

AMATH 483/583

High Performance Scientific Computing

Lecture 8:

BLAS, Strassen's Algorithm, Roofline Model

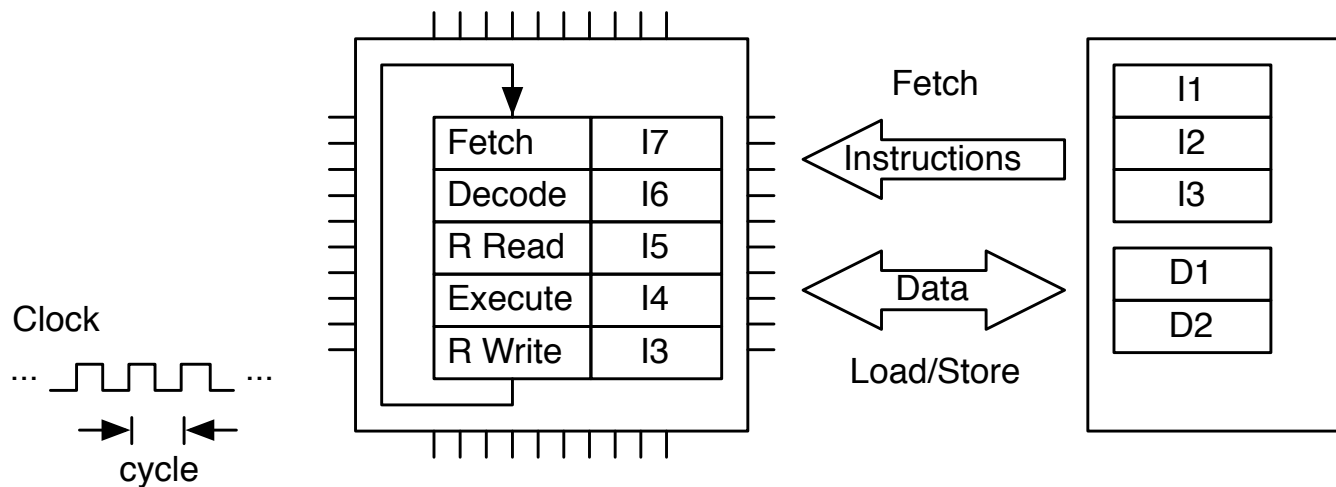
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Overview

- Finish SIMD
- Revisit pipelining, hoisting, copying
- BLAS
- Strassen's Algorithm
- Roofline Model

Processor Core Instruction Handling

- By pipelining, multiple instructions can be executed at each clock cycle
- Form of instruction-level parallelism (ILP)



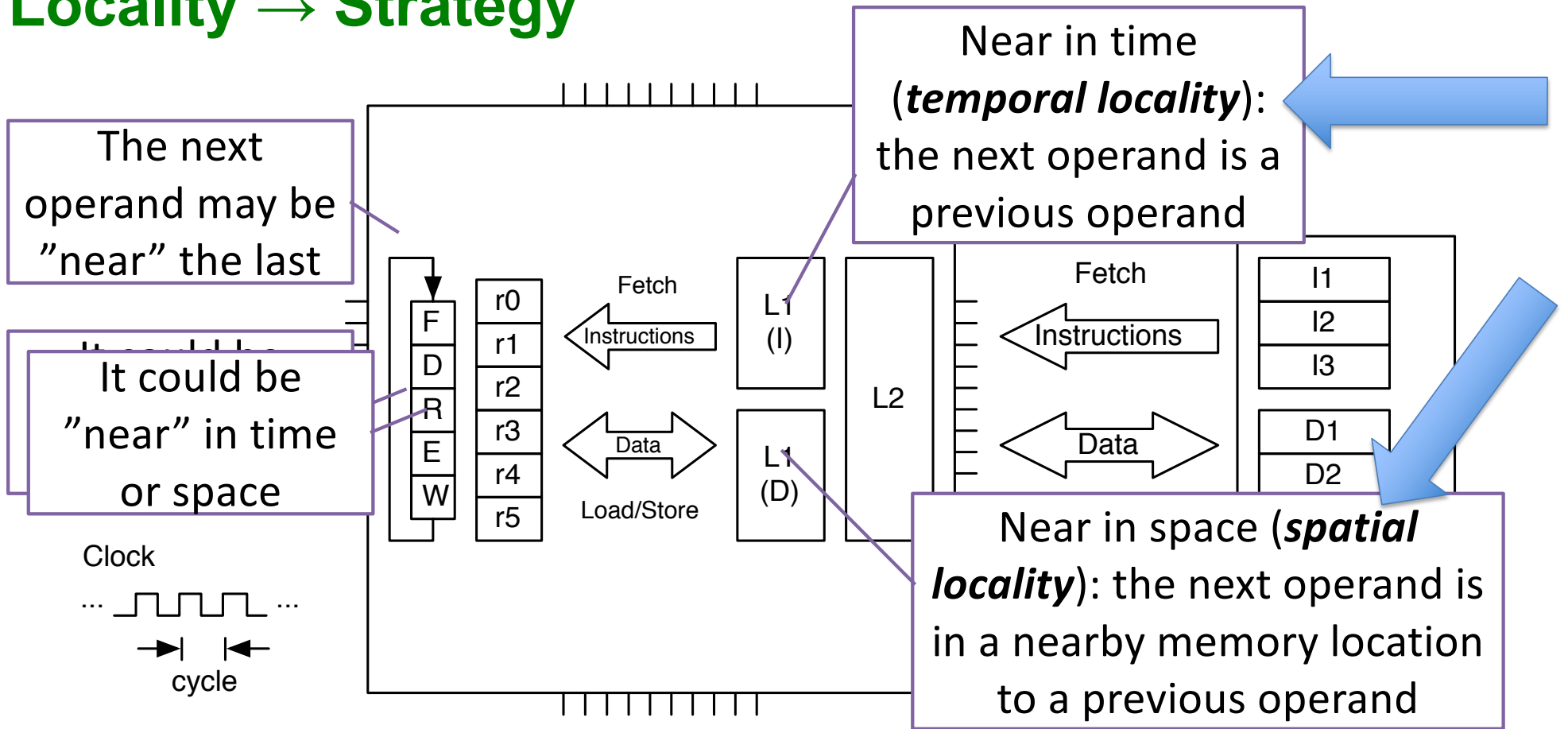
Performance-Oriented Architecture Features

- Execution Pipeline
 - Stages of functionality to process issued instructions
 - Hazards are conflicts with continued execution
 - Forwarding supports closely associated operations exhibiting precedence constraints
- Out of Order Execution
 - Uses reservation stations
 - Hides some core latencies and provide fine grain asynchronous operation supporting concurrency
- Branch Prediction
 - Permits computation to proceed at a conditional branch point prior to resolving predicate value
 - Overlaps follow-on computation with predicate resolution
 - Requires roll-back or equivalent to correct false guesses
 - Sometimes follows both paths, and several deep

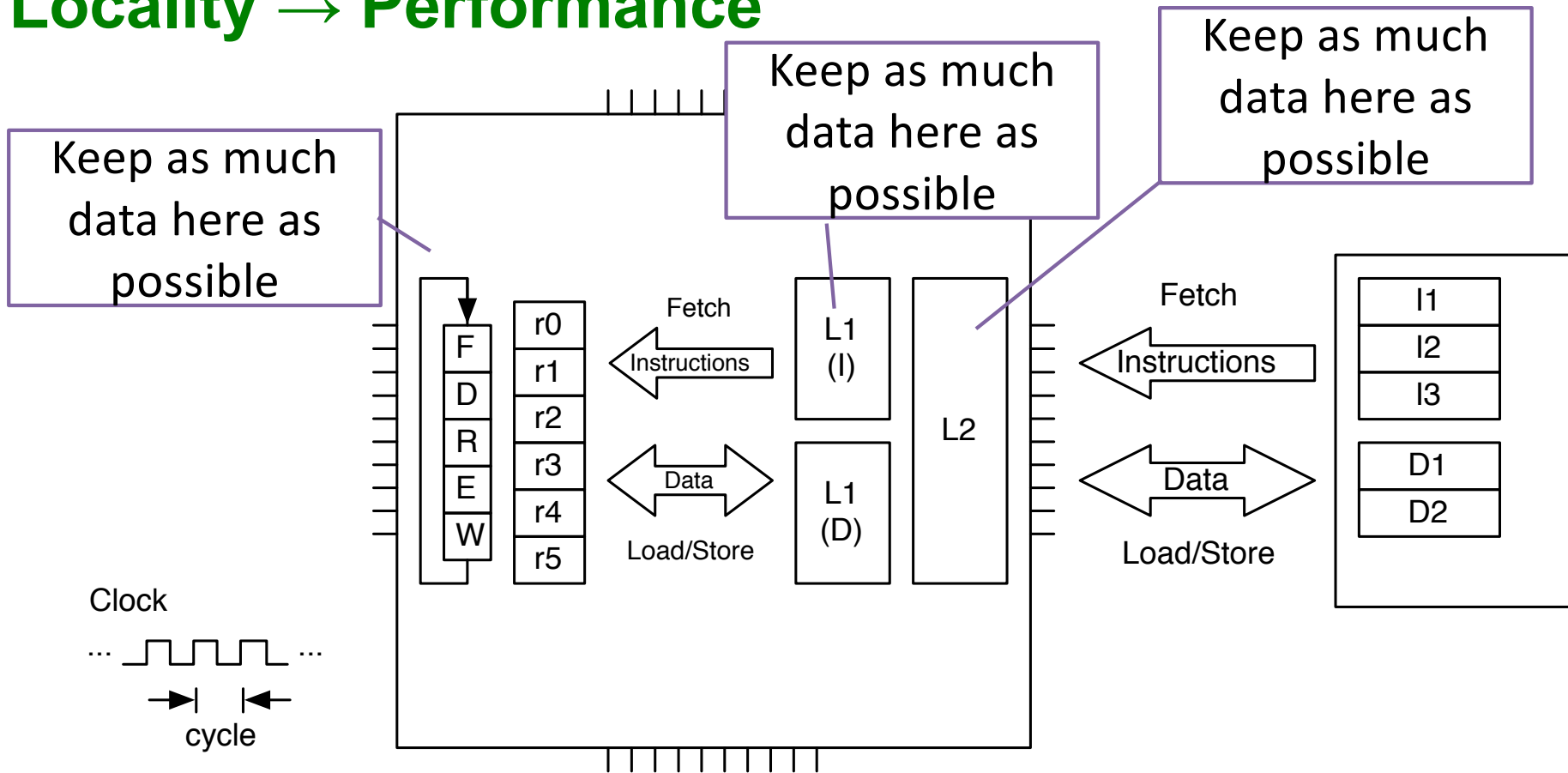
Unrolling and inlining
can help these

But compilers are
really good at that

Locality → Strategy



Locality → Performance



Our Matrix class

Matrix.hpp

```
class Matrix {  
public:  
    Matrix(size_t M, size_t N) : num_rows_(M), num_cols_(N), storage_(num_rows_ * num_cols_) {}  
  
    double& operator()(size_t i, size_t j)      { return storage_[i * num_cols_ + j]; }  
    const double& operator()(size_t i, size_t j) const { return storage_[i * num_cols_ + j]; }  
  
    size_t num_rows() const { return num_rows_; }  
    size_t num_cols() const { return num_cols_; }  
  
private:  
    size_t          num_rows_, num_cols_;  
    std::vector<double> storage_;  
};
```

Overloaded
operator()

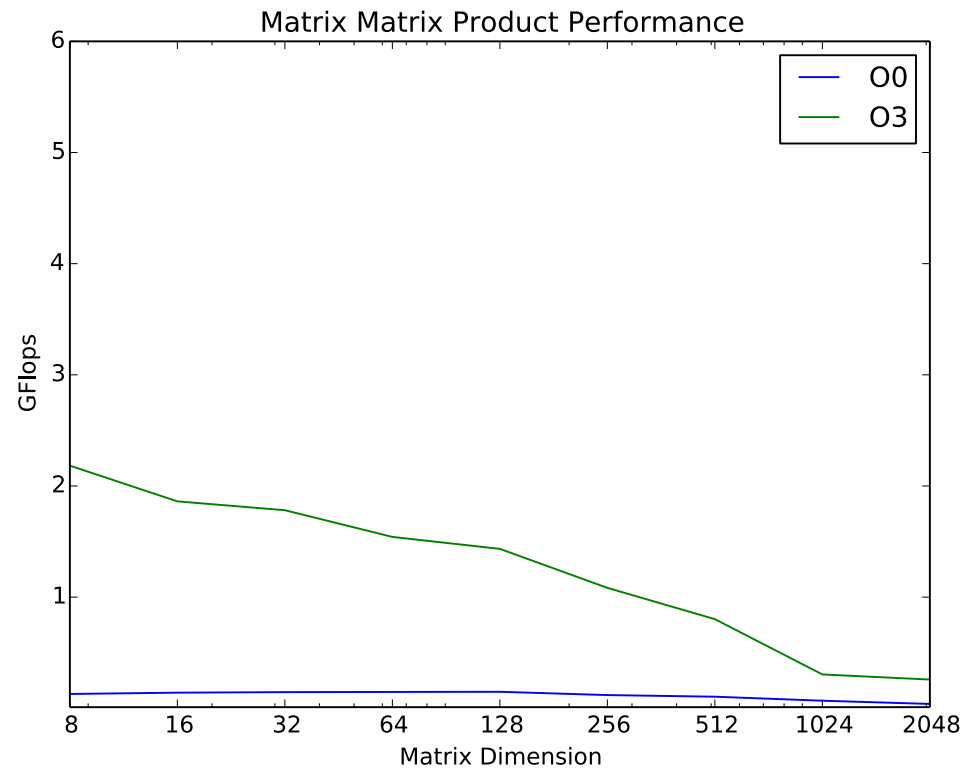
Just For Benchmarking

```
Matrix operator*(const Matrix& A, const Matrix&B) {  
    Matrix C(A.num_rows(), B.num_cols());  
    multiply(A, B, C);  
    return C;  
}  
  
void multiply(const Matrix& A, const Matrix&B, Matrix&C) {  
    for (size_t i = 0; i < A.num_rows(); ++i) {  
        for (size_t j = 0; j < B.num_cols(); ++j) {  
            for (size_t k = 0; k < A.num_cols(); ++k) {  
                C(i,j) += A(i,k) * B(k,j);  
            }  
        }  
    }  
}
```

C++ Core Guideline
Violation

F.20: For "out" output
values, prefer return
values to output
parameters

Base Performance Results



The Three Most Important Requirements for HPC

- Locality
- Locality
- Locality

Improving Locality

```
void multiply(const Matrix& A, const Matrix&B, Matrix&C) {  
    for (size_t i = 0; i < A.num_rows(); ++i) {  
        for (size_t j = 0; j < B.num_cols(); ++j) {  
            for (size_t k = 0; k < A.num_cols(); ++k) {  
                C(i,j) += A(i,k) * B(k,j);  
            }  
        }  
    }  
}
```

What can be reused?

- Load $C(i, j)$ into register
- Load $A(i, k)$ into register
- Load $B(k, j)$ into register
- Multiply
- Add
- Store $C(i, j)$

- Four memory operations and two floating point operations per iteration
- $2/6 = 1/3$ flop per cycle (if each operation is one cycle)

Hoisting

Hoist C(i,j)

Why not automatically?

- Load A(i, k)
- Load B(k, j)
- Multiply
- Add

```
void multiply(const Matrix& A, const Matrix&B, Matrix&C) {  
    for (size_t i = 0; i < A.num_rows(); ++i) {  
        for (size_t j = 0; j < B.num_cols(); ++j) {  
            double t = C(i,j);  
            for (size_t k = 0; k < A.num_cols(); ++k) {  
                t += A(i,k) * B(k,j);  
            }  
            C(i,j) = t;  
        }  
    }  
}
```

- Two memory operations and two floating point operations per iteration
- $2/4 = 1/2$ flop per cycle (if each operation is one cycle)

Improving Locality: Unroll and Ja

```
void tiledMultiply2x2(const Matrix& A, const Matrix& B) {
    for (size_t i = 0; i < A.num_rows(); i += 2) {
        for (size_t j = 0; j < B.num_cols(); j += 2) {
            for (size_t k = 0; k < A.num_cols(); ++k) {
                C(i, j) += A(i, k) * B(k, j);
                C(i, j+1) += A(i, k) * B(k, j+1);
                C(i+1, j) += A(i+1, k) * B(k, j);
                C(i+1, j+1) += A(i+1, k) * B(k, j+1);
            }
        }
    }
}
```

