

Lecture 3:

A Modern Multi-Core Processor

(Forms of parallelism + understanding latency and bandwidth)

Parallel Computer Architecture and Programming
CMU 15-418/15-618, Spring 2021

Quick review

- 1. Why has single-instruction-stream performance only improved very slowly in recent years? ***
- 2. What prevented us from obtaining maximum speedup from the parallel programs we performed in the first lecture?**

* Self check 1: What do I mean by “single-instruction stream”?

Self check 2: When we talked about the optimization of superscalar execution, were we talking about optimizing the

performance of executing a single-instruction stream?

Today

- **Today we will talk computer architecture**
- **Four key concepts about how modern computers work**
 - Two concern parallel execution
 - Two concern challenges of accessing memory
- **Understanding these architecture basics will help you**
 - Understand and optimize the performance of your parallel programs
 - Gain intuition about what workloads might benefit from fast parallel machines

Part 1: Parallel Execution

Example program

Compute $\sin(x)$ using Taylor expansion: $\sin(x) = x - x^3/3! + x^5/5! - x^7/7! + \dots$

for each element of an array of N floating-point numbers

```
void sinx(int N, int terms, float* x, float* result)
{
    for (int i=0; i<N; i++)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom;
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

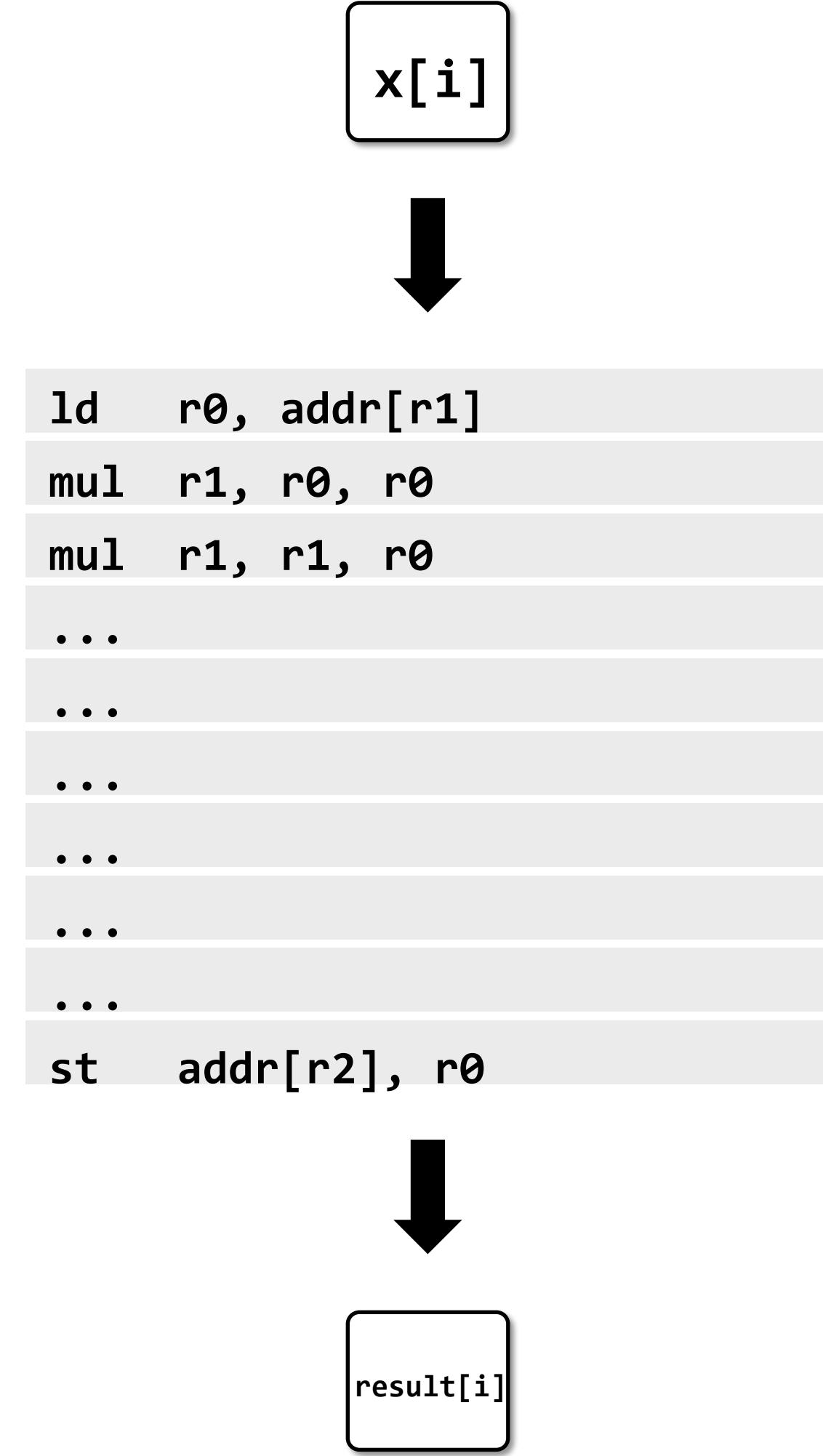
        result[i] = value;
    }
}
```

Compile program

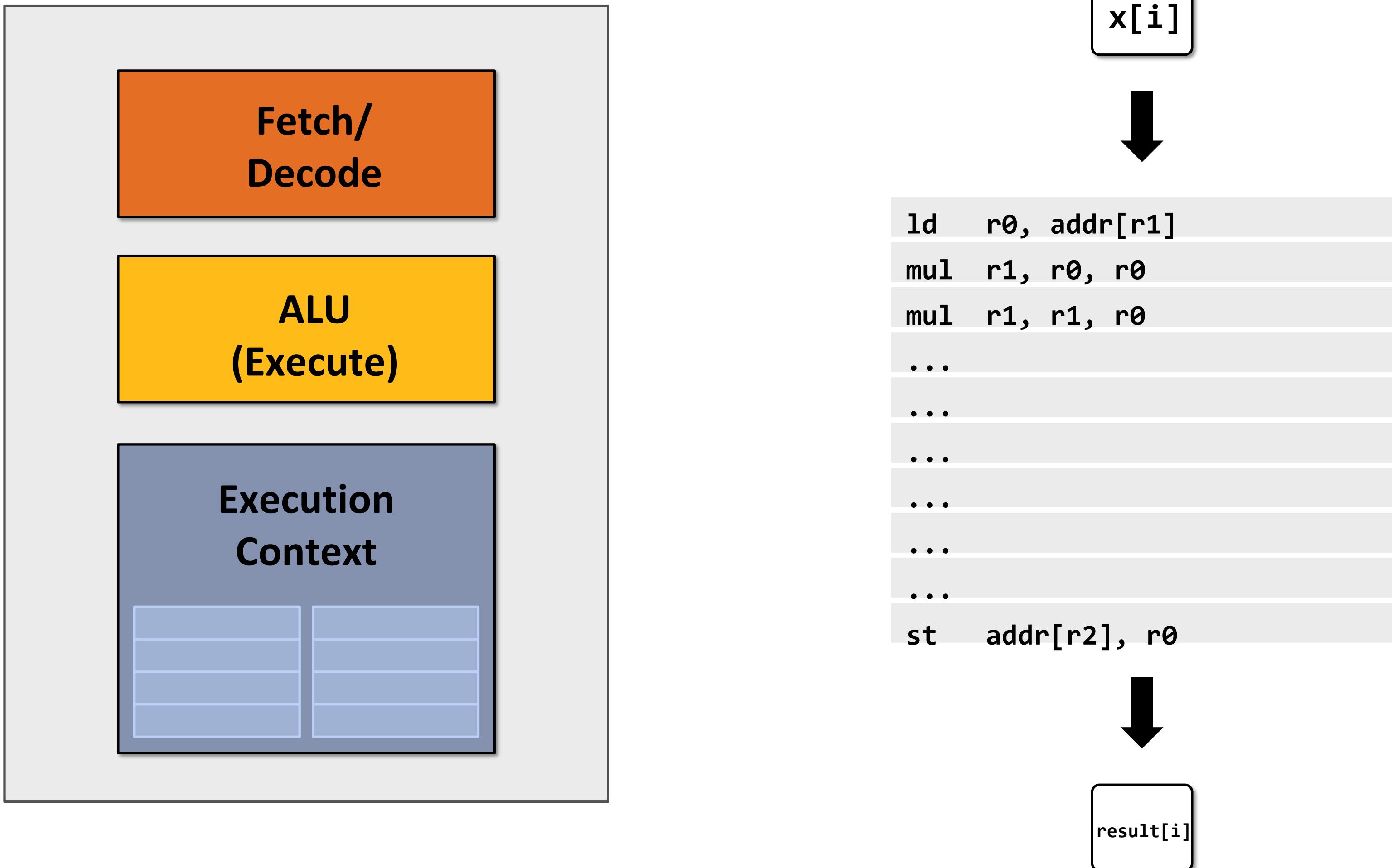
```
void sinx(int N, int terms, float* x, float* result)
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    for (int i=0; i<N; i++)
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        float value = x[i];
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        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom;
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

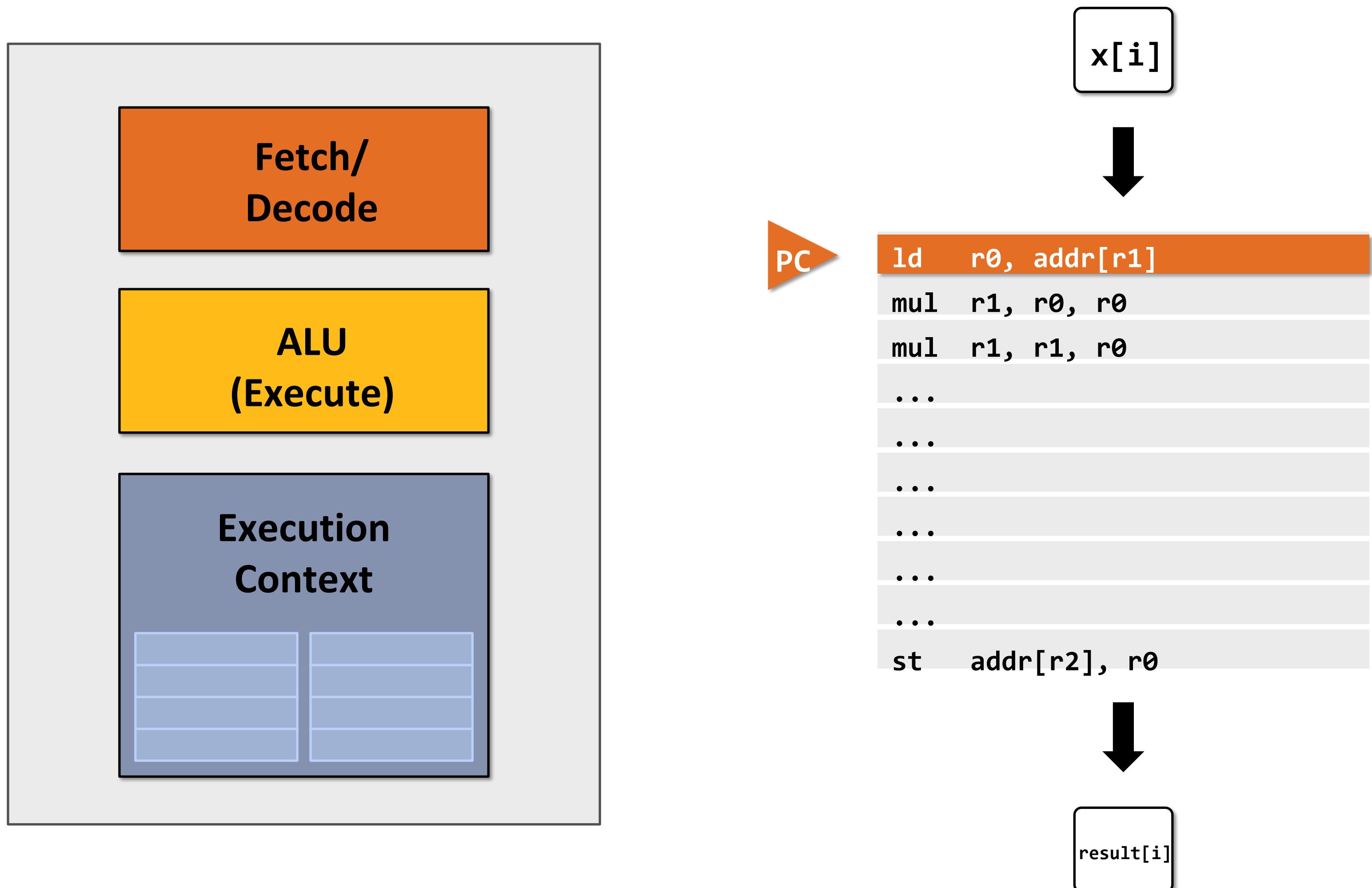


Execute program (on an idealized machine)



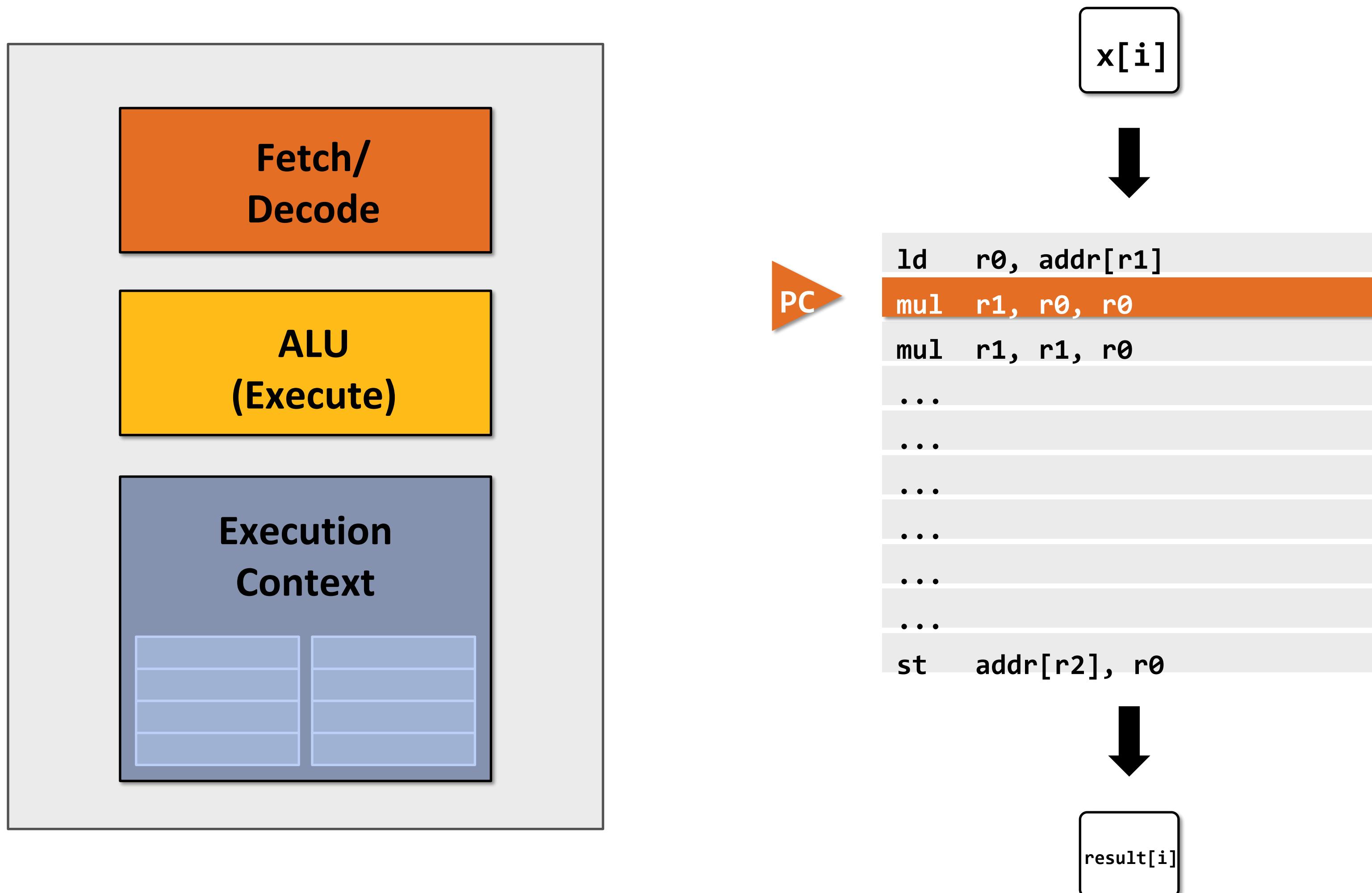
Execute program

My very simple processor: executes one instruction per clock



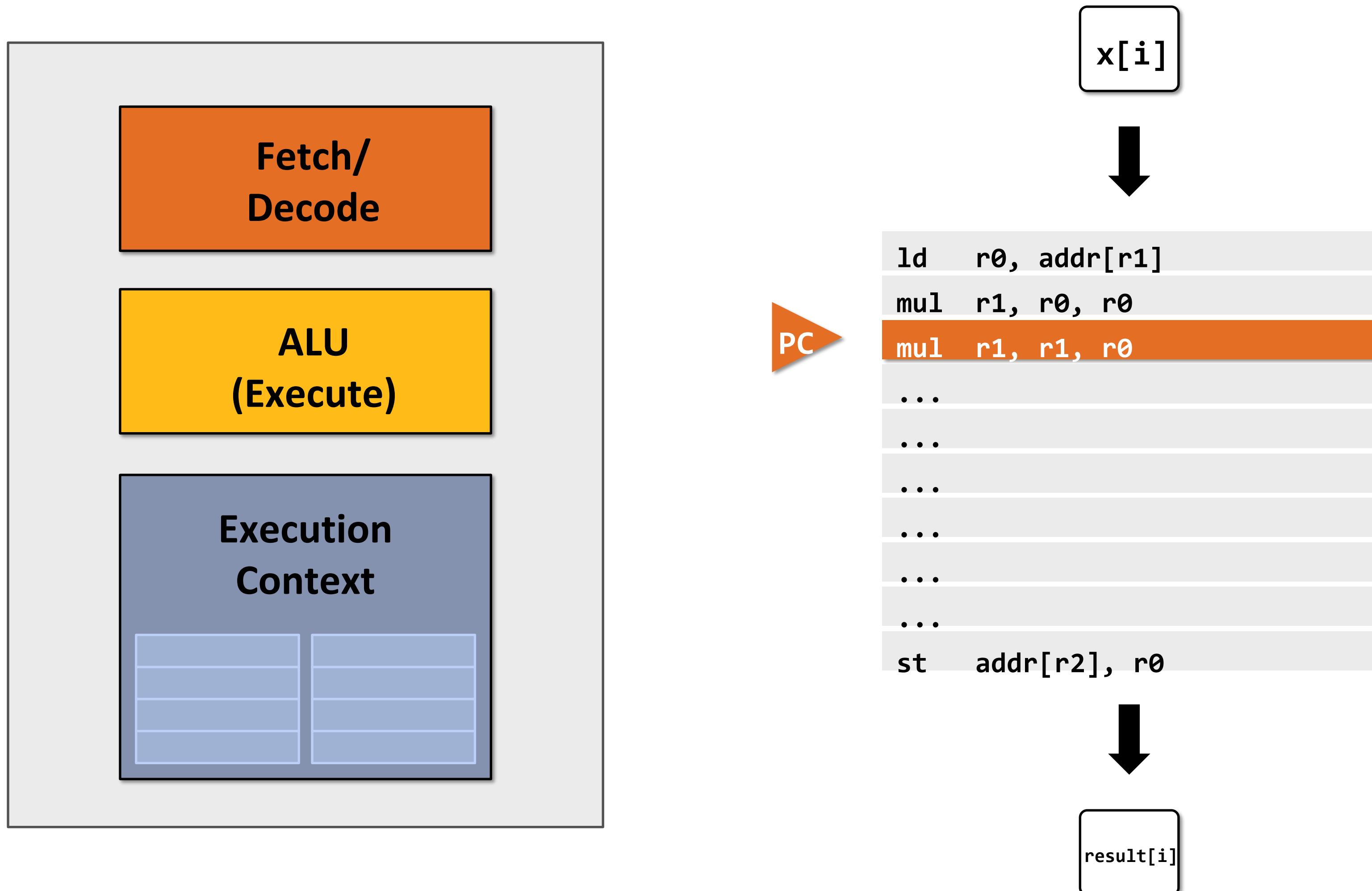
Execute program

My very simple processor: executes one instruction per clock



Execute program

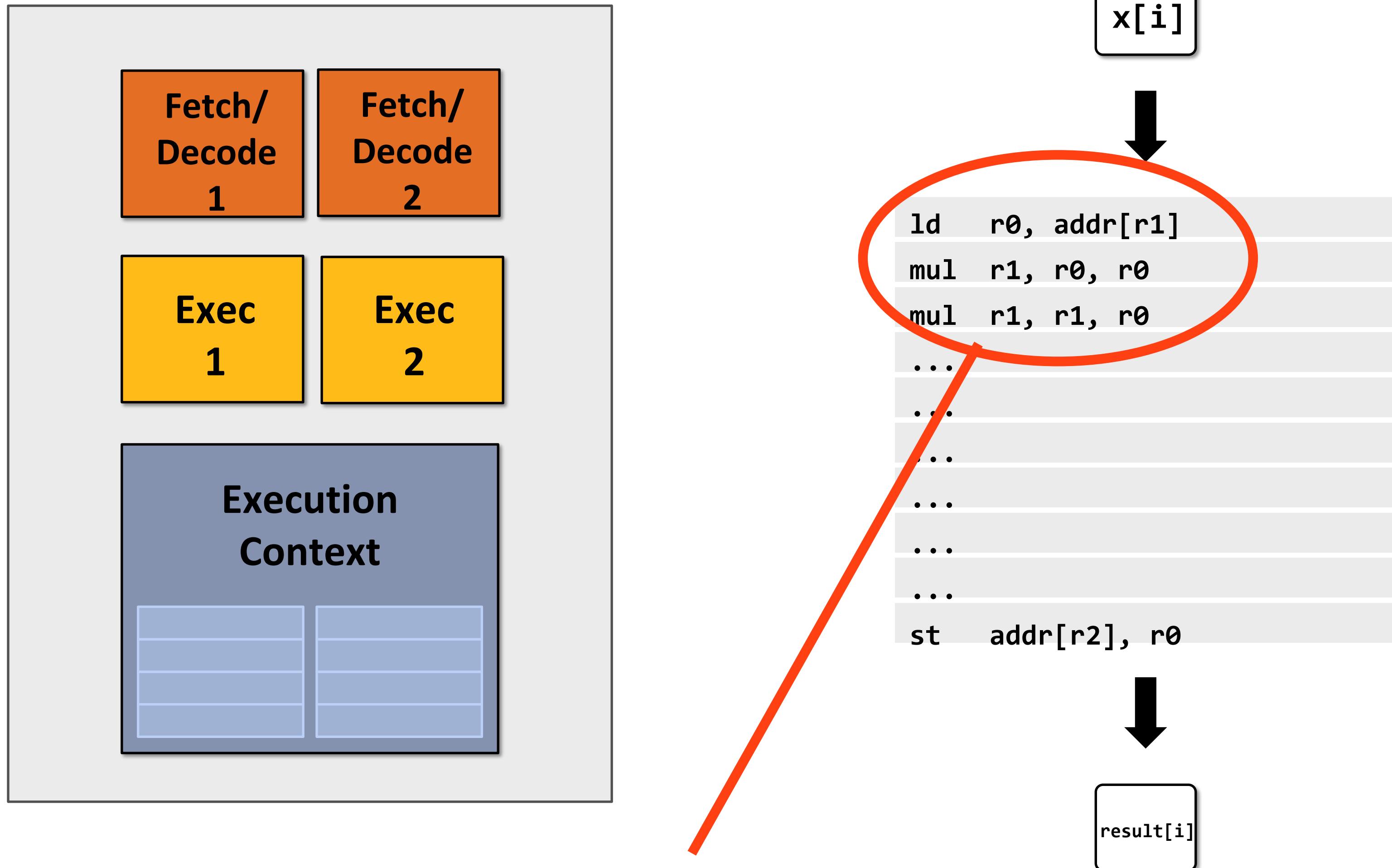
My very simple processor: executes one instruction per clock



Superscalar (in-order) processor

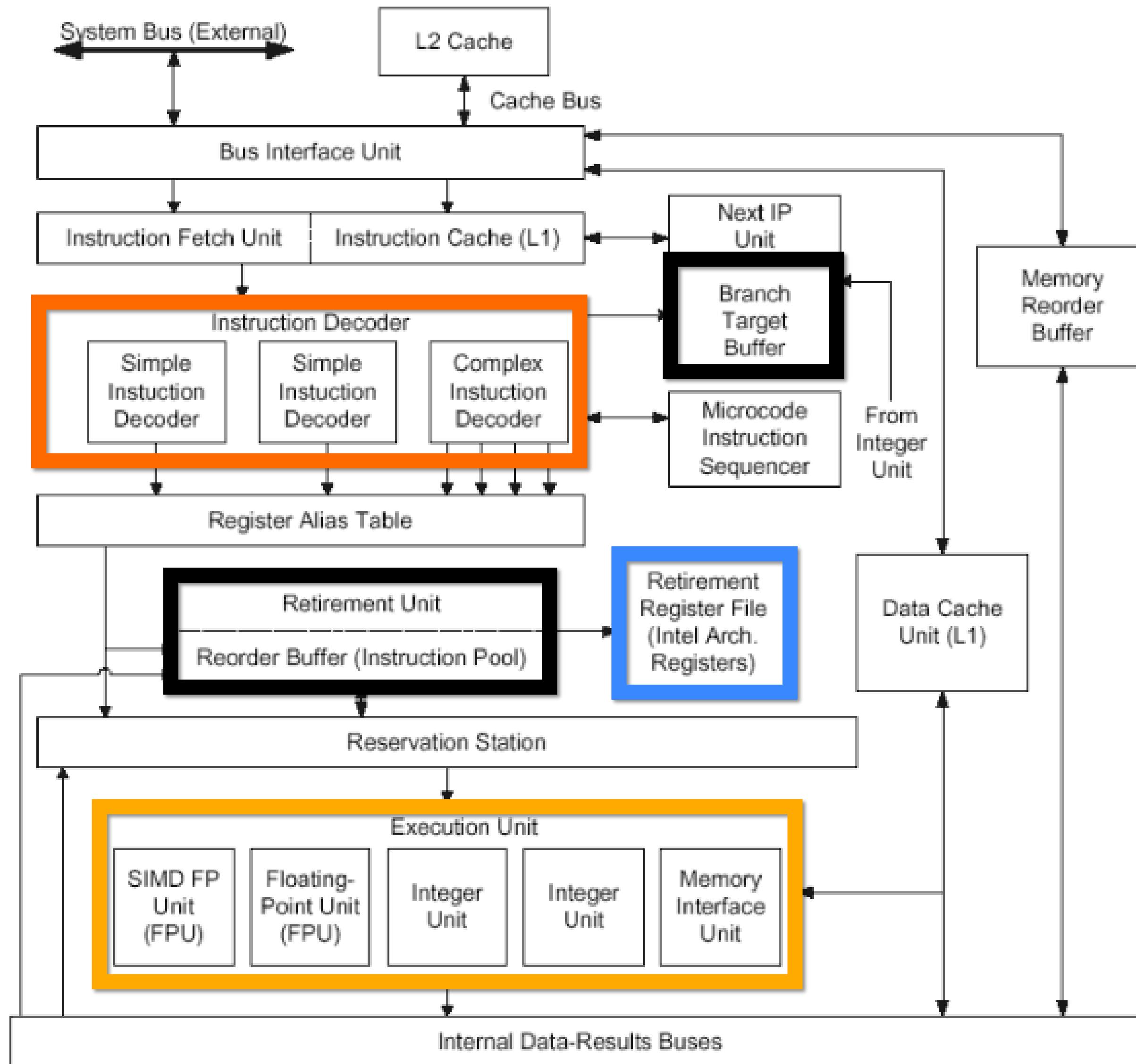
Recall from last class: instruction level parallelism (ILP)

Decode and execute two instructions per clock (if possible)



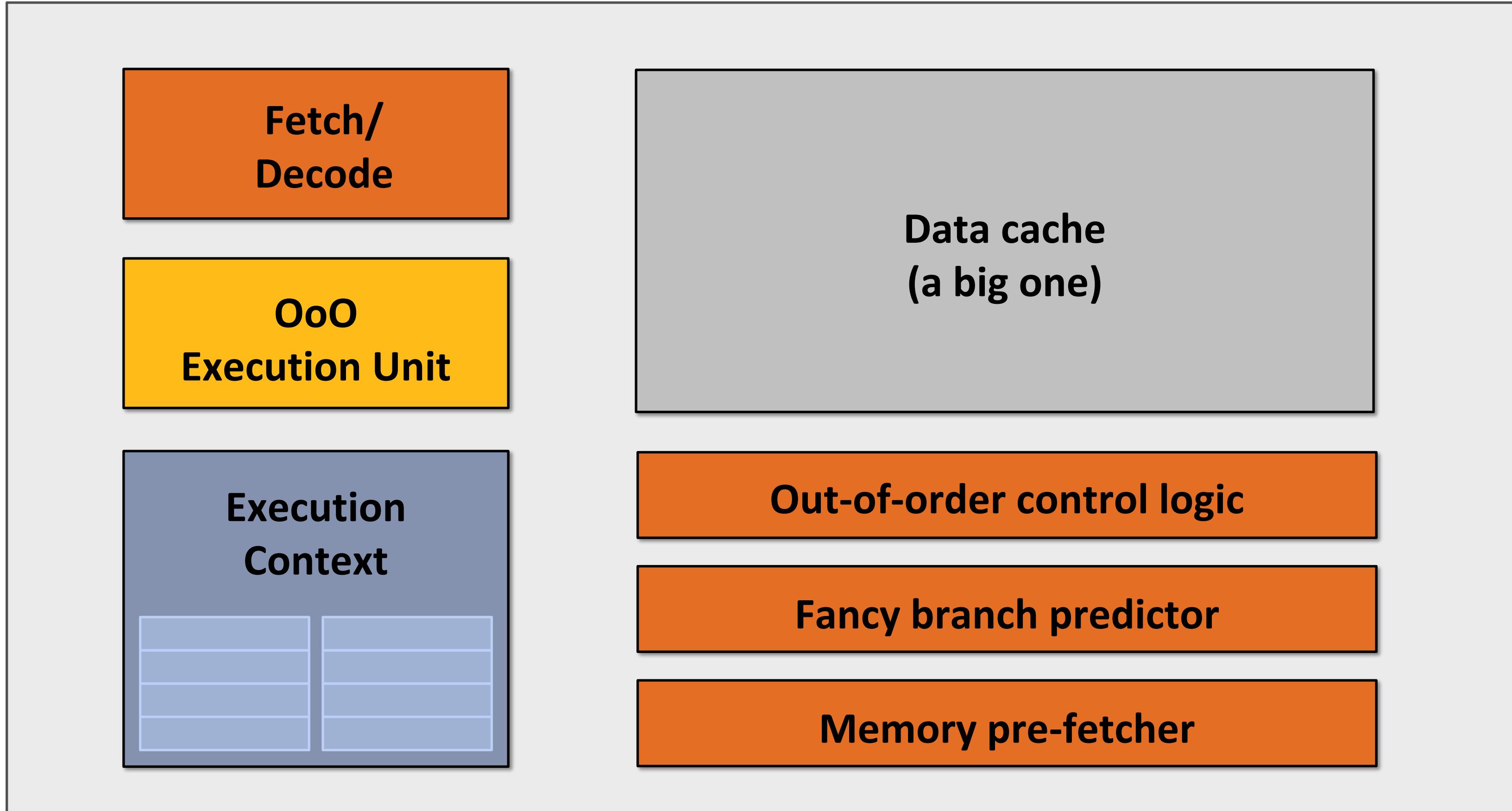
Note: No ILP exists in this region of the program

Aside: Pentium 4



Processor: pre multi-core era

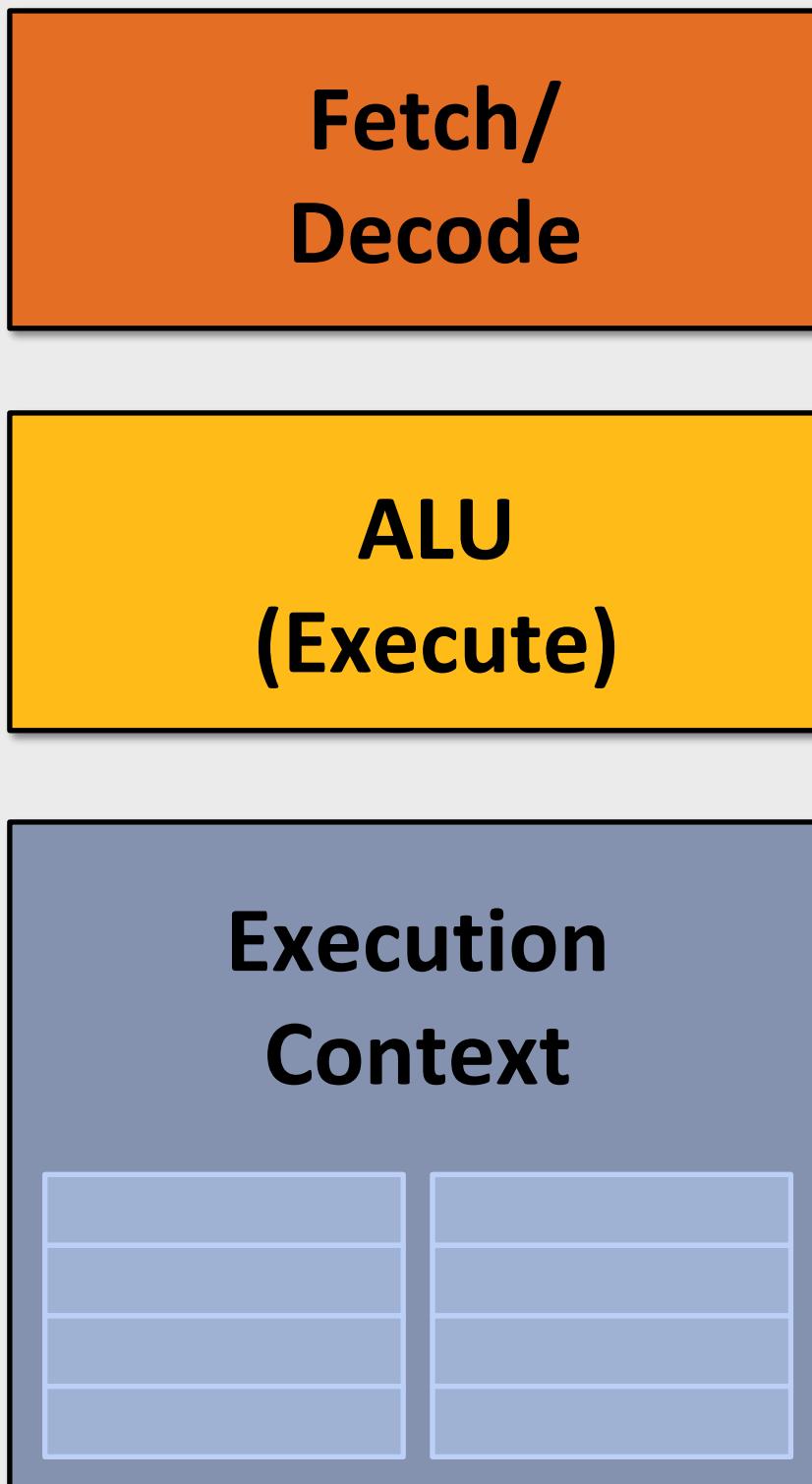
Majority of chip transistors used to perform operations that help a single instruction stream run fast



More transistors = larger cache, smarter out-of-order logic, smarter branch predictor, etc.

(Also: more transistors → smaller transistors → higher clock frequencies)

Processor: multi-core era

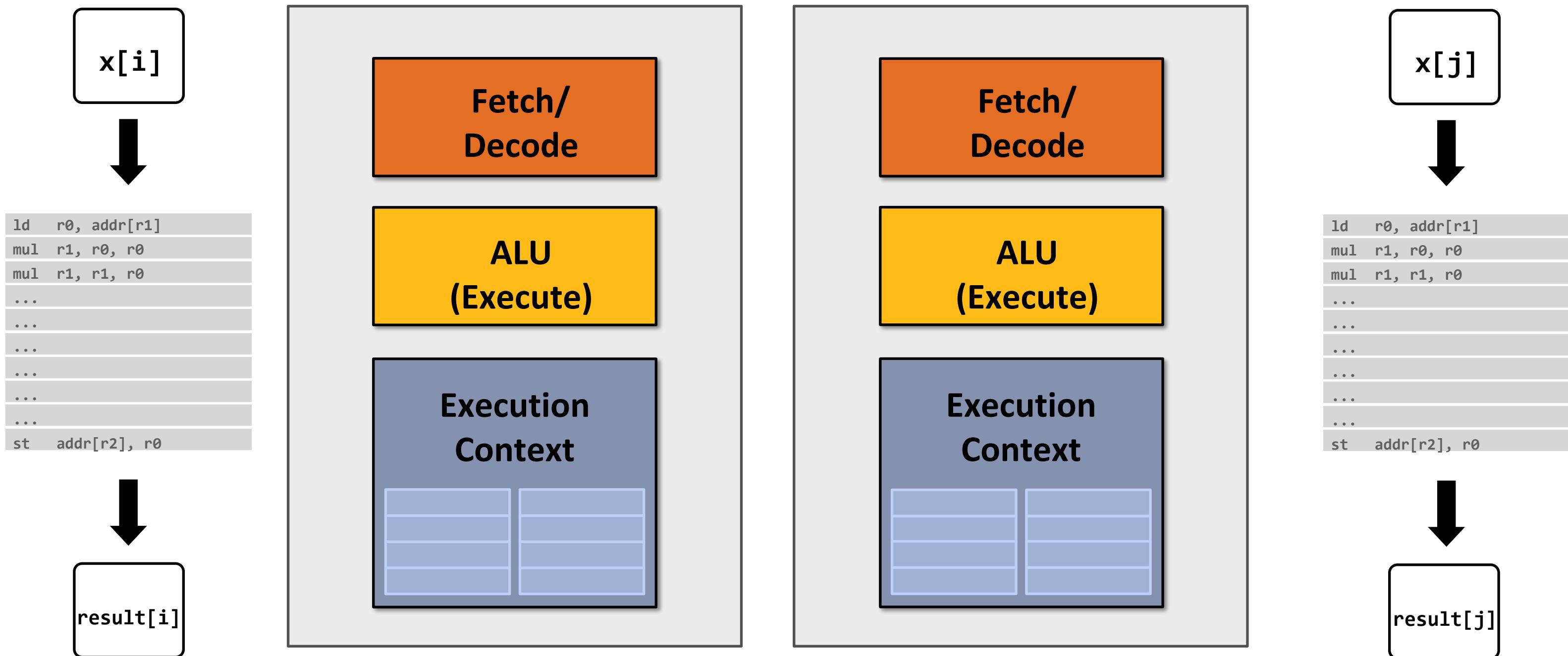


Idea #1:

Use increasing transistor count to add more cores to the processor

Rather than use transistors to increase sophistication of processor logic that accelerates a single instruction stream (e.g., out-of-order and speculative operations)

Two cores: compute two elements in parallel



Simpler cores: each core is slower at running a single instruction stream than our original “fancy” core (e.g., 25% slower)

But there are now two cores: $2 \times 0.75 = 1.5$ (potential for speedup!)

But our program expresses no parallelism!

