

SIMD Computing

Performance you have already payed for



I am building Unum since 2015

A neuro-symbolic computing framework

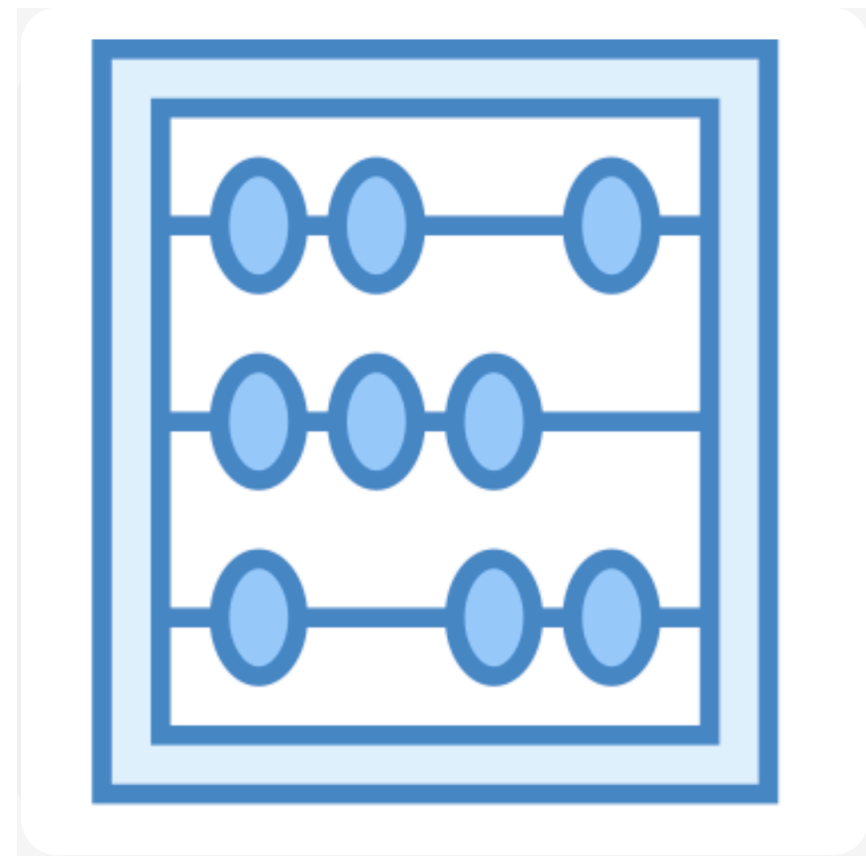
Hey, I'm Ashot!

- 👶 Wrote my first line of code in the elementary school.
- 👦 Received my first freelance Web-Dev order in the middle school.
- 👦 Launched my first profitable IT business in the high school.
- 🔭 Dropped my Astrophysics degree. Twice.
- 🏢 Already spent 5 years building **Unum** without external funding.
- 🌍 Visited over 50 countries across 4 continents, lived in 11 of them.
- 🗣️ Fluent in Russian, Armenian & English. Intermediate in a few other languages.
- 💻 These days I code in C++ 20, Python, Swift & LISPs.

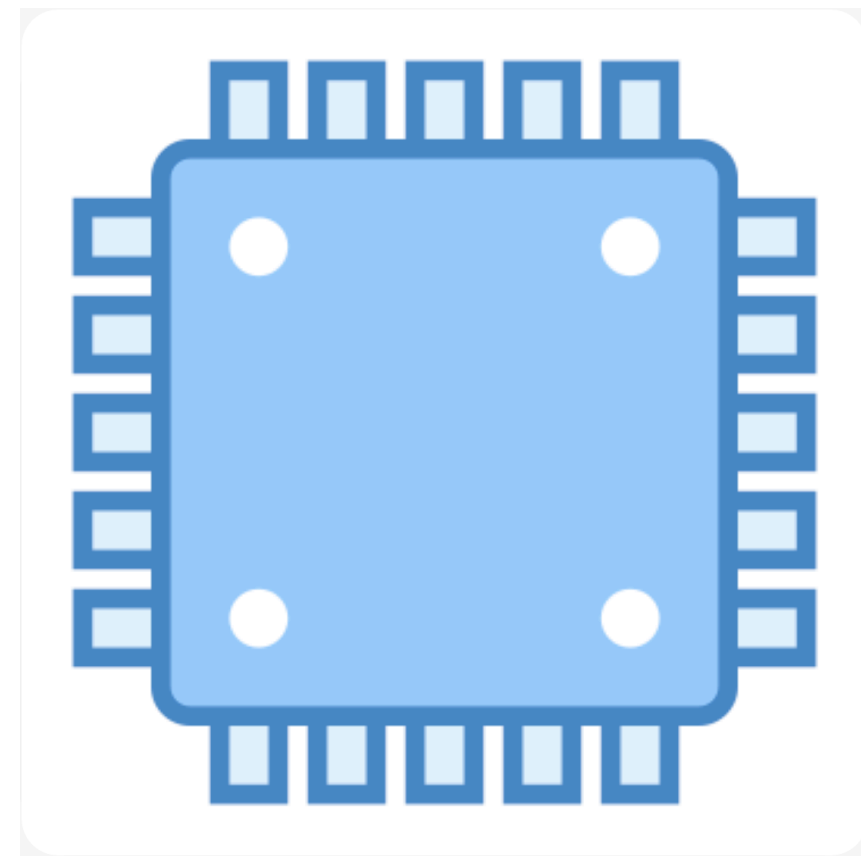


Why am I here?

