CSE 599 I
Accelerated Computing - Programming GPUS

OpenCL / OpenACC

NVIDIA

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Lecture 20 – Related Programming Models: OpenCL

Lecture 20.1 - OpenCL Data Parallelism Model

Objective

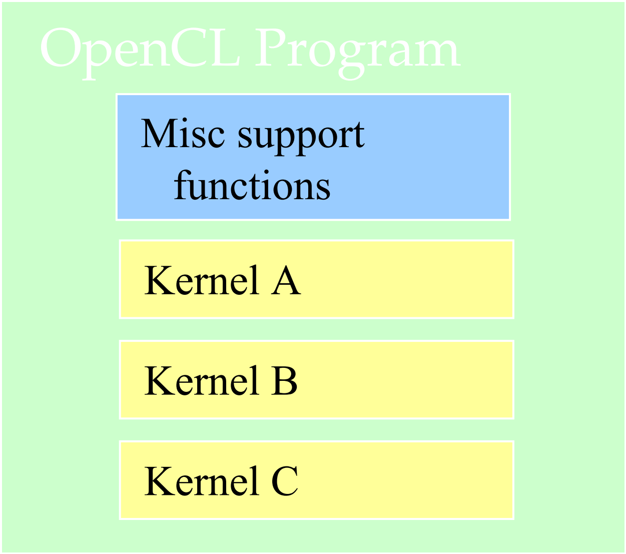
- To Understand the OpenCL programming model
  - basic concepts and data types
  - Kernel structure
  - Application programming interface
  - Simple examples

Background

- OpenCL was initiated by Apple and maintained by the Khronos Group (also home of OpenGL) as an industry standard API
  - For cross-platform parallel programming in CPUs, GPUs, DSPs, FPGAs,…
- OpenCL draws heavily on CUDA
  - Easy to learn for CUDA programmers
- OpenCL host code is much more complex and tedious due to desire to maximize portability and to minimize burden on vendors

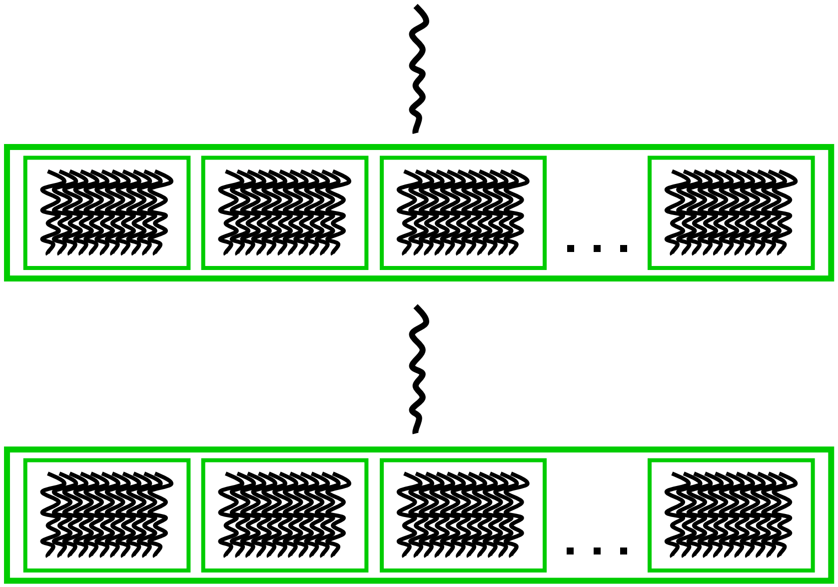
OpenCL Programs

- An OpenCL "program" is a C program that contains one or more "kernels" and any supporting routines that run on a target device
- An OpenCL kernel is the basic unit of parallel code that can be executed on a target device



OpenCL Execution Model

- Integrated host+device app C program
  - Serial or modestly parallel parts in host C code
  - Highly parallel parts in device SPMD kernel C code



Mapping between OpenCL and CUDA data parallelism model concepts.

OpenCL Parallelism Concept	CUDA Equivalent
host	host
device	device
kernel	kernel
host program	host program
NDRange (index space)	grid
work item	thread
work group	block

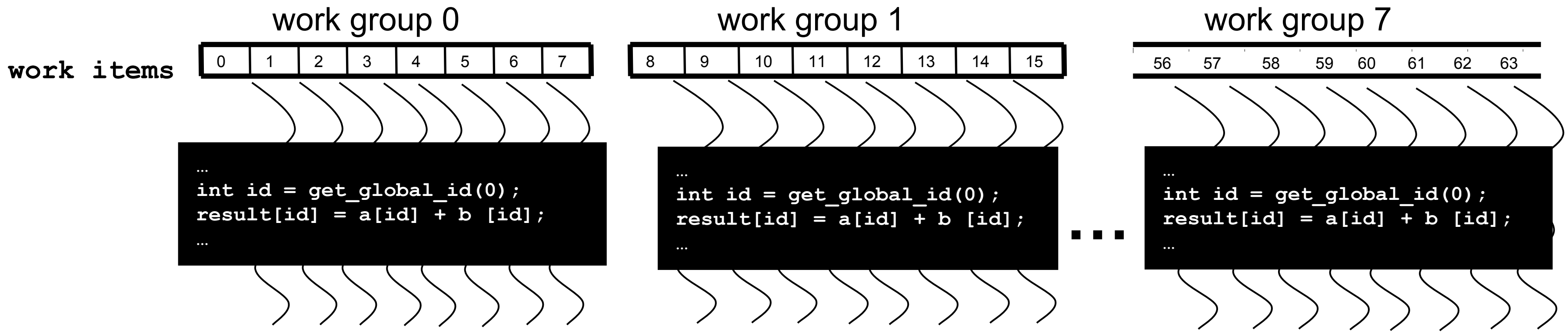
OpenCL Kernels

- Code that executes on target devices
- Kernel body is instantiated once for each work item
  - An OpenCL work item is equivalent to a CUDA thread
- Each OpenCL work item gets a unique index

```
__kernel void  vadd(__global const float *a,
                          __global const float *b,
                        __global float *result)
{
    int id = get_global_id(0);
    result[id] = a[id] + b[id];
}
```