B(k,j) is used twice

B(k,j+1) is used twice

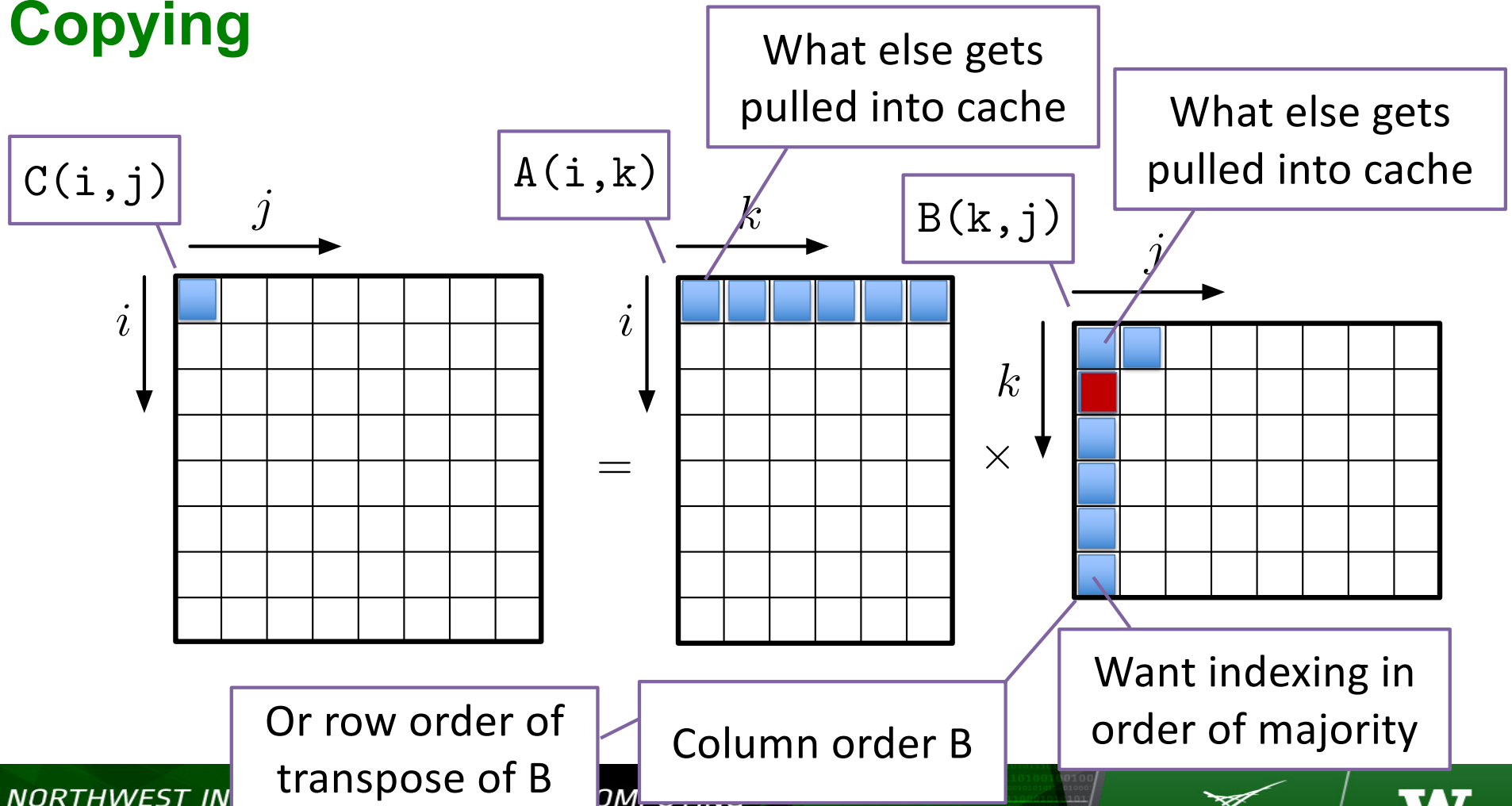
A(i,k) is used twice

A(i+1,k) is used twice

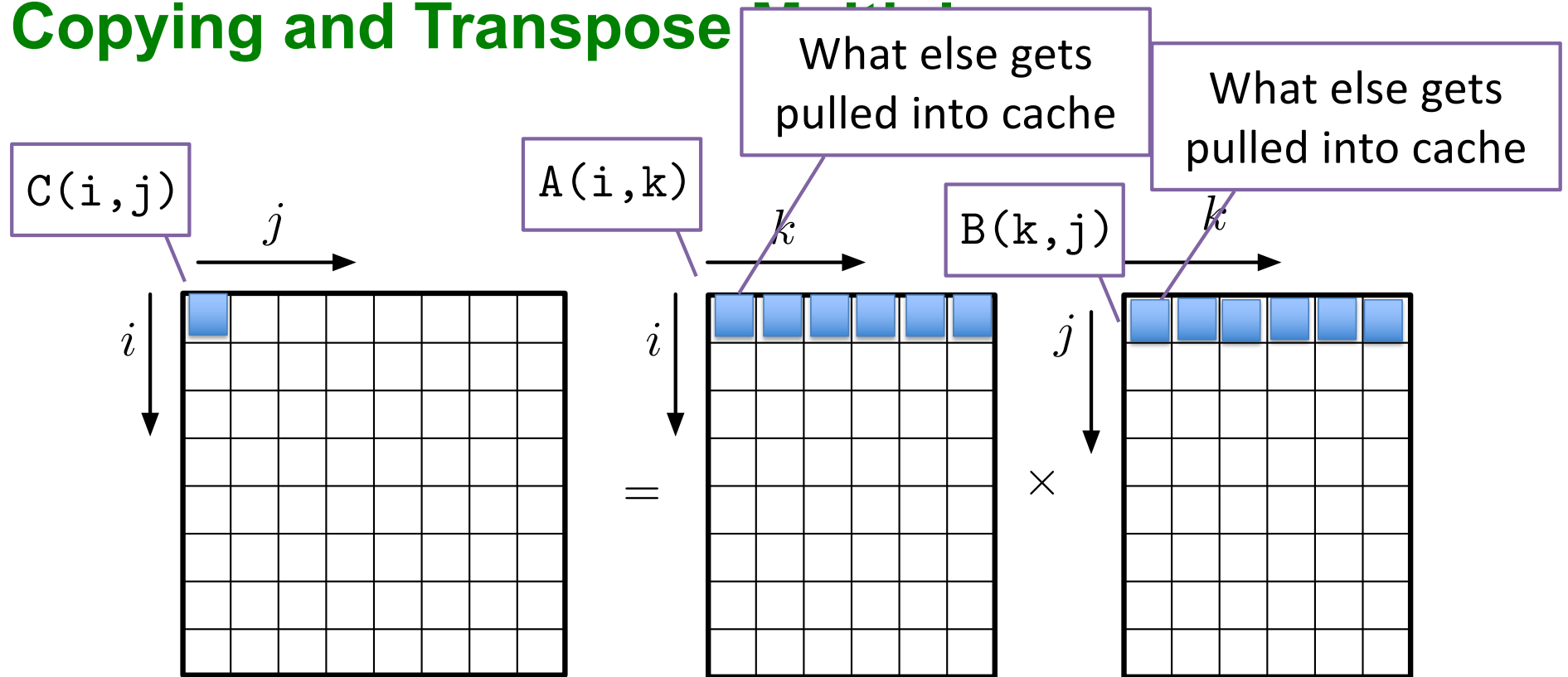
Can also hoist (independent of k)

- Four memory operations and eight floating point operations per iteration
- $8/12 = 2/3$ flop per cycle (if each operation is one cycle) – 2X the base case

Copying



Copying and Transpose

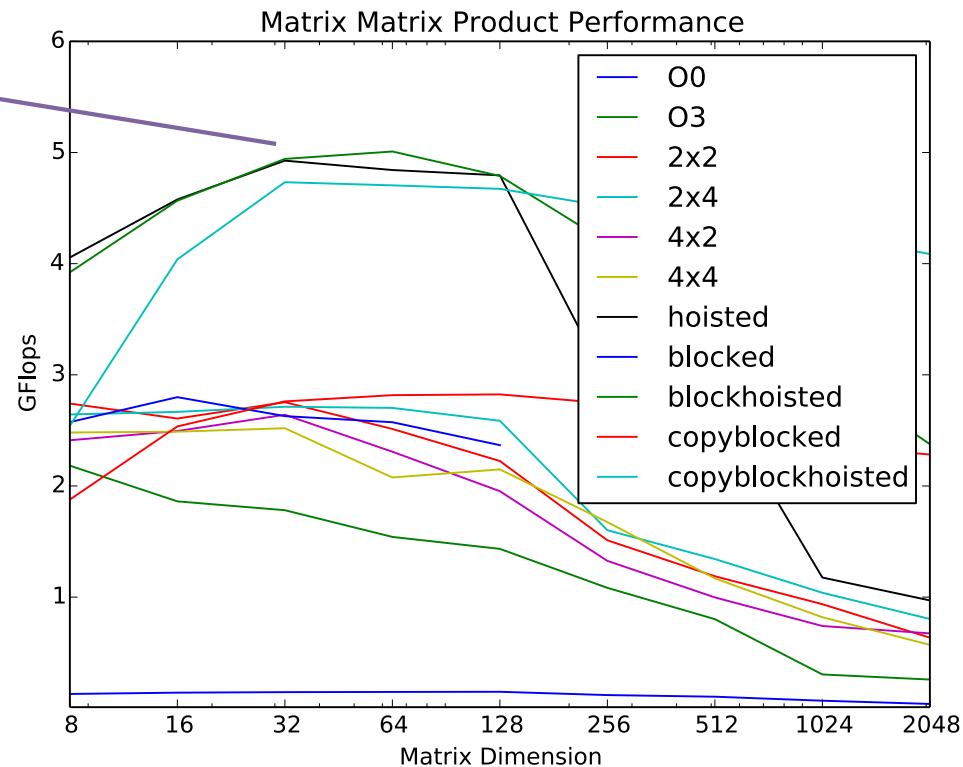


Blocking and Tiling and Hoisting and Copying

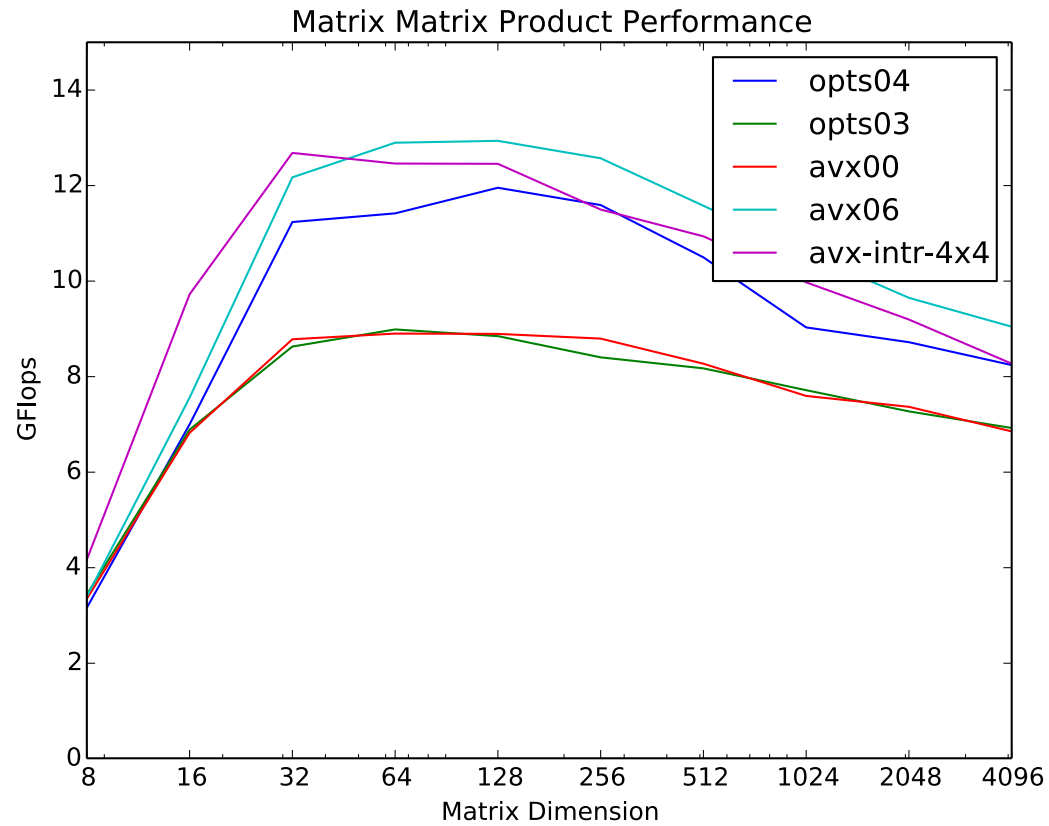
Is this the best we can do?

How good is it anyway?

(cf PS 4A)



Writing Faster Matrix Matrix Product



Under the Hood

```

for (int i = ii; i < ii+blocksize; i += 4) {
  for (int j = jj, jb = 0; j < jj+blocksize; j += 4, jb += 4) {
    __m256d t0x = _mm256_load_pd(&C(i, j));
    __m256d t1x = _mm256_load_pd(&C(i+1,j));
    __m256d t2x = _mm256_load_pd(&C(i+2,j));
    __m256d t3x = _mm256_load_pd(&C(i+3,j));

    for (int k = kk, kb = 0; k < kk+blocksize; ++k, ++kb) {
      __m256d bx = _mm256_setr_pd(BB(jb,kb), BB(jb+1,kb), BB(jb+2,kb), BB(jb+3,kb));

      __m256d a0 = _mm256_broadcast_sd(&A(i, j,k));
      a0 = _mm256_mul_pd(bx, a0);
      t0x = _mm256_add_pd(t0x, a0);

      __m256d a1 = _mm256_broadcast_sd(&A(i+1,k));
      a1 = _mm256_mul_pd(bx, a1);
      t1x = _mm256_add_pd(t1x, a1);

      __m256d a2 = _mm256_broadcast_sd(&A(i+2,k));
      a2 = _mm256_mul_pd(bx, a2);
      t2x = _mm256_add_pd(t2x, a2);

      __m256d a3 = _mm256_broadcast_sd(&A(i+3,k));
      a3 = _mm256_mul_pd(bx, a3);
      t3x = _mm256_add_pd(t3x, a3);
    }

    _mm256_store_pd(&C(i, j), t0x);
    _mm256_store_pd(&C(i+1,j), t1x);
    _mm256_store_pd(&C(i+2,j), t2x);
    _mm256_store_pd(&C(i+3,j), t3x);
  }
}

```



<code>vbroadcastsd</code>	<code>(%rdx,%r8,8), %ymm3</code>
<code>vfmadd213pd</code>	<code>%ymm4, %ymm8, %ymm3</code>
<code>vbroadcastsd</code>	<code>(%rsi,%r8,8), %ymm2</code>
<code>vfmadd213pd</code>	<code>%ymm5, %ymm8, %ymm2</code>
<code>vbroadcastsd</code>	<code>(%rbx,%r8,8), %ymm1</code>
<code>vfmadd213pd</code>	<code>%ymm6, %ymm8, %ymm1</code>
<code>vbroadcastsd</code>	<code>(%rdi,%r8,8), %ymm0</code>
<code>vfmadd213pd</code>	<code>%ymm7, %ymm8, %ymm0</code>

Fused Multiply-Add

Multiply-Add are separate here

8 FLOPS per cycle?

Vector Operations from C++

```

for (int i = ii; i < ii+blocksize; i += 2) {
  for (int j = jj, jb = 0; j < jj+blocksize; j += 2, jb += 2) {
    double t00 = C(i,j);      double t01 = C(i,j+1);
    double t10 = C(i+1,j);    double t11 = C(i+1,j+1);

    for (int k = kk, kb = 0; k < kk+blocksize; ++k, ++kb) {
      t00 += A(i , k) * BB(jb , kb);
      t01 += A(i , k) * BB(jb+1, kb);
      t10 += A(i+1, k) * BB(jb , kb);
      t11 += A(i+1, k) * BB(jb+1, kb);
    }

    C(i,  j) = t00;  C(i,  j+1) = t01;
    C(i+1,j) = t10;  C(i+1,j+1) = t11;
  }
}

```



Fused
Multiply-Add

256 bit
registers

```

vmovupd    (%r8,%r13,8), %ymm4
vmovupd    (%r11,%r13,8), %ymm5
vfmadd231pd %ymm4, %ymm5, %ymm3
vmovupd    -32(%r9,%r13,8), %ymm6
vfmadd231pd %ymm4, %ymm6, %ymm2
vmovupd    (%rdx,%r13,8), %ymm4
vfmadd231pd %ymm5, %ymm4, %ymm1
vfmadd231pd %ymm6, %ymm4, %ymm0
vmovupd    (%rcx,%r13,8), %ymm4
vmovupd    32(%r11,%r13,8), %ymm5
vfmadd231pd %ymm4, %ymm5, %ymm3
vmovupd    (%r9,%r13,8), %ymm6
vfmadd231pd %ymm4, %ymm6, %ymm2
vmovupd    (%rbx,%r13,8), %ymm4
vfmadd231pd %ymm5, %ymm4, %ymm1
vfmadd231pd %ymm6, %ymm4, %ymm0

```

LLVM

NORTHWEST INSTITUTE for ADVANCED COMPUTING

AMATH 483/583 High-Performance Scientific Computing Spring 2019
University of Washington by Andrew Lumsdaine


Pacific Northwest
NATIONAL LABORATORY
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Compiler Diagnostics

- There are some flags to see what the compiler is doing

```
optflags      :  
              echo 'int;' | $(CXX) -xc++ $(CXXFLAGS) - -o /dev/null -\#\#\#  
  
defreport     :  
              $(CXX) -dM -E -x c++ /dev/null  
  
Matrix.o .    :  
              $(CXX) -c $(CXXFLAGS) -Rpass=.* -o Matrix.o
```

Print flags passed
to compiler

Print internal
#defines

Print what optimizations
are applied (and where)

Internal #define

defreport

:

`$(CXX) -dM -E -x c++ /dev/null`

```
#define OBJC_NEW_PROPERTIES 1
#define _LP64 1
#define __APPLE_CC__ 6000
#define __APPLE__ 1
#define __ATOMIC_ACQUIRE 2
#define __ATOMIC_ACQ_REL 4
#define __ATOMIC_CONSUME 1
#define __ATOMIC_RELAXED 0
#define __ATOMIC_RELEASE 3
#define __ATOMIC_SEQ_CST 5
#define __BLOCKS__ 1
#define __CHAR16_TYPE__ unsigned short
#define __CHAR32_TYPE__ unsigned int
```

340+ total

Very useful for
conditional compilation

```
#ifdef __AVX__
    __m128d a = _mm256_extractf128_pd(tx, 0);
    __m128d b = _mm256_extractf128_pd(tx, 1);
    _mm_store_pd(&C(i,j), a);
    _mm_store_pd(&C(i+1, j), b);
#endif // __AVX__
```

Optimization Report

Matrix.o

:

```
$(CXX) -c $(CXXFLAGS) -Rpass=.* -o Matrix.o
```

```
Matrix.cpp: 52: 7: remark: vectorized loop (vectorization width: 4, interleaved count: 4) [-  
  for (int k = 0; k < A.numCols(); ++k) {  
  ^
```

```
Matrix.cpp: 52: 7: remark: unrolled loop by a factor of 2 with run-time trip count [-Rpass=]
```

```
Matrix.cpp: 50: 5: remark: unrolled loop by a factor of 8 with run-time trip count [-Rpass=]  
  for (int j = 0; j < B.numCols(); ++j) {
```

```
for (int j = 0; j < B.numCols(); ++j) {  
  double t = C(i,j);  
  for (int k = 0; k < A.numCols(); ++k) {  
    t += A(i,k) * B(k,j);  
  }  
  C(i,j) = t;  
}
```

Selects all

Unroll
Vectorization
Inline

As a Last Resort

```
%.s : %.cpp  
$(CXX) -S $(CXXFLAGS) $<
```

```
Matrix.s.opt.05  
New Open Recent Revert Save Print Undo Redo Cut Copy Paste Search Preferences Help  
## Parent Loop BB11_25 Depth=4  
## Parent Loop BB11_26 Depth=5  
## => This Inner Loop Header:  
Depth=6  
vmovupd (%r8,%r13,8), %ymm4  
vmovupd (%r11,%r13,8), %ymm5  
vfmadd231pd %ymm4, %ymm5, %ymm3  
vmovupd -32(%r9,%r13,8), %ymm6  
vfmadd231pd %ymm4, %ymm6, %ymm2  
vmovupd (%rdx,%r13,8), %ymm4  
vfmadd231pd %ymm5, %ymm4, %ymm1  
vfmadd231pd %ymm6, %ymm4, %ymm0  
vmovupd (%rcx,%r13,8), %ymm4  
vmovupd 32(%r11,%r13,8), %ymm5  
vfmadd231pd %ymm4, %ymm5, %ymm3  
vmovupd (%r9,%r13,8), %ymm6  
vfmadd231pd %ymm4, %ymm6, %ymm2  
vmovupd (%rbx,%r13,8), %ymm4  
vfmadd231pd %ymm5, %ymm4, %ymm1  
vfmadd231pd %ymm6, %ymm4, %ymm0  
addq $8, %r13  
cmpq %r13, %rsi  
jne LBB11_39  
LBB11_40: ## in Loop: Header=BB11_26 Depth=5  
-: ** - Matrix.s.opt.05 32% (3043,0) (Assembler WordWrap) Wed Apr 19 8:04AM 1.45  
25
```

Advanced Vector Extensions

SIMD?

