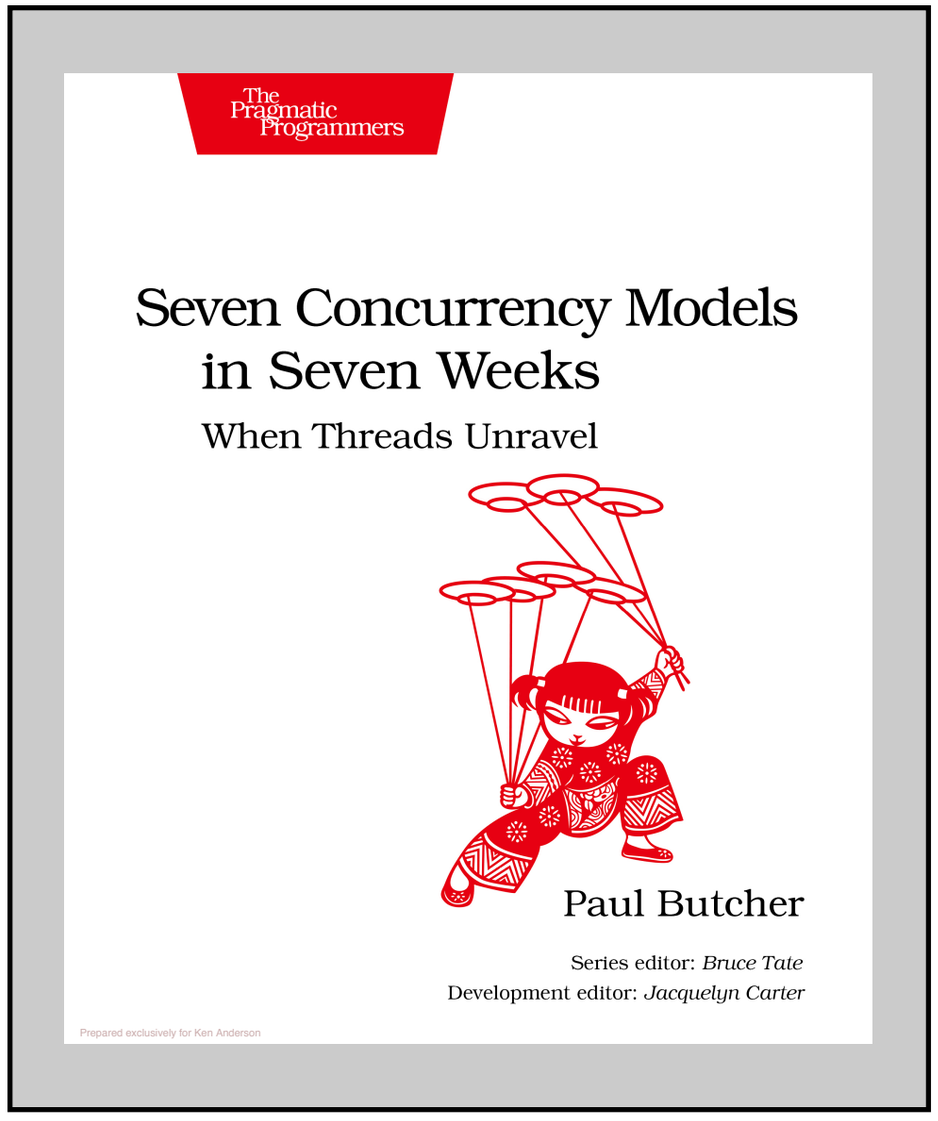
Data Parallelism

CSCI 5828: Foundations of Software Engineering
Lecture 28 — 12/01/2016

Goals

- Cover the material in Chapter 7 of Seven Concurrency Models in Seven Weeks by Paul Butcher
    - Data Parallelism
        - Using OpenCL to create parallel programs on the GPU
    - Also look at two examples that use OpenCL and OpenGL together

