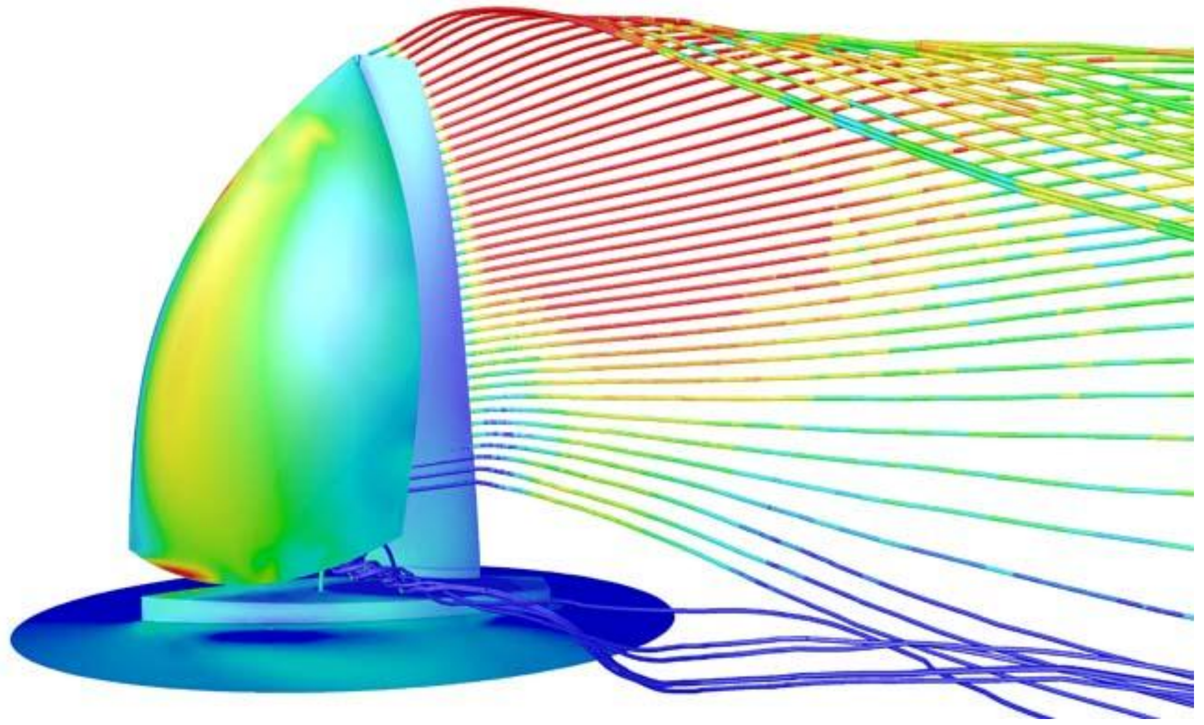
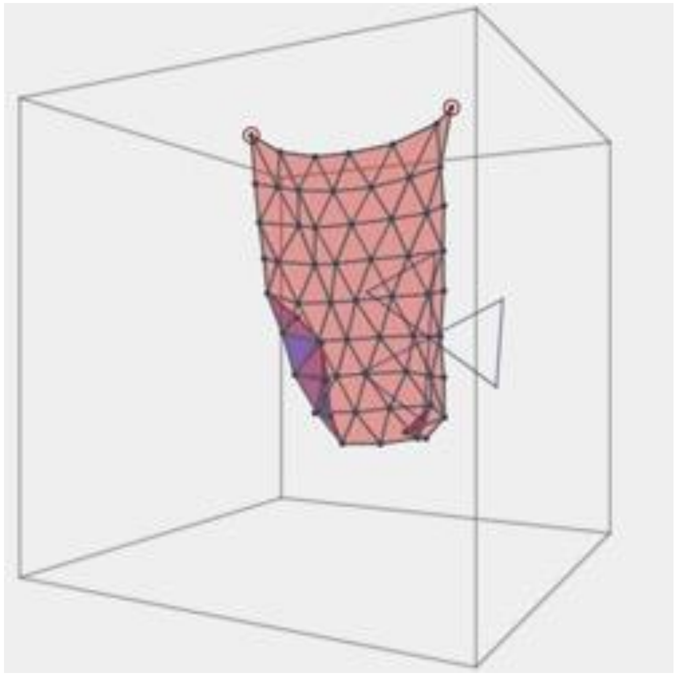
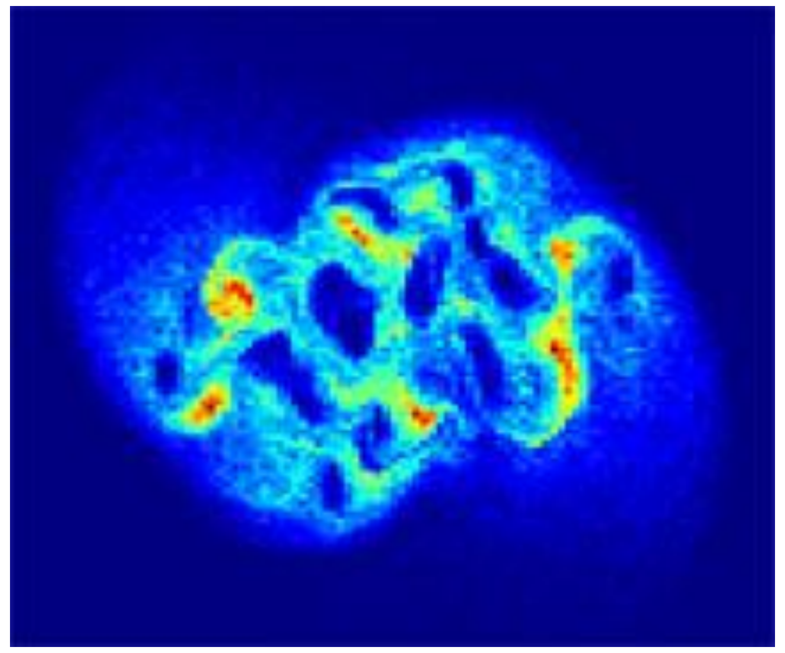
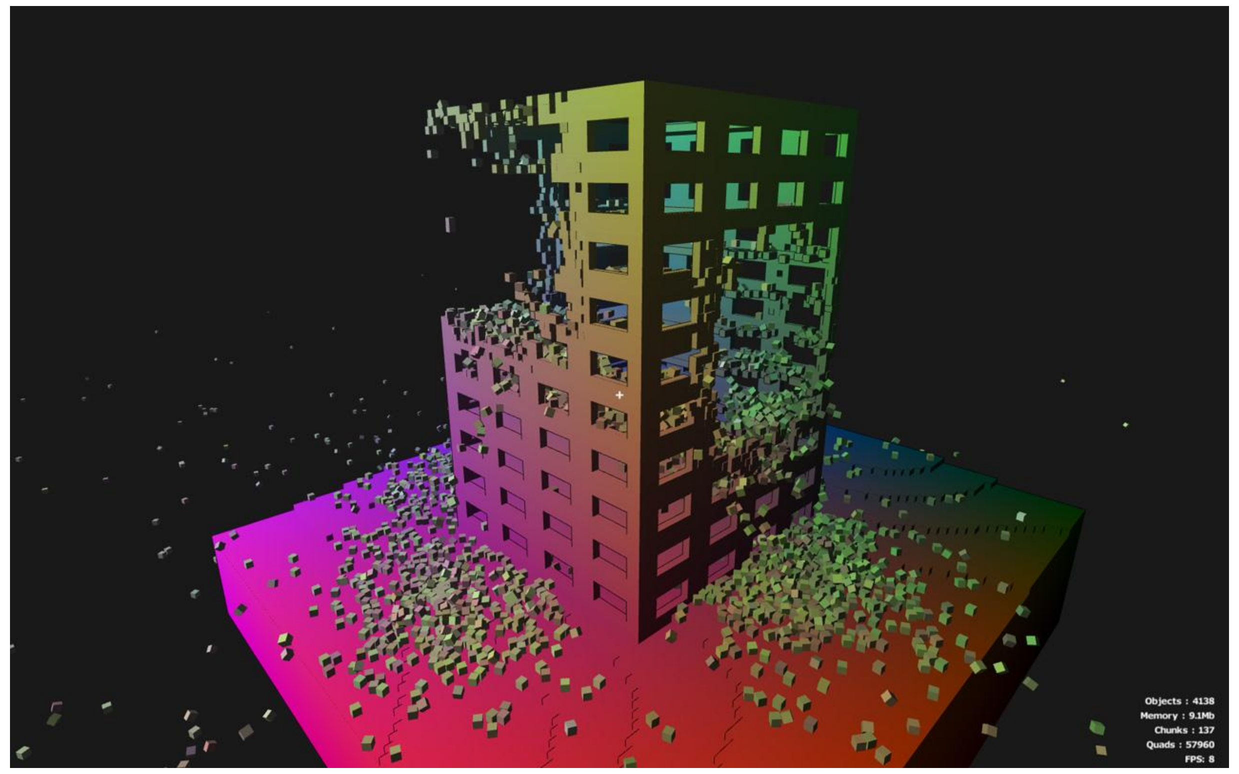
   

Introduction to GPU Architecture

Ofer Rosenberg,

PMTS SW, OpenCL Dev. Team

AMD

Based on
“From Shader Code to a Teraflop: How GPU Shader Cores Work”,
By Kayvon Fatahalian, Stanford University

Content

1. Three major ideas that make GPU processing cores run fast

2. Closer look at real GPU designs
   – NVIDIA GTX 580
   – AMD Radeon 6970

3. The GPU memory hierarchy: moving data to processors

4. Heterogeneous Cores

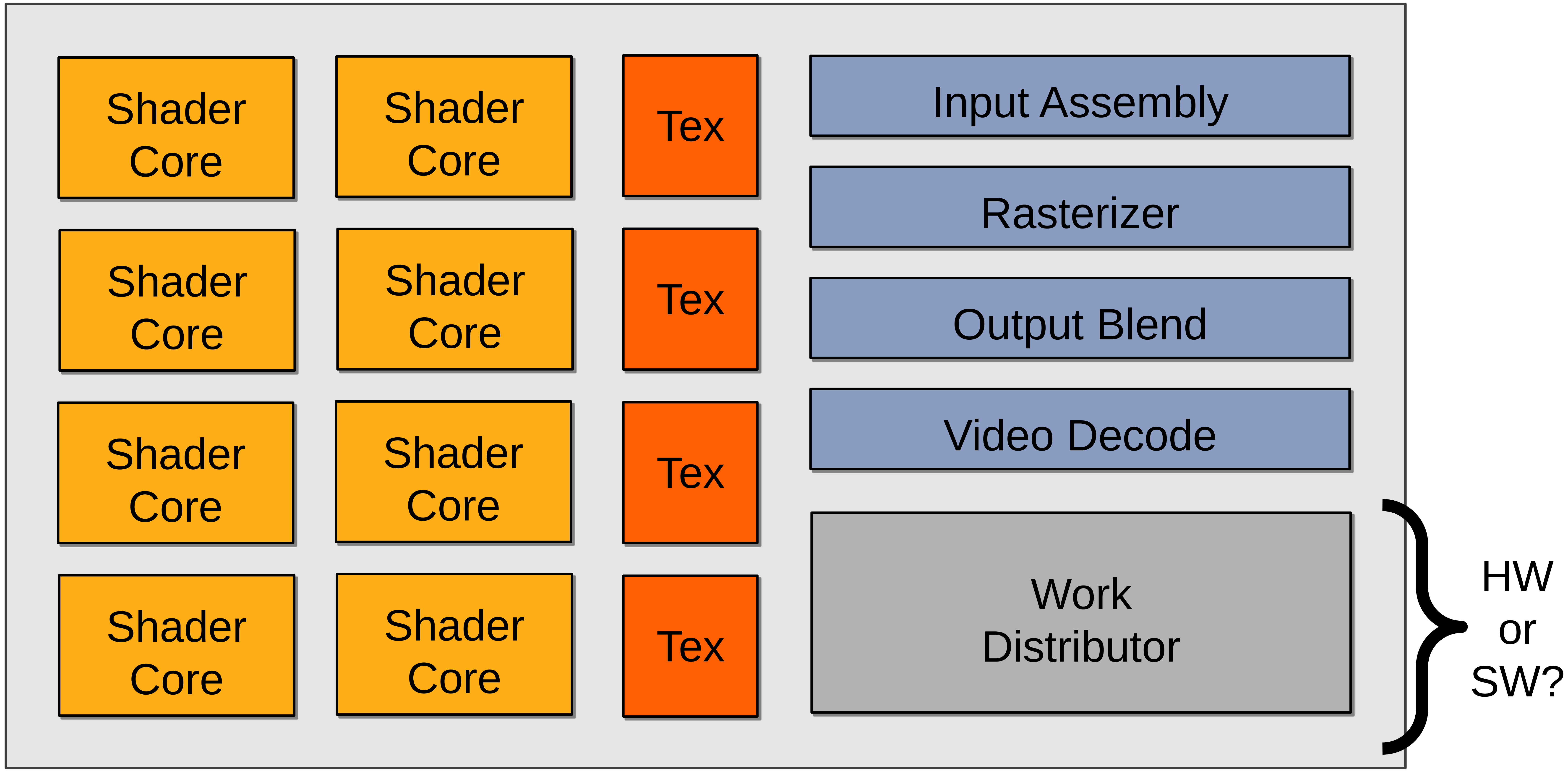
Part 1: throughput processing

- Three key concepts behind how modern GPU processing cores run code

- Knowing these concepts will help you:
  1. Understand space of GPU core (and throughput CPU core) designs
  2. Optimize shaders/compute kernels
  3. Establish intuition: what workloads might benefit from the design of these architectures?

What’s in a GPU?

A GPU is a heterogeneous chip multi-processor (highly tuned for graphics)



A diffuse reflectance shader

```
sampler mySamp;
Texture2D<float3> myTex;
float3 lightDir;

float4 diffuseShader(float3 norm, float2 uv)
{
  float3 kd;
  kd = myTex.Sample(mySamp, uv);
  kd *= clamp( dot(lightDir, norm), 0.0, 1.0);
  return float4(kd, 1.0);
}
```

Shader programming model:

Fragments are processed independently,
but there is no explicit parallel programming

Compile shader

1 unshaded fragment input record

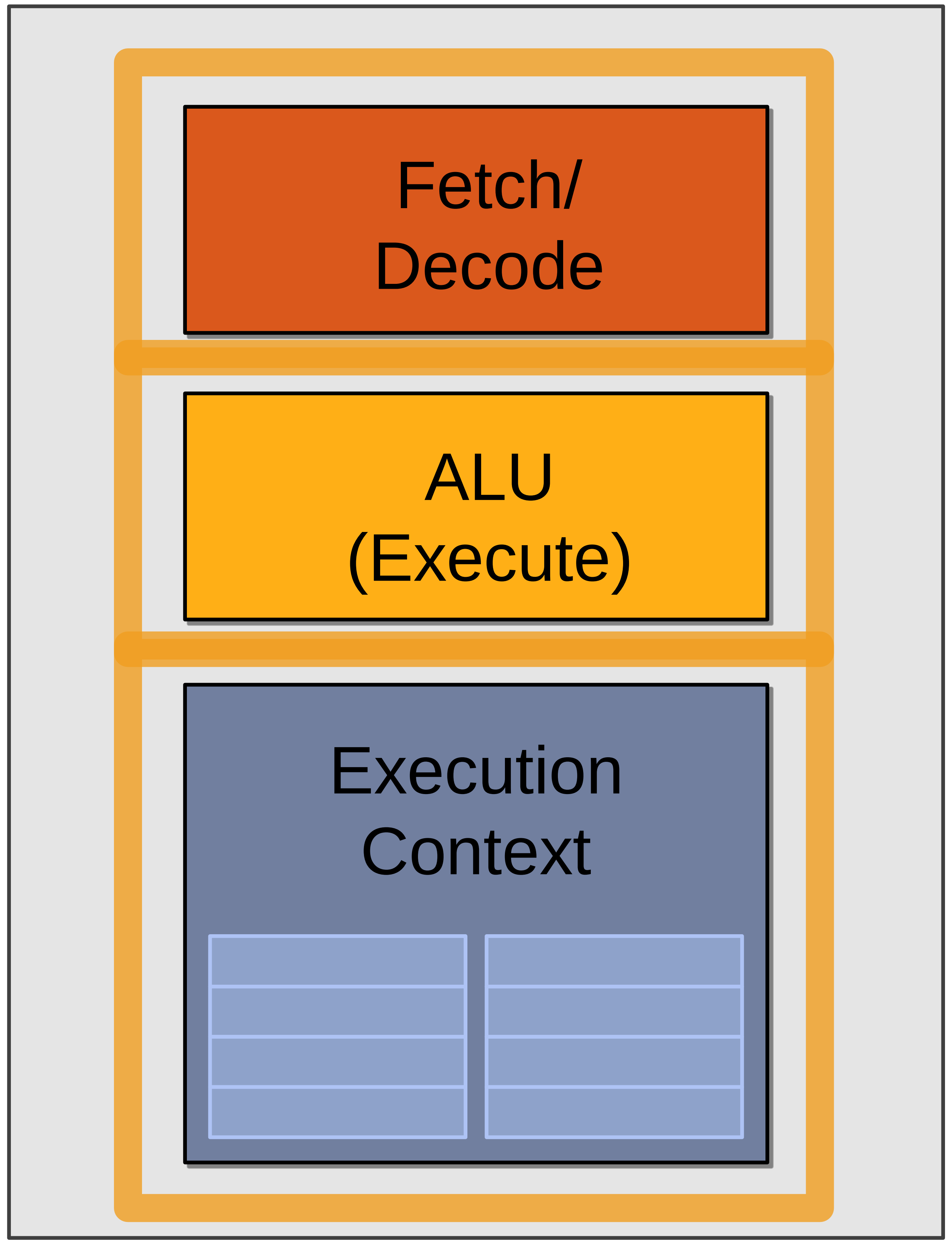
```
sampler mySamp;
Texture2D<float3> myTex;
float3 lightDir;

float4 diffuseShader(float3 norm, float2 uv)
{
  float3 kd;
  kd = myTex.Sample(mySamp, uv);
  kd *= clamp( dot(lightDir, norm), 0.0, 1.0);
  return float4(kd, 1.0);
}
```

```
<diffuseShader>:
sample r0, v4, t0, s0
mul  r3, v0, cb0[0]
madd r3, v1, cb0[1], r3
madd r3, v2, cb0[2], r3
clmp r3, r3, l(0.0), l(1.0)
mul  o0, r0, r3
mul  o1, r1, r3
mul  o2, r2, r3
mov  o3, l(1.0)
```

1 shaded fragment output record

Execute shader

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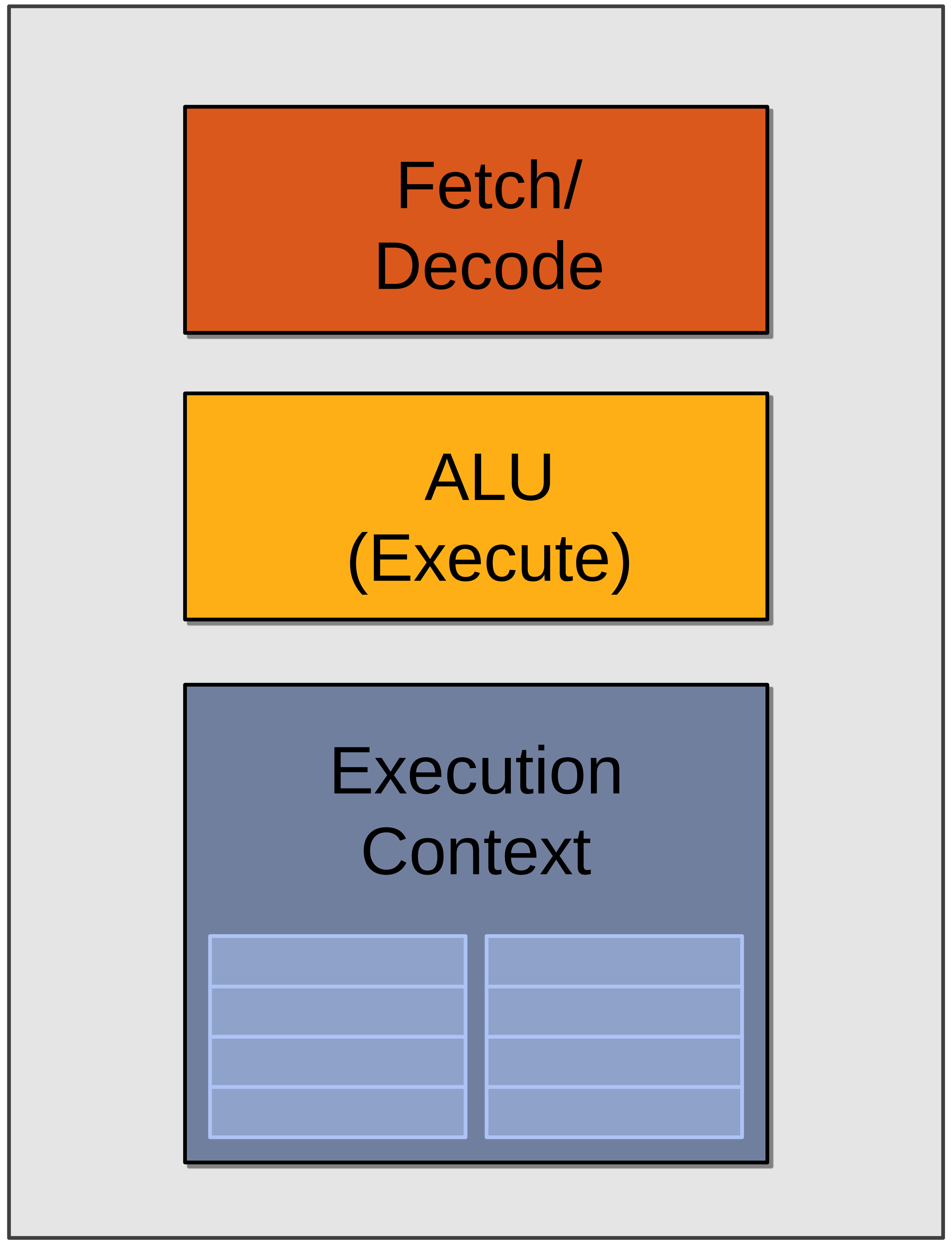
mul  o1, r1, r3
mul  o2, r2, r3
mov  o3, l(1.0)
```

Execute shader

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mul  o0, r0, r3
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mul  o2, r2, r3
mov  o3, l(1.0)
```
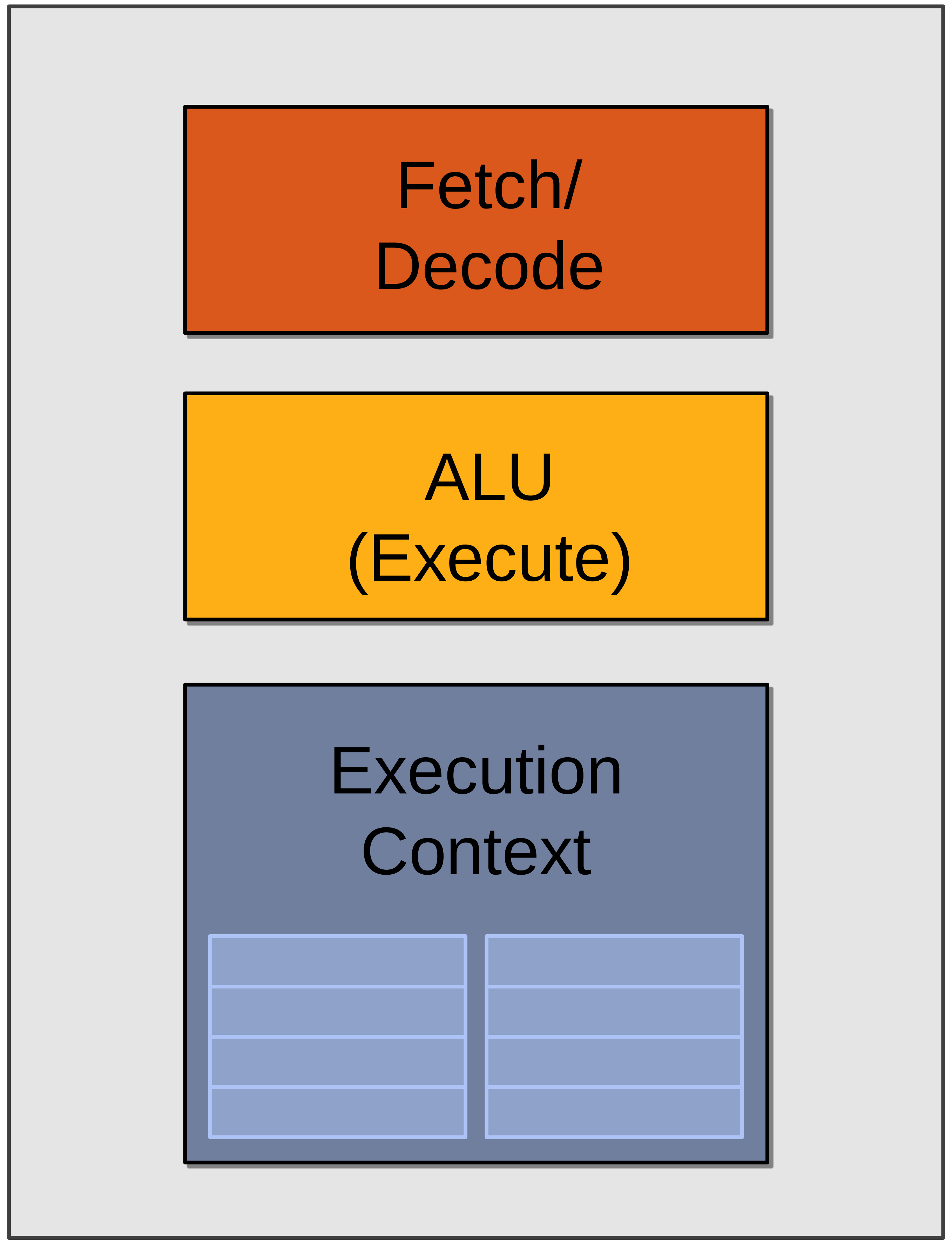
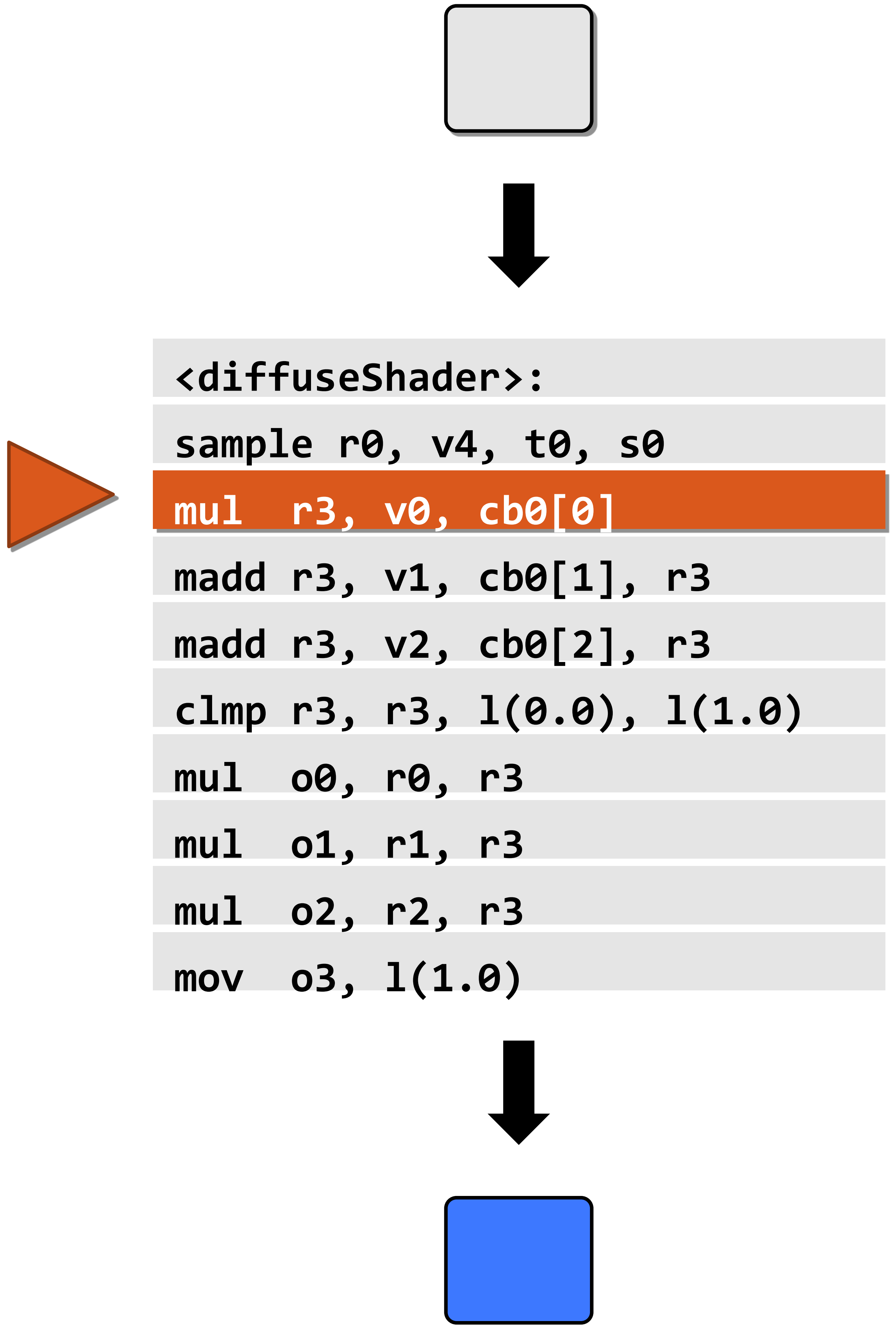
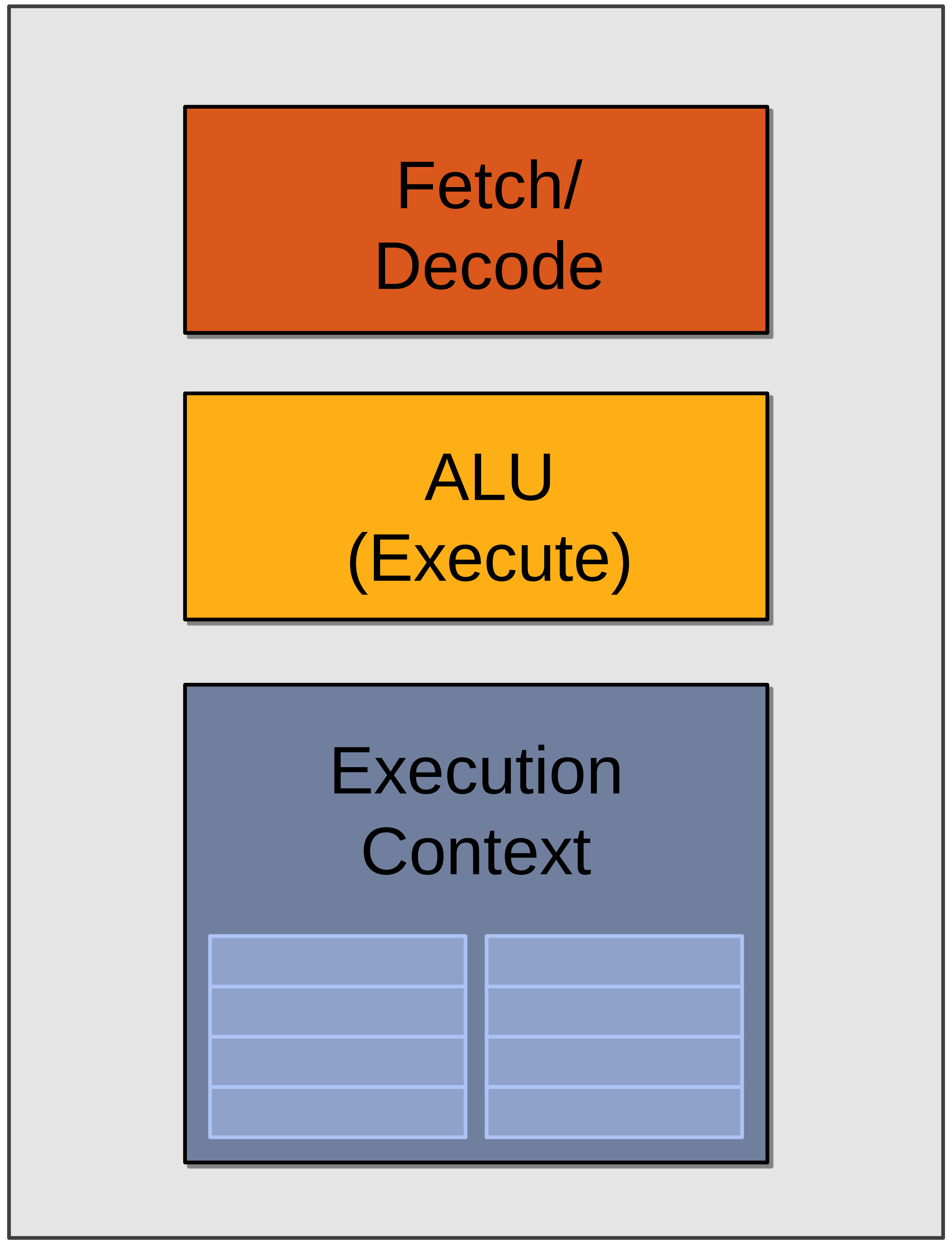

