

Lecture 3:

Parallel Programming Abstractions

(and their corresponding HW/SW implementations)

**Parallel Computing
Stanford CS149, Fall 2021**

Finishing up from last time + Review

REVIEW

HOW IT ALL FITS TOGETHER:

**superscalar execution,
SIMD execution,
multi-core execution,
and hardware multi-threading**

Running code on a simple processor

C program source

```
void sinx(int N, int terms, float* x, float* y)
{
    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;
        }

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

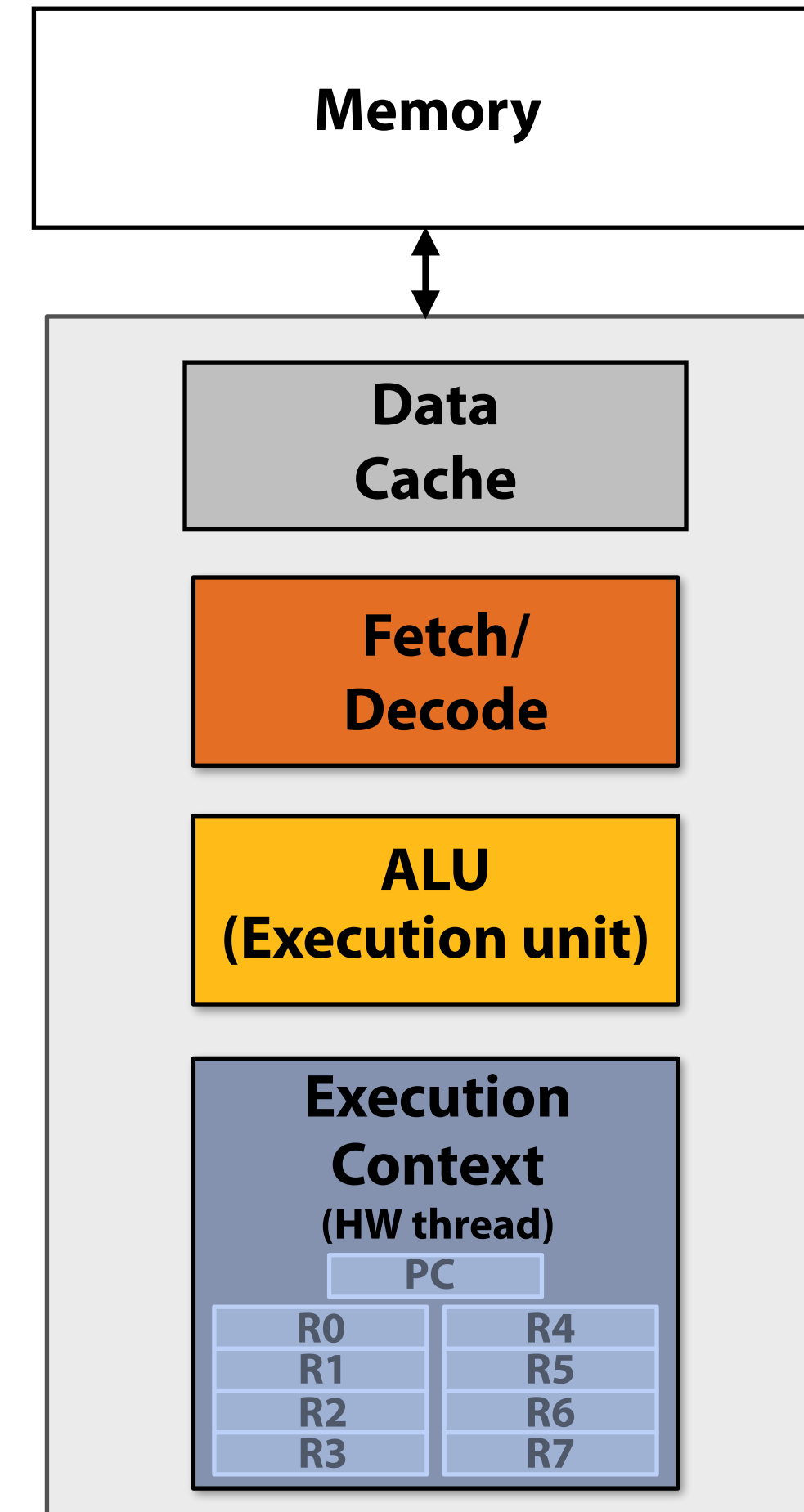
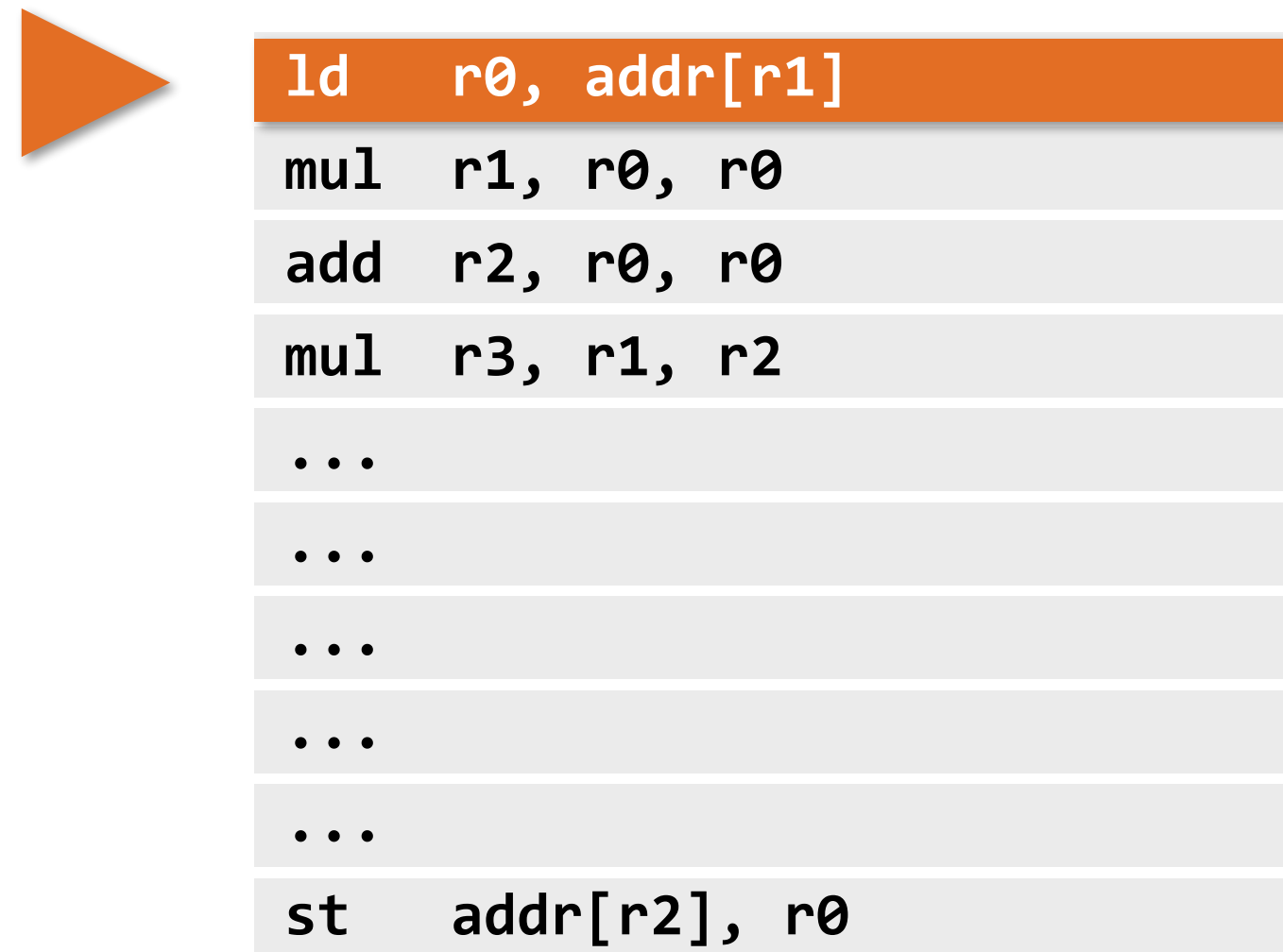
compiler

Compiled instruction stream (scalar instructions)

