B_{13}); \\
 M_6 &:= (A_1 + A_{13} + A_3 + A_{15})(B_2 + B_{14} + B_3 + B_{15}); \\
 M_7 &:= (A_8 + A_{12} + A_{11} + A_{15})(B_0 + B_3); \\
 M_8 &:= (A_{10} + A_{14} + A_{11} + A_{15})(B_0); \\
 M_9 &:= (A_8 + A_{12})(B_1 + B_3); \\
 M_{10} &:= (A_{11} + A_{15})(B_2 + B_0);
 \end{aligned}$$

$$\begin{aligned}
 C_0 &+= M_0; & C_3 &+= M_0; & C_{12} &+= M_0; & C_{15} &+= M_0; \\
 C_2 &+= M_1; & C_3 &- = M_1; & C_{14} &+= M_1; & C_{15} &- = M_1; \\
 C_1 &+= M_2; & C_3 &+= M_2; & C_{13} &+= M_2; & C_{15} &+= M_2; \\
 C_0 &+= M_3; & C_2 &+= M_3; & C_{12} &+= M_3; & C_{14} &+= M_3; \\
 C_0 &- = M_4; & C_1 &+= M_4; & C_{12} &- = M_4; & C_{13} &+= M_4; \\
 C_3 &+= M_5; & C_{15} &+= M_5; & & & & \\
 C_0 &+= M_6; & C_{12} &+= M_6; & & & & \\
 C_8 &+= M_7; & C_{11} &+= M_7; & C_{12} &- = M_7; & C_{15} &- = M_7; \\
 C_{10} &+= M_8; & C_{11} &- = M_8; & C_{14} &- = M_8; & C_{15} &+= M_8; \\
 C_9 &+= M_9; & C_{11} &+= M_9; & C_{13} &- = M_9; & C_{15} &- = M_9; \\
 C_8 &+= M_{10}; & C_{10} &+= M_{10}; & C_{12} &- = M_{10}; & C_{14} &- = M_{10};
 \end{aligned}$$

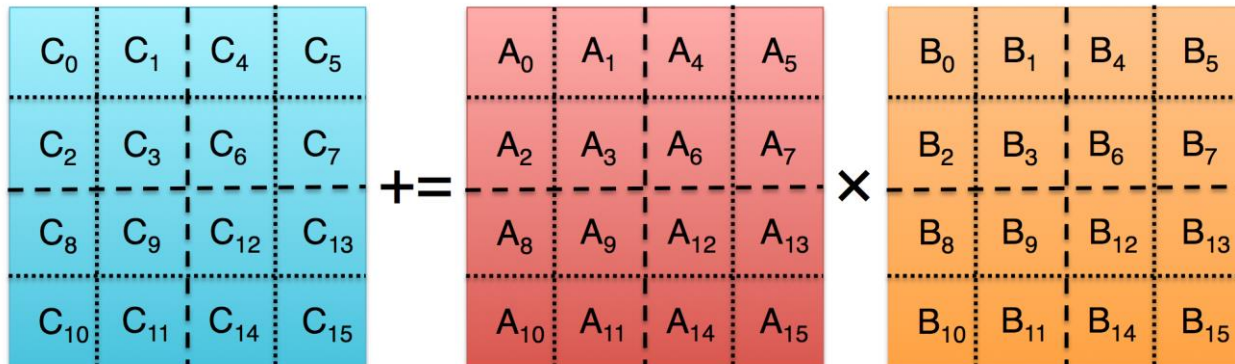
$$\begin{aligned}
 &\vdots \\
 M_{40} &:= (A_{10} + A_2 + A_8 + A_0)(B_0 + B_4 + B_1 + B_5); \\
 M_{41} &:= (A_9 + A_1 + A_{11} + A_3)(B_2 + B_6 + B_3 + B_7); \\
 M_{42} &:= (A_4 + A_{12} + A_7 + A_{15})(B_8 + B_{12} + B_{11} + B_{15}); \\
 M_{43} &:= (A_6 + A_{14} + A_7 + A_{15})(B_8 + B_{12}); \\
 M_{44} &:= (A_4 + A_{12})(B_9 + B_{13} + B_{11} + B_{15}); \\
 M_{45} &:= (A_7 + A_{15})(B_{10} + B_{14} + B_8 + B_{12}); \\
 M_{46} &:= (A_4 + A_{12} + A_5 + A_{13})(B_{11} + B_{15}); \\
 M_{47} &:= (A_6 + A_{14} + A_4 + A_{12})(B_8 + B_{12} + B_9 + B_{13}); \\
 M_{48} &:= (A_5 + A_{13} + A_7 + A_{15})(B_{10} + B_{14} + B_{11} + B_{15});
 \end{aligned}$$

$$\begin{aligned}
 C_{15} &+= M_{40}; \\
 C_{12} &+= M_{41}; \\
 C_0 &+= M_{42}; & C_3 &+= M_{42}; \\
 C_2 &+= M_{43}; & C_3 &- = M_{43}; \\
 C_1 &+= M_{44}; & C_3 &+= M_{44}; \\
 C_0 &+= M_{45}; & C_2 &+= M_{45}; \\
 C_0 &- = M_{46}; & C_1 &+= M_{46}; \\
 C_3 &+= M_{47}; \\
 C_0 &+= M_{48};
 \end{aligned}$$

$$\mathbf{U} = \begin{bmatrix} 1 & 0 & 1 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 & -1 \end{bmatrix}$$

$$\mathbf{V} = \begin{bmatrix} 1 & 1 & 0 & -1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & -1 & 0 & 1 & 0 & 1 \end{bmatrix}$$

$$\mathbf{W} = \begin{bmatrix} 1 & 0 & 0 & 1 & -1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & -1 & 1 & 0 & 0 & 1 & 0 \end{bmatrix}$$



$$\boxed{[U \otimes U, V \otimes V, W \otimes W]}$$

L-level Fast Matrix Multiplication

for $r = 0, \dots, \prod_{l=0}^{L-1} R_l - 1$,

$$M_r := \left(\prod_{l=0}^{L-1} \tilde{m}_l \tilde{k}_l - 1 \sum_{i=0}^{\tilde{m}_l \tilde{k}_l - 1} \left(\bigotimes_{l=0}^{L-1} U_l \right)_{i,r} A_i \right) \times \left(\prod_{l=0}^{L-1} \tilde{k}_l \tilde{n}_l - 1 \sum_{j=0}^{\tilde{k}_l \tilde{n}_l - 1} \left(\bigotimes_{l=0}^{L-1} V_l \right)_{j,r} B_j \right);$$

$$C_p := \left(\bigotimes_{l=0}^{L-1} W_l \right)_{p,r} M_r \quad (p = 0, \dots, \prod_{l=0}^{L-1} \tilde{m}_l \tilde{n}_l - 1)$$

L-level Morton-like ordering index

The set of coefficients of an L -level $\langle \tilde{m}_l, \tilde{k}_l, \tilde{n}_l \rangle$ ($l=0, 1, \dots, L-1$) FMM algorithm can be denoted as $\llbracket \bigotimes_{l=0}^{L-1} U_l, \bigotimes_{l=0}^{L-1} V_l, \bigotimes_{l=0}^{L-1} W_l \rrbracket$.

Outline

- Background
 - High-performance GEMM
 - High-performance Strassen
- Fast Matrix Multiplication (FMM)
- Code Generation
- Performance Model
- Experiments
- Conclusion

Generating skeleton framework

- Compute the Kronecker Product.

$$\llbracket \bigotimes_{l=0}^{L-1} U_l, \bigotimes_{l=0}^{L-1} V_l, \bigotimes_{l=0}^{L-1} W_l \rrbracket$$

- Generate matrix partitions by conceptually morton-like ordering indexing.

$$\langle \widetilde{m}_l, \widetilde{k}_l, \widetilde{n}_l \rangle$$

- Fringes: dynamic peeling.

$$\prod_{l=0}^{L-1} \widetilde{m}_l, \prod_{l=0}^{L-1} \widetilde{k}_l, \prod_{l=0}^{L-1} \widetilde{n}_l$$

$$A = \left(\begin{array}{c|c} A_{11} & a_{12} \\ \hline a_{21} & a_{22} \end{array} \right) \quad B = \left(\begin{array}{c|c} B_{11} & b_{12} \\ \hline b_{21} & b_{22} \end{array} \right) \quad C = \left(\begin{array}{c|c} C_{11} & c_{12} \\ \hline c_{21} & c_{22} \end{array} \right)$$

$$C_{11} = a_{12}b_{21} + C_{11} \quad c_{12} = (A_{11} \quad a_{12}) \begin{pmatrix} b_{12} \\ b_{22} \end{pmatrix} \quad (c_{21} \quad c_{22}) = (a_{21} \quad a_{22}) B$$

*Mithuna Thottethodi, Siddhartha Chatterjee, and Alvin R. Lebeck. "Tuning Strassen's matrix multiplication for memory efficiency." *Proceedings of the 1998 ACM/IEEE conference on Supercomputing*. IEEE Computer Society, 1998.