Execute shader





Execute shader

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mul  r3, v0, cb0[0]
madd r3, v1, cb0[1], r3
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clmp r3, r3, l(0.0), l(1.0)
mul  o0, r0, r3
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mul  o2, r2, r3
mov  o3, l(1.0)
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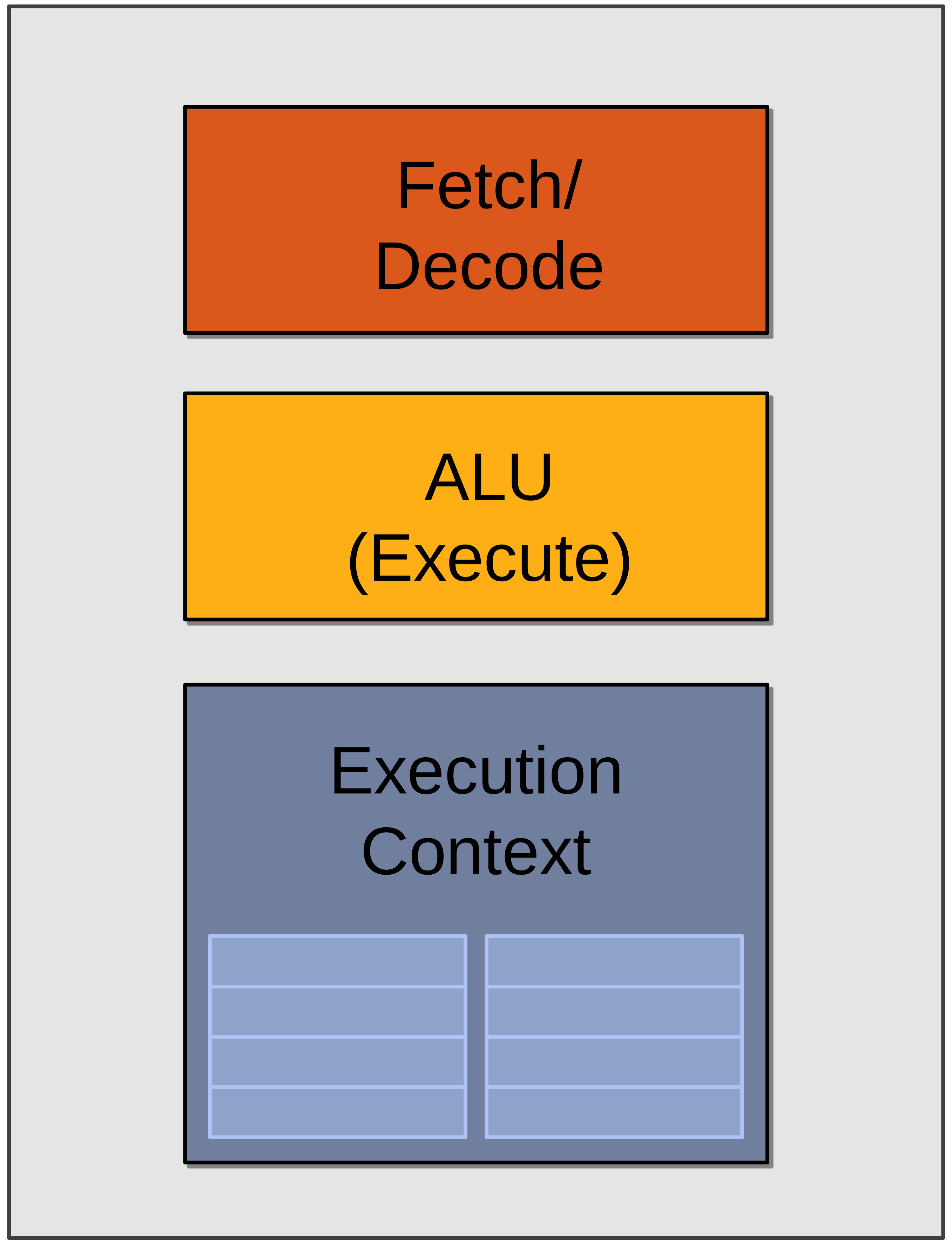
Execute shader

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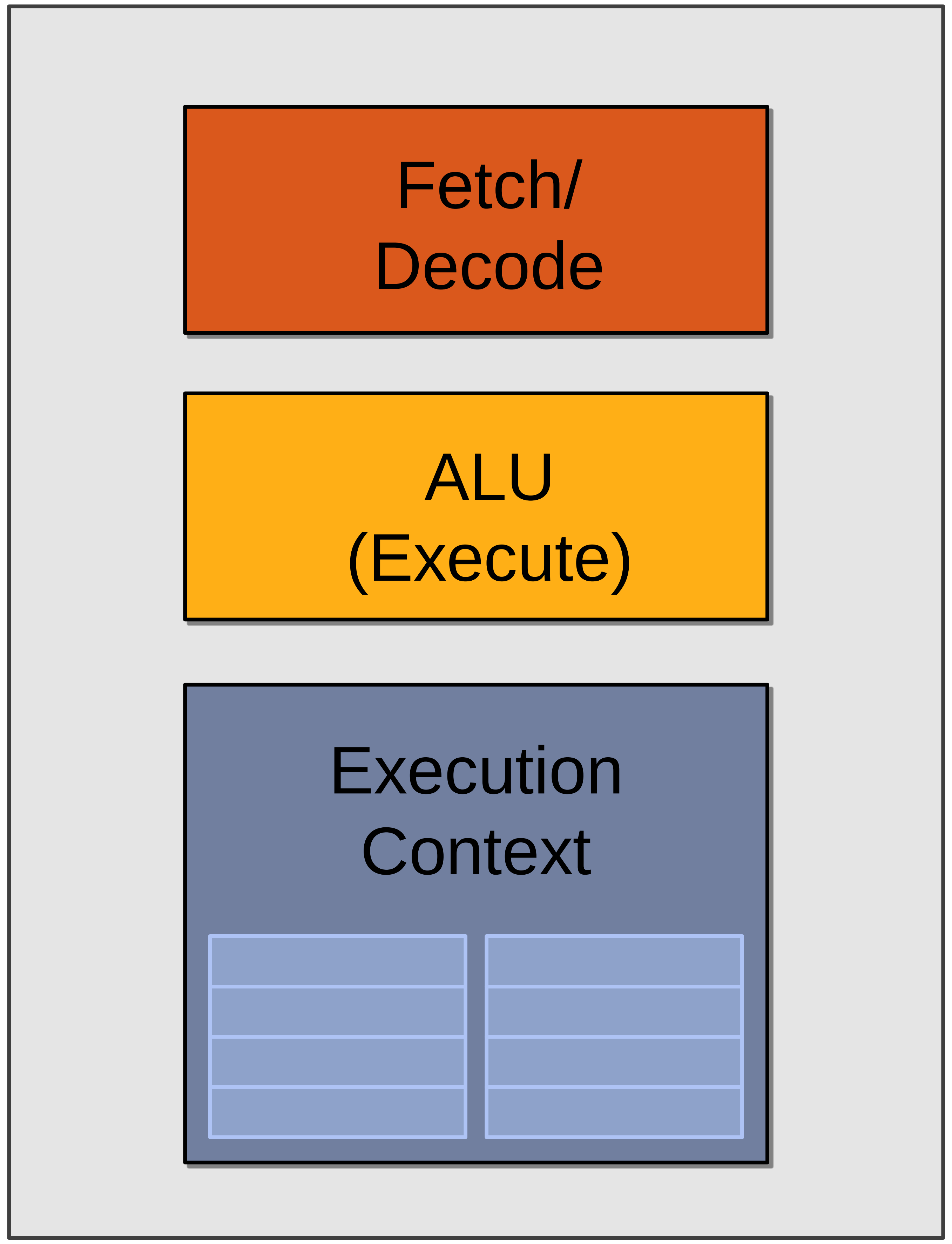
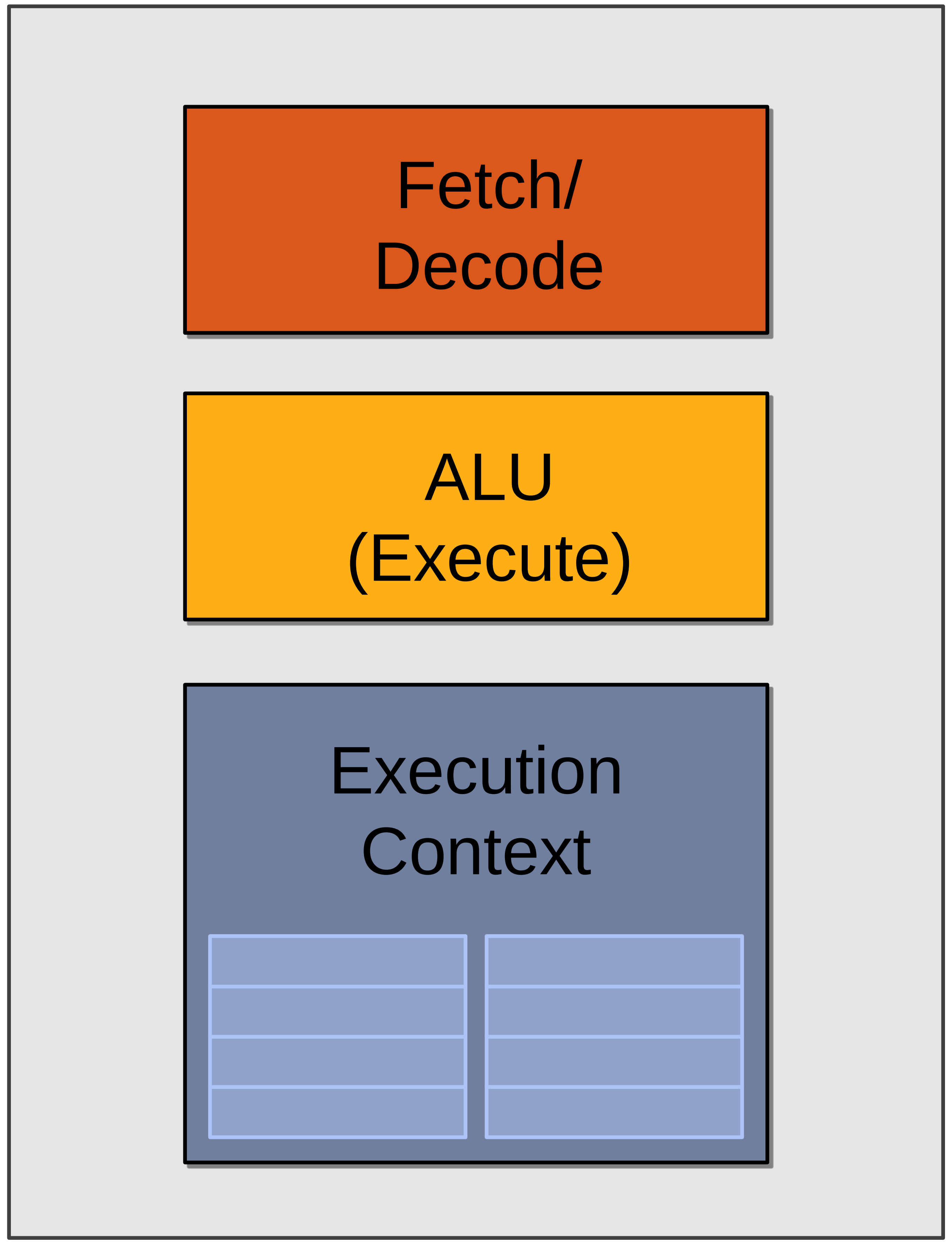
clmp r3, r3, l(0.0), l(1.0)
mul  o0, r0, r3
mul  o1, r1, r3
mul  o2, r2, r3
mov  o3, l(1.0)
```

Execute shader




```
<diffuseShader>:
sample r0, v4, t0, s0
mul  r3, v0, cb0[0]
madd r3, v1, cb0[1], r3
madd r3, v2, cb0[2], r3
clmp r3, r3, l(0.0), l(1.0)
mul  o0, r0, r3
mul  o1, r1, r3
mul  o2, r2, r3
mov  o3, l(1.0)
```

Execute shader