I love all kinds of computing and want to share!



Analog



Electrical



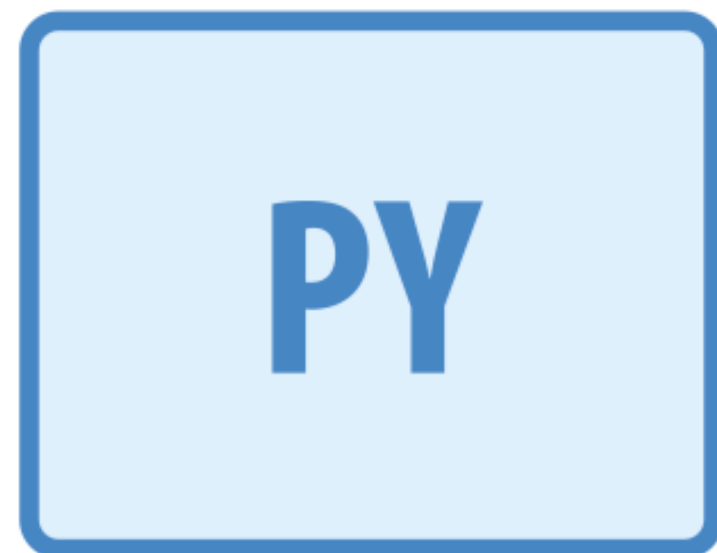
Optical



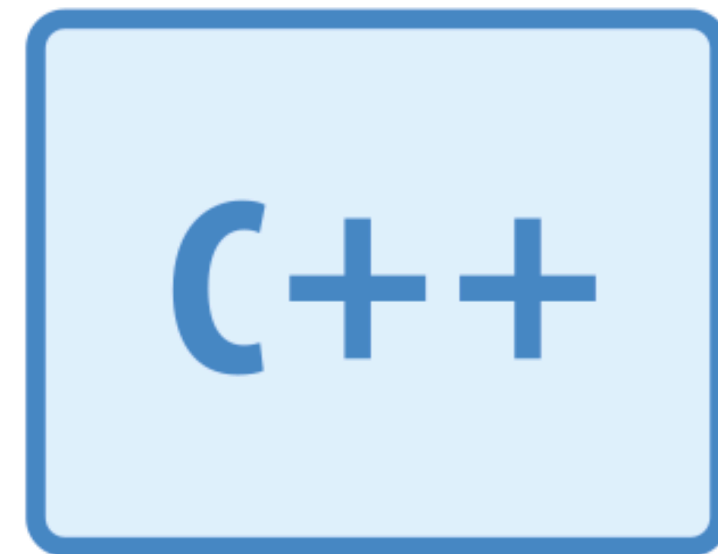
Quantum

Why are you here?

Let's compare substring search performance on x86 silicon



Python
10 MB/s



C/C++
2 GB/s



SIMD
12 GB/s

[github.com](#) →
AshVardanian →
CppBenchSubstrSearch

The contents

Won't be covered

- What's parallelism?
- What's SIMD?
- Branchless coding
- Boyer-Moore-Horspool
- Knuth-Morris-Pratt
- Rabin-Karp
- Aho-Corasic
- Commentz-Walter

Will be covered

- Brute Force Substring Search
- AVX2
- Speculative execution
- ARM NEON vs. x86 AVX-2
- The evil in AVX-512
- L0, L1, L2 Licenses
- Tools & Benchmarks
- Recommendations & Stories

Definitions

According to Intel

- **Mnemonic** is a register-invariant operation name.
 - Compare Equality.
 - Add.
 - Multiply.
 - And.
- **Intrinsic** is a built-into-compiler function that is replaced with instruction(s).
 - `__m256i _mm256_cmpeq_epi32 (__m256i a, __m256i b);`
- **Instruction** is register-specific.
 - `vpcmpeqdy 0x3 (%rcx), %ymm0, %ymm4`

SIMD Computing

Substring Search


```
inline bool are_equal(std::string_view a, std::string_view b) noexcept {  
    if (a.size() != b.size())  
        return false;  
    for (size_t i = 0; i < a.size(); i++)  
        if (a[i] != b[i])  
            return false;  
    return true;  
}
```

```
inline bool are_equal(std::string_view a, std::string_view b) noexcept {  
    if (a.size() != b.size())  
        return false;  
    size_t i = 0;  
    for (; i < a.size() && a[i] == b[i]; i++)  
        ;  
    return i == a.size();  
}
```

```
inline bool are_equal(char const *a, char const *b, char const *const a_end) noexcept {  
    for (; a != a_end && *a == *b; a++, b++)  
        ;  
    return a_end == a;  
}
```

(until
C++11)

(1) C++11)
(until

(since
C++20)

(until
C++20)

(since
C++20)

(until
C++20)

(since $C \perp L \mid Z_0$)

(until C++11)

(4) C++11)
(until

(since
C++20)