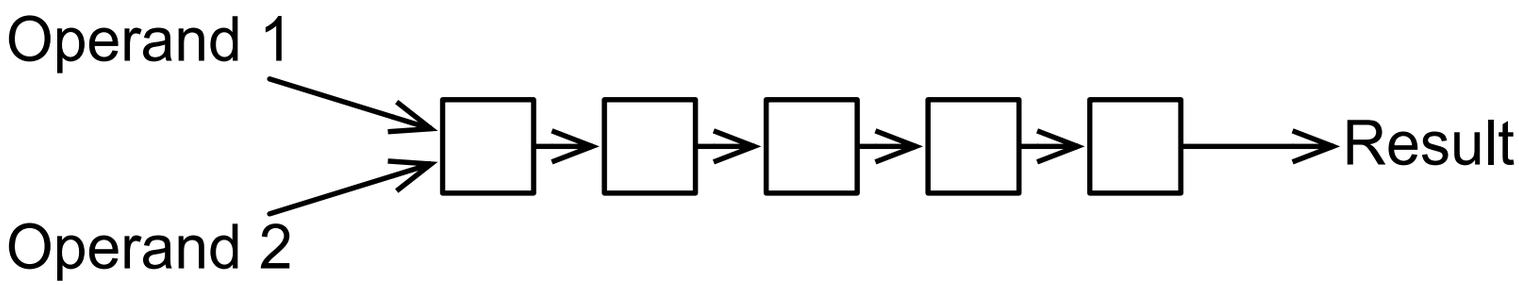


Data Parallelism

- Data Parallelism is an approach to concurrent programming that can perform number crunching on a computer's GPU
  - You typically create a bunch of arrays and load them onto the GPU
  - You also create a "kernel"; a program that is loaded onto the GPU
- The kernel then applies the operations of its program to the elements of the array in parallel.
  - So, if you had two arrays of 1024 floating point numbers and you wanted to multiply those arrays together, the GPU might be able to perform that multiplication on all 1024 pairs "at once"
    - In actuality, the kernel is transformed into a program for your particular GPU that makes use of pipelining and multiple ALUs to process the operation as efficiently as possible

Pipelining (I)

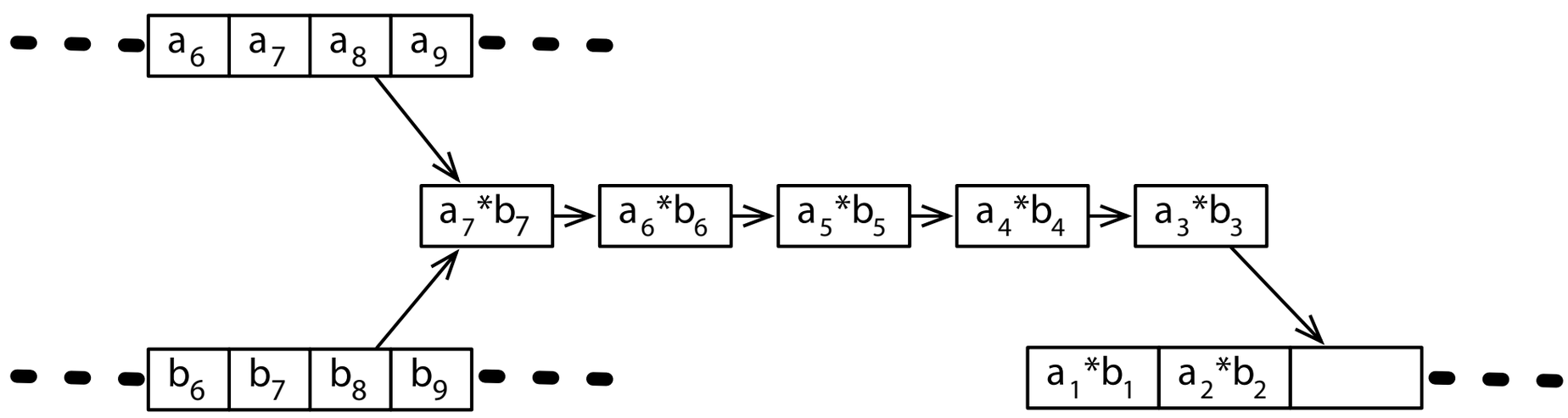
- One way that data parallelism can be implemented is via pipelining
  - int result = 13 * 2;
- We might think of the above multiplication as an atomic operation
  - but on the CPU, at the level of “gates”, it takes several steps
- Those steps are typically arranged as a pipeline



- In this example, if each step takes one clock cycle, it would take 5 clock cycles to perform the multiplication

Pipelining (II)