Array of Work Items

- An OpenCL kernel is executed by an array of work items
  - All work items run the same code (SPMD)
  - Each work item can call get_global_id() to get its index for computing memory addresses and make control decisions



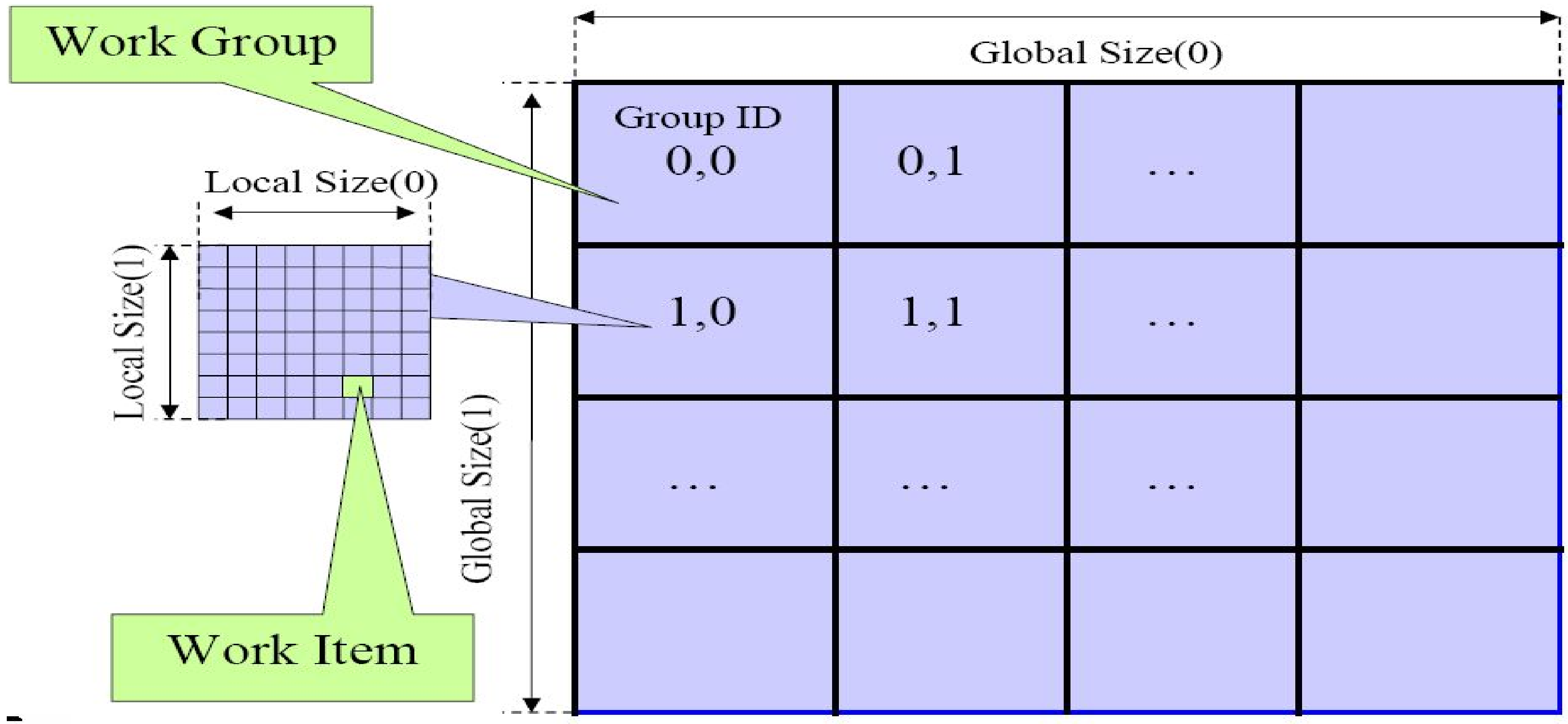
Work Groups: Scalable Cooperation

- Divide monolithic work item array into work groups
  - Work items within a work group cooperate via shared memory and barrier synchronization
  - Work items in different work groups cannot cooperate
- OpenCL counterpart of CUDA Thread Blocks

OpenCL Dimensions and Indices

OpenCL API Call	Explanation	CUDA Equivalent
get_global_id(0);	global index of the work item in the x dimension	blockIdx.x*blockDim.x +threadIdx.x
get_local_id(0)	local index of the work item within the work group in the x dimension	threadIdx.x
get_global_size(0);	size of NDRange in the x dimension	gridDim.x*blockDim.x
get_local_size(0);	Size of each work group in the x dimension	blockDim.x

Multidimensional Work Indexing



OpenCL Data Parallel Model Summary

- Parallel work is submitted to devices by launching kernels
- Kernels run over global dimension index ranges (NDRange), broken up into “work groups”, and “work items”
- Work items executing within the same work group can synchronize with each other with barriers or memory fences
- Work items in different work groups can’t sync with each other, except by terminating the kernel

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Module 20 – Related Programming Models: OpenCL

