

# **MATRIX MULTIPLICATION AND PERFORMANCE**

A Short Journey into High Performance Computing (HPC)

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Kevin Waters

# **MATRIX MULTIPLICATION AND PERFORMANCE**

The Time I Accidentally Bested NumPy

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- The code and talk for this presentation can be found [here](#).

The screenshot shows a GitHub repository interface. At the top, the repository name is 'Small exploration of Matrix Multiply' by user 'kwaters'. The main content area displays a file tree with folders like 'data', 'include', 'lib', 'python', 'src', 'test', and 'typslides', and files like 'CMakeLists.txt' and 'README.md'. The 'README' file is selected, showing the title 'Matrix Multiplication Exploration'. On the right sidebar, there are sections for 'About', 'Releases', 'Packages', and 'Languages'. The 'Languages' section shows a bar chart with the following data:

Language	Percentage
C	38.4%
Typst	35.4%
Python	23.6%
CMake	2.3%
TeX	0.3%

# CONTENTS

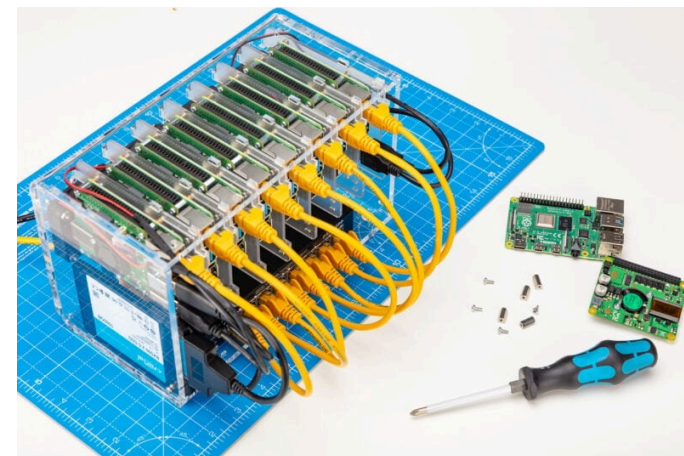
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1. What is High Performance Computing (HPC)?
2. Matrix Multiplication
3. Matrix Multiplication in Python (Easy Part)
4. Matrix Multiplication in C (Hard Part)
5. More Discussion

# WHAT IS HIGH PERFORMANCE COMPUTING (HPC)?

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- AI (Training/Inference)?
- Large-scale distributed memory computations?
- Distributed and scalable web services?
- Performance-aware programming:<sup>1</sup>
  - x86 aware?
  - Platform aware (CPU vs. GPU)?
  - Instruction set architecture (ISA) aware?
  - Cache-size aware?



*Raspberry Pi cluster<sup>2</sup>*

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<sup>1</sup>Term taken from Casey Muratori <https://www.computerenhance.com/p/welcome-to-the-performance-aware>

<sup>2</sup><https://www.raspberrypi.com/tutorials/cluster-raspberry-pi-tutorial/>

# MATRIX MULTIPLICATION

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- A few examples of applications (Where is linear algebra used today?):
  - **Finite element analysis** - Aerospace, automotive, material's properties...
  - **Electronic structure theory** - Density Functional Theory, Hartree-Fock++...
  - **Machine learning/data science** - Data analysis, pattern recognition, neural nets...
  - **Genetics** - genotype distribution
  - **Solving (partial) differential equations...** and much more

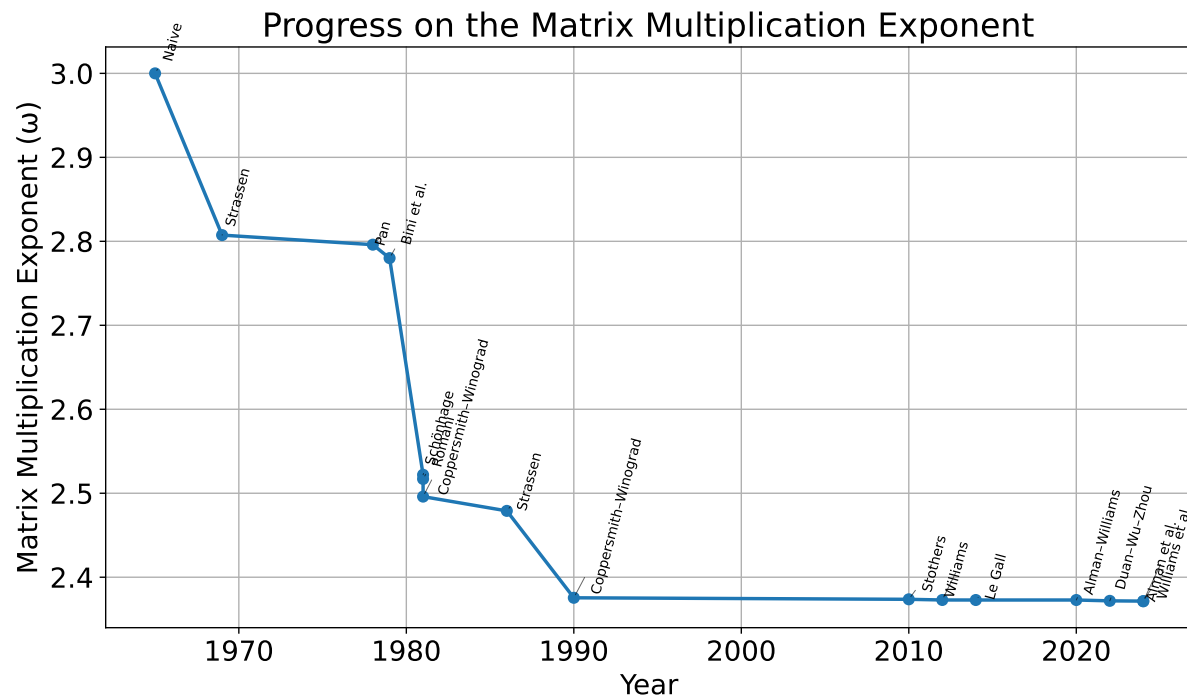


$$AB = C$$

$$\begin{pmatrix} a_{00} & a_{01} & a_{02} & \dots & a_{0n} \\ a_{10} & a_{11} & a_{12} & \dots & a_{1n} \\ a_{20} & a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \\ a_{n0} & a_{n1} & a_{n3} & \dots & a_{nn} \end{pmatrix} * \begin{pmatrix} b_{00} & b_{01} & b_{02} & \dots & b_{0n} \\ b_{10} & b_{11} & b_{12} & \dots & b_{1n} \\ b_{20} & b_{21} & b_{22} & \dots & b_{2n} \\ \vdots & \vdots & \vdots & \ddots & \\ b_{n0} & b_{n1} & b_{n3} & \dots & b_{nn} \end{pmatrix} = \begin{pmatrix} c_{00} & c_{01} & c_{02} & \dots & c_{0n} \\ c_{10} & c_{11} & c_{12} & \dots & c_{1n} \\ c_{20} & c_{21} & c_{22} & \dots & c_{2n} \\ \vdots & \vdots & \vdots & \ddots & \\ c_{n0} & c_{n1} & c_{n3} & \dots & c_{nn} \end{pmatrix}$$

