GPU Architecture and Programming with OpenCL

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Today's Topic

- GPU architecture
  - What and why
  - The good
  - The bad
- Compute Models for GPUs
  - Data-parallel
- OpenCL
  - Programming model
  - Memory model
  - Hello World
- Ideas for Ph.D. student projects

GPU Architecture: Why?

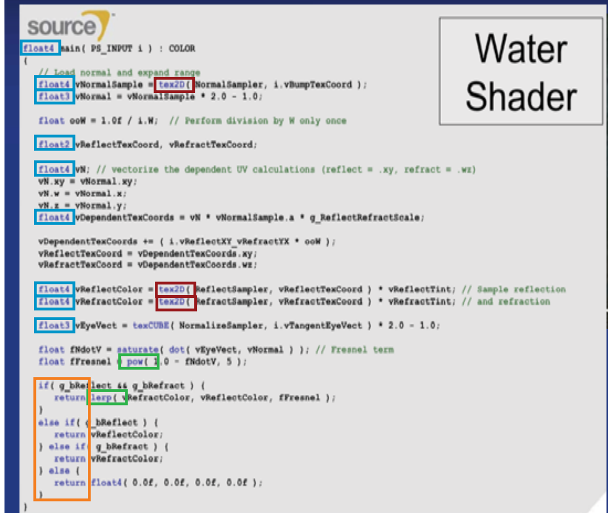
- Answer: Triangles
- Real Answer: Games
- Really Real Answer: Money

GPUs: Architectures for Drawing Triangles Fast

Images from caig.cs.nctu.edu.tw/course/CG2007

- Basic processing:
  - Project triangles into 2D
  - Find the pixels for each triangle
  - Determine color for each pixel
- Where is most of the work?
  - 10k triangles (30k vertices)
    - Project, clip, calculate lighting
  - 1920x1200 = 2.3M pixels
    - 8x oversampling = 18.4M pixels
    - 7 texture lookups
    - 43 shader ops
  - @ 60fps
    - Compute: 47.5 GOPs
    - Memory: 123GB/s
    - Intel Nehalem: 106 GFLOPs, 32GB/s

Example Shader: Water




```
float4 main( PS_INPUT i ) : COLOR
{
   // Load normal and expand range
   float4 vNormalSample = tex2D( NormalSampler, i.vBumpTexCoord );
   float3 vNormal = vNormalSample * 2.0 - 1.0;

   float ooW = 1.0f / i.W;  // Perform division by W only once

   float2 vReflectTexCoord, vRefractTexCoord;

   float4 vN; // vectorize the dependent UV calculations (reflect = .xy, refract = .wz)
   vN.xy = vNormal.xy;
   vN.w = vNormal.x;
   vN.z = vNormal.y;
   float4 vDependentTexCoords = vN * vNormalSample.a * g_ReflectRefractScale;

   vDependentTexCoords += ( i.vReflectXY_vRefractYX * ooW );
   vReflectTexCoord = vDependentTexCoords.xy;
   vRefractTexCoord = vDependentTexCoords.wz;

   float4 vReflectColor = tex2D( ReflectSampler, vReflectTexCoord ) * vReflectTint; // Sample reflection
   float4 vRefractColor = tex2D( RefractSampler, vRefractTexCoord ) * vRefractTint; // and refraction

   float3 vEyeVect = texCUBE( NormalizeSampler, i.vTangentEyeVect ) * 2.0 - 1.0;

   float fNdotV = saturate( dot( vEyeVect, vNormal ) ); // Fresnel term
   float fFresnel = pow( 1.0 - fNdotV, 5 );

   if( g_bReflect && g_bRefract ) {
      return lerp( vRefractColor, vReflectColor, fFresnel );
   }
   else if( g_bReflect ) {
      return vReflectColor;
   } else if( g_bRefract ) {
      return vRefractColor;
   } else {
      return float4( 0.0f, 0.0f, 0.0f, 0.0f );
   }
}
```

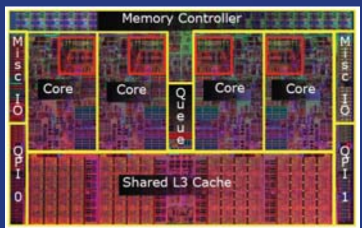
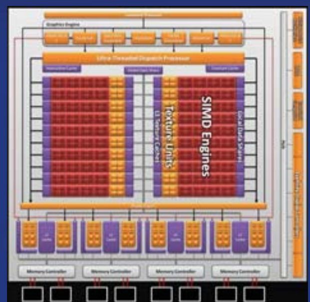
- Vectors
- Texture lookups
- Complex math
- Function calls
- Control flow
- No loops

From http://www2.ati.com/developer/gdc/D3DTutorial10_Half-Life2_Shading.pdf

GPGPU: General Purpose GPUs

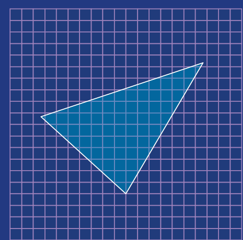
- Question: Can we use GPUs for non-graphics tasks?
- Answer: Yes!
  - They're incredibly fast and awesome
- Answer: Maybe
  - They're fast, but hard to program
- Answer: Not really
  - My algorithm runs slower on the GPU than on the CPU
- Answer: No
  - I need more precision/memory/synchronization/other

Why Should You Care?

Intel Nehalem 4-core	AMD Radeon 5870
	
130W, $263mm^2$ **32 GB/s** BW, **106 GFLOPs** (SP) Big caches (8MB) Out-of-order 0.8 GFLOPs/W	188W, $334mm^2$ **154 GB/s** BW, **2720 GFLOPs** (SP) Small caches (<1MB) Hardware thread scheduling 14.5 GFLOPs/W

GPU Design

1) Process pixels in parallel



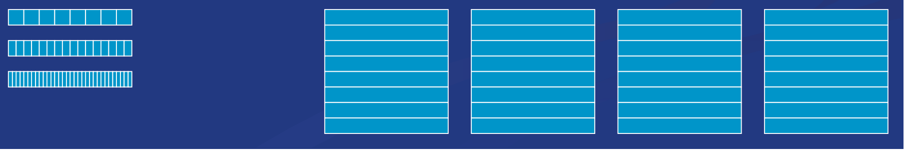
- Data-parallel:
  - 2.3M pixels per frame
    => lots of work
  - All pixels are independent
    => no synchronization
  - Lots of spatial locality
    => regular memory access
- Great speedups
  - Limited only by the amount of hardware

GPU Design

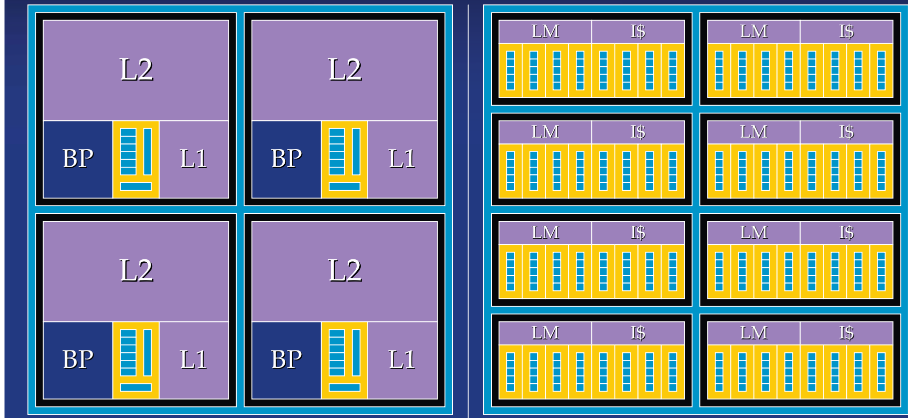
2) Focus on throughput, not latency

- Each pixel can take a long time…
  …as long as we process many at the same time.
- Great scalability
  - Lots of simple parallel processors
  - Low clock speed

Latency-optimized (fast, serial) Throughput-optimized (slow, parallel)



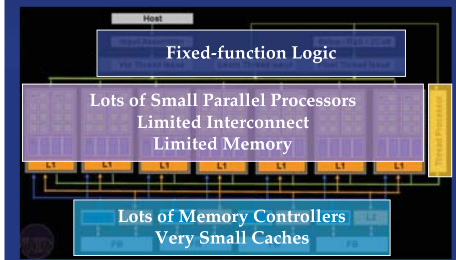
CPU vs. GPU Philosophy: Performance

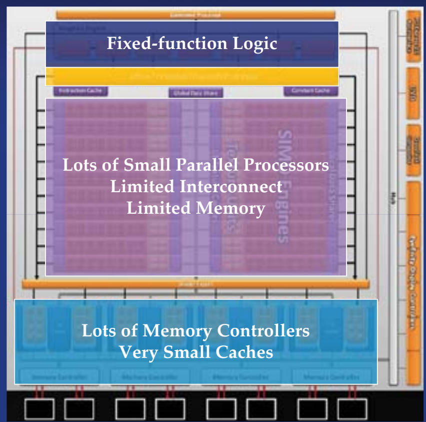


4 Massive CPU Cores: Big caches, branch predictors, out-of-order, multiple-issue, speculative execution, double-precision…
About 2 IPC per core, 8 IPC total @3GHz

8*8 Wimpy GPU Cores: No caches, in-order, single-issue, single-precision…
About 1 IPC per core, 64 IPC total @1.5GHz

Example GPUs





Nvidia G80 **AMD 5870**

CPU Memory Philosophy

Instructions

```
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
b= a+1
```

CPU Memory Philosophy

Instructions

g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
b= a+1

+

ld/st

Cycle 0

CPU Memory Philosophy

Instructions

g= f+1
f=ld(e)
d= d+1
c= b+a

+
b= a+1

ld/st
e=ld(d)

Cycle 0

CPU Memory Philosophy

Instructions

g= f+1
f=ld(e)
d= d+1
c= b+a

+
b= a+1

ld/st
e=ld(d)

