Towards ML System Extensibility

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RAY
Anyscale

The rise of large models

Distributed optimizations for ML systems:

Trend: Current distributed ML systems focus on **performance** at the cost of **extensibility**.

But can current systems meet future application demands?

The extensibility problem

1. **Codesign:** Can the developer introduce performance optimizations specialized to the workload?
2. **Placement flexibility:** Can the developer control when and where computations should execute?
3. **Interoperability:** Can the system be easily and efficiently composed with other systems?

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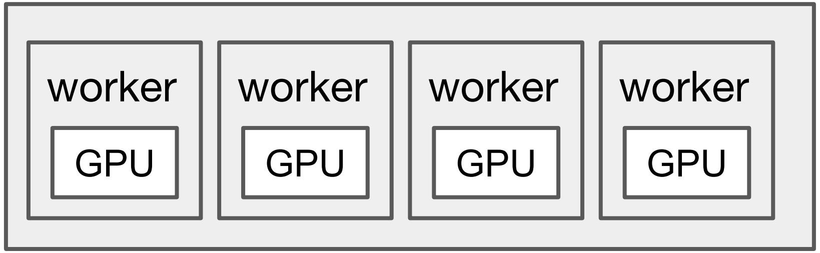
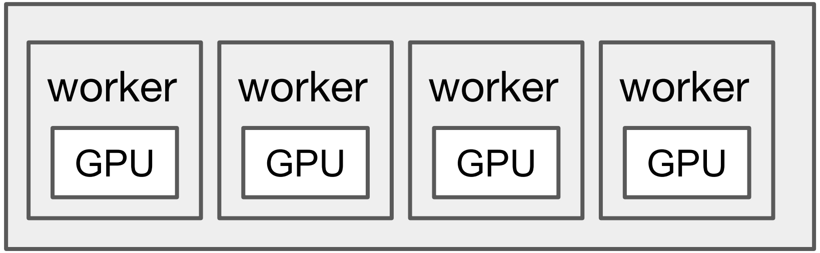
Distributed ML frameworks today

Training
DeepSpeed, Megatron-LM,
PyTorch FSDP, …



Inference
vLLM, SGLang,
TensorRT-LLM, …



Distributed execution strategies interact in complex ways.
→ **Uneven support across frameworks.**

Placement flexibility in distributed training

	Megatron-LM	DeepSpeed	PyTorch
2019	Data parallelism (DP) **Tensor parallelism (TP)**	DP	DP
2020	Pipeline parallelism (PP)	**ZeRO / FSDP** PP	
2021		EP	
2022	Sequence parallelism (SP) Expert parallelism (EP)		**ZeRO / FSDP**
2023	Context parallelism (CP)	**TP** CP	
2024	**ZeRO / FSDP**		

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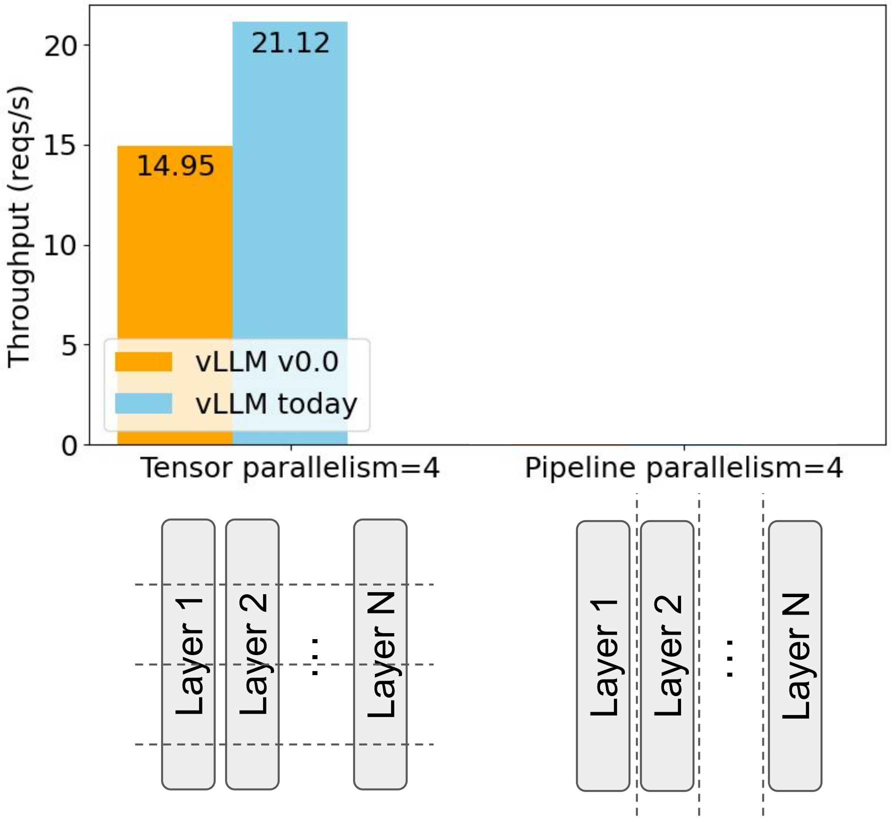
2024	**ZeRO / FSDP**		

