Motivation

CPU

Kernel

GPU

CPU

GPU

CPU

GPU 1

GPU 2
Leveraging Multiple Devices

- Writing *correct* multi-device applications is challenging
- Writing *efficient* multi-device applications is even harder

- The optimal division of labor depends on:
  - Hardware characteristics
  - Input data set
  - Behavior of other applications
  - Metric being optimized

- Efficiently orchestrating the data movement and kernel invocations is complicated:
  - Set appropriate flags based on hardware and software characteristics
  - Use multiple buffers to overlap operations
Goal: Automatically load balance a single-device application across multiple (heterogeneous) devices
Outline

- Motivation
- Our approach: dynamic chunking
- Load balancing framework
- Preliminary results
- Conclusions and future work
Our Approach: Dynamic Chunking

- Break the kernel into multiple chunks
  - Key distinction: # chunks > # devices
- Dynamically schedule chunks to devices
  - Scheduling decisions and chunk sizes based on online profiling
**Chunking**

- Chunk: a contiguous set of work groups

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**Original NDRange**

**Chunks**

**Chunks**
Chunking: Kernel + Data

Application

Kernel

Data

GPU

CPU

Chunk 1

Chunk 2

CPU

GPU

Chunk 3
**Chunking: Advantages & Challenges**

**Advantages:**
- No training required, even as hardware changes
- Can respond to dynamic performance changes due to:
  - Data-dependent behavior
  - Contention from other applications
- Can overlap kernel execution and data transfer

**Challenges:**
- Managing contention
  - Contention from other applications
  - CPU is both host and compute device
  - Memory contention between CPU & GPU operations
- Dispatch overhead
- Determining which data is accessed by each chunk
  - Difficult data structures / access patterns
Chunking: Overlapping Operations

No chunking:
- Transfer
- Computation

Chunking:
- Transfer: 1, 2, 3, 4
- Computation: 1, 2, 3, 4
Load-Balancing Framework
Framework Overview

Application

OpenCL Runtime

OpenCL API calls

Application View

System View

Application

Load-Balancing Framework

OpenCL Runtime
Framework Requirements

1. Intercept OpenCL API calls
2. Determine what data to transfer to each device
3. Orchestrate and balance execution across the devices
**Framework Components**

1. API intercept layer
   - Intercepts and transforms calls from application to OpenCL runtime

2. Access pattern extractor
   - Analyzes kernel source code to extract data access patterns

3. Chunk scheduler
   - Breaks kernels into chunks and schedules them onto devices
**API Intercept Layer**

- Intercepts each OpenCL API call and replicates it across multiple devices or transforms it

<table>
<thead>
<tr>
<th>OpenCL API Function</th>
<th>Application View</th>
<th>System View</th>
</tr>
</thead>
<tbody>
<tr>
<td>clCreateCommandQueue</td>
<td>GPU</td>
<td>GPU</td>
</tr>
<tr>
<td>clCreateBuffer</td>
<td>GPU</td>
<td>CPU</td>
</tr>
</tbody>
</table>
Access Pattern Extractor

- Need a mechanism for sending the right data to each device

- Given the kernel source, determines:
  - Mapping from chunk to memory region
  - Preferred chunking direction

- Kernel source code is available from intercepting call to the OpenCL compiler

- Output: function that returns the region of memory accessed by a given chunk
  - Callable by the chunk scheduler
  - Works for arbitrary chunk sizes
Access Pattern Extractor: Details

- Built on Clang (LLVM’s front-end)
  - Clang’s OpenCL support is under active development
  - For now, add an implicit header to define built-in data types and functions

- Basic idea: traverse the kernel AST
  - Identify accesses to memory buffers
  - Express buffer offsets in terms of values that can be reasoned about at kernel invocation time
  - Determine relationship between accesses from different work items
Access Pattern Extractor: Example

