Hedgehog: A Performance-Oriented General-Purpose Library for Multi-GPU Systems

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Motivation – Hardware

- **Servers**
  - AMD EPYC 7702P **w/64 cores**, Intel Xeon Platinum 8253 Processor **w/16 cores**

- **Desktops**
  - AMD Ryzen Threadripper 3990X **w/64 cores**, AMD Ryzen 9 PRO 3900 **w/12 cores**
  - Intel Core i9-10980XE Extreme Edition **w/18 cores (3x hyperthreading)**

- **Laptops**
  - AMD Ryzen 7 4800H **w/8 cores**, Intel Core i9-9980HK **w/8 cores**

- **Mobile CPU:** Kryo 585 **w/8 cores**

- **GPUs:**
  - GeForce RTX 2080: **9362 (SP), 292.6 (DP), 18720 (HP) GFLOPS**
  - Tesla T4 GPU accelerator: **8100 (single precision) GFLOPS**
Motivation – Understandable Scalable Programs

- Abstract model of execution

- Explicit representation of an algorithm
  - Exists during execution
  - Used to instrument and reason about performance

- Experimentation for performance using high-level abstractions
  - Without loss of potential performance
Requirements

- Manage a node with many cores and one or multiple GPUs
- Explicit representation of an algorithm (that exists during execution)
- High-level abstractions (without loss of potential performance)
Outline

- Basic concepts
- Hedgehog
- Experimentations
Basic Concepts

- Data flow graph
- Data pipelining
- HTGS & library
Asynchronous Data Flow Graph

- Program model
  - Directed graph representation
  - 1 entry and 1 exit point (source and sink)

- Components
  - Nodes: computations or state management
  - Edges: directed information flow

Addition algorithm

\[ A + B = C \]

Data Flow representation

\[ A + B \rightarrow C \]
Data Pipelining

Data Pipelining representation

Stage start as soon as data becomes available
- Asynchronous behavior

Data1 • Data2 • Data3

Read • Compute • Write

Overlapping computation

Time

Hedgehog—A. Bardakoff & T. Blattner
Hybrid Task Graph Scheduler - HTGS

- **Coarse-Grained** Parallelism
  - **Pipelined** Multi-Threaded
  - **Multi-CPU** and **Multi-GPU**

- **C++ 11** headers-only library
  - **Visual Debugging** Feature
  - **Rich** API


Blattner, T. et al., J Sign Process Syst (2017) 89: 457 [https://doi.org/10.1007/s11265-017-1262-6](https://doi.org/10.1007/s11265-017-1262-6)
Hedgehog

Overview
API
Usage
Example
Overview

- **Coarse grain** parallelism
  - Dataflow graph representation
  - Data pipelining to obtain performance & keep hardware busy
  - Separation of concerns:
    - Tasks; State; Memory Management

- **C++ 17**, headers-only library
  - General purpose
  - Open source and available

- Metaprogramming for type safety
Methodology

Methodology used in Hedgehog
API - Nodes

- Multiple Inputs - Single Output
- Shutdown virtual method to break cycles

Tasks

- Step of an algorithm / **Computation kernels**
  - **Special task** for (NVIDIA) GPU computations
- **Multithreaded**

State manager—single-threaded

- **Local** computation’s **state** management
- State shared between different managers in the graph
API - Memory Manager

- Throttles memory usage
- Links to a task or state
- Pool of available pieces of data

- Static
  - Create \( n \) objects calling a specific constructor
  - Ensure constructor signature by using SFINAE construct

- Dynamic
  - Create \( n \) objects calling default constructor

- Mechanism to recycle memory / objects
API - Graph

- Graph
  - Algorithm representation
  - Group nodes (tasks, state manager, memory manager)
  - Can be part of another graph
    - Share or compose algorithms
  - Bind a graph to a GPU
  - Only object used by an end-user

- Execution Pipeline
  - Duplicate graph
    - Data decomposition rules
    - Associate each graphs to GPUs
Explicit representation

