# CS 61C: Great Ideas in Computer Architecture (Machine Structures)

*Lecture 28: GP-GPU Programming*

Lecturer:
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## GPUs

- Hardware specialized for graphics calculations
  - Originally developed to facilitate the use of CAD programs
- Graphics calculations are extremely data parallel
  - e.g. translate every vertex in a 3D model to the right
- Programmers found that that could rephrase some of their problems as graphics manipulations and run them on the GPU
  - Incredibly burdensome for the programmer to use
  - More usable these days – openCL, CUDA

## Overview

- GP-GPU: What and why
- OpenCL, CUDA, and programming GPUs
- GPU Performance demo

## CPU vs. GPU

| CPU | GPU |
|---|---|
| Latency optimized | Throughput optimized |
| A couple threads of execution | Many, many threads of execution |
| Each thread executes quickly | Each thread executes slowly |
| Serial code | Parallel code |
| Lots of caching | Lots of memory bandwidth |

## A Quick Review: Classes of Parallelism

- ILP:
  - Run multiple instructions from one stream in parallel (e.g. pipelining)
- TLP:
  - Run multiple instruction streams simultaneously (e.g. openMP)
- DLP:
  - Run the same operation on multiple data at the same time (e.g. SSE intrinsics)

GPUs are here

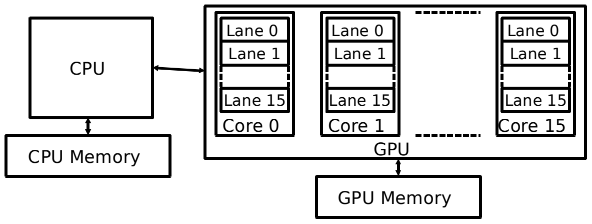
## OpenCL and CUDA

- Extensions to C which allow for relatively easy GPU programming
- CUDA is NVIDIA proprietary
  - NVIDIA cards only
- OpenCL is opensource
  - Can be used with NVIDA or ATI cards
  - Intended for general heterogeneous computing
    - Means you can use it with stuff like FPGAs
    - Also means it's relatively clunky
- Similar tools, but different jargon

## Kernels

- Kernels define the computation for one array index
- The GPU runs the kernel on each index of a specified range
- Similar functionality to map, but you get to know the array index <u>and</u> the array value.
- Call the work at a given index a *work-item, a cuda thread*, or a *µthread.*
- The entire range is called an *index-space* or *grid.*

## Hardware Execution Model



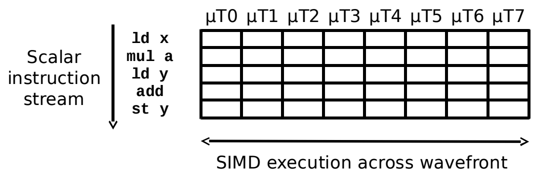
- GPU is built from multiple parallel cores, each core contains a multithreaded SIMD processor.
- CPU sends whole index-space over to GPU, which distributes work-groups among cores (each work-group executes on one core)
  - Programmer unaware of number of cores
- Notice that the GPU and CPU have different memory spaces. That'll be important when we start considering which jobs are a good fit for GPUs, and which jobs are a poor fit.

## OpenCL vvadd

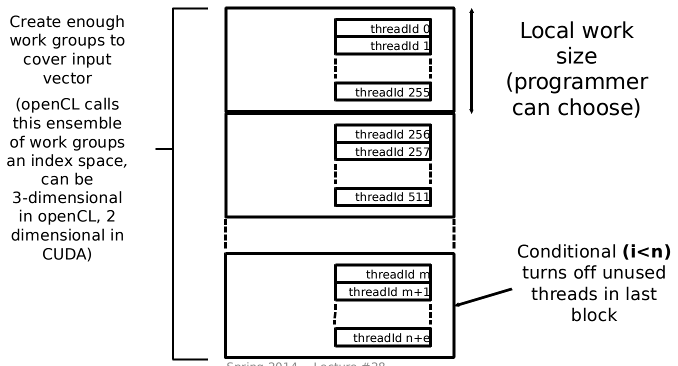
```
/* C version. */
void vvadd(float *dst, float *a, float *b, unsigned n) {
    for(int i = 0; i < n; i++)
        dst[i] = a[i] + b[i]
}
/* openCL Kernel. */
__kernel void vvadd(__global float *dst, __global float *a,
                    __global float *b, unsigned n) {
    unsigned tid = get_global_id(0);
    if (tid < n)
        dst[tid] = a[tid] + b[tid];
}
```

## “Single Instruction, Multiple Thread”

- GPUs use a SIMT model, where individual scalar instruction streams for each work item are grouped together for SIMD execution on hardware (Nvidia groups 32 CUDA threads into a *warp.* OpenCL refers to them as *wavefronts*.)


µT0 µT1 µT2 µT3 µT4 µT5 µT6 µT7
Scalar instruction stream
ld x
mul a
ld y
add
st y
SIMD execution across wavefront

## Programmer's View of Execution


Create enough work groups to cover input vector
(openCL calls this ensemble of work groups an index space, can be 3-dimensional in openCL, 2 dimensional in CUDA)
threadId 0
threadId 1
threadId 255
threadId 256
threadId 257
threadId 511
threadId m
threadId m+1
threadId n+e
Local work size (programmer can choose)
Conditional (i<n) turns off unused threads in last block

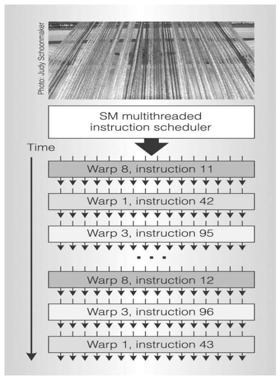
## Teminology Summary

- Kernel: The function that is mapped across the input.
- Work-item: The basic unit of execution. Takes care of one index. Also called a microthread or cuda thread.
- Work-group/Block: A group of work-items. Each work-group is sent to one core in the GPU.
- Index-space/Grid: The range of indices over which the kernel is applied.
- Wavefront/Warp: A group of microthreads (work-items) scheduled to be SIMD executed with eachother.

