UNIVERSITY OF CAMBRIDGE
COMPUTER LABORATORY

RAINBOW GRAPHICS GROUP

Advanced Graphics & Image Processing

Parallel programming in OpenCL

Part 1/3 – OpenCL framework

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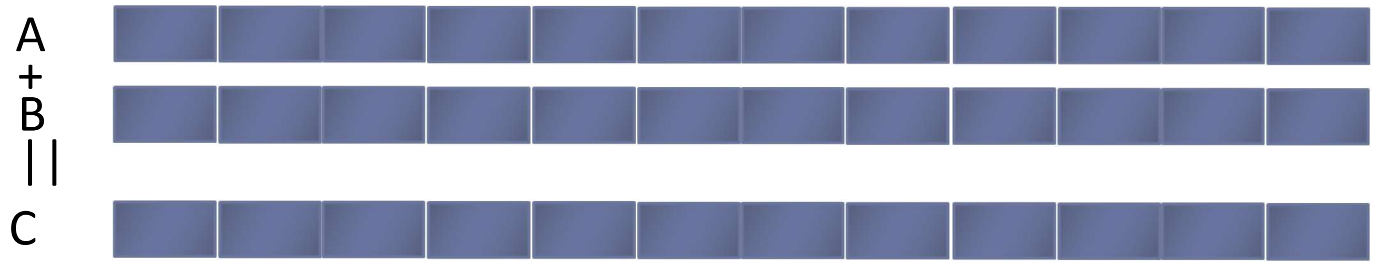
Single Program Multiple Data (SPMD)

- Consider the following vector addition example

```
for( i = 0:11 ) {
  C[ i ] = A[ i ] + B[ i ]
}
```

Serial program:
one program completes
the entire task



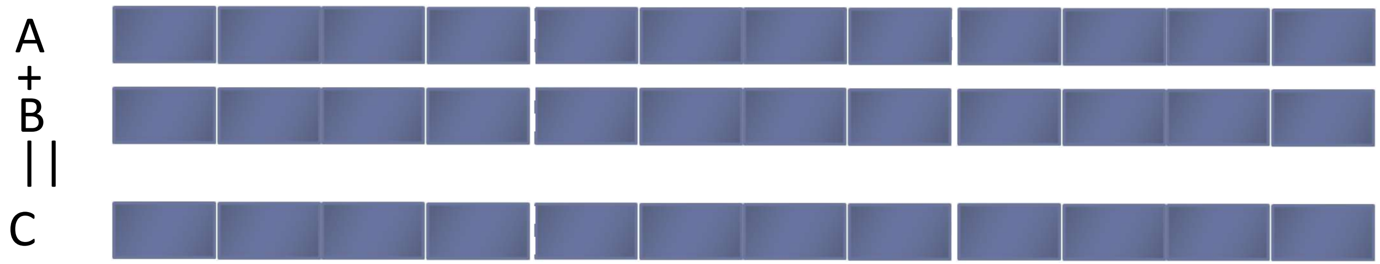
Multiple copies of the same program execute on different data in parallel

```
for( i = 0:3 ) {
  C[ i ] = A[ i ] + B[ i ]
}
```

```
for( i = 4:7 ) {
  C[ i ] = A[ i ] + B[ i ]
}
```

```
for( i = 8:11 ) {
  C[ i ] = A[ i ] + B[ i ]
}
```

SPMD program:
multiple copies of the
same program run on
different chunks of the
data



From: OpenCL 1.2 University Kit - http://developer.amd.com/partners/university-programs/

Parallel Software – SPMD

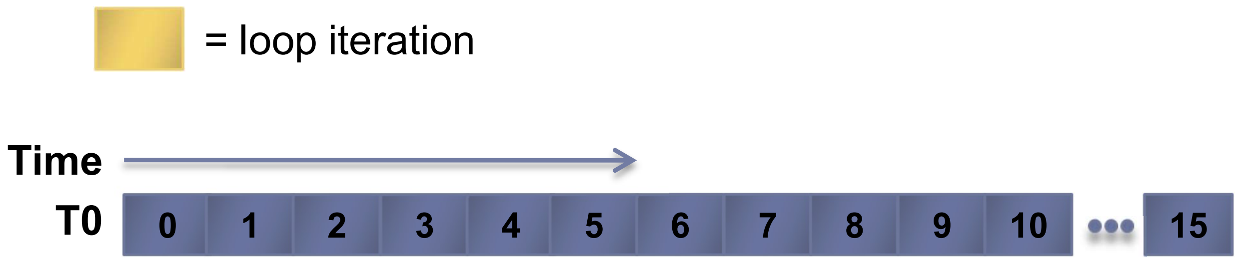
- In the vector addition example, each chunk of data could be executed as an independent thread
- On modern CPUs, the overhead of creating threads is so high that the chunks need to be large
  - In practice, usually a few threads (about as many as the number of CPU cores) and each is given a large amount of work to do
- For GPU programming, there is low overhead for thread creation, so we can create one thread per loop iteration

From: OpenCL 1.2 University Kit - http://developer.amd.com/partners/university-programs/

Parallel Software – SPMD

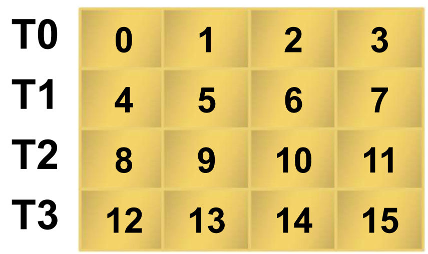
Single-threaded (CPU)

```
// there are N elements
for(i = 0; i < N; i++)
  C[i] = A[i] + B[i]
```



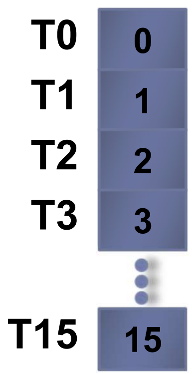
Multi-threaded (CPU)

```
// tid is the thread id
// P is the number of cores
for(i = 0; i < tid*N/P; i++)
  C[i] = A[i] + B[i]
```



Massively Multi-threaded (GPU)