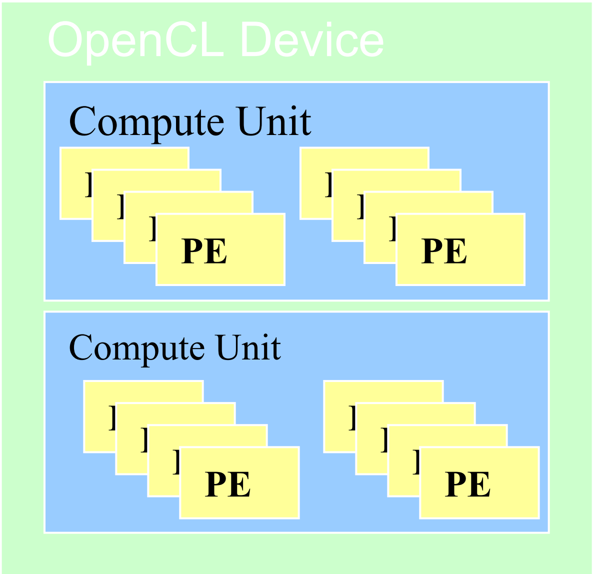
Lecture 20.2 - OpenCL Device Architecture

Objective

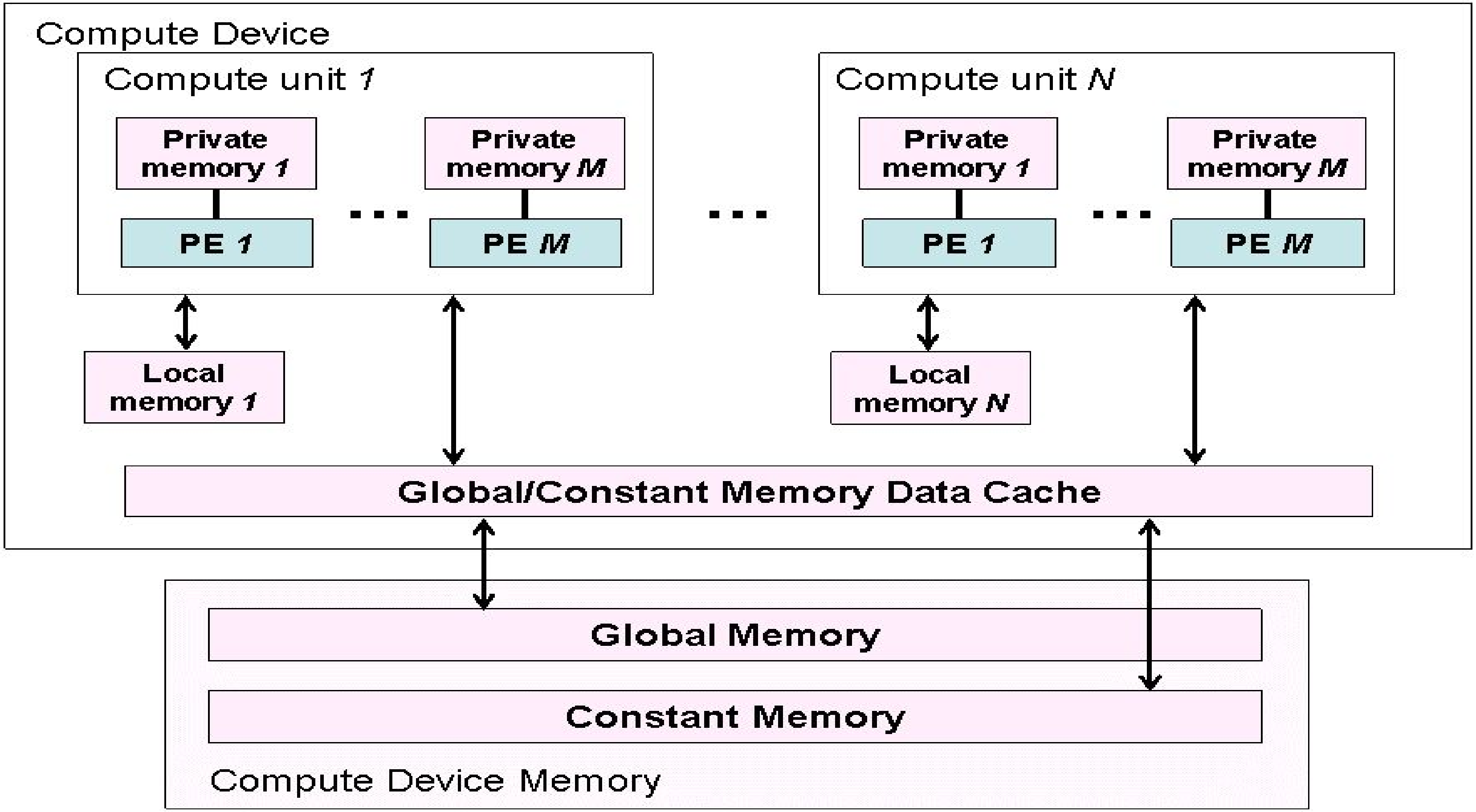
- To Understand the OpenCL device architecture
  - Foundation to terminology used in the host code
  - Also needed to understand the memory model for kernels

OpenCL Hardware Abstraction

- OpenCL exposes CPUs, GPUs, and other Accelerators as "devices"
- Each device contains one or more "compute units", i.e. cores, Streaming Multiprocessors, etc...
- Each compute unit contains one or more SIMD "processing elements", (i.e. SP in CUDA)



