Hedgehog: Understandable Scheduler-Free Heterogeneous Asynchronous Multithreaded Data-Flow Graphs

Alexandre Bardakoff

Bruno Bachelet – Timothy Blattner – Walid Keyrouz – Gerson Kroiz – Loïc Yon

National Institute of Standards and Technology
U.S. Department of Commerce

Université Clermont Auvergne

LIMOS

INFORMATION TECHNOLOGY LABORATORY

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Context: High-end heterogeneous node

- High degree of hardware parallelism
  - High core count CPU, 2×64 cores (+ hyperthreading)
  - Multiple accelerators and GPUs, 4 to 8 per node
  - Hardware is widely accessible
- To obtain performance with software:
  - Compose optimized compute kernels and efficient data transfers
  - Express locality of data
  - Overlap data motion and computation
- Given that high-end hardware is widely available, software should:
  - Be approachable by non-HPC experts
  - Have an understandable program and execution model

Problem

How to develop an **understandable parallel** program/algorithm on a **heterogeneous** node?

MODEL

- Explicit
- Understandable

LIBRARY

- High level
  - Expressive
  - Simple
- Targets various hardware platforms
- Feedback mechanism
- Experiment for performance

RESULTS

- Reasonable amount of effort
- Utilizes hardware
  - Keeps hardware busy
- Utilizes existing libraries
- Portable designs for performance

Outline

- Model
- Hedgehog
- Theoretical example
- Experimentations

Model

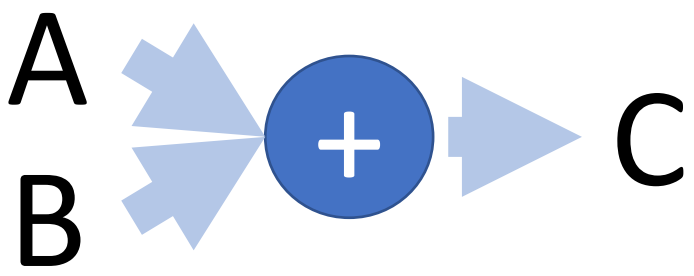
Data flow graph

Data pipelining

Asynchronous Data Flow Graph

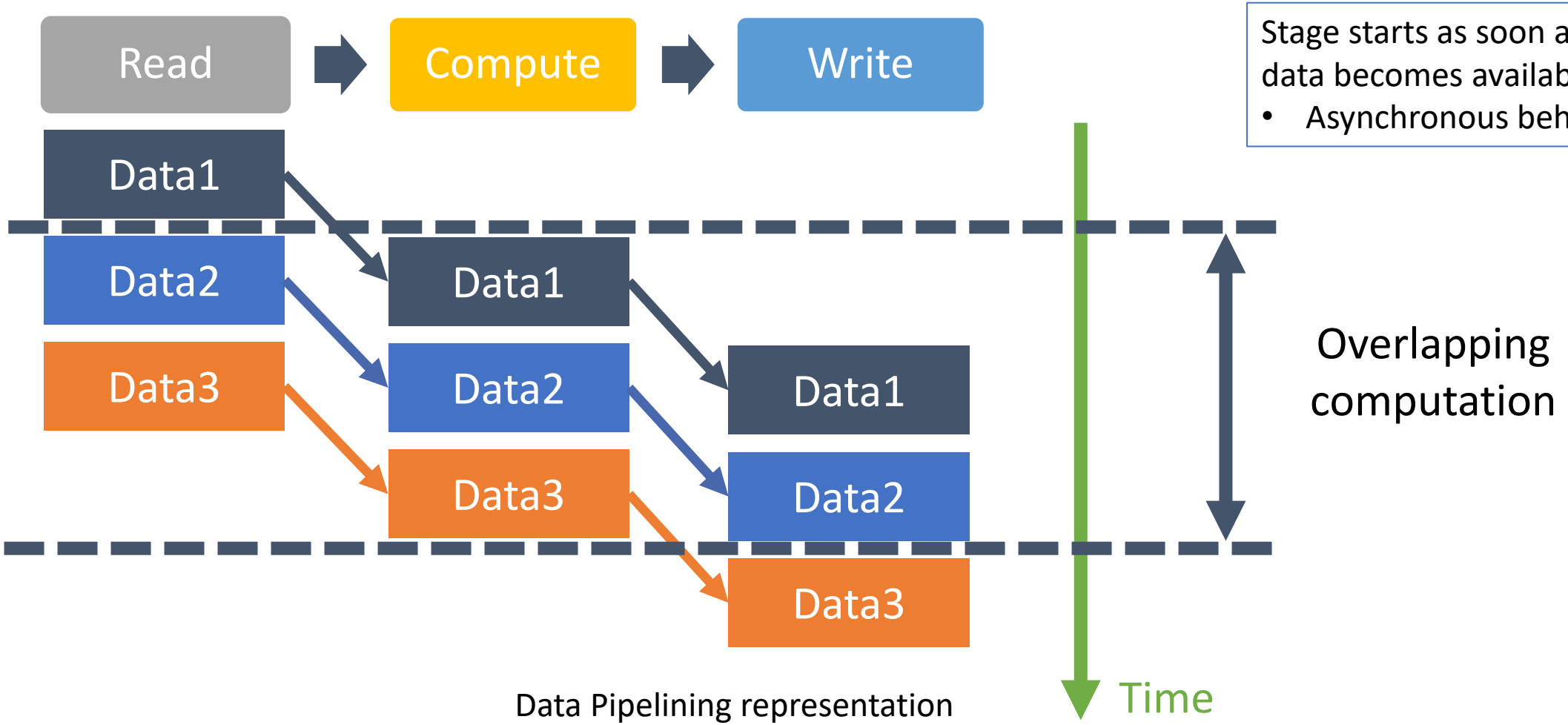
- Program model
  - Directed graph representation
  - 1 entry and 1 exit point (source and sink)
- Components
  - Nodes: computations or state management
  - Edges: directed information flow