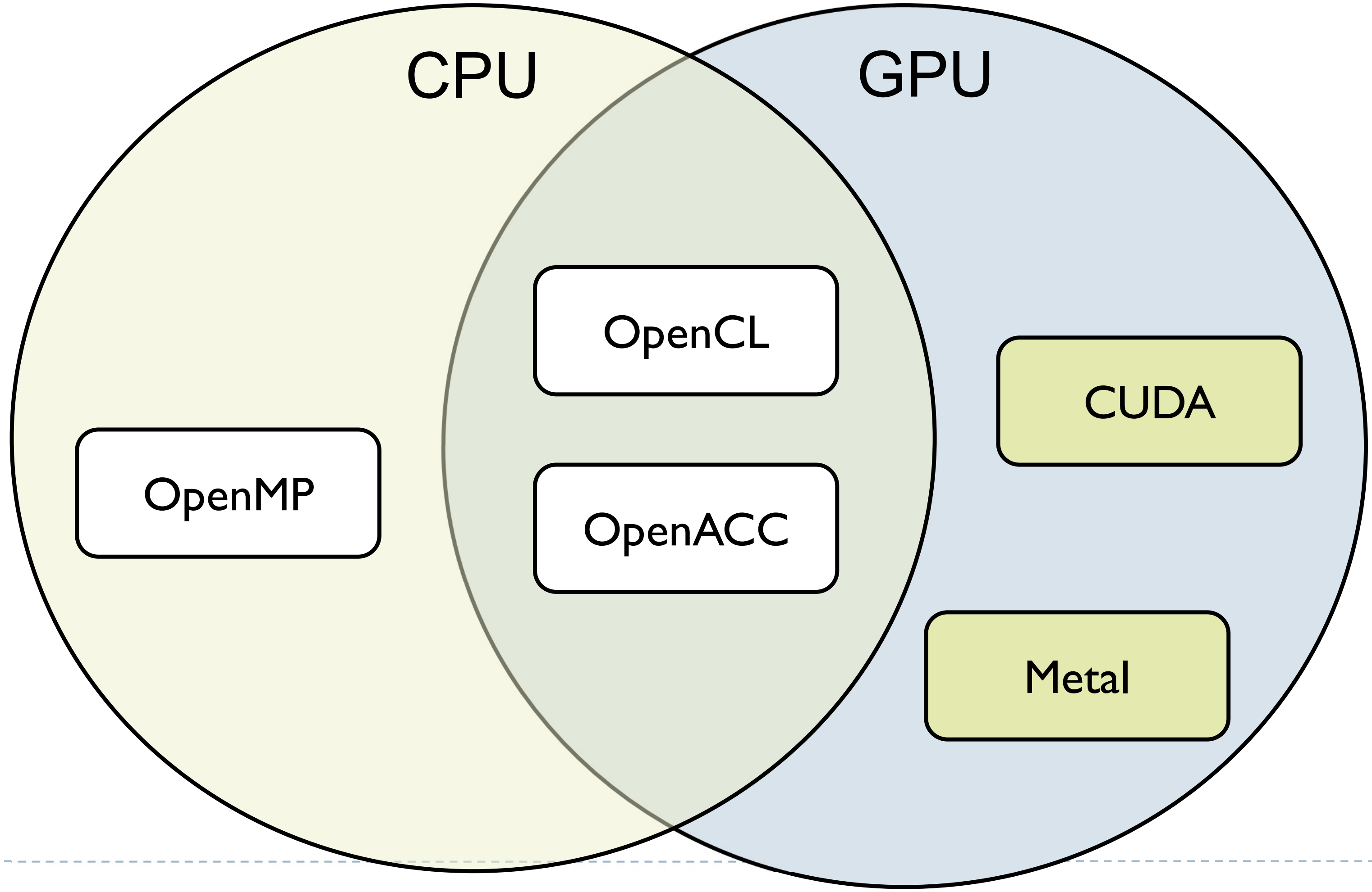
```
// tid is the thread id
C[tid] = A[tid] + B[tid]
```



From: OpenCL 1.2 University Kit - http://developer.amd.com/partners/university-programs/

Parallel programming frameworks

- These are some of more relevant frameworks for creating parallelized code

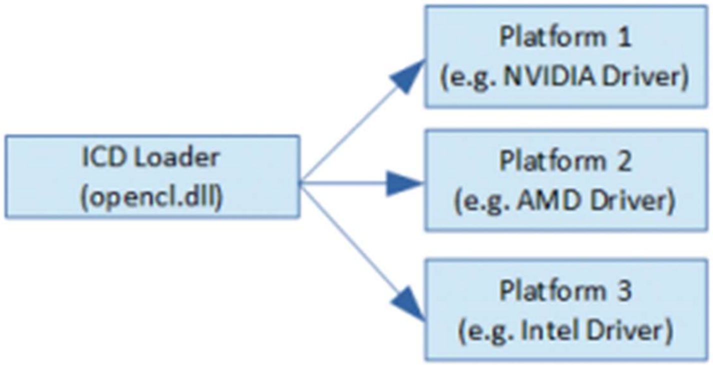


OpenCL

- OpenCL is a framework for writing parallelized code for CPUs, GPUs, DSPs, FPGAs and other processors
- Initially developed by Apple, now supported by AMD, IBM, Qualcomm, Intel and Nvidia
- Versions
  - Latest: OpenCL 3.0
    - OpenCL C++ kernel language
    - SPIR-V as intermediate representation for kernels
      - Vulcan uses the same Standard Portable Intermediate Representation
    - AMD, Intel, Nvidia
  - Mostly supported: OpenCL 1.2
    - OSX, older GPUs

OpenCL platforms and drivers

- To run OpenCL code you need:
  - Generic ICD loader
    - Included in the OS
  - Installable Client Driver
    - From Nvidia, Intel, etc.
  - This applies to Windows and Linux, only one platform on Mac

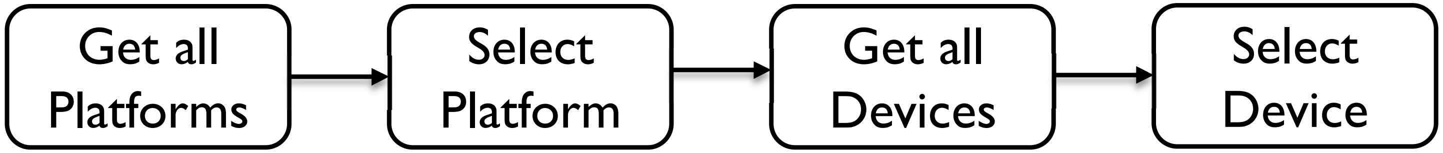


- To develop OpenCL code you need:
  - OpenCL headers/libraries
    - Included in the SDKs
      - Nvidia – CUDA Toolkit
      - Intel OpenCL SDK
    - But lightweight options are also available

Programming OpenCL

- OpenCL natively offers C99 API
- But there is also a standard OpenCL C++ API wrapper
  - Strongly recommended – reduces the amount of code
- Programming OpenCL is similar to programming shaders in OpenGL
  - Host code runs on CPU and invokes **kernels**
  - Kernels are written in C-like programming language
    - In many respects similar to GLSL
  - Kernels are passed to API as strings and compiled at runtime
    - Kernels are usually stored in text files
    - Kernels can be precompiled into SPIR from OpenCL 2.1

Example: Step 1 - Select device




```cpp
//get all platforms (drivers)
std::vector<cl::Platform> all_platforms;
cl::Platform::get(&all_platforms);
if (all_platforms.size() == 0){
    std::cout << " No platforms found. Check OpenCL installation!\n";
    exit(1);
}
cl::Platform default_platform = all_platforms[0];
std::cout << "Using platform: " << default_platform.getInfo<CL_PLATFORM_NAME>() << "\n";

//get default device of the default platform
std::vector<cl::Device> all_devices;
default_platform.getDevices(CL_DEVICE_TYPE_ALL, &all_devices);
if (all_devices.size() == 0){
    std::cout << " No devices found. Check OpenCL installation!\n";
    exit(1);
}
cl::Device default_device = all_devices[0];
std::cout << "Using device: " << default_device.getInfo<CL_DEVICE_NAME>() << "\n";
```