C++17)
(until

(since C++20)

```

struct stl_t {

    size_t next_offset(span_t haystack, span_t needle) noexcept {
        using str_view_t = std::basic_string_view<uint8_t>;
        str_view_t h_stl {haystack.data, haystack.len};
        str_view_t n_stl {needle.data, needle.len};
        size_t off = h_stl.find(n_stl);
        return off == str_view_t::npos ? not_found_k : off;
    }
};

/**
 * \return Total number of matches.
 */
template <typename engine_at, typename callback_at>
size_t find_all(span_t haystack, span_t needle, engine_at &&engine, callback_at &&callback) {

    size_t last_match = 0;
    size_t next_offset = 0;
    size_t count_matches = 0;
    for (; (last_match = engine.next_offset(haystack.after_n(next_offset), needle)) != not_found_k;
        count_matches++, next_offset = last_match + 1)
        callback(last_match);

    return count_matches;
}

```



```
struct naive_t {  
    size_t next_offset(span_t haystack, span_t needle) noexcept {  
        if (haystack.len < needle.len)  
            return not_found_k;  
        for (size_t off = 0; off <= haystack.len - needle.len; off++) {  
            if (are_equal(haystack.data + off, needle.data, needle.len))  
                return off;  
        }  
        return not_found_k;  
    }  
};
```

What have we accomplished so far?

Meet our lab rats!

Benchmark	IoT	Laptop	Server
python	4 MB/s	14 MB/s	11 MB/s
stl_t	560 MB/s	1,2 GB/s	1,3 GB/s
naive_t	520 MB/s	1 GB/s	900 MB/s




```

struct prefixed_t {
    size_t next_offset(span_t haystack, span_t needle) noexcept {

        if (needle.len < 5)
            return naive_t {}.next_offset(haystack, needle);

        // Precomputed constants.
        uint8_t const *h_ptr = haystack.data;
        uint8_t const *const h_end = haystack.data + haystack.len - needle.len;
        size_t const n_suffix_len = needle.len - 4;
        uint32_t const n_prefix = *reinterpret_cast<uint32_t const *>(needle.data);
        uint8_t const *n_suffix_ptr = needle.data + 4;

        for (; h_ptr <= h_end; h_ptr++) {
            if (n_prefix == *reinterpret_cast<uint32_t const *>(h_ptr))
                if (are_equal(h_ptr + 4, n_suffix_ptr, n_suffix_len))
                    return h_ptr - haystack.data;
        }

        return not_found_k;
    }
};

```

3 levels of IFs instead of 2 ?!

What have we accomplished

With prefix matching

Benchmark	IoT	Laptop	Server
python	4 MB/s	14 MB/s	11 MB/s
stl_t	560 MB/s	1,2 GB/s	1,3 GB/s
naive_t	520 MB/s	1 GB/s	900 MB/s
prefixed_t	2 GB/s	3,3 GB/s	3,5 GB/s



SIMD Computing

Speculative Out-of-Order Execution

```

struct prefixed_t {
    size_t next_offset(span_t haystack, span_t needle) noexcept {

        if (needle.len < 5)
            return naive_t {}.next_offset(haystack, needle);

        // Precomputed constants.
        uint8_t const *h_ptr = haystack.data;
        uint8_t const *const h_end = haystack.data + haystack.len - needle.len;
        size_t const n_suffix_len = needle.len - 4;
        uint32_t const n_prefix = *reinterpret_cast<uint32_t const *>(needle.data);
        uint8_t const *n_suffix_ptr = needle.data + 4;

        for (; h_ptr <= h_end; h_ptr++) {
            if (n_prefix == *reinterpret_cast<uint32_t const *>(h_ptr))
                if (are_equal(h_ptr + 4, n_suffix_ptr, n_suffix_len))
                    return h_ptr - haystack.data;
        }

        return not_found_k;
    }
};

```

3 levels of IFs instead of 2 ?!

Yes, with 4x less comparisons

```

uint8_t const *const h_end = haystack.data + haystack.len - needle.len;
__m256i const n_prefix = _mm256_set1_epi32(*(uint32_t const *)(needle.data));

uint8_t const *h_ptr = haystack.data;
for (; (h_ptr + 32) <= h_end; h_ptr += 32) {

    __m256i h0 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const *)(h_ptr)), n_prefix);
    __m256i h1 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const *)(h_ptr + 1)), n_prefix);
    __m256i h2 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const *)(h_ptr + 2)), n_prefix);
    __m256i h3 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const *)(h_ptr + 3)), n_prefix);
    __m256i h_any = _mm256_or_si256(_mm256_or_si256(h0, h1), _mm256_or_si256(h2, h3));
    int mask = _mm256_movemask_epi8(h_any);

    if (mask) {
        for (size_t i = 0; i < 32; i++) {
            if (are_equal(h_ptr + i, needle.data, needle.len))
                return i + (h_ptr - haystack.data);
        }
    }
}

```

256 bits fits 8x 32-bit integers!

Let's compare 4x8 prefixes per loop cycle!

```
uint32_t needles[8] = {0,0,0,0,0,0,0,0};
```

```
_mm256_set1_epi32(*(uint32_t const*)(needle.data));
```

```
uint32_t matches[8] = {a[0] == b[0], a[1] == b[1], ... };
```

```
__m256i h1 = _mm256_cmpeq_epi32(  
    _mm256_loadu_si256((__m256i const*)(h_ptr))  
    , n_prefix);
```

```
__m256i h_any = _mm256_or_si256(_mm256_or_si256(h0, h1), _mm256_or_si256(h2, h3));  
int mask = _mm256_movemask_epi8(h_any);
```

```
(matches0 | matches1) | (matches2 | matches3)
```

```
__m256i → int → bool
```


What have we accomplished so far?