Generating typical operations

$$M_r := \left(\prod_{l=0}^{L-1} \tilde{m}_l \tilde{k}_l - 1 \sum_{i=0}^{L-1} \left(\bigotimes_{l=0}^{L-1} U_l \right)_{i,r} A_i \right) \times \left(\prod_{l=0}^{L-1} \tilde{k}_l \tilde{n}_l - 1 \sum_{j=0}^{L-1} \left(\bigotimes_{l=0}^{L-1} V_l \right)_{j,r} B_j \right);$$

$$C_p += \left(\bigotimes_{l=0}^{L-1} W_l \right)_{p,r} M_r (p = 0, \dots, \prod_{l=0}^{L-1} \tilde{m}_l \tilde{n}_l - 1)$$

- Packing routines:

$$\prod_{l=0}^{L-1} \tilde{m}_l \tilde{k}_l - 1 \sum_{i=0}^{L-1} \left(\bigotimes_{l=0}^{L-1} U_l \right)_{i,r} A_i \rightarrow \tilde{A}_i$$

$$\prod_{l=0}^{L-1} \tilde{k}_l \tilde{n}_l - 1 \sum_{j=0}^{L-1} \left(\bigotimes_{l=0}^{L-1} V_l \right)_{j,r} B_j \rightarrow \tilde{B}_p$$

- Micro-kernel:

- A hand-coded GEMM kernel
- Automatically generated updates to multiple submatrices of C.

$$C_p += \left(\bigotimes_{l=0}^{L-1} W_l \right)_{p,r} M_r (p = 0, \dots, \prod_{l=0}^{L-1} \tilde{m}_l \tilde{n}_l - 1)$$

Variations on a theme

- Naïve FMM

$$M_r := \left(\sum_{i=0}^{\prod_{l=0}^{L-1} \tilde{m}_l \tilde{k}_l - 1} \left(\bigotimes_{l=0}^{L-1} U_l \right)_{i,r} A_i \right) \times \left(\sum_{j=0}^{\prod_{l=0}^{L-1} \tilde{k}_l \tilde{n}_l - 1} \left(\bigotimes_{l=0}^{L-1} V_l \right)_{j,r} B_j \right);$$

$$C_p += \left(\bigotimes_{l=0}^{L-1} W_l \right)_{p,r} M_r (p = 0, \dots, \prod_{l=0}^{L-1} \tilde{m}_l \tilde{n}_l - 1)$$

- A traditional implementation with temporary buffers.

- AB FMM

- Integrate the addition of matrices into $\tilde{A}_i$ and $\tilde{B}_p$.

$$\sum_{i=0}^{\prod_{l=0}^{L-1} \tilde{m}_l \tilde{k}_l - 1} \left(\bigotimes_{l=0}^{L-1} U_l \right)_{i,r} A_i \rightarrow \tilde{A}_i$$

$$\sum_{j=0}^{\prod_{l=0}^{L-1} \tilde{k}_l \tilde{n}_l - 1} \left(\bigotimes_{l=0}^{L-1} V_l \right)_{j,r} B_j \rightarrow \tilde{B}_p$$

- ABC FMM

- Integrate the addition of matrices into $\tilde{A}_i$ and $\tilde{B}_p$.

- Integrate the update of multiple submatrices of C in the micro-kernel.

$$C_p += \left(\bigotimes_{l=0}^{L-1} W_l \right)_{p,r} M_r (p = 0, \dots, \prod_{l=0}^{L-1} \tilde{m}_l \tilde{n}_l - 1)$$

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Performance Model

- Performance Metric

$$\text{Effective GFLOPS} = \frac{2 \cdot m \cdot n \cdot k}{\text{time (in seconds)}} \cdot 10^{-9}$$

- Total Time Breakdown

$$T = T_a + T_m$$



Arithmetic
Operations



Memory
Operations

$$T_a = N_a^\times \cdot T_a^\times + N_a^{A+} \cdot T_a^{A+} + N_a^{B+} \cdot T_a^{B+} + N_a^{C+} \cdot T_a^{C+}$$

	type	τ	GEMM	L -level
$T_a^\times$	-	τ_a	$2mnk$	$2 \frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{n}}{\widetilde{N}_L} \frac{\widetilde{k}}{\widetilde{K}_L}$
T_a^{A+}	-	τ_a	-	$2 \frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{k}}{\widetilde{K}_L}$
T_a^{B+}	-	τ_a	-	$2 \frac{\widetilde{k}}{\widetilde{K}_L} \frac{\widetilde{n}}{\widetilde{N}_L}$
T_a^{C+}	-	τ_a	-	$2 \frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{n}}{\widetilde{N}_L}$

	GEMM	L -level		
		ABC	AB	Naive
$N_a^\times$	1	R_L	R_L	R_L
N_a^{A+}	-	$nnz(\otimes U)-R_L$	$nnz(\otimes U)-R_L$	$nnz(\otimes U)-R_L$
N_a^{B+}	-	$nnz(\otimes V)-R_L$	$nnz(\otimes V)-R_L$	$nnz(\otimes V)-R_L$
N_a^{C+}	-	$nnz(\otimes W)$	$nnz(\otimes W)$	$nnz(\otimes W)$

$$\widetilde{M}_L = \prod_{l=0}^{L-1} \widetilde{m}_l, \widetilde{K}_L = \prod_{l=0}^{L-1} \widetilde{k}_l, \widetilde{N}_L = \prod_{l=0}^{L-1} \widetilde{n}_l, R_L = \prod_{l=0}^{L-1} R_l.$$

$$\otimes U = \otimes_{l=0}^{L-1} U_l, \otimes V = \otimes_{l=0}^{L-1} V_l, \otimes W = \otimes_{l=0}^{L-1} W_l.$$

$$T_a = N_a^\times \cdot T_a^\times + N_a^{A+} \cdot T_a^{A+} + N_a^{B+} \cdot T_a^{B+} + N_a^{C+} \cdot T_a^{C+}$$

$$T_m = N_m^{A\times} \cdot T_m^{A\times} + N_m^{B\times} \cdot T_m^{B\times} + N_m^{C\times} \cdot T_m^{C\times} + N_m^{A+} \cdot T_m^{A+} + N_m^{B+} \cdot T_m^{B+} + N_m^{C+} \cdot T_m^{C+}$$

	type	τ	GEMM	L -level
$T_a^\times$	-	τ_a	$2mnk$	$2 \frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{n}}{\widetilde{N}_L} \frac{\widetilde{k}}{\widetilde{K}_L}$
T_a^{A+}	-	τ_a	-	$2 \frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{k}}{\widetilde{K}_L}$
T_a^{B+}	-	τ_a	-	$2 \frac{\widetilde{k}}{\widetilde{K}_L} \frac{\widetilde{n}}{\widetilde{N}_L}$
T_a^{C+}	-	τ_a	-	$2 \frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{n}}{\widetilde{N}_L}$
$T_m^{A\times}$	r	τ_b	$mk \lceil \frac{n}{n_c} \rceil$	$\frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{k}}{\widetilde{K}_L} \lceil \frac{n/\widetilde{N}_L}{n_c} \rceil$
$\widetilde{T}_m^{A\times}$	w	τ_b	$mk \lceil \frac{n}{n_c} \rceil$	$\frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{k}}{\widetilde{K}_L} \lceil \frac{n/\widetilde{N}_L}{n_c} \rceil$
$T_m^{B\times}$	r	τ_b	nk	$\frac{\widetilde{n}}{\widetilde{N}_L} \frac{\widetilde{k}}{\widetilde{K}_L}$
$\widetilde{T}_m^{B\times}$	w	τ_b	nk	$\frac{\widetilde{n}}{\widetilde{N}_L} \frac{\widetilde{k}}{\widetilde{K}_L}$
$T_m^{C\times}$	r/w	τ_b	$2\lambda mn \lceil \frac{k}{k_c} \rceil$	$2\lambda \frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{n}}{\widetilde{N}_L} \lceil \frac{k/\widetilde{K}_L}{k_c} \rceil$
T_m^{A+}	r/w	τ_b	mk	$\frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{k}}{\widetilde{K}_L}$
T_m^{B+}	r/w	τ_b	nk	$\frac{\widetilde{n}}{\widetilde{N}_L} \frac{\widetilde{k}}{\widetilde{K}_L}$
T_m^{C+}	r/w	τ_b	mn	$\frac{\widetilde{m}}{\widetilde{M}_L} \frac{\widetilde{n}}{\widetilde{N}_L}$