```
void sinx(int N, int terms, float* x, float* result)
{
    for (int i=0; i<N; i++)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom;
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

This program, compiled with gcc will run as one thread on one of the processor cores.

If each of the simpler processor cores was 25% slower than the original single complicated one, our program now runs 25% slower. :-)

Expressing parallelism using pthreads

```
typedef struct {
    int N;
    int terms;
    float* x;
    float* result;
} my_args;

void parallel_sinx(int N, int terms, float* x, float* result)
{
    pthread_t thread_id;
    my_args args;

    args.N = N/2;
    args.terms = terms;
    args.x = x;
    args.result = result;

    pthread_create(&thread_id, NULL, my_thread_start, &args); // launch thread
    sinx(N - args.N, terms, x + args.N, result + args.N); // do work
    pthread_join(thread_id, NULL);
}

void my_thread_start(void* thread_arg)
{
    my_args* thread_args = (my_args*)thread_arg;
    sinx(args->N, args->terms, args->x, args->result); // do work
}
```

```
void sinx(int N, int terms, float* x, float* result)
{
    for (int i=0; i<N; i++)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

Child thread does first half of range
Main thread does second half

Data-parallel expression

(in our fictitious data-parallel language)

```
void sinx(int N, int terms, float* x, float* result)
{
    // declare independent loop iterations
    forall (int i from 0 to N-1)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

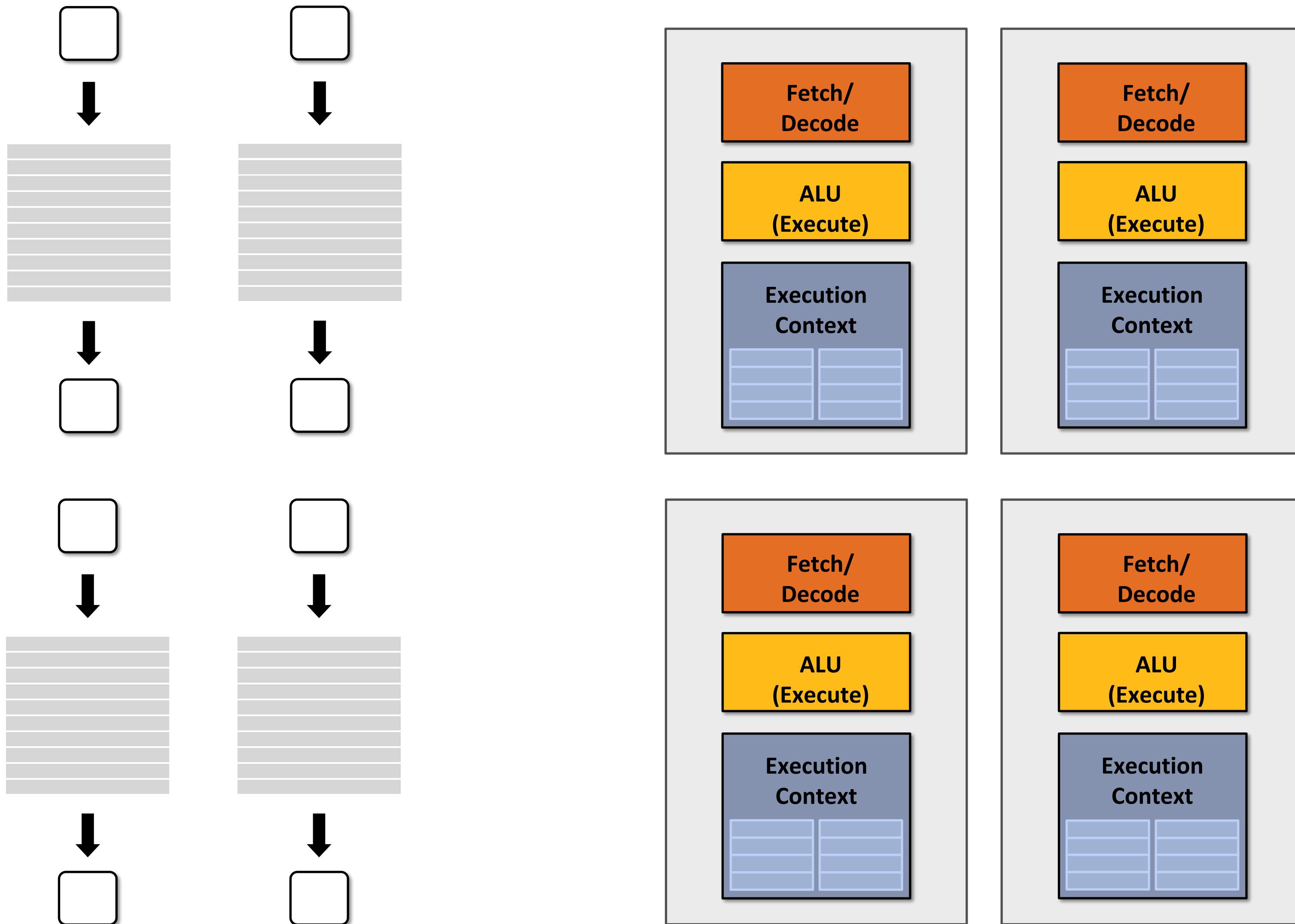
        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom;
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

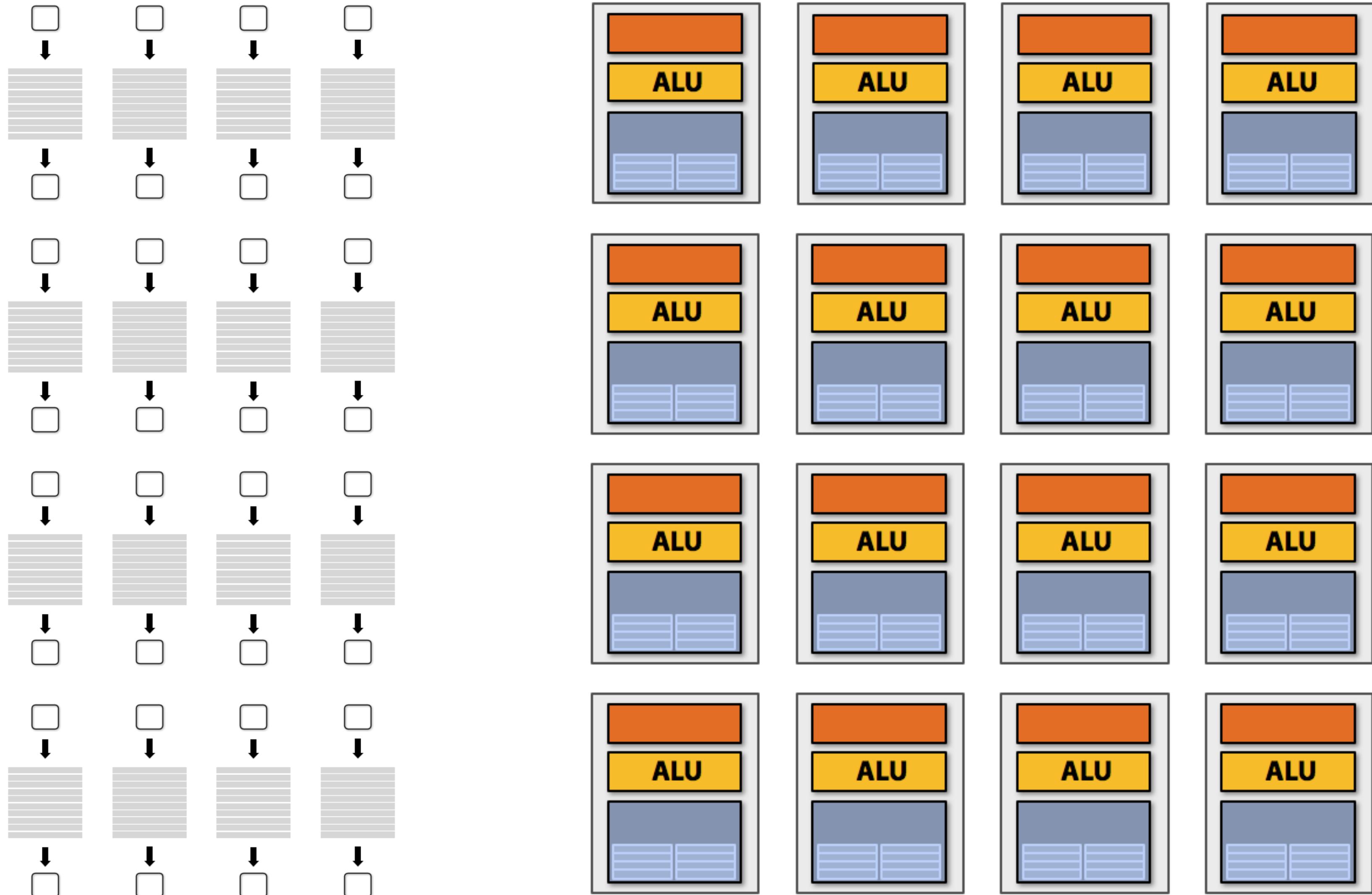
Loop iterations declared by the programmer to be independent

With this information, you could imagine how a compiler might automatically generate parallel threaded code

Four cores: compute four elements in parallel

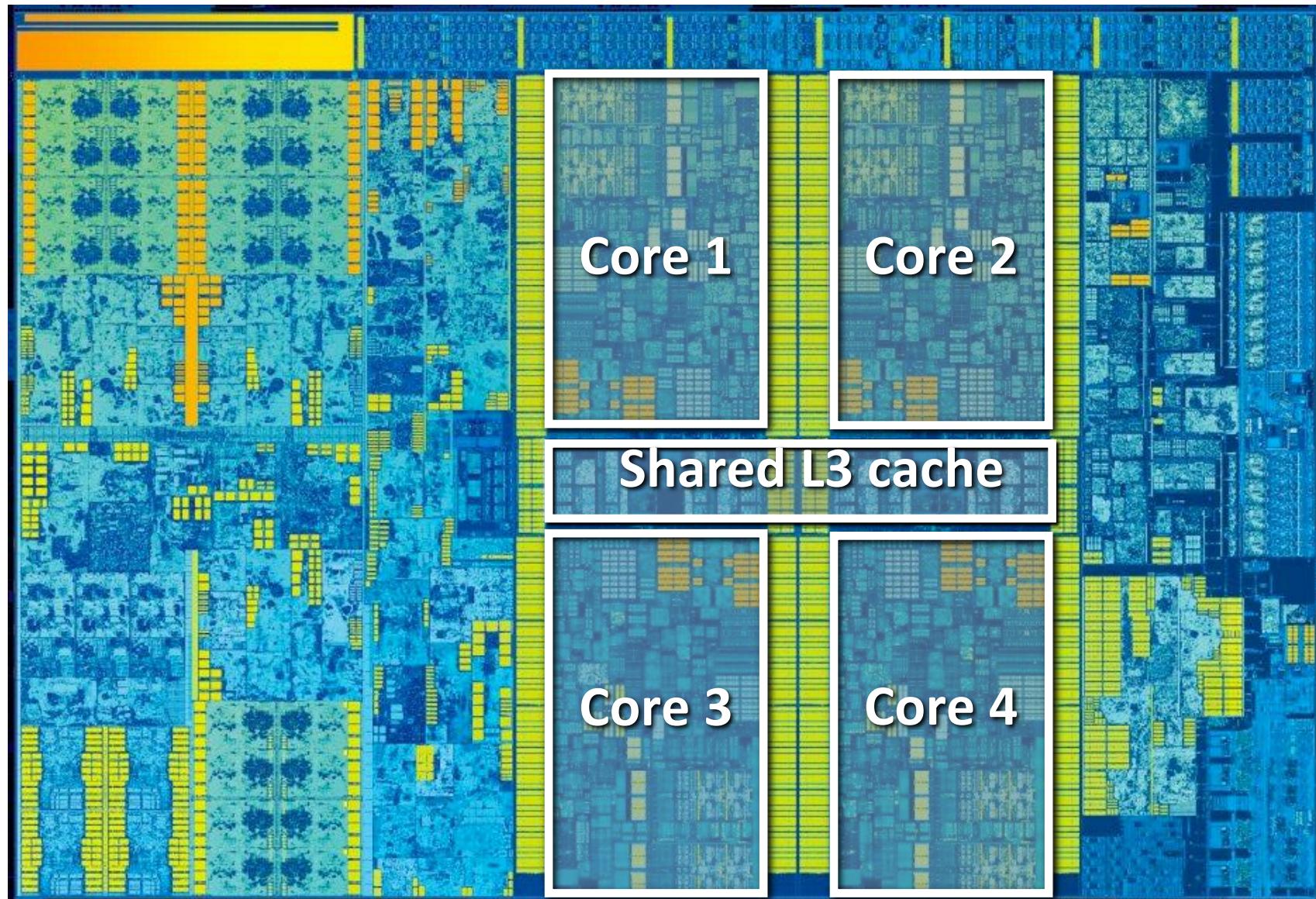


Sixteen cores: compute sixteen elements in parallel



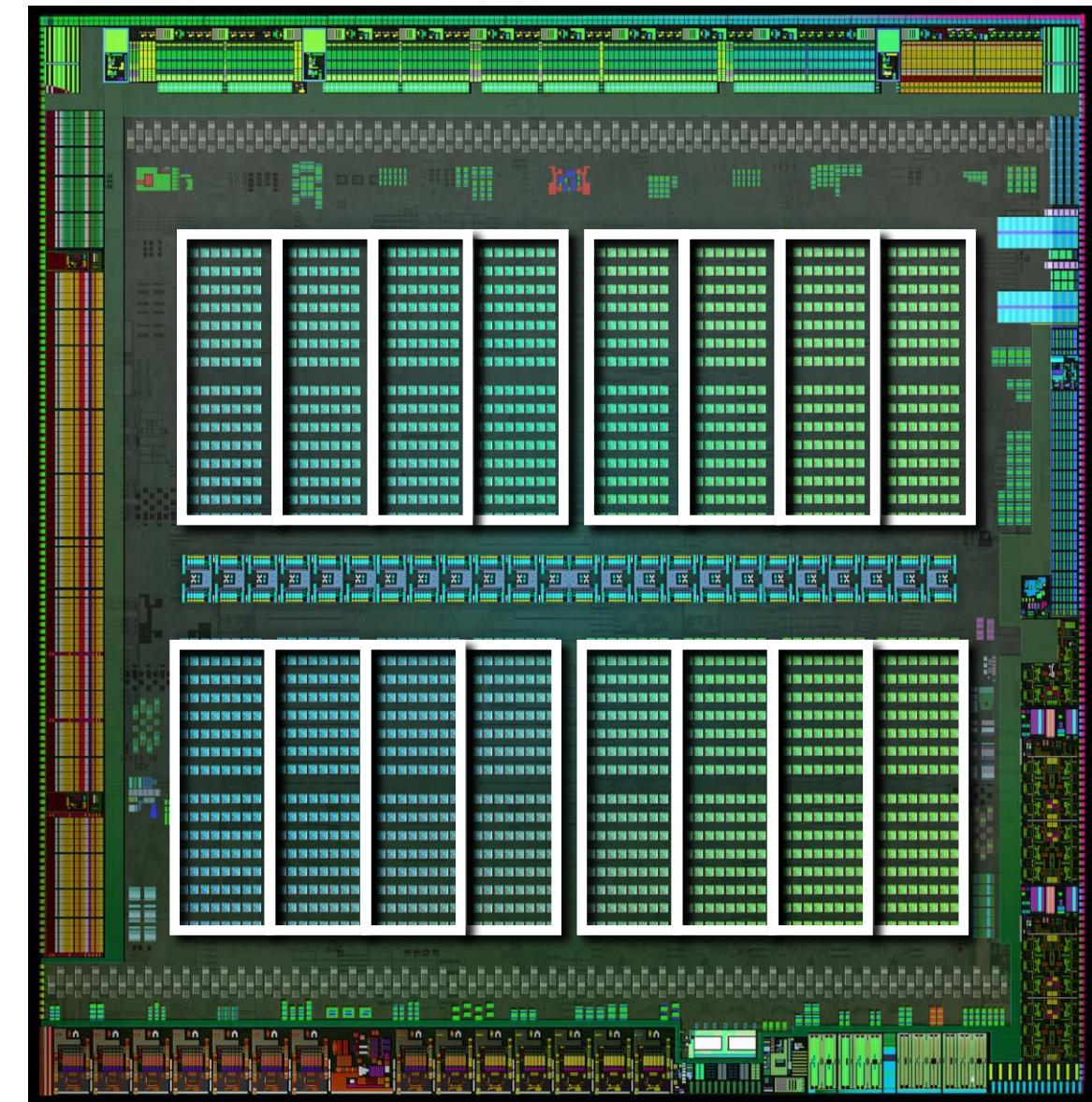
Sixteen cores, sixteen simultaneous instruction streams

Multi-core examples



Intel “Skylake” Core i7 quad-core CPU
(2015)

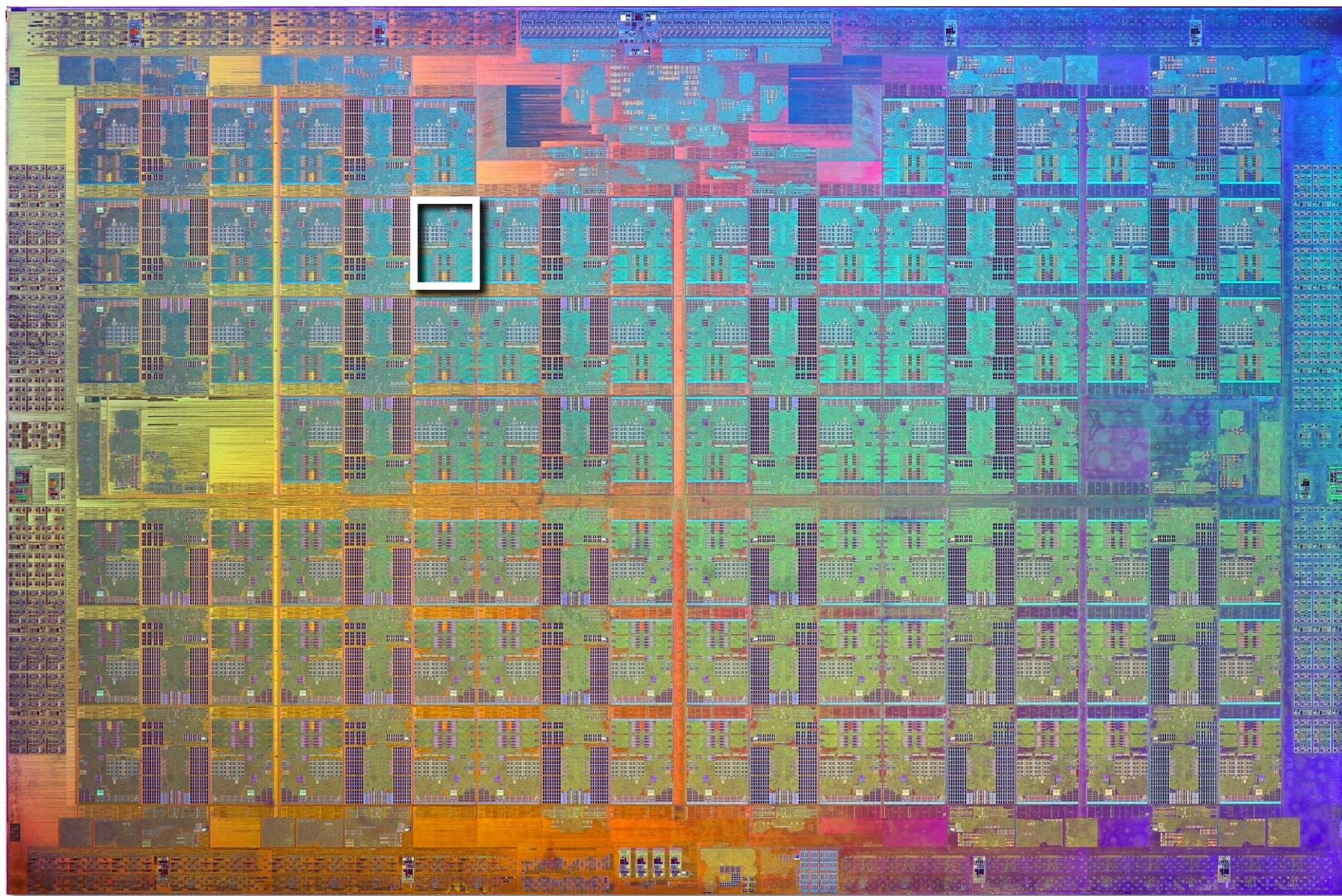
Each core is sophisticated, out-of-order processor to maximize ILP