Example: Step 2 - Build program

Create context → Load sources (usually from files) → Create Program → Build Program

```
cl::Context context({ default_device });

cl::Program::Sources sources;
// kernel calculates for each element C=A+B
std::string kernel_code =
    "__kernel void simple_add(__global const int* A, __global const int* B, __global int* C) {"
    "    int index = get_global_id(0);"
    "    C[index] = A[index] + B[index];"
    "};";
sources.push_back({ kernel_code.c_str(), kernel_code.length() });

cl::Program program(context, sources);
try {
    program.build({ default_device });
}
catch (cl::Error err) {
    std::cout << " Error building: " <<
        program.getBuildInfo<CL_PROGRAM_BUILD_LOG>(default_device) << "\n";
    exit(1);
}
```

Example: Step 3 - Create Buffers and copy memory

Create Buffers → Create Queue → Enqueue Memory Copy

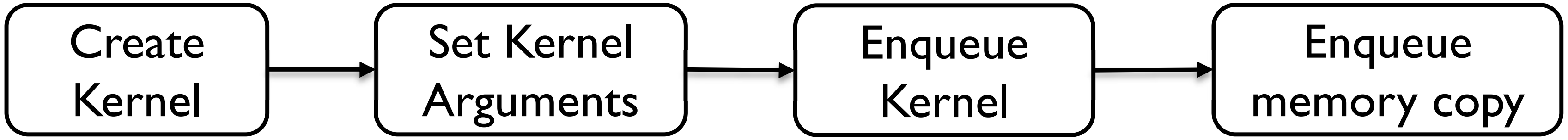
```
// create buffers on the device
cl::Buffer buffer_A(context, CL_MEM_READ_WRITE, sizeof(int) * 10);
cl::Buffer buffer_B(context, CL_MEM_READ_WRITE, sizeof(int) * 10);
cl::Buffer buffer_C(context, CL_MEM_READ_WRITE, sizeof(int) * 10);

int A[] = { 0, 1, 2, 3, 4, 5, 6, 7, 8, 9 };
int B[] = { 0, 1, 2, 0, 1, 2, 0, 1, 2, 0 };

//create queue to which we will push commands for   the device.
cl::CommandQueue queue(context, default_device);

//write arrays A and B to the device
queue.enqueueWriteBuffer(buffer_A, CL_TRUE, 0, sizeof(int) * 10, A);
queue.enqueueWriteBuffer(buffer_B, CL_TRUE, 0, sizeof(int) * 10, B);
```

Example: Step 4 - Execute Kernel and retrieve the results




```
cl::Kernel kernel(program, "simple_add");

kernel.setArg(0, buffer_A);
kernel.setArg(1, buffer_B);
kernel.setArg(2, buffer_C);
queue.enqueueNDRangeKernel(kernel, cl::NullRange, cl::NDRange(10), cl::NullRange);

int C[10];
//read result C from the device to array C
queue.enqueueReadBuffer(buffer_C, CL_TRUE, 0, sizeof(int) * 10, C);
queue.finish();

std::cout << " result: \n";
for (int i = 0; i < 10; i++){
    std::cout << C[i] << " ";
}
std::cout << std::endl;
```

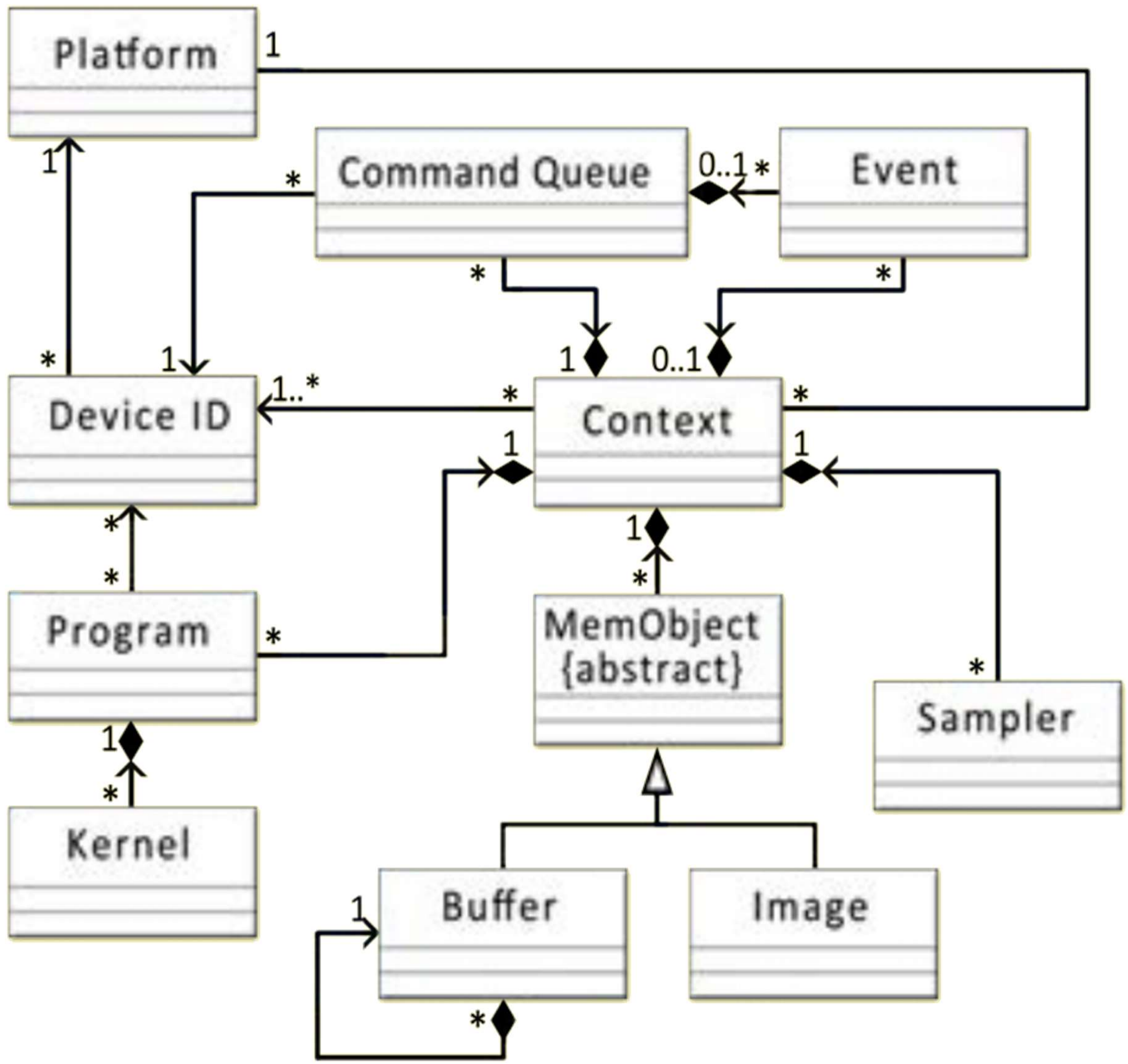
Our Kernel was

```
__kernel void simple_add(__read_only const int* A,
                         __read_only const int* B,
                         __write_only int* C) {

    int index = get_global_id(0);
    C[index]=A[index]+B[index];
};
```