```
ld    r0, addr[r1]
mul   r1, r0, r0
add   r2, r0, r0
mul   r3, r1, r2
...
...
...
...
...
st    addr[r2], r0
```


Running code on a simple processor

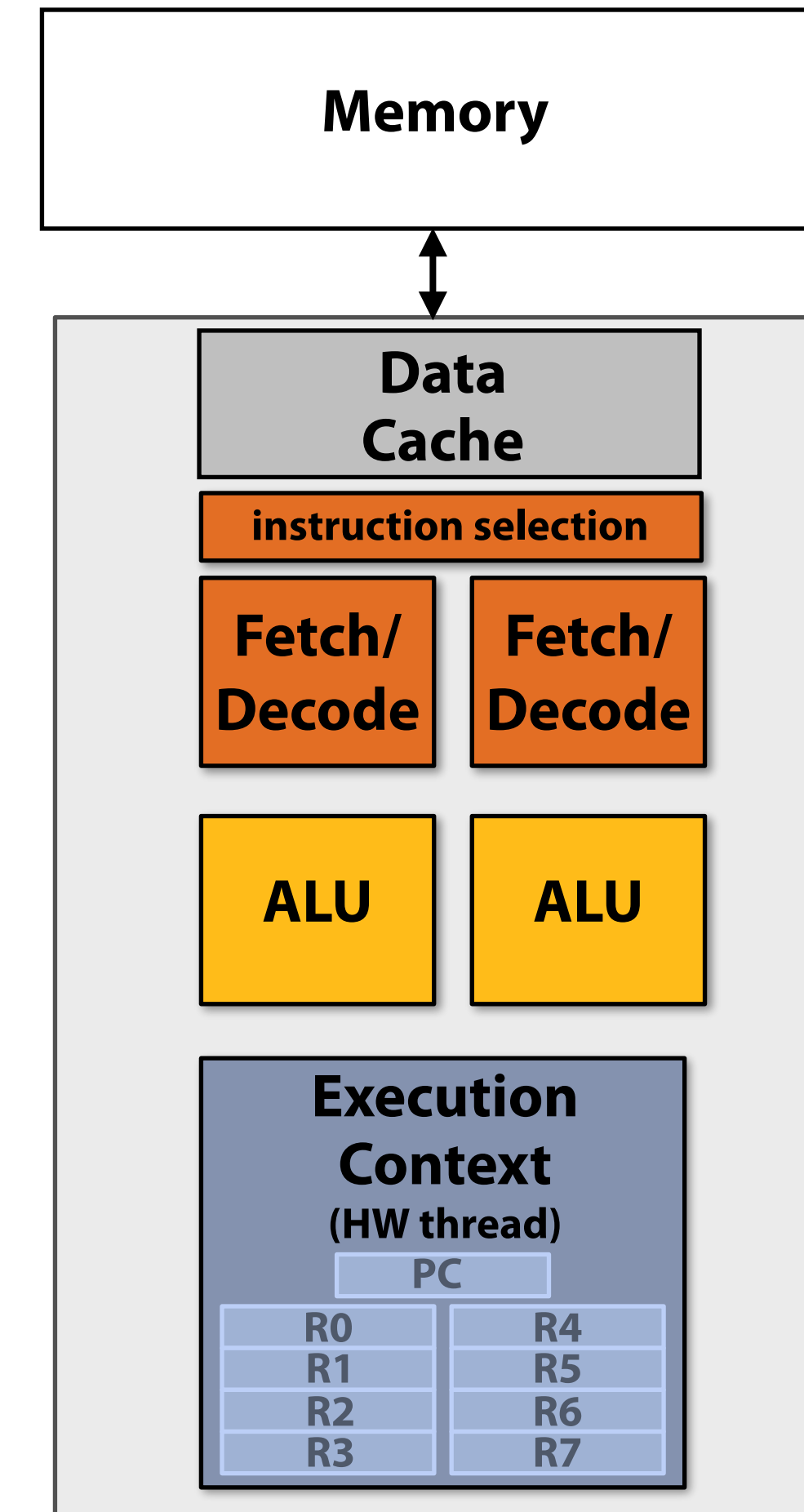
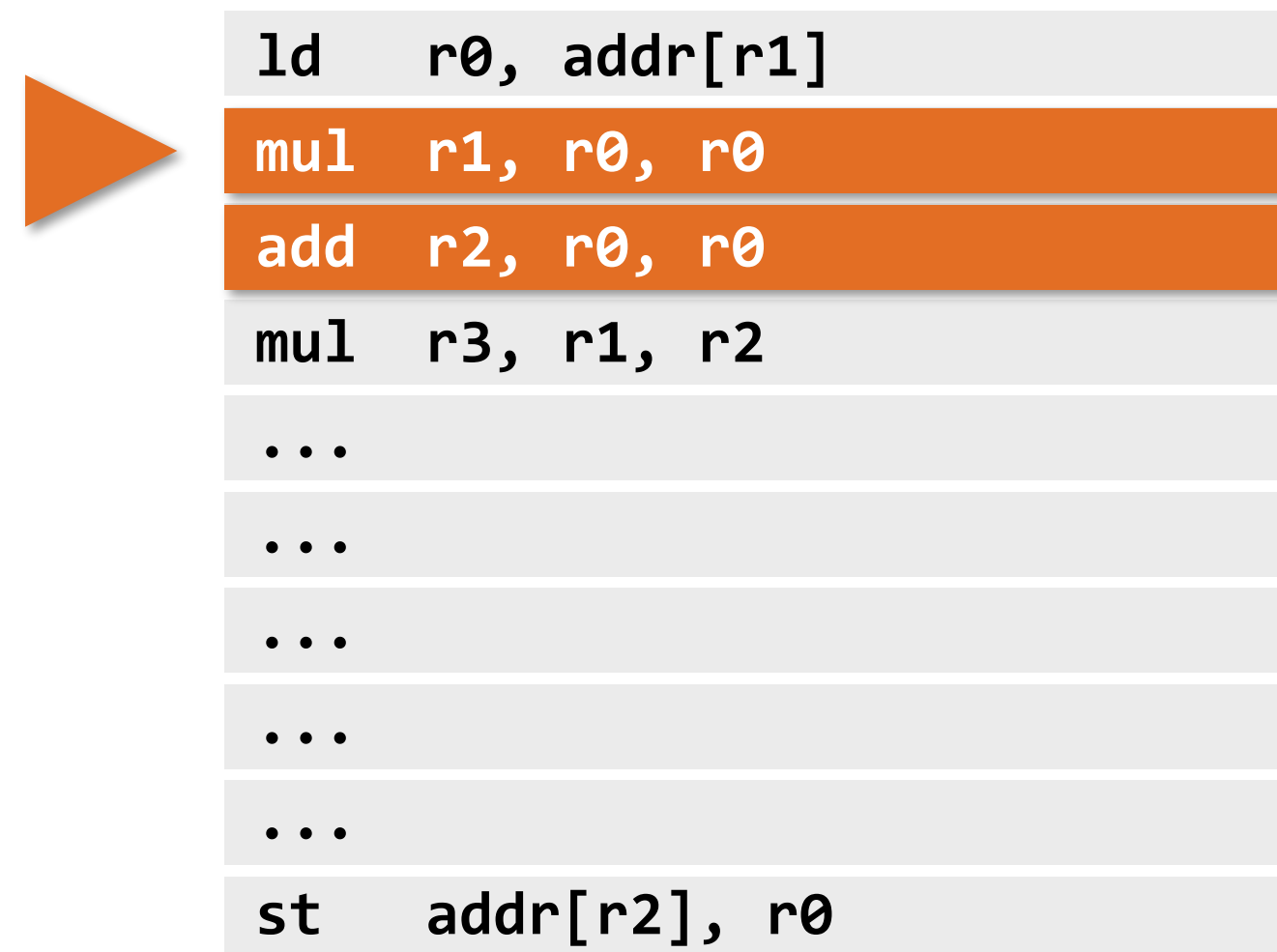
Instruction stream



Single core processor, single-threaded core.
Can run one scalar instruction per clock

Superscalar core

Instruction stream

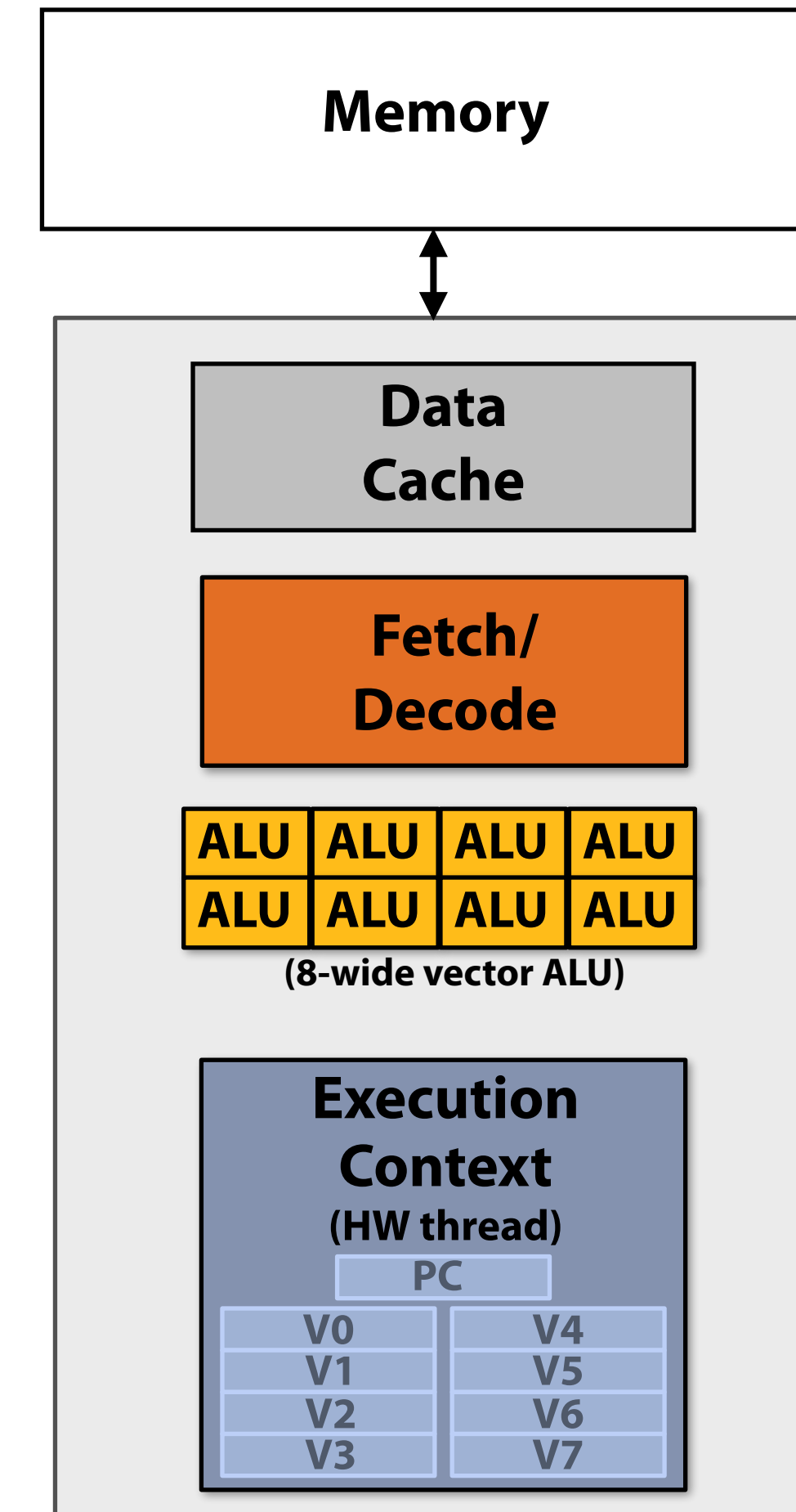


Single core processor, single-threaded core.
Two-way superscalar core:
can run up to two independent scalar instructions
per clock from one instruction stream (one hardware thread)

SIMD execution capability

Instruction stream (now with vector instructions)

vector_ld	v0, vector_addr[r1]
vector_mul	v1, v0, v0
vector_add	v2, v0, v0
vector_mul	v3, v1, v2
...	
...	
...	
...	
...	
vector_st	addr[r2], v0

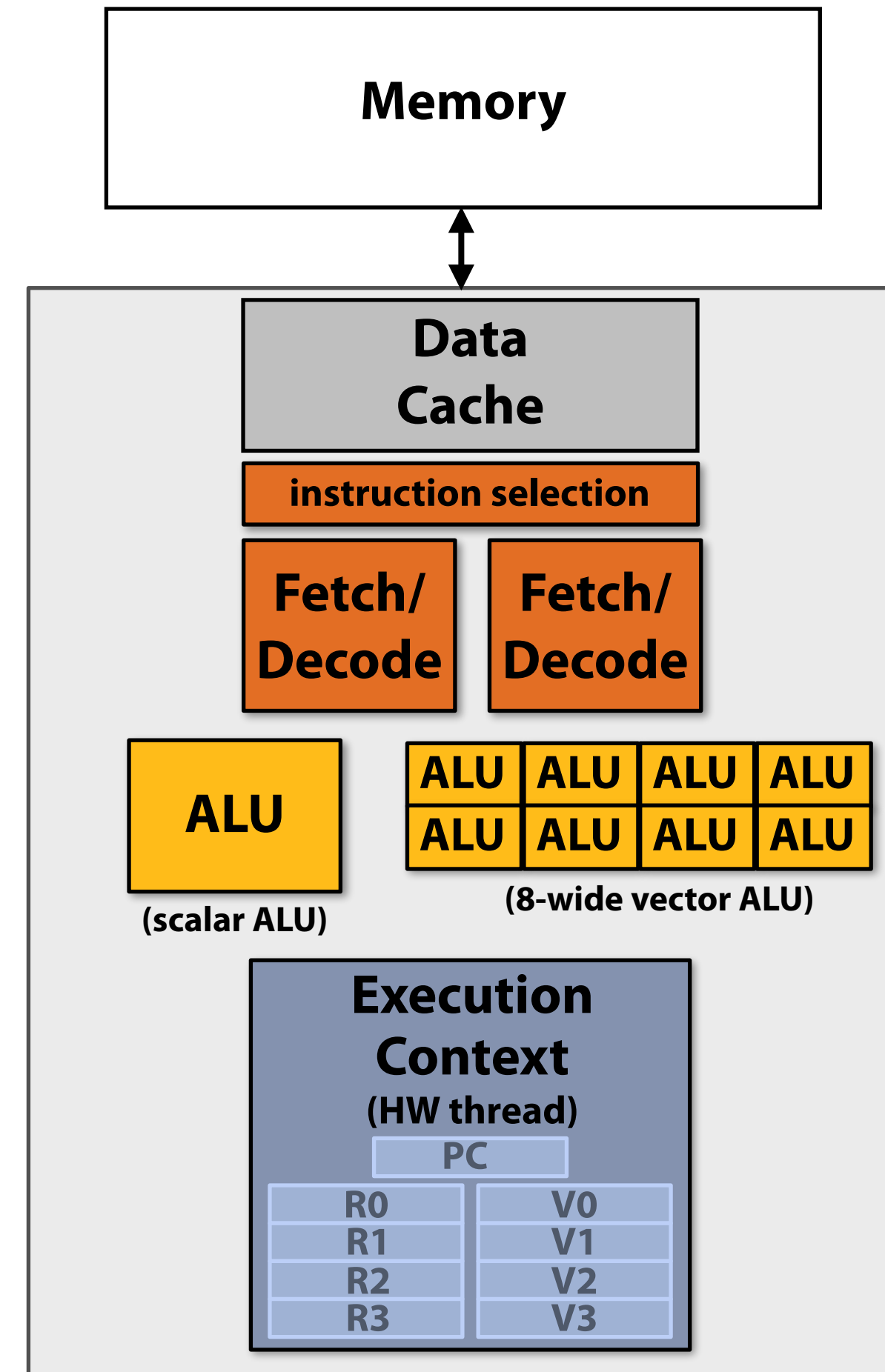


**Single core processor, single-threaded core.
can run one 8-wide SIMD vector instruction from
one instruction stream**

Heterogeneous superscalar (scalar + SIMD)

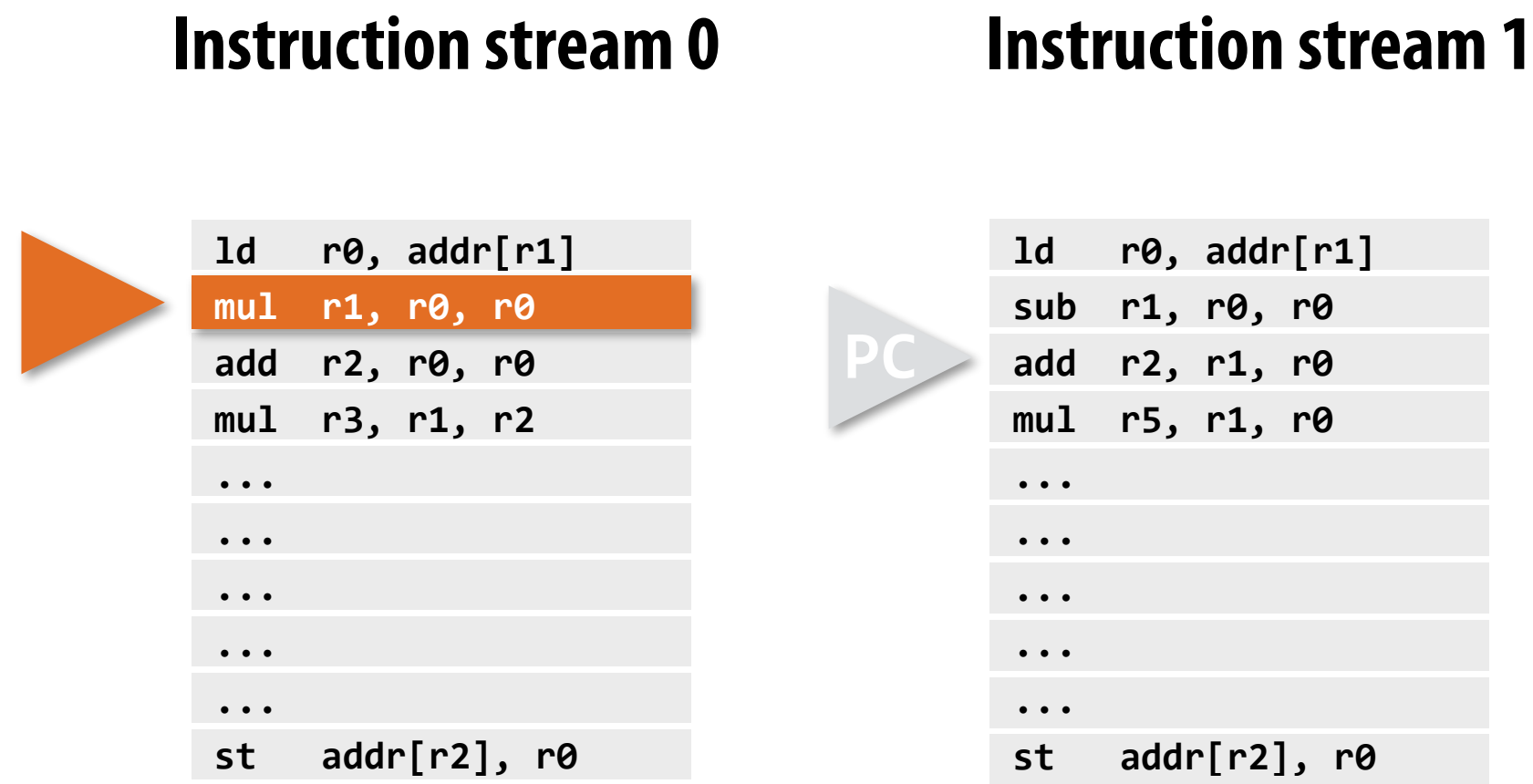
Instruction stream

vector_ld	v0, vector_addr[r1]
vector_mul	v1, v0, v0
add	r2, r1, r0
vector_add	v2, v0, v0
vector_mul	v3, v1, v2...
...	
...	
...	
...	
vector_st	addr[r2], v0



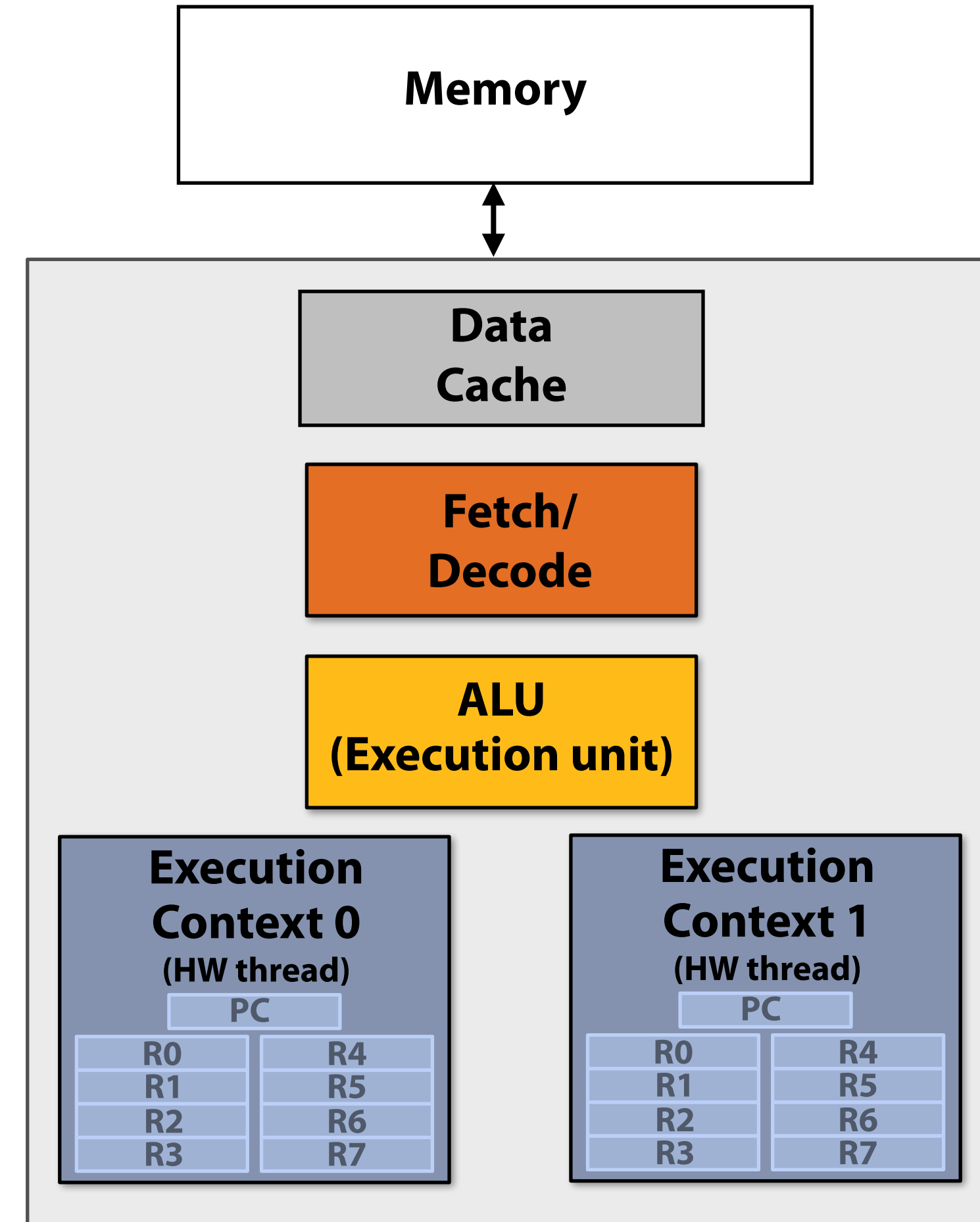
**Single core processor, single-threaded core.
Two-way superscalar core:
can run up to two independent instructions per clock from one
instruction stream, provided one is scalar and the other is vector**

Multi-threaded core



Note: threads can be running completely different instruction streams (and be at different points in these streams)

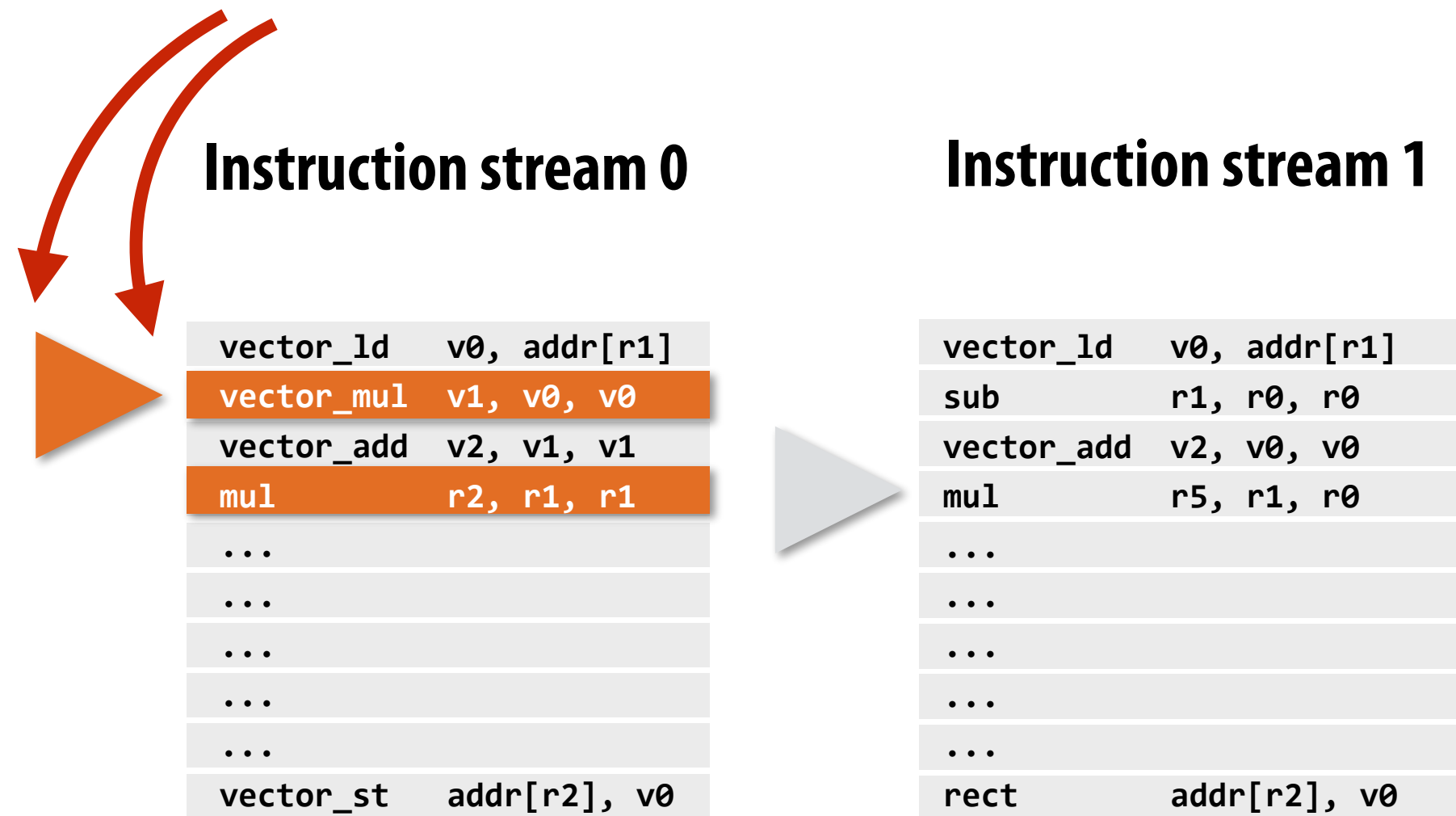
Execution of hardware threads is interleaved in time.



**Single core processor, multi-threaded core (2 threads).
Can run one scalar instruction per clock from
one of the instruction streams (hardware threads)**

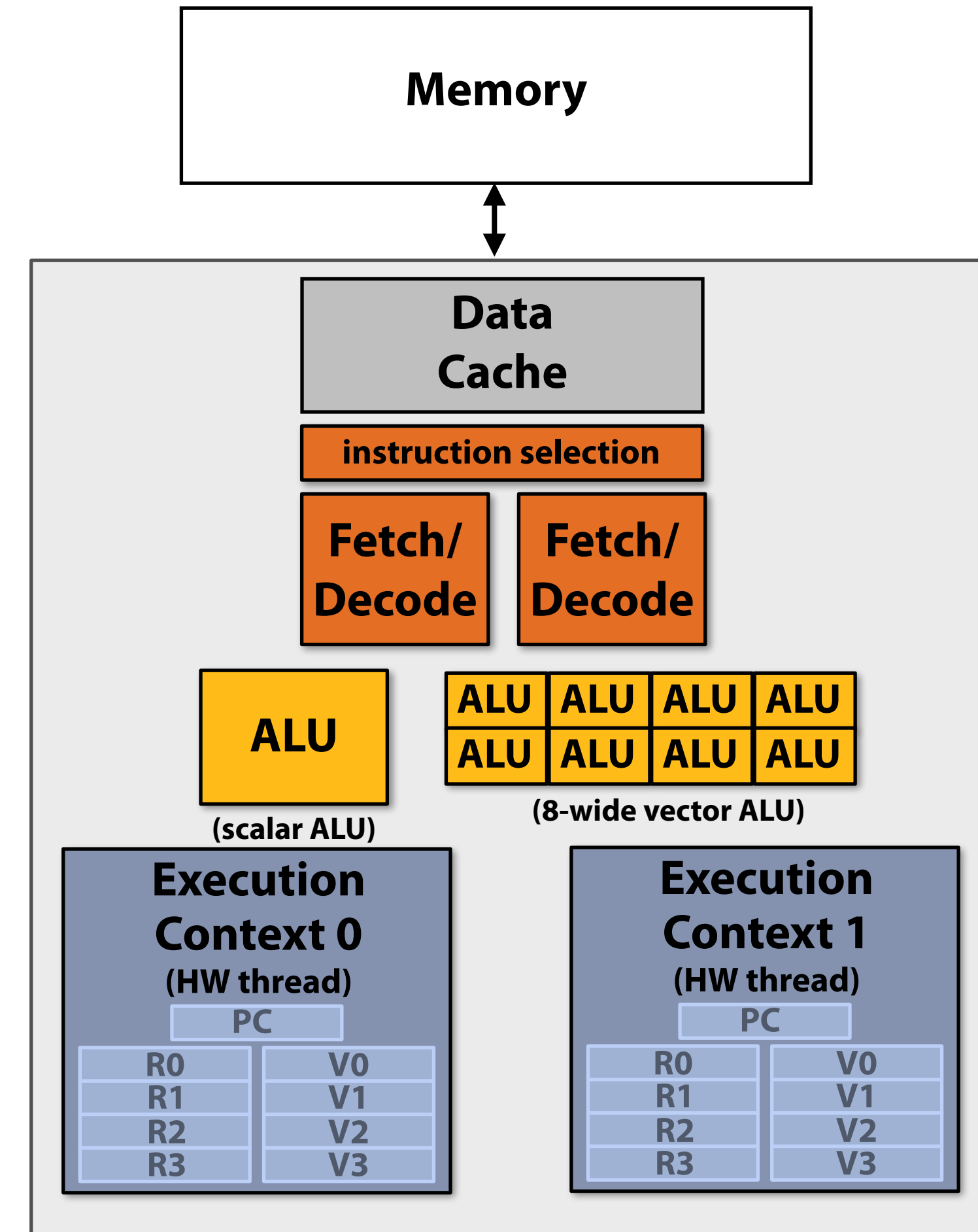
Multi-threaded, superscalar core

In this example: two instructions from the same thread.
(Superscalar execution, interleaved multi-threading)



Note: threads can be running completely different instruction streams (and be at different points in these streams)

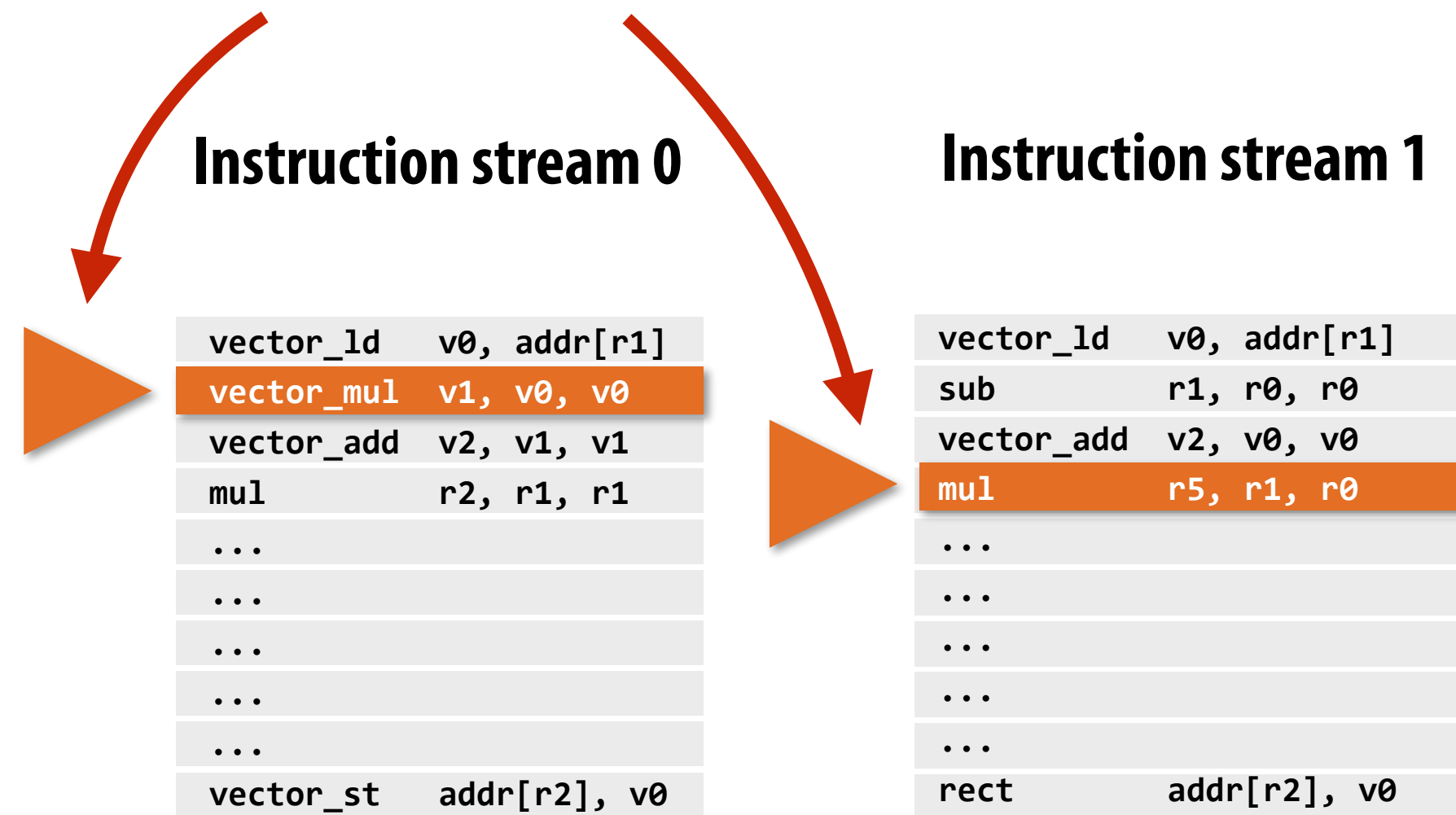
Execution of hardware threads is interleaved in time.



Single core processor, multi-threaded core (2 threads).
Two-way superscalar core: in this example, my core is capable of running up to two independent instructions per clock, provided one is scalar and the other is vector

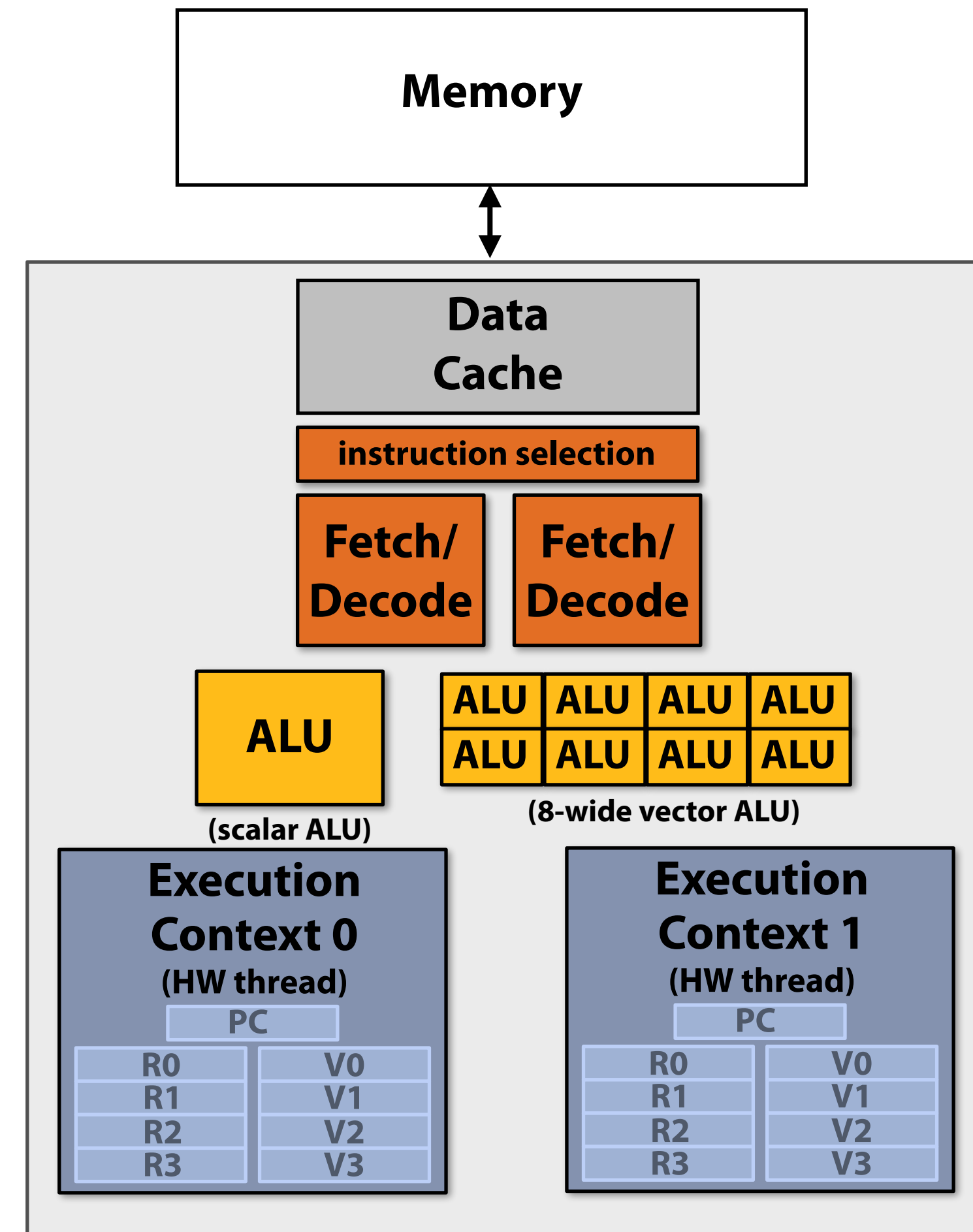
Multi-threaded, superscalar core

In this example: two instructions from different threads.
(simultaneous multi-threading)



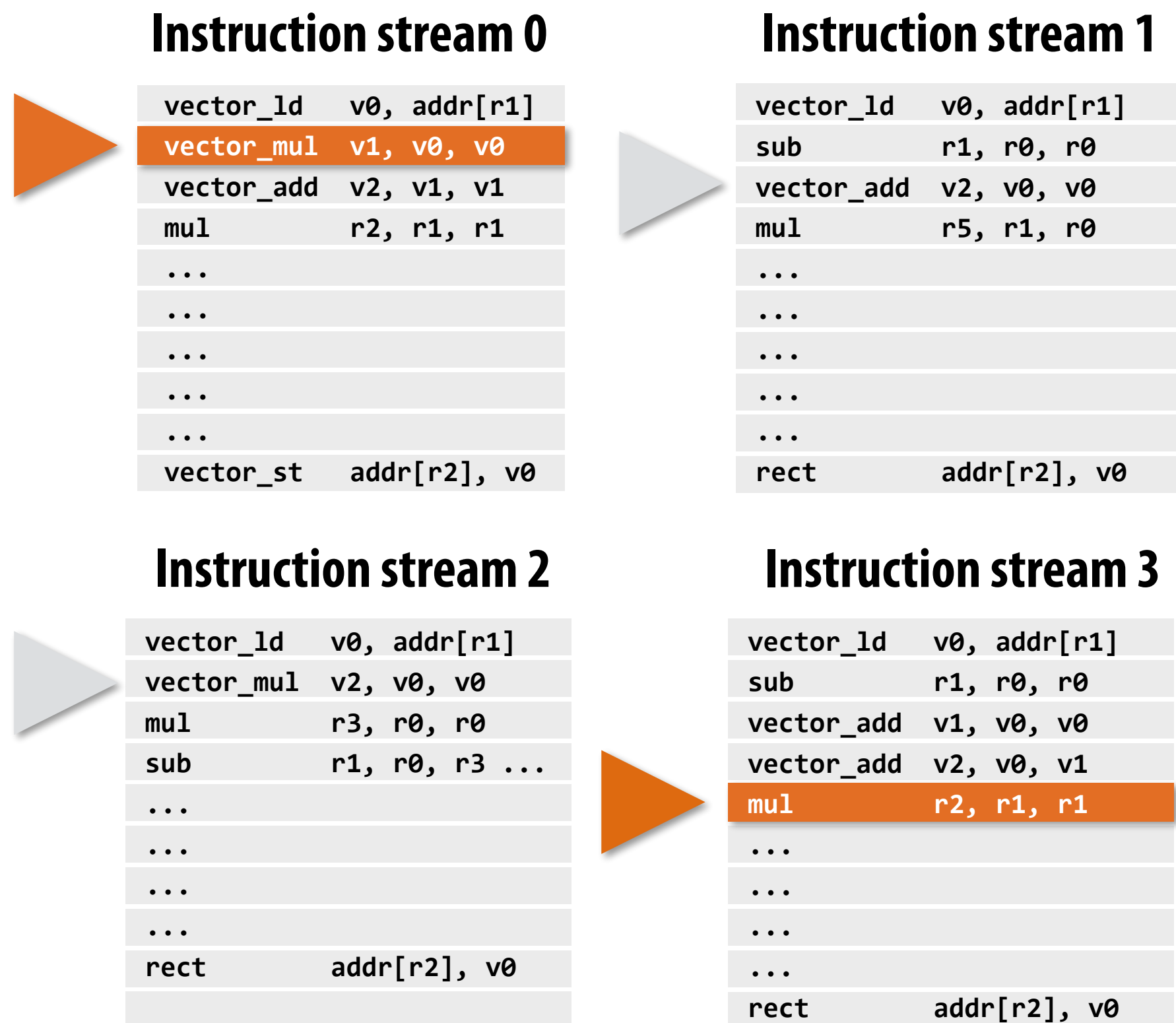
Note: threads can be running completely different instruction streams (and be at different points in these streams)

Simultaneous execution of two hardware threads.

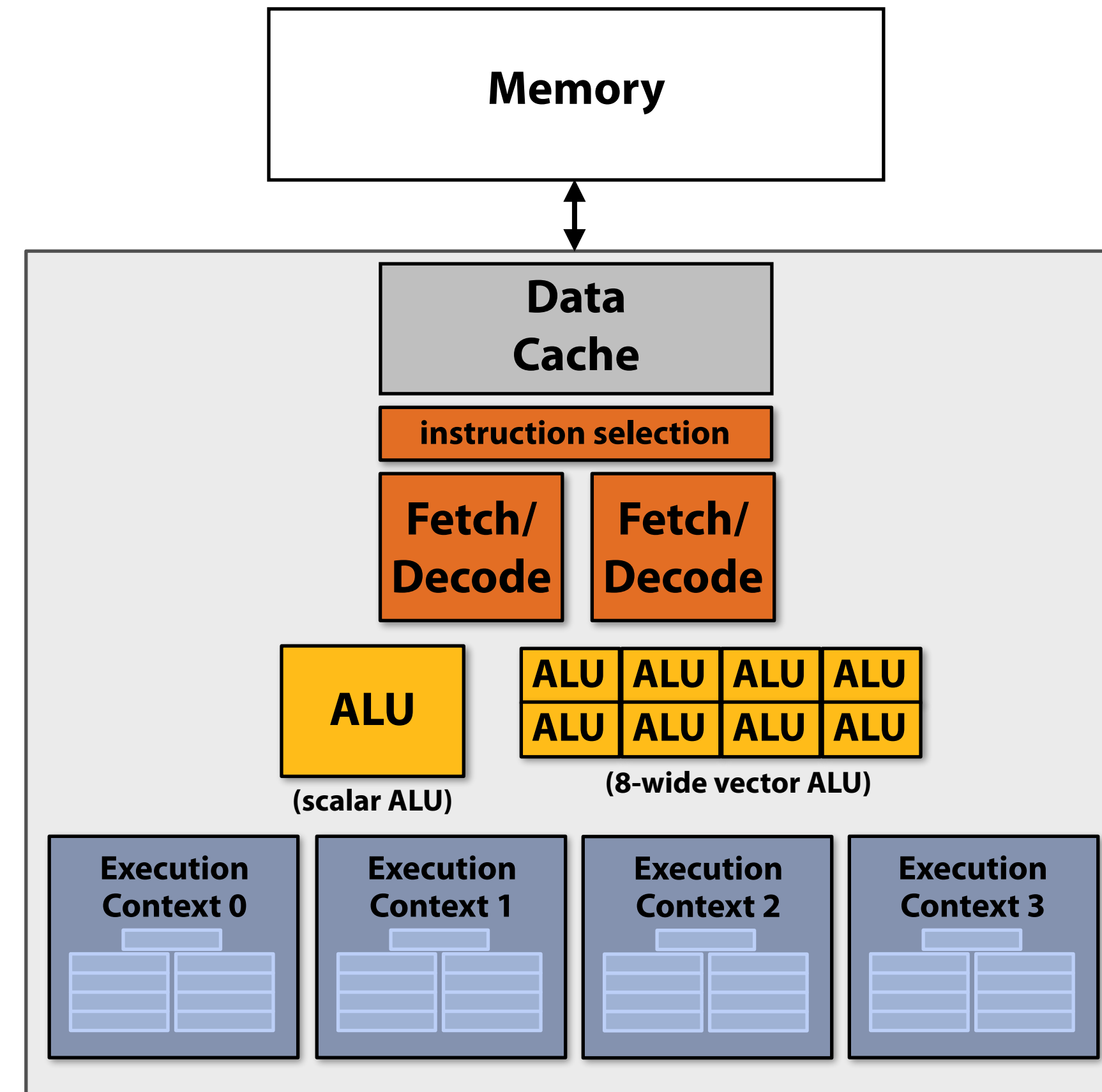


Single core processor, multi-threaded core (2 threads).
Two-way superscalar core: in this example, my core is capable of running up to two independent instructions per clock, provided one is scalar and the other is vector

Multi-threaded, superscalar core



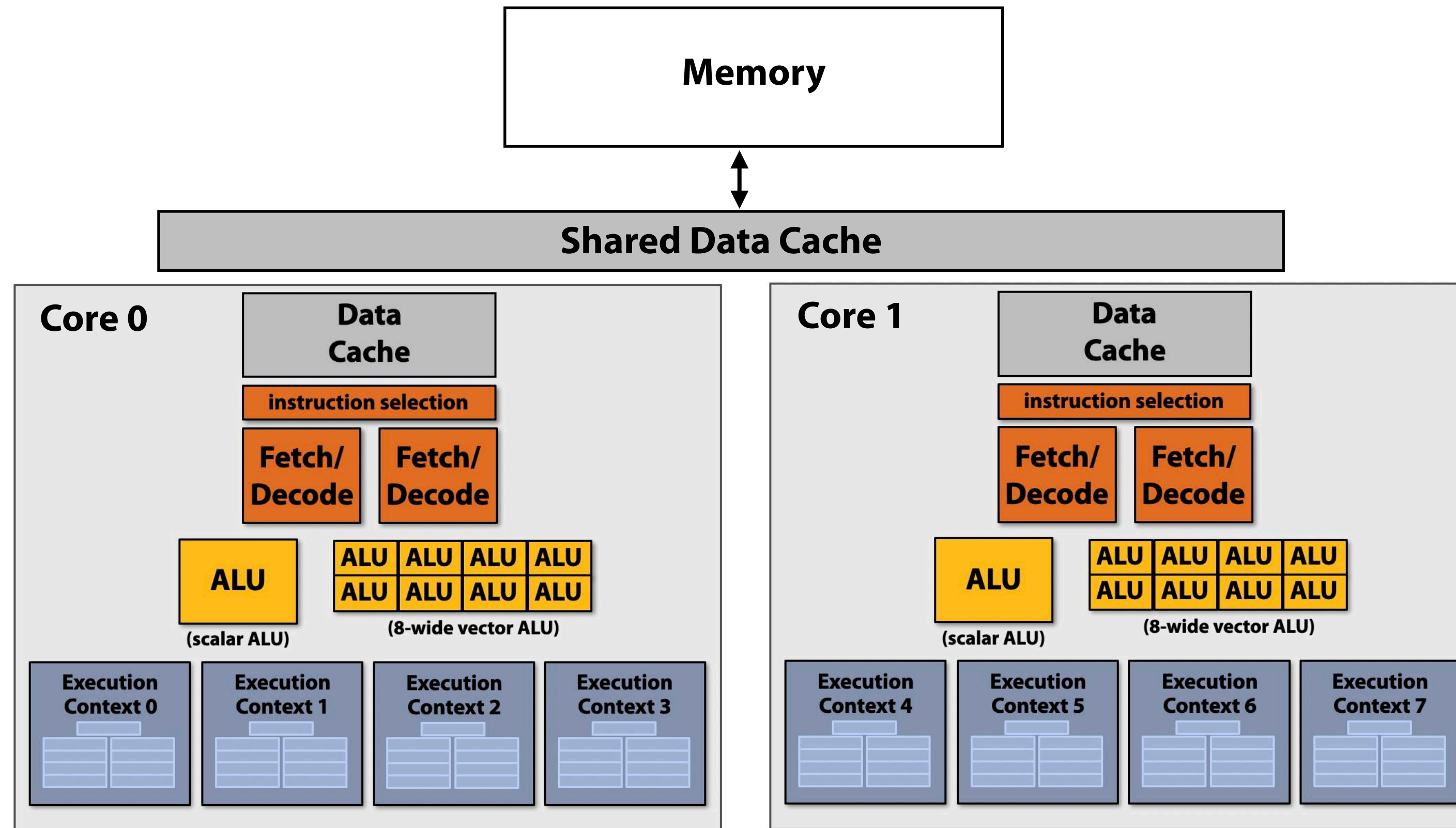
Execution of hardware threads may or may not be interleaved in time (instructions from different threads may be running simultaneously)



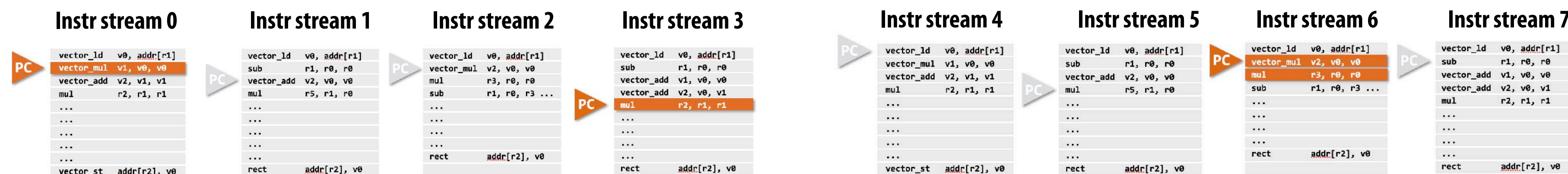
Single core processor, multi-threaded core (4 threads).

Two-way superscalar core:
can run up to two independent instructions per clock from any of the threads, provided one is scalar and the other is vector

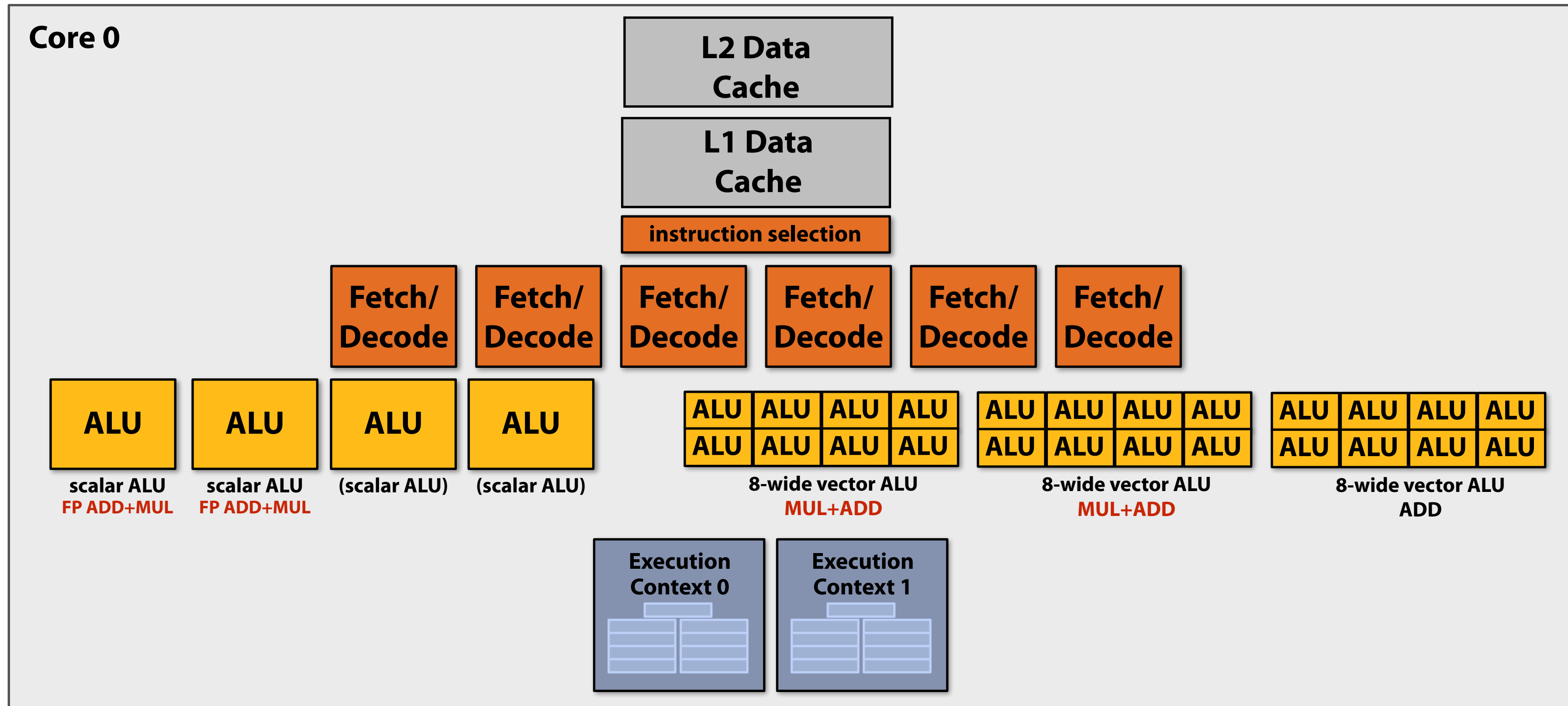
Multi-core, with multi-threaded, superscalar cores



**Dual-core processor, multi-threaded cores (4 threads/core).
Two-way superscalar cores: each core can run up to two independent instructions per clock from any of its threads, provided one is scalar and the other is vector**