OpenCL Device Architecture

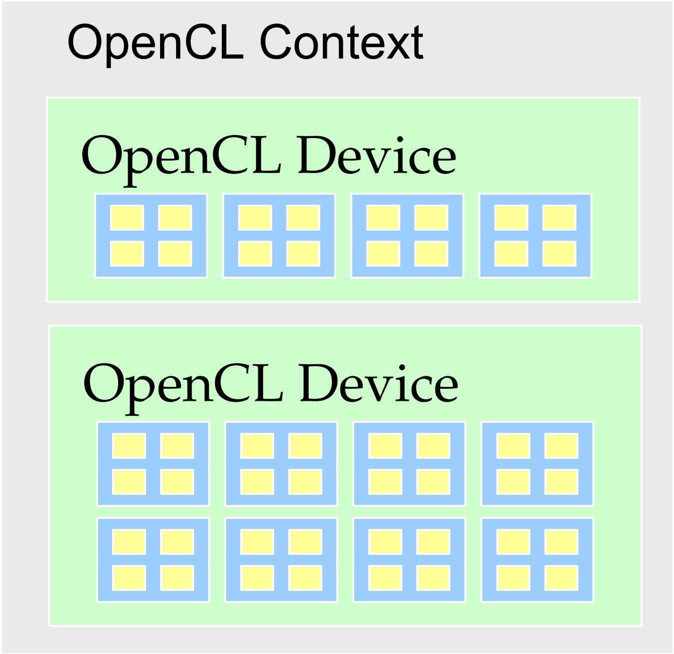


OpenCL Device Memory Types

Memory Type	Host access	Device access	CUDA Equivalent
global memory	Dynamic allocation; Read/write access	No allocation; Read/write access by all work items in all work groups, large and slow but may be cached in some devices.	global memory
constant memory	Dynamic allocation; read/write access	Static allocation; read-only access by all work items.	constant memory
local memory	Dynamic allocation; no access	Static allocation; shared read-write access by all work items in a work group.	shared memory
private memory	No allocation; no access	Static allocation; Read/write access by a single work item.	registers and local memory

OpenCL Context

- Contains one or more devices
- OpenCL device memory objects are associated with a context, not a specific device



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Module 20 – Related Programming Models: OpenCL

Lecture 20.3 - OpenCL Host Code

Objective

- To learn to write OpenCL host code
  - Create OpenCL context
  - Create work queues for task parallelism
  - Device memory Allocation
  - Kernel compilation
  - Kernel launch
  - Host-device data copy

OpenCL Context

- Contains one or more devices
- OpenCL memory objects are associated with a context, not a specific device
- clCreateBuffer() is the main data object allocation function
  - error if an allocation is too large for any device in the context
- Each device needs its own work queue(s)
- Memory copy transfers are associated with a command queue (thus a specific device)

OpenCL Context Setup Code (simple)

```
cl_int clerr = CL_SUCCESS;
cl_context clctx = clCreateContextFromType(0, CL_DEVICE_TYPE_ALL,
NULL, NULL, &clerr);

size_t parmsz;
clerr = clGetContextInfo(clctx, CL_CONTEXT_DEVICES, 0, NULL, &parmsz);

cl_device_id* cldevs = (cl_device_id *) malloc(parmsz);
clerr = clGetContextInfo(clctx, CL_CONTEXT_DEVICES, parmsz, cldevs,
NULL);

cl_command_queue clcmdq = clCreateCommandQueue(clctx, cldevs[0], 0,
&clerr);
```

OpenCL Kernel Compilation: vadd

OpenCL kernel source code as a big string

```
const char* vaddsrc =
   "__kernel void vadd(__global float *d_A, __global float *d_B,
__global float *d_C, int N) { \n"   [...etc and so forth...]
```

Gives raw source code string(s) to OpenCL

```
cl_program clpgm;
clpgm = clCreateProgramWithSource(clctx, 1, &vaddsrc, NULL,
&clerr);
```

Set compiler flags, compile source, and retrieve a handle to the "vadd" kernel

```
char clcompileflags[4096];
sprintf(clcompileflags, "-cl-mad-enable");
clerr = clBuildProgram(clpgm, 0, NULL, clcompileflags, NULL, NULL);
cl_kernel clkern = clCreateKernel(clpgm, "vadd", &clerr);
```

OpenCL Device Memory Allocation

- clCreateBuffer();
  - Allocates object in the device Global Memory
  - Returns a pointer to the object
  - Requires five parameters
    - OpenCL context pointer
    - Flags for access type by device (read/write, etc.)
    - Size of allocated object
    - Host memory pointer, if used in copy-from-host mode
    - Error code
- clReleaseMemObject()
  - Frees object
    - Pointer to freed object

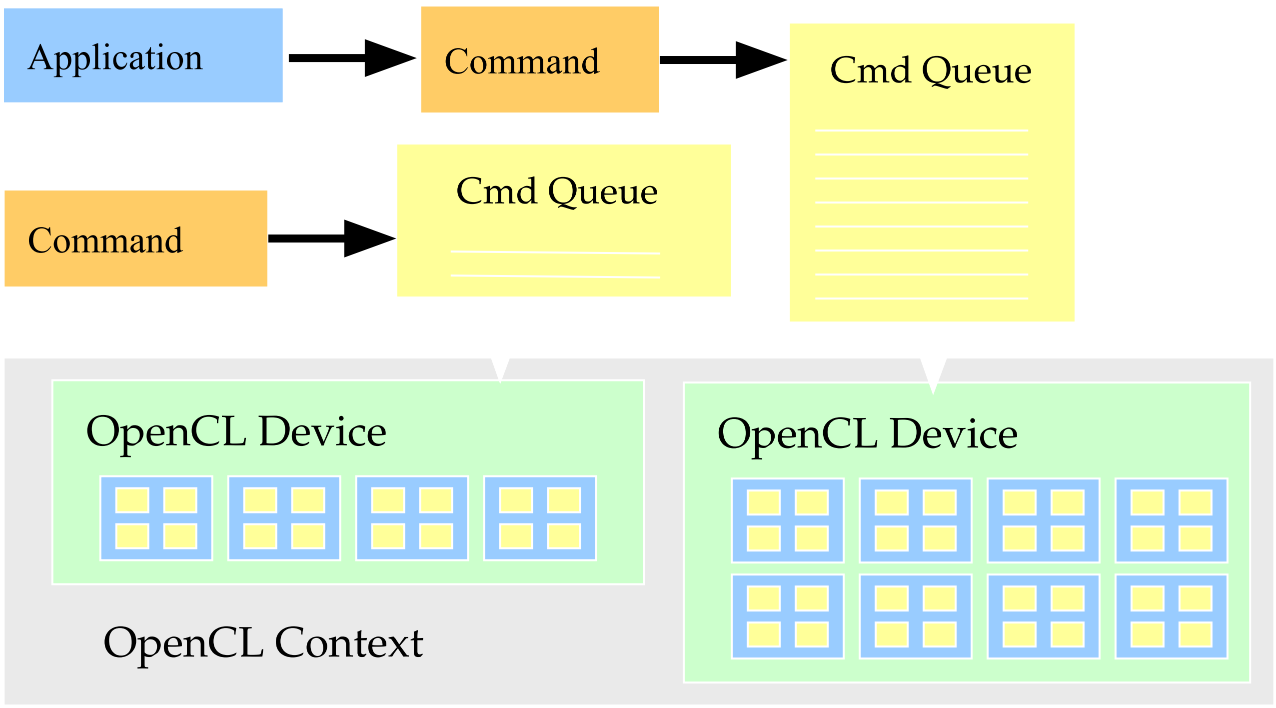
OpenCL Device Memory Allocation (cont.)