Memory access will take ~100 cycles…

Cycle 0

CPU Memory Philosophy

Instructions

g= f+1
f=ld(e)
d= d+1
c= b+a

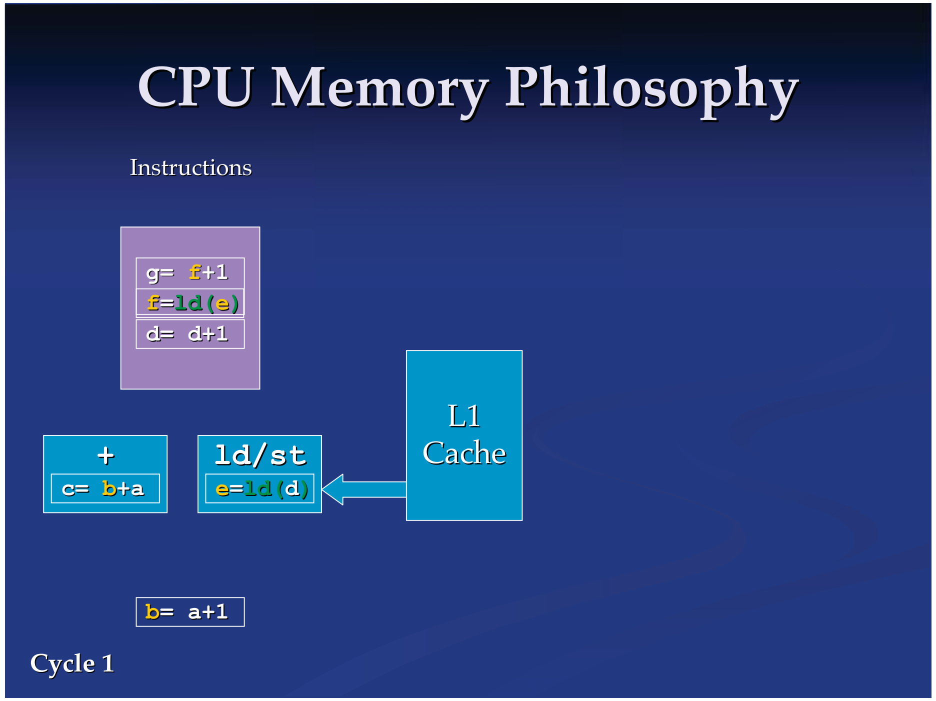
+
b= a+1

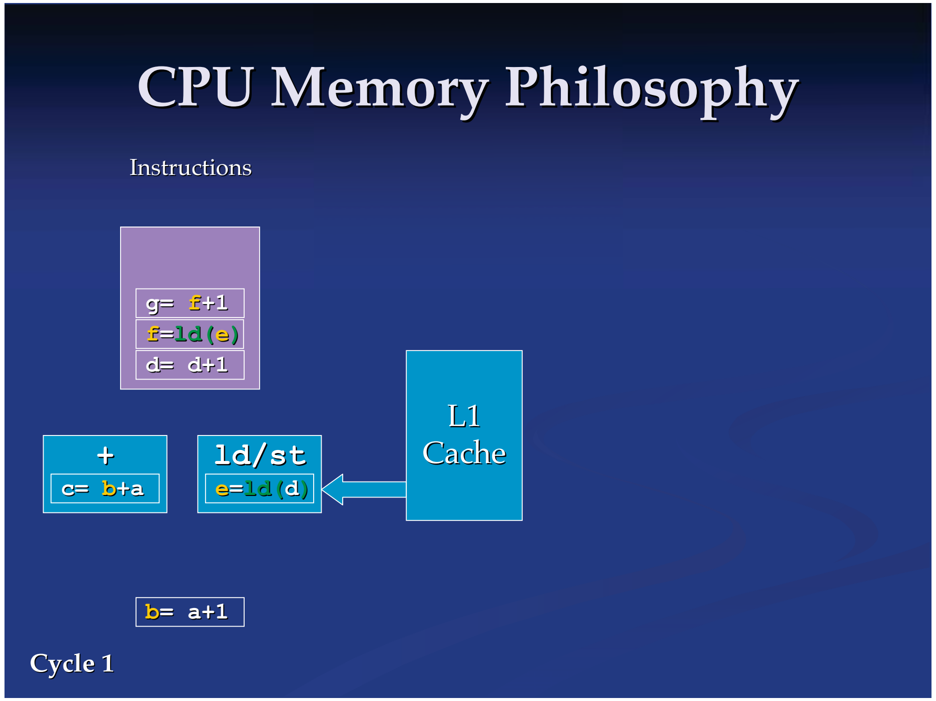
ld/st
e=ld(d)

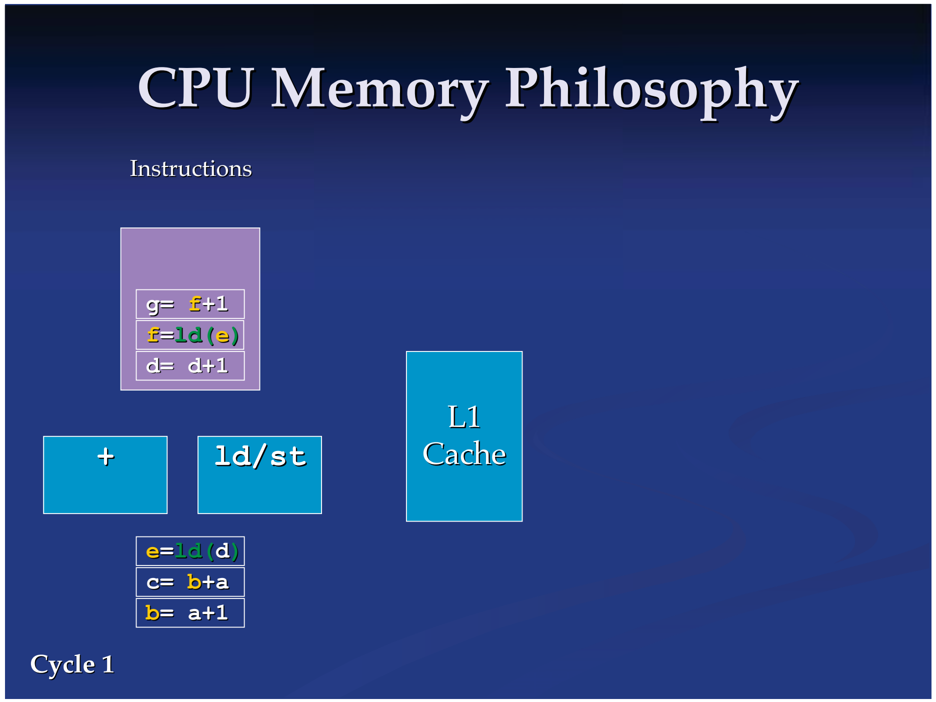
L1
Cache

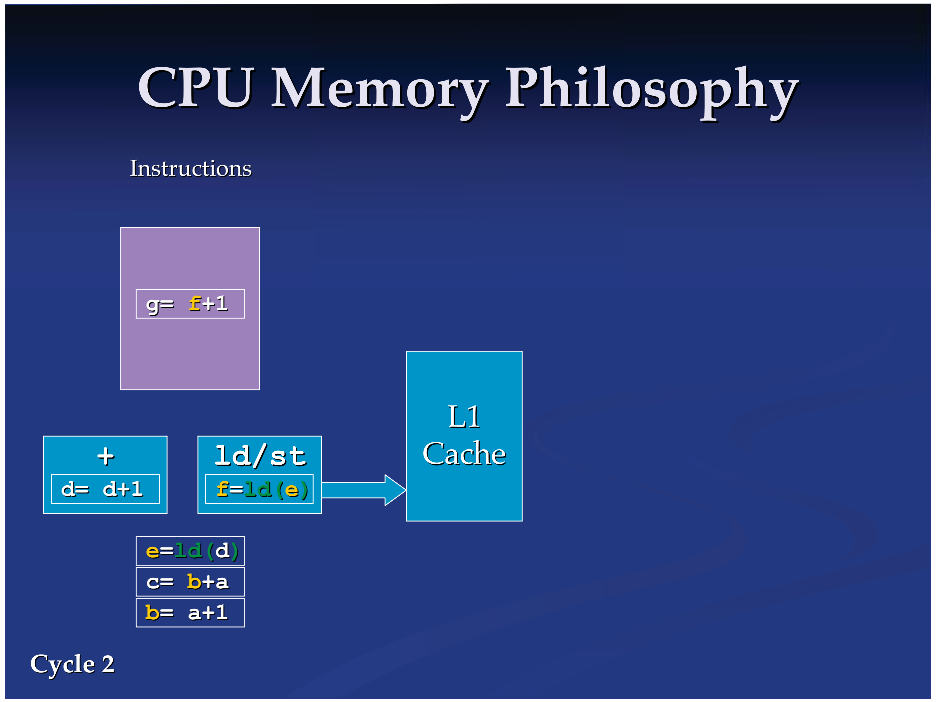
Hit!