Not including time to:

- Optimize performance
- Support variants of each strategy
- Ensure feature compatibility
- Support more models
- Fix bugs
- …

Placement flexibility in LLM inference



- Tensor parallelism (TP): Shard within a layer
- Pipeline parallelism (PP): Shard by layer

→ Improving support for one placement worsened performance for the other.

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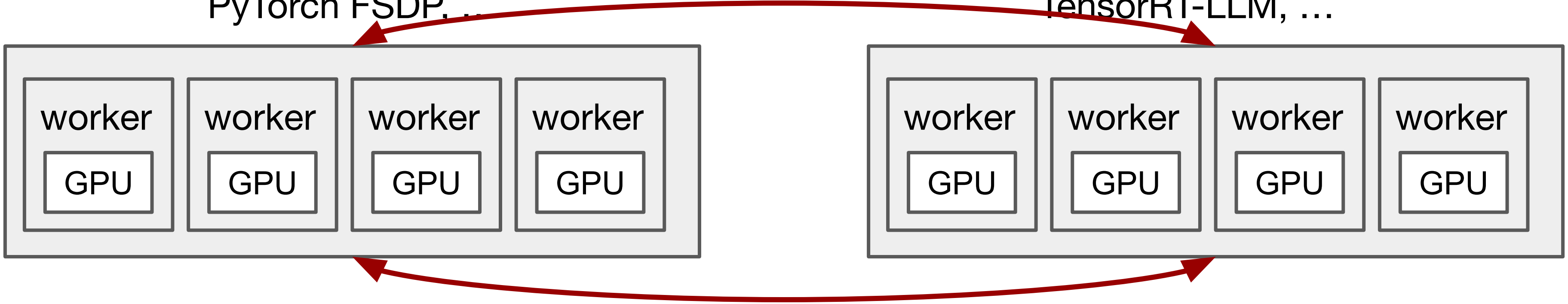
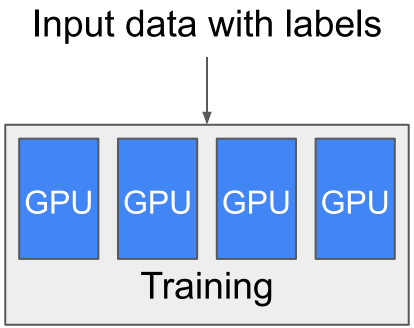


Frameworks are built monolithically.
→ **Difficult to efficiently compose models and frameworks.**