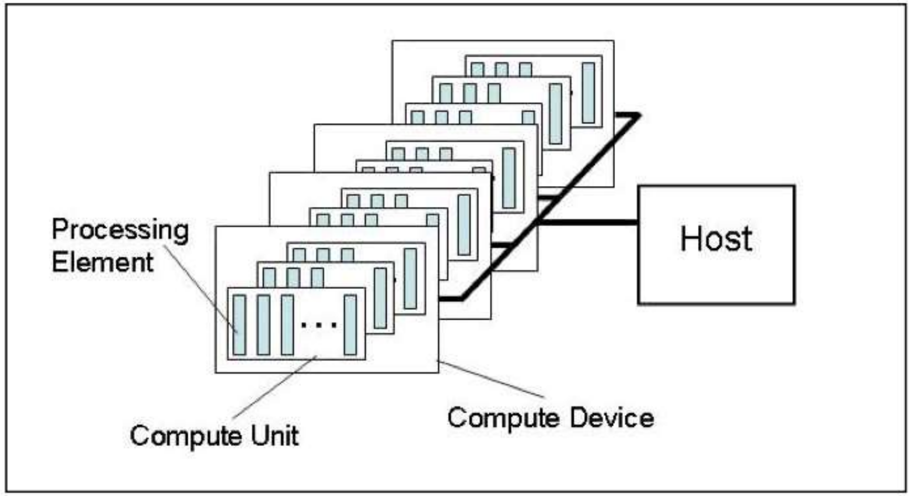
OpenCL API Class Diagram

- *Platform* – Nvidia CUDA
- *Device* – GeForce 1080
- *Program* – collection of *kernels*
- *Buffer or Image* – device memory
- *Sampler* – how to interpolate values for *Image*
- *Command Queue* – put a sequence of operations there
- *Event* – to notify that something has been done



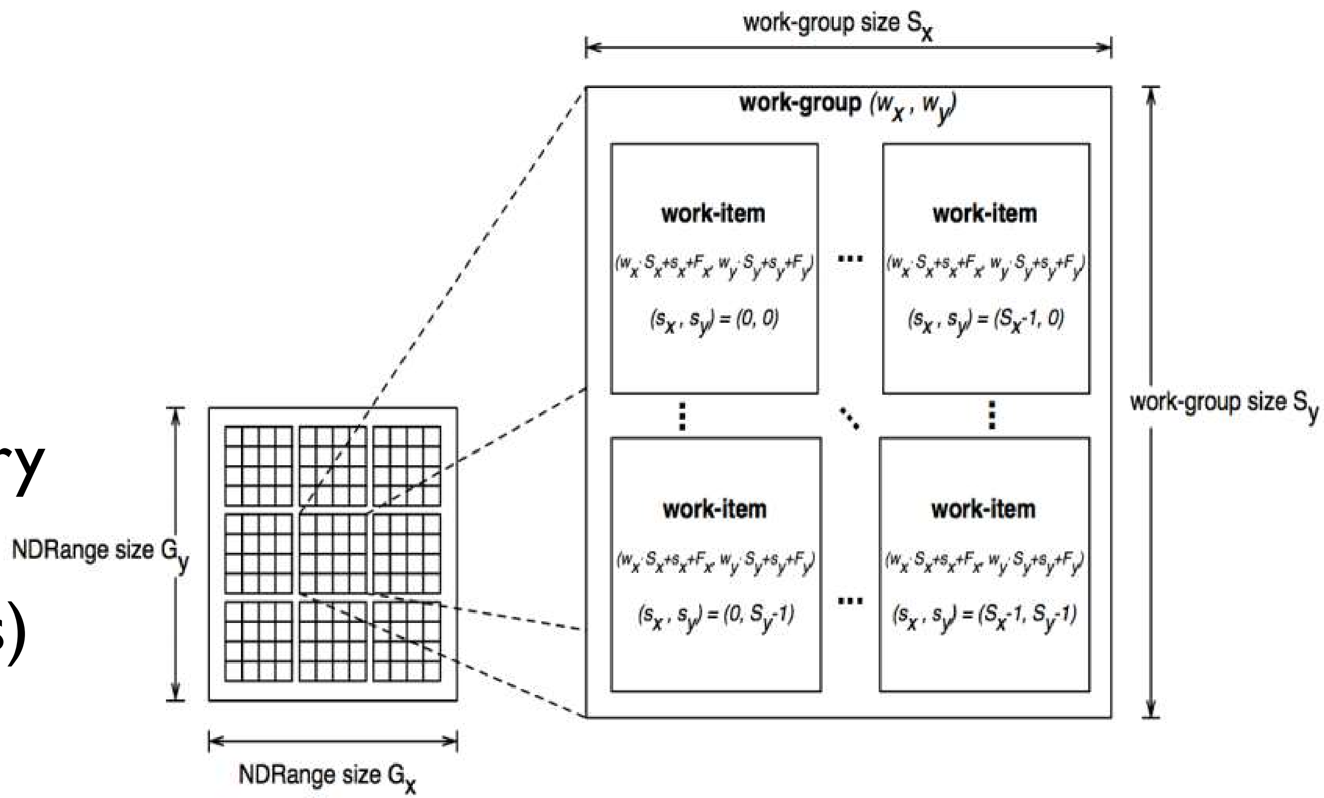
Platform model

- The host is whatever the OpenCL library runs on
  - Usually x86 CPUs for both NVIDIA and AMD
- Devices are processors that the library can talk to
  - CPUs, GPUs, DSP,s and generic accelerators
- For AMD
  - All CPUs are combined into a single device (each core is a compute unit and processing element)
  - Each GPU is a separate device