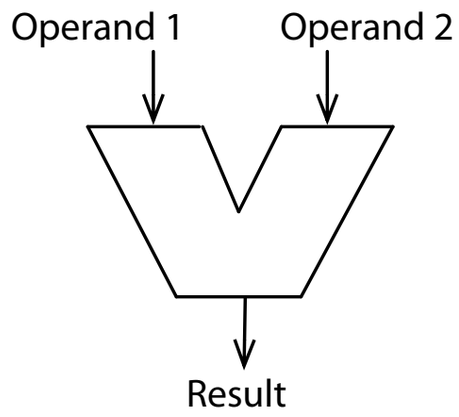
- If we only sent two numbers to this pipeline, our code would be inefficient
  - Instead, if we have lots of numbers to multiply, we can insert new numbers to multiply at the start of the pipeline for each new clock cycle



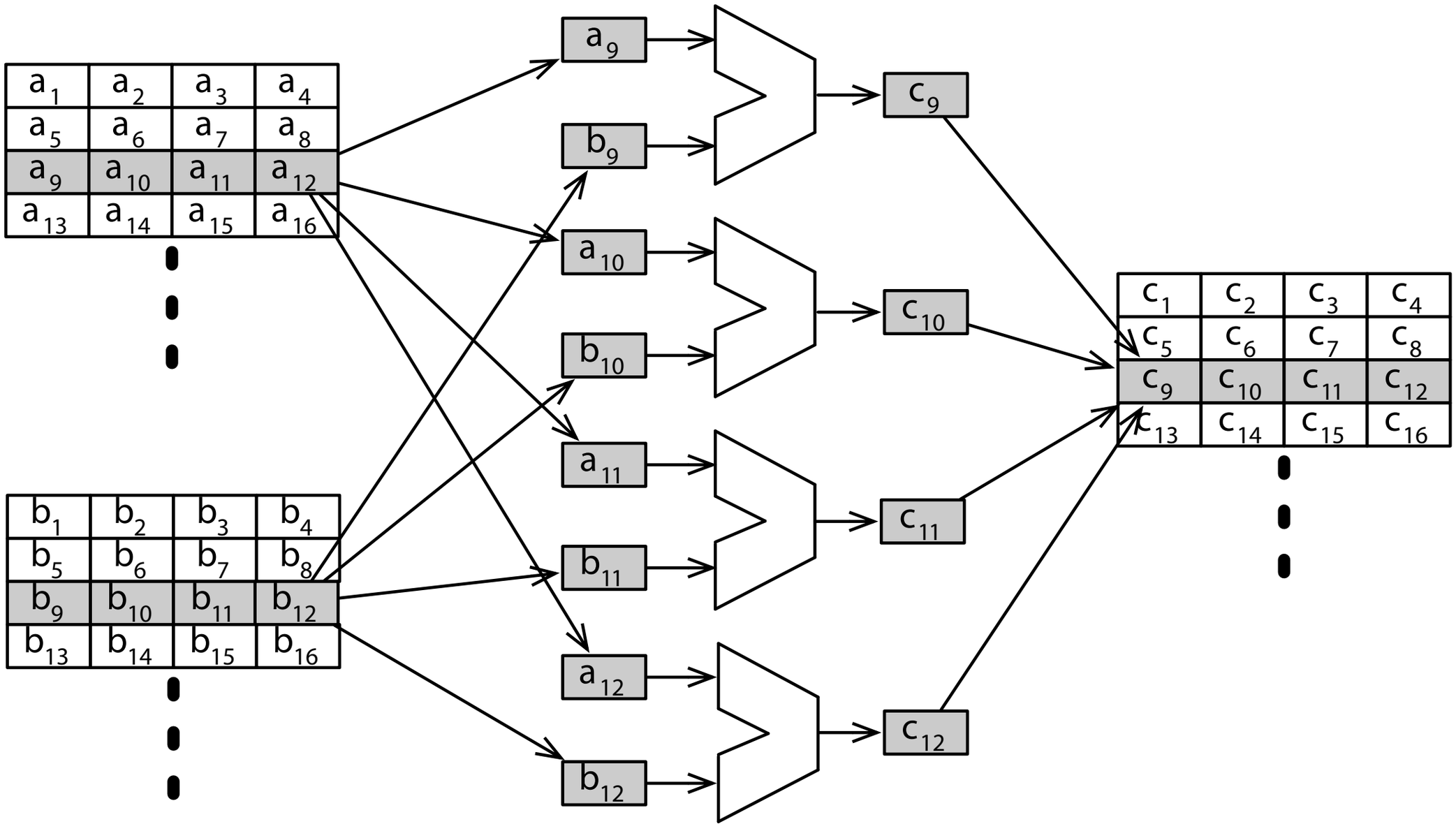
- Here, arrays A and B are being multiplied and we're inserting one new element of each array into the start of the pipeline, each clock cycle
  - 1000 numbers would take ~1000 clock cycles to multiply (rather than 5000)!