- Code example:
  - Allocate a 1024 single precision float array
  - Attach the allocated storage to d_a
  - "d_" is often used to indicate a device data structure

```
VECTOR_SIZE = 1024;
cl_mem d_a;
int size = VECTOR_SIZE* sizeof(float);

d_a = clCreateBuffer(clctx,
     CL_MEM_READ_ONLY, size, NULL, NULL);
…
clReleaseMemObject(d_a);
```

OpenCL Device Command Execution



OpenCL Host-to-Device Data Transfer

- `clEnqueueWriteBuffer();`
  - Memory data transfer to device
  - Requires nine parameters
    - OpenCL command queue pointer
    - Destination OpenCL memory buffer
    - Blocking flag
    - Offset in bytes
    - Size (in bytes) of written data
    - Source host memory pointer
    - List of events to be completed before execution of this command
    - Event object tied to this command

OpenCL Device-to-Host Data Transfer

- `clEnqueueReadBuffer();`
  - Memory data transfer to host
  - requires nine parameters
    - OpenCL command queue pointer
    - Source OpenCL memory buffer
    - Blocking flag
    - Offset in bytes
    - Size of bytes of read data
    - Destination host memory pointer
    - List of events to be completed before execution of this command
    - Event object tied to this command

OpenCL Host-Device Data Transfer (cont.)

- Code example:
  - Transfer a 64 * 64 single precision float array
  - a is in host memory and d_a is in device memory

```
clEnqueueWriteBuffer(clcmdq, d_a, CL_FALSE, 0,
        mem_size, (const void * )a, 0, 0, NULL);

clEnqueueReadBuffer(clcmdq, d_result, CL_FALSE,
      0,
        mem_size, (void * ) host_result, 0, 0,
      NULL);
```

OpenCL Host-Device Data Transfer (cont.)

- `clCreateBuffer` and `clEnqueueWriteBuffer` can be combined into a single command using special flags.
- Eg:

```
d_A=clCreateBuffer(clctxt,CL_MEM_READ_ONLY | CL_MEM_COPY_HOST_PTR,
mem_size, h_A, NULL);
```

- Combination of 2 flags here. `CL_MEM_COPY_HOST_PTR` to be used only if a valid host pointer is specified.
- This creates a memory buffer on the device, and copies data from h_A into d_A.
- Includes an implicit `clEnqueueWriteBuffer` operation, for all devices/command queues tied to the context clctxt.

Device Memory Allocation and Data Transfer for vadd

```
float *h_A = …,    *h_B = …;
    // allocate device (GPU) memory
   cl_mem d_A, d_B, d_C;
   d_A = clCreateBuffer(clctx, CL_MEM_READ_ONLY |
          CL_MEM_COPY_HOST_PTR, N *sizeof(float), h_A, NULL);
   d_B = clCreateBuffer(clctx, CL_MEM_READ_ONLY |
          CL_MEM_COPY_HOST_PTR, N *sizeof(float), h_B, NULL);
   d_C = clCreateBuffer(clctx, CL_MEM_WRITE_ONLY,
    N *sizeof(float), NULL, NULL);
```

Device Kernel Configuration Setting for vadd

```
clkern=clCreateKernel(clpgm, “vadd", NULL);
…
clerr= clSetKernelArg(clkern, 0, sizeof(cl_mem),(void *)&d_A);
clerr= clSetKernelArg(clkern, 1, sizeof(cl_mem),(void *)&d_B);
clerr= clSetKernelArg(clkern, 2, sizeof(cl_mem),(void *)&d_C);
clerr= clSetKernelArg(clkern, 3, sizeof(int), &N);
```

Device Kernel Launch and Remaining Code for vadd

```
cl_event event=NULL;
clerr= clEnqueueNDRangeKernel(clcmdq, clkern, 2, NULL,
      Gsz, Bsz, 0, NULL,    &event);
clerr= clWaitForEvents(1, &event);
clEnqueueReadBuffer(clcmdq, d_C, CL_TRUE, 0,
      N*sizeof(float), h_C, 0, NULL, NULL);
clReleaseMemObject(d_A);
clReleaseMemObject(d_B);
clReleaseMemObject(d_C);
}
```

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Lecture 21.1 - Related Programming Models: OpenACC

Introduction to OpenACC

Objective

- To understand the OpenACC programming model
  - basic concepts and pragma types
  - simple examples

OpenACC

- The OpenACC Application Programming Interface provides a set of
  - compiler directives (pragmas)
  - library routines and
  - environment variables

  that can be used to write data parallel Fortran, C and C++ programs that run on accelerator devices including GPUs and CPUs

OpenACC Pragmas

- In C and C++, the #pragma directive is the method to provide to the compiler information that is not specified in the standard language.
  - These pragmas extend the base language