Our first SIMD approach using AVX2 is 3x faster!

Benchmark	IoT	Laptop	Server
python	4 MB/s	14 MB/s	11 MB/s
stl_t	560 MB/s	1,2 GB/s	1,3 GB/s
naive_t	520 MB/s	1 GB/s	900 MB/s
prefixed_t	2 GB/s	3,3 GB/s	3,5 GB/s
prefixed_avx2_t		8,5 GB/s	10,5 GB/s

Let's speculate a little!

```
uint8_t const *const h_end = haystack.data + haystack.len - needle.len;
__m256i const n_prefix = _mm256_set1_epi32(*(uint32_t const *)(needle.data));

uint8_t const *h_ptr = haystack.data;
for (; (h_ptr + 32) <= h_end; h_ptr += 32) {

    __m256i h0_prefixes = _mm256_loadu_si256((__m256i const *)(h_ptr));
    int masks0 = _mm256_movemask_epi8(_mm256_cmpeq_epi32(h0_prefixes, n_prefix));
    __m256i h1_prefixes = _mm256_loadu_si256((__m256i const *)(h_ptr + 1));
    int masks1 = _mm256_movemask_epi8(_mm256_cmpeq_epi32(h1_prefixes, n_prefix));
    __m256i h2_prefixes = _mm256_loadu_si256((__m256i const *)(h_ptr + 2));
    int masks2 = _mm256_movemask_epi8(_mm256_cmpeq_epi32(h2_prefixes, n_prefix));
    __m256i h3_prefixes = _mm256_loadu_si256((__m256i const *)(h_ptr + 3));
    int masks3 = _mm256_movemask_epi8(_mm256_cmpeq_epi32(h3_prefixes, n_prefix));
```

```

__m256i h0 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const*)(h_ptr)), n_prefix);
__m256i h1 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const*)(h_ptr + 1)), n_prefix);
__m256i h2 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const*)(h_ptr + 2)), n_prefix);
__m256i h3 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const*)(h_ptr + 3)), n_prefix);
__m256i h_any = _mm256_or_si256(_mm256_or_si256(h0, h1), _mm256_or_si256(h2, h3));
int mask = _mm256_movemask_epi8(h_any);

```

Same Mnemonics + More Instructions = Higher Performance?!

```

__m256i h0_prefixes = _mm256_loadu_si256((__m256i const*)(h_ptr));
int masks0 = _mm256_movemask_epi8(_mm256_cmpeq_epi32(h0_prefixes, n_prefix));
__m256i h1_prefixes = _mm256_loadu_si256((__m256i const*)(h_ptr + 1));
int masks1 = _mm256_movemask_epi8(_mm256_cmpeq_epi32(h1_prefixes, n_prefix));
__m256i h2_prefixes = _mm256_loadu_si256((__m256i const*)(h_ptr + 2));
int masks2 = _mm256_movemask_epi8(_mm256_cmpeq_epi32(h2_prefixes, n_prefix));
__m256i h3_prefixes = _mm256_loadu_si256((__m256i const*)(h_ptr + 3));
int masks3 = _mm256_movemask_epi8(_mm256_cmpeq_epi32(h3_prefixes, n_prefix));
int mask = masks0 | masks1 | masks2 | masks3;

```


What have we accomplished so far?

Speculation-restricting SIMD is ~30% slower than flexible.

Benchmark	IoT	Laptop	Server
prefixed_t	2 GB/s	3,3 GB/s	3,5 GB/s
prefixed_avx2_t		8,5 GB/s	10,5 GB/s
speculative_avx2_t		12 GB/s	9,7 GB/s
speculative_avx512_t			10 GB/s
speculative_neon_t	4,3 GB/s		

How much can the CPU speculate?

intel.com doesn't say

Intel® Core™ i9-9880H Processor

16M Cache, up to 4.80 GHz

[Specifications](#)

Essentials

[CPU Specifications](#)

[Supplemental Information](#)

[Memory Specifications](#)

[Processor Graphics](#)

[Expansion Options](#)

[Package Specifications](#)

[Advanced Technologies](#)

[Security & Reliability](#)

[Ordering and Compliance](#)


[Product Images](#)



[Compatible Products](#)

[Drivers and Software](#)






[Technical Documentation](#)

Essentials

 [Export specifications](#)


Product Collection	9th Generation Intel® Core™ i9 Processors
Code Name	Products formerly Coffee Lake
Vertical Segment	Mobile
Processor Number 	i9-9880H
Status	Launched
Launch Date 	Q2'19
Lithography 	14 nm
Recommended Customer Price 	\$556.00

CPU Specifications

# of Cores 	8
# of Threads 	16
Processor Base Frequency 	2.30 GHz
Max Turbo Frequency 	4.80 GHz
Cache 	16 MB Intel® Smart Cache

How much can the CPU speculate?

wikichip.org knows the L1 cache size



Cache Organization ⓘ					[Edit/Modify Cache Info]
L1\$	512 KiB	L1I\$	256 KiB 8x32 KiB	8-way set associative	write-back
		L1D\$	256 KiB 8x32 KiB	8-way set associative	
L2\$	2 MiB		8x256 KiB	4-way set associative	write-back
L3\$	16 MiB		8x2 MiB	16-way set associative	write-back

