

CSE113: Parallel Programming

- Topics:
 - Intro to GPUs



Announcements

- Midterm graded.

Tips to improve understanding going into the final:

- Attend class, study the slides
- Do readings
- Experiment with homework
- Focus on understanding and problem solving

Announcements

- HW2 grades announced by the end of this week.
- HW3 due today (+ 3 days if you need it)

Announcements

- Rest of the quarter schedule, so that we can make it through
- Module 4: GPU for three sessions
- Module 5: advanced topics – Concurrent sets, barriers and memory models

Previous quiz + Review

Previous quiz + Review

A DOALL Loop must have:

-
- A loop variable that starts at 0 and is incremented by 1

 - loop iterations that are independent

 - be unrolled and interleaved

 - not access any memory locations
-

Previous quiz + Review

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Which one of the following is NOT a drawback of a global workstealing parallel schedule

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- Requires a concurrent data structure

 - Contention on shared cache lines

 - Contention on a single location with RMWs

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Contention on shared cache lines

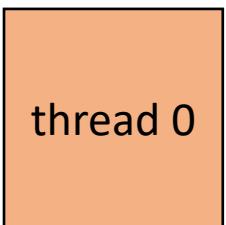
Contention on a single location with RMWs

Work stealing - global implicit worklist

- Global worklist: threads take tasks (iterations) dynamically

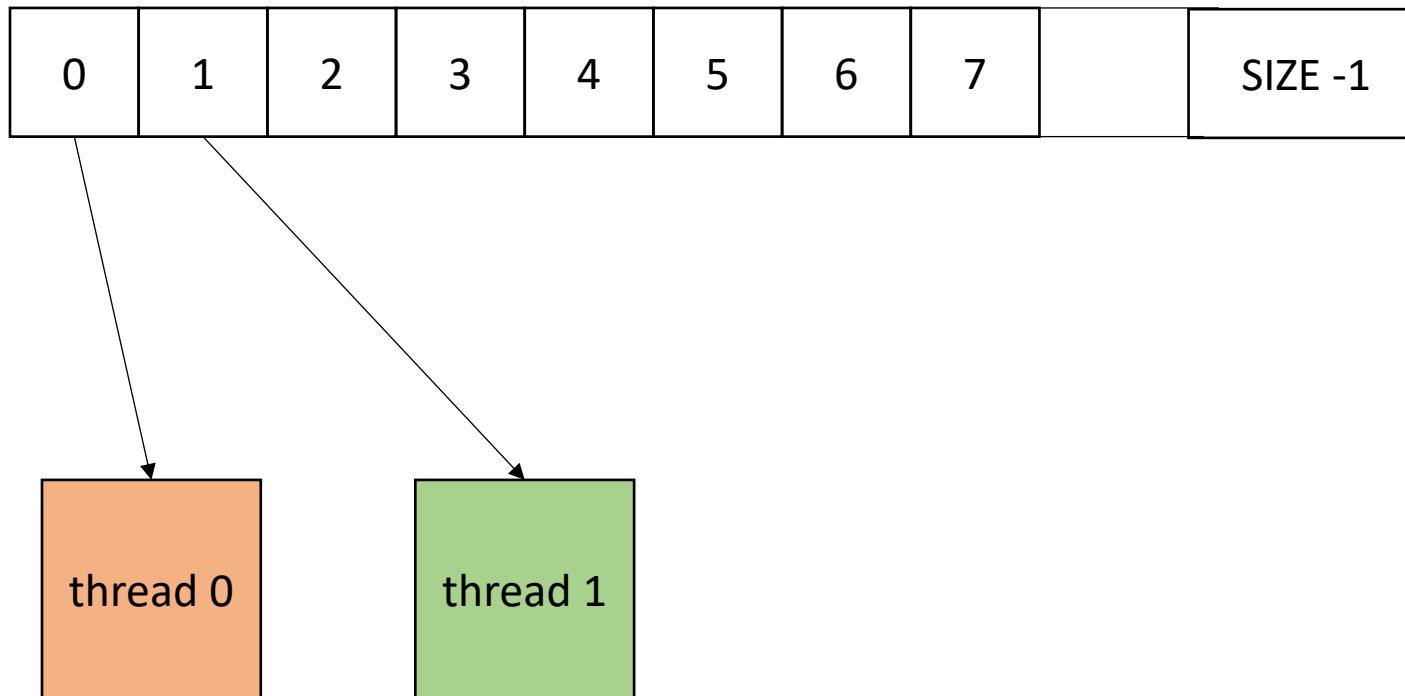
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cannot color initially!



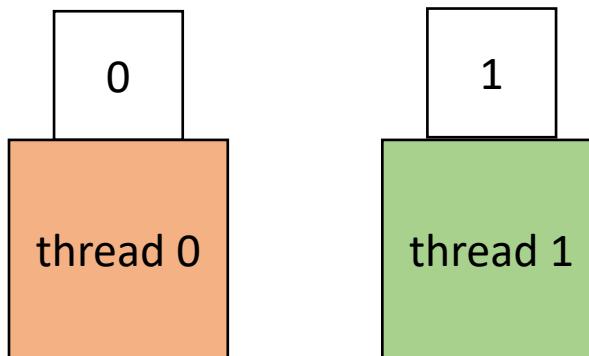
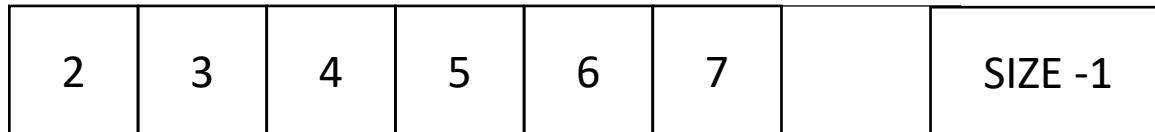
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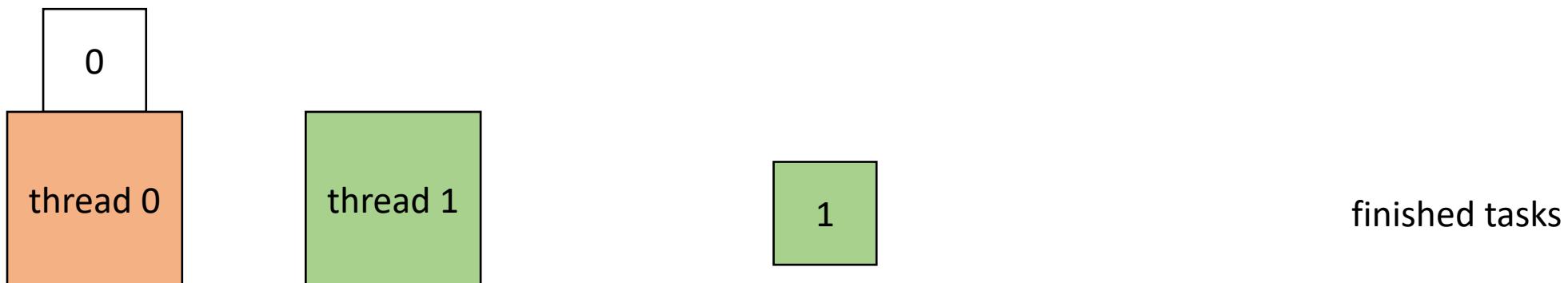
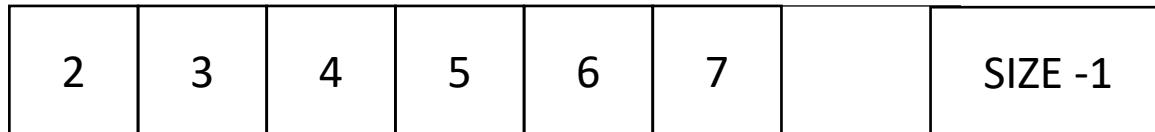
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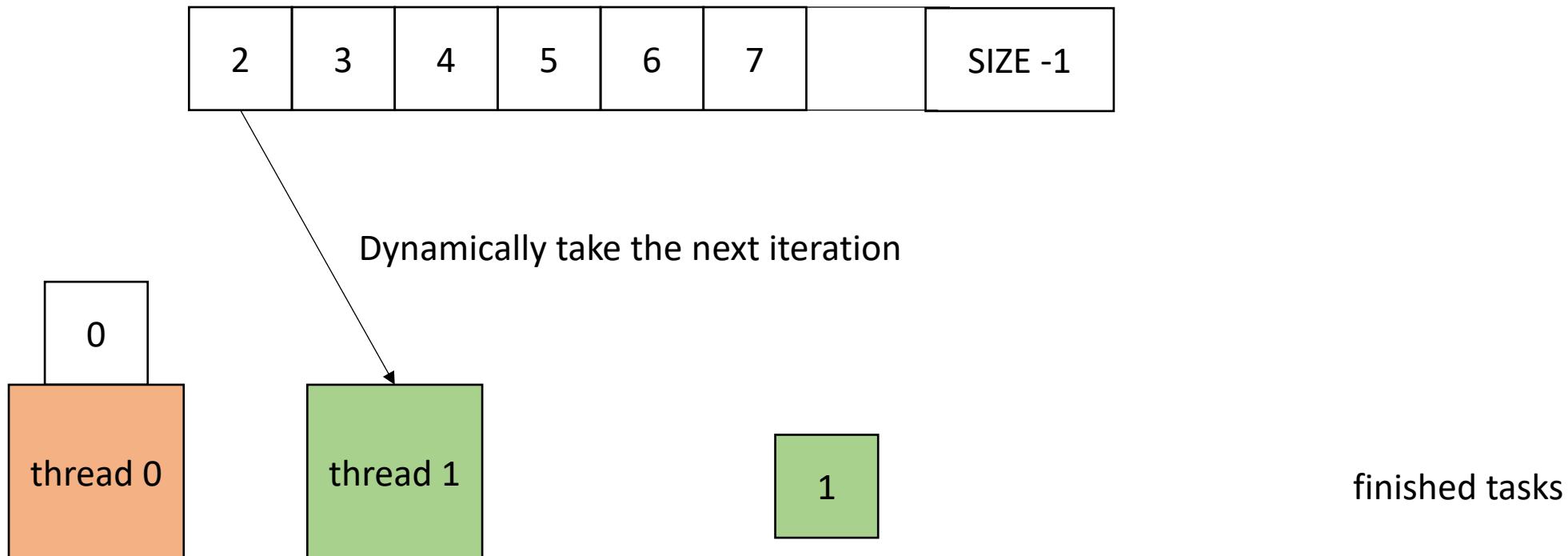
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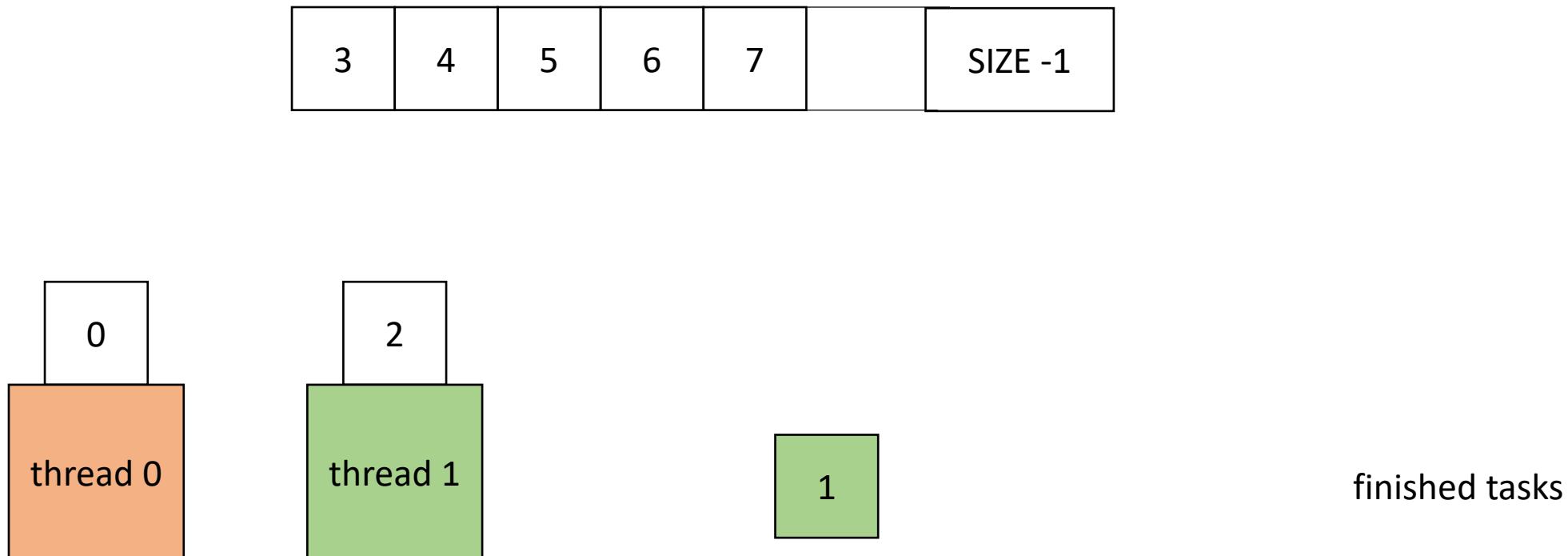
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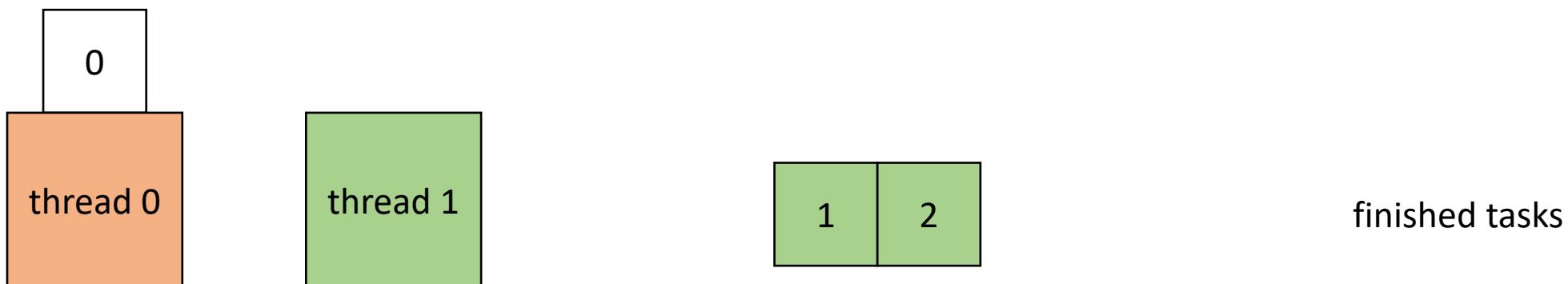
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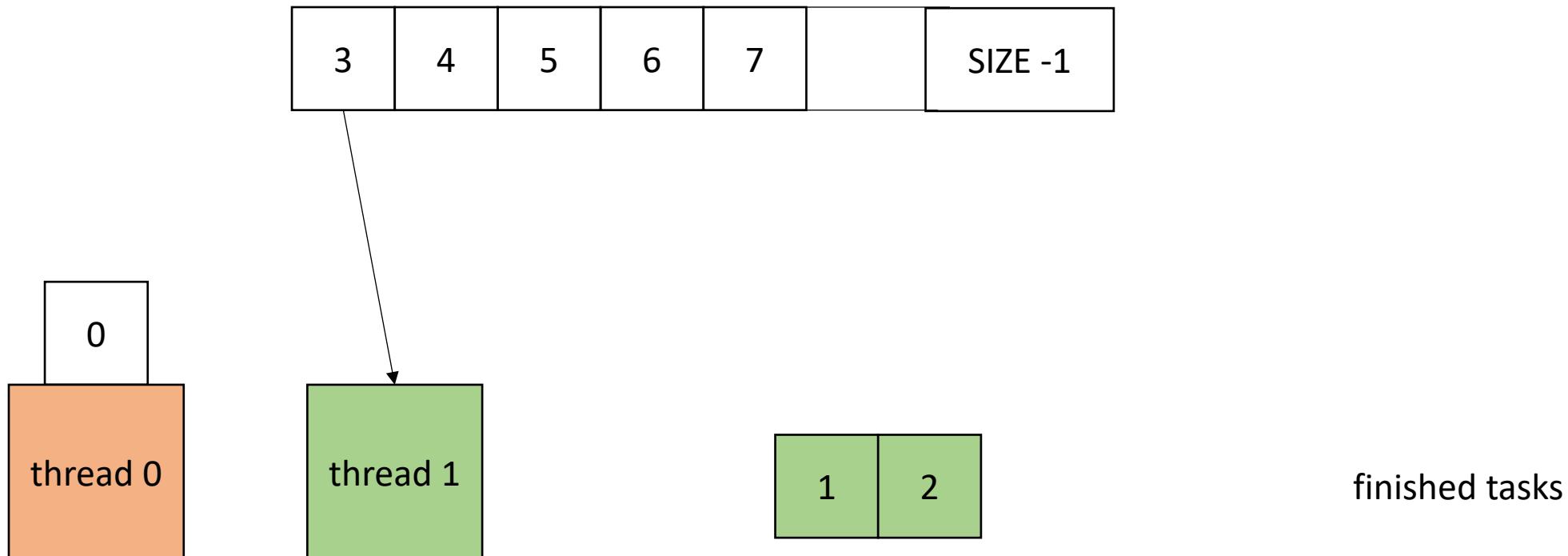
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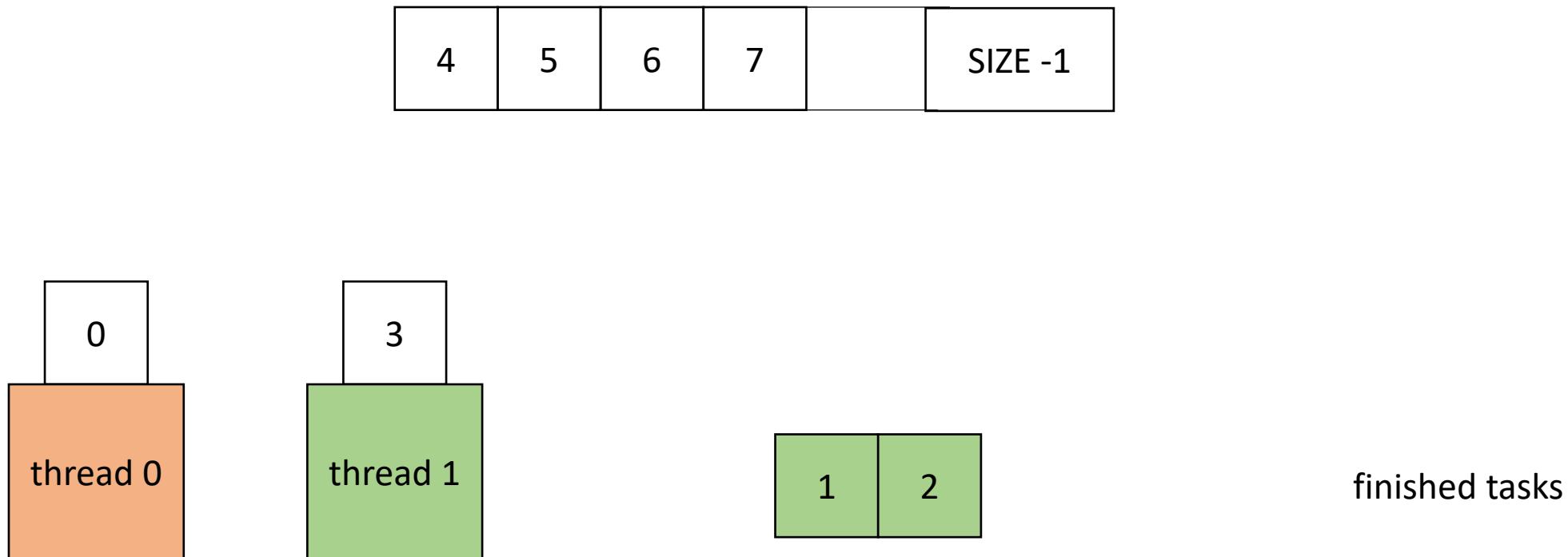
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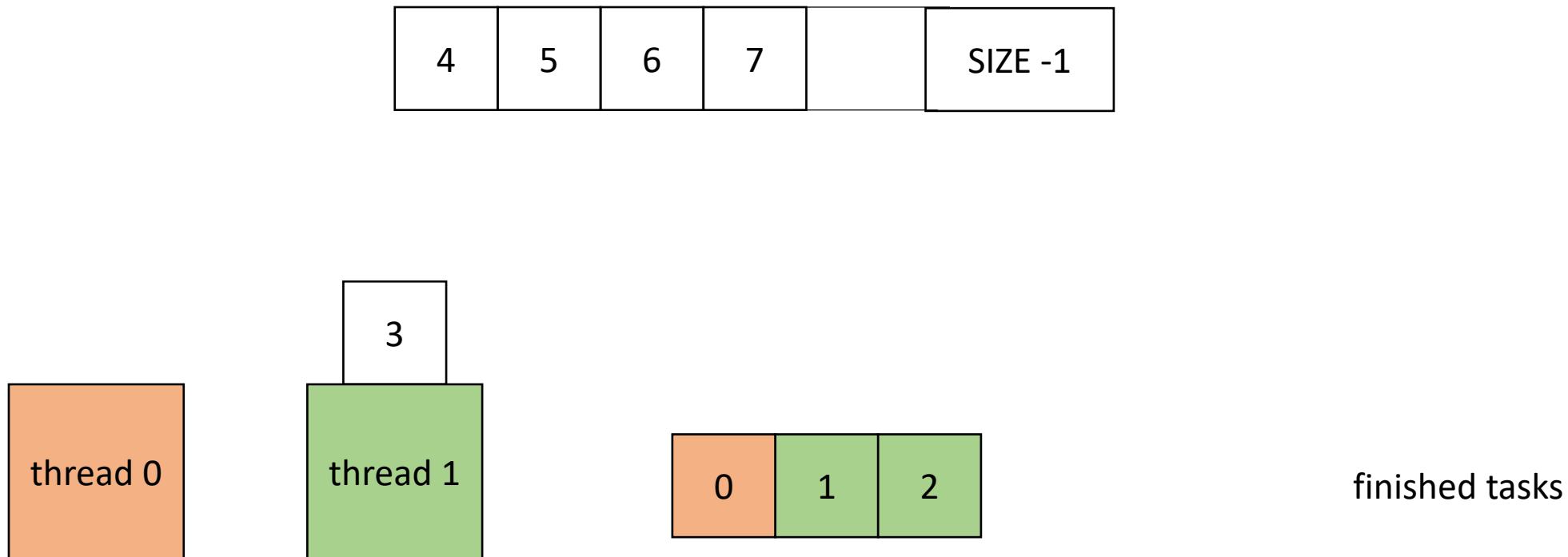
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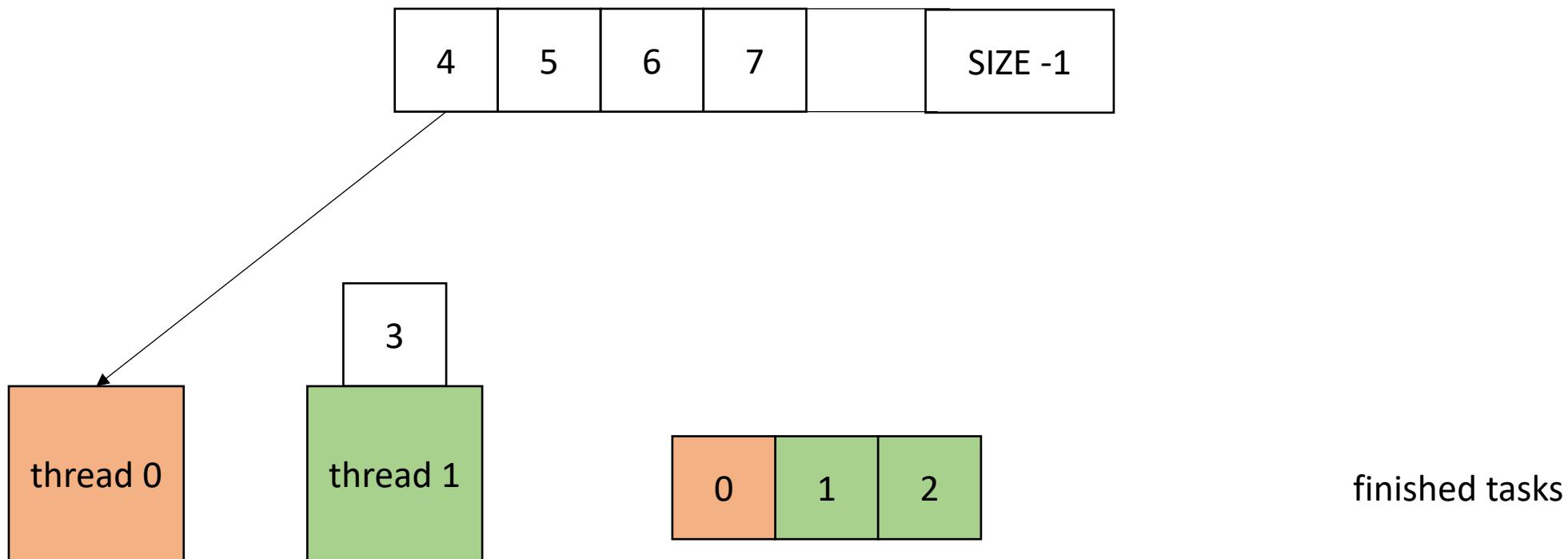
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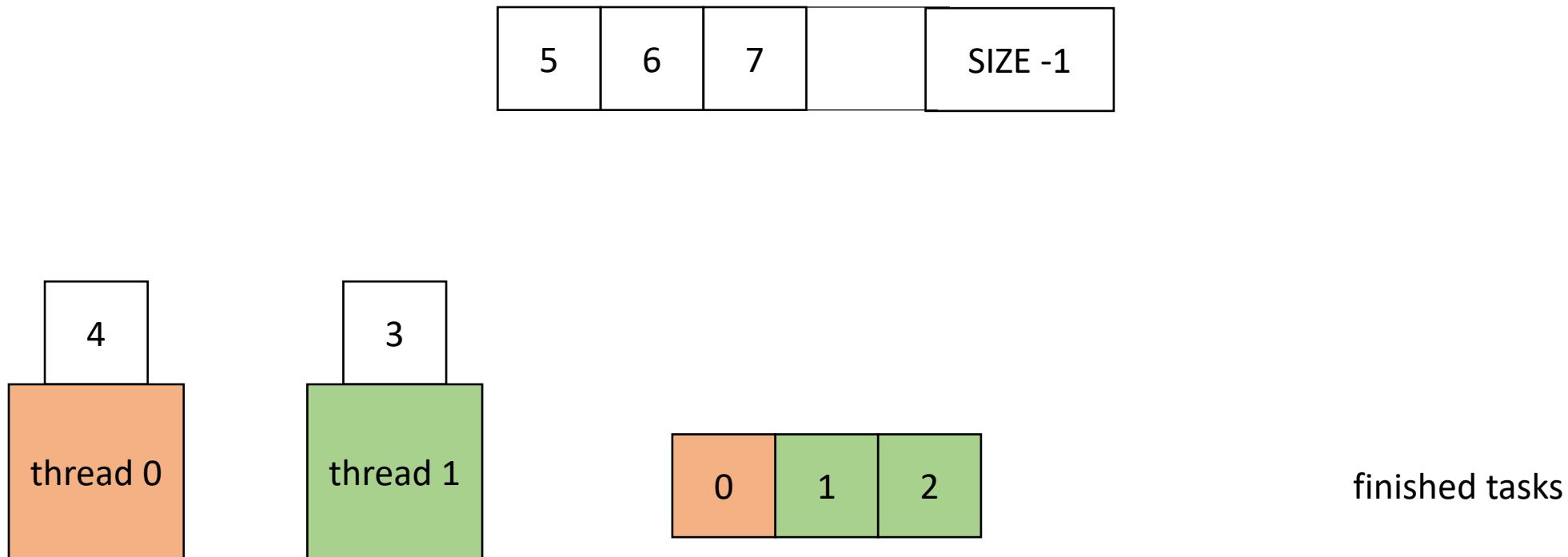
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Previous quiz + Review

