Graph abstraction for efficient scheduling of asynchronous workloads on GPU CExA Coffee Time

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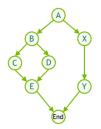




Context

Many computational physics simulations need to efficiently schedule **asynchronous** workloads:

- ► FEM assembly
- ▶ linear algebra
- your routines 9



Reproduced from [Gra19].

Asynchronous execution models

- 1. Execution space instances
- 2. Kokkos::Graph

Abstraction of the day "

Kokkos::Graph

Outline

- 1. Get to know Kokkos::Graph
 - Need for a graph abstraction
 - Under the hood
- 2. Towards broad adoption of Kokkos::Graph
 - Obstacles and constraints
 - Proposal
 - Future extensions
- 3. Application

Why bother with Kokkos::Graph?

Gloomy points 🕏

- 1. Ad hoc scheduling of many asynchronous workloads is an additional burden to your code base as
 - it will kill readability,
 - and cause headaches for portability.
- 2. Handmade solutions might not fully exploit the available execution resources.

A graph abstraction comes to your rescue! •

- 1. Describe your computational graph to Kokkos::Graph:
 - Semantics are clear.
 - You get portability.
- 2. Exposing the **whole computational graph** to the compiler/driver ahead of execution enables **as many optimisations as possible**.

Example: vanilla Kokkos versus Kokkos::Graph

Two AXPBY's followed by a dot product



```
// Async. with execution space instances.
const Kokkos::Cuda exec_1 {}, exec_2 {};
using policy_t = Kokkos::RangePolicy<Kokkos::Cuda>;
Kokkos::parallel_for(
                       policy_t(exec_1, 0, N), Axpby{x, y, alpha, beta});
                       policy_t(exec_2, 0, N), Axpby{z, y, alpha, gamma});
Kokkos::parallel_for(
exec_2.fence();
Kokkos::parallel_reduce(policy_t(exec_1, 0, N), Dotp{x, z}, dotp);
// Async. with Kokkos::Graph.
const Kokkos::Cuda exec {};
auto graph = Kokkos::Experimental::create_graph(exec, [&](const auto& root) {
   auto xpy = root.then_parallel_for(N, Axpby{x, y, alpha, beta});
   auto zpy = root.then_parallel_for(N, Axpby{z, y, alpha, gamma});
   Kokkos::Experimental::when_all(xpy, zpy).then_parallel_reduce(
       N, Dotp\{x, z\}, dotp
graph.submit(exec);
```

Inspired by [Lif].

What is Kokkos::Graph exactly?

How to think about it?

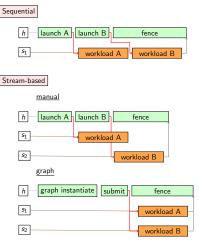
From a semantic standpoint, Kokkos::Graph must be used in a three-phase way (simplified):

- definition describe your DAG of workloads (topology)
- instantiation check DAG for flaws and prepare the executable graph
- <u>submission</u> launch the executable graph

Implementation details

- Portable wrapper around:
 - cudaGraph_t
 - ▶ hipGraph_t
 - sycl::ext::oneapi::experimental::command_graph
- Default implementation for "unsupported" backends.

Under the hood: graph overhead and amortization



Reproduced from [TA24].

Cuda API calls aren't for free:

- launching a kernel on a stream
- building and submitting a graph

When to use a graph?

- workloads are organised as a DAG
- the performance bottleneck is CPU scheduling overhead rather than GPU execution

Amortize graph definition and instantiation - possibly across multiple submissions - until you beat the *manual stream-based* implementation.

Past and current research focus

Some recent work (emphasis mine):

- core(graph): **promote instantiate** to public API (Aug. 22 24)
- core(graph): allow submission onto an arbitrary exec space instance (Aug. 28 - 24)
- raph(fix): defaulted graph submit control flow (Sep. 6 24)
- core(graph): allow create_graph without closure (Sep. 10 24)
- ♣ graph: allow access to native graph object (Oct. 7 24)
- graph(diagnostic): enable compile-time diagnostic of illegal reduction target (Oct. 18 - 24)



The following content is new.

Future extensions / opportunities worth a try

Missing features for broader adoption 🤳

Integrate more backend features in Kokkos::Graph³:

- ✓ add a node depending on a runtime condition (MPI partitioning)
- graph capture (cuSPARSE, external libraries not using Kokkos)
- enable/disable a node between 2 successive launches
- onditional if/while (routine branching, solvers like CG)
- memory node (parallel reduction target)
- update kernel parameters (range policy bounds)
- node priority (longer kernels scheduled first)
- O host node (MPI exchange?)

³Note that not all backends support all the above (except Cuda).

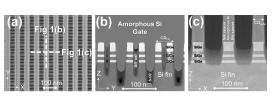
Computational metrology in semi-conductor assembly lines

Optical metrology

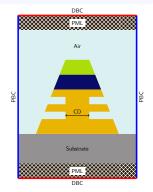
Use light to gather data about the physical properties of objects.

Focus

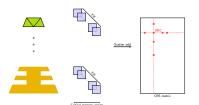
Swift FEM computed samples are needed to train a probabilistic inverse problem method.



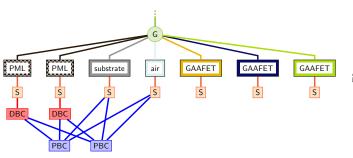
GAAFET (forksheet) [BNG⁺24]

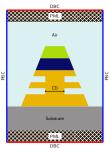


Organizing (in)dependent computations as a DAG graph



- Dependencies between workloads are clearly expressed.
- Once predecessor workloads are done, child nodes can run concurrently, once resources are available.





References I

- Janusz Bogdanowicz, Thomas Nuytten, Andrzej Gawlik, Stefanie Sergeant, Yusuke Oniki, Pallavi Puttarame Gowda, Hans Mertens, and Anne-Laure Charley, *Taming the Distribution of Light in Gate-All-Around Semiconductor Devices*, Nano Letters **24** (2024), no. 4, 1191–1196.
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References II

