# Lecture 17: Heterogeneous Parallel Programming

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CSE513: Parallel Runtimes for Modern Processors

#### Lecture 17: Heterogeneous Parallel Programming

## Last Lecture (Recap)

 Multicore processors are latency oriented, whereas GPUs are throughput oriented

#### int\* a = new int[size];

#### int\* b = new int[size]; // create 'a' vector on the GPU

```
compute::vector<int> vector_a(size, context);
```

```
// create 'b' vector on the GPU
// copy data from the host to the device
```

```
compute::future<void> future_a = compute::copy_asyn
```

```
a, a+size, vector_a.begin(), queue
```

```
);
// woit 1
```

```
// wait for copy to finish
future_a.wait();
// Create function defining the body of kernel
```

```
BOOST_COMPUTE_FUNCTION(int, vector_sum, (int x), {
    return x * 1.9;
```

#### });

// Launch the computation on the GPU using
// the command queue created above
compute::transform(

```
vector_a.begin(),
vector_a.end(),
vector_b.begin(),
vector_sum
```

);

// transfer results back to the host array 'c'
compute::copy(vector\_b.begin(), vector\_b.end(), b);



#### **Executing OpenCL Programs**

- I. Query host for OpenCL devices
- 2. Create a context to associate OpenCL devices
- 3. Create programs for execution on one or more associated devices
- 4. Select kernels to execute from the programs
- 5. Create memory objects accessible from the host and/or the device
- 6. Copy memory data to the device as needed
- 7. Provide kernels to command queue for execution
- 6. Copy results from the device to the host



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# **Today's Class**

- Amdahl's law revisited
  - Integrated CPU-GPU architectures
  - Runtime solution for hybrid CPU-GPU parallelism



# Amdahl's Law Revisited

- Recall, maximum possible speedup for a program having fraction "f" of its total execution "W" parallelizable on N processing resources
  - $\circ \quad Speedup(f, N) = T_{Sequential} / (T_{Sequential} + T_{Parallel}) = W / \{(1-f)W + fW/N\}$
  - o Speedup(f, N) = 1 / { (1-f) + f/N }
- The assumption is that there is uniform scalability of processing resources when using more processors



# Amdahl's Law Revisited (Symmetric Cores)

- Examples of different possible multicore processors that are using the same number of total processing resources
  - Each processor has identical cores (symmetric processor)
  - Each processor is using the same number of resources (N=16)
    - E.g., N could be total number of transistors on a processor
  - Each core is consuming R number of these resources





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# Amdahl's Law Revisited (Symmetric Cores)

- Serial fraction of the program would now have a single core (sequential) performance on these combinations as:
  - $\circ$  (1-f) / Perf<sub>R</sub>
    - Perf<sub>R</sub> is the performance of each of the single core of the processor type R shown below
- Parallel fraction use N/R cores at the rate Perf(R) each
   f / (Perf(R) \* (N/R)) = f\*R / Perf(R)\*N
- Speedup(f, R, N) = 1 / ( {(1-f)/Perf(R)} + {f\*R/(Perf(R)\*N)} )





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# Amdahl's Law Revisited (Symmetric Cores)

Symmetric multicore processor with total resources N=16. Perf(R) approximated as square root of R (adding resources won't give linear performance – Why?)
 Speedup(f, R, 16) = 1 / ( {(1-f)/Perf(R)} + {f\*R/(Perf(R)\*16)} )



# Amdahl's Law Revisited (Asymmetric Cores)

- Examples of different possible asymmetric multicore processors
  - Symmetric processor requires all cores to be equal, but  $\bigcirc$ asymmetric processor could have a mix of big and little cores
  - Each processor is using the same number of total resources (**N=16**)  $\bigcirc$ 
    - One Big core with R<sub>B</sub> resources would leave N-R<sub>R</sub> resources for little cores
    - Assuming each little core has R=1, total number of little cores are  $N-R_B$





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# Amdahl's Law Revisited (Asymmetric Cores)

- Serial fraction would still be represented as in symmetric  $\circ$  (1-f) / Perf(R<sub>B</sub>)
- Parallel fraction using one big core with Perf(R<sub>B</sub>) performance and N-R<sub>B</sub> little cores with Perf(1)=1 performance would now be
   f / (Perf(R<sub>B</sub>) + N R<sub>B</sub>)
- Speedup(f,  $R_B$ , N) = 1 / ( {(1-f) / Perf( $R_B$ )} + {f/(Perf( $R_B$ ) + N  $R_B$ )})



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# Amdahl's Law Revisited (Asymmetric Cores)

• Asymmetric multicore processor with total resources N=8. Perf( $R_B$ ) modeled as square root of  $R_B$ 

• Speedup(f,  $R_B$ , 16) = 1 / ( {(1-f) / Perf( $R_B$ )} + {f/(Perf( $R_B$ ) + 16 -  $R_B$ )})



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## **Software Issues with Asymmetric Multicore**

- When to use the big core v/s little cores?
  - Or, how to use them simultaneously if such application arrives
- Managing the locality
- Achieving energy efficiency execution



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# **Qualcomm Snapdragon Mobile SoC**





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# Intel Heterogeneous SoC Architecture



- Alder Lake S (2021)
  - 8 Performance and 8 Efficient cores
    - P cores max frequency 5Gz
    - E cores max frequency 3.8GHz
    - Up to 24 threads supported
  - Integrated GPU with 32 Execution Units
  - Shared memory across CPU and GPU

Picture source: https://en.wikichip.org/wiki/intel/microarchitectures/alder\_lake