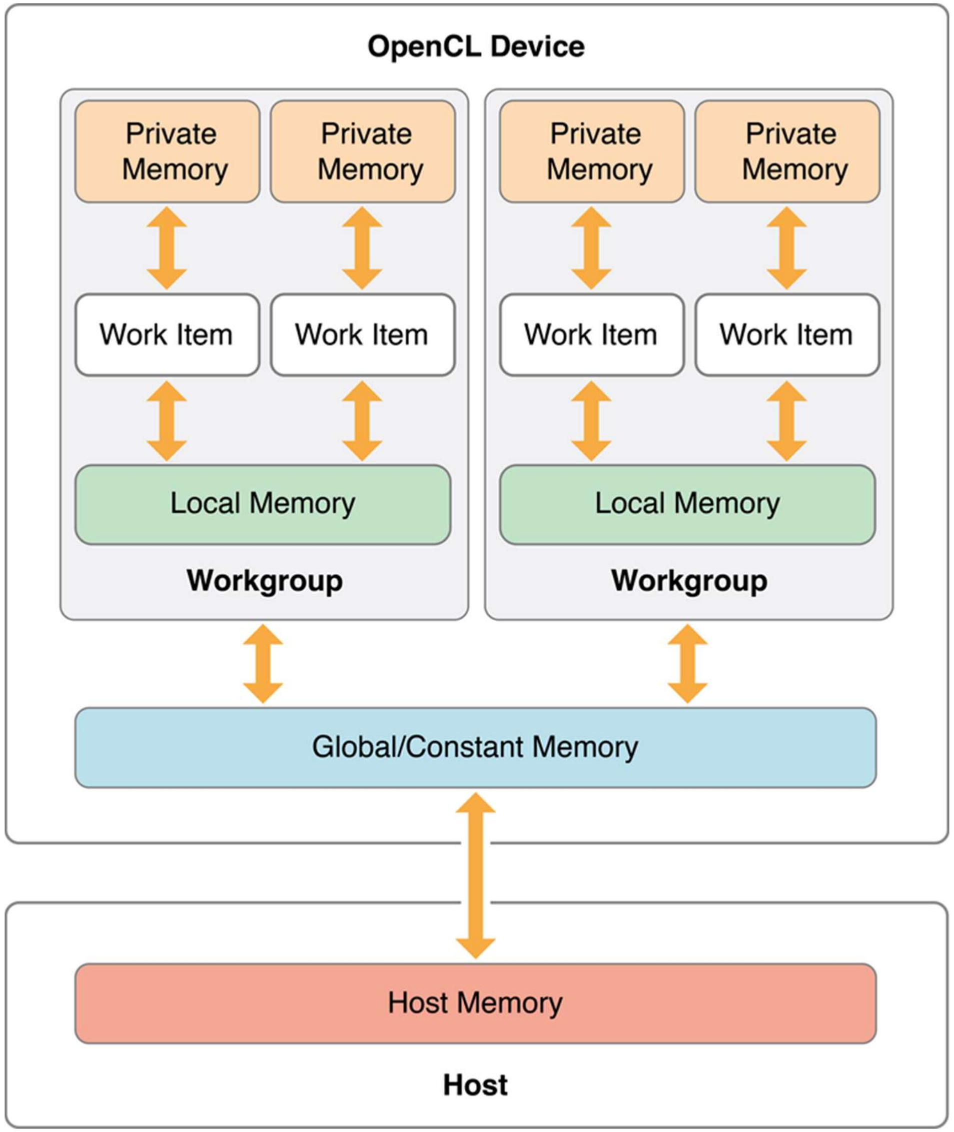
Execution model

- Each kernel executes on 1D, 2D or 3D array (NDRange)
- The array is split into work-groups
- Work items (threads) in each work-group share some local memory
- Kernel can querry
  - `get_global_id(dim)`
  - `get_group_id(dim)`
  - `get_local_id(dim)`
- Work items are not bound to any memory entity (unlike GLSL shaders)

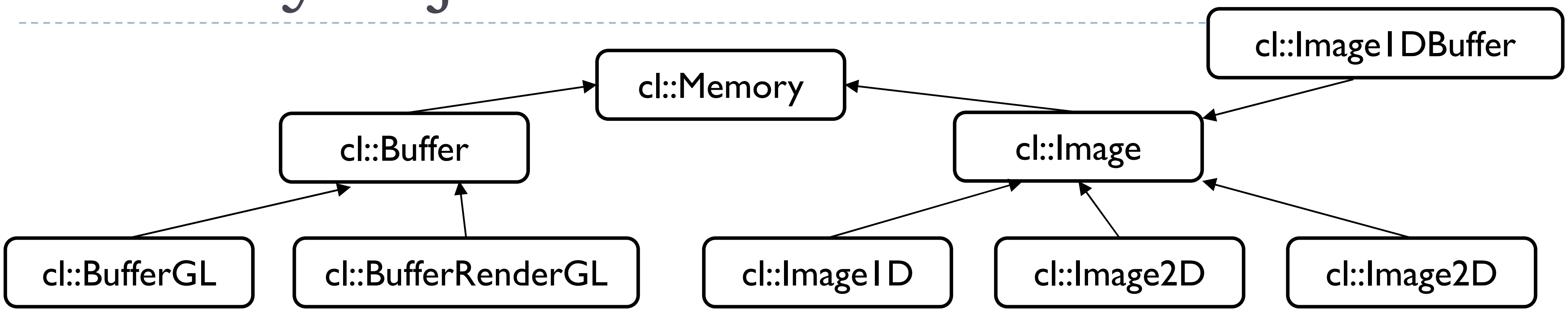


Memory model

- Host memory
  - Usually CPU memory, device does not have access to that memory
- Global memory [__*global*]
  - Device memory, for storing large data
- Constant memory [__*constant*]
- Local memory [__*local*]
  - Fast, accessible to all work-items (threads) within a workgroup
- Private memory [__*private*]
  - Accessible to a single work-item (thread)



Memory objects



This diagram is incomplete – there are more memory objects

- Buffer
  - ArrayBuffer in OpenGL
  - Accessed directly via C pointers
- Image
  - Texture in OpenGL
  - Access via texture look-up function
  - Can interpolate values, clamp, etc.