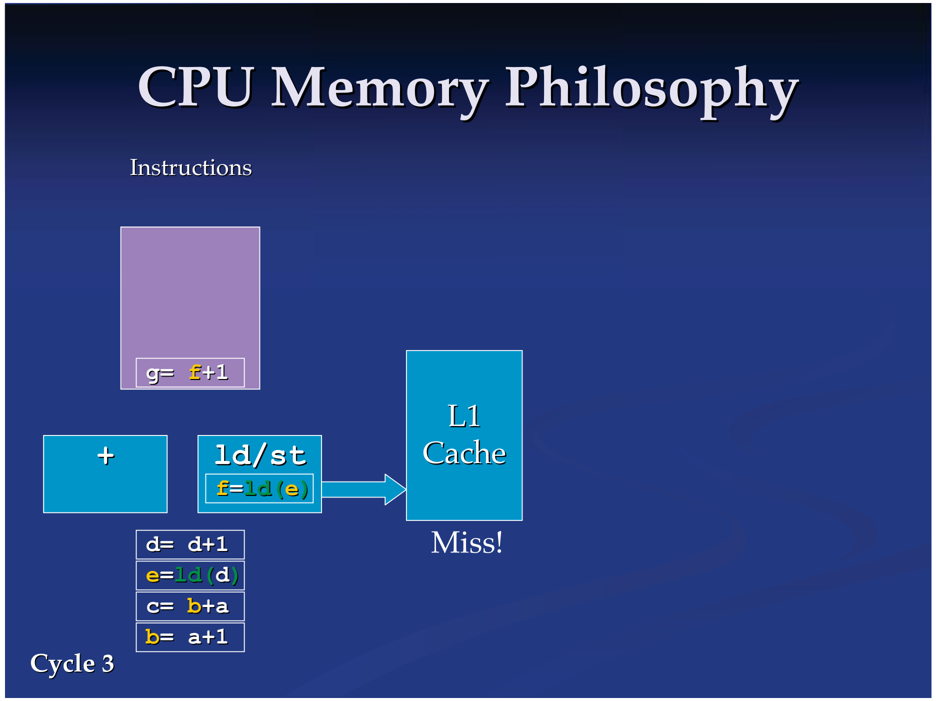
Cycle 0

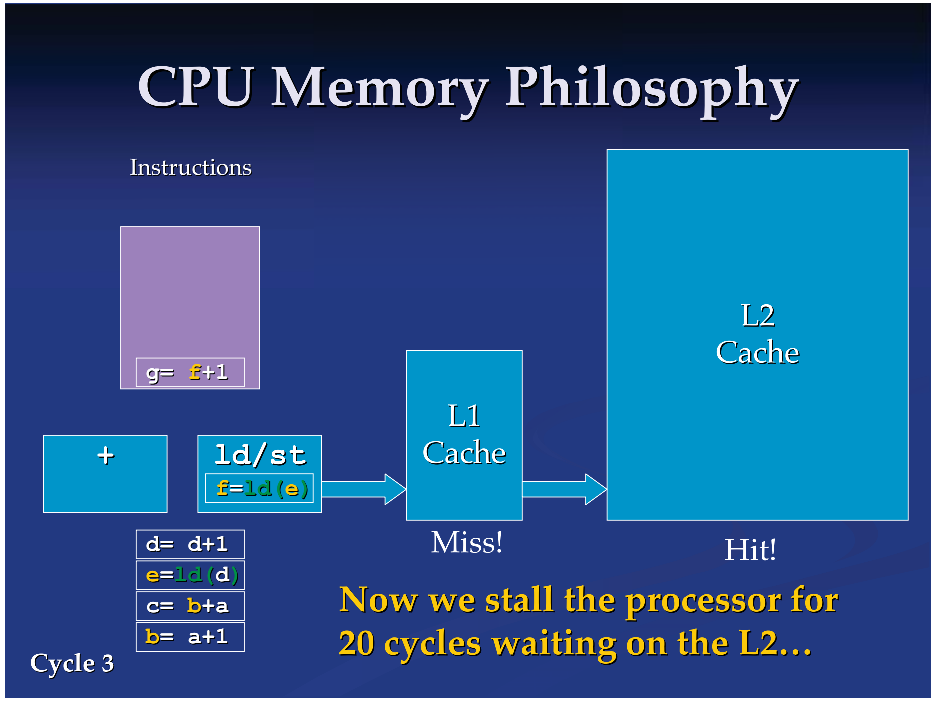

CPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
+
c= b+a
ld/st
e=ld(d)
L1
Cache
b= a+1
Cycle 1

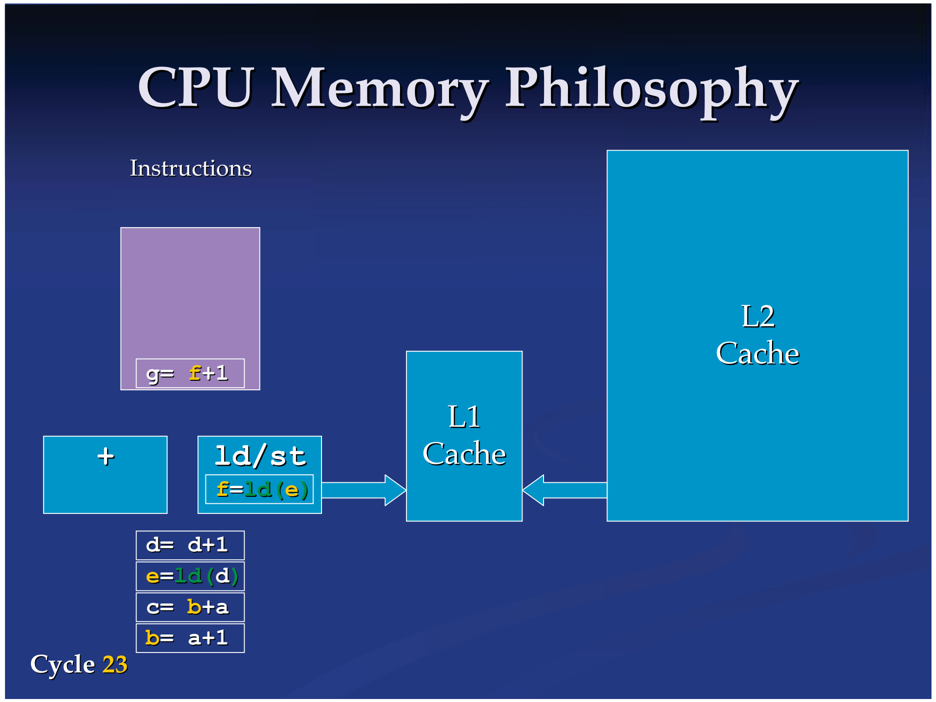

CPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
+
c= b+a
ld/st
e=ld(d)
L1
Cache
b= a+1
Cycle 1

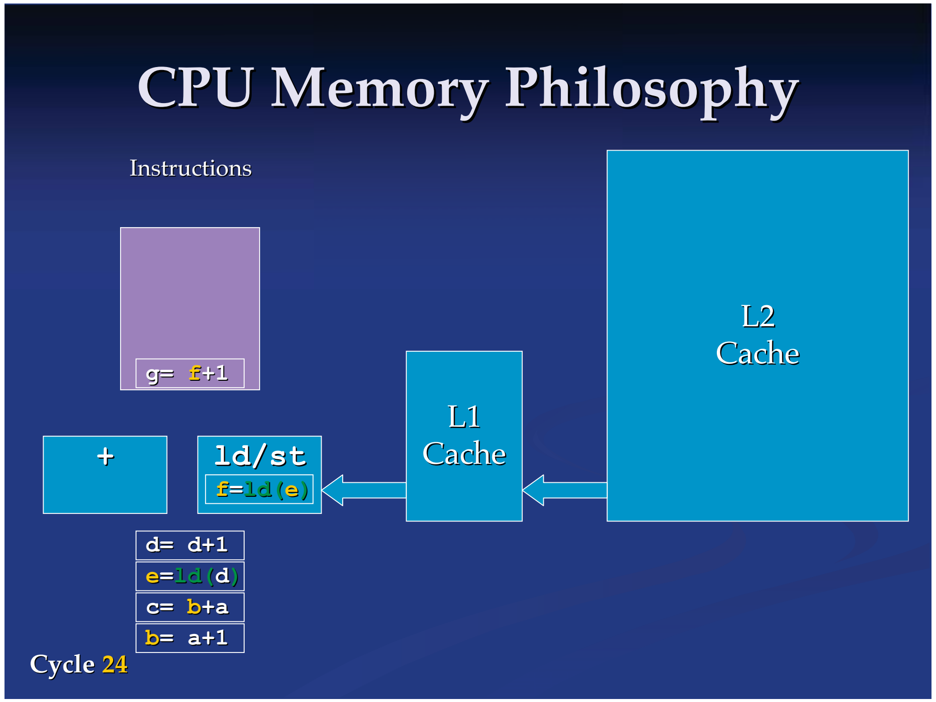

CPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
+
ld/st
L1
Cache
e=ld(d)
c= b+a
b= a+1
Cycle 1


CPU Memory Philosophy
Instructions
g= f+1
+
d= d+1
ld/st
f=ld(e)
L1
Cache
e=ld(d)
c= b+a
b= a+1
Cycle 2

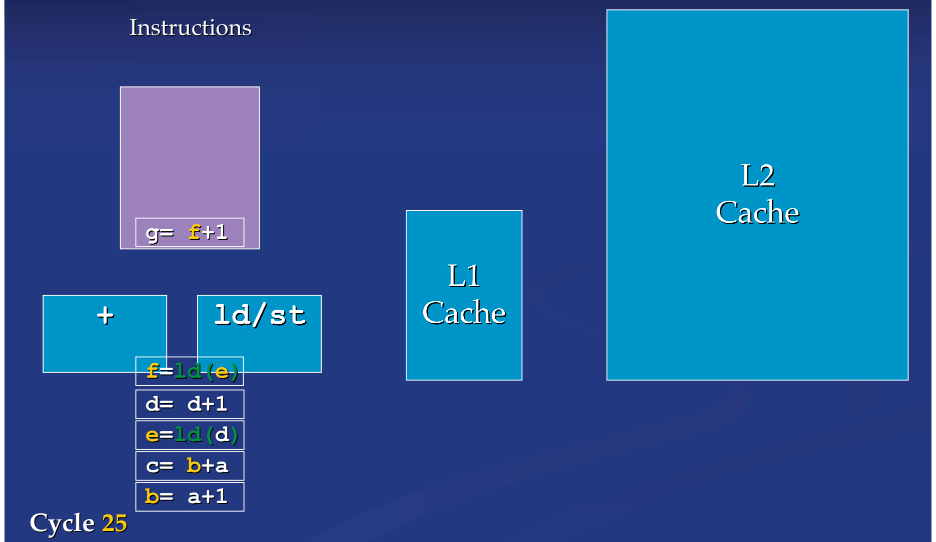

CPU Memory Philosophy
Instructions
g= f+1
+
ld/st
f=ld(e)
L1
Cache
Miss!
d= d+1
e=ld(d)
c= b+a
b= a+1
Cycle 3


CPU Memory Philosophy
Instructions
g= f+1
+
ld/st
f=ld(e)
L1
Cache
Miss!
L2
Cache
Hit!
d= d+1
e=ld(d)
c= b+a
b= a+1
Now we stall the processor for
20 cycles waiting on the L2…
Cycle 3

