How to get peak FLOPS (CPU) — What I wish I knew when I was twenty about CPU —

Kenjiro Taura

Contents

- Introduction
- 2 An endeavor to nearly peak FLOPS
- 3 Latency limit
- Overcoming latency
- **5** Superscalar processors
- 6 A slightly more realistic example
- A simple yet fairly fast single-core matrix multiply

Contents

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- 2 An endeavor to nearly peak FLOPS
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- 4 Overcoming latency
- **6** Superscalar processors
- 6 A slightly more realistic example
- 7 A simple yet fairly fast single-core matrix multiply

What you need to know to get a nearly peak FLOPS

- so you now know how to use multicores and SIMD instructions
- they are two key elements to get a nearly peak FLOPS
- the last key element: Instruction Level Parallelism (ILP) of superscalar processors

Contents

- Introduction
- 2 An endeavor to nearly peak FLOPS
- 3 Latency limit
- 4 Overcoming latency
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- 6 A slightly more realistic example
- 7 A simple yet fairly fast single-core matrix multiply

An endeavor to nearly peak FLOPS

• let's run the simplest code you can think of

```
#if __AVX512F__
const int vwidth = 64;

#elif __AVX__
const int vwidth = 32;

#else
#error "you'd better have a better machine"
#endif

const int valign = sizeof(float);
typedef float floatv __attribute__((vector_size(vwidth),aligned(valign)));
/* SIMD lanes */
const int L = sizeof(floatv) / sizeof(float);
```

```
floatv a, x, c;
for (i = 0; i < n; i++) {
    x = a * x + c;
}
```

 \bullet the code performs $L \times n$ FMAs and almost nothing else

Notes on experiments

- the source code for the following experiments is in <code>06axpb</code> directory
- the computation is trivial but the measurement part is Linux-specific
 - perf_event_open to get CPU clocks (not reference clocks)
 - clock_gettime to get time in nano second resolution
- it will compile on MacOS too, but the results are incomplete and less accurate
 - CPU clocks not available
 - gettimeofday (micro second granularity) substitutes for clock_gettime (nano second granularity)

Notes on experiments

• on Linux, you need to allow user processes to get performance events by

```
1 $ sudo sysctl -w kernel.perf_event_paranoid=-1
```

• exact results depend on the CPU microarchitecture and ISA

```
s cat /proc/cpuinfo
```

and google the model name (e.g., "Xeon Gold 6126")

- the following experiments show results on an Skylake X CPU
 - Skylake X is a variant of Skylake supporting AVX-512
 - taulec, login node of the IST cluster, and the big partition of IST cluster
- there is a Skylake, which has the same microarchitecture but does not support AVX-512 (laptop CPUs)

• compile

```
$ g++ -o axpb.g++ -03 -fopenmp -march=native axpb.cc
```

compile

```
f g++ -o axpb.g++ -03 -fopenmp -march=native axpb.cc
```

• and run!

```
login000:06axpb$ ./axpb.g++ -a simd
     algo = simd
        bs = 1 (cuda block size)
        c = 1 (the number of variables to update in the inner loop)
       m = 16 (the number of FP numbers to update)
5
        n = 1000000 (the number of times to update each variable)
        L = 16 (SIMD lanes on the CPU)
    1403468 nsec
    3641400 ref clocks
10
    4022127 cpu clocks
11
12
    1.403468 nsec
                        for performing x=ax+b for 16 variables once
    3.641400 ref clocks for performing x=ax+b for 16 variables once
13
    4.022127 cpu clocks for performing x=ax+b for 16 variables once
14
15
   22.800662 flops/nsec
16
   8.787829 flops/ref clock
17
   7.955989 flops/cpu clock
18
   X[7] = 0.005949
```

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How to investigate

• put a landmark in the assembly code

```
asm volatile ("# axpb_simd: ax+b loop begin");
for (long i = 0; i < n; i++) {
    x = a * x + b;
}
sam volatile ("# axpb_simd: ax+b loop end");</pre>
```

How to investigate

• put a landmark in the assembly code

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asm volatile ("# axpb_simd: ax+b loop begin");
for (long i = 0; i < n; i++) {
    x = a * x + b;
}
sam volatile ("# axpb_simd: ax+b loop end");</pre>
```

• compile into assembly