__kernel void blackScholes(const __global float4 *randArray,
    ...
    __global float4 *put, int width) {

    size_t xPos = get_global_id(0);
    size_t yPos = get_global_id(1);
    float4 inRand = randArray[yPos * width + xPos];
    ...
    put[yPos * width + xPos] = KexpMinusRT * phiD2 - S * phiD1;
**Access Pattern Extractor: Input vs. Output Buffers**

- **Input buffers:**
  - Can afford to be imprecise
  - Approach: determine minimum and maximum offset and transfer entire range

- **Output buffers:**
  - Need to be precise
  - Approach: determine parameters of strided access
**Scheduler**

- Breaks kernel into chunks
- For each chunk:
  - Sends input data to device
  - Launches kernel on device
  - Copies output data back to host

- Mapping of chunks to devices is determined dynamically, based on online profiling data
**Dynamic Scheduling**

- If number of work groups is small, skip chunking and send whole kernel to one device

- Otherwise, send initial chunks to each device:
  - Initial chunk size set to exactly fill each device

- Maintain two chunks outstanding to each device to hide dispatch overheads

- Exponentially increase chunk sizes for “fast” devices until “slow” device has completed a chunk

- Once performance data is available for all devices:
  - Distribute a portion of the remaining work to all devices based on relative performance
  - Maintain aggregate history information, but decay it exponentially
Dynamic Scheduling Example
Preliminary Results
Experimental Systems

1. CPU + GPU:
   - AMD Radeon HD 5870 (Cypress)
   - Intel Core i7 920: quad-core, hyper-threaded, 2.67 GHz

2. Homogenous Multi-GPU:
   - 2 x AMD Radeon HD 5870

3. Heterogeneous Multi-GPU:
   - AMD Radeon HD 5870
   - AMD Radeon HD 6570 (Turks)
Synthetic Benchmark: Computation-to-Communication Ratio

10 / 90
- Data Transfer
- KE

50 / 50
- Data Transfer
- Kernel Execution

90 / 10
- DT
- Kernel Execution
Synthetic Benchmark Results

Percent Kernel Execution vs. Speedup for Multi-GPU and CPU-GPU configurations.
Sample Applications

- From Rodinia benchmark suite:
  - SRAD
- From AMD APP SDK:
  - Mandelbrot
  - Black-Scholes
Results: CPU + GPU, SRAD
Results: Heterogeneous Multi-GPU, Mandelbrot
Results: Homogeneous Multi-GPU, Black-Scholes*
Previous Work: Qilin

- Divides a CUDA kernel across a CPU and GPU

- Limitations:
  - Requires manual creation of CPU & GPU versions of kernel
  - Requires a training phase
  - Scheduling is static
  - Only works on NVIDIA GPUs

Previous Work: Single Compute Device Image

- Divides an OpenCL kernel across multiple GPUs

- Limitations:
  - Naïve scheduling: each device gets an equal amount of work
  - Only works on NVIDIA GPUs

Challenges and Future Work

- Tune the framework for different hardware and software configurations

- Optimize for different metrics

- One version of the kernel for multiple devices
  - Optimizations for GPU may hurt performance on CPU and vice versa
  - Supporting device-specific kernels would allow a tradeoff between programmer effort and performance

- Multiple kernel calls
  - Need to understand data flow between kernel calls

- Possible (but rare) for work groups to communicate with each other using atomic instructions
  - Difficult to support across multiple devices efficiently

- Deployment possibilities:
  - OpenCL layer targeting standalone applications
  - Layer in the Fusion software stack
Conclusions

- Heterogeneous multi-device systems (like Fusion) are becoming ubiquitous
  - Effectively utilizing the available devices is difficult

- Our framework automatically load balances unmodified OpenCL applications across multiple (possibly heterogeneous) devices
  - Extracts access patterns to determine mapping of work groups to data
  - Uses online profiling to guide scheduling decisions

- Preliminary performance results are encouraging
Questions
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