The framework formerly known as Legate-Jax

Dec 4, 2024: Legion Retreat

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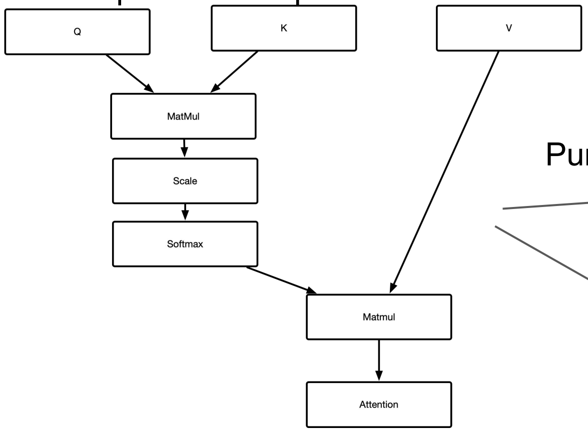
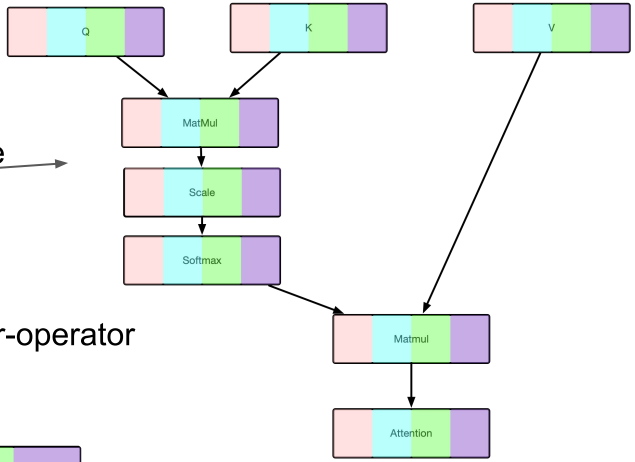
Goal of Jax work is to enable arbitrary inter- and intra-operator parallelism via auto or user-guided parallelization

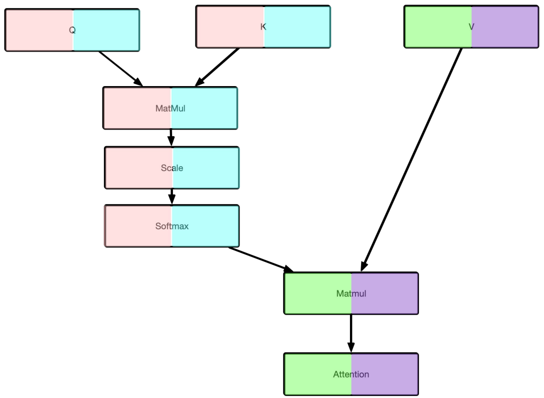
Operation Graph



Pure SPMD (intra-operator) schedule



Mixed intra- and inter-operator MPMD schedule

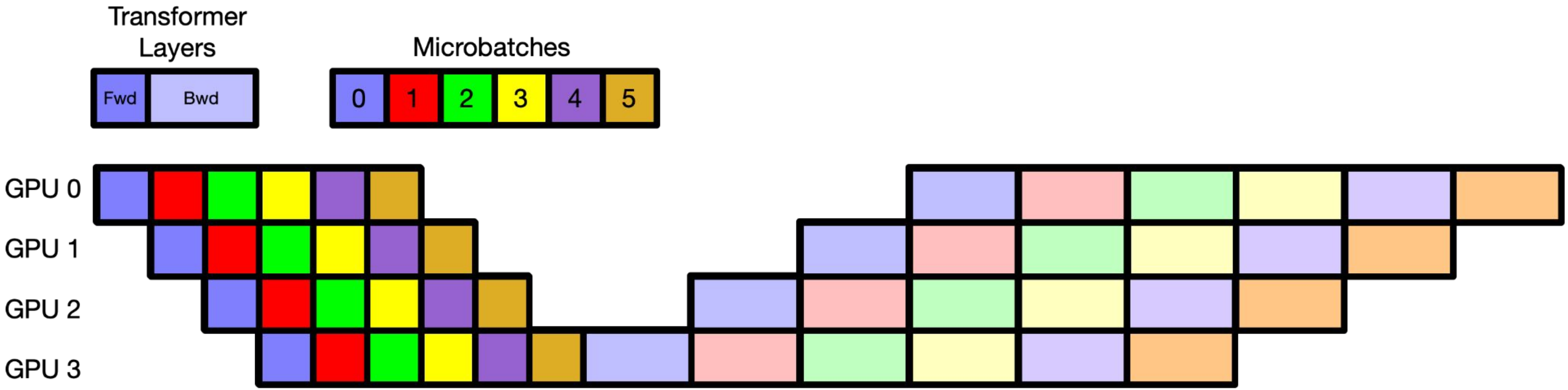


Jax/XLA only natively supports intra-operator (SPMD)

Goal: improve performance for large-scale training (256-100K GPUs) via MPMD parallelism

- Realm *execution model* improves perf
  - Keep *device* executing critical path overlapped with *host-driven* off-critical path tasks
- Legate *programming model* makes complicated patterns easier to express
  - 1F1B, load balancing irregular stages, multiple overlapping communications naturally described with a sequential semantic + mapper
- Make MPMD execution easy to express in Jax *user-level libraries*
  - Simple decorators for defining arbitrary MPMD event graphs in sequential user code

Pipeline parallelism (with exceptions) is inter-operator parallelism (MPMD)