Which of the following is NOT an overhead of the local worklist workstealing parallel schedule (that we studied in class)

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- Initialization of the queues

 - Checking a global variable to ensure all work is completed

 - Managing concurrent enqueues to the worklists

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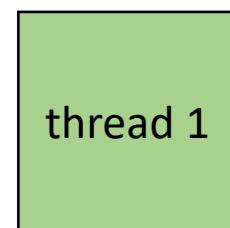
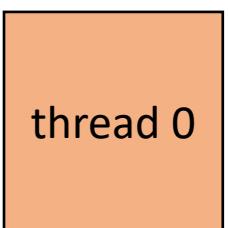
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Work stealing - local worklists

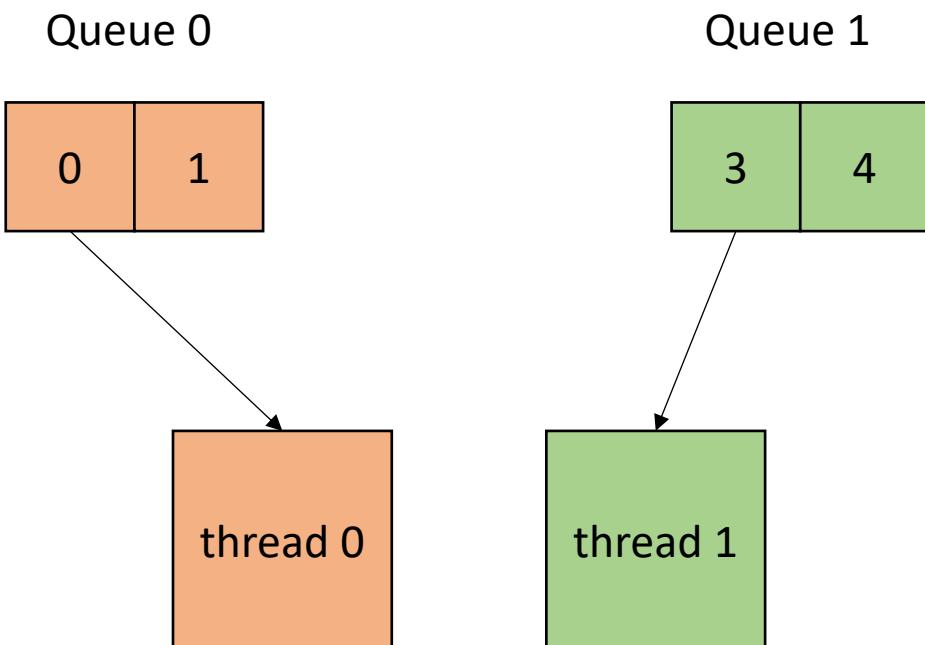
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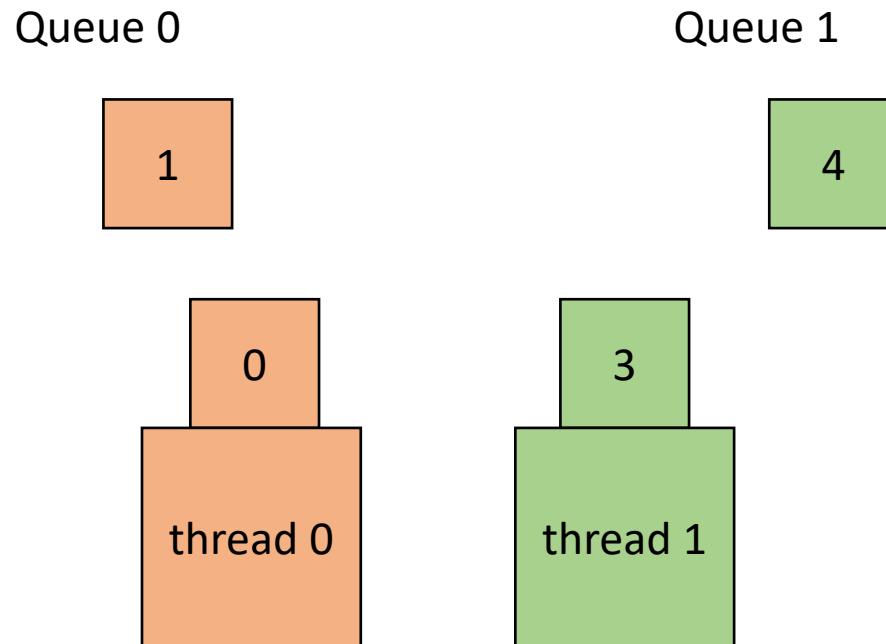
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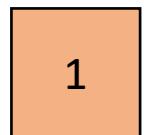
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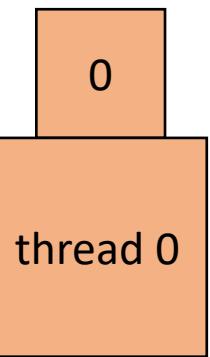
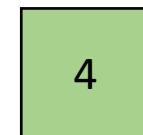
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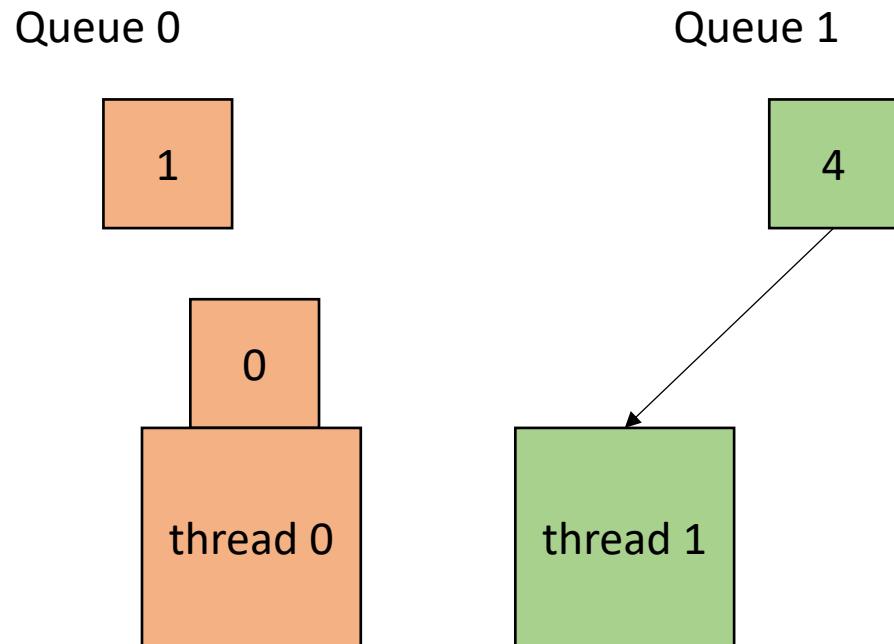


Queue 1



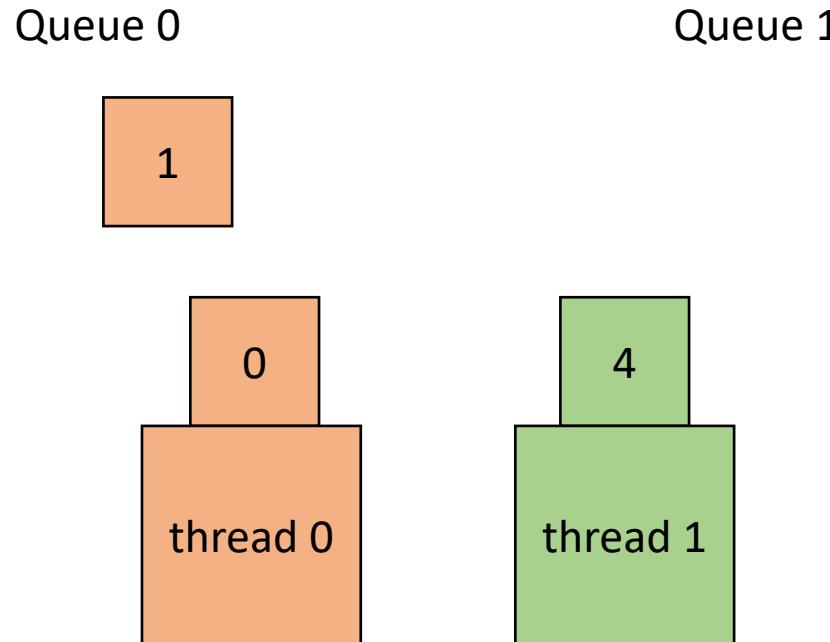
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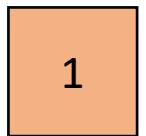
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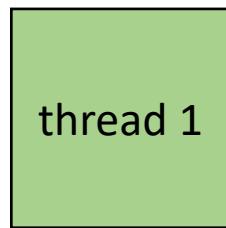
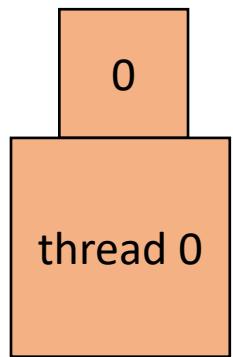
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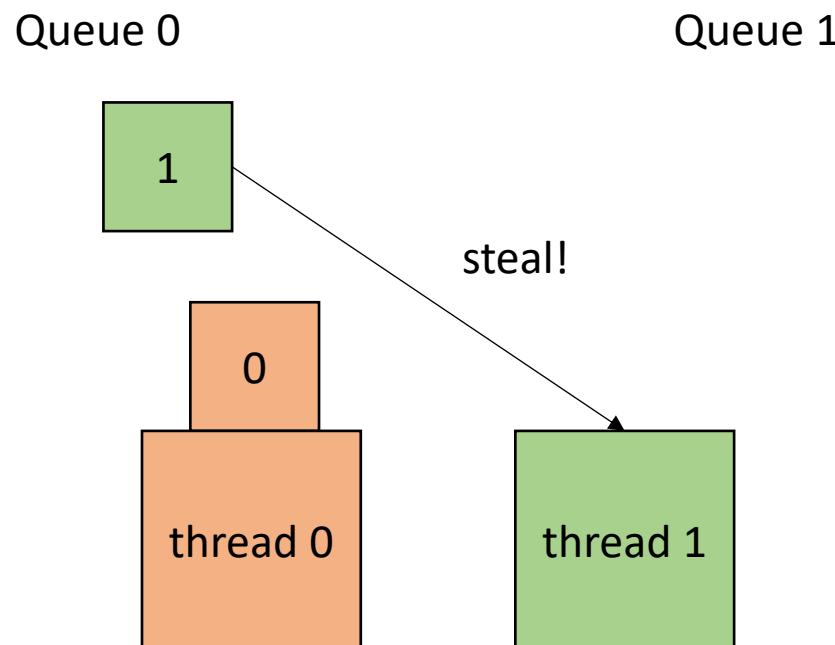


Queue 1



Work stealing - local worklists

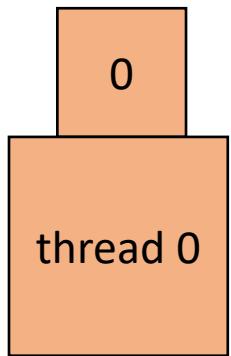
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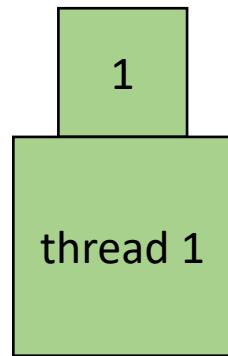
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Queue 1



Previous quiz + Review

Which of the following solutions can guarantee that a static schedule will not be out of bounds?

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- The last thread always checks to get the minimum between the end of the array or the value allocated

 - The last thread always get the end of the array

 - The last thread never receives more than N tasks

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Previous quiz + Review

Write a few sentences about the pros and cons of using local workstealing queues over the global implicit worklist

Previous quiz + Review

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Simple vs. More efficient

Previous quiz + Review

Given what we've learned: what role do you believe the compiler should play in parallelizing DOALL loops?

For example, should it: (1) identify them? (2) parallelize them? (3) pick a parallel schedule?