Addition algorithm



Data Flow representation

Data Pipelining



Stage starts as soon as data becomes available

- Asynchronous behavior

Data Pipelining representation

Hybrid Task Graph Scheduler - HTGS

- **First implementation of model**
- **Coarse-grained p**arallelism
  - **Pipelined** multi-threaded
  - **Multi-CPU** and m**ulti-GPU**
- **C++ 11** headers-only library
  - **Visual debugging f**eature
  - **Rich** API

- The Hybrid Task Graph Scheduler API
  - https://github.com/usnistgov/HTGS
- A Hybrid Task Graph Scheduler for High Performance Image Processing Workflows, Blattner T. et al., J. Sign. Process. Syst. (2017) 89: 457
  - DOI: 10.1007/s11265-017-1262-6

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Hedgehog

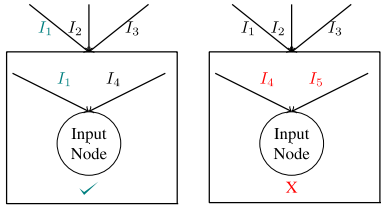
Overview

Methodology

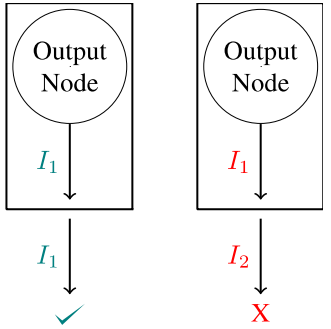
API

Overview

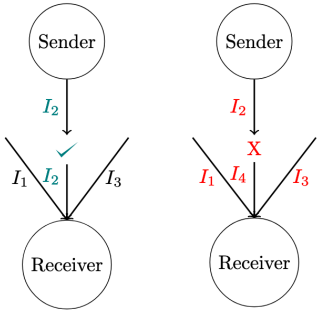
- C++ 17, headers-only library
  - General purpose
  - Open source and available
- Hedgehog design
  - Dataflow graph representation
  - Data pipelining to obtain performance & keep hardware busy
  - Coarse-grained parallelism
  - **No scheduler**
    - Operates based on the presence of data
  - Separation of concerns:
    - Tasks; State; Memory Management
- Metaprogramming for type safety



Input Check

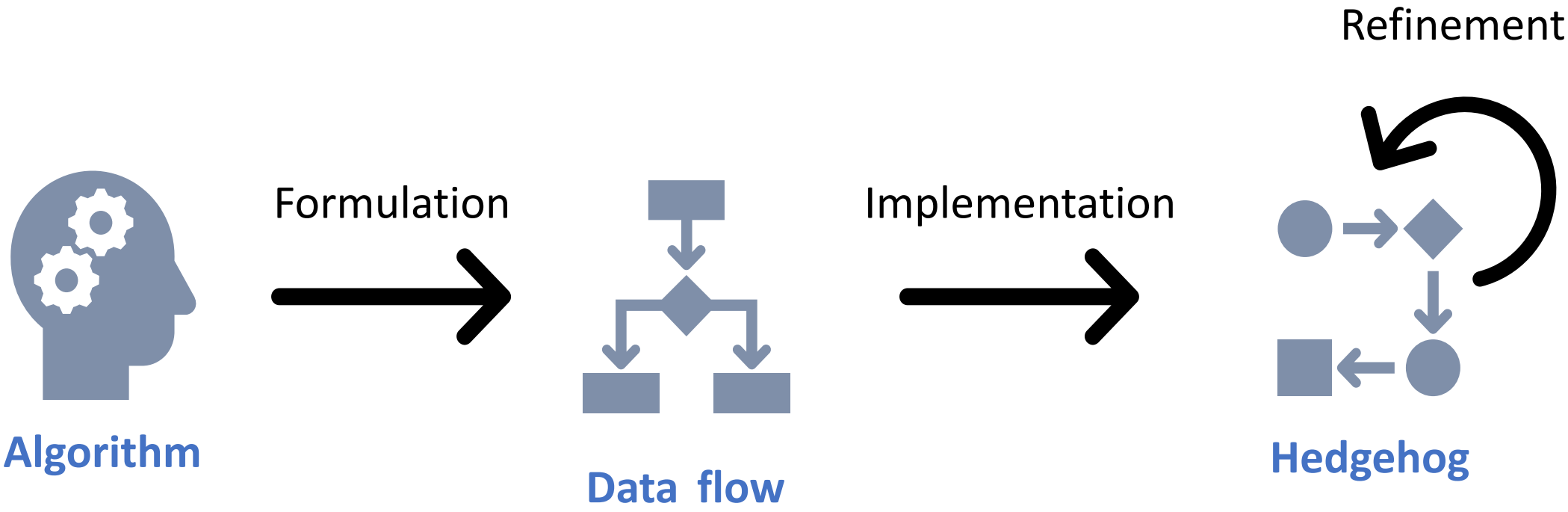


Output Check



Compatibility Check

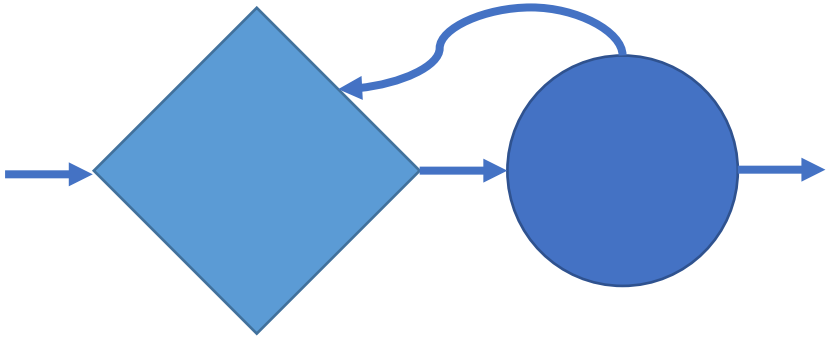
Methodology



Methodology used in Hedgehog

API - Nodes

- **Tasks**
  - Step of an algorithm / **Computation kernels**
  - **Specialized task** for (NVIDIA) GPU computations
  - **Multithreaded**
- State manager (single-threaded)
  - **Local** computation's **state** management
  - State can be shared between different managers in the graph
- Multiple Inputs - Single Output
- *canTerminate*, virtual method, to break cycles