```
1 $ g++ -o axpb.S -S -O3 -fopenmp -march=native axpb.cc
```

• and see axpy.S in your editor

Assembly

```
# axpy_simd: ax+b loop begin
# 0 "" 2
#NO_APP
         %rdi, %rdi
 testq
 jle .L659
 xorl %edx, %edx
  .p2align 4,,10
  .p2align 3
.1.660:
  addq $1,%rdx
 vfmadd132ps %zmm0,%zmm1,%zmm2
 cmpq %rdx,%rdi
 jne .L660
.1.659:
#APP
# 63 "axpy.cc" 1
  # axpy_simd: ax+b loop end
```

• why?



Suspect looping overhead?

• if you suspect the overhead of other instructions, here is an unrolled version that has much fewer overhead instructions

10

11

12

• its performance is identical

```
.L1662:
addq $8, %rdx
vfmadd132ps %zmm0,%zmm1,%zmm2
vfmadd132ps %zmm0,%zmm1,%zmm2
cmpq %rdx,%rdi
vfmadd132ps %zmm0,%zmm1,%zmm2
jne .L1662
```

Contents

- Introduction
- 2 An endeavor to nearly peak FLOPS
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Latency and throughput

- a (Skylake-X) core can execute *two* vfmaddps *instructions* every cycle
- yet, it does *not* mean the result of vfmaddps at line 3 below is available in the next cycle for vfmaddps at the next line

```
1 .L1662:
2 addq $8, %rdx
3 vfmadd132ps %zmm0,%zmm1,%zmm2
4 vfmadd132ps %zmm0,%zmm1,%zmm2
5 cmpq %rdx,%rdi
6 vfmadd132ps %zmm0,%zmm1,%zmm2
7 ...
8 vfmadd132ps %zmm0,%zmm1,%zmm2
9 jne .L1662
```

Latency and throughput

- a (Skylake-X) core can execute *two* vfmaddps *instructions* every cycle
- yet, it does *not* mean the result of vfmaddps at line 3 below is available in the next cycle for vfmaddps at the next line

- what you need to know:
 - "two vfmadd132ps instructions every cycle" refers to the throughput
 - each instruction has a specific latency (> 1 cycle)

Latencies

instruction	Haswell	Broadwell	Skylake
fp add	3	3	4
fp mul	5	3	4
fp fmadd	5	5	4
typical integer ops	1	1	1

Valuable resources for detailed analyses

- Software optimization resources by Agner
 - The microarchitecture of Intel, AMD and VIA CPUs: An optimization guide for assembly programmers and compiler makers
 - Instruction tables: Lists of instruction latencies, throughputs and micro-operation breakdowns for Intel, AMD and VIA CPUs
- Intel Intrinsics Guide
- Intel Architecture Code Analyzer (later)

Our code in light of latencies

- in our code, a vfmadd uses the result of the immediately preceding vfmadd
- that was obvious from the source code too

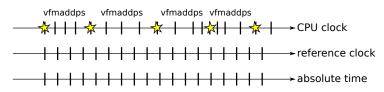
Conclusion:

the loop can't run faster than 4 cycles/iteration



CPU clocks vs. reference clocks

- CPU changes clock frequency depending on the load (DVFS)
- reference clock runs at the same frequency (it is always proportional to the absolute time)
- an instruction takes a specified number of *CPU clocks*, not reference clocks
- the CPU clock is more predictable and thus more convenient for a precise reasoning of the code

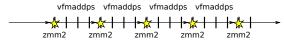


Contents

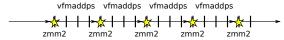
- Introduction
- 2 An endeavor to nearly peak FLOPS
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- you *can't* make a serial chain of computation run faster (change the algorithm if you want to)



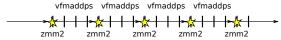
- increase parallelism (no other ways)!
- you *can't* make a serial chain of computation run faster (change the algorithm if you want to)



• you *can* only increase *throughput*, by running multiple *independent* chains



- increase parallelism (no other ways)!
- you *can't* make a serial chain of computation run faster (change the algorithm if you want to)



• you *can* only increase *throughput*, by running multiple *independent* chains



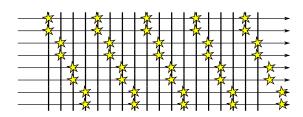
• we expect the following to finish in the same number of cycles as the original one, despite it performs twice as many flops