There is no right or wrong answer here, but it is interesting to think about!

On to new stuff!

- GPUs

GPUs: a brief history

First chapter of CUDA by Example
<https://www.techspot.com/article/650-history-of-the-gpu/>

The very beginning

- Specialized hardware to accelerate graphics rendering
- One of the first real-time computers:
Whirlwind 1 at MIT (1951)
 - Flight simulator for bombers
 - Vector graphics

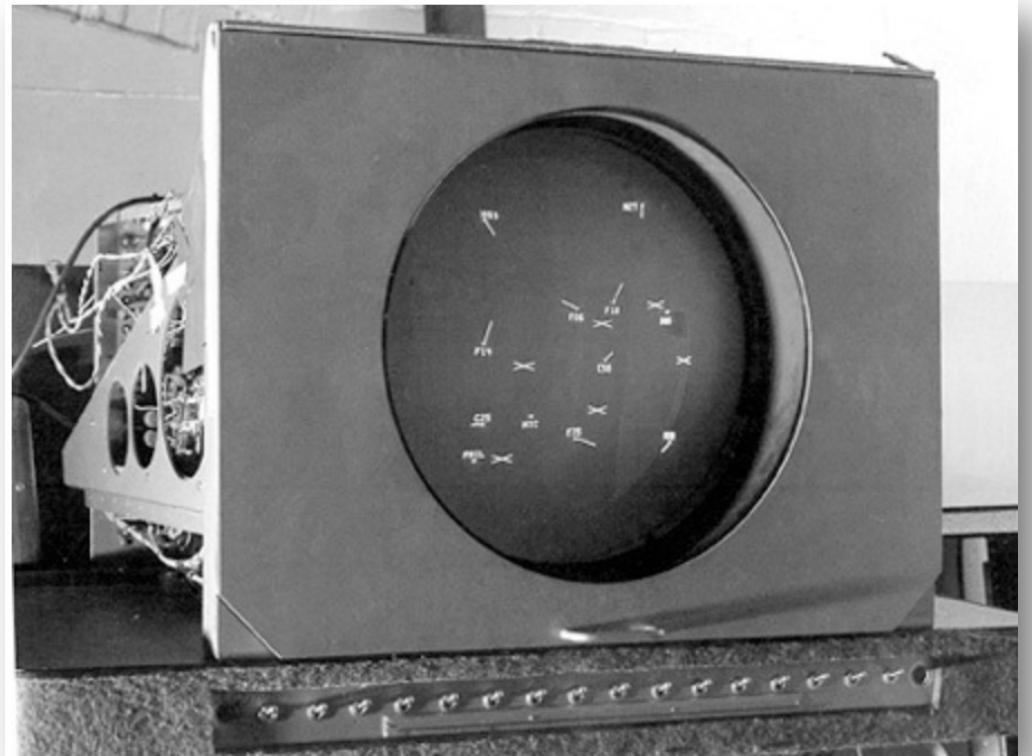


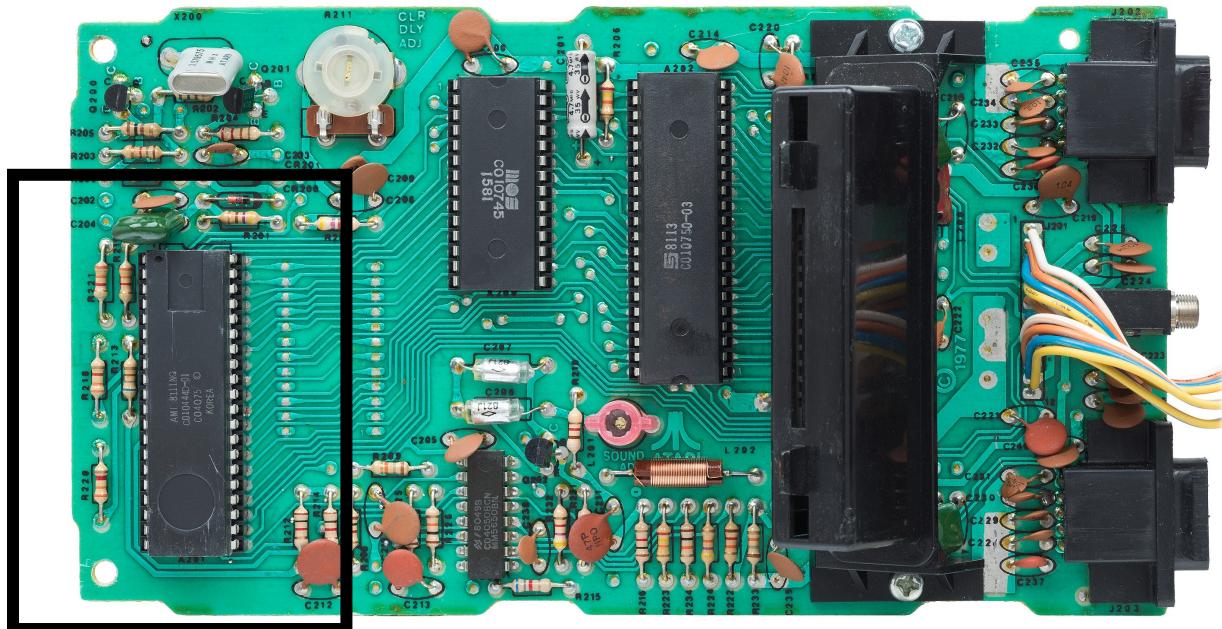
Image from: <https://ohiostate.pressbooks.pub/graphicshistory/chapter/2-1-whirlwind-and-sage/>

Specialization

- Next 30 years, specialized hardware for specialized software to display 2D graphics
- Specialized
 - Typically ran specific programs
 - Portability was not a top priority
 - Even the idea of portable ISAs for CPUs were not mainstream

Multi-program devices

- 1977: Television Interface Adapter
 - One of the first (and widely produced) portable (i.e. multiple program) GPUs



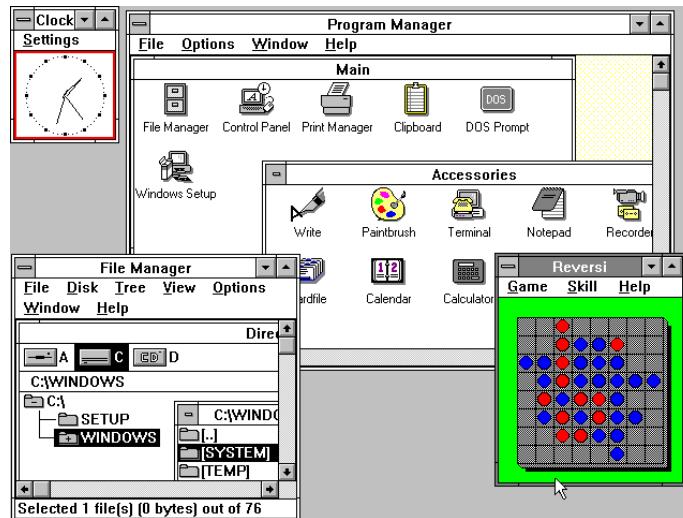
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River Raid Game

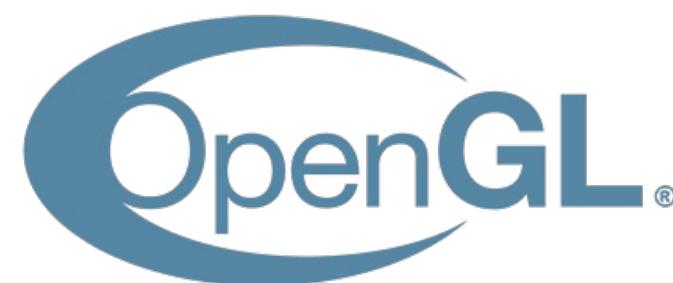


OS integration

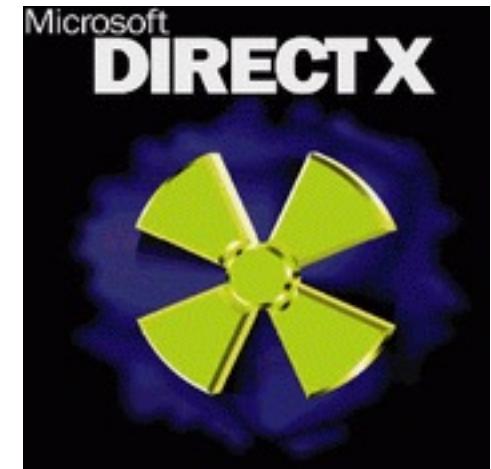
- 1990s: Windows: a graphical operating systems, required chips to support 2D graphics.
- New APIs started appearing, to enable GUI programs



Windows 3 (1990)



1992



1995

<https://en.wikipedia.org/wiki/DirectX>
https://en.wikipedia.org/wiki/Microsoft_Windows
<https://en.wikipedia.org/wiki/OpenGL>

3D graphics in consoles (1993)

- Super Nintendo was not powerful enough to draw 3D graphics
- Shigeru Miyamoto (Super Mario developer) really wanted a 3D flight simulator though
- Worked with a British software company to develop...

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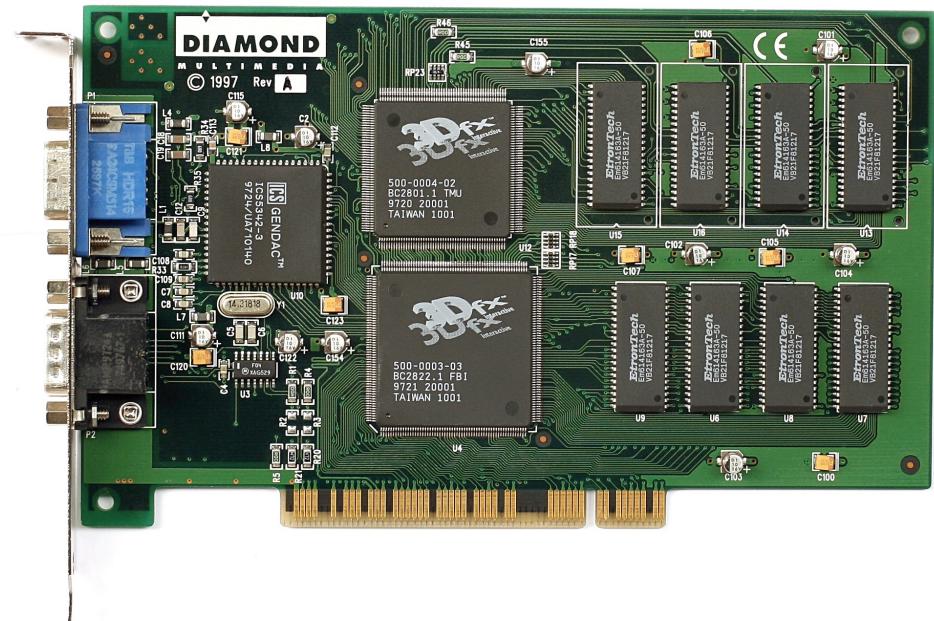
3D graphics in consoles (1993)

- Game cartridges shipped with a “mini GPU” on them:
 - the Super FX



3D graphics acceleration

- 1996 : First 3D graphics accelerator: Voodoo from 3Dfx
 - Discrete GPU
 - Early 3D games: e.g. tomb raider
 - Acquired by Nvidia in 2002



3D graphics acceleration

- 3D accelerators continued, many companies competing:
 - Nvidia
 - ATI (acquired by AMD)
 - 3Dfx
 - and more...
- Next milestone in 1999:
 - Nvidia coins the term “GPU”
 - Compare with modern website

Programmable 3D accelerators

- 2001: Microsoft DirectX 8 required programmable vertex and pixel shaders.
- 2001: First GPU to satisfy the requirement was Nvidia GeForce 3
 - Used on the original Xbox
- Programmers started writing general programs for these GPUs:
 - Present your data as a graphical input (e.g. Textures and Triangles)
 - Read the output after a series of “graphics” API calls

GPGPU Programming

- 2006: Nvidia releases CUDA: programming language for their GPUs
 - Supported by 8th generation CUDA devices.
 - Integrated vertex and pixel cores into “shader cores”
 - Support for IEEE floating point
- Soon after...

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- 2008: The Khronos Group launches OpenCL for cross vendor GPGPU:
 - including AMD, Intel, Qualcomm

Khronos Group



- Started in 2000 by Apple as a standards body for graphics API to counter Microsoft's DirectX:
 - A way to unify APIs across many different vendors
 - at the time: ATI, Nvidia, Intel, Sun Microsystems (and a few others)
 - now: Many companies, including AMD, Nvidia, Intel, Qualcomm, ARM, Google
- OpenGL is maybe the biggest standard they maintain (for graphics)
- OpenCL is big for compute
- Vulkan unifies compute + graphics (mostly graphics)
- Apple deprecated Khronos group standards to support Metal in 2018
 - iPhone used to have GPUs from a company called Imagination, a British company. Apple took their engineers.
 - Our laptops may have GPUs from Intel or ADM. Now apple laptops has apple GPUs.

Where are we now?

- Nvidia CUDA is widely used, driving many HPC and ML applications
 - Nvidia heavily invested in its software stack and made it accessible, and this made it widely used.
 - Nvidia GPUs are not designed power efficient, and are not used much in mobile devices.
- OpenCL is used to program other GPUs (although it is not as widely used)
- Metal is used for Apple devices
- Vulkan has momentum, but mostly in graphics
- New GPGPU programming languages are on the horizon:
 - WebGPU - a javascript interface to unite Metal, Vulkan and DirectX
 - Its ambitious! Will it work?!

GPU Shortages?

- Cryptocurrency:
 - 2018 reported tripling of GPU prices and shortages due to increase demand from miners.
 - Still happening with lots of market fluctuations.
 - Still plenty of GPUs in your phone, laptop, etc. ☺

GPUs in 2024

- Nvidia is now the 4th most valuable company in the world (1.9T)
 - More valuable than Google currently (1.7T)
- Graphics are still a valuable domain, but AI seems to be more valuable
 - Valuable to learn general purpose GPU programming (GPGPU)
- Many companies make their own GPUs:
 - AMD, Apple, Qualcomm, ARM, Intel, Imagination, Broadcom
- Many startups in the Valley making new AI chips similar to GPUs

Teaching GPU programming

- This is difficult!
- Nvidia GPUs have the most straightforward programming model (CUDA).
- It is extremely difficult to get a class of 120 students access to Nvidia GPUs these days.
 - AWS? Expensive and often oversubscribed w.r.t. GPUs
 - Department? ML folks get priority and super computing clusters are painful

Plan

- The GPU programming lectures will use CUDA
 - It is widely used
 - The programming model is straightforward
- Homework will use WebGPU, because it is widely supported
 - *There are more non-Nvidia GPUs in this room than Nvidia GPUs*

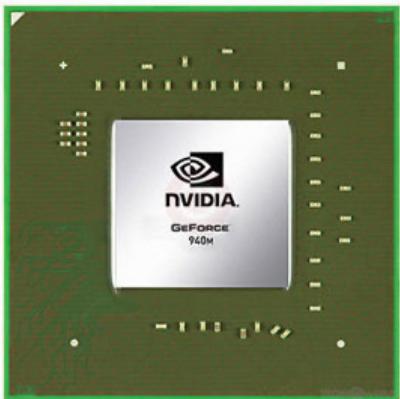
Plan

- The homework uses Javascript as its “CPU” language, and WebGPU as its “GPU” language.
- We have provided generous skeletons for the homework. We can go over some javascript, but it is a high-level language and should not be hard to figure out what you need to do.
- The WebGPU portion is straight forward and I will provide a mapping directly from what we talked about to what you need.

Start on GPU lectures

Programming a GPU

Tiny GPU in an embedded system



Nvidia Jetson Nano (whole chip, CPU + GPU)

2 Billion transistors

10 TDP

Est. \$99

<https://www.techpowerup.com/gpu-specs/geforce-940m.c2648>

https://www.alibaba.com/product-detail/Intel-Core-i7-9700K-8-Cores_62512430487.html

<https://www.prolast.com/prolast-elevated-boxing-rings-22-x-22/>

Fight!



The CPU



Intel i7-9700K

2.16 Billion transistors

95 TDP

Est. \$316

Programming a GPU

- The problem: Vector addition

Embarrassingly parallel

Computation
can easily be
divided into
threads

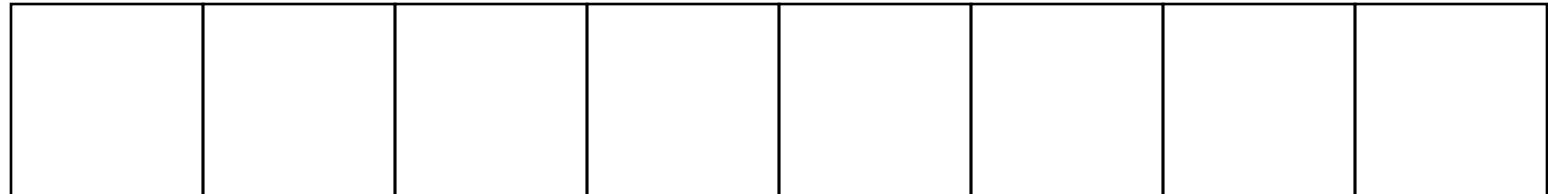
Thread 0 - Blue
Thread 1 - Yellow
Thread 2 - Green
Thread 3 - Orange

array a



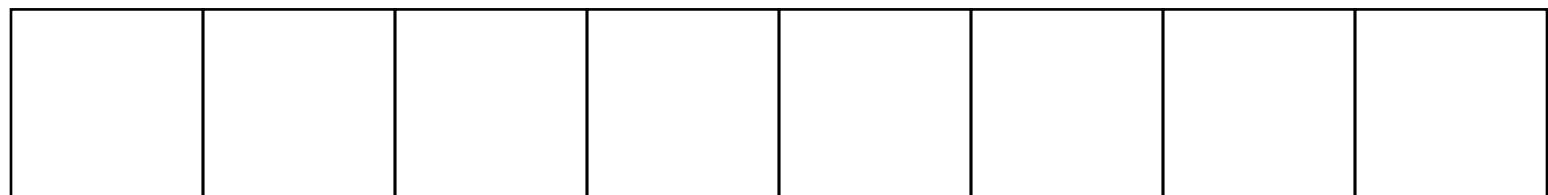
+ + + + + + + +

array b



= = = = = = = =

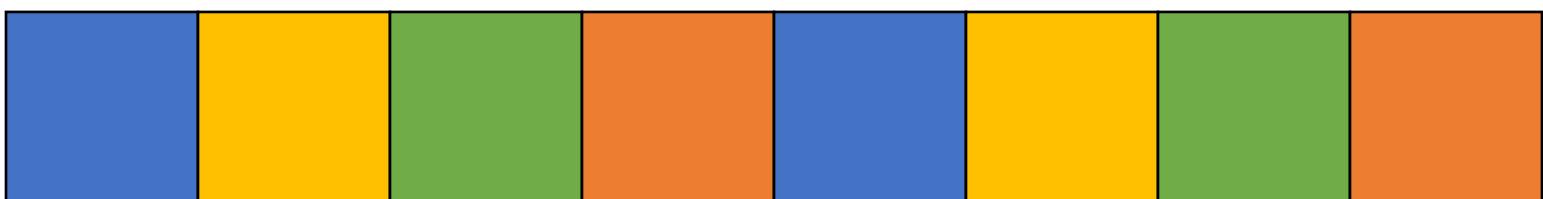
array c



Parallel Schedules

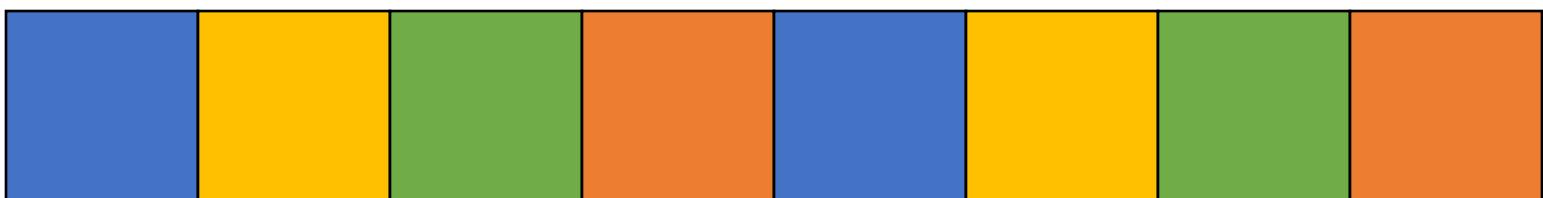
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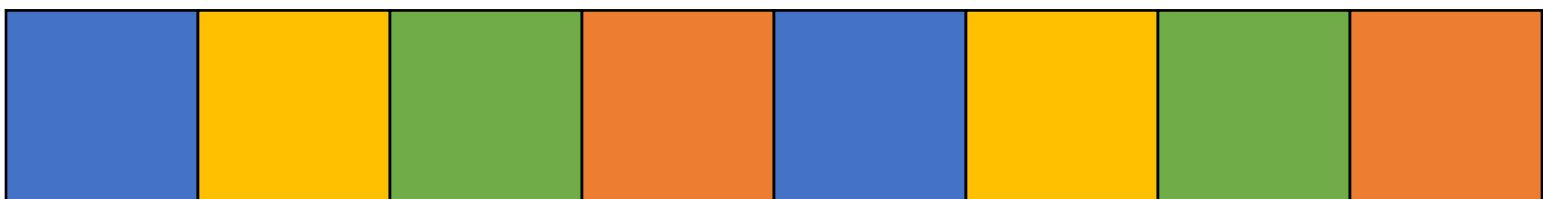
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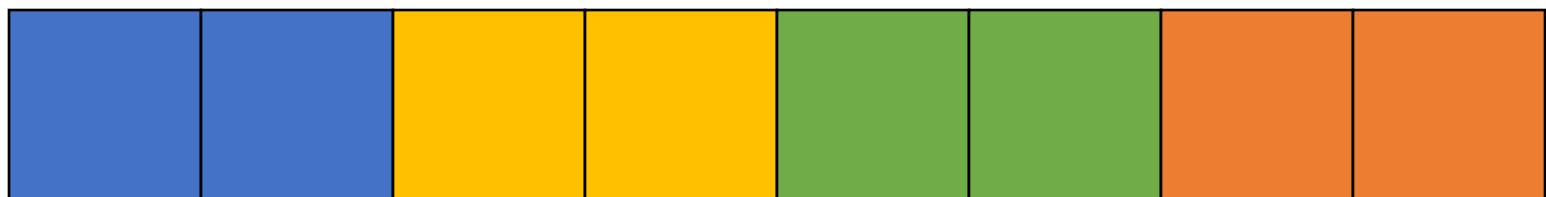
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Programming a GPU

- The problem: Vector addition
- Who can do it faster?