Programming model

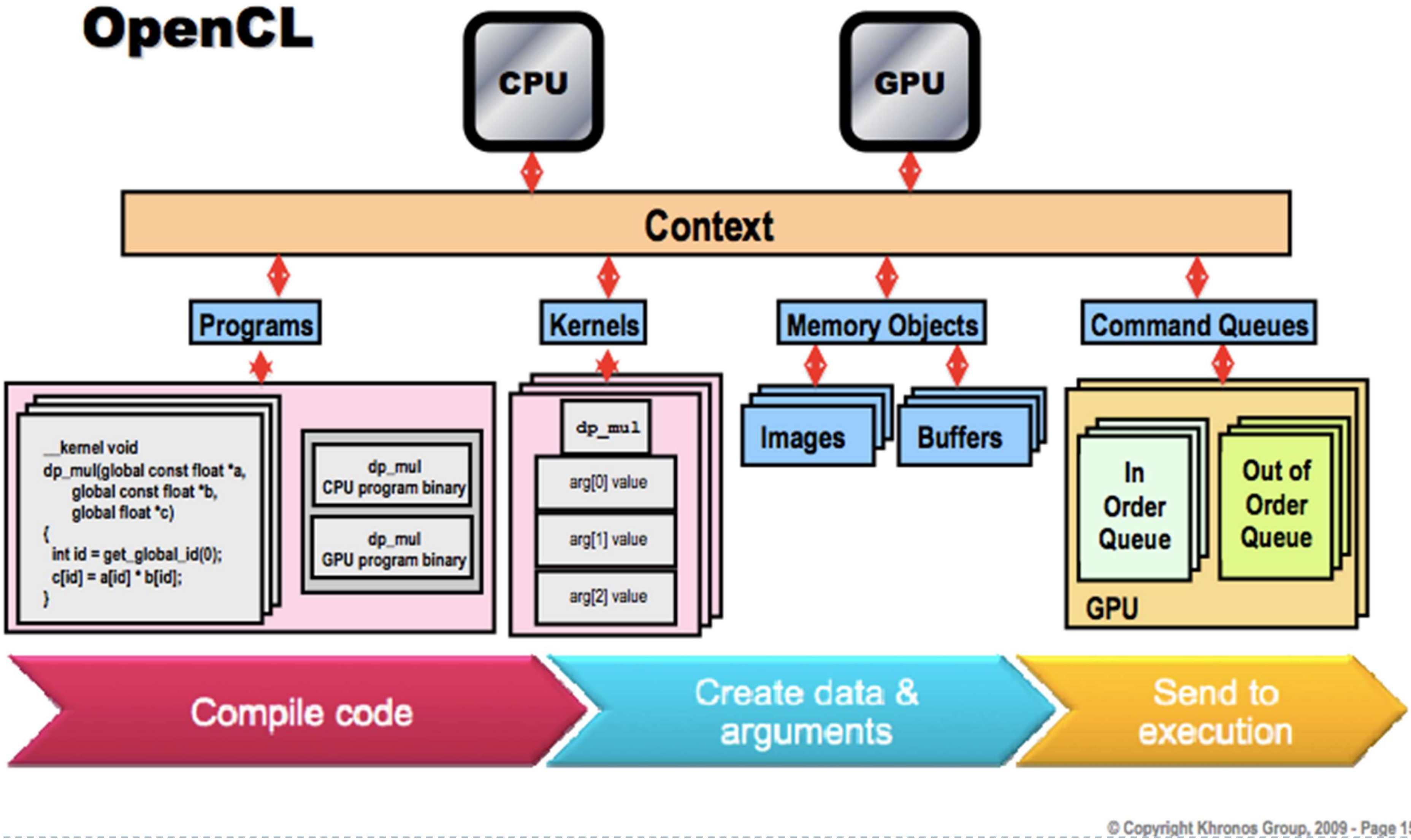
- Data parallel programming
  - Each NDRange element is assigned to a work-item (thread)
  - Each kernel can use vector-types of the device (float4, etc.)
- Task-parallel programming
  - Multiple different kernels can be executed in parallel
- Command queue

CL_QUEUE_OUT_OF_ORDER_EXEC_MODE_ENABLE
Execute out-of-order if specified, in order otherwise

```
clCreateCommandQueue(
    cl_context context,
    cl_device_id device,
    cl_command_queue_properties properties,
    cl_int* errcode_ret)
```

  - Provides means to both synchronize kernels and execute them in parallel

Big Picture



OpenCL
CPU
GPU
Context
Programs
Kernels
Memory Objects
Command Queues
__kernel void
dp_mul(global const float *a,
global const float *b,
global float *c)
{
int id = get_global_id(0);
c[id] = a[id] * b[id];
}
dp_mul
CPU program binary
dp_mul
GPU program binary
dp_mul
arg[0] value
arg[1] value
arg[2] value
Images
Buffers
In Order Queue
Out of Order Queue
GPU
Compile code
Create data & arguments
Send to execution
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Part 2/3 – Thread mapping

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Thread Mapping

- By using different mappings, the same thread can be assigned to access different data elements
  - The examples below show three different possible mappings of threads to data (assuming the thread id is used to access an element)

Mapping

```
int tid =
get_global_id(1) *
get_global_size(0) +
get_global_id(0);
```

Thread IDs

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

Mapping

```
int tid =
get_global_id(0) *
get_global_size(1) +
get_global_id(1);
```

Thread IDs

0	4	8	12
1	5	9	13
2	6	10	14
3	7	11	15

Mapping

```
int group_size =
get_local_size(0) *
get_local_size(1);

int tid =
get_group_id(1) *
get_num_groups(0) *
group_size +
get_group_id(0) *
group_size +
get_local_id(1) *
get_local_size(0) +
get_local_id(0)
```

Thread IDs

0	1	4	5
2	3	6	7
8	9	12	13
10	11	14	15

*assuming 2x2 groups

From: OpenCL 1.2 University Kit - http://developer.amd.com/partners/university-programs/

Thread Mapping

- Consider a serial matrix multiplication algorithm

```
for (i1=0; i1 < M; i1++)
    for (i2=0; i2 < N; i2++)
        for (i3=0; i3 < P; i3++)
            C[i1][i2] += A[i1][i3]*B[i3][i2];
```

- This algorithm is suited for output data decomposition
  - We will create *N x M* threads
    - Effectively removing the outer two loops
  - Each thread will perform *P* calculations
    - The inner loop will remain as part of the kernel
- Should the index space be MxN or NxM?

 From: OpenCL 1.2 University Kit - http://developer.amd.com/partners/university-programs/

Thread Mapping

- Thread mapping 1: with an MxN index space, the kernel would be:

```
int tx = get_global_id(0);
int ty = get_global_id(1);
for(i3=0; i3<P; i3++)
    C[tx][ty] += A[tx][i3]*B[i3][ty];
```

Mapping for C

0	4	8	12
1	5	9	13
2	6	10	14
3	7	11	15

- Thread mapping 2: with an NxM index space, the kernel would be:

```
int tx = get_global_id (0);
int ty = get_global_id (1);
for(i3=0; i3<P; i3++)
    C[ty][tx] += A[ty][i3]*B[i3][tx];
```

Mapping for C

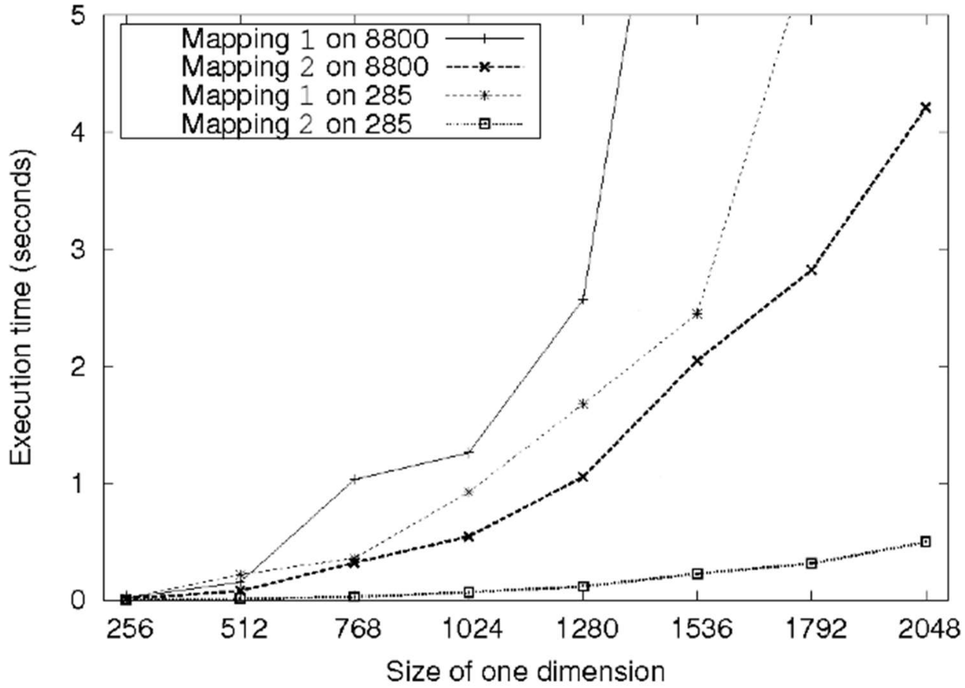
0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