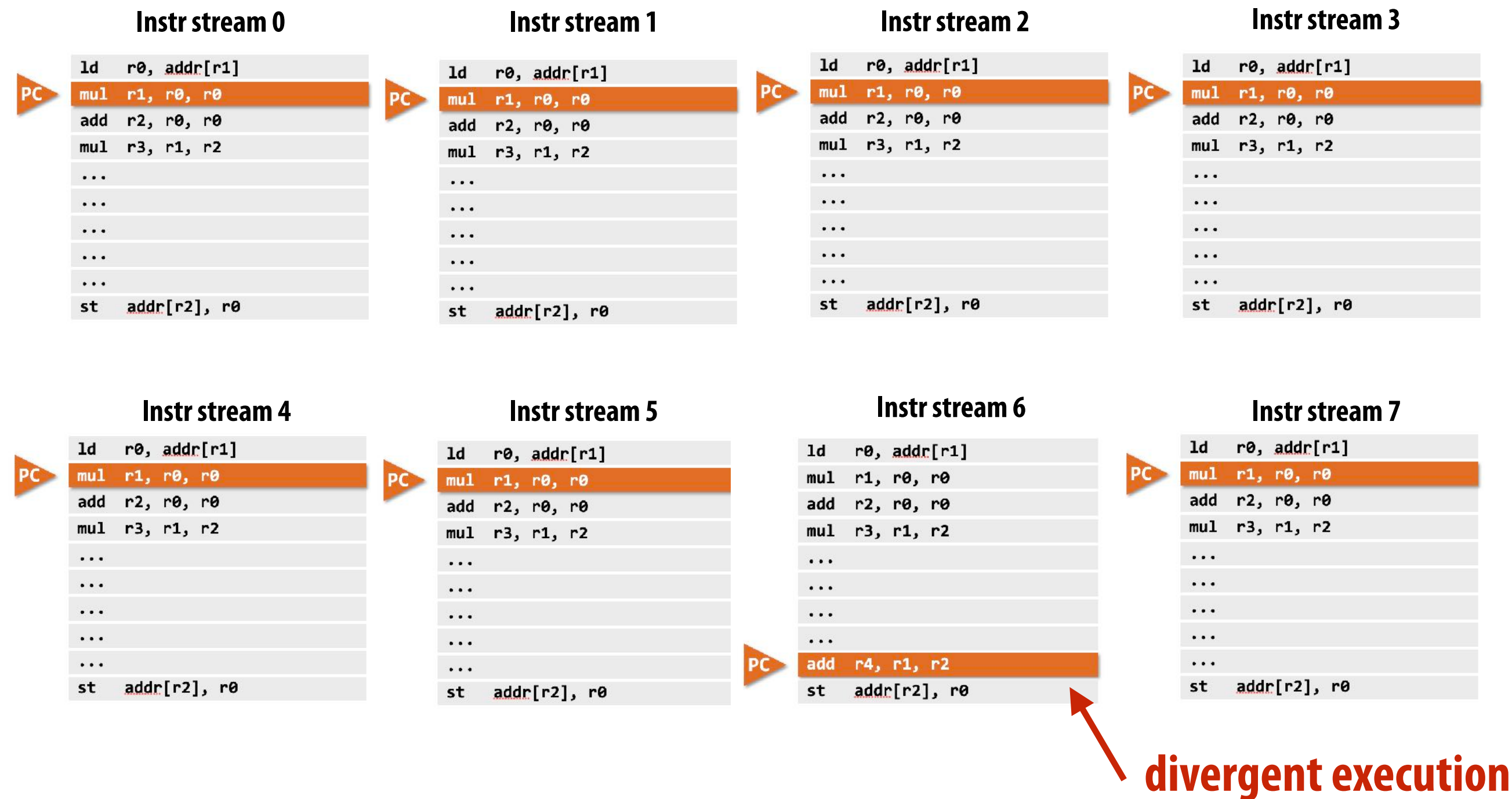


Example: Intel Skylake core



**Two-way multi-threaded cores (2 threads).
Each core can run multiple independent scalar
instructions and multiple 8-wide vector instructions
(up to 2 vector mul or 3 vector add)**

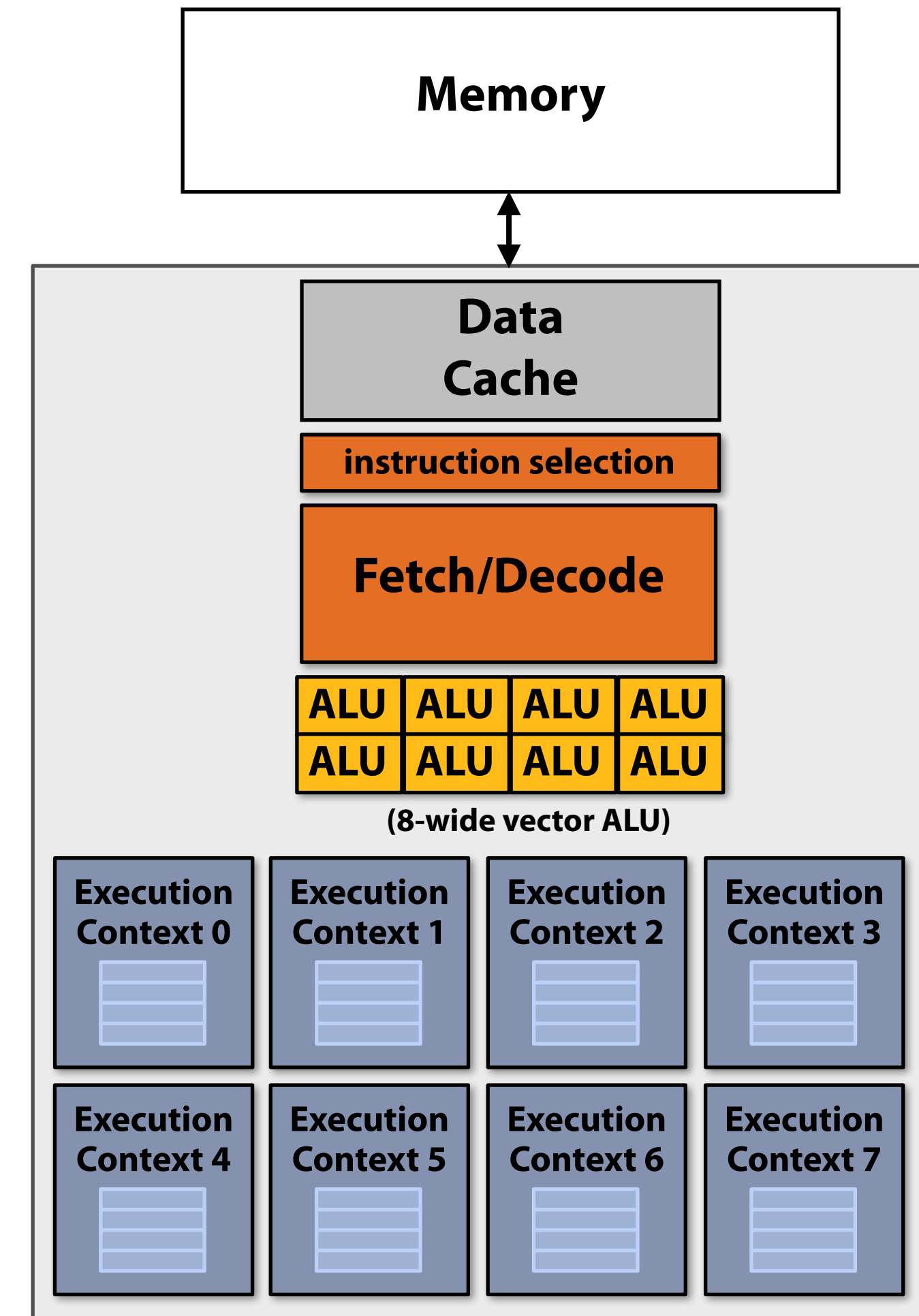
GPU "SIMT" (single instruction multiple thread)



Many modern GPUs execute hardware threads that run instruction streams with only scalar instructions.

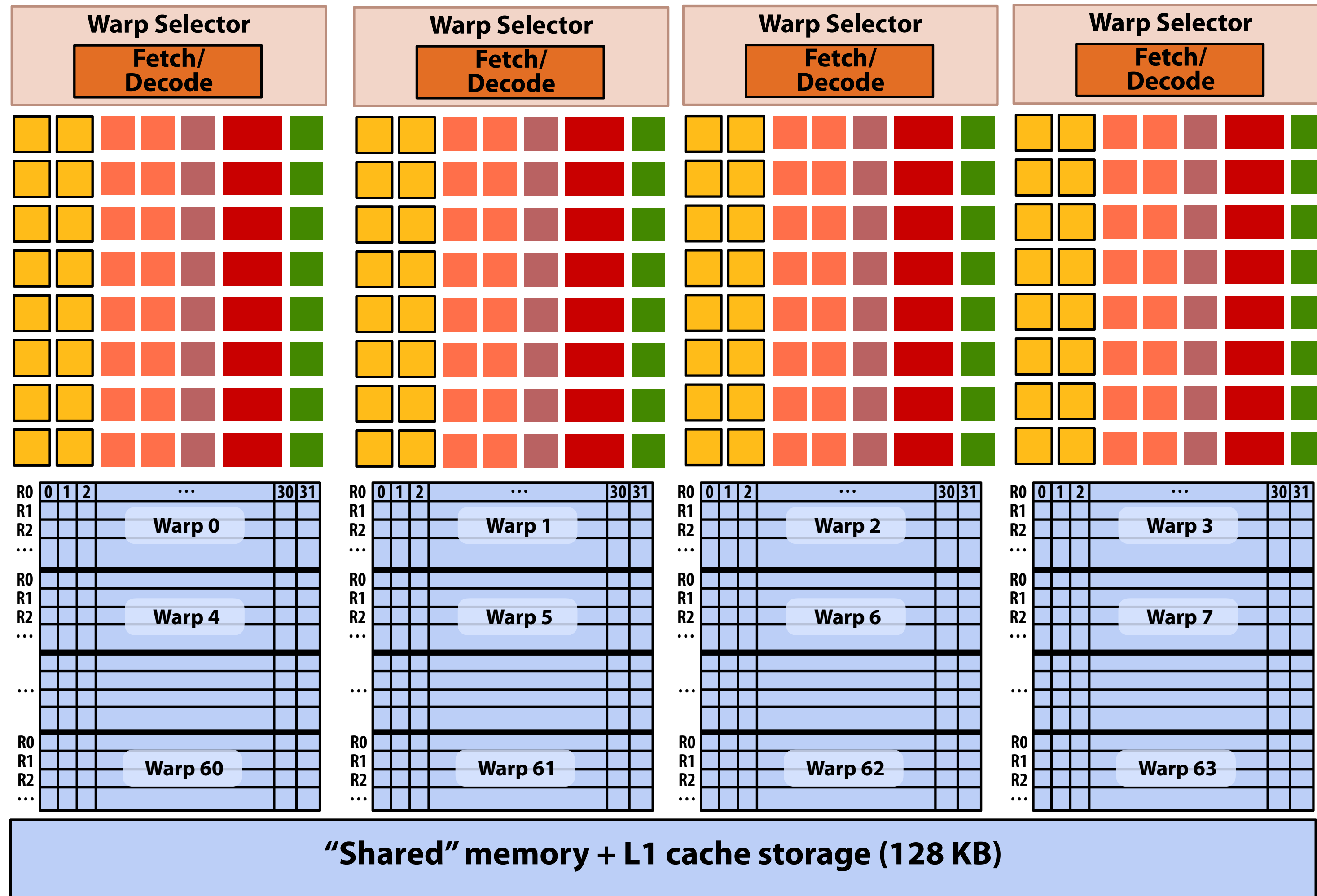
GPU cores detect when different hardware threads are executing the same instruction, and implement simultaneous execution of up to SIMD-width threads using SIMD ALUs.

Here ALU 6 would be "masked off" since thread 6 is not executing the same instruction as the other hardware threads.



GPUs: extreme throughput-oriented processors

This is one NVIDIA V100 streaming multi-processor (SM) unit



64 “warp” execution contexts per SM

Wide SIMD: 16-wide SIMD ALUs (carry out 32-wide SIMD execute over 2 clocks)

64 x 32 = up to 2048 data items processed concurrently per “SM” core

64 KB registers per sub-core

256 KB registers in total per SM

Registers divided among (up to) 64 “warps” per SM

= SIMD fp32 functional unit, control shared across 16 units (16 x MUL-ADD per clock *)
 = SIMD int functional unit, control shared across 16 units (16 x MUL/ADD per clock *)
 = SIMD fp64 functional unit, control shared across 8 units (8 x MUL/ADD per clock **)
 = Tensor core unit
 = Load/store unit

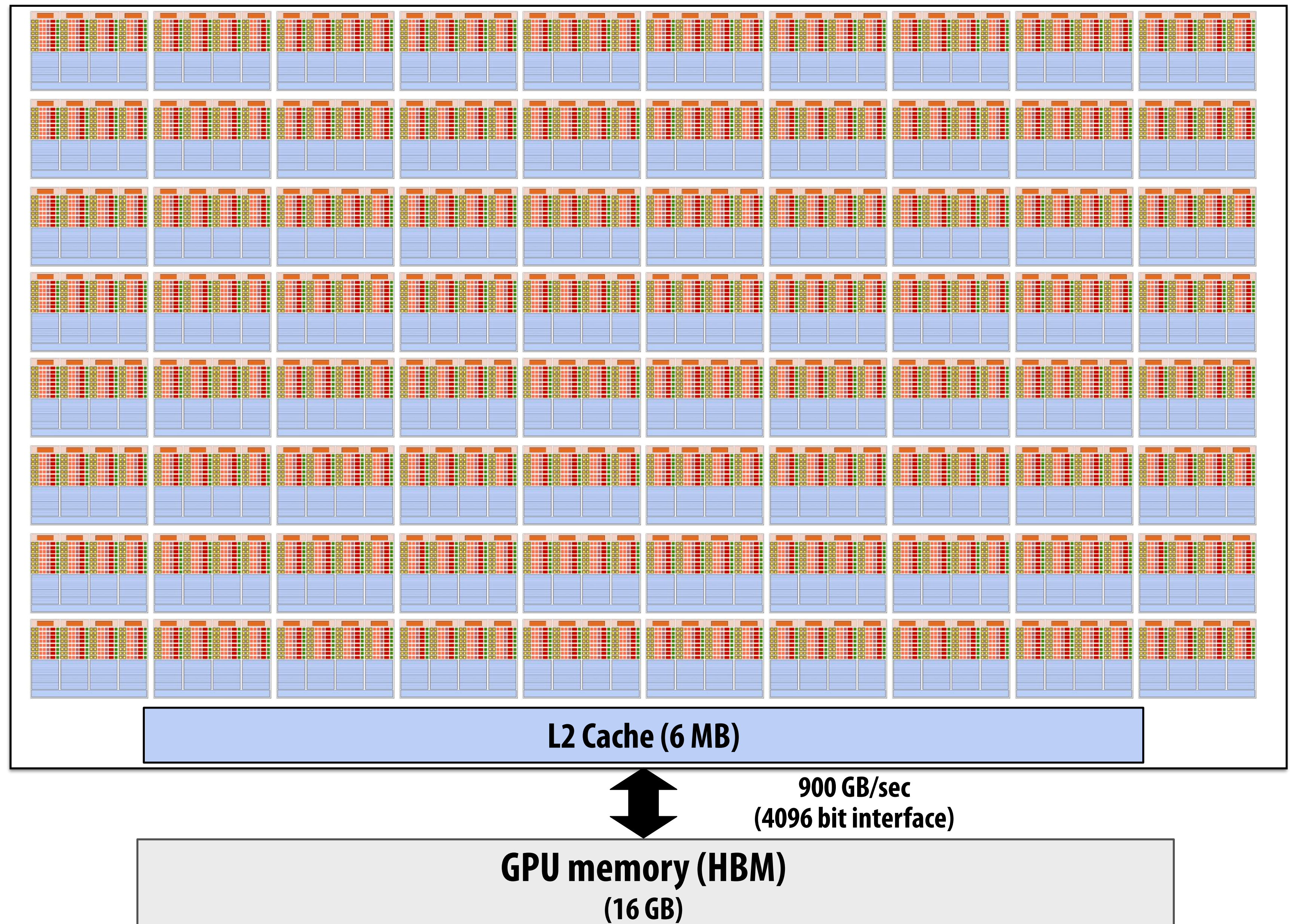
* one 32-wide SIMD operation every 2 clocks

** one 32-wide SIMD operation every 4 clocks

NVIDIA V100

There are 80 SM cores on the V100:

That's 163,840 pieces of data being processed concurrently to get maximal latency hiding!



The story so far...

To utilize modern parallel processors efficiently, an application must:

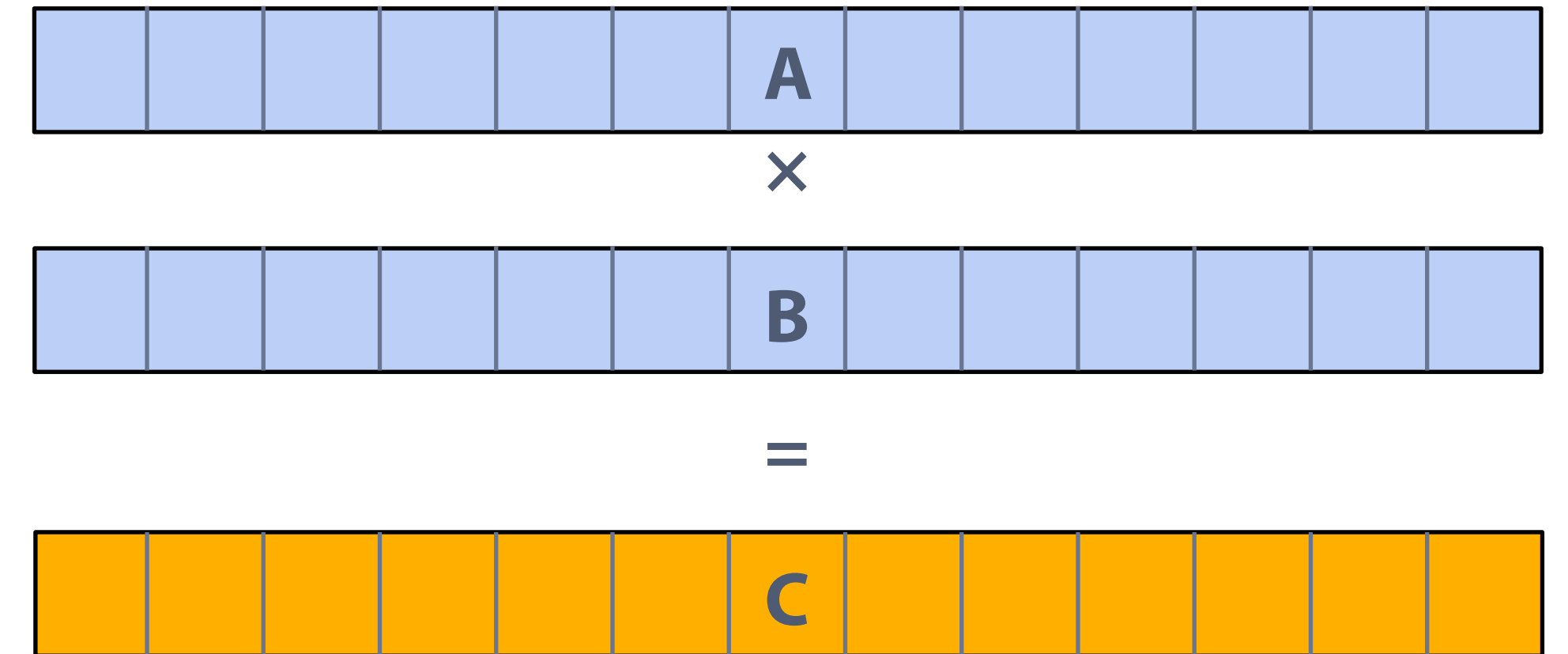
- 1. Have sufficient parallel work to utilize all available execution units
(across many cores and many execution units per core)**
- 2. Groups of parallel work items must require the same sequences of instructions
(to utilize SIMD execution)**
- 3. Expose more parallel work than processor ALUs to enable interleaving of work
to hide memory stalls**

Thought experiment

Task: 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 $C[i]$



Is this a good application to run on a modern throughput-oriented parallel processor?

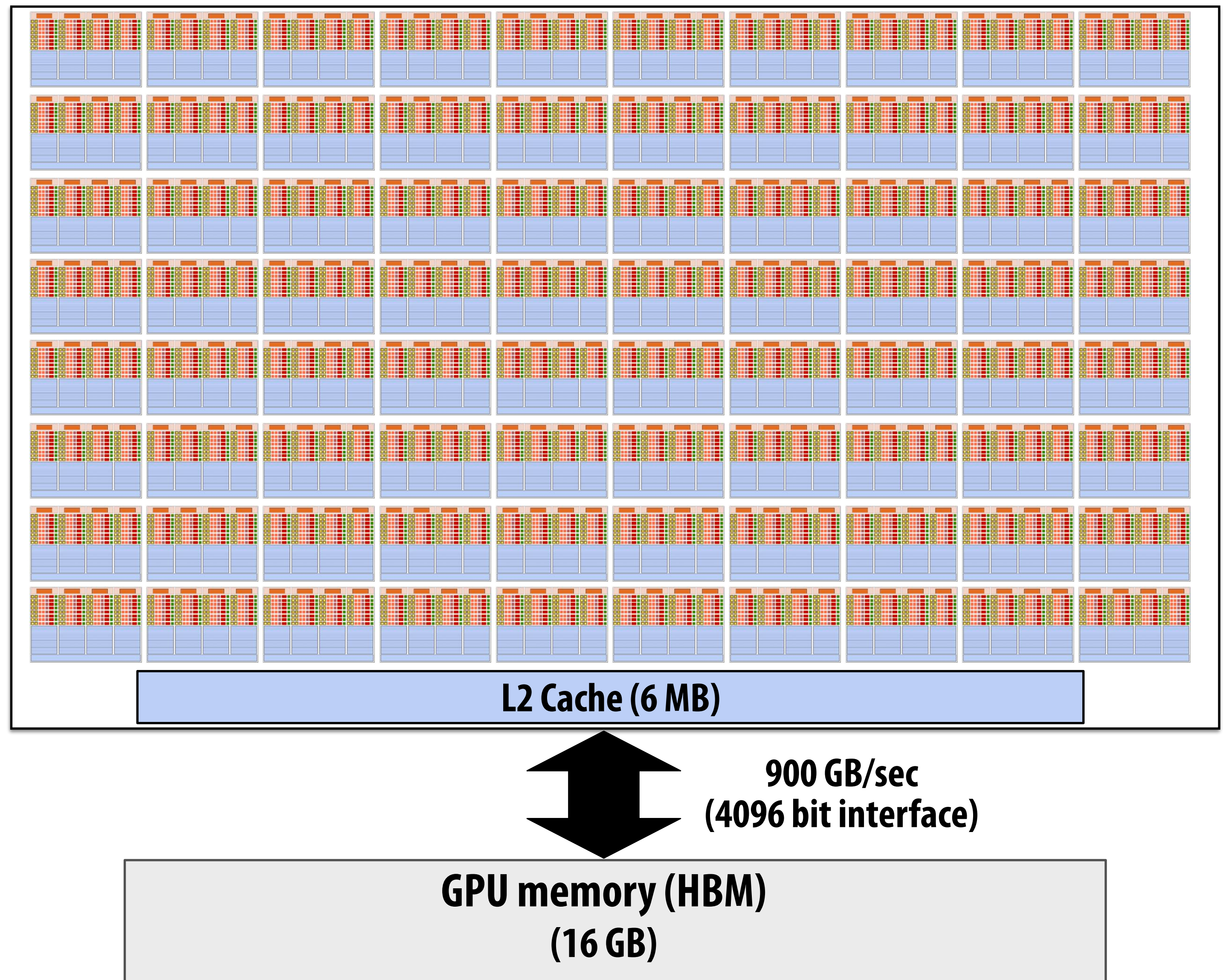


NVIDIA V100

There are 80 SM cores on the V100:

80 SM x 64 fp32 ALUs per SM = 5120 ALUs

Think about supplying all those ALUs with data each clock. 🐱



Understanding latency and bandwidth

The school year is starting... gotta get back to Stanford



San Francisco fog vs. South Bay sun

When it looks like this in SF



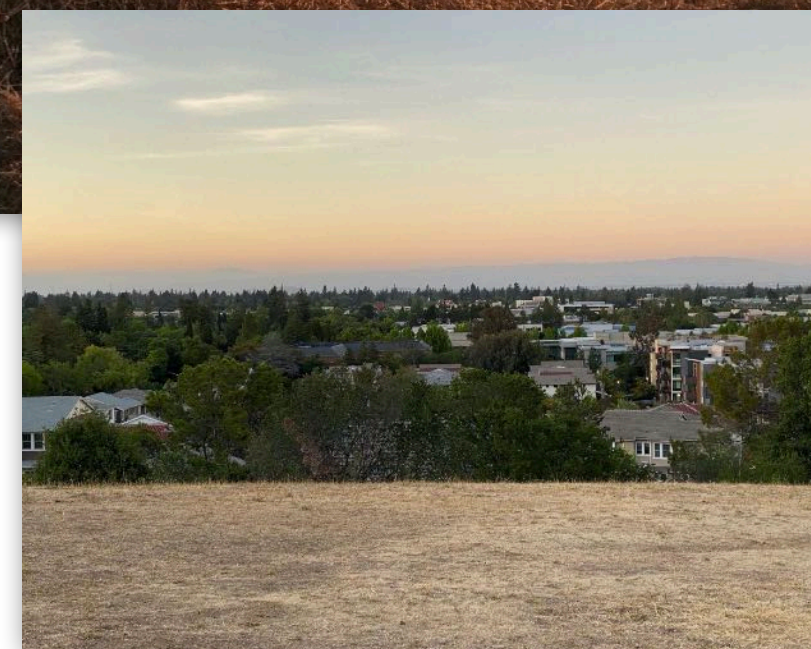
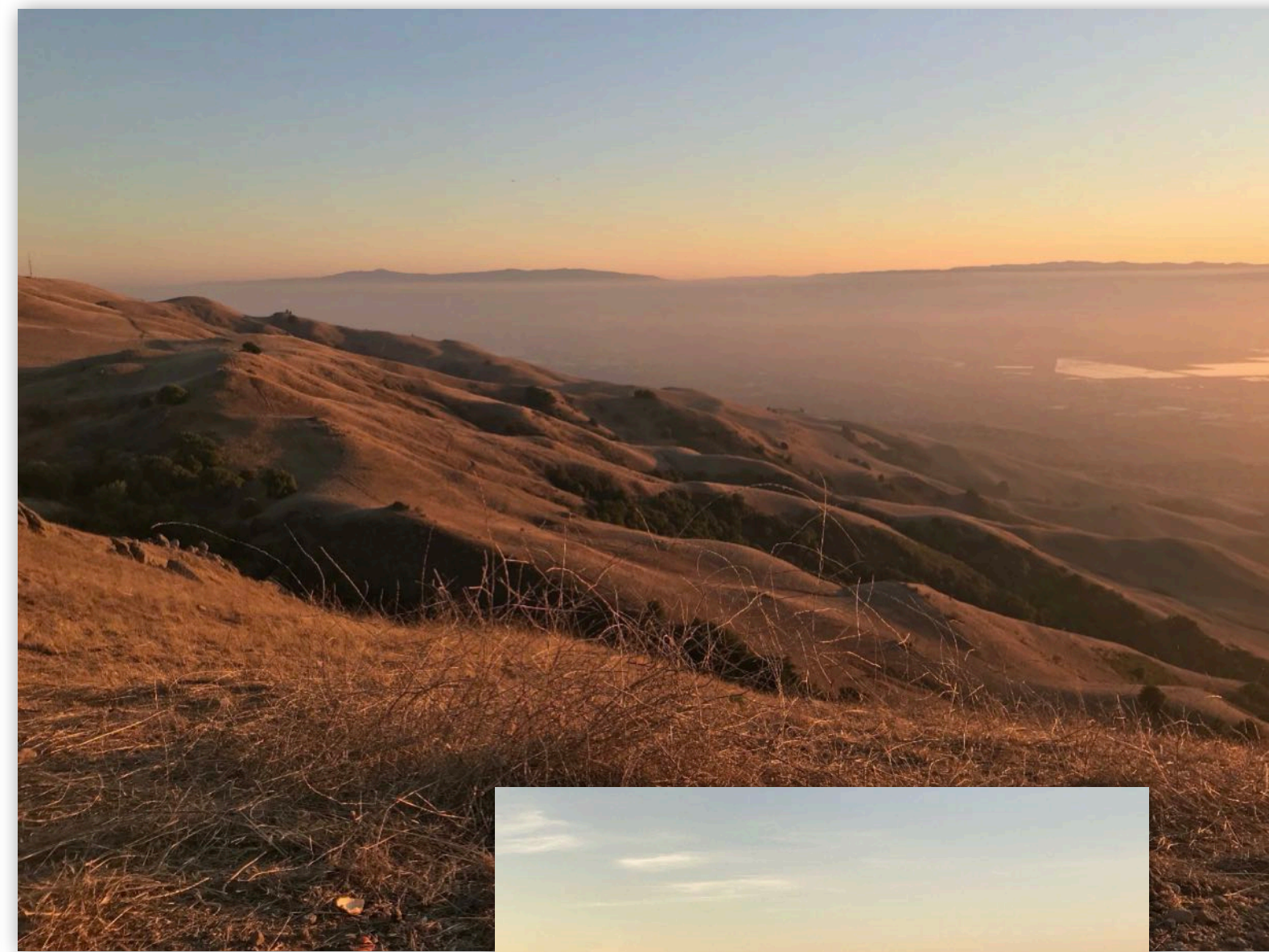
It looks like this at Stanford



Why the south bay? Great social distancing opportunities

- Quick plug:

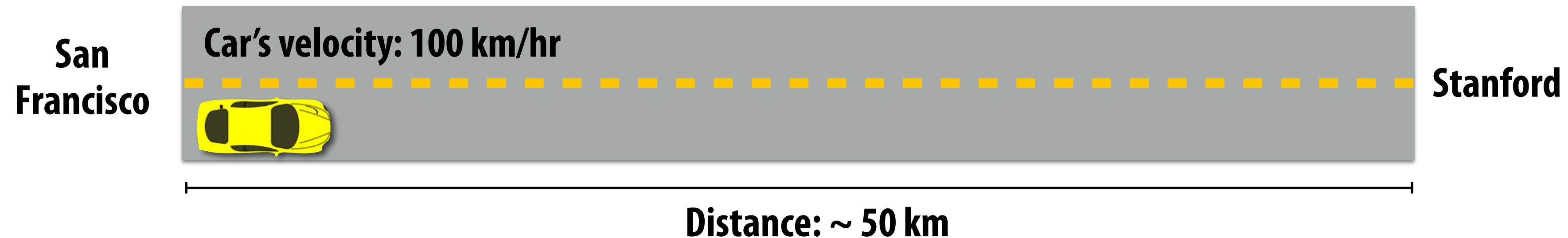
- Kayvon's guide to local bay area hikes
- http://graphics.stanford.edu/~kayvonf/misc/local_hikes.pdf



Everyone wants to get to back to the South Bay!

Assume only one car in a lane of the highway at once.

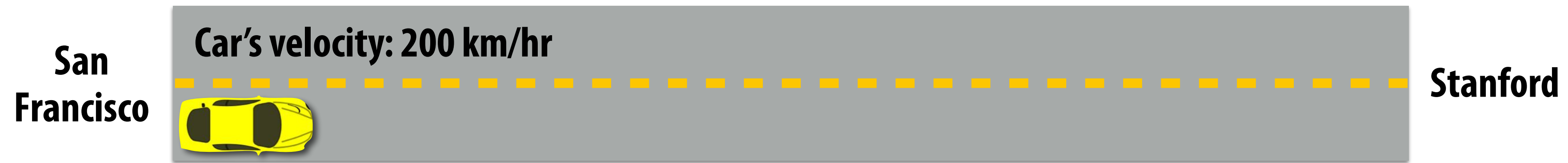
When car on highway reaches Stanford, the next car leaves San Francisco.



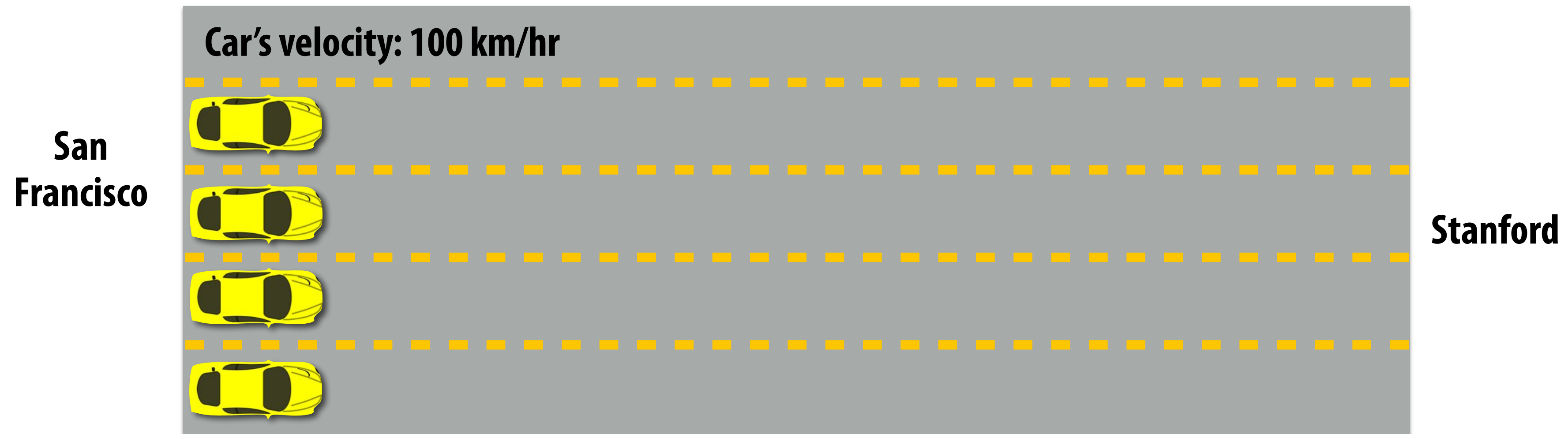
Latency of driving from San Francisco to Stanford: 0.5 hours

Throughput: 2 cars per hour

Improving throughput

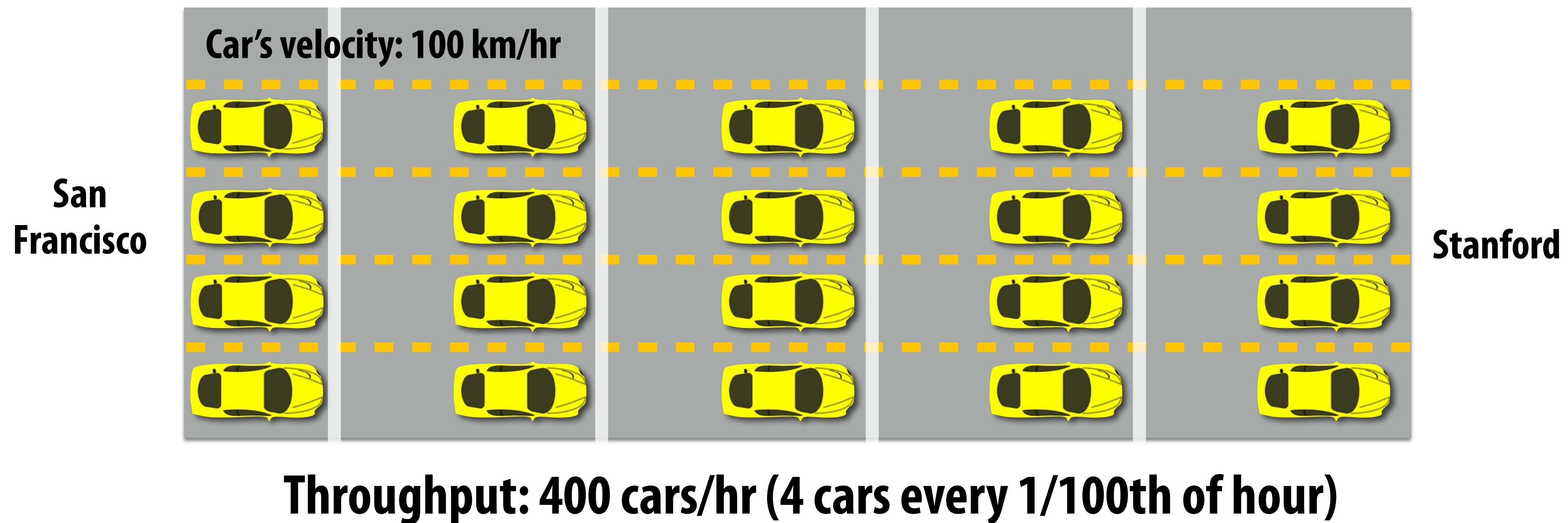
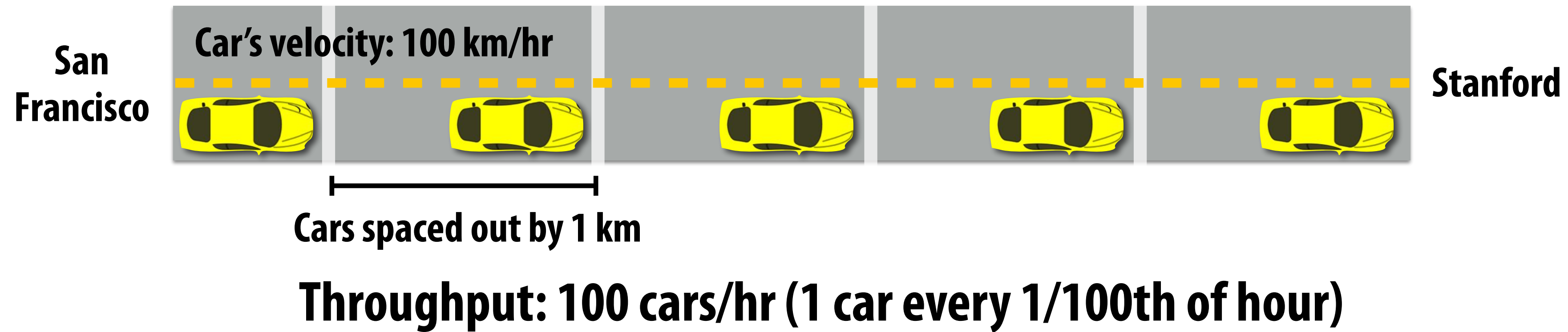


Approach 1: drive faster!
Throughput = 4 cars per hour



Approach 2: build more lanes!
Throughput = 8 cars per hour (2 cars per hour per lane)

Using the highway more efficiently



Terminology