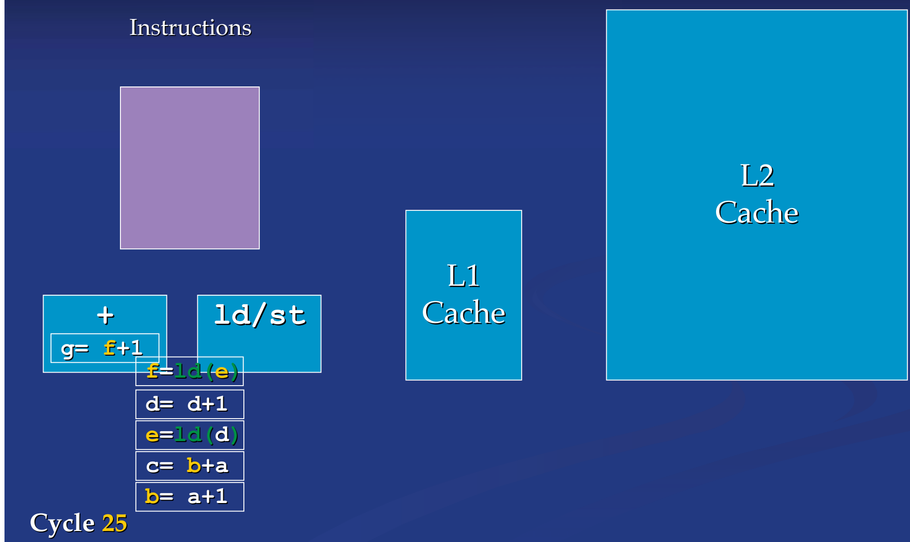

CPU Memory Philosophy
Instructions
g= f+1
+
ld/st
f=ld(e)
L1
Cache
L2
Cache
d= d+1
e=ld(d)
c= b+a
b= a+1
Cycle 23


CPU Memory Philosophy
Instructions
g= f+1
+
ld/st
f=ld(e)
L1
Cache
L2
Cache
d= d+1
e=ld(d)
c= b+a
b= a+1
Cycle 24

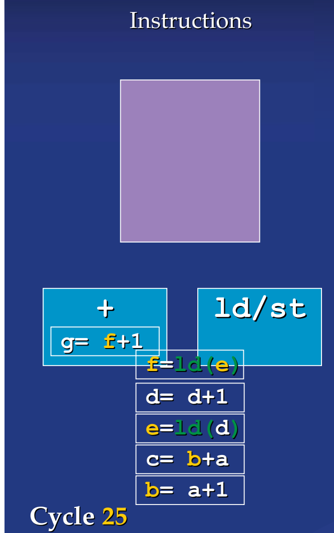
CPU Memory Philosophy



CPU Memory Philosophy

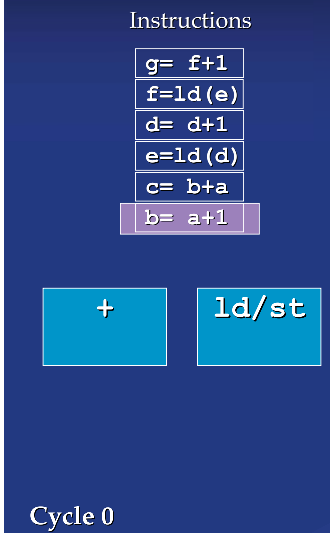


CPU Memory Philosophy



- Big caches + instruction window + out-of-order + multiple-issue
- Approach
  - **Reduce** memory latencies **with caches**
  - **Hide** memory latencies **with other instructions**
- As long as you **hit in the cache** you get **good performance**

GPU Memory Philosophy



GPU Memory Philosophy

Instructions

```
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
```

```
+        ld/st
b= a+1
```

Cycle 0

GPU Memory Philosophy

Instructions

```
g= f+1
f=ld(e)
d= d+1
e=ld(d)
```

```
+        ld/st
c= b+a
```

```
b= a+1
```

Cycle 1

GPU Memory Philosophy

Instructions

Solution: Give Up

```
g= f+1
f=ld(e)
d= d+1
```

```
+        ld/st
         e=ld(d)
```

No cache ~ 100+ cycles

Memory

```
c= b+a
b= a+1
```

Cycle 2

GPU Memory Philosophy

Instructions

```
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
b= a+1
```

```
g= f+1
f=ld(e)
d= d+1
```