Multi Media Extensions

Streaming SIMD Extensions

Advanced Vector Extensions

1980

1997

1999

2001

2004
2006
2007
2008

2011

2013

2016

8087

MMX

SSE

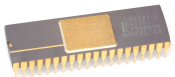
SSE2

SSE3
SSE3.1
SSE4.1
SSE4.2

AVX

AVX2

AVX512



8 80-bit stack registers

8 64-bit registers

8 128-bit registers (single) (xmm)

8 128-bit registers (double)

Many new instructions

16 256-bit registers (ymm)

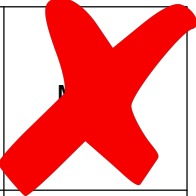
32 512-bit registers (zmm)

Flynn's Taxonomy (Aside)

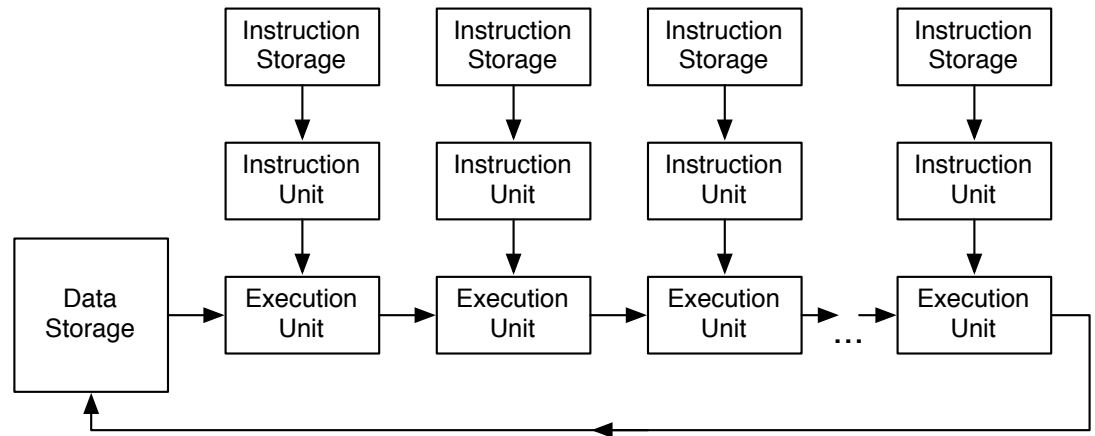
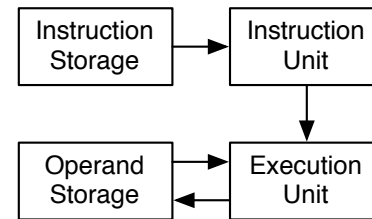
Anyone in HPC must know Flynn's taxonomy

- **Classic** classification of parallel architectures (Michael Flynn, 1966)

Plain old sequential

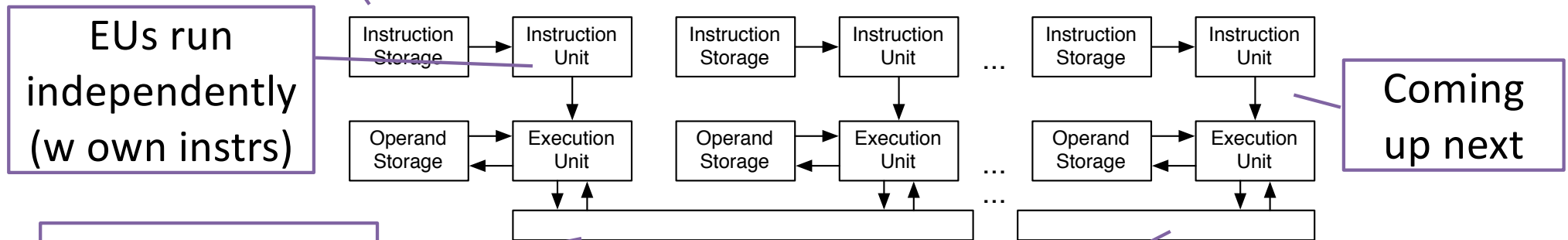
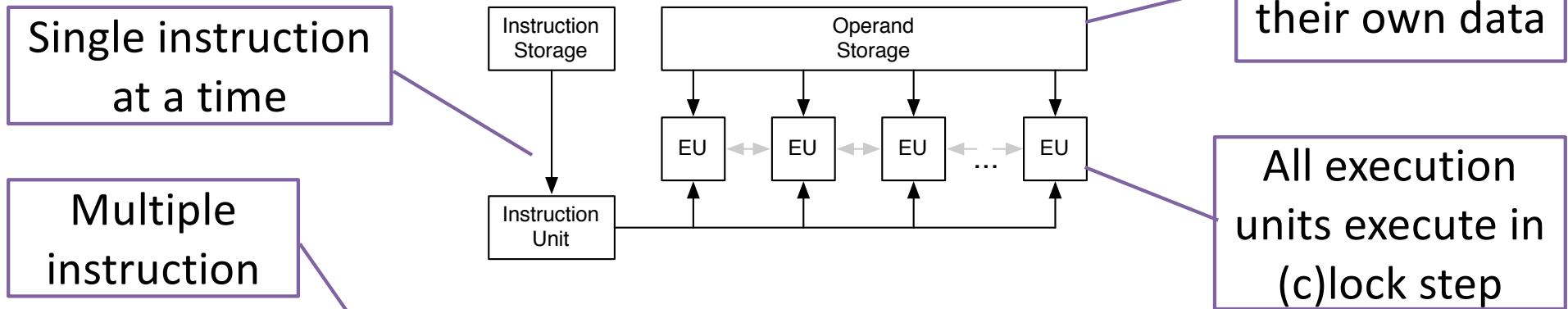
	Single Instruction	Multiple Instruction
Single Data	SISD	
Multiple Data	SIMD	MIMD

Based on multiplicity of instruction streams, data storage



SIMD and MIMD

- Two principal parallel computing paradigms (multiple cores) But each have their own data



Shared Memory

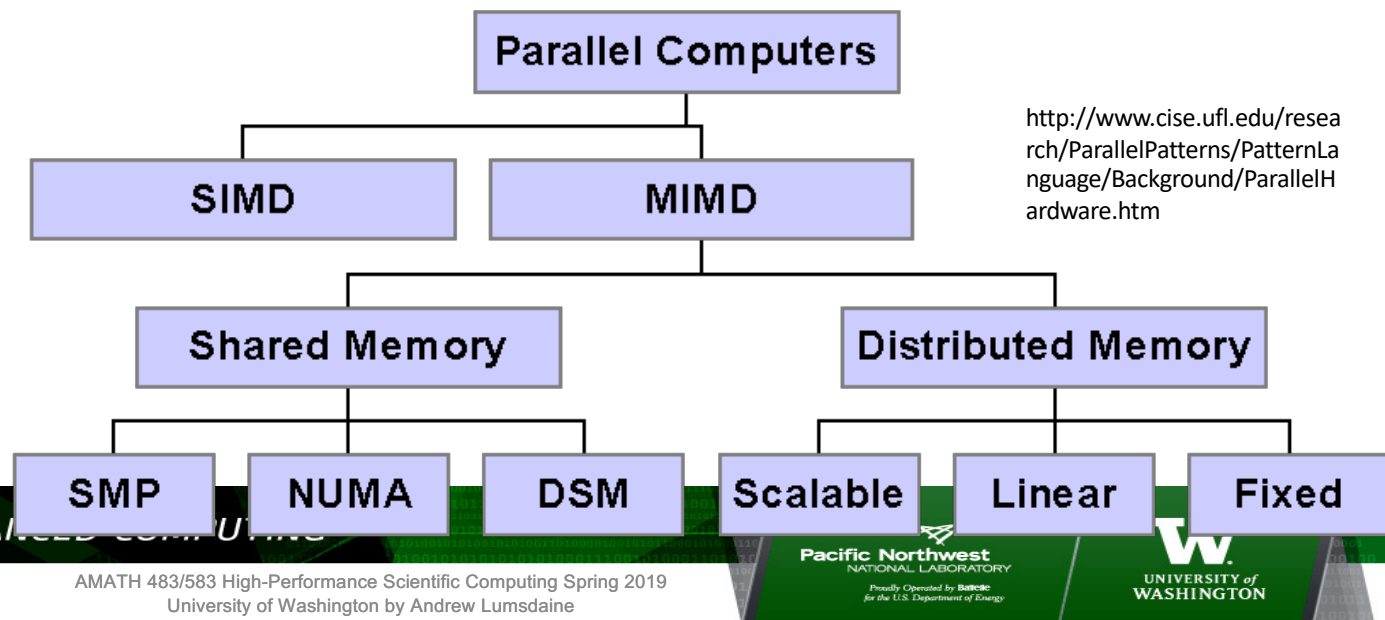
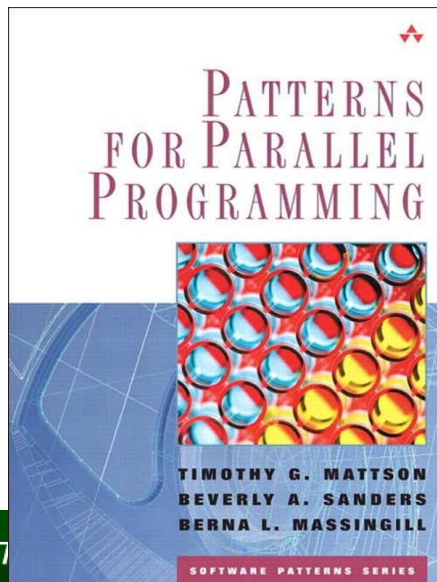
Not Shared



A More Refined (Programmer-Oriented) Taxonomy

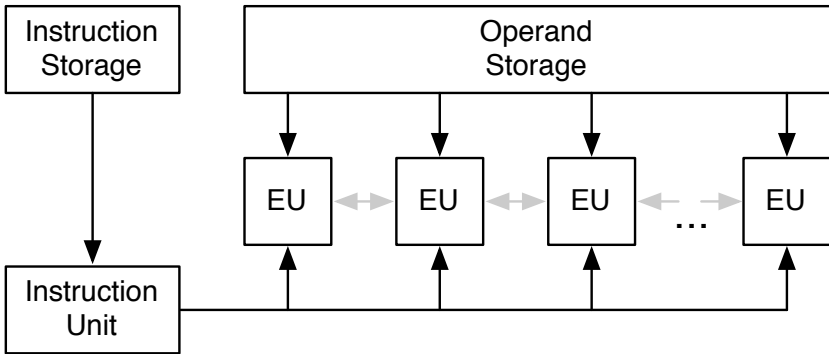
- Three major modes of parallel computation: Shared Memory, Distributed Memory, and Hybrid Memory (associated with MPI for distributed)
- Different programming models and different modes of communication
- A modern supercomputer will have all three major modes present

We will come back to this soon



SIMD in SSE/AVX

Flynn's original conceptual model

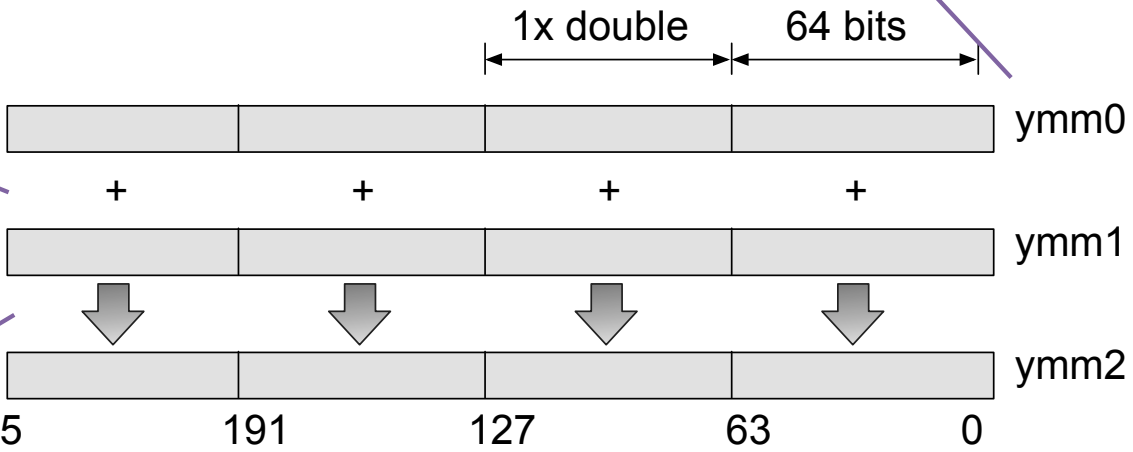


ymm are 256 bit registers

```
vfadd231pd %ymm0, %ymm1, %ymm2
```

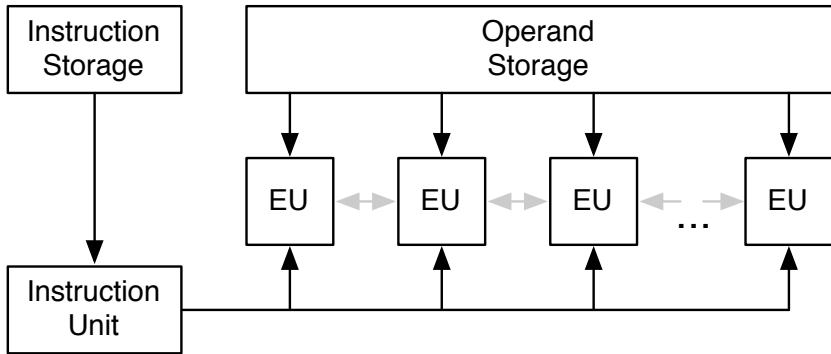
One machine instruction

Adds all four doubles *simultaneously*

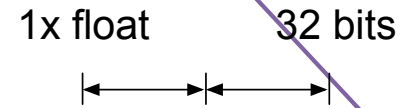


SIMD in SSE/AVX

Flynn's original conceptual model

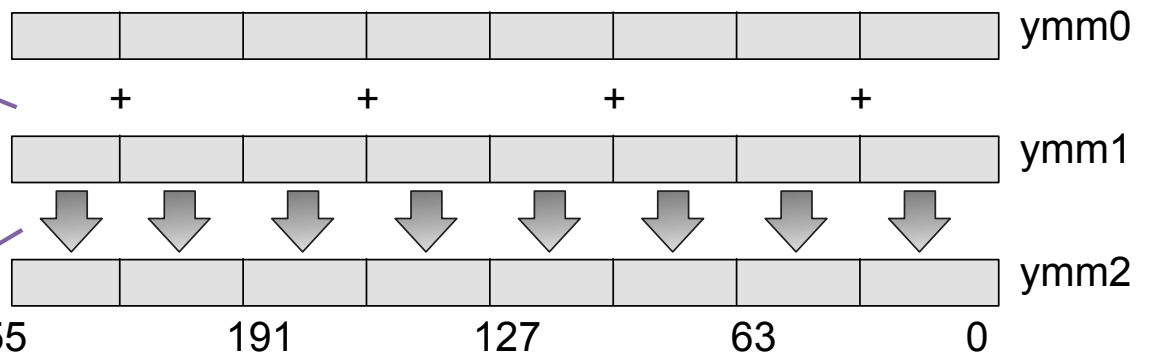


ymm are 256 bit registers



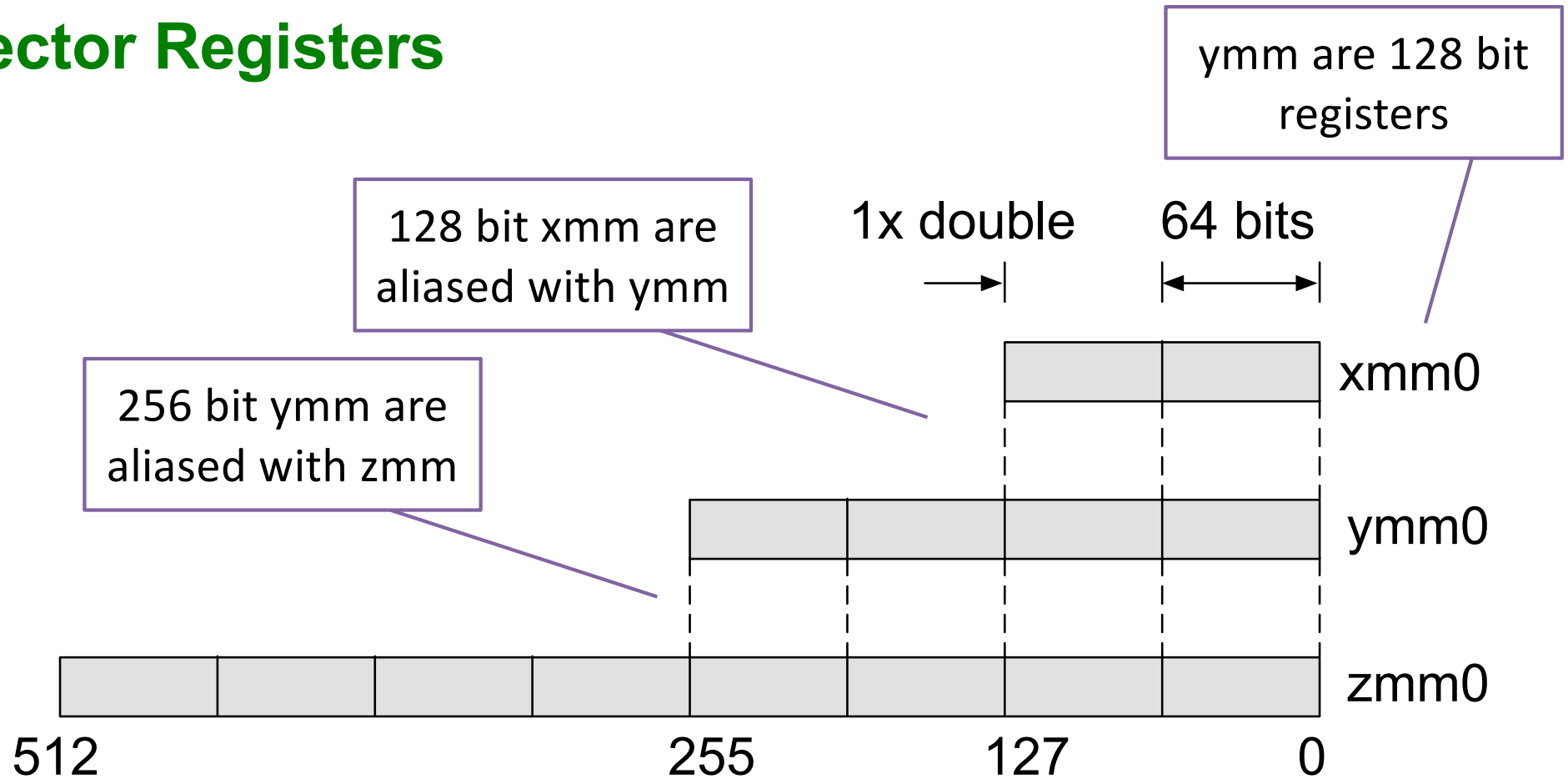
```
vfadd231ps %ymm0, %ymm1, %ymm2
```

One machine instruction



Adds all eight floats *simultaneously*

Vector Registers



Intel Intrinsic Guide



The Intel Intrinsic Guide is an interactive reference tool for Intel intrinsic instructions, which are C style functions that provide access to many Intel instructions - including Intel® SSE, AVX, AVX-512, and more - without the need to write assembly code. ✕