Vector Addition in OpenACC

```
void VecAdd(float * __restrict__ output, const float * input1, const float * input 2, int inputLength)
{
 #pragma acc parallel loop copyin(input1[0:inputLength],input2[0:inputLength]),
copyout(output[0:inputLength])
    for(i = 0; i < inputLength; ++i) {
        output[i] = input1[i] + input2[i];
    }
}
```

Simple Matrix-Matrix Multiplication in OpenACC

```
void computeAcc(float *P, const float *M, const float *N, int Mh, int Mw, int Nw)
{
 #pragma acc parallel loop copyin(M[0:Mh*Mw]) copyin(N[0:Mw*Nw]) copyout(P[0:Mh*Nw])
 for (int i=0; i<Mh; i++) {
   #pragma acc loop
     for (int j=0; j<Nw; j++) {
         float sum = 0;
         for (int k=0; k<Mw; k++) {
             float a = M[i*Mw+k];
               float b = N[k*Nw+j];
               sum += a*b;
           }
           P[i*Nw+j] = sum;
      }
  }
}
```

Some Observations (1)

```
1. void computeAcc(float *P, const float *M, const float *N, int Mh, int Mw, int Nw)
2. {
3.  #pragma acc parallel loop copyin(M[0:Mh*Mw]) copyin(N[0:Mw*Nw]) copyout(P[0:Mh*Nw])
4.  for (int i=0; i<Mh; i++) {
5.    #pragma acc loop
6.      for (int j=0; j<Nw; j++) {
7.          float sum = 0;
8.          for (int k=0; k<Mw; k++) {
9.              float a = M[i*Mw+k];
10.             float b = N[k*Nw+j];
11.             sum += a*b;
12.         }
13.         P[i*Nw+j] = sum;
14.     }
15.  }
16. }
```

The code is almost identical to the sequential version, except for the two lines with #pragma at line 3 and line 5.

Some Observations (2)

```
1. void computeAcc(float *P, const float *M, const float *N, int Mh, int Mw, int Nw)
2. {
3.  #pragma acc parallel loop copyin(M[0:Mh*Mw]) copyin(N[0:Mw*Nw]) copyout(P[0:Mh*Nw])
4.  for (int i=0; i<Mh; i++) {
5.    #pragma acc loop
6.      for (int j=0; j<Nw; j++) {
7.          float sum = 0;
8.          for (int k=0; k<Mw; k++) {
9.              float a = M[i*Mw+k];
10.             float b = N[k*Nw+j];
11.             sum += a*b;
12.         }
13.         P[i*Nw+j] = sum;
14.     }
15.  }
16. }
```

The #pragma at line 3 tells the compiler to generate code for the ‘i’ loop at line 4 through 15 so that the loop iterations are executed at the first level of parallelism on the accelerator.

Some Observations (3)

```
void computeAcc(float *P, const float *M, const float *N, int Mh, int Mw, int Nw)
{
 #pragma acc parallel loop copyin(M[0:Mh*Mw]) copyin(N[0:Mw*Nw]) copyout(P[0:Mh*Nw])
 for (int i=0; i<Mh; i++) {
   #pragma acc loop
    for (int j=0; j<Nw; j++) {
        float sum = 0;
        for (int k=0; k<Mw; k++) {
            float a = M[i*Mw+k];
              float b = N[k*Nw+j];
              sum += a*b;
          }
          P[i*Nw+j] = sum;
      }
 }
}
```

The copyin() clause and the copyout() clause specify how the compiler should arrange for the matrix data to be transferred between the host and the accelerator.

Some Observations (4)

```
1. void computeAcc(float *P, const float *M, const float *N, int Mh, int Mw, int Nw)
2. {
3.  #pragma acc parallel loop copyin(M[0:Mh*Mw]) copyin(N[0:Mw*Nw]) copyout(P[0:Mh*Nw])
4.  for (int i=0; i<Mh; i++) {
5.    #pragma acc loop
6.     for (int j=0; j<Nw; j++) {
7.         float sum = 0;
8.         for (int k=0; k<Mw; k++) {
9.              float a = M[i*Mw+k];
10.             float b = N[k*Nw+j];
11.             sum += a*b;
12.          }
13.          P[i*Nw+j] = sum;
14.     }
15.  }
16. }
```

The #pragma at line 5 instructs the compiler to map the inner 'j' loop to the second level of parallelism on the accelerator.