■ Memory bandwidth

- The rate at which the memory system can provide data to a processor
- Example: 20 GB/s

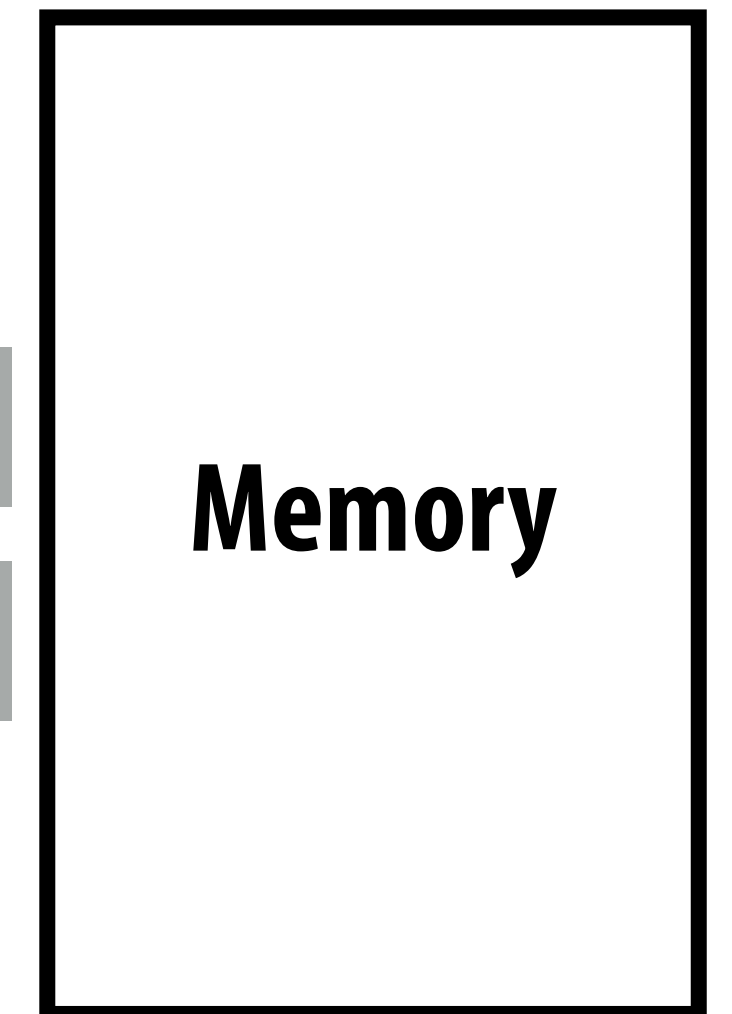


Latency of transferring any one item: ~2 sec

Terminology

■ Memory bandwidth

- The rate at which the memory system can provide data to a processor
- Example: 20 GB/s



Bandwidth: ~ 8 items/sec

Latency of transferring any one item: ~2 sec

Example: doing your laundry

Operation: do your laundry

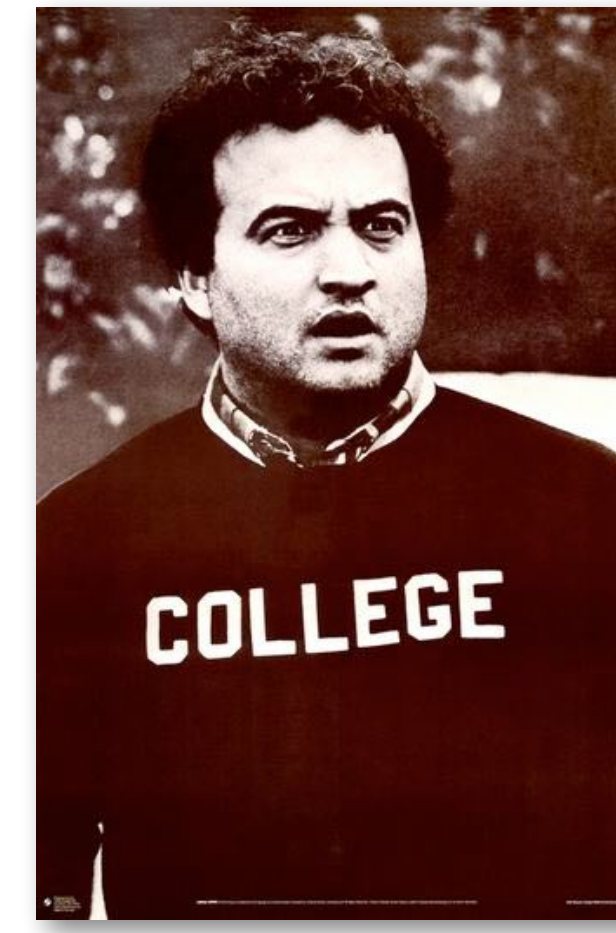
1. Wash clothes
2. Dry clothes
3. Fold clothes



Washer
45 min



Dryer
60 min



College Student
15 min

Latency of completing 1 load of laundry = 2 hours

Increasing laundry throughput

Goal: maximize throughput of many loads of laundry

**One approach: duplicate execution resources:
use two washers, two dryers, and call a friend**



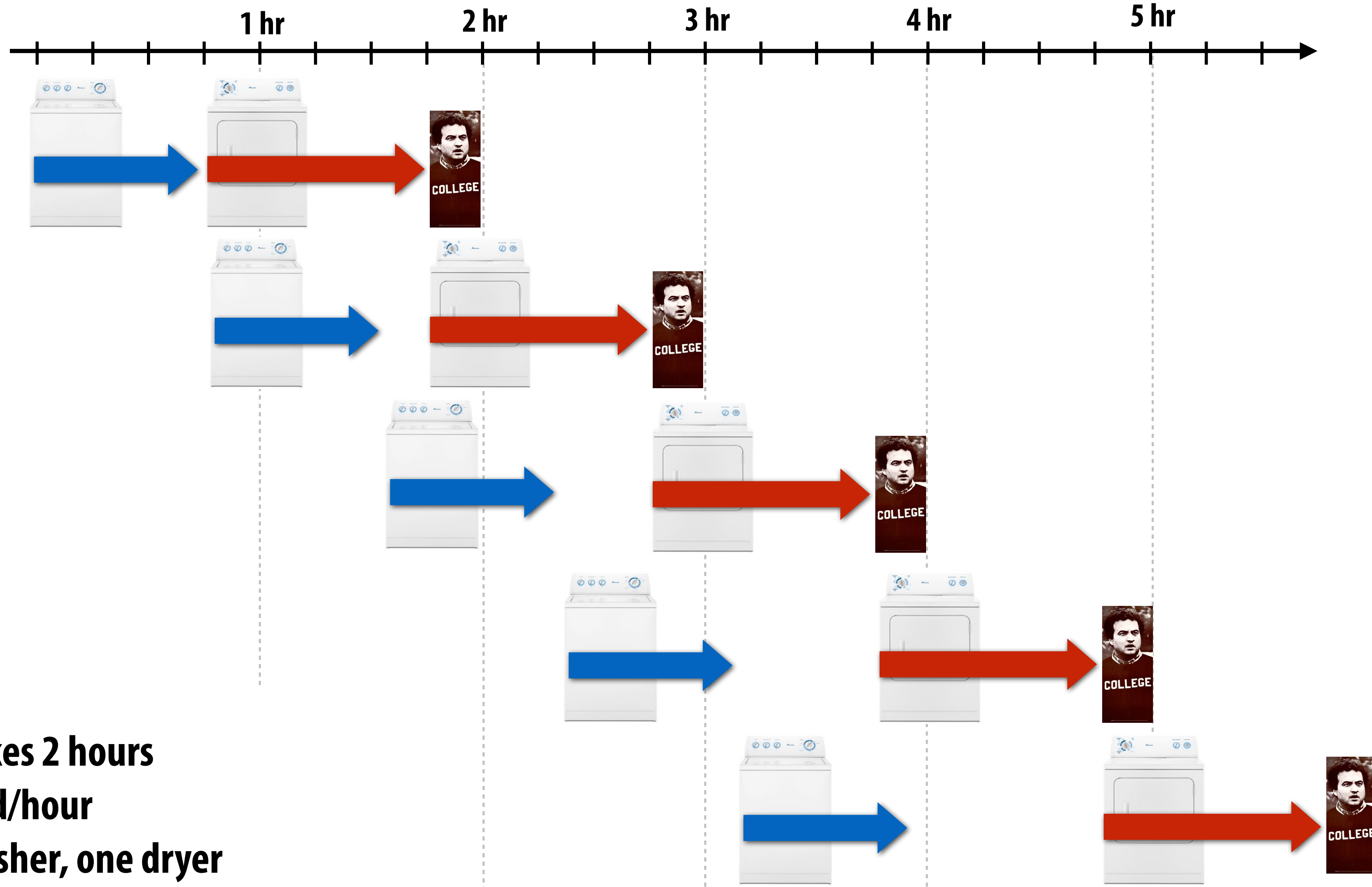
Latency of completing 2 loads of laundry = 2 hours

Throughput increases by 2x: 1 load/hour

Number of resources increased by 2x: two washers, two dryers

Pipelining

Goal: maximize throughput of doing many loads of laundry

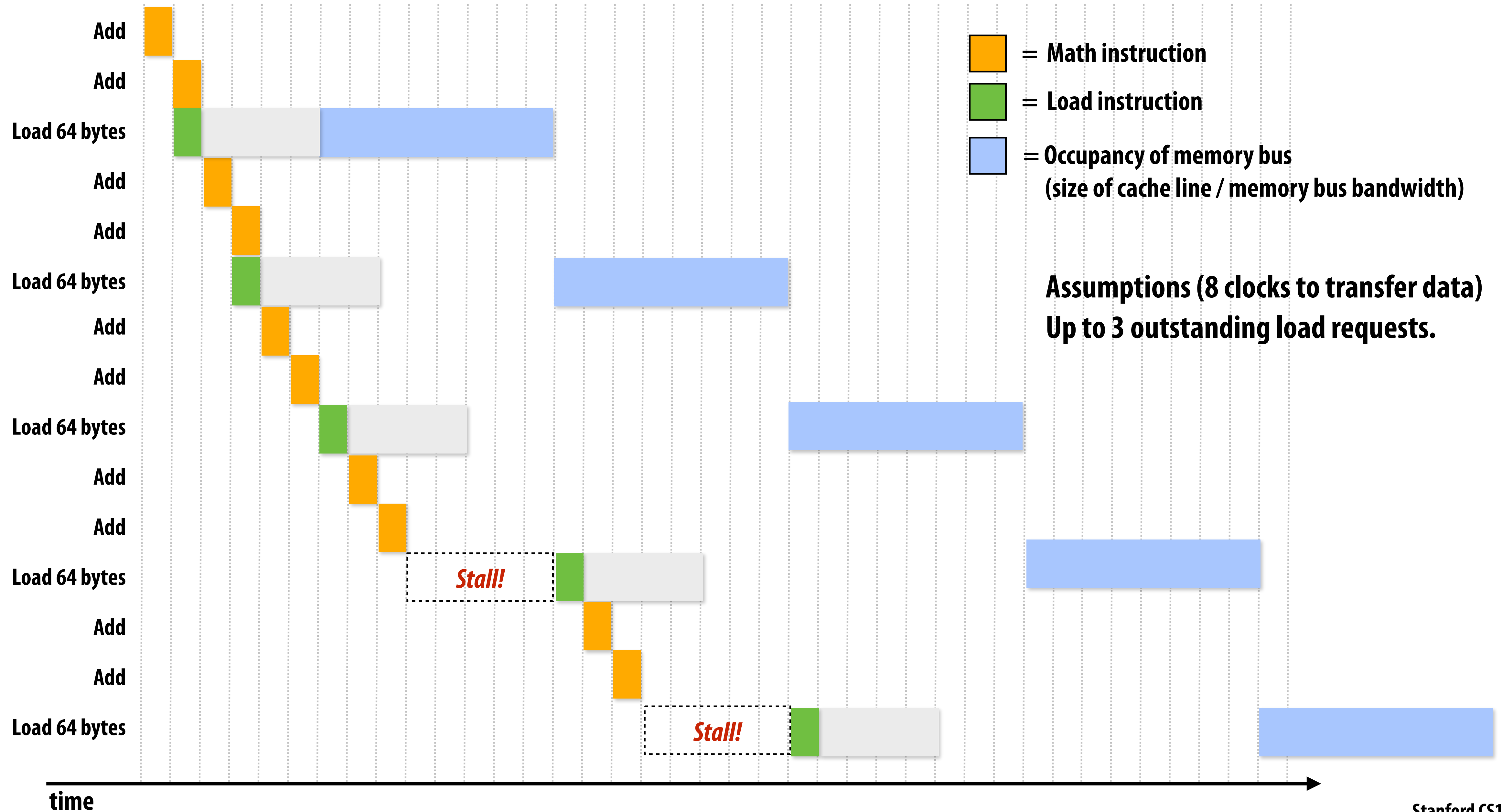


Latency: 1 load takes 2 hours

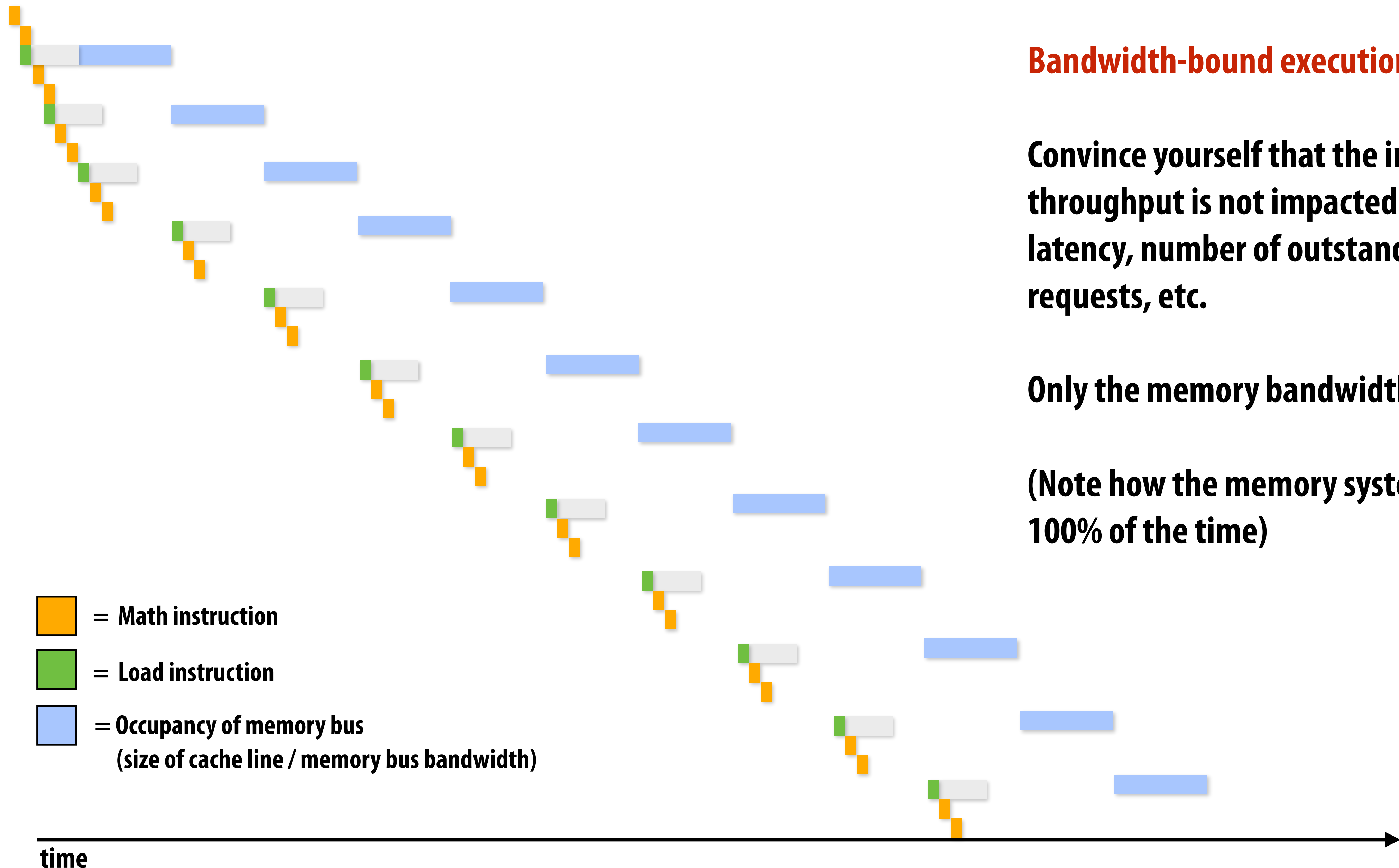
Throughput: 1 load/hour

Resources: one washer, one dryer

Consider a processor that can do one add per clock (+ can co-issue LD)

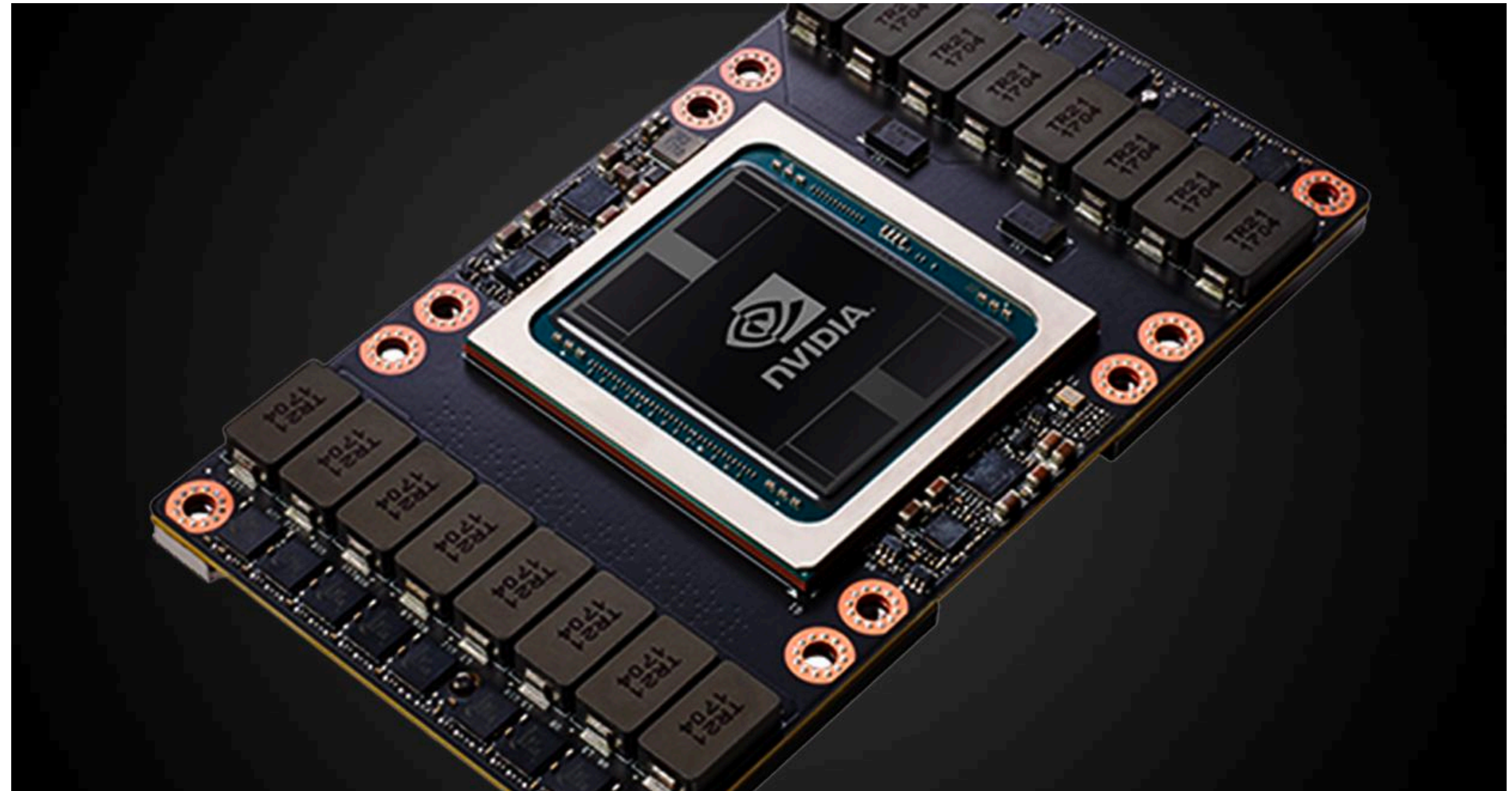


Rate of math instructions limited by available bandwidth



High bandwidth memories

- Modern GPUs leverage high bandwidth memories located near processor
- Example:
 - V100 uses HBM2
 - 900 GB/s

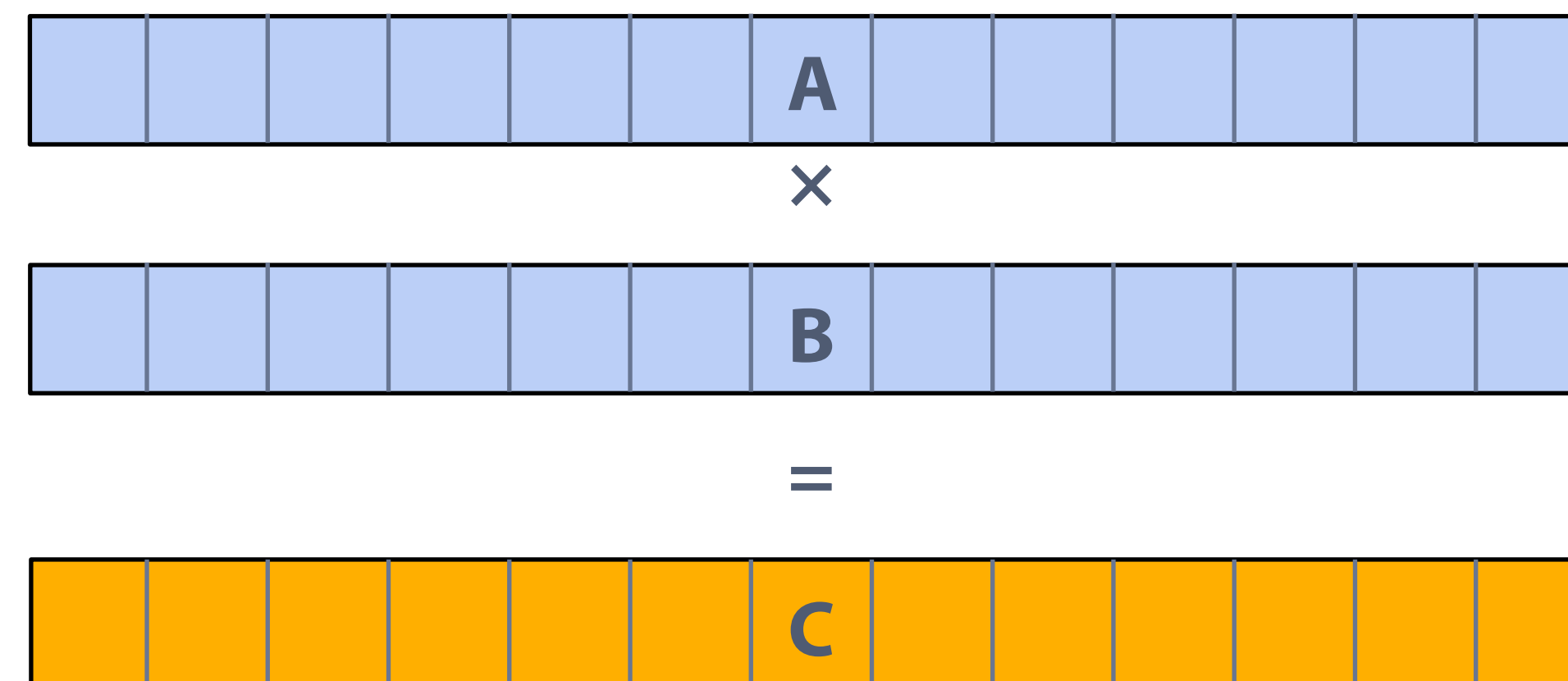


Thought experiment

Task: 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 V100 GPU can do 5120 fp32 MULs per clock (@ 1.6 GHz)

Need ~98 TB/sec of bandwidth to keep functional units busy

<1% GPU efficiency... but still 12x faster than eight-core CPU!

(3.2 GHz Xeon E5v4 eight-core CPU connected to 76 GB/sec memory bus: ~3% efficiency on this computation)

This computation is bandwidth limited!

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

**Overcoming bandwidth limits is often the most important
challenge facing software developers targeting modern
throughput-optimized systems.**

In modern computing, bandwidth is the critical resource

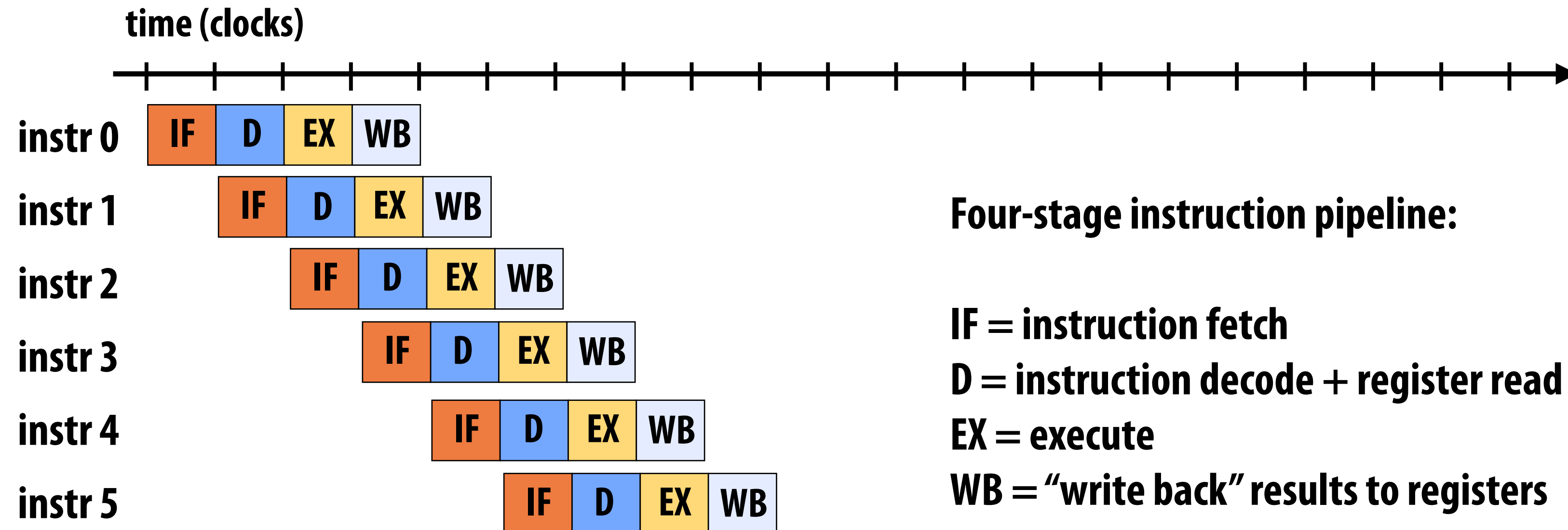
Performant parallel programs will:

- Organize computation to fetch data from memory less often
 - Reuse data previously loaded by the same thread
(temporal locality optimizations)
 - Share data across threads (inter-thread cooperation)
- Favor performing additional arithmetic to storing/reloading values (the math is “free”)
- Main point: programs must access memory infrequently to utilize modern processors efficiently

Another example: an instruction pipeline

Many students have asked how a processor can complete a multiply in a clock.

When we say a core does one operation per clock, we are referring to **INSTRUCTION THROUGHPUT, NOT LATENCY.**



Latency: 1 instruction takes 4 cycles

Throughput: 1 instruction per cycle

(Yes, care must be taken to ensure program correctness when back-to-back instructions are dependent.)

Intel Core i7 pipeline is variable length (it depends on the instruction) ~20 stages

And now today's topic...

Pay attention!

Today's theme is a critical idea in this course.

And today's theme is:

Abstraction vs. implementation

**Conflating abstraction with implementation is a common cause
for confusion in this course.**

An example:
Programming with ISPC

ISPC

- **Intel SPMD Program Compiler (ISPC)**
- **SPMD: single program multiple data**

- **<http://ispc.github.com/>**

- **A great read: “The Story of ISPC” (by Matt Pharr)**
 - **<https://pharr.org/matt/blog/2018/04/30/ispc-all.html>**

Recall: example program from last class

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;
    }
}
```