ALUs (I)

- Arithmetic logic units (ALUs) perform computations for CPUs
  - They take two inputs and perform a result
- Another way to perform parallel operations on a GPU is to:
  - create a series of linked ALUs that compute a result
  - and combine it with a “wide bus” that allows multiple operands to be fetched at the same time



ALUs (II)

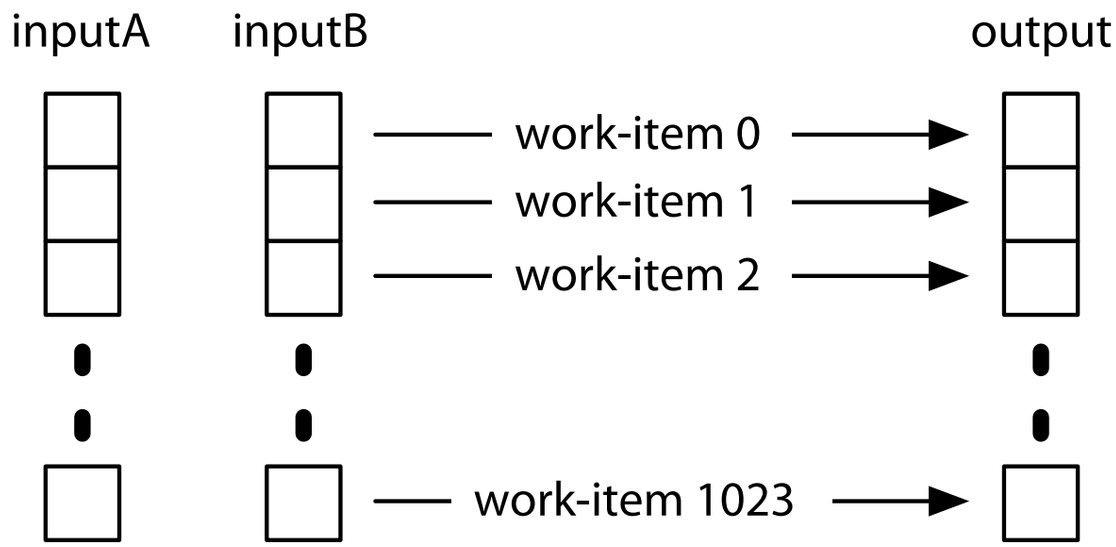


The Basics of OpenCL (I)

- The key to any OpenCL program is defining its work items
  - In traditional approaches to concurrency, you have to
    - create a bunch of threads and make sure that there is enough work to do so that you fully utilize all of the cores on your system
      - otherwise, you end up with poor performance as thread overhead dominates your program's run-time as opposed to actual work
- With OpenCL programs, the goal is to create lots of small work items
  - The smaller the better, so that OpenCL can make use of pipelining and multiple ACLs to maximally distribute the computations across all of the cores in the GPU

The Basics of OpenCL (II)

- "multiplying two arrays" example
  - create one work item for each multiplication
  - depending on the structure of our GPU, we might be able to perform all of the multiplications with one instruction
    - if not, we'd do as many multiplications as possible at once and then load the rest
      - since it's being done in parallel, the number of instructions will be drastically less than doing the same amount of work on the CPU



The Basics of OpenCL (III): Find the Platform

- OpenCL programs have a basic structure
  - You first ask if a platform is available
    - In C
      - `cl_platform_id platform;`
      - `clGetPlatformIDs(1, &platform, NULL);`
    - In Java
      - `CL.create();`
      - `CLPlatform platform = CLPlatform.getPlatforms().get(0);`
- Getting access to the platform object, allows you to look for devices

The Basics of OpenCL (IV): Find the Devices

- Once you have the platform, you can locate a device to use
  - In C
    - `cl_device_id device;`
    - `clGetDeviceIDs(platform, CL_DEVICE_TYPE_GPU, 1, &device, NULL);`
  - In Java
    - `List<CLDevice> devices = platform.getDevices(CL_DEVICE_TYPE_GPU);`
- Here, we are specifically asking for GPUs, but there can be more than one type of device and we could ask for all of them (if needed)
  - devices can also include the CPU and specialized OpenCL accelerators