Jax + Legate programming model share a core philosophy

Jax parallelization starts from sequential user code, finishes with asynchronous parallel execution

```
import jax.numpy as jnp

def layer(mlp, x)
  x = jnp.einsum("bh,hm->bm", x, mlp)

def model(params, batch):
  mlp0, mlp1 = params
  x, labels = batch
  x = layer(x)
  x = layer(x)
  diff = x - labels
  return (diff*diff).sum()

loss = jax.jit(model)(params, batch)
```

Sequential code defining the model (no parallelism yet)

JIT compilation of model to GPU device code

Jax parallelization starts from sequential user code, finishes with asynchronous parallel execution

```
import jax.numpy as jnp
from jax import with_sharding_constraint as shard
from jax.sharding import PartitionSpec as P

def layer(mlp, x)
  mlp = shard(mlpx, P(“model”, None))
  x = jnp.einsum(“bh,hm->bm”, x, mlp)
  return shard(x, P(“batch”, “model”))

def model(params, batch):
  mlp0, mlp1 = params
  x, labels = batch
  x = layer(x)
  x = layer(x)
  diff = x - labels
  return (diff*diff).sum()

params = init()
batch = load_batch()

loss = jax.jit(model)(params, batch)
```

Assign names to the tensor axes to use for sharding later

Jax parallelization starts from sequential user code, finishes with asynchronous parallel execution

```
import jax.numpy as jnp
from jax import with_sharding_constraint as shard
from jax.sharding import PartitionSpec as P, Mesh

def layer(mlp, x)
  mlp = shard(mlpx, P(“model”, None))
  x = jnp.einsum(“bh,hm->bm”, x, mlp)
  return shard(x, P(“batch”, “model”))

def model(params, batch):
  mlp0, mlp1 = params
  x, labels = batch
  x = layer(x)
  x = layer(x)
  diff = x - labels
  return (diff*diff).sum()

params = init()
batch = load_batch()

devices = np.array(jax.devices()).reshape(2,2)
with Mesh(devices, (‘batch’, ‘model’)):
  loss = jax.jit(model)(params, batch)
```

Define logical to physical mapping of axis names in device msh

Define device mesh as 2x2

jitted function executes with sharded data in parallel

Jax and Legate/Legion share a core philosophy

- Write sequential code
- Define partitions (shardings) on tensors
- Let the compiler/runtime system automatically infer and schedule parallelism

Jax requires a uniform, global mesh for all tensors which prevents MPMD and pipeline parallelism

```
import jax.numpy as jnp
from jax import with_sharding_constraint as shard
from jax.sharding import PartitionSpec as P, Mesh

def layer(mlp, x)
  mlp = shard(mlpx, P(“model”, None))
  x = jnp.einsum(“bh,hm->bm”, x, mlp)
  return shard(x, P(“batch”, “model”))

def model(params, batch):
  mlp0, mlp1 = params
  x, labels = batch
  x = layer(x)
  x = layer(x)
  diff = x - labels
  return (diff*diff).sum()

params = init()
batch = load_batch()

devices = np.array(jax.devices()).reshape(2,2)
with Mesh(devices, (‘batch’, ‘model’)):
  loss = jax.jit(model)(params, batch)
```

Mesh is uniform and global for all tensors!

Legate programming + execution model
brings asynchronous MPMD parallelism to Jax

Legate-Jax can define submeshes for different operations

```
import jax.numpy as jnp
from legate.jax import with_sharding_constraint as shard
from legate.jax import task, parallelize
from jax.sharding import PartitionSpec as P, Mesh

def layer(mlp, x):
  mlp = shard(mlp0, P("model", None))
  x = jnp.einsum('bh,hm->bm', x, mlp)
  return shard(x, P("batch", 'model')

def model(params, batch):
  mlp0, mlp1 = params
  x = task(layer, mesh=...)(mlp0, x)
  x = task(layer, mesh=...)(mlp1, x)
  diff = x - labels
  return (diff*diff).sum()

params = init()
batch = load_batch()

loss_fxn = parallelize(model)(params, batch)
loss = loss_fxn(params, batch)
```