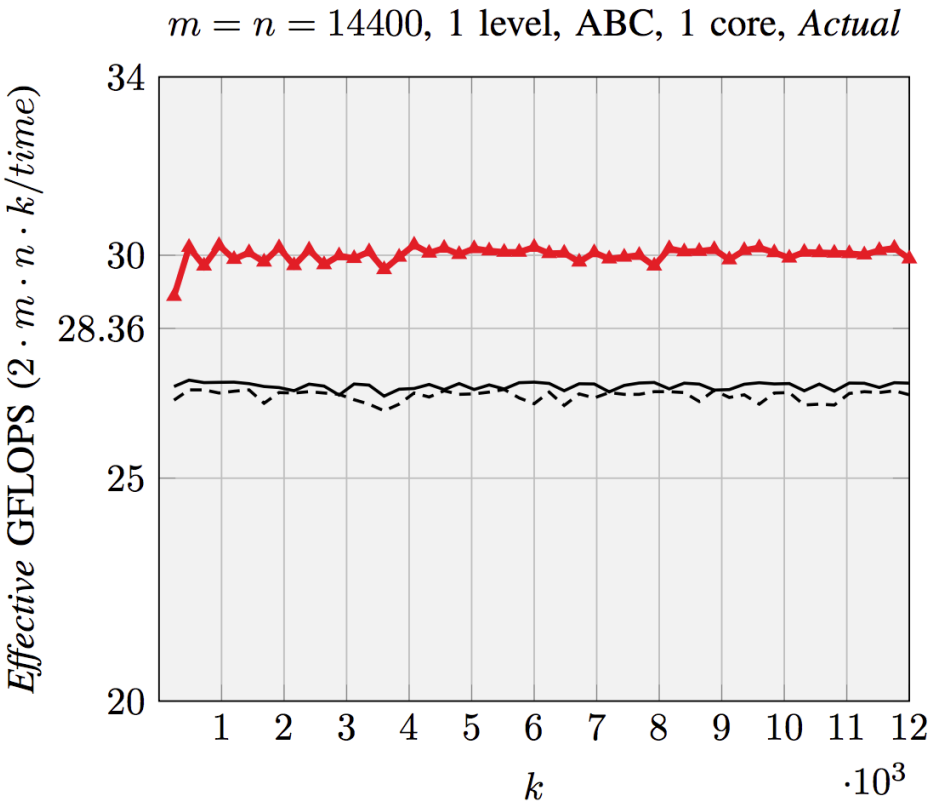
	GEMM	L -level		
		ABC	AB	Naive
$N_a^\times$	1	R_L	R_L	R_L
N_a^{A+}	-	$nnz(\otimes U)-R_L$	$nnz(\otimes U)-R_L$	$nnz(\otimes U)-R_L$
N_a^{B+}	-	$nnz(\otimes V)-R_L$	$nnz(\otimes V)-R_L$	$nnz(\otimes V)-R_L$
N_a^{C+}	-	$nnz(\otimes W)$	$nnz(\otimes W)$	$nnz(\otimes W)$
$N_m^{A\times}$	1	$nnz(\otimes U)$	$nnz(\otimes U)$	R_L
$\widetilde{N}_m^{A\times}$	-	-	-	-
$N_m^{B\times}$	1	$nnz(\otimes V)$	$nnz(\otimes V)$	R_L
$\widetilde{N}_m^{B\times}$	-	-	-	-
$N_m^{C\times}$	1	$nnz(\otimes W)$	R_L	R_L
N_m^{A+}	-	-	-	$nnz(\otimes U)+R_L$
N_m^{B+}	-	-	-	$nnz(\otimes V)+R_L$
N_m^{C+}	-	-	$3nnz(\otimes W)$	$3nnz(\otimes W)$

$$\widetilde{M}_L = \prod_{l=0}^{L-1} \widetilde{m}_l, \widetilde{K}_L = \prod_{l=0}^{L-1} \widetilde{k}_l, \widetilde{N}_L = \prod_{l=0}^{L-1} \widetilde{n}_l, R_L = \prod_{l=0}^{L-1} R_l.$$

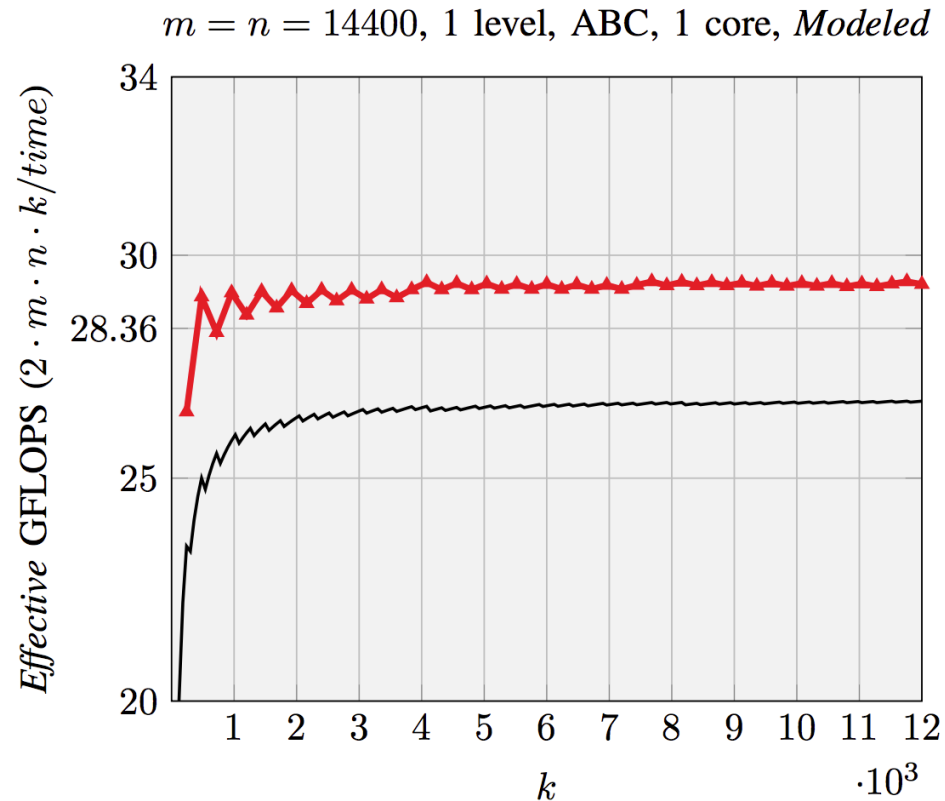
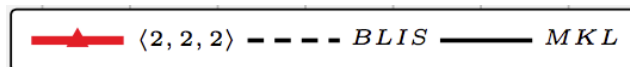
$$\otimes U = \otimes_{l=0}^{L-1} U_l, \otimes V = \otimes_{l=0}^{L-1} V_l, \otimes W = \otimes_{l=0}^{L-1} W_l.$$

Actual vs. Modeled Performance

Intel Xeon E5-2680 v2 (Ivy Bridge, 10 core/socket)