```
<diffuseShader>:
sample r0, v4, t0, s0
mul  r3, v0, cb0[0]
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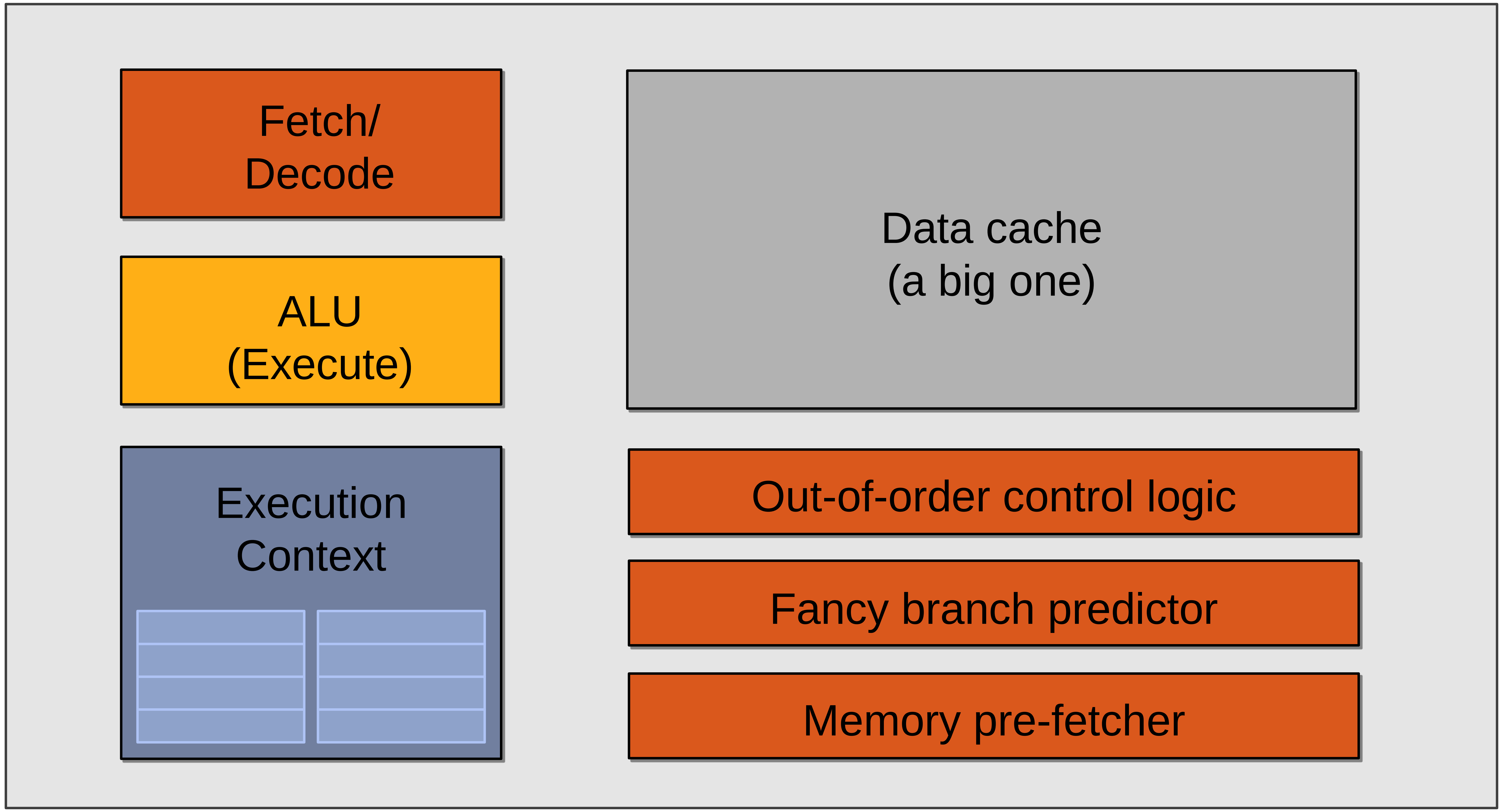
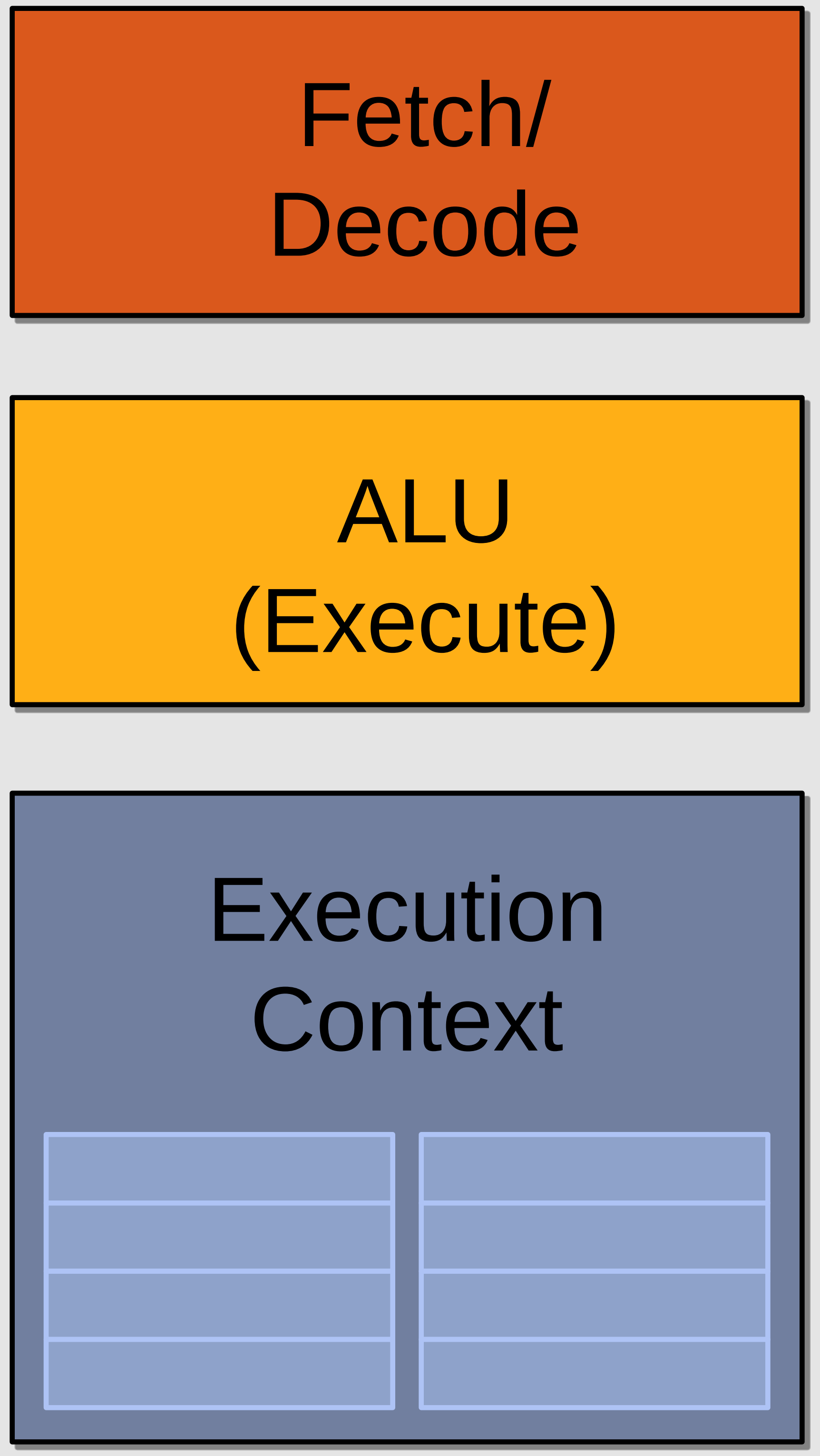
madd r3, v2, cb0[2], r3
clmp r3, r3, l(0.0), l(1.0)
mul  o0, r0, r3
mul  o1, r1, r3
mul  o2, r2, r3
mov  o3, l(1.0)
```

“CPU-style” cores



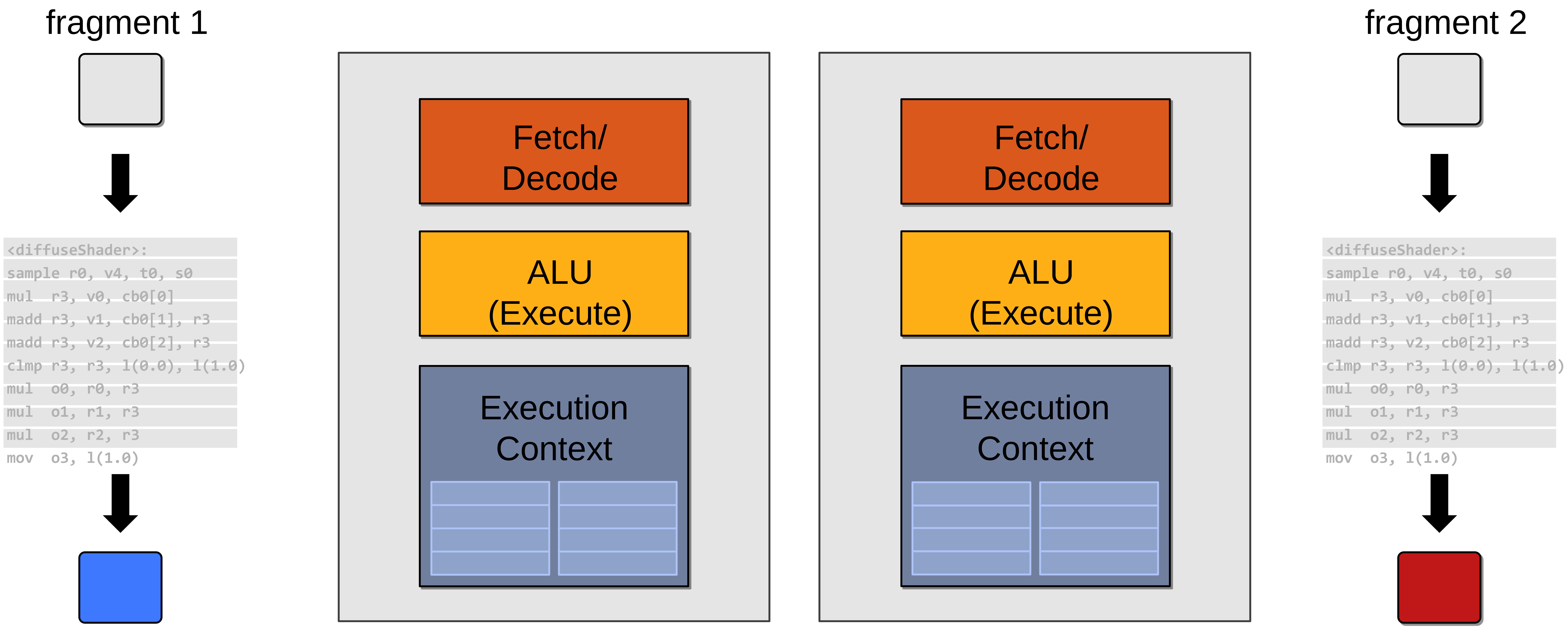
Slimming down



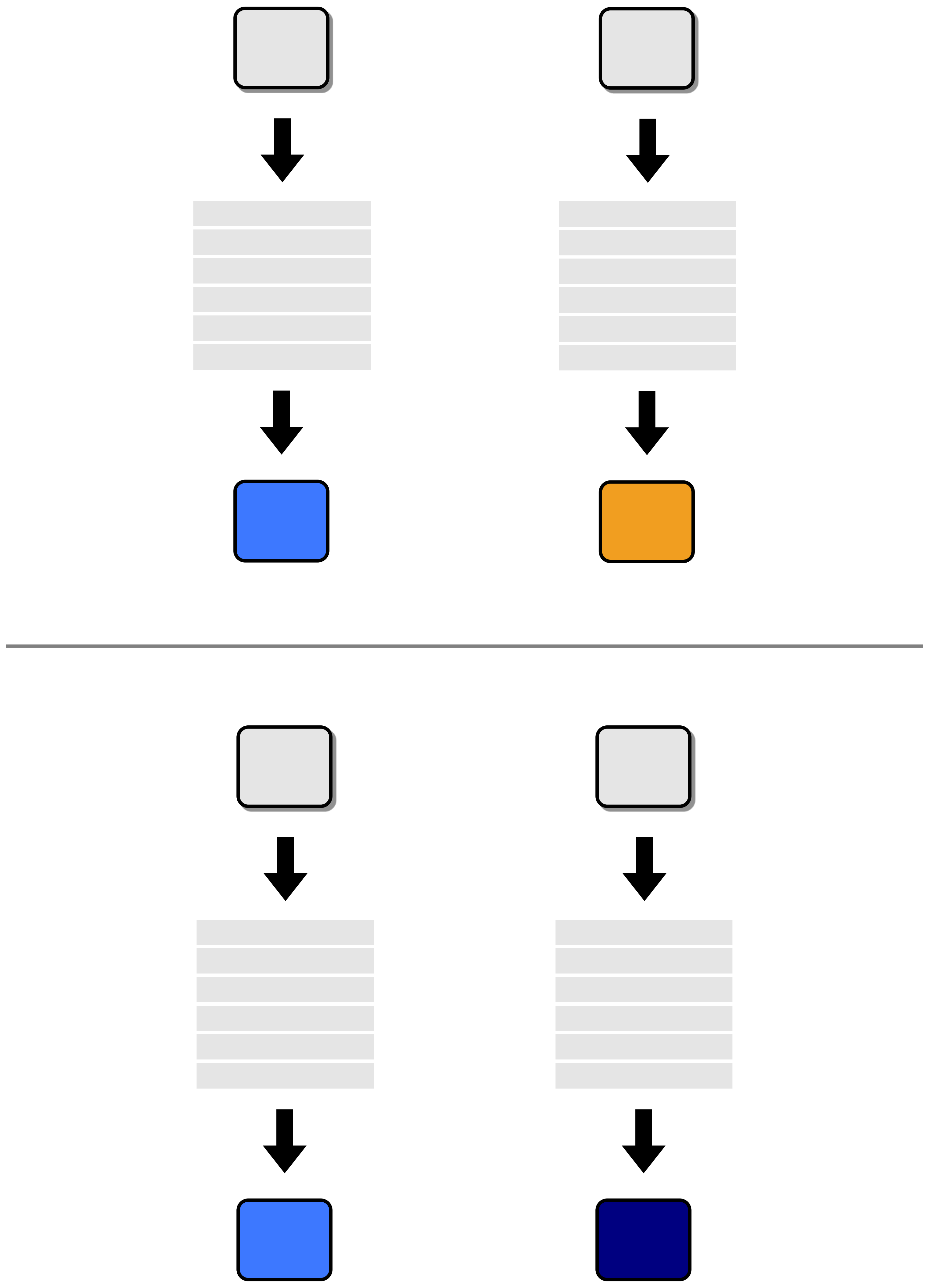
Idea #1:

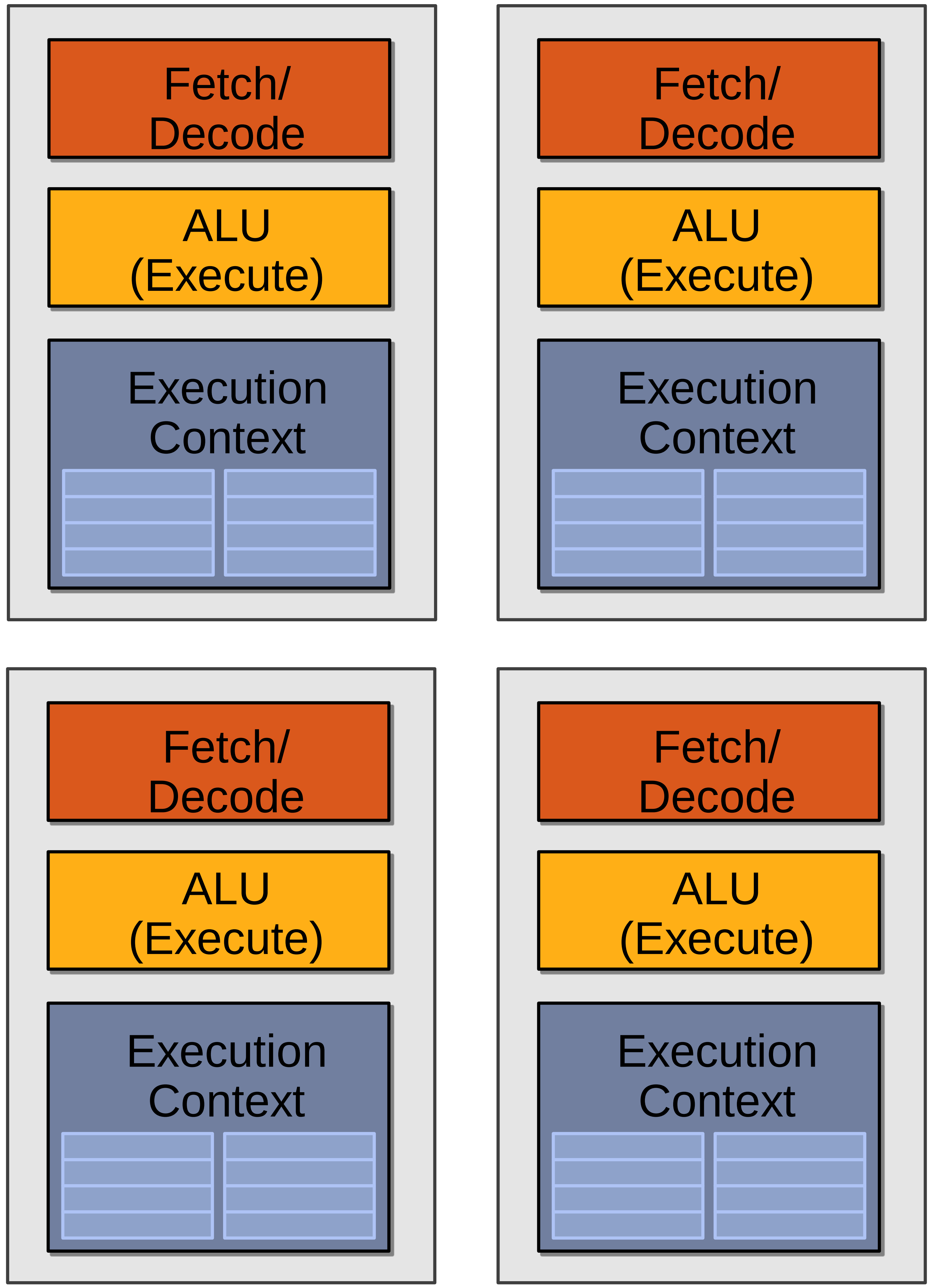
Remove components that help a single instruction stream run fast

Two cores (two fragments in parallel)

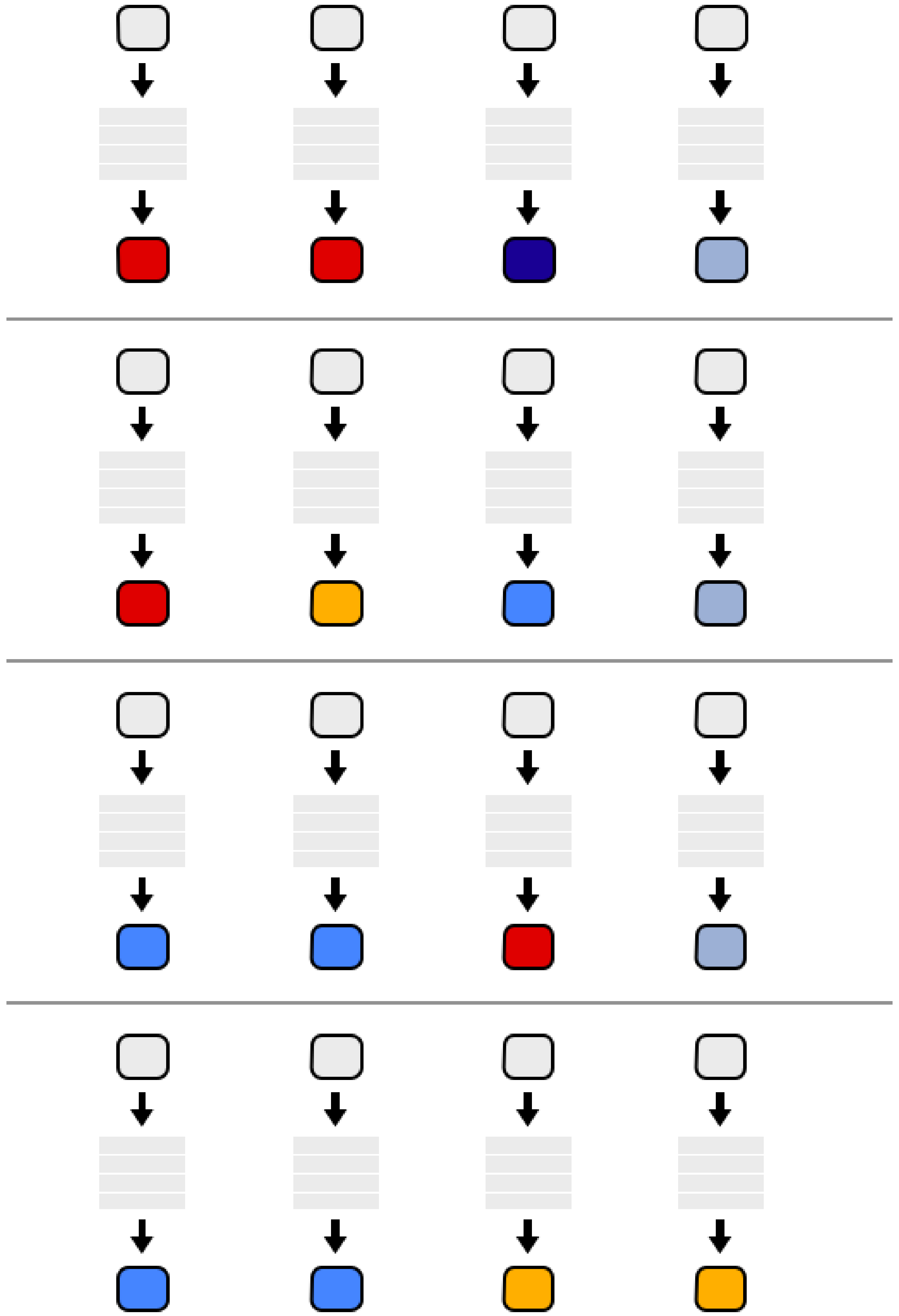


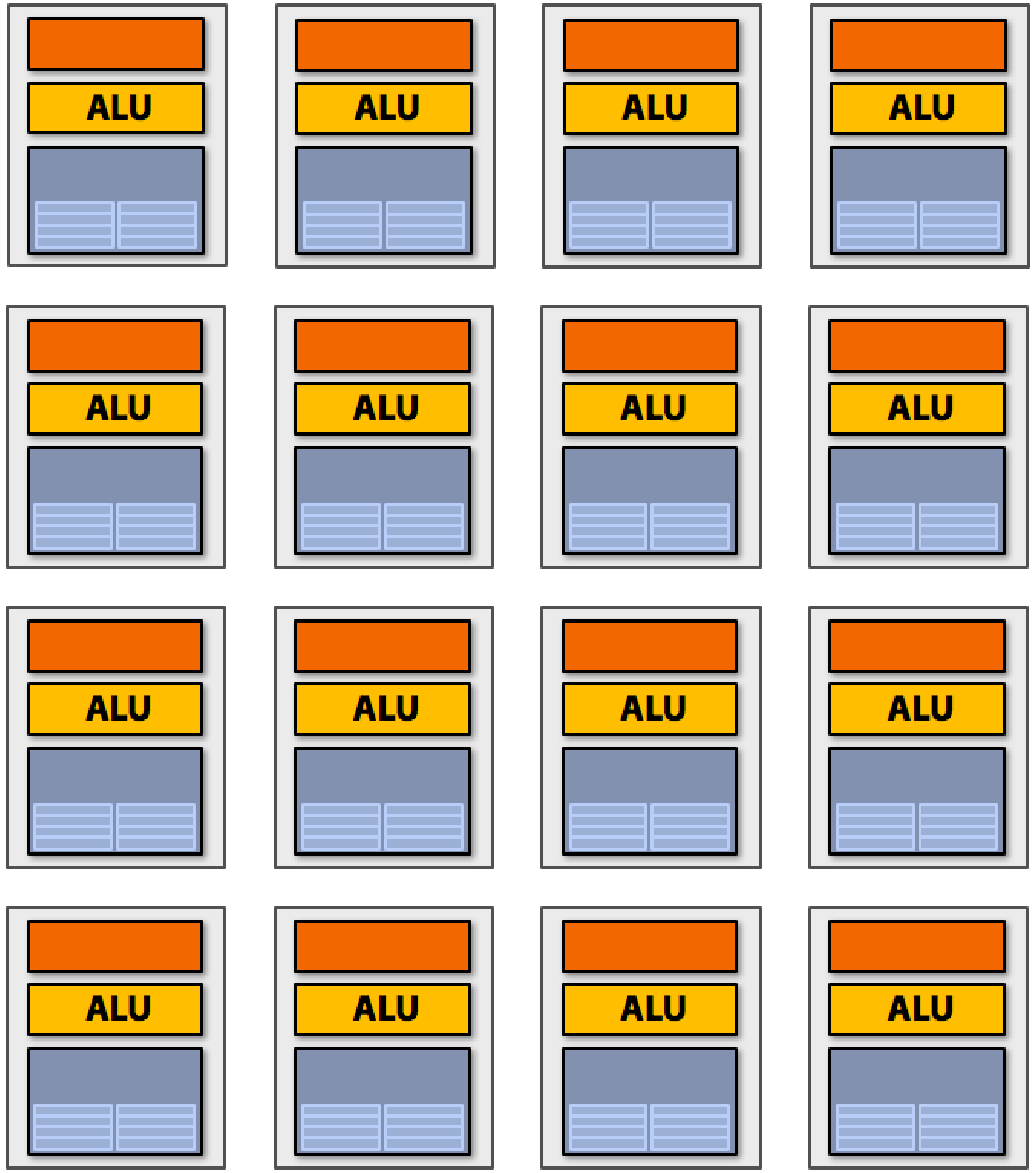
Four cores (four fragments in parallel)





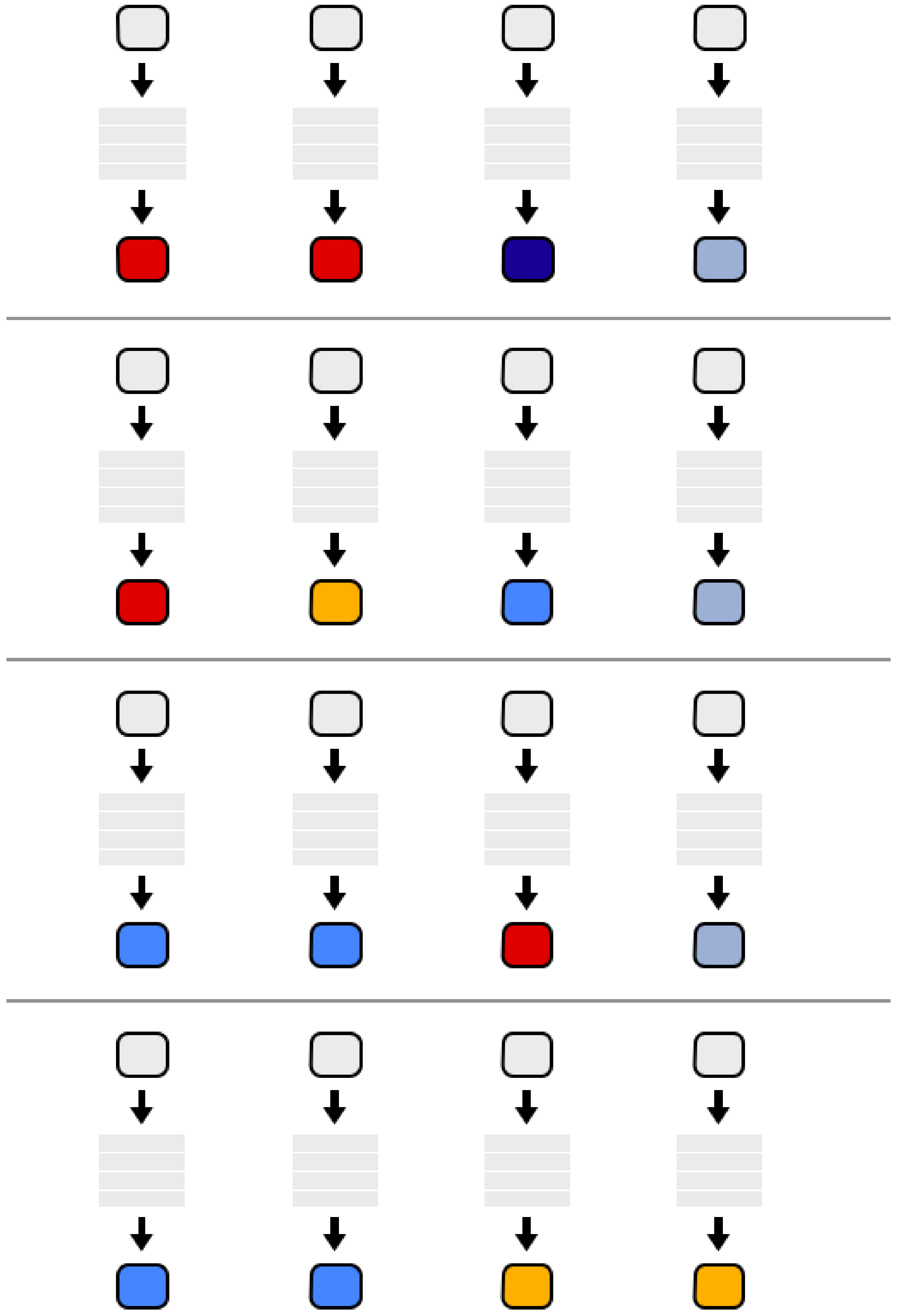
Sixteen cores (sixteen fragments in parallel)





16 cores = 16 simultaneous instruction streams

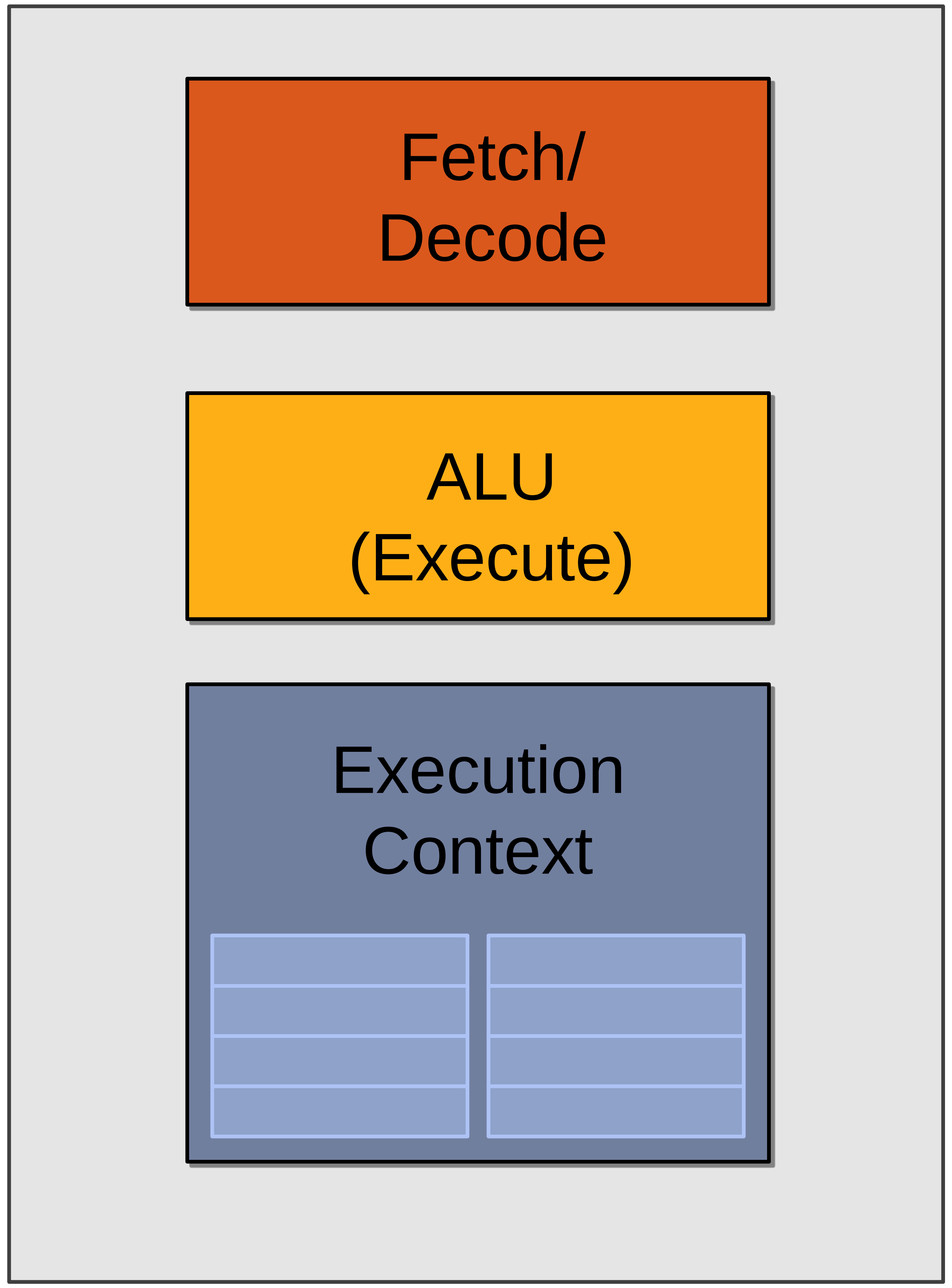
Instruction stream sharing



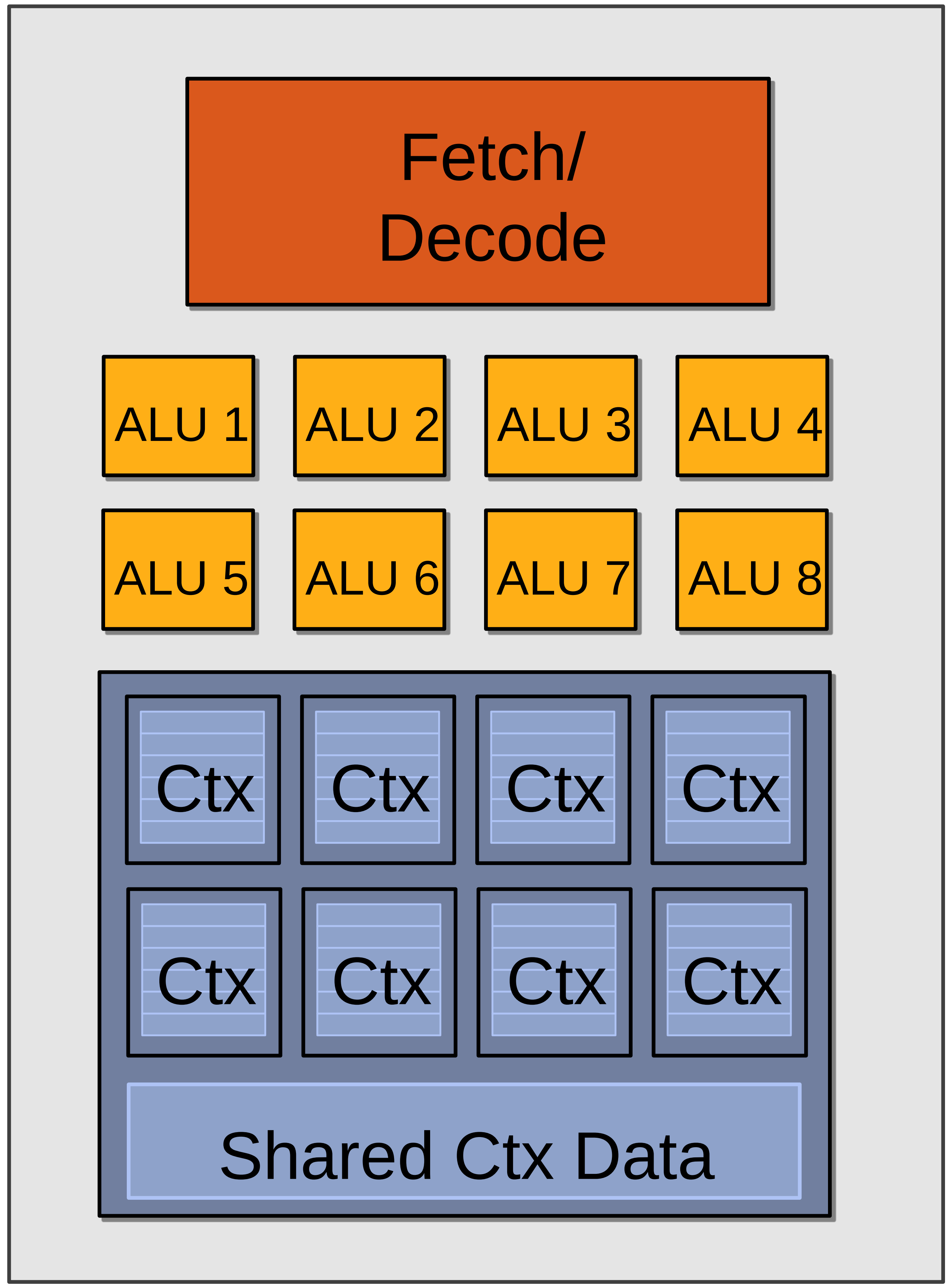
But ... many fragments should be able to share an instruction stream!

```
<diffuseShader>:
sample r0, v4, t0, s0
mul  r3, v0, cb0[0]
madd r3, v1, cb0[1], r3
madd r3, v2, cb0[2], r3
clmp r3, r3, l(0.0), l(1.0)
mul  o0, r0, r3
mul  o1, r1, r3
mul  o2, r2, r3
mov  o3, l(1.0)
```

Recall: simple processing core



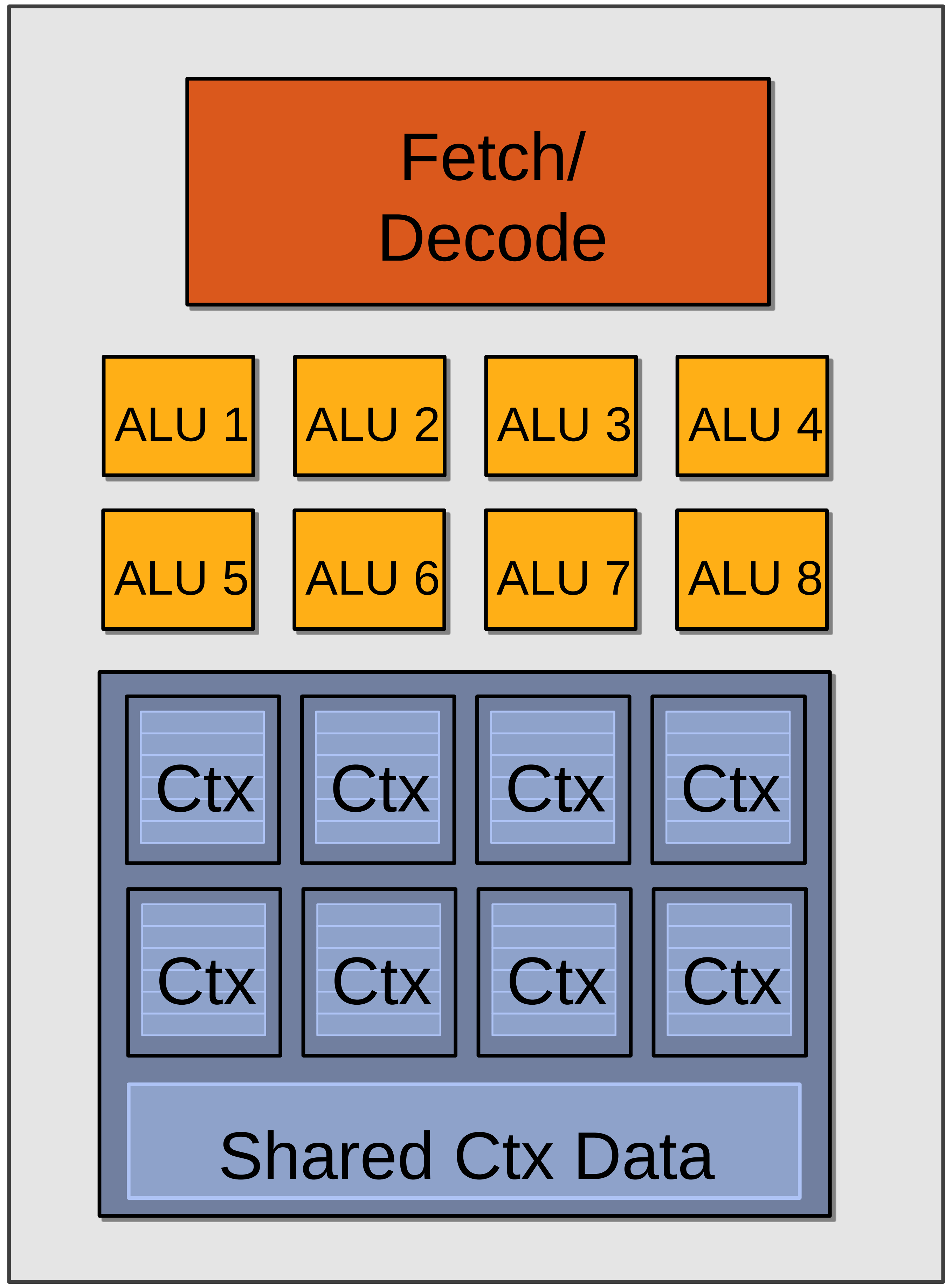
Add ALUs



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

SIMD processing

Modifying the shader

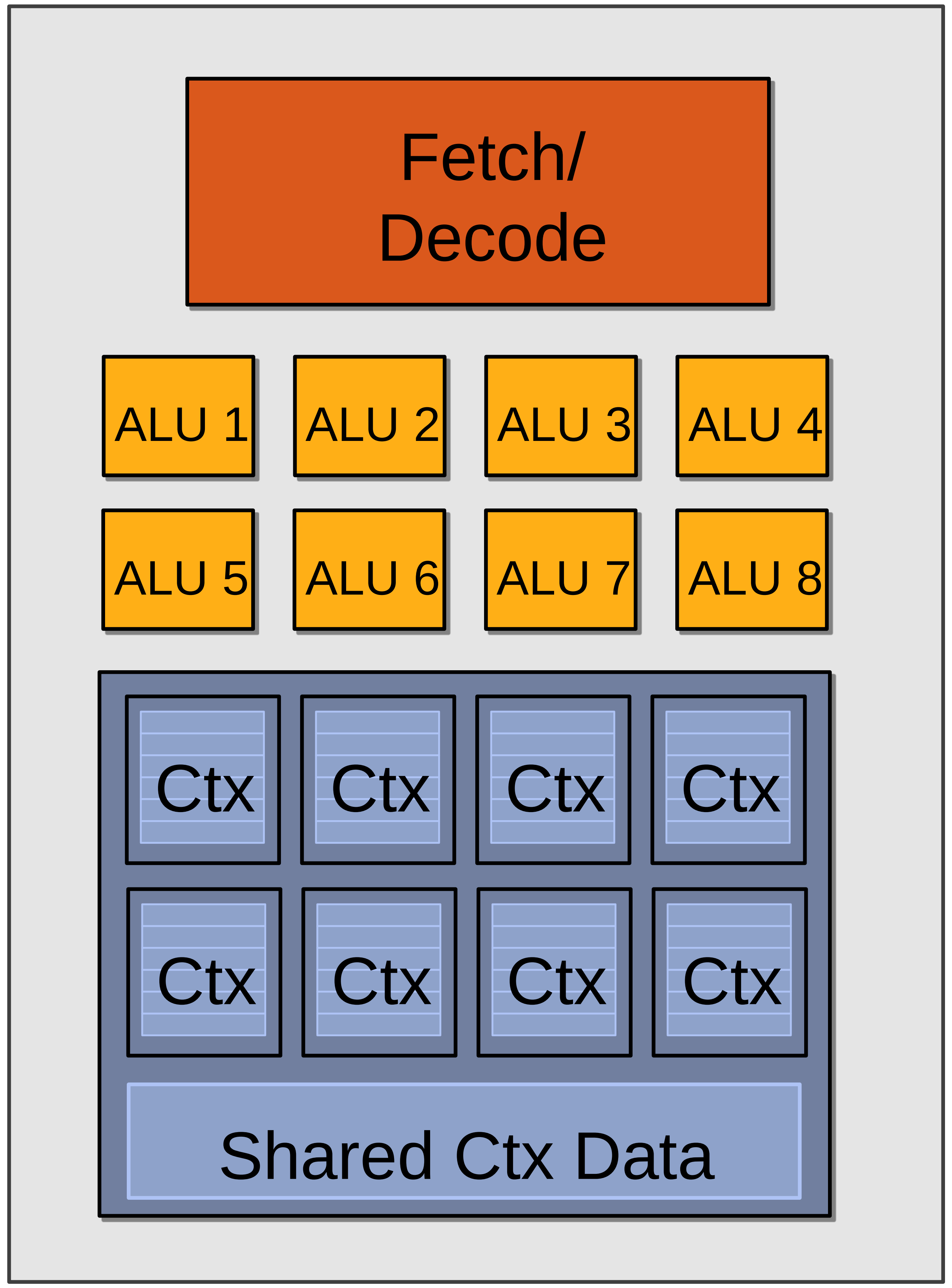