- Both mappings produce functionally equivalent versions of the program

 From: OpenCL 1.2 University Kit - http://developer.amd.com/partners/university-programs/

Thread Mapping

- This figure shows the execution of the two thread mappings on NVIDIA GeForce 285 and 8800 GPUs



- Notice that mapping 2 is far superior in performance for both GPUs

 From: OpenCL 1.2 University Kit - http://developer.amd.com/partners/university-programs/

Thread Mapping

- The discrepancy in execution times between the mappings is due to data accesses on the global memory bus
  - Assuming row-major data, data in a row (i.e., elements in adjacent columns) are stored sequentially in memory
  - To ensure coalesced accesses, consecutive threads in the same wavefront should be mapped to columns (the second dimension) of the matrices
    - This will give coalesced accesses in Matrices B and C
    - For Matrix A, the iterator *i3* determines the access pattern for row-major data, so thread mapping does not affect it

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Part 3/3 – Reduction

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Reduction

- GPU offers very good performance for tasks in which the results are stored independently
  - Process N data items and store in N memory location

```
float reduce_sum(float* input, int length)
{
  float accumulator = input[0];
  for(int i = 1; i < length; i++)
    accumulator += input[i];
  return accumulator;
}
```

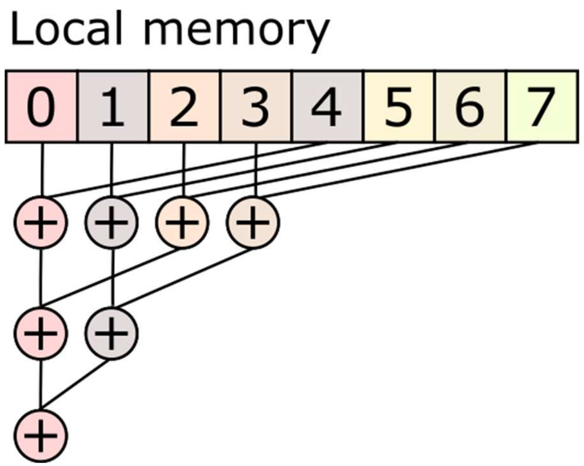
- But many common operations require reducing N values into 1 or few values
  - sum, min, max, prod, min, histogram, …
- Those operations require an efficient implementation of reduction

- The following slides are based on AMD's OpenCL™ Optimization Case Study: Simple Reductions
  - http://developer.amd.com/resources/articles-whitepapers/opencl-optimization-case-study-simple-reductions/

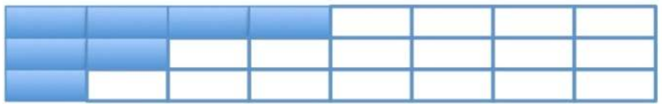
Reduction tree for the min operation

```
__kernel
void reduce_min(__global float* buffer,
            __local float* scratch,
            __const int length,
            __global float* result) {

  int global_index = get_global_id(0);
  int local_index = get_local_id(0);
  // Load data into local memory
  if (global_index < length) {
    scratch[local_index] = buffer[global_index];
  } else {
    scratch[local_index] = INFINITY;
  }
  barrier(CLK_LOCAL_MEM_FENCE);
  for(int offset = get_local_size(0) / 2;
      offset > 0; offset >>= 1) {
    if (local_index < offset) {
      float other = scratch[local_index + offset];
      float mine = scratch[local_index];
      scratch[local_index] = (mine < other) ? mine :
other;
    }
    barrier(CLK_LOCAL_MEM_FENCE);
  }
  if (local_index == 0) {
    result[get_group_id(0)] = scratch[0];
  }
}
```

- `barrier` ensures that all threads (work units) in the local group reach that point before execution continue
- Each iteration of the for loop computes next level of the reduction pyramid

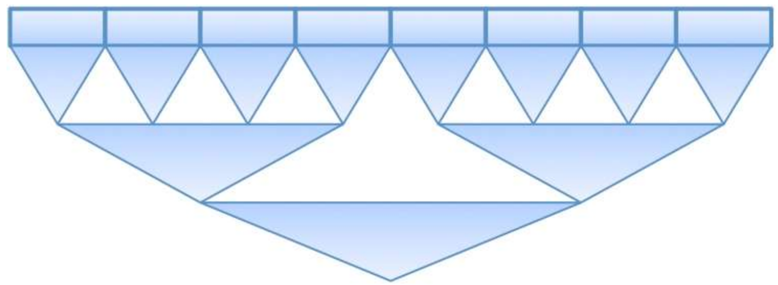


Parallel Reduction Tree for Commutative Operator



SIMD Utilization for Reduction Tree

Multistage reduction



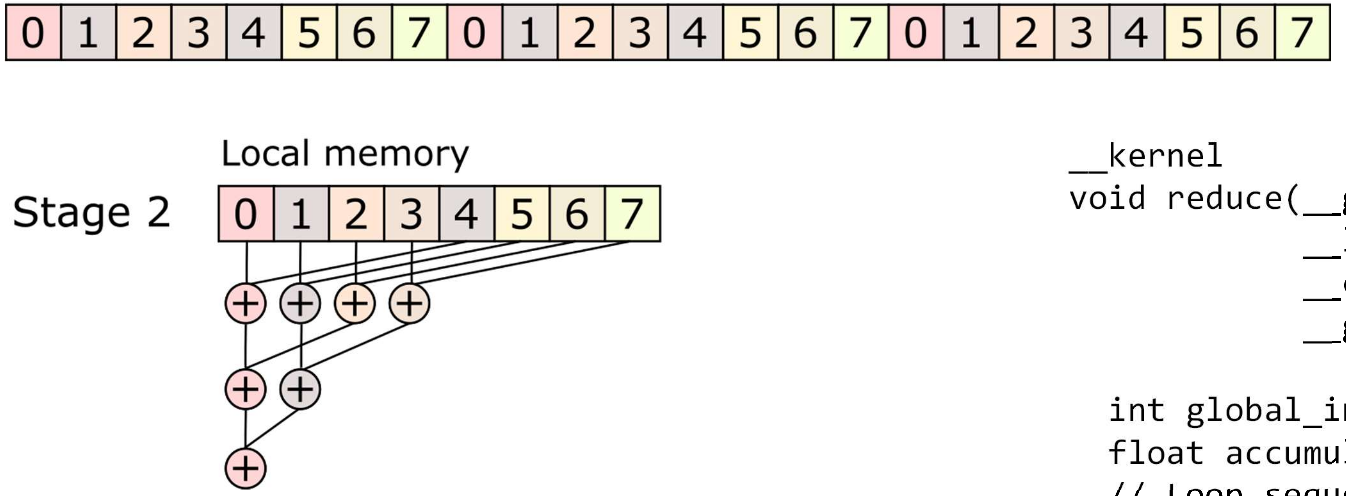
- The local memory is usually limited (e.g. 50kB), which restricts the maximum size of the array that can be processed
- Therefore, for large arrays need to be processed in multiple stages
  - The result of a local memory reduction is stored in the array and then this array is reduced