Actual

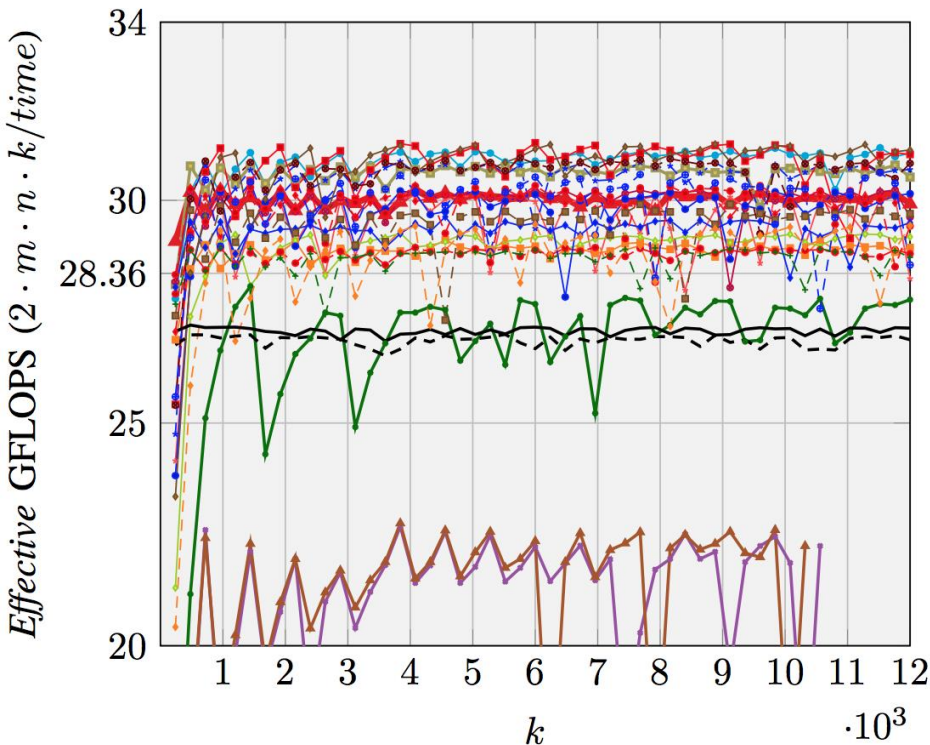


Modeled

Actual vs. Modeled Performance

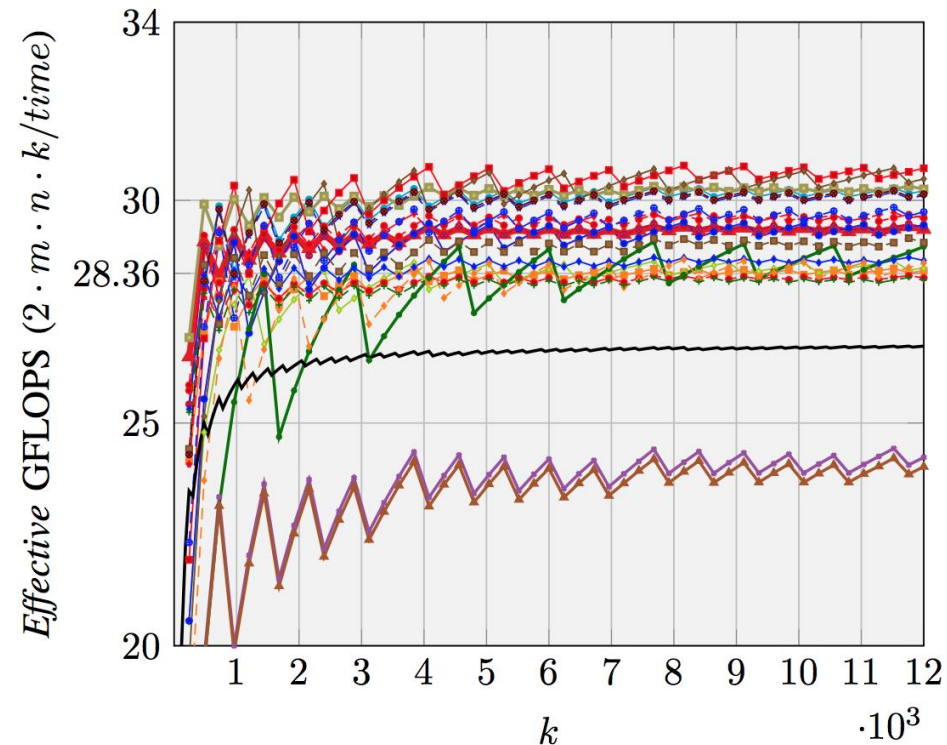
Intel Xeon E5-2680 v2 (Ivy Bridge, 10 core/socket)

$m = n = 14400$, 1 level, ABC, 1 core, *Actual*

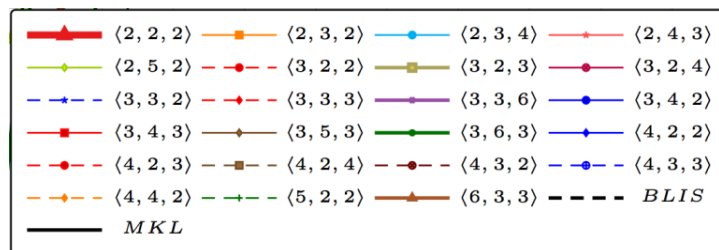


Actual

$m = n = 14400$, 1 level, ABC, 1 core, *Modeled*



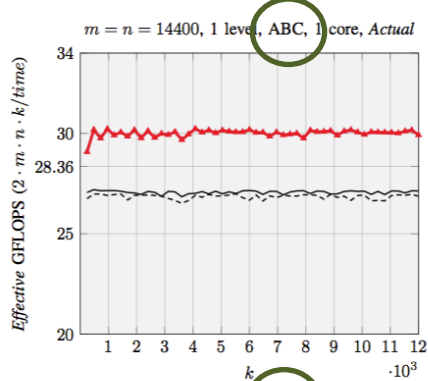
Modeled



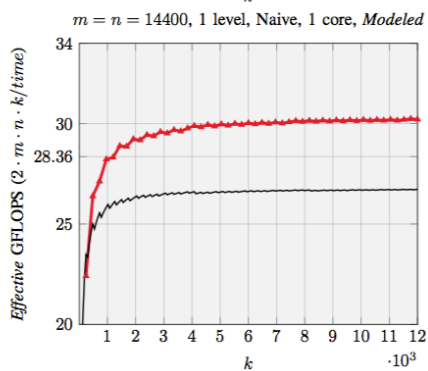
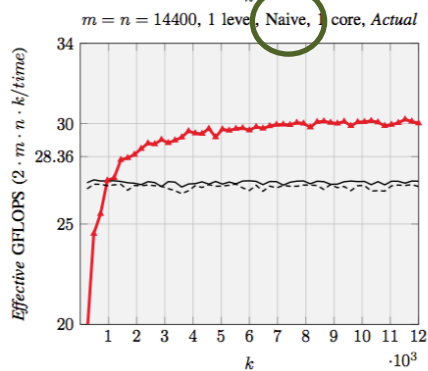
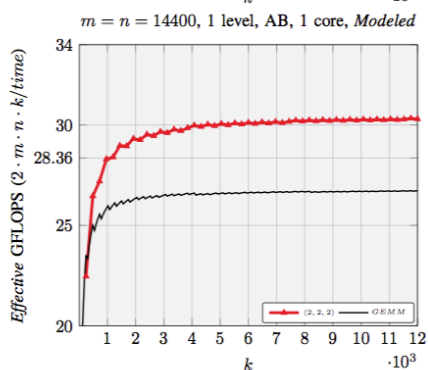
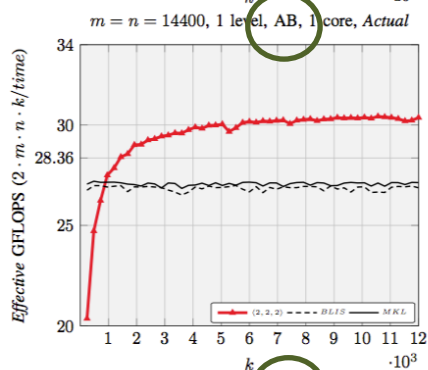
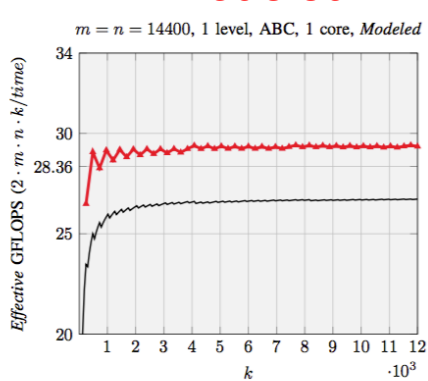
—▲— $\langle 2, 2, 2 \rangle$
- - - BLIS
 — MKL