Two layers can be dispatched to different submeshes

Use MPMD parallelization instead of jitting on global mesh

Legate/Legion brings flexible mappings to Jax

Phase 1

Use Jax + MLIR + XLA to create Legion tasks

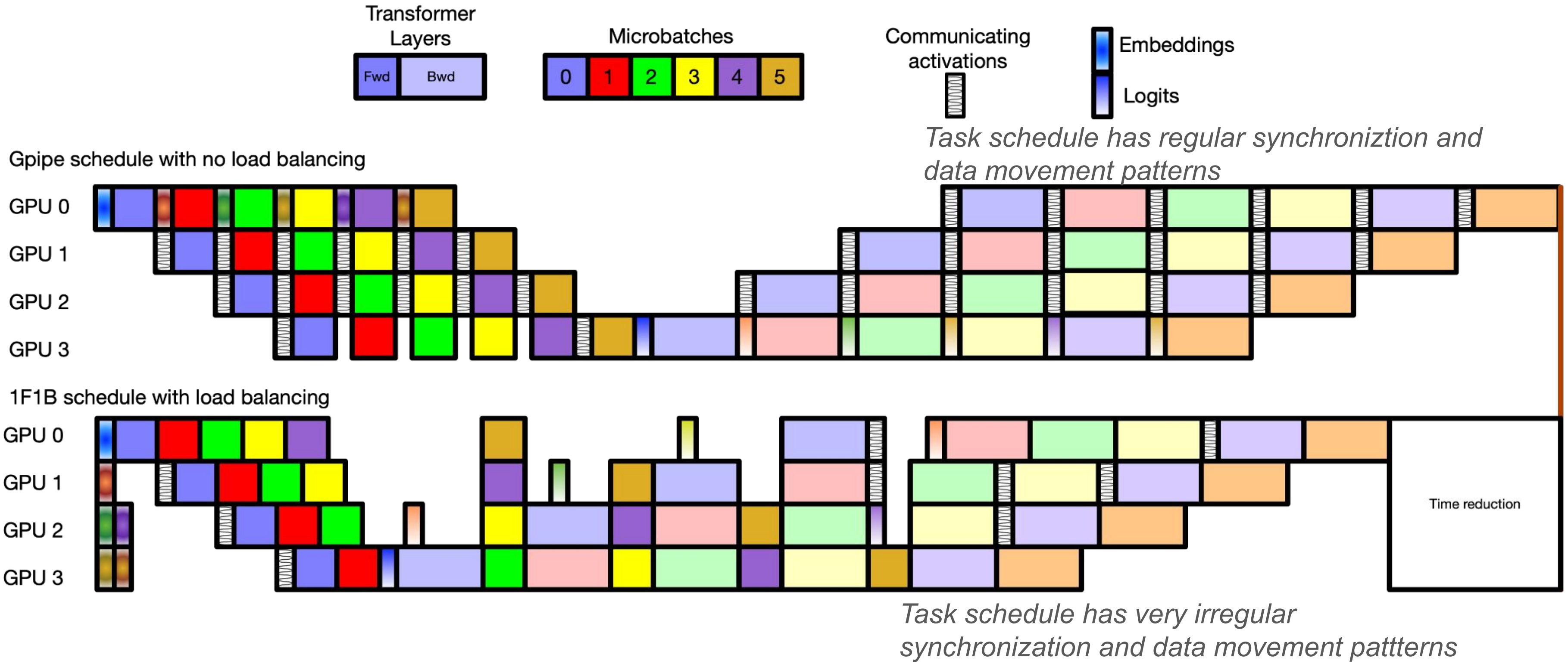
Phase 2

Legion maps pipelines stages to different submeshes, automagically generating pipeline parallelism

Phase 3

Profit

Programming model makes irregular schedules (1F1B with load balancing) easy to express with sequential semantic and mapper



Programming model expresses logical flow of application agnostic to communication, synchronization, and buffer allocation

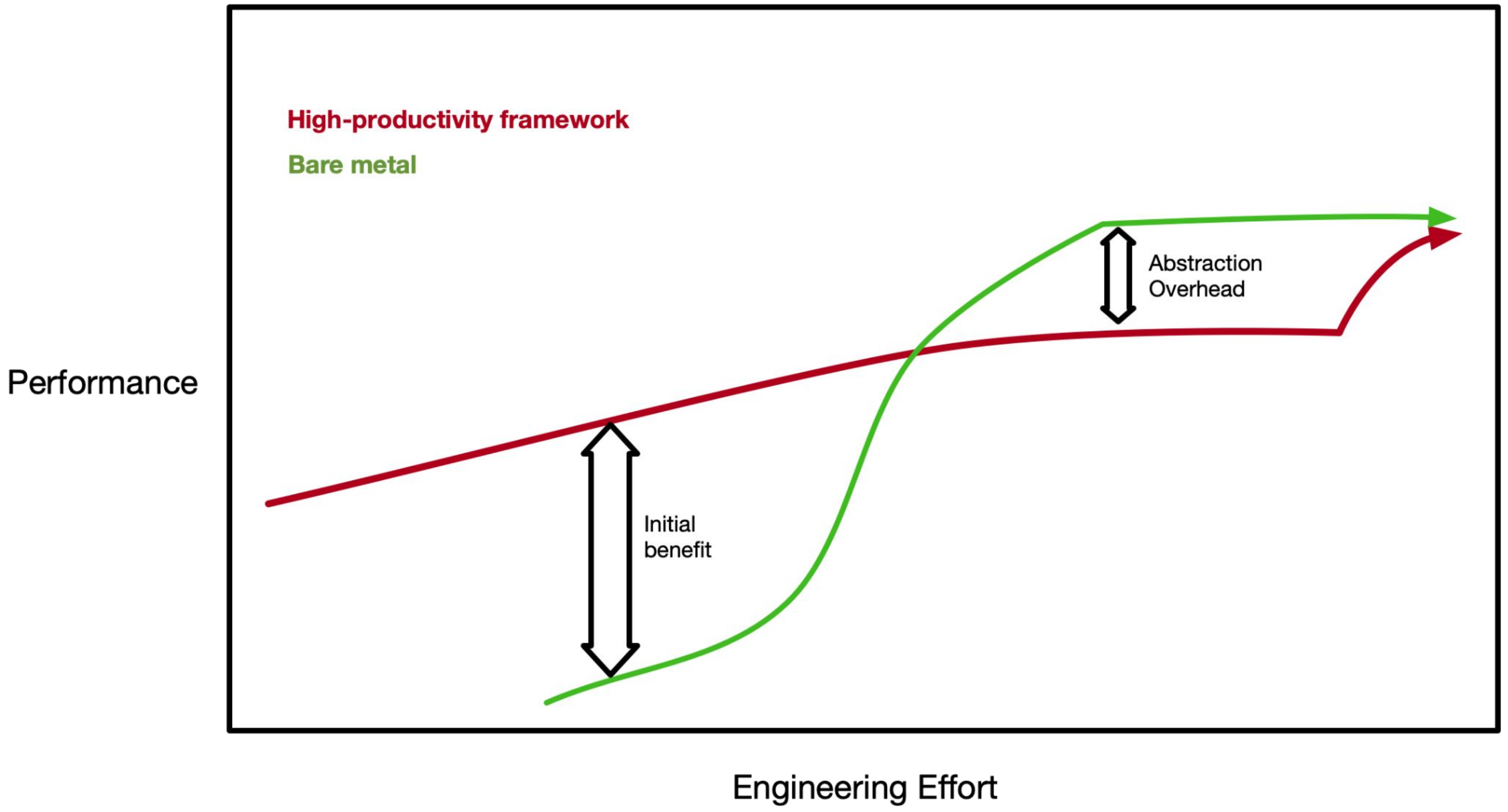
```
struct Task {
  vector<Store> inputs;
  vector<Store> outputs;
  int stage;
  int microbatch;
  bool forward;
  DeviceList mesh;
};

// Extracted from HLO pipeline passes
vector<Task> tasks = MpmdPartition(mlir_module);

// Scheduler chooses ordering and mesh assignment
vector<Task> ordered = ScheduleTasks(std::move(tasks));
```