Re-order buffer

From Wikipedia, the free encyclopedia

Instruction window

From Wikipedia, the free encyclopedia

Speculative execution

From Wikipedia, the free encyclopedia

Out-of-order execution

From Wikipedia, the free encyclopedia

In theory we have up to 32KiB instructions cache per core.
The practical OoOE queue depth should probably be closer to 16 load/store entries.


```

__m256i h0 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const*)(h_ptr)), n_prefix);
__m256i h1 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const*)(h_ptr + 1)), n_prefix);
__m256i h2 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const*)(h_ptr + 2)), n_prefix);
__m256i h3 = _mm256_cmpeq_epi32(_mm256_loadu_si256((__m256i const*)(h_ptr + 3)), n_prefix);
__m256i h_any = _mm256_or_si256(_mm256_or_si256(h0, h1), _mm256_or_si256(h2, h3));
int mask = _mm256_movemask_epi8(h_any);

```

ARM & x86: How different are they?

```

uint32x4_t masks0 = vceqq_u32(vld1q_u32((uint32_t const*)(h_ptr)), n_prefix);
uint32x4_t masks1 = vceqq_u32(vld1q_u32((uint32_t const*)(h_ptr + 1)), n_prefix);
uint32x4_t masks2 = vceqq_u32(vld1q_u32((uint32_t const*)(h_ptr + 2)), n_prefix);
uint32x4_t masks3 = vceqq_u32(vld1q_u32((uint32_t const*)(h_ptr + 3)), n_prefix);

uint32x4_t masks = vorrq_u32(vorrq_u32(masks0, masks1), vorrq_u32(masks2, masks3));
uint64x2_t masks64x2 = vreinterpretq_u64_u32(masks);
bool has_match = vgetq_lane_u64(masks64x2, 0) | vgetq_lane_u64(masks64x2, 1);









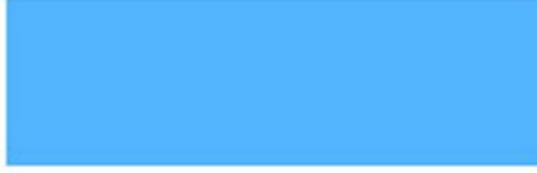

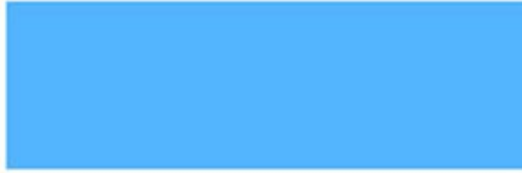


```

ARM is efficient!

	IoT	IoT	IoT	Laptop	Server
ISA	ARM	ARM	ARM	X86	X86
Process	12 nm TSMC	12 nm TSMC	12 nm TSMC	14 nm Intel	14 nm Intel
Cores	2	4	8	8 (16t)	22 (44t)
TDP/Core	2 W	1 W	0,5 W	5,6 W	6,3 W
CPU Frequency	2,1 GHz	1,7 GHz	1,2 GHz	2,3 GHz	2,1 GHz
Performance/Core	3,3 GB/s	2,5 GB/s	2,1 GB/s	12 GB/s	10,5 GB/s
Bytes/Joule	1,6 GB/J	2,5 GB/J	4,2 GB/J	2,1 GB/J	1,6 GB/J

ARM-ageddon

Is coming to consumer desktops

	iMac (27-inch Retina Mid 2020) Intel Core i7-10700K @ 3.8 GHz (8 cores)	8019	
	iMac Pro (Late 2017) Intel Xeon W-2140B @ 3.2 GHz (8 cores)	7994	
	Mac Pro (Late 2019) Intel Xeon W-3223 @ 3.5 GHz (8 cores)	7989	
	MacBook Air (2020) Apple Silicon M1 @3.2GHz (8 cores)	7433	
	Mac Pro (Late 2013) Intel Xeon E5-2697 v2 @ 2.7 GHz (12 cores)	7015	
	MacBook Pro (16-inch Late 2019) Intel Core i9-9980HK @ 2.4 GHz (8 cores)	6870	
	MacBook Pro (16-inch Late 2019) Intel Core i9-9880H @ 2.3 GHz (8 cores)	6549	

- Intel i9-9980HK
 - 45 W
 - 6870 points
 - 152 points/W
- Apple Silicon M1
 - 10 W
 - 7433 points
 - 753 points/W

5 nm ARM is 5x more efficient than 14 nm Intel.

Can the the compiler replace us?