DEMO

The Basics of OpenCL (V): Get a Context

- Once you have a device (or devices), you can create a context for execution
  - In C
    - `cl_context context =`
      - `clCreateContext(NULL, 1, &device, NULL, NULL, NULL);`
  - In Java
    - `CLContext context =`
      - `CLContext.create(platform, devices, null, null, null);`
- Contexts can be used to pull in other information for OpenCL, such as OpenGL drawing environments (as we will see in a later example)
  - but the primary use of a context is to create a queue for processing work items

The Basics of OpenCL (VI): Create a Queue

- Now we are ready to create a command queue
  - In C
    - `cl_command_queue queue = clCreateCommandQueue(context, device, 0, NULL);`
  - In Java
    - `CLCommandQueue queue =`
      - `clCreateCommandQueue(context, devices.get(0), 0, null);`
- We now have the ability to send commands to the device and get it to perform work for us
  - I'm now going to switch to showing an example in C, we'll return to the Java example later

The Basics of OpenCL (VII): Compile a Kernel

- OpenCL defines a C-like language that allows work-items to be specified
  - Programs written in this language are called kernels
    - Before we can use our queue, we need to compile the kernel. It is this step that creates a program that works with your specific GPU
      - `char* source = read_source(“multiply_arrays.cl");`
      - `cl_program program =`
        - `clCreateProgramWithSource(`
          - `context, 1, (const char**)&source, NULL, NULL);`
      - `free(source);`
      - `clBuildProgram(program, 0, NULL, NULL, NULL, NULL);`
      - `cl_kernel kernel = clCreateKernel(program, "multiply_arrays", NULL);`
- At the end of this step, we have our kernel in memory, ready to execute
  - I’ll show you the “multiply_arrays.cl” code in a moment

The Basics of OpenCL (VIII): Create Buffers

- Kernels are typically passed buffers (i.e. arrays) of data that they operate on
    - `#define NUM_ELEMENTS 1024`
    - `cl_float a[NUM_ELEMENTS], b[NUM_ELEMENTS];`
    - `random_fill(a, NUM_ELEMENTS);`
    - `random_fill(b, NUM_ELEMENTS);`
    - `cl_mem inputA = clCreateBuffer(context, CL_MEM_READ_ONLY | CL_MEM_COPY_HOST_PTR, sizeof(cl_float) * NUM_ELEMENTS, a, NULL);`
    - `cl_mem inputB = clCreateBuffer(context, CL_MEM_READ_ONLY | CL_MEM_COPY_HOST_PTR, sizeof(cl_float) * NUM_ELEMENTS, b, NULL);`
    - `cl_mem output = clCreateBuffer(context, CL_MEM_WRITE_ONLY, sizeof(cl_float) * NUM_ELEMENTS, NULL, NULL);`
- Here we create two C arrays, fill them with random numbers, and then copy them into two OpenCL buffers. We also create a buffer to store the output

The Basics of OpenCL (IX): Perform the Work

- Now, we need to pass the buffers to the kernel
  - `clSetKernelArg(kernel, 0, sizeof(cl_mem), &inputA);`
  - `clSetKernelArg(kernel, 1, sizeof(cl_mem), &inputB);`
  - `clSetKernelArg(kernel, 2, sizeof(cl_mem), &output);`
- Perform the work
  - `size_t work_units = NUM_ELEMENTS;`
  - `clEnqueueNDRangeKernel(`
    `queue, kernel, 1, NULL, &work_units, NULL, 0, NULL, NULL);`
- Retrieve the results
  - `cl_float results[NUM_ELEMENTS];`
  - `clEnqueueReadBuffer(queue, output, CL_TRUE, 0,`
    `sizeof(cl_float) * NUM_ELEMENTS, results, 0, NULL, NULL);`

The Basics of OpenCL (X): Clean Up

- Finally, we have to deallocate all OpenCL-related data structures
  - `clReleaseMemObject(inputA);`
  - `clReleaseMemObject(inputB);`
  - `clReleaseMemObject(output);`
  - `clReleaseKernel(kernel);`
  - `clReleaseProgram(program);`
  - `clReleaseCommandQueue(queue);`
  - `clReleaseContext(context);`
- Now, we're ready to look at a kernel

Our First Kernel: Multiply Arrays (I)

- Here's a small kernel, written in OpenCL's C-like language

```
__kernel void multiply_arrays(
  __global const float* inputA,
  __global const float* inputB,
  __global float* output) {
    int i = get_global_id(0);
    output[i] = inputA[i] * inputB[i];
}
```