Where:

$$c_{ij} = \sum a_{ik} b_{kj}$$



*Progress of Computation Complexity of Matrix Multiply<sup>3</sup>*

<sup>3</sup>Sourced from [https://en.wikipedia.org/wiki/Computational\\_complexity\\_of\\_matrix\\_multiplication](https://en.wikipedia.org/wiki/Computational_complexity_of_matrix_multiplication)

- Naive Matrix multiplication's computational complexity is  $\theta(n^3)$ 
  - Others scale better, but there are trade-offs
- What does that mean?
  - 2x2 results in 8 multiplication steps and 4 addition steps:

$$\begin{pmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{pmatrix} \begin{pmatrix} b_{00} & b_{01} \\ b_{10} & b_{11} \end{pmatrix} = \begin{pmatrix} a_{00}b_{00}+a_{01}b_{10} & a_{00}b_{01}+a_{01}b_{11} \\ a_{10}b_{00}+a_{11}b_{10} & a_{10}b_{01}+a_{11}b_{11} \end{pmatrix}$$

- For the general case the number of operations is given by the following:

$$2n^3 + n^2$$

- $2n^3$  multiply operations.
    - $n^2$  addition operations.

# MATRIX MULTIPLICATION IN PYTHON

## (EASY PART)

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## Python Benchmark

```
> python python_plain.py
1024x1024 matrix multiply...
Int      Time: 80.576309 seconds
Float    Time: 97.653700 seconds
```

- There are many things working against python, just-in-time-compilation (JIT), arbitrary size integers...

- NumPy is a highly-tuned library where typically expensive functions are implemented in compiled languages such as C/C++ or FORTRAN. (BLAS & LAPACK)

## Python (NumPy) Benchmark

```
> python python_numpy.py
1024x1024 matrix multiply...
Int32      Time: 1.895825 seconds
Int64      Time: 1.884659 seconds
Float      Time: 0.005361 seconds
Double     Time: 0.010751 seconds
```

- These results are interesting...

# MATRIX MULTIPLICATION IN C (HARD PART)

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- All matrices are square.
- All matrices sizes are a power of 2.
- Matrices are populated with ints (32-bits) randomly distributed  $[-5,5]$ .
- For benchmarking, one warm-up was followed by five trials (times are per trials).
- To count cycles, the following x86 instruction was used “rdtsc()” (Time Stamp Counter).
- Time stamps were called using `clock_gettime()`.
- Compile flags for all timed runs:
  - *-Wall -O3 -march=native -funroll-loops*
- Work per cycle was calculated using the following:

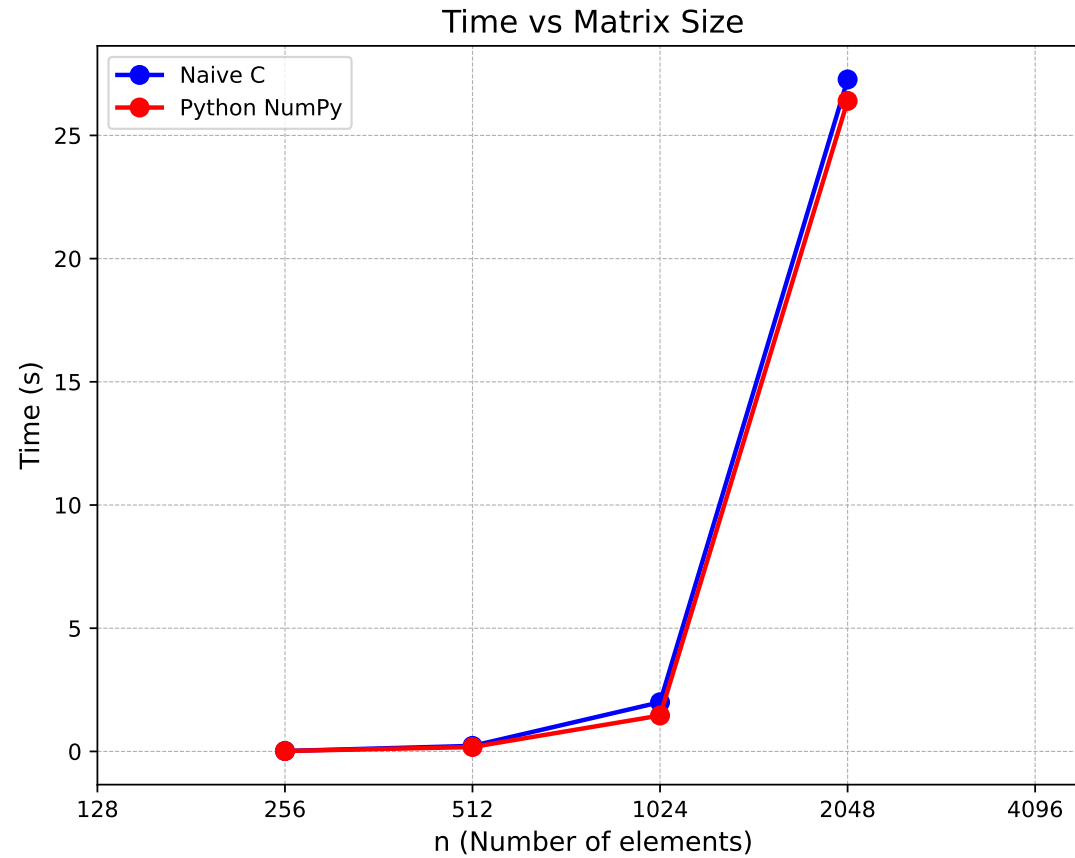
$$\frac{\text{Work Required}}{\text{Clock Cycle}} = \frac{3n^3 + n^2}{\# \text{ cycles\_elapsed}}$$



## Simple Matrix Multiply

```
for (int i = 0; i < n; i++) {  
    for (int j = 0; j < n; j++) {  
        for (int k = 0; k < n; k++) {  
            result[i * n + j] += matrix1[i * n + k] * matrix2[k * n + j];  
        }  
    }  
}
```