- Create a graphical representation
  - Very low overhead (task level)

- Information gathered
  - Graph: execution & creation times
  - Nodes: wait & execution times

- Node colors
  - Based on execution & wait times

- Multiple options (all threads)
Library Example (Fast Loader)

Fast Loader architecture

File level 1

Algorithm

Fast Loader Graph

File level n
Safety @ Compile Time (Metaprogramming)

- Checks coherency rules with **traits** and **constexpr**:
  - A graph's input task has at least one of this input type corresponding to one of the graph's input type
  - Two linked tasks have at least one common type: task output's type correspond to at least to one of the other input types' task

- Checks restriction rule with **traits**:
  - To connect a memory manager to a node, the managed type is the node's output type

- Generates code with **SFINAE** construct:
  - Generate constructor for managed types

- Can be easily modified to take advantage of C++20
System latency

Latency analysis for different number of task's threads

- 1 Input type
- 5 Input types
- 10 Input types

Latency (μs)

Task's threads

Hedgehog—A. Bardakoff & T. Blattner
Usability (Summer 2019)

- Rising sophomore student

- No knowledge about
  - C++
  - Parallel programming

- In < 3 months:
  - Learned enough C++ to use the library
  - Created base graphs to represent algorithm
  - Prototyped several numerical linear algebra operations
  - Got (good) results…
Example

- **Goal**
  - API overview
  - Increment all elements in an array

- **Algorithm**
  - Split array into chunks
  - Increment chunks in parallel

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**Algorithm representation**
Example: Some data

#include <hedgehog/hedgehog.h>

const size_t SIZE = 10000000000;  // 10^9 --- ginormous size

using MYARRAY = std::array<int, SIZE>;

struct ItBeginEnd {
    MYARRAY::iterator begin_,
    end_;

    ItBeginEnd(MYARRAY::iterator const &begin, MYARRAY::iterator const &end)
        : begin_(begin), end_(end) {}
};
Example: Tasks / Split vector

class SplitVector : public hh::AbstractTask<ItBeginEnd, MYARRAY> {

private:
    size_t batchSize_ = 0;

public:
    explicit SplitVector(size_t batchSize) : AbstractTask("Split Vector Task"), batchSize_(batchSize) {} 

    void execute(std::shared_ptr<MYARRAY> v) override {
        for (size_t pos = 0; pos < SIZE; pos += batchSize_)
            this->addResult(
                std::make_shared<ItBeginEnd>(v->begin() + pos, v->begin() + std::min(SIZE, pos + batchSize_)));
    }
};
Example: Tasks / Batch Increment

class BatchIncrement : public hh::AbstractTask<void, ItBeginEnd> {

private:
    size_t increment_ = 0;

public:
    explicit BatchIncrement(int increment, size_t numberThreads)
        : AbstractTask("Batch Increment Task", numberThreads), increment_(increment) {}

    std::shared_ptr<AbstractTask < void, ItBeginEnd>> copy() override {
        return std::make_shared<BatchIncrement>(increment_, this->numberThreads());
    }

    void execute(std::shared_ptr<ItBeginEnd> ptr) override {
        std::for_each(ptr->begin_, ptr->end_, [this] (int& x) { x += increment_; });
    }
};
Example: main

```cpp
int main() {
    auto myArray = std::make_shared<MYARRAY>();
    // Instantiate graph parts
    auto graph = std::make_shared<hh::Graph<void, MYARRAY>>("Increment Array Graph");
    auto splitVectorTask = std::make_shared<SplitVector>(1000); // batchSize:1000
    auto batchIncrementTask = std::make_shared<BatchIncrement>(100, 10); // +100, 10 threads
    // Construct Graph: link tasks and set graph's input / output, and run it
    graph->input(splitVectorTask);
    graph->addEdge(splitVectorTask, batchIncrementTask);
    graph->output(batchIncrementTask);
    graph->executeGraph();
    // Send data to the graph, and wait for termination
    graph->pushData(myArray);
    graph->finishPushingData();
    graph->waitFORTermination();
    // Create dot representation after computation completes
    graph->createDotFile("Test.dot", hh::ColorScheme::EXECUTION, hh::StructureOptions::ALL);
}
```
Example: Graph Representation