```
for (i = 0; i < n; i++) {
    x0 = a * x0 + c;
    x1 = a * x1 + c;
}
```

Increase the number of chains further ...

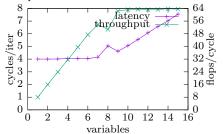
• we expect to reach peak FLOPS with $\geq 2/(1/4) = 8$ chains

```
template<int nv>
long axpy_simd_c( ... ) {
  for (long i = 0; i < n; i++) {
  for (long j = 0; j < nv; j++) {
    X[j] = a * X[j] + c;
  } }
}</pre>
```



Results

a compile-time constant number of variables



```
for (i = 0; i < n; i++) {
  x0 = a * x0 + b;
  x1 = a * x1 + b;
  ...
}
```

chains	clocks/iter	flops/clock
1	4.010	7.979
2	4.003	15.987
3	4.013	23.916
4	4.043	31.653
5	4.043	39.568
6	4.047	47.439
7	4.157	53.878
8	5.044	50.751
9	4.621	62.314
10	5.057	63.270
11	5.549	63.427
12	6.076	63.194
13	6.573	63.283
14	7.022	63.794
15	7.552	63.558
·		·

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- 4 Overcoming latency
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- 6 A slightly more realistic example
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What you need to know:

• instructions are decoded in the program order,

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 - *latency:* imposed by *dependencies* between instructions

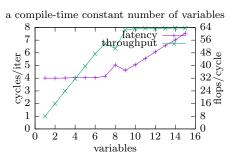
Superscalar processors

What you need to know:

- instructions are decoded in the program order,
- but the execution orders are not constrained by it (out of order execution)
- ullet as a crude approximation, performance is constrained only by
 - *latency:* imposed by *dependencies* between instructions
 - throughput: imposed by execution resources of the processor (e.g., two fmadds/cycle)

A general theory of workload performance on aggressive superscalar machines

- *dependency* constrains how fast a computation can proceed, even if there are infinite number of execution resources
- increase the number of independent computations and you increase *throughput*, until it hits the limit of execution resources



Contents

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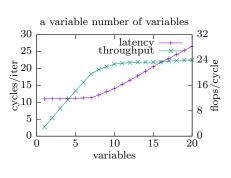
What if the number of chains is a variable?

- purpose: illustrate the same concept with a slightly more complex/common case
- let's try the following code, identical to the one we successfully achieved nearly peak performance for, except that the number of variables (m) is now a variable (not a compile-time constant)

```
void axpy_simd_m(..., long m) {
for (long i = 0; i < n; i++) {
for (long j = 0; j < m; j++) {
    X[j] = a * X[j] + c;
} } }</pre>
```

When we experiment . . .

chains	clocks/iter	flops/clock
1	11.034	2.899
2	11.062	5.785
3	11.047	8.689
4	11.150	11.479
5	11.199	14.286
6	11.308	16.951
7	11.389	19.666
8	12.174	21.027
9	13.159	21.885
10	14.071	22.741
17	22.977	23.675
18	24.171	23.829
19	25.345	23.988
20	26.605	24.055



- the pattern is similar, but there are two differences:
 - the latency of a single update became ≈ 11 cycles
 - the throughput hits the plateau at ≈ 24 flops/cycles (≈ 0.75 vfmaddps/cycle)

Take a look at assembly

• it looks like:

```
.L1811:

vmovaps %zmm0, %zmm2

addq $64, %rcx

vfmadd132ps -64(%rcx), %zmm1, %zmm2

vmovups %zmm2, -64(%rcx)

cmpq %rcx, %r8

jne .L1811
```

• what's the difference from the code we have seen before (whose latency = 4 cycles)?