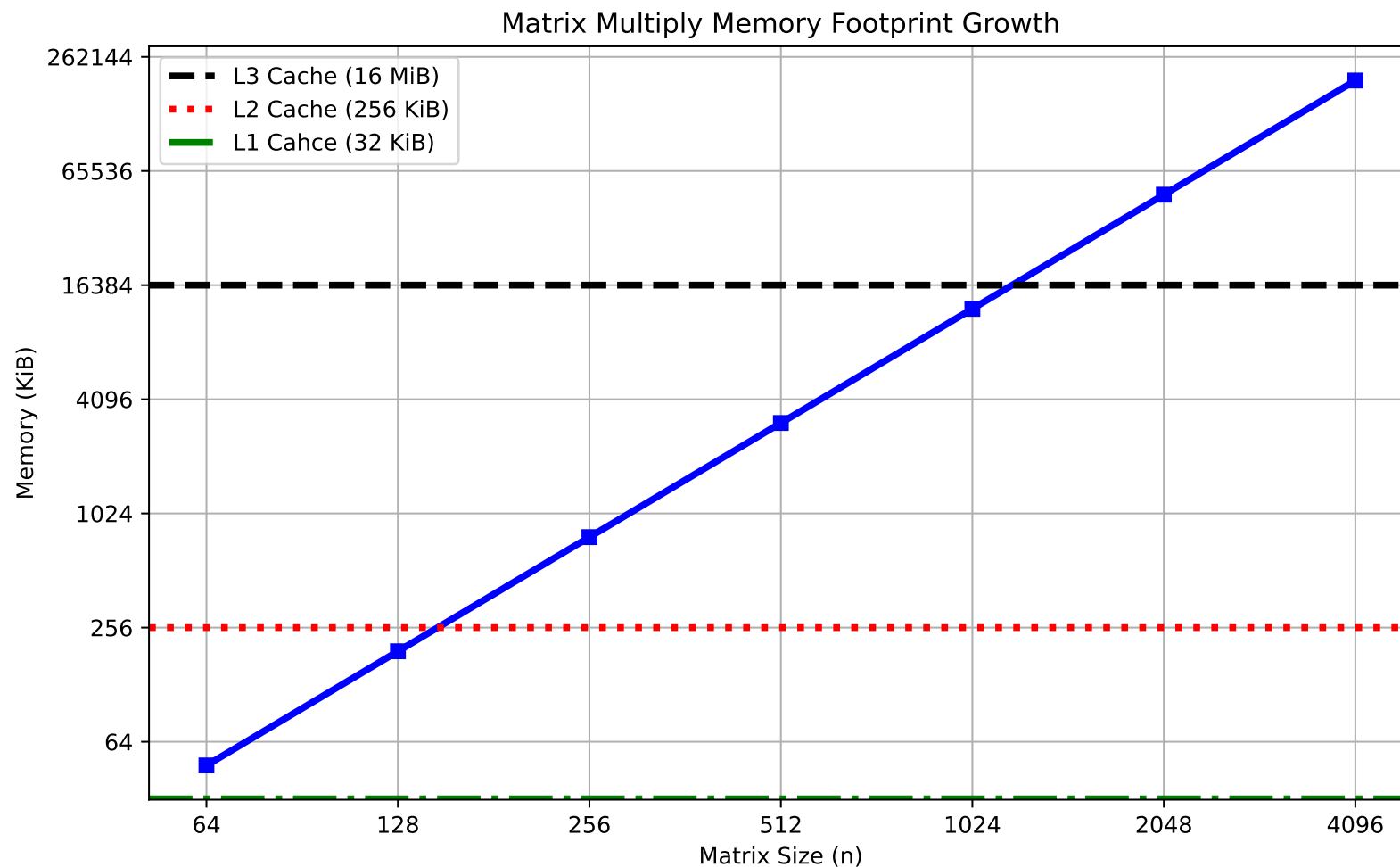
- Readable, simple, and slow.



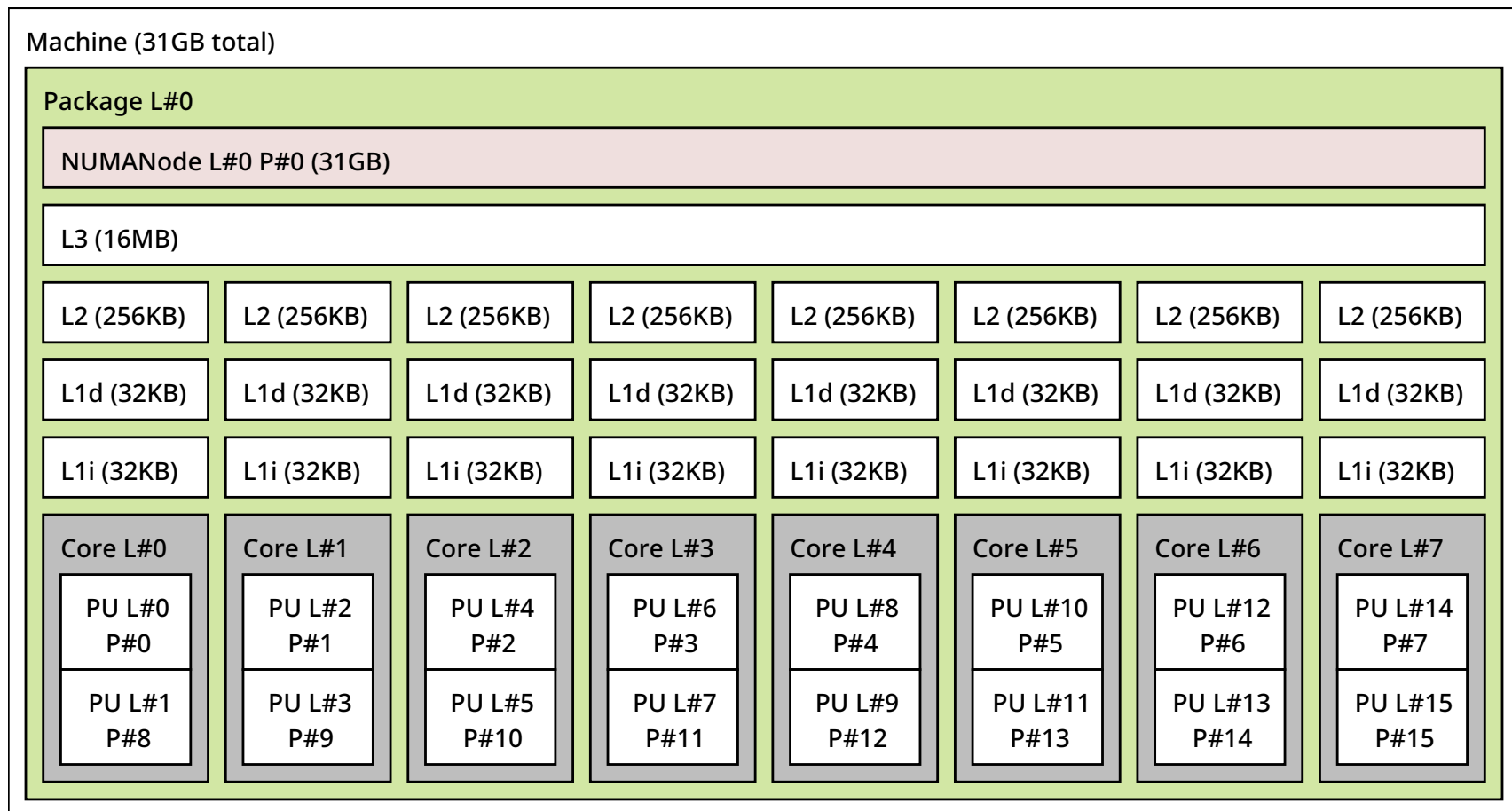
- Assuming 32-bit integers or 32-bit floats

<b>n</b>	<b>Elements (<math>n^2</math>)</b>	<b>Memory/Matrix (KiB)</b>	<b>Total Memory (KiB)</b>
64	4096	16	48
128	16384	64	192
256	65536	256	768
512	262144	1024	3072
1024	1048576	4096	12288
2048	4194304	16384	49152
4096	16777216	65536	196608

- Total memory is 3x the memory per matrix.