Where things break down…

Productivity and performance are the same thing!



Different customers may have different a different calculus for cost/benefit on engineering effort

Customer	No. accelerators	Abstraction overhead	Accelerator TCO (hypothetical)	Optimization impact	Deadline
A	10K	10%	$10K	$ 10M	3 month delivery
B	1M	1%	$10K	$ 100M	None, ongoing

*These numbers are totally made up and do not corresponding to any actual customers or products, real or perceived

Jax (training LLMs) are not typical Legion workloads and expose missing features and pain points

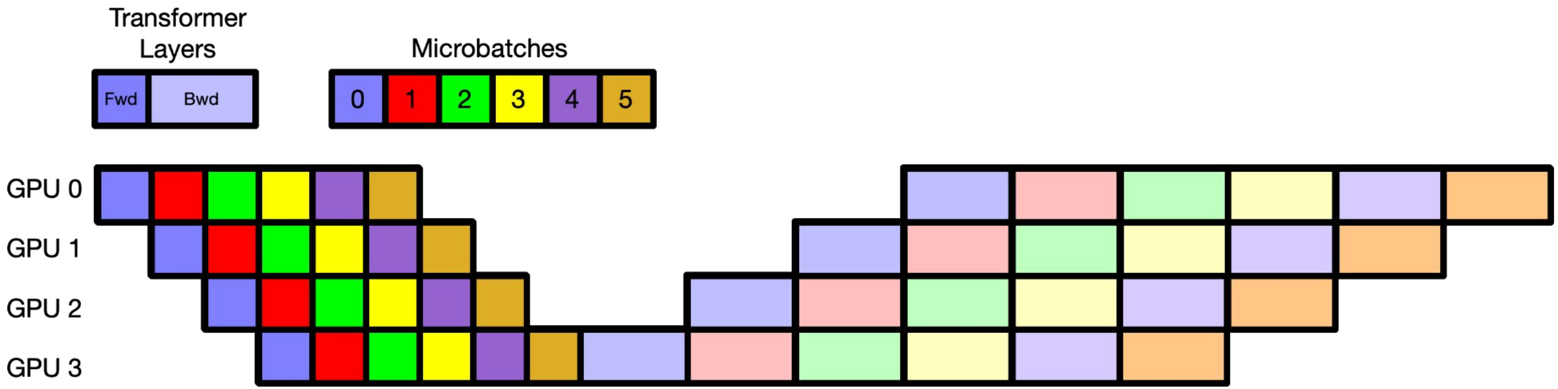
Dependency analysis and control replication overheads are problematic at 1000s of processes with hundreds of inputs/outputs

- Dozens of tensors can be inputs/outputs in LLM
  - Projection matrices, bias terms, MLP layers
  - Parameters, gradients, and optimizer state
- Dozens of scalar metrics (generated from NCCL all-reduce)
  - Future maps? Replicated writes?
- Inscrutable scaling bottlenecks due to thousands of small, control messages
  - Critical path analysis helpful, but still difficult to identify gaps in Legion prof

Jax (training LLMs) are not typical Legion workloads and expose missing features and pain points

Pipeline parallelism needs a well-defined task ordering

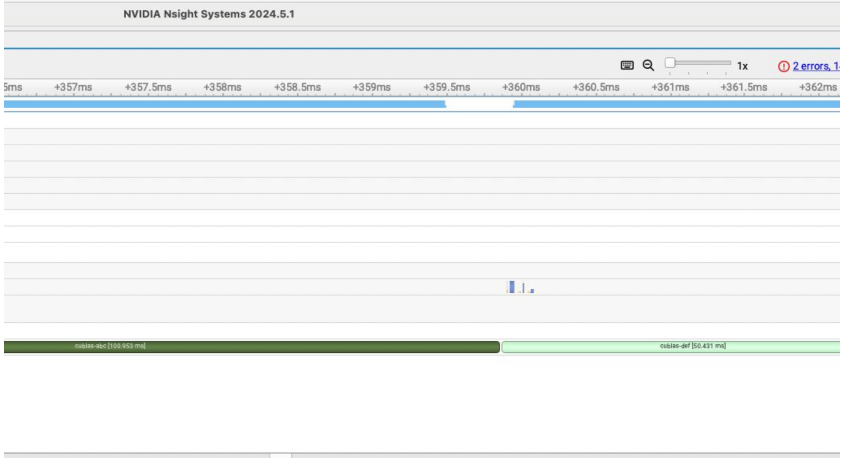
- The compiler has already statically derived an "optimal" schedule
- Dynamic reordering can delay the critical path and increase execution time
- Legate/Legion has no built-in mechanism for lightweight ordering of tasks