```
1 .L1800:
2 addq $1, %rdx
3 vfmadd132ps %zmm0, %zmm1, %zmm2
4 cmpq %rdx, %rdi
5 jne .L1800
```

The reason of the latency (11 cycles)

- both stem from the fact that the code now involves load/stores
- what you need to know: just like FMA, each instruction has its own latency

Latencies of various instructions

instruction	Haswell	Broadwell	Skylake
fp add	3	3	4
fp mul	5	3	4
fp fmadd	5	5	4
typical integer ops	1	1	1
load	3	3	3(*)
store	4	4	3(*)
		•••	

• 3 + 4 + 3 = 10 ≠ 11; I could not get information that confirms the extra cycle, but a simpler experiment shows the same result ¹may be 512 bit store takes 4 cycles?)



The reason of the *throughput*

- what you need to know:

 Just like FMA, all instructions have their own throughput limits, due to execution resources (dispatch ports and execution units)
- "two vfmadds per cycle" is just an example of it

Some representative throughput limits

• Throughput = the number of that instruction that can be executed by cycle

instruction	Haswell	Broadwell	Skylake
fp add/mul/fmadd	2	2	2
load	2	2	2
store	1	1	1
typical integer ops	4	4	4
		•••	

• Note: I couldn't get the reason for $\approx 0.75 < 1$ (iterations/cycle)

A back of envelope calculation

instruction	type	1/throughput
vmovaps %zmm0,%zmm2	register move	0.33
addq \$64,%rcx	int op	0.25
vfmadd132ps -64(%rcx),%zmm1,%zmm2	load + FMA	0.5, 0.5
vmovups %zmm2,-64(%rcx)	store	1.0
cmpq %rcx,%r8	compare	0.25
jne .L1811	jump	1-2

- I don't know what 1-2 means
- \bullet we can conclude that the throughput ≤ 1 due to the store
- ullet more general cases require understanding $dispatch\ ports$

Dispatch ports

- each instruction
 (μ-operation) is dispatched
 to a specific port
- Skylake X ports
 - fmadd \rightarrow port 0 or 1
 - load \rightarrow port 2 or 3
 - store \rightarrow port 4
 - load/store address generation \rightarrow port 7
 - int \rightarrow port 0, 1, 5, or 6
 - etc.
- each port can take only a single operation per cycle
 - this determines the aggregate throughput of all instructions that go to that port
- with destination ports of instructions, one can calculate the throughput limit of a given loop



source: https://en.wikichip.org/wiki/intel/

microarchitectures/skylake_(server)

Intel Architecture Code Analyzer

- a great tool to analyze the throughput (and latency to some extent) limit
- https://software.intel.com/en-us/articles/ intel-architecture-code-analyzer

											J		
Num Of				Por	ts pre	ssure	in cvc	les					1
Uops	0	- DV	1	2 -	- D	3	– D´	4	5	6	7	į	İ
													-
0* 0*													vmovaps ymm10, ymm0
2^	1.0			1.0	1.0								vmovaps ymm11, ymm0
0*	1.0		-	1.0	1.0								vfmadd132ps ymm10, ymm1, ymmword ptr [rax] vmovaps ymm12, ymm0
2^						0,2		1.0			0.8	CP	vmovaps ymmuz, ymmu vmovaps ymmword ptr [rax], ymm10
0*			1			0.2		1.0		ł	0.0	UF.	vmovaps ymmWord ptr [rax], ymmio
0*										-			vmovaps ymm13, ymm0
0*			i							ł		i	vmovaps ymm15, ymm0
2-			1.0			1,0	1.0						vfmadd132ps ymm11, ymm1, ymmword ptr [rax+0x20]
2^	1.0		1	1.0	1.0			i	i	i	i	i	vfmadd132ps ymm12, ymm1, ymmword ptr [rax+0x40]
2^ 2-			1,0			1.0	1,0			i	i	i	vfmadd132ps ymm13, ymm1, ymmword ptr [rax+0x60]
2^	1.0			1.0	1.0			i	i	i	i	i	vfmadd132ps ymm14, ymm1, ymmword ptr [rax+0x80]
2^ 2-			i			i		1.0	i	i	1.0	CP	vmovaps ymmword ptr [rax+0x20], ymm11
0*	i		i	i		i			i	i			vmovaps vmm2, vmm0
0*	i		İ	İ		İ		İ	İ	İ	İ	İ	vmovaps ymm3, ymm0
2^	į .		1.0	İ		1.0	1.0	İ	İ	İ	İ	İ	vfmadd132ps ymm15, ymm1, ymmword ptr [rax+0xa0]
2° 2° 2° 1	1.0		1	1.0	1.0	1			1				vfmadd132ps ymm2, ymm1, ymmword ptr [rax+0xc0]
2^						1		1.0			1.0	CP	vmovaps ymmword ptr [rax+0x40], ymm12
2~			1.0			1.0	1.0						vfmadd132ps ymm3, ymm1, ymmword ptr [rax+0xe0]
									1.0				add rax, 0x100
2^								1.0			1.0	CP	vmovaps ymmword ptr [rax-0xa0], ymm13
2^				0.3		0.2		1.0			0.5	CP	vmovaps ymmword ptr [rax-0x80], ymm14
2^ 2^ 2^				0.2		0.3		1.0		ļ	0.5	CP	vmovaps ymmword ptr [rax-0x60], ymm15
2"				0.5		0.5		1.0				CP	vmovaps ymmword ptr [rax-0x40], ymm2
2^ 1				0.3		0.2		1.0			0.5	CP	vmovaps ymmword ptr [rax-0x20], ymm3
1 0F			1							1.0		!	cmp r8, rax
	04 11-	2	,	1		1		l .	1	1	1	ı	jnz 0xffffffffffffff68
otal Num	UT UO	ps: 34	+										

• checking the web site, I realized Intel now says it reached End Of Life and suggests use of LLVM-MCA (I will show 36/56

How to overcome the throughput limit?

- the goal is two iterations/cycle (throughput limit of FMA)
- the bottleneck is a store instruction (1/cycle)
- we obviously need to quit loading/storing data for every single fmadd