Example of connected nodes
Diamond: State Manager
Circle: Computational Task
Edges: Flow of data

API - Memory Manager

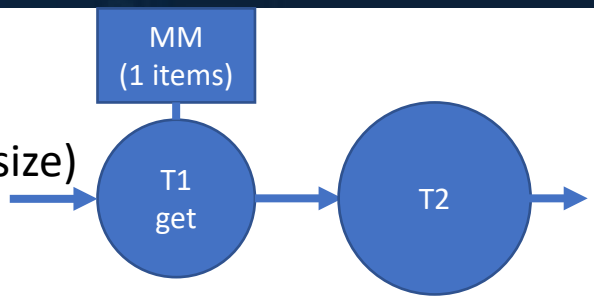
- Throttles memory usage
- Links to a task or state
- Pool of available pieces of data

- Static
  - Creates *n* objects calling a specific constructor
  - Ensures constructor signature

- Dynamic
  - Creates *n* objects calling default constructor

- Mechanism to recycle memory / objects

Memory manager usage
Circle: Computational Task
Rectangle: Memory manager (pool size)
Square: Managed data
Edges: Flow of data



Time

API - Memory Manager

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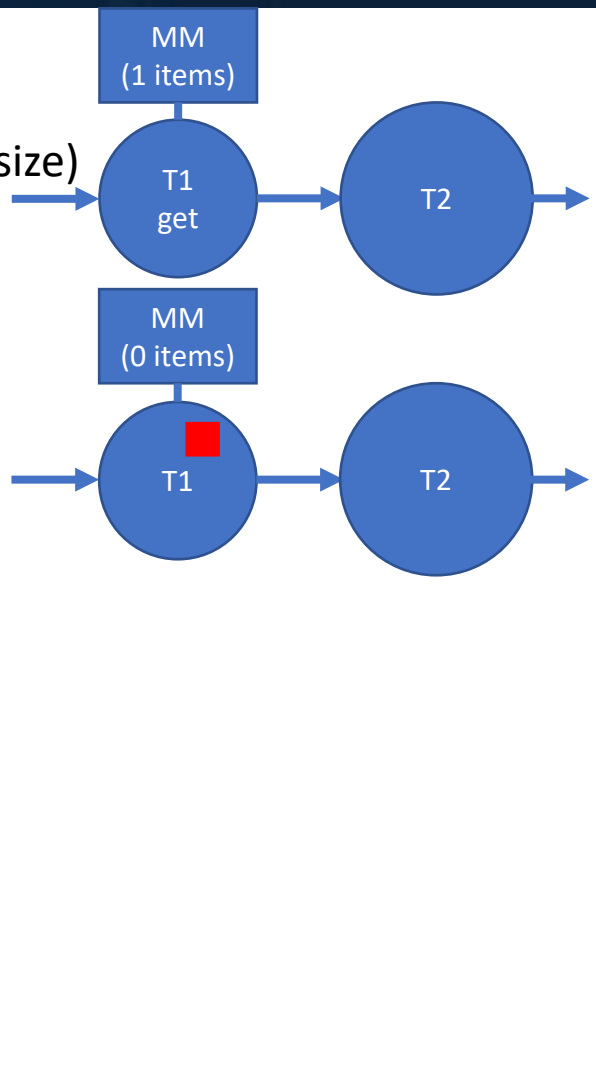

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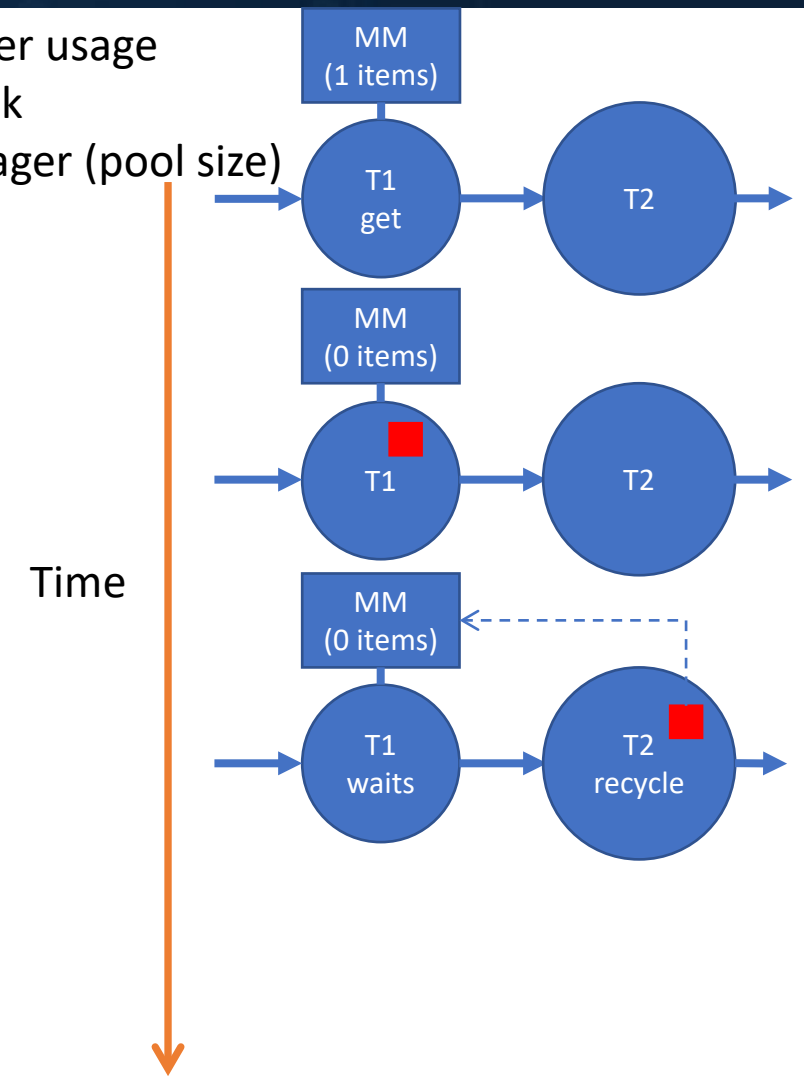