```
<diffuseShader>:
sample r0, v4, t0, s0
mul  r3, v0, cb0[0]
madd r3, v1, cb0[1], r3
madd r3, v2, cb0[2], r3
clmp r3, r3, l(0.0), l(1.0)
mul  o0, r0, r3
mul  o1, r1, r3
mul  o2, r2, r3
mov  o3, l(1.0)
```

Original compiled shader:

Processes one fragment using scalar ops on scalar registers

Modifying the shader

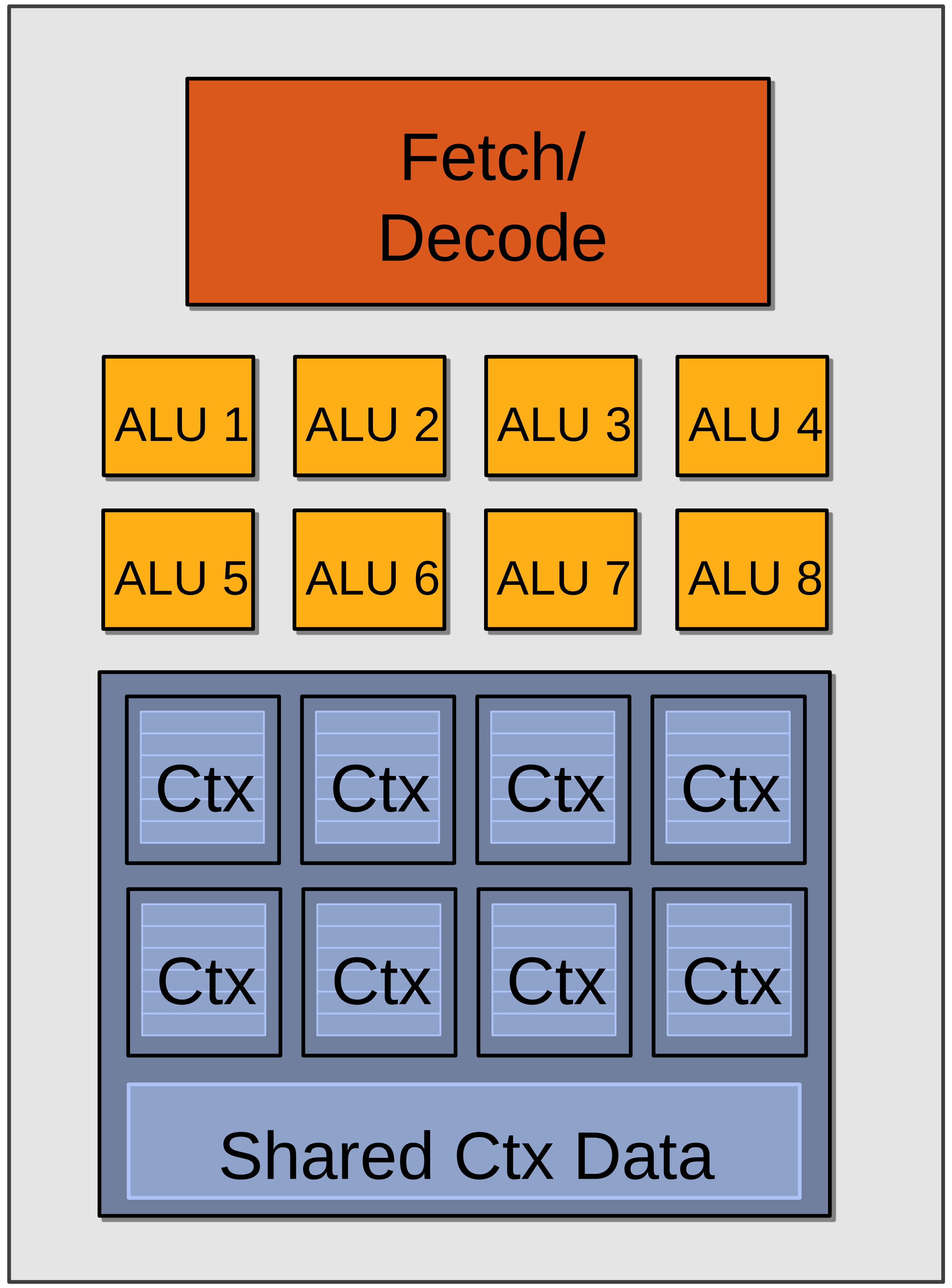


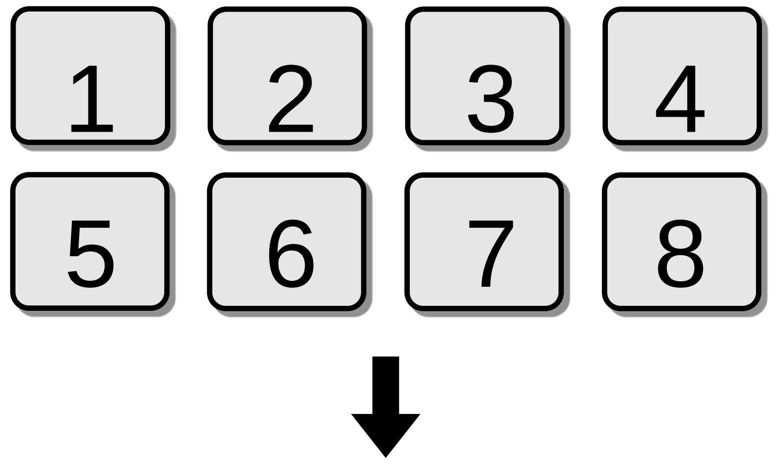

```
<VEC8_diffuseShader>:
VEC8_sample vec_r0, vec_v4, t0, vec_s0
VEC8_mul  vec_r3, vec_v0, cb0[0]
VEC8_madd vec_r3, vec_v1, cb0[1], vec_r3
VEC8_madd vec_r3, vec_v2, cb0[2], vec_r3
VEC8_clmp vec_r3, vec_r3, l(0.0), l(1.0)
VEC8_mul  vec_o0, vec_r0, vec_r3
VEC8_mul  vec_o1, vec_r1, vec_r3
VEC8_mul  vec_o2, vec_r2, vec_r3
VEC8_mov  o3, l(1.0)
```

New compiled shader:

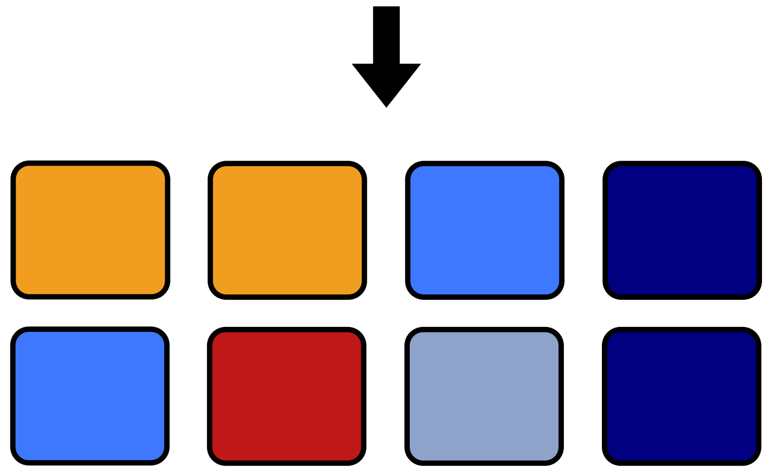
Processes eight fragments using vector ops on vector registers

Modifying the shader

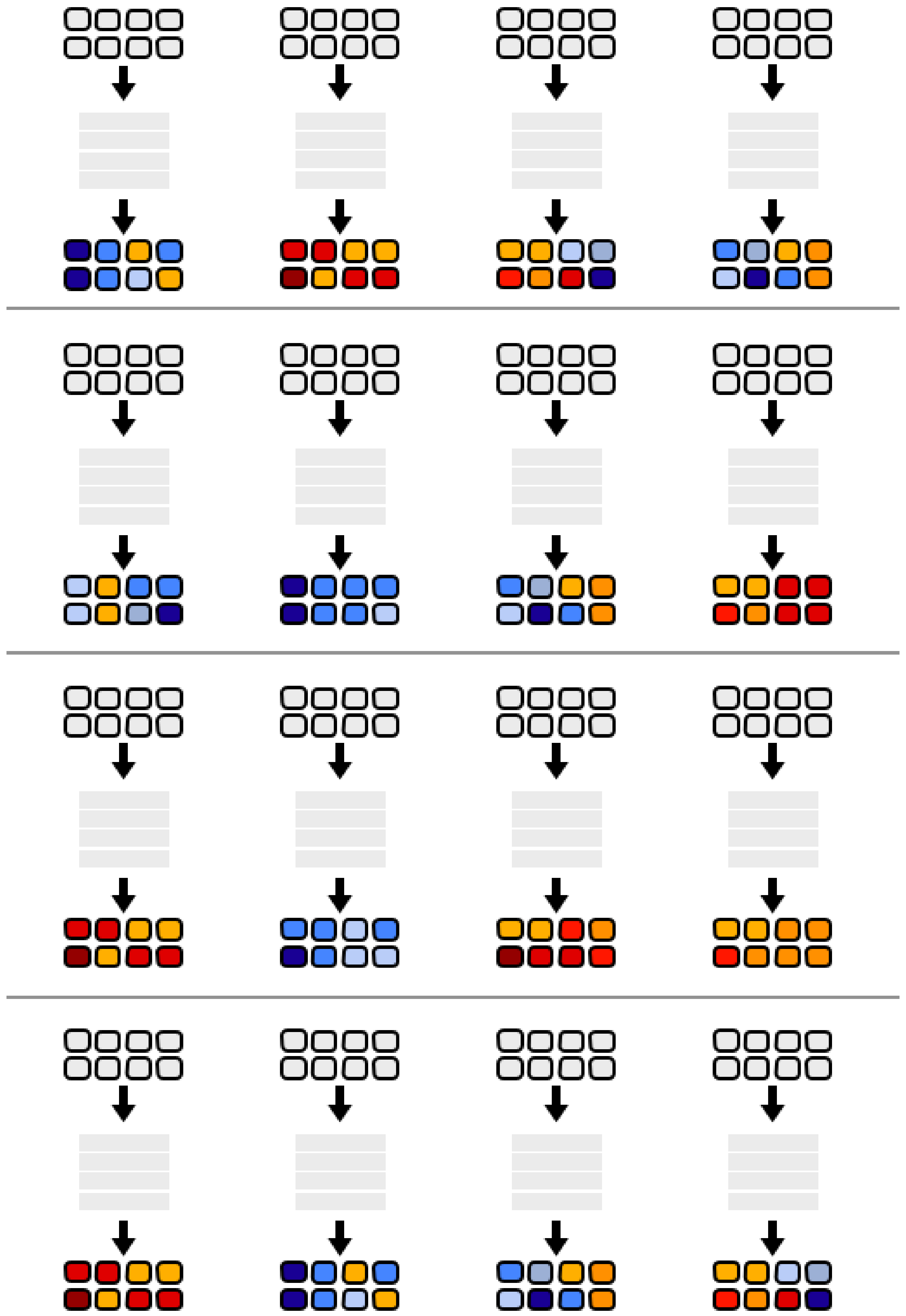


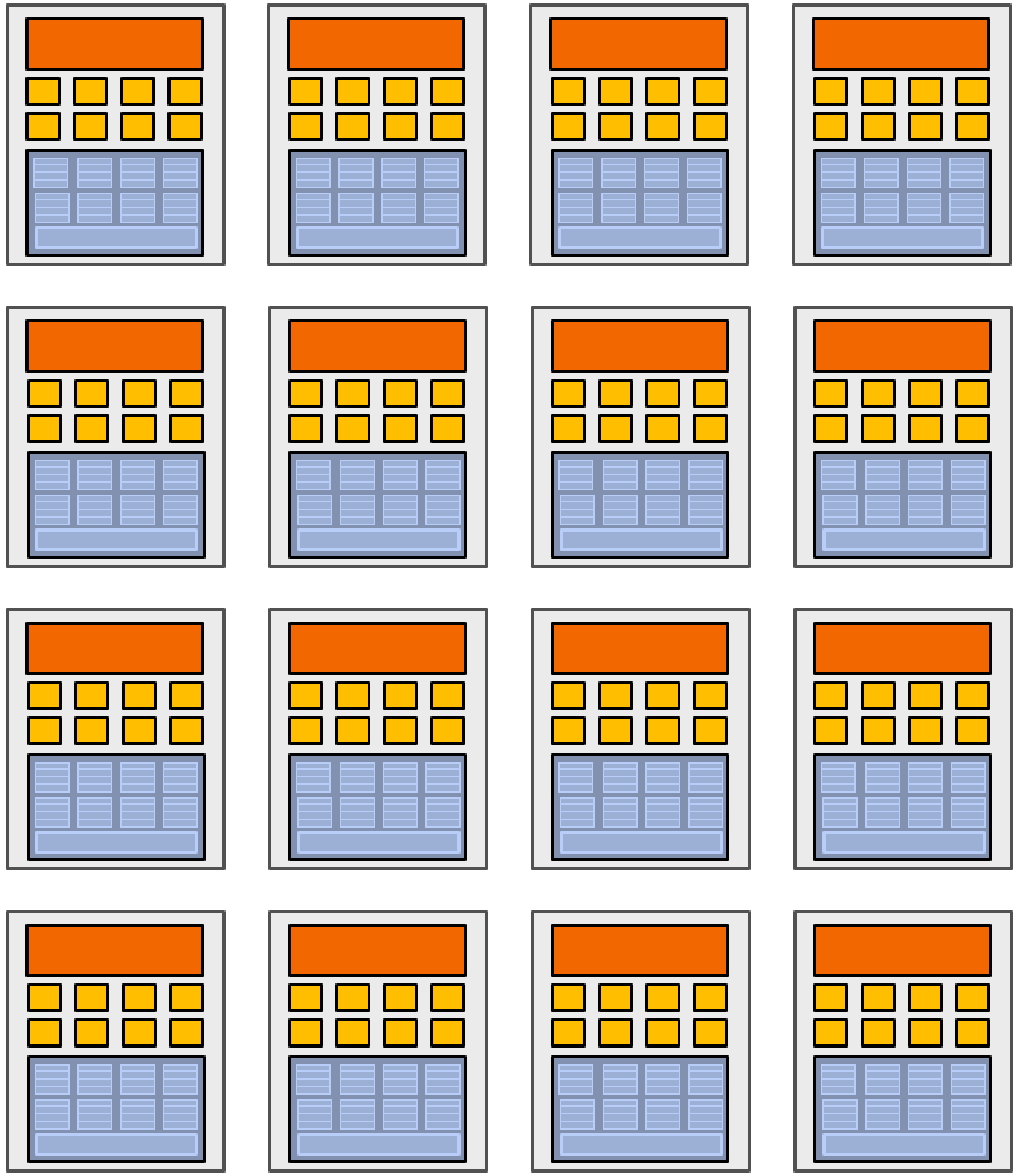



```
<VEC8_diffuseShader>:
VEC8_sample vec_r0, vec_v4, t0, vec_s0
VEC8_mul  vec_r3, vec_v0, cb0[0]
VEC8_madd vec_r3, vec_v1, cb0[1], vec_r3
VEC8_madd vec_r3, vec_v2, cb0[2], vec_r3
VEC8_clmp vec_r3, vec_r3, l(0.0), l(1.0)
VEC8_mul  vec_o0, vec_r0, vec_r3
VEC8_mul  vec_o1, vec_r1, vec_r3
VEC8_mul  vec_o2, vec_r2, vec_r3
VEC8_mov  o3, l(1.0)
```



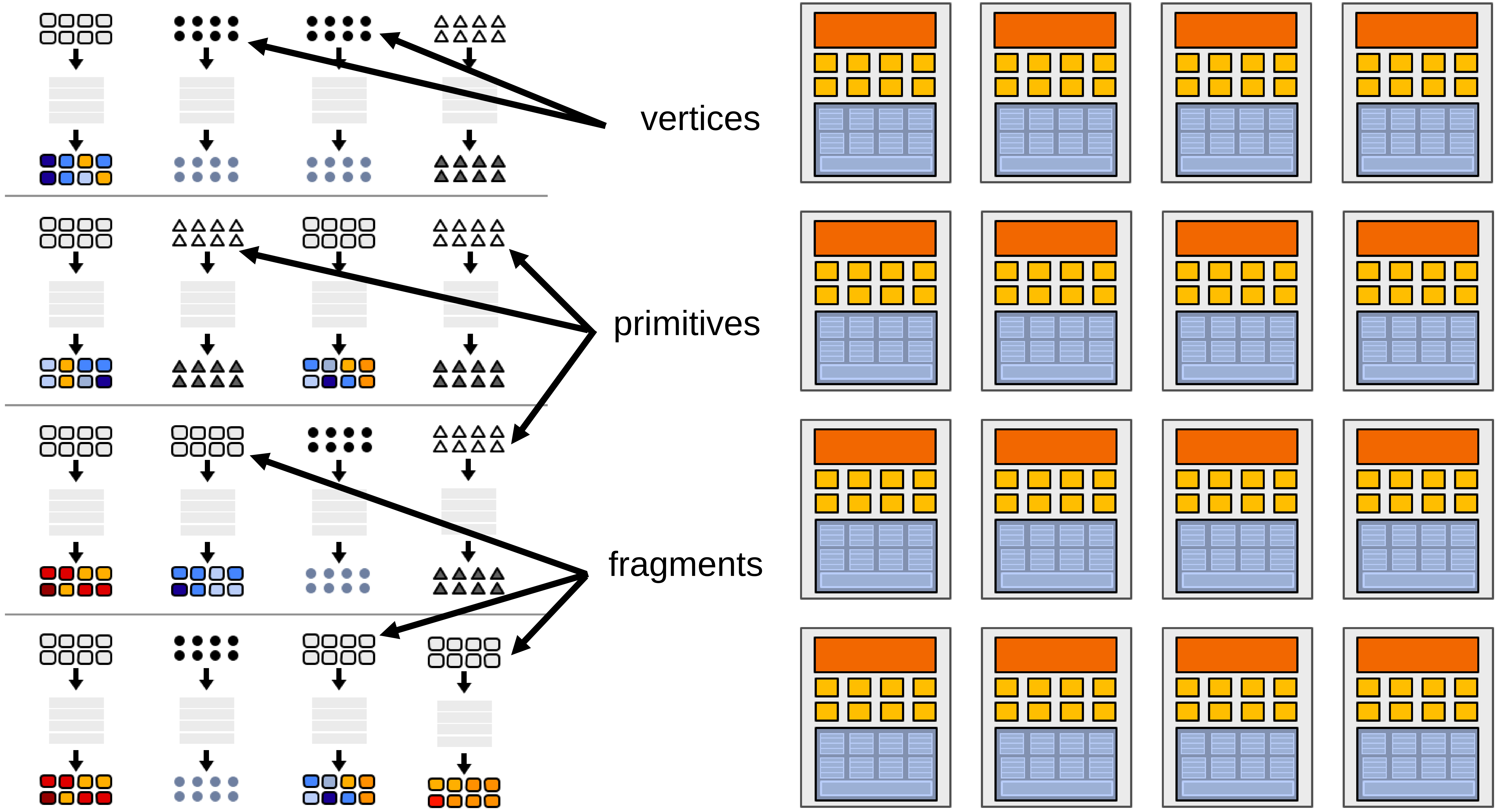
128 fragments in parallel



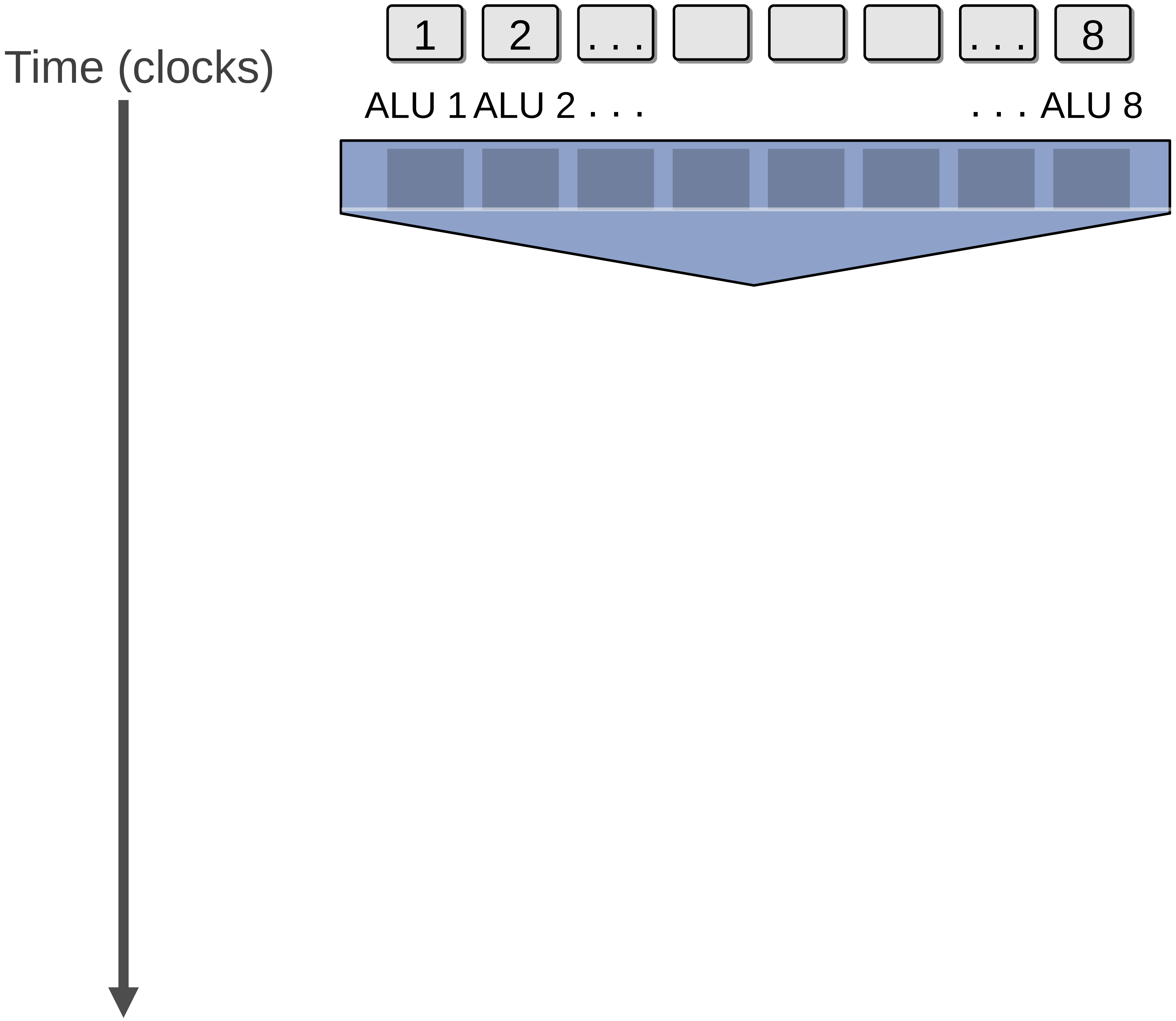


16 cores = 128 ALUs , 16 simultaneous instruction streams

128 [vertices/fragments
primitives
OpenCL work items] in parallel



But what about branches?

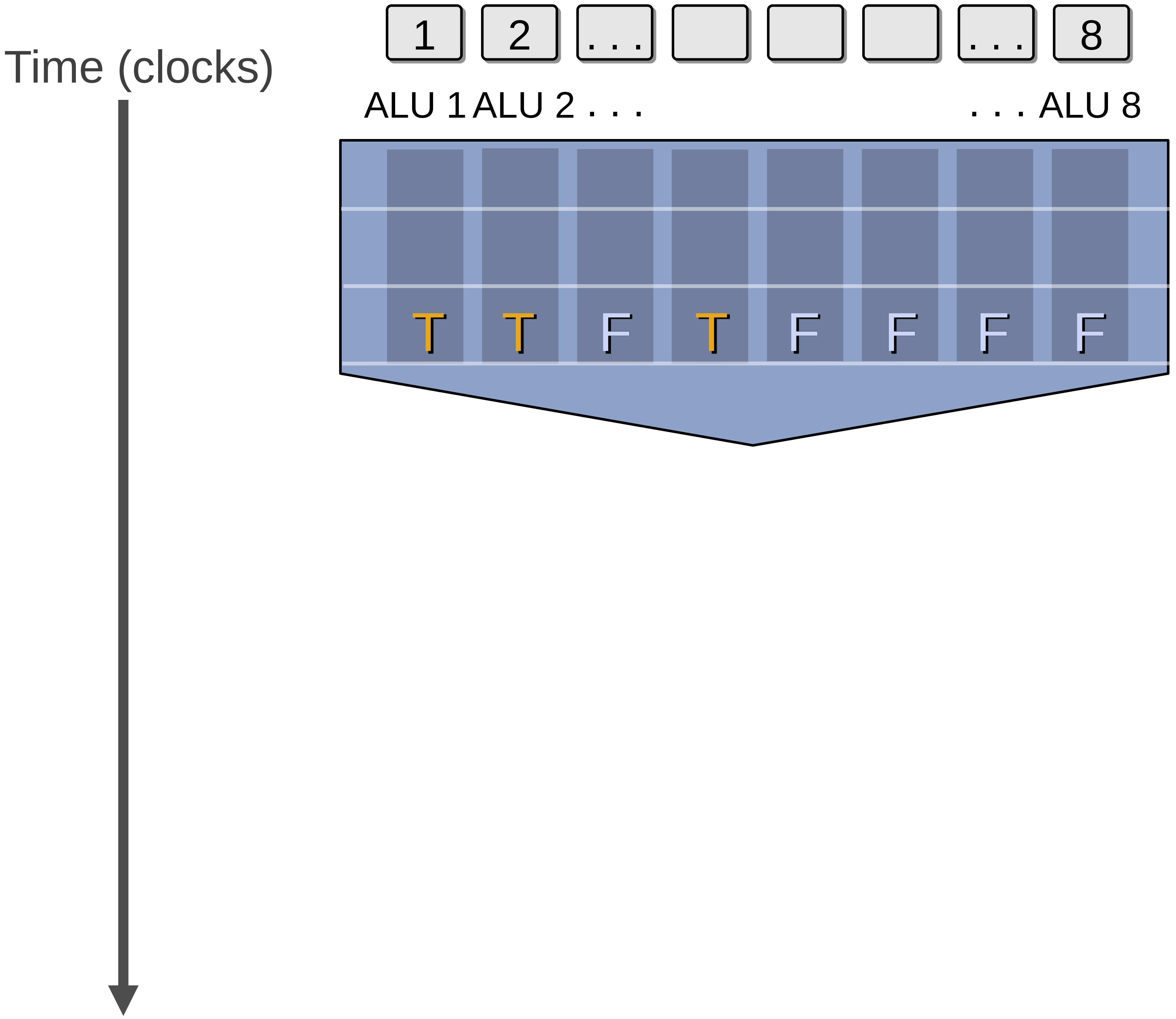



```
<unconditional
 shader code>

if (x > 0) {
    y = pow(x, exp);
    y *= Ks;
    refl = y + Ka;
} else {
    x = 0;
    refl = Ka;
}