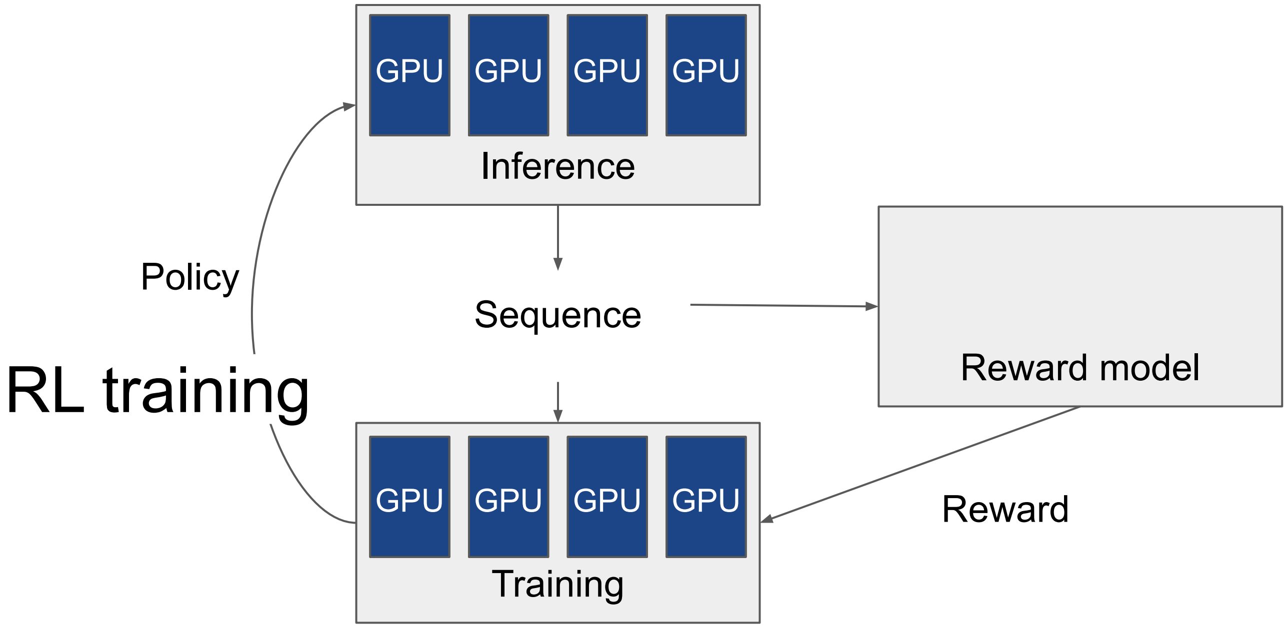
Interoperability in RL for LLMs

Supervised learning



Interoperability in RL for LLMs

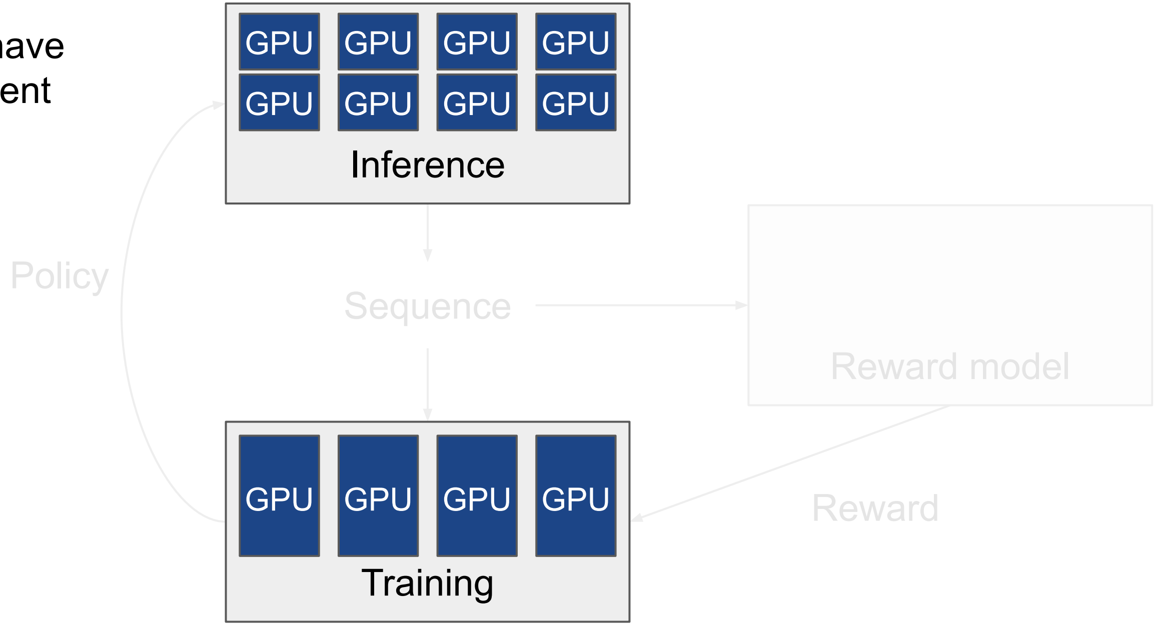
Reinforcement learning (RL) for LLMs requires **composition.**