Technologies

- MMX
- SSE
- SSE2
- SSE3
- SSSE3
- SSE4.1
- SSE4.2
- AVX
- AVX2
- FMA
- AVX-512
- KNC
- SVMML
- Other

Choose family

Categories

- Application-Targeted
- Arithmetic
- Bit Manipulation
- Cast
- Compare

Choose operation

<code>__m64 _mm_add_pi32 (__m64 a, __m64 b)</code>	<code>paddw</code>
<code>__m64 _mm_add_pi8 (__m64 a, __m64 b)</code>	<code>paddb</code>
<code>__m64 _mm_adds_pi16 (__m64 a, __m64 b)</code>	<code>paddsw</code>
<code>__m64 _mm_adds_pi8 (__m64 a, __m64 b)</code>	<code>paddsb</code>
<code>__m64 _mm_adds_pu16 (__m64 a, __m64 b)</code>	<code>paddusw</code>
<code>__m64 _mm_adds_pu8 (__m64 a, __m64 b)</code>	<code>paddusb</code>
<code>__m64 _mm_madd_pi16 (__m64 a, __m64 b)</code>	<code>pmaddwd</code>
<code>__m64 _mm_mulhi_pi16 (__m64 a, __m64 b)</code>	<code>pmulhw</code>
<code>__m64 _mm_mull_pi16 (__m64 a, __m64 b)</code>	<code>pmullw</code>
<code>__m64 _mm_paddb (__m64 a, __m64 b)</code>	<code>paddb</code>
<code>__m64 _mm_paddsw (__m64 a, __m64 b)</code>	<code>paddsw</code>
<code>__m64 _mm_paddsb (__m64 a, __m64 b)</code>	<code>paddsb</code>
<code>__m64 _mm_paddusw (__m64 a, __m64 b)</code>	<code>paddusw</code>
<code>__m64 _mm_paddusb (__m64 a, __m64 b)</code>	<code>paddusb</code>

Get back
intrinsic

Intrinsics

```
__m512d _mm512_fmadd_pd (__m512d a, __m512d b, __m512d c)
```

vfnmadd132pd, vfnmadd213pd, vfnmadd231pd

Synopsis

```
__m512d _mm512_fmadd_pd (__m512d a, __m512d b, __m512d c)  
#include "immintrin.h"  
Instruction: vfnmadd132pd zmm {k}, zmm, zmm  
            vfnmadd213pd zmm {k}, zmm, zmm  
            vfnmadd231pd zmm {k}, zmm, zmm  
CPUID Flags: AVX512F for AVX-512, KNCNI for KNC
```

How to access
AVX instructions
from C/C++

Description

Multiply packed double-precision (64-bit) floating-point elements in *a* and *b*, and store the results in *dst*.

The machine instruction(s)
that is/are generated

c, and store the

Operation

```
FOR j := 0 to 7  
  i := j*64  
  dst[i+63:i] := -(a[i+63:i] * b[i+63:i]) + c[i+63:i]  
ENDFOR  
dst[MAX:512] := 0
```

Does your CPU support
this instruction?

Performance

Architecture	Latency	Throughput
Knights Landing	6	0.5

CPU ID

- The cpuid machine instruction can be used to query the CPU about what features it supports

```
$ docker run amath583/cpuinfo
```

```
This CPU supports CPUID_EAX_CORE2_DUO_8K
```

```
This CPU supports CPUID_EBX_AVX2
```

```
This CPU supports CPUID_ECX_SSE3
```

```
This CPU supports CPUID_ECX_SSSE3
```

```
This CPU supports CPUID_ECX_FMA
```

```
This CPU supports CPUID_ECX_SSE41
```

```
This CPU supports CPUID_ECX_SSE42
```

```
This CPU supports CPUID_ECX_AES
```

```
This CPU supports CPUID_ECX_AVX
```

```
This CPU supports CPUID_ECX_F16C
```

```
This CPU supports CPUID_ECX_HYPERVISOR
```

Processor family

Supported features

Under docker the cpu will be in hypervisor mode

Issuing ASM directly

```
int input = 0, output = 0;
```

C++ variables

```
__asm__(  
    "cpuid;"  
    : "=a" (output)  
    : "a" (input)  
    : "%ebx", "%ecx", "%edx"); // clobbered registers
```

cpuid instruction

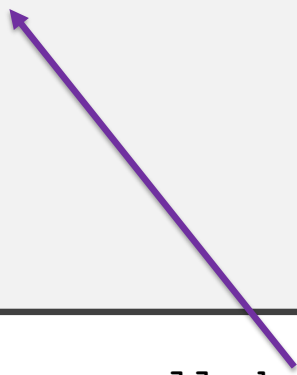
The register EAX is mapped to variable "output" on completion

The variable "input" is mapped to register EAX at start

Preserve these registers

What Does the Compiler Look for?

```
void basicMultiply(const Matrix& A, const Matrix&B, Matrix&C) {  
    for (int i = 0; i < A.numRows(); ++i) {  
        for (int j = 0; j < B.numCols(); ++j) {  
            for (int k = 0; k < A.numCols(); ++k) {  
                C(i,j) += A(i,k) * B(k,j);  
            }  
        }  
    }  
}
```



Matrix.cpp:31:7: remark: unrolled loop by a factor of 4 \
with run-time trip count [-Rpass=loop-unroll]

```
for (int k = 0; k < A.numCols(); ++k) {
```

Unrolling

```
void basicMultiply(const Matrix& A, const Matrix&B, Matrix&C) {  
    for (int i = 0; i < A.numRows(); ++i) {  
        for (int j = 0; j < B.numCols(); ++j) {  
            for (int k = 0; k < A.numCols(); k += 4) {  
                C(i,j) += A(i, k + 0) * B(k + 0, j);  
                C(i,j) += A(i, k + 1) * B(k + 1, j);  
                C(i,j) += A(i, k + 2) * B(k + 2, j);  
                C(i,j) += A(i, k + 3) * B(k + 3, j);  
            }  
        }  
    }  
}
```

Generated Code

```
vmovsd    (%rdi,%r11,8), %xmm1
vmulsd    -8(%r13), %xmm1, %xmm1
vaddsd    %xmm1, %xmm0, %xmm0
vmovsd    %xmm0, (%rdx,%r14,8)
vmovsd    (%r10,%rdi), %xmm1
vmulsd    (%r13), %xmm1, %xmm1
vaddsd    %xmm1, %xmm0, %xmm0
vmovsd    %xmm0, (%rdx,%r14,8)
```

What Does the Compiler Look for?

```
void hoistedMultiply(const Matrix& A, const Matrix&B, Matrix&C) {  
    for (int i = 0; i < A.numRows(); ++i) {  
        for (int j = 0; j < B.numCols(); ++j) {  
            double t = C(i,j);  
            for (int k = 0; k < A.numCols(); ++k) {  
                t += A(i,k) * B(k,j);  
            }  
            C(i,j) = t;  
        }  
    }  
}
```

Matrix.cpp:52:7: remark: vectorized loop \
(vectorization width: 4, interleaved count: 4) [-Rpass=

```
    for (int k = 0; k < A.numCols(); ++k) {  
        ^
```

Matrix.cpp:52:7: remark: unrolled loop by a factor of 2 \
with run-time trip count [-Rpass=loop-unroll]

Matrix.cpp:50:5: remark: unrolled loop by a factor of 8 \
with run-time trip count [-Rpass=loop-unroll]

```
    for (int j = 0; j < B.numCols(); ++j) {  
        ^
```


What Does the Compiler Look for?

```
./Matrix.hpp:26:69: remark: _ZNKSt3__16vectorIdNS_9allocatorIdEEEixEm inlined into
_ZNK6MatrixclEmm [-Rpass=inline]
  const double &operator()(size_type i, size_type j) const { return arrayData[i*jCols + j];
./Matrix.hpp:25:69: remark: _ZNSt3__16vectorIdNS_9allocatorIdEEEixEm inlined into
_ZN6MatrixclEmm [-Rpass=inline]
  double &operator()(size_type i, size_type j) { return arrayData[i*jCols + j];
```

Signatures get
mangled

operator()()
Function

Function call is
replaced with
body of code

Easier if body is
available to
compiler

No function call!!

i.e., if it is
*defined in the
header file*

```
vmovsd    (%rdi,%r11,8), %xmm1
vmulsd    -8(%r13), %xmm1, %xmm1
vaddsd    %xmm1, %xmm0, %xmm0
vmovsd    %xmm0, (%rdx,%r14,8)
vmovsd    (%r10,%rdi), %xmm1
vmulsd    (%r13), %xmm1, %xmm1
vaddsd    %xmm1, %xmm0, %xmm0
vmovsd    %xmm0, (%rdx,%r14,8)
```

Without Inlining

operator()
function call

```
movq    -8(%rbp), %rdi
movslq  -28(%rbp), %rsi
movslq  -36(%rbp), %rdx
callq   __ZNK6MatrixclEmm
movsd   (%rax), %xmm0
movq    -16(%rbp), %rdi
movslq  -36(%rbp), %rsi
movslq  -32(%rbp), %rdx
movsd   %xmm0, -72(%rbp)
```

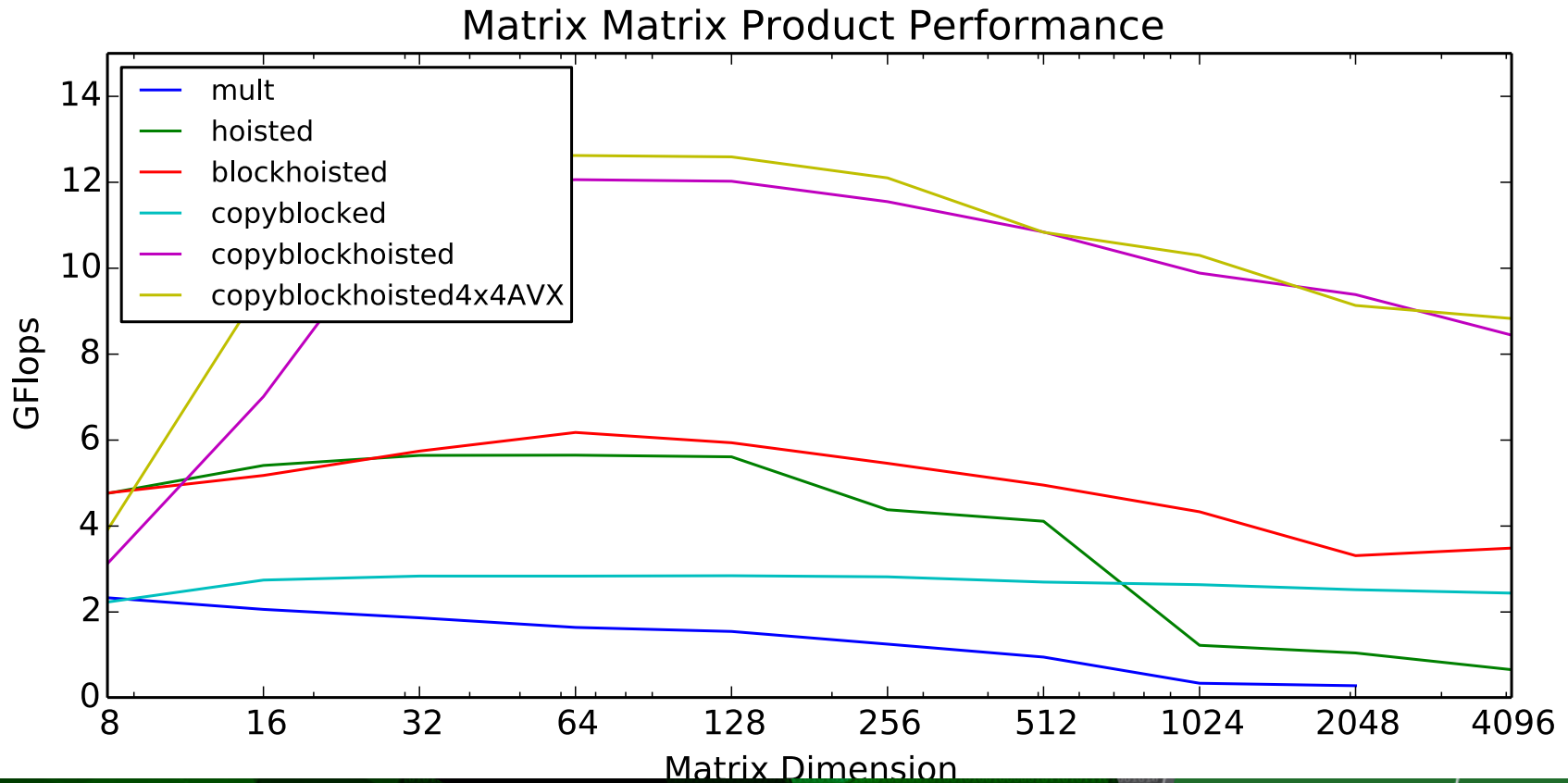
operator()
function call

```
callq   __ZNK6MatrixclEmm
movsd   -72(%rbp), %xmm0
mulsd   (%rax), %xmm0
movq    -24(%rbp), %rdi
movslq  -28(%rbp), %rsi
movslq  -32(%rbp), %rdx
movsd   %xmm0, -80(%rbp)
```

operator()
function call

```
callq   __ZN6MatrixclEmm
movsd   -80(%rbp), %xmm0
addsd   (%rax), %xmm0
movsd   %xmm0, (%rax)
```

Summary



Recommendations

Inlining, unrolling, vectorization

- Avoid programming in assembler
- If you can't avoid that, use intrinsics – but you will need to match the instructions to the hardware (which is not portable)
- In general, let compiler determine hardware, pick instructions, and optimize
- Check your performance against performance models
- Monitor what your compiler is doing
 - Optimization report
 - Full set of flags
 - Last resort – read the assembler

Most important is to have a mental model for the vector registers and to be aware of what is possible and how to write code to be optimizable

Review

- High Performance = Writing software to use hardware effectively
- Hardware
 - Fast clock
 - Branch prediction, other magic on chip
 - Hierarchical memory
 - Pipelining instructions
 - Vector registers and vector instructions ("SIMD")
- Software techniques to use all of these
- Compilers!
- Our first parallel computations

Basic Linear Algebra Subprograms (BLAS)

- Standardized set of core / kernel algorithms for numerical linear algebra
- Fortran – but various extensions to C have been created
 - Matrix ordering and function calling disciplines are main Fortran/C issues
- Originally derived from needs of LINPACK / EISPACK then LAPACK
- Four precisions: single, double, single complex, double complex
 - “s”, “d”, “c”, “z” prefixes
- Level-1: Vector-vector operations
 - Double precision vector addition = “daxpy”
- Level-2: Matrix-vector operations
 - Double precision matrix-vector product = “dgemv”
- Level-3: Matrix-matrix operations
 - Double precision matrix-matrix product = “dgemm”
- There are also sparse BLAS and a next-generation BLAS, but neither are well-supported by vendors

BLAS

- (Updated set of) Basic Linear Algebra Subprograms
- The BLAS functionality is divided into three levels:
 - **Level 1:** contains vector operations of the form:

$$y \leftarrow \alpha x + y$$

as well as scalar dot products and vector norms

- **Level 2:** contains matrix-vector operations of the form

$$y \leftarrow \alpha Ax + \beta y$$

as well as $Tx = y$ solving for x with T being triangular

- **Level 3:** contains matrix-matrix operations of the form

$$C \leftarrow \alpha AB + \beta C$$

as well as solving $B \leftarrow \alpha T^{-1}B$ for triangular matrices T . This level contains the widely used General Matrix Multiply operation.

BLAS

- Several implementations for different languages exist
 - Reference implementation (F77 and C-wrapper)
<http://www.netlib.org/blas/>
 - ATLAS, highly optimized for particular processor architectures
 - A generic C++ template class library providing BLAS functionality: uBLAS
<http://www.boost.org>
 - Several vendors provide libraries optimized for their architecture (AMD, HP, IBM, Intel, NEC, NViDIA, Sun)

BLAS: F77 naming conventions

- Each routine has a name which specifies the operation, the type of matrices involved and their precisions.

Names are in the form: P_{MM}OO

SP symmetric packed
HE hermitian
HB hermitian band
HP hermitian packed
TR triangular
TB triangular band
TP triangular packed

- Some of the most common operations (OO):

- **DOT** scalar product, $x^T y$
AXPY vector sum, $\alpha x + y$
MV matrix-vector product, $A x$
SV matrix-vector solve, $\text{inv}(A) x$
MM matrix-matrix product, $A B$
SM matrix-matrix solve, $\text{inv}(A) B$

- The types of matrices are (MM)

- **GE** general
GB general band
SY symmetric
SB symmetric band

- Each operation is defined for four precisions (P)

- **S** single real
D double real
C single complex
Z double complex

- Examples

SGEMM stands for “single-precision general matrix-matrix multiply”

DGEMM stands for “double-precision matrix-matrix multiply”.