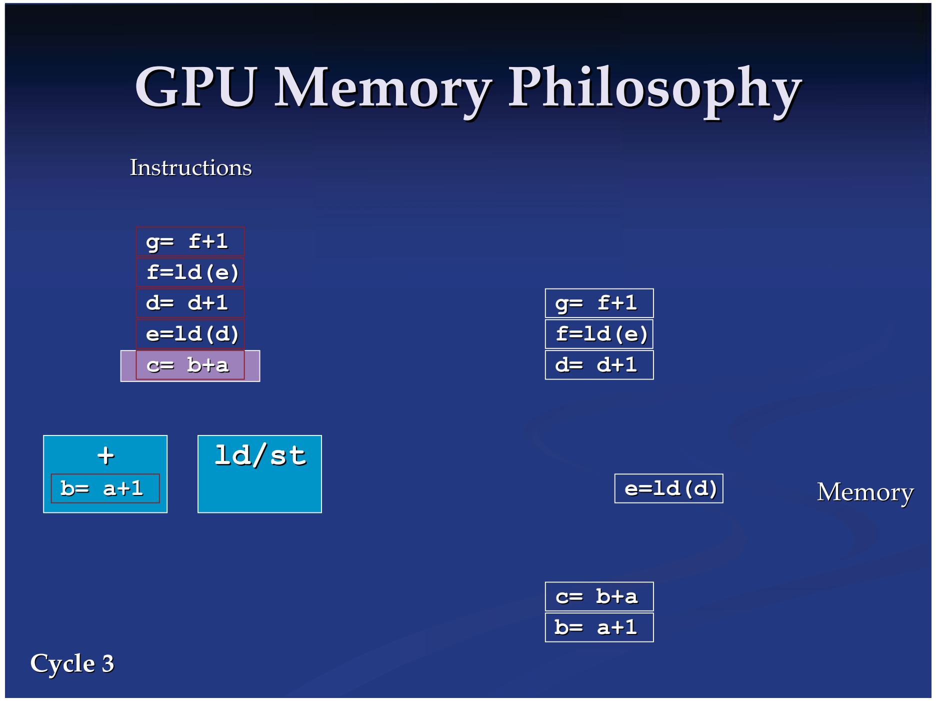
```
+        ld/st
```

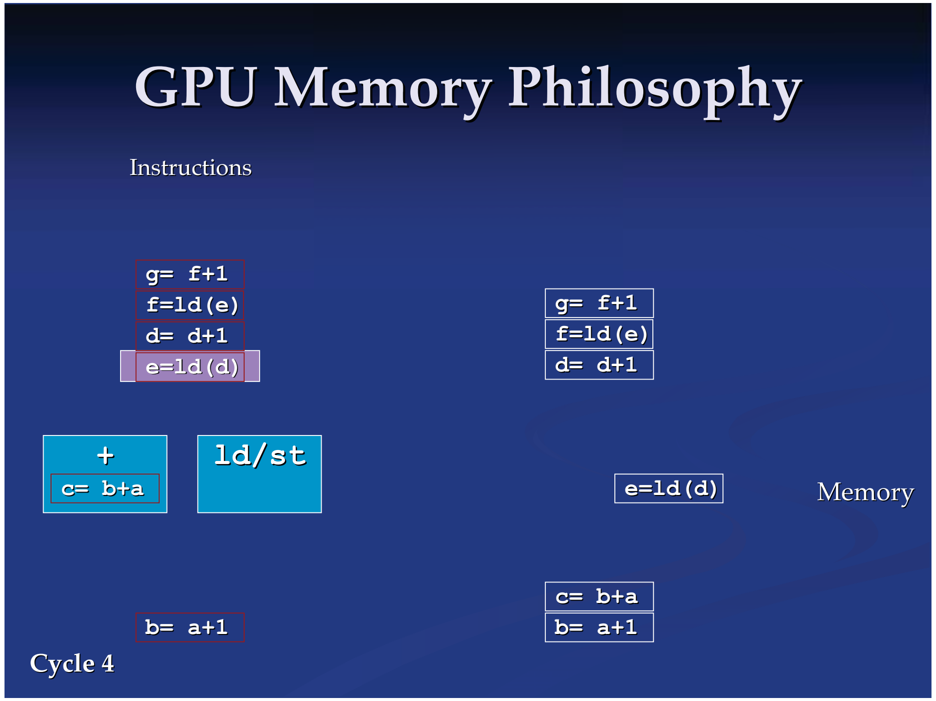
```
e=ld(d)
```

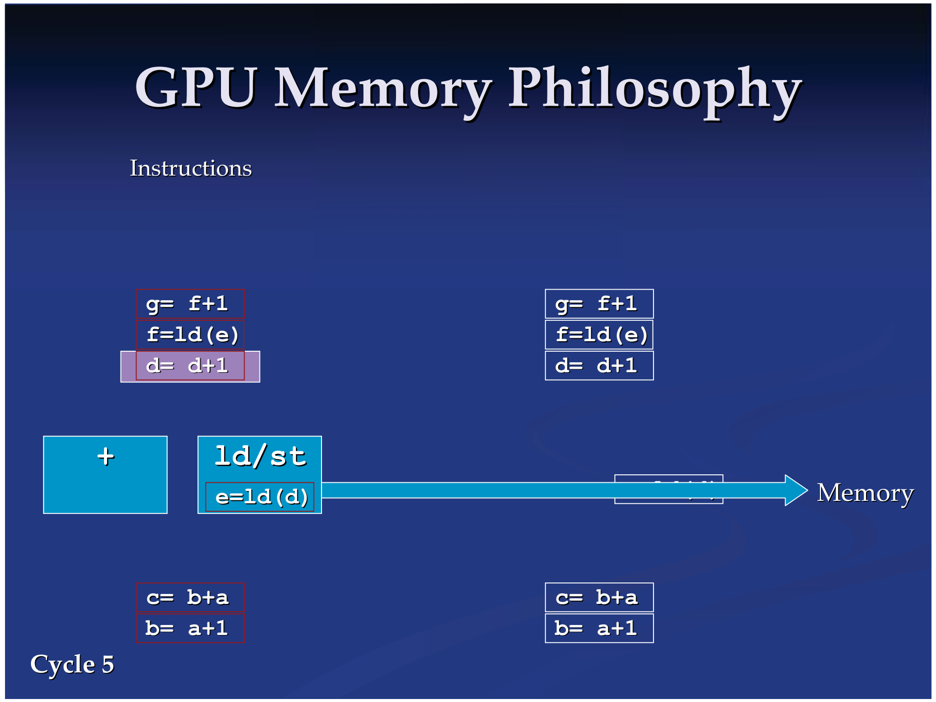
Memory

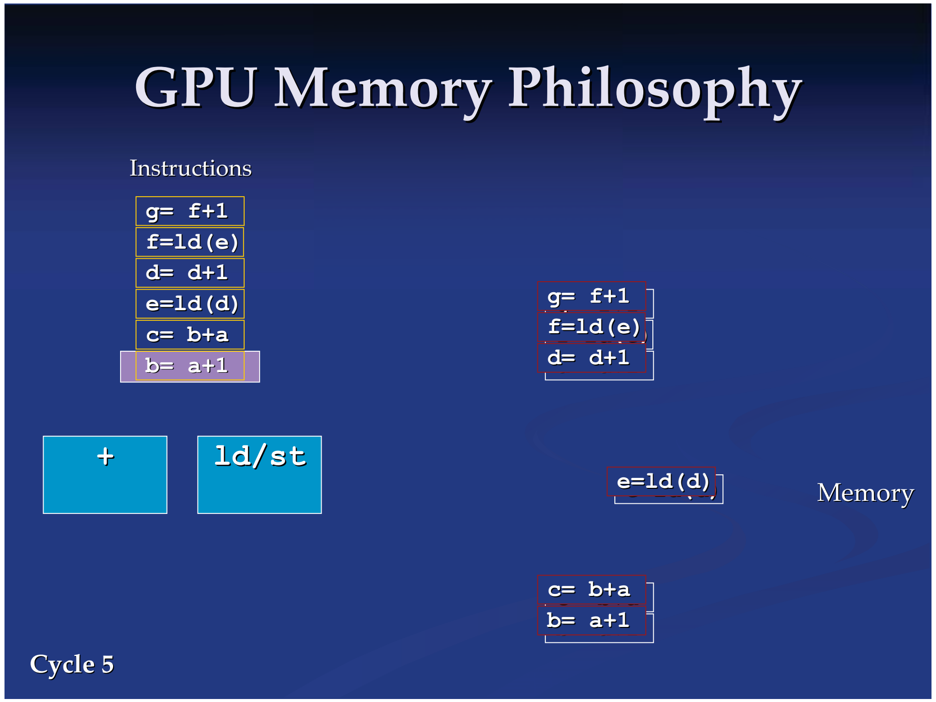
```
c= b+a
b= a+1
```

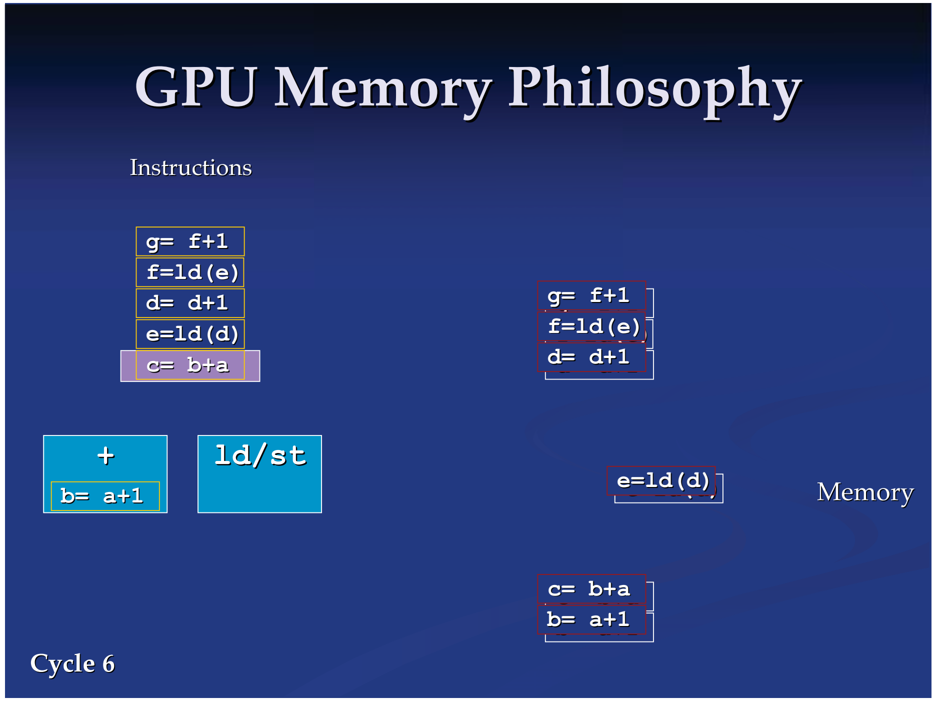
Cycle 2

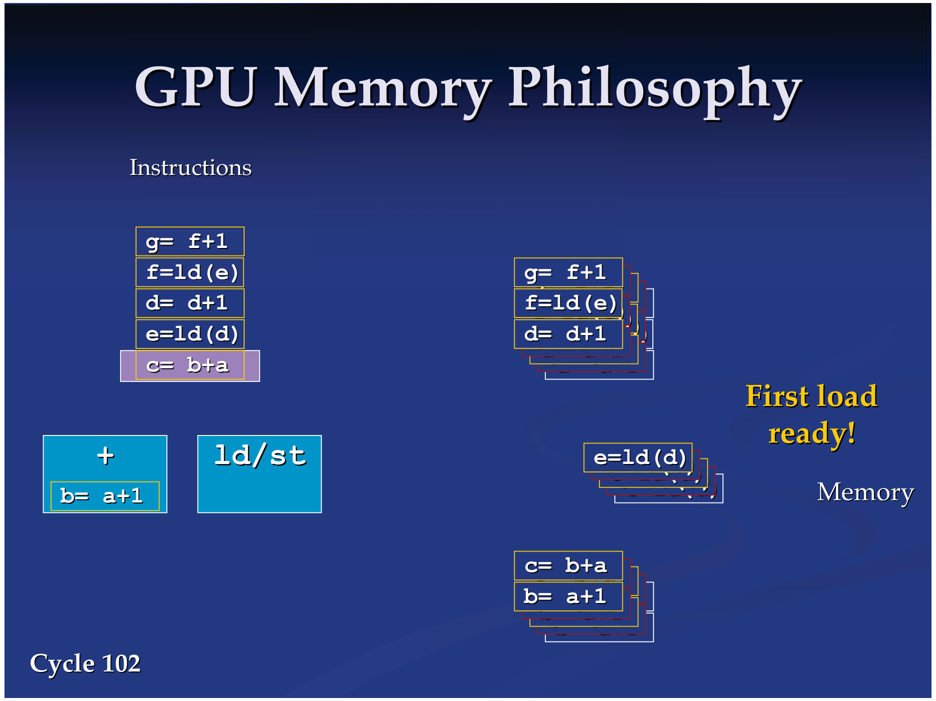

GPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
g= f+1
f=ld(e)
d= d+1
+
b= a+1
ld/st
e=ld(d)
Memory
c= b+a
b= a+1
Cycle 3

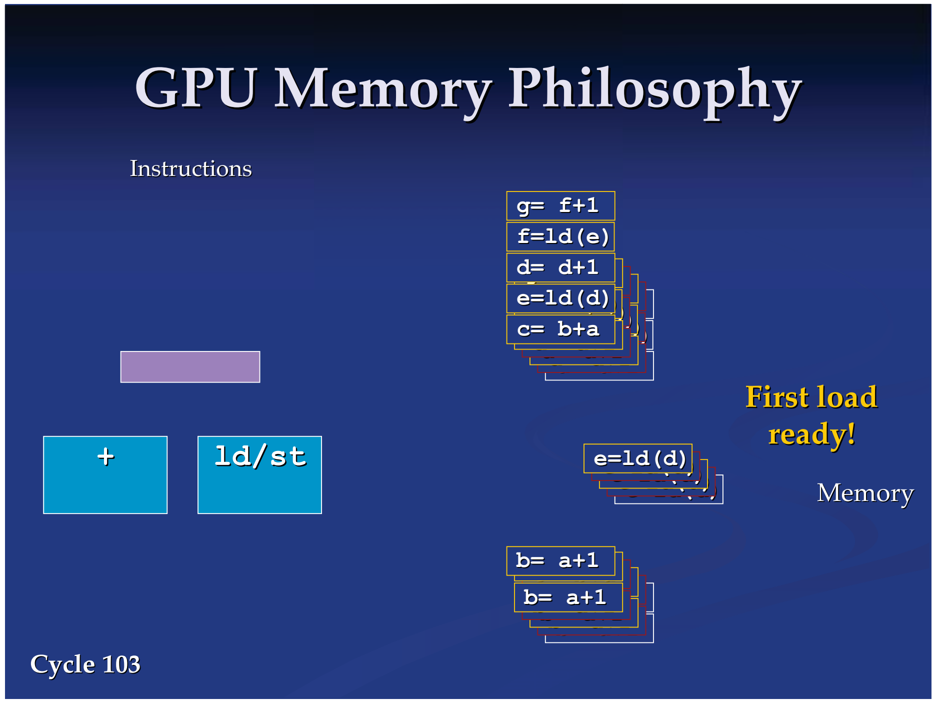

GPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
e=ld(d)
g= f+1
f=ld(e)
d= d+1
+
c= b+a
ld/st
e=ld(d)
Memory
b= a+1
c= b+a
b= a+1
Cycle 4