Invoking `sinx()`

C++ code: `main.cpp`

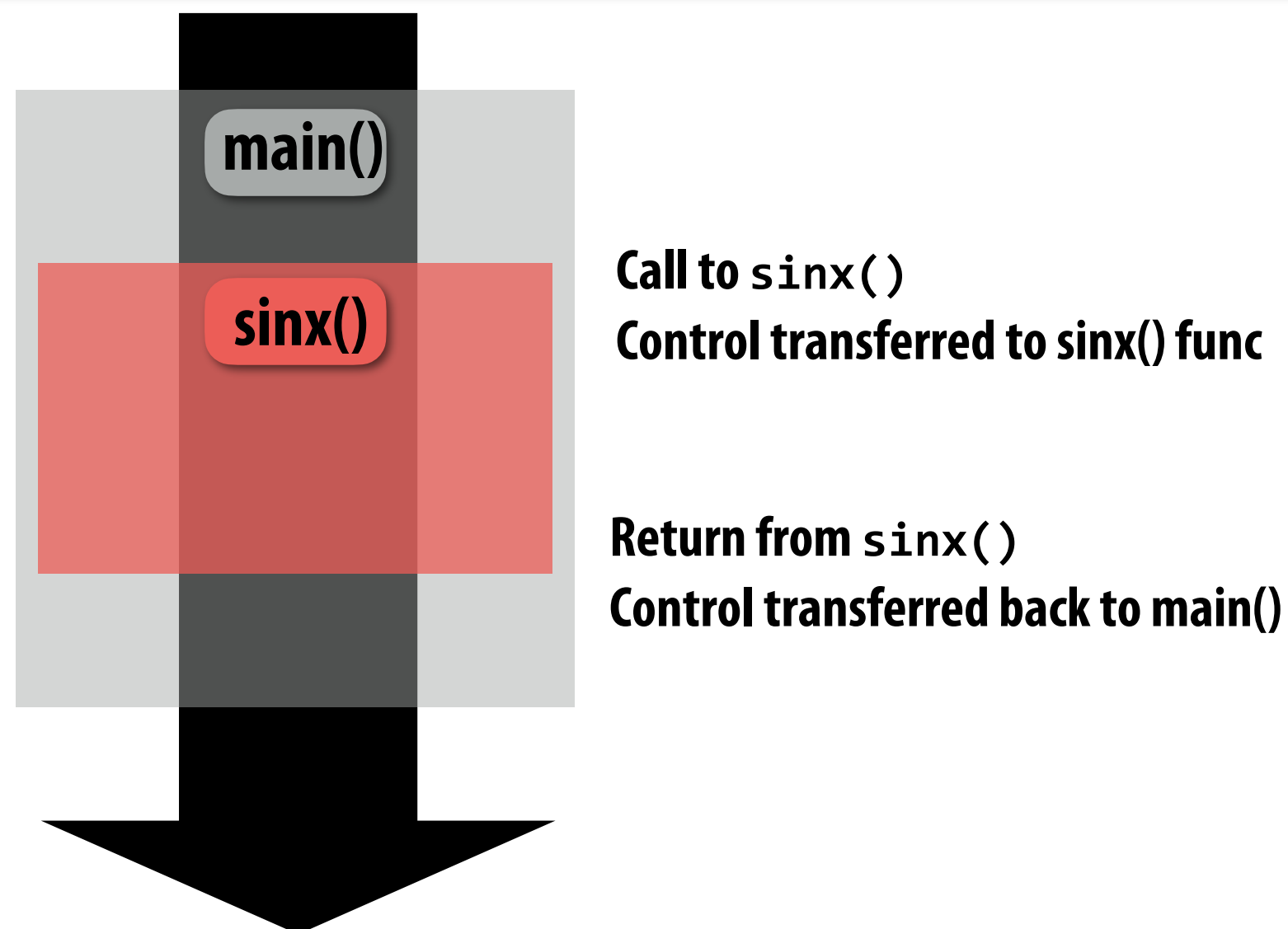
```
#include "sinx.h"

int main(int argc, void** argv) {
    int N = 1024;
    int terms = 5;
    float* x = new float[N];
    float* result = new float[N];

    // initialize x here

    sinx(N, terms, x, result);

    return 0;
}
```



C++ code: `sinx.cpp`

```
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!
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        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;
    }
}
```

sinx() in ISPC

C++ code: main.cpp

```
#include "sinx_ispc.h"

int main(int argc, void** argv) {
    int N = 1024;
    int terms = 5;
    float* x = new float[N];
    float* result = new float[N];

    // initialize x here

    // execute ISPC code
    ispc_sinx(N, terms, x, result);
    return 0;
}
```

SPMD programming abstraction:

Call to ISPC function spawns “gang” of ISPC
“program instances”

All instances run ISPC code concurrently

Each instance has its own copy of local variables
(blue variables in code, we’ll talk about “uniform” later)

Upon return, all instances have completed

ISPC code: sinx.ispc

```
export void ispc_sinx(
    uniform int N,
    uniform int terms,
    uniform float* x,
    uniform float* result)
{
    // assume N % programCount = 0
    for (uniform int i=0; i<N; i+=programCount)
    {
        int idx = i + programIndex;
        float value = x[idx];
        float numer = x[idx] * x[idx] * x[idx];
        uniform int denom = 6; // 3!
        uniform int sign = -1;

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


Invoking `sinx()` in ISPC

C++ code: main.cpp

```
#include "sinx_ispc.h"

int main(int argc, void** argv) {
    int N = 1024;
    int terms = 5;
    float* x = new float[N];
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    // initialize x here

    // execute ISPC code
    ispc_sinx(N, terms, x, result);
    return 0;
}
```

SPMD programming abstraction:

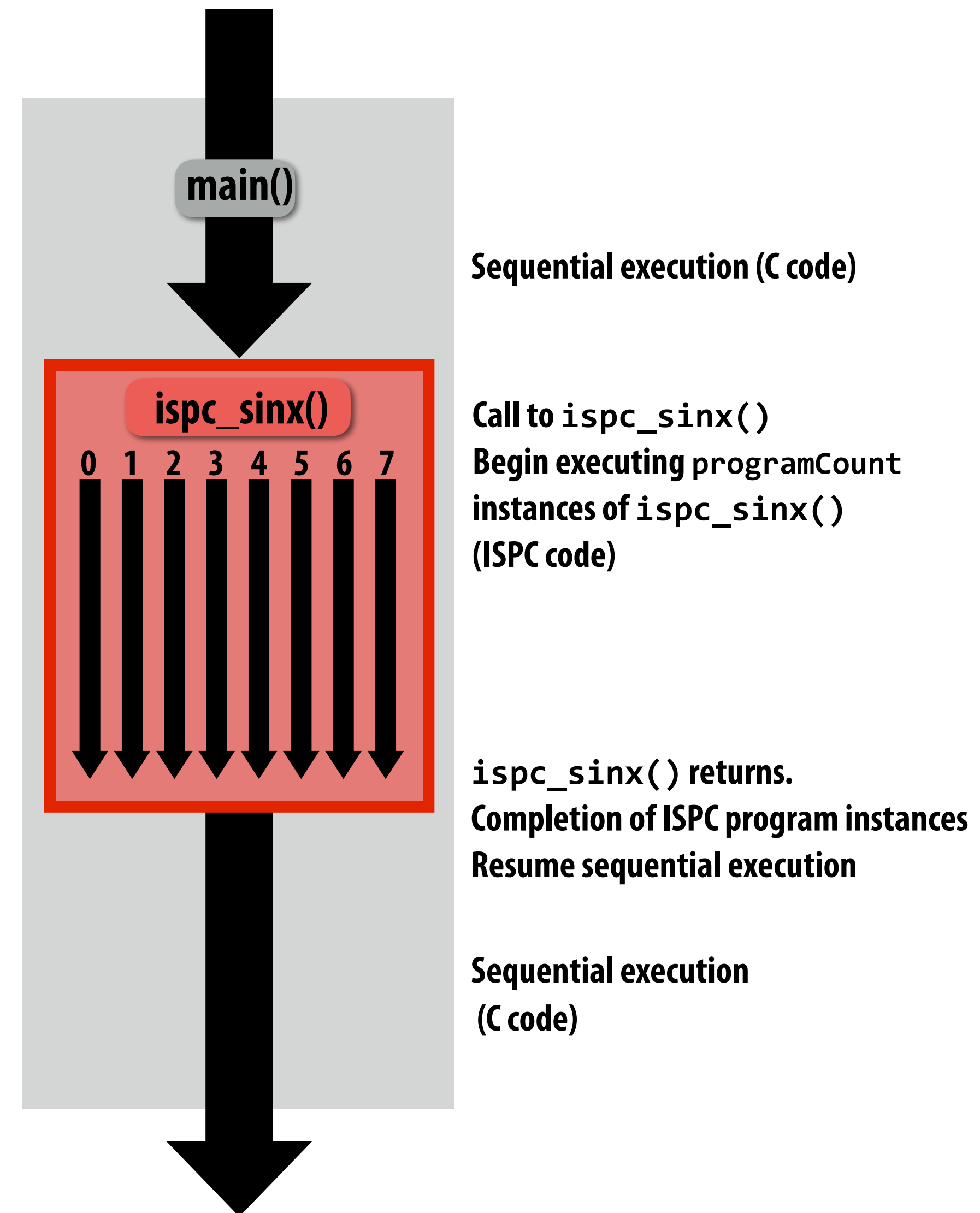
Call to ISPC function spawns "gang" of ISPC "program instances"

All instances run ISPC code concurrently

Each instance has its own copy of local variables

Upon return, all instances have completed

In this illustration `programCount = 8`



sinx() in ISPC

“Interleaved” assignment of array elements to program instances

C++ code: main.cpp

```
#include "sinx_ispc.h"

int main(int argc, void** argv) {
    int N = 1024;
    int terms = 5;
    float* x = new float[N];
    float* result = new float[N];

    // initialize x here

    // execute ISPC code
    ispc_sinx(N, terms, x, result);
    return 0;
}
```

ISPC language keywords:

programCount: number of simultaneously executing instances in the gang (uniform value)

programIndex: id of the current instance in the gang. (a non-uniform value: “varying”)

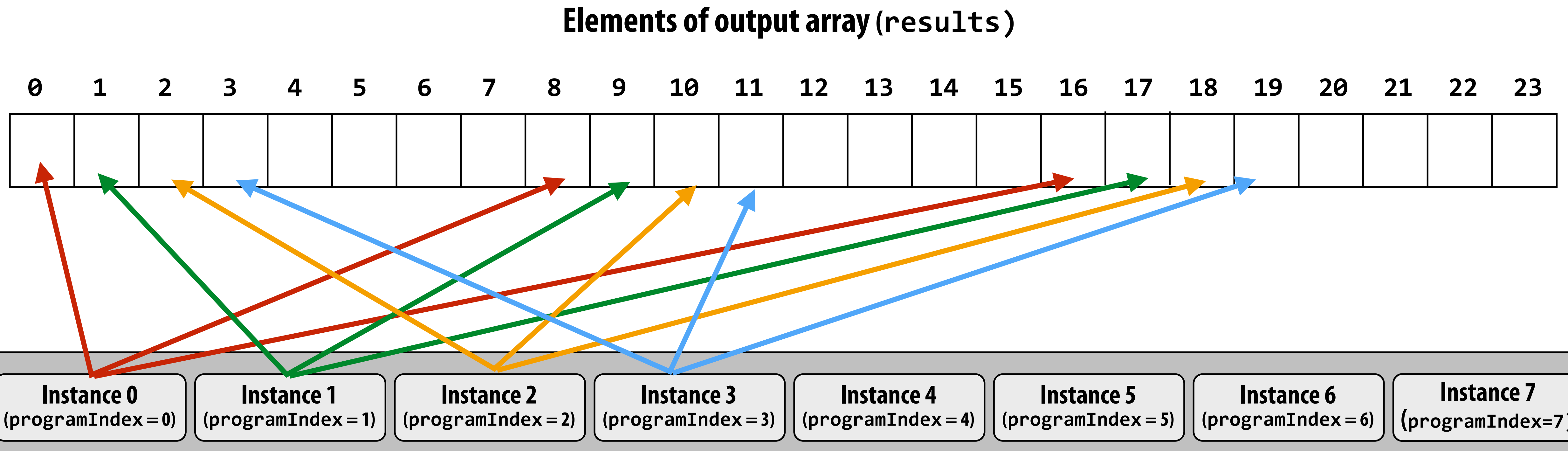
uniform: A type modifier. All instances have the same value for this variable. Its use is purely an optimization. Not needed for correctness.

ISPC code: sinx.ispc

```
export void ispc_sinx(
    uniform int N,
    uniform int terms,
    uniform float* x,
    uniform float* result)
{
    // assumes N % programCount = 0
    for (uniform int i=0; i<N; i+=programCount)
    {
        int idx = i + programIndex;
        float value = x[idx];
        float numer = x[idx] * x[idx] * x[idx];
        uniform int denom = 6; // 3!
        uniform int sign = -1;

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

Interleaved assignment of program instances to loop iterations



ISPC implements the gang abstraction using SIMD instructions

C++ code: main.cpp

```
#include "sinx_ispc.h"

int main(int argc, void** argv) {
    int N = 1024;
    int terms = 5;
    float* x = new float[N];
    float* result = new float[N];

    // initialize x here

    // execute ISPC code
    ispc_sinx(N, terms, x, result);
    return 0;
}
```

SPMD programming abstraction:

Call to ISPC function spawns "gang" of ISPC "program instances"

All instances run ISPC code simultaneously

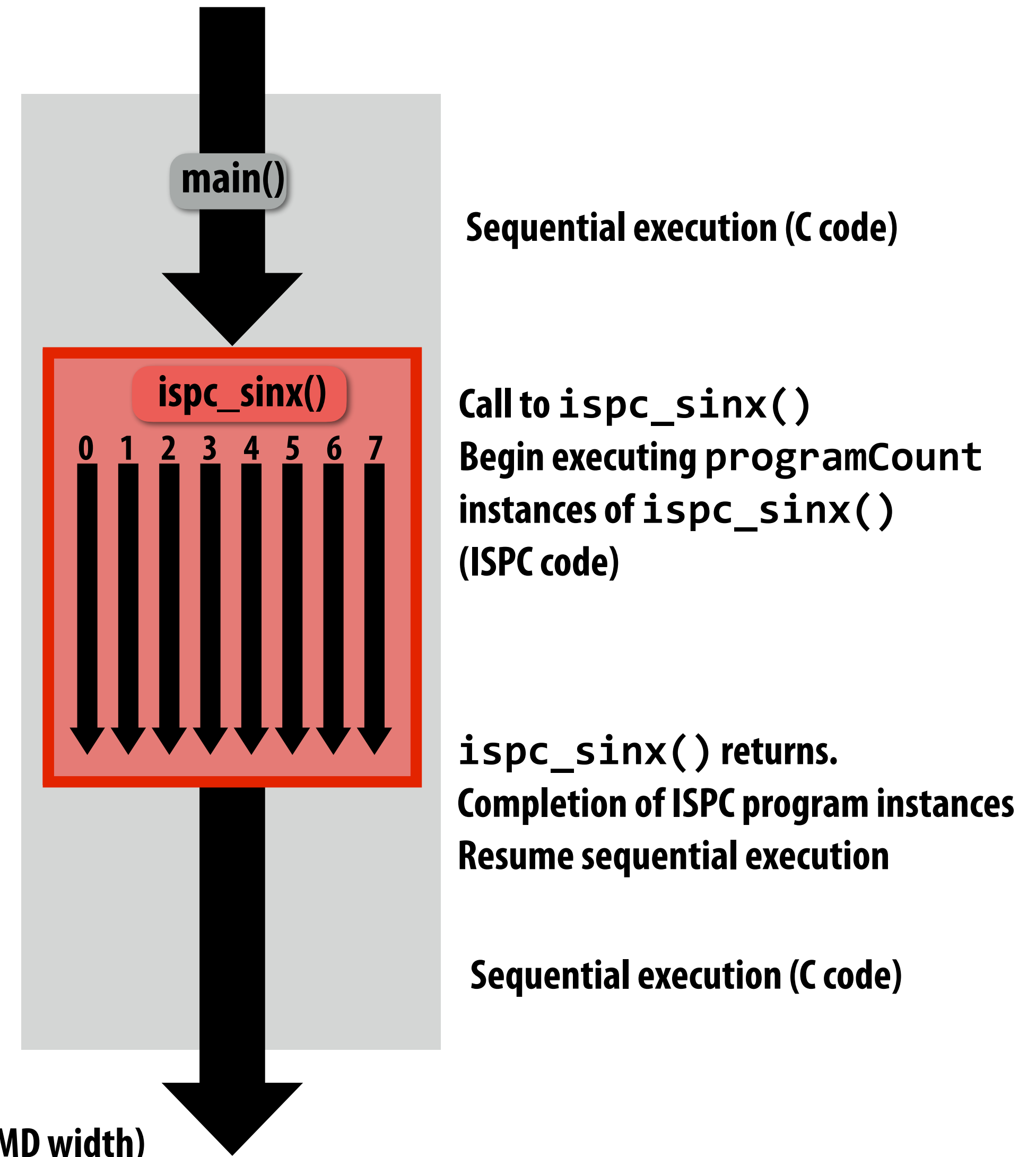
Upon return, all instances have completed

ISPC compiler generates SIMD implementation:

Number of instances in a gang is the SIMD width of the hardware (or a small multiple of SIMD width)

ISPC compiler generates a C++ function binary (.o) whose body contains SIMD instructions

C++ code links against generated object file as usual



sinx() in ISPC: version 2

“Blocked” assignment of array elements to program instances

C++ code: main.cpp

```
#include "sinx_ispc.h"

int main(int argc, void** argv) {
    int N = 1024;
    int terms = 5;
    float* x = new float[N];
    float* result = new float[N];

    // initialize x here

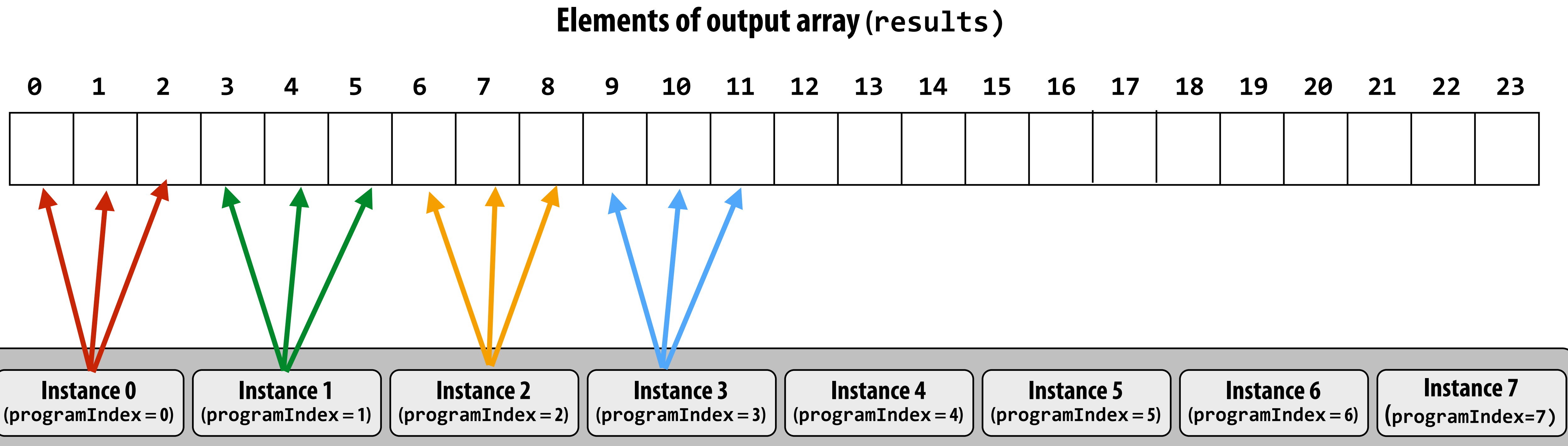
    // execute ISPC code
    ispc_sinx_v2(N, terms, x, result);
    return 0;
}
```