Interoperability in RL for LLMs

Reinforcement learning (RL) for LLMs requires **composition.**

1. Training and inference have different optimal placement strategies



Interoperability in RL for LLMs

Reinforcement learning (RL) for LLMs requires **composition.**

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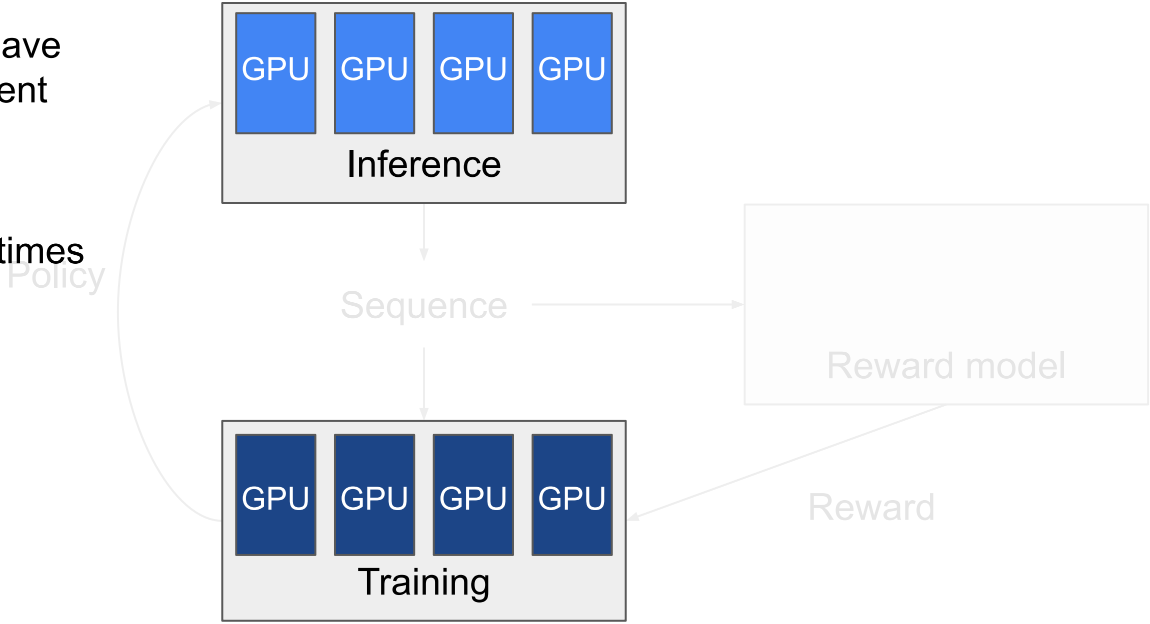
2. Different algorithms synchronize at different times



Interoperability in RL for LLMs

Reinforcement learning (RL) for LLMs requires **composition.**

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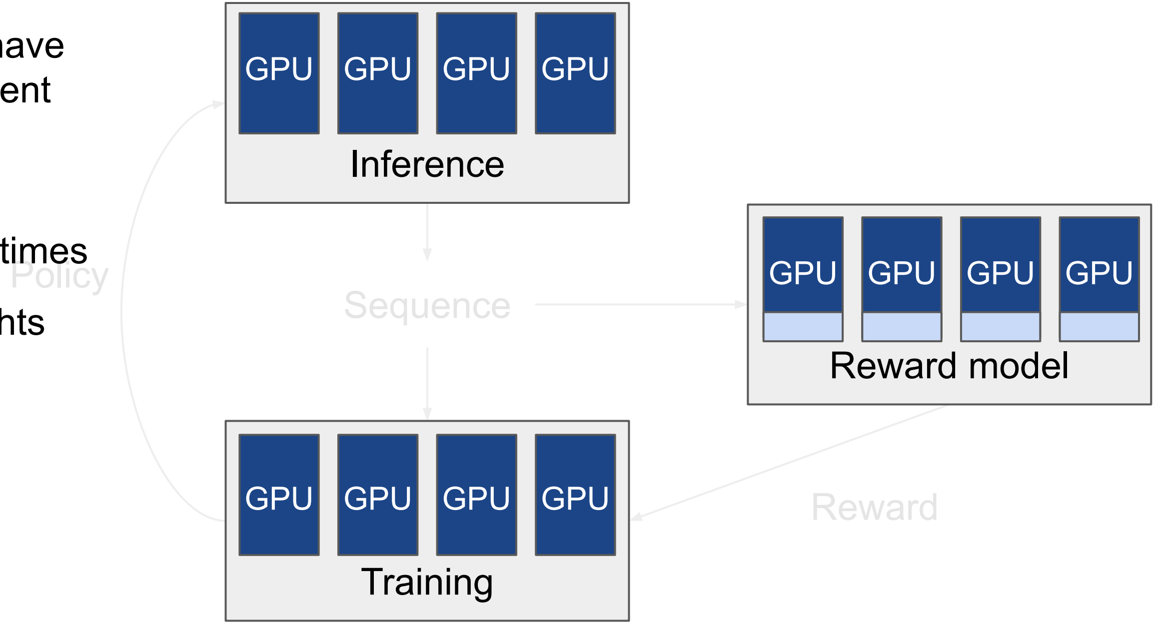
2. Different algorithms synchronize at different times
3. Models may share weights



