Automatic Compiler-Based Optimization of Graph Analytics for the GPU

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NVIDIA GTC
Parallel Graph Processing is not easy

USA Road Network
24M nodes, 58M edges

LiveJournal Social Network
5M nodes, 69M edges

HD-BFS: 299ms, 84ms
LB-BFS: 692ms, 41ms
Observations from the “field”

• Different algorithms require different optimizations
  – BFS vs SSSP vs Triangle Counting
• Different inputs require different optimizations
  – Road vs Social Networks
• Hypothesis: High-performance graph analytics code must be customized for inputs and algorithms
  – No “one-size fits all” implementation
  – If true, we'll need a lot of code
How IrGL fits in

- IrGL is a language for graph algorithm kernels
  - *Slightly* higher-level than CUDA
- IrGL kernels are compiled to CUDA code
  - Incorporated into larger applications
- IrGL compiler applies 3 *throughput* optimizations
  - User can select exact combination
  - Yields multiple implementations of algorithm
- Let the compiler generate all the interesting variants!
Outline

• IrGL Language
• IrGL Optimizations
• Results
IrGL Constructs

- Representation for irregular data-parallel algorithms
- Parallelism
  - ForAll
- Synchronization
  - Atomic
  - Exclusive
- Bulk Synchronous Execution
  - Iterate
  - Pipe
IrGL Synchronization Constructs

- Atomic: Blocking atomic section

  ```
  Atomic (lock) {
      critical section
  }
  ```

- Exclusive: Non-blocking, atomic section to obtain multiple locks with priority for resolving conflicts

  ```
  Exclusive (locks) {
      critical section
  }
  ```
IrGL Pipe Construct

- IrGL kernels can use worklists to track work
- Pipe allows multiple kernels to communicate worklists
- All items put on a worklist by a kernel are forwarded to the next (dynamic) kernel

```plaintext
Pipe {
  // input: bad triangles
  // output: new triangles
  Invoke refine_mesh(...) 
  // check for new bad tri.
  Invoke chk_bad_tri(...)
}
```

```
not worklist.empty()
```

refine_mesh

chk_bad_tri
Example: Level-by-Level BFS

Kernel bfs(graph, LEVEL)
  ForAll(node in Worklist)
    ForAll(edge in graph.edges(node))
      if(edge.dst.level == INF)
        edge.dst.level = LEVEL
        Worklist.push(edge.dst)
  src.level = 0
Iterate bfs(graph, LEVEL) [src] {
  LEVEL++
}
Three Optimizations for Bottlenecks

1. Iteration Outlining
   - Improve GPU utilization for short kernels

2. Nested Parallelism
   - Improve load balance

3. Cooperative Conversion
   - Reduce atomics

• Unoptimized BFS
  - ~15 lines of CUDA
  - 505ms on USA road network

• Optimized BFS
  - ~200 lines of CUDA
  - 120ms on the same graph

4.2x Performance Difference!
Outline

- IrGL Language
- IrGL Optimizations
- Results
Optimization #1: Iteration Outlining
Bottleneck #1: Launching Short Kernels

```plaintext
Kernel bfs(graph, LEVEL)
    ForAll(node in Worklist)
        ForAll(edge in graph.edges(node))
            if(edge.dst.level == INF)
                edge.dst.level = LEVEL
                Worklist.push(edge.dst)

    src.level = 0
    Iterate bfs(graph, LEVEL) [src] {
        LEVEL++
    }
```

- USA road network: 6261 bfs calls
- Average bfs call duration: 16 µs
- Total time should be 16*6261 = 100 ms
- Actual time is 320 ms: 3.2x slower!
Iterative Algorithm Timeline

- **CPU**
  - Time
  - Launch
  - Idling
  - bfs
  - Idling
  - bfs
  - Idling
  - bfs

- **GPU**
  - bfs
  - Idling
  - bfs
  - Idling
  - bfs
GPU Utilization for Short Kernels

![Graph showing GPU utilization over time for different kernel invocations with various cards.]
Improving Utilization

- Generate Control Kernel to execute on GPU
- Control kernel uses function calls on GPU for each iteration
- Separates iterations with device-wide barriers
  - Tricky to get right!
Benefits of Iteration Outlining

- Iteration Outlining can deliver up to 4x performance improvements
- Short kernels occur primarily in high-diameter, low-degree graphs
  - e.g. road networks
Optimization #2: Nested Parallelism
Kernel bfs(graph, LEVEL)
  ForAll(node in Worklist)
    ForAll(edge in graph.edges(node))
      if(edge.dst.level == INF)
        edge.dst.level = LEVEL
        Worklist.push(edge.dst)
  src.level = 0
Iterate bfs(graph, LEVEL) [src] {
  LEVEL++
}
Exploiting Nested Parallelism