ISPC code: sinx.ispc

```
export void ispc_sinx_v2(
    uniform int N,
    uniform int terms,
    uniform float* x,
    uniform float* result)
{
    // assume N % programCount = 0
    uniform int count = N / programCount;
    int start = programIndex * count;
    for (uniform int i=0; i<count; i++)
    {
        int idx = start + i;
        float value = x[idx];
        float numer = x[idx] * x[idx] * x[idx];
        uniform int denom = 6; // 3!
        uniform int sign = -1;

        for (uniform int j=1; j<=terms; j++)
        {
            value += sign * numer / denom
            numer *= x[idx] * x[idx];
            denom *= (j+3) * (j+4);
            sign *= -1;
        }
        result[idx] = value;
    }
}
```

Blocked assignment of program instances to loop iterations



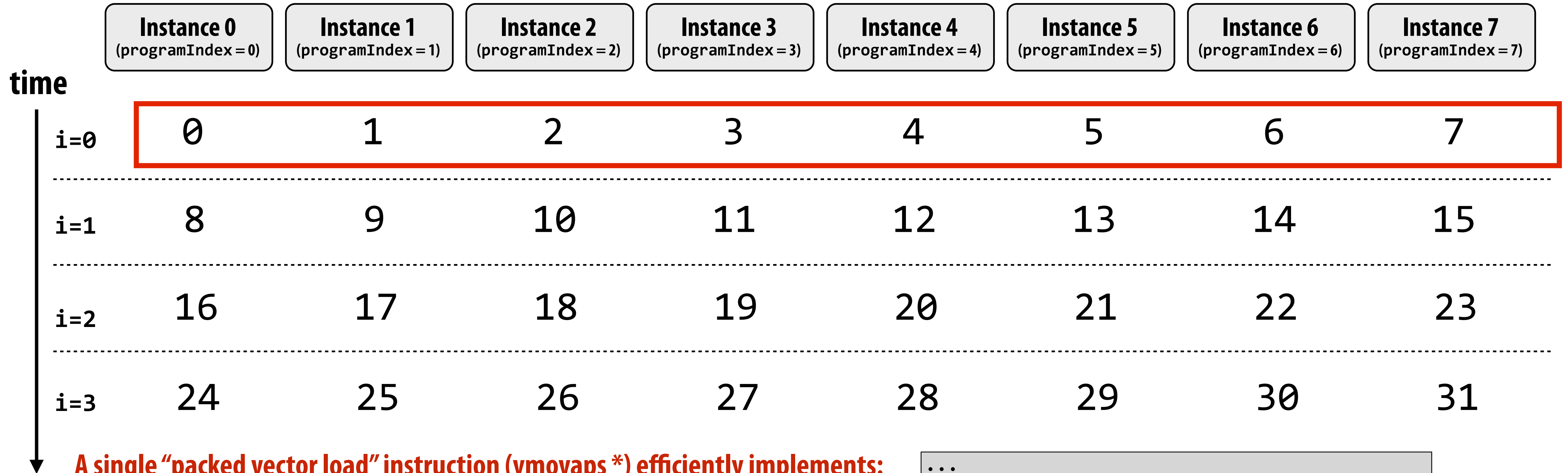
“Gang” of ISPC program instances

In this illustration: gang contains eight instances: programCount = 8

Schedule: interleaved assignment

“Gang” of ISPC program instances

Gang contains four instances: programCount = 8



A single “packed vector load” instruction (`vmovaps *`) efficiently implements:
`float value = x[idx];`
for all program instances, since the eight values are contiguous in memory

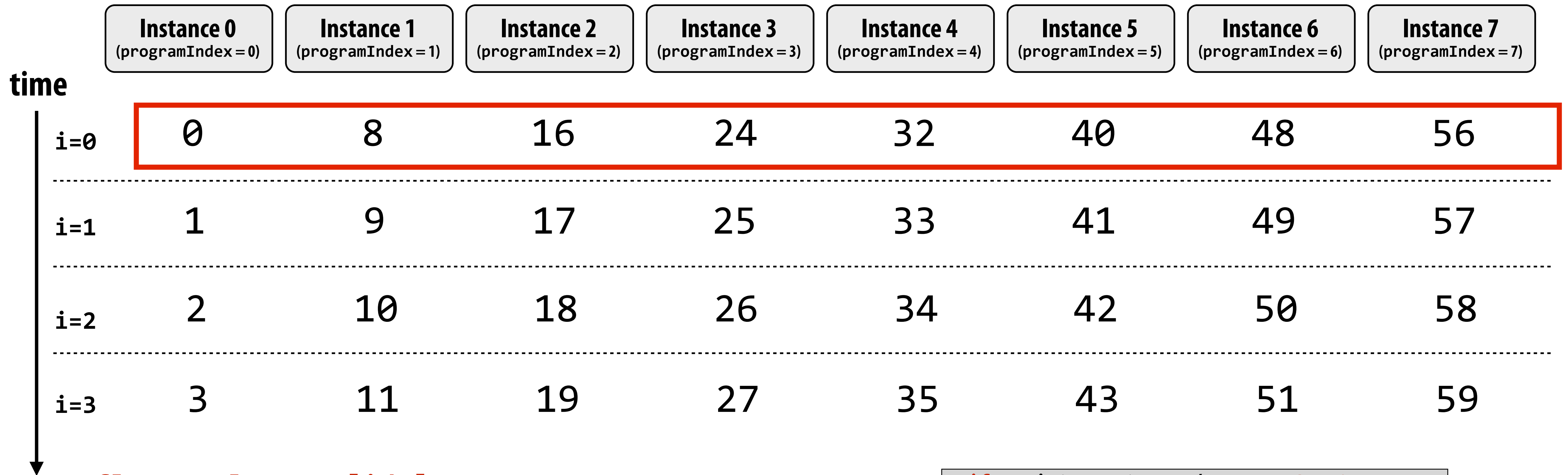
```
...  
// assumes N % programCount = 0  
for (uniform int i=0; i<N; i+=programCount)  
{  
    int idx = i + programIndex;  
    float value = x[idx];  
}  
...
```

* see `_mm256_load_ps()` intrinsic function

Schedule: blocked assignment

“Gang” of ISPC program instances

Gang contains four instances: programCount = 8



float value = x[idx];
For all program instances now touches eight non-contiguous values in memory. Need “gather” instruction (vgatherdps *) to implement (gather is a more complex, and more costly SIMD instruction...)

```
uniform int count = N / programCount;  
int start = programIndex * count;  
for (uniform int i=0; i<count; i++) {  
    int idx = start + i;  
    float value = x[idx];  
    ...  
}
```

* see `_mm256_i32gather_ps()` intrinsic function

Raising level of abstraction with foreach

C++ code: main.cpp

```
#include "sinx_ispc.h"

int N = 1024;
int terms = 5;
float* x = new float[N];
float* result = new float[N];

// initialize x here

// execute ISPC code
sinx(N, terms, x, result);
```

ISPC code: sinx.ispc

```
export void ispc_sinx(
    uniform int N,
    uniform int terms,
    uniform float* x,
    uniform float* result)
{
    foreach (i = 0 ... N)
    {
        float value = x[i];
        float numer = x[i] * x[i] * x[i];
        uniform int denom = 6; // 3!
        uniform int sign = -1;

        for (uniform 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;
    }
}
```

foreach: key ISPC language construct

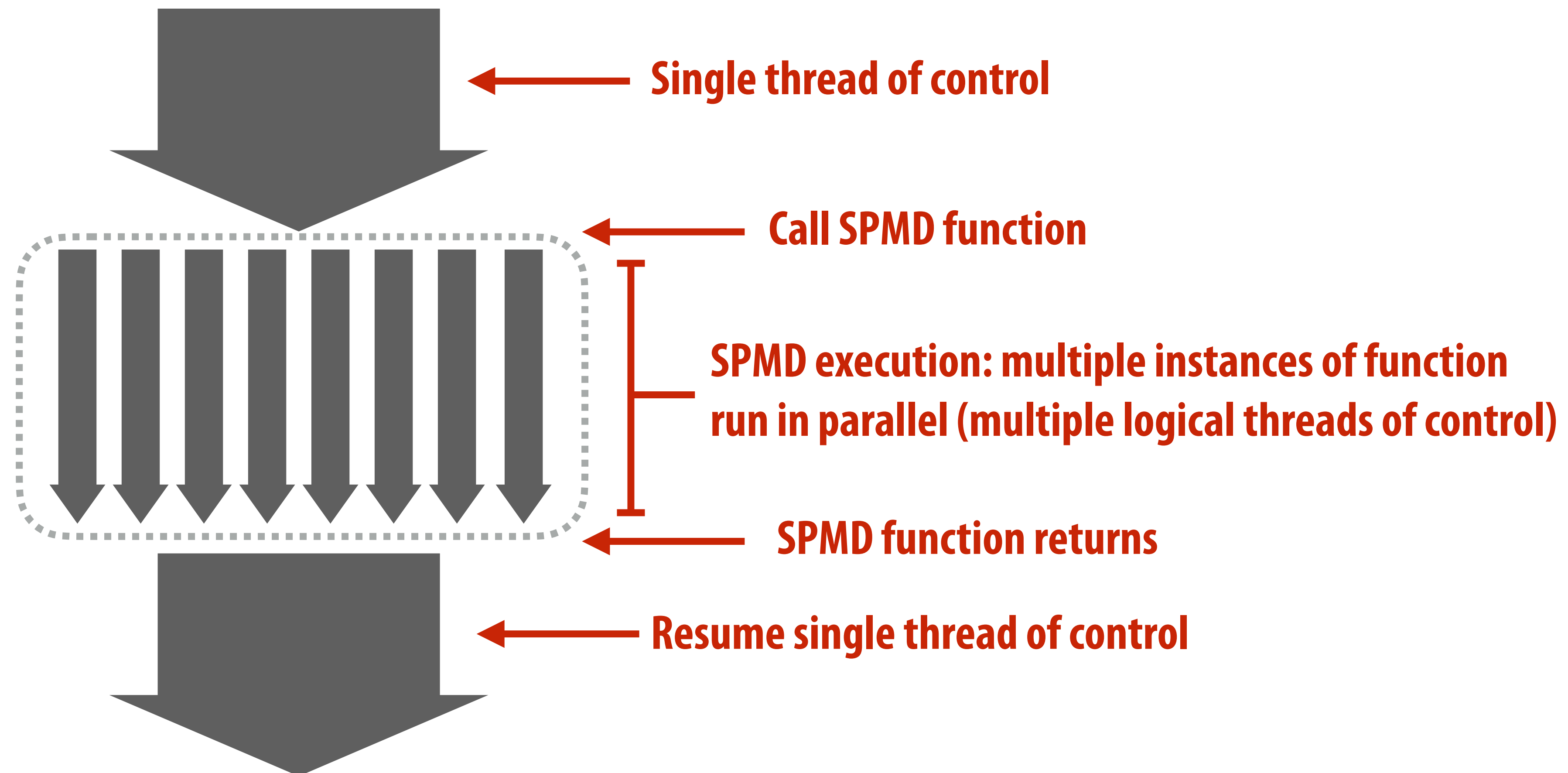
- **foreach declares parallel loop iterations**
 - Programmer says: these are the iterations the entire gang (not each instance) must perform
- **ISPC implementation assigns iterations to program instances in the gang**
 - Current ISPC implementation will perform a static interleaved assignment (but the abstraction permits a different assignment)

ISPC: abstraction vs. implementation

- **Single program, multiple data (SPMD) programming model**
 - Programmer “thinks”: running a gang is spawning `programCount` logical instruction streams (each with a different value of `programIndex`)
 - This is the programming abstraction
 - Program is written in terms of this abstraction
- **Single instruction, multiple data (SIMD) implementation**
 - ISPC compiler emits vector instructions (e.g., AVX2, ARM NEON) that carry out the logic performed by a ISPC gang
 - ISPC compiler handles mapping of conditional control flow to vector instructions (by masking vector lanes, etc. like you do manually in assignment 1)
- **Semantics of ISPC can be tricky**
 - SPMD abstraction + uniform values
(allows implementation details to peek through abstraction a bit)

SPMD programming model summary

- SPMD = “single program, multiple data”
- Define one function, run multiple instances of that function in parallel on different input arguments



ISPC tasks

- **The ISPC gang abstraction is implemented by SIMD instructions that execute within on thread running on one x86 core of a CPU.**
- **So all the code I've shown you in the previous slides would have executed on only one of the four cores of the myth machines.**
- **ISPC contains another abstraction: a “task” that is used to achieve multi-core execution. I'll let you read up about that.**

Part 2 of today's lecture

■ Three parallel programming models

- That differ in what communication abstractions they present to the programmer
- Programming models are important because they (1) influence how programmers think when writing programs and (2) influence the design of parallel hardware platforms designed to execute them efficiently

■ Corresponding machine architectures

- Abstraction presented by the hardware to low-level software

■ We'll focus on differences in communication/synchronization

Three programming models (abstractions)

1. Shared address space

2. Message passing

3. Data parallel

Shared address space model

Review: a program's memory address space

- A computer's memory is organized as a array of bytes
- Each byte is identified by its "address" in memory (its position in this array)
(in this class we assume memory is byte-addressable)

"The byte stored at address 0x8 has the value 32."

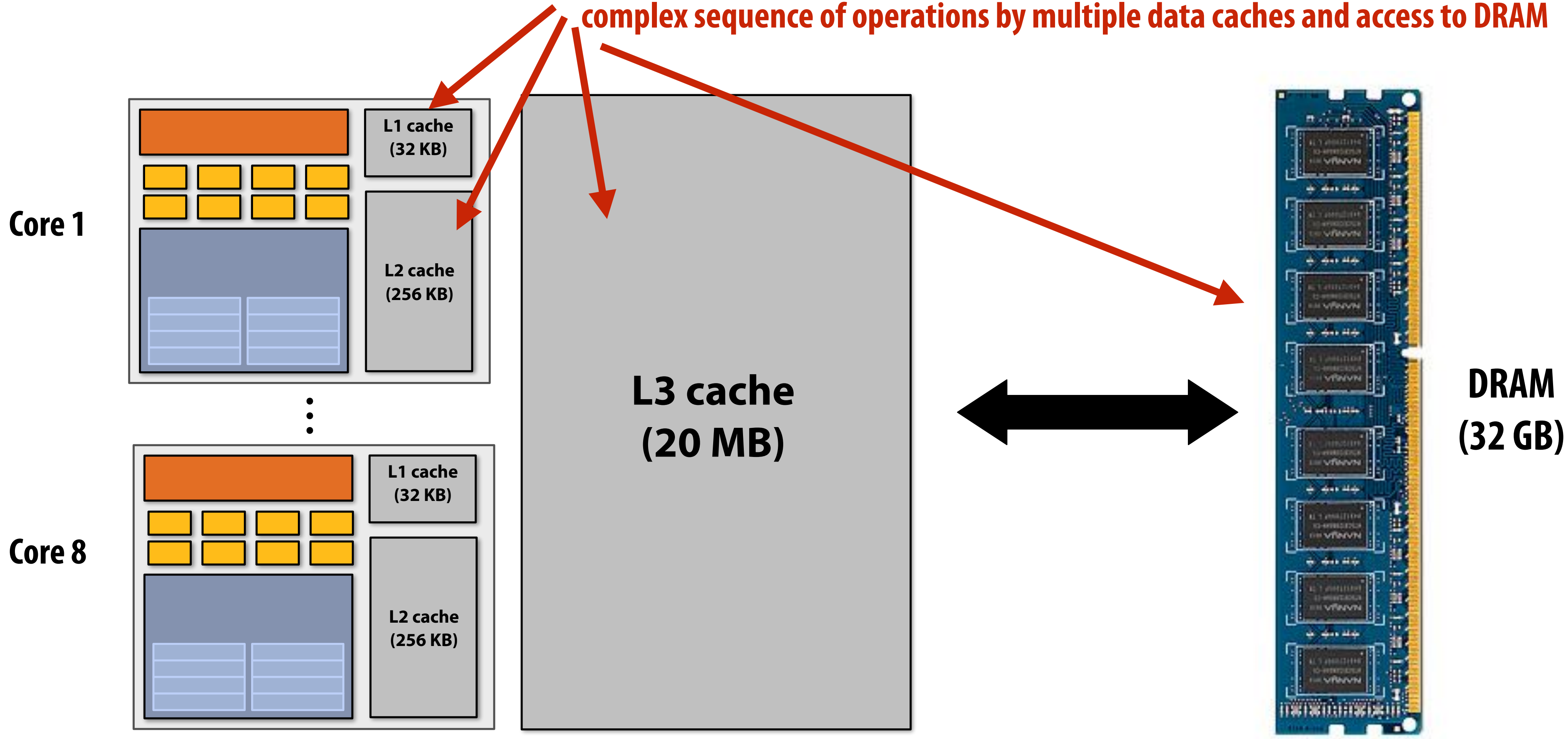
"The byte stored at address 0x10 (16) has the value 128."

In the illustration on the right, the program's memory address space is 32 bytes in size (so valid addresses range from 0x0 to 0x1F)

Address	Value
0x0	16
0x1	255
0x2	14
0x3	0
0x4	0
0x5	0
0x6	6
0x7	0
0x8	32
0x9	48
0xA	255
0xB	255
0xC	255
0xD	0
0xE	0
0xF	0
0x10	128
⋮	⋮
0x1F	0

The implementation of the linear memory address space abstraction on a modern computer is complex

The instruction "load the value stored at address X into register R0" might involve a complex sequence of operations by multiple data caches and access to DRAM



Shared address space model (abstraction)

Threads communicate by reading/writing to locations in a shared address space (shared variables)

Thread 1:

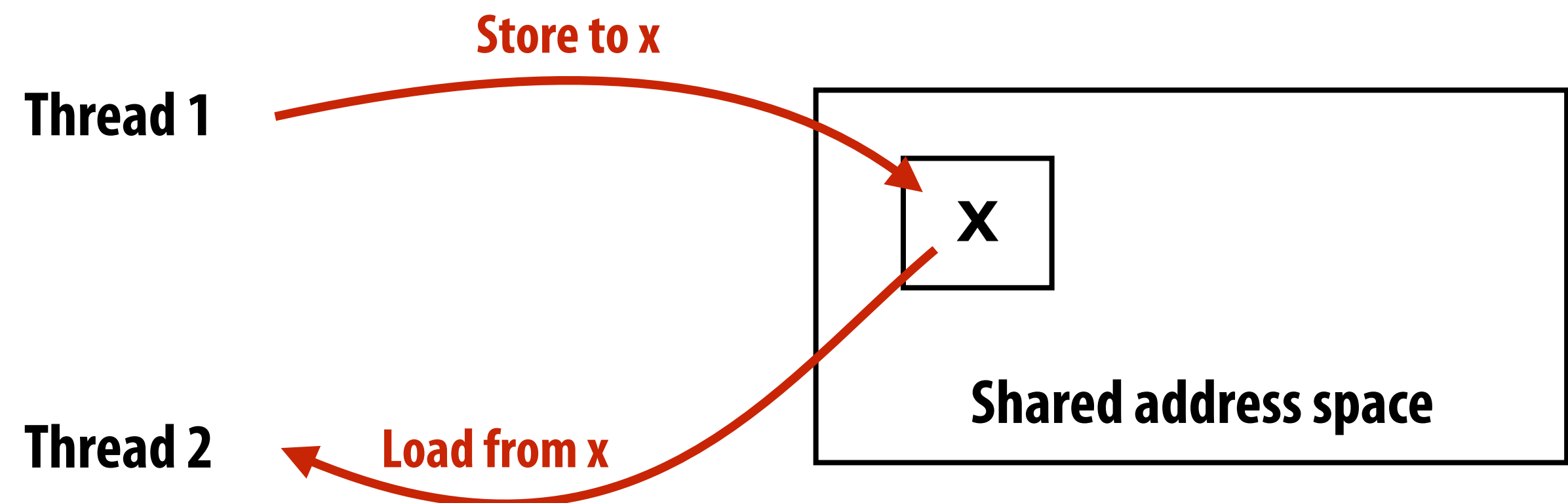
```
int x = 0;
spawn_thread(foo, &x);

// write to address holding
// contents of variable x
x = 1;
```

Thread 2:

```
void foo(int* x) {

    // read from addr storing
    // contents of variable x
    while (x == 0) {}
    print x;
}
```



**A common metaphor:
A shared address space is
like a bulletin board

(Everyone can read/write)**



Coordinating access to shared variables with synchronization

Thread 1:

```
int x = 0;
Lock my_lock;

spawn_thread(foo, &x, &my_lock);

mylock.lock();
x++;
mylock.unlock();
```

Thread 2:

```
void foo(int* x, Lock* my_lock) {
    my_lock->lock();
    x++;
    my_lock->unlock();

    print(x);
}
```

Review: why do we need mutual exclusion?

- Each thread executes
 - Load the value of variable x from a location in memory into register $r1$
(this stores a copy of the value in memory in the register)
 - Add the contents of register $r2$ to register $r1$
 - Store the value of register $r1$ into the address storing the program variable x
- One possible interleaving: (let starting value of $x=0$, $r2=1$)

T1	T2	
$r1 \leftarrow x$		T1 reads value 0
	$r1 \leftarrow x$	T2 reads value 0
$r1 \leftarrow r1 + r2$		T1 sets value of its $r1$ to 1
	$r1 \leftarrow r1 + r2$	T2 sets value of its $r1$ to 1
$x \leftarrow r1$		T1 stores 1 to address of x
	$x \leftarrow r1$	T2 stores 1 to address of x

- Need this set of three instructions must be “atomic”

Mechanisms for preserving atomicity

- **Lock/unlock mutex around a critical section**

```
mylock.lock();  
// critical section  
mylock.unlock();
```

- **Some languages have first-class support for atomicity of code blocks**

```
atomic {  
    // critical section  
}
```

- **Intrinsics for hardware-supported atomic read-modify-write operations**

```
atomicAdd(x, 10);
```

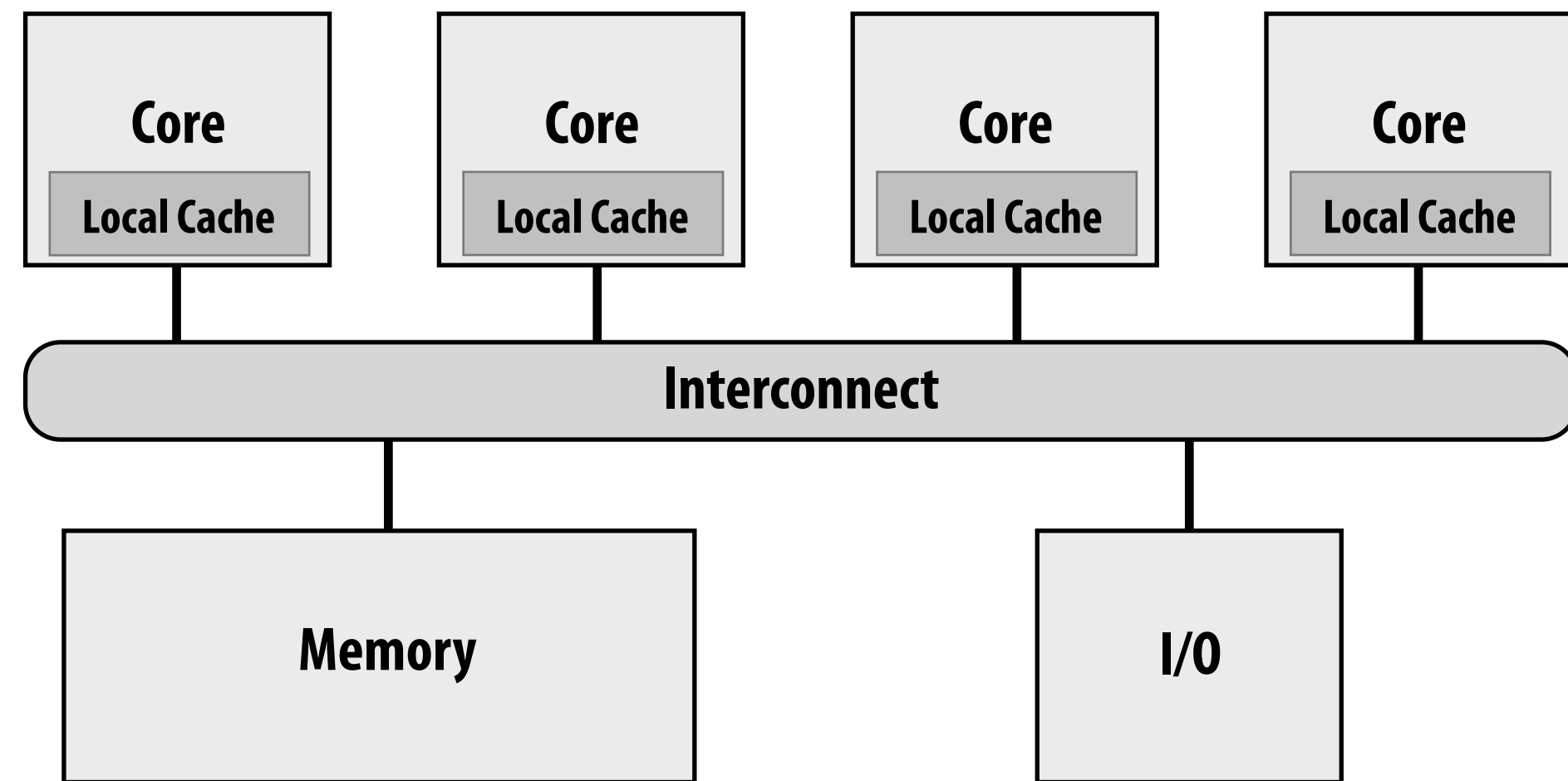

Review: shared address space model

- **Threads communicate by:**
 - **Reading/writing to shared variables in a shared address space**
 - **Inter-thread communication is implicit in memory loads/stores**
 - **Manipulating synchronization primitives**
 - **e.g., ensuring mutual exclusion via use of locks**