Lets set up the CPU

```
void vec_add(double *a, double *b, double *c, int size,
int tid, int num_threads) {
    int chunk = size / num_threads;
    int start = chunk * tid;
    int end = start + chunk;
    for (int j = 0; j < OUTER; j++) {
        for (int i = start; i < end; i++) {
            a[i] = b[i] + c[i];
        }
    }
}

for (int i = 0; i < num_threads; i++)
    thread_array[i] = thread(vec_add, a, b, c, SIZE, i,
num_threads);

for (int i = 0; i < num_threads; i++)
    thread_array[i].join();
```

Now for the GPU

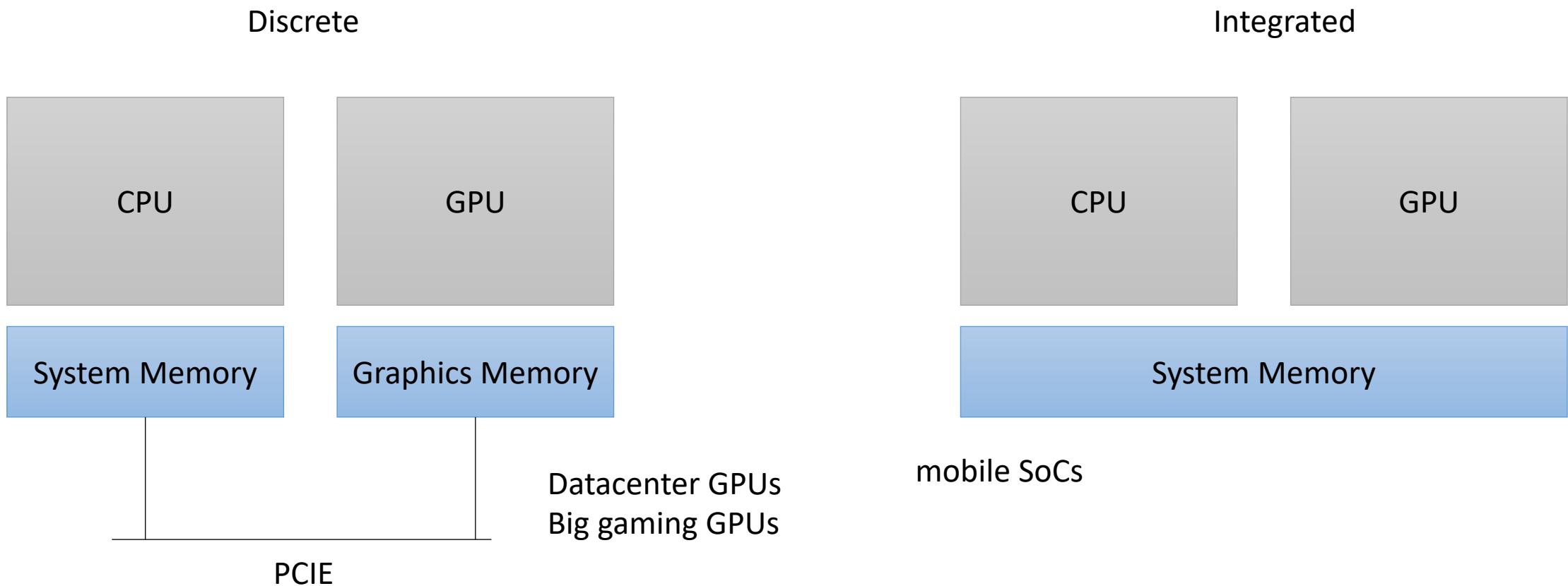
- Its going to take a bit of work....

GPU set up

- We need to allocate and initialize memory

GPU set up

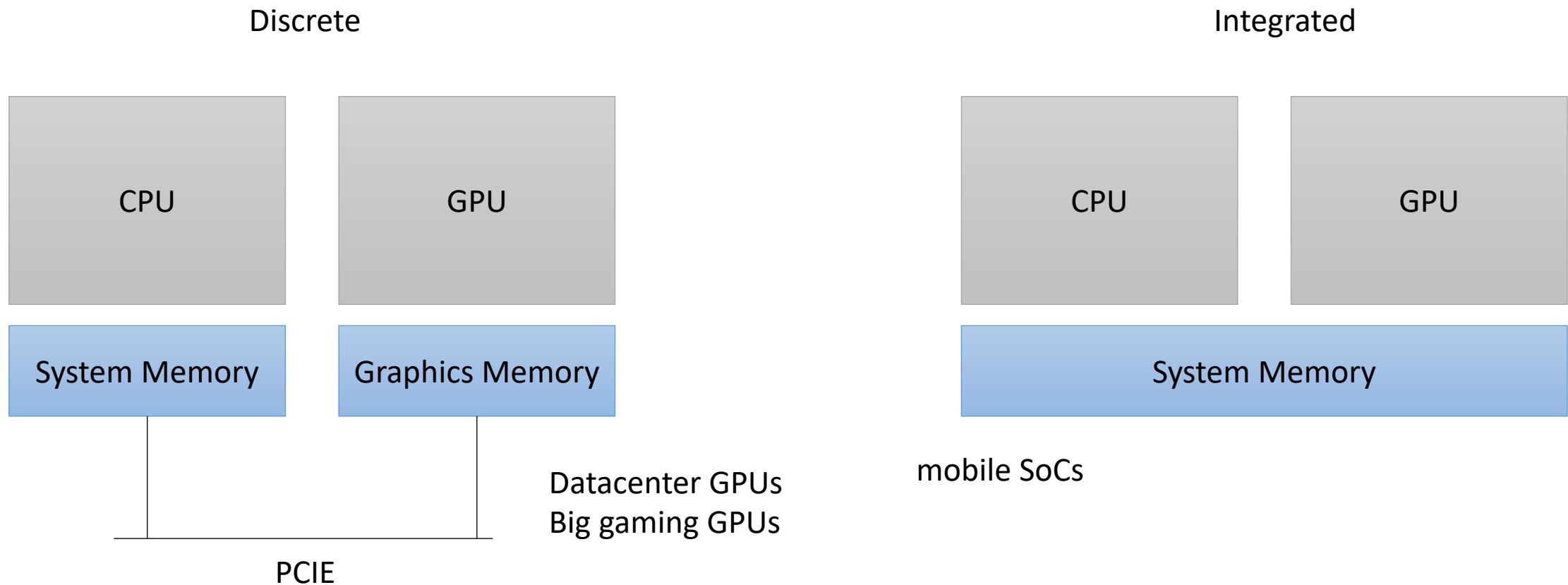
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GPU set up

Pros and cons of each?

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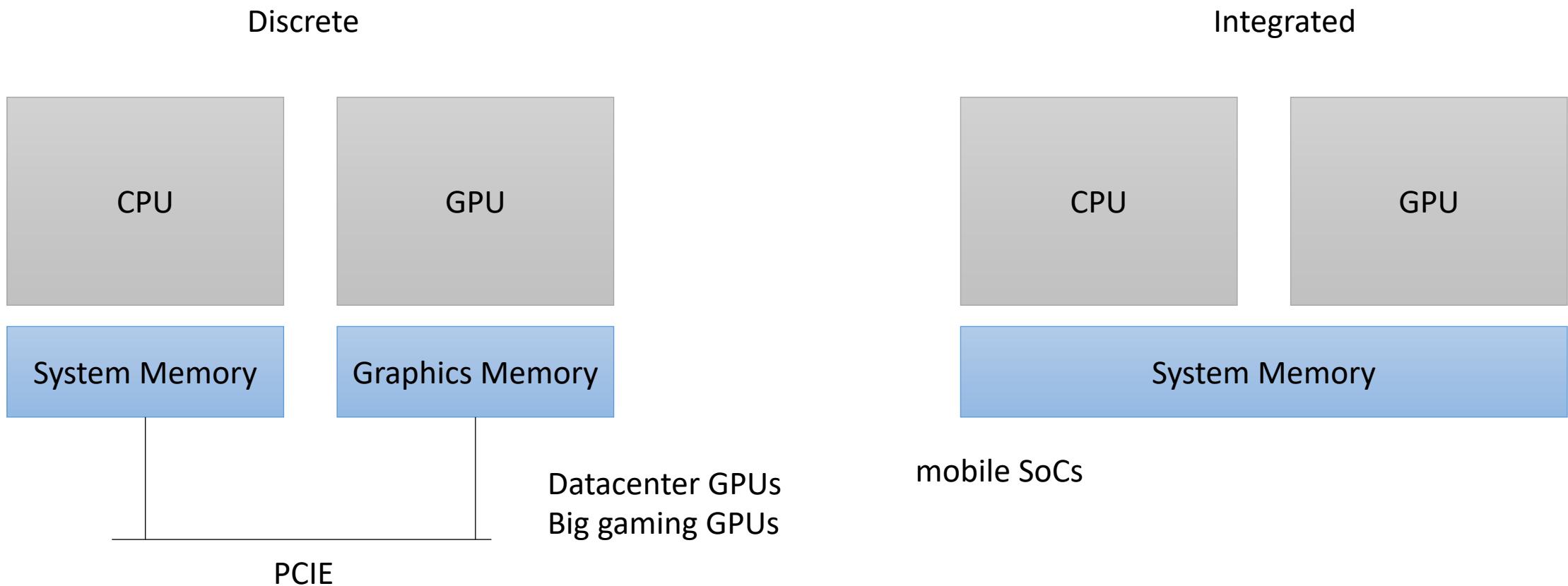


GPU set up

- GPUs come in two flavors

Pros and cons of each?

- *Different types of memory for discrete
- *Swappable for discrete
- *More energy efficient for integrated
- *Better memory utilization for integrated

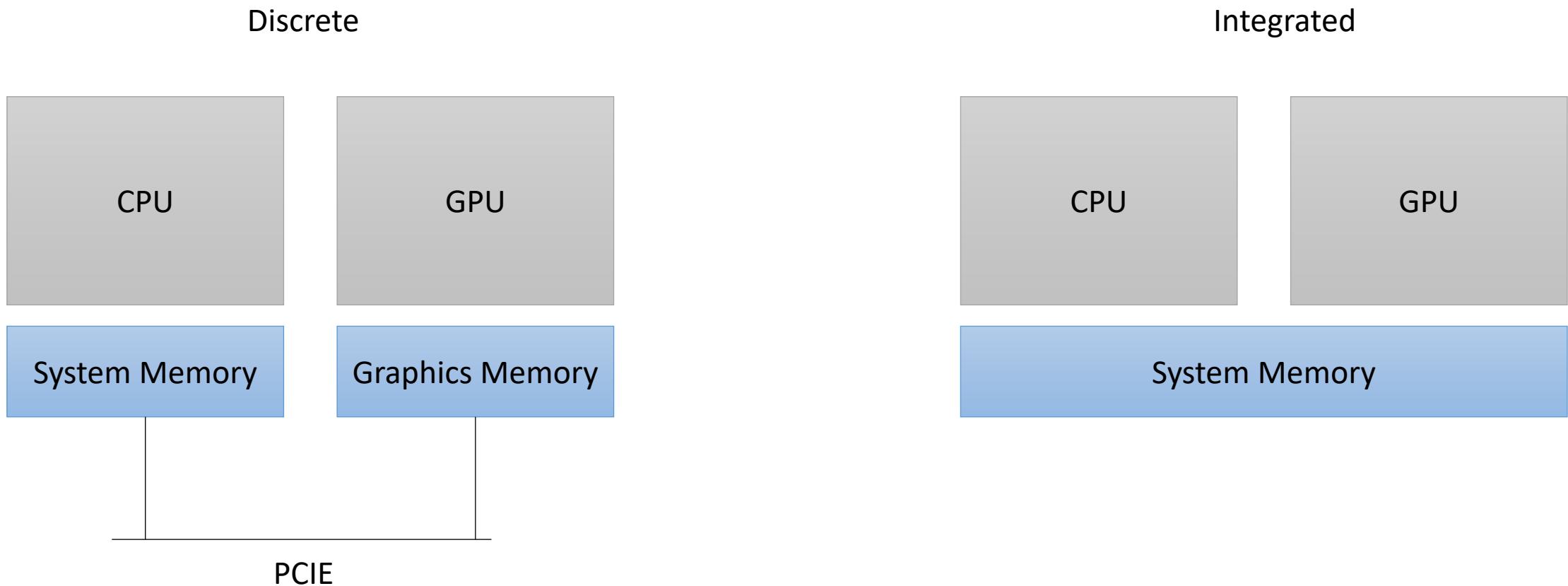


GPU set up

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Although mobile GPUs share the system memory,
Most still require you to program as if they didn't
have shared memory.

Why?

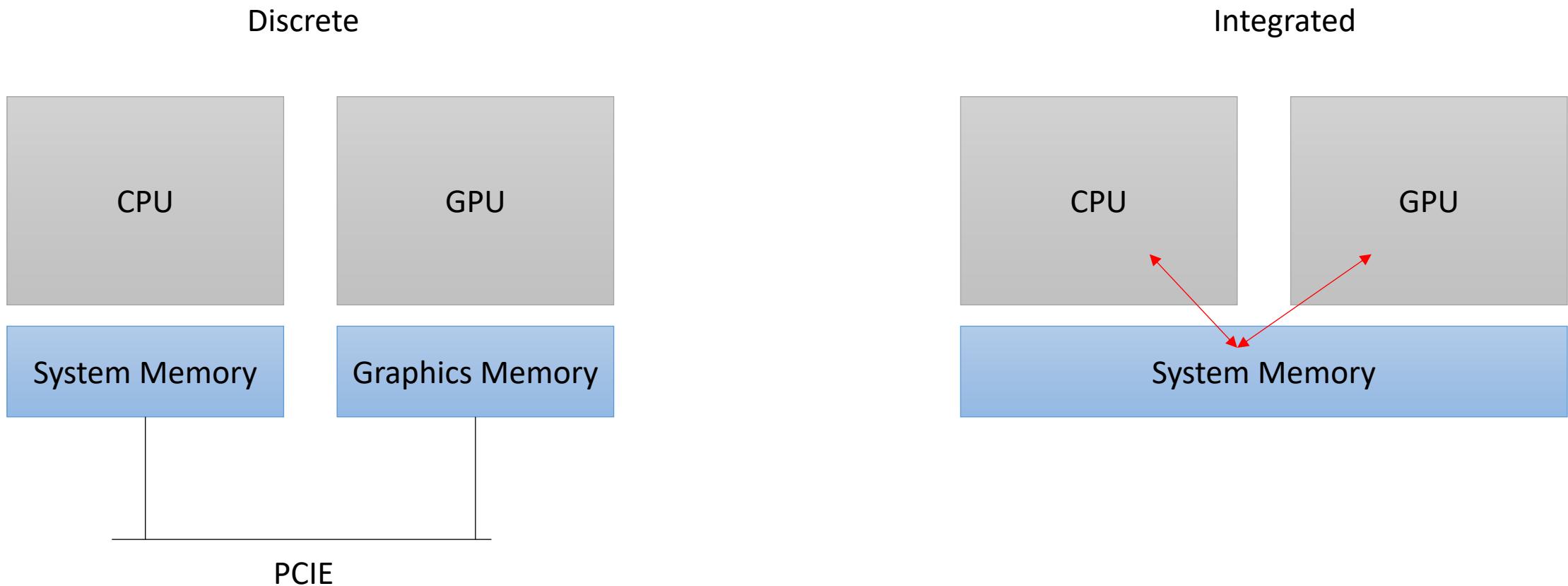


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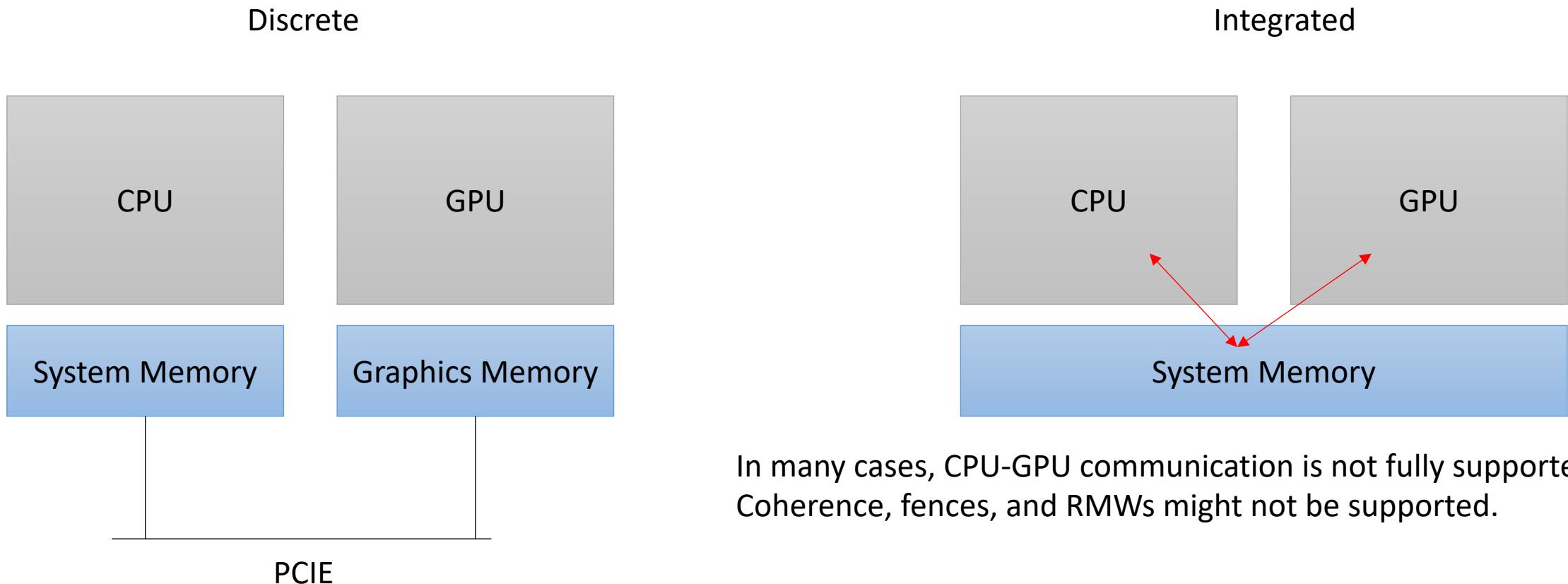