$m = n = 14400$, 1 level

Actual

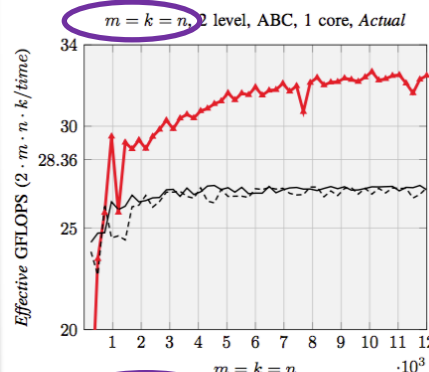


Modeled

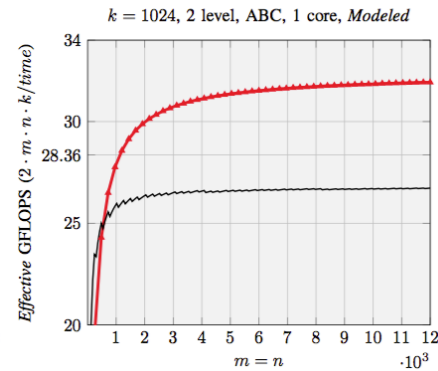
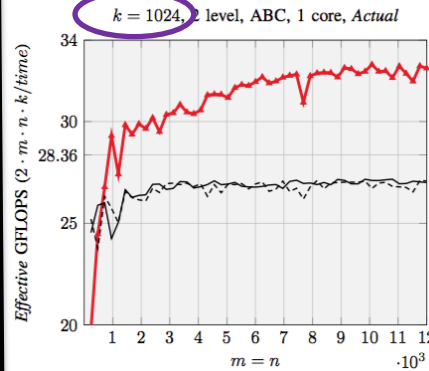
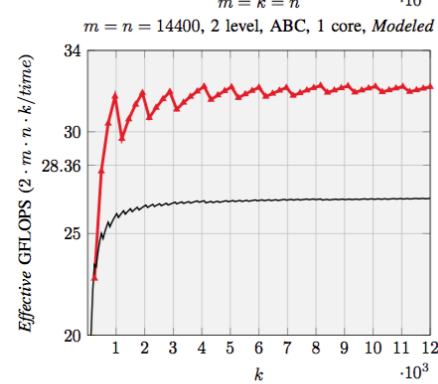
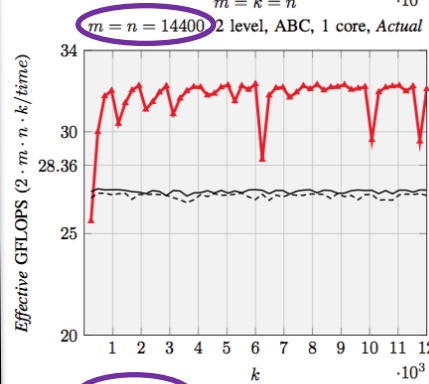
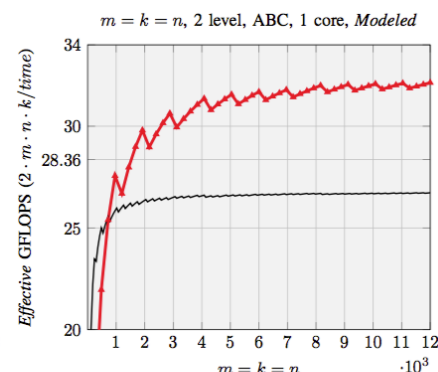


2 level, ABC

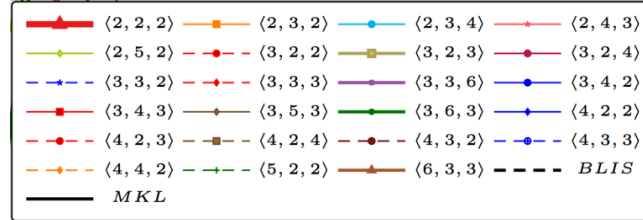
Actual



Modeled



$m = n = 14400$, 1 level



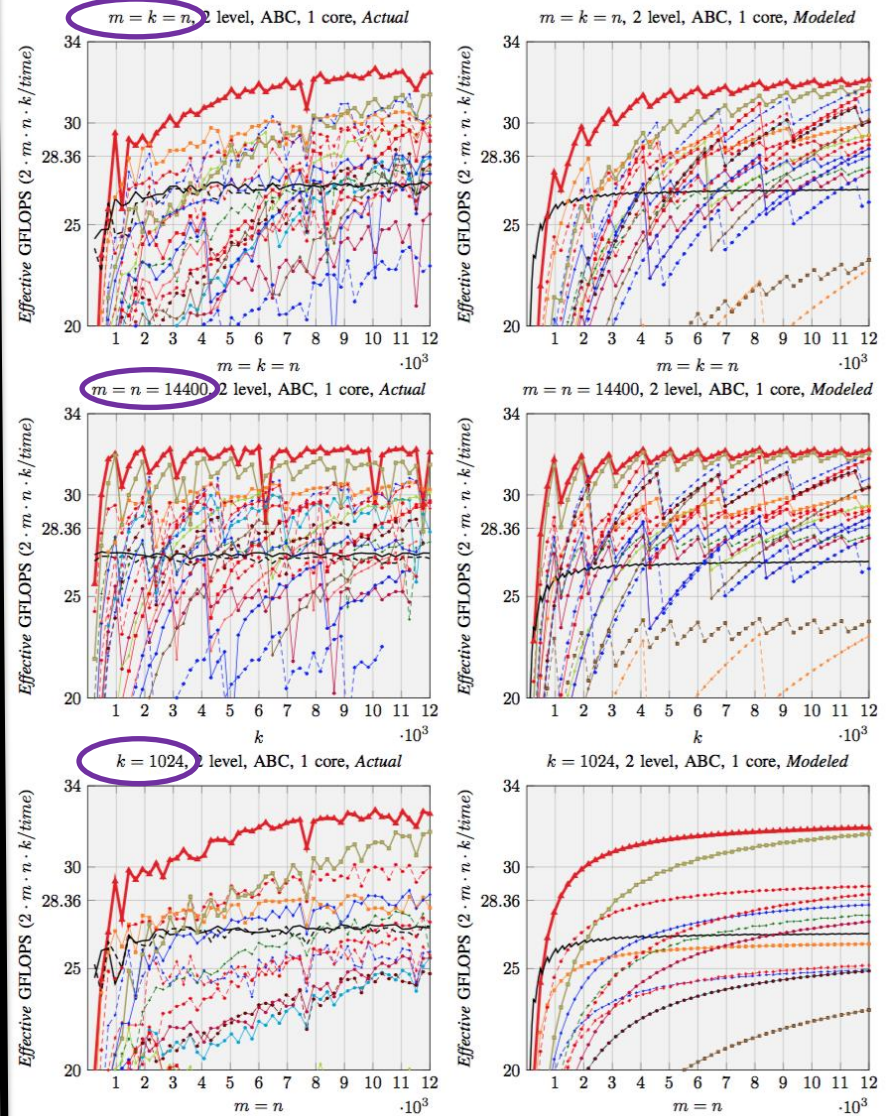
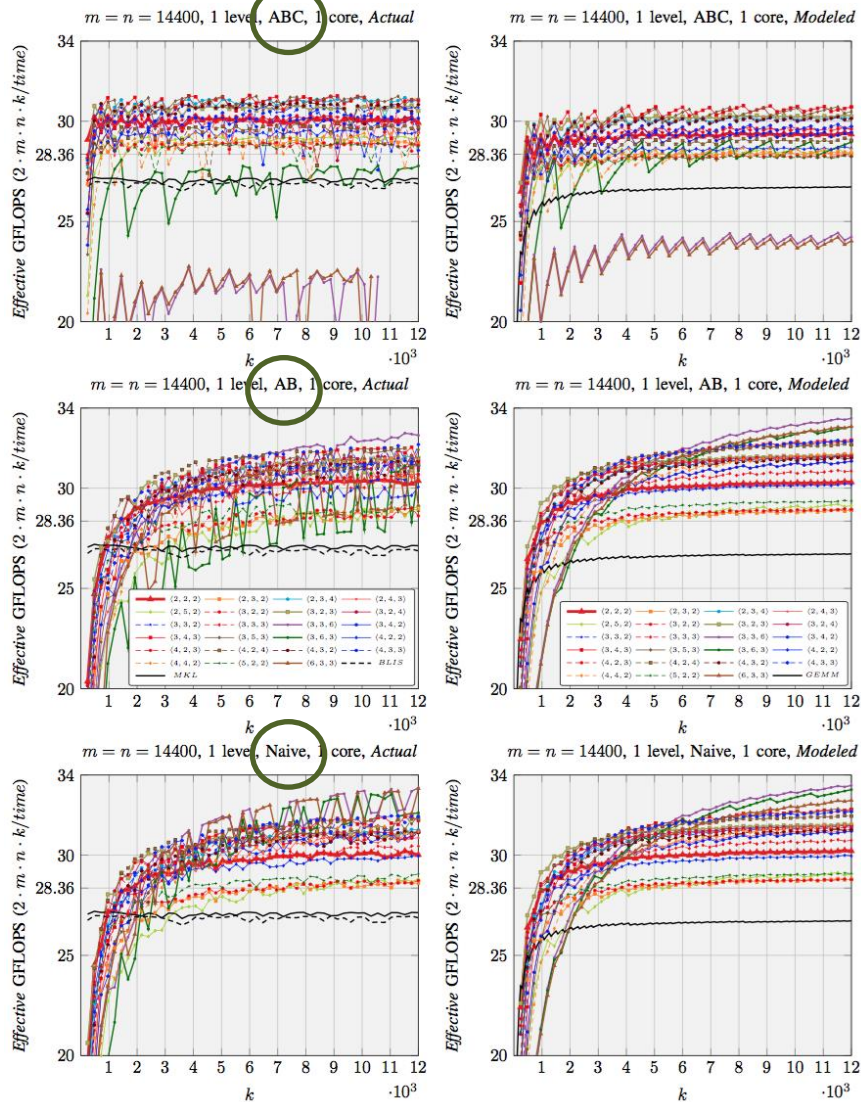
2 level, ABC