Increment Array Graph
Execution time: 29.497s
Creation time: 847us

Algorithm dot representation
Experiments

Linear Algebra Routines
Matrix Multiplications experiments
Matrix decomposition inside operation
- Most linear algebra implementations take advantage of this internally

Matrix decomposition outside operation
- Allows for streaming mode of computation
  - Output blocks can be used immediately
  - Time for using computed data should immensely decrease
- Not available with other numerical linear algebra libraries
Hedgehog Matrix Block Library (HMBLib)

- Hedgehog - API that aids to obtain performance
  - Designed for single system with many CPU cores & multiple GPUs

- Linear algebra subroutines (graphs)
  - Tasks
  - State-Managers
    - States

- Reuse kernels from existing libraries

Example Graph (A + B = C)
Linear Algebra - General Matrix Multiplication

- Compatible with BLAS (gemm)
- Multiply Blocks with same inner dimension
  - Uses OpenBLAS (gemm)
- Add blocks together
  - Add sum to corresponding block of matrix C
- Output final block

Matrix Multiplication Representation

\[ A \times B + C = C \]
Factor a matrix as the product of two triangular matrices
- Used to solve: \( Ax = B \)
- Compatible with LAPACK’s `getrf`

Recursive algorithm

Row swapping enabled
- Allows for more generalized matrices
- Uses LAPACK’s `laswp`
Linear Algebra - Performance Study with HMBLib

- HMBLib v. OpenBLAS (gemm) & LAPACK (getrf)
- 32,768 x 32,768 sized double precision matrices
  - Over 1 billion objects
  - ~16 GBs each

Computer specifications for study:
- 1 node, 2x 14 physical cores (56 logical)
  - 2 x Xeon E5-2680 @ 2.40 GHz
    - AVX2 (256-bit SIMD vector instruction)
- 512 GB Memory
Linear Algebra - Matrix Multiplication Performance Study

- HMBLib vs OpenBLAS (gemm) overall computation comparison
  - ~660 GFlops vs. ~445 GFlops
  - 1.50x performance improvement

Performance = \frac{\text{OpenBLAS Time(s)}}{\text{Computation Time(s)}}
Linear Algebra - Releasing Final Blocks (GEMM)

- First block time - time to release first block data
- Average block time - time to release average block data
- HMBLib vs OpenBLAS (gemm) time for first output comparison
  - 57x less for first output of computed data
Linear Algebra - LU w/PP Performance Study

- HMBLib v LAPACK (getrf) overall computation comparison
  - ~238 v. ~224 GFlops
  - 1.06x performance improvement

Performance = \frac{\text{LAPACK Time(s)}}{\text{Computation Time(s)}}
Linear Algebra - LU w/PP Performance Study

- HMBLib v LAPACK (getrf) time for first output comparison
  - 42x less time for first computed data
Hedgehog CUDA Acceleration Experiment

Objective:
- Adapt Hedgehog OpenBLAS GEMM to use cuBLAS

Goals:
- Analyze performance to observe overhead related to Hedgehog
  - Compared with cublasXT and cublasMG as baselines
- Use CUDA optimization techniques to keep the GPU(s) busy

Hardware:
- SuperMicro SYS-2029GP-TR Server
  - 2x 16 core Intel Xeon Silver 4216 CPUs @ 2.1 GHz
  - 792 GB DDR4
  - 4x Tesla V100-PCIe w/ 32 GB HBM2
Hedgehog(HH)-GEMM CUDA Optimizations