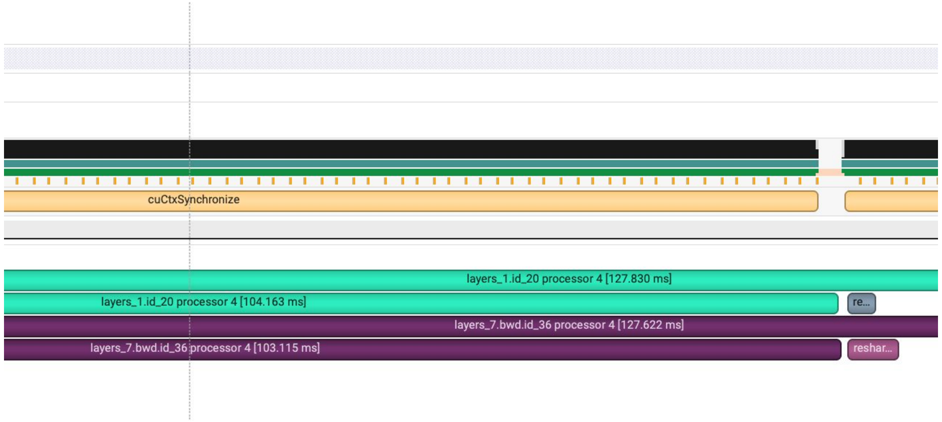


Jax (training LLMs) are not typical Legion workloads and expose missing features and pain points

Task completion semantics prevent task lookahead with pipelining

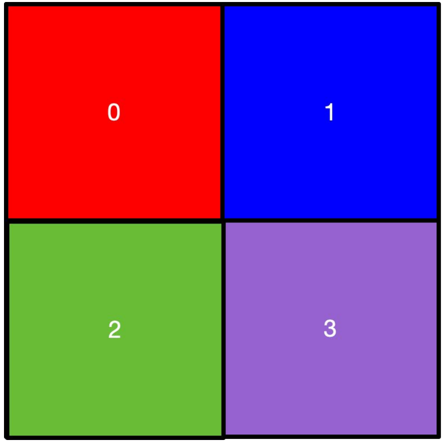
- It is a pipeline! No task parallelism to hide task startup latency.
- Tasks are not marked done until all *data effects on the GPU* are visible
- Bubble in GPU utilization from end of task to start of next GPU kernel



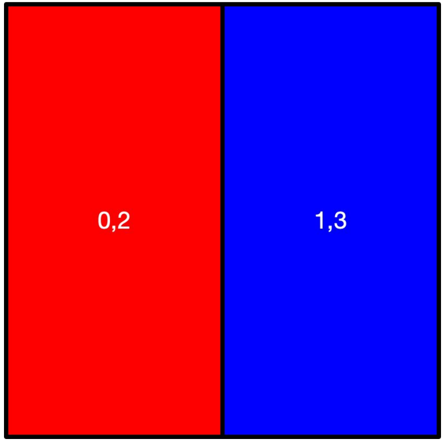


Jax (training LLMs) are not typical Legion workloads and expose missing features and pain points

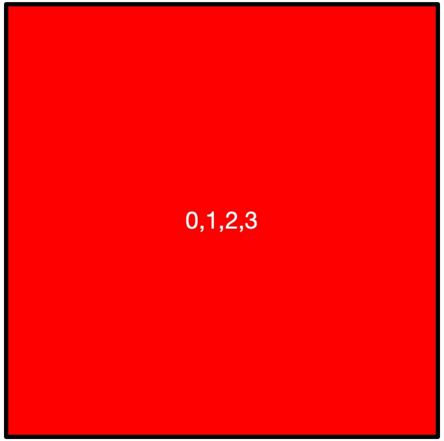
- Communication-avoiding sharding (i.e. data parallelism) writes replicated output
  - Not technically valid in a sequential semantic, but Mike heroically added support
  - Partially replicated/partially sharded data patterns not easily expressed in Legate
  - If done naively, replicated scalar outputs produce *huge* control overhead



Fully-sharded
(disjoint partition)



Partially replicated
(non-disjoint partition)

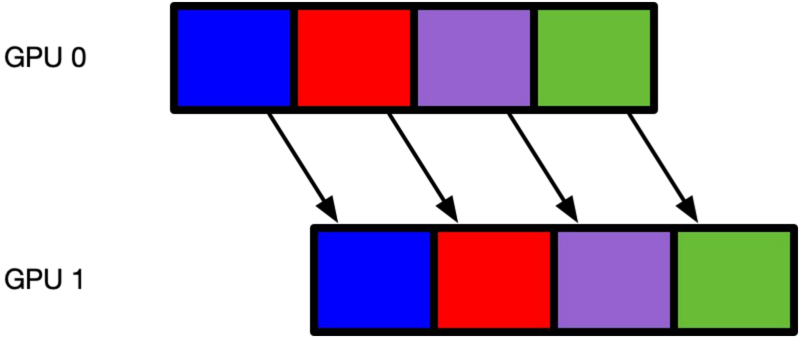


Fully replicated

Jax (training LLMs) are not typical Legion workloads and expose missing features and pain points

Memory highly constrained, but difficult to optimize instance validation and reuse

- Large models can be 40GB of optimizer state, 30GB of activations
- Pipelined activations computed on node A read on node B are no longer needed on node A, but instance stays alive on node A
  - Can not use a different logical region for each logically distinct activation tensor
- *Abstraction inversion alert*: implemented a Legate store cache with reuse/invalidation that hopefully causes buffers to be allocated in desired way