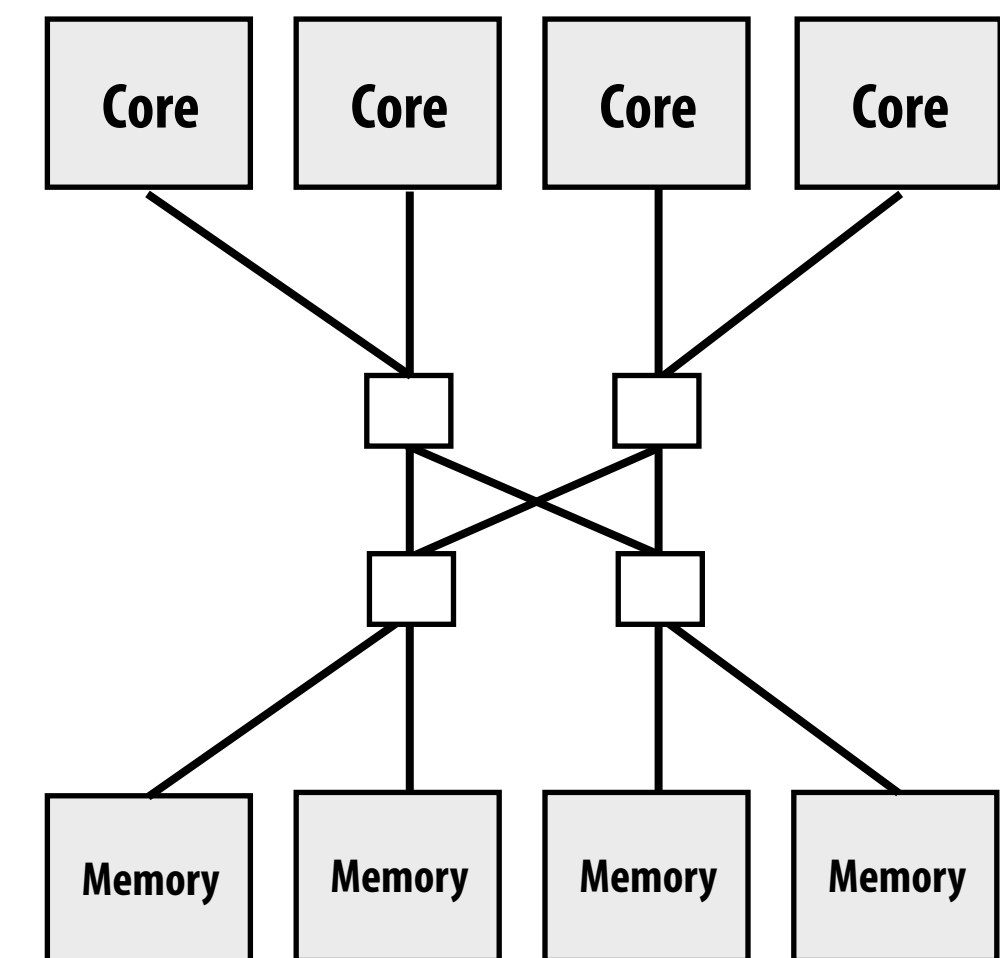
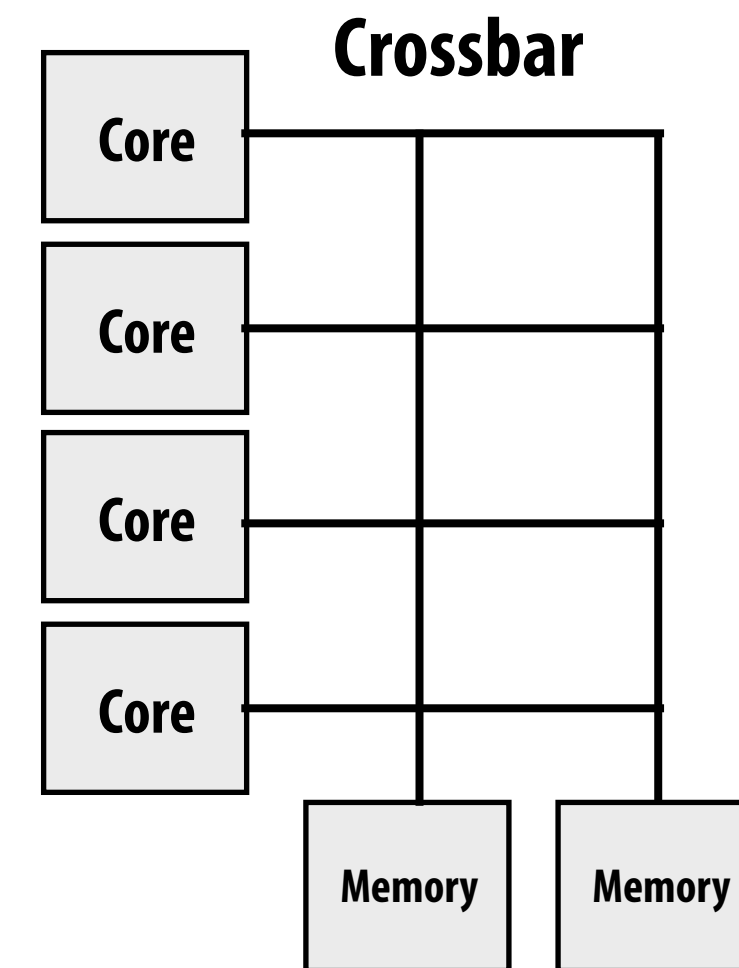
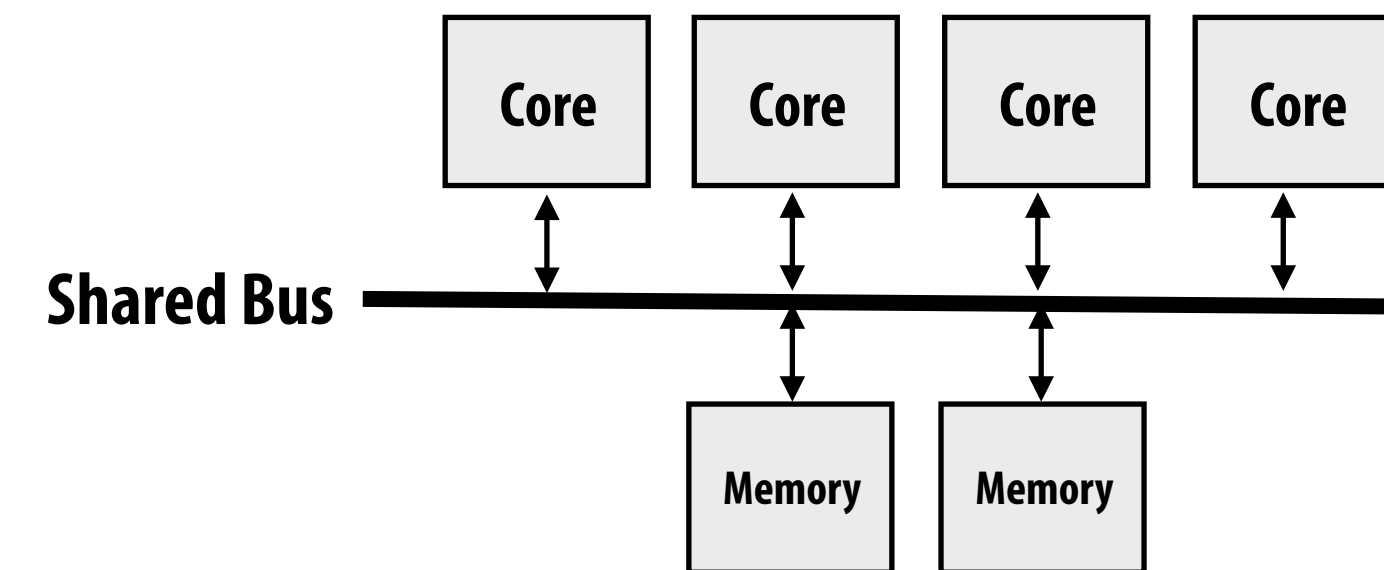
- **This is a natural extension of sequential programming**
 - **In fact, all our discussions in class have assumed a shared address space so far!**

Hardware implementation of a shared address space

Key idea: any processor can directly reference contents of any memory location



Examples of interconnects

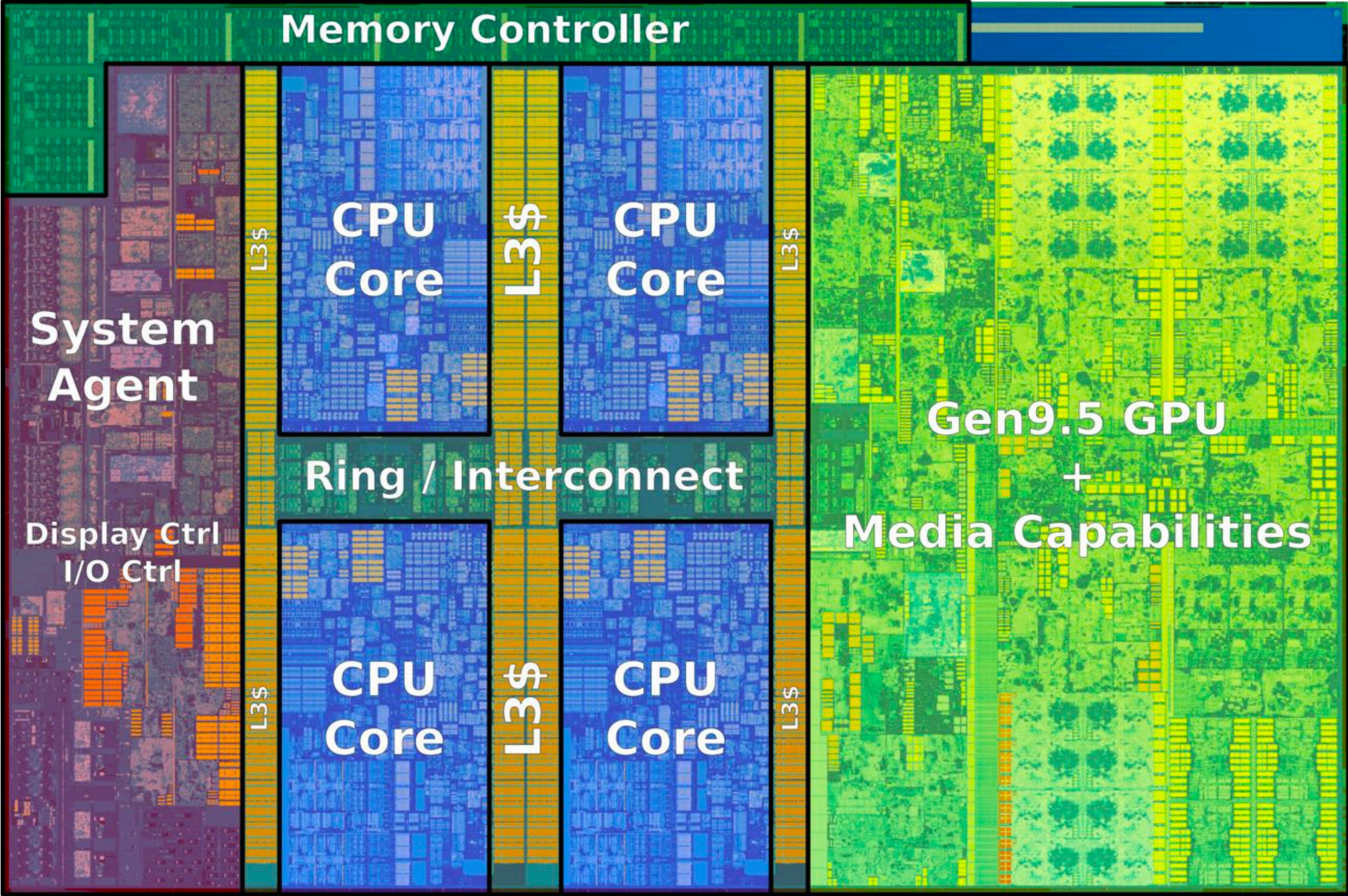


Multi-stage network

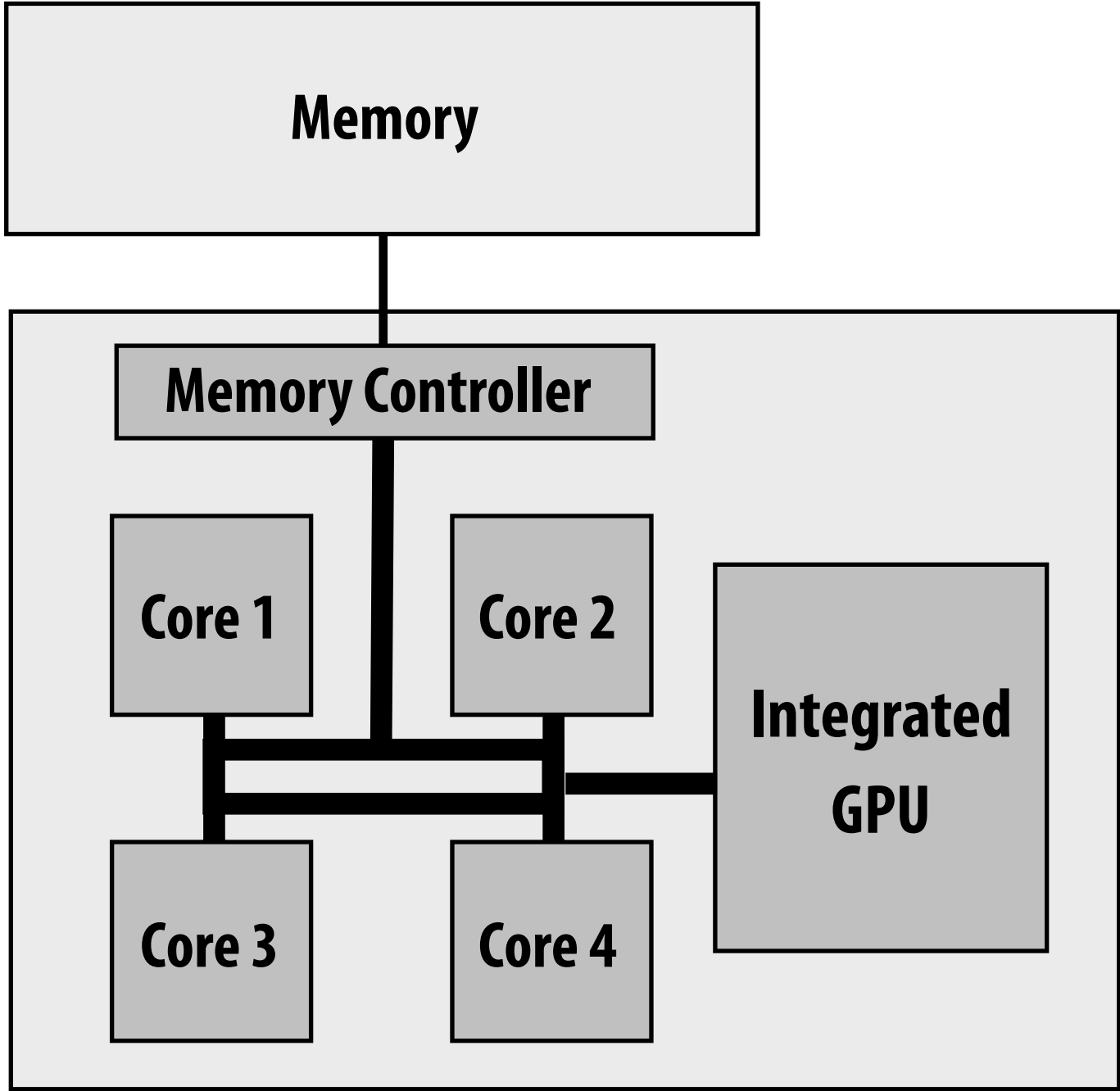
* Caches (not shown) are another implementation of a shared address space (more on this in a later lecture)

Shared address space hardware architecture

Any processor can directly reference any memory location



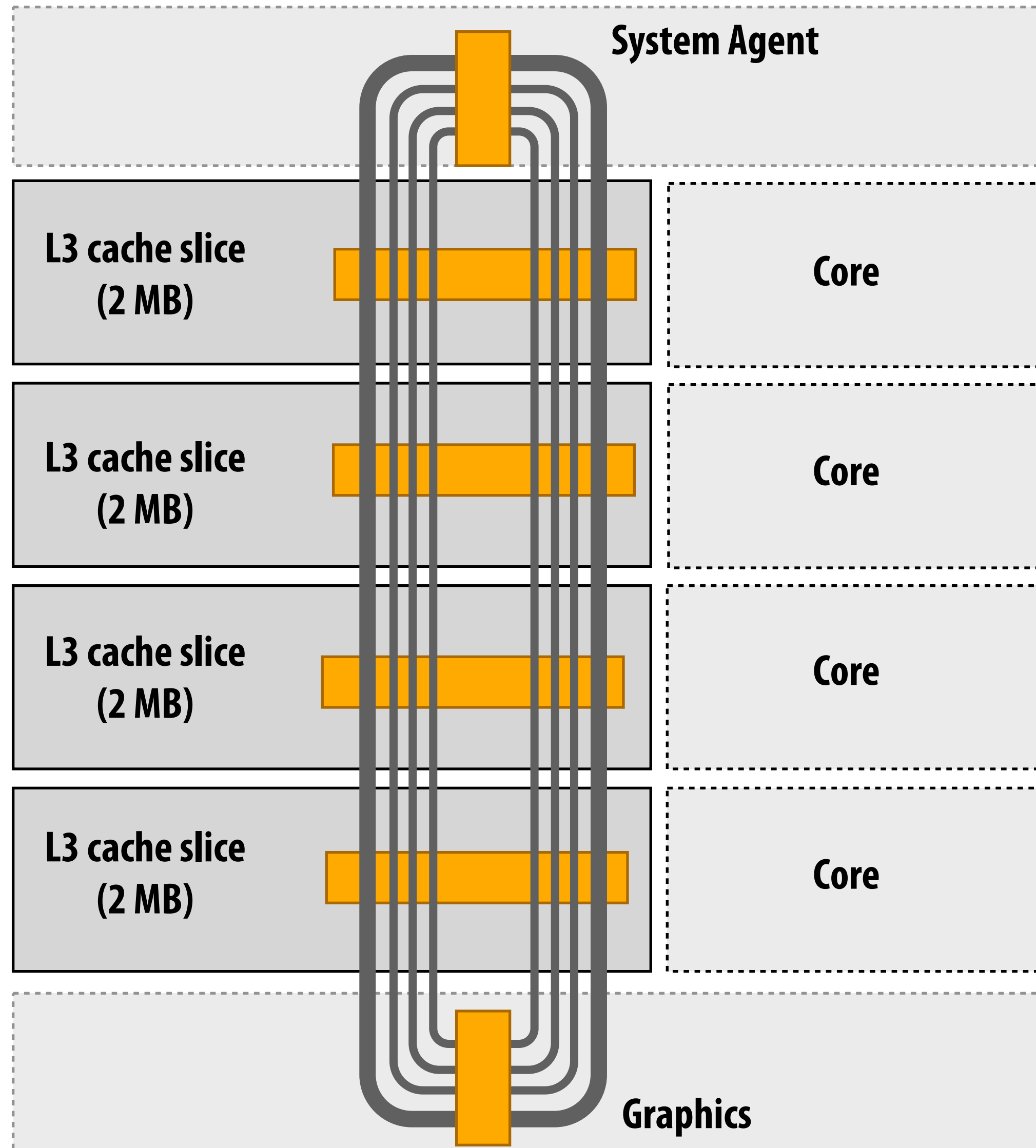
Example: Intel Core i7 processor (Kaby Lake)



Intel Core i7 (quad core)
(interconnect is a ring)

Intel's ring interconnect

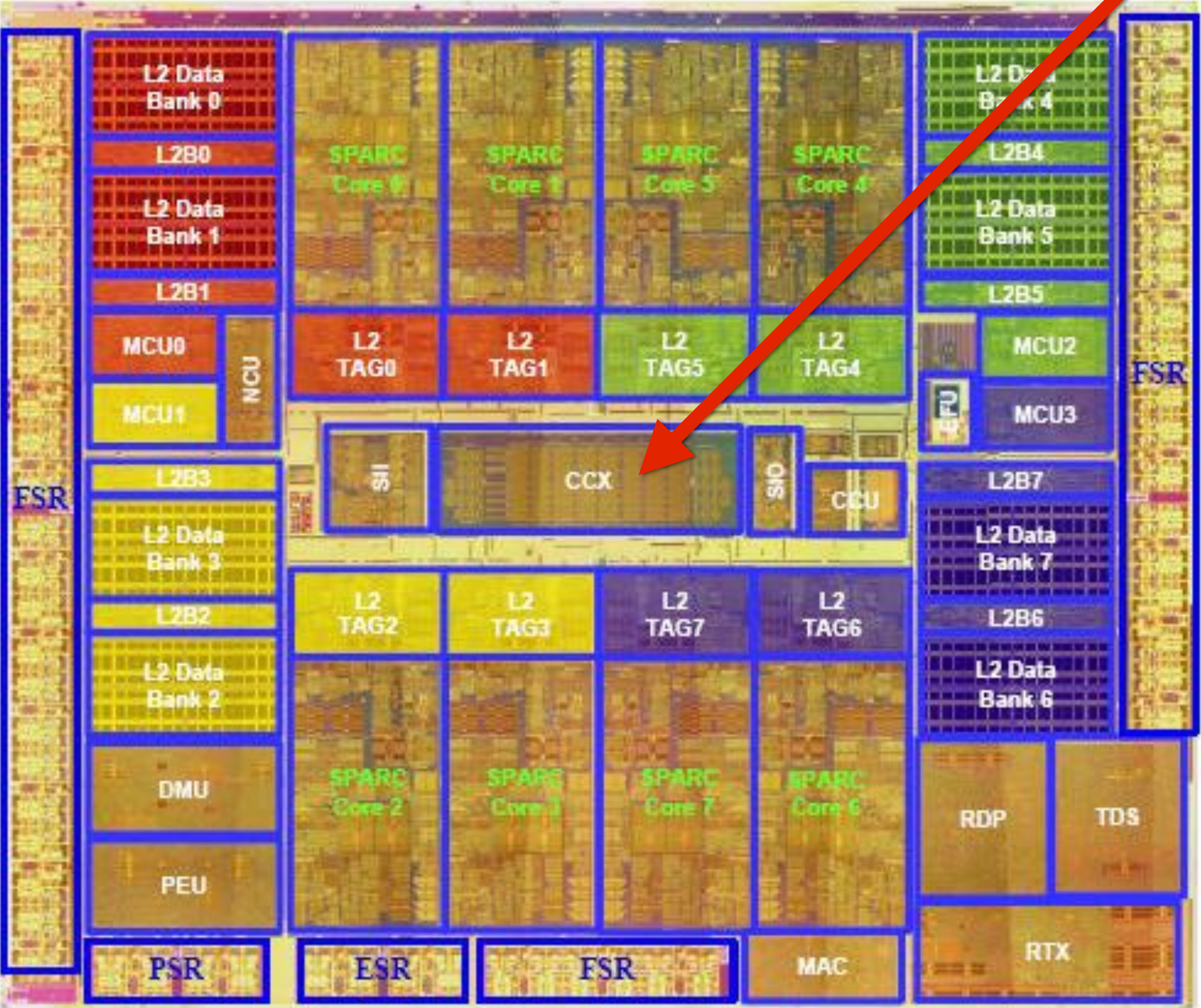
Introduced in Sandy Bridge microarchitecture



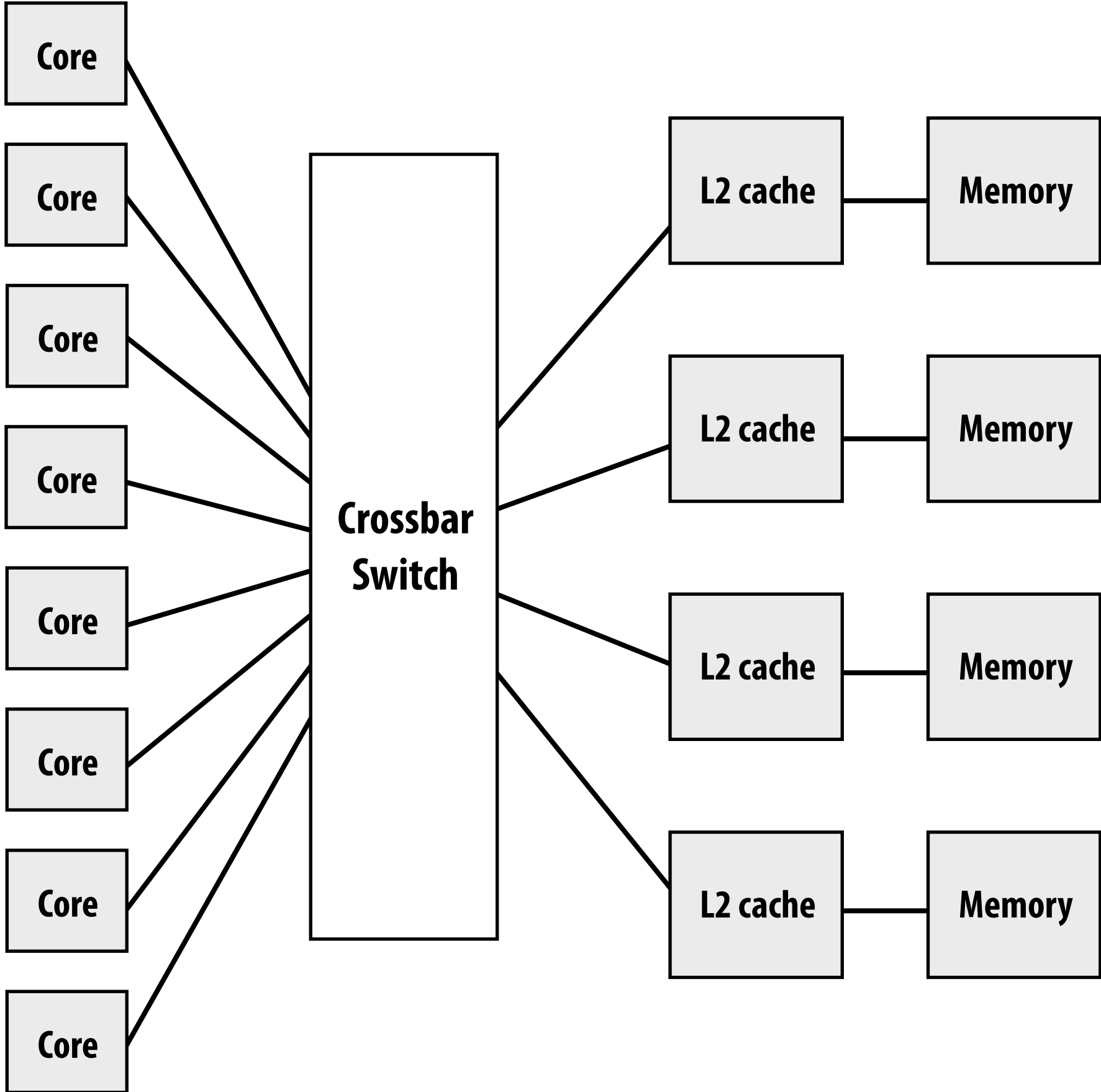
- **Four rings**
 - request
 - snoop
 - ack
 - data (32 bytes)
- **Six interconnect nodes: four “slices” of L3 cache + system agent + graphics**
- **Each bank of L3 connected to ring bus twice**
- **Theoretical peak BW from cores to L3 at 3.4 GHz ~ 435 GB/sec**
 - When each core is accessing its local slice

SUN Niagara 2 (UltraSPARC T2): crossbar interconnect

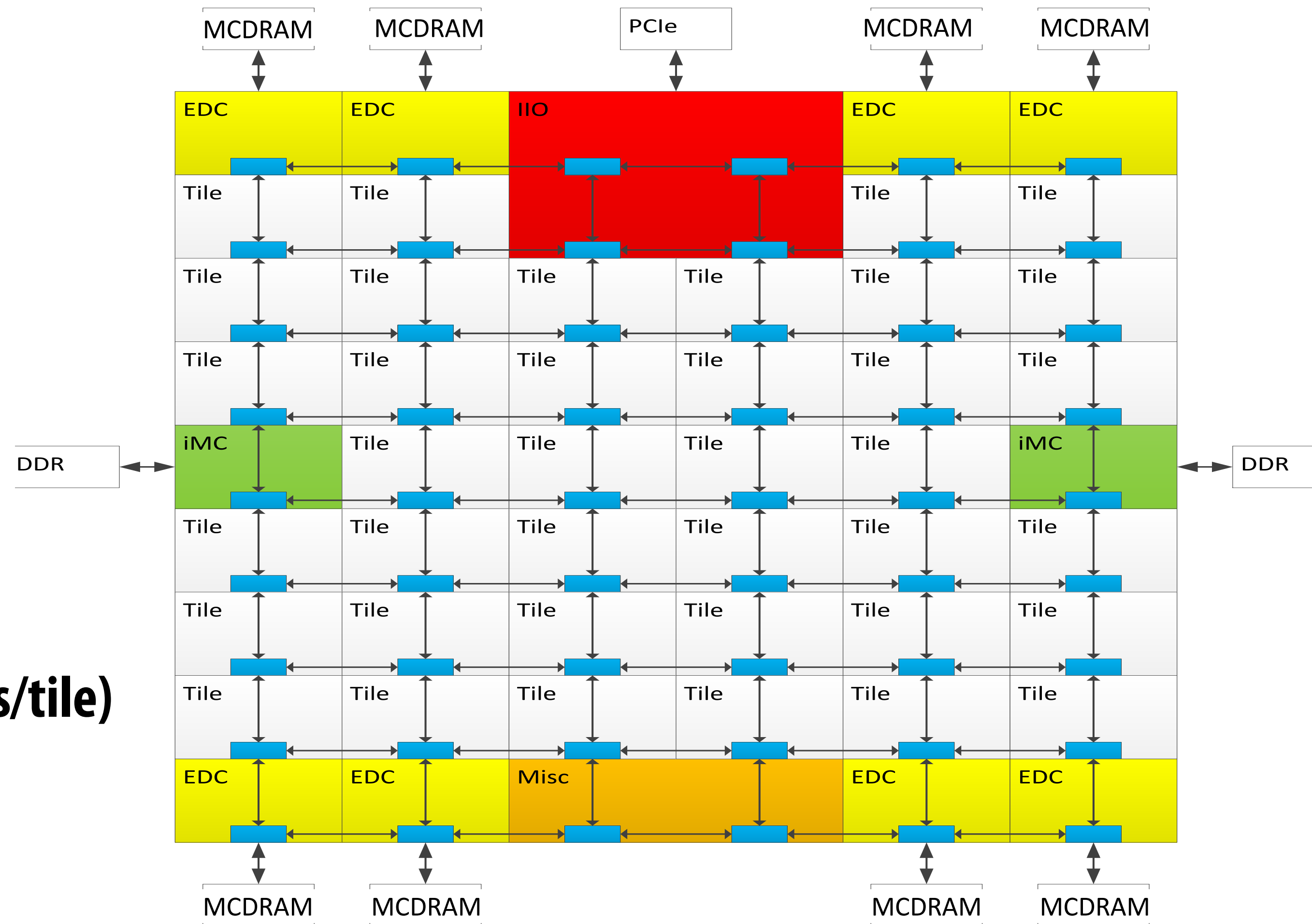
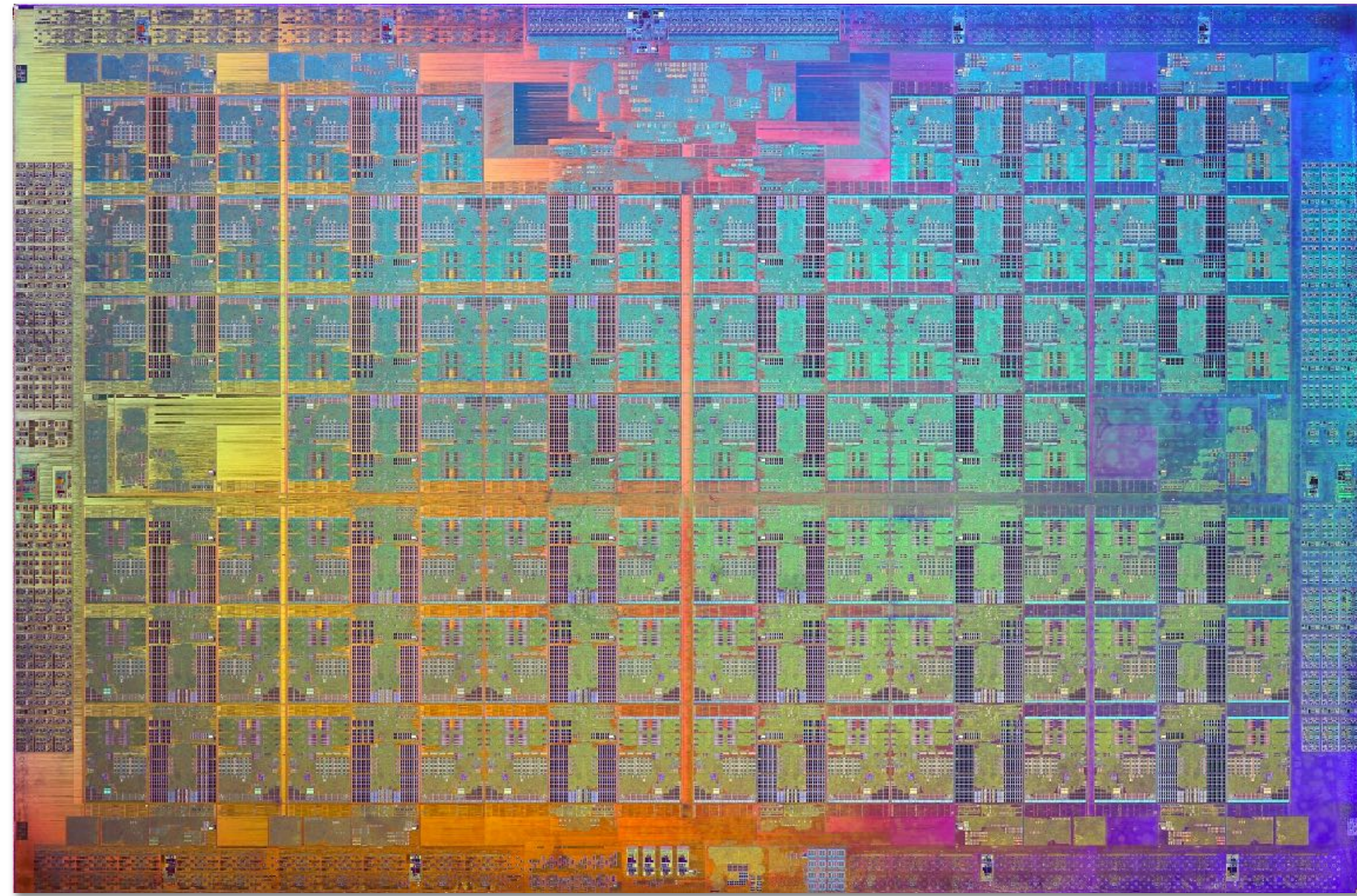
Note area of crossbar (CCX):
about same area as one core on chip