```
for (i = 0; i < n; i++) {
  for (j = 0; j < nv; j++) {
    x[j] = a * x[j] + c; // load; fmadd; store
}
}
</pre>
```

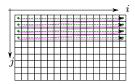
• the minimum "unit" of a computation should look like:

```
load x[j] to a register;
do "a * x + c" several times on the register;
store the result to x[j];
```

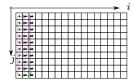
• and run multiple independent units

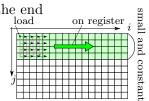
Several ways to arrange computation

• take a variable at a time and run it until the end (suffer from latency)

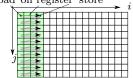


 advance all variables one step at a time (suffer from the store throughput)





• strategy 2: advance all variables, a few steps at a time load on register store



Implementing strategy 1

• say we advance ten elements at a time

```
for (j = 0; j < nv; j += b) {
    /* run b variables until the end */
    for (i = 0; i < n; i++) {
        for (jj = j; jj < j + b; jj++) {
            xx[jj] = a * xx[jj] + c;
        }
    }
}</pre>
```

- we hope it loads/stores each variable only once through the *i* loop (line 2)!
- this coding *depends on the compiler's smartness* we have witnessed
 - promote fixed-sized arrays into registers

Implementing strategy 2

• advance all variables, say three, steps at a time

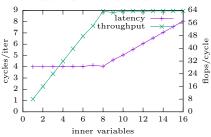
```
for (i = 0; i < n; i += 3) {
    /* run all variables 3 steps */
    for (j = 0; j < m; j++) {
        for (ii = 0; ii < 3; ii++) {
            x[j] = a * x[j] + c;
        }
    }
}</pre>
```

- again, we hope the compiler's smartness to eliminate intermediate load/stores (purple parts)
- ullet the latency of a single j iteration increases, but we hope the j loop exposes lots of independent computations

Results (strategy I)

a compile-time constant number of variables in the innermost loop

chains	clocks/iter	flops/clock
1	4.002	7.994
2	4.001	15.992
3	4.005	23.968
4	4.014	31.886
5	4.021	39.788
6	4.022	47.734
7	4.133	54.196
8	4.032	63.478
9	4.599	62.613
10	5.034	63.558
11	5.539	63.544
12	6.051	63.452
13	6.538	63.628
14	7.043	63.608
15	7.544	63.626
16	8.044	63.646

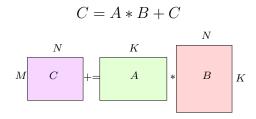


Contents

- Introduction
- 2 An endeavor to nearly peak FLOPS
- 3 Latency limit
- 4 Overcoming latency
- **6** Superscalar processors
- 6 A slightly more realistic example
- A simple yet fairly fast single-core matrix multiply

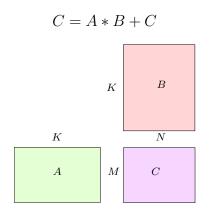
Developing near peak FLOPS matrix multiply

- let's develop a (single core) matrix multiply that runs at fairly good FLOPS on Skylake-X