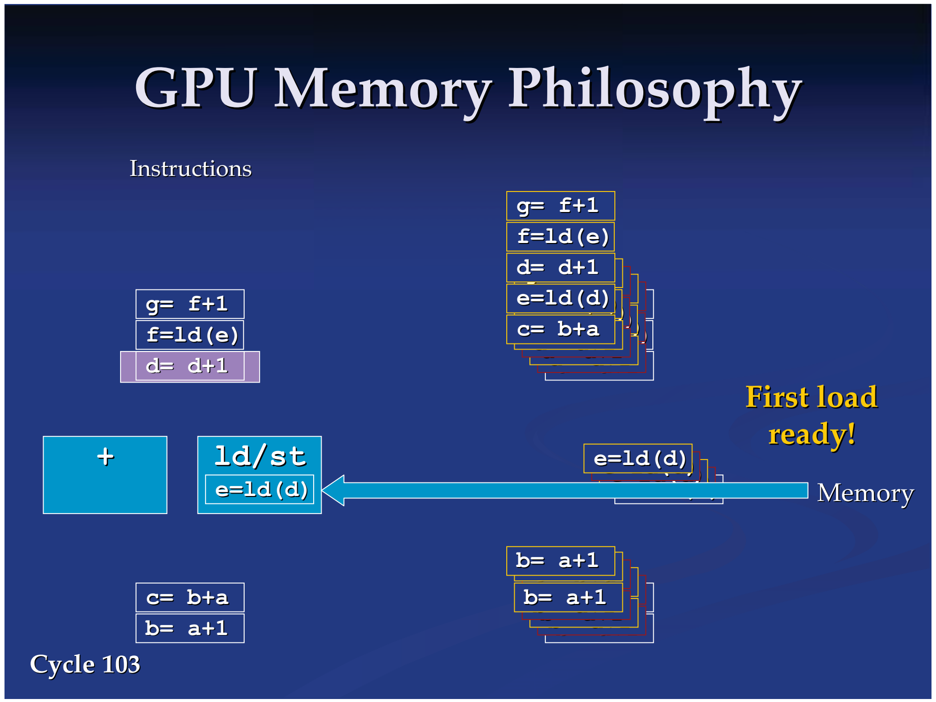

GPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
g= f+1
f=ld(e)
d= d+1
+
ld/st
e=ld(d)
Memory
c= b+a
b= a+1
c= b+a
b= a+1
Cycle 5


GPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
b= a+1
g= f+1
f=ld(e)
d= d+1
+
ld/st
e=ld(d)
Memory
c= b+a
b= a+1
Cycle 5

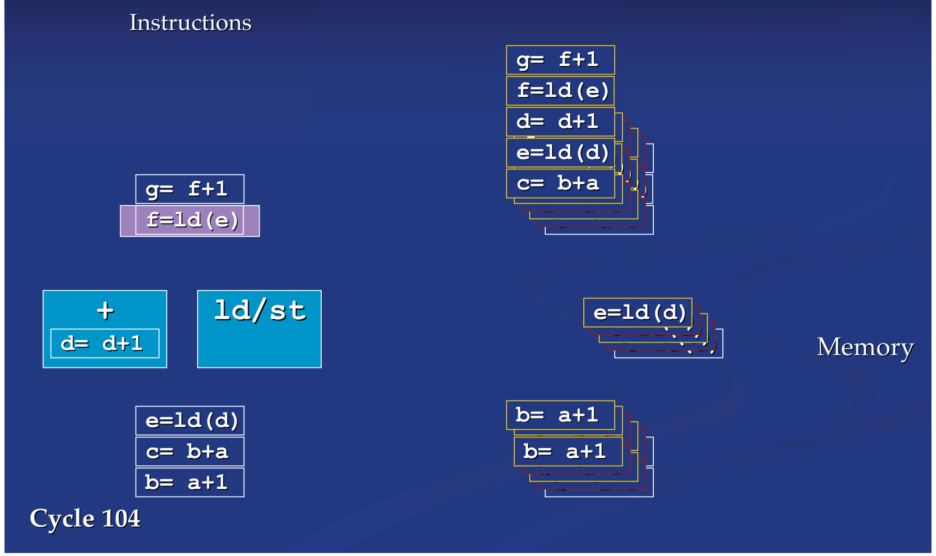

GPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
+
b= a+1
ld/st
g= f+1
f=ld(e)
d= d+1
e=ld(d)
Memory
c= b+a
b= a+1
Cycle 6


GPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
+
b= a+1
ld/st
g= f+1
f=ld(e)
d= d+1
First load ready!
e=ld(d)
Memory
c= b+a
b= a+1
Cycle 102


GPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
First load ready!
+
ld/st
e=ld(d)
Memory
b= a+1
b= a+1
Cycle 103

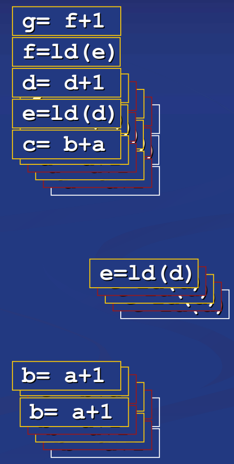

GPU Memory Philosophy
Instructions
g= f+1
f=ld(e)
d= d+1
e=ld(d)
c= b+a
g= f+1
f=ld(e)
d= d+1
First load ready!
+
ld/st
e=ld(d)
e=ld(d)
Memory
b= a+1
b= a+1
c= b+a
b= a+1
Cycle 103

GPU Memory Philosophy



GPU Memory Philosophy

- Thousands of hardware threads
- 1 cycle context switching
- Hardware thread scheduling
- As long as there is **enough work** in other threads **to cover latency** you get **high throughput**.

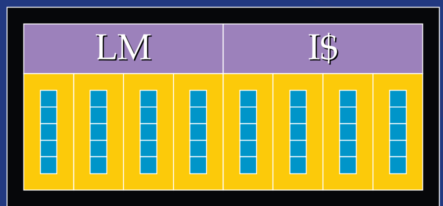


Notes:
- GPUs have caches for textures
- GPUs will soon have data caches

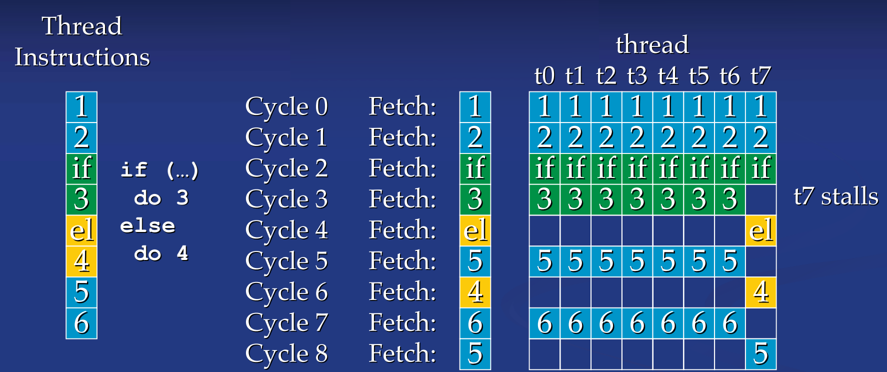
GPU Instruction Bandwidth

- GPU compute units fetch 1 instruction per cycle…

  …and share it with 8 processor cores.
- What if they don't all want the same instruction? (divergent execution)



Divergent Execution



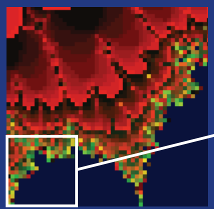
Divergent execution can dramatically hurt performance. Avoid it on GPUs today.

Divergent Execution for Real

Per-pixel Mandelbrot calculation:

```
while (x*x + y*y <= (4.0f) && iteration < max_iterations) {
 float xtemp = x*x - y*y + x0;
 y = 2*y*x + y0;
 x = xtemp;
 iteration++;
}
color = iteration;
```

Color determined by iteration count…
…each color took a different number of iterations.



Every different color is a divergent execution of a work-item.

Instruction Divergence

- Some architectures are worse…
  - AMD's GPUs are 4-way SIMD
    If you don't process 4-wide vectors you lose.
  - Intel's Larabee is(was?) 16-way SIMD
    Theoretically the compiler can handle this.
- Some architectures are getting better…
  - Nvidia Fermi can fetch 2 instructions per cycle
  - But it has twice as many cores
- In general:
  - Data-parallel will always be fastest
  - Penalty for control-flow varies from none to huge

CPU and GPU Architecture

- GPUs are throughput-optimized
  - Each thread may take a long time, but thousands of threads
- CPUs are latency-optimized
  - Each thread runs as fast as possible, but only a few threads

- GPUs have hundreds of wimpy cores
- CPUs have a few massive cores

- GPUs excel at regular math-intensive work
  - Lots of ALUs for math, little hardware for control
- CPUs excel at irregular control-intensive work
  - Lots of hardware for control, few ALUs

OpenCL

What is OpenCL?

Low-level language for high-performance heterogeneous data-parallel computation.

- Access to all compute devices in your system:
  - CPUs
  - GPUs
  - Accelerators (e.g., CELL)
- Based on C99
- Portable across devices
- Vector intrinsics and math libraries
- Guaranteed precision for operations
- Open standard

Demo

What is OpenCL Good For?

- Anything that is:
  - Computationally intensive
  - Data-parallel
  - Single-precision*

Note: I am going to focus on the GPU

*This is changing, the others are not.

Computational Intensity

- Proportion of **math** ops : **memory** ops
  Remember: memory is slow, math is fast
- Loop body: Low-intensity:

```
A[i] = B[i] + C[i]              1:3
A[i] = B[i] + C[i] * D[i]       2:4
A[i]++                          1:2
```

- Loop body: High(er)-intensity:

```
Temp+= A[i]*A[i]          2:1
A[i] = exp(temp)*erf(temp)     X:1
```

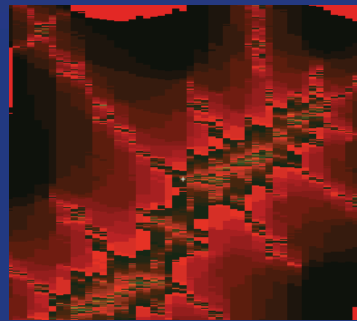
Data-Parallelism

- Same *independent* operations on lots of data*
- Examples:
  - Modify every pixel in an image with *the same* filter
  - Update every point in a grid using *the same* formula

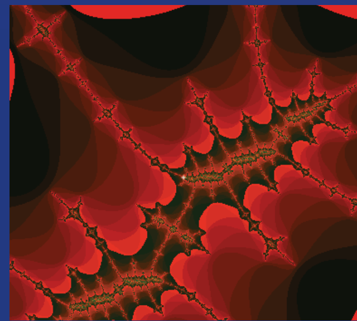
*Performance may fall off a cliff if not exactly the same.