- Generate code to execute inner loop in parallel
  - Inner loop trip counts not known until runtime
- Use Inspector/Executor approach at runtime
- Primary challenges:
  - Minimize Executor overhead
  - Best-performing Executor varies by algorithm and input
Scheduling Inner Loop Iterations

Example schedulers from Merrill et al., Scalable GPU Graph Traversal, PPoPP 2012
Multi-Scheduler Execution

Use thread-block (TB) for high-degree nodes

Use fine-grained (FG) for low-degree nodes

Thread-block (TB) + Finegrained (FG) Scheduling

*Example schedulers from* Merrill et al., Scalable GPU Graph Traversal, PPoPP 2012
## Which Schedulers?

<table>
<thead>
<tr>
<th>Policy</th>
<th>BFS</th>
<th>SSSP-NF</th>
<th>Triangle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Serial Inner Loop</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>TB</td>
<td>0.25</td>
<td>0.33</td>
<td>0.46</td>
</tr>
<tr>
<td>Warp</td>
<td>0.86</td>
<td>1.42</td>
<td>1.52</td>
</tr>
<tr>
<td>Finegrained (FG)</td>
<td>0.64</td>
<td>0.72</td>
<td>0.87</td>
</tr>
<tr>
<td>TB+Warp</td>
<td>1.05</td>
<td>1.40</td>
<td>1.51</td>
</tr>
<tr>
<td>TB+FG</td>
<td>1.10</td>
<td>1.46</td>
<td><strong>1.55</strong></td>
</tr>
<tr>
<td>Warp+FG</td>
<td>1.14</td>
<td>1.56</td>
<td>1.23</td>
</tr>
<tr>
<td>TB+Warp+FG</td>
<td><strong>1.15</strong></td>
<td><strong>1.60</strong></td>
<td>1.24</td>
</tr>
</tbody>
</table>

*Speedup relative to Serial execution of inner-loop iterations on a synthetic scale-free RMAT22 graph. Higher is faster. Legend: SSSP NF -- SSSP NearFar*
Benefits of Nested Parallelization

- Speedups depend on graph, but seen up to 1.9x
- Benefits graphs containing nodes with high degree
  - e.g. social networks
- Negatively affects graphs with low, uniform degrees
  - e.g. road networks
  - Future work: low-overhead schedulers
Optimization #3: Cooperative Conversion
Bottleneck #3: Atomics

Kernel bfs(graph, LEVEL)
   ForAll(node in Worklist)
      ForAll(edge in graph.edges(node))
         if(edge.dst.level == INF)
            edge.dst.level = LEVEL
            Worklist.push(edge.dst)
   src.level = 0
   Iterate bfs(graph, LEVEL) [src] {
      LEVEL++
   }

• Atomic Throughput on GPU: 1 per clock cycle
  - Roughly translated: 2.4 GB/s
  - Memory bandwidth: 288GB/s
Aggregating Atomics: Basic Idea

atomicAdd(..., 1)

Thread

atomicAdd(..., 5)

Write

Thread
Challenge: Conditional Pushes

if(edge.dst.level == INF)
    Worklist.push(edge.dst)
Challenge: Conditional Pushes

```
if(edge.dst.level == INF)
    Worklist.push(edge.dst)
```

Must aggregate atomics *across* threads
Cooperative Conversion

- Optimization to reduce atomics by cooperating across threads

- IrGL compiler supports all 3 possible GPU levels:
  - Thread
  - Warp (32 contiguous threads)
  - Thread Block (up to 32 warps)

- Primary challenge:
  - Safe placement of barriers for synchronization
  - Solved through novel Focal Point Analysis
Kernel bfs_kernel(graph, ...) 
ForAll(node in Worklist) 
  ForAll(edge in graph.edges(node)) 
    if(edge.dst.level == INF) 
      ... 
      start = Worklist.reserve_warp(1) 
      Worklist.write(start, edge.dst)
Inside reserve_warp

reserve_warp
(assume a warp has 8 threads)

<table>
<thead>
<tr>
<th>T0</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>T6</th>
<th>T7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

(size)

(warp prefix sum)

<table>
<thead>
<tr>
<th>T0</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>T6</th>
<th>T7</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>

_offset

T0: pos = atomicAdd(Worklist.length, 5)
broadcast pos to other threads in warp

return pos + _offset
Thread-block aggregation?

```
Kernel bfs(graph, ...)
    ForAll(node in Worklist)
        ForAll(edge in graph.edges(node))
            if (edge.dst.level == INF)
                start = Worklist.reserve_tb(1)
                Worklist.write(start, edge.dst)
```
Inside reserve_tb

Barrier required to synchronize warps, so can't be placed in conditionals
reserve_tb is incorrectly placed!