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# **Programming Integrated CPU-GPU SoC**

- 1. Setup inputs on the host CPU
- 2. Allocate memory on the host CPU
- 3. Allocate memory on the CPU
- 4. Copy inputs from the host to GPU
- 5. Start GPU kernel
- 6. Copy output from the GPU to host

- Intel integrated CPU-GPU architecture
  - Host and the device share the same physical DRAM unlike the discrete GPUs
    - Enables using the same copy of memory between the CPU and GPU
      - Avoids explicit memory transfers for GPU kernel execution
- Supported by OpenCL 2.0 Shared Virtual Memory (SVM) feature

## **OpenCL 2.0 Shared Virtual Address Space**



- Allows sharing pointers across host and device
  - Coherency in the shared data modified across host and device on Intel integrated GPUs
- Supported by Boost.compute using simple APIs

Source: https://www.intel.com/content/www/us/en/developer/articles/technical/opencl-20-shared-virtual-memory-overview.html



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# Using Boost.Compute SVM on Intel SoC

- Demo of programs available in course GitHub repository
  - GPU-only vector addition
    - https://github.com/hipec/cse513/blob/main/lec17/vecadd.cpp
  - Hybrid CPU-GPU matrix multiplication
    - https://github.com/hipec/cse513/blob/main/lec17/matmul.cpp



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# **Hybrid CPU-GPU Matrix Multiplication**



Percentage of computation offloaded to GPU

• Experiment using the hybrid CPU-GPU matrix multiplication inside the course GitHub repo (size=1024x1024)

#### Intel i7-6700 processor

- 4-core CPU @ 3.4GHz
- o 24-EU GPU @ 350MHz
- Optimal execution at 80% offload
  - Would vary depending on application, processor, and computation size



### Software Challenges with Integrated CPU-GPU

- Scheduling when to use the big core (or CPU) v/s little cores (or GPU)?
  - Heavily depends on the type of application
    - Offloading 80% computation on GPU was optimal in case of matrix multiplication, but it might be suboptimal in case of vector addition
      - Why?
    - Offloading percentage would be different for different kind of workloads (IObound, memory-bound, CPU-bound, etc.)
  - Depends on optimization criteria (time, or energy, or best of both, etc.)
- Programming manually partitioning the workload would hurt programmer's productivity
- Solution runtime assisted scheduling!

- Classification of work-load into eight categories during actual execution (i.e., online profiling)
  - Memory-bound or Compute-bound
    - Ratio of LLC misses to total instructions retired
  - CPU or GPU suitable

| Workload Category       | CPU Time | GPU Time |
|-------------------------|----------|----------|
| CPU biased              | Short    | Long     |
| GPU biased              | Long     | Short    |
| Balanced short workload | Short    | Short    |
| Balanced long workload  | Long     | Long     |

[1] https://dl.acm.org/doi/abs/10.1145/2854038.2854052



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#### • Power usage with CPU long v/s short

- Assume one job consumes 45W package power when only using the CPUs, and the same job consumes 30W when only using the GPU
- Increasing the GPU offload from 0-100%
  - Power usage drops slowly for CPU-long
    - Concave shaped curve
  - Power usage drops quickly for CPU-short
    - Convex shaped curve



#### • How to do an online profiling in a running application?

- Classify the work-load by running a few iterations of the for-loop on both CPU & GPU simultaneously (as categorized in Slide #20)
- Compare the findings of the online profiling either with a pre-trained processor specific model (on-the-fly is also possible, and is discussed in several papers)
  - A one-time characterization of the processor's power usage by measuring the power used by different kinds of workloads by varying the value of alpha (α → percentage of tasks offloaded to GPU)
    - Measured once on each experimental machine
  - This would give a power curve  $P(\alpha)$  for different categories of programs
    - $P(\alpha)$  is captured in form of polynomial expression



- Steps for energy aware runtime scheduling of parallel\_for
  - 1. If  $\alpha$  exists for this computation
    - Schedule iterations over CPU-GPU using this known α value
      - Any applications falling in this category that we have already used before?
  - 2. If α does not exists for this computation then perform repetitive profiling to determine the minimum value of the target object function (objective could be energy, EDP, etc.)
    - a) Divide fixed sized  $N_{Chunks}$  between CPU-GPU by changing  $\alpha$  in the range 0...100% (where,  $N_{Total} \% N_{Chunks} = 0$ )
      - If N<sub>total</sub> is too small then exit this loop and launch entire computation on CPU only
    - b) Profile the CPU and GPU executions (CPU & GPU throughputs, memory bandwidth, etc.)
    - c) Characterize work-load and determine corresponding power curve
    - d) Increment  $\alpha$  in step of 0.1 and repeat the above steps until half of the  $N_{chunks}$  remaining

Recall, Intel GPUs have EUs akin to a CPU-core, and are also N-way SMT with wide vector units

How to

choose the

value of

N<sub>chunks</sub>?





# **Reading Materials**

- Amdahl's law in the multicore era
  - o <u>https://www.cs.washington.edu/mssi/2008/talks/hill\_msr\_uw\_0808.pdf</u>
- OpenCL 2.0 shared virtual memory overview
  - <u>https://www.intel.com/content/www/us/en/developer/articles/technical/</u> <u>opencl-20-shared-virtual-memory-overview.html</u>
- A black-box approach to energy-aware scheduling on integrated CPU-GPU Systems
  - o <u>https://dl.acm.org/doi/abs/10.1145/2854038.2854052</u>



# **Next Lecture**

• Power management in multicore processors

#### • Quiz-3

o Syllabus: Lectures 15-17