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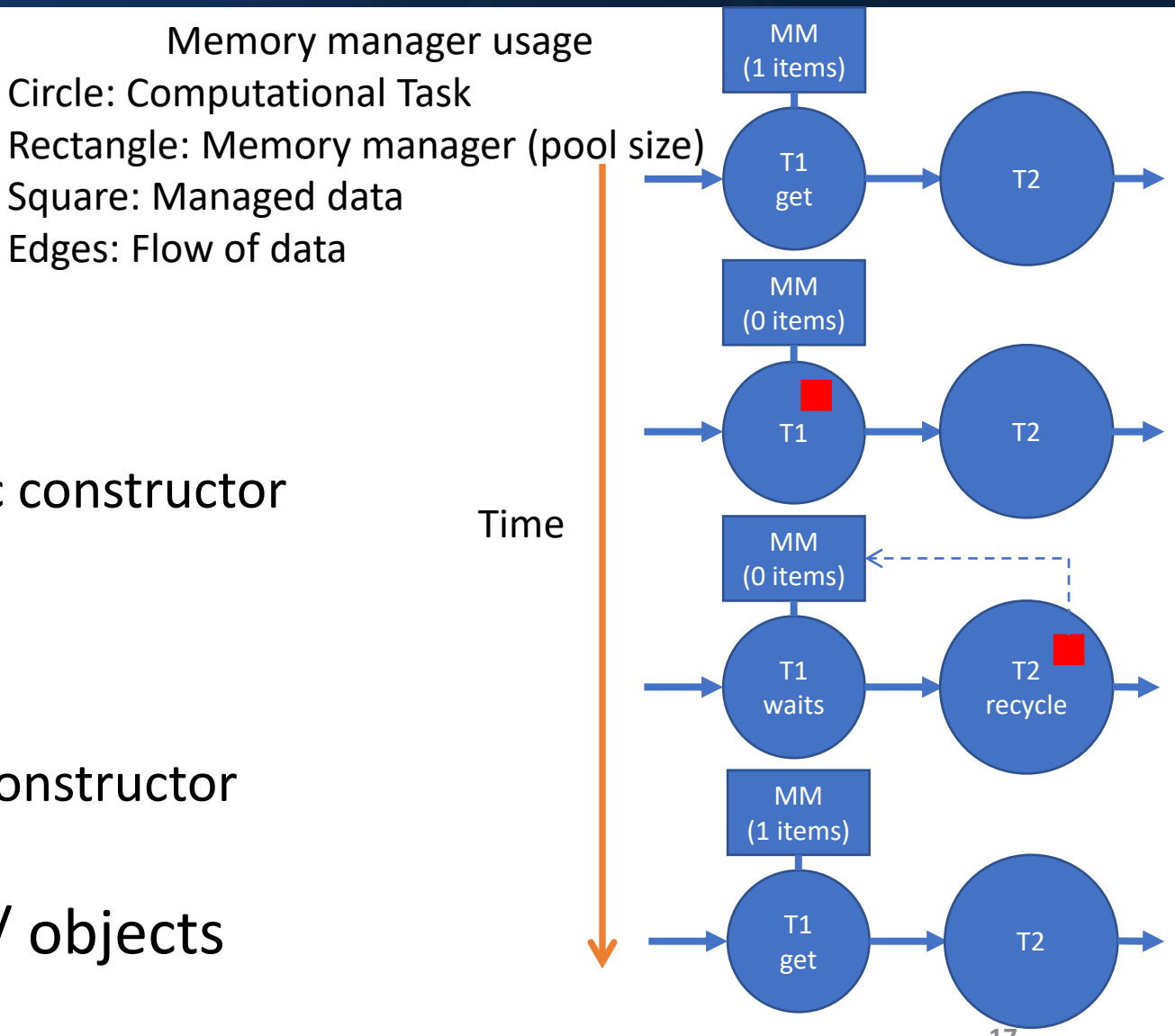
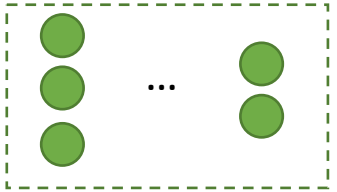


API - Graph

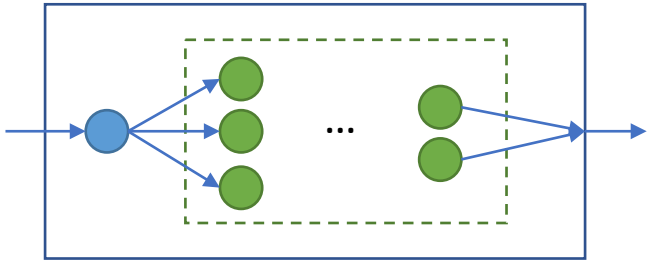
- Graph
  - Algorithm representation
  - Group nodes (tasks, state manager, memory manager)
  - Can be part of another graph
    - Share or compose algorithms
  - Binds a graph to a device
  - Only object used by an end-user

- Execution Pipeline
  - Duplicates graph
    - Data decomposition rules
    - Associates each graph copy to a specific device