Interoperability in RL for LLMs

Reinforcement learning (RL) for LLMs requires **composition.**

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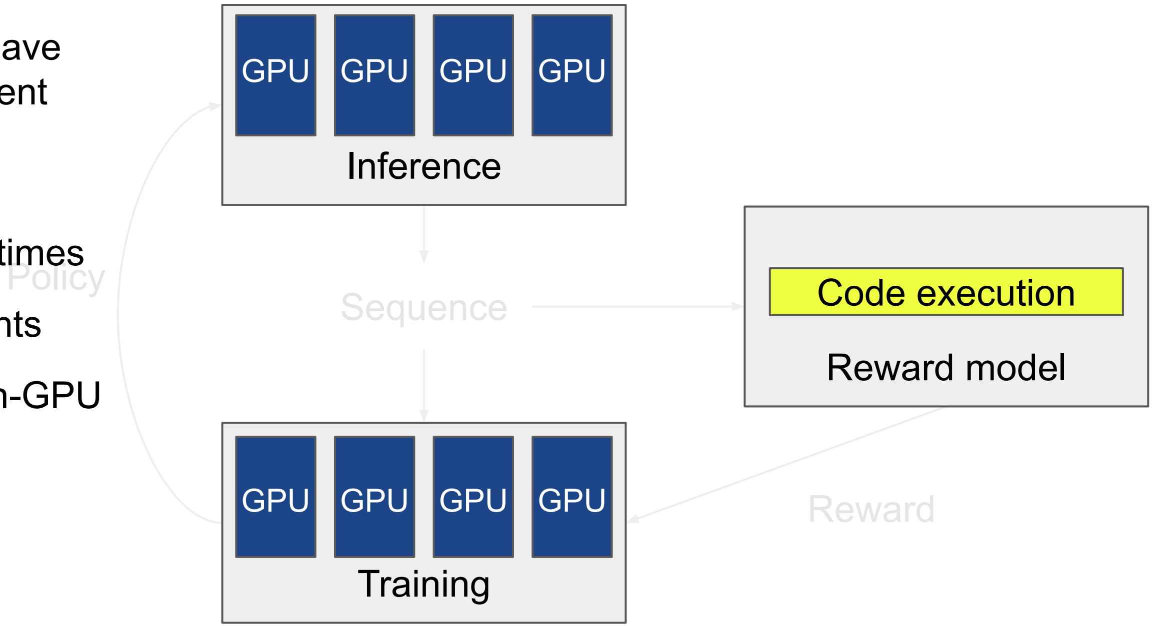
2. Different algorithms synchronize at different times
3. Models may share weights
4. Reward may require non-GPU resources