Actual

Modeled

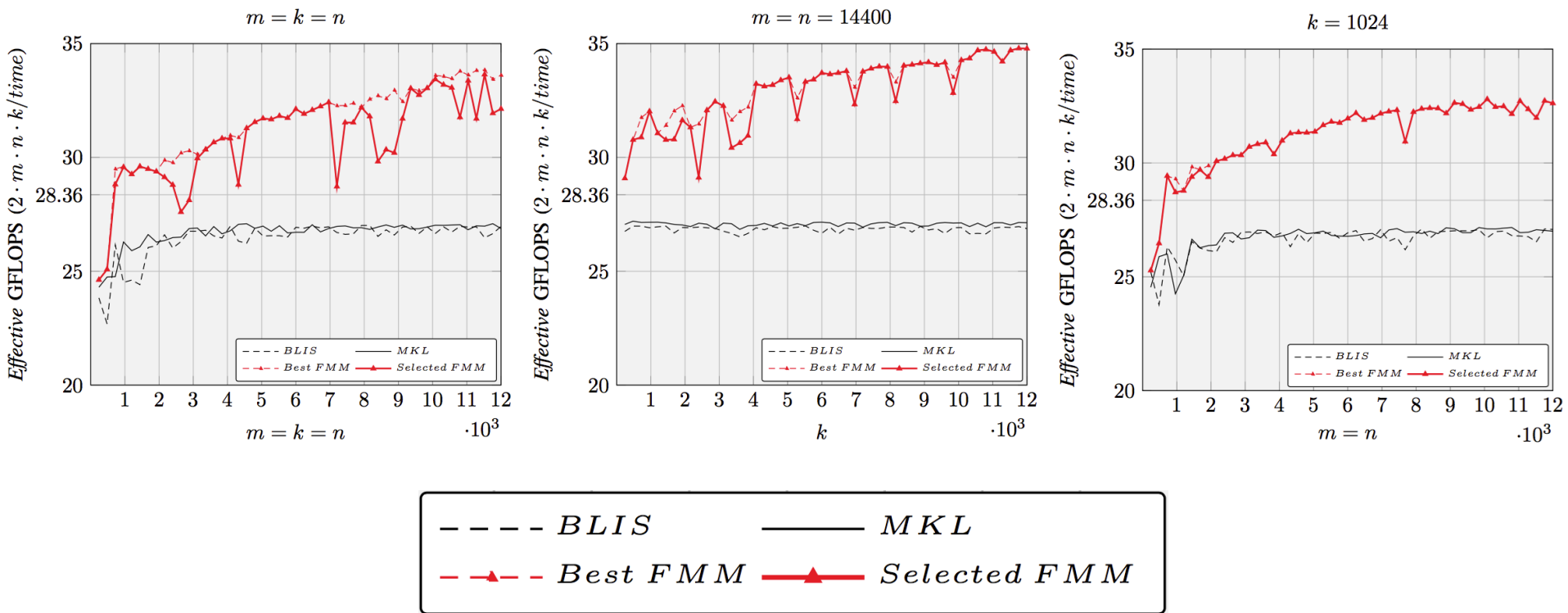
Actual

Modeled



Selecting FMM implementation with performance model

Intel Xeon E5-2680 v2 (Ivy Bridge, 10 core/socket)



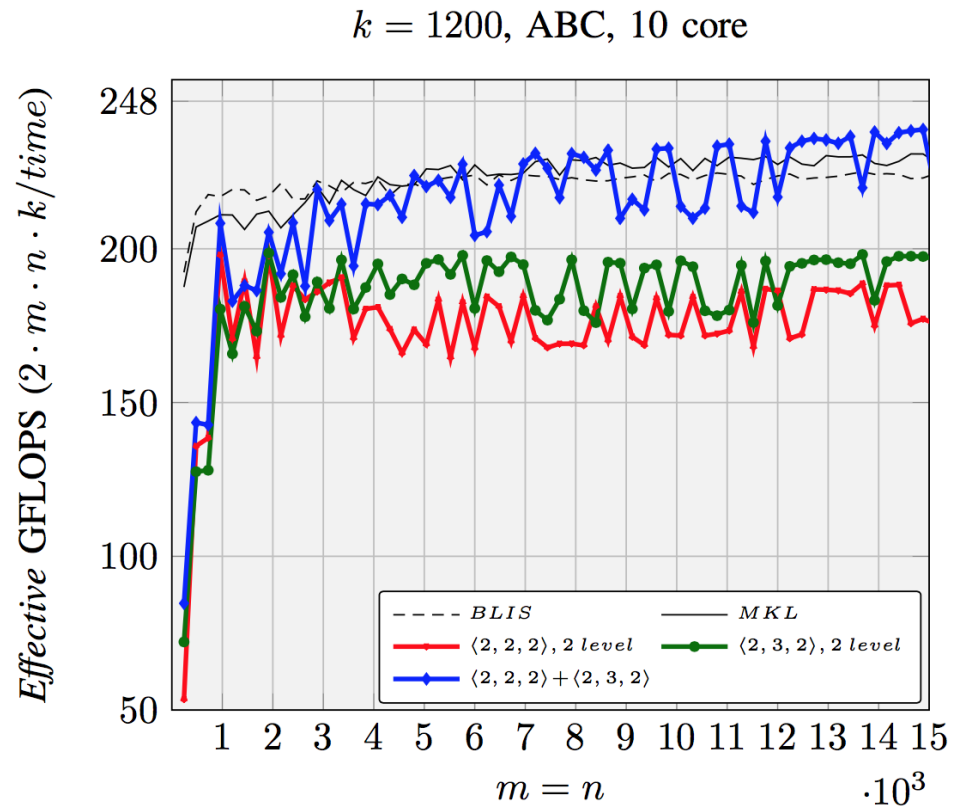
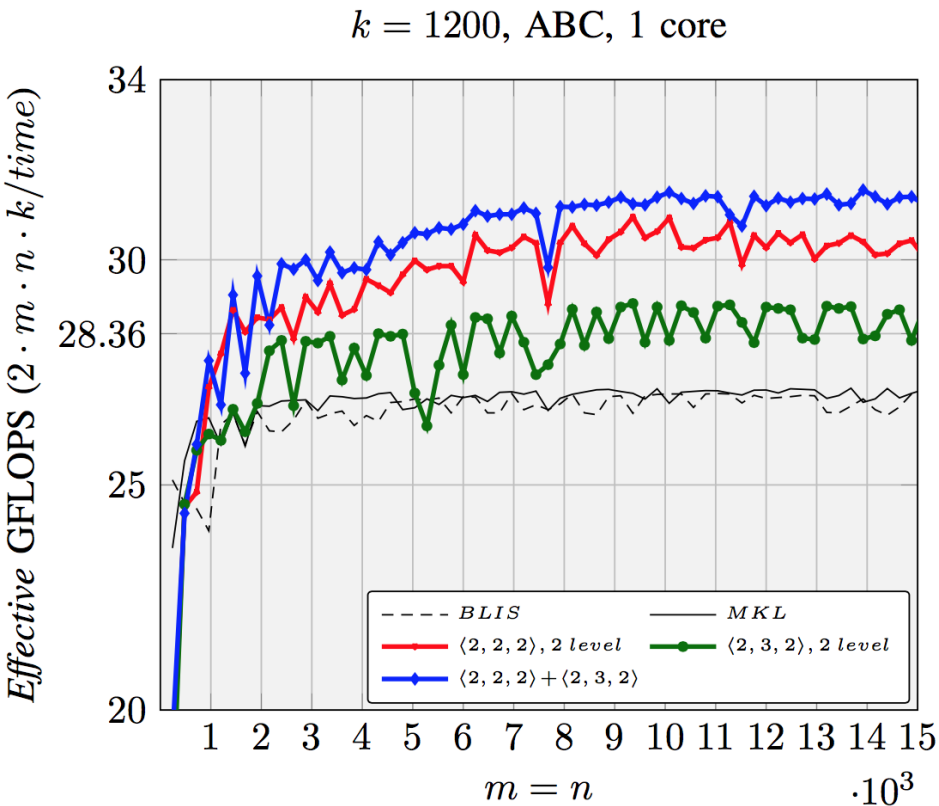
Best FMM: Best implementation among 20+ FMM with ABC, AB, Naïve implementations
Selected FMM: Selected FMM implementation with the guidance of performance model