BLAS: C naming conventions

- F77 routine name is changed to lowercase and prefixed with `blas_`
- All routines accepting two dimensional arrays have a new additional first parameter specifying the matrix memory layout (row major or column major)
- Character parameters are replaced by corresponding enum values
- Input arguments are declared `const`
- Non-complex scalar input parameters are passed by value
- Complex scalar input arguments are passed using a `void*`
- Arrays are passed by address
- Output scalar arguments are passed by address
- Complex functions become subroutines which return the result via an additional last parameter (`void*`), appending `_sub` to the name

_axpy

cblas_daxpy

Computes a constant times a vector plus a vector (double-precision).

```
void cblas_daxpy (  
    const int N,  
    const double alpha,  
    const double *X,  
    const int incX,  
    double *Y,  
    const int incY  
);
```

Parameters

N

Number of elements in the vectors.

alpha

Scaling factor for the values in *x*.

X

Input vector *x*.

incX

Stride within *x*. For example, if *incX* is 7, every 7th element is used.

Y

Input vector *y*.

incY

Stride within *y*. For example, if *incY* is 7, every 7th element is used.

Discussion

On return, the contents of vector *Y* are replaced with the result. The value computed is $(\text{alpha} * X[i]) + Y[i]$.

Availability

Available in OS X v10.2 and later.

Declared In

`cblas.h`

cblas_dgemm

cblas_dgemm

Multiplies two matrices (double-precision).

```
void cblas_dgemm (
    const enum CBLAS_ORDER Order,
    const enum CBLAS_TRANSPOSE TransA,
    const enum CBLAS_TRANSPOSE TransB,
    const int M,
    const int N,
    const int K,
    const double alpha,
    const double *A,
    const int lda,
    const double *B,
    const int ldb,
    const double beta,
    double *C,
    const int ldc
);
```

Parameters

Order

Specifies row-major (C) or column-major (Fortran) data ordering.

TransA

Specifies whether to transpose matrix A.

TransB

Specifies whether to transpose matrix B.

M

Number of rows in matrices A and C.

N

Number of columns in matrices B and C.

K

Number of columns in matrix A; number of rows in matrix B.

alpha

Scaling factor for the product of matrices A and B.

A

Matrix A.

lda

The size of the first dimension of matrix A; if you are passing a matrix A[m][n], the value should be m.

B

Matrix B.

ldb

The size of the first dimension of matrix B; if you are passing a matrix B[m][n], the value should be m.

beta

Scaling factor for matrix C.

C

Matrix C.

ldc

The size of the first dimension of matrix C; if you are passing a matrix C[m][n], the value should be m.

Basic Linear Algebra Subprograms (BLAS)

- Level 1: Vector-Vector operations

name	description	equation	prefixes
_rotg	generate plane rotation		s, d
_rotmg	generate modified plane rotation		s, d
_rot	apply plane rotation		s, d
_rotm	apply modified plane rotation		s, d
_swap	swap vectors	$x \leftrightarrow y$	s, d, c, z
_scal	scale vector	$y = \alpha y$	s, d, c, z, cs, zd
_copy	copy vector	$y = x$	s, d, c, z
_axpy	update vector	$y = y + \alpha x$	s, d, c, z
_dot	dot product	$= x^t y$	s, d, ds
_dotc	complex conj dot	$= x^h y$	c, z
_dotu	complex dot	$= x^t y$	c, z
__dot		$= \alpha + x^t y$	sds
_nrm2	2-norm	$= \ x\ _2$	s, d, sc, dz
_asum	1-norm	$= \ \text{Re}(x)\ _1 + \ \text{Im}(x)\ _1$	s, d, sc, dz
i_amax	∞ -norm	$= i$ such that $ \text{Re}(x_i) + \text{Im}(x_i) $ is max	s, d, c, z

name	description	equation	prefixes
_gemv	general matrix-vector multiply	$y = \alpha A^* x + \beta y$	s, d, c, z
_gbmv	(banded)	$y = \alpha A^* x + \beta y$	s, d, c, z
_hemv	hermetian mat-vec	$y = \alpha Ax + \beta y$	c, z
_hbm	(banded)	$y = \alpha Ax + \beta y$	c, z
_hpmv	(packed)	$y = \alpha Ax + \beta y$	c, z
_symv	symmetric mat-vec	$y = \alpha Ax + \beta y$	s, d, (c, z)†
_sbmv	(banded)	$y = \alpha Ax + \beta y$	s, d
_spmv	(packed)	$y = \alpha Ax + \beta y$	s, d, (c, z)†
_trmv	triangular mat-vec	$x = A^* x$	s, d, c, z
_tbmv	(banded)	$x = A^* x$	s, d, c, z
_tpmv	(packed)	$x = A^* x$	s, d, c, z
_trsv	triangular solve	$x = A^{-*} x$	s, d, c, z
_tbsv	(banded)	$x = A^{-*} x$	s, d, c, z
_tpsv	(packed)	$x = A^{-*} x$	s, d, c, z

A^* denotes A , A^T , or A^H ;

A^{-*} denotes A^{-1} , A^{-T} , or A^{-H} , depending on options and data type.

A is $m \times n$ or $n \times m$.

name	description	equation	prefixes
_ger	general rank-1 update	$A = A + \alpha xy^T$	s, d
_geru	(complex)	$A = A + \alpha xy^T$	c, z
_gerc	(complex conj)	$A = A + \alpha xy^H$	c, z
_her	hermetian rank-1 update	$A = A + \alpha xx^H$	c, z
_hpr	(packed)	$A = A + \alpha xx^H$	c, z
_her2	hermetian rank-2 update	$A = A + \alpha xy^H + y(\alpha x)^H$	c, z
_hpr2	(packed)	$A = A + \alpha xy^H + y(\alpha x)^H$	c, z
_syr	symmetric rank-1 update	$A = A + \alpha xx^T$	s, d, (c, z)†
_spr	(packed)	$A = A + \alpha xx^T$	s, d, (c, z)†
_syr2	symmetric rank-2 update	$A = A + \alpha xy^T + \alpha yx^T$	s, d
_spr2	(packed)	$A = A + \alpha xy^T + \alpha yx^T$	s, d

name	description	equation	prefixes
_gemm	general matrix-matrix multiply	$C = \alpha A^* B^* + \beta C$	s, d, c, z
_symm	symmetric mat-mat	$C = \alpha AB + \beta C$	s, d, c, z
_hemm	hermetian mat-mat	$C = \alpha AB + \beta C$	c, z
_syrk	symmetric rank- k update	$C = \alpha AA^T + \beta C$	s, d, c, z
_herk	hermetian rank- k update	$C = \alpha AA^H + \beta C$	c, z
_syr2k	symmetric rank- $2k$ update	$C = \alpha AB^T + \bar{\alpha} BA^T + \beta C$	s, d, c, z
_her2k	hermetian rank- $2k$ update	$C = \alpha AB^H + \bar{\alpha} BA^H + \beta C$	c, z
_trmm	triangular mat-mat	$B = \alpha A^* B$ or $B = \alpha BA^*$	s, d, c, z
_trsm	triangular solve mat	$B = \alpha A^{-*} B$ or $B = \alpha BA^{-*}$	s, d, c, z

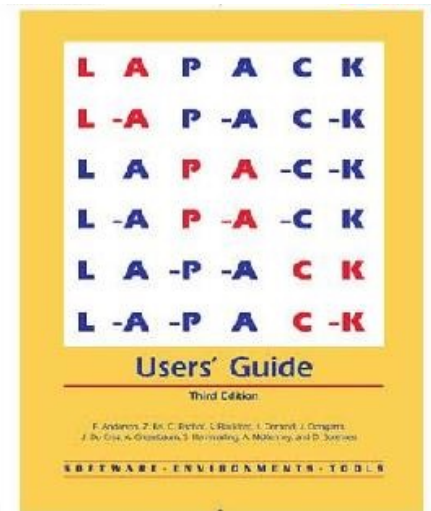
A^* denotes A , A^T , or A^H ;

A^{-*} denotes A^{-1} , A^{-T} , or A^{-H} , depending on options and data type.

The destination matrix is $m \times n$ or $n \times n$. For mat-mat, the common dimension of A and B is k .

LAPACK

- F77, based on blocked algorithms (BLAS 3)
- Driver routines (simple and expert) used to solve a complete problem
 - Solve a linear system of equations
 - Least squares solutions
 - Eigenvalue problems
 - Singular value problems
- Routines for distinct computational tasks
 - LU / Cholesky / QR / SVD factorization
 - Schur / generalized Schur decomposition
- Auxiliary
 - Estimate condition numbers
 - Unblocked algorithms
 - Future extensions to BLAS



<http://www.netlib.org/lapack>

LAPACK naming conventions

- Similar to BLAS
 - **XYZZZ**
 - **X**: data type
 - **S**: REAL
 - **D**: DOUBLE PRECISION
 - **C**: COMPLEX
 - **Z**: COMPLEX*16 or DOUBLE COMPLEX
 - **YY**: matrix type
 - **BD**: bidiagonal
 - **DI**: diagonal
 - **GB**: general band
 - **GE**: general (i.e., unsymmetric, in some cases rectangular)
 - **GG**: general matrices, generalized problem (i.e., a pair of general matrices)
 - **GT**: general tridiagonal
 - **HB**: (complex) Hermitian band
 - **HE**: (complex) Hermitian
 - **HG**: upper Hessenberg matrix, generalized problem (i.e. a Hessenberg and a triangular matrix)
 - **HP**: (complex) Hermitian, packed storage
 - **HS**: upper Hessenberg
 - **OP**: (real) orthogonal, packed storage
 - **OR**: (real) orthogonal
 - **PB**: symmetric or Hermitian positive definite band
- **YY**: more matrix types
 - **PO**: symmetric or Hermitian positive definite
 - **PP**: symmetric or Hermitian positive definite, packed storage
 - **PT**: symmetric or Hermitian positive definite tridiagonal
 - **SB**: (real) symmetric band
 - **SP**: symmetric, packed storage
 - **ST**: (real) symmetric tridiagonal
 - **SY**: symmetric
 - **TB**: triangular band
 - **TG**: triangular matrices, generalized problem (i.e., a pair of triangular matrices)
 - **TP**: triangular, packed storage
 - **TR**: triangular (or in some cases quasi-triangular)
 - **TZ**: trapezoidal
 - **UN**: (complex) unitary
 - **UP**: (complex) unitary, packed storage
- **ZZZ**: performed computation
 - Linear systems
 - Factorizations
 - Eigenvalue problems
 - Singular value decomposition
 - Etc.

Roofline Model

- Performance: locality, locality, locality
- Because computation is really really fast
- And moving data is expensive
- Limits on performance: Bandwidth, Latency, Peak Compute

$$\text{Performance} = \frac{\text{GFlops}}{\text{second}} = \min \left\{ \begin{array}{l} \text{CPU Peak} \\ \text{Bandwidth} \end{array} \right.$$

Williams, Samuel, Andrew Waterman, and David Patterson. "Roofline: an insightful visual performance model for multicore architectures." *Communications of the ACM* 52.4 (2009): 65-76.

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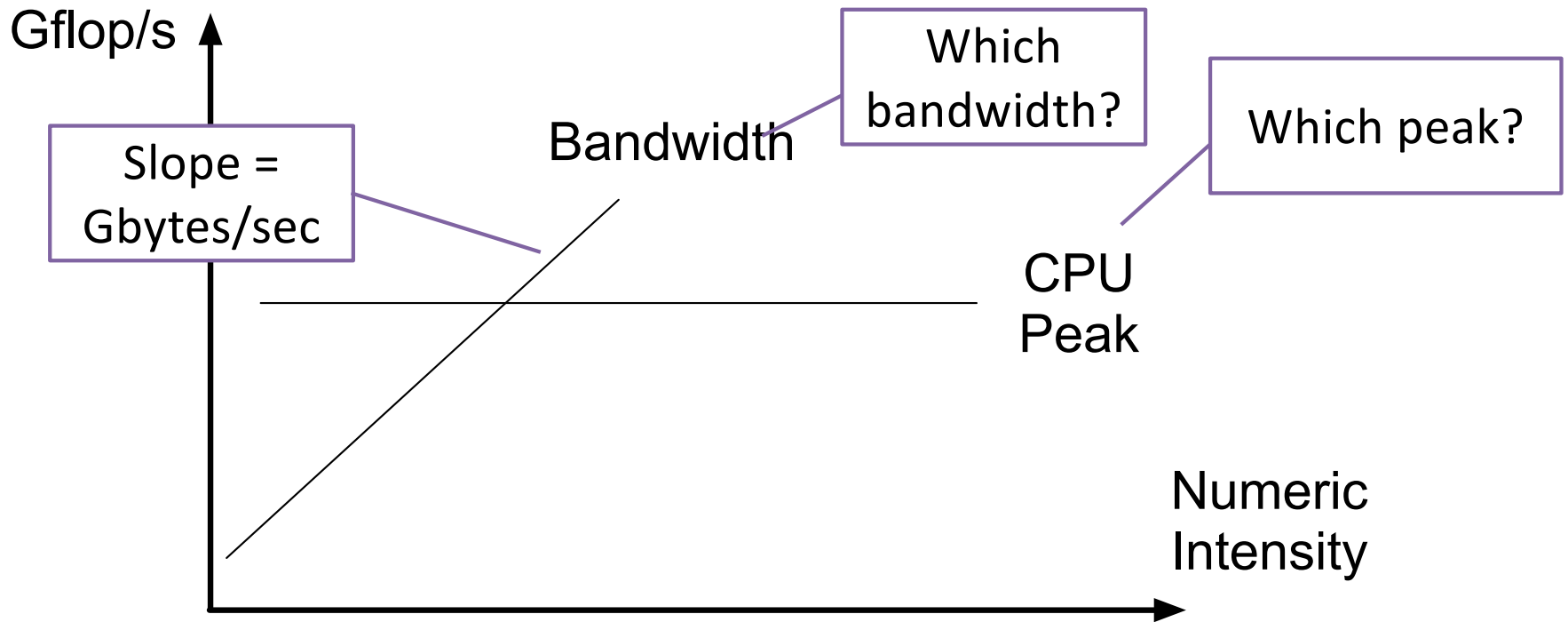
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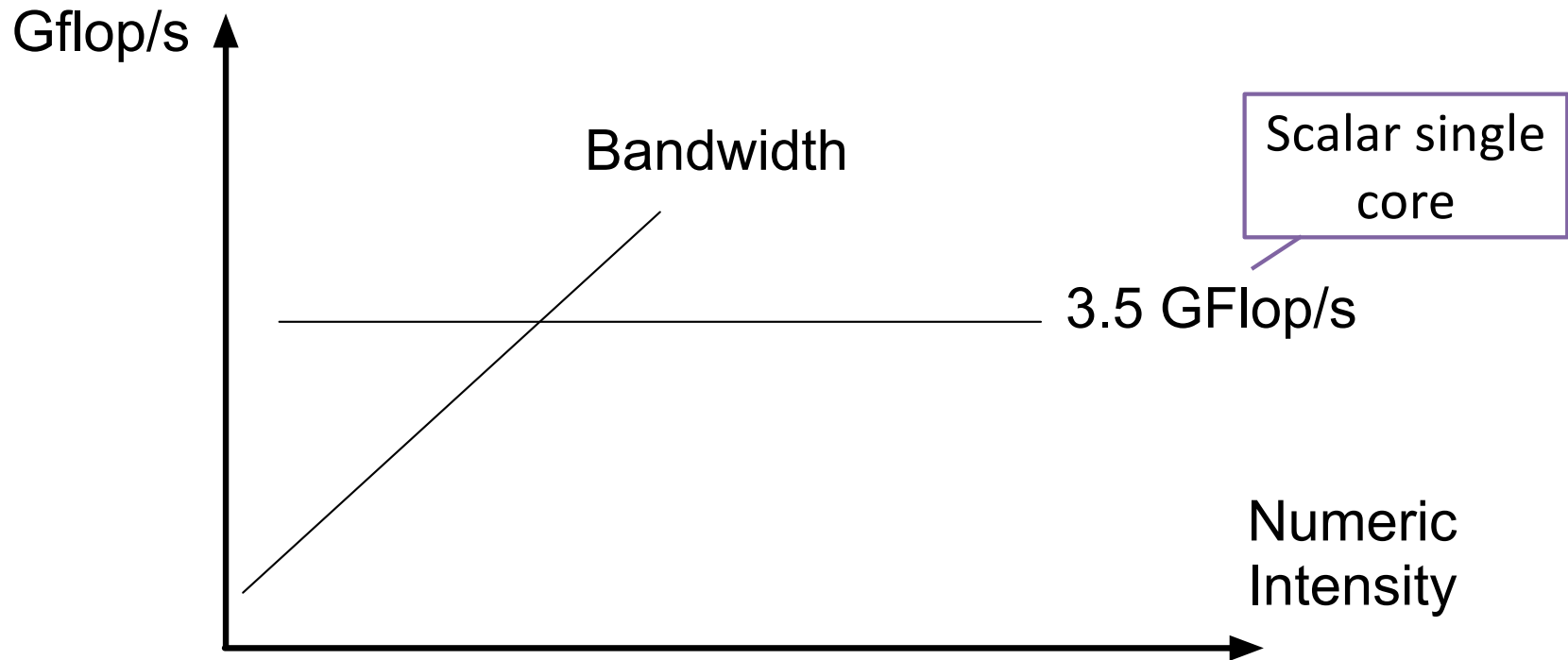
$$\text{Performance} = \frac{\text{GFlops}}{\text{second}} = \min \left\{ \begin{array}{l} \text{CPU Peak } \frac{\text{GFlops}}{\text{second}} \\ \text{Bandwidth } \frac{\text{Gbytes}}{\text{second}} \times \text{Numerical Intensity } \frac{\text{GFlops}}{\text{Gbyte}} \end{array} \right.$$