Motivation

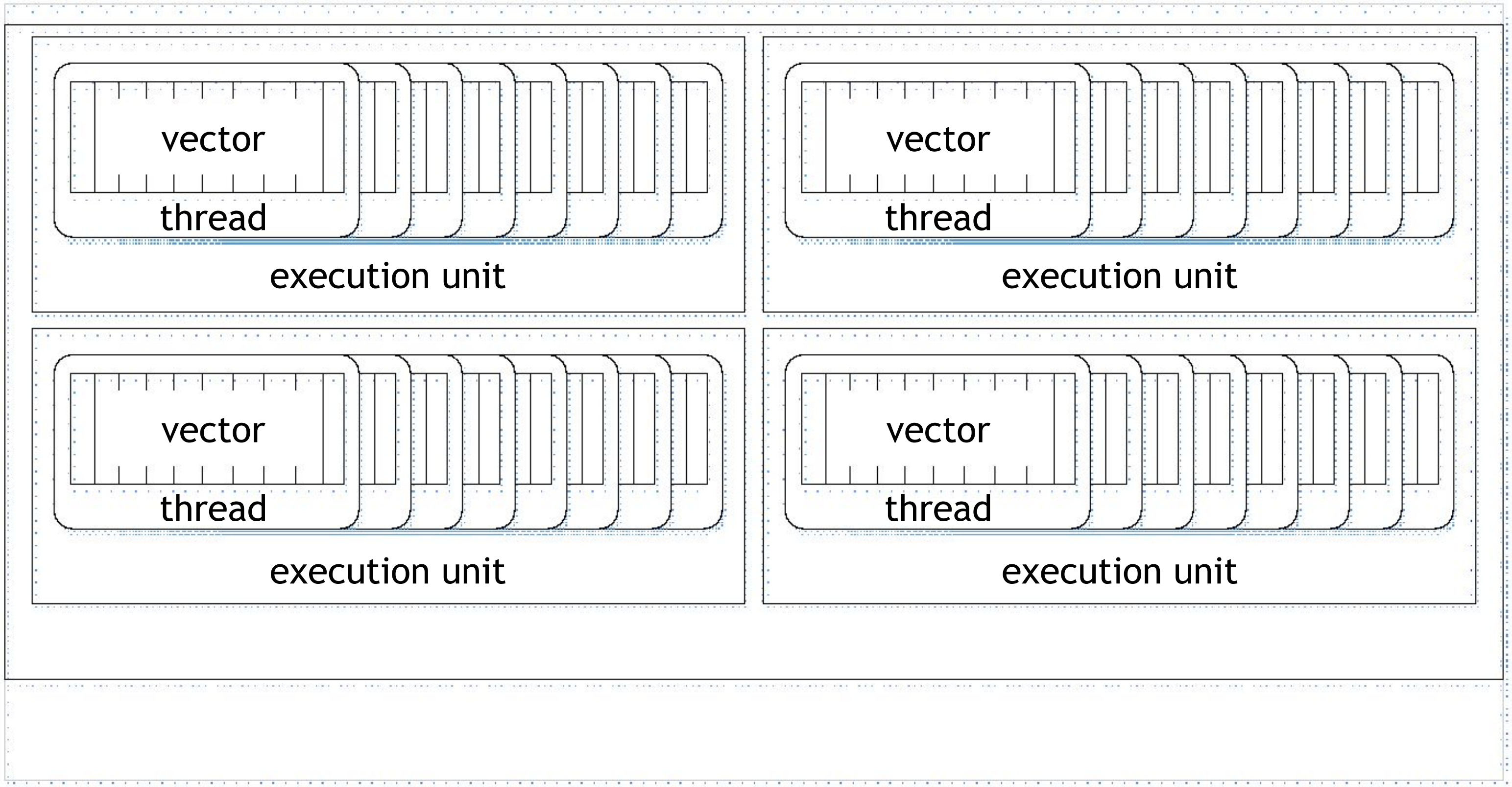
- OpenACC programmers can often start with writing a sequential version and then annotate their sequential program with OpenACC directives.
  - leave most of the details in generating a kernel, memory allocation, and data transfers to the OpenACC compiler.

- OpenACC code can be compiled by non-OpenACC compilers by ignoring the pragmas.

Frequently Encountered Issues

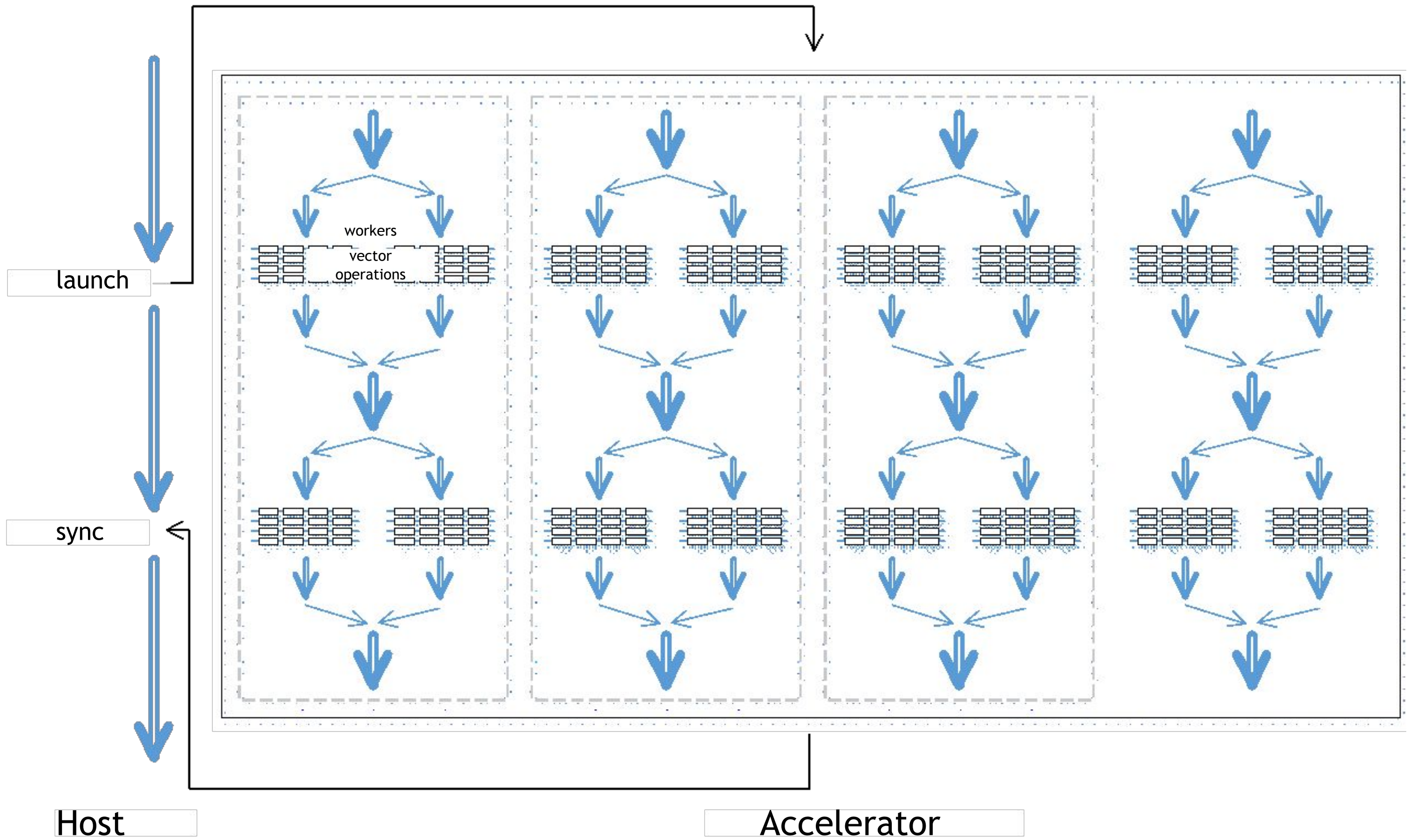
- Some OpenACC pragmas are hints to the OpenACC compiler, which may or may not be able to act accordingly
  - The performance of an OpenACC program depends heavily on the quality of the compiler.
  - It may be hard to figure out why the compiler cannot act according to your hints
  - The uncertainty is much less so for CUDA or OpenCL programs