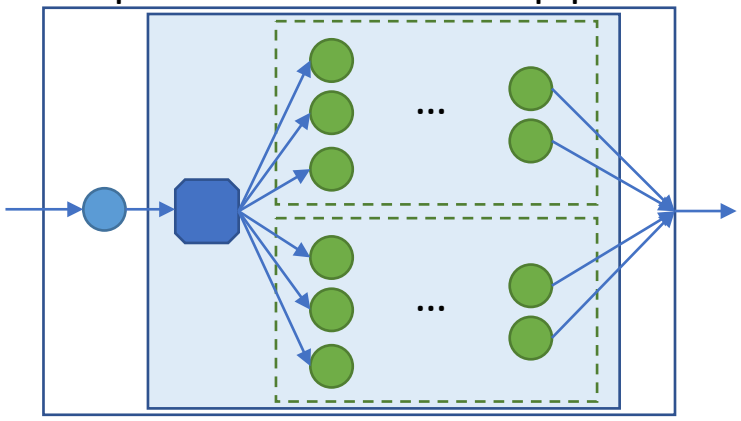
GPU Graph



Graph with an inner graph as output node

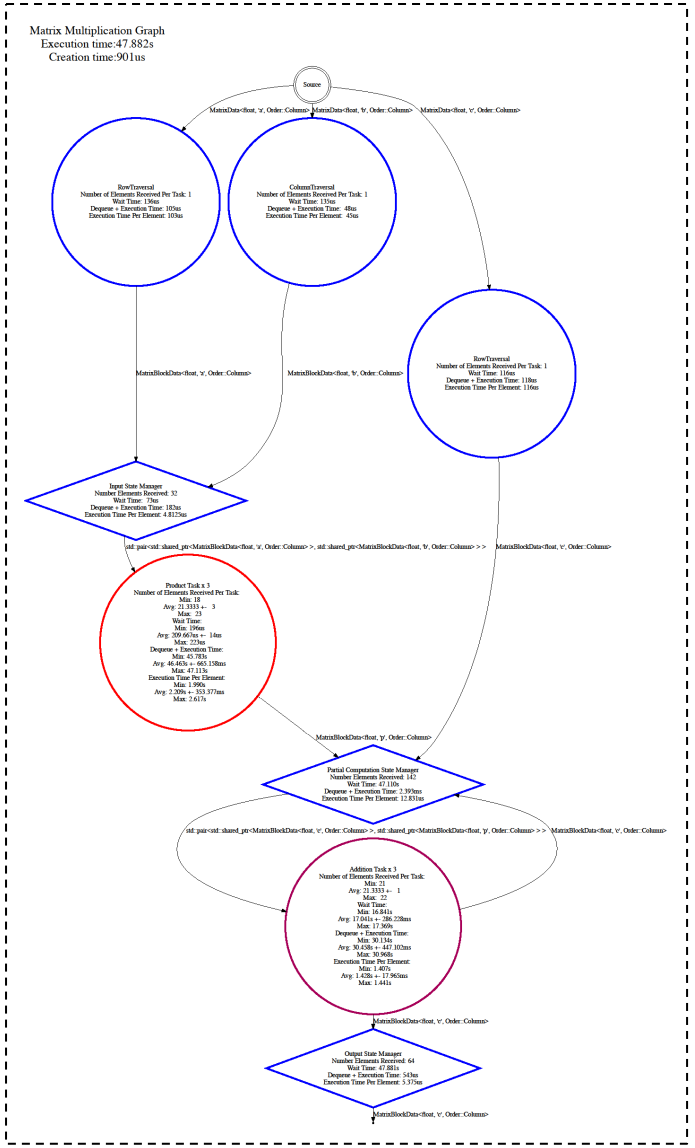


Graph with an execution pipeline as output node



Explicit representation

- Graphical representation
  - Contains profiling
  - 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)



Dot representation

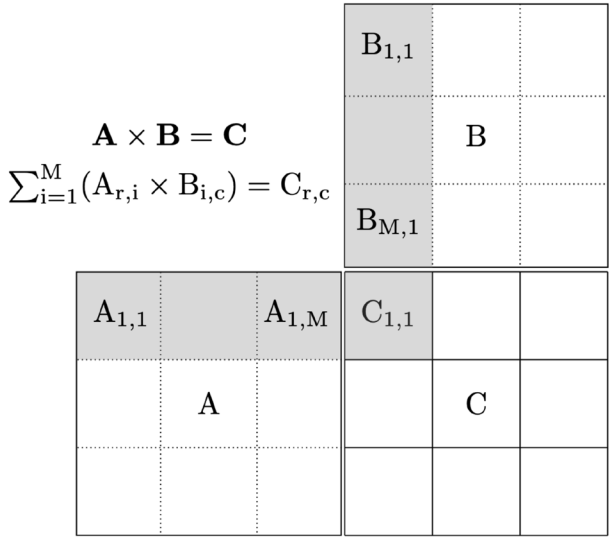
Theoretical example

CPU Matrix Multiplication

CPU Matrix Multiplication

- Matrix Multiplication $C = A \times B + C$
  - Parallel approach:
    - Based on block decomposition → **Input Blocks**
    - Block based partial matrix multiplication (multithreaded) → **Partial Block Result**
    - Aggregation of Partial Block Result (multithreaded) → **Partial Block Result or Final Block Result**
    - Filters Final Block Result → **Final Block Result**

Matrix multiplication decomposition



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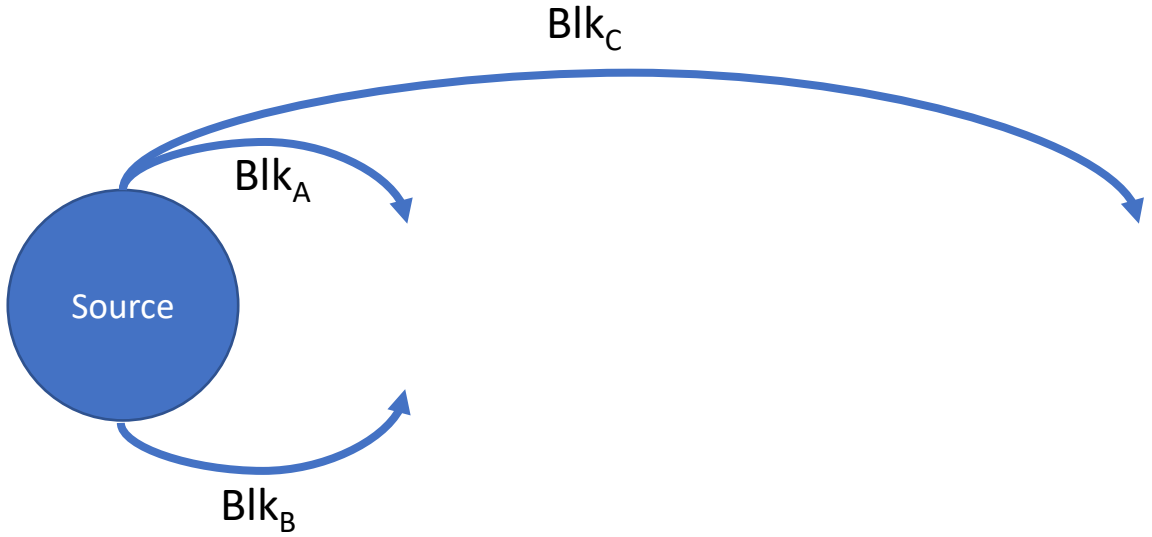