Roofline Model

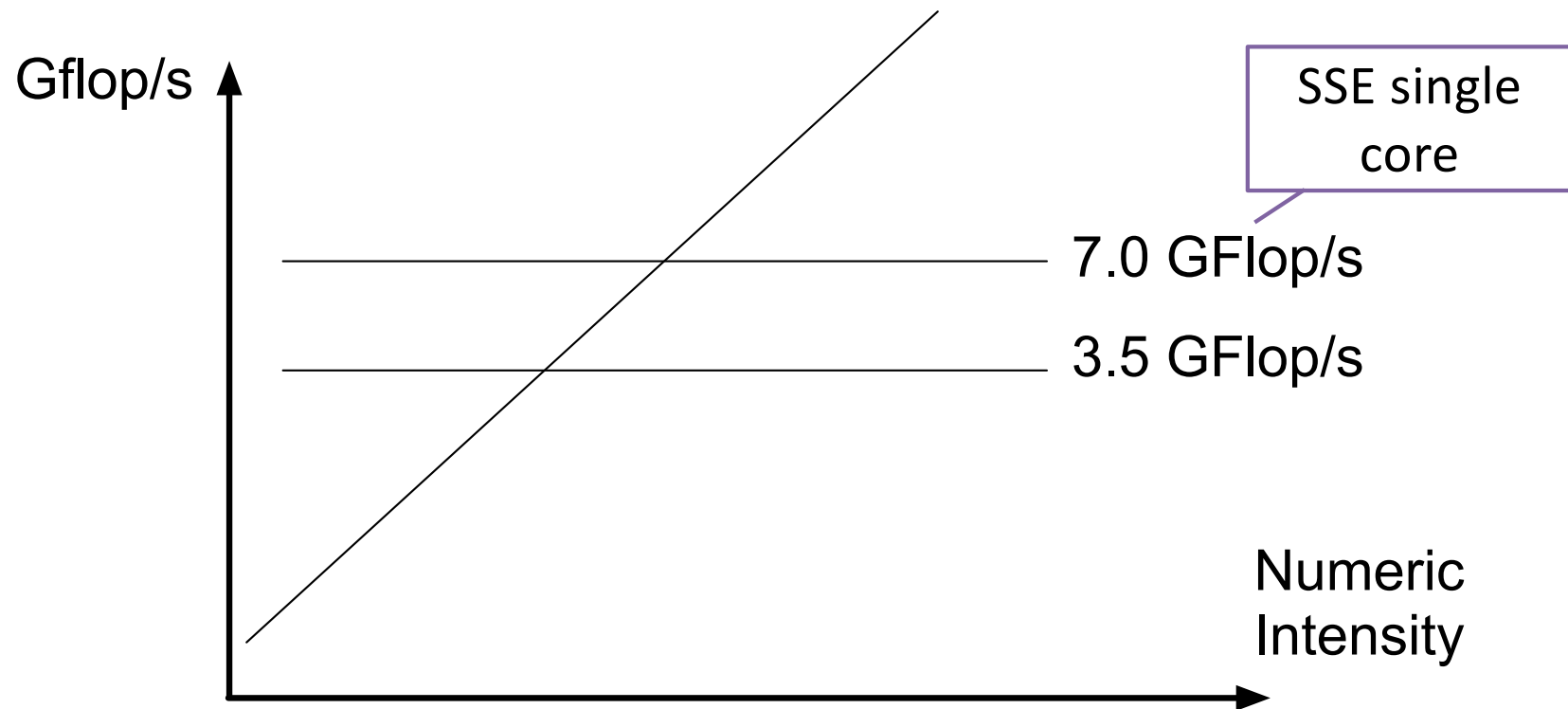
$$\text{Performance} = \frac{\text{GFlops}}{\text{second}} = \min \left\{ \begin{array}{l} \text{CPU Peak } \frac{\text{GFlops}}{\text{second}} \\ \text{Bandwidth } \frac{\text{Gbytes}}{\text{second}} \times \text{Numerical Intensity } \frac{\text{GFlops}}{\text{Gbyte}} \end{array} \right.$$