<resume unconditional
 shader code>
```

But what about branches?

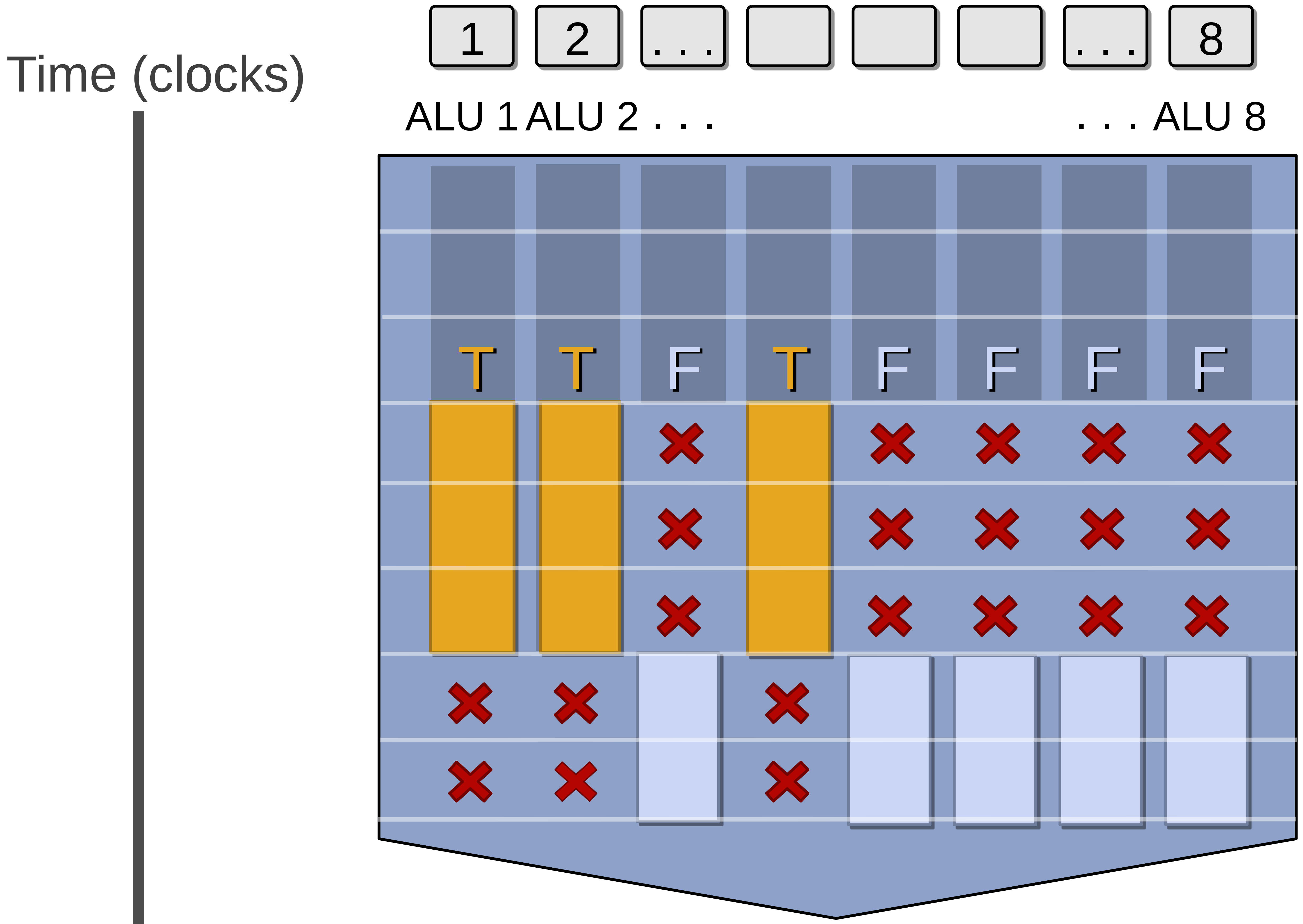



```
<unconditional
 shader code>

if (x > 0) {
    y = pow(x, exp);
    y *= Ks;
    refl = y + Ka;
} else {
    x = 0;
    refl = Ka;
}

<resume unconditional
 shader code>
```

But what about branches?

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if (x > 0) {
      y = pow(x, exp);
      y *= Ks;
      refl = y + Ka;
} else {
      x = 0;
      refl = Ka;
}

<resume unconditional
 shader code>
```
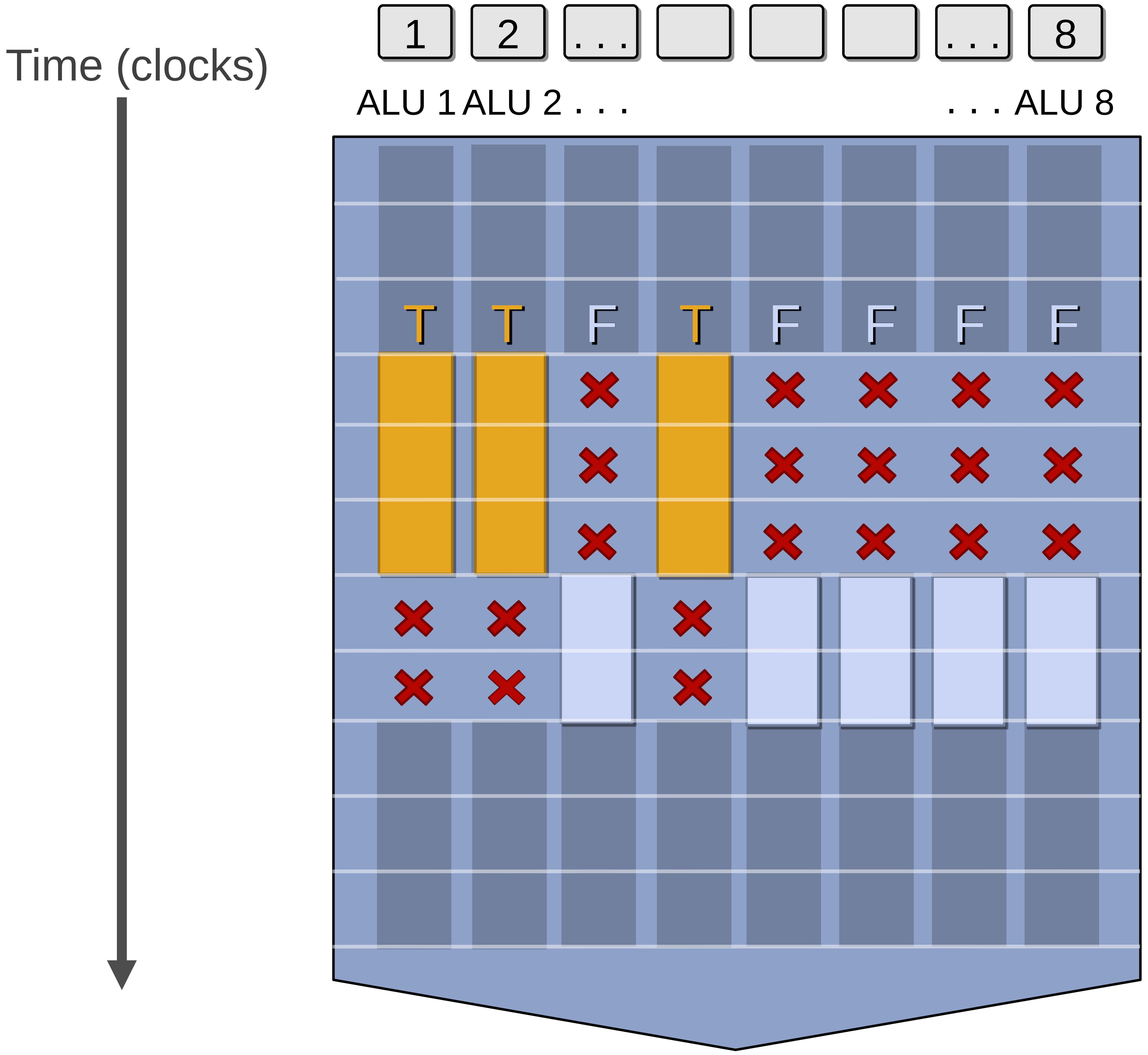

Not all ALUs do useful work!
Worst case: 1/8 peak performance

But what about branches?

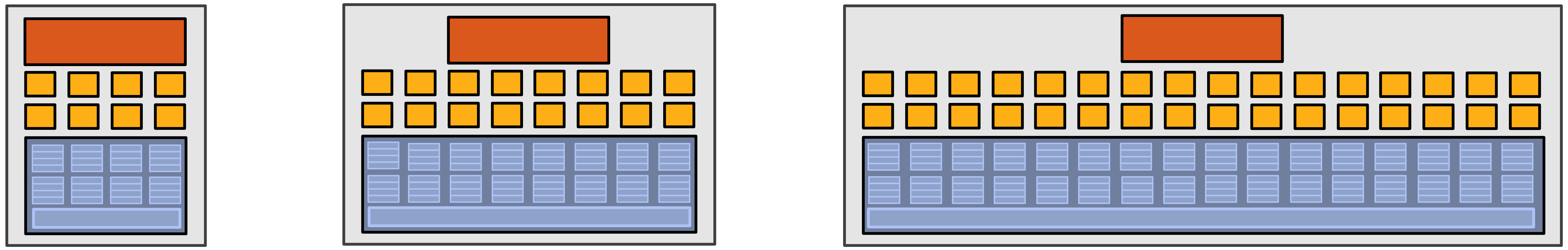



```
<unconditional
 shader code>

if (x > 0) {
    y = pow(x, exp);
    y *= Ks;
    refl = y + Ka;
} else {
    x = 0;
    refl = Ka;
}

<resume unconditional
 shader code>
```

Clarification

SIMD processing does not imply SIMD instructions

- Option 1: explicit vector instructions
  – x86 SSE, AVX, Intel Larrabee
- Option 2: scalar instructions, implicit HW vectorization
  – HW determines instruction stream sharing across ALUs (amount of sharing hidden from software)
  – NVIDIA GeForce (“SIMT” warps), ATI Radeon architectures (“wavefronts”)



In practice: 16 to 64 fragments share an instruction stream.

Stalls!

Stalls occur when a core cannot run the next instruction because of a dependency on a previous operation.

Texture access latency = 100’s to 1000’s of cycles

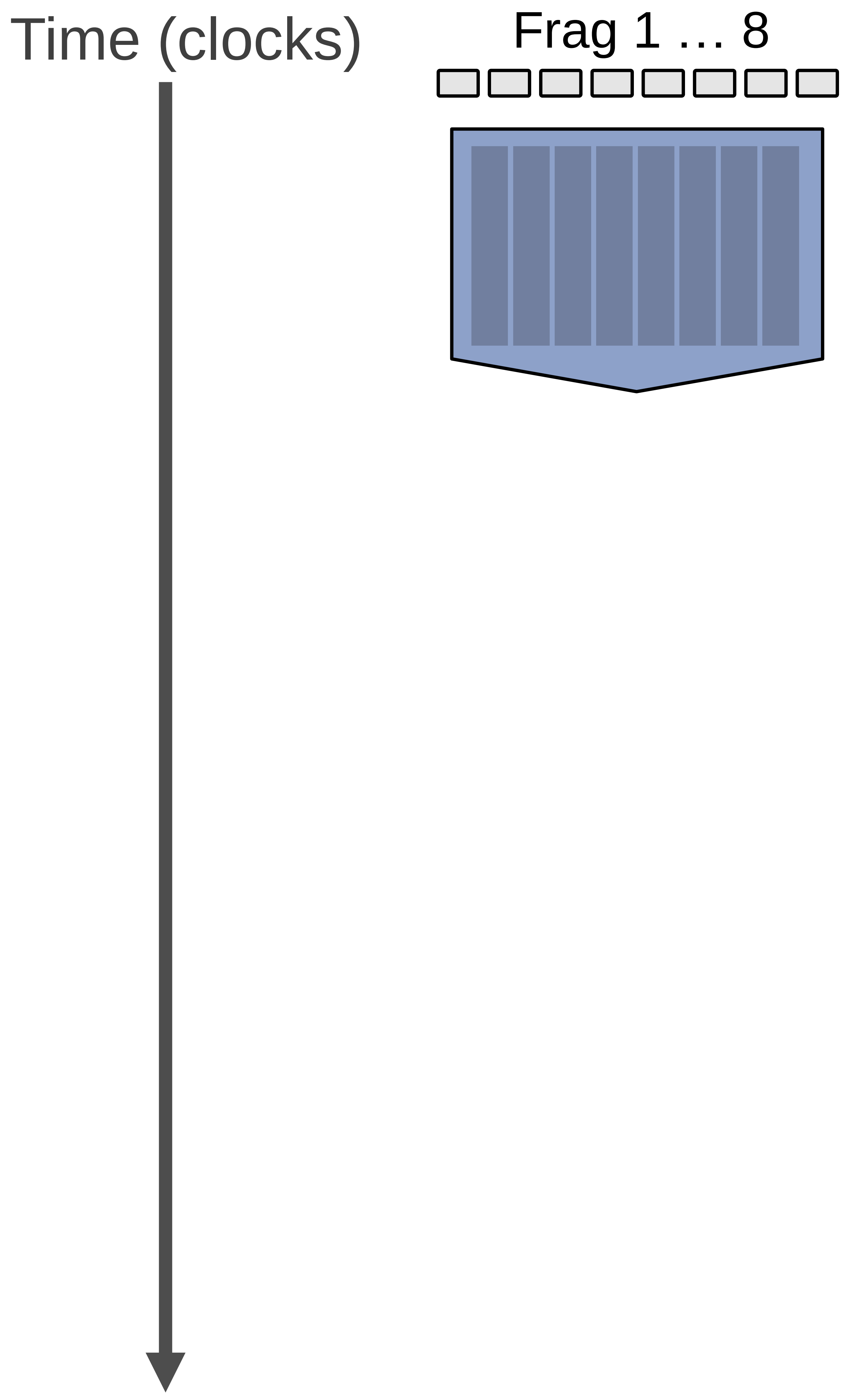
We’ve removed the fancy caches and logic that helps avoid stalls.

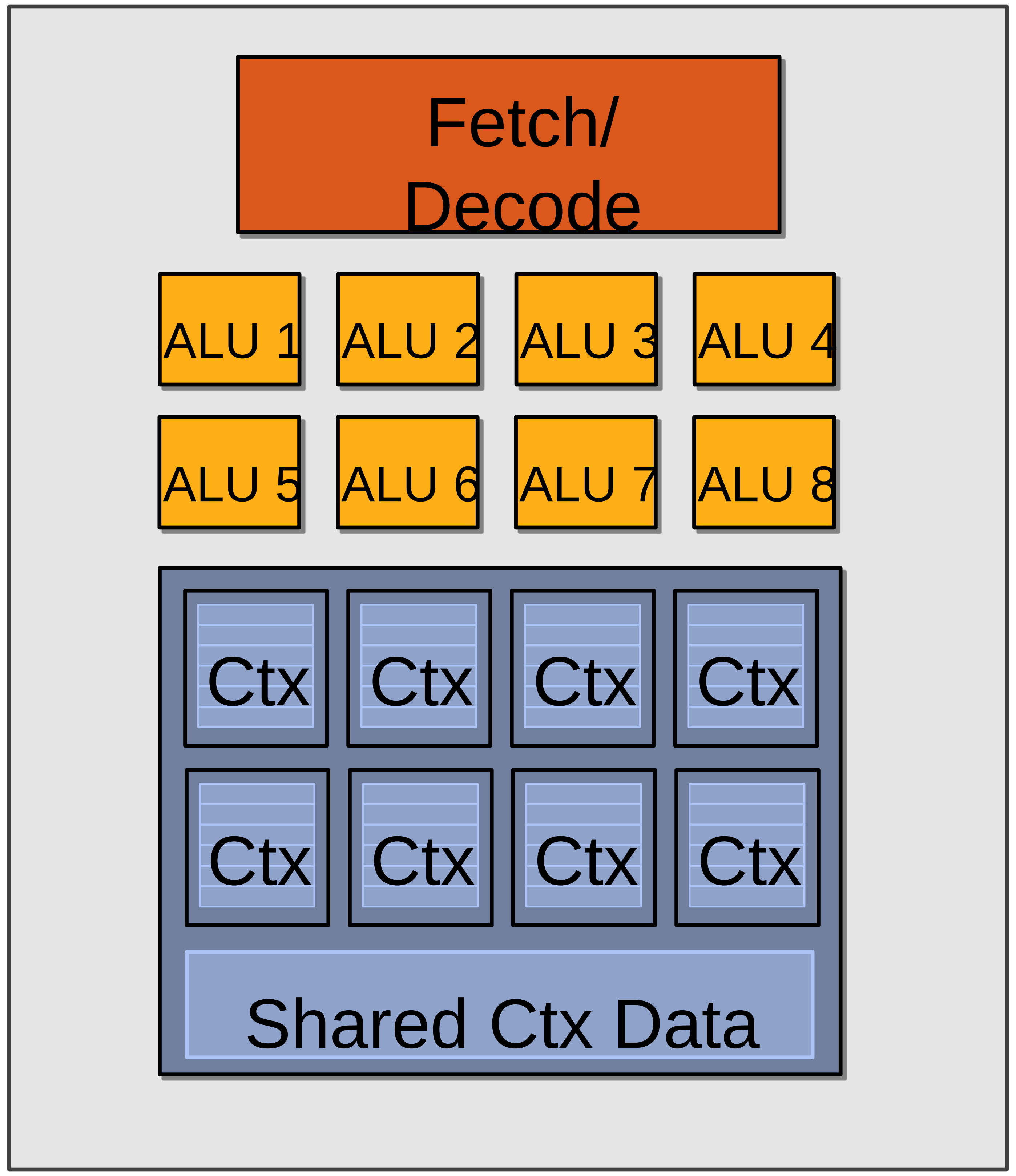
But we have LOTS of independent fragments.

Idea #3:

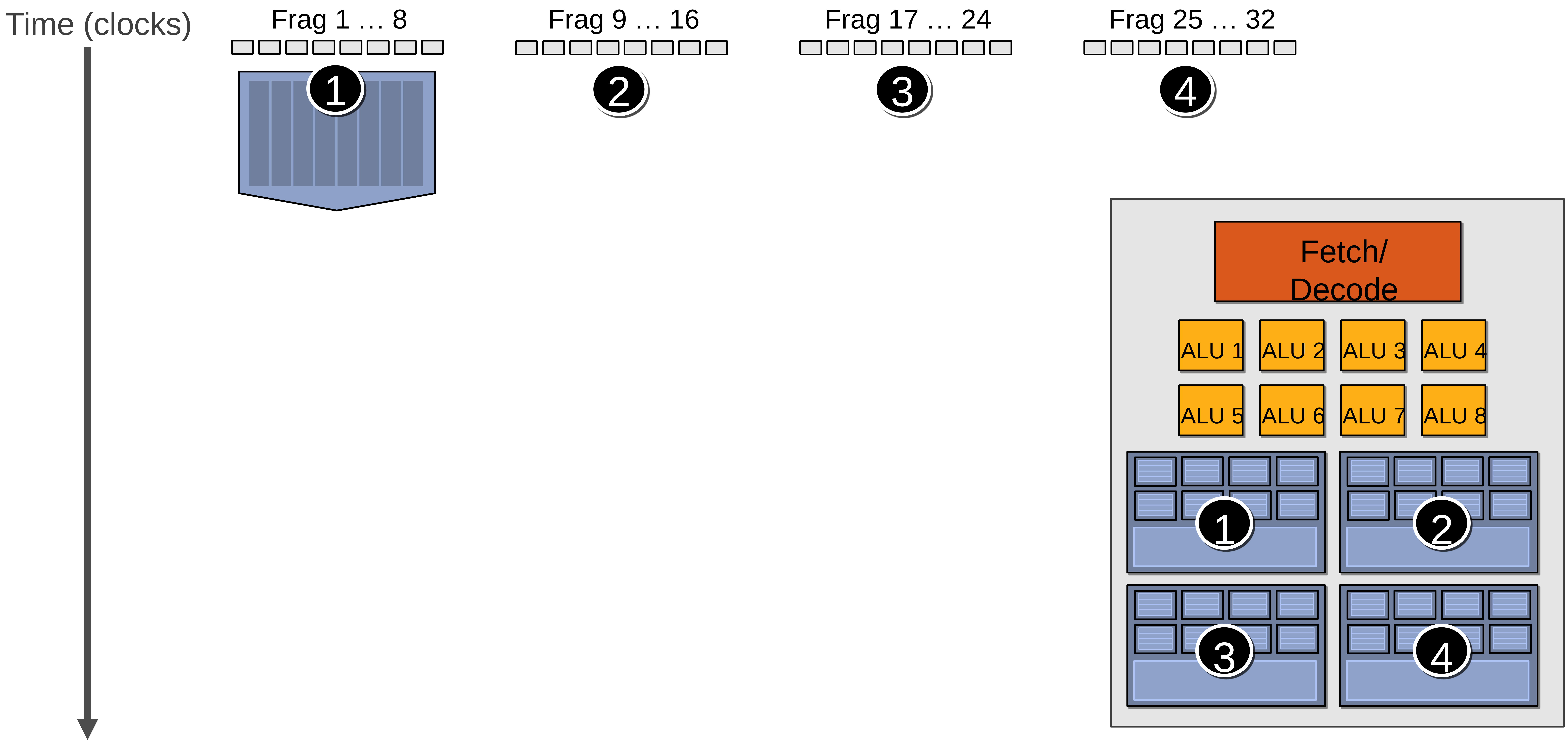
Interleave processing of many fragments on a single core to avoid stalls caused by high latency operations.