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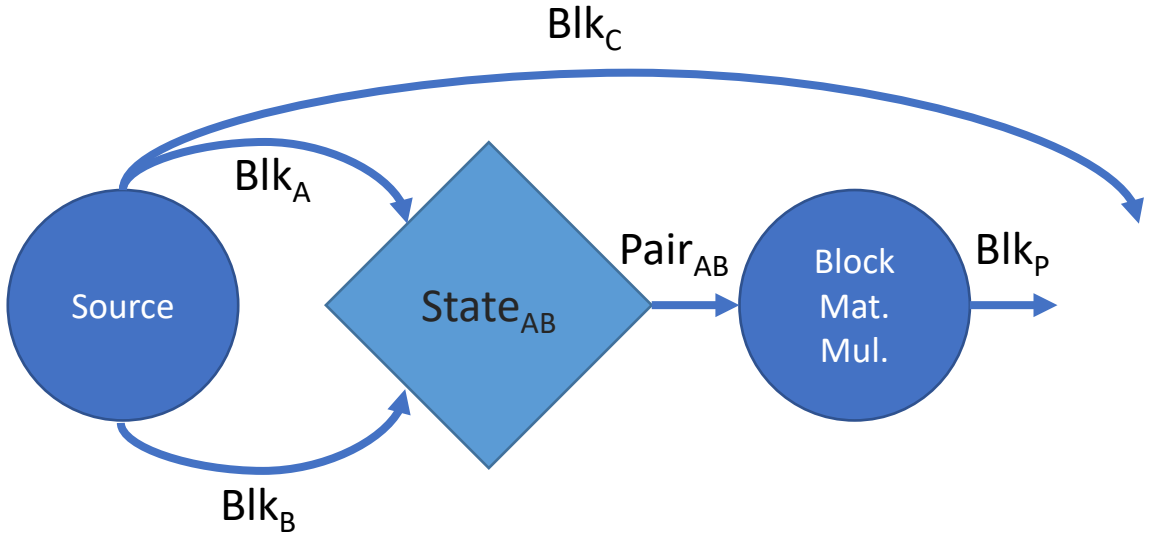

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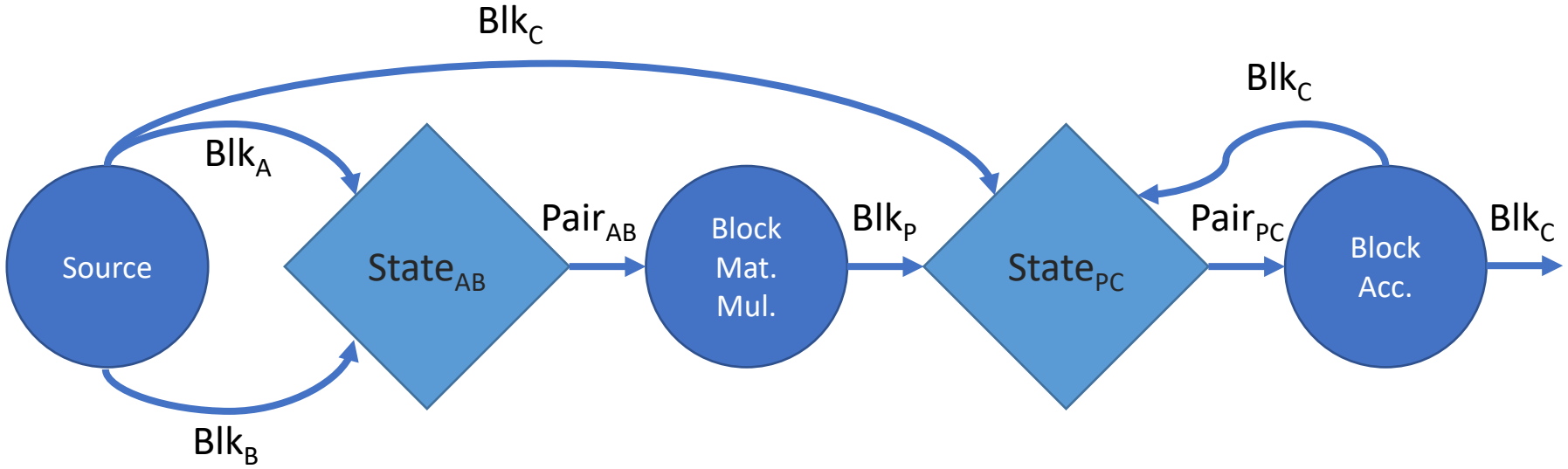