*Memory requirement for three  $n \times n$  matrices.*



*8-core client Skylake topology (\$ lstopo)*

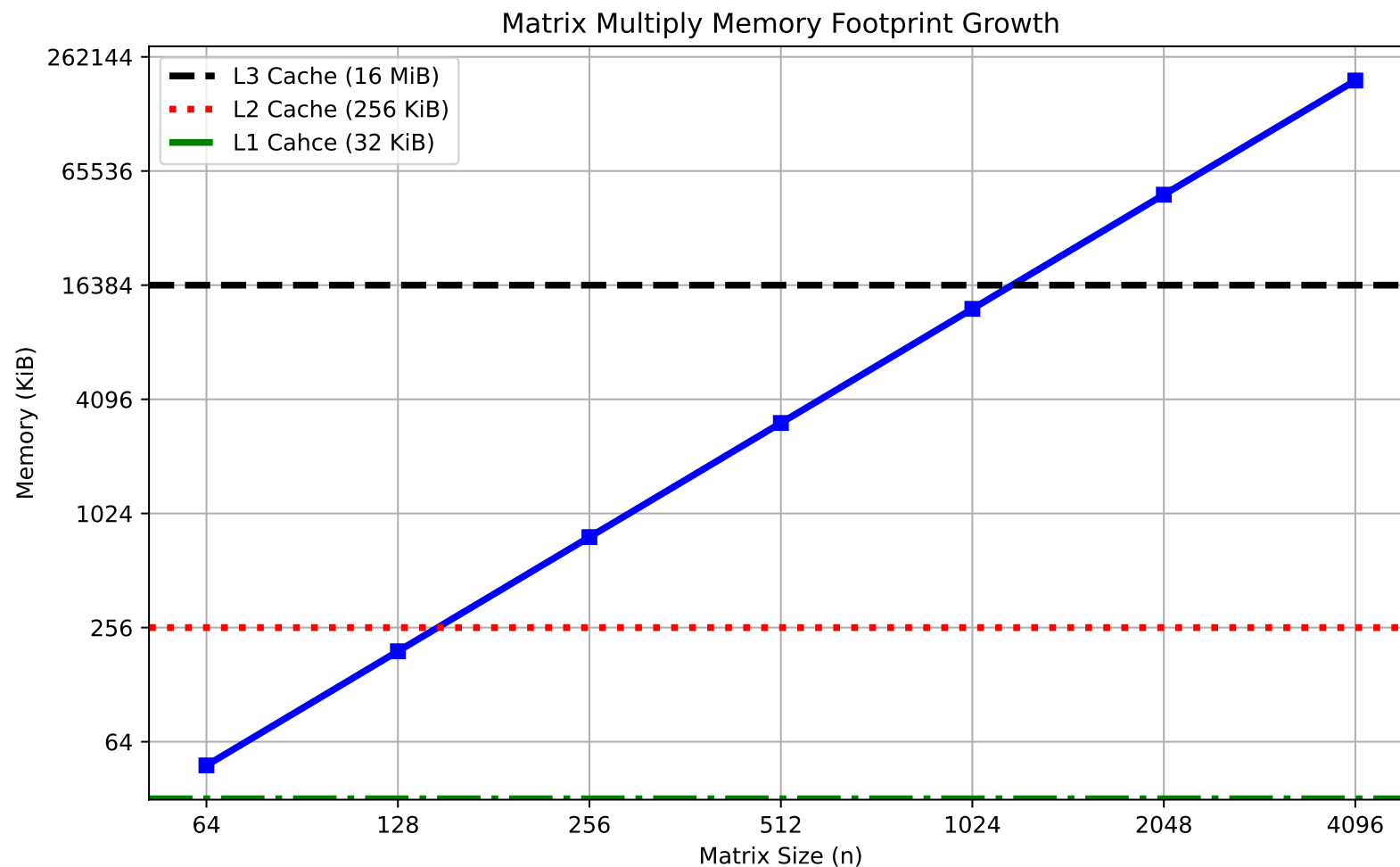
- One NUMA domain
- One 16 MiB shared L3 cache
- Individual 256 KiB L2 cache
- Individual 32 KiB instruction and data caches
- Two logical cores per physical core (8 physical, 16 logical)

L1 cache reference	0.5 ns			
Branch mispredict	5 ns			
L2 cache reference	7 ns			14x L1 cache
Mutex lock/unlock	25 ns			
Main memory reference	100 ns			20x L2 cache, 200x L1 cache
Send 1K bytes over 1 Gbps network	10,000 ns	10 us		
Read 4K randomly from SSD	150,000 ns	150 us		1GB/sec SSD
Read 1 MB sequentially from memory	250,000 ns	250 us		
Read 1 MB sequentially from SSD	1,000,000 ns	1,000 us	1 ms	1GB/sec SSD, 4X memory
Disk seek	10,000,000 ns	10,000 us	10 ms	10x datacenter roundtrip
Read 1 MB sequentially from disk	20,000,000 ns	20,000 us	20 ms	80x memory, 20X SSD

Latencies to generate intuition for the cost of an operation.<sup>4</sup>

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<sup>4</sup>Originally by Peter Norvig: <http://norvig.com/21-days.html#answers>



*Memory requirement for three  $n \times n$  matrices.*



## Intermediate Sum

```
> perf stat -e cycles,instructions,cache-references,cache-misses ./build/driver 2048 2048 5
n, trials, req. memory (KiB), time/trial (s), work/cycle, Read Bandwidth (GiB/s)
s2048, 5, 49152, 21.019992, 0.215482, 0.000297
```

Performance counter stats for './build/driver 2048 2048 5':