- it is a great application of the concept you have just learned



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A few simplifying assumptions

- we add assumptions that M, N, and K are multiple of certain numbers along the way, (forget how to process "remainder" rows/columns in this slide)
- we assume matrix sizes are known at compile time and are "convenient" (e.g., they are small)
- multiplication of larger (and unknown size) matrices can be built on top of this

Step 1: Baseline code

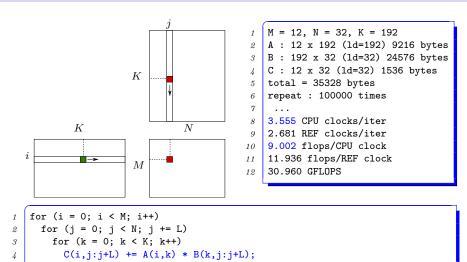
```
./mmc00
                                              M = 12, N = 32, K = 192
                                             A : 12 x 192 (ld=192) 9216 bytes
                                            B : 192 x 32 (ld=32) 24576 bytes
                    K
                                             C : 12 \times 32 \text{ (ld=32)} 1536 \text{ bytes}
                                             total = 35328 bytes
                                              3.456 CPU clocks/iter
         K
                                              2.520 REF clocks/iter
                                             0.579 flops/CPU clock
i
                                              0.794 flops/REF clock
                                         11
                    M
                                              2.058 GFLOPS
                                         12
for (i = 0; i < M; i++)
  for (j = 0; j < N; j++)
    for (k = 0; k < K; k++)
       C(i,j) += A(i,k) * B(k,j);
```

- it runs at ≈ 3.5 clocks / innermost loop
- latency of fmadd on C(i,j) fraction

Step 1: analysis

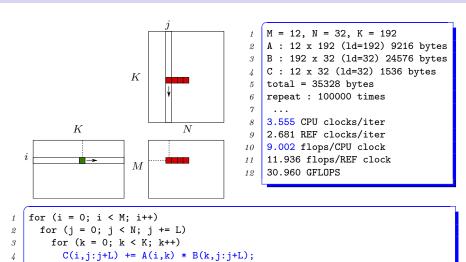
- latency limit : latency of FMA
 - I don't know why it's slightly *smaller* than 4, but note that the true dependence occurs only for additions
- throughput limit: not important
- $\rightarrow \approx 2 \text{ flops } / 4 \text{ cycles} = 0.5 \text{ flops/cycle}$

Step 2: Vectorization



• assumption: N is a multiple of SIMD lanes (L)

Step 2: Vectorization

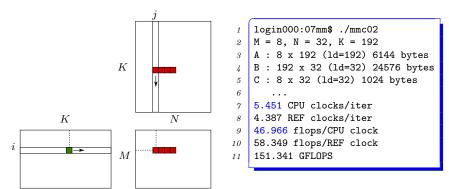


• assumption: N is a multiple of SIMD lanes (L)

Step 2: analysis

- almost the same as step 1, except that each iteration now does 16 FMAs (as opposed to an FMA)
- $\rightarrow \approx 32 \text{ flops } / 4 \text{ cycles} = 8 \text{ flops/cycle}$

Step 3: increase parallelism!



• update bM vector elements of C concurrently

```
for (i = 0; i < M; i += bM)

for (j = 0; j < N; j += L)

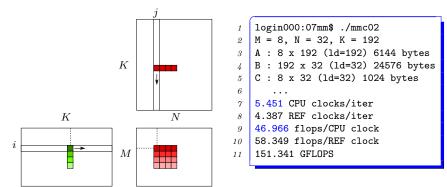
for (k = 0; k < K; k++)

for (di = 0; di < bM; di++)