GPU set up

- GPUs come in two flavors

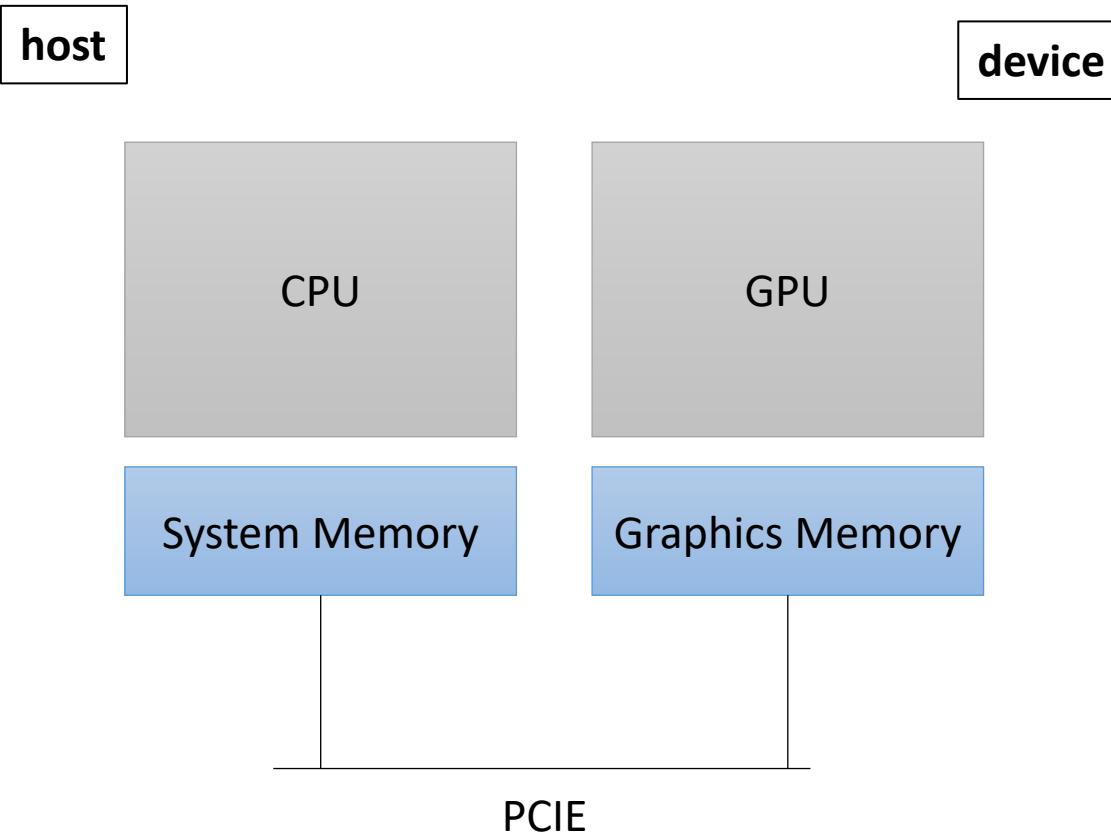
Although mobile GPUs share the system memory,
Most still require you to program as if they didn't
have shared memory.

Why?



GPU set up

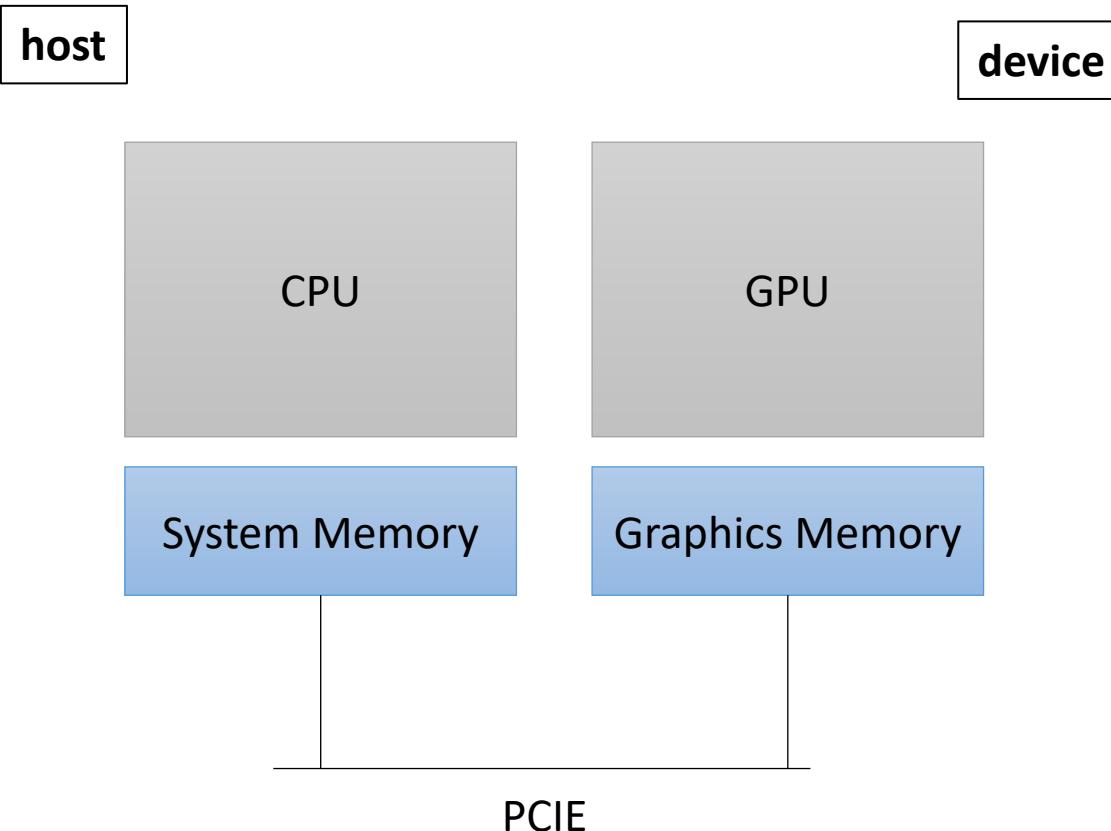
- Our heterogeneous, parallel, programming model



GPU set up

- Our heterogeneous, parallel, programming model

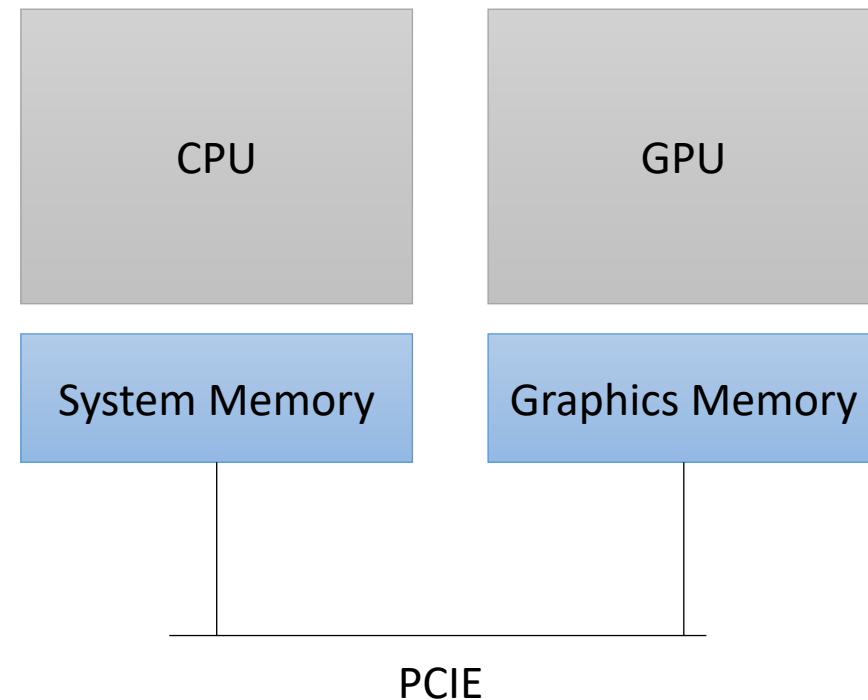
The host (CPU) will write a C++-like program that allocates and sets up memory on the GPU. The host will then call a GPU program called a kernel.



GPU set up

How do we allocate memory on a CPU?

- Our heterogeneous, parallel, programming model

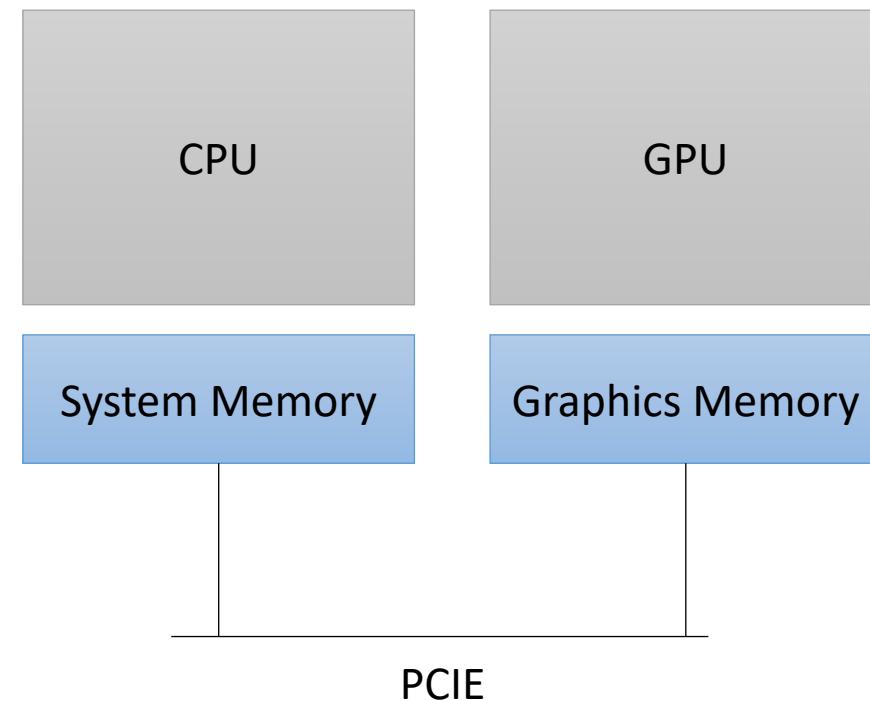


GPU set up

How do we allocate CPU memory on the host?

- Our heterogeneous, parallel, programming model

```
int *x = (int*) malloc(sizeof(int)*SIZE);
```

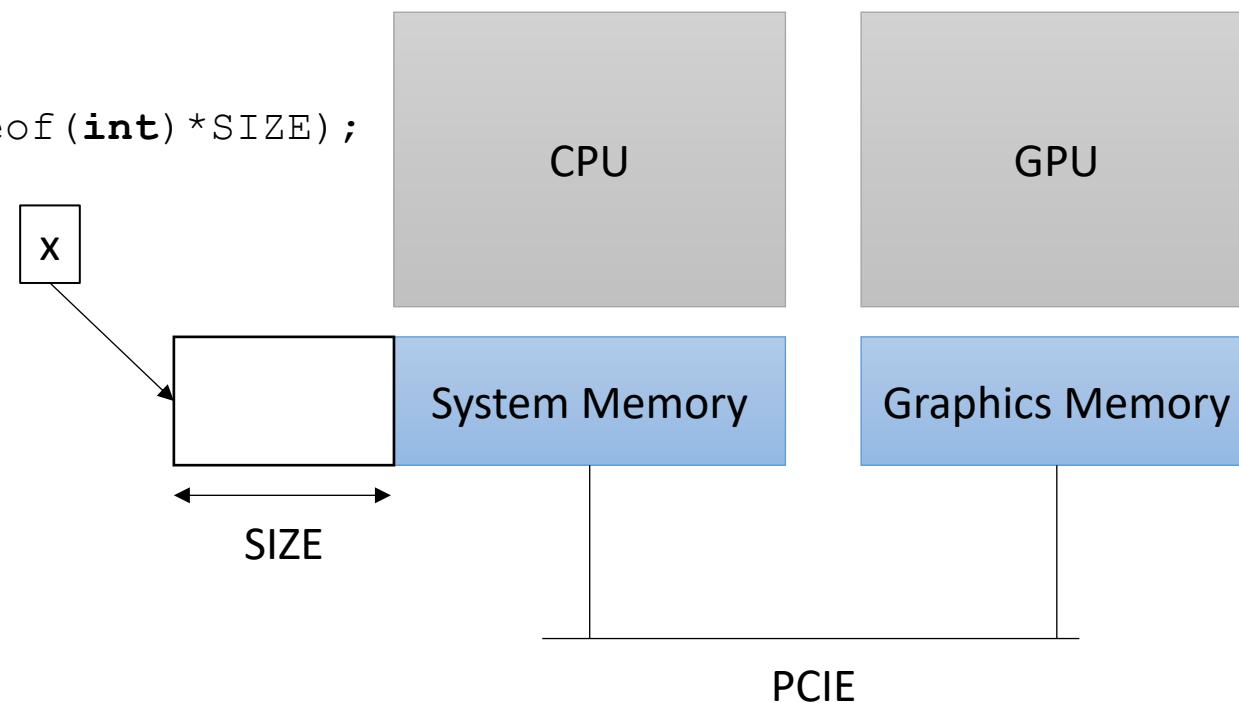


GPU set up

How do we allocate CPU memory on the host?

- Our heterogeneous, parallel, programming model

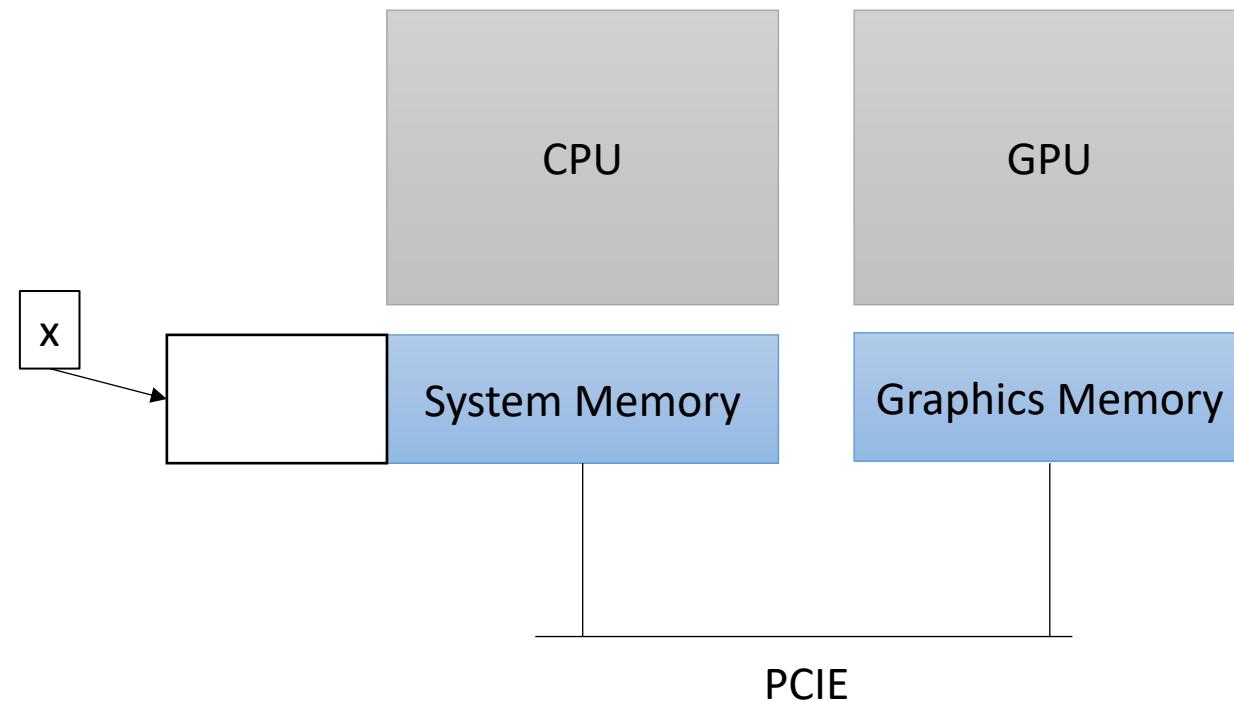
```
int *x = (int*) malloc(sizeof(int)*SIZE);
```



GPU set up

We need to allocate GPU memory on the host

- Our heterogeneous, parallel, programming model

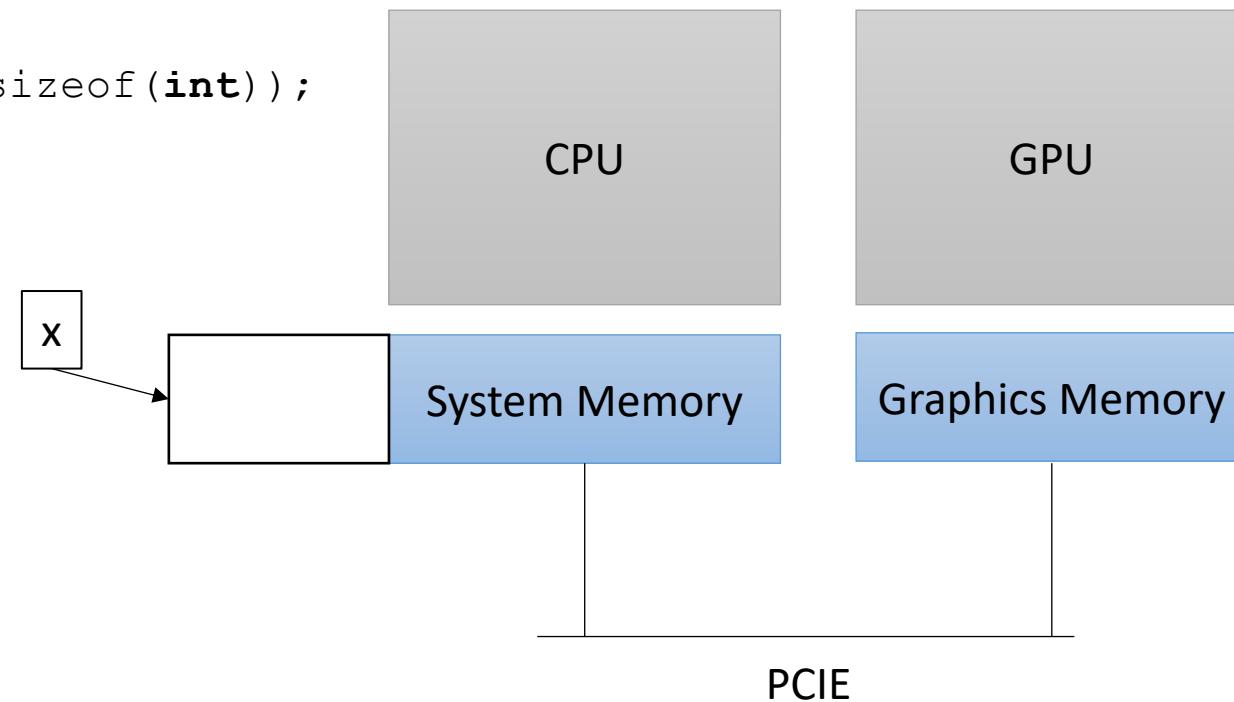


GPU set up

We need to allocate GPU memory on the host

- Our heterogeneous, parallel, programming model

```
int *d_x;  
cudaMalloc(&d_x, SIZE*sizeof(int));
```