Auto-vectorization quality varies between LLVM & GCC

Benchmark	IoT	Laptop	Server
prefixed_t	2 GB/s	3,3 GB/s	3,5 GB/s
prefixed_avx2_t		8,5 GB/s	10,5 GB/s
speculative_avx2_t		12 GB/s	9,7 GB/s
speculative_avx512_t			10 GB/s
speculative_neon_t	4,3 GB/s		
prefixed_autovec_t		~ 1,5 GB/s	~ 4 GB/s

SIMD Computing

Tooling & Benchmarks

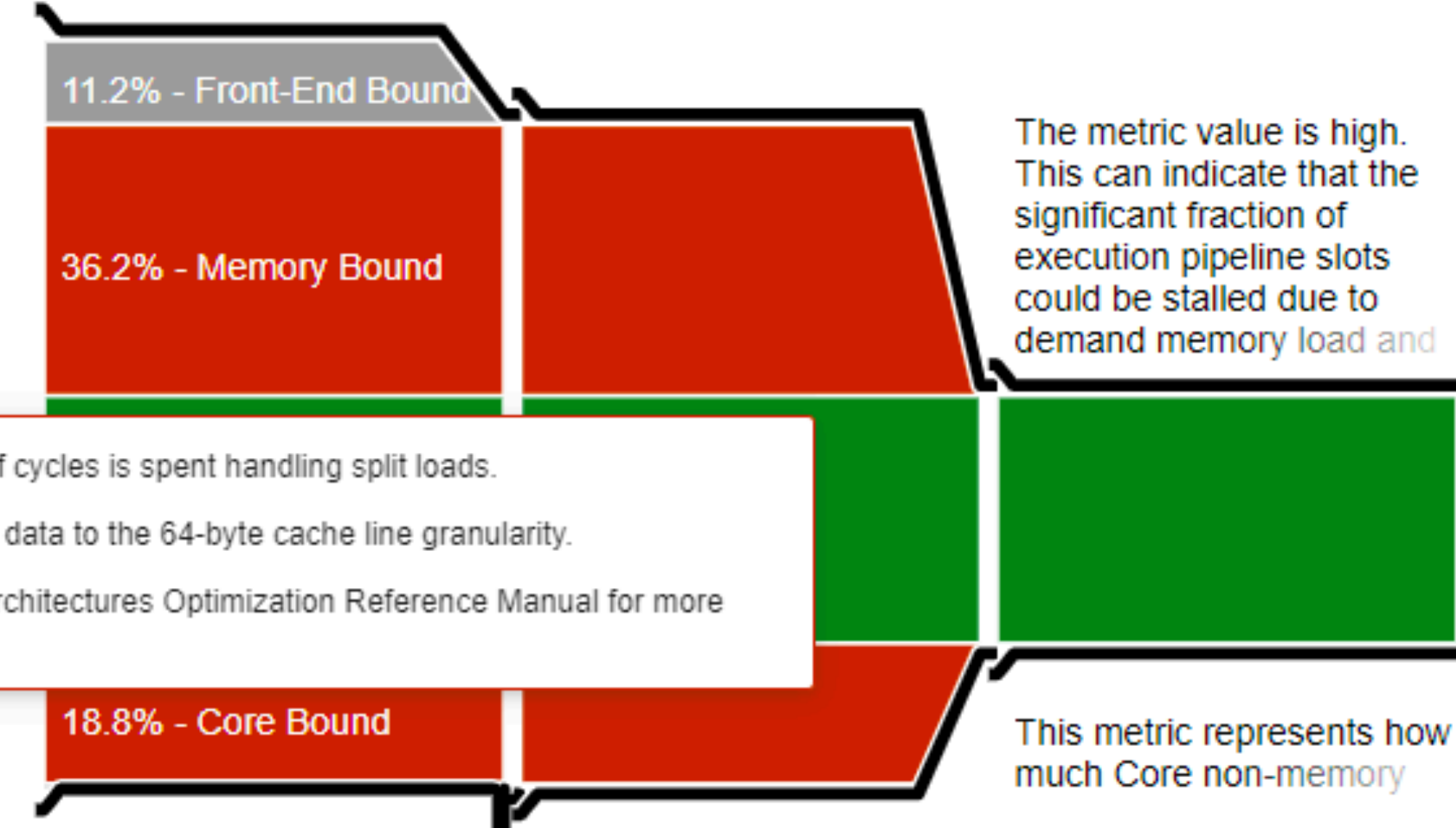
Elapsed Time[®]: 53.168s

Clockticks:	824,638,500,000
Instructions Retired:	753,207,000,000
CPI Rate [®] :	1.095
MUX Reliability [®] :	0.991
Retiring [®] :	33.1% of Pipeline Slots
Front-End Bound [®] :	11.2% of Pipeline Slots
Bad Speculation [®] :	0.7% of Pipeline Slots
Back-End Bound [®] :	55.0% of Pipeline Slots
Memory Bound [®] :	
L1 Bound [®] :	
DTLB Overhead [®] :	
Loads Blocked by Store Forwarding [®] :	
Lock Latency [®] :	
Split Loads [®] :	
4K Aliasing [®] :	
FB Full [®] :	
L2 Bound [®] :	
L3 Bound [®] :	
Contested Accesses [®] :	
Data Sharing [®] :	
L3 Latency [®] :	
SQ Full [®] :	
DRAM Bound [®] :	
Store Bound [®] :	
Core Bound [®] :	
Divider [®] :	
Port Utilization [®] :	
Cycles of 0 Ports Utilized [®] :	
Cycles of 1 Port Utilized [®] :	
Cycles of 2 Ports Utilized [®] :	
Cycles of 3+ Ports Utilized [®] :	
Vector Capacity Usage (FPU) [®] :	
Average CPU Frequency [®] :	2.7 GHz
Total Thread Count:	327
Paused Time [®] :	0s

Issue: A significant portion of cycles is spent handling split loads.



Tips: Consider aligning your data to the 64-byte cache line granularity.