Hiding shader stalls

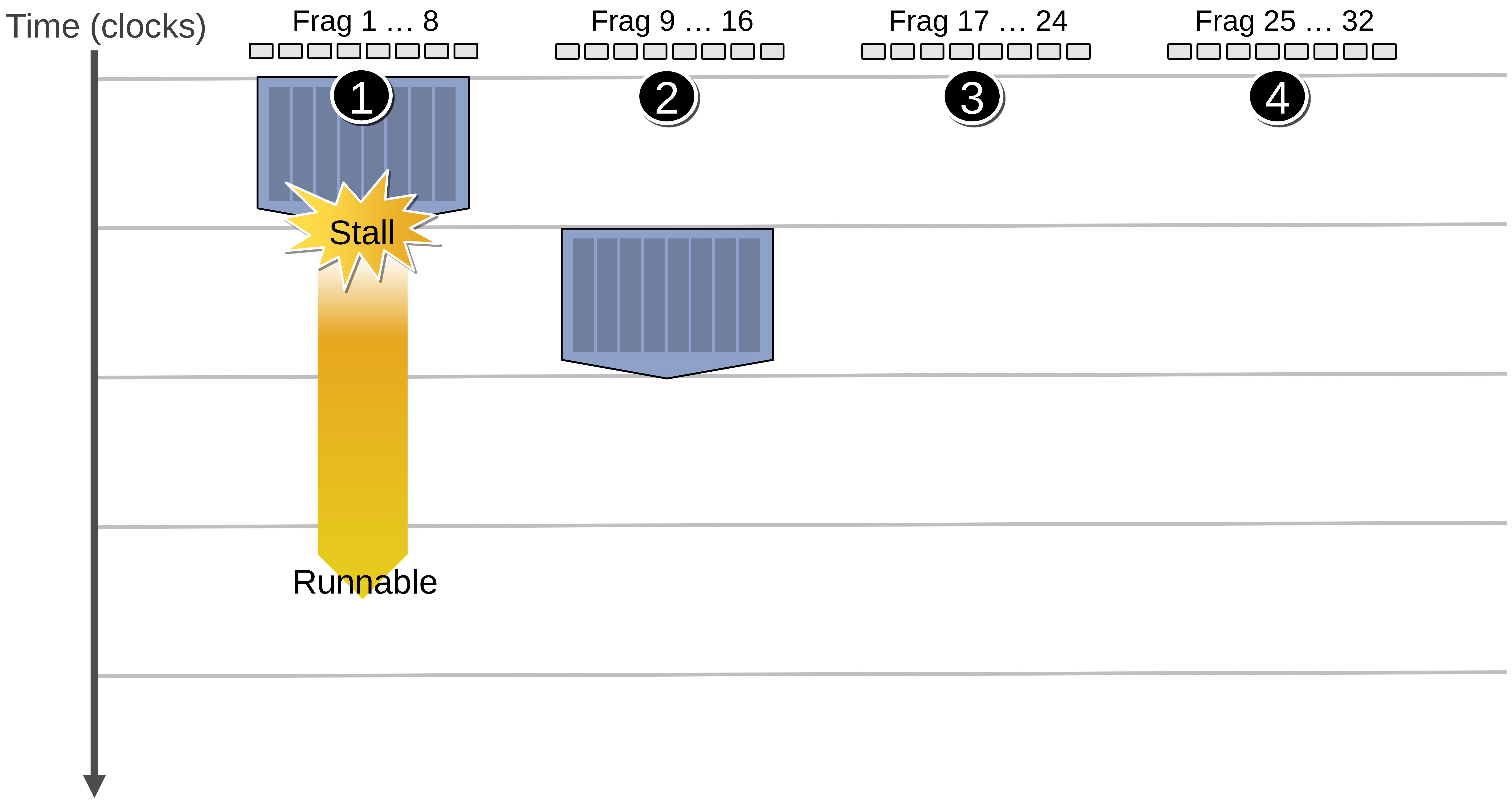




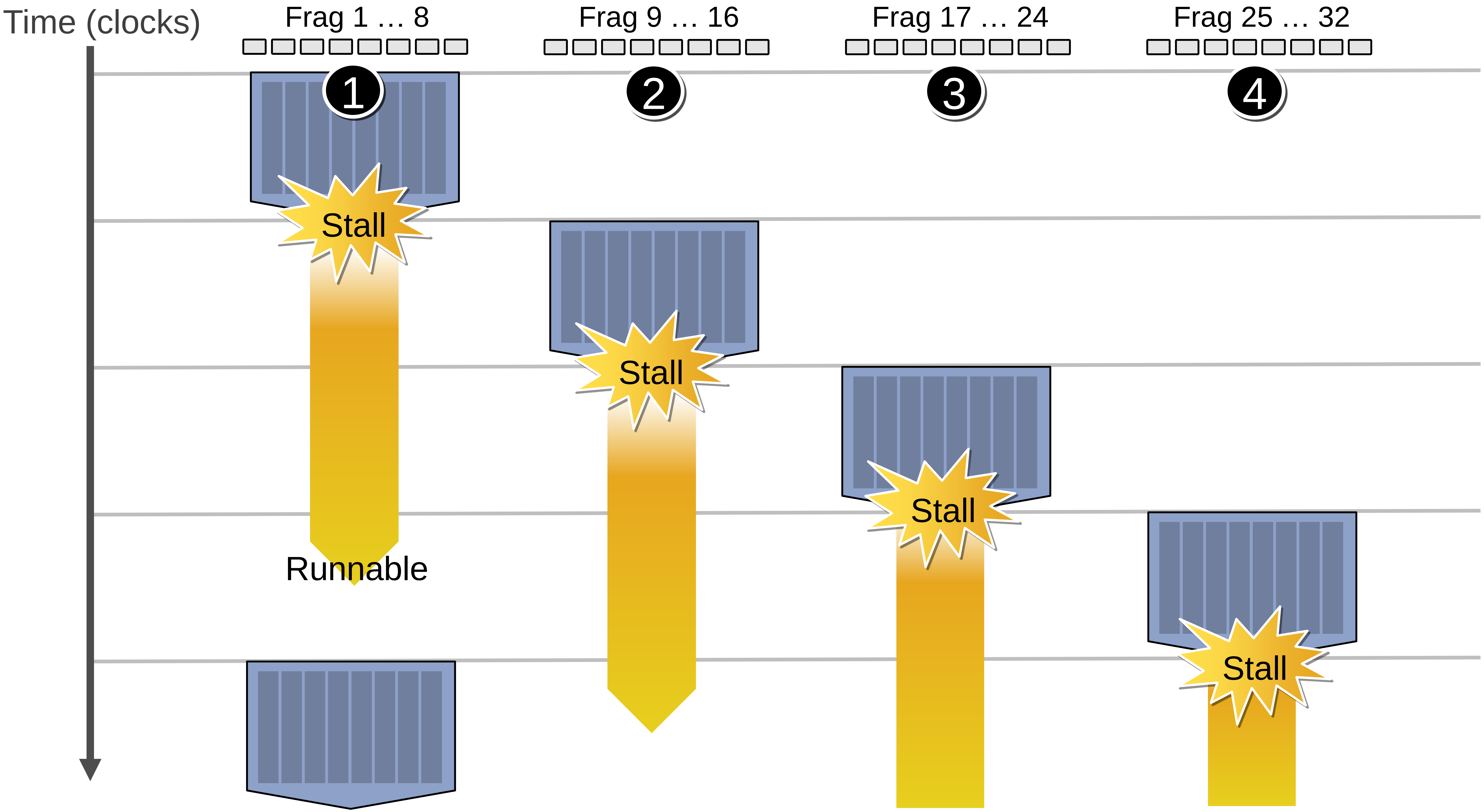
Hiding shader stalls



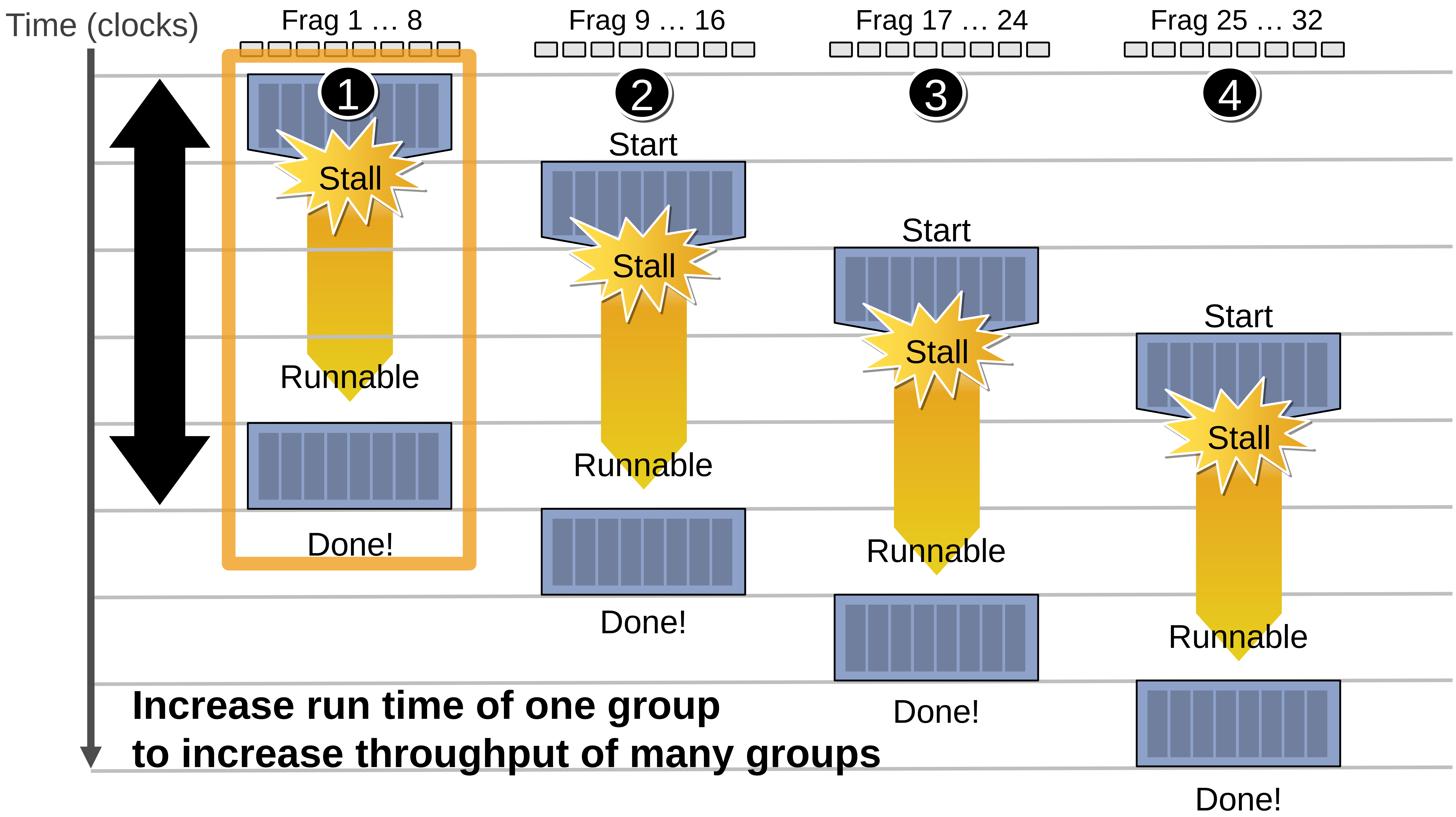
Hiding shader stalls



Hiding shader stalls

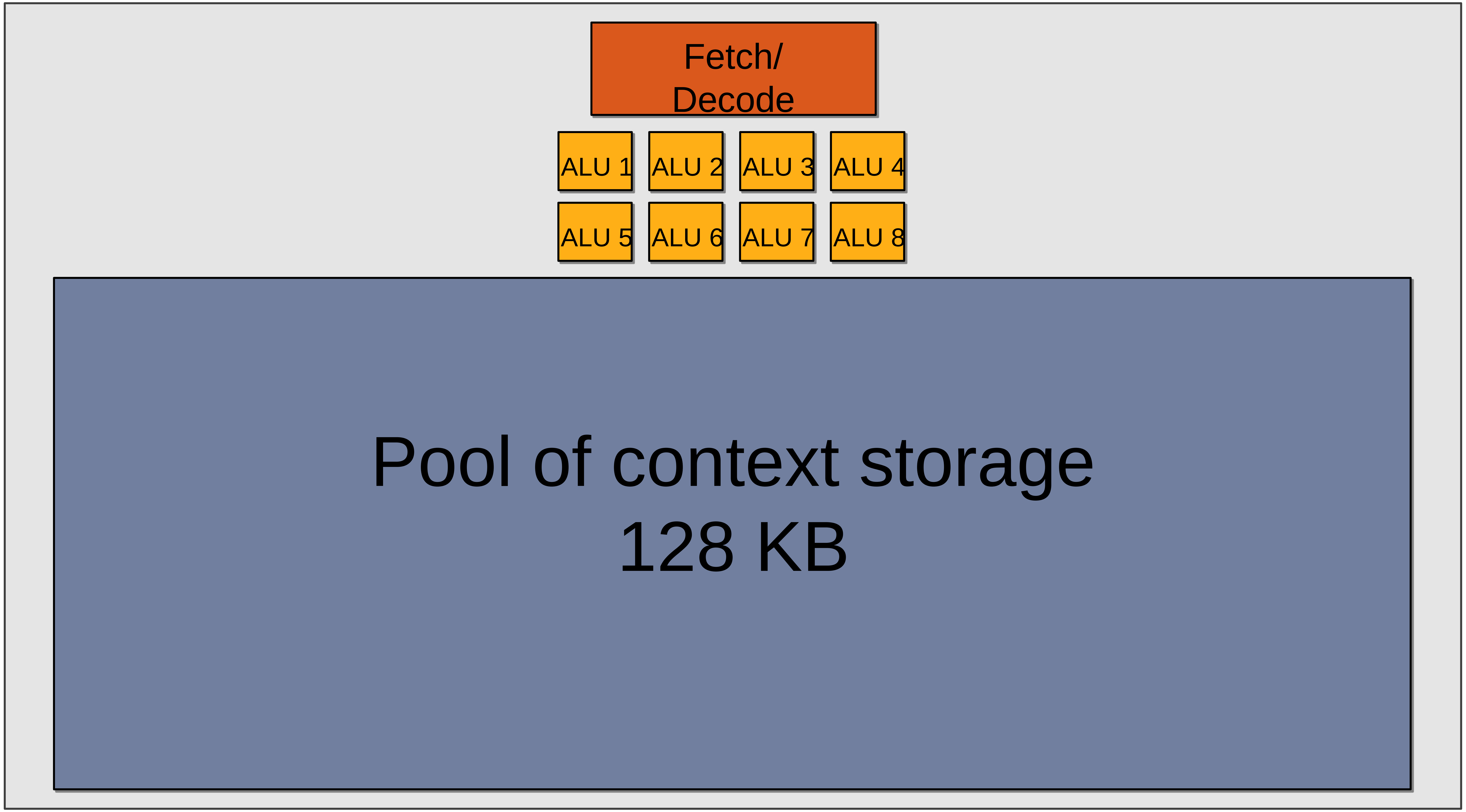


Throughput!

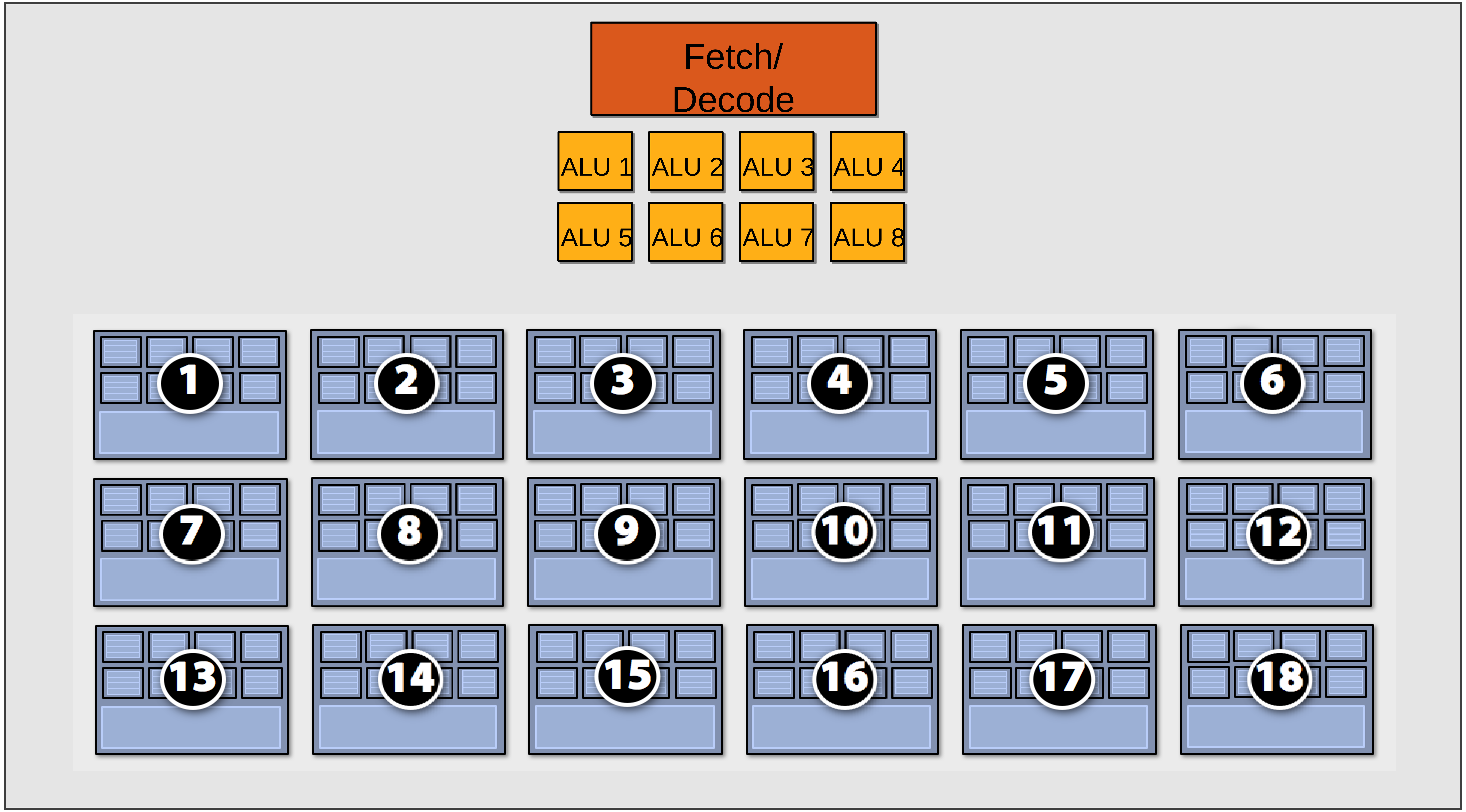


Increase run time of one group to increase throughput of many groups

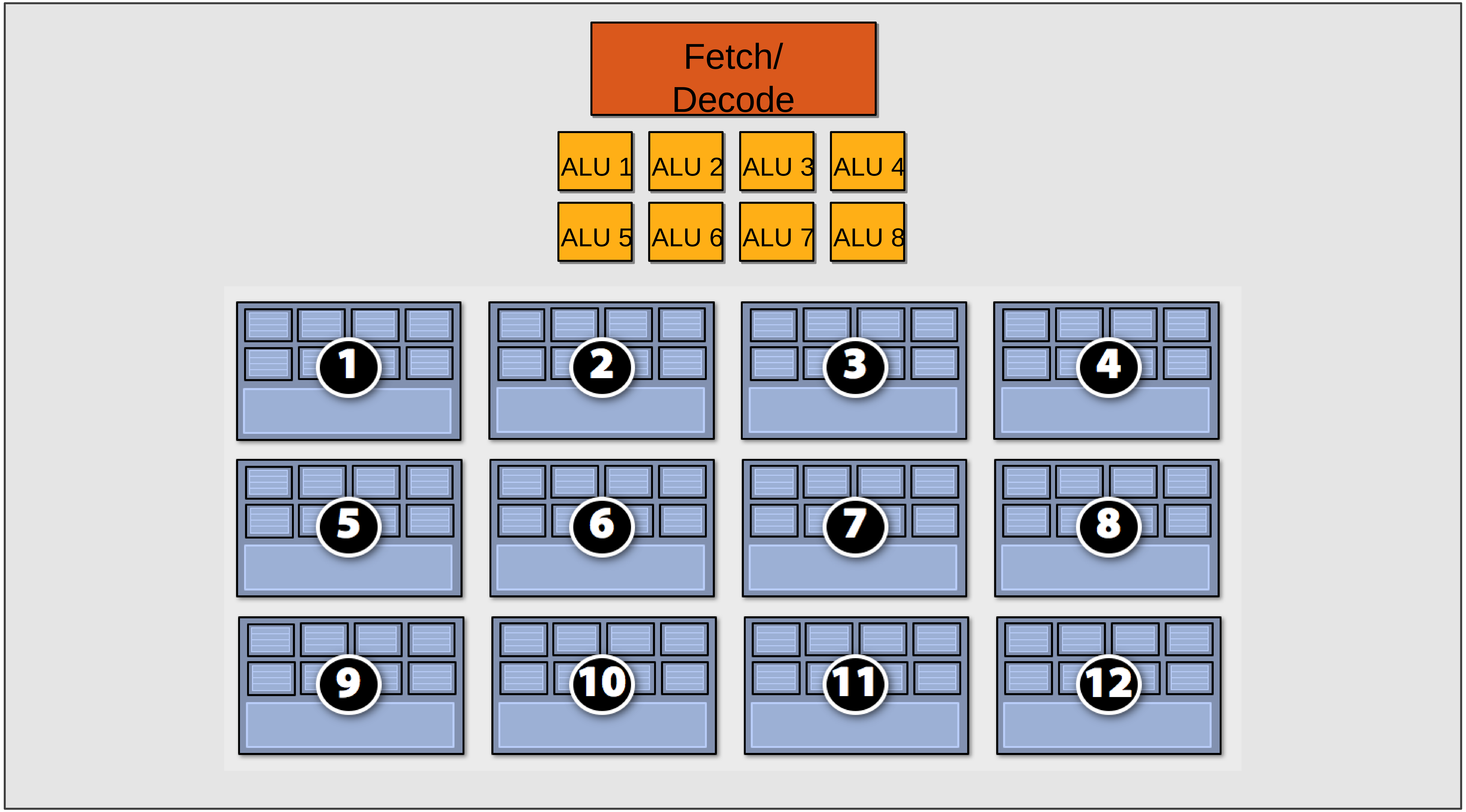
Storing contexts



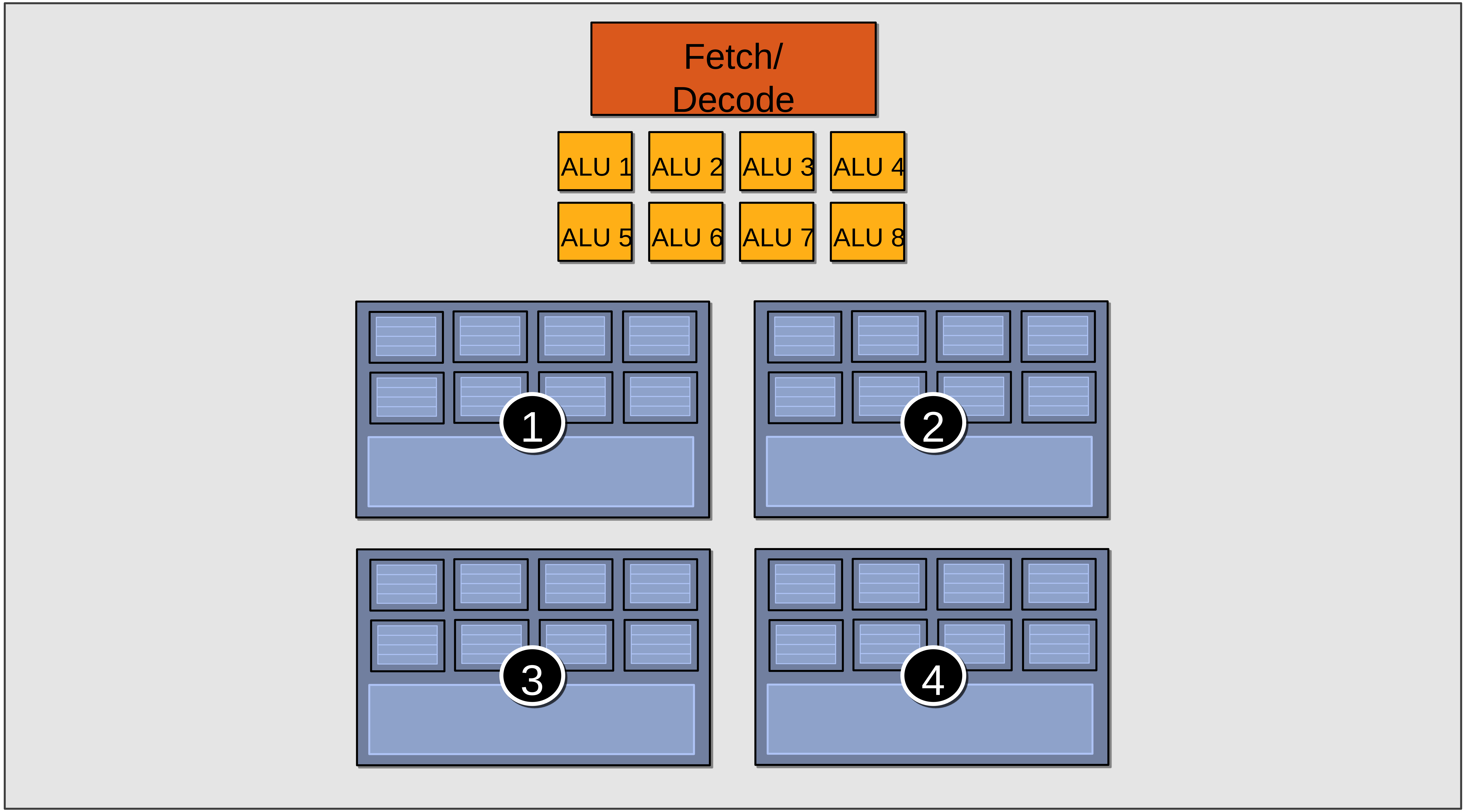
Eighteen small contexts (maximal latency hiding)



Twelve medium contexts



Four large contexts (low latency hiding ability)



Clarification

Interleaving between contexts can be managed by hardware or software (or both!)

- NVIDIA / AMD Radeon GPUs
  - HW schedules / manages all contexts (lots of them)
  - Special on-chip storage holds fragment state
- Intel Larrabee
  - HW manages four x86 (big) contexts at fine granularity
  - SW scheduling interleaves many groups of fragments on each HW context
  - L1-L2 cache holds fragment state (as determined by SW)

Example chip

16 cores

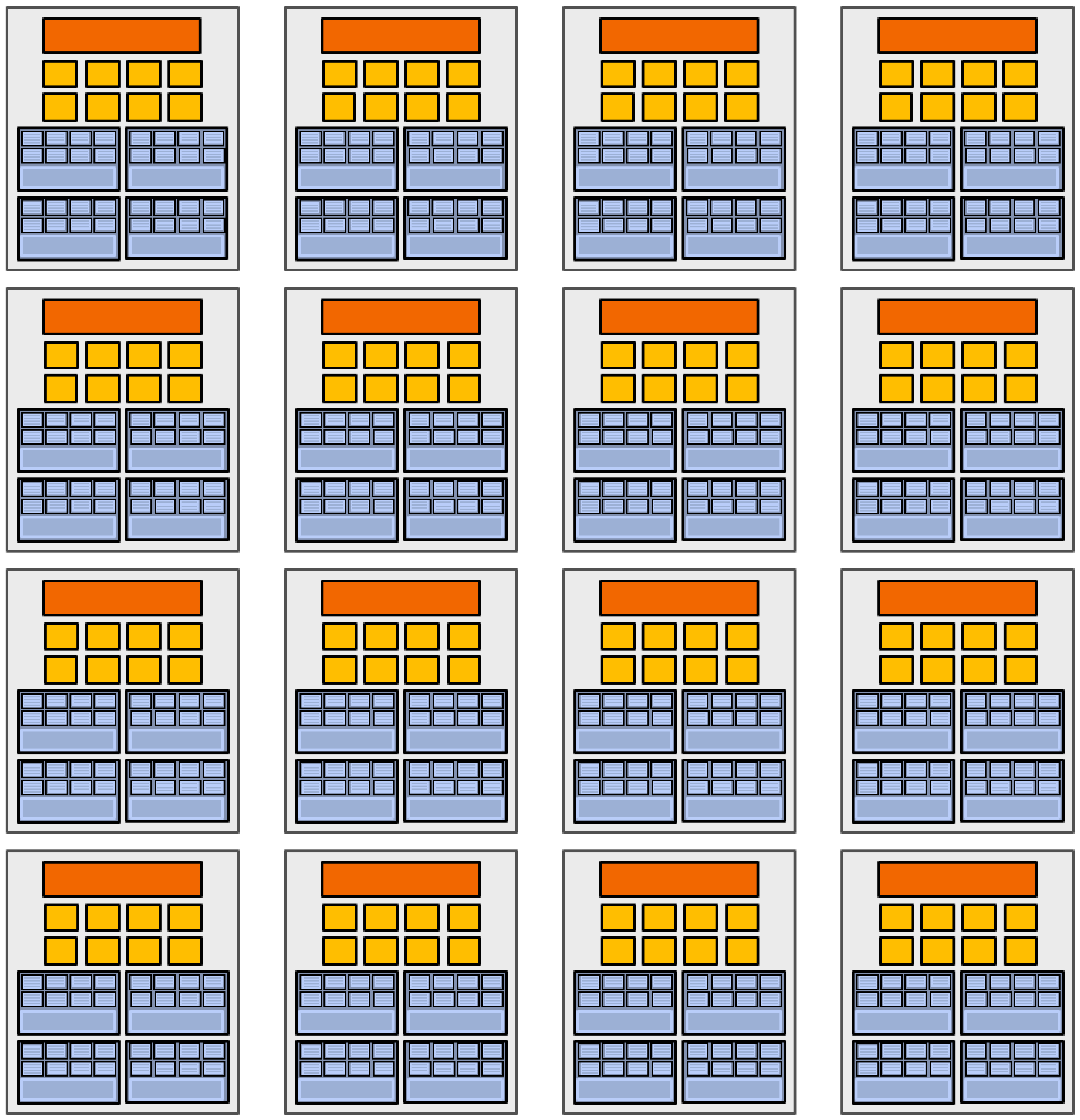
8 mul-add ALUs per core
(128 total)

16 simultaneous
instruction streams

64 concurrent (but interleaved)
instruction streams

512 concurrent fragments

= 256 GFLOPs (@ 1GHz)



Summary: three key ideas

1. Use many “slimmed down cores” to run in parallel

2. Pack cores full of ALUs (by sharing instruction stream across groups of fragments)
   – Option 1: Explicit SIMD vector instructions
   – Option 2: Implicit sharing managed by hardware

3. Avoid latency stalls by interleaving execution of many groups of fragments
   – When one group stalls, work on another group

Part 2:
Putting the three ideas into practice:
A closer look at real GPUs

NVIDIA GeForce GTX 580

AMD Radeon HD 6970

Disclaimer

- The following slides describe “a reasonable way to think” about the architecture of commercial GPUs

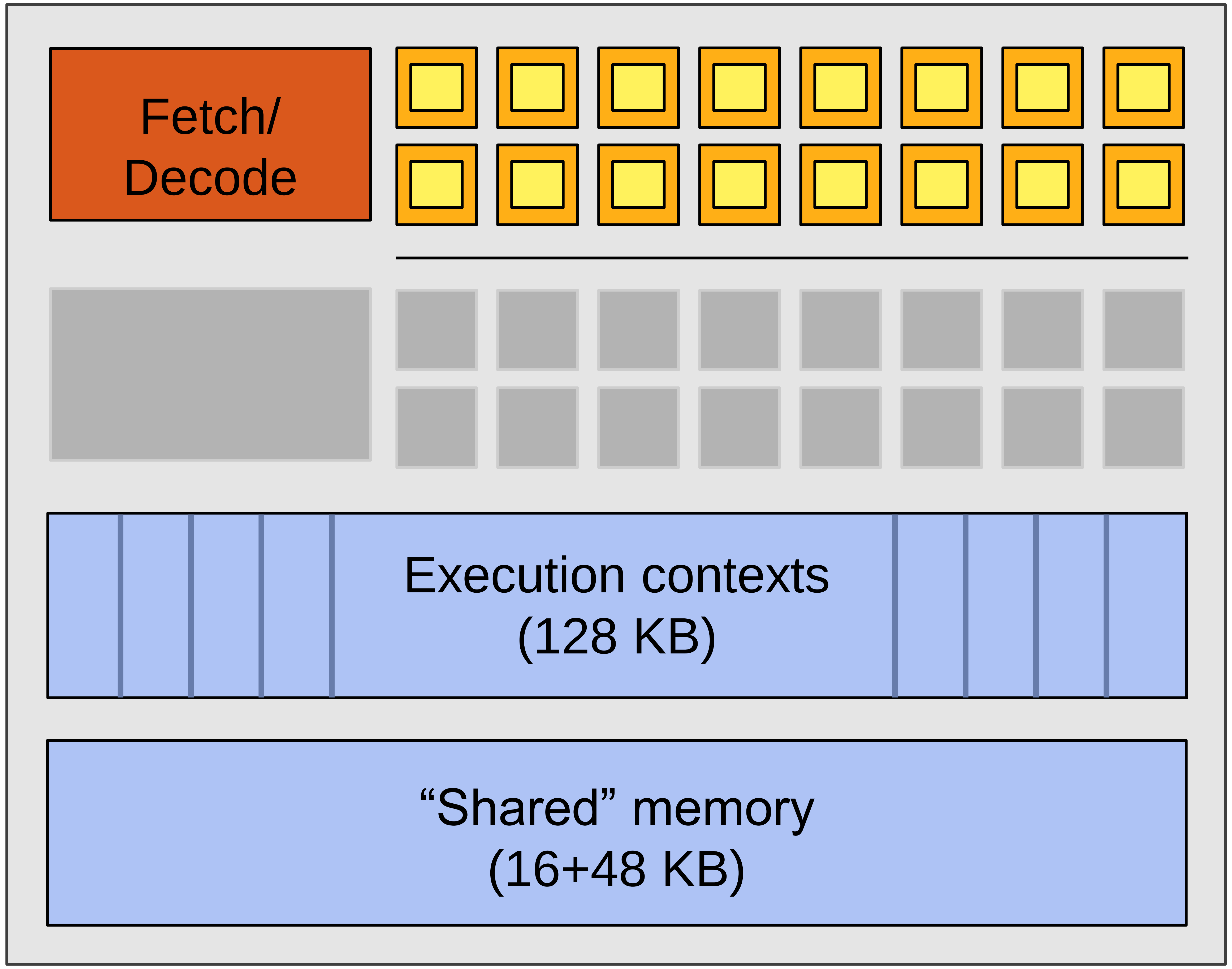
- Many factors play a role in actual chip performance

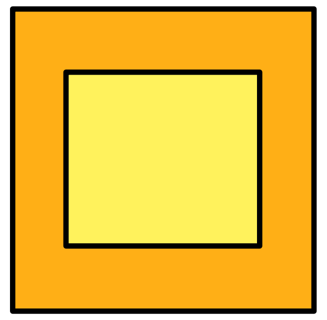
NVIDIA GeForce GTX 580 (Fermi)

- NVIDIA-speak:
  - 512 stream processors (“CUDA cores”)
  - “SIMT execution”

- Generic speak:
  - 16 cores
  - 2 groups of 16 SIMD functional units per core

NVIDIA GeForce GTX 580 “core”

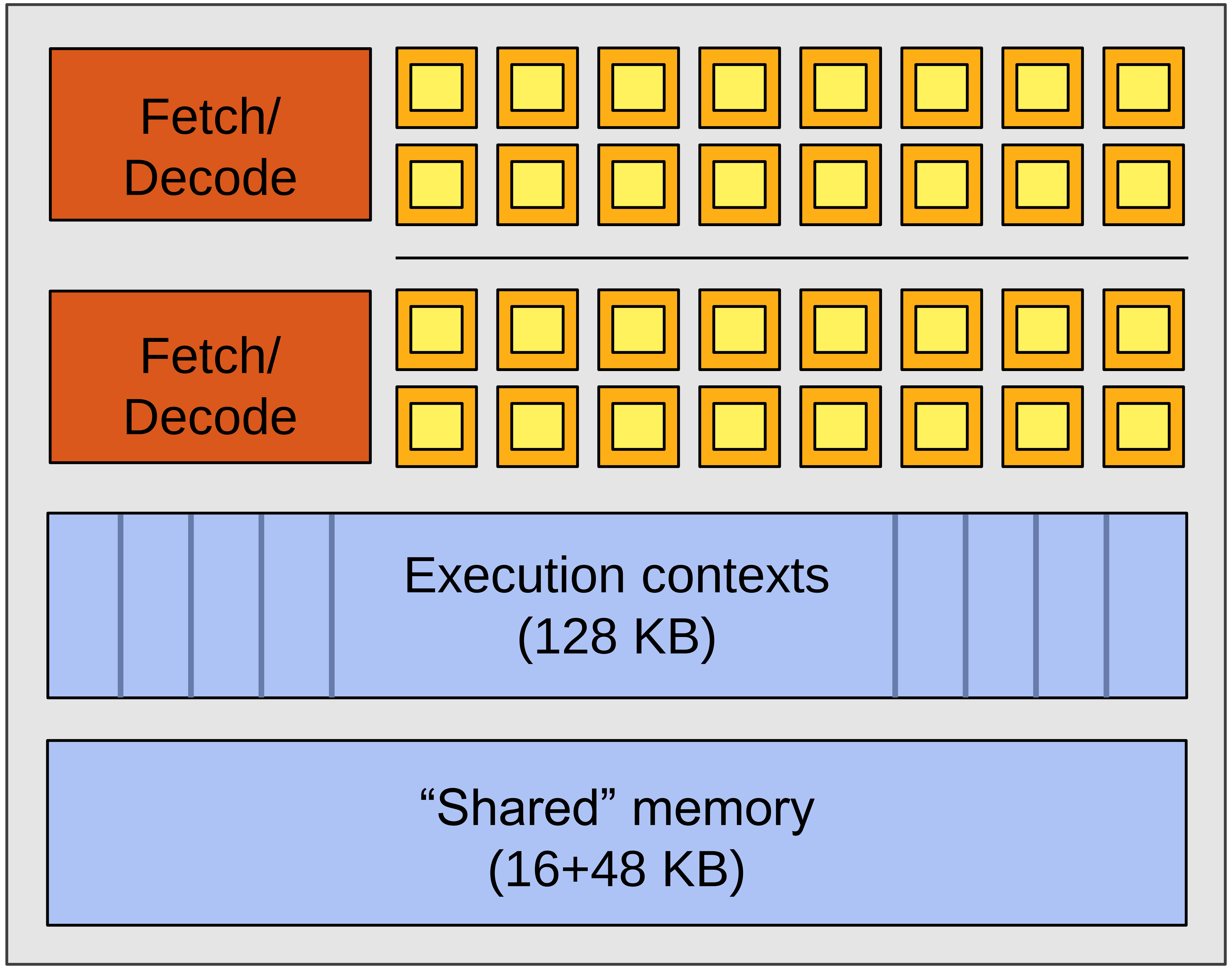




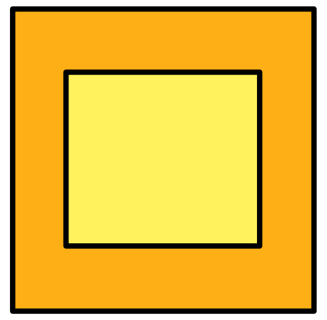
- Groups of 32 [fragments/vertices/CUDA threads] share an instruction stream
- Up to 48 groups are simultaneously interleaved
- Up to 1536 individual contexts can be stored