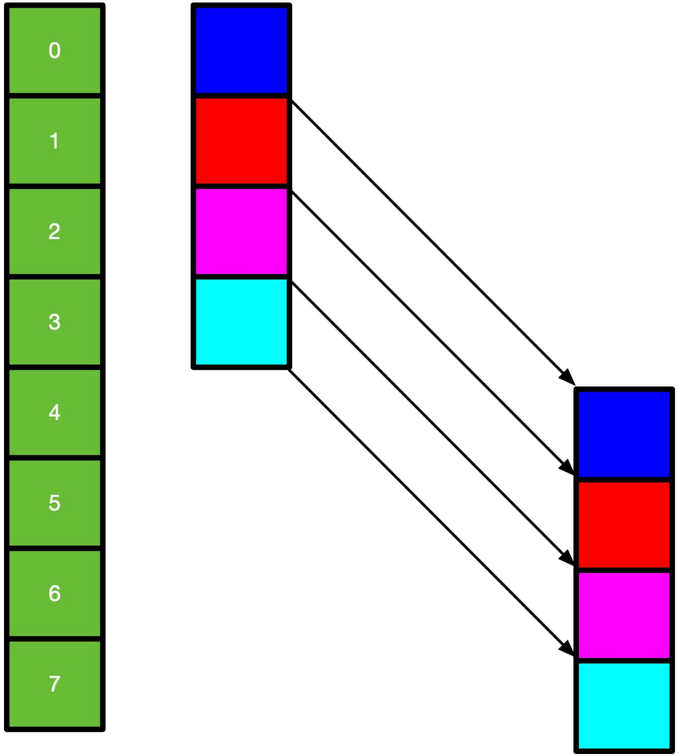
A new C++ productivity layer
built directly on Realm

Deep-learning requires only *some* of what Legate/Legion has to offer

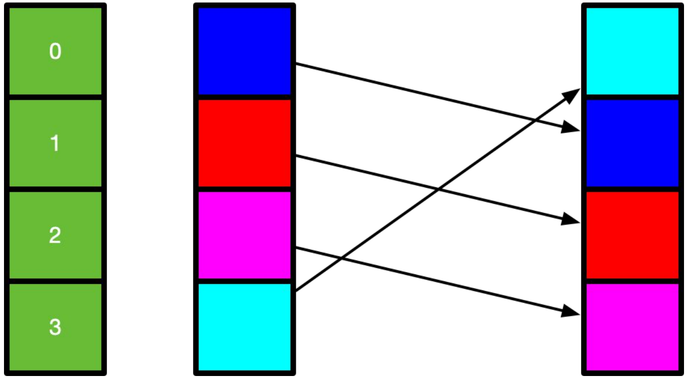
Requirements

- Flexibly assign tasks and sharded tensors to different submeshes
- Efficient cross-mesh resharding communication primitives
- Execution dependencies for tuning task ordering
- (Simple) fine-grained control over instance reuse and invalidation

Asynchronous cross-mesh resharding is most important library primitive

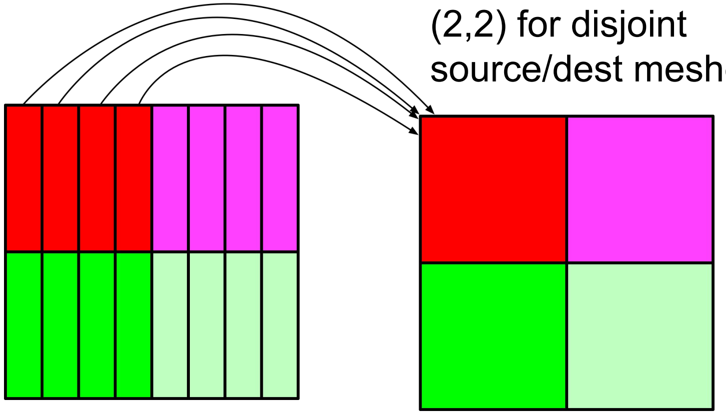


Point-to-point for disjoint source/dest meshes



Permute within a single submesh

N:M resharding (2,8) -> (2,2) for disjoint source/dest meshes



New lightweight, data-effects C++ layer built directly on top of Realm with simplifications

Simplifications

- Multi-controller execution with control replication allow dependency analysis to be restricted to *local shards* only
  - Dependency analysis happens in shared memory!
- Control replication forces all processes to agree on inter-process *reshard* operations to move data between submeshes
- No separation of logical and physical arrays
- No fancy slicing/aliasing/hierarchical data tree

Realm event model made writing asynchronous task-based framework *very easy*

defer(...) takes a lambda and arguments and performs dependency analysis on arguments

Reshard is a library function that inspects the sharding of input/output and constructs resharding plan using Realm instance copies

```
DeviceList first_mesh = …;
DeviceList second_mesh = …;
auto waiter = on(ProcessorGroup::Local()).defer([=](Processor p) {
  Store<ShardedArray> source = ShardedArray::Create(
      GetShape(first_mesh, size), {.processor = p});
  Store<ShardedArray> dest = ShardedArray::Create(
      GetShape(second_mesh, size), {.processor = p});
  across(first_mesh).on(p).defer([](ShardedArray& array){
    int* data = array.tile().ptr<int>();
    // write some values
  }, source);
  Reshard(p, source, dest);
  across(second_mesh).on(p).defer([](const ShardedArray& array){
    const int* data = array.tile().ptr<int>();
    // read some values
  }, dest);
}
```

const-ref input automatically tells dependency analysis to use read-only privileges