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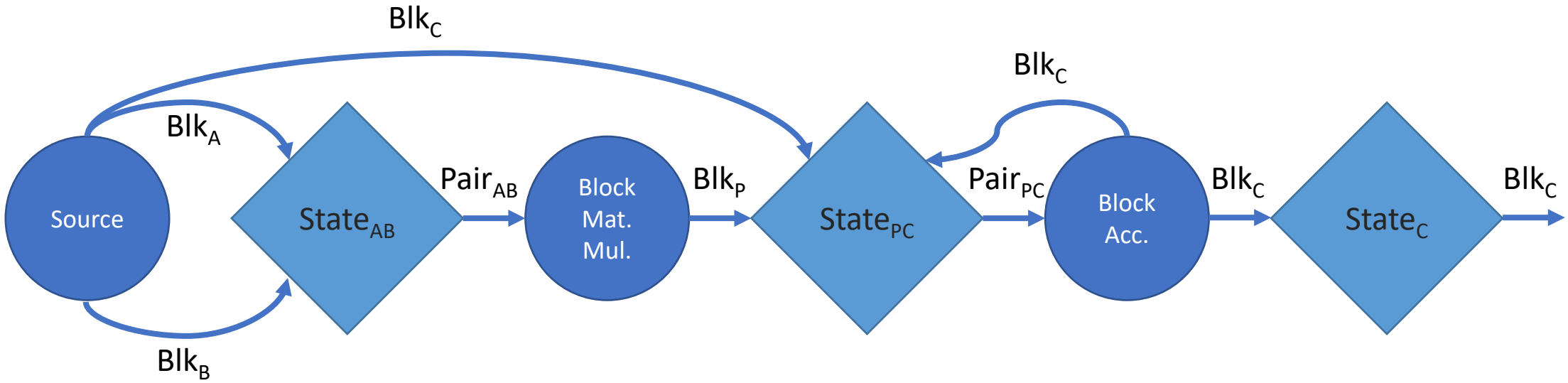


Matrix multiplication decomposition

Experiments

Latency

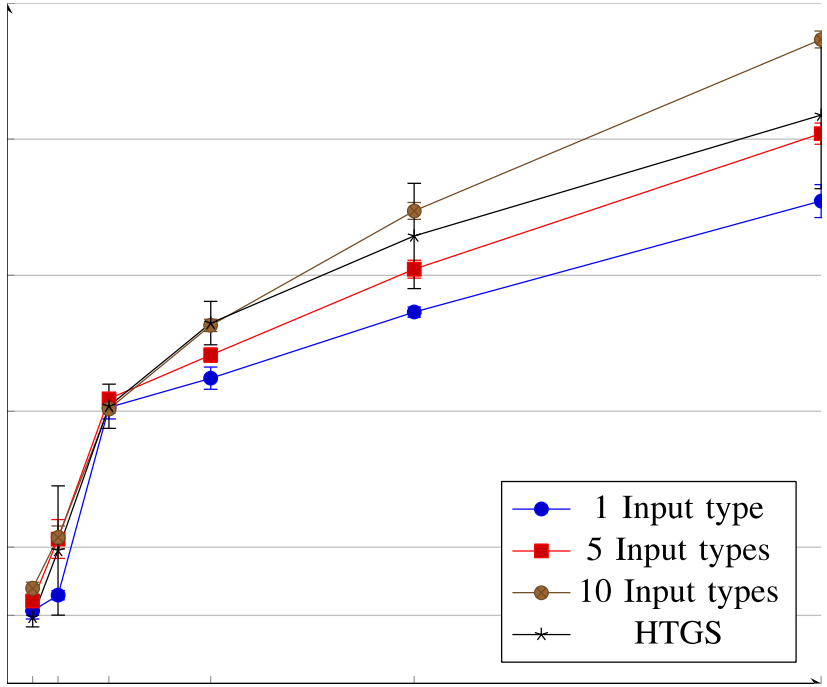
Feedback Profiling

CPU only LU with partial pivoting

Multi-GPU Matrix Multiplication

Latency

- Latency
  - Data transfer between nodes/tasks
- Parameters
  - Number of threads per task
  - Number of input types
    - HTGS can only have 1 input type
- Pipelining hides latency costs
- Hedgehog performance
  - Coarse-grained parallelism
    - Not too big or too small

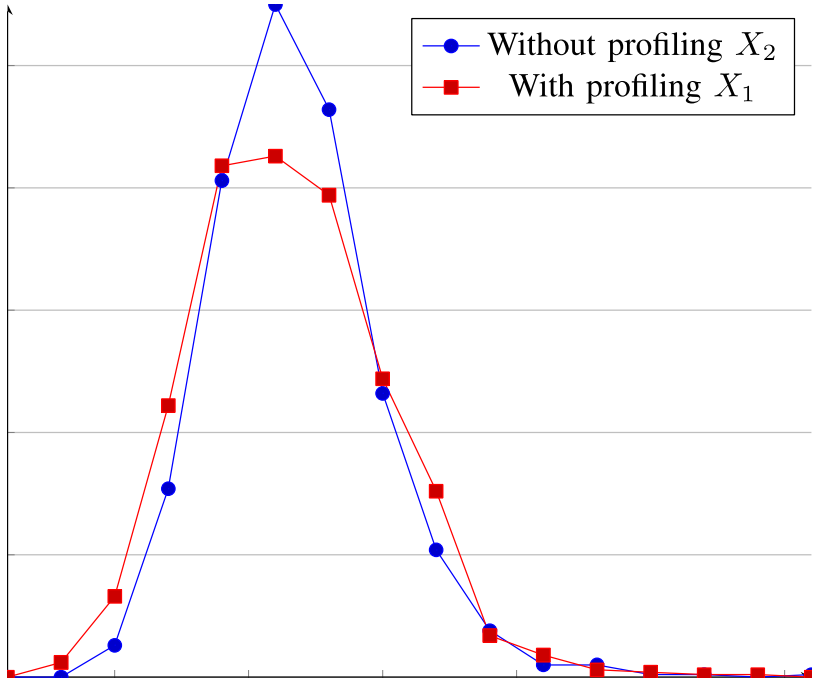


Latency analysis for varying number of threads per task

Profiling cost

- Tutorial 1 (Hadamard product w/ 1 task)
  - 1000 runs
    - with profiling (X_1)
    - without profiling (X_2)
  - $\overline{X_1}$ and $\overline{X_2}$ follow a normal distribution
- H_0: $\mu_1 = \mu_2$
- We pose: $X = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_1^2}{N} - \frac{s_2^2}{N}}}$