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

NVIDIA GeForce GTX 580 “core”



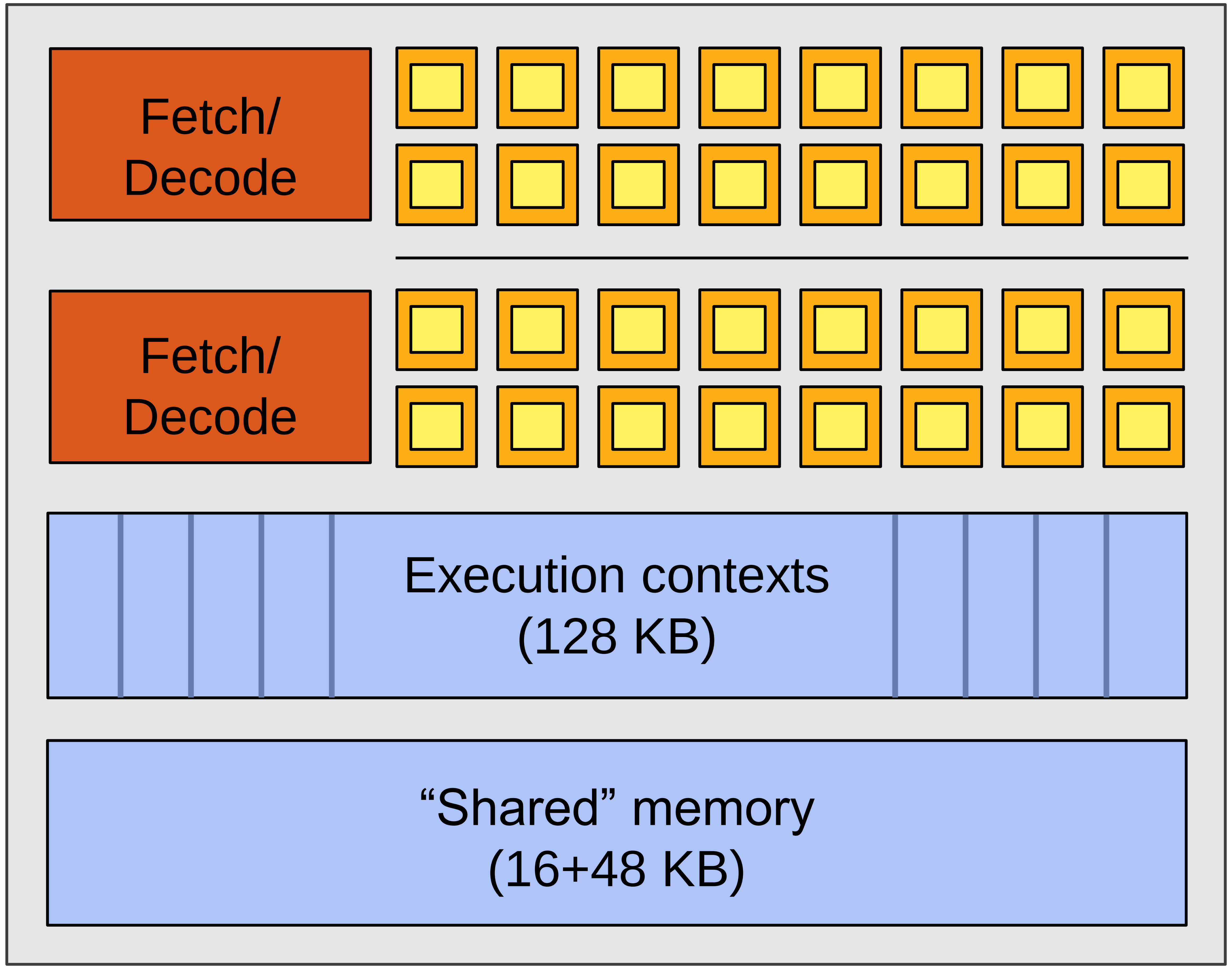
Source: Fermi Compute Architecture Whitepaper
CUDA Programming Guide 3.1, Appendix G

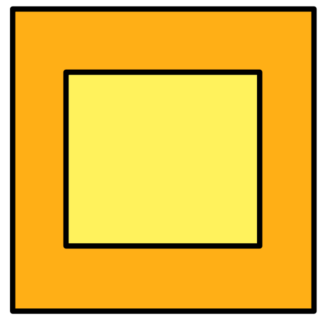


= SIMD function unit,
control shared across 16 units
(1 MUL-ADD per clock)

- The core contains 32 functional units
- Two groups are selected each clock (decode, fetch, and execute two instruction streams in parallel)

NVIDIA GeForce GTX 580 “SM”



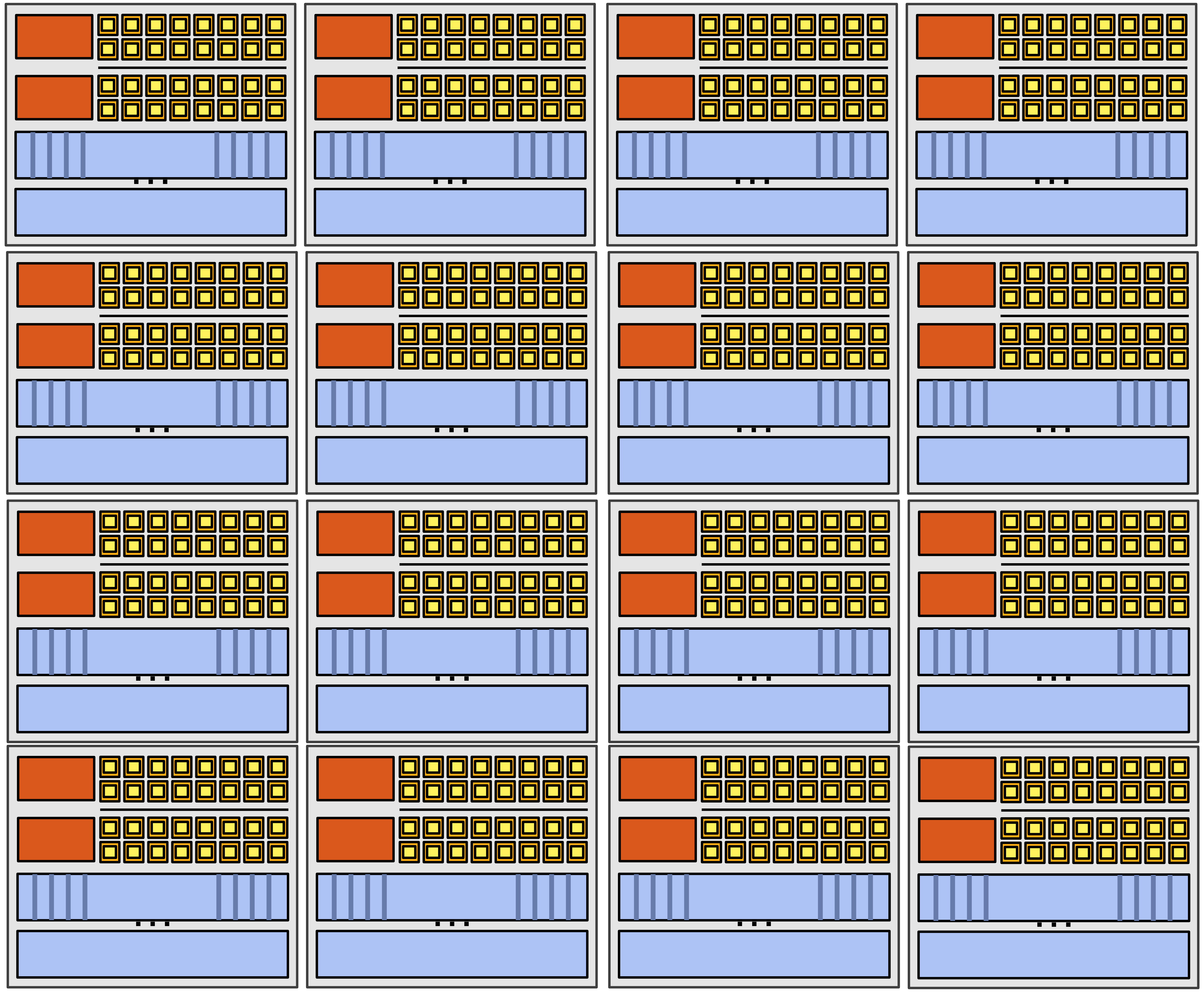


= CUDA core
(1 MUL-ADD per clock)

- The SM contains 32 CUDA cores
- Two warps are selected each clock (decode, fetch, and execute two warps in parallel)
- Up to 48 warps are interleaved, totaling 1536 CUDA threads

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

NVIDIA GeForce GTX 580



There are 16 of these things on the GTX 480:

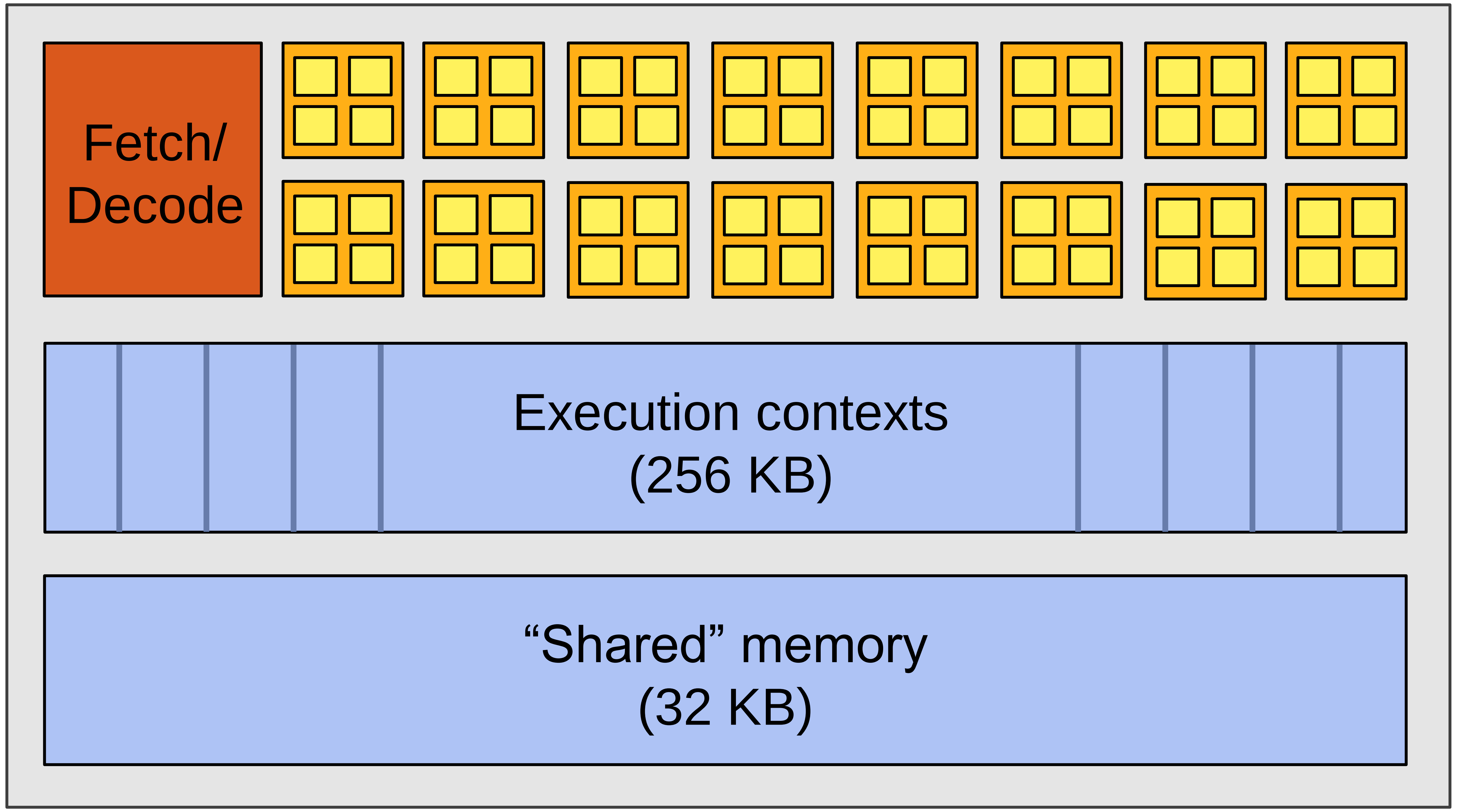
That’s 24,500 fragments!
Or 24,000 CUDA threads!

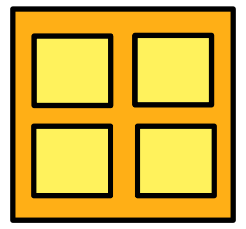
AMD Radeon HD 6970 (Cayman)

- AMD-speak:
  - 1536 stream processors

- Generic speak:
  - 24 cores
  - 16 “beefy” SIMD functional units per core
  - 4 multiply-adds per functional unit (VLIW processing)

ATI Radeon HD 6970 “core”



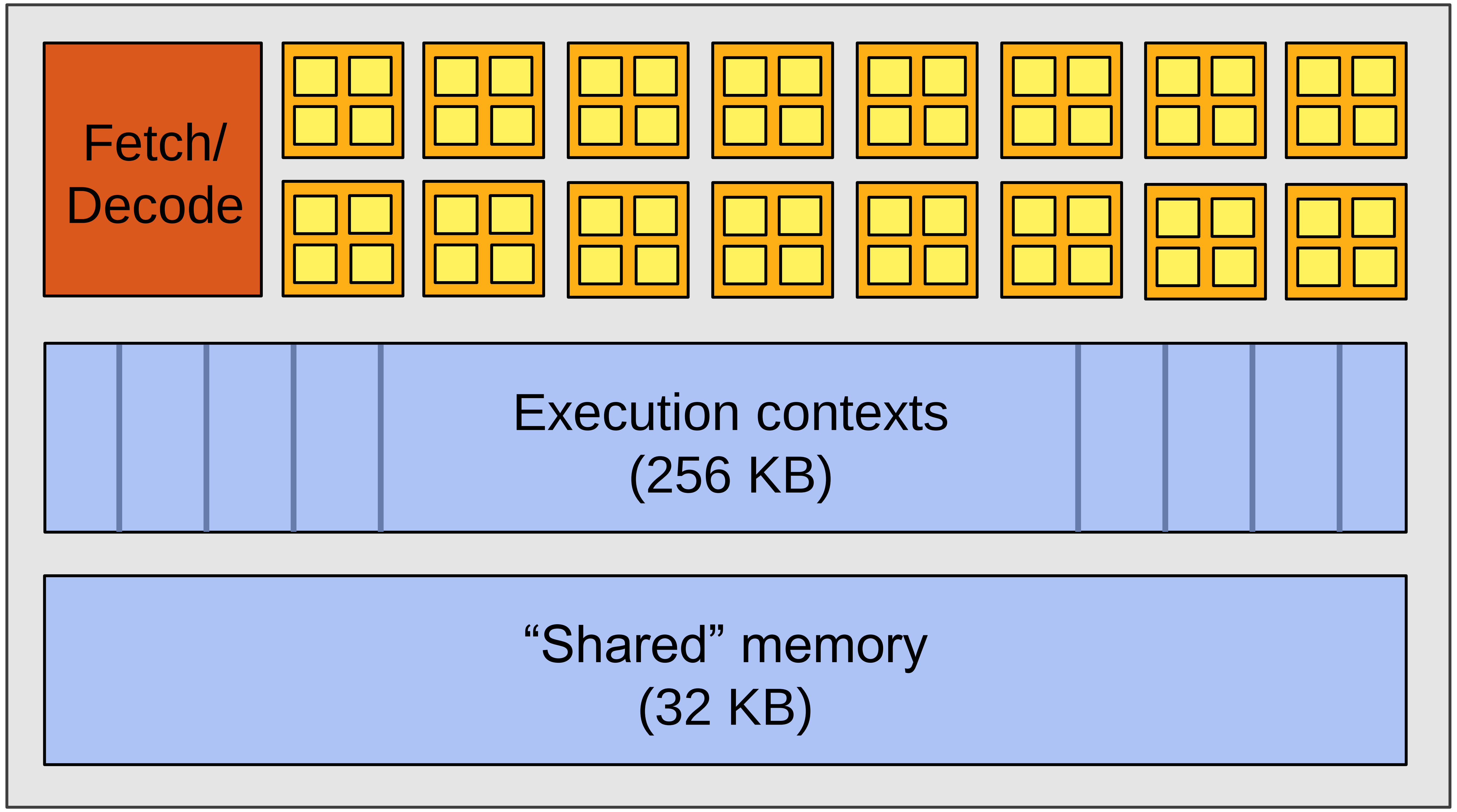


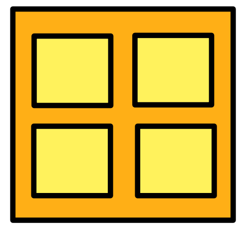
= SIMD function unit,
control shared across 16 units
(Up to 4 MUL-ADDs per clock)

- Groups of 64 [fragments/vertices/etc.] share instruction stream
- Four clocks to execute an instruction for all fragments in a group

Source: ATI Radeon HD5000 Series: An Inside View (HPG 2010)

ATI Radeon HD 6970 “SIMD-Engine”

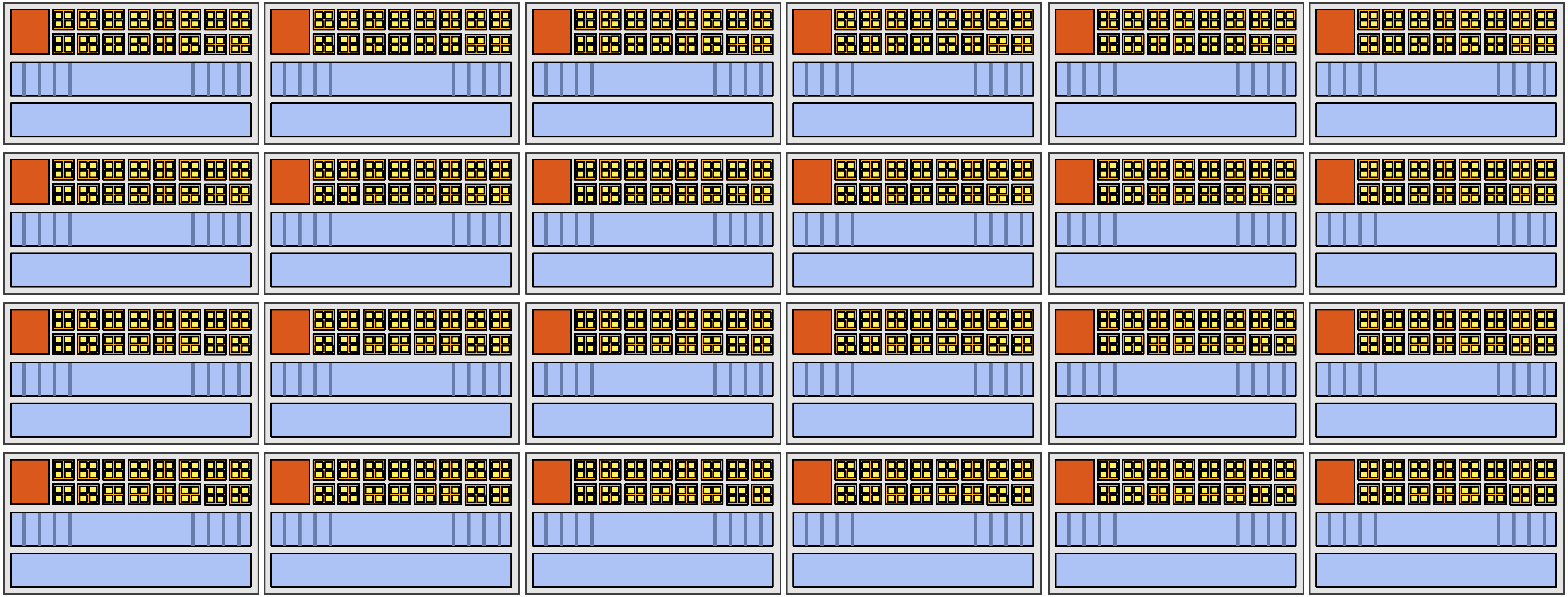


 = Stream Processor, control shared across 16 units (Up to 4 MUL-ADDs per clock)

- Groups of 64 [fragments/vertices/etc.] are in a “wavefront”
- Four clocks to execute an instruction for an entire “wavefront”

Source: ATI Radeon HD5000 Series: An Inside View (HPG 2010)

ATI Radeon HD 6970



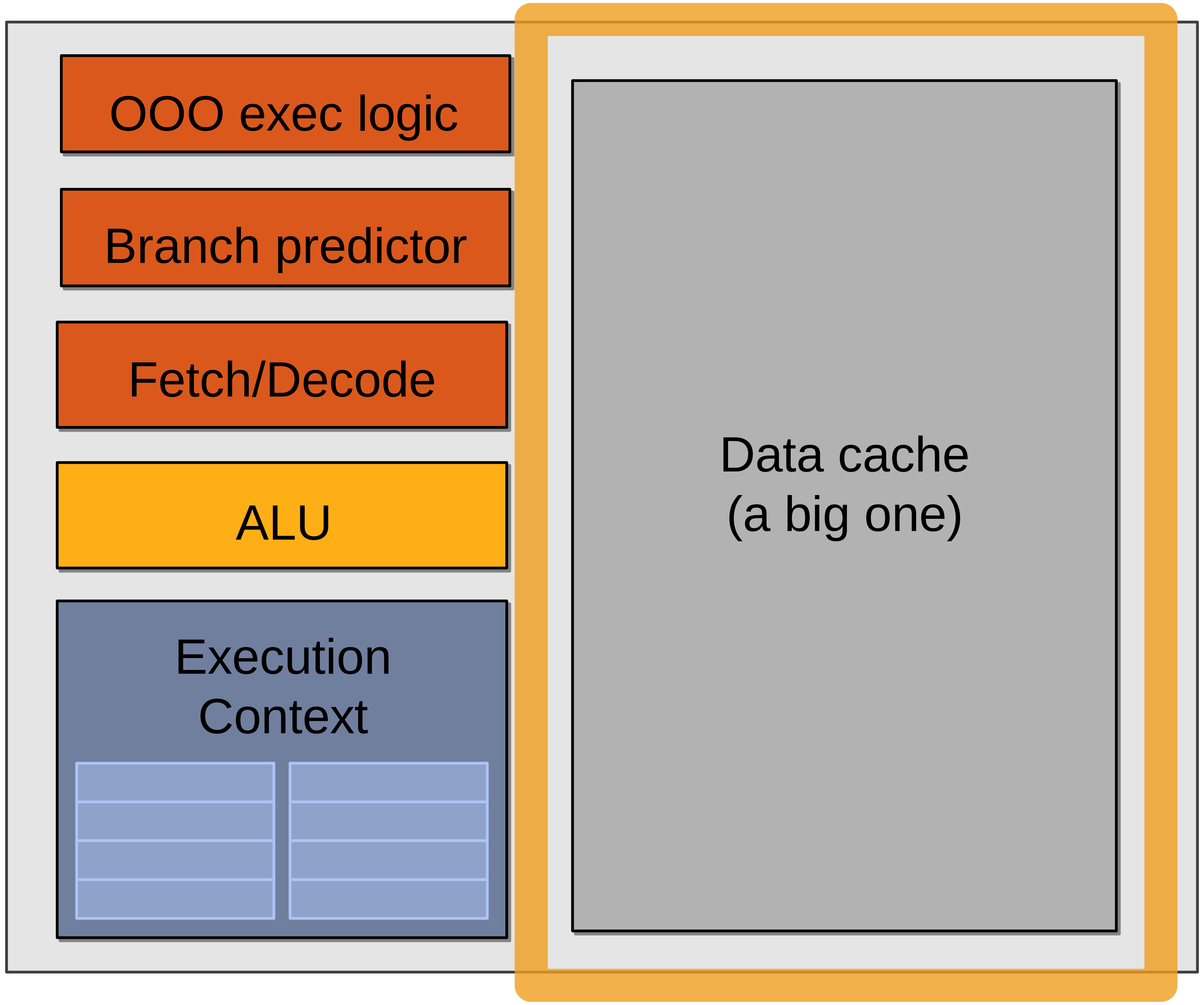
There are 24 of these “cores” on the 6970: that’s about 32,000 fragments!