Outline

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Hybrid Partitions

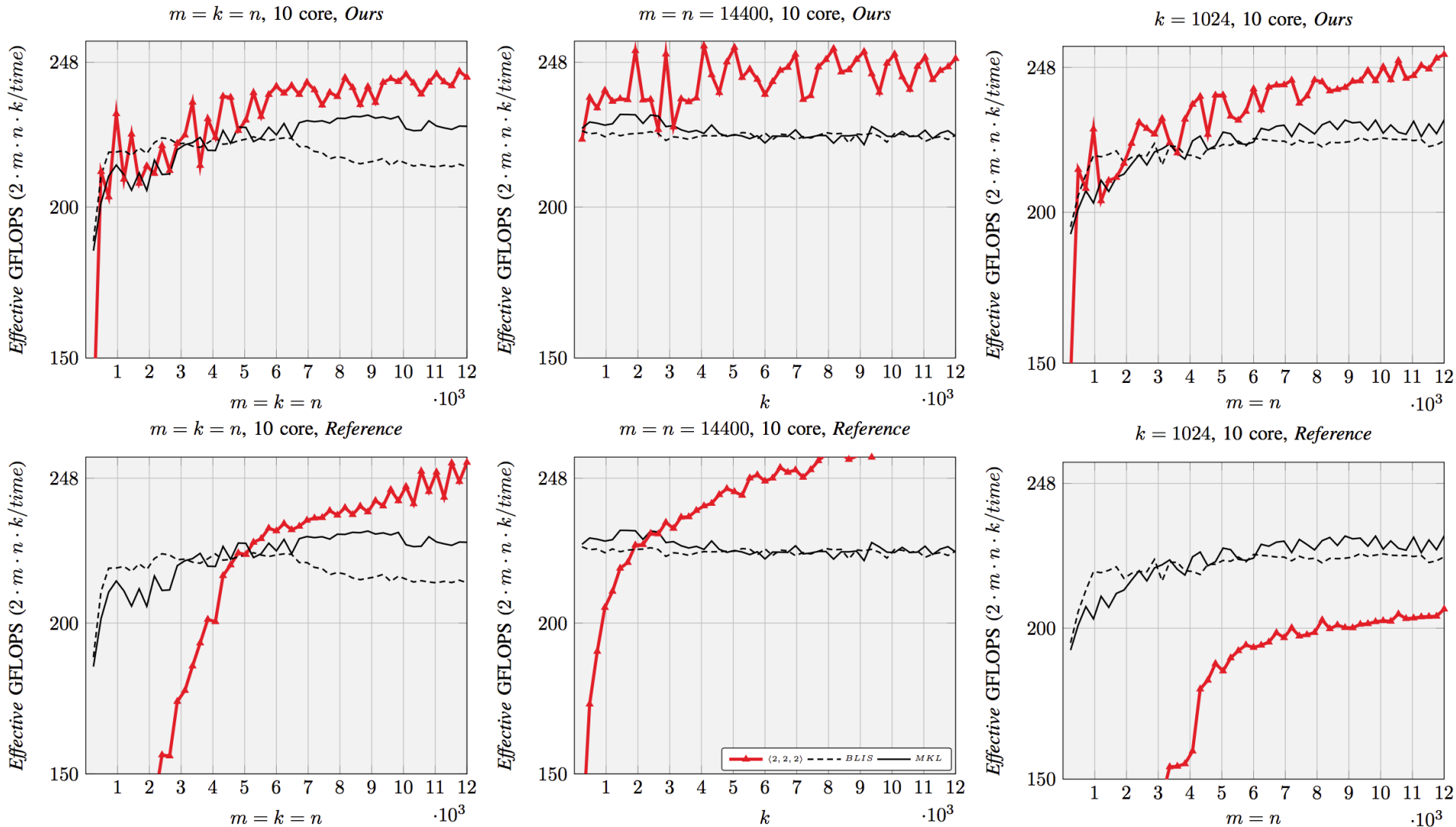
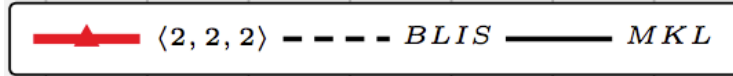
Intel Xeon E5-2680 v2 (Ivy Bridge, 10 core/socket)



$$[[U \otimes U', V \otimes V', W \otimes W']]$$

Parallel performance

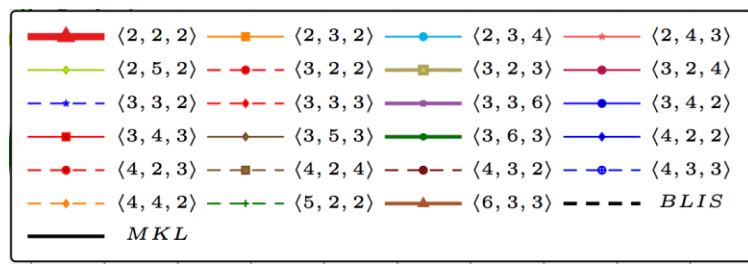
Intel Xeon E5-2680 v2 (Ivy Bridge, 10 core/socket)



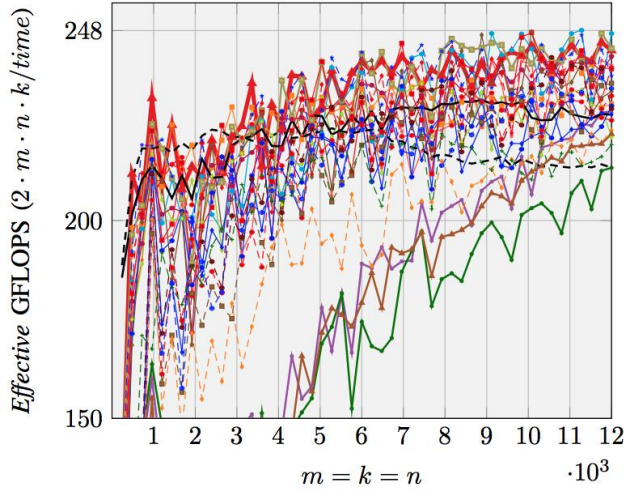
* *Reference*: Austin R. Benson, and Grey Ballard. "A framework for practical parallel fast matrix multiplication." in *PPoPP2015*.

Parallel performance

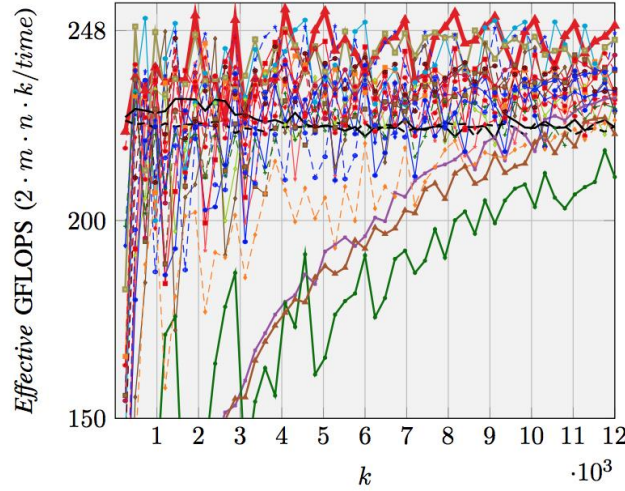
Intel Xeon E5-2680 v2 (Ivy Bridge, 10 core/socket)