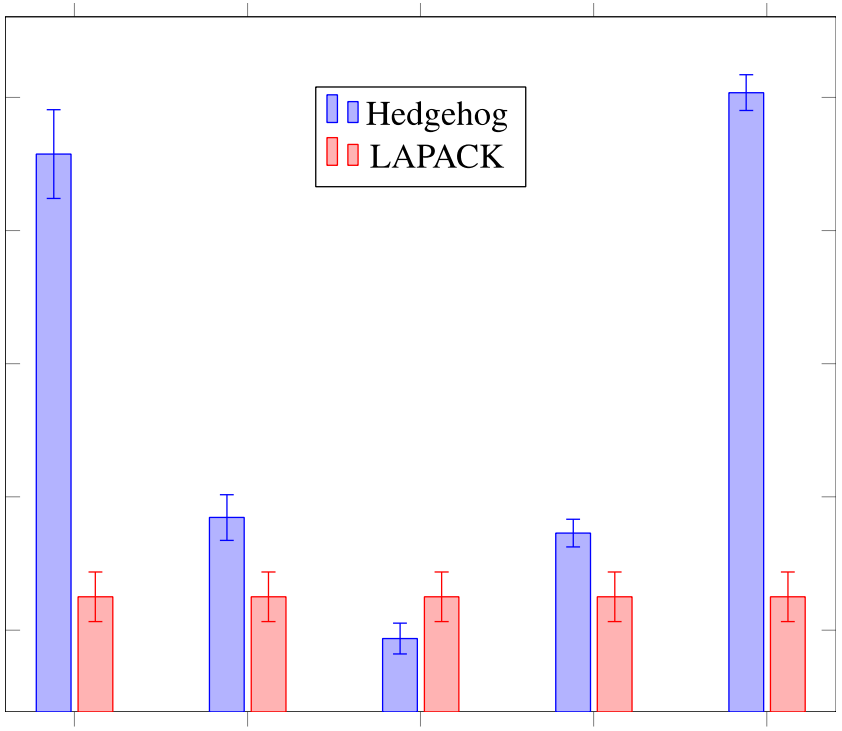
  (standard normal distribution)
- $x = -1{,}32$, p-value $= 0.4066$
- Accept H_0 with a 95% confidence



Execution time distribution for 1000 experiments on $16k \times 16k$ matrices and $2k \times 2k$ blocks with and without profiling

LU with partial pivoting (CPU)

- Methodology allows developers to
  - Reason about complex dependencies
  - Instrument code
- Comparable overall performance to the baseline (LAPACK)
  - When selecting optimal block size
- Get partial fully computed results $40\times$ times faster than entire matrix

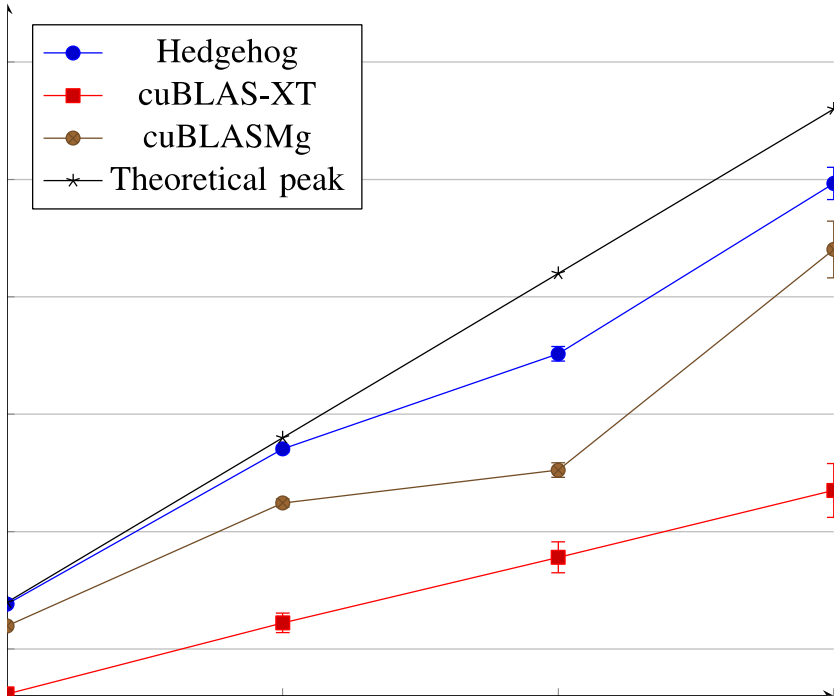


LU with partial pivoting performance for a matrix of $32k \times 32k$ elements

Hardware: Two Xeon E5-2680 v4 @ 2.40 GHz (28 physical cores)
512 GiB DDR4 RAM

Multi-GPU Matrix Multiplication

- Iterative development
  1. Start with CPU only
  2. Augment to GPU
  3. Augment to Multiple GPUs
- Heterogeneous computation
  - Block matrix multiplication on GPUs
  - Block matrix accumulation on CPU
- Task Reuse
  - Tasks that decompose the matrices into blocks
  - State to manage the computation
  - GPU computation and I/O graph



Matrix multiplication on a matrix of $64k \times 64k$ elements decomposed in $8k \times 8k$ block elements

Hardware: Two Xeon Silver 4216 @ 2.10 GHz (32 physical cores)
768 GiB DDR4 RAM, 4x Tesla V100 PCIe with 32 GB HBM2

Conclusion

How to develop an **understandable parallel** program/algorithm on **heterogeneous** nodes?

- Explicit data-flow graph representation
  - Design = Execution
- Costless graphical feedback
  - Understand the computation
  - Detect bottlenecks
    - Gain insight
- API based on separation of concerns
  - Distinct components:
    - Compute vs. state manager
  - Graph composability / reuse
  - Target heterogeneous nodes / Memory locality
- Results
  - Partial result streaming
  - Portable design for performance

Future work

- Extend Hedgehog to clusters
  - External libraries/tools for cluster communication
  - One Hedgehog graph per cluster node

- Static Analysis of the graph
  - Run at compile time algorithm to test further the graph
  - Detect possible race conditions, cycles, or deadlocks

Thank you

Contact us for more information

- Alexandre Bardakoff (alexandre.bardakoff@nist.gov)
- Timothy Blattner (timothy.blattner@nist.gov)

Get the code and tutorials

- Hedgehog:
  - https://github.com/usnistgov/hedgehog
- Tutorials:
  - https://pages.nist.gov/hedgehog-Tutorials
  - https://github.com/usnistgov/hedgehog-Tutorials