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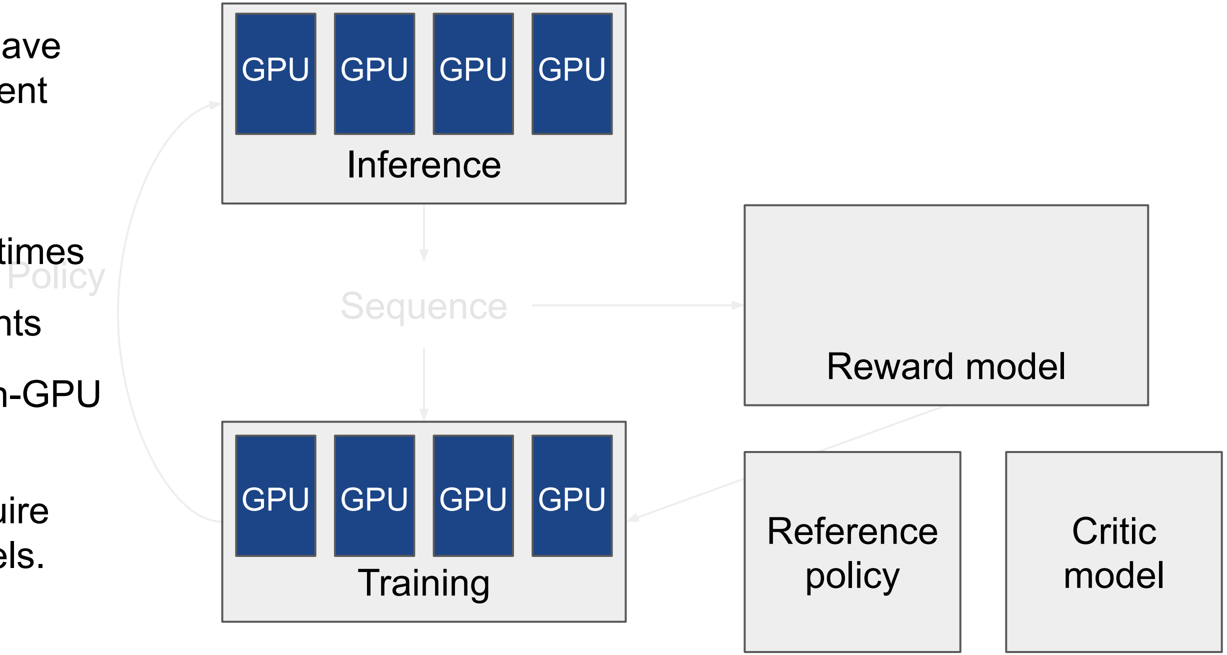
Reinforcement learning (RL) for LLMs requires **composition.**

1. Training and inference have different optimal placement strategies
2. Different algorithms synchronize at different times
3. Models may share weights
4. Reward may require non-GPU resources
5. Different algorithms require different additional models.



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4. Reward may require non-GPU resources
5. Different algorithms require different additional models.
6. …

Diverse composition strategies

→ **Diverse data movement and scheduling strategies**

The extensibility problem

1. **Codesign:** Can the developer introduce performance optimizations specialized to the workload?
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Current distributed ML systems use **single program multiple data**.
→ **Codesign** at the cost of **placement flexibility** and **interoperability**.

SPMD: Single program, multiple data

SPMD: Each accelerator runs a copy of the same program.

```
# Compose two models A and B
model = modelA if self.rank == 0 else modelB
while True:
  if self.rank == 0:
    inp = torch.rand(N, device="cuda")
    tensor: torch.Tensor = model.execute(inp)
    send(tensor, peer=1)                        A
sync
  else:
    tensor = torch.zeros(N)
    recv(tensor, peer=0)
    output = model.execute(tensor)              B
```

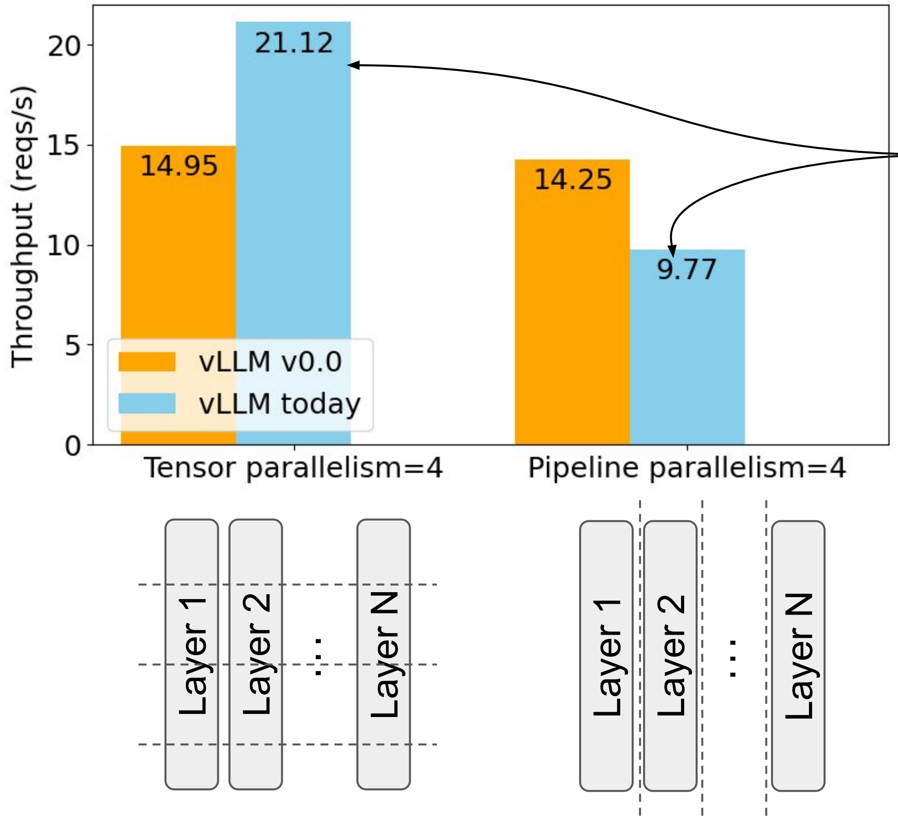
Pros:

- Simple
- Efficient

Cons:

- Couples user code to a *specific placement*
- Couples user code to a *static* execution strategy
- *Composition* is difficult

Placement flexibility in LLM inference

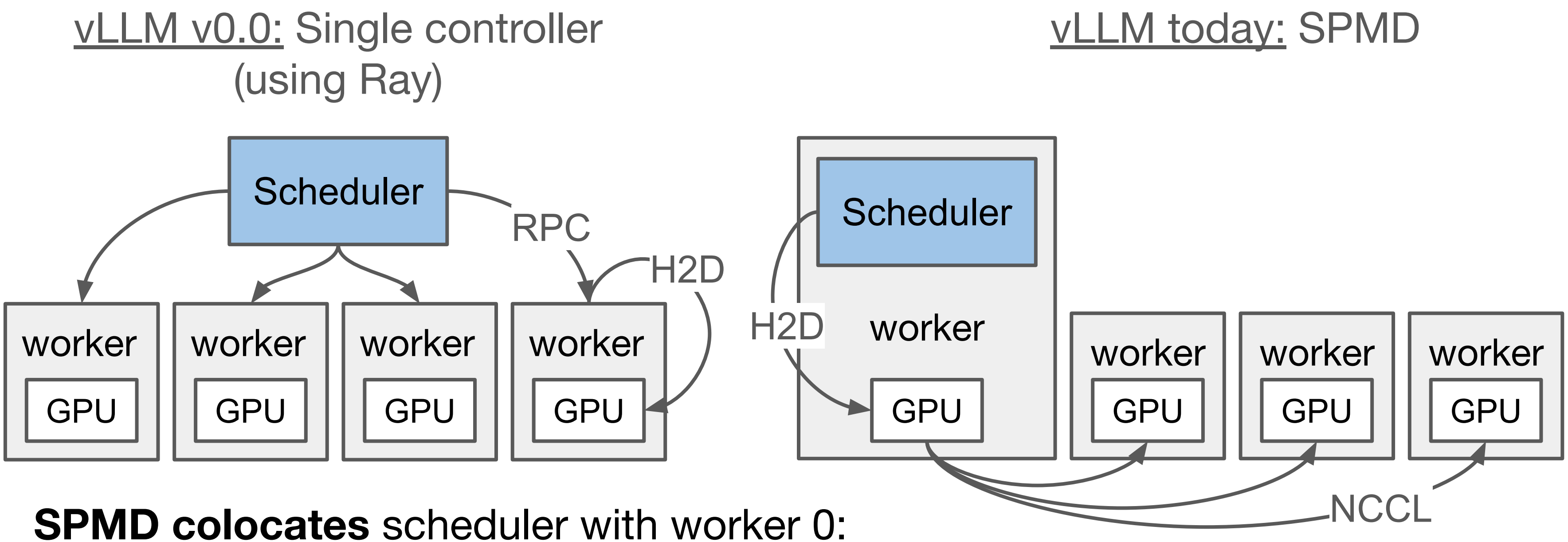


Using SPMD

TP vs PP is a **placement** decision.

Improving support for one placement worsened performance for the other.

Placement flexibility: Single controller vs. SPMD