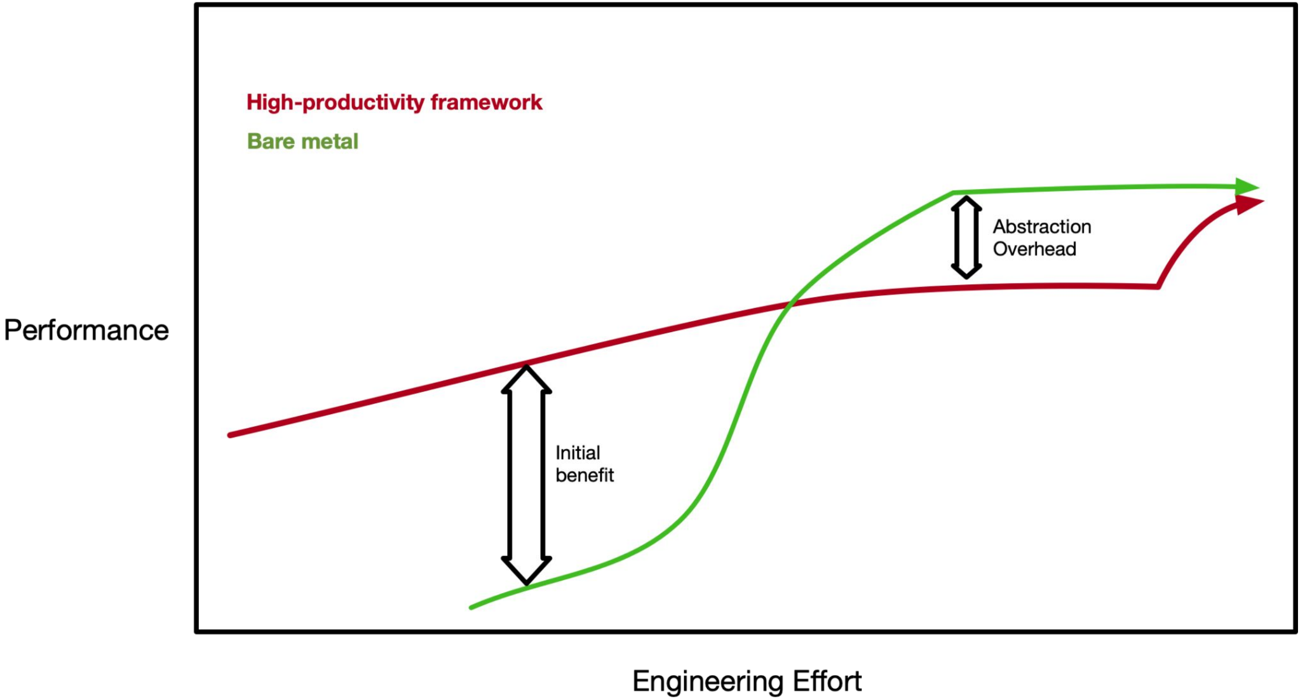
```
auto event = across(devices)
         .if_on(p)
         .after(precondition)
         .stream_ordered()
         .defer(
             [](Stream* s,
                std::shared_ptr<LegateCompiler> compiler,
                ro_vector<ShardedArray> inputs,
                rw_vector<ShardedArray> outputs,
                const ArrayTile &temp) {
               …
             }, std::move(devices), compiler, std::move(inputs),
                std::move(outputs),std::move(temp));
```

Lightweight ordering mechanism on execution preconditions

Declares data effects on the input/output tensors

Conclusions

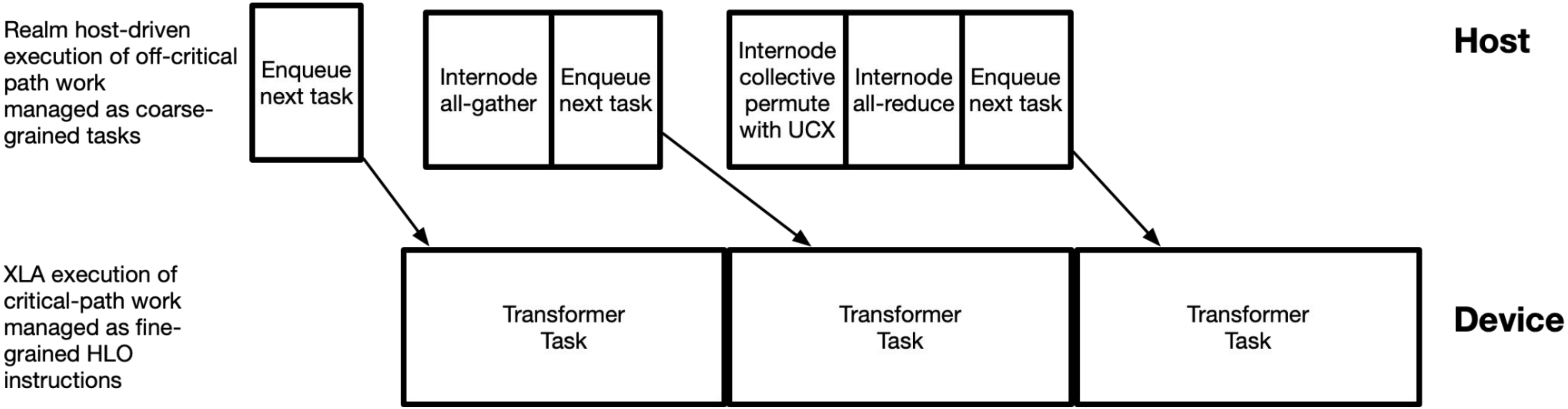
- Legate/Legion was ***great*** for 80% solution at modest (128 GPU) scale
- 99% solution with Realm required less engineering effort than Legion
- Good or bad is entirely a matter of customer and use-case requirements