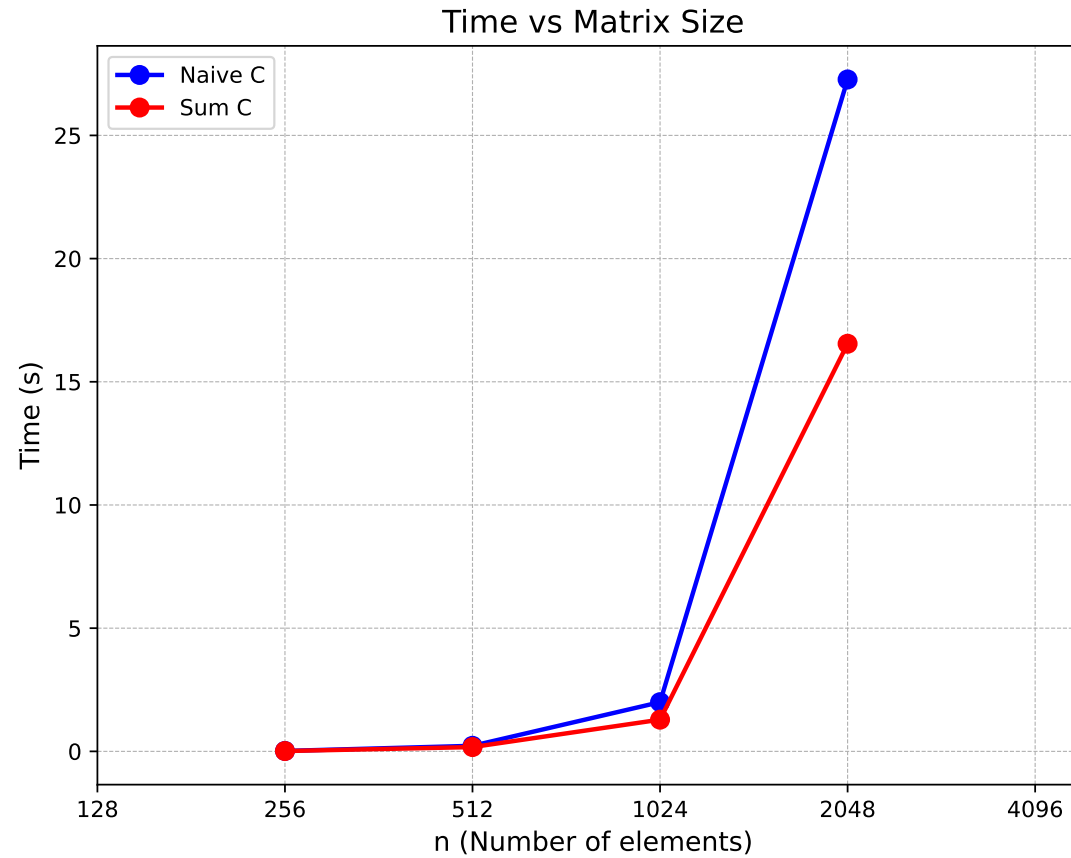
603,229,008,482	cycles:u		
156,197,169,903	instructions:u	#	0.26 insn per cycle
100,483,589,712	cache-references:u		
7,718,024,466	cache-misses:u	#	7.68% of all cache refs

- More targeted data can be found with PAPI (Performance Application Programming Interface).

## Intermediate Sum

```
for (int i = 0; i < n; i++) {  
    for (int j = 0; j < n; j++) {  
        int sum = 0;  
        for (int k = 0; k < n; k++) {  
            sum = matrix1[i * n + k] * matrix2[k * n + j] + sum;  
        }  
        result[i * n + j] = sum;  
    }  
}
```

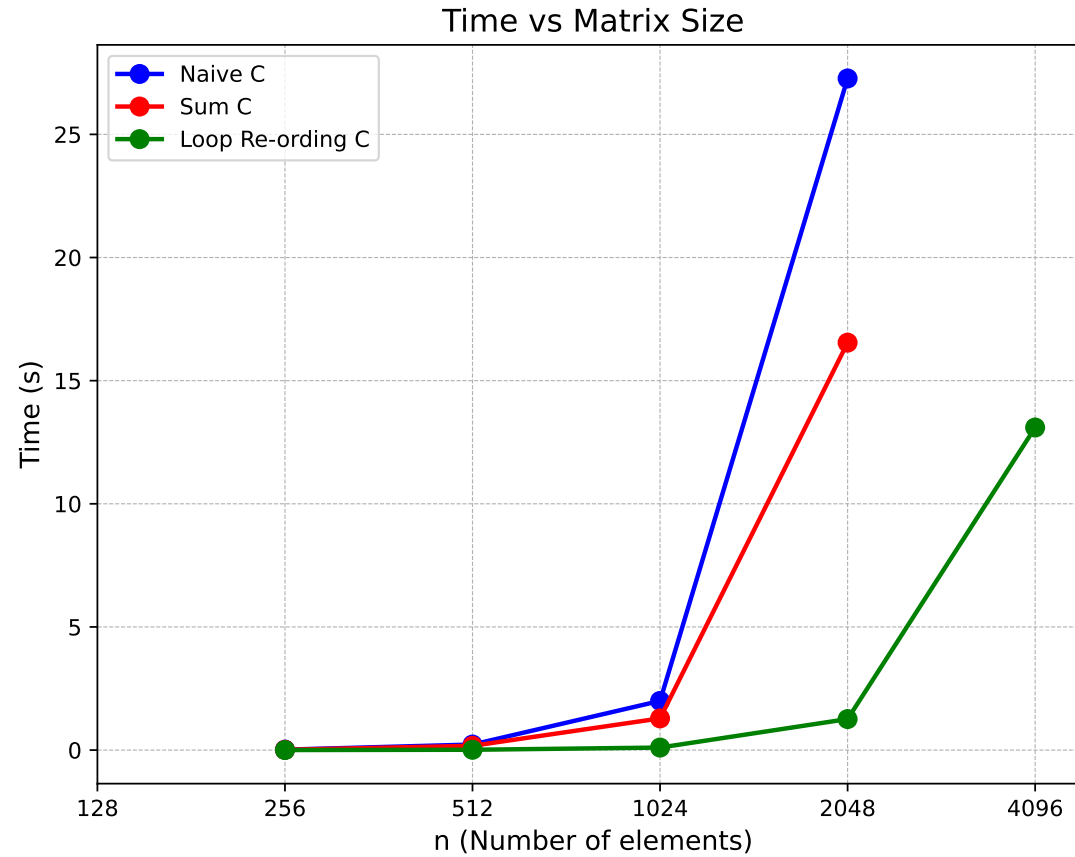
- Allows for sum to stay in registers requiring less fetching from memory, a little bit faster.