Kernel bfs(graph, ...)  
  ForAll(node in Worklist)  
    ForAll(edge in graph.edges(node))  
      if(edge.dst.level == INF)  
        start = Worklist.reserve_tb(1)  
        Worklist.write(start, edge.dst)
Solution: Place reserve_tb at a Focal Point

- Focal Points [Pai and Pingali, OOPSLA 2016]
  - All threads pass through a focal point all the time
  - Can be computed from control dependences
  - Informally, if the execution of some code depends only on uniform branches, it is a focal point

- Uniform Branches
  - branch decided the same way by all threads [in scope of a barrier]
  - Extends to loops: Uniform loops
reserve_tb placed

```
Kernel bfs(graph, ...) {
    ForAll(node in Worklist)
        UniformForAll(edge in graph.edges(node))
            will_push = 0
            if(edge.dst.level == INF)
                will_push = 1
                to_push = edge

    start = Worklist.reserve_tb(will_push)
    Worklist.write_cond(willpush, start, to_push)

    Made uniform by nested parallelism
```
Benefits of Cooperative Conversion

- Decreases number of worklist atomics by 2x to 25x
  - Varies by application
  - Varies by graph
- Benefits all graphs and all applications that use a worklist
  - Makes concurrent worklist viable
  - Leads to work-efficient implementations
Summary

- IrGL compiler performs 3 key optimizations
  - Iteration Outlining
    - eliminates kernel launch bottlenecks
  - Nested Data Parallelism
    - reduces inner-loop serialization
  - Cooperative Conversion
    - reduces atomics in lock-free data-structures
- Allows auto-tuning for optimizations
Outline

- IrGL Language
- IrGL Optimizations
- Results
Evaluation

- Eight irregular algorithms
  - Breadth-First Search (BFS) [Merrill et al., 2012]
  - Connected Components (CC) [Soman et al., 2010]
  - Maximal Independent Set (MIS) [Che et al., 2013]
  - Minimum Spanning Tree (MST) [da Silva Sousa et al. 2015]
  - PageRank (PR) [Elsen and Vaidyanathan, 2014]
  - Single-Source Shortest Path (SSSP) [Davidson et al. 2014]
  - Triangle Counting (TRI) [Polak et al. 2015]
  - Delaunay Mesh Refinement (DMR) [Nasre et al., 2013]
System and Inputs

- Tesla K40 GPU
- Graphs
  - Road Networks
    - USA: 24M vertices, 58M edges
    - CAL: 1.9M vertices, 4.7M edges
    - NY: 262K vertices, 600K edges
  - RMAT (synthetic scale-free)
    - RMAT22: 4M vertices, 16M edges
    - RMAT20: 1M vertices, 4M edges
    - RMAT16: 65K vertices, 256K edges
  - Grid (1024x1024)
  - DMR Meshes: 10M points, 5M points, 1M points
Conclusion

- Graph analytics on GPUs requires 3 key *throughput* optimizations to obtain good performance
  - Iteration Outlining
  - Nested Parallelization
  - Cooperative Conversion
- The IrGL compiler automates these optimizations
  - Faster by up to 6x, median 1.4x
Overall Performance

Note: Each benchmark had a single set of optimizations applied to it
Comparison to NVIDIA nvgraph SSSP

![Graph showing runtime comparison between NVGRAPH, IrGL SSSP, and IrGL SSSP-NF for different input graphs: NY, rmat22, USA. The bars indicate the runtime for each graph type. In the USA input graph, NVGRAPH takes 227s, IrGL SSSP takes 131s.]
Irregular Data-Parallel Algorithms

- Graph Algorithms
- Sparse Linear Algebra
- Discrete-event Simulation
- Adaptive Simulations
- Brute-force Searches
  - Constraint solvers
- Graph databases
- ...
Conclusion

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  - Iteration Outlining
  - Nested Parallelism
  - Cooperative Conversion
- The IrGL compiler automates these optimizations
  - Faster by up to 6x, median 1.4x
  - Faster than nvgraph
Thank you!
Questions?
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