- CUDA technologies used
  - Unified memory
  - Asynchronous pre-fetch
  - Concurrent kernel execution
  - Synchronization through events

- HH-GEMM CUDA
  - Operates with user-specified block-size
  - Each block is contiguous and allocated outside of graph
    - No support for 2D cudaMemPrefetchAsync
HH-GEMM CUDA Graph

Sub-graph (1 per GPU)

Block

Prefetch-In

A or B

Block

MatMul State

Pair

GEMM

Block

Addition State

Pair

Addition

Threads

2

(1 stream per thread)

1

(1 stream per thread)

1

N

Functionality

HH Get Mem_{A \| B}
Prefetch Mem_{A \| B} CPU→GPU
Create Event_1

HH Get Mem_{Partial(P)}
Prefetch Mem_p CPU→GPU
Synchronize Event_1
cublasSgemm(Mem_p ,Mem_A ,Mem_B)
Synchronize Stream
Recycle Mem_{A \& B}
Prefetch Mem_p GPU→CPU
Create Event_2

Pair Mem_p with C

Synchronize Event_2
C = Mem_p + C
Recycle Mem_p

HH—A. Bardakoff & T. Blattner
HH-GEMM CUDA Results 16 GB Size Matrices

Runtime (s) comparison between Hedgehog, CublasMG and CublasXT for matrix of 64kx64k elements with 4 GPUs.

Performance for matrix of 64kx64k elements decomposed in blocks of 8kx8k.
Streaming Linear Algebra with HH-GEMM CUDA

- Streaming linear algebra
  - Required minor modifications to code to switch between inner/outer traversals
    - Change loop order for pushing block data into graph
    - Alter memory pool size to have sufficient memory for both A and B
  - Performance can be detrimental if there is insufficient GPU memory (unified memory paging)
H-GEMM Results 64 GB Size Matrices

Performance for matrix of 128kx128k elements decomposed in blocks of 8kx8k.

- Theoretical peak
- Hedgehog
- CublasMG
- CublasXT

Performance for matrix of 128kx128k elements decomposed in blocks of 8kx8k.

- Hedgehog
- CublasMG
- CublasXT
- Theoretical peak

Number of GPUs

Gflops

% of peak Gflops

Hedgehog—A. Bardakoff & T. Blattner
Users
Processing Hardware:
- 2x - Xeon Gold 5120 “Skylake” 14-core CPUs
- 2x - NVIDIA GTX Titan V graphics cards

100,000 x 50,000 pixel images
- Traditional computer vision
- Inference using TensorRT
  - Object Detection (Yolo V3)
  - Classification (Resnet50)

End-to-end 60-90 seconds
- Scales to number of GPUs
Comprehensive Nuclear-Test-Ban Treaty Preparatory Commission

- Processing Hardware:
  - DGX-1 server (8xV100s)

- Monitors the nuclear test ban treaty
  - 300+ stations with 1000+ sensors globally

- 2.268 billion cross correlations per second
  - 8 GPUs
  - Scales with number of GPUs
Which library allows us to manage a node with a lot of threads and one or multiple GPU, with an explicit representation of an algorithm (that exists during execution), and a high-level abstractions (without loss of potential performance)?

- **Hedgehog**
  - Based on an explicit **Data Flow Graph** using **Data Pipelining**
  - With a costless feedback that allows refinement

- **HMBLib**
  - **Concept of streaming data shows promise**
    - Relevant for GPU and CPU computation
    - Potential Applications: Large image processing, Galaxy and space mapping

- **Available**
  - **Hedgehog**: [https://github.com/usnistgov/hedgehog](https://github.com/usnistgov/hedgehog)
Future

- Experiments with extending Hedgehog to operate beyond a single node

- General purpose libraries based around Hedgehog
  - Streaming full-slide microscopy analysis

- Compile-time static graph analyses
  - Check race conditions
  - Deadlock

- Principled dataflow-based “code generation”
  - Automated rule generation
Thank you

Any questions?