## Loop Re-ordering Sum

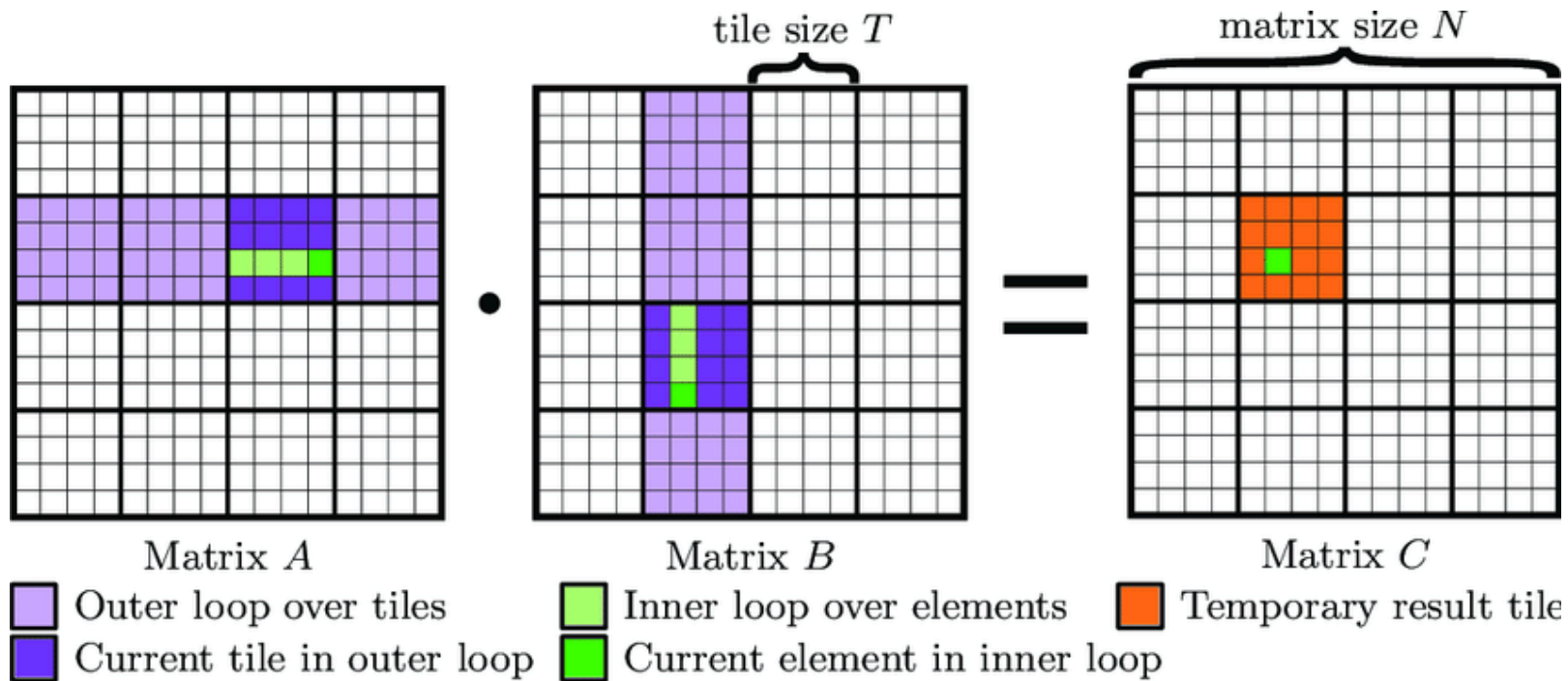
```
for (int i = 0; i < n; i++) {  
    for (int k = 0; k < n; k++) {  
        for (int j = 0; j < n; j++) {  
            result[i * n + j] += matrix1[i * n + k] * matrix2[k * n + j];  
        }  
    }  
}
```

- Re-ordering the last two loops (j with k) enabling better caching behavior.



## Blocking

```
for (int ii = 0; ii < n; ii+= BLOCK_SIZE) {  
    for (int kk = 0; kk < n; kk+= BLOCK_SIZE) {  
        for (int jj = 0; jj < n; jj+= BLOCK_SIZE) {  
            int limit_i = ((ii + BLOCK_SIZE) < n) ? (ii + BLOCK_SIZE) : n;  
            int limit_j = ((jj + BLOCK_SIZE) < n) ? (jj + BLOCK_SIZE) : n;  
            int limit_k = ((kk + BLOCK_SIZE) < n) ? (kk + BLOCK_SIZE) : n;  
            for (int i = ii; i < limit_i; ++i) {  
                for (int k = kk; k < limit_k; ++k) {  
                    int ki = i * n + k;  
                    for (int j = jj; j < limit_j; j++) {  
                        result[i * n + j] += matrix1[ki] * matrix2[k * n + j];  
                    }  
                }  
            }  
        }  
    }  
}
```

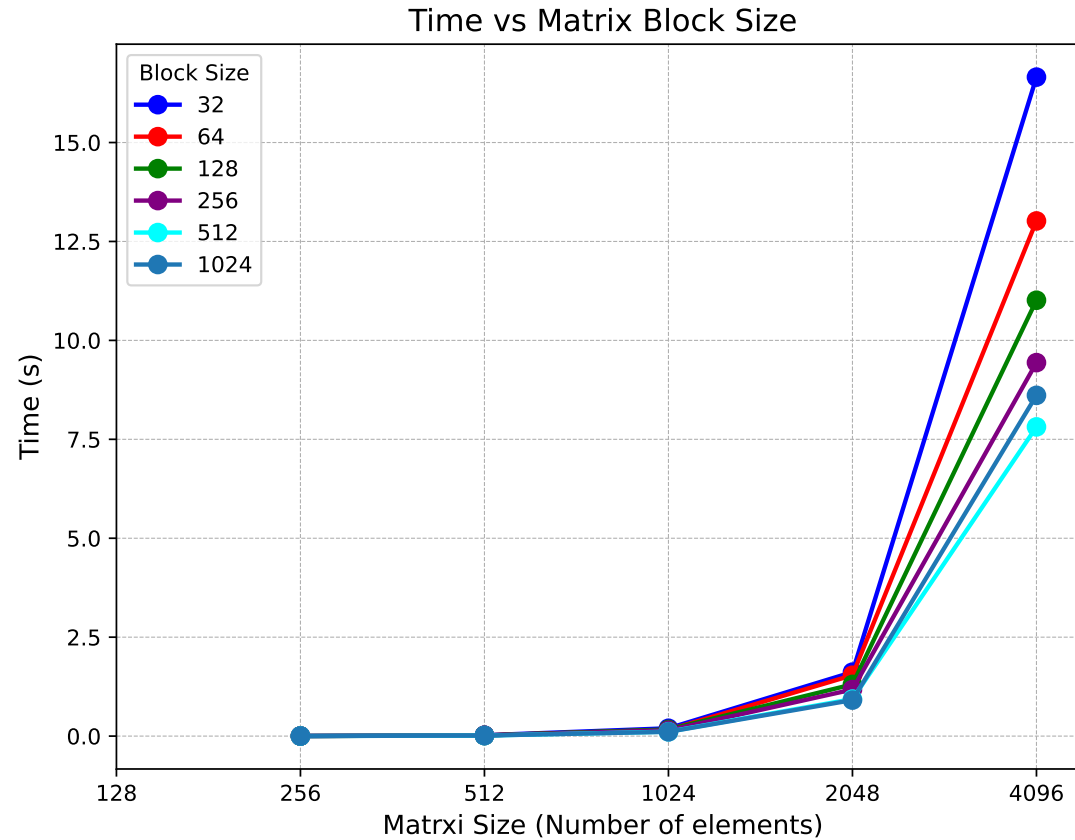


*GEMM tiling or BLOCK\_SIZE.*<sup>5</sup>

<sup>5</sup>Mathhes et. al. Tuning and Optimization for a Variety of Many-Core Architectures Without Changing a Single Line of Implementation Code Using the Alpaka Library (2017)

- This is where optimizations start becoming unpleasant as it is not hardware agnostic, however we do not have intrinsics yet!
- The `BLOCK_SIZE` variable is a compile time constant, requiring the library to be recompiled.
- We will recompile until we find an optimal `BLOCK_SIZE` value.