See the Intel 64 and IA-32 Architectures Optimization Reference Manual for more details.



This diagram represents inefficiencies in CPU usage. Treat it as a pipe with an output flow equal to the "pipe efficiency" ratio: (Actual Instructions Retired)/(Maximum Possible Instruction Retired). If there are pipeline stalls decreasing the pipe efficiency, the pipe shape gets more narrow.

Intel VTune

Retiring:	35.1%	of Pipeline Slots
Front-End Bound:	4.3%	of Pipeline Slots
Bad Speculation:	0.2%	of Pipeline Slots
Back-End Bound:		
Memory Bound:		
L1 Bound:		
L2 Bound:	42.5% 	of Clockticks
L3 Bound:	0.4%	of Clockticks
DRAM Bound:	2.2%	of Clockticks
Store Bound:	0.0%	of Clockticks
Core Bound:	12.8% 	of Pipeline Slots

This metric shows how often machine was stalled on L2 cache. Avoiding cache misses (L1 misses/L2 hits) will improve the latency and increase performance.

We collected 19e9 L1 cache hits and 30e9 L1 cache misses, when requesting nearby addresses!

Some mysteries are just not meant to be solved!


```

bm::RegisterBenchmark("stl", search<stl_t>)->MinTime(default_secs_k);
bm::RegisterBenchmark("naive", search<naive_t>)->MinTime(default_secs_k);
bm::RegisterBenchmark("prefixed", search<prefixed_t>)->MinTime(default_secs_k);

#ifdef __AVX2__
bm::RegisterBenchmark("simultaneous_avx2", search<speculative_avx2_t>)
    ->MeasureProcessCPUTime()
    ->MinTime(default_secs_k)
    ->UseRealTime()
    ->Threads(1)
    ->Threads(2)
    ->Threads(count_threads_k / 2)
    ->Threads(count_threads_k);
#endif

```

Google Benchmark!

Benchmark	Time		CPU		Iterations	UserCounters...
stl/min_time:5.000	417237303	ns	415840765	ns	17	bytes/s=1.29105G/s bytes/s/core=1.29105G/s
naive/min_time:5.000	463408929	ns	462852933	ns	15	bytes/s=1.15992G/s bytes/s/core=1.15992G/s
prefixed/min_time:5.000	148634454	ns	148470213	ns	47	bytes/s=3.61602G/s bytes/s/core=3.61602G/s
prefixed_avx2/min_time:5.000	53778471	ns	53723628	ns	129	bytes/s=9.9932G/s bytes/s/core=9.9932G/s
hybrid_avx2/min_time:5.000	53606280	ns	53586867	ns	128	bytes/s=10.0187G/s bytes/s/core=10.0187G/s
speculative_avx2/min_time:5.000	43984034	ns	43962859	ns	156	bytes/s=12.2119G/s bytes/s/core=12.2119G/s
simultaneous_avx2/min_time:5.000/real_time/threads:1	44952777	ns	44931867	ns	158	bytes/s=11.943G/s bytes/s/core=11.943G/s
simultaneous_avx2/min_time:5.000/real_time/threads:2	21819874	ns	43626261	ns	318	bytes/s=24.6047G/s bytes/s/core=12.3023G/s
simultaneous_avx2/min_time:5.000/real_time/threads:8	6588667	ns	52572785	ns	800	bytes/s=81.484G/s bytes/s/core=10.1855G/s
simultaneous_avx2/min_time:5.000/real_time/threads:16	9680513	ns	149853379	ns	672	bytes/s=55.4589G/s bytes/s/core=3.46618G/s
naive/[a-z]/min_time:5.000	441841304	ns	441581643	ns	14	bytes/s=1.21579G/s bytes/s/core=1.21579G/s
naive/[A-Za-z]/min_time:5.000	344485733	ns	344315800	ns	20	bytes/s=1.55924G/s bytes/s/core=1.55924G/s

The Tools

And the pitfalls

- Intel Advisor.
 - Static analysis.
- Godbolt.
 - Less assembly doesn't mean faster.
 - Code execution order is loosely defined on OoOE CPUs.
- Intel VTune.
 - Runtime profiling.
 - When measuring code vectorization - only includes floats.
 - Subjectively, as complicated as CMake.
- **Google Benchmark.**
 - **CPU frequency scaling** should be turned off on desktop.

SIMD Computing

Pitfalls & Recommendations

Diminishing returns with AVX-512

High Complexity

Year	1997	1999	2001	2004	2006	2006	2008	2011	2013	2015
Extension	MMX	SSE	SSE2	SSE3	SSSE3	SSE4.1/2	AVX	FMA	AVX2	AVX-512
Mnemonics	+46	+62	+70	+10	+16	+54	+89	+20	+135	+347

Minimal Support (Intel-only)

AVX-512 Subset	F	CD	ER	PF	4FMAPS	4VNNIW	VPOPCNTDQ	VL	DQ	BW	IFMA	VBMI	VNNI	BF16	VBMI2	BITALG	VPCLMULQDQ	GFNI	VAES	VP2INTERSECT					
Knights Landing (Xeon Phi x200) processors (2016)	Yes		Yes		No																				
Knights Mill (Xeon Phi x205) processors (2017)					Yes	Yes	No																		
Skylake-SP, Skylake-X processors (2017)			No		No	No	Yes	No																	
Cannon Lake processors (2018)								Yes	No																
Cascade Lake processors (2019)								No	Yes	No															
Cooper Lake processors (2020)										Yes	Yes	No													
Ice Lake processors (2019)						Yes		Yes	Yes	No	Yes	Yes	No	Yes											No
Tiger Lake processors (2020)														Yes											Yes