OpenACC Device Model



Currently OpenACC does not expose synchronization across threads to the programmers.

OpenACC Execution Model



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Lecture 21.2 - Related Programming Models: OpenACC

OpenACC Subtleties

Objective

- To understand some important and sometimes subtle details in OpenACC programming
  - parallel loops
  - simple examples to illustrate basic concepts and functionalities

Parallel vs. Loop Constructs

```
#pragma acc parallel loop copyin(M[0:Mh*Mw]) copyin(N[0:Mw*Nw])
copyout(P[0:Mh*Nw])
for (int i=0; i<Mh; i++) {
…
}
```

is equivalent to:

```
#pragma acc parallel copyin(M[0:Mh*Mw]) copyin(N[0:Mw*Nw])
copyout(P[0:Mh*Nw])
{
    #pragma acc loop
    for (int i=0; i<Mh; i++) {
        …
    }
}
```

(a parallel region that consists of a single loop)

More on Parallel Construct

```
#pragma acc parallel copyout(a) num_gangs(1024) num_workers(32)
{
    a = 23;
}
```

1024*32 workers will be created. a=23 will be executed redundantly by all 1024 gang leads

- A parallel construct is executed on an accelerator
- One can specify the number of gangs and number of workers in each gang
  - Equivalent to CUDA blocks and threads

What Does Each “Gang Loop” Do?

```
#pragma acc parallel num_gangs(1024)
{
    for (int i=0; i<2048; i++) {
        …
    }
}
```

```
#pragma acc parallel num_gangs(1024)
{
#pragma acc loop gang
    for (int i=0; i<2048; i++) {
        …
    }
}
```

Worker Loop

```
#pragma acc parallel num_gangs(1024) num_workers(32)
{
    #pragma acc loop gang
    for (int i=0; i<2048; i++) {
        #pragma acc loop worker
        for (int j=0; j<512; j++) {
            foo(i,j);
        }
    }
}
```

1024*32=32K workers will be created, each executing 1M/32K = 32 instance of foo()

A More Substantial Example

- Statements 1, 3, 5, 6 are redundantly executed by 32 gangs

```
#pragma acc parallel num_gangs(32)
{
    Statement 1;
    #pragma acc loop gang
    for (int i=0; i<n; i++) {
        Statement 2;
    }
    Statement 3;
    #pragma acc loop gang
    for (int i=0; i<m; i++) {
        Statement 4;
    }
    Statement 5;
    if (condition) Statement 6;
}
```

A More Substantial Example

- The iterations of the n and m for-loop iterations are distributed to 32 gangs
- Each gang could further distribute the iterations to its workers
  - The number of workers in each gang will be determined by the compiler/runtime

```
#pragma acc parallel num_gangs(32)
{
    Statement 1;
    #pragma acc loop gang
    for (int i=0; i<n; i++) {
        Statement 2;
    }
    Statement 3;
    #pragma acc loop gang
    for (int i=0; i<m; i++) {
        Statement 4;
    }
    Statement 5;
    if (condition) Statement 6;
}
```

Avoiding Redundant Execution

- Statements 1, 3, 5, 6 will be executed only once
- Iterations of the n and m loops will be distributed to 32 workers

```
#pragma acc parallel
num_gangs(1) num_workers(32)
{
    Statement 1;
    #pragma acc loop worker
    for (int i=0; i<n; i++) {
        Statement 2;
    }
    Statement 3;
    #pragma acc loop worker
    for (int i=0; i<m; i++) {
        Statement 4;
    }
  Statement 5;
  if (condition)  Statement 6;
}
```

Kernel Regions

- Kernel constructs are descriptive of programmer intentions
  - The compiler has a lot of flexibility in its use of the information
- This is in contrast with Parallel, which is prescriptive of the action for the compile follow

```
#pragma acc kernels
{
    #pragma acc loop gang(1024)
    for (int i=0; i<2048; i++) {
        a[i] = b[i];
    }
    #pragma acc loop gang(512)
    for (int j=0; j<2048; j++) {
        c[j] = a[j]*2;
    }
    for (int k=0; k<2048; k++) {
        d[k] = c[k];
    }
}
```

Kernel Regions

- Code in a kernel region can be broken into multiple CUDA/OpenCL kernels
- The i, j, k loops can each become a kernel
  - The k-loop may even remain as host code
- Each kernel can have a different gang/worker configuration

```
#pragma acc kernels
{
    #pragma acc loop gang(1024)
    for (int i=0; i<2048; i++) {
        a[i] = b[i];
    }
    #pragma acc loop gang(512)
    for (int j=0; j<2048; j++) {
        c[j] = a[j]*2;
    }
    for (int k=0; k<2048; k++) {
        d[k] = c[k];
    }
}
```

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