- This is NOT C, it's just designed to look like C.
  - The OpenCL compiler can take this program and generate machine code to run on a particular device (in this case a GPU) in a massively parallel fashion

Our First Kernel: Multiply Arrays (II)

```
__kernel void multiply_arrays(
  __global const float* inputA,
  __global const float* inputB,
  __global float* output) {
   int i = get_global_id(0);
   output[i] = inputA[i] * inputB[i];
}
```

- We see that this kernel expects three inputs: each an array of floats
  - Our call to `clSetKernelArg()` on slide 16 assigns our buffers to these args
  - All three of these arrays are stored in the GPU's global memory
- To perform work, we find out what work item we are (`get_global_id()`)
  - We use that id to index into the arrays
- OpenCL will try to complete as many work items in parallel as it can

The single threaded version?

- How do we decide if all this work is worth it
  - Let's compare the GPU version of the program with the single-threaded version that runs on the CPU. Here it is
    - ```
      for (int i = 0; i < NUM_ELEMENTS; ++i) {
        results[i] = a[i] * b[i];
      }
      ```
  - (This code reuses the definitions of a, b, and results seen previously)
- Paul Butcher's book shows how to profile OpenCL code
  - (see Chapter 7 of that book for details)
      ```

The results?

- Multiply two arrays of 200,000 random float values

- Total (GPU): 1717845 ns
  - Elapsed (GPU): **86000 ns** <= how long did the multiplications take?
- Elapsed (CPU): **886752 ns** <= single-threaded version

- The GPU version is ten times faster
  - Finishing in .08 milliseconds
- The CPU finished in 0.8 milliseconds

- Worth it? Not for this simple program. But, in general, YES!

Working in Multiple Dimensions

- Our first example showed how to operate on buffers that were the same length and that had a single index to organize the work
  - We can work with multiple dimensions (such as multiplying matrices) by employing a common trick
    - We store a multidimensional matrix into a linear array
      - If we have a 2x2 matrix, we can store its values in a 4-element array
- We then use a “width” parameter and x,y coordinates to calculate where in the linear array a particular value is stored. Rather than
  - a[x][y] = 10
- We write
  - a[x*width+y] = 10

Our Second Kernel: Matrix Multiplication

```
__kernel void matrix_multiplication(uint widthA,
                                    __global const float* inputA,
                                    __global const float* inputB,
                                    __global float* output) {

  int i = get_global_id(0);
  int j = get_global_id(1);

  int outputWidth = get_global_size(0);
  int outputHeight = get_global_size(1);
  int widthB = outputWidth;

  float total = 0.0;
  for (int k = 0; k < widthA; ++k) {
    total += inputA[j * widthA + k] * inputB[k * widthB + i];
  }
  output[j * outputWidth + i] = total;
}
```

Our work items have been configured to have two dimensions

The size of the output matrix was set as a global variable.

Configuring OpenCL to Work with this Kernel

```
size_t work_units[] = {WIDTH_OUTPUT, HEIGHT_OUTPUT};
CHECK_STATUS(clEnqueueNDRangeKernel(queue, kernel, 2, NULL, work_units,
  NULL, 0, NULL, NULL));
```

To ensure our kernel has the information it needs, we have to change how we add work items to the queue

The “2” tells OpenCL that the work items have two dimensions

The work_units array tells OpenCL the range of the two dimensions

The results?

- The book multiplies a 200x400 matrix (of random floating point values) by a 300x200 matrix producing a 300x400 matrix as a result

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- Total (GPU): 4899413 ns
  - Elapsed (GPU): **3840000 ns** <= 78% of the time spent multiplying
- Elapsed (CPU): **65459804 ns** <= single-threaded version