Eight core processor



Intel Xeon Phi (Knights Landing)



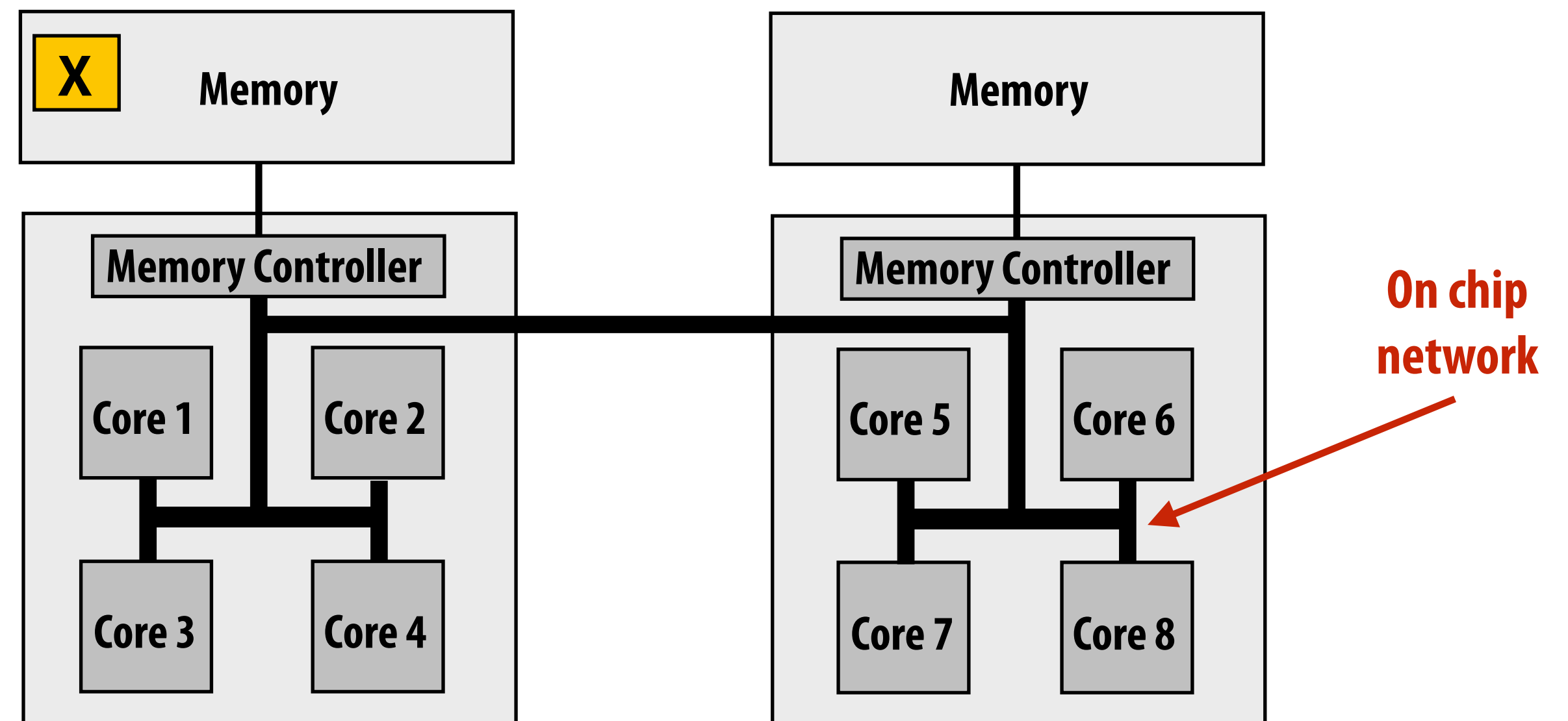
- **72 cores, arranged as 6x6 mesh of tiles (2 cores/tile)**
- **YX routing of messages:**
 - **Message travels in Y direction**
 - **“Turn”**
 - **Message travels in X direction**

Non-uniform memory access (NUMA)

The latency of accessing a memory location may be different from different processing cores in the system
Bandwidth from any one location may also be different to different CPU cores *



Example: modern multi-socket configuration



* In practice, you'll find NUMA behavior on a single-socket system as well (recall: different cache slices are a different distance from each core)

Summary: shared address space model

■ Communication abstraction

- Threads read/write variables in shared address space
- Threads manipulate synchronization primitives: locks, atomic ops, etc.
- Logical extension of uniprocessor programming *

■ Requires hardware support to implement efficiently

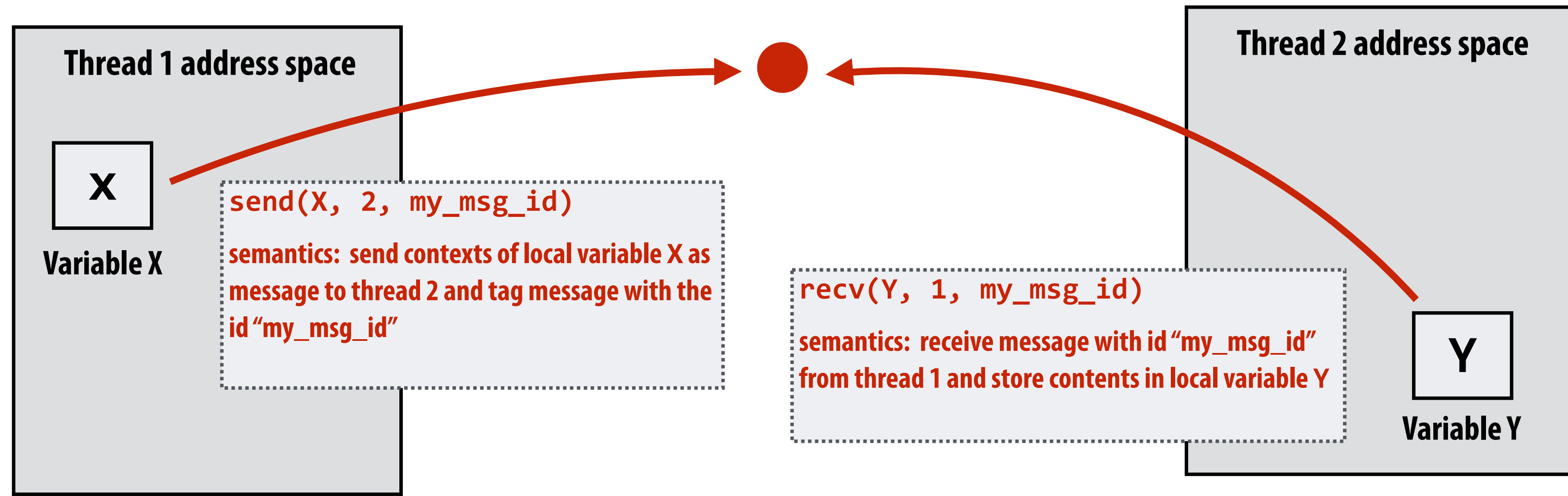
- Any processor can load and store from any address
- Can be costly to scale to large numbers of processors
(one of the reasons why high-core count processors are expensive)

* But NUMA implementations requires reasoning about locality for performance optimization

Message passing model of communication

Message passing model (abstraction)

- Threads operate within their own private address spaces
- Threads communicate by sending/receiving messages
 - send: specifies recipient, buffer to be transmitted, and optional message identifier (“tag”)
 - receive: sender, specifies buffer to store data, and optional message identifier
 - Sending messages is the only way to exchange data between threads 1 and 2
 - Why?



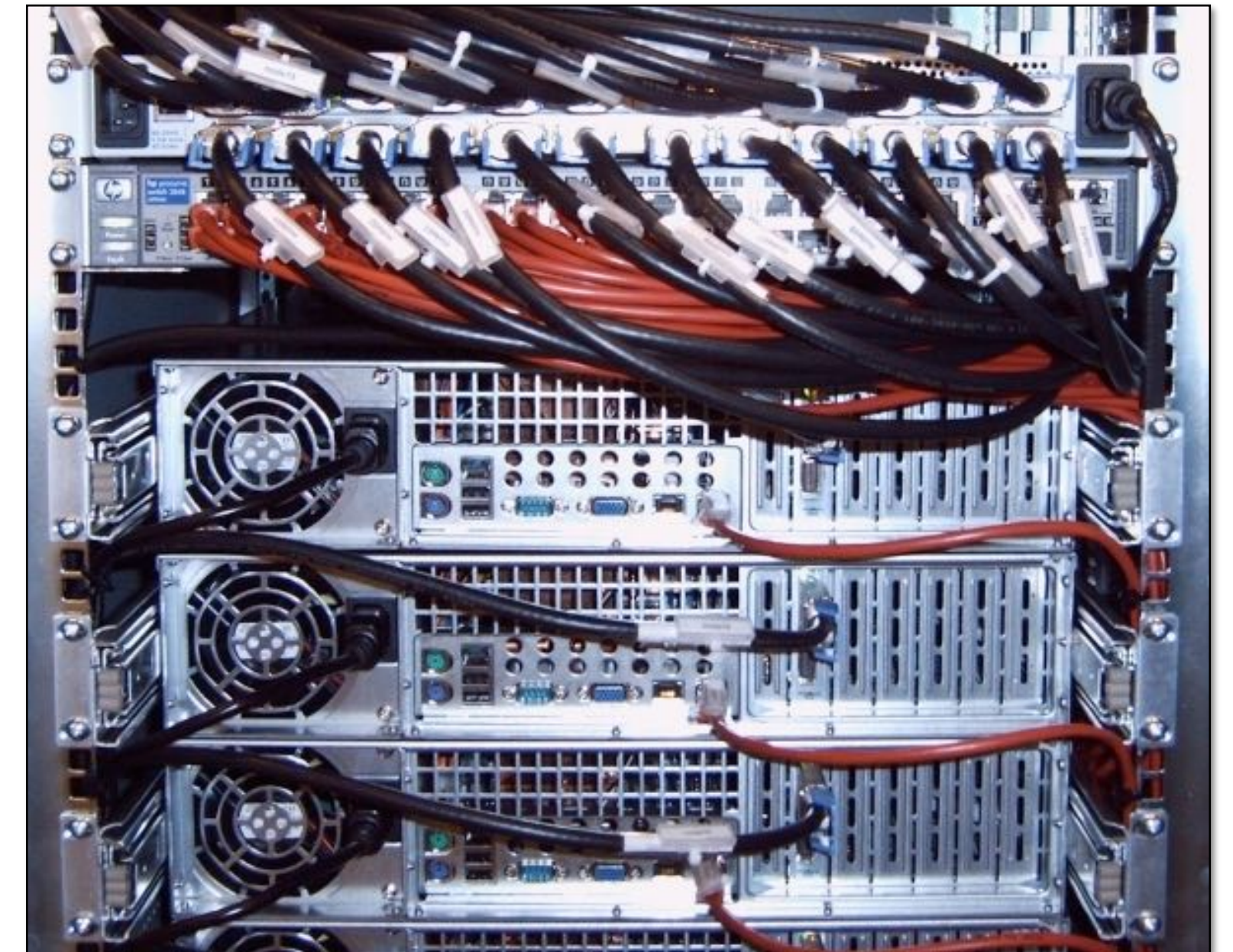
(Communication operations shown in red)

A common metaphor: snail mail



Message passing (implementation)

- **Hardware need not implement system-wide loads and stores to execute message passing programs (it need only communicate messages between nodes)**
 - **Can connect commodity systems together to form a large parallel machine (message passing is a programming model for clusters and supercomputers)**



**Cluster of workstations
(Infiniband network)**

The data-parallel model

Programming models provide a way to think about the organization of parallel programs (by imposing structure)

- **Shared address space: very little structure to communication**
 - All threads can read and write to all shared variables
- **Message passing: communication is structured in the form of messages**
 - All communication occurs in the form of messages
 - Communication is explicit in source code—the sends and receives)
- **Data parallel structure: more rigid structure to computation**
 - Perform same function on elements of large collections

Data-parallel model *

- **Organize computation as operations on sequences of elements**
 - e.g., perform same function on all elements of a sequence
- **A well-known modern example: NumPy: $C = A + B$**
(A, B, and C are vectors of same length)

Something you've seen early in the lecture...

* We'll have multiple lectures in the course about data-parallel programming and data-parallel thinking: this is just a taste

Key data type: sequences

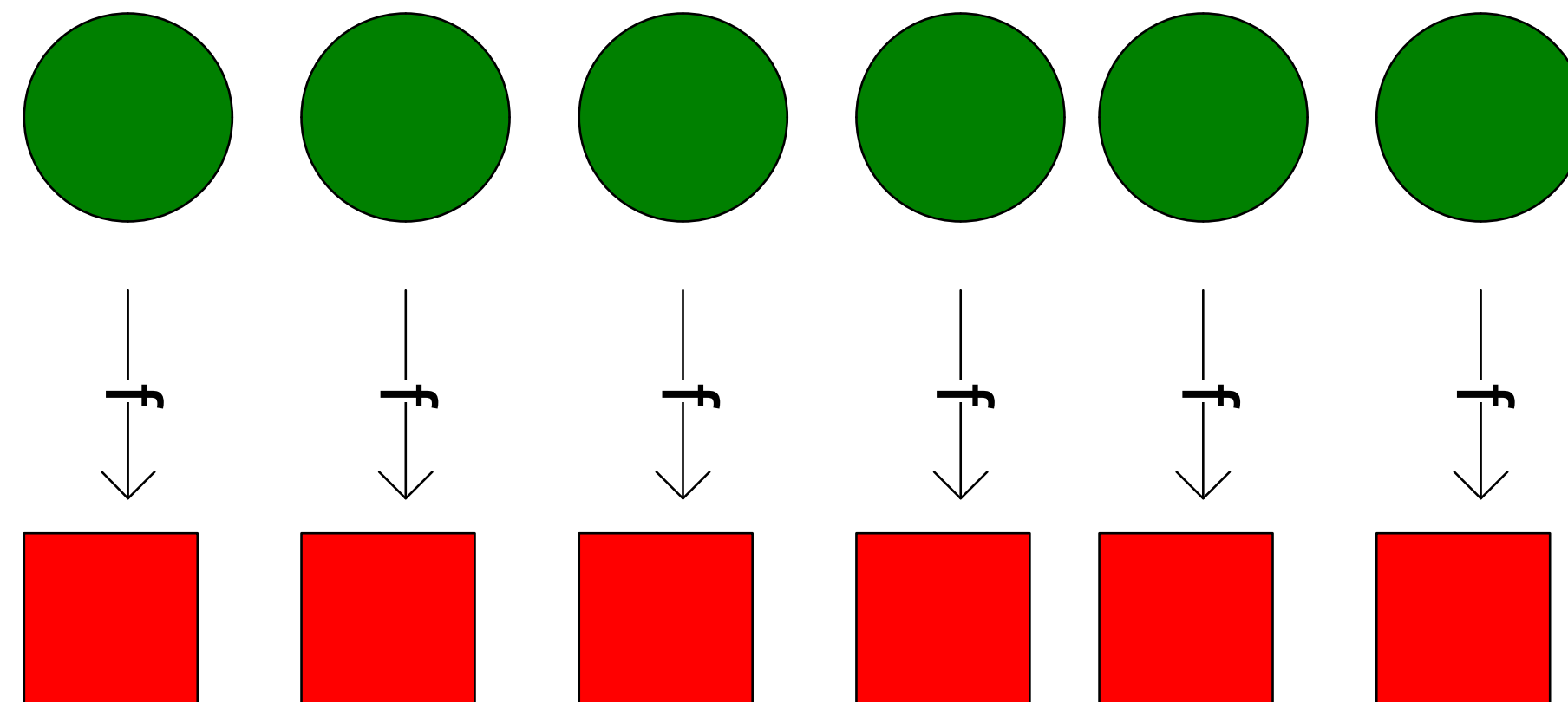
- **Ordered collection of elements**
- **For example, in a C++ like language: Sequence<T>**
- **Scala lists: List[T]**
- **In a functional language (like Haskell): seq T**

- **Program can only access elements of sequence through sequence operators:**
 - **map, reduce, scan, shift, etc.**

Map

- Higher order function (function that takes a function as an argument) that operates on sequences
- Applies side-effect-free unary function $f :: a \rightarrow b$ to all elements of input sequence, to produce output sequence of the same length
- In a functional language (e.g., Haskell)
 - `map :: (a -> b) -> seq a -> seq b`
- In C++:

```
template<class InputIt, class OutputIt, class UnaryOperation>  
OutputIt transform(InputIt first1, InputIt last1,  
                  OutputIt d_first,  
                  UnaryOperation unary_op);
```



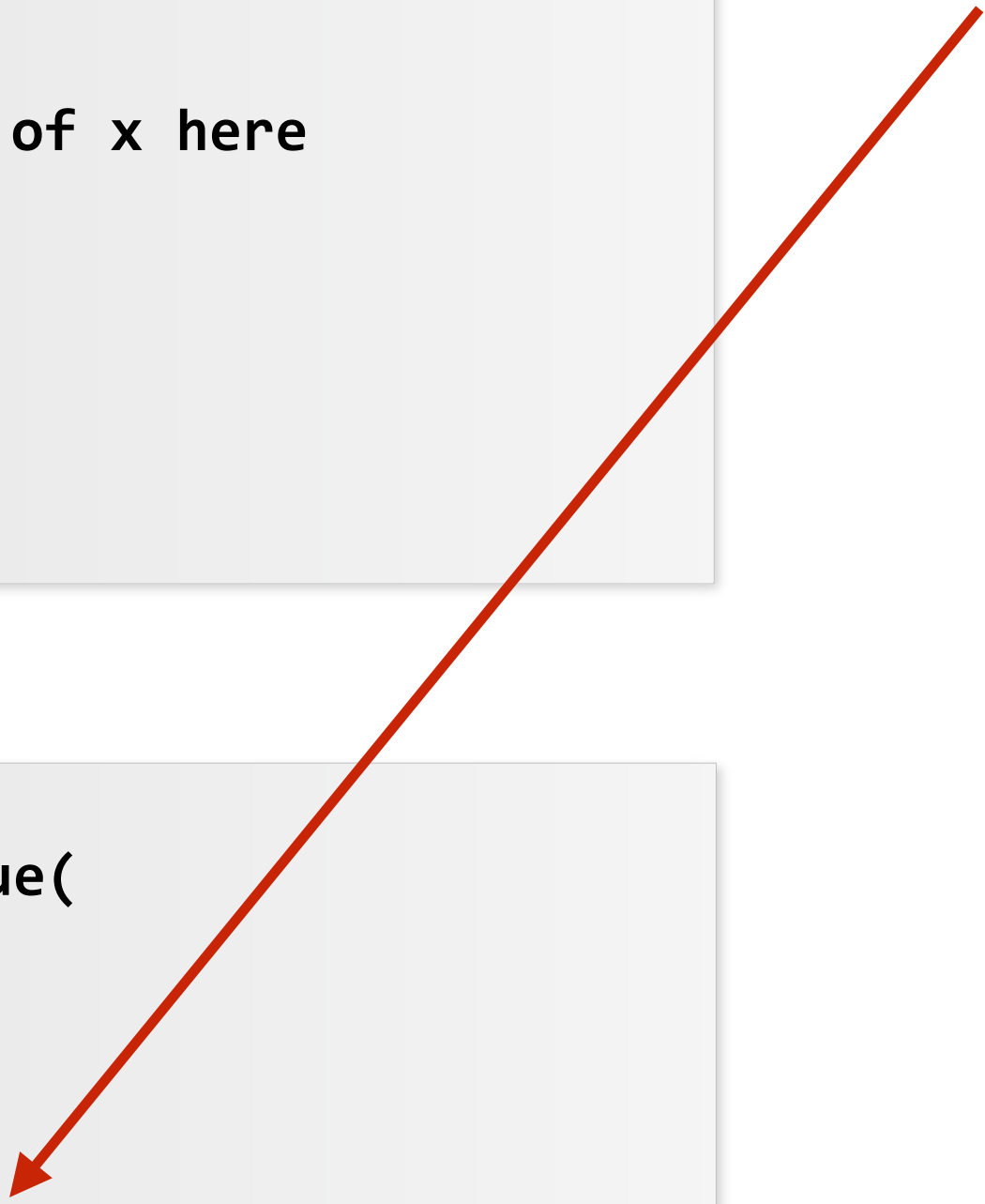
Parallelizing map

- Since $f :: a \rightarrow b$ is a function (side-effect free), then applying f to all elements of the sequence can be done **in any order** without changing the output of the program
- The implementation of map has flexibility to reorder/parallelize processing of elements of sequence however it sees fit

Data parallelism in ISPC

```
// main C++ code:  
const int N = 1024;  
float* x = new float[N];  
float* y = new float[N];  
  
// initialize N elements of x here  
  
absolute_value(N, x, y);
```

```
// ISPC code:  
export void absolute_value(  
    uniform int N,  
    uniform float* x,  
    uniform float* y)  
{  
    foreach (i = 0 ... N)  
    {  
        if (x[i] < 0)  
            y[i] = -x[i];  
        else  
            y[i] = x[i];  
    }  
}
```



foreach construct

Think of loop body as a function

Given this program, it is reasonable to think of the program as using foreach to “map the loop body onto each element” of the arrays X and Y.

But if we want to be more precise: a sequence is not a first-class ISPC concept. It is implicitly defined by how the program has implemented array indexing logic in the foreach loop.

(There is no operation in ISPC with the semantic: “map this code over all elements of this sequence”)

Data parallelism in ISPC

```
// main C++ code:
const int N = 1024;
float* x = new float[N/2];
float* y = new float[N];

// initialize N/2 elements of x here

absolute_repeat(N/2, x, y);
```

```
// ISPC code:
export void absolute_repeat(
    uniform int N,
    uniform float* x,
    uniform float* y)
{
    foreach (i = 0 ... N)
    {
        if (x[i] < 0)
            y[2*i] = -x[i];
        else
            y[2*i] = x[i];
        y[2*i+1] = y[2*i];
    }
}
```

Think of loop body as a function

The input/output sequences being mapped over are implicitly defined by array indexing logic

This is also a valid ISPC program!

It takes the absolute value of elements of x, then repeats it twice in the output array y

(Less obvious how to think of this code as mapping the loop body onto existing sequences.)

Data parallelism in ISPC

```
// main C++ code:  
const int N = 1024;  
float* x = new float[N];  
float* y = new float[N];  
  
// initialize N elements of x  
  
shift_negative(N, x, y);
```

```
// ISPC code:  
export void shift_negative(  
    uniform int N,  
    uniform float* x,  
    uniform float* y)  
{  
    foreach (i = 0 ... N)  
    {  
        if (i >= 1 && x[i] < 0)  
            y[i-1] = x[i];  
        else  
            y[i] = x[i];  
    }  
}
```

Think of loop body as a function

The input/output sequences being mapped over are implicitly defined by array indexing logic

The output of this program is undefined!

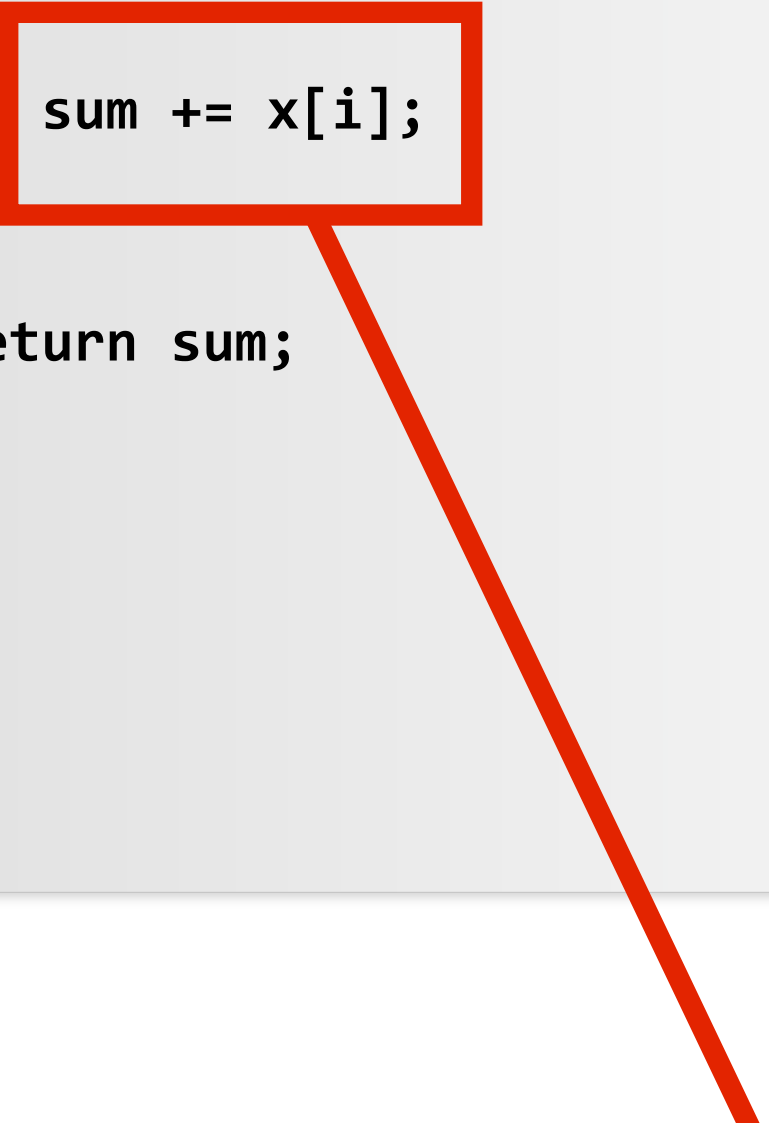
Possible for multiple iterations of the loop body to write to same memory location

Data-parallel model (foreach) provides no specification of order in which iterations occur

ISPC discussion: sum “reduction”

Compute the sum of all array elements in parallel

```
export uniform float sumall1(  
    uniform int N,  
    uniform float* x)  
{  
    uniform float sum = 0.0f;  
    foreach (i = 0 ... N)  
    {  
        sum += x[i];  
    }  
    return sum;  
}
```



```
export uniform float sumall2(  
    uniform int N,  
    uniform float* x)  
{  
    uniform float sum;  
    float partial = 0.0f;  
    foreach (i = 0 ... N)  
    {  
        partial += x[i];  
    }  
  
    // from ISPC math library  
    sum = reduce_add(partial);  
  
    return sum;  
}
```

Correct ISPC solution

sum is of type uniform float (one copy of variable for all program instances)
x[i] is not a uniform expression (different value for each program instance)
Result: compile-time type error

ISPC discussion: sum “reduction”

Each instance accumulates a private partial sum
(no communication)

Partial sums are added together using the `reduce_add()` cross-instance communication primitive. The result is the same total sum for all program instances (`reduce_add()` returns a uniform float)

The ISPC code at right will execute in a manner similar to handwritten C + AVX intrinsics implementation below. *

```
float sumall2(int N, float* x) {  
  
    float tmp[8]; // assume 16-byte alignment  
    __mm256 partial = __mm256_broadcast_ss(0.0f);  
  
    for (int i=0; i<N; i+=8)  
        partial = __mm256_add_ps(partial, __mm256_load_ps(&x[i]));  
  
    __mm256_store_ps(tmp, partial);  
  
    float sum = 0.f;  
    for (int i=0; i<8; i++)  
        sum += tmp[i];  
  
    return sum;  
}
```

```
export uniform float sumall2(  
    uniform int N,  
    uniform float* x)  
{  
    uniform float sum;  
    float partial = 0.0f;  
    foreach (i = 0 ... N)  
    {  
        partial += x[i];  
    }  
  
    // from ISPC math library  
    sum = reduce_add(partial);  
  
    return sum;  
}
```

*** Self-test: If you understand why this implementation complies with the semantics of the ISPC gang abstraction, then you’ve got a good command of ISPC**

Summary: data-parallel model

- **Data-parallelism is about imposing rigid program structure to facilitate simple programming and advanced optimizations**
- **Basic structure: map a function onto a large collection of data**
 - **Functional: side-effect free execution**
 - **No communication among distinct function invocations**
(allow invocations to be scheduled in any order, including in parallel)
- **Other data parallel operators express more complex patterns on sequences: gather, scatter, reduce, scan, shift, etc.**
 - **This will be a topic of a later lecture**
- **You will think in terms of data-parallel primitives often in this class, but many modern performance-oriented data-parallel languages do not enforce this structure in the language**
 - **Many languages (like ISPC, CUDA, etc.) choose flexibility/familiarity of imperative C-style syntax over the safety of a more functional form**

Summary

Summary

- **Programming models provide a way to think about the organization of parallel programs.**
- **They provide abstractions that permit multiple valid implementations.**
- ***I want you to always be thinking about abstraction vs. implementation for the remainder of this course.***