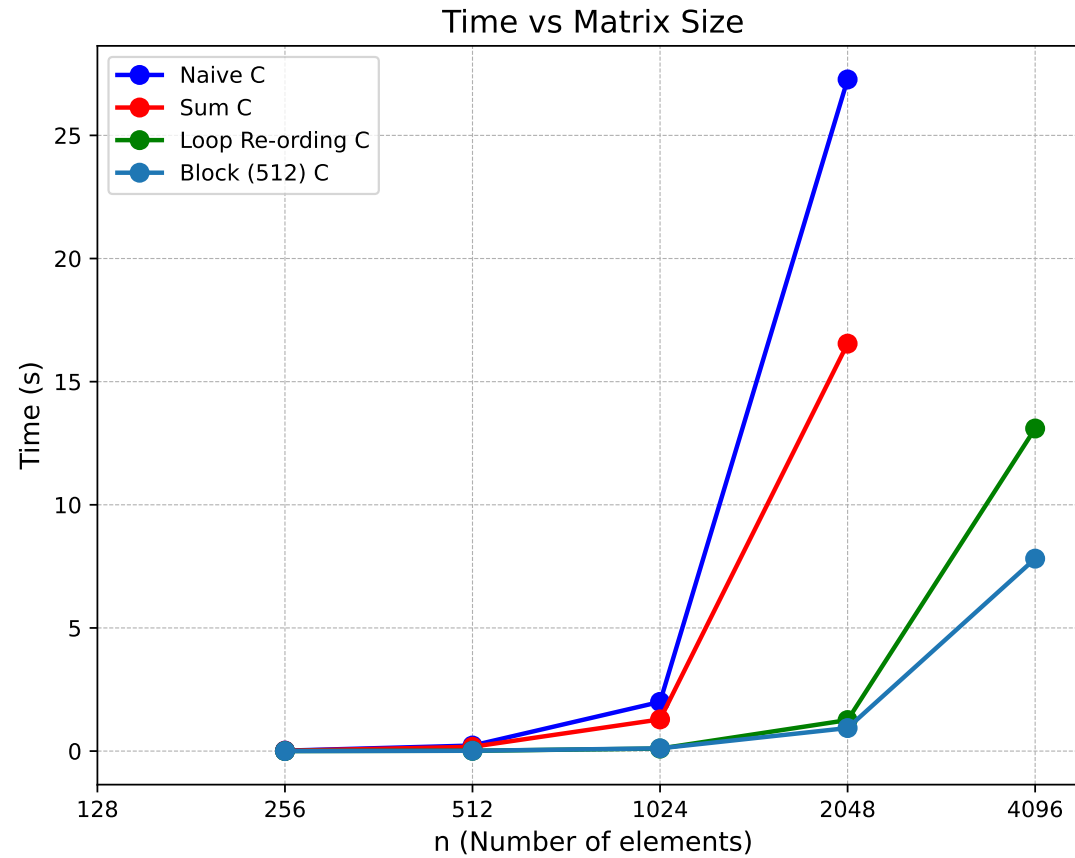
## BLOCK\_SIZE 512

```
> perf stat -e cycles,instructions,cache-references,cache-misses ./build/driver 2048 2048 5  
2048, 5, 49152, 0.792592, 5.714694, 0.007886
```

Performance counter stats for './build/driver 2048 2048 5':

22,990,040,828	cycles:u		
26,574,845,684	instructions:u	#	1.16 insn per cycle
7,550,989,191	cache-references:u		
121,521,554	cache-misses:u	#	1.61% of all cache refs

- Naive L3 cache misses was 7.68%, PAPI would give better resolution. There is still better cache performance possible.



```
> for i in Architecture "CPU(s):" "Model name" Thread Socket "NUMA node(s)"; do  
lscpu | grep "$i" | grep -v "node0"; done
```

```
Architecture: x86_64
CPU(s): 16
Model name: Intel(R) Core(TM) i7-10700KF CPU @ 3.80GHz
Thread(s) per core: 2
Socket(s): 1
NUMA node(s): 1
```

- x86<sup>6</sup> SIMD<sup>7</sup> extensions:
  - **SSE (Streaming SIMD Extensions)** - 128-bit floating point registers
  - **SSE2** - 128-bit doubles and integer registers
  - **AVX (Advanced Vector Extensions)** - 256-bit floating/double point registers
  - **AVX2** - 256-bit integer SSE instructions
  - **AVX512** - 512 bit registers!
- **FMA(Fused Multiply-Add)** - Exists in AVX, AVX512, but only for floats and doubles.

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<sup>6</sup>ARM has different names for everything

<sup>7</sup>Single Instruction, Multiple Data

## Checking the Architecture and ISA

```
> cat /sys/devices/cpu/caps/pmu_name  
skylake
```

```
> for isa in sse sse2 avx avx2 avx512 fma; do grep -q "$isa" /proc/cpuinfo && echo "$isa 1" ||  
echo "$isa 0"; done  
sse 1  
sse2 1  
avx 1  
avx2 1  
avx512 0  
fma 1
```

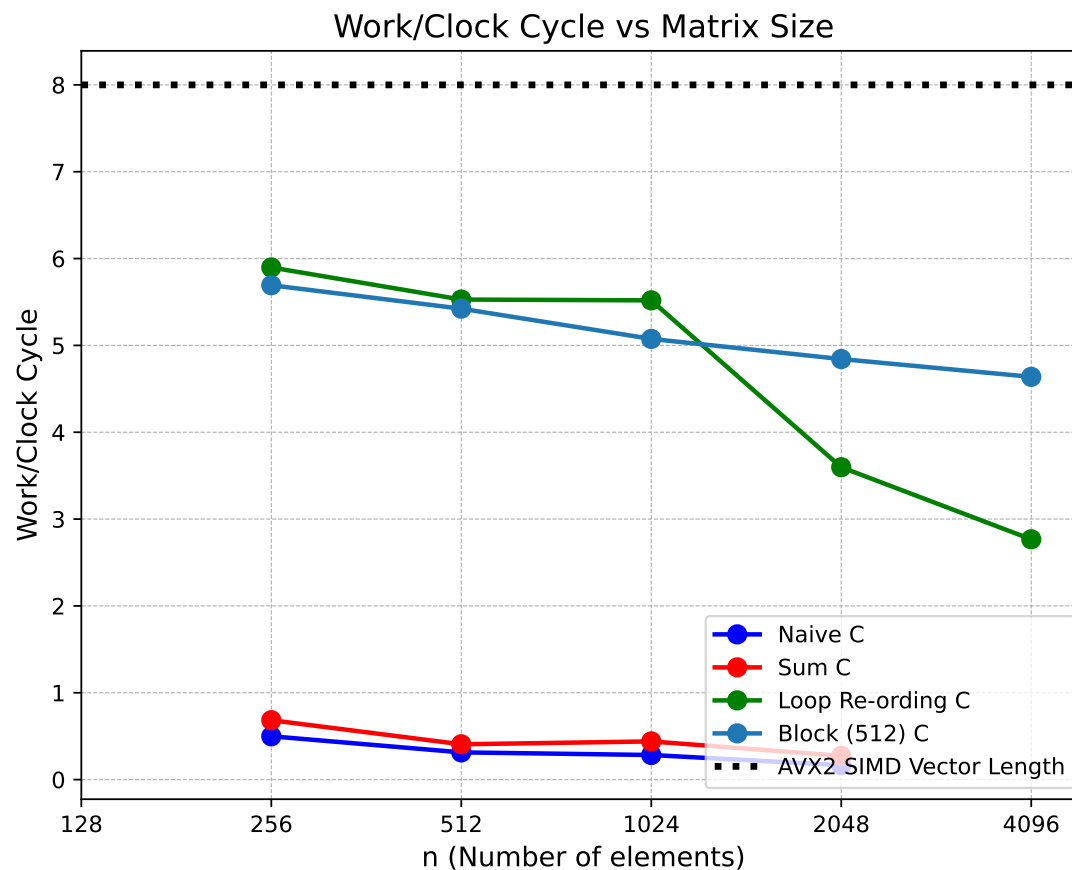
## Checking for SIMD (AVX2)

```
10b0: c4 c2 7d 40 4c 8a a0 vpmulld -0x60(%r10,%rcx,4),%ymm0,%ymm1
10b7: c4 c2 7d 40 54 8a c0 vpmulld -0x40(%r10,%rcx,4),%ymm0,%ymm2
10be: c4 c2 7d 40 5c 8a e0 vpmulld -0x20(%r10,%rcx,4),%ymm0,%ymm3
10c5: c4 c2 7d 40 24 8a vpmulld (%r10,%rcx,4),%ymm0,%ymm4
10cb: c4 c1 75 fe 4c 88 a0 vpadd -0x60(%r8,%rcx,4),%ymm1,%ymm1
10d2: c4 c1 6d fe 54 88 c0 vpadd -0x40(%r8,%rcx,4),%ymm2,%ymm2
10d9: c4 c1 65 fe 5c 88 e0 vpadd -0x20(%r8,%rcx,4),%ymm3,%ymm3
10e0: c4 c1 5d fe 24 88 vpadd (%r8,%rcx,4),%ymm4,%ymm4
10e6: c4 c1 7e 7f 4c 88 a0 vmovdqu %ymm1,-0x60(%r8,%rcx,4)
10ed: c4 c1 7e 7f 54 88 c0 vmovdqu %ymm2,-0x40(%r8,%rcx,4)
10f4: c4 c1 7e 7f 5c 88 e0 vmovdqu %ymm3,-0x20(%r8,%rcx,4)
10fb: c4 c1 7e 7f 24 88 vmovdqu %ymm4, (%r8,%rcx,4)
```