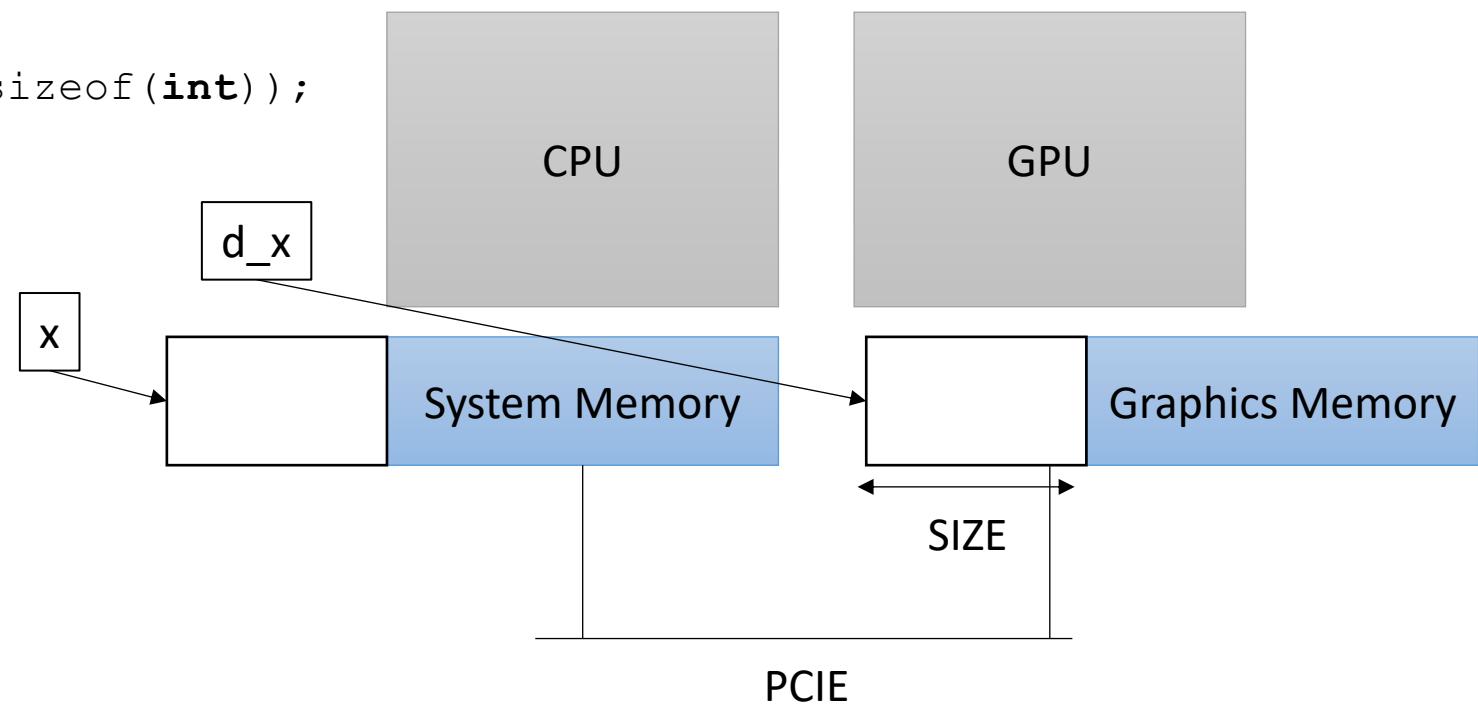


GPU set up

We need to allocate GPU memory on the host

- Our heterogeneous, parallel, programming model

```
int *d_x;  
cudaMalloc(&d_x, SIZE*sizeof(int));
```



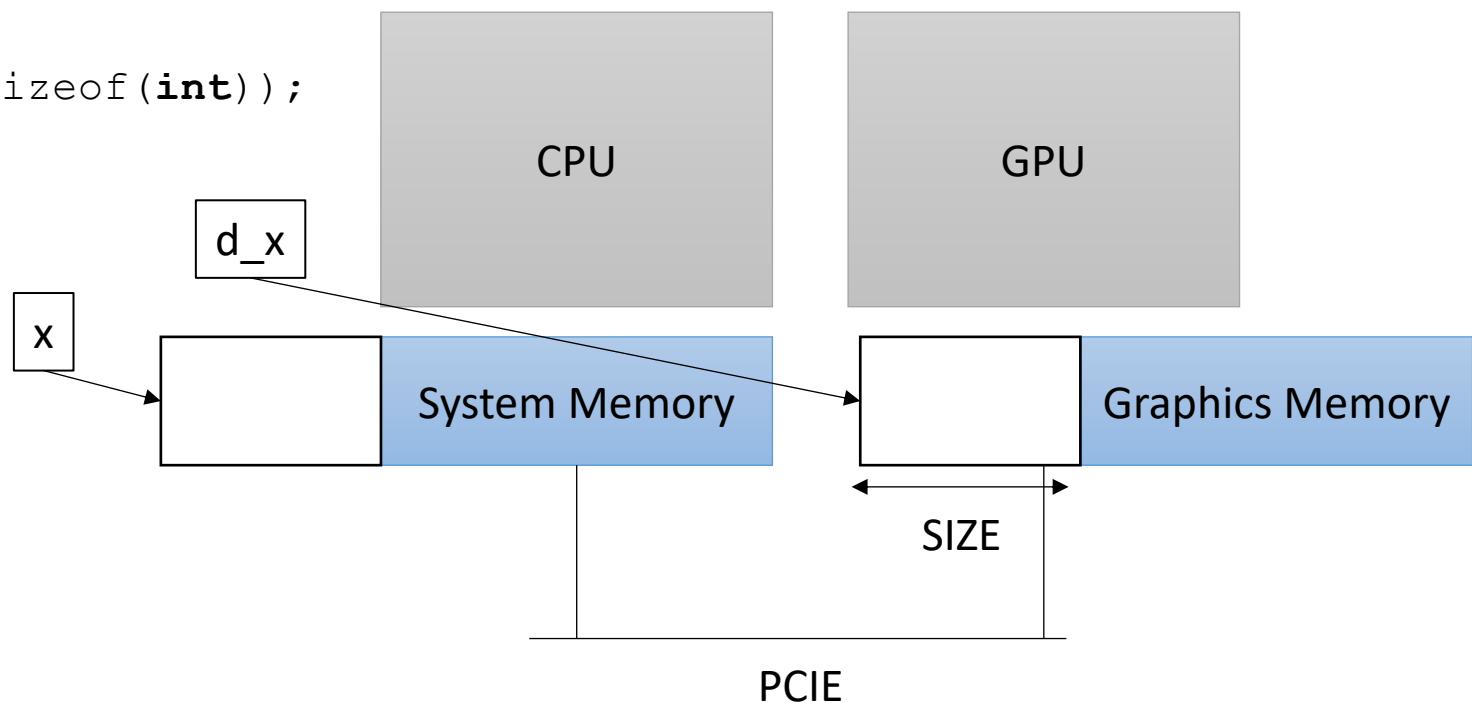
GPU set up

We need to allocate GPU memory on the host

- Our heterogeneous, parallel, programming model

```
int *d_x;  
cudaMalloc(&d_x, SIZE*sizeof(int));
```

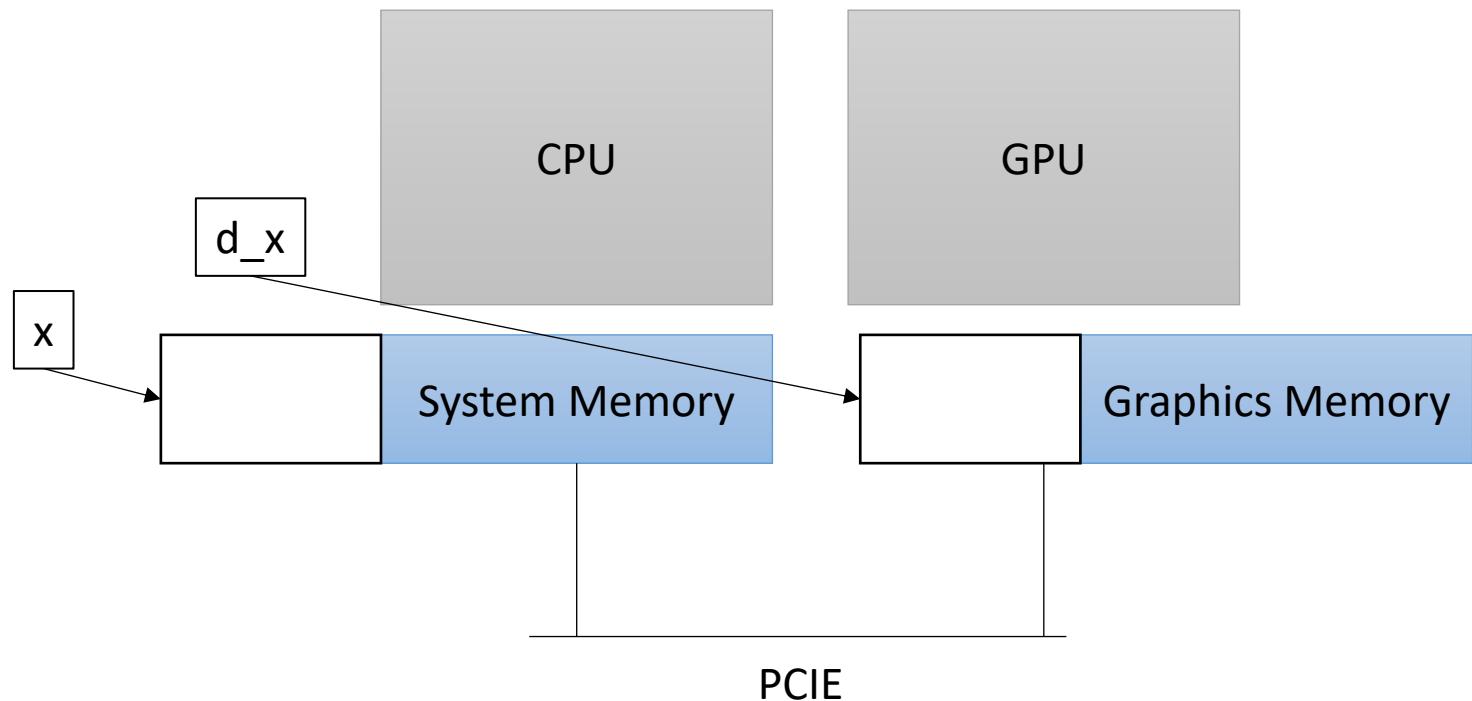
`d_x` is a pointer, in the CPU program, that points to memory on the GPU.



We can pass the pointer around, but the CPU cannot access the data i.e. `d_x[0]` gives an error!

GPU set up

- Our heterogeneous, parallel, programming model

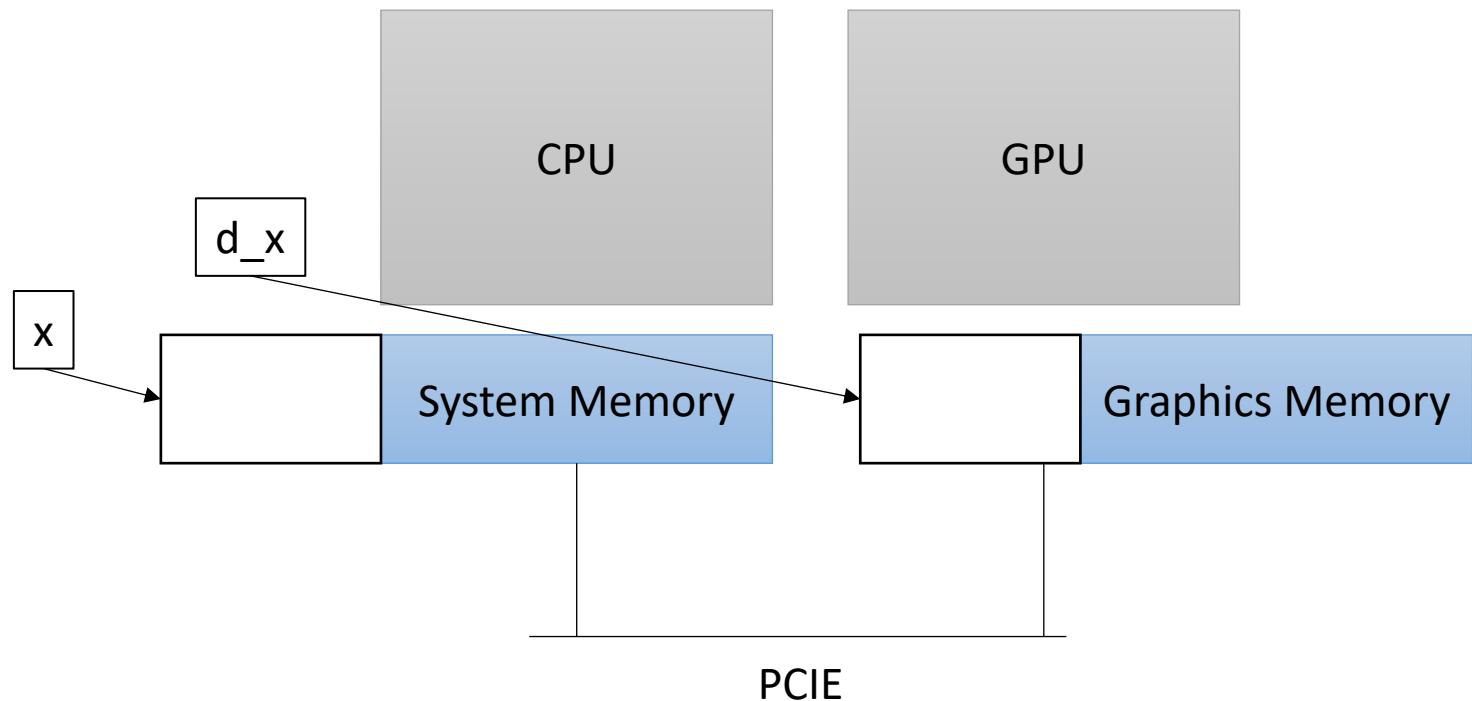


GPU set up

- Our heterogeneous, parallel, programming model

If we can't access d_x on the CPU, how do we initialize the memory?

GPU has no access to input devices e.g. disk



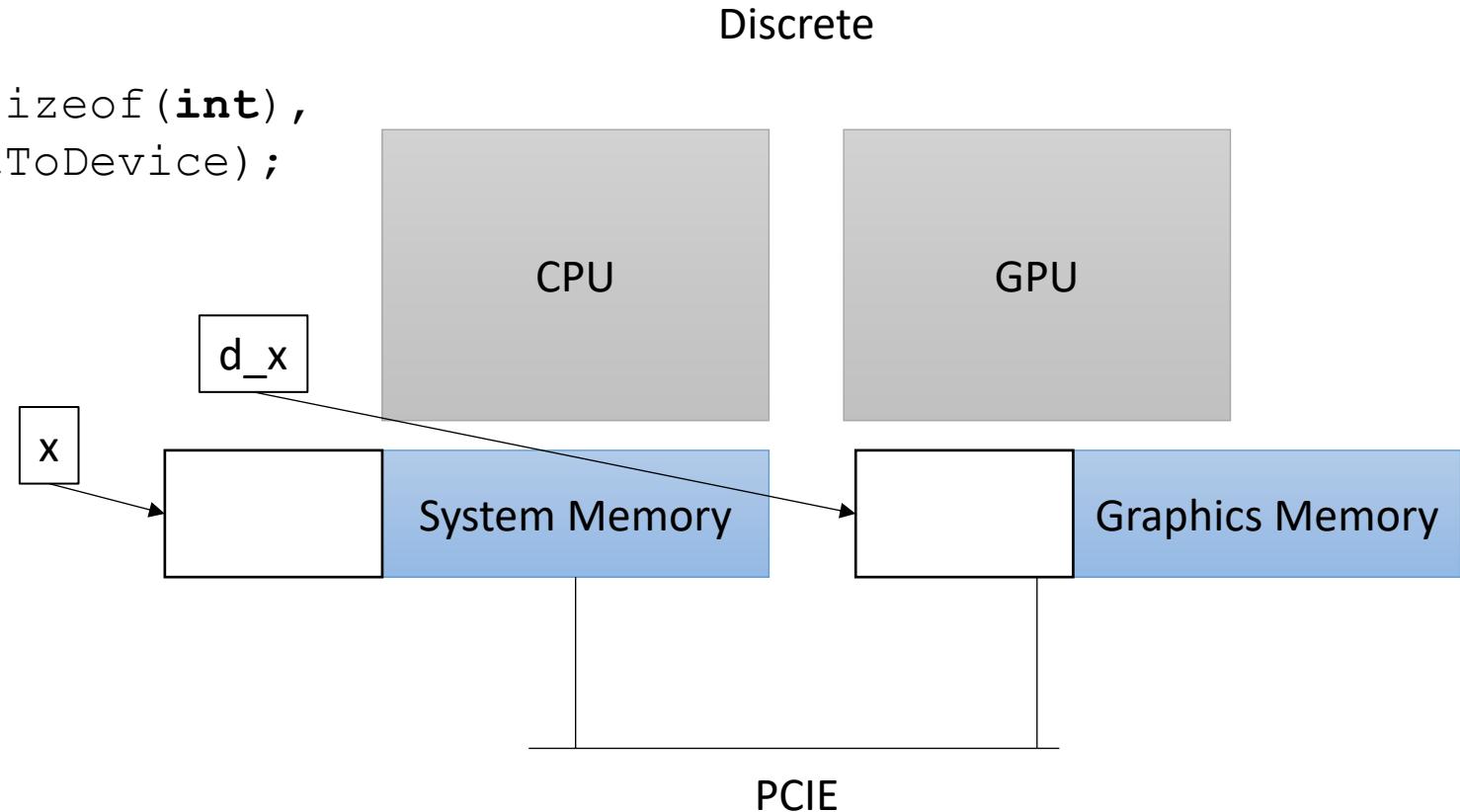
GPU set up

- Our heterogeneous, parallel, programming model

If we can't access `d_x` on the CPU, how do we initialize the memory?