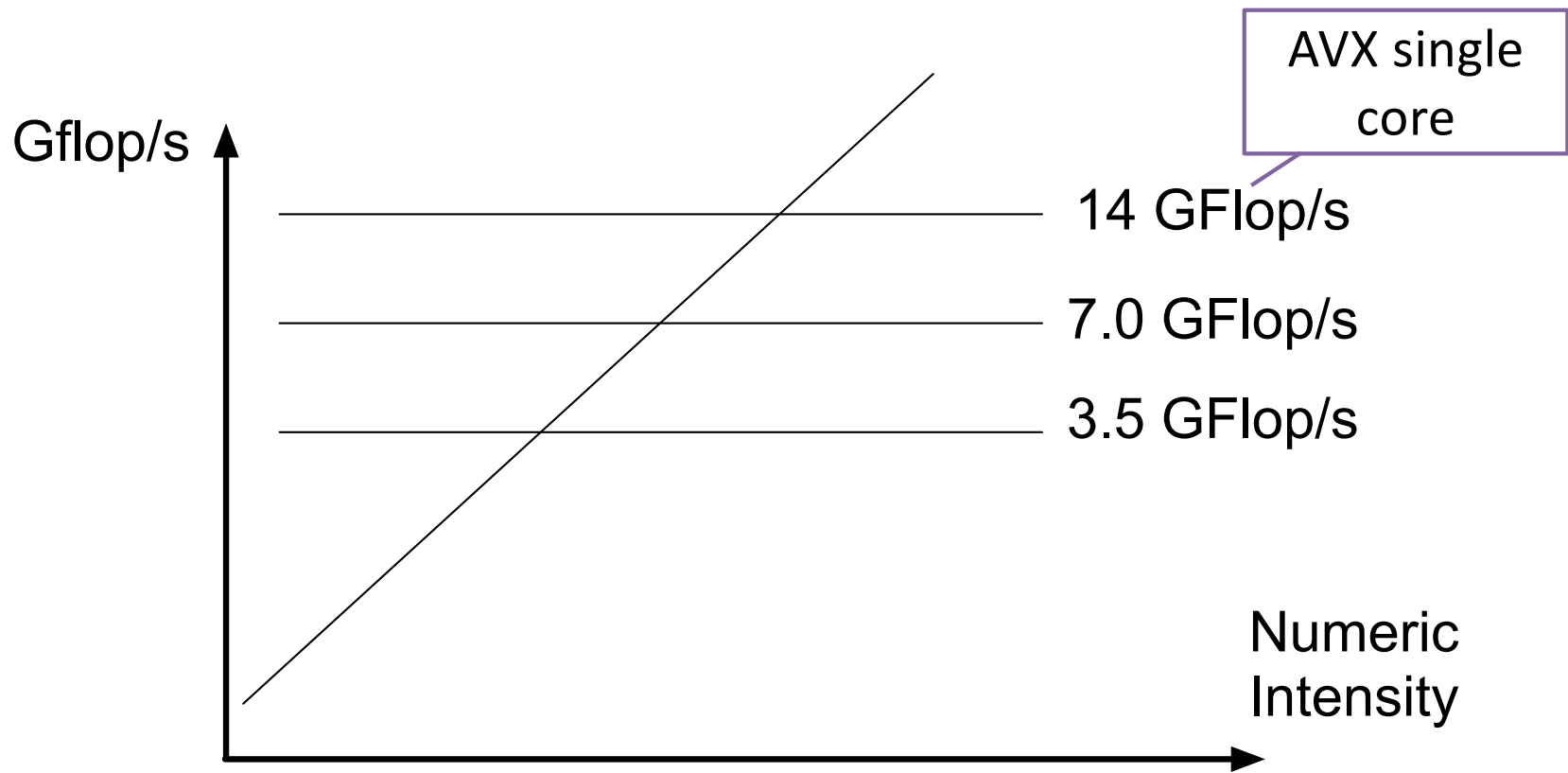
Roofline Model



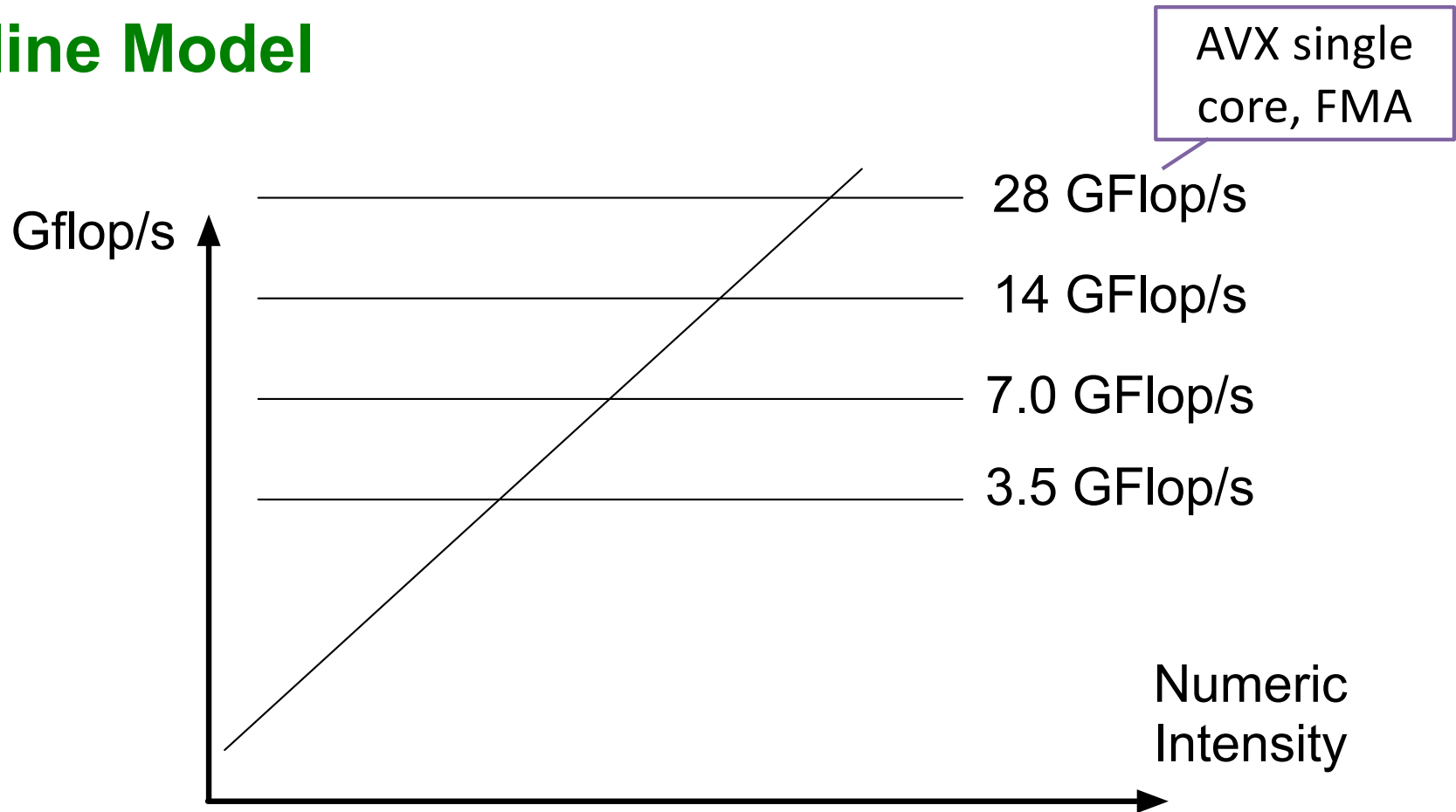
Roofline Model



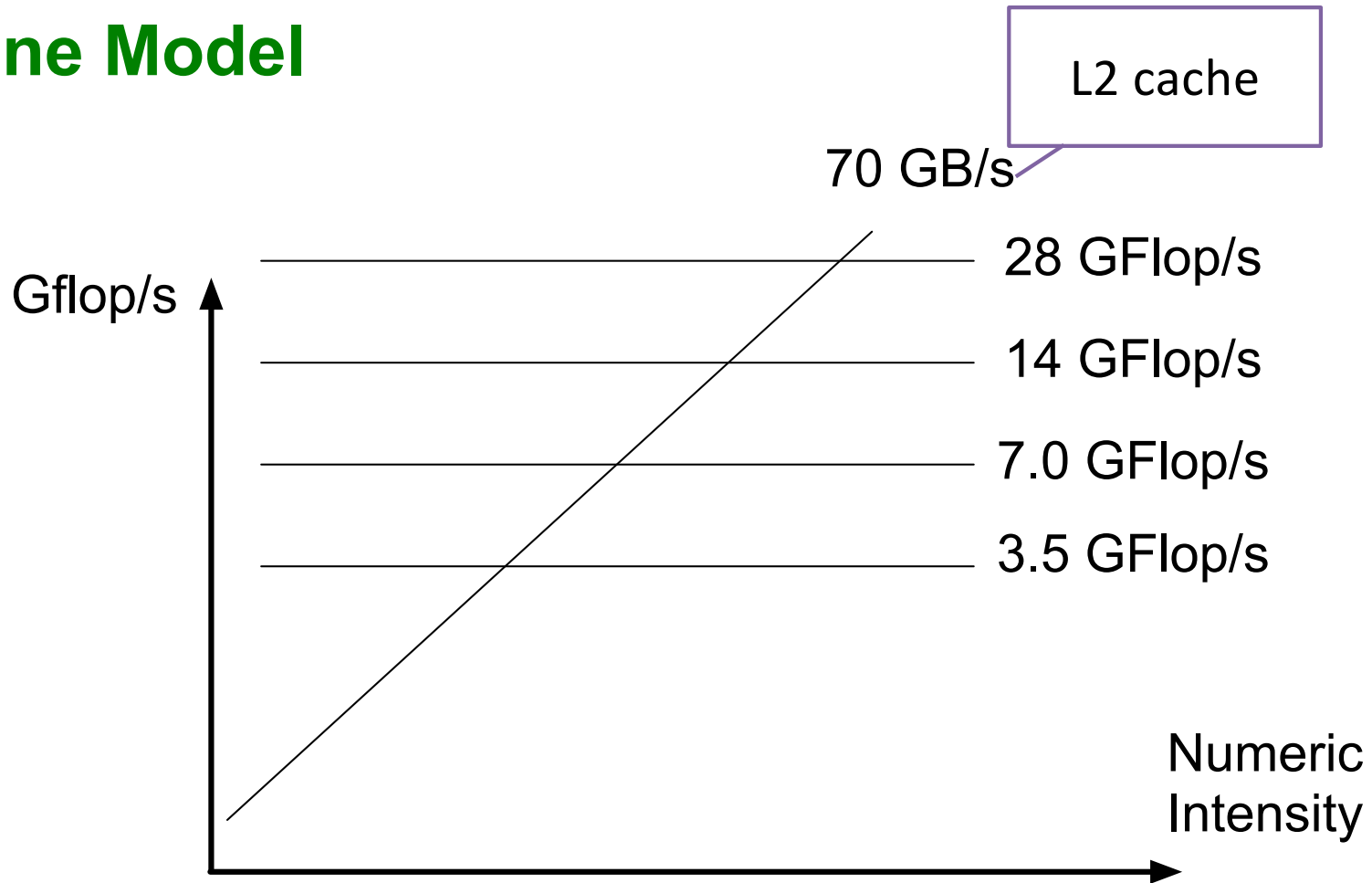
Roofline Model



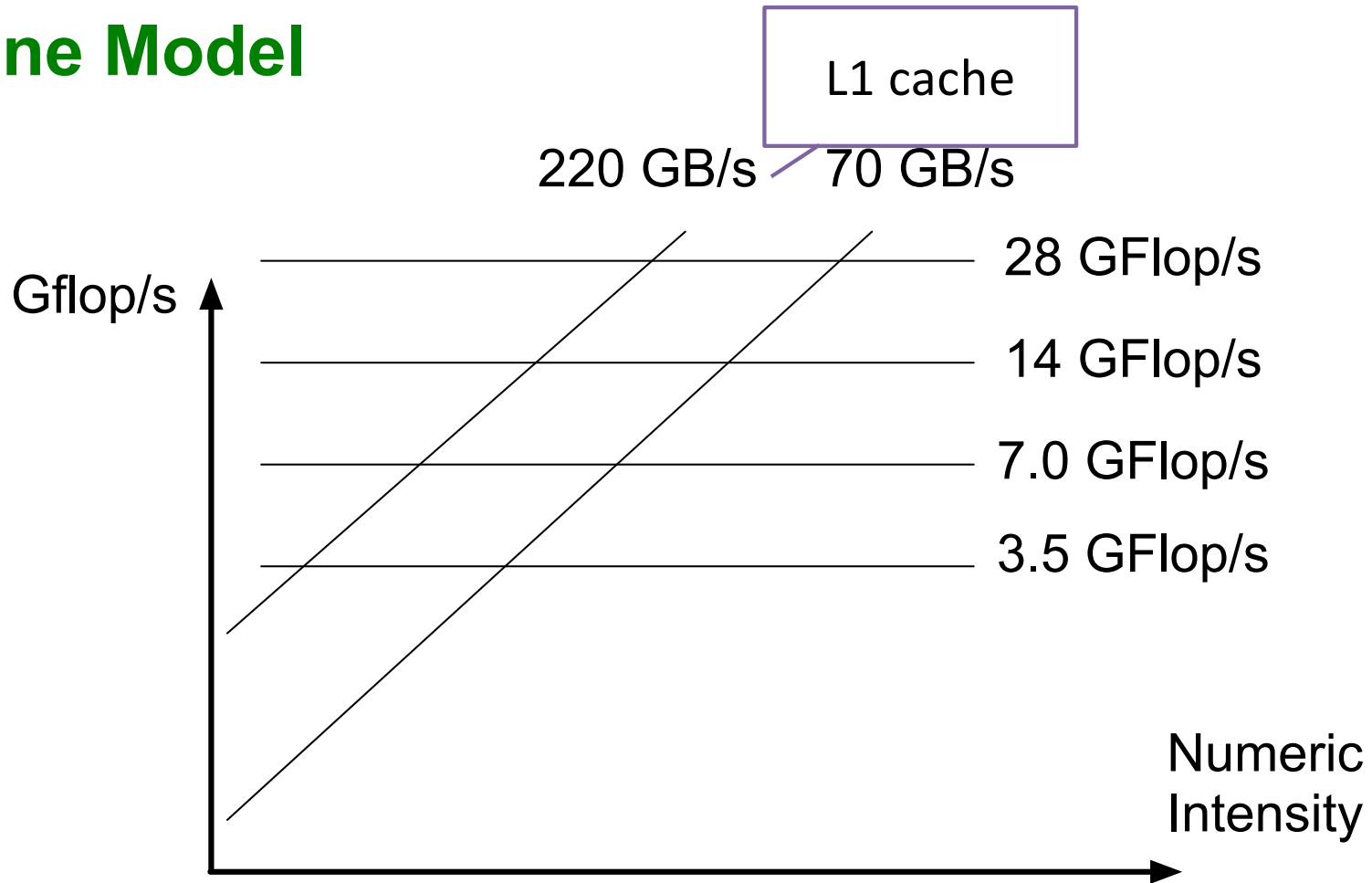
Roofline Model



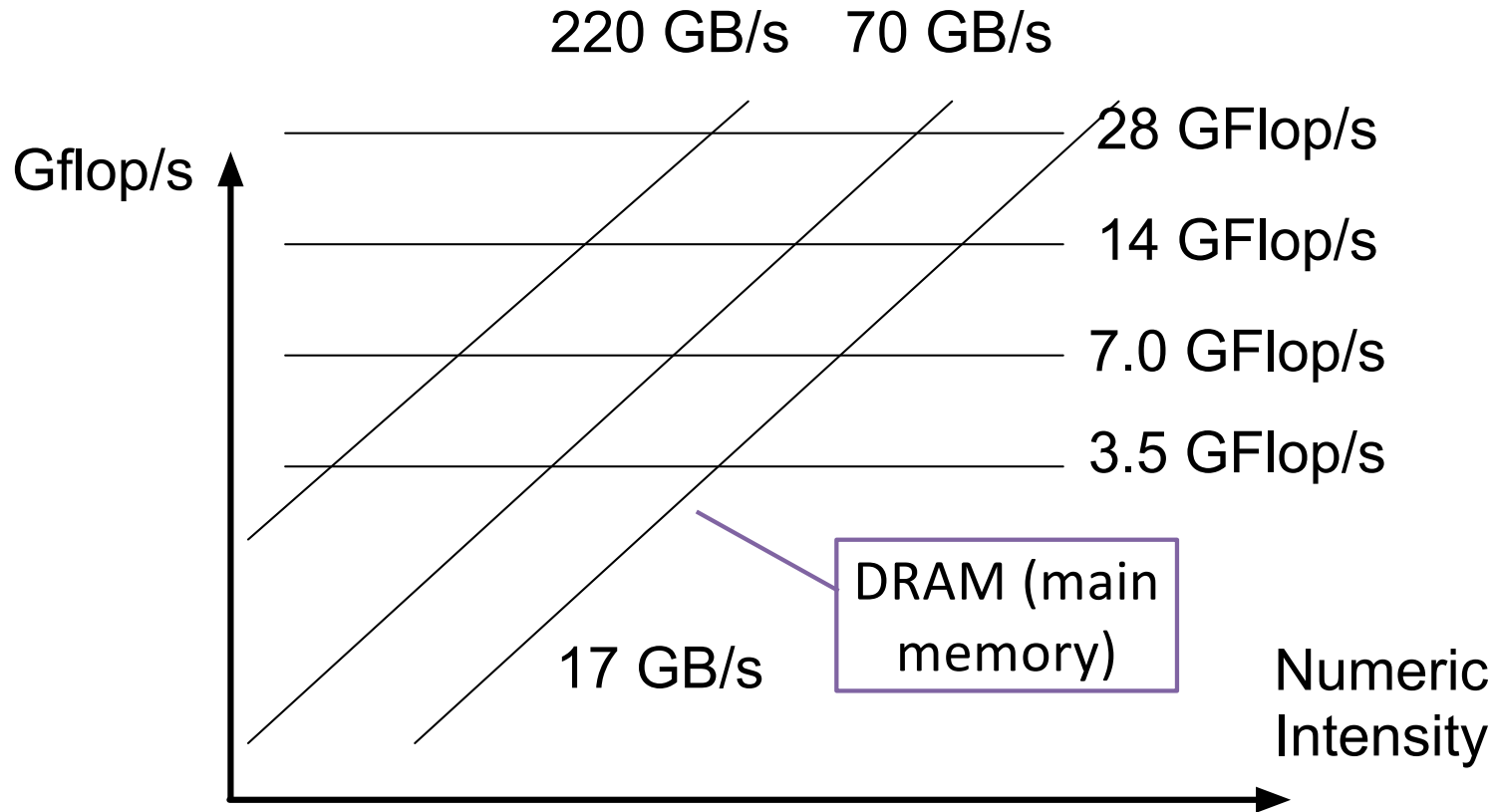
Roofline Model



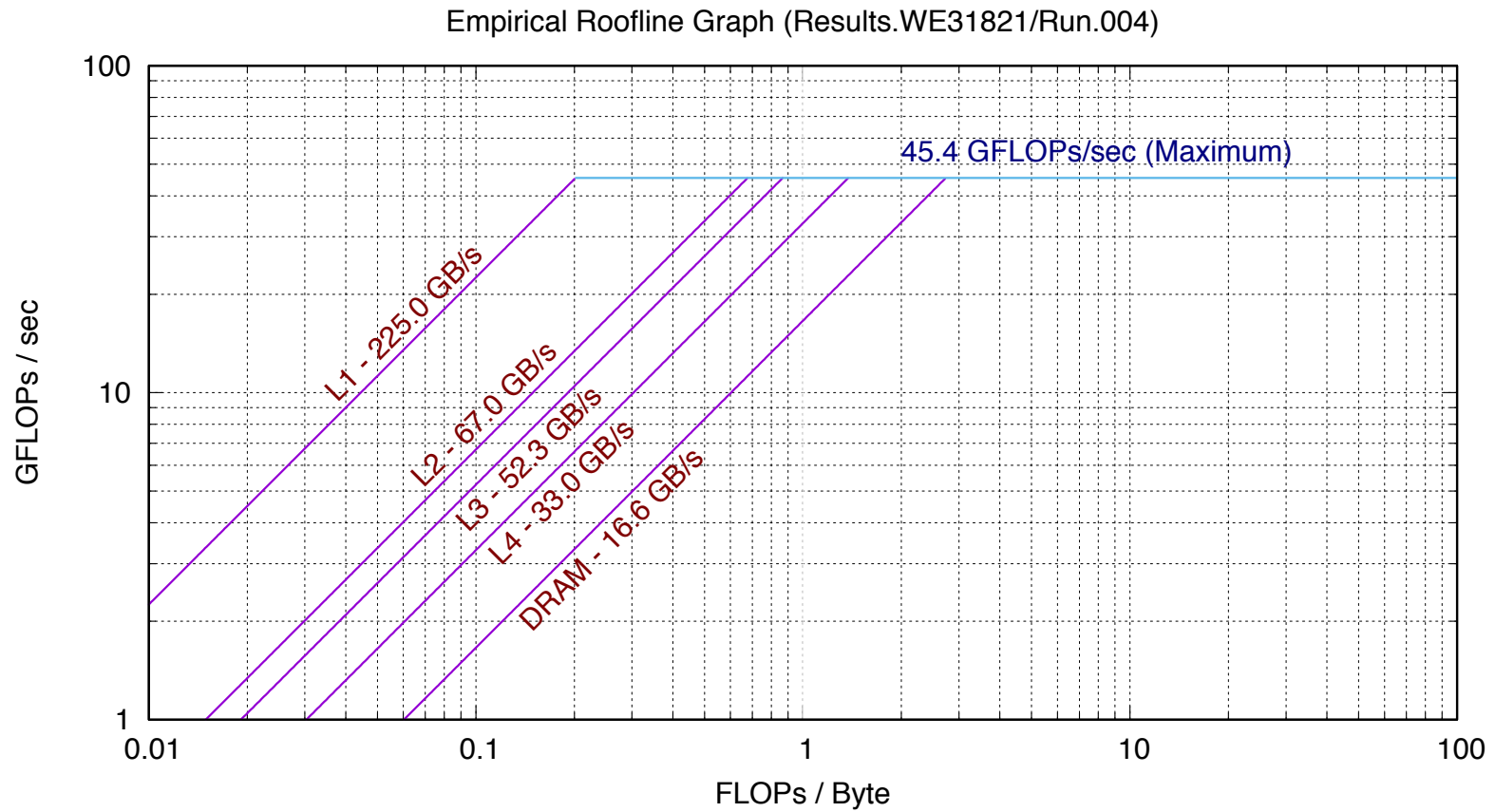
Roofline Model



Roofline Model



Measured



Numerical Intensity

```
void matvec_dense(const Matrix& A, const Vector& x, Vector& y) {  
    for (size_t i = 0; i < A.num_rows(); ++i) {  
        for (size_t j = 0; j < A.num_cols(); ++j) {  
            y(i) += A(i, j) * x(j);  
        }  
    }  
}
```

Three doubles
= 24 bytes?

Two flops

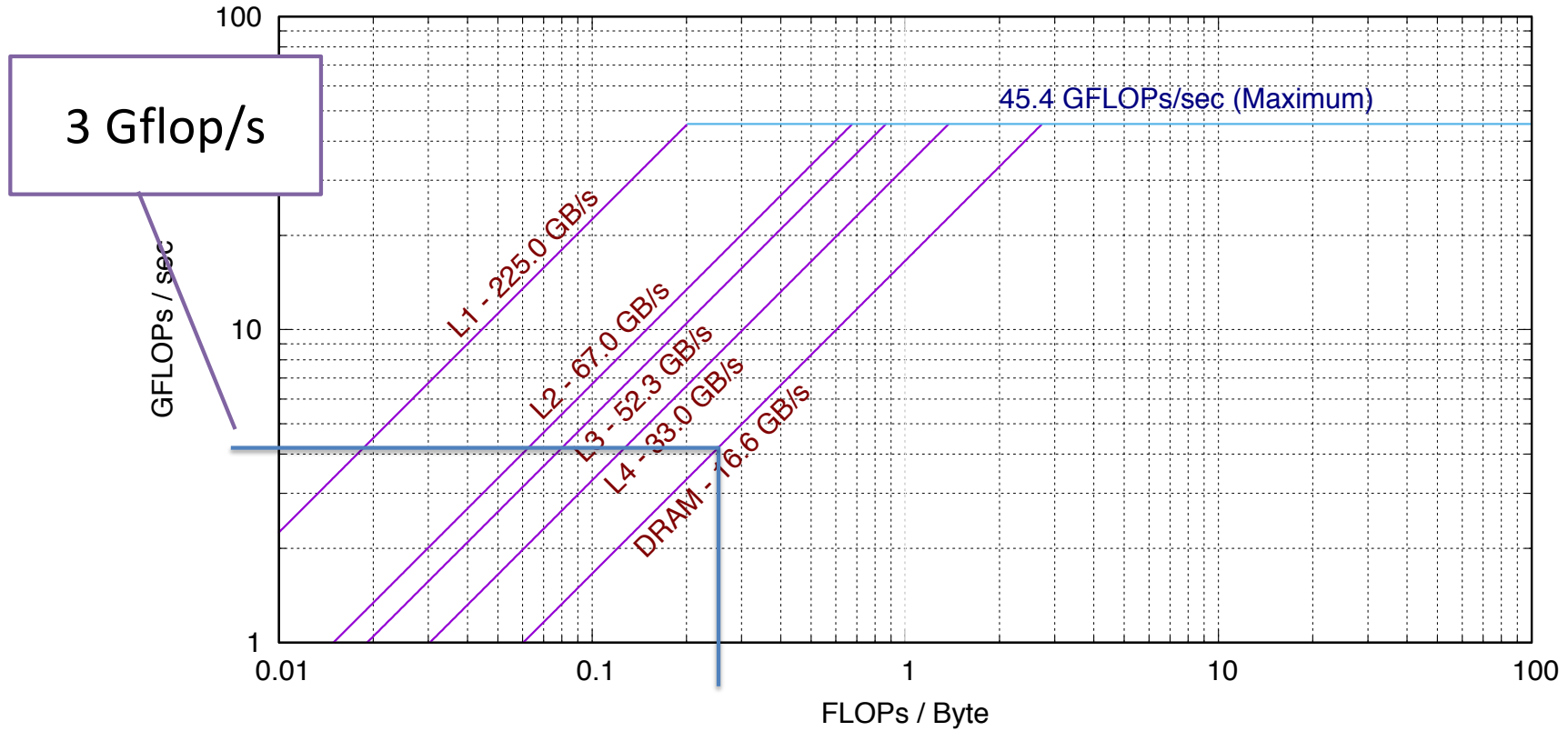
$2N^2$ Flops

$(N^2 + 2N)$ doubles
= $8(N^2 + 2N)$ bytes

$\frac{1 \text{ Flop}}{4 \text{ byte}}$

Measured

Empirical Roofline Graph (Results.WE31821/Run.004)



Numerical Intensity

```
void matvec(const Vector& x, Vector& y) const {  
    for (size_type k = 0; k < arrayData.size(); ++k) {  
        y(rowIndices[k]) += arrayData[k] * x(rowIndices[k]);  
    }  
}
```

Three doubles + 2 ints
= 32 bytes? (36 bytes?)

Two flops

2 NNZ Flops

10N
Flops

5N

7N doubles =
56 bytes

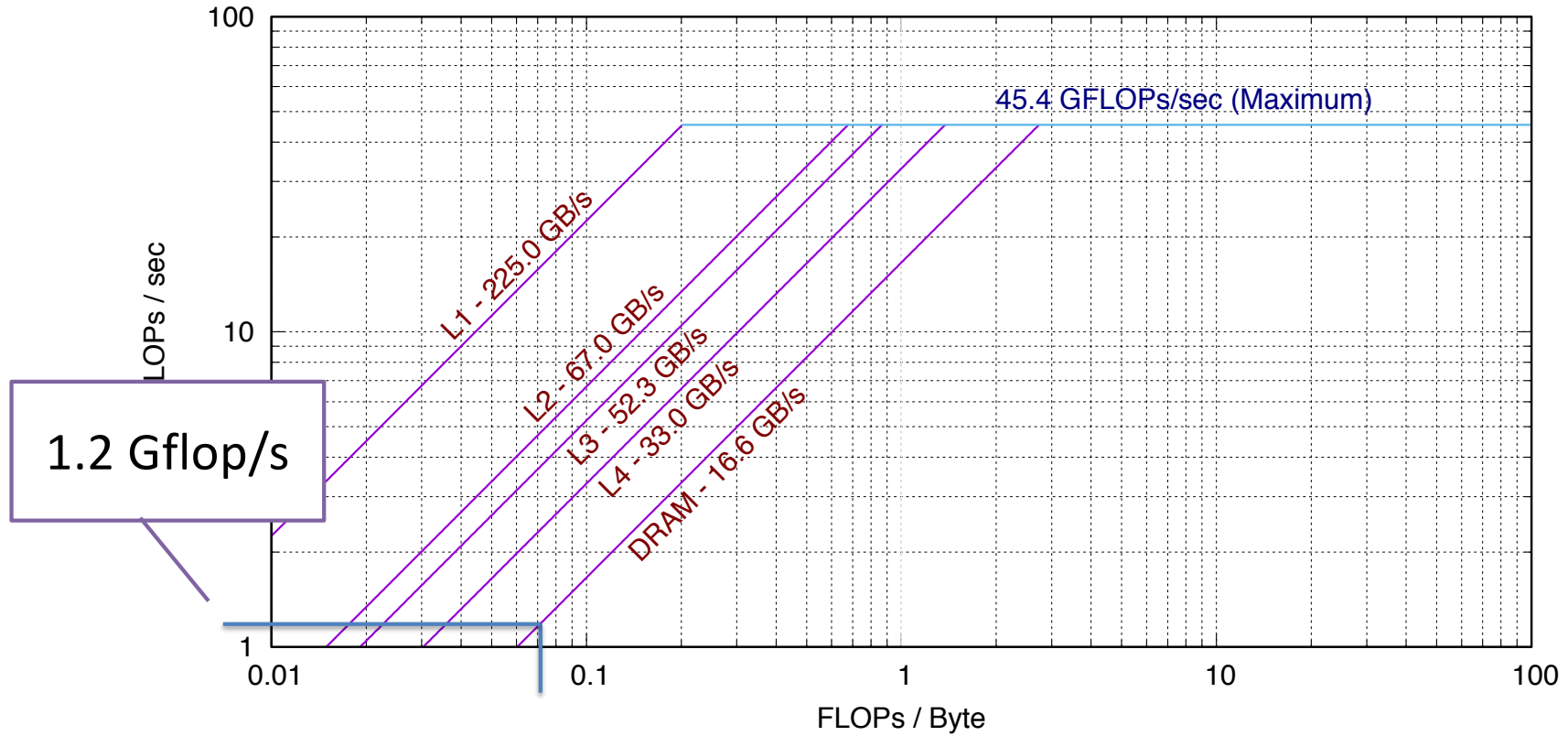
NNZ doubles
+2 NNZ indexes
+2N doubles

$\frac{1}{14}$ Flop
 $\frac{1}{14}$ byte

10N indexes =
40, 80 bytes

Measured

Empirical Roofline Graph (Results.WE31821/Run.004)



Numerical Intensity

```
void matmat_dense(const Matrix& A, const Matrix& B, Matrix& C) {  
    for (size_t i = 0; i < C.num_rows(); ++i) {  
        for (size_t j = 0; j < C.num_cols(); ++j) {  
            for (size_t k = 0; k < A.num_cols(); ++k) {  
                C(i, j) += A(i, k) * B(k, j);  
            }  
        }  
    }  
}
```

Three doubles
= 24 bytes?

Two flops

$\frac{N \text{ Flop}}{12 \text{ byte}}$

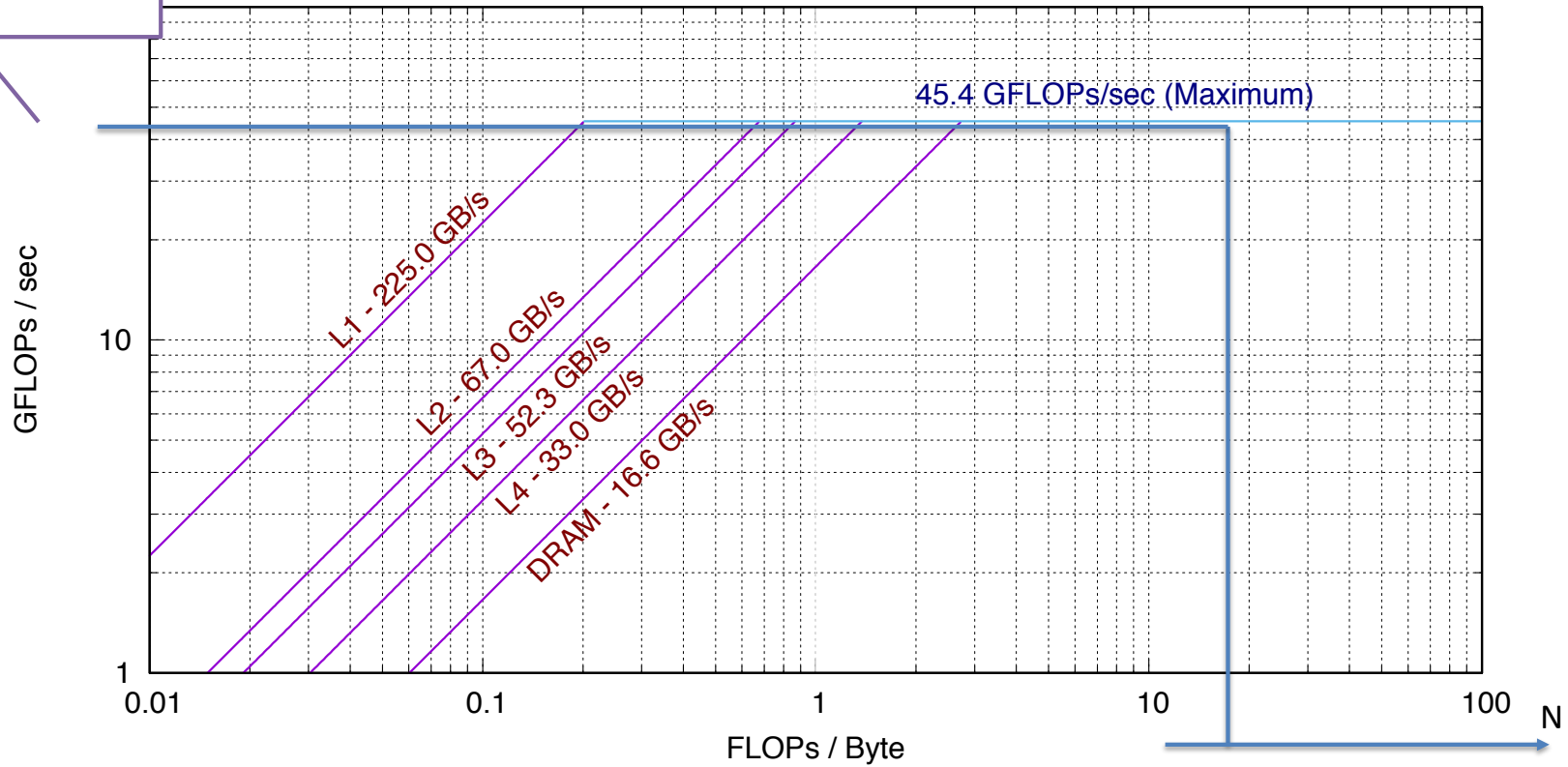
$2N^3$ Flops

$3N^2$ doubles
= $24N^2$ bytes

Measured

45 GFLOPs/s

Empirical Roofline Graph (Results.WE31821/Run.004)



Numerical Intensity

```
void matmat_dense(const Matrix& A, const Matrix& B, Matrix& C) {  
    for (size_t i = 0; i < C.num_rows(); ++i) {  
        for (size_t j = 0; j < C.num_cols(); ++j) {  
            for (size_t k = 0; k < A.num_cols(); ++k) {  
                C(i, j) += A(i, k) * B(k, j);  
            }  
        }  
    }  
}
```

Three doubles
= 24 bytes?