C(i+di,j:j+L) += A(i+di,k) * B(k,j:j+L);
```

• Skylake requires $bM \geq 8$ to reach peak FLOPS

Step 3: increase parallelism!



 \bullet update bM vector elements of C concurrently

```
for (i = 0; i < M; i += bM)

for (j = 0; j < N; j += L)

for (k = 0; k < K; k++)

for (di = 0; di < bM; di++)

C(i+di,j:j+L) += A(i+di,k) * B(k,j:j+L);
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• Skylake requires $bM \geq 8$ to reach peak FLOPS

Step 3: analysis

```
for (i = 0; i < M; i += bM)

for (j = 0; j < N; j += L)

for (k = 0; k < K; k++)

for (di = 0; di < bM; di++)

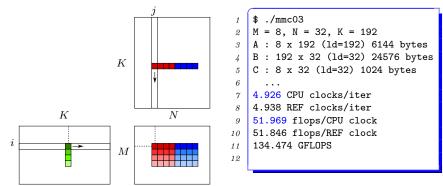
C(i+di,j:j+L) += A(i+di,k) * B(k,j:j+L);
```

- the for loop at line 4 performs
 - bM loads (broadcasts) for A(i+di,k)
 - 1 load for B(k,j:j+L)
 - **bM** FMAs
- remember the load throughput = 2 loads/cycle
- to achieve 2 FMAs/cycle, we must have

the number of loads \leq the number of FMAs

• we need to remove an extra load instruction

Step 4: Reuse an element of A



• update $bM' \times bN$ block rather than $bM \times 1$

```
for (i = 0; i < M; i += bM')
for (j = 0; j < N; j += bN * L)
for (k = 0; k < K; k++)

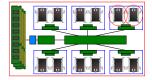
for (di = 0; di < bM'; di++)
for (dj = 0; dj < bN * L; dj += L)
C(i+di,j+dj:j+dj+L) += A(i+di,k) * B(k,j+dj:j+L);</pre>
```

Step 4: Analysis

- the for loop at line 4 performs
 - bM' loads (broadcast) for A(i+di,k)
 - bN loads for B(k,j:j+L)
 - $bM' \times bN$ FMAs
- the minimum requirement for it to achieve the peak FLOPS is $bM' \times bN \ge 8$
- in the experiments, when we set bM' = 6 and bN = 2, it gets 59 flops/cycle (92% of the peak)
- we need to note that this happens only when the matrix is small (M = 12, N = 32, K = 160) and we repeat it many times
- the issue for large matrices will be the next topic

Simultaneous Multithreading (SMT)

- each physical core has several *hardware threads* or *virtual* cores
 - recent Xeon processors (including Skylake-X): 2
 - Knights Landing/Mill: 4
 - IBM Power: 8
- a.k.a. Hyperthreading^(R)
- virtual cores on a single physical core
 - are concurrently executed by the hardware
 - have their own registers (switching between them have almost no overhead)
 - share most execution resources (dispatch ports, floating point units, L1/L2 caches, etc.)



Performance implications of virtual cores

- having as many threads as virtual cores on a physical core
 - helps improve throughput of *latency-bound* applications, but
 - does not help *throughput-bound* applications
- note: if you have more threads than virtual cores, operating systems get involved to switch between them (in a much coarser granularity, say 1 ms (10^{-3} sec) rather than every cycle ~ 1 ns (10^{-9} sec))
 - it never helps mitigate the latency of arithmetic operations
 - it helps mitigate the latency of much bigger I/O latencies (say when accessing HDD)

Takeaways (1)

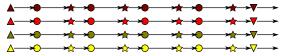
- peak FLOPS of recent Intel CPUs = "execute two fmadds every cycle" (no other combinations)
 - other processors have different limits, but the basic is the same
- no, single-core performance is not about reducing the number of instructions
- it's about how to increase parallelism
 - SIMD
 - ILP

Takeaways (2)

• dependent instructions incur latencies and hinder parallelism



• independent instructions are executed in parallel, up to throughput limits



• throughput limits are determined by dispatch ports