GPU has no access to input devices e.g. disk

```
//initialize x on host  
cudaMemcpy(d_x, x, SIZE*sizeof(int),  
          cudaMemcpyHostToDevice);
```



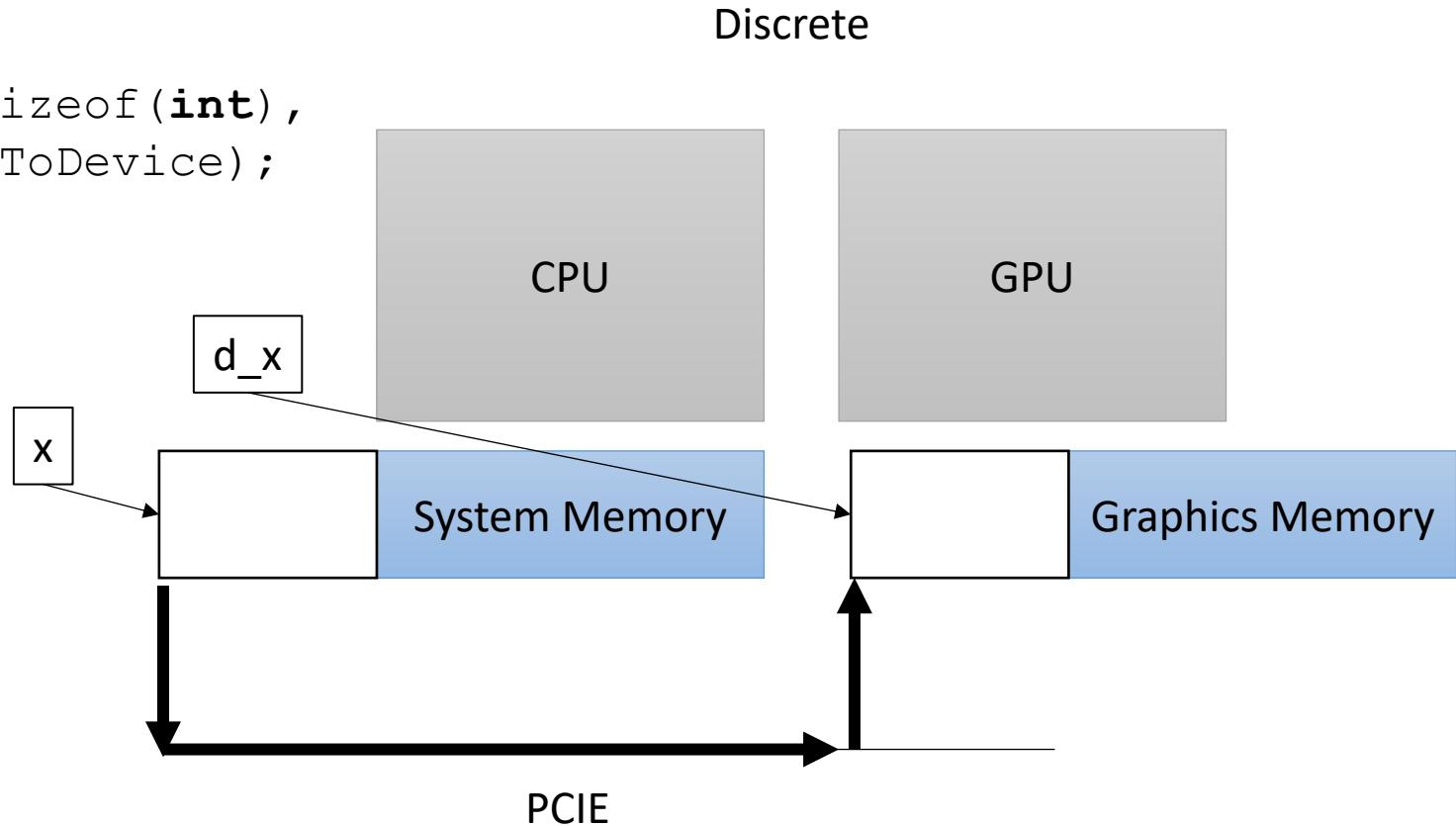
GPU set up

- Our heterogeneous, parallel, programming model

If we can't access `d_x` on the CPU, how do we initialize the memory?

GPU has no access to input devices e.g. disk

```
//initialize x on host  
cudaMemcpy(d_x, x, SIZE*sizeof(int),  
          cudaMemcpyHostToDevice);
```



How does this look in code?

```
float *a = new float[SIZE];
float *b = new float[SIZE];
float *c = new float[SIZE];

for (int i = 0; i < SIZE; i++) {
    a[i] = 0.0f;
    b[i] = i;
    c[i] = 1.0f;
}

float *d_a, *d_b, *d_c;
int e = 0;
e = cudaMalloc(&d_a, SIZE*sizeof(float));
e |= cudaMalloc(&d_b, SIZE*sizeof(float));
e |= cudaMalloc(&d_c, SIZE*sizeof(float));

e |= cudaMemcpy(d_a, a, SIZE*sizeof(float), cudaMemcpyHostToDevice);
e |= cudaMemcpy(d_b, b, SIZE*sizeof(float), cudaMemcpyHostToDevice);
e |= cudaMemcpy(d_c, c, SIZE*sizeof(float), cudaMemcpyHostToDevice);
```

The GPU Program

- Write a special function in your C++ code.
 - Called a Kernel
 - Use the new keyword `__global__`
 - Keywords in
 - OpenCL `__kernel`
 - Metal kernel
- Write it how you'd write any other function

The GPU Program

```
__global__ void vector_add(int * a, int * b, int * c, int size) {
    for (int i = 0; i < size; i++) {
        a[i] = b[i] + c[i];
    }
}
```

The GPU Program

```
__global__ void vector_add(int * a, int * b, int * c, int size) {  
    for (int i = 0; i < size; i++) {  
        a[i] = b[i] + c[i];  
    }  
}
```

calling the function

```
vector_add<<<1,1>>>(d_a, d_b, d_c, size);
```

The GPU Program

```
__global__ void vector_add(int * a, int * b, int * c, int size) {
    for (int i = 0; i < size; i++) {
        a[i] = b[i] + c[i];
    }
}
```

calling the function

What in the world?

special new CUDA syntax. We will talk more soon

```
vector_add<<<1,1>>>(d_a, d_b, d_c, size);
```

The GPU Program

```
__global__ void vector_add(int * d_a, int * d_b, int * d_c, int size) {
    for (int i = 0; i < size; i++) {
        d_a[i] = d_b[i] + d_c[i];
    }
}
```

calling the function

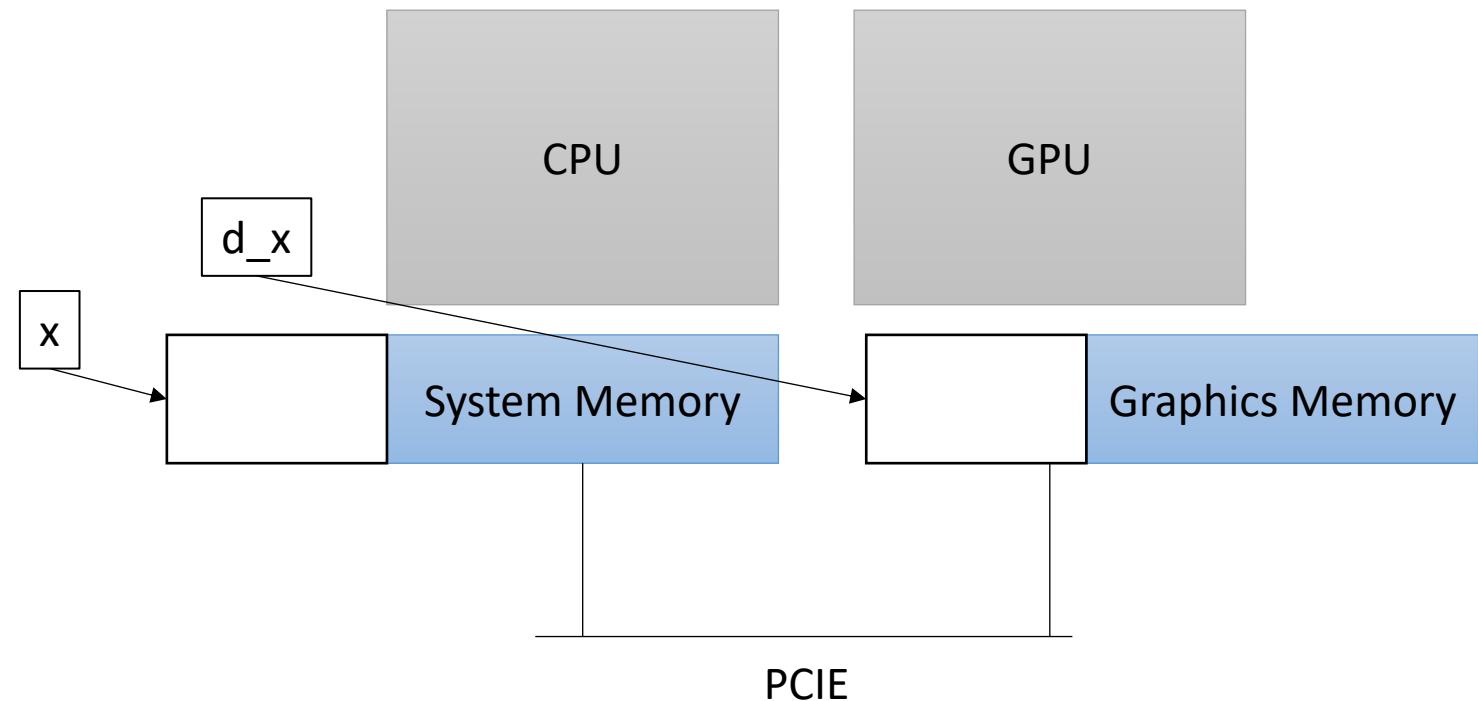
Pass in pointers to memory on the device

```
vector_add<<<1,1>>>(d_a, d_b, d_c, size);
```

GPU set up

- Our heterogeneous, parallel, programming model

Remember, GPU needs to access its own memory



The GPU Program

```
__global__ void vector_add(int * d_a, int * d_b, int * d_c, int size) {
    for (int i = 0; i < size; i++) {
        d_a[i] = d_b[i] + d_c[i];
    }
}
```

*Constants can be passed in regularly
calling the function*

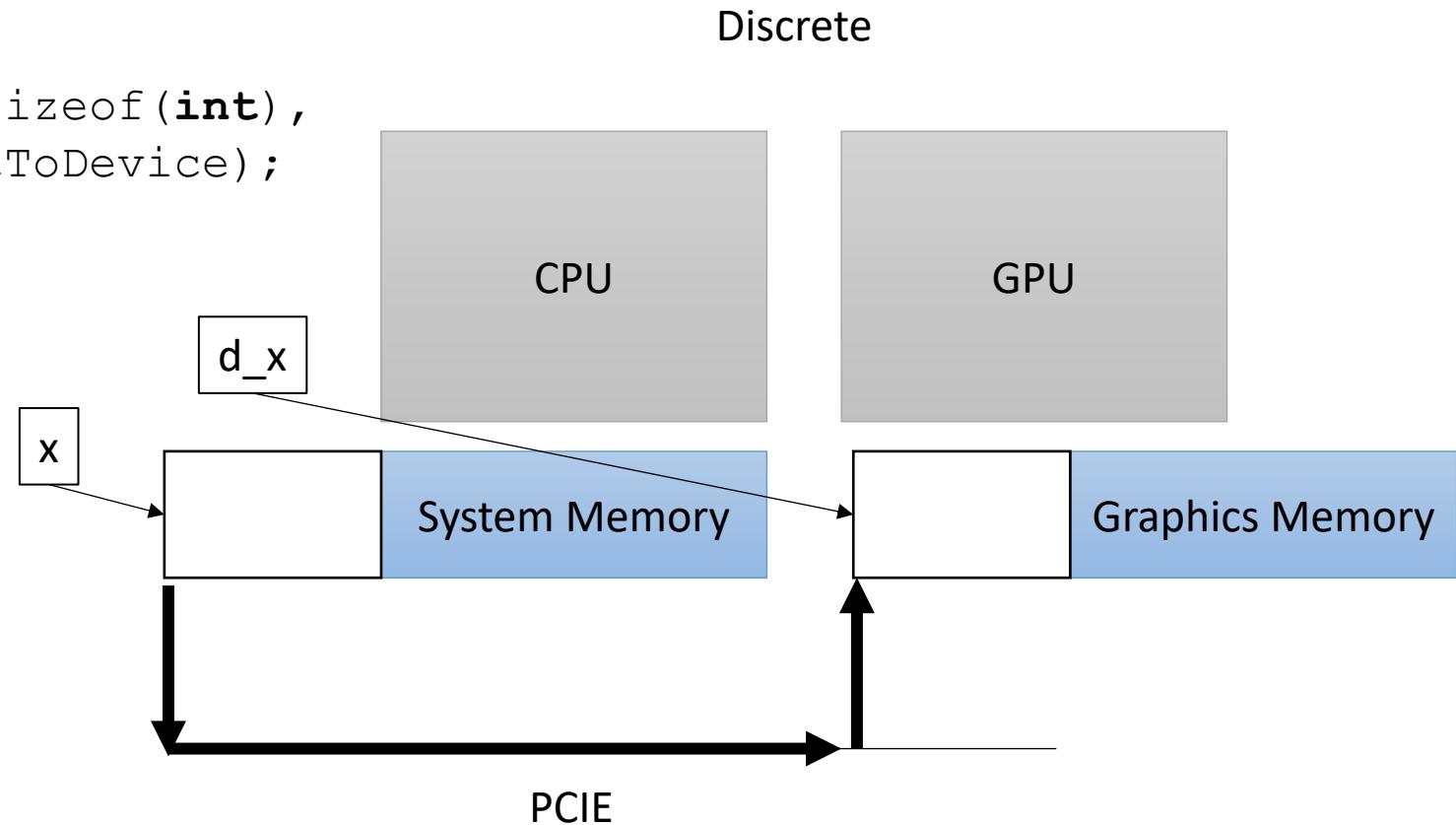
```
vector_add<<<1,1>>>(d_a, d_b, d_c, size);
e |= cudaDeviceSynchronize();
```

```
$ nvcc main.cu -o main
```

GPU set up

- Our heterogeneous, parallel, programming model

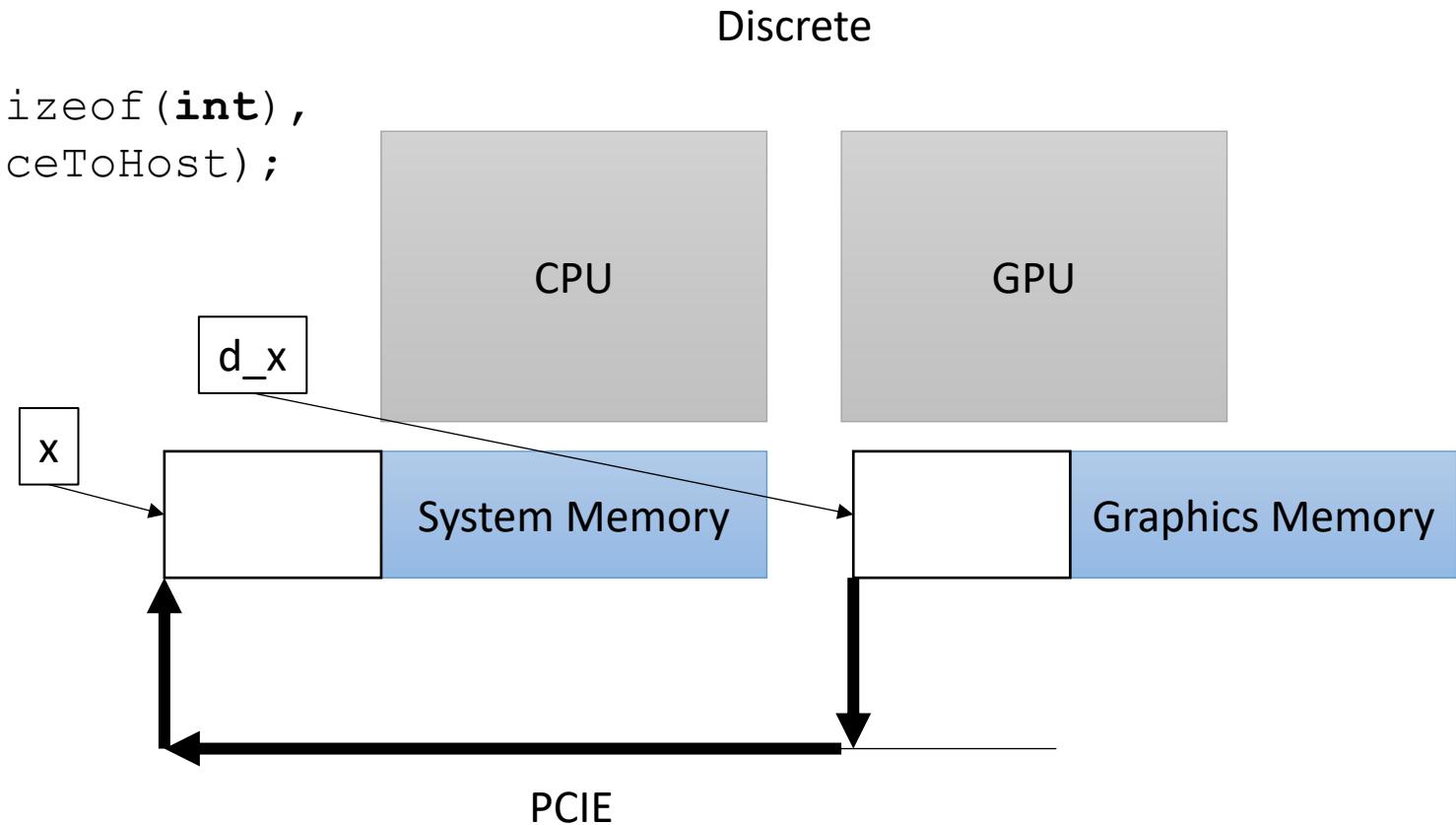
```
//initialize x on host  
cudaMemcpy(d_x, x, SIZE*sizeof(int),  
          cudaMemcpyHostToDevice);
```



GPU set up

- Our heterogeneous, parallel, programming model

```
//initialize x on host  
cudaMemcpy(x, d_x, SIZE*sizeof(int),  
          cudaMemcpyDeviceToHost);
```



The GPU Program

- The operating system expects the GPU kernel to be fast to render graphics.
- It kills the kernel if it takes more than ~5 seconds.
- If GPU is used for both display and CUDA.

The GPU Program



1000x slower on GPU?
It didn't do so well...

One GPU core is much slower than a single CPU core

First parallelization attempt

- Lets look at some GPU documentation.
- The Maxwell whitepaper shows a diagram of one of the GPU cores





woah, 32 cores!

We should parallelize our application!

First parallelization attempt

```
__global__ void vector_add(int * d_a, int * d_b, int * d_c, int size) {
    for (int i = 0; i < size; i++) {
        d_a[i] = d_b[i] + d_c[i];
    }
}
```

calling the function

```
vector_add<<<1, 1>>>(d_a, d_b, d_c, size);
```

First parallelization attempt

```
__global__ void vector_add(int * d_a, int * d_b, int * d_c, int size) {
    for (int i = 0; i < size; i++) {
        d_a[i] = d_b[i] + d_c[i];
    }
}
```

calling the function

```
vector_add<<<1, 32>>>(d_a, d_b, d_c, size);
```

number of threads to launch the program with

First parallelization attempt

```
__global__ void vector_add(int * d_a, int * d_b, int * d_c, int size) {  
    int chunk_size = size/blockDim.x;  
    int start = chunk_size * threadIdx.x;  
    int end = start + chunk_size;  
    for (int i = start; i < end; i++) {  
        d_a[i] = d_b[i] + d_c[i];  
    }  
}
```

calling the function

```
vector_add<<<1,32>>>(d_a, d_b, d_c, size);
```

number of threads

First parallelization attempt

```
__global__ void vector_add(int * d_a, int * d_b, int * d_c, int size) {
    int chunk_size = size/blockDim.x;
    int start = chunk_size * threadIdx.x;
    int end = start + chunk_size;
    for (int i = start; i < end; i++) {
        d_a[i] = d_b[i] + d_c[i];
    }
}
```

calling the function

```
vector_add<<<1,32>>>(d_a, d_b, d_c, size);
```

number of threads
thread id

First parallelization attempt

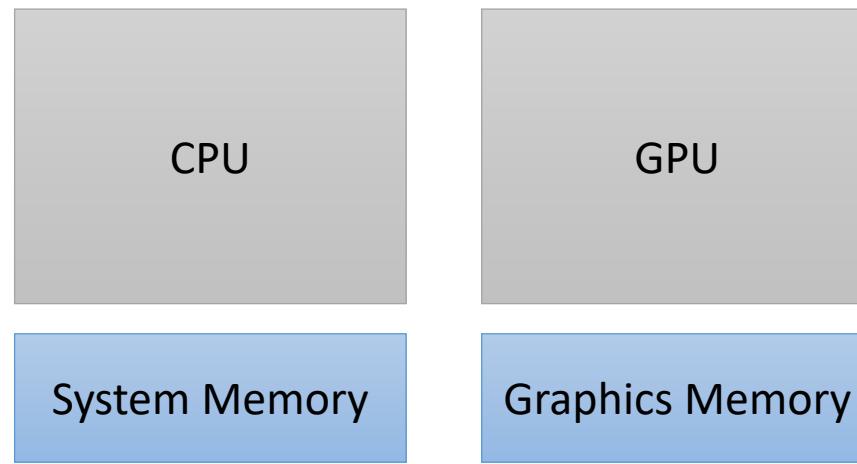
That gives us about 14x speedup!

First parallelization attempt



Getting better but we have a long ways to go!