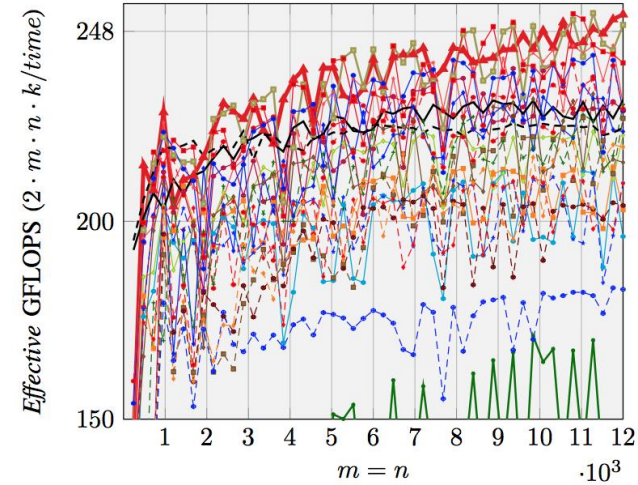
$m = k = n$, 10 core, *Ours*



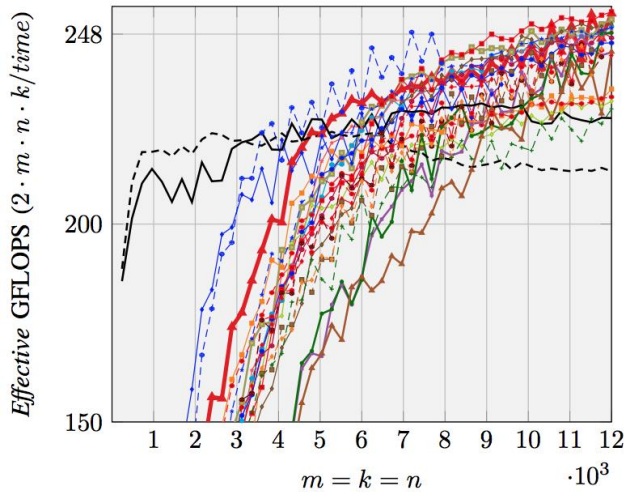
$m = n = 14400$, 10 core, *Ours*



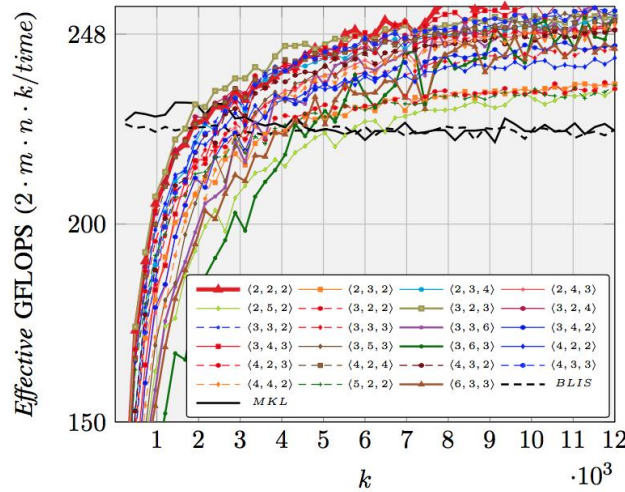
$k = 1024$, 10 core, *Ours*



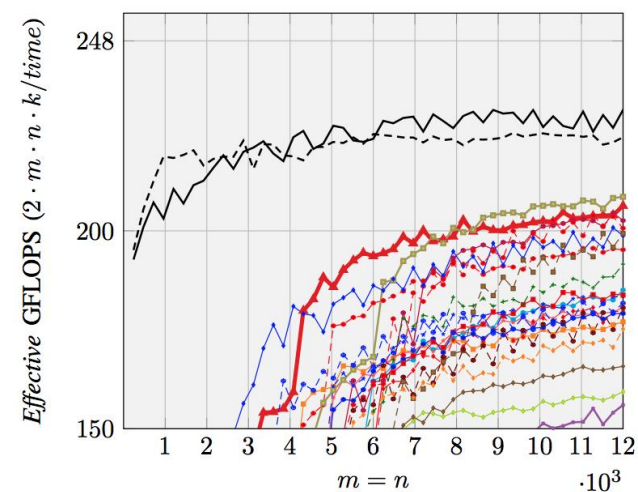
$m = k = n$, 10 core, *Reference*



$m = n = 14400$, 10 core, *Reference*



$k = 1024$, 10 core, *Reference*



* *Reference*: Austin R. Benson, and Grey Ballard. "A framework for practical parallel fast matrix multiplication." in *PPoPP2015*.

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Our code generator ...

- Implement families of FMM algorithms automatically.

$\langle 2, 2, 2 \rangle \langle 2, 3, 2 \rangle \langle 2, 3, 4 \rangle \langle 2, 4, 3 \rangle \langle 2, 5, 2 \rangle \langle 3, 2, 2 \rangle \dots \langle 6, 3, 3 \rangle$

- Express multi-level FMM as Kronecker product.

$$[[U \otimes U', V \otimes V', W \otimes W']]$$

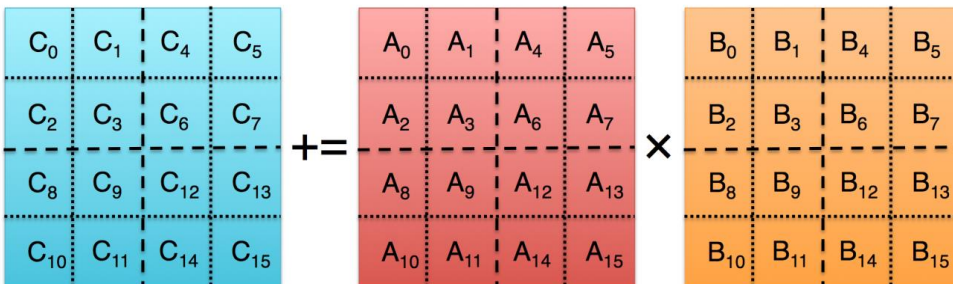
- Incorporate matrix summations into operations inside GEMM.

$$\prod_{l=0}^{L-1} \tilde{m}_l \tilde{k}_l - 1 \sum_{i=0}^{L-1} \left(\bigotimes_{l=0}^{L-1} U_l \right)_{i,r} A_i \rightarrow \tilde{A}_i$$

$$\prod_{l=0}^{L-1} \tilde{k}_l \tilde{n}_l - 1 \sum_{j=0}^{L-1} \left(\bigotimes_{l=0}^{L-1} V_l \right)_{j,r} B_j \rightarrow \tilde{B}_p$$

$$C_p += \left(\bigotimes_{l=0}^{L-1} W_l \right)_{p,r} M_r (p = 0, \dots, \prod_{l=0}^{L-1} \tilde{m}_l \tilde{n}_l - 1)$$

- Generate relatively accurate performance model.

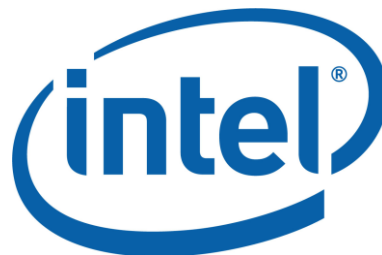


for $r = 0, \dots, \prod_{l=0}^{L-1} R_l - 1$,

$$M_r := \left(\prod_{l=0}^{L-1} \tilde{m}_l \tilde{k}_l - 1 \sum_{i=0}^{L-1} \left(\bigotimes_{l=0}^{L-1} U_l \right)_{i,r} A_i \right) \times \left(\prod_{l=0}^{L-1} \tilde{k}_l \tilde{n}_l - 1 \sum_{j=0}^{L-1} \left(\bigotimes_{l=0}^{L-1} V_l \right)_{j,r} B_j \right);$$

$$C_p += \left(\bigotimes_{l=0}^{L-1} W_l \right)_{p,r} M_r (p = 0, \dots, \prod_{l=0}^{L-1} \tilde{m}_l \tilde{n}_l - 1)$$

Acknowledgement



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- A gift from Qualcomm Foundation.
- Intel Corporation through an Intel Parallel Computing Center (IPCC).
- Access to the Maverick and Stampede supercomputers administered by TACC.

We thank [Austin Benson](#) and [Grey Ballard](#) for sharing their open source code and helpful discussions, the anonymous reviewers for their constructive comments, and the rest of the SHPC team (<http://shpc.ices.utexas.edu>) for their supports.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Thank you!

The source code can be downloaded from:

<https://github.com/flame/fmm-gen>

Related work

- [1]: Systematic way to identify and implement new FMM algorithms based on conventional calls to GEMM.
- [2]: Strassen can be incorporated into high-performance GEMM
- [3]: Kronecker product for expressing multi-level Strassen's algorithm

*[1] Austin R. Benson, Grey Ballard. "A framework for practical parallel fast matrix multiplication." *PPoPP*15.

*[2] Jianyu Huang, Tyler Smith, Greg Henry, and Robert van de Geijn. "Strassen's Algorithm Reloaded." In *SC'16*.

*[3] C-H Huang, Jeremy R. Johnson, and Robert W. Johnson. "A tensor product formulation of Strassen's matrix multiplication algorithm." *Applied Mathematics Letters* 3.3 (1990): 67-71.