(there is a global limitation of 496 wavefronts)

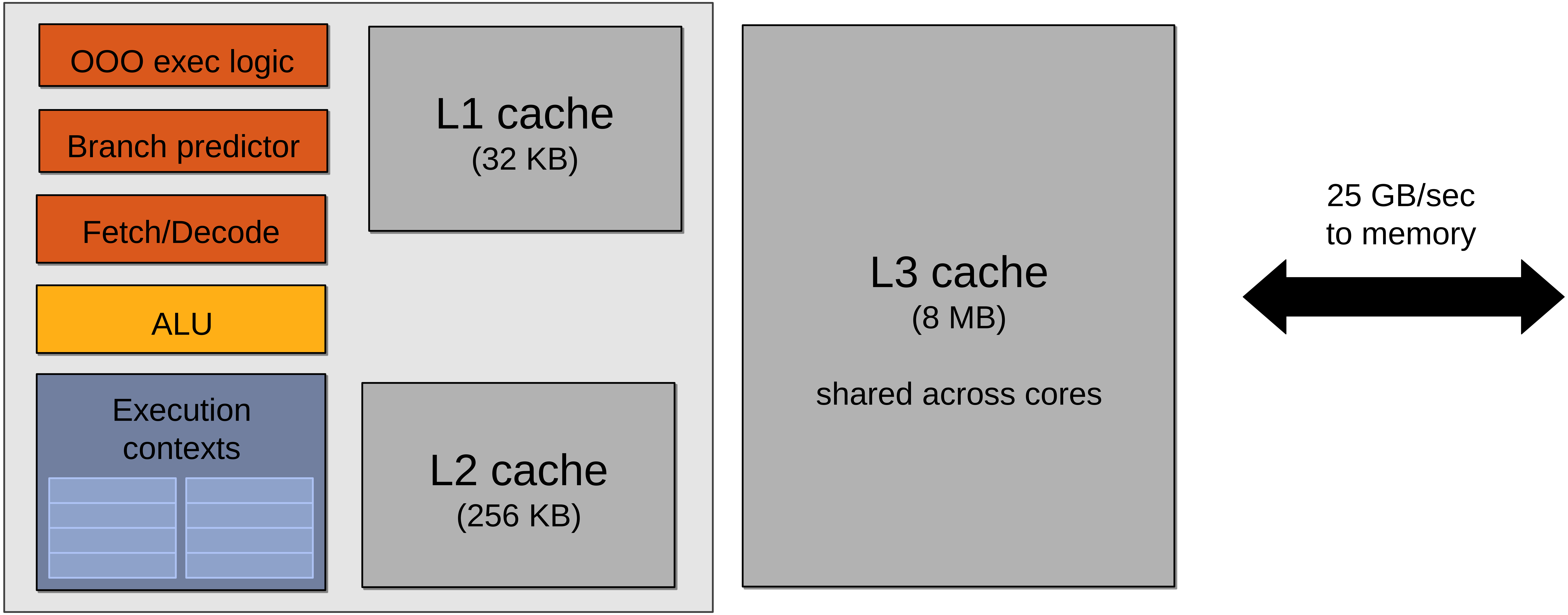
The talk thus far: processing data

Part 3: moving data to processors

Recall: “CPU-style” core

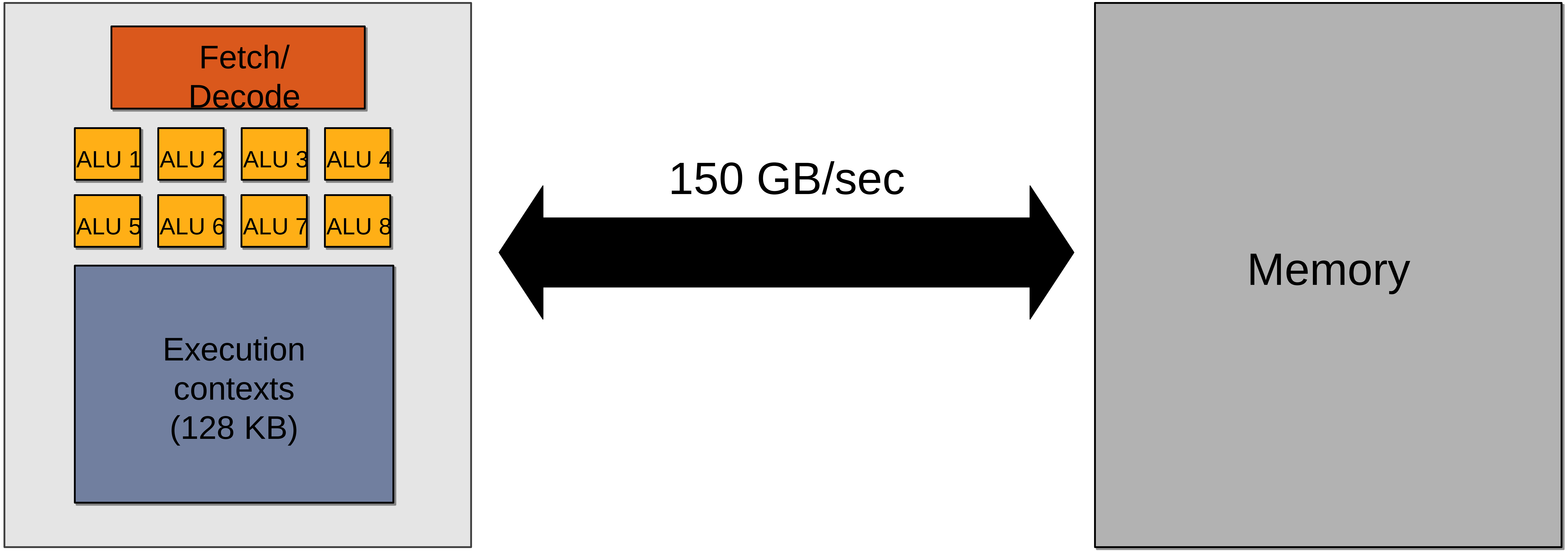


“CPU-style” memory hierarchy



CPU cores run efficiently when data is resident in cache
(caches reduce latency, provide high bandwidth)

Throughput core (GPU-style)



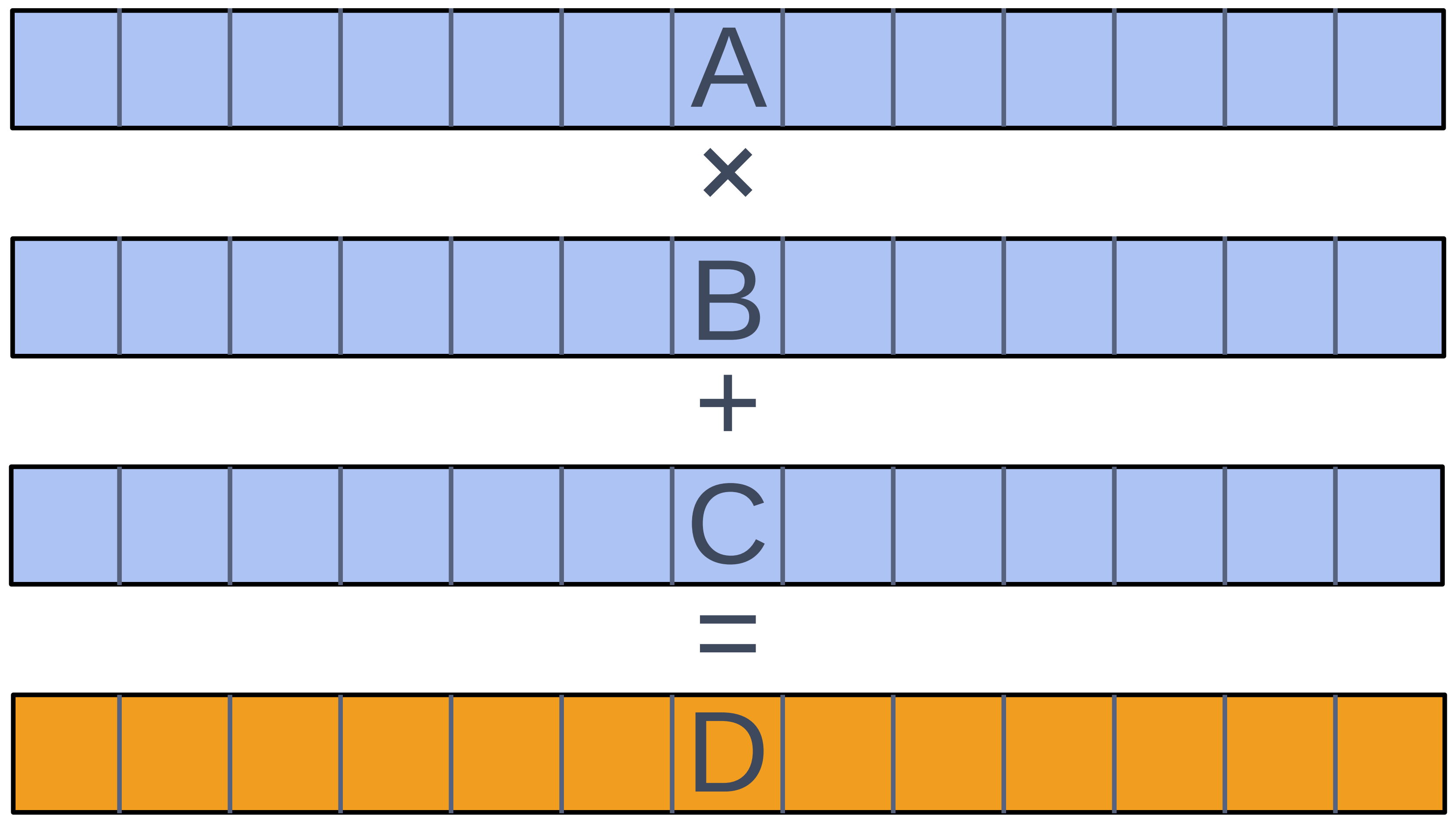
More ALUs, no large traditional cache hierarchy:
Need high-bandwidth connection to memory

Bandwidth is a critical resource

- A high-end GPU (e.g. Radeon HD 6970) has...
  - Over twenty times (2.7 TFLOPS) the compute performance of quad-core CPU
  - No large cache hierarchy to absorb memory requests

- GPU memory system is designed for throughput
  - Wide bus (150 GB/sec)
  - Repack/reorder/interleave memory requests to maximize use of memory bus
  - Still, this is only six times the bandwidth available to CPU

Bandwidth thought experiment



Task: element-wise multiply two long vectors A and B

1. Load input A[i]
2. Load input B[i]
3. Load input C[i]
4. Compute A[i] × B[i] + C[i]
5. Store result into D[i]

Four memory operations (16 bytes) for every MUL-ADD

Radeon HD 6970 can do 1536 MUL-ADDS per clock

Need ~20 TB/sec of bandwidth to keep functional units busy

Less than 1% efficiency… but 6x faster than CPU!

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 GPU-compute application developers.

Reducing bandwidth requirements

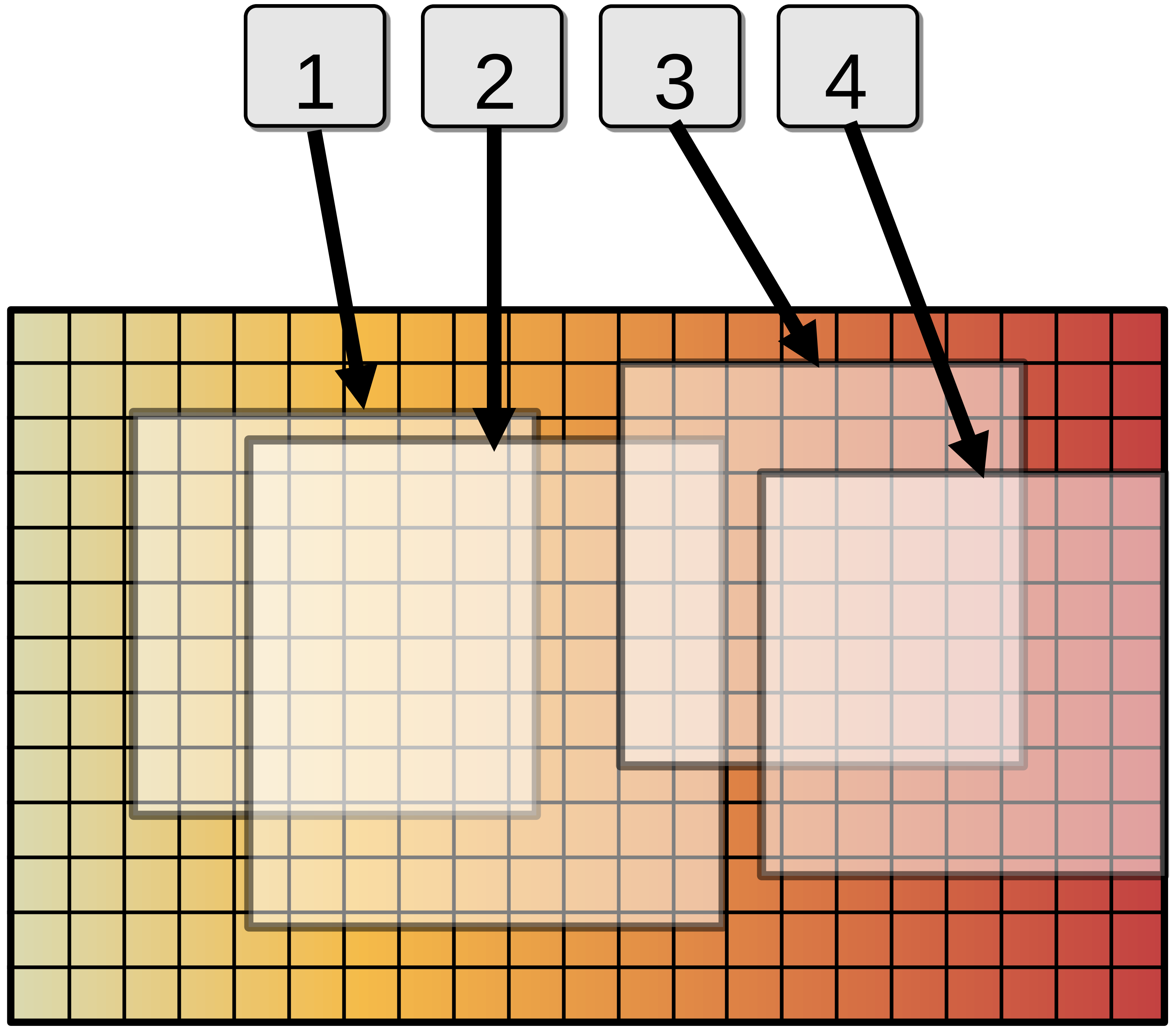
- Request data less often (instead, do more math)
  - “arithmetic intensity”

- Fetch data from memory less often (share/reuse data across fragments
  - on-chip communication or storage

Reducing bandwidth requirements

- Two examples of on-chip storage
  - Texture caches
  - OpenCL “local memory” (CUDA shared memory)

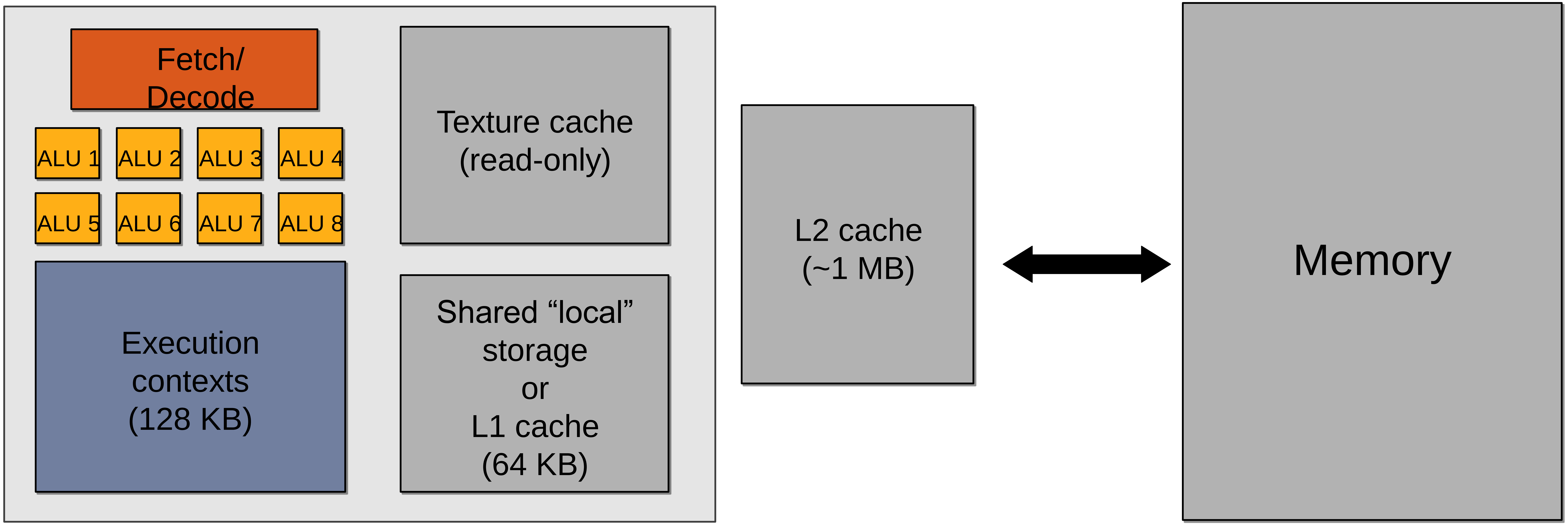
Texture data



Texture caches:

Capture reuse across fragments, not temporal reuse within a single shader program

Modern GPU memory hierarchy



On-chip storage takes load off memory system.
Many developers calling for more cache-like storage (particularly GPU-compute applications)

Don’t forget about offload cost…

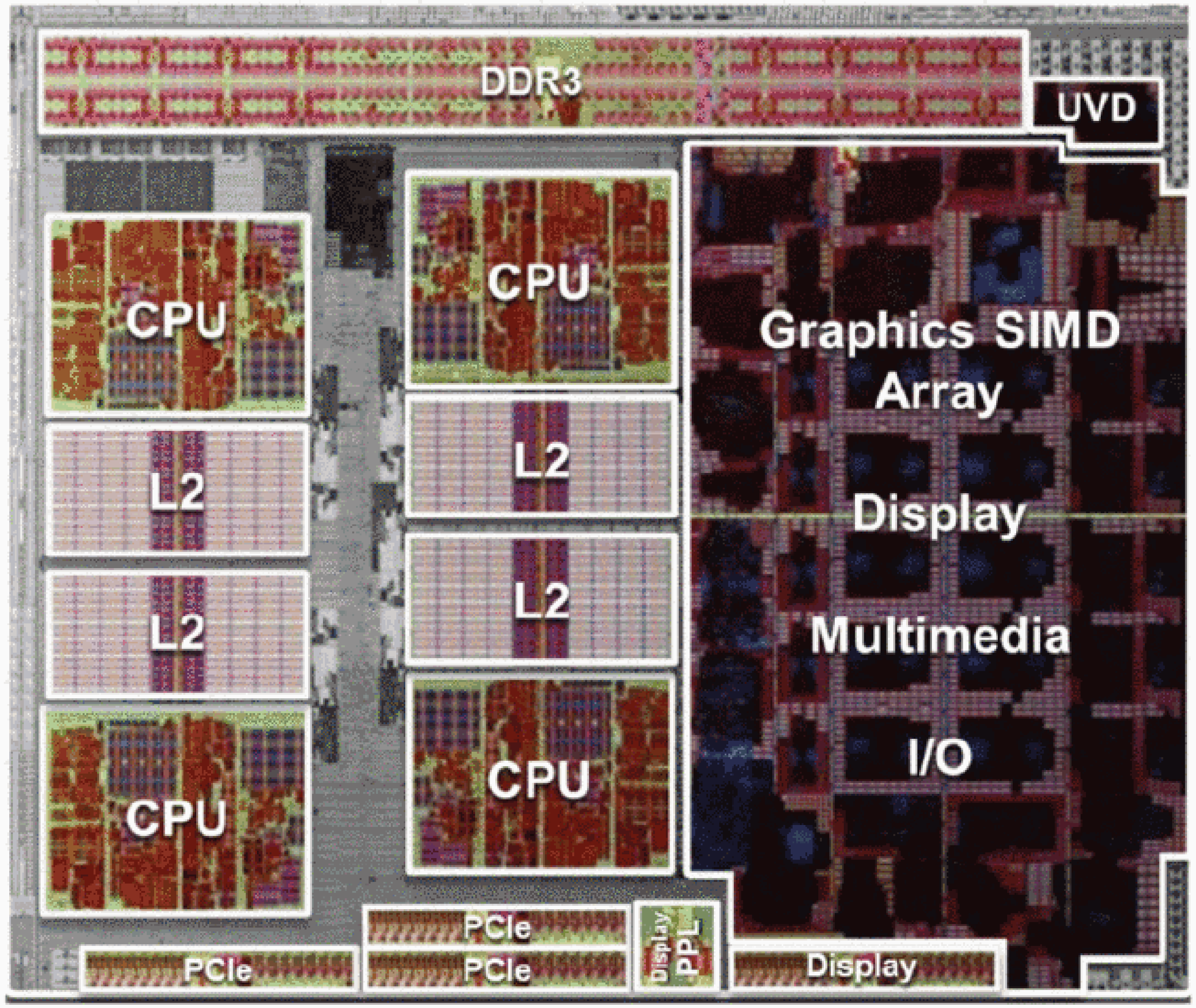
- PCIe bandwidth/latency
  - 8GB/s each direction in practice
  - Attempt to pipeline/multi-buffer uploads and downloads

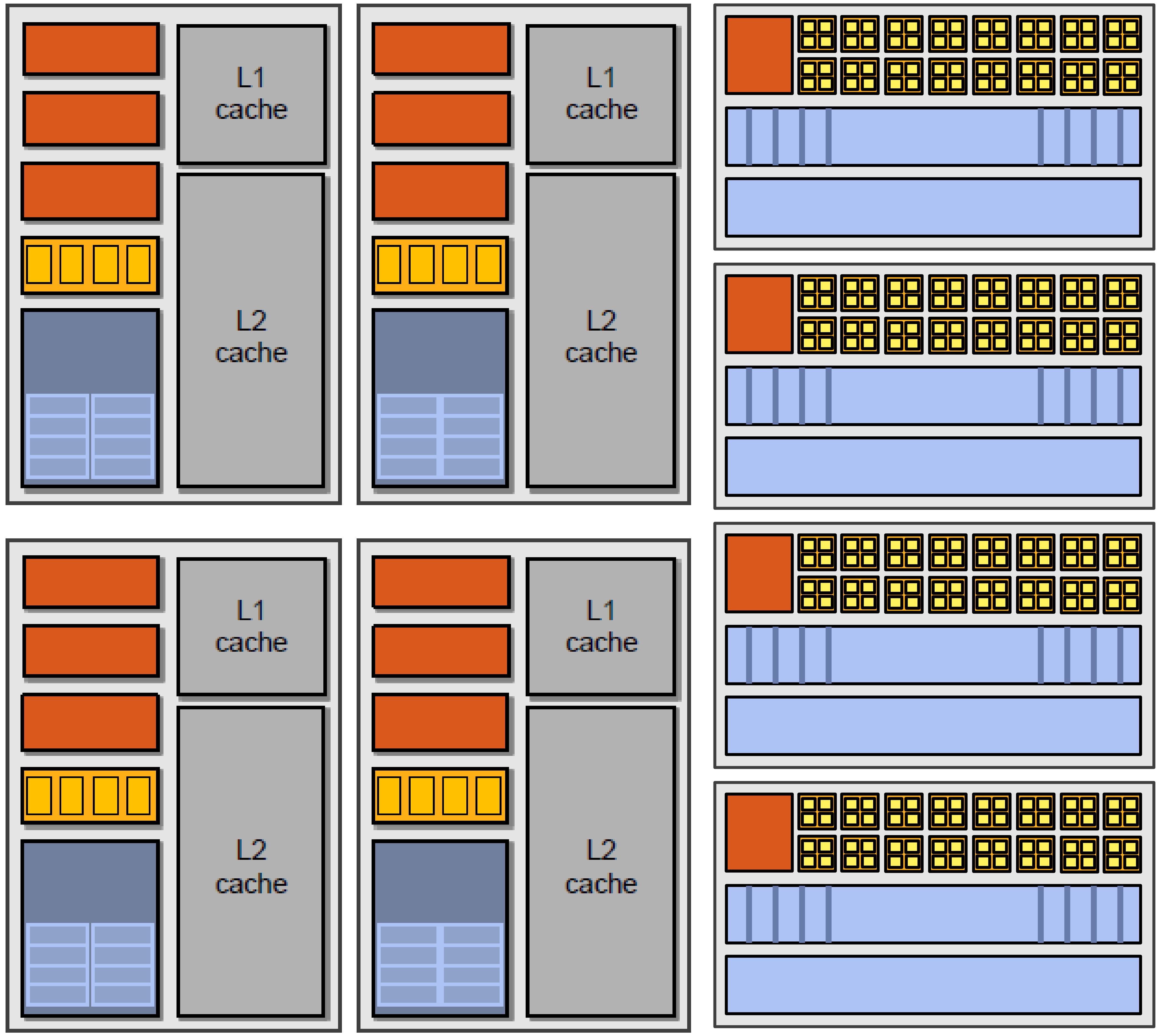
- Dispatch latency
  - O(10) usec to dispatch from CPU to GPU
  - This means offload cost if O(10M) instructions

Heterogeneous cores to the rescue ?

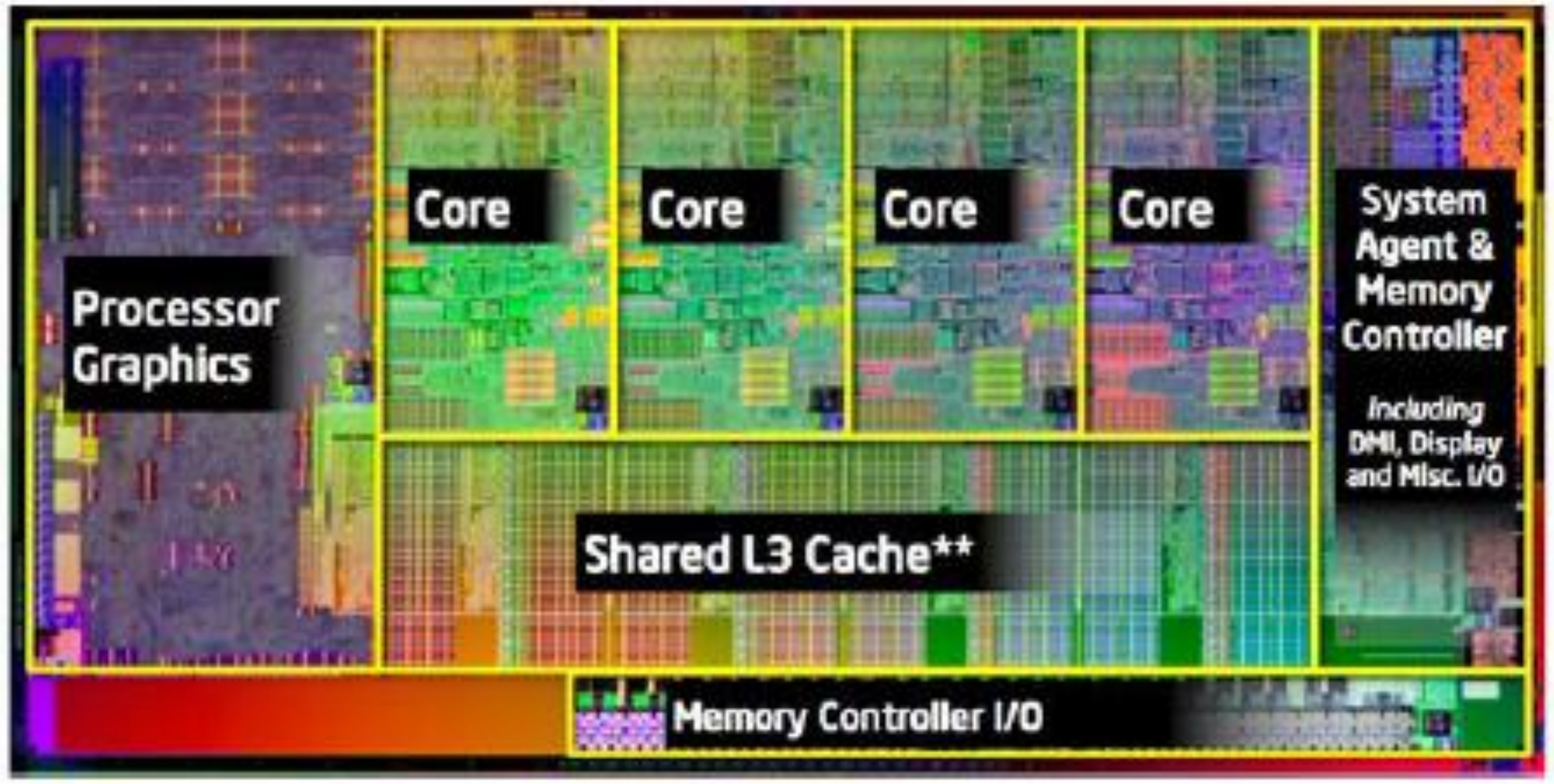
- Tighter integration of CPU and GPU style cores
  - Reduce offload cost
  - Reduce memory copies/transfers
  - Power management
- Industry shifting rapidly in this direction
  - AMD Fusion APUs
  - Intel SandyBridge
  - …
  - NVIDIA Tegra 2
  - Apple A4 and A5
  - QUALCOMM Snapdragon
  - TI OMAP
  - …

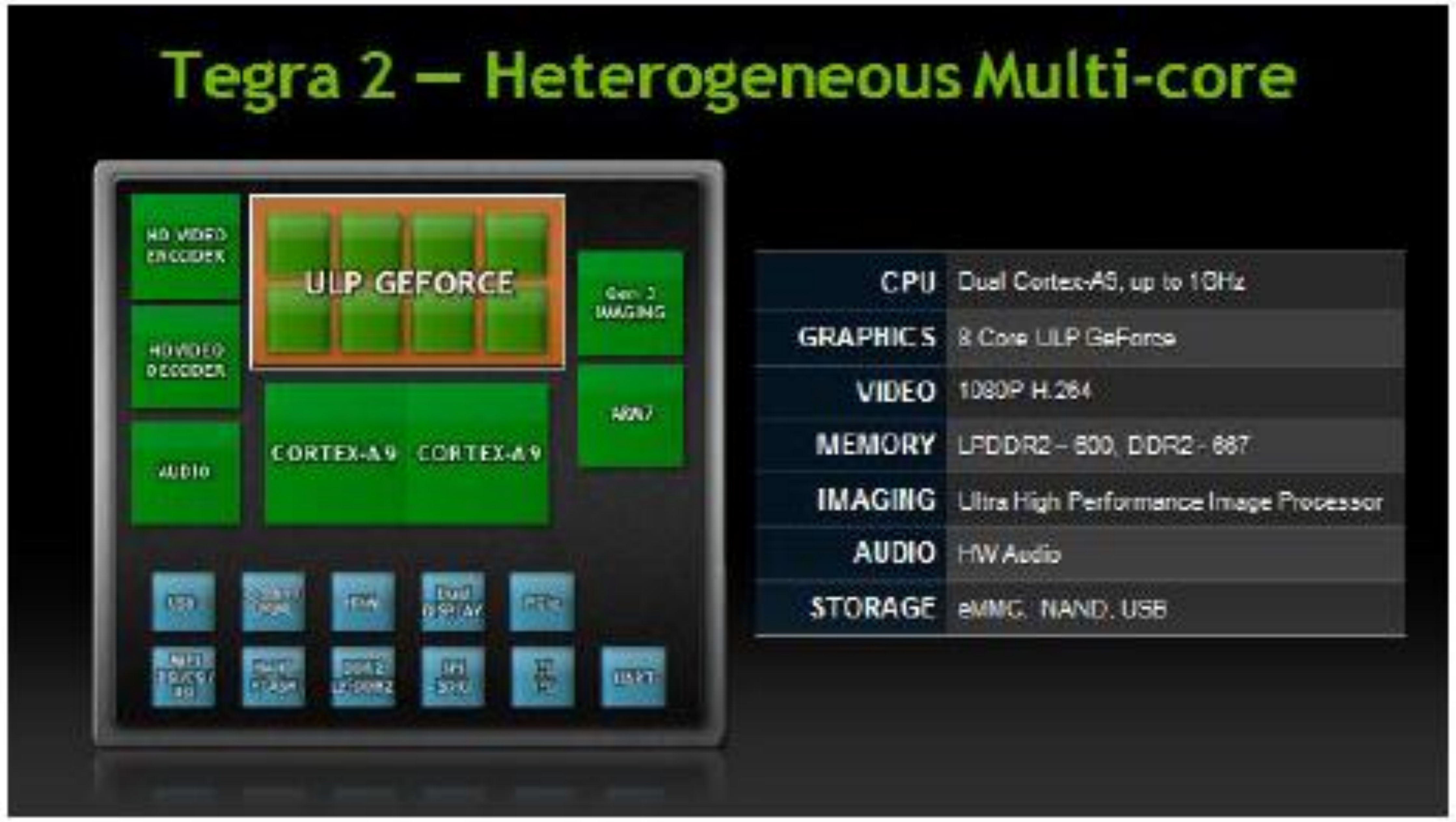
AMD A-Series APU (“Llano”)





Others – GPU is not compute ready, yet





Intel SandyBridge

NVIDIA Tegra 2