Single Precision

32 bits should be enough for anything…



Single Precision



Double Precision

This is changing. Expect double precision everywhere in 2 years.

OpenCL Compute Model

- Parallelism is defined by the 1D, 2D, or 3D global dimensions for each kernel execution
- A work-item is executed for every point in the global dimensions
- Examples

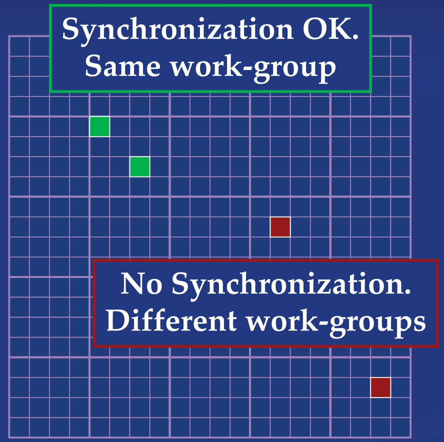
1k audio:	1024	1024 work-items
HD video:	1920x1080	2M work-items
3D MRI:	256x256x256	16M work-items
HD per line:	1080	1080 work-items
HD per 8x8 block:	240x135	32k work-items

Local Dimensions

- The global dimensions are broken down into **local work-groups**
- Each work-group is logically executed together on one compute unit
- Synchronization is **only** allowed between **work-items in the same work-group**

This is important.

Local Dimensions and Synchronization

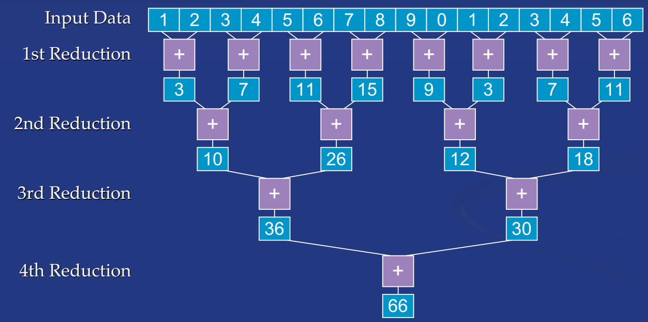


Global domain: 20x20
Work-group size: 4x4

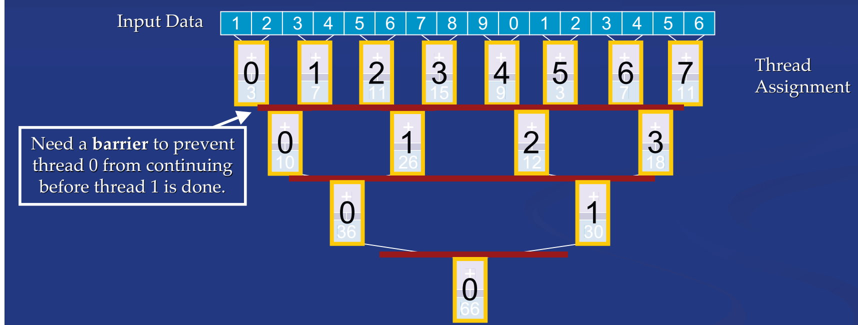
Work-group size limited by hardware. (~512)

Implications for algorithms: e.g., reduction size.

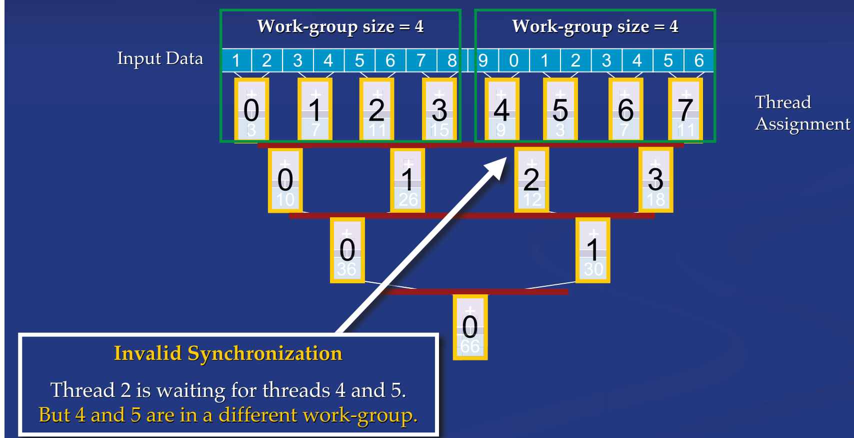
Synchronization Example: Reduction



Synchronization Example: Reduction

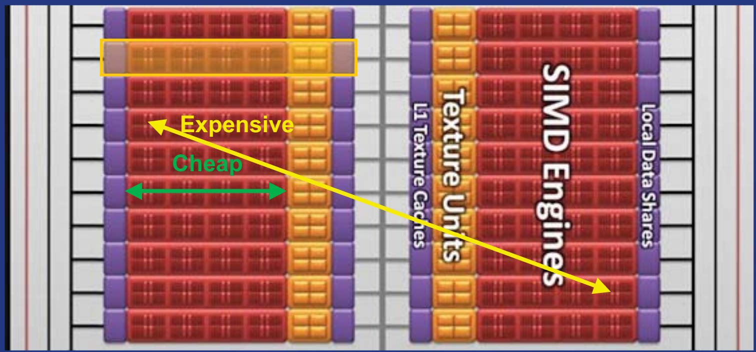


Synchronization Example: Reduction



Why Limited Synchronization?

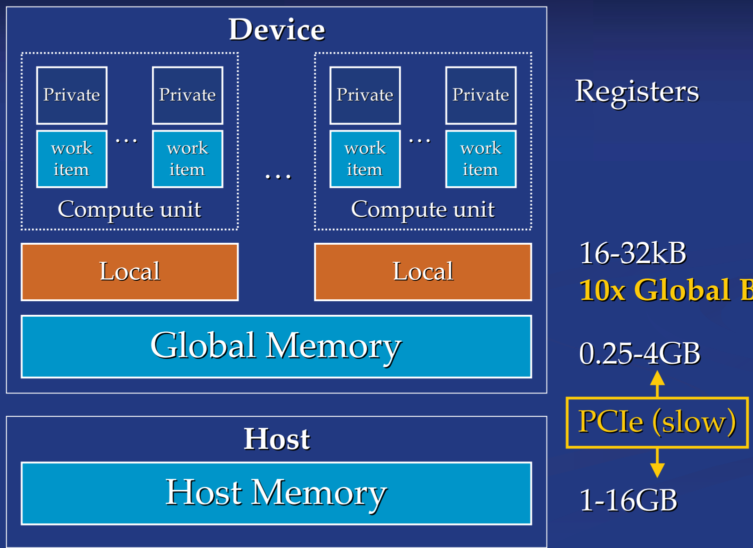
- Scales well in hardware
  - Only work-items within a work-group need to communicate
  - GPUs run 32-128 work-groups in parallel



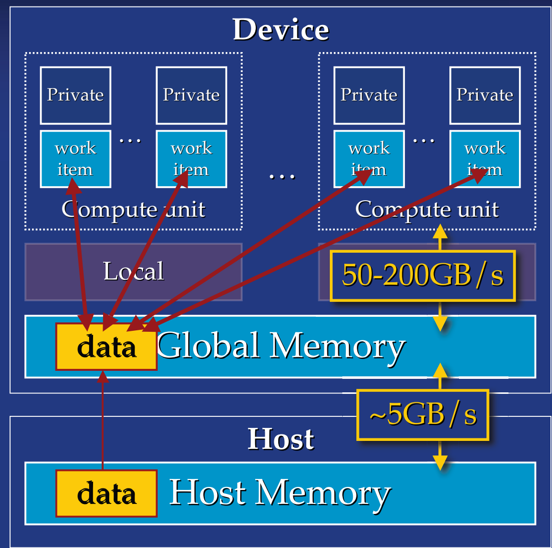
Choosing Local and Global Dimensions

- **Global dimensions**
  - Natural division for the problem
  - Too few: no latency hiding
  - Too many: (too little work each) too much overhead
  - In general:
    - GPU: >2000
    - CPU: ~2*#CPU cores
- **Local dimensions**
  - May be determined by the algorithm
  - Optimize for best processor utilization (hardware-specific)