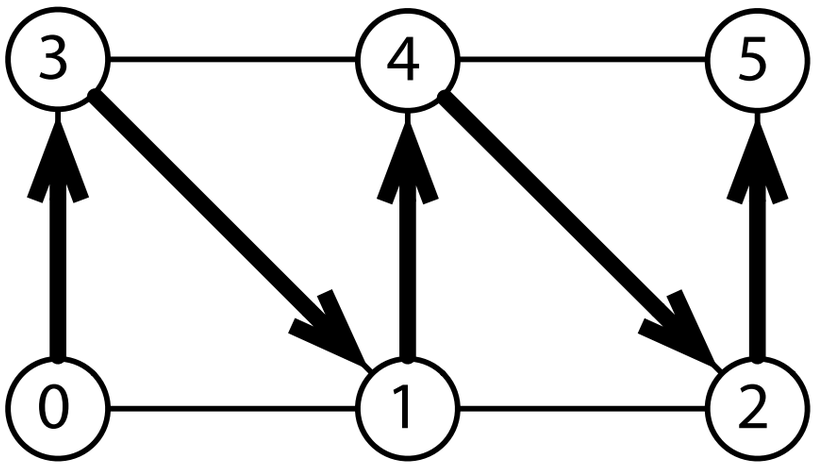
- The GPU version is 17 times faster!
  - Finishing in 3.84 milliseconds
- The CPU finished in 65.5 milliseconds
- Worth it? For a program that has to do a lot of these multiplications?
  - YOU BET!

OpenCL and OpenGL: Match Made in Heaven?

- One use of OpenCL code is to work with OpenGL to perform graphics-related calculations on the GPU, freeing up the CPU to perform other operations
  - OpenGL is a standard for creating 3D programs/animations
- Our book presents two OpenGL applications that make use of OpenCL to perform operations on triangles
- In the first example, we create a “mesh” of triangles and use OpenGL to display them
  - we then send the vertices of the mesh to an OpenCL program that multiplies there values by 1.01 increasing the spacing of the vertices by 1% on each iteration
  - This has the visual effect of zooming in on the mesh

Background (I)

- The mesh of triangles can be conceptualized like this



There's an index buffer that captures the existence of each index: 0, 1, 2

There's also a vertex buffer that captures the position of each index:
Index 1 => {0, 0, 0} i.e. x, y, z

```
int vertexBuffer = glGenBuffers();
glBindBuffer(GL_ARRAY_BUFFER, vertexBuffer);
glBufferData(GL_ARRAY_BUFFER, mesh.vertices, GL_DYNAMIC_DRAW);

int indexBuffer = glGenBuffers();
glBindBuffer(GL_ELEMENT_ARRAY_BUFFER, indexBuffer);
glBufferData(GL_ELEMENT_ARRAY_BUFFER, mesh.indices, GL_STATIC_DRAW);
```

When we create the vertex buffer, we tell OpenGL that it will change

Background (II)

- Our kernel for zooming is simple

```
__kernel void zoom(__global float* vertices) {

  unsigned int id = get_global_id(0);
  vertices[id] *= 1.01;
}
```

- get each value, (x, y, z), and increase its size by 1%

Background (III)

- The key to making this work is to then associate an OpenGL buffer with an OpenCL buffer
  - In a loop do the following
    - draw the OpenGL buffer
    - associate the OpenGL buffer with an OpenCL buffer
    - allow OpenCL to apply the kernel to the OpenCL buffer (which changes the OpenGL buffer automatically)
    - call “finish” to ensure that all OpenCL operations have completed
- OpenGL will then draw the new mesh, the next time through the loop

Background (IV): In Code

```
while (!Display.isCloseRequested()) {
  glClear(GL_COLOR_BUFFER_BIT | GL_DEPTH_BUFFER_BIT);
  glLoadIdentity();
  glTranslatef(0.0f, 0.0f, planeDistance);
  glDrawElements(GL_TRIANGLE_STRIP, mesh.indexCount, GL_UNSIGNED_SHORT, 0);

  Display.update();

  Util.checkCLError(clEnqueueAcquireGLObjects(queue, vertexBufferCL, null, null));
  kernel.setArg(0, vertexBufferCL);
  clEnqueueNDRangeKernel(queue, kernel, 1, null, workSize, null, null, null);
  Util.checkCLError(clEnqueueReleaseGLObjects(queue, vertexBufferCL, null, null));
  clFinish(queue);
}
```