It gets worse

L0, L1, L2 Frequencies on Intel Xeon Gold 5120

Mode	Base	Turbo Frequency/Active Cores													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Normal	2,200 MHz	3,200 MHz	3,200 MHz	3,000 MHz	3,000 MHz	2,900 MHz	2,900 MHz	2,900 MHz	2,900 MHz	2,700 MHz	2,700 MHz	2,700 MHz	2,700 MHz	2,600 MHz	2,600 MHz
AVX2	1,800 MHz	3,100 MHz	3,100 MHz	2,900 MHz	2,900 MHz	2,700 MHz	2,700 MHz	2,700 MHz	2,700 MHz	2,300 MHz	2,300 MHz	2,300 MHz	2,300 MHz	2,200 MHz	2,200 MHz
AVX512	1,200 MHz	2,900 MHz	2,900 MHz	2,500 MHz	2,500 MHz	1,900 MHz	1,900 MHz	1,900 MHz	1,900 MHz	1,600 MHz	1,600 MHz	1,600 MHz	1,600 MHz	1,600 MHz	1,600 MHz

Frequency scaling

Brands by Intel

- 2005, Enhanced Intel SpeedStep Technology (EIST)
- 2006, Dynamic Acceleration Technology (DAT)
- 2008, Turbo Boost Technology (TBT)
- 2010, Turbo Boost Technology 2.0 (TBT 2.0)
- 2015, Speed Shift Technology (SST)
- 2016, Turbo Boost Max Technology 3.0 (TBMT)
- 2018, Thermal Velocity Boost (TVB)
- 2019, Speed Select Technology (SST)

Frequency scaling licenses

In case of Intel

Mode	Instruction	Base Frequency	All Turbo Frequency	1-Core Turbo Frequency	Potential Base Loss	Potential Turbo Loss
L0	<code>_mm_add_epi64,</code> <code>_mm256_add_epi64,</code> <code>_mm256_addnot_si256</code>	2,2 GHz	2,6 GHz	3,2 GHz	0%	0%
L1	<code>_mm256_mul_epu32,</code> <code>_mm256_add_ps,</code> <code>_mm512_mul_epi64</code>	1,8 GHz	2,2 GHz	3,1 GHz	18%	31%
L2	<code>_mm256_mullo_epi64,</code> <code>_mm512_add_ps,</code> <code>_mm512_mullox_epi64</code>	1,2 GHz	1,6 GHz	2,9 GHz	45%	38%

Mixing Light & Heavy instructions

Causes Soft & Hard Transitions and CPU Halting

- Heavy operations:
 - Load/Store
 - All float operations
 - Integer multiplication $\geq 256b$
 - Shuffle/Blend $\geq 256b$
- Use of any AVX-512 causes hard L1 transition
- Other transitions are soft and need sufficient demand
- Mean transition time is ~8 micro seconds or ~25K CPU cycles!

Final Recipe

What to use aside from vanilla C++?

- Integer operations:
 - 256b AVX2 instructions on x86
 - 128b NEON instructions on ARM
- Floating-point operations:
 - Most FP programs are data-parallel and auto-vectorizable
 - For other critical operations use 128b instructions
- Avoid integer divisions & modulus at any cost of 50 cycles on Cannon Lake!
- Obviously don't use AVX-512 unless you absolutely need to
 - Video coders process 8x8 pixels x8-bits per color = 512 bits at a time

Final Recipe

When to use? To optimize hot data path

- When you have less data than GPU threads
- More data than GPU memory
- When latency is more important than throughput, examples:
 - Deep Learning inference
- Solution has linear worst case complexity
- Solution isn't data parallel, examples:
 - Compression
 - Encoding
 - Parsing

What's the future like

For Assembly developers

- CISC becomes CISC-ier:
 - X86 receives Advanced Matrix eXtensions
 - ARM receives SVE • NEON = SVE2 with up to 2048-bit registers
 - L4 cache prefetching intrinsics for Sapphire Rapids?
- RISC becomes ~~RISC-ier~~ more popular!
 - A RISC core already lives in every CISC core
 - Simpler ISAs generally have higher frequencies to compensate throughput
 - Custom chips for every workload in hyperscalers: AWS, GCP, Azure
 - Flexible compilers, domain-specific plugins: MLIR, TVM

Expected Results

What we have achieved @ unum.xyz

- ML-oriented Geometry:
 - Vanilla Cpp ~16 ns
 - SIMD ~3 ns
- Set Lookups:
 - `std::unordered_set` ~ 150 ns
 - `unum::set` ~ 15 ns
- Random Numbers Generators:
 - `rand()` ~ 900 MB/s
 - `unum::rand()` ~ 12 GB/s
- RegEx Matching:
 - `std::regex` ~ 300 MB/s
 - `unum::regex` ~ 14 GB/s
- DB Scans:
 - PostgreSQL ~ 50 MB/s
 - UnumDB ~ 3 GB/s
- Text Indexing:
 - Elasticsearch ~ 10 MB/s
 - UnumDB ~ 450 MB/s