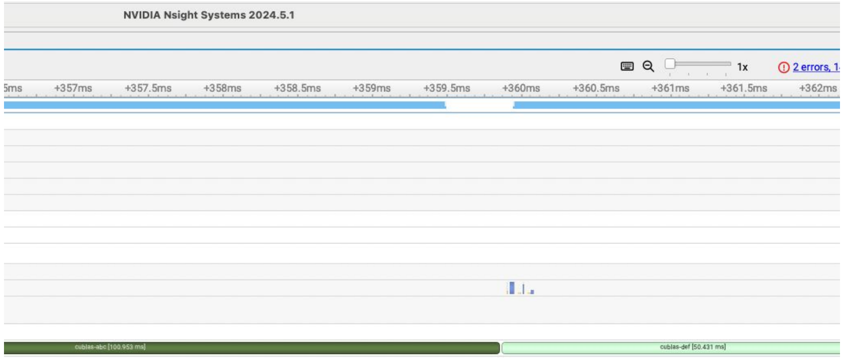
NVIDIA

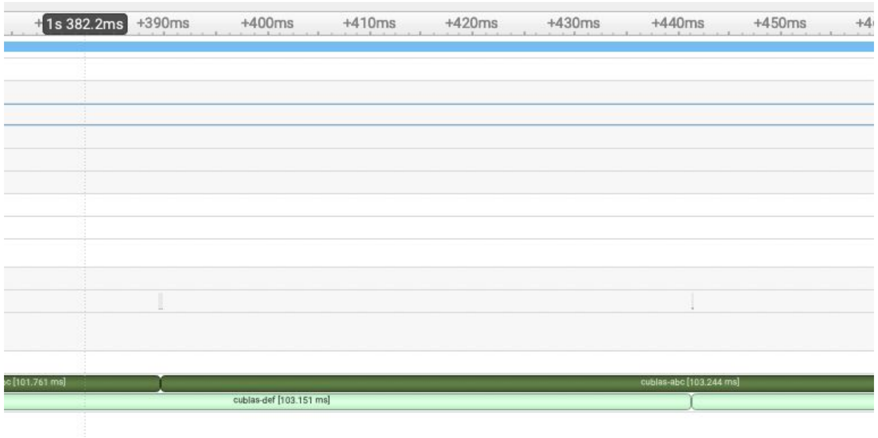
Extras

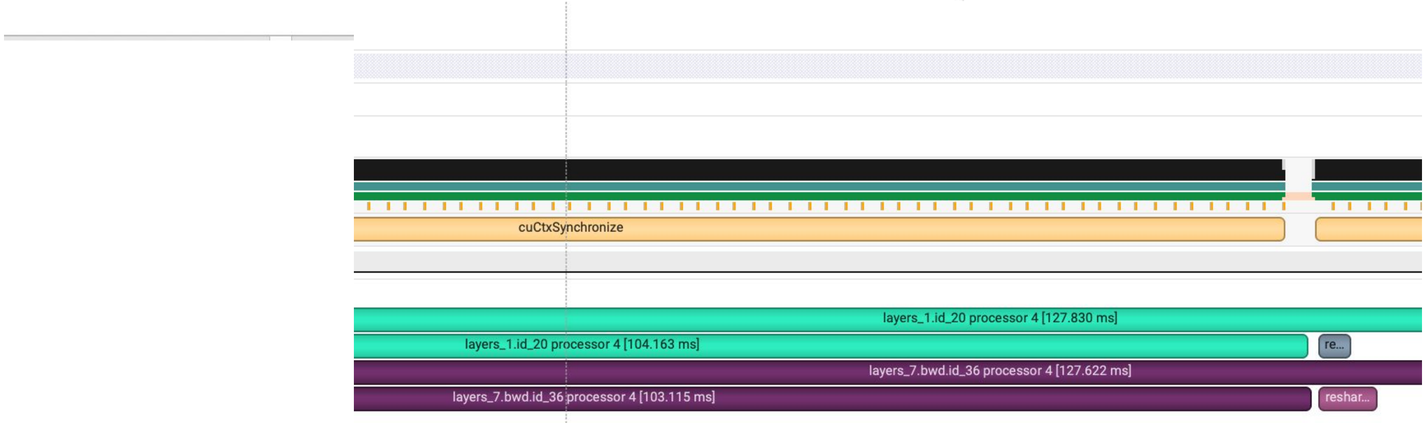
Realm execution model schedules coarse-grained work units, overlaps data movement/scheduling with critical path



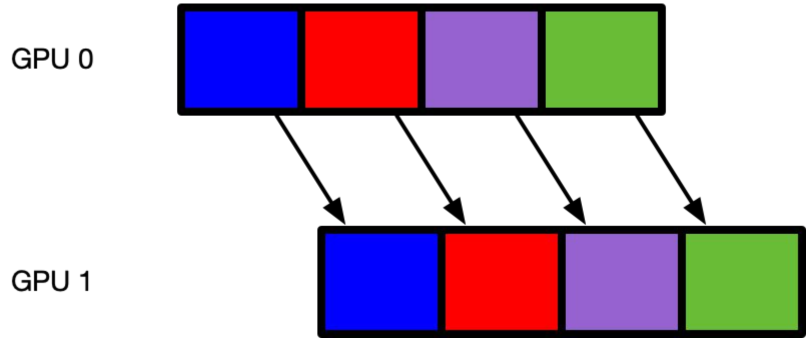
Delays at end of task







Problem with instances



Requirements

- Flexibly assign tasks and sharded tensors to different submeshes
- Efficient cross-mesh resharding communication primitives
    - Legion doesn't always see higher-level structure of required data movement
- Execution dependencies for tuning task ordering
    - Not exposed
- Fine-grained control over instance reuse and invalidation
    - Not exposed

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