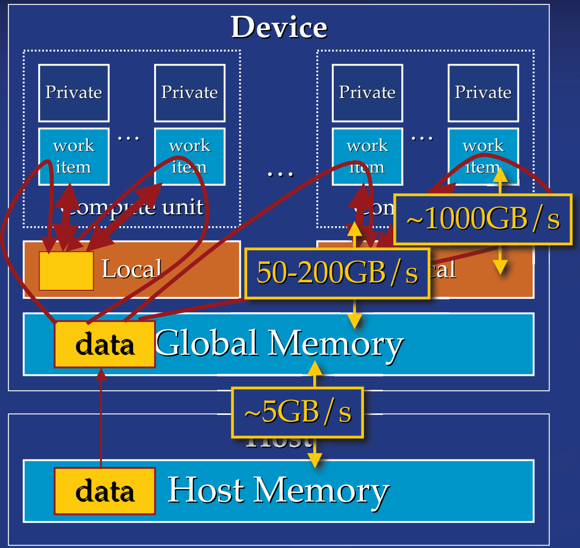
OpenCL Memory Model



OpenCL Memory Model



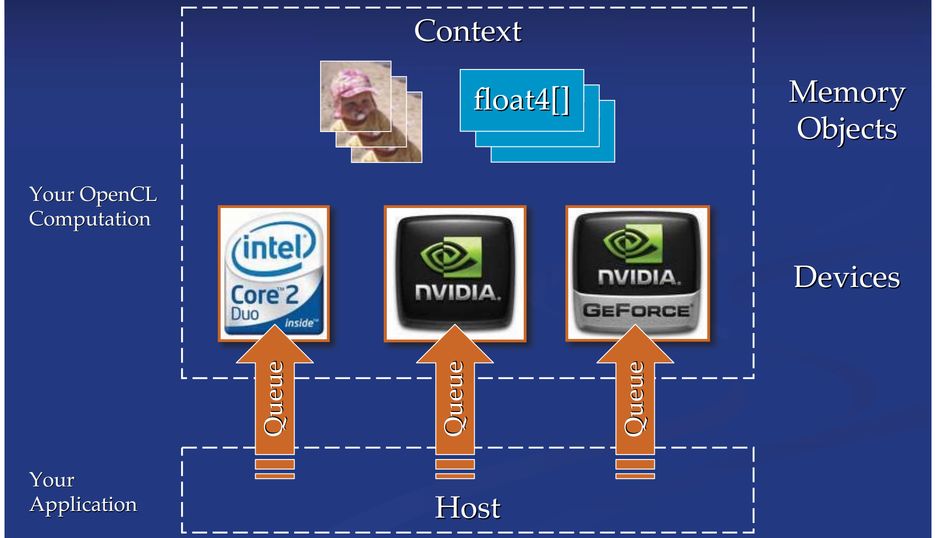
OpenCL Memory Model



Moving Data

- No automatic data movement
- You must explicitly:
  - **Allocate** global data
  - **Write** to it from the host
  - **Allocate** local data
  - **Copy** data from global to local (and back)
- But…
  - You get full control for performance! (Isn't this great?)

OpenCL Execution Model



OpenCL Execution Model

- Devices
  - CPU, GPU, Accelerator
- Contexts
  - A collection of devices that share data
- Queues
  - Submit (enqueue) work to devices

- Notes:
  - Queues are asynchronous with respect to each other
  - No automatic distribution of work across devices

OpenCL Kernels

- A unit of code that is executed in parallel
- C99 syntax (no recursion or function ptrs)
- Think of the kernel as the "inner loop"

```
Regular C:

void calcSin(float *data) {
  for (int id=0; id<1023; id++)
    data[id] = sin(data[id]);
}
```

```
OpenCL Kernel:

void kernel calcSin(global float *data) {
  int id = get_global_id(0);
  data[id] = sin(data[id]);
}
```

An OpenCL Program

1. Get the devices
2. Create contexts and queues
3. Create programs and kernels
4. Create memory objects
5. **Enqueue writes** to initialize memory objects
6. **Enqueue kernel** executions
7. **Wait** for them to finish
8. **Enqueue reads** to get back data
9. Repeat 5-8

OpenCL Hello World

- Get the device
- Create a context
- Create a command queue

```
            clGetDeviceIDs(NULL, CL_DEVICE_TYPE_DEFAULT,
                           1, &device, NULL);

context =   clCreateContext(NULL, 1, &device,
                           NULL, NULL, NULL);

queue =     clCreateCommandQueue(context, device,
                       (cl_command_queue_properties)0, NULL);
```

This example has no error checking. This is very foolish.

OpenCL Hello World

- Create a program with the source
- Build the program and create a kernel

```
char *source = {
"kernel calcSin(global float *data) {    \n"
"  int id = get_global_id(0);             \n"
"  data[id] = sin(data[id]);              \n"
"}                                        \n"};

program =     clCreateProgramWithSource(context, 1,
                    (const char**)&source, NULL, NULL);

              clBuildProgram(program, 0,
                    NULL, NULL, NULL, NULL);

kernel =      clCreateKernel(program, "calcSin", NULL);
```

OpenCL Hello World

- Create and initialize the input

```
buffer =      clCreateBuffer(context, CL_MEM_COPY_HOST_PTR,
                             sizeof(cl_float)*10240,
                             data, NULL);
```

Note that the buffer specifies the **context** so OpenCL knows which devices may share it.

OpenCL Hello World

- Set the kernel arguments
- Enqueue the kernel

```
      clSetKernelArg(kernel, 0, sizeof(buffer), &buffer);

size_t global_dimensions[] = {LENGTH,0,0};

      clEnqueueNDRangeKernel(queue, kernel,
                             1, NULL, global_dimensions, NULL,
                             0, NULL, NULL);
```

Local dimensions are NULL. OpenCL will pick reasonable ones automatically. (Or so you hope…)

OpenCL Hello World

- Read back the results

```
      clEnqueueReadBuffer(queue, buffer,
                          CL_TRUE,
                          0, sizeof(cl_float)*LENGTH,
                          data, 0, NULL, NULL);
```

The **CL_TRUE** argument specifies that the call should **block** until the read is complete. Otherwise you would have to explicitly wait for it to finish.

OpenCL Hello World

The Demo

More OpenCL

- Querying Devices
- Images
- Events

Querying Devices

- Lots of information via clGetDeviceInfo()
  - CL_DEVICE_MAX_COMPUTE_UNITS*
    Number of compute units that can run work-groups in parallel
  - CL_DEVICE_MAX_CLOCK_FREQUENCY*
  - CL_DEVICE_GLOBAL_MEM_SIZE*
    Total global memory available on the device
  - CL_DEVICE_IMAGE_SUPPORT
    Some GPUs don't support images today
  - CL_DEVICE_EXTENSIONS
    double precision, atomic operations, OpenGL integration

*Unfortunately this doesn't tell you how much memory is available right now or which device will run your kernel fastest.

Images

- **2D and 3D Native Image Types**
  - R, RG, RGB, RGBA, INTENSITY, LUMINANCE
  - 8/16/32 bit signed/unsigned, float
  - Linear interpolation, edge wrapping and clamping
- **Why?**
  - Hardware accelerated access on GPUs
  - Want to enable this fast path
  - GPUs cache texture lookups today
- **But…**
  - Slow on the CPU (which is why Larabee does this in HW)
  - Not all formats supported on all devices (check first)
  - Writing to images is not fast, and can be very slow

Events

- Subtle point made earlier:

  Queues for **different devices** are **asynchronous with respect to each other**
- Implication:
  - You must **explicitly synchronize** operations **between devices**

(Also applies to out-of-order queues)

Events

- Every clEnqueue() command can:
  - Return an **event** to track it
  - Accept an **event wait-list**

```
clEnqueueNDRangeKernel(queue, kernel,
                       1, NULL, global_dimensions, NULL,
                       numberOfEventsInList, &waitList,
                       eventReturned);
```

  - Events can also report profiling information
    - Enqueue->Submit->Start->End

Event Example

- **Kernel A** output -> **Kernel B** input
- **Kernel A** runs on the CPU
- **Kernel B** runs on the GPU
- Need to ensure that **B** waits for **A** to finish

```
clEnqueueNDRangeKernel(CPU_queue, kernelA,
                       1, NULL, global_dimensions, NULL,
                       0, NULL, kernelA_event);

clEnqueueNDRangeKernel(GPU_queue, kernelB,
                       1, NULL, global_dimensions, NULL,
                       1, &kernelA_event, NULL);
```

Performance Optimizations

- Host-Device Memory (100x)
  - PCIe is slow and has a large overhead
  - Do a lot of compute for every transfer
  - Keep data on the device as long as possible
- Memory Accesses (~10x)
  - Ordering matters for coalescing
  - Addresses should be sequential across threads
  - Newer hardware is more forgiving
- Local Memory (~10x)
  - Much larger bandwidth
  - Must manually manage
  - Look out for bank conflicts
- Divergent execution (up to 8x)
- Vectors (2-4x on today's hardware)
  - On vector HW this is critical (AMD GPUs, CPUs)
  - OpenCL will scalarize automatically if needed
- Math (2x on intensive workloads)
  - fast_ and native_ variants may be faster (at reduced precision)

Debugging (Or Not)

- Very little debugging support on GPUs
- Start on the CPU
  - At least you can use printf()…
- Watch out for system watchdog timers
  - Long-running kernels will lock the screen
  - Your kernel will be killed after a few seconds
  - Your app will crash
  - Your users will be sad

GPU Projects

Approaches

- Data-parallel
  - Simplest mapping
  - Just need right compute-to-memory ratio
- Thread-parallel
  - Generally a bad mapping
  - Threads that don't do the same thing pay a big penalty
  - Only cheap local synchronization
- Reduction
  - Require synchronization between stages
  - Tricky across work-groups
- Scan-based
  - Handles variable length data
  - Brute-force, but fully data-parallel

Scan Algorithms

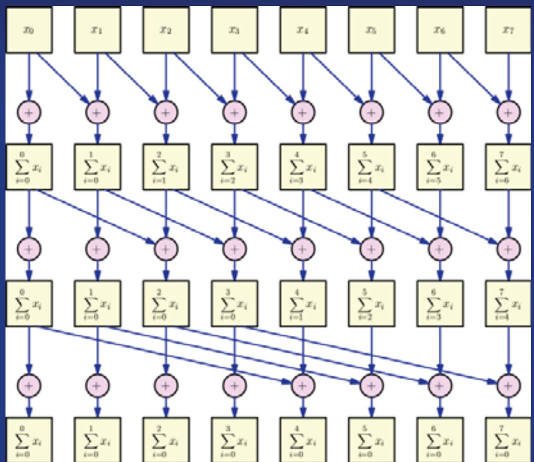


Image from http://en.wikipedia.org/wiki/Prefix_sum

Simple Scan

- Produces all sums of the elements
- Also works with min, max, or, etc.
- Log scaling with the number of elements
- Data-parallel

- Can do conditional operations too
  - Pass in a second array of flags
  - Conditionally propagate data based on flags
  - Allows for *data-parallel execution of variable-length operations* (this is awesome)

http://mgarland.org/files/papers/nvr-2008-003.pdf
http://developer.download.nvidia.com/compute/cuda/sdk/website/projects/scan/doc/scan.pdf

Project Ideas

- JPEG zero-run encoding performance for varying sizes
  - 64 quantized coefficients; need to count zeros and then Huffman encode
  - Parallel scan vs. serial for RLE
- Variable length processing
  - Serial scan has nearly 2x the data bandwidth
  - But it's fully parallel
  - At what level does it make sense?
    - Local memory
    - Global memory