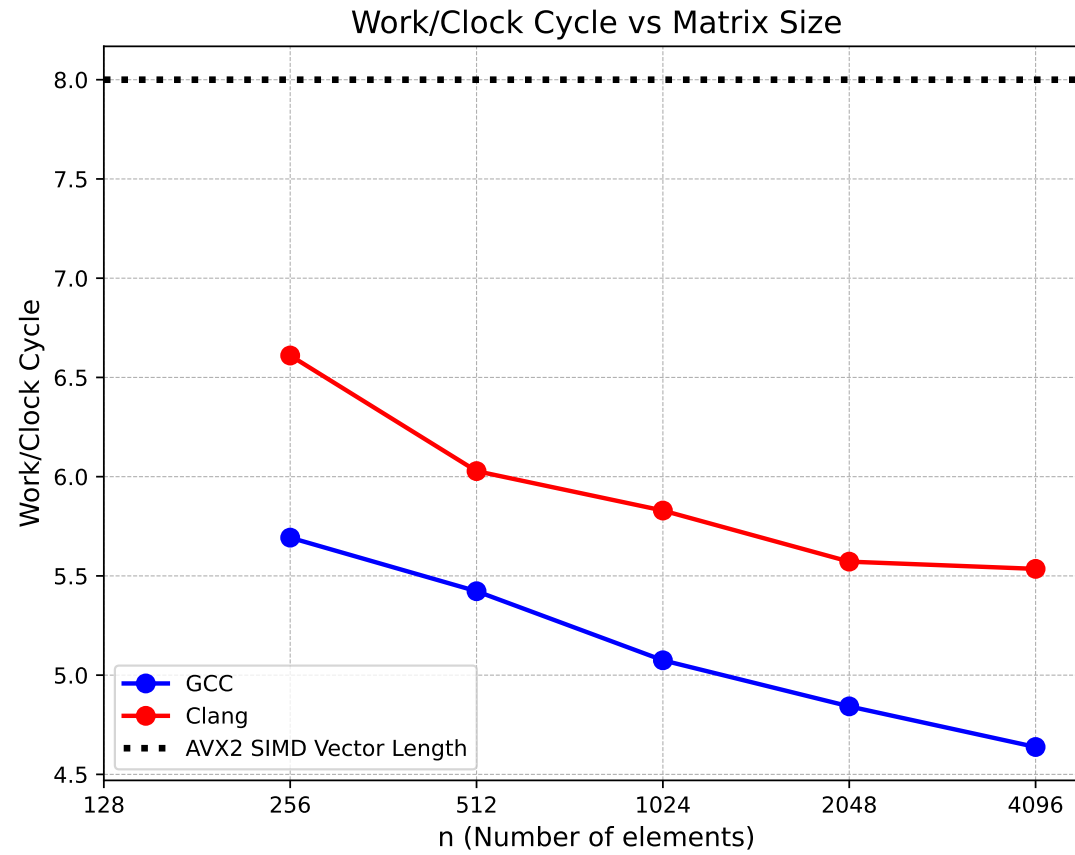
- Excerpt from multiplication library (appears some pipelining is going on!)<sup>8</sup>.

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<sup>8</sup>More details can be found in the Intel Intrinsics Guide







	Runtime (s)		
Matrix size (n)	Pure Python	Python (NumPy)	Blocked C
256	0.24	0.02	0.001
512	1.79	0.18	0.01
1024	15.32	1.46	0.10
2048		26.40	0.81
4096			6.55

- Final results with the different run times. More optimization is possible for C and NumPy.

# MORE DISCUSSION

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- Libraries exist with hyper optimized floating-point matrix operations standardized by BLAS<sup>9</sup>.
  - **ATLAS** - Automatically Tuned Linear Algebra Software
  - **OpenBLAS** - open-source CPU based BLAS
  - **rocBLAS** - AMD's GPUs version via ROCM
  - and many more<sup>10</sup>
- Sparsity may drive to different algorithms.
- If working with integers you may have to write your own kernels.
- If working with Boolean matrices they allow for new algorithms using look-up tables<sup>11</sup>

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<sup>9</sup>Basic Linear Algebra Subprograms

<sup>10</sup>[https://en.wikipedia.org/wiki/Basic\\_Linear\\_Algebra\\_Subprograms#Implementations](https://en.wikipedia.org/wiki/Basic_Linear_Algebra_Subprograms#Implementations)

<sup>11</sup>Method of Four Russians

- **OpenMP/PThreads**
  - Using all cores on a socket/node
- **Simultaneous Multithreading (SMT/HyperThreading)**
  - Should it be used?
- **Non-Uniform Memory Access (NUMA)**
  - Even more levels to the memory subsystem
  - AMD's Core Complex (CCX) have made this harder
- **MPI/SHMEM**
  - Inter-node communication using remote direct memory access (RDMA)

Questions?