GPU Memory



GPU Memory

CPU Memory:

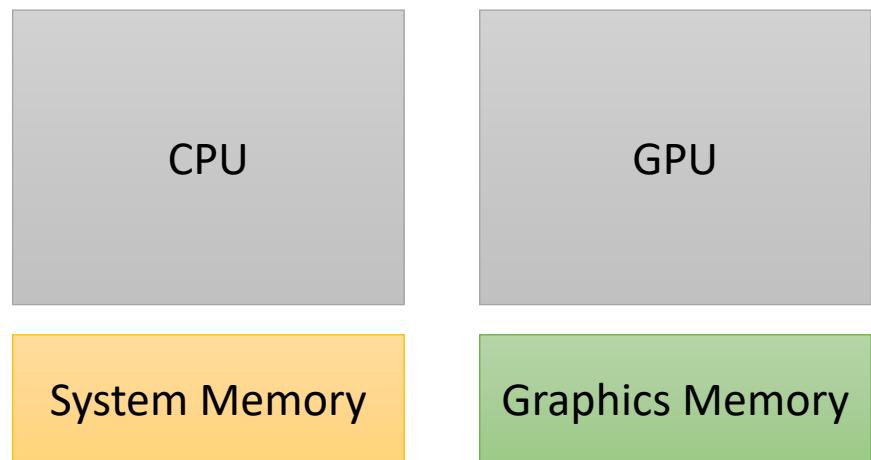
Fast: Low Latency

Easily saturated: Low Bandwidth

Scales well: up to 1 TB

DDR

*2-lane straight highway
driven on by sports cars*



Different technologies

GPU Memory:

slow: High Latency

hard to saturate: High Bandwidth

doesn't scale: 32 GB

GDDR, HBM

*16-lane highway on a windy
road driven by semi trucks*

GPU Memory

bandwidth:

~700 GB/s for GPU

~50 GB/s for CPUs



memory Latency:

~600 cycles for GPU memory

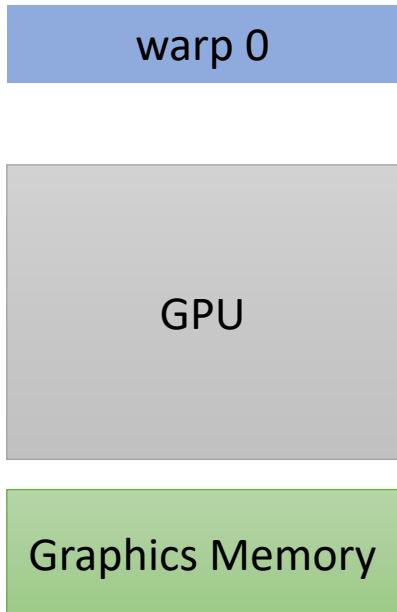
~200 cycles for CPU memory

Cache Latency:

~28 cycles for L1 hit for GPU

~4 cycles for L1 hit on CPUs

Preemption and concurrency?



Preemption and concurrency?

warp 0

all threads load from memory.

GPU

Graphics Memory

Preemption and concurrency?

warp 0

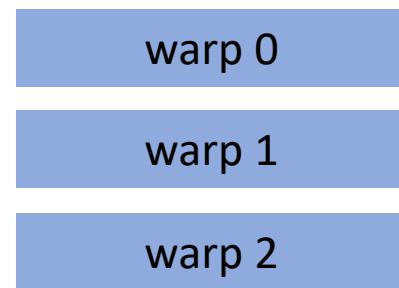
all threads load from memory.

GPU

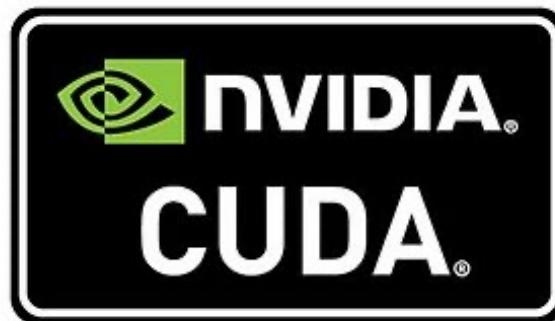
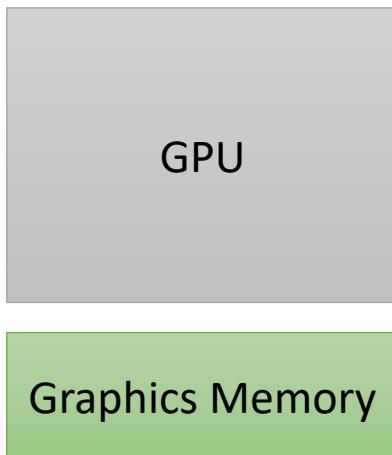
600 cycles!

Graphics Memory

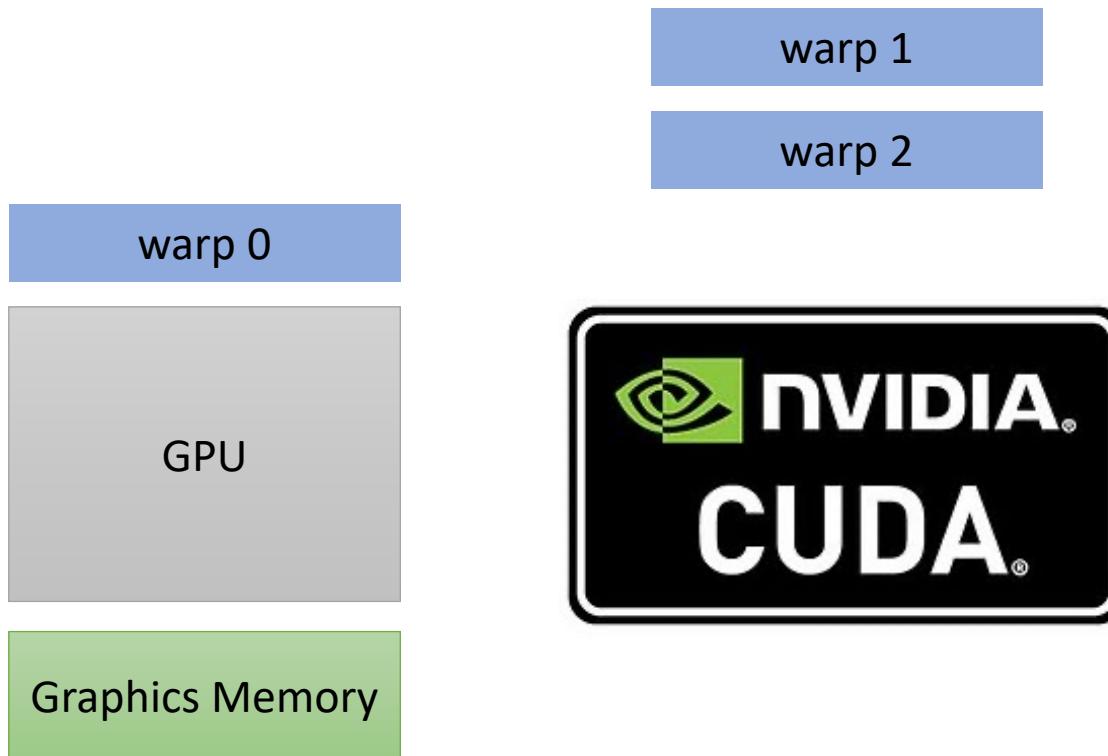
Preemption and concurrency?



We can hide latency through
preemption and concurrency!



Preemption and concurrency?

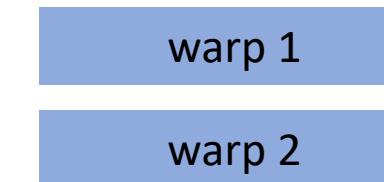
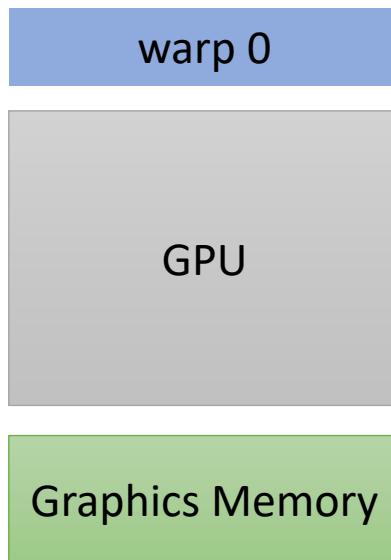


We can hide latency through
preemption and concurrency!



Preemption and concurrency?

memory access
600 cycles

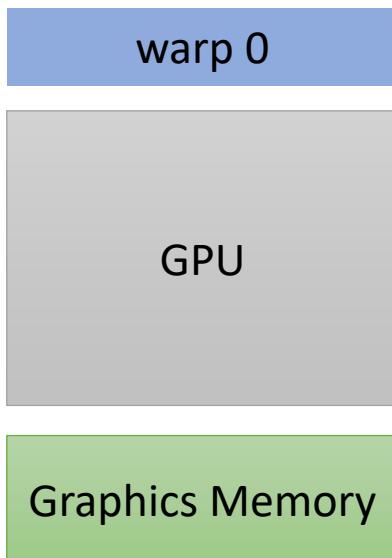


We can hide latency through
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Preemption and concurrency?

memory access
600 cycles



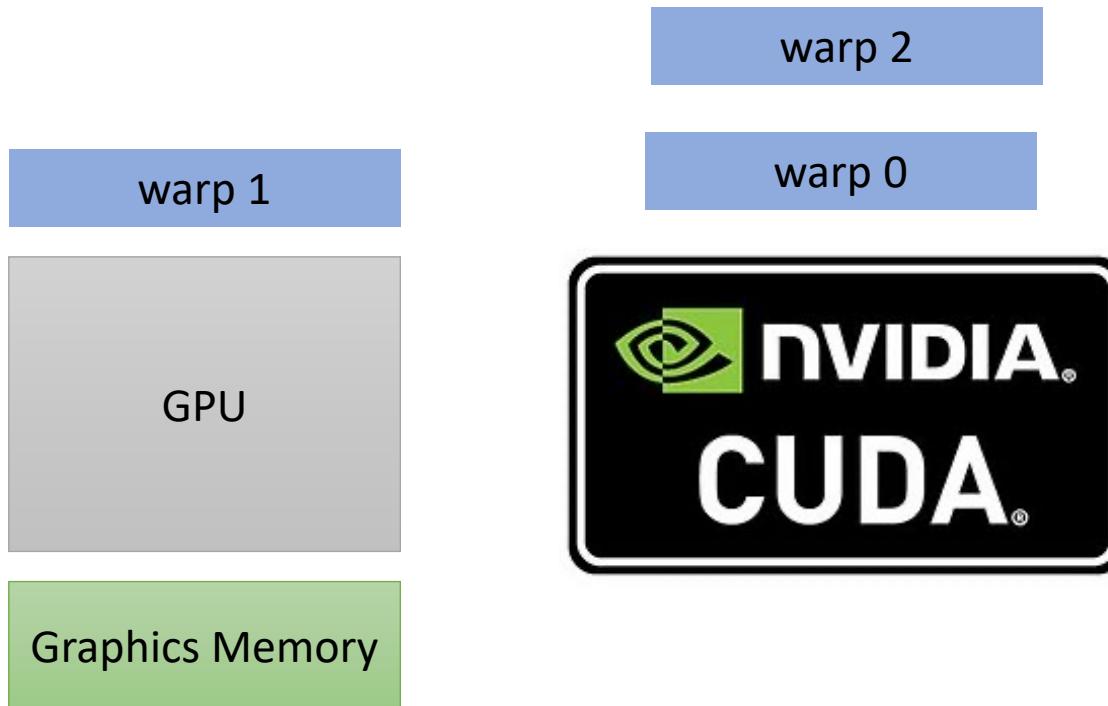
preempt warp 0
and put warp 1 on

warp 1

warp 2

We can hide latency through
preemption and concurrency!

Preemption and concurrency?

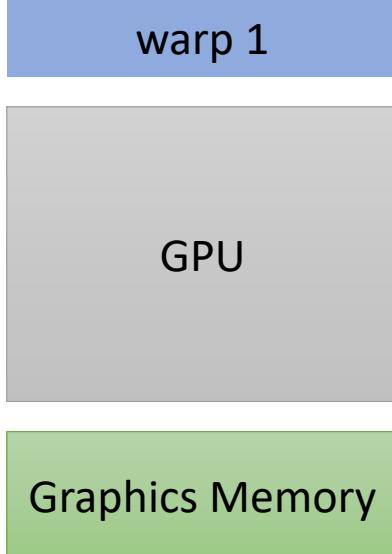


We can hide latency through
preemption and concurrency!



Preemption and concurrency?

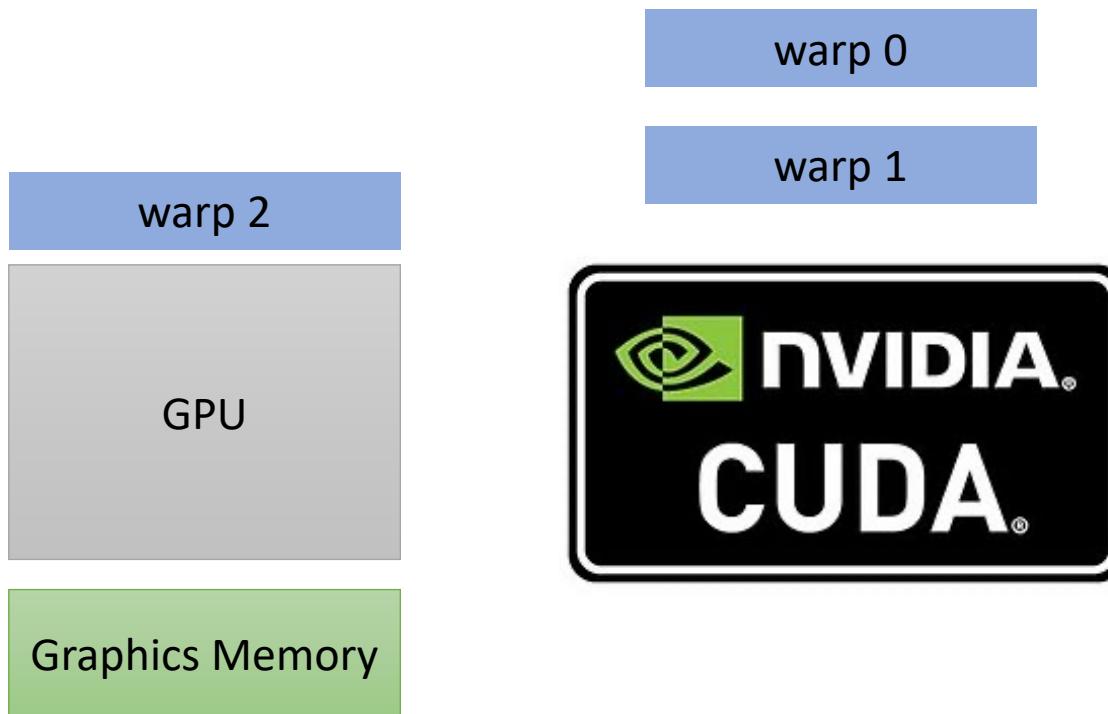
memory access
600 cycles



preempt warp 1
and put warp 2 on

We can hide latency through
preemption and concurrency!

Preemption and concurrency?

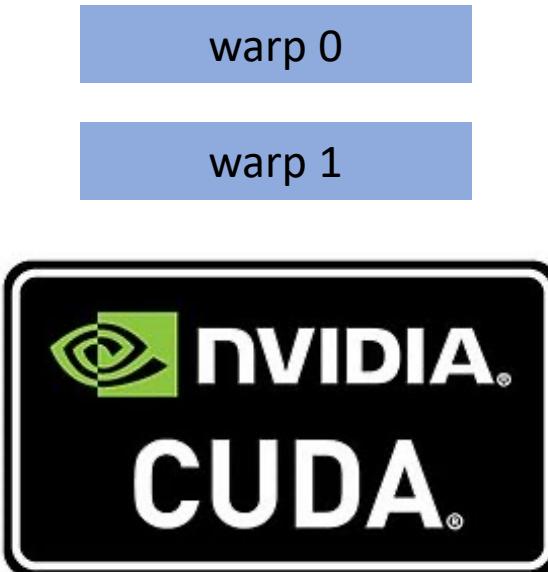
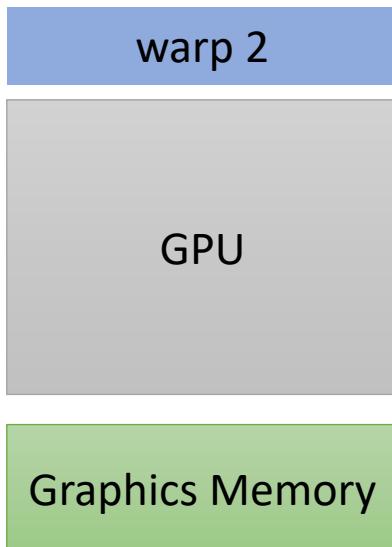


We can hide latency through
preemption and concurrency!



Preemption and concurrency?

memory access
600 cycles

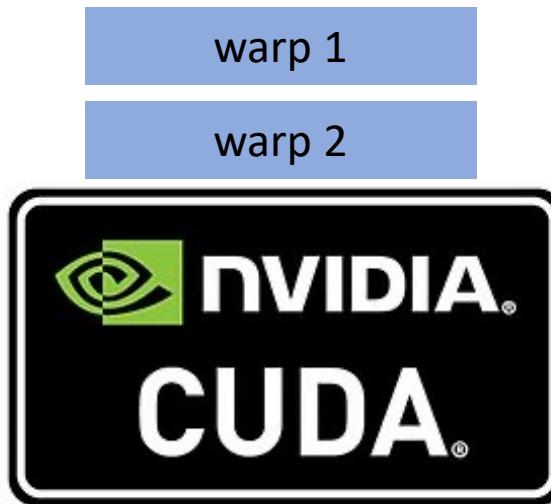
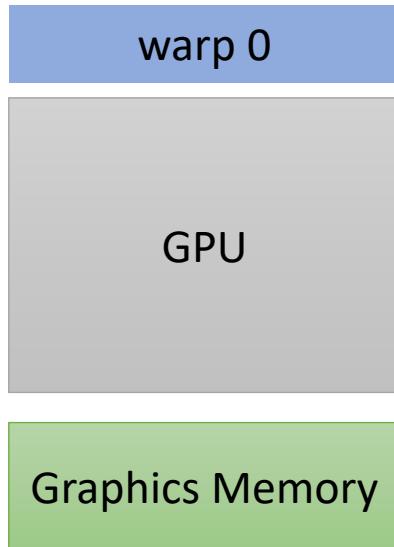


preempt warp 2
and put warp 0 on

We can hide latency through
preemption and concurrency!

Preemption and concurrency?

Hey, my memory has arrived!



preempt warp 2
and put warp 0 on

We can hide latency through
preemption and concurrency!

Preemption and concurrency?

But wait, I thought preemption was expensive?

Preemption and concurrency?



But wait, I thought preemption was expensive?

bound on number of warps: 32

Preemption and concurrency?



But wait, I thought preemption was expensive?

Registers all stay on chip. Large register file.

Preemption and concurrency?



But wait, I thought preemption was expensive?

dedicated scheduler logic

Go back to our program

```
__global__ void vector_add(int * d_a, int * d_b, int * d_c, int size) {  
    int chunk_size = size/blockDim.x;  
    int start = chunk_size * threadIdx.x;  
    int end = start + chunk_size;  
    for (int i = start; i < end; i++) {  
        d_a[i] = d_b[i] + d_c[i];  
    }  
}
```

calling the function

Lets launch with 32 warps

```
vector_add<<<1, 32>>>(d_a, d_b, d_c, size);
```

Go back to our program

```
__global__ void vector_add(int * d_a, int * d_b, int * d_c, int size) {
    int chunk_size = size/blockDim.x;
    int start = chunk_size * threadIdx.x;
    int end = start + chunk_size;
    for (int i = start; i < end; i++) {
        d_a[i] = d_b[i] + d_c[i];
    }
}
```

calling the function

Lets launch with 32 warps

```
vector_add<<<1, 1024>>>(d_a, d_b, d_c, size);
```

Concurrent warps

This is about 2x faster.

Concurrent warps

This is about 2x faster.



Getting better!