## Administrivia

- Homework 4 is due Sunday (April 6th)

## Warps (wavefronts) are multithreaded on a single core

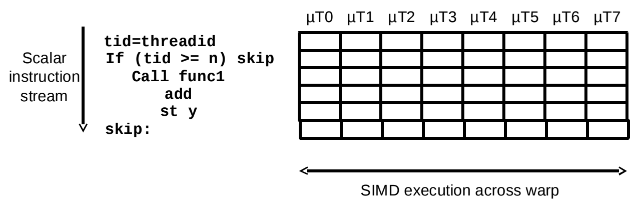


- One warp of 32 µthreads is a single thread in the hardware
- Multiple warp threads are interleaved in execution on a single core to hide latencies (memory and functional unit)
- A single thread block can contain multiple warps (up to 512 µT max in CUDA), all mapped to single core
- Can have multiple blocks executing on one core

[Nvidia, 2010]

## Conditionals in the SIMT Model

- Simple if-then-else are compiled into predicated execution, equivalent to vector masking
- More complex control flow compiled into branches
- How to execute a vector of branches?

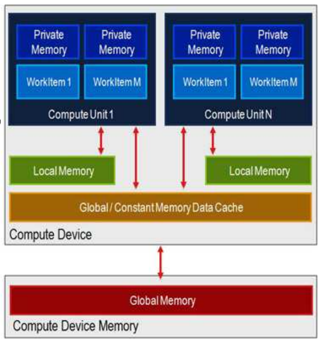


```
tid=threadid
If (tid >= n) skip
   Call func1
       add
       st y
skip:
```

Scalar instruction stream
µT0 µT1 µT2 µT3 µT4 µT5 µT6 µT7
SIMD execution across warp

## OpenCL Memory Model

- Global – read and write by all work-items and work-groups
- Constant – read-only by work-items; read and write by host
- Local – used for data sharing; read/write by work-items in the same work group
- Private – only accessible to one work-item



## Branch Divergence

- Hardware tracks which µthreads take or don't take branch
- If all go the same way, then keep going in SIMD fashion
- If not, create mask vector indicating taken/not-taken
- Keep executing not-taken path under mask, push taken branch PC+mask onto a hardware stack and execute later
- When can execution of µthreads in warp reconverge?

## SIMT

- Illusion of many independent threads
- But for efficiency, programmer must try and keep µthreads aligned in a SIMD fashion
- Try to do unit-stride loads and store so memory coalescing kicks in
- Avoid branch divergence so most instruction slots execute useful work and are not masked off

## VVADD

```
/* C version. */
void vvadd(float *dst, float *a, float *b, unsigned n) {
    #pragma omp parallel for
    for(int i = 0; i < n; i++)
        dst[i] = a[i] + b[i]
}

/* openCL Kernel. */
__kernel void vvadd(__global float *dst, __global float *a,
                    __global float *b, unsigned n) {
    unsigned tid = get_global_id(0);
    if (tid < n)
        dst[tid] = a[tid] + b[tid];
}
```

A: CPU faster
B: GPU faster

## VVADD

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/* C version. */
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    for(int i = 0; i < n; i++)
        dst[i] = a[i] + b[i]
}
```

- Only 1 flop per three memory accesses => memory bound calculation.
- "A many core processor ≡ A device for turning a compute bound problem into a memory bound problem" – Kathy Yelick

## VECTOR_COP

```
/* C version. */
void vector_cop(float *dst, float *a, float *b, unsigned n) {
    #pragma omp parallel for
    for(int i = 0; i < n; i++) {
        dst[i] = 0;
        for (int j = 0; j < A_LARGE_NUMBER; j++)
            dst[i] += a[i]*2*b[i] – a[i]*a[i] – b[i]*b[i];
    }
}
/* OpenCL kernel. */
__kernel void vector_cop(__global float *dst, __global float *a,
                         __global float *b, unsigned n) {
    unsigned i = get_global_id(0);
    if (tid < n) {
        dst[i] = 0;
        for (int j = 0; j < A_LARGE_NUMBER; j++)
            dst[i] += a[i]*2*b[i] – a[i]*a[i] – b[i]*b[i];
    }
}
```

A: CPU faster
B: GPU faster

## GP-GPU in the future

- High-end desktops have separate GPU chip, but trend towards integrating GPU on same die as CPU (already in laptops, tablets and smartphones)
  - Advantage is shared memory with CPU, no need to transfer data
  - Disadvantage is reduced memory bandwidth compared to dedicated smaller-capacity specialized memory system
    - Graphics DRAM (GDDR) versus regular DRAM (DDR3)
- Will GP-GPU survive? Or will improvements in CPU DLP make GP-GPU redundant?
  - On same die, CPU and GPU should have same memory bandwidth
  - GPU might have more FLOPS as needed for graphics anyway

## Acknowledgements

- These slides contain materials developed and copyright by
  - Krste Asanovic (UCB)
  - AMD
  - codeproject.com

## And in conclusion…

- GPUs thrive when
  - The calculation is data parallel
  - The calculation is CPU-bound
  - The calculation is large
- CPUs thrive when
  - The calculation is largely serial
  - The calculation is small
  - The programmer is lazy

## Bonus

- OpenCL source code for vvadd and vector_cop demos available at

  http://www-inst.eecs.berkeley.edu/~cs61c/sp13/lec/39/demo.tar.gz