DEMO

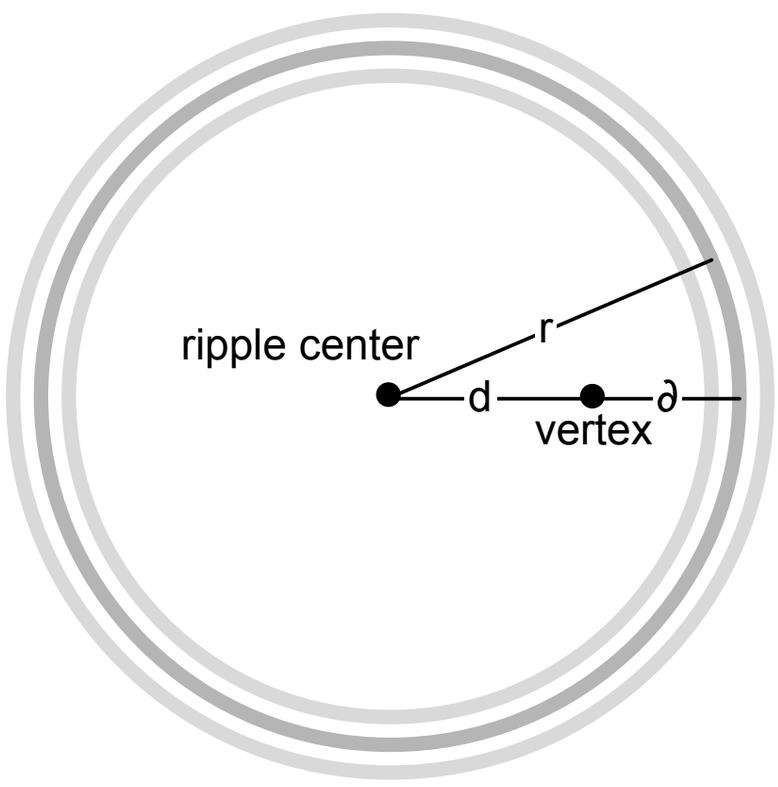
Ripple (I)

- In the previous example, the z values were initialized to zero
  - And, 0 * 1.01 == 0
- As a result, the “zoom” of the previous example was achieved by just spacing out the triangles' x and y values until they were offscreen

- The second example is more interesting, the kernel targets the z value of a triangle’s vertices
  - As a result, it will morph the mesh into “3D shapes”
- And, just to be fancy, the program supports up to 16 ripples at a time!

Ripple (II)

- Each click on the mesh (up to 16), creates a “center point” for a wave that ripples out over the mesh
    - Our kernel looks at **each** vertex and calculates the impact of **each** ripple on the z coordinate of that vertex, using the following equation and conceptual model



$$z = Ae^{-Dr^2}e^{-W\delta^2}\cos(F\pi\delta)$$

A is the amplitude of the wave; D is the decay of the wave; W is the width of the wave; F is the frequency of the wave

Ripple (III): The Kernel

```
#define AMPLITUDE 0.1
#define FREQUENCY 10.0
#define SPEED 0.5
#define WAVE_PACKET 50.0
#define DECAY_RATE 2.0
__kernel void ripple(__global float* vertices,
                     __global float* centers,
                     __global long* times,
                     int num_centers,
                     long now) {
  unsigned int id = get_global_id(0);
  unsigned int offset = id * 3;
  float x = vertices[offset];
  float y = vertices[offset + 1];
  float z = 0.0;

  for (int i = 0; i < num_centers; ++i) {
    if (times[i] != 0) {
      float dx = x - centers[i * 2];
      float dy = y - centers[i * 2 + 1];
      float d = sqrt(dx * dx + dy * dy);
      float elapsed = (now - times[i]) / 1000.0;
      float r = elapsed * SPEED;
      float delta = r - d;
      z += AMPLITUDE *
        exp(-DECAY_RATE * r * r) *
        exp(-WAVE_PACKET * delta * delta) *
        cos(FREQUENCY * M_PI_F * delta);
    }
  }
  vertices[offset + 2] = z;
}
```

Three arrays are passed along with two parameters to each one-dimensional work item

Our id retrieves the vertex that we're working on. The centers array contains the center point of each ripple. The times array contains the time each ripple was created. The now variable contains the current time.

With that information, we can use the equation on the previous slide, to update the z value for each ripple

OpenCL ensures that ALL vertices are updated IN PARALLEL. That's the true power of this approach.

DEMO

Summary

- We scratched the surface of data parallelism and GPU programming with OpenCL
  - We looked at a range of examples of OpenCL kernels
    - an abstract way of defining a “work item”
      - This specification is compiled into code that performs the specified operations on as many data points as possible in parallel
  - We saw the power of this technique by showing how OpenCL can support the transformation of OpenGL objects, the GPU performs most of the calculations, freeing up the CPU to handle other tasks
- This approach stands in contrast to the other concurrency alternatives
  - our programs were all single threaded; instead we used the GPU to perform calculations in parallel when it was needed