Two flops

1 Flop
12 byte

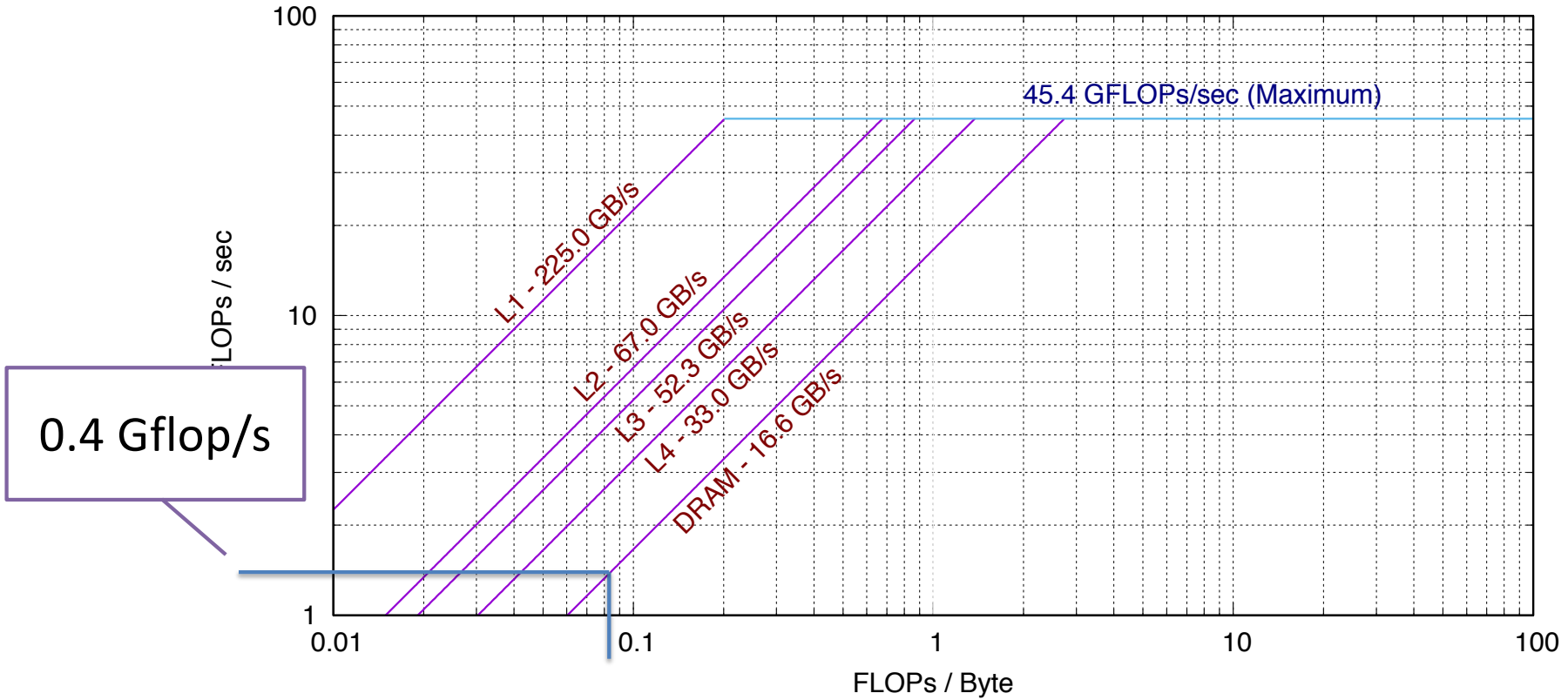
$2N^3$ Flops

$3N^3$ doubles
= $24N^3$ bytes

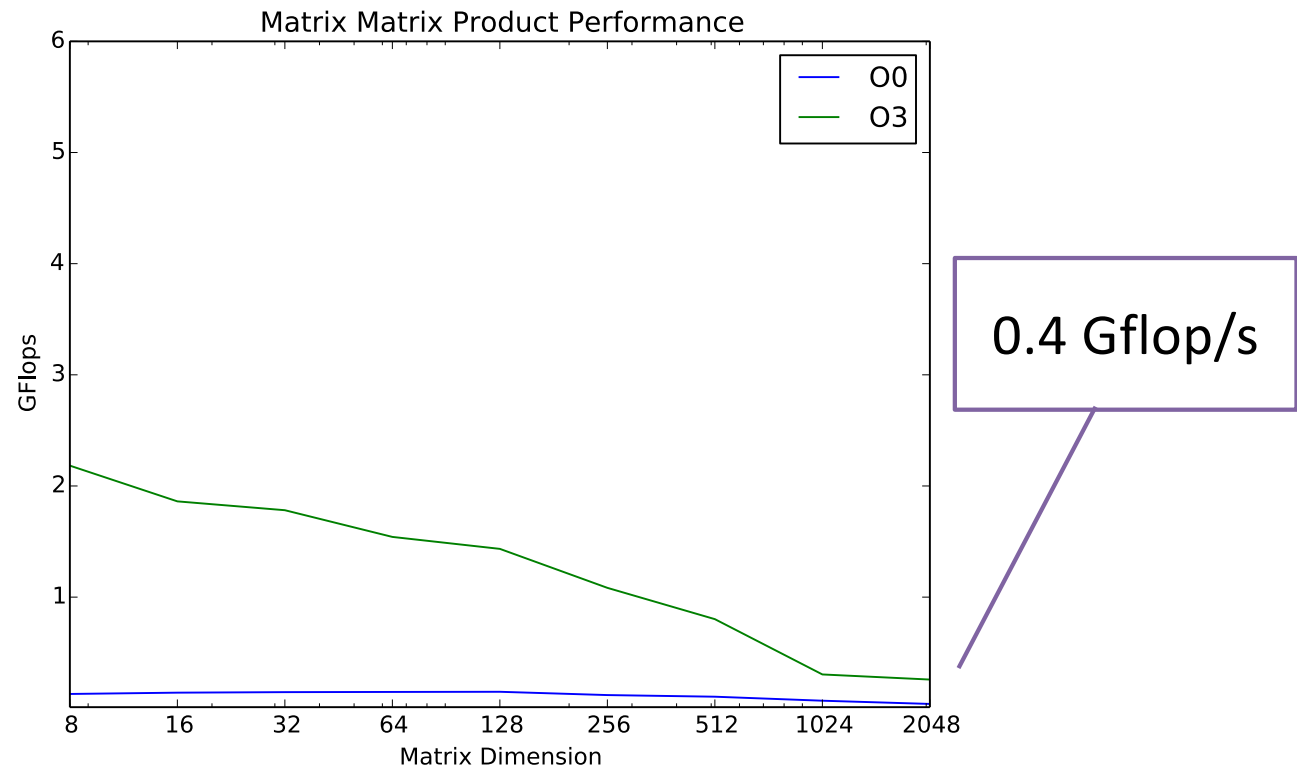
No reuse

Measured

Empirical Roofline Graph (Results.WE31821/Run.004)

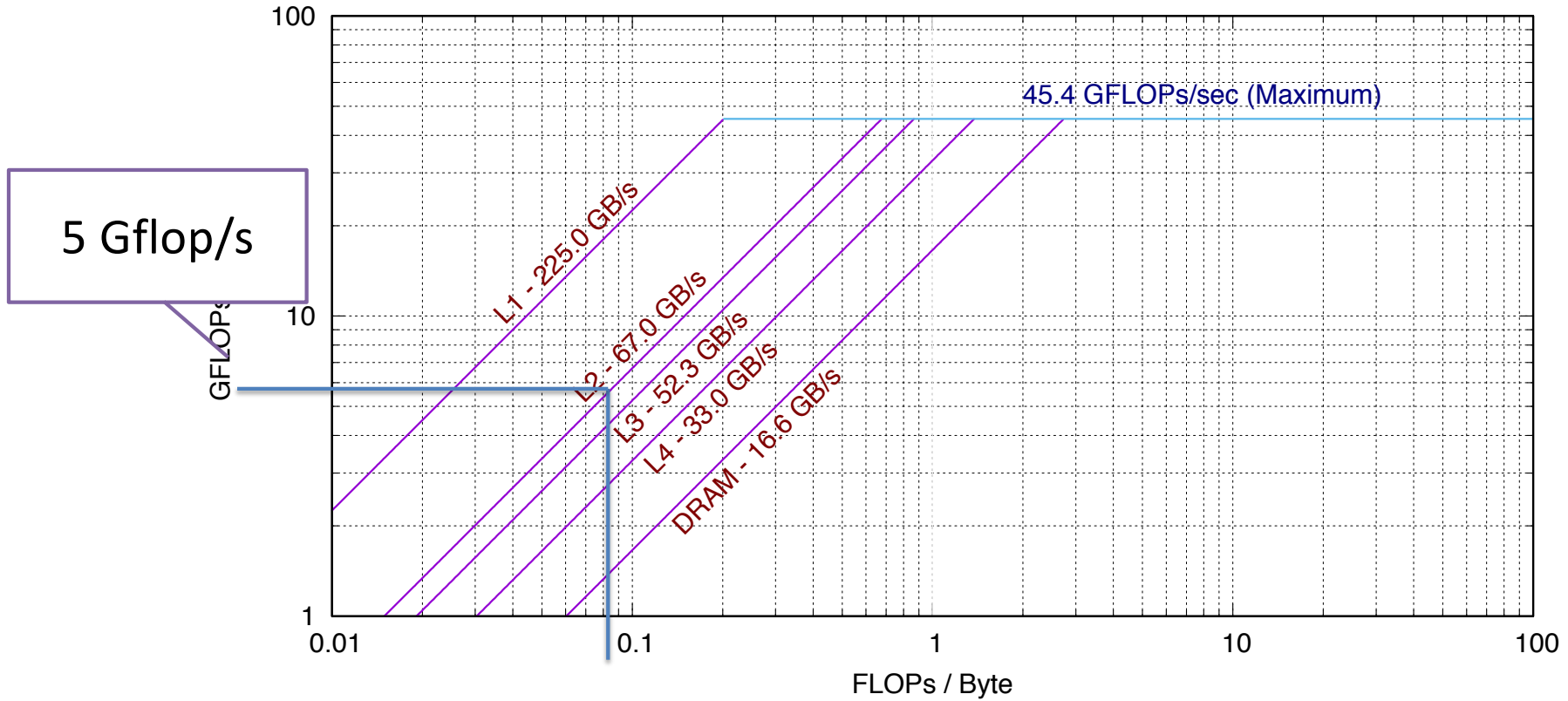


Recall



Hoisting / tiling etc: L2

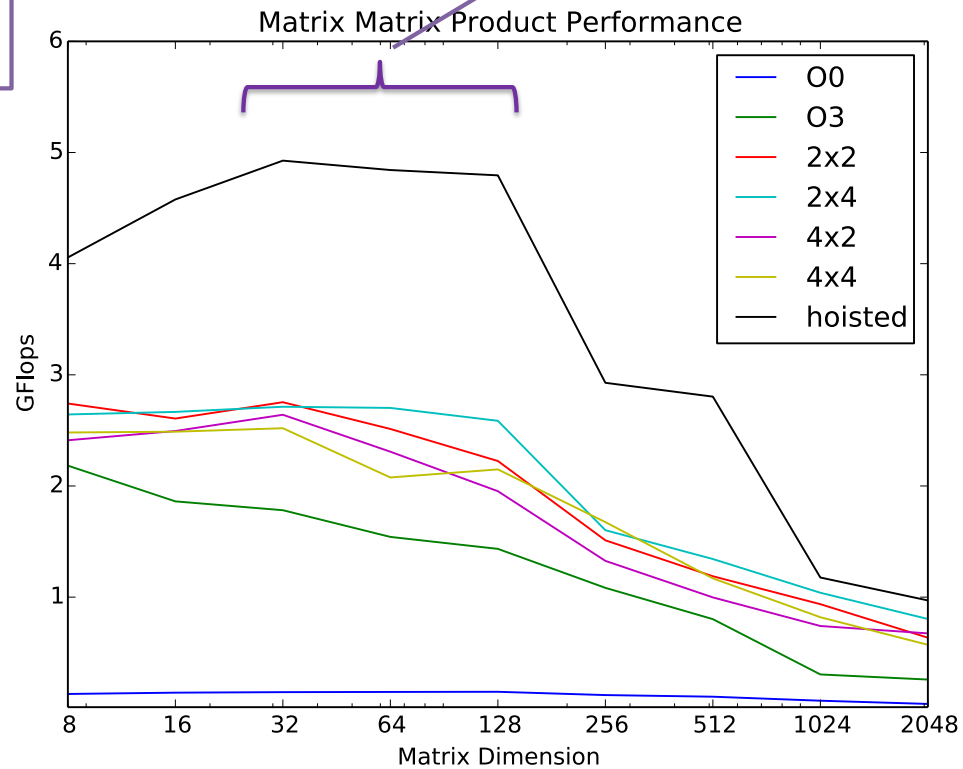
Empirical Roofline Graph (Results.WE31821/Run.004)



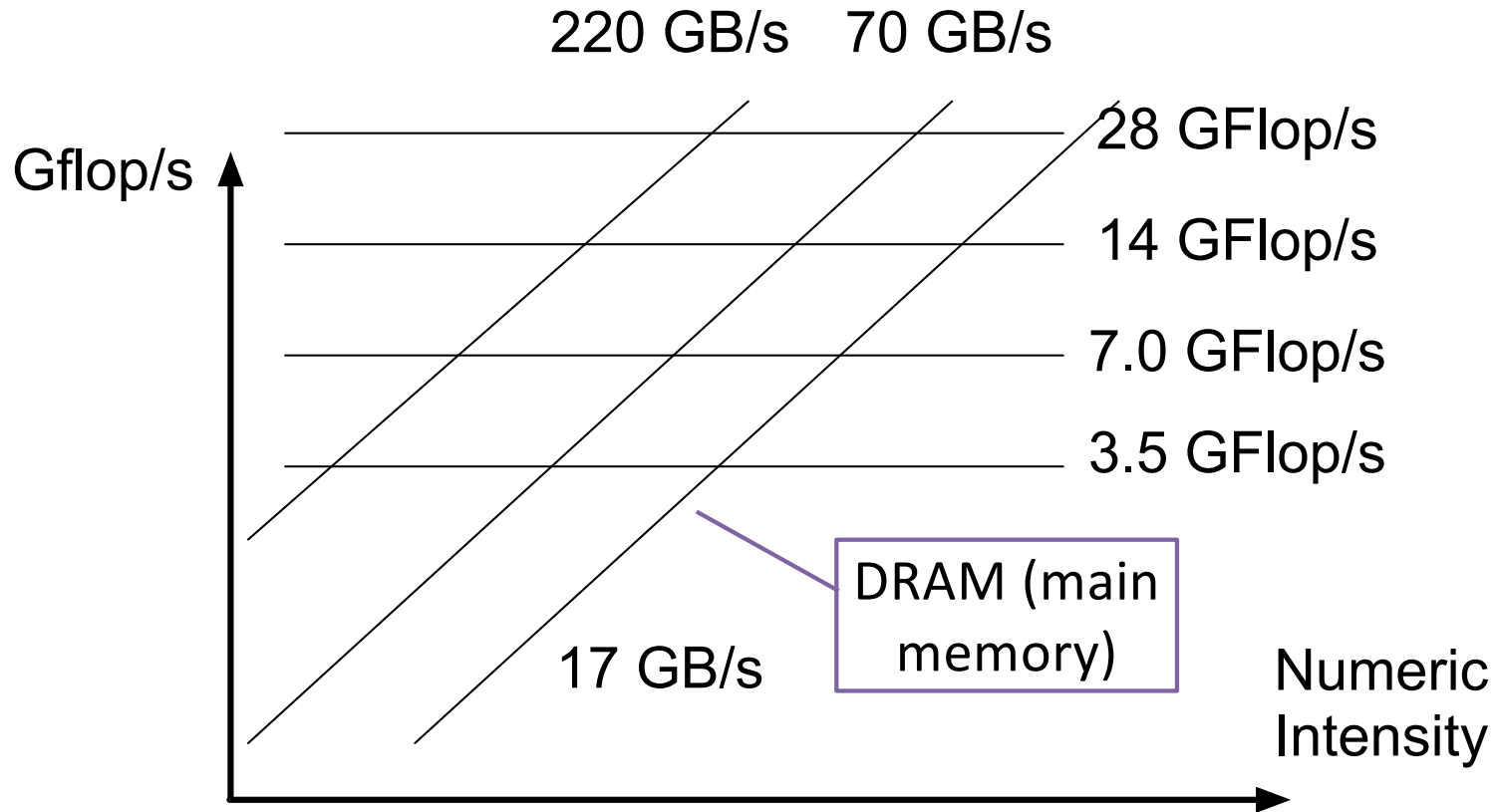
Hoisting / tiling etc: L2

5 Gflop/s

L2 zone



Summary (Roofline Model)



Thank You!

NORTHWEST INSTITUTE for ADVANCED COMPUTING

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AMATH 483/583 High-Performance Scientific Computing Spring 2019
University of Washington by Andrew Lumsdaine


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