Two-stage reduction

Stage 1

Different colours denote different threads

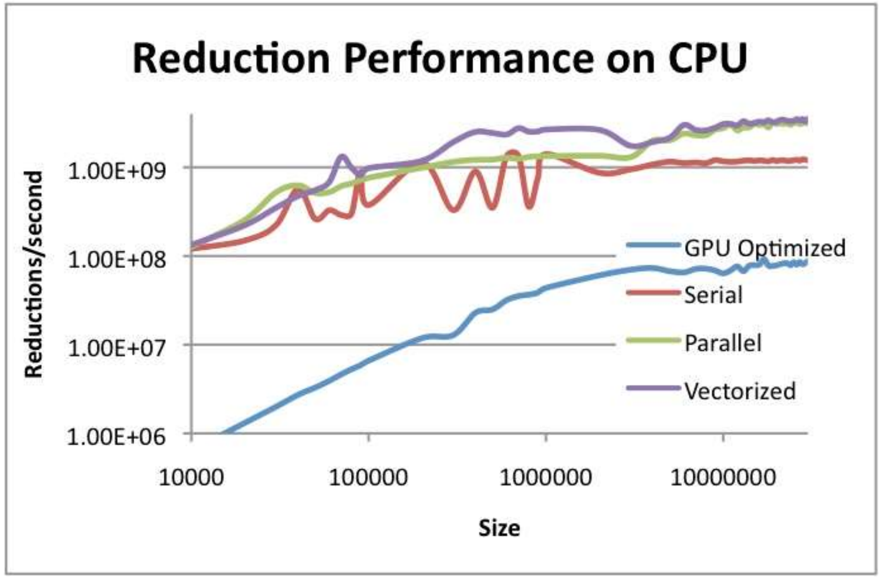
Global memory

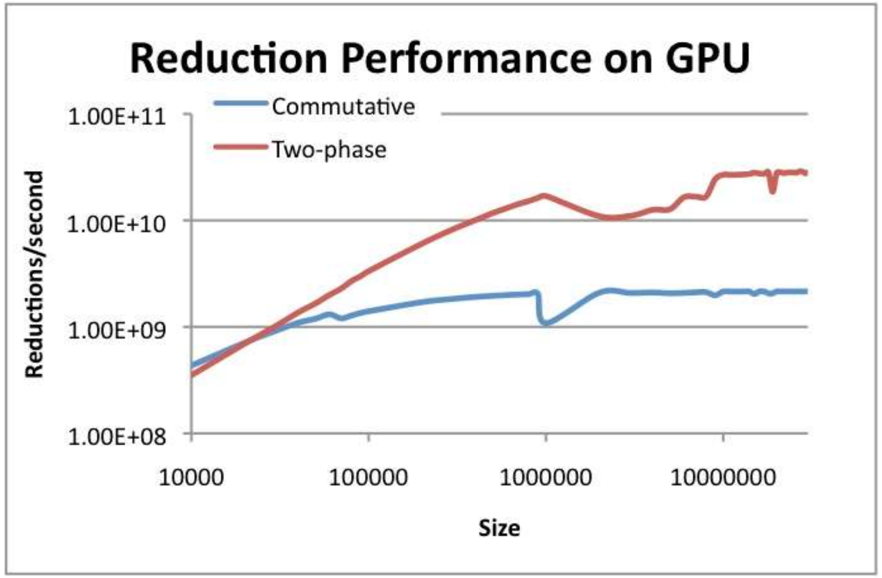



```
__kernel
void reduce(__global float* buffer,
            __local float* scratch,
            __const int length,
            __global float* result) {

  int global_index = get_global_id(0);
  float accumulator = INFINITY;
  // Loop sequentially over chunks of input
vector
  while (global_index < length) {
    float element = buffer[global_index];
    accumulator = (accumulator < element) ?
accumulator : element;
    global_index += get_global_size(0);
  }

  // Perform parallel reduction
  [The same code as in the previous example]
}
```

- First stage: serial reduction by N concurrent threads
  - Number of threads < data items
- Second stage: parallel reduction in local memory

Reduction execution times on CPU/GPU



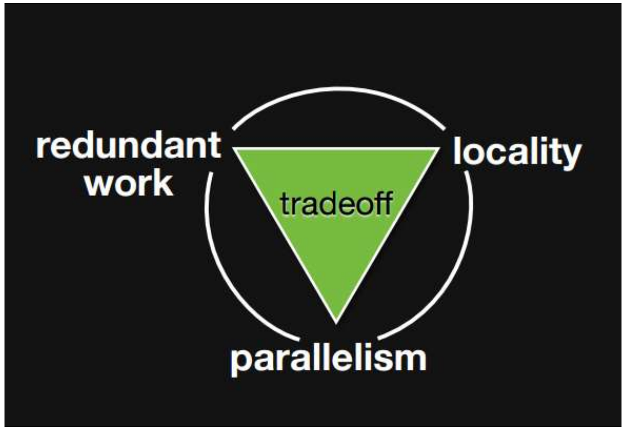


- Different reduction algorithm may be optimal for CPU and GPU
- This can also vary from one GPU to another

- The results from: http://developer.amd.com/resources/articles-whitepapers/opencl-optimization-case-study-simple-reductions/

Better way?

- **Halide** - a language for image processing and computational photography
  - http://halide-lang.org/
  - Code written in a high-level language, then translated to x86/SSE, ARM, CUDA, OpenCL
  - The optimization strategy defined separately as a *schedule*
  - Auto-tune software can test thousands of schedules and choose the one that is the best for a particular platform
  - (Semi-)automatically find the best trade-offs for a particular platform
  - Designed for image processing but similar languages created for other purposes



OpenCL resources

- https://www.khronos.org/registry/OpenCL/
- Reference cards
  - Google: "OpenCL API Reference Card"
- AMD OpenCL Programming Guide
  - http://developer.amd.com/wordpress/media/2013/07/AMD_Accelerated_Parallel_Processing_OCL_Programming_Guide-2013-06-21.pdf