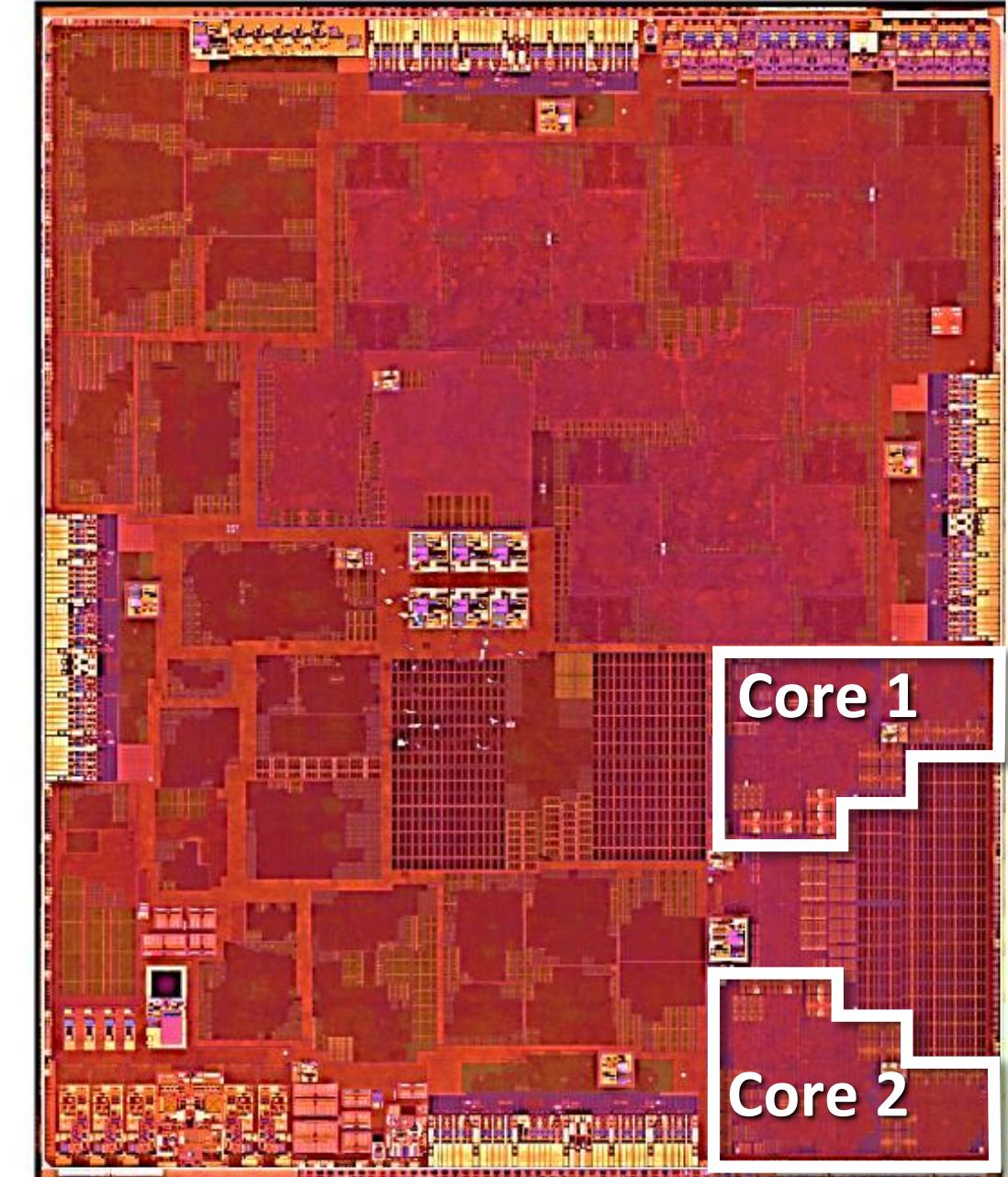
NVIDIA GTX 980 GPU
16 replicated processing cores (“SM”)
(2014)

Each core processes vectors of data

More multi-core examples



Intel Xeon Phi "Knights Landing" 76-core CPU
(2015)



Apple A9 dual-core CPU
(2015)

Data-parallel expression

(in our fictitious data-parallel language)

```
void sinx(int N, int terms, float* x, float* result)
{
    // declare independent loop iterations
    forall (int i from 0 to N-1)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6;    // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom;
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

Another interesting property of this code:

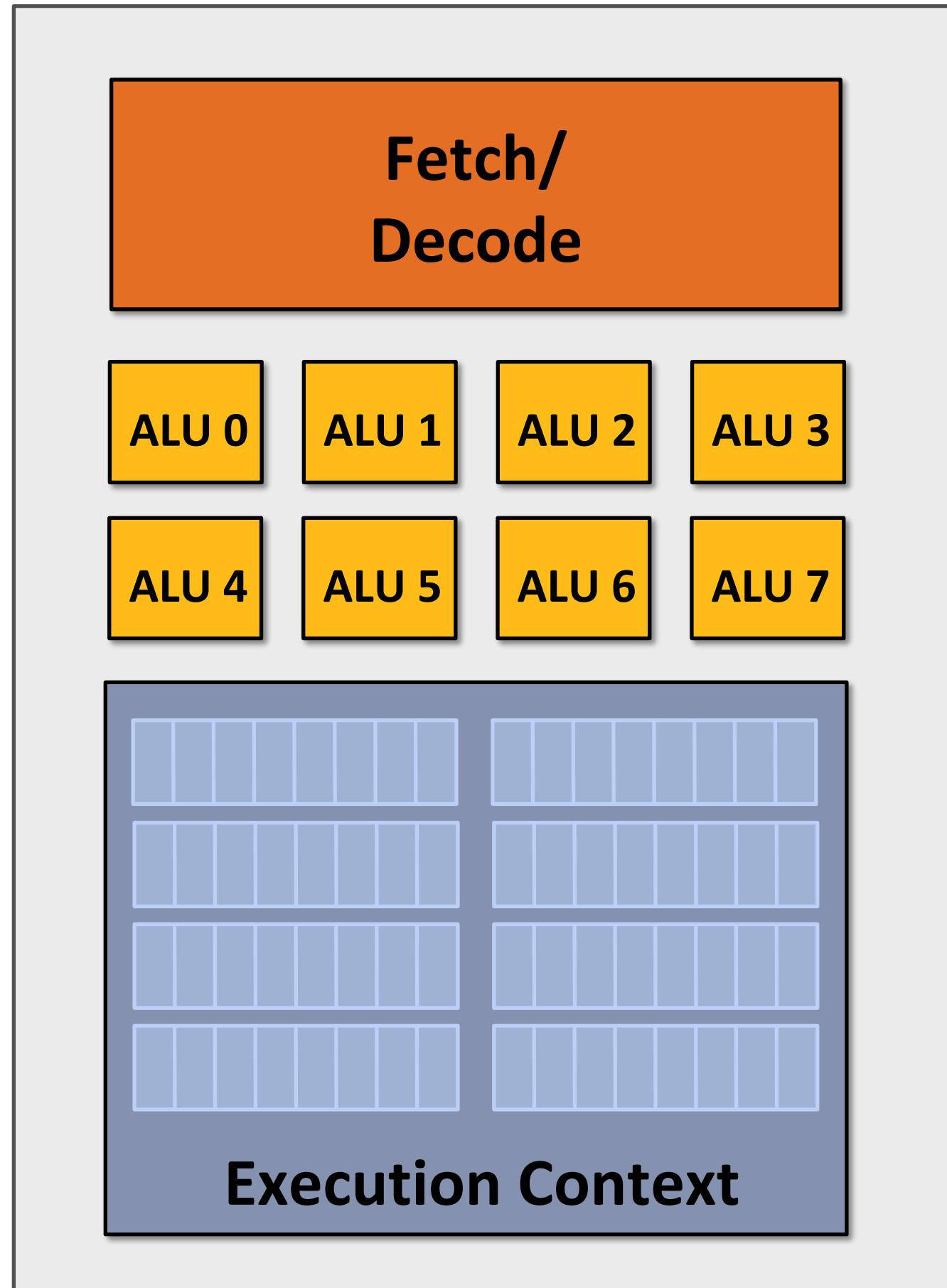
Parallelism is across iterations of the loop.

All the iterations of the main loop do the same thing: compute the sine of a single input number

The inner loop is executed the same number of times every time

There are no conditionals

Add ALUs to increase compute capability

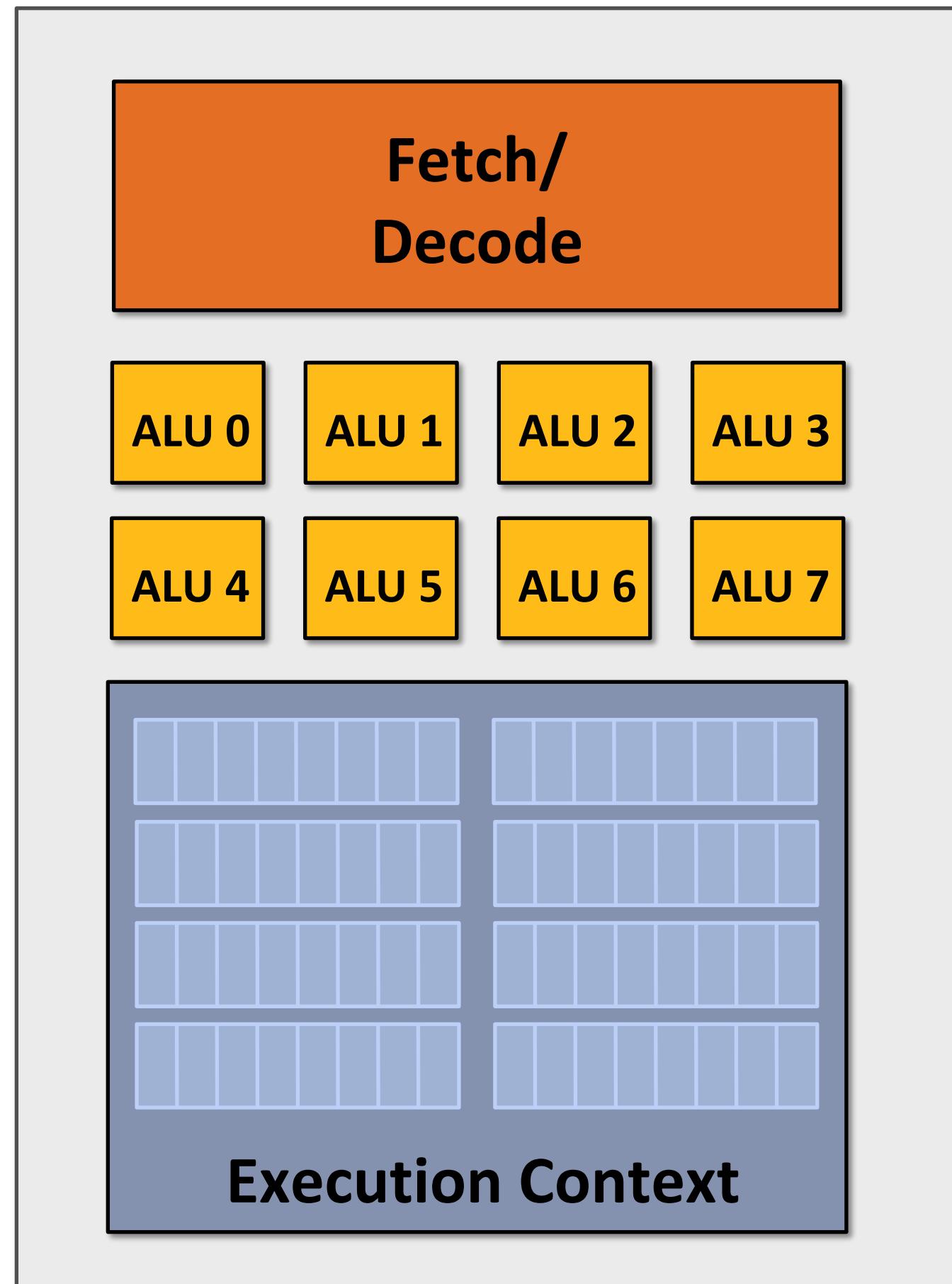


Idea #2:
Amortize cost/complexity of managing an instruction stream across many ALUs

SIMD processing
Single instruction, multiple data

Same instruction broadcast to all ALUs
Executed in parallel on all ALUs

Add ALUs to increase compute capability



```
ld  r0, addr[r1]
mul r1, r0, r0
mul r1, r1, r0
...
...
...
...
...
...
...
...
...
st  addr[r2], r0
```

**Recall original compiled program:
Instruction stream processes one array
element at a time using scalar
instructions on scalar registers (e.g., 32-
bit floats)**

Scalar program

```
void sinx(int N, int terms, float* x, float* result)
{
    for (int i=0; i<N; i++)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom;
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

Original compiled program:

Processes one array element using scalar instructions on scalar registers (e.g., 32-bit floats)

| | |
|-----|--------------|
| ld | r0, addr[r1] |
| mul | r1, r0, r0 |
| mul | r1, r1, r0 |
| ... | |
| ... | |
| ... | |
| ... | |
| ... | |
| ... | |
| ... | |
| st | addr[r2], r0 |

Vector program (using AVX intrinsics)

```
#include <immintrin.h>

void sinx(int N, int terms, float* x, float* result)
{
    float three_fact = 6; // 3!
    for (int i=0; i<N; i+=8)
    {
        __m256 origx = _mm256_load_ps(&x[i]);
        __m256 value = origx;
        __m256 numer = _mm256_mul_ps(origx, _mm256_mul_ps(origx, origx));
        __m256 denom = _mm256_set1ps(three_fact);
        float sign = -1;

        for (int j=1; j<=terms; j++)
        {
            // value += sign * numer / denom
            __m256 tmp = _mm256_div_ps(_mm256_mul_ps(_mm256_set1ps(sign), numer), denom);
            value = _mm256_add_ps(value, tmp);

            numer = _mm256_mul_ps(numer, _mm256_mul_ps(origx, origx));
            denom = _mm256_mul_ps(denom, _mm256_set1ps((2*j+2) * (2*j+3)));
            sign *= -1;
        }
        _mm256_store_ps(&result[i], value);
    }
}
```

Intrinsics available to C programmers

Vector program (using AVX intrinsics)

```
#include <immintrin.h>

void sinx(int N, int terms, float* x, float* result)
{
    float three_fact = 6; // 3!
    for (int i=0; i<N; i+=8)
    {
        __m256 origx = _mm256_load_ps(&x[i]);
        __m256 value = origx;
        __m256 numer = _mm256_mul_ps(origx, _mm256_mul_ps(origx, origx));
        __m256 denom = _mm256_set1ps(three_fact);
        float sign = -1;

        for (int j=1; j<=terms; j++)
        {
            // value += sign * numer / denom
            __m256 tmp = _mm256_div_ps(_mm256_mul_ps(_mm256_set1ps(sign), numer), denom);
            value = _mm256_add_ps(value, tmp);

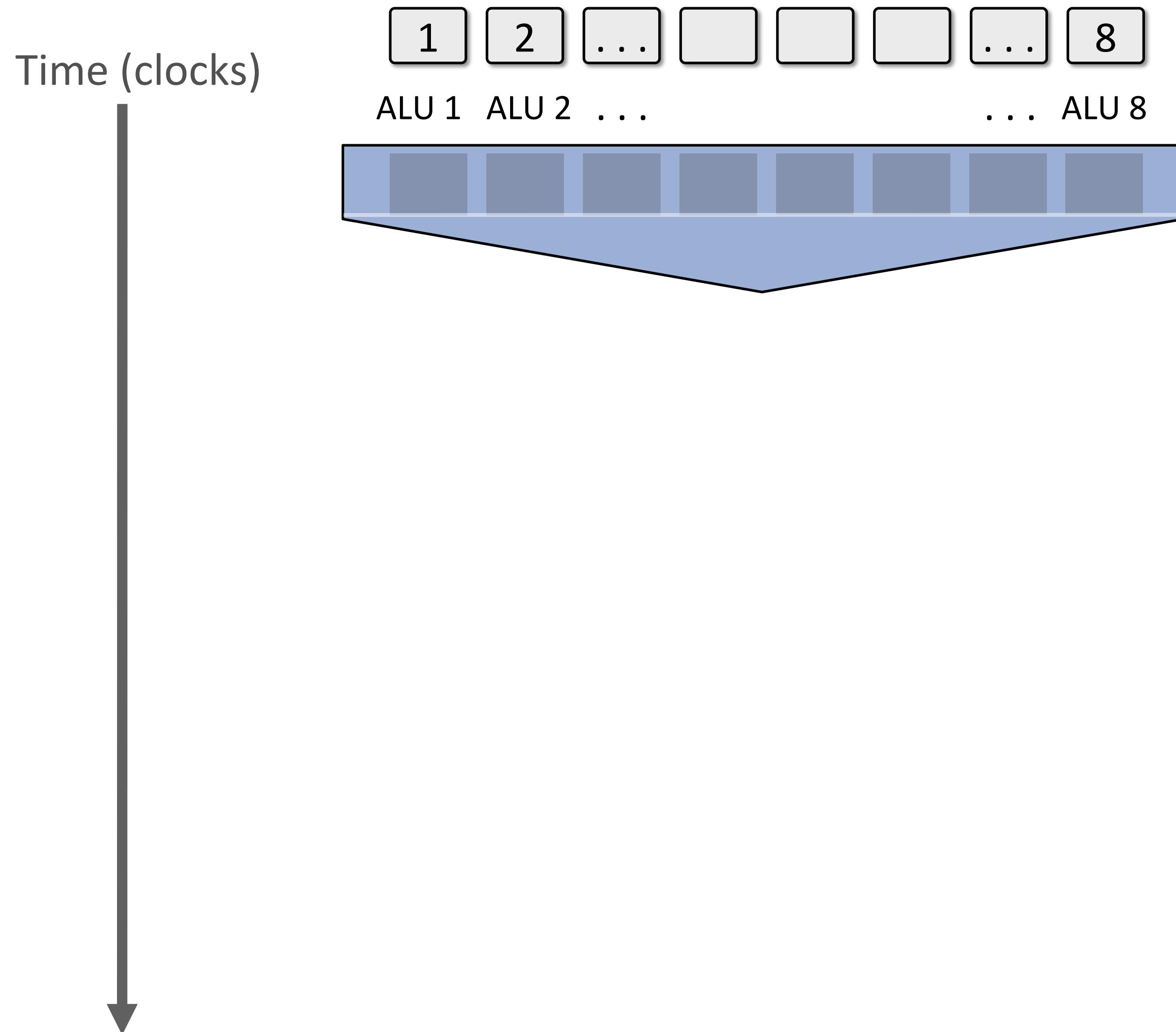
            numer = _mm256_mul_ps(numer, _mm256_mul_ps(origx, origx));
            denom = _mm256_mul_ps(denom, _mm256_set1ps((2*j+2) * (2*j+3)));
            sign *= -1;
        }
        _mm256_store_ps(&result[i], value);
    }
}
```

```
vloadps  xmm0, addr[r1]
vmulps   xmm1, xmm0, xmm0
vmulps   xmm1, xmm1, xmm0
...
...
...
...
...
...
...
...
vstoreps addr[xmm2], xmm0
```

Compiled program:
Processes eight array elements simultaneously using vector instructions on 256-bit vector registers

$$256 = 8 * 32$$

What about conditional execution?



(assume logic below is to be executed for each element in input array 'A', producing output into the array 'result')

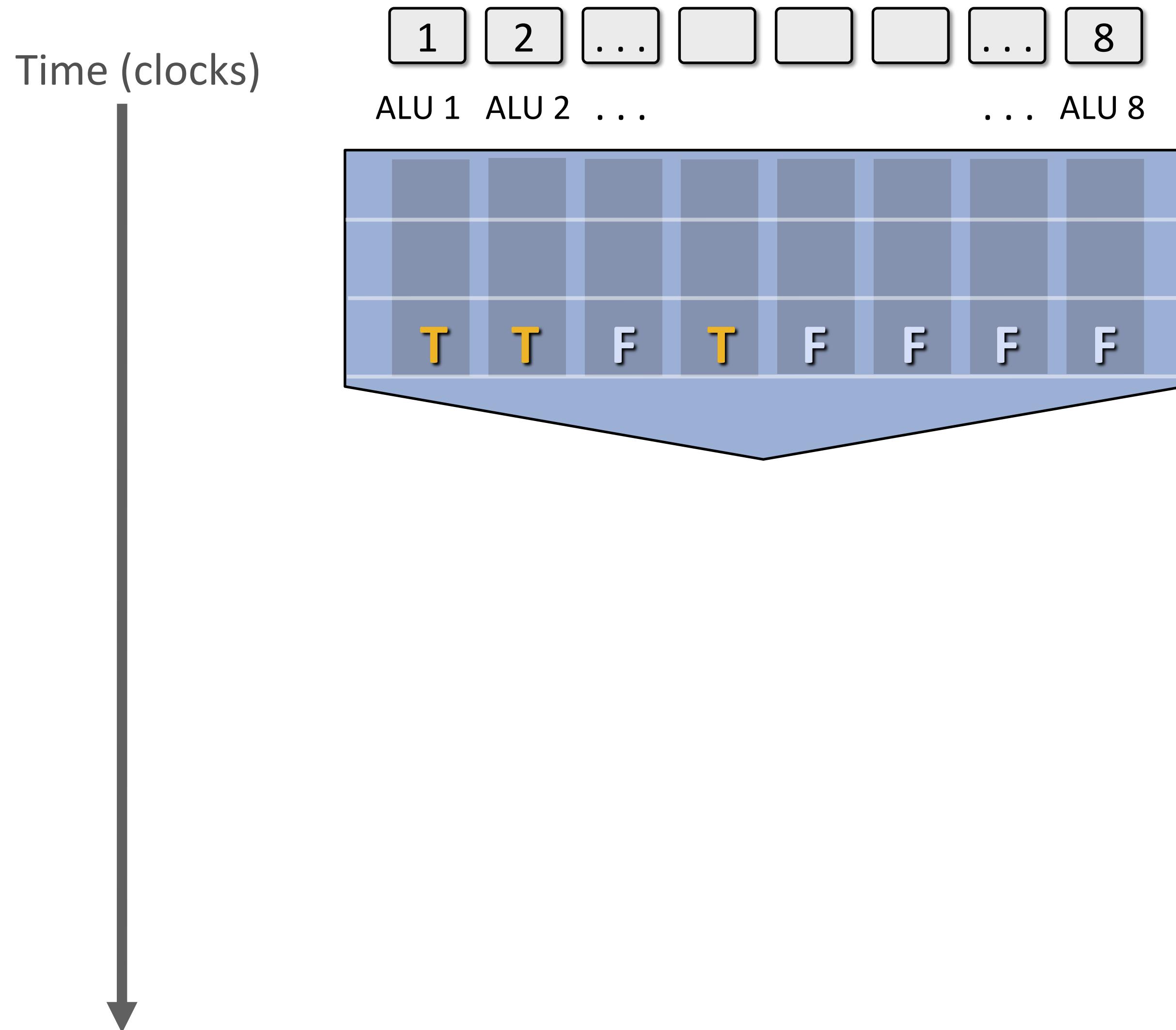
<unconditional code>

```
float x = A[i];  
  
if (x > 0) {  
  
    float tmp = exp(x,5.f);  
  
    tmp *= kMyConst1;  
  
    x = tmp + kMyConst2;  
} else {  
  
    float tmp = kMyConst1;  
  
    x = 2.f * tmp;  
}
```

<resume unconditional code>

```
result[i] = x;
```

What about conditional execution?



(assume logic below is to be executed for each element in input array 'A', producing output into the array 'result')

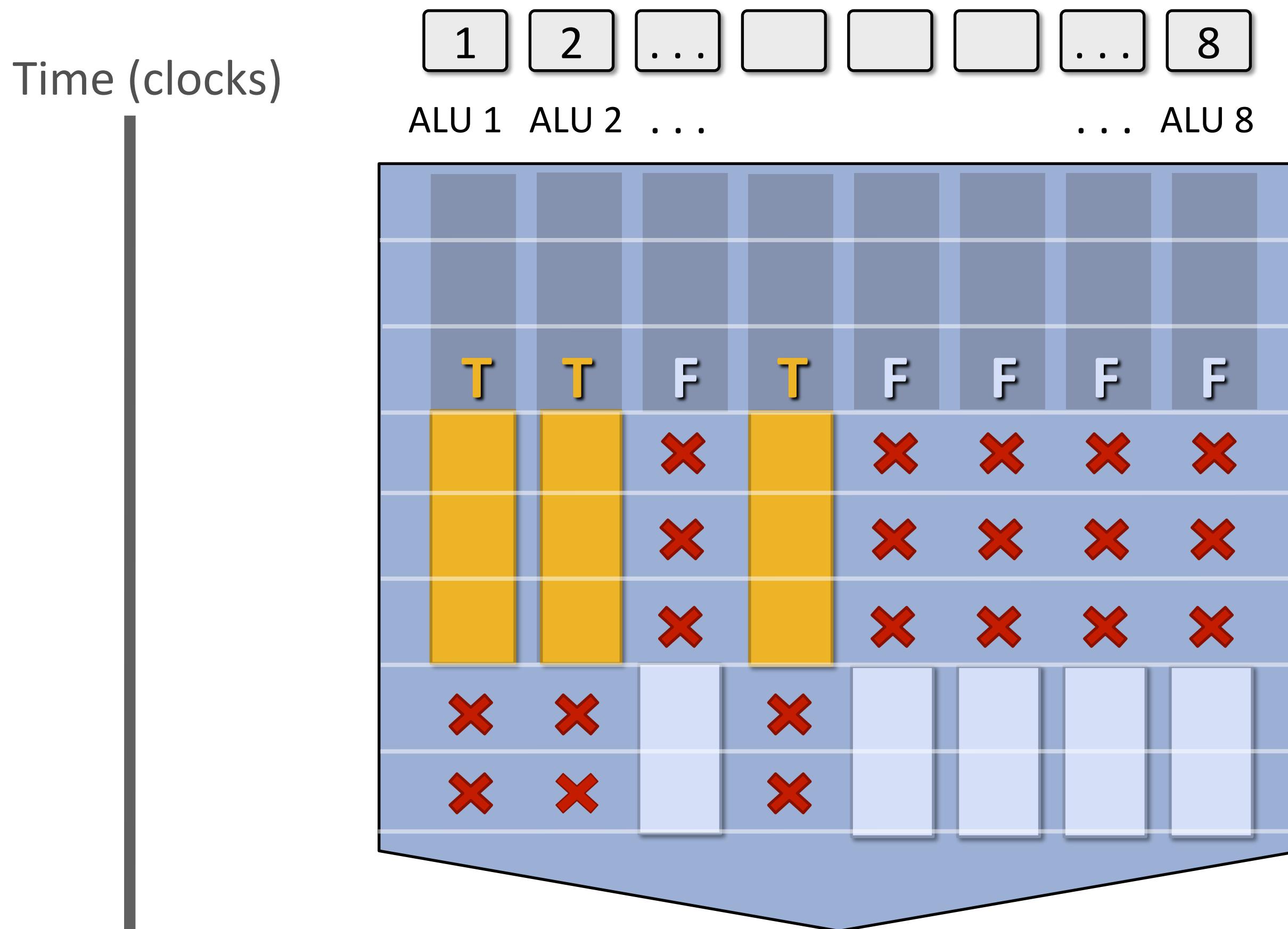
<unconditional code>

```
float x = A[i];  
  
if (x > 0) {  
  
    float tmp = exp(x,5.f);  
  
    tmp *= kMyConst1;  
  
    x = tmp + kMyConst2;  
} else {  
    float tmp = kMyConst1;  
  
    x = 2.f * tmp;  
}
```

<resume unconditional code>

```
result[i] = x;
```

Mask (discard) output of ALU



Not all ALUs do useful work!

Worst case: 1/8 peak performance

(assume logic below is to be executed for each element in input array 'A', producing output into the array 'result')

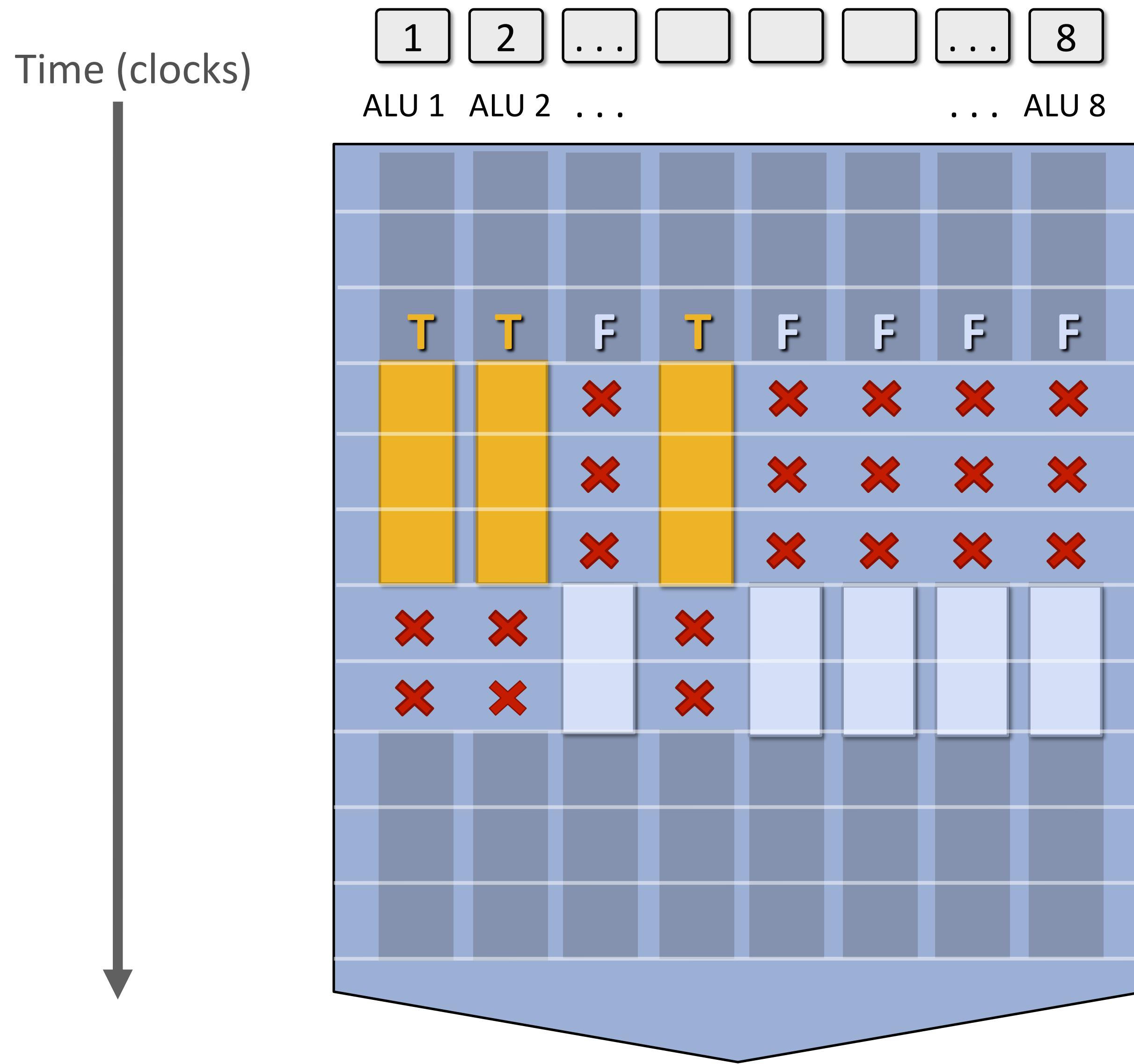
<unconditional code>

```
float x = A[i];  
  
if (x > 0) {  
    float tmp = exp(x,5.f);  
    tmp *= kMyConst1;  
    x = tmp + kMyConst2;  
} else {  
    float tmp = kMyConst1;  
    x = 2.f * tmp;  
}
```

<resume unconditional code>

```
result[i] = x;
```

After branch: continue at full performance



(assume logic below is to be executed for each element in input array 'A', producing output into the array 'result')

<unconditional code>

```
float x = A[i];  
  
if (x > 0) {  
    float tmp = exp(x,5.f);  
    tmp *= kMyConst1;  
    x = tmp + kMyConst2;  
} else {  
    float tmp = kMyConst1;  
    x = 2.f * tmp;  
}
```

<resume unconditional code>

```
result[i] = x;
```

Terminology

- **Instruction stream coherence (“coherent execution”)**
 - Same instruction sequence applies to all elements operated upon simultaneously
 - Coherent execution is necessary for efficient use of SIMD processing resources
 - Coherent execution IS NOT necessary for efficient parallelization across cores, since each core has the capability to fetch/decode a different instruction stream
- **“Divergent” execution**
 - A lack of instruction stream coherence
- **Warning: don’t confuse instruction stream coherence with “cache coherence” (a major topic later in the course)**

SIMD execution on modern CPUs

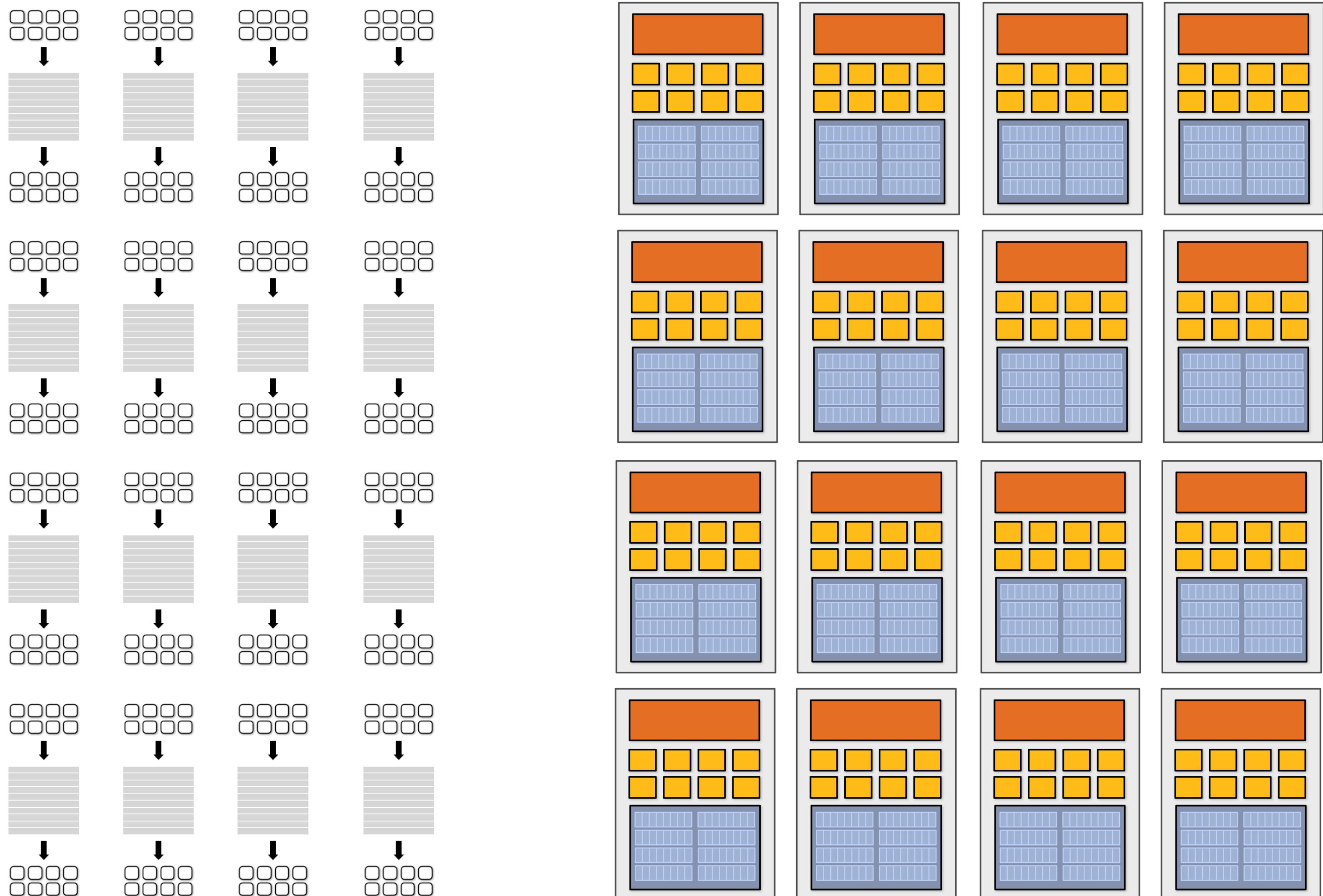
- SSE instructions: 128-bit operations: 4x32 bits or 2x64 bits (4-wide float vectors)
- AVX instructions: 256-bit operations: 8x32 bits or 4x64 bits (8-wide float vectors)
- AVX512 instructions: 512-bit ops: 16x32 bits or 8x64 bits (16-wide float vectors)
- Instructions are generated by the compiler
 - Parallelism explicitly requested by programmer using intrinsics
 - Parallelism conveyed using parallel language semantics (e.g., `forall` example)
 - Parallelism inferred by dependency analysis of loops (hard problem, even best compilers are not great on arbitrary C/C++ code)
- Terminology: “explicit SIMD”: SIMD parallelization is performed at compile time
 - Can inspect program binary and see instructions (`vstoreps`, `vmulps`, etc.)

SIMD execution on many modern GPUs

- “Implicit SIMD”
 - Compiler generates a scalar binary (scalar instructions)
 - But N instances of the program are *always run together on the processor*

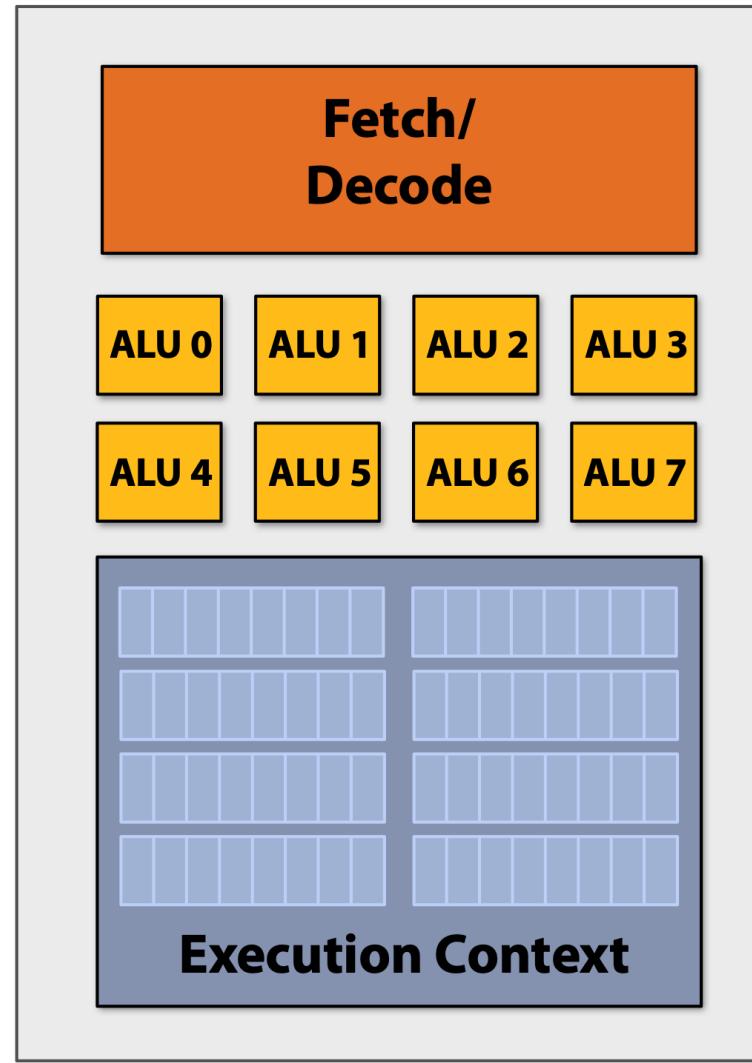
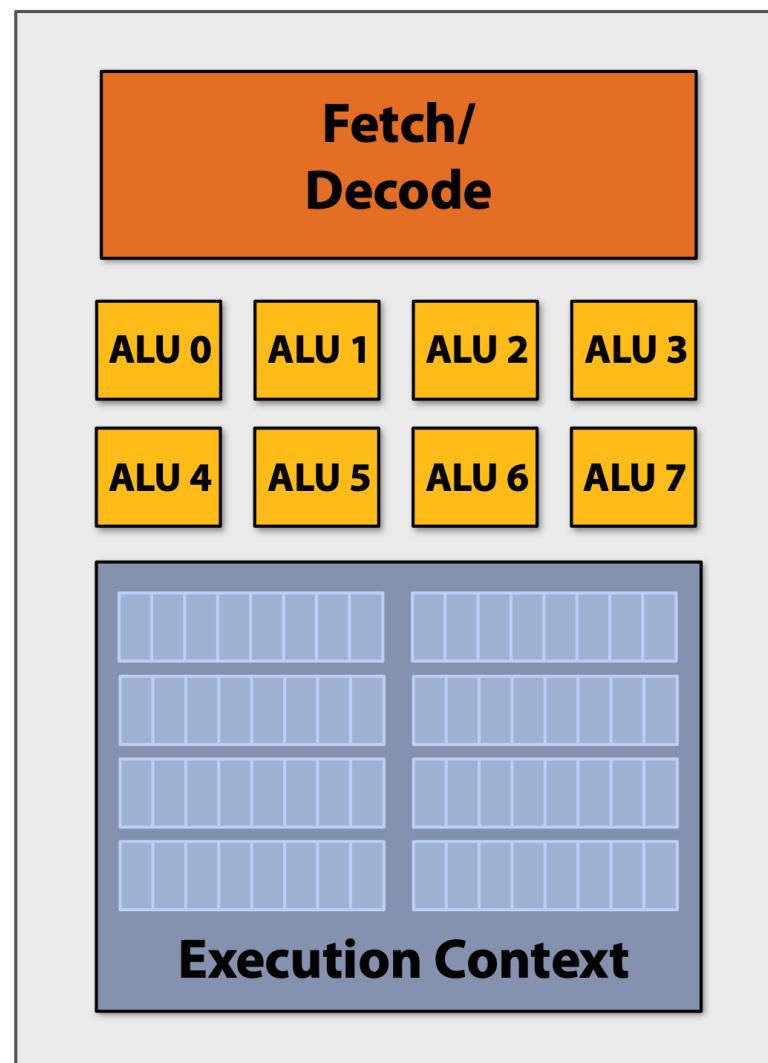
```
execute(my_function, N)  // execute my_function N times
```
 - In other words, the interface to the hardware itself is data-parallel
 - Hardware (not compiler) is responsible for simultaneously executing the same instruction from multiple instances on different data on SIMD ALUs
- SIMD width of most modern GPUs ranges from 8 to 32
 - Divergence can be a big issue: poorly written code might execute at 1/32 the peak capability of the machine!

SIMD + Multi-core

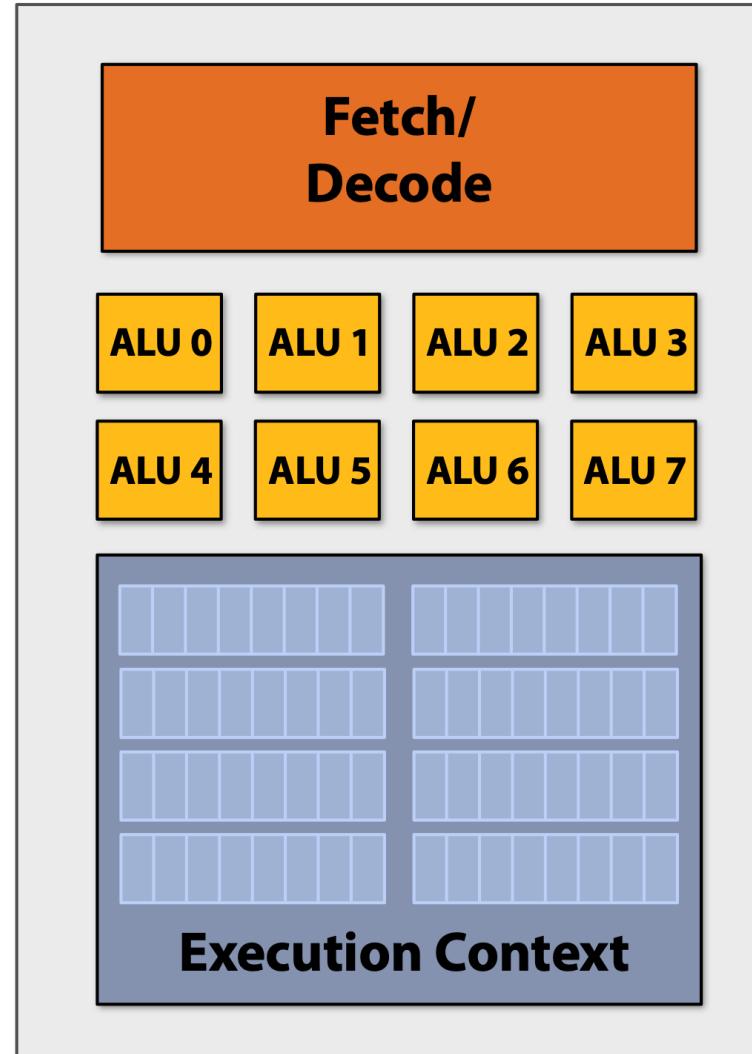
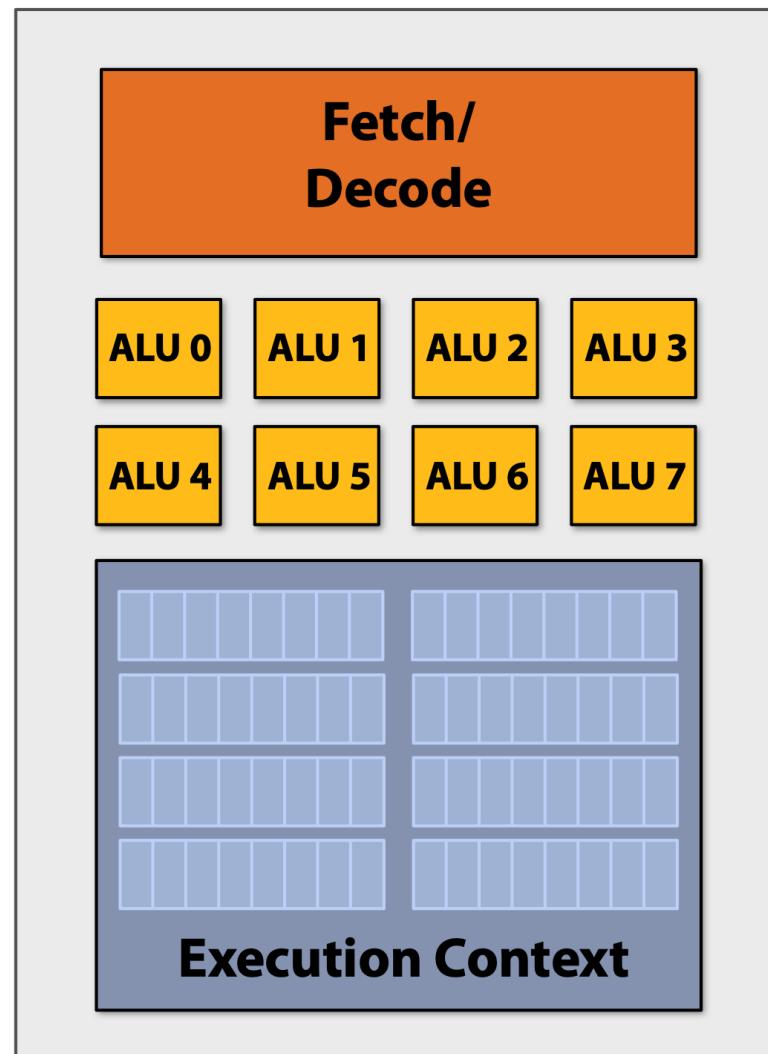


16 cores, 128 ALUs, 16 simultaneous instruction streams

Example: Intel Core i7



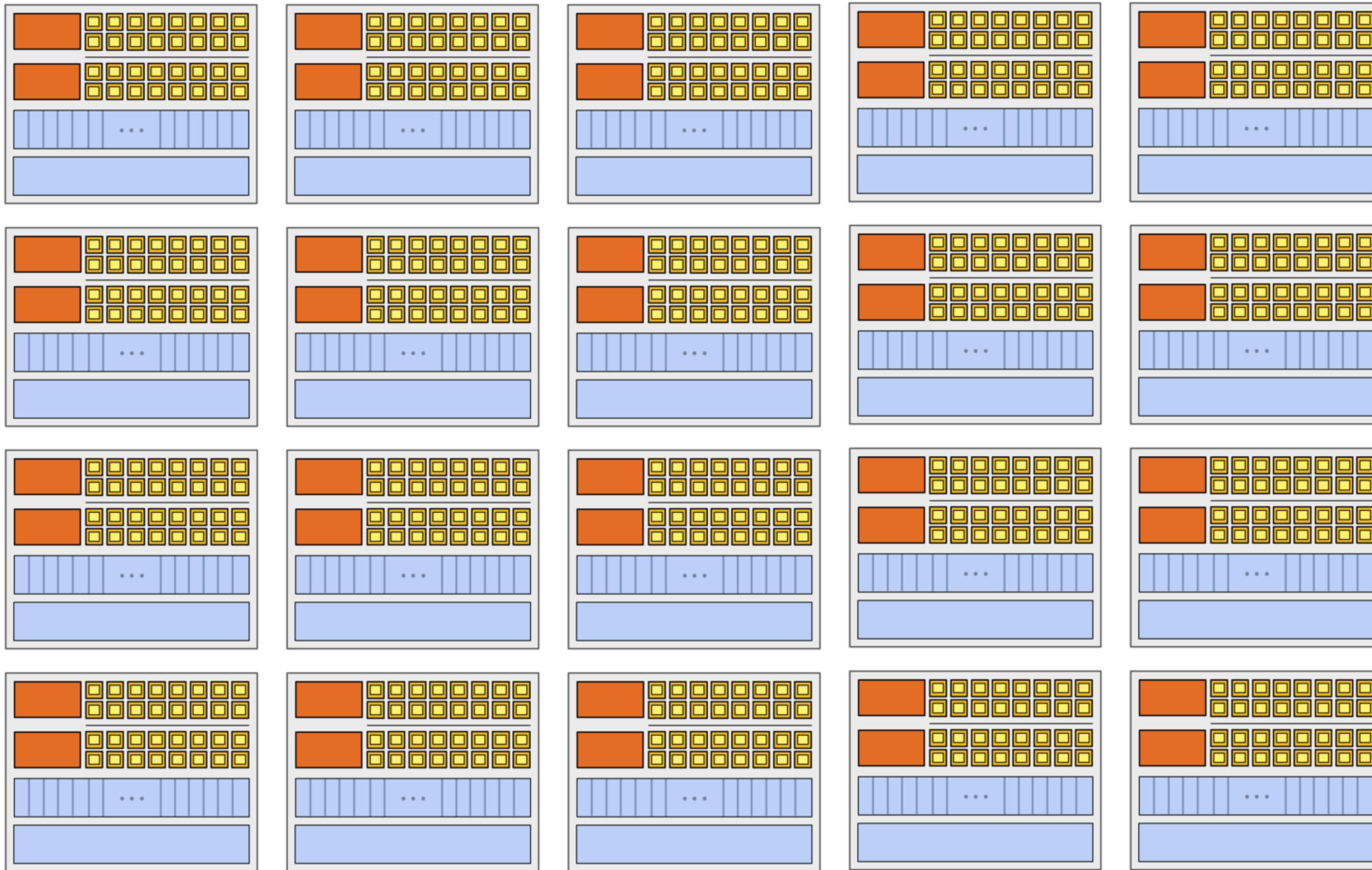
4+ cores
Out-of-order
Speculation
Wide superscalar
One thread per core
8 SIMD ALUs per core
AVX instructions
32-bit floats



On campus:
GHC machines:
8 cores
8 SIMD ALUs per core

Latedays cluster:
12 cores
8 SIMD ALUs per core

Example: NVIDIA GTX RTX 2080 (in the Gates 5 lab)



- 46 cores (“streaming multiprocessors”)
 - 10 SIMD ALUs per core
 - In-order, narrow superscalar
 - Many threads per core
- 16 TFLOPS
 - Special hardware for ray tracing
 - Special hardware for neural nets

Data-parallel expression

(in our fictitious data-parallel language)

```
void sinx(int N, int terms, float* x, float* result)
{
    // declare independent loop iterations
    forall (int i from 0 to N-1)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

Compiler understands loop iterations are independent, and that same loop body will be executed on a large number of data elements.

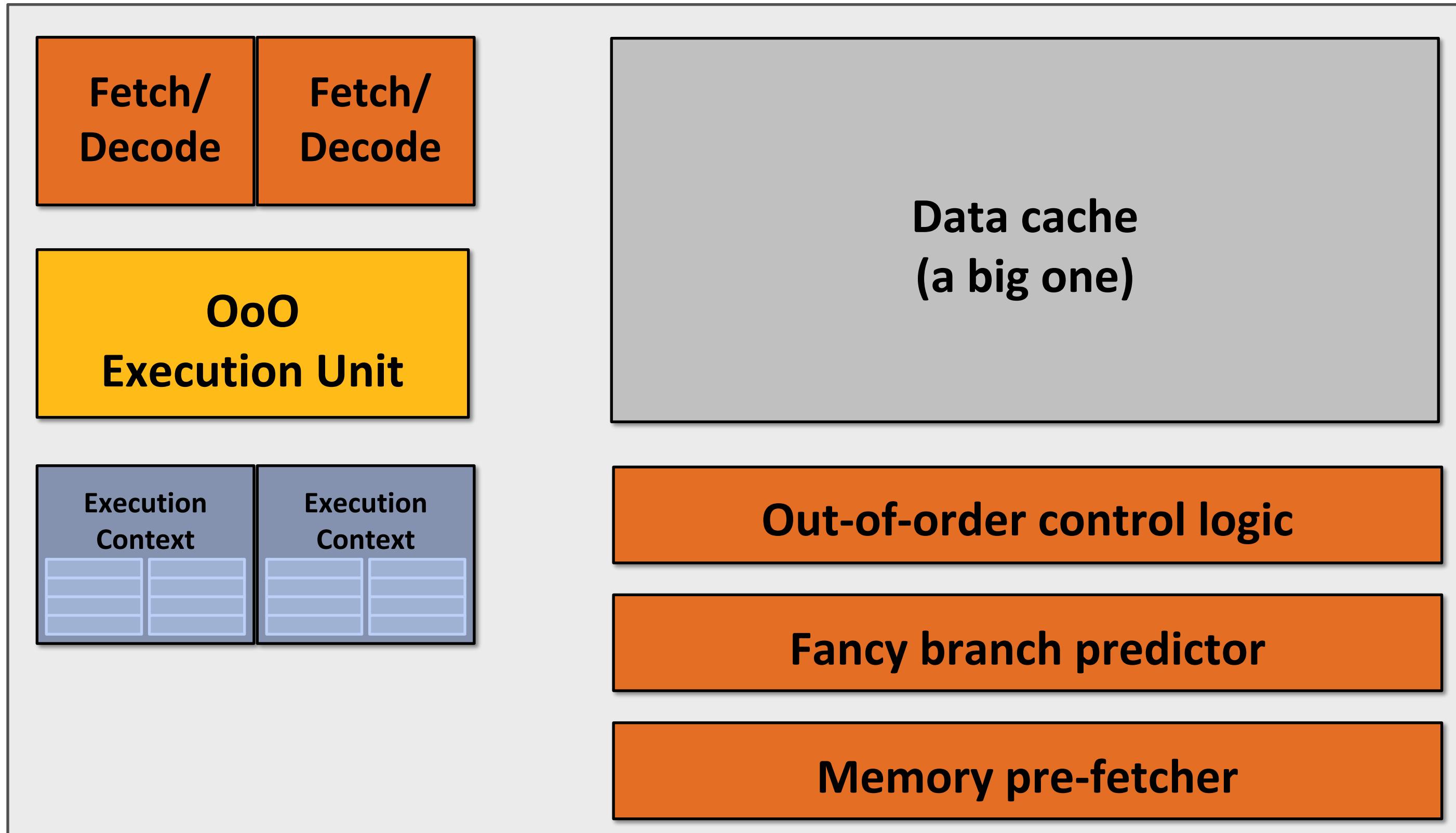
Goal: Abstraction facilitates automatic generation of both multi-core parallel code, and vector instructions to make use of SIMD processing capabilities within a core.

Summary: parallel execution

Several forms of parallel execution in modern processors

- Multi-core: use multiple processing cores
 - Provides **thread-level parallelism**: simultaneously execute a completely different instruction stream on each core
 - Software decides when to create threads (e.g., via pthreads API)
- SIMD: use multiple ALUs controlled by same instruction stream (within a core)
 - Efficient design for **data-parallel** workloads: control amortized over many ALUs
 - Vectorization can be done by compiler (explicit SIMD) or at runtime by hardware
 - [Lack of] dependencies is known prior to execution (usually declared by programmer, but can be inferred by loop analysis by advanced compiler)
- Superscalar: exploit **instruction-level parallelism (ILP)** within an instruction stream. Process different instructions from the same stream in parallel (within a core)
 - Parallelism automatically and dynamically discovered by the hardware during execution (not programmer visible)

Aside: Simultaneous Multi-Threading (Hyperthreading)



Single core does the work of multiple cores

Fetch/decode independent instruction streams from **different threads**

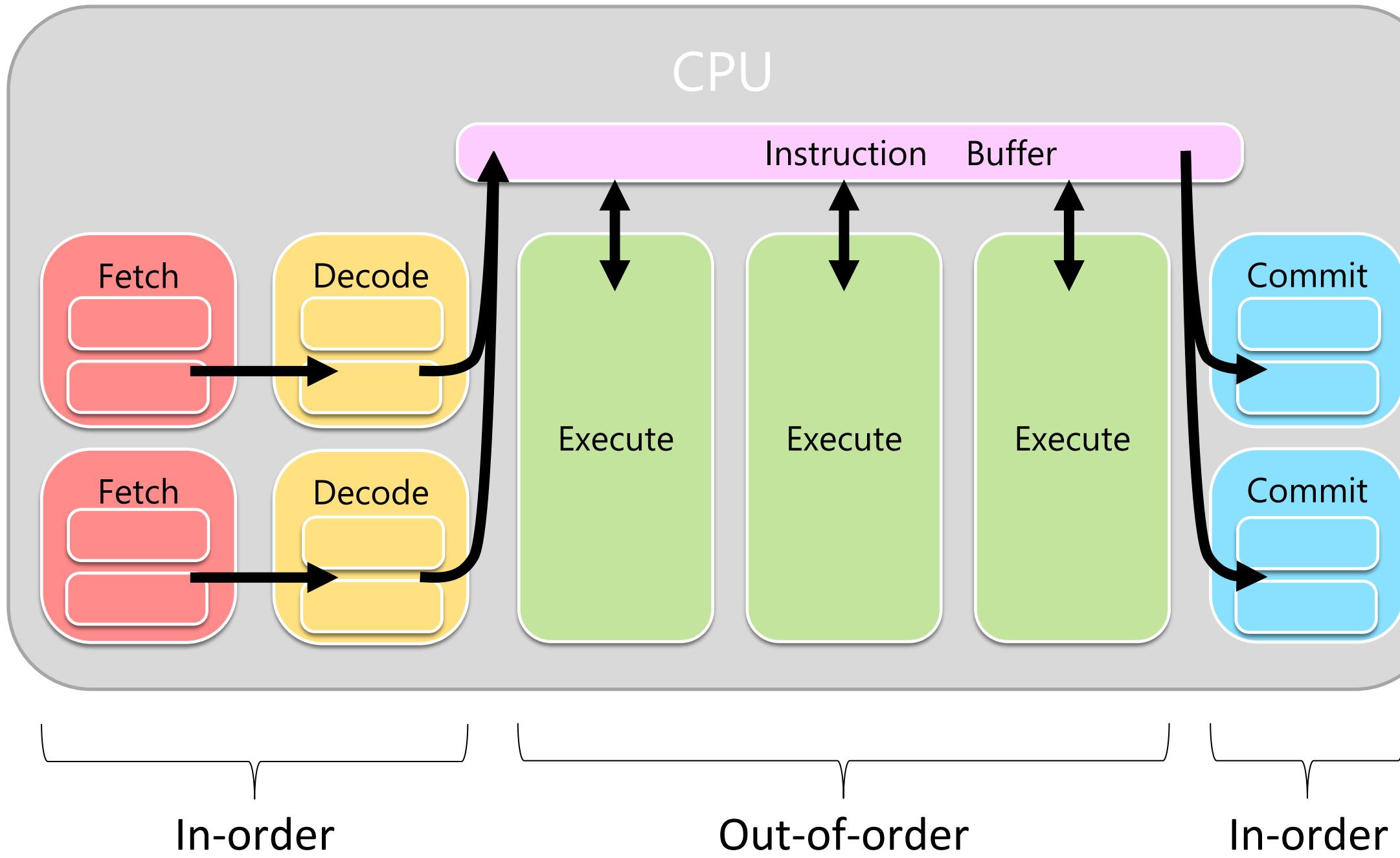
Map onto **shared** out-of-order execution unit

Make fuller use of execution unit when ILP is low

Reduce impact of stalls / mispredictions

(Relatively) small cost to add to an out-of-order superscalar core

Another View of SMT



Replicate in-order resources

Share out-of-order resources

Does not improve (or penalize) single-thread performance

May get improved multi-threaded performance

Part 2: accessing memory

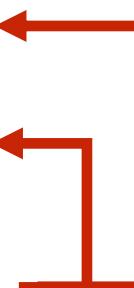
Terminology

- **Memory latency**
 - The amount of time for a memory request (e.g., load, store) from a processor to be serviced by the memory system
 - Example: 100 cycles, 100 nsec
- **Memory bandwidth**
 - The rate at which the memory system can provide data to a processor
 - Example: 20 GB/s

Stalls

- A processor “stalls” when it cannot run the next instruction in an instruction stream because of a dependency on a previous instruction.
- Accessing memory is a major source of stalls

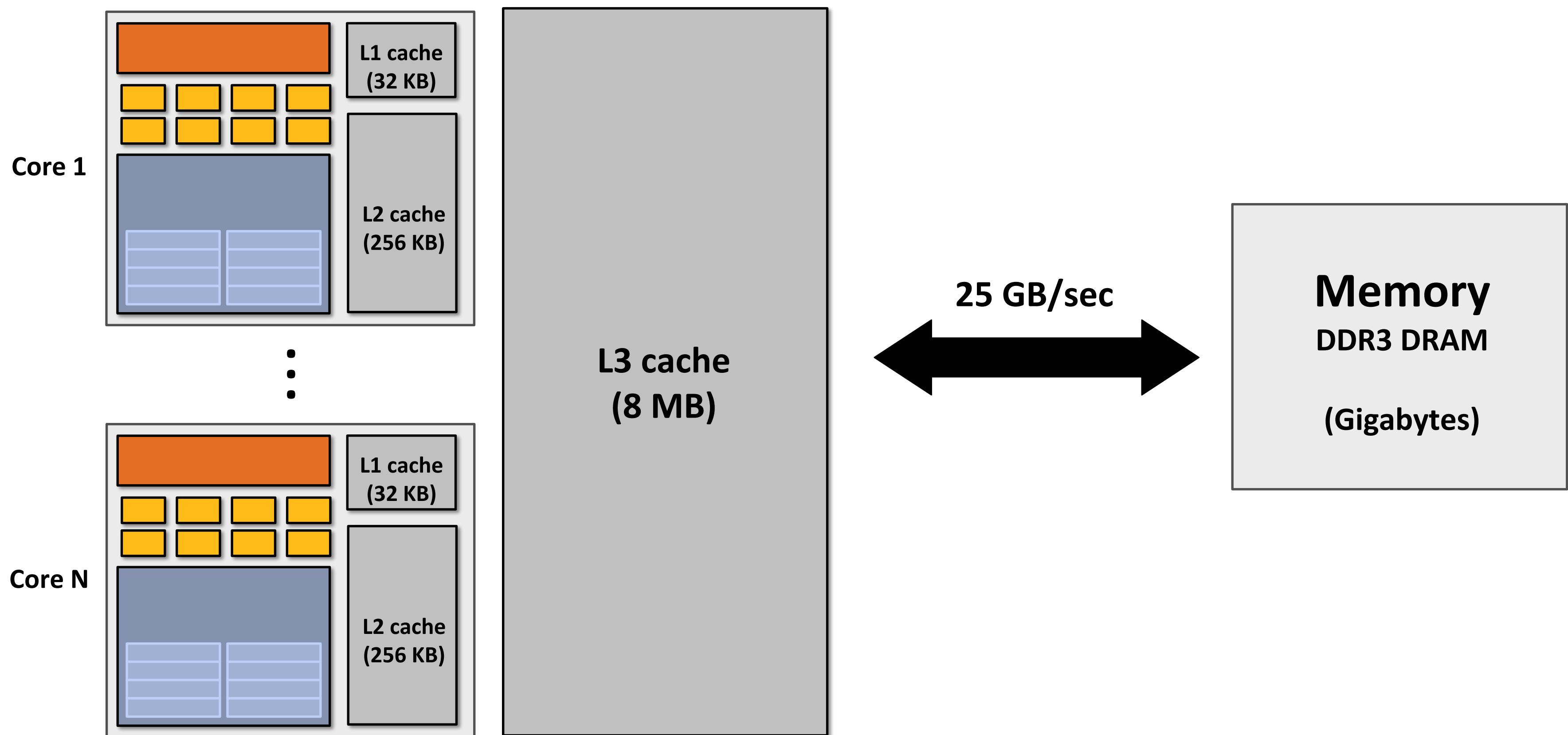
```
ld r0 mem[r2]  
ld r1 mem[r3]  
add r0, r0, r1
```



Dependency: cannot execute ‘add’ instruction until data at mem[r2] and mem[r3] have been loaded from memory

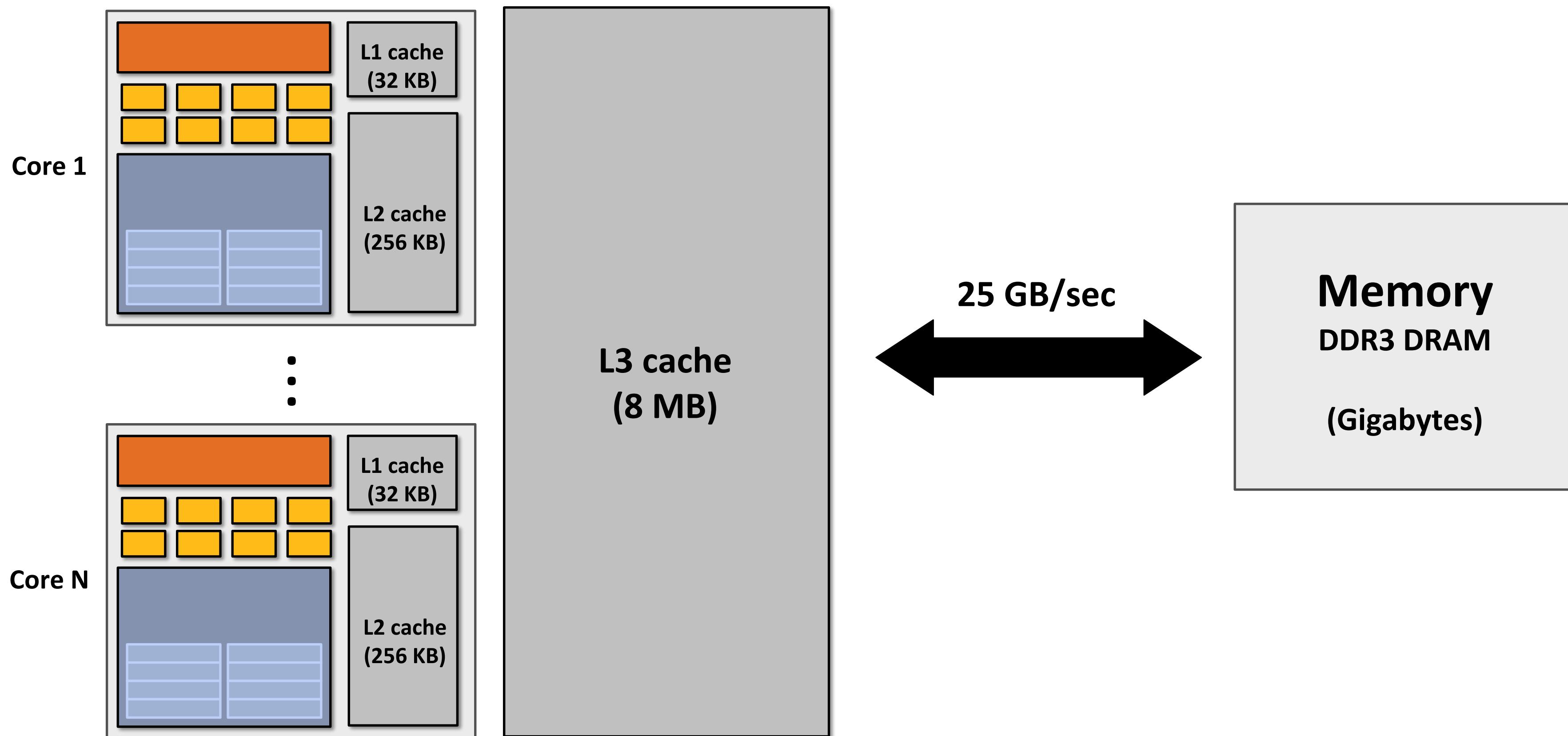
- Memory access times \sim 100’s of cycles
 - Memory “access time” is a measure of latency

Review: why do modern processors have caches?



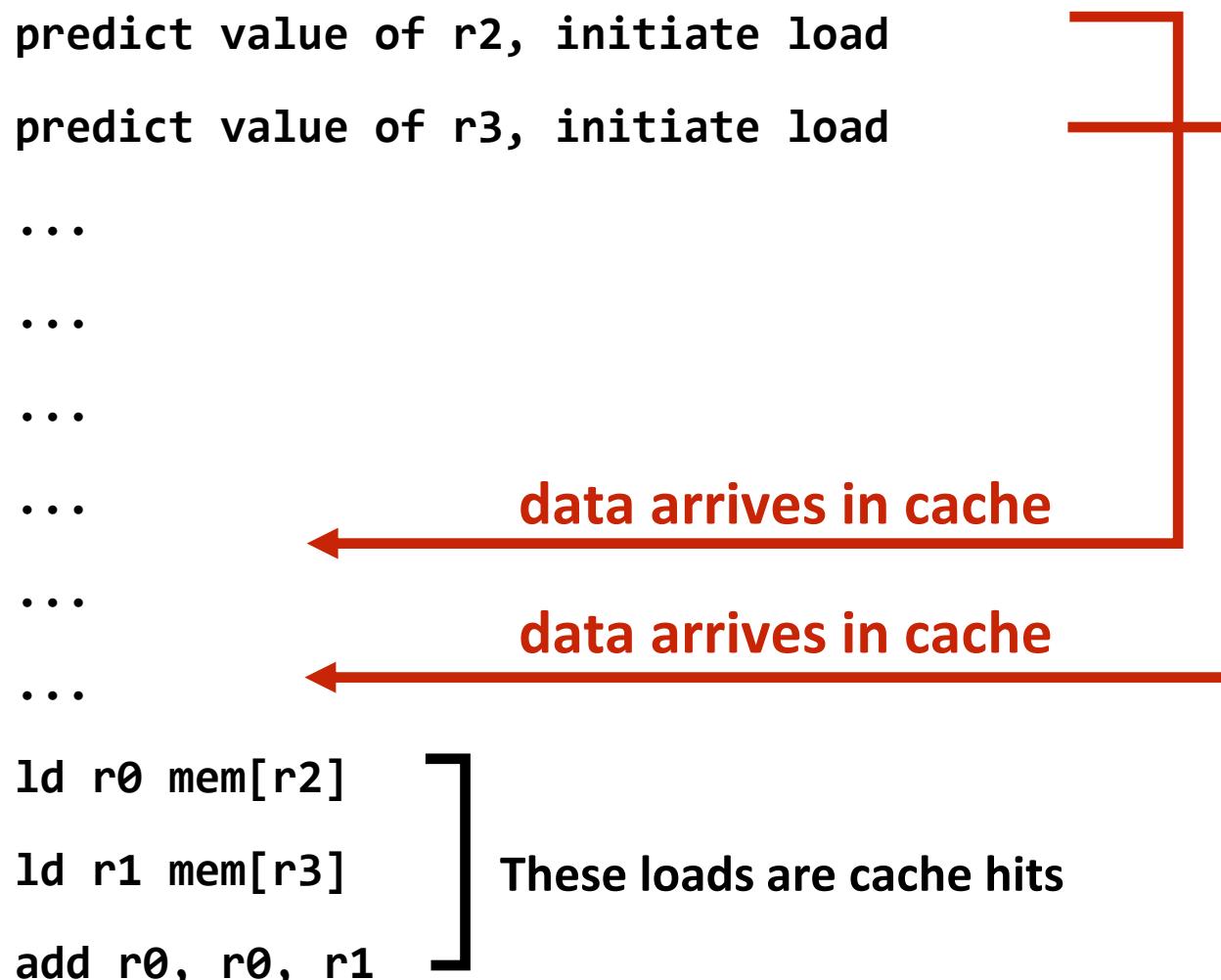
Caches reduce length of stalls (reduce latency)

Processors run efficiently when data is resident in caches
Caches reduce memory access latency & increase bandwidth



Prefetching reduces stalls (hides latency)

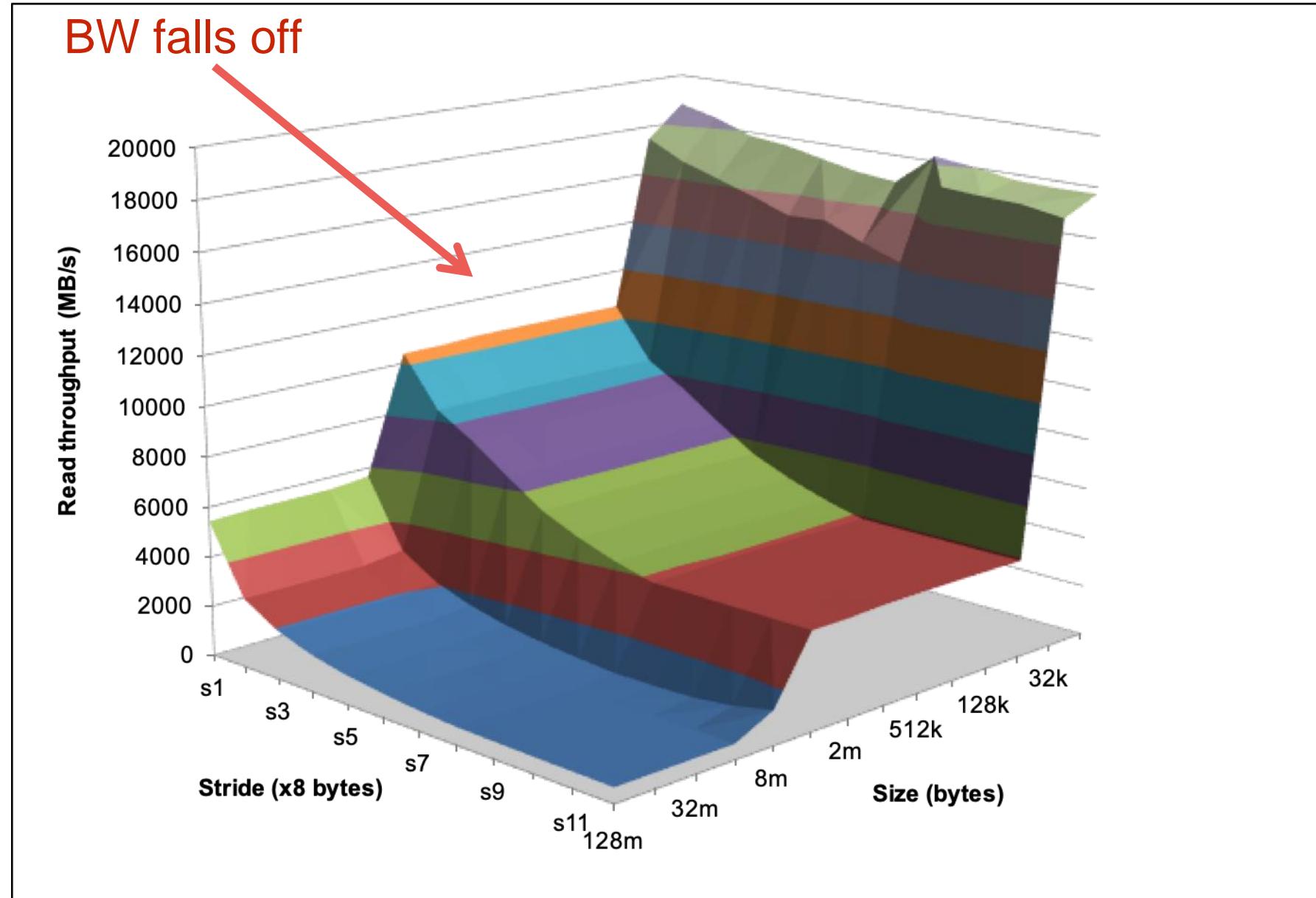
- All modern CPUs have logic for prefetching data into caches
 - Dynamically analyze program's access patterns, predict what it will access soon
 - *Microarchitectural* optimization (i.e., invisible to software)
 - Software prefetching instructions also exist (not used very often)
- Reduces stalls since data is resident in cache when accessed



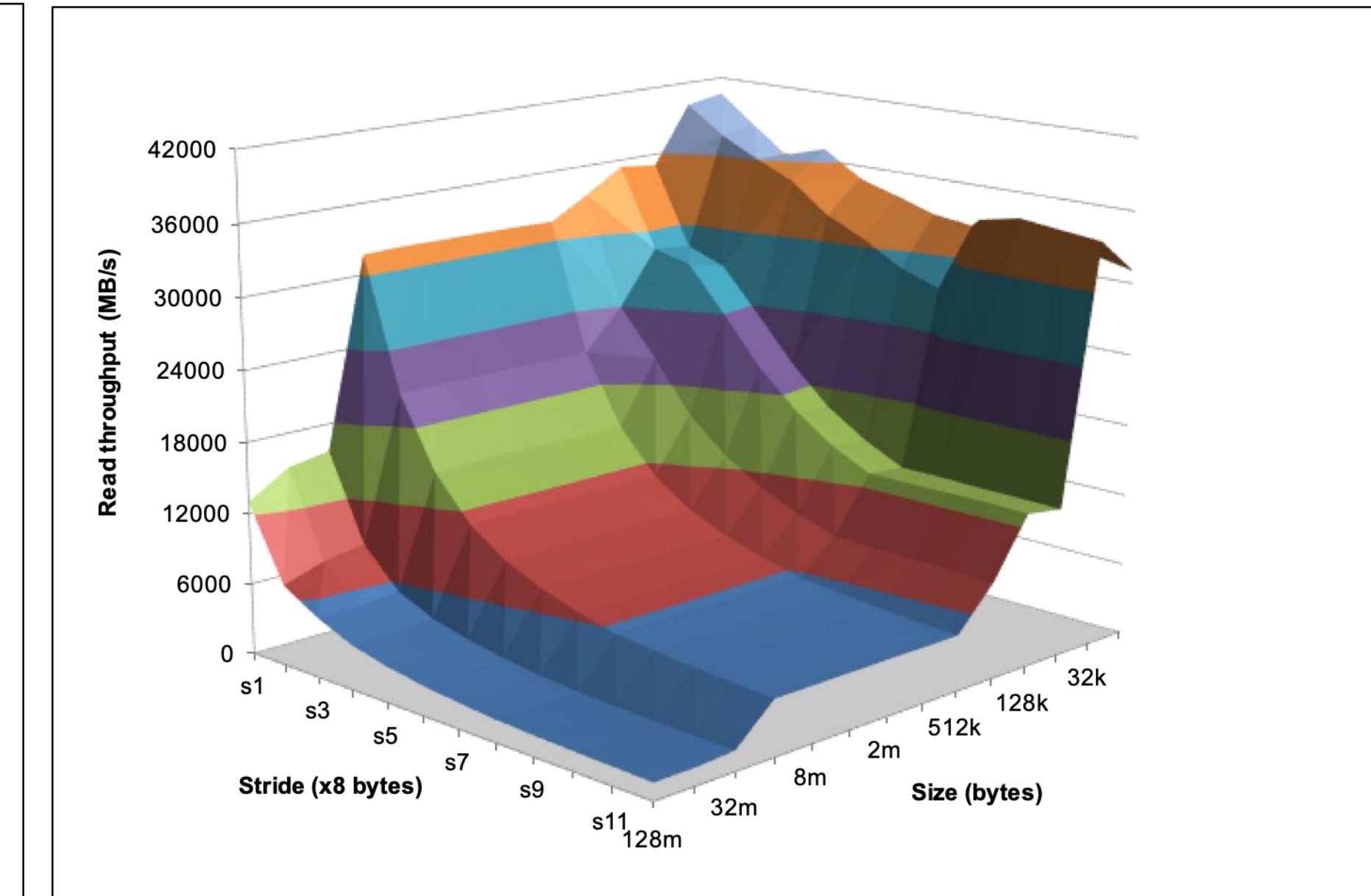
Note: Prefetching can also reduce performance if the guess is wrong (hogs bandwidth, pollutes caches)

Prefetching in Action

iMac Core 2 Duo (2008 Penryn?)



GHC32: Xeon E5-1660v4 (2016 Broadwell)



- **Two levels of cache**
- **No prefetching**
- **Big drop-off in performance for stride=1 as fall out of L1 cache**
- **Three levels of cache**

- **Prefetching**
- **Stride=1 performance high as long as fit into L3 cache**

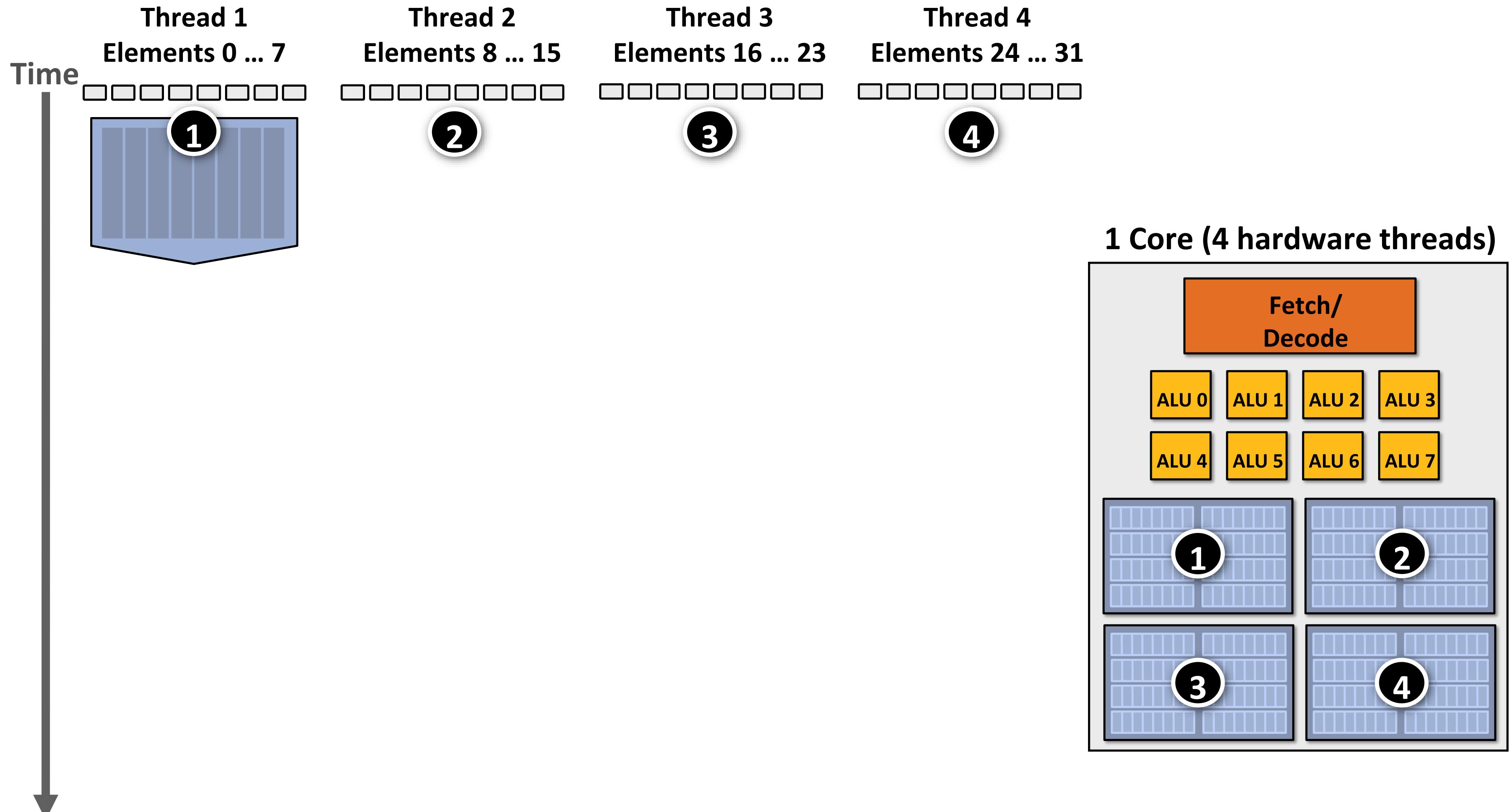
Multi-threading reduces stalls

- Idea: interleave processing of multiple threads on the same core to hide stalls
- Helps even with in-order processing of instructions
- Like prefetching, multi-threading is a latency hiding, not a latency reducing technique
- We will consider several forms of multi-threading

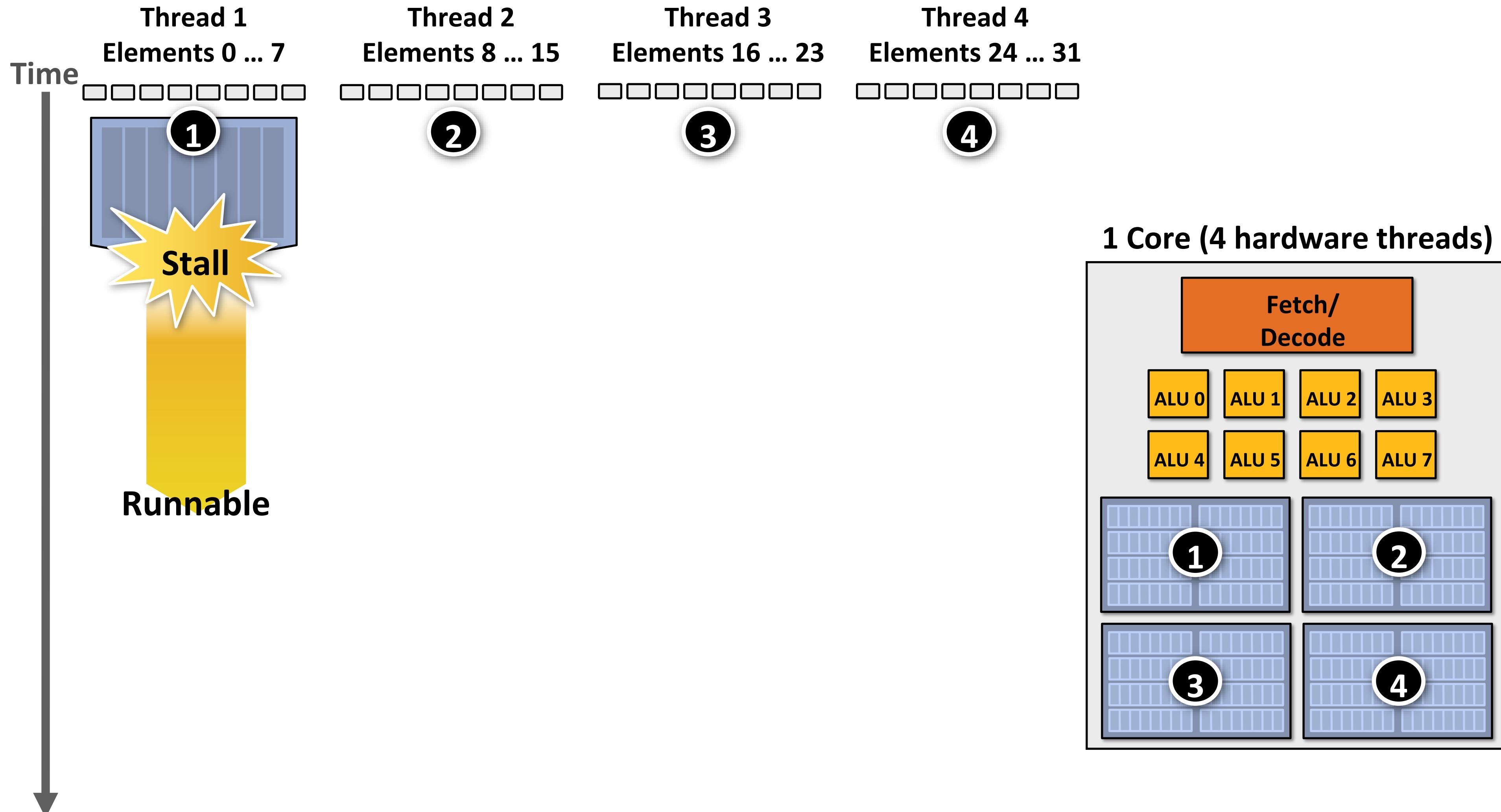
Hiding stalls with Multi-Threading



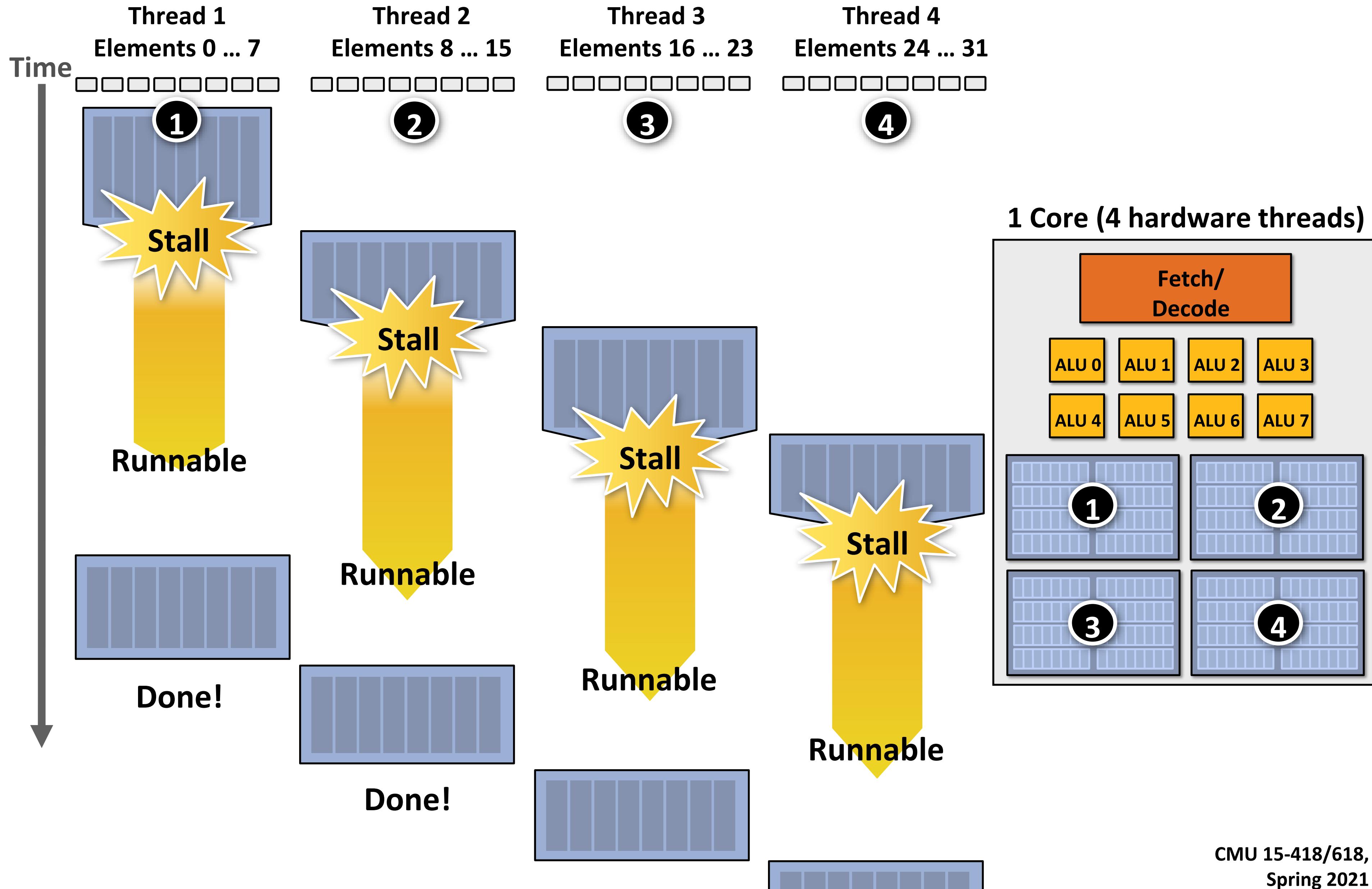
Hiding stalls with Multi-Threading



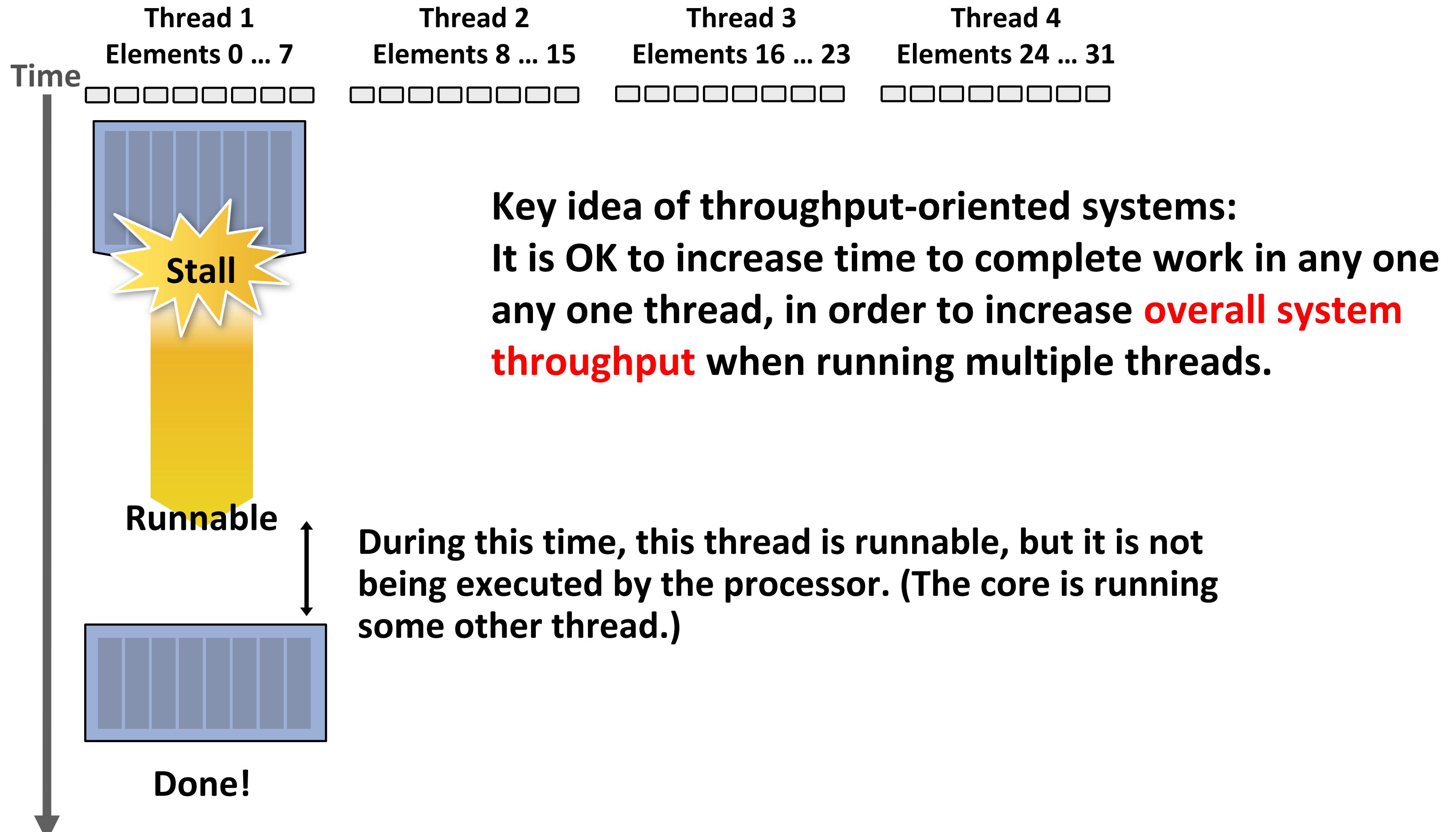
Hiding stalls with Multi-Threading



Hiding stalls with Multi-Threading



Throughput computing trade-off



Hardware-supported multi-threading

- **Core manages execution contexts for multiple threads**
 - Runs instructions from runnable threads (processor makes decision about which thread to run each clock, not the operating system)
 - Core still has the same number of ALU resources: multi-threading only helps use them more efficiently in the face of high-latency operations like memory access
- **Interleaved multi-threading (a.k.a. temporal multi-threading)**
 - As described on the previous slides: each clock, the core chooses a thread, and runs an instruction from the thread on the ALUs
- **Simultaneous multi-threading (SMT)**
 - Extension of out-of-order CPU design
 - Example: Intel Hyper-threading (2 threads per core)

Multi-threading summary

- **Benefit: Use core's execution resources more efficiently**
 - Hide memory latency
 - Fill multiple functional units of superscalar architecture (when one thread has insufficient ILP)
- **Costs**
 - Requires additional storage for thread contexts
 - Increases run time of any single thread (often not a problem, we usually care about throughput in parallel apps)
 - Requires additional independent work in a program (more independent work than ALUs!)
 - Relies heavily on memory bandwidth
 - More threads → larger working set → less cache space per thread
 - May go to memory more often, but can hide the latency

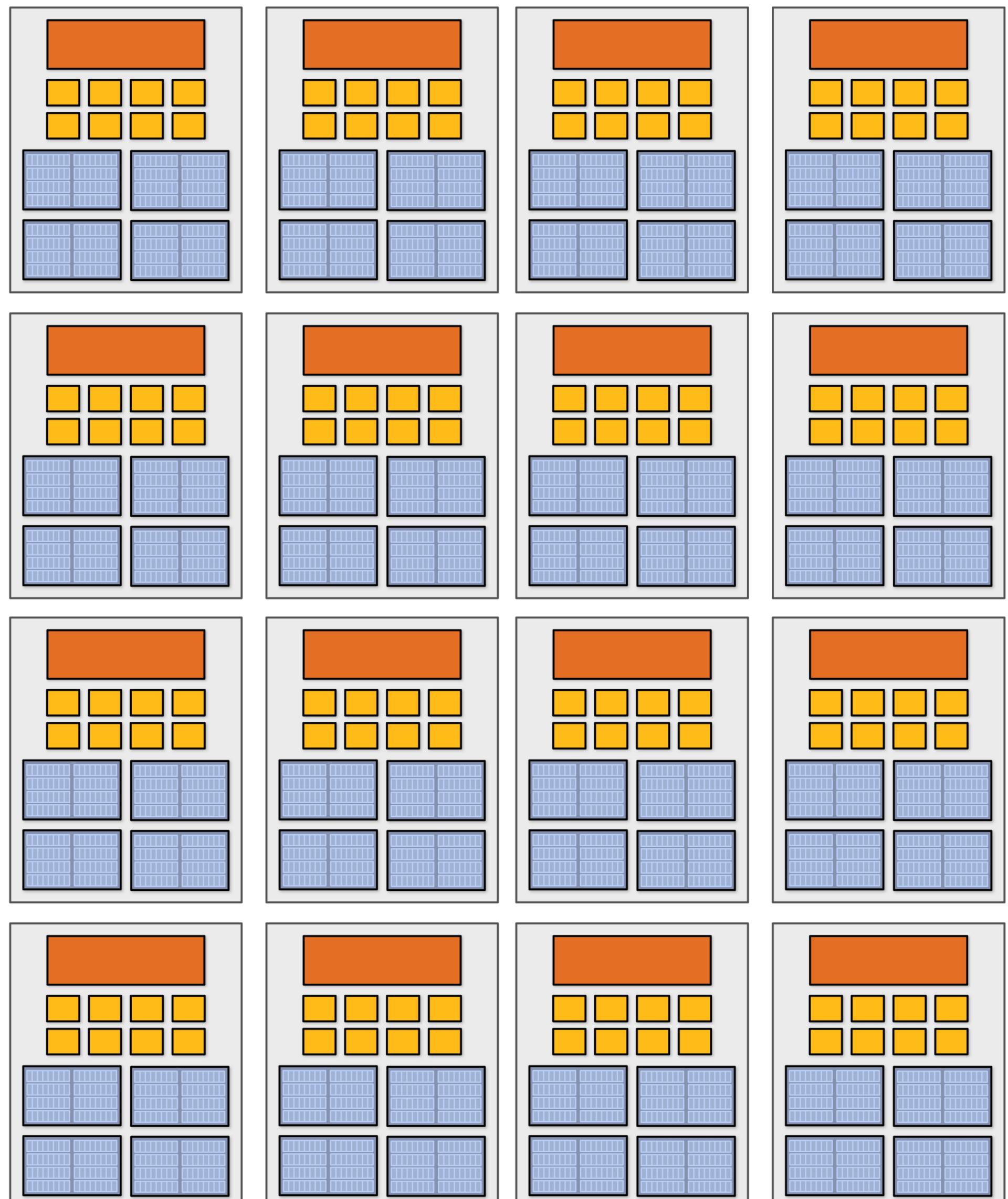
Our fictitious multi-core chip

16 cores \times
8 SIMD ALUs per core
= 128 total ALUs

\times 4 threads / core
→ ≥ 512 independent
operations needed to
run chip at peak
efficiency

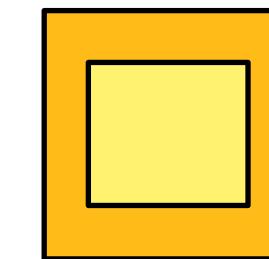
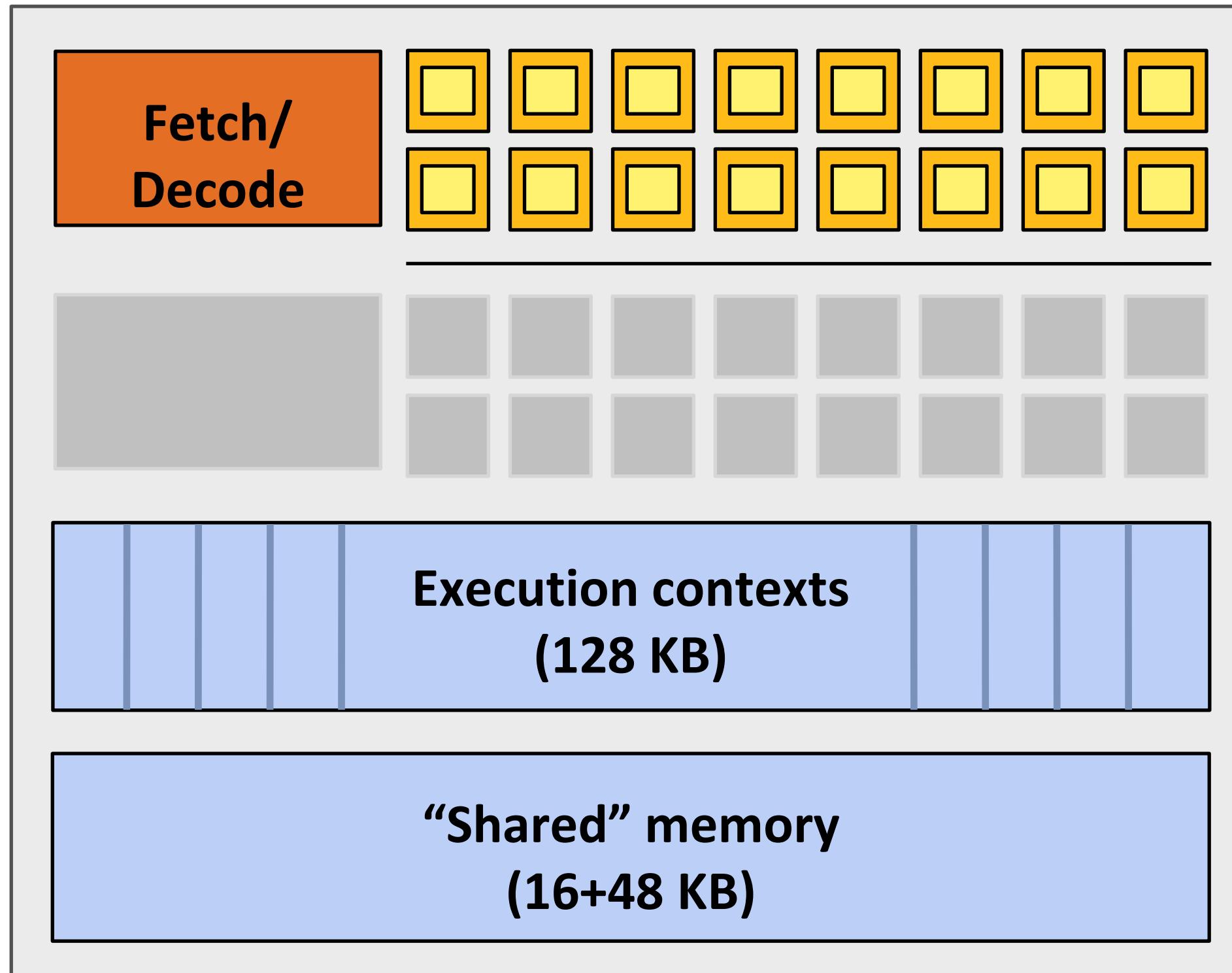
in 64 total concurrent
instruction streams

with 16 running
simultaneously



GPUs: Extreme throughput-oriented processors

NVIDIA GTX 480 core



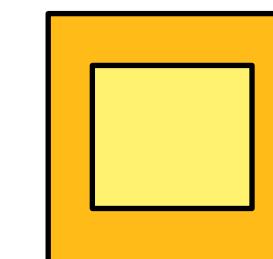
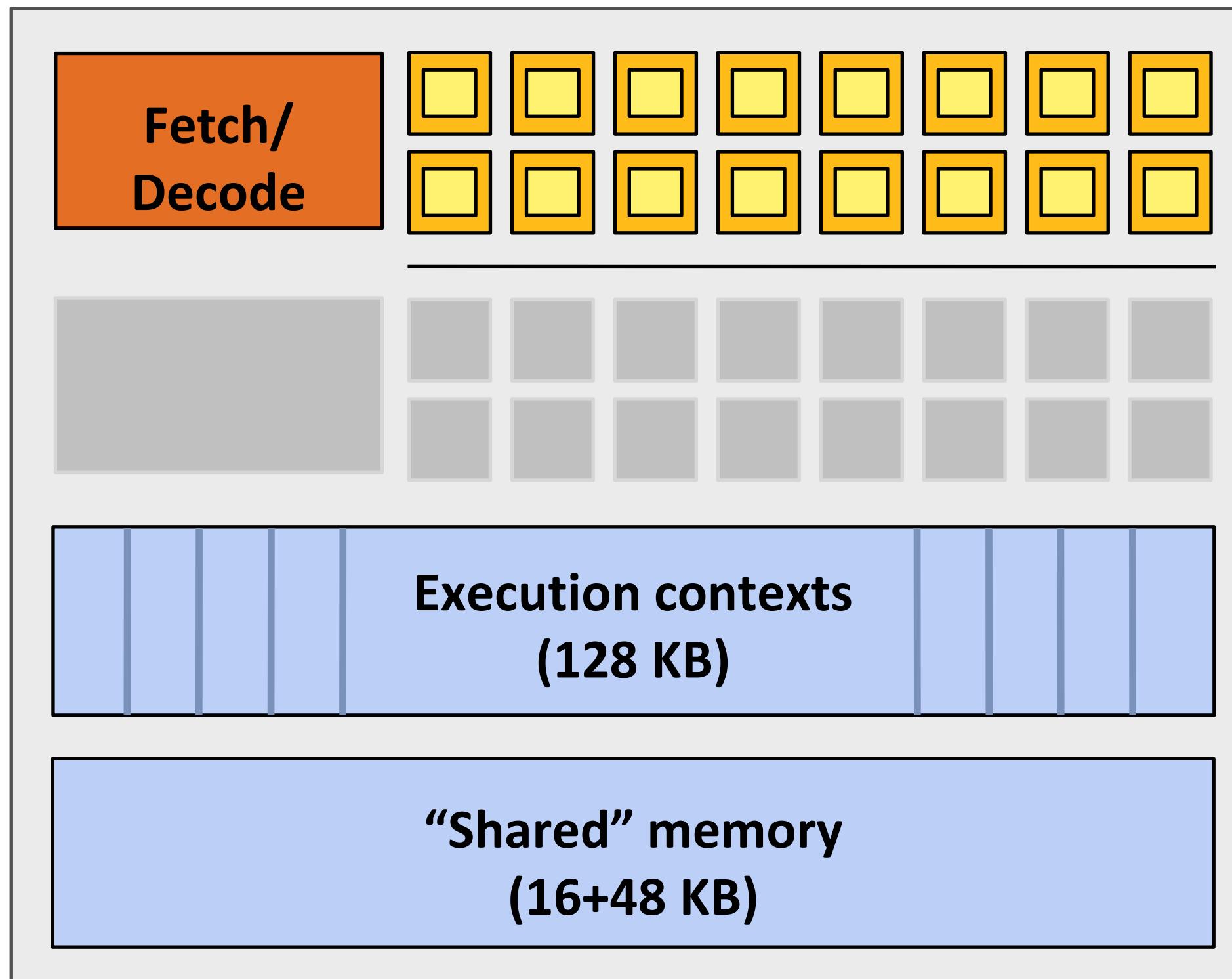
= SIMD function unit,
control shared across 16 units
(1 MUL-ADD per clock)

- Instructions operate on 32 pieces of data at a time (called “warps”).
- Think: warp = thread issuing 32-wide vector instructions
- Up to 48 warps are simultaneously interleaved
- $48 \times 32 = 1536$ elements can be processed concurrently by a core

Source: Fermi Compute Architecture Whitepaper
CUDA Programming Guide 3.1, Appendix G

NVIDIA GTX 480: more detail (just for the curious)

NVIDIA GTX 480 core



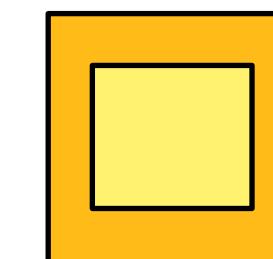
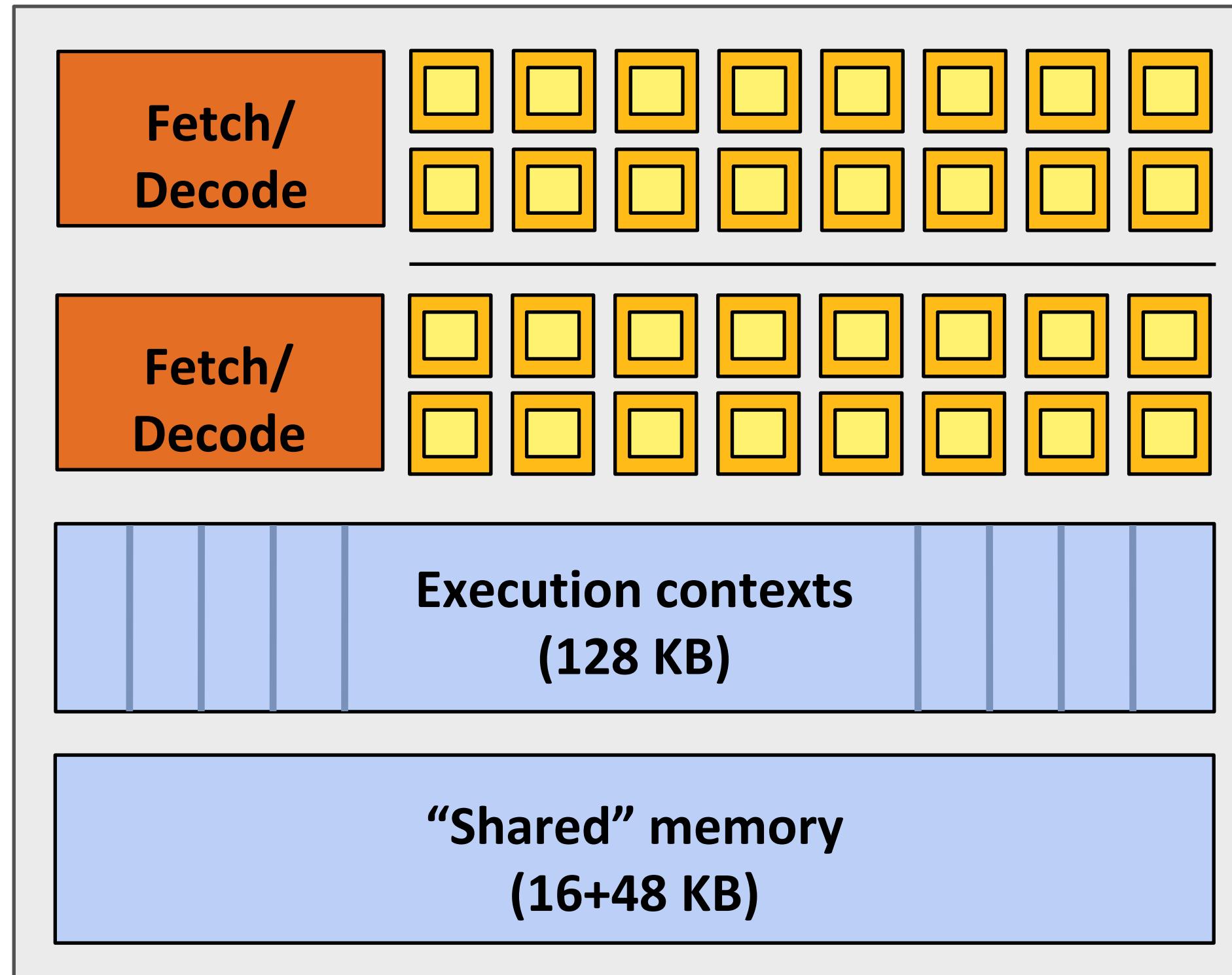
= SIMD function unit,
control shared across 16 units
(1 MUL-ADD per clock)

- Why is a warp 32 elements and there are only 16 SIMD ALUs?
- It's a bit complicated: ALUs run at twice the clock rate of rest of chip. So each decoded instruction runs on 32 pieces of data on the 16 ALUs over two ALU clocks. (but to the programmer, it behaves like a 32-wide SIMD operation)

Source: Fermi Compute Architecture Whitepaper
CUDA Programming Guide 3.1, Appendix G

NVIDIA GTX 480: more detail (just for the curious)

NVIDIA GTX 480 core

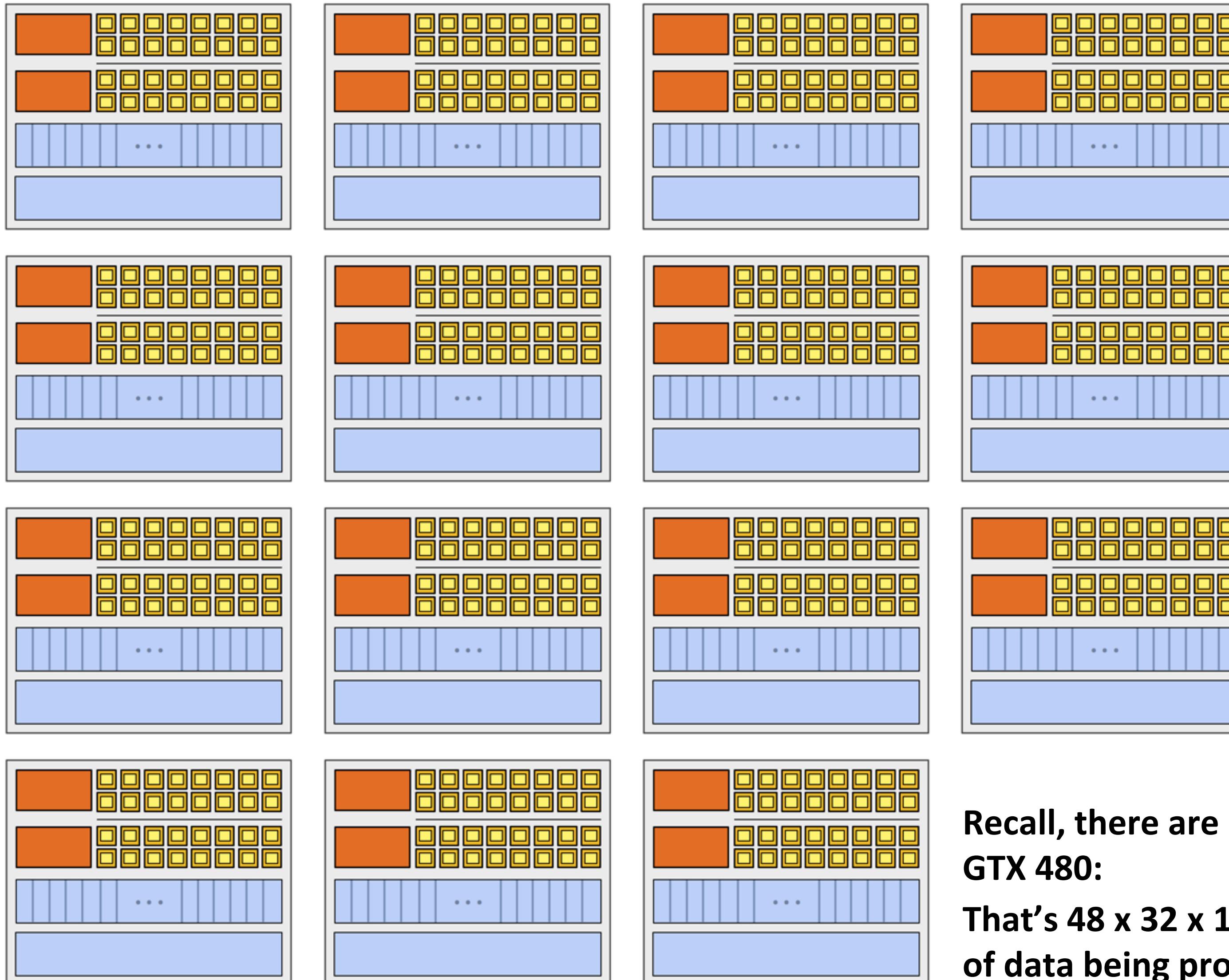


= SIMD function unit,
control shared across 16 units
(1 MUL-ADD per clock)

- This process occurs on another set of 16 ALUs as well
- So there are 32 ALUs per core
- $15 \text{ cores} \times 32 = 480 \text{ ALUs per chip}$

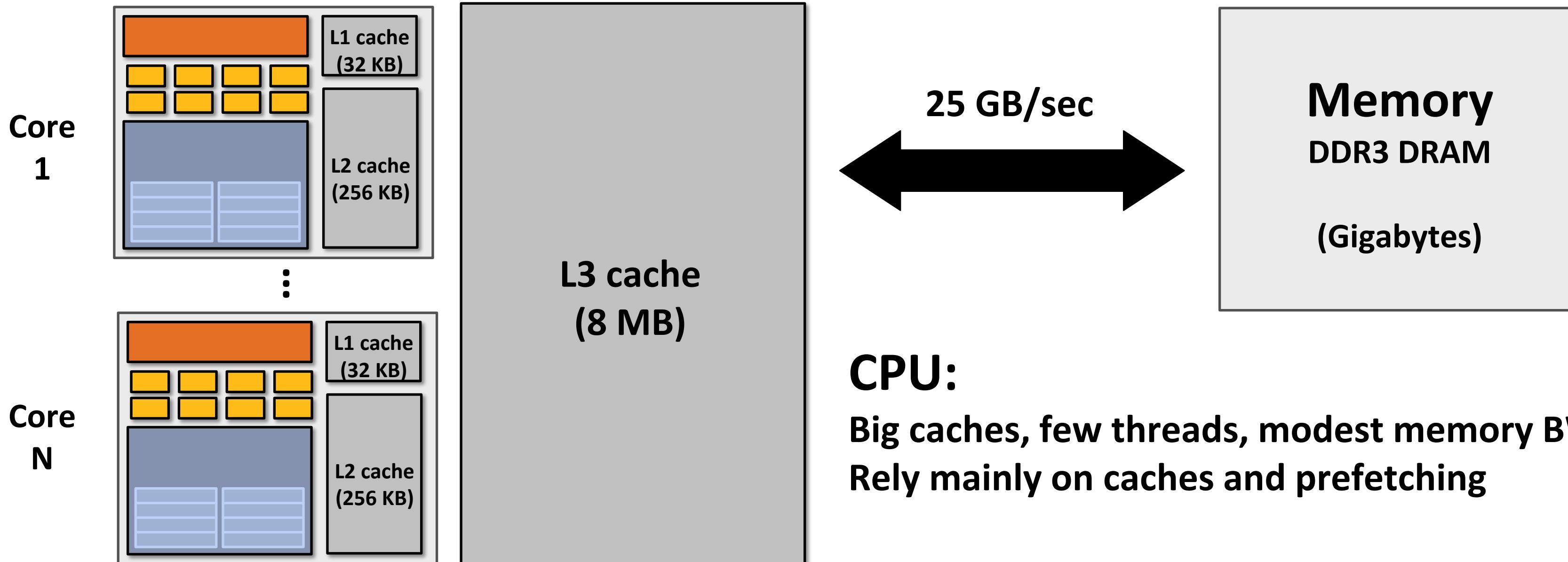
Source: Fermi Compute Architecture Whitepaper
CUDA Programming Guide 3.1, Appendix G

NVIDIA GTX 480

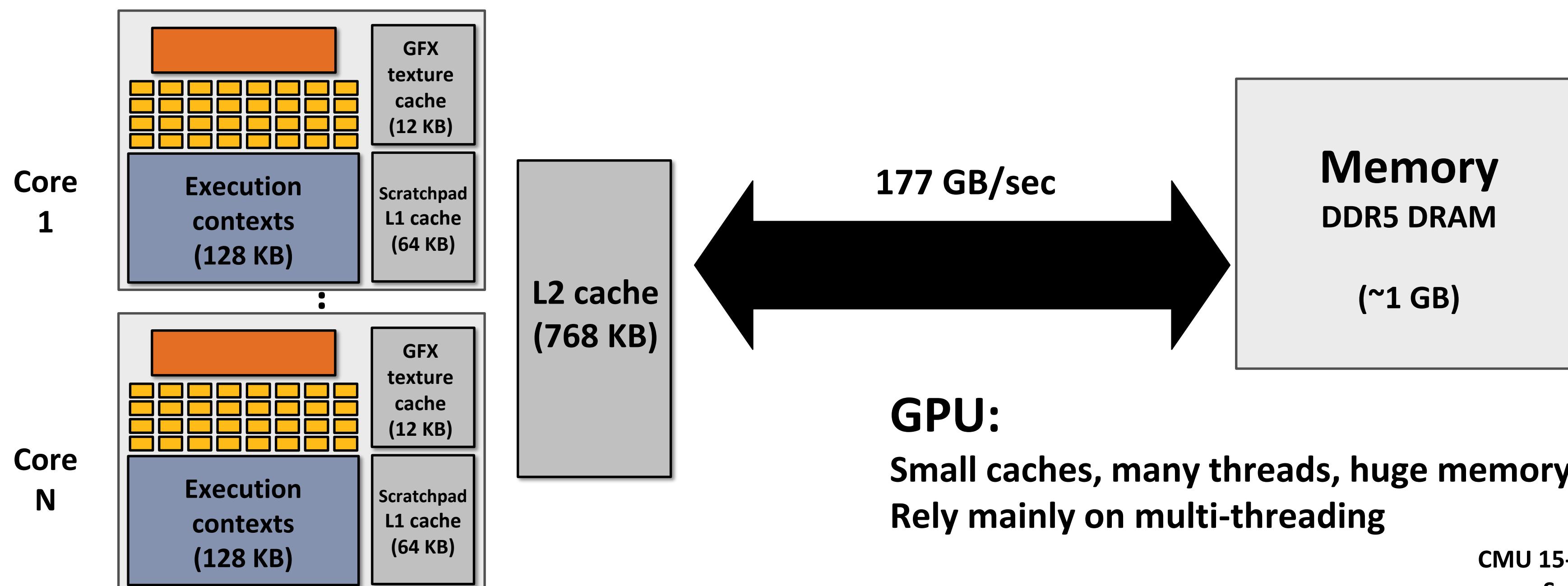


Recall, there are 15 cores on the GTX 480:
That's $48 \times 32 \times 15 = 23,040$ pieces of data being processed concurrently!

CPU vs. GPU memory hierarchies



CPU:
Big caches, few threads, modest memory BW
Rely mainly on caches and prefetching



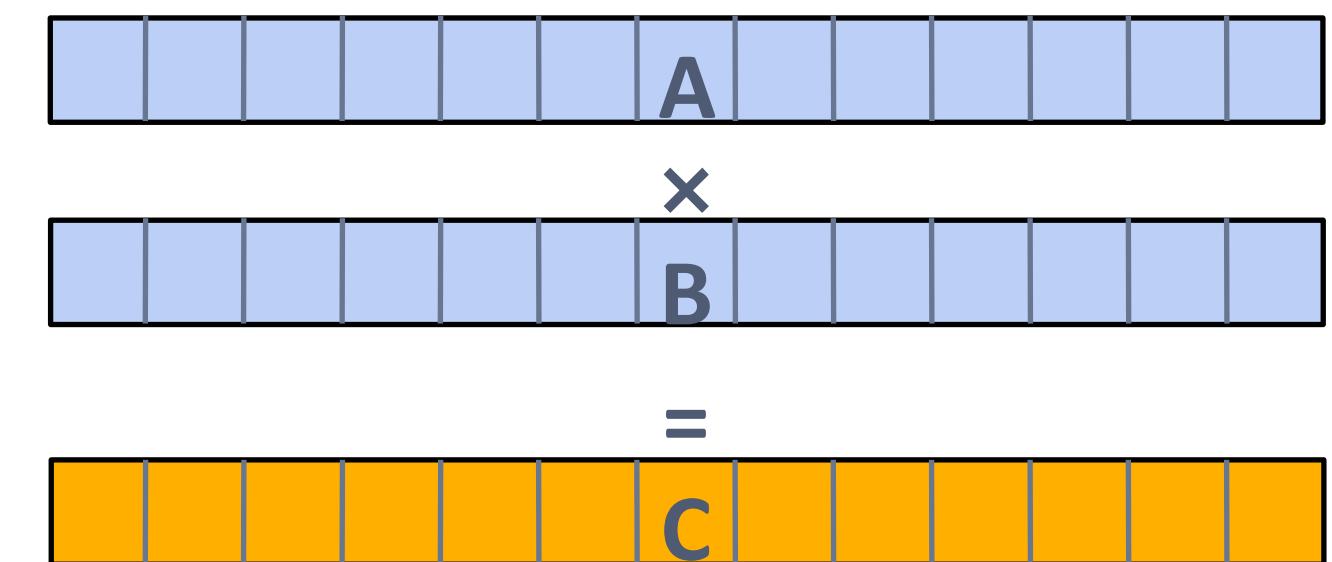
GPU:
Small caches, many threads, huge memory BW
Rely mainly on multi-threading

Thought experiment

Element-wise multiplication of two vectors A and B

Assume vectors contain millions of elements

- Load input A[i]
- Load input B[i]
- Compute $A[i] \times B[i]$
- Store result into C[i]



Three memory operations (12 bytes) for every MUL

NVIDIA GTX 480 GPU can do 480 MULs per clock (@ 1.2 GHz)

Need ~6.4 TB/sec of bandwidth to keep functional units busy (only have 177 GB/sec)

~ 3% efficiency... but 7x faster than quad-core CPU!
(2.6 GHz Core i7 Gen 4 quad-core CPU connected to 25 GB/sec memory bus
will exhibit similar efficiency on this computation)

Bandwidth limited!

If processors request data at too high a rate, the memory system cannot keep up.

No amount of latency hiding helps this.

Overcoming bandwidth limits are a common challenge for application developers on throughput-optimized systems.

Bandwidth is a critical resource

Performant parallel programs will:

- Organize computation to fetch data from memory less often
 - Reuse data previously loaded by the same thread
(traditional intra-thread temporal locality optimizations)
 - Share data across threads (inter-thread cooperation)
- Request data less often (instead, do more arithmetic: it's “free”)
 - Useful term: “arithmetic intensity” — ratio of math operations to data-access operations in an instruction stream
 - Main point: programs must have high arithmetic intensity to utilize modern processors efficiently

Summary

- **Three major ideas that all modern processors employ to varying degrees**
 - **Employ multiple, simpler processing cores**
 - Embrace thread-level parallelism over instruction-level parallelism
 - **Amortize instruction fetch & decode over many ALUs (SIMD)**
 - Increase compute capability with little extra cost
 - **Use multi-threading to make more efficient use of processing resources**
 - Hide latencies, fill all available resources
- **Due to high arithmetic capability on modern chips, many parallel applications (on both CPUs and GPUs) are bandwidth-bound**
- **GPU architectures use these same throughput-computing ideas as CPUs, but GPUs push these concepts to extreme scales**

For the rest of this class, know these terms

- **Multi-core processor**
- **SIMD execution**
- **Coherent control flow**
- **Hardware multi-threading**
 - **Interleaved multi-threading**
 - **Simultaneous multi-threading**
- **Memory latency**
- **Memory bandwidth**
- **Bandwidth bound application**
- **Arithmetic intensity**

Another example: for review and to check your understanding

(if you understand the following sequence you understand this lecture)

Running code on a simple processor

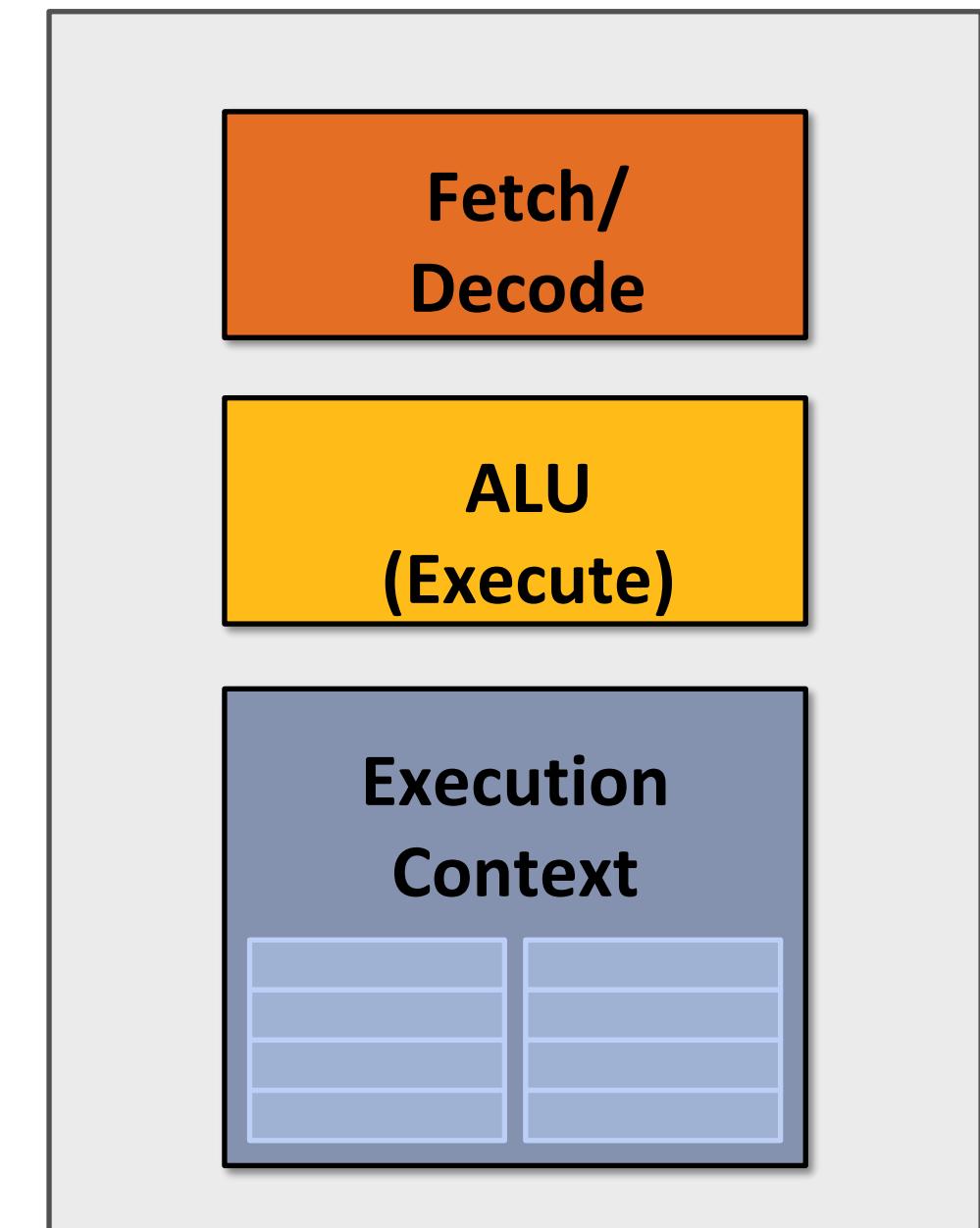
**My very simple program:
compute $\sin(x)$ using Taylor expansion**

```
void sinx(int N, int terms, float* x, float* result)
{
    for (int i=0; i<N; i++)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom;
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

**My very simple processor:
completes one instruction per clock**



Review: superscalar execution

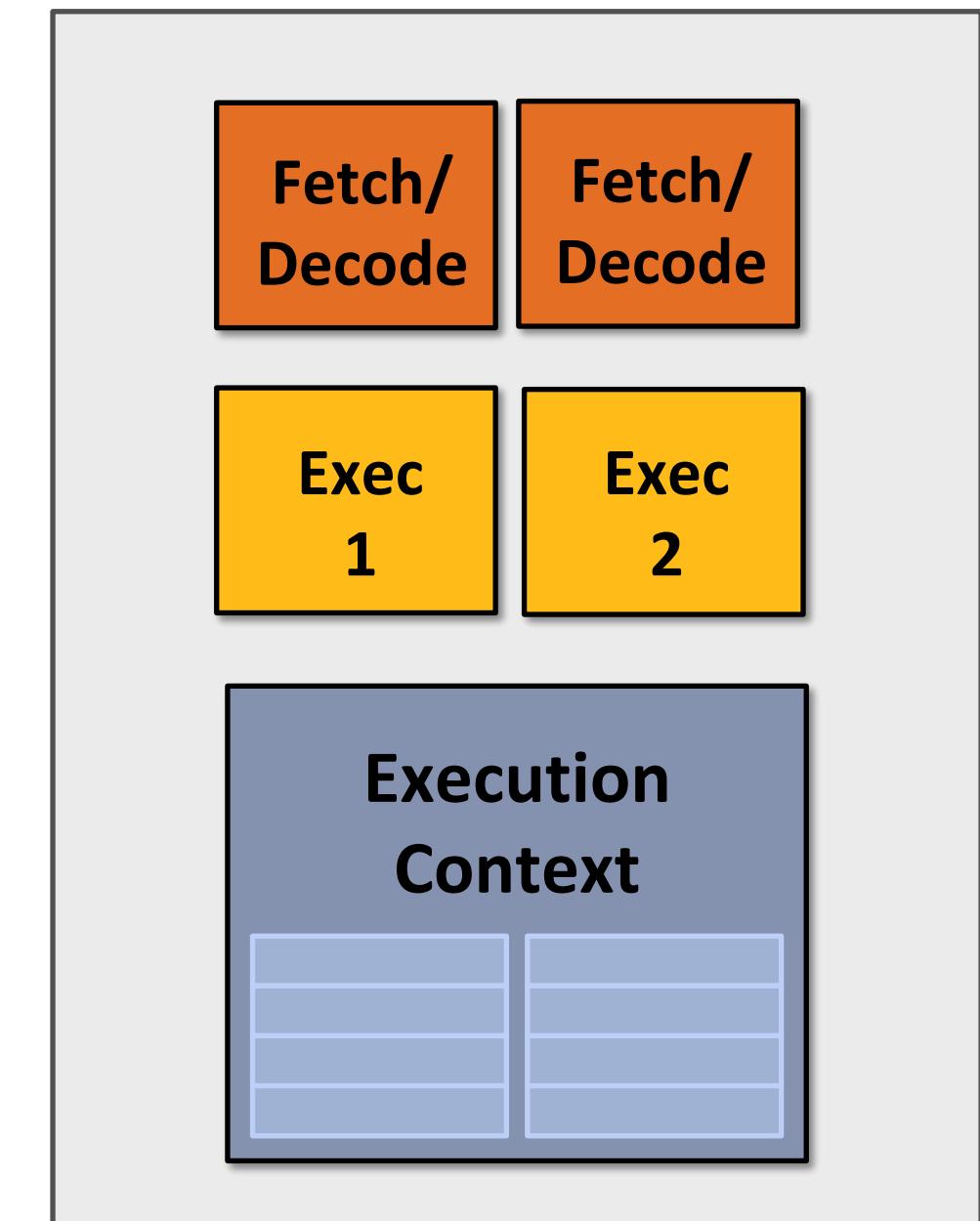
Unmodified program

```
void sinx(int N, int terms, float* x, float* result)
{
    for (int i=0; i<N; i++)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom;
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

My single core, superscalar processor:
executes up to two instructions per clock
from a single instruction stream.



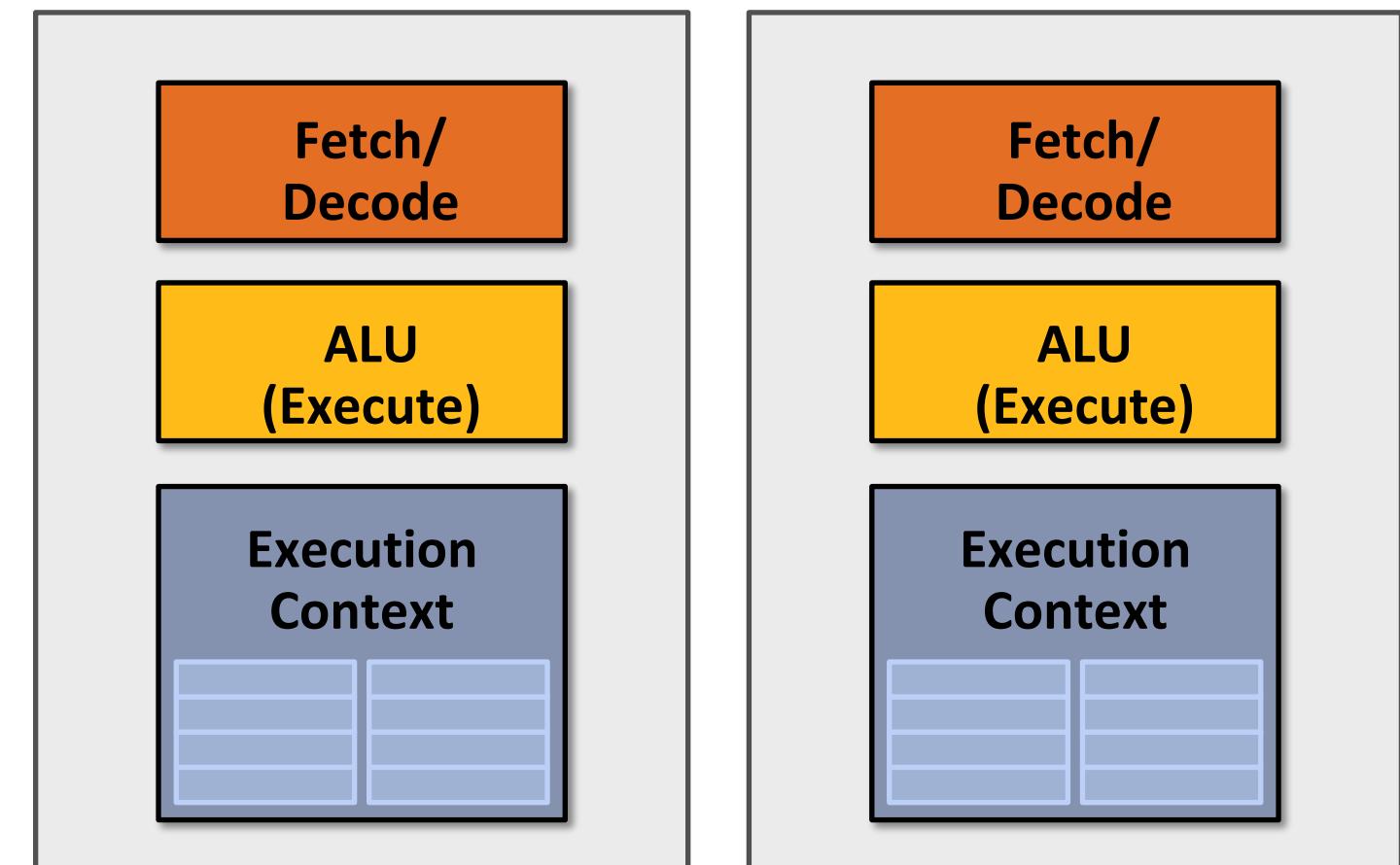
Independent operations in instruction stream
(They are detected by the processor at run-time and may be executed in parallel on execution units 1 and 2)

Review: multi-core execution (two cores)

Modify program to create two threads of control (two instruction streams)

```
typedef struct {  
    int N;  
    int terms;  
    float* x;  
    float* result;  
} my_args;  
  
void parallel_sinx(int N, int terms, float* x, float* result)  
{  
    pthread_t thread_id;  
    my_args args;  
  
    args.N = N/2;  
    args.terms = terms;  
    args.x = x;  
    args.result = result;  
  
    pthread_create(&thread_id, NULL, my_thread_start, &args); // launch thread  
    sinx(N - args.N, terms, x + args.N, result + args.N); // do work  
    pthread_join(thread_id, NULL);  
}  
  
void my_thread_start(void* thread_arg)  
{  
    my_args* thread_args = (my_args*)thread_arg;  
    sinx(args->N, args->terms, args->x, args->result); // do work  
}
```

My dual-core processor:
executes one instruction per clock
from an instruction stream on each core.

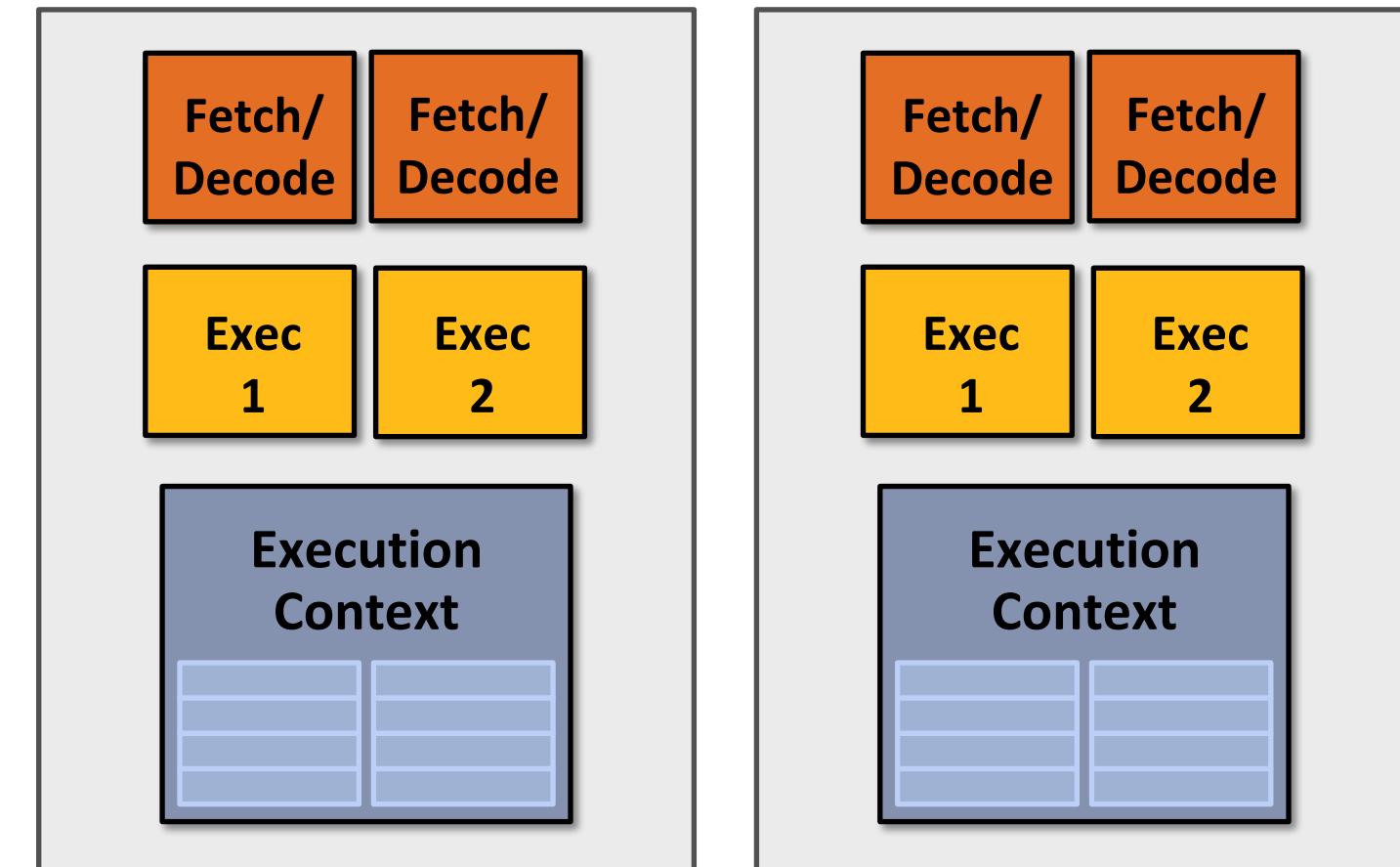


Review: multi-core + superscalar execution

Modify program to create two threads of control (two instruction streams)

```
typedef struct {  
    int N;  
    int terms;  
    float* x;  
    float* result;  
} my_args;  
  
void parallel_sinx(int N, int terms, float* x, float* result)  
{  
    pthread_t thread_id;  
    my_args args;  
  
    args.N = N/2;  
    args.terms = terms;  
    args.x = x;  
    args.result = result;  
  
    pthread_create(&thread_id, NULL, my_thread_start, &args); // launch thread  
    sinx(N - args.N, terms, x + args.N, result + args.N); // do work  
    pthread_join(thread_id, NULL);  
}  
  
void my_thread_start(void* thread_arg)  
{  
    my_args* thread_args = (my_args*)thread_arg;  
    sinx(args->N, args->terms, args->x, args->result); // do work  
}
```

My superscalar dual-core processor:
executes up to two instructions per clock
from an instruction stream on each core.



Review: multi-core (four cores)

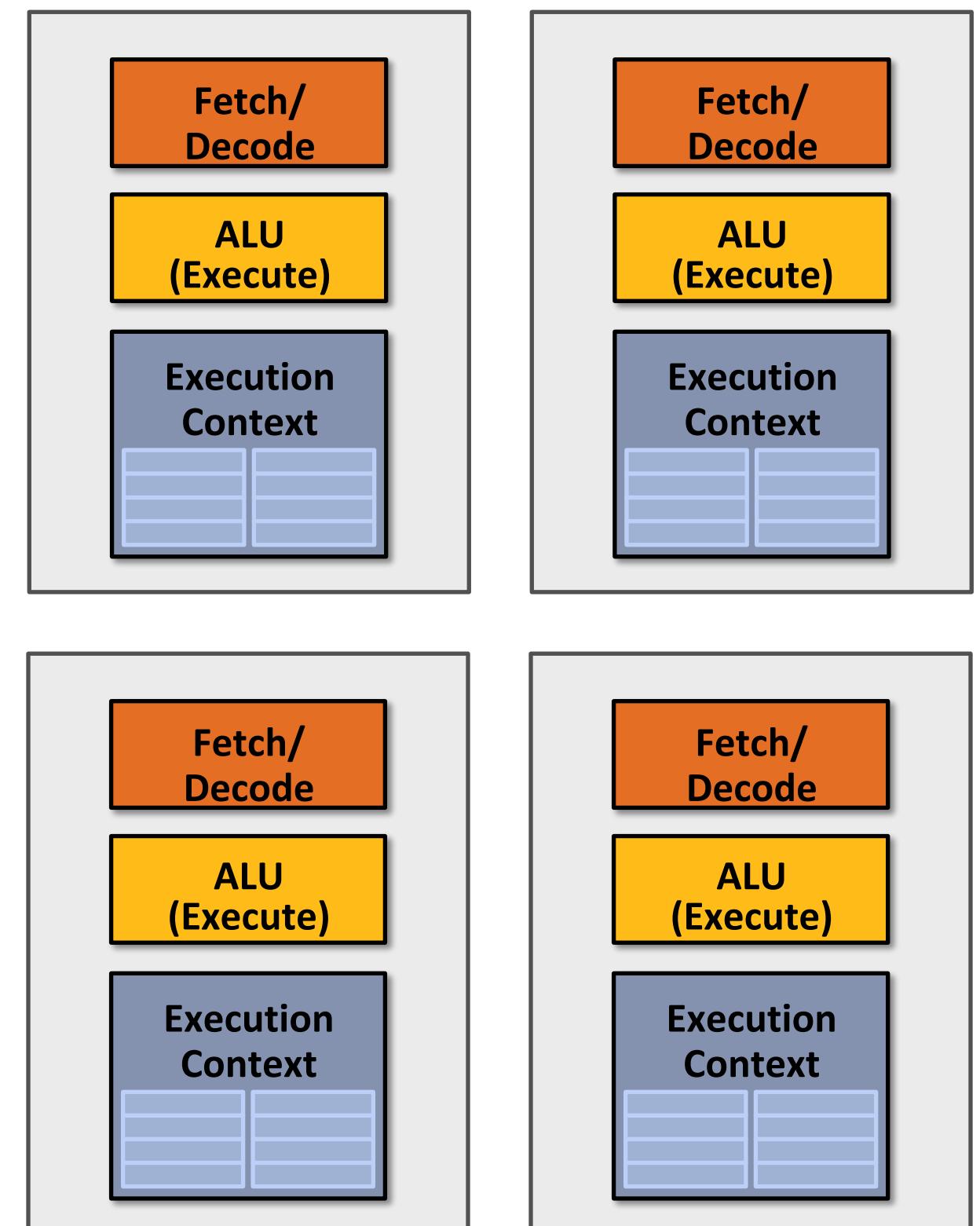
Modify program to create many threads of control: recall our fictitious language

```
void sinx(int N, int terms, float* x, float* result)
{
    // declare independent loop iterations
    forall (int i from 0 to N-1)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

My quad-core processor:
executes one instruction per clock
from an instruction stream on each core.



Review: four, 8-wide SIMD cores

Observation: program must execute many iterations of the same loop body.

Optimization: share instruction stream across execution of multiple iterations
(single instruction multiple data = SIMD)

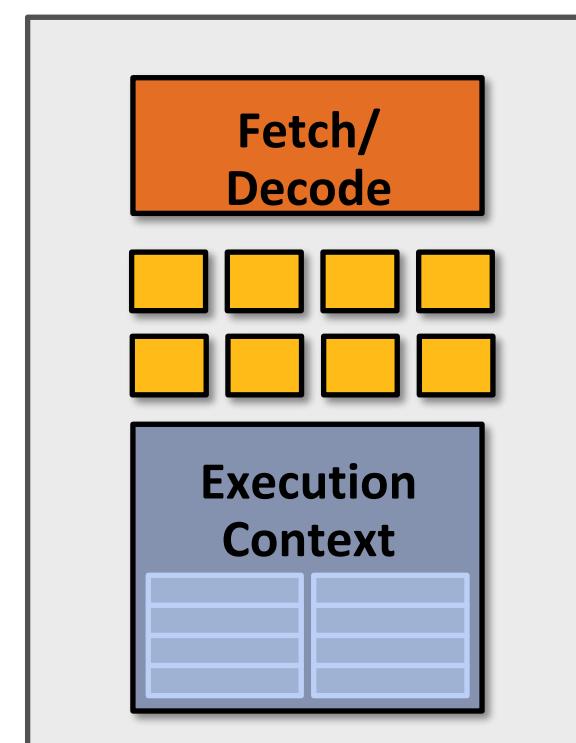
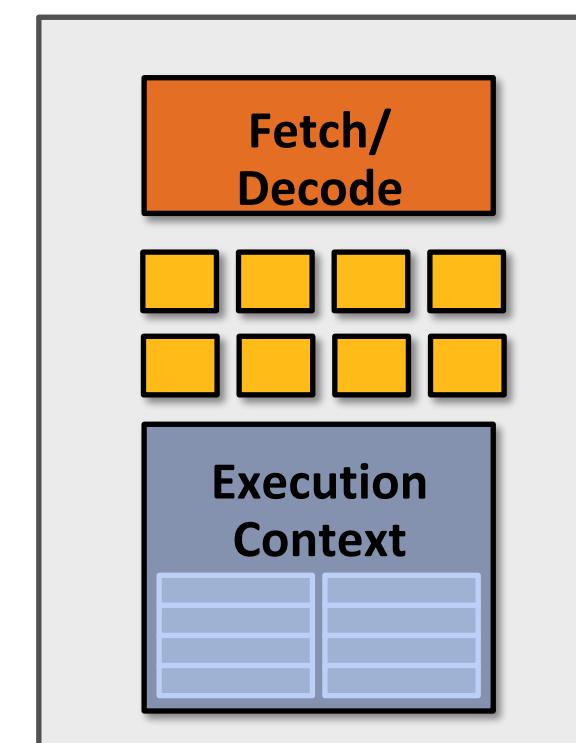
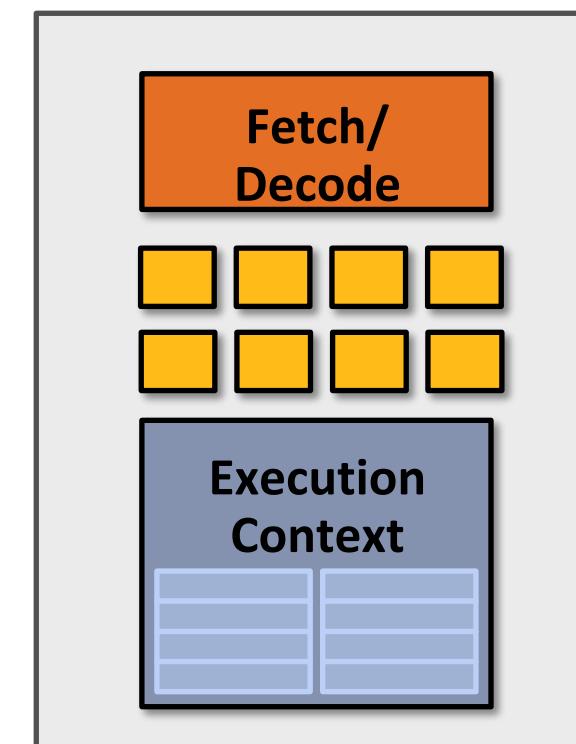
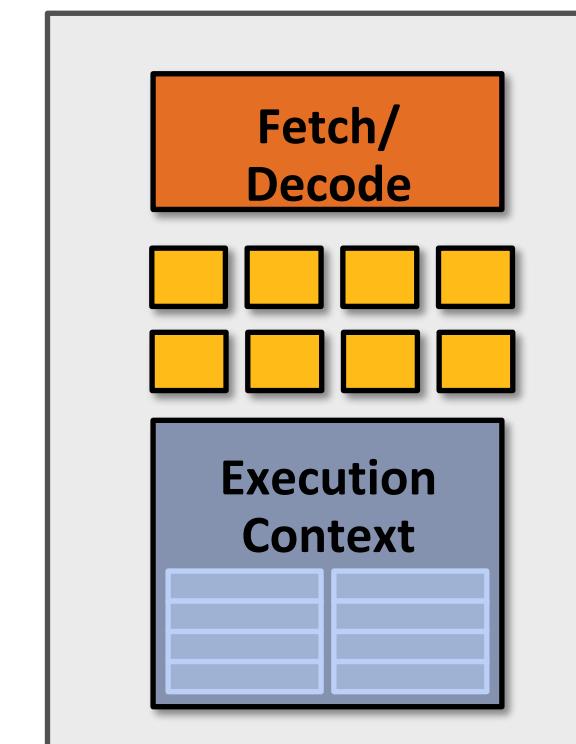
```
void sinx(int N, int terms, float* x, float* result)
{
    // declare independent loop iterations
    forall (int i from 0 to N-1)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value;
    }
}
```

My SIMD quad-core processor:

executes one 8-wide SIMD instruction per
clock from an instruction stream on each core.



Review: four SIMD, multi-threaded cores

Observation: memory operations have very long latency

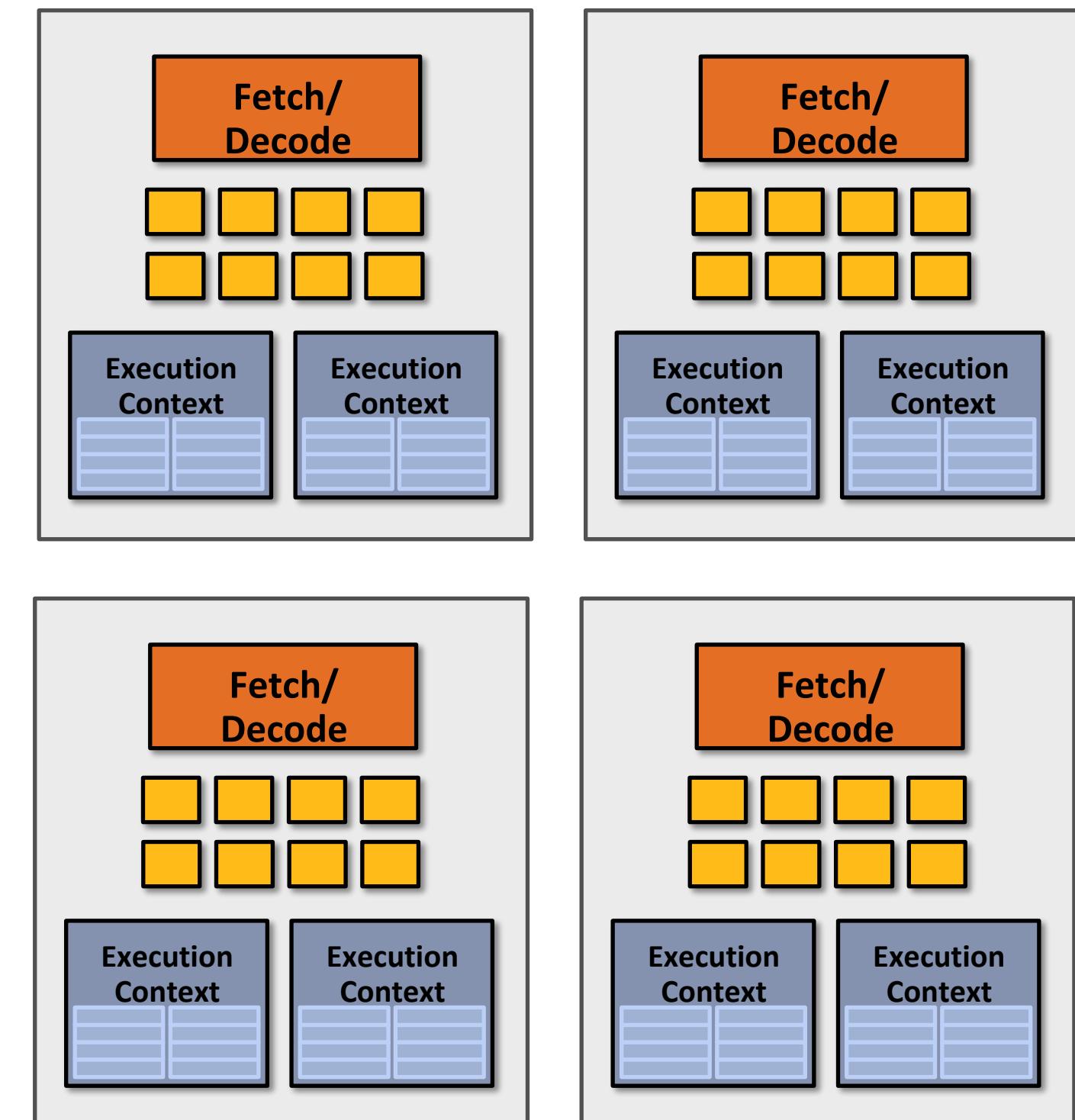
Solution: hide latency of loading data for one iteration by executing arithmetic instructions from other iterations

```
void sinx(int N, int terms, float* x, float* result)
{
    // declare independent loop iterations
    forall (int i from 0 to N-1)
    {
        float value = x[i]; x[i] Memory load
        float numer = x[i] * x[i] * x[i];
        int denom = 6; // 3!
        int sign = -1;

        for (int j=1; j<=terms; j++)
        {
            value += sign * numer / denom
            numer *= x[i] * x[i];
            denom *= (2*j+2) * (2*j+3);
            sign *= -1;
        }

        result[i] = value; Memory store
    }
}
```

My multi-threaded, SIMD quad-core processor: executes one SIMD instruction per clock from one instruction stream on each core. But can switch to processing the other instruction stream when faced with a stall.

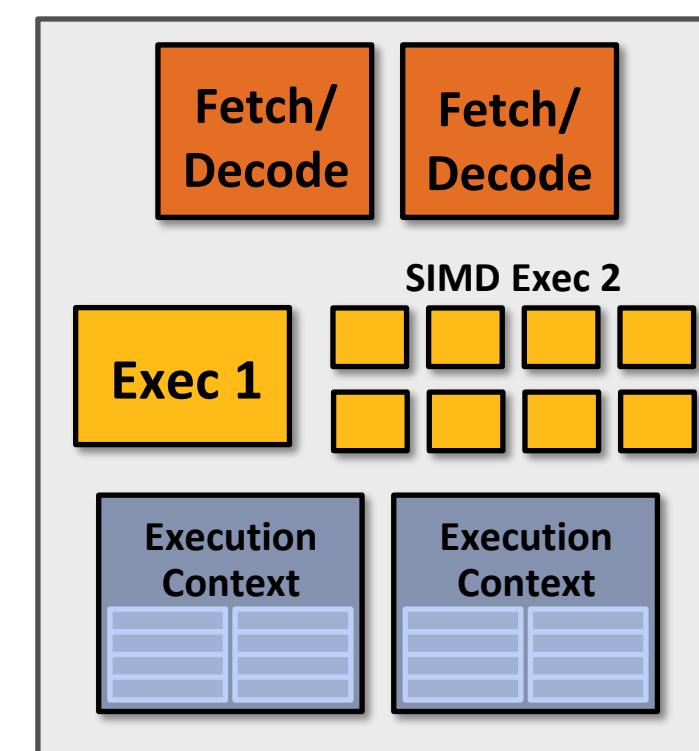
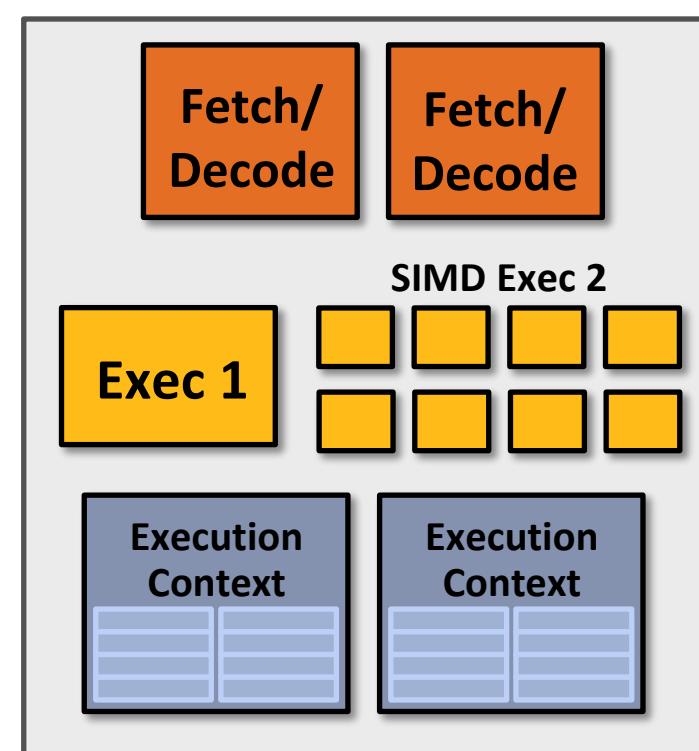
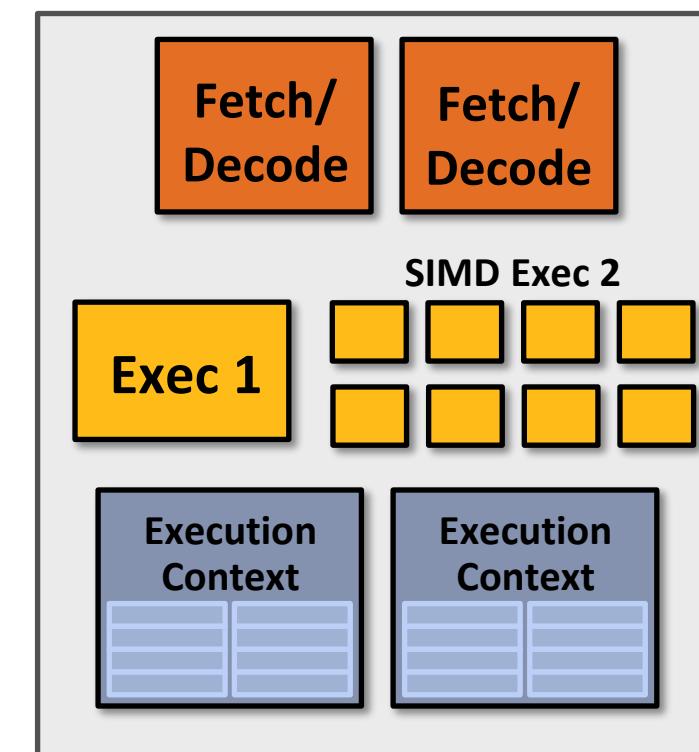
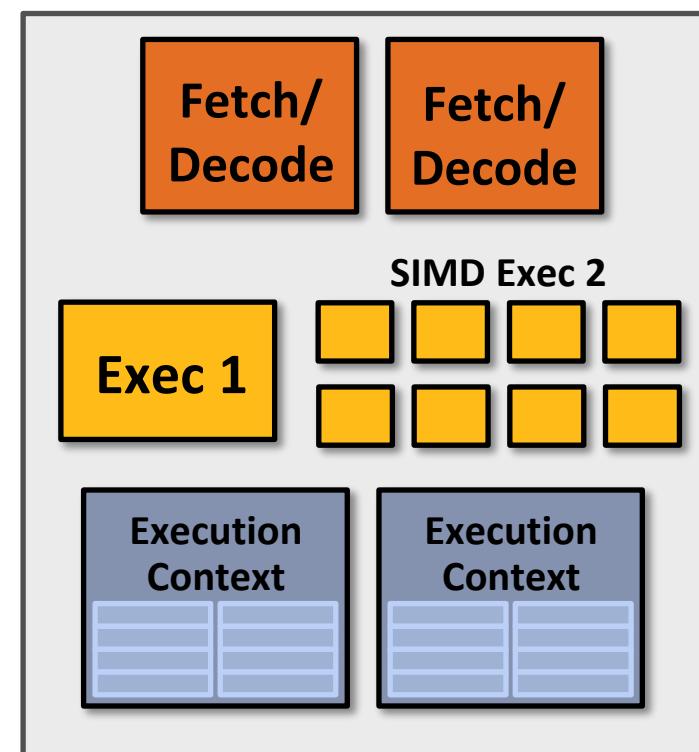


Summary: four superscalar, SIMD, multi-threaded cores

My multi-threaded, superscalar, SIMD quad-core processor:

Executes up to two instructions per clock from one instruction stream on each core (in this example: one SIMD instruction + one scalar instruction).

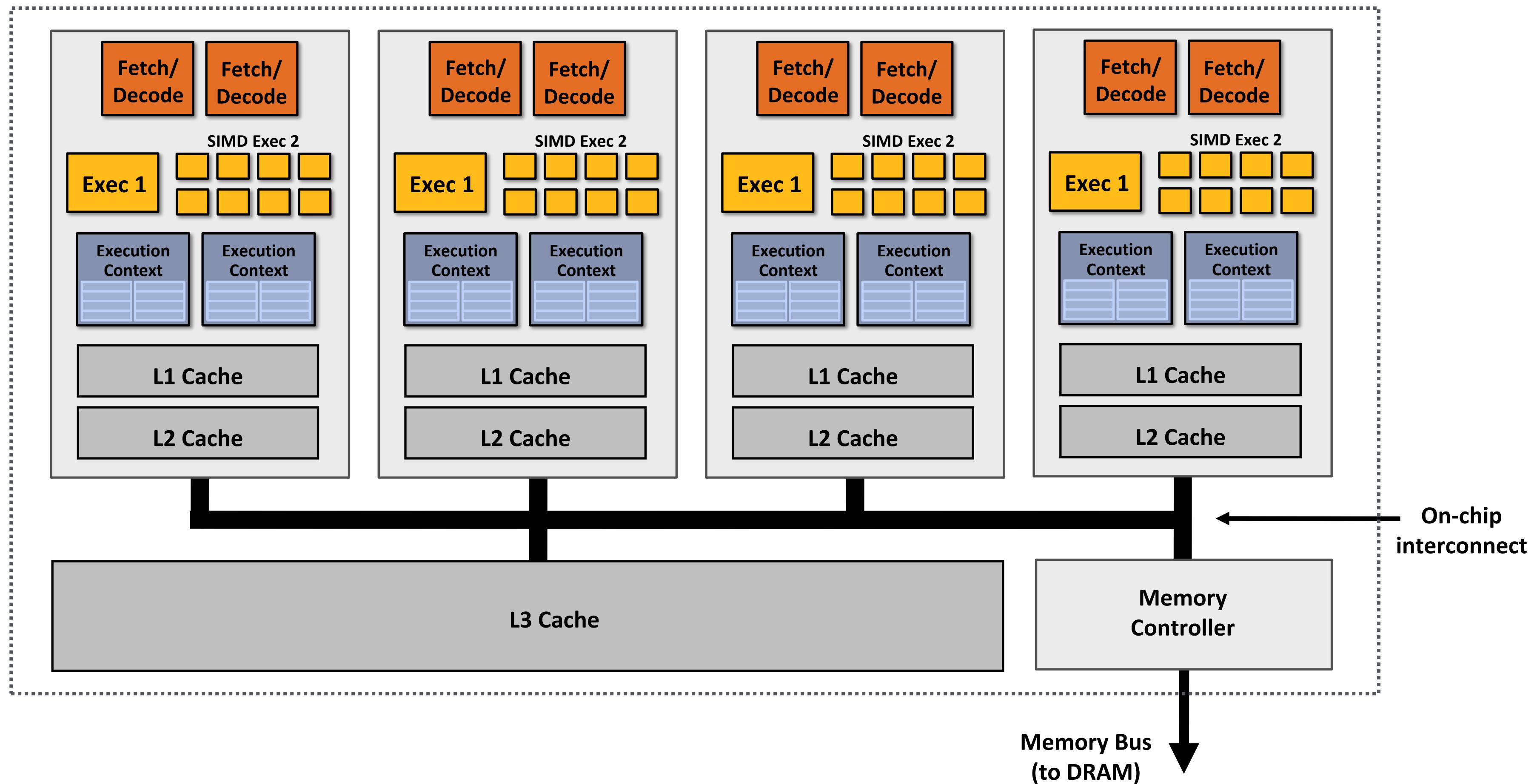
Processor can switch to execute the other instruction stream when faced with stall.



Connecting it all together

Our simple quad-core processor:

Four cores, two-way multi-threading per core (max eight threads active on chip at once), up to two instructions per clock per core (one of those instructions is 8-wide SIMD)



Thought experiment

- You write a C application that spawns two pthreads
- The application runs on the processor shown below
 - Two cores, two-execution contexts per core, up to 8 instructions per clock, one instruction is an 8-wide SIMD instruction.
- Question: “who” is responsible for mapping your pthreads to the processor’s thread execution contexts?
Answer: the operating system
- Question: If you were the OS, how would you assign the two threads to the four available execution contexts?
- Another question: How would you assign threads to execution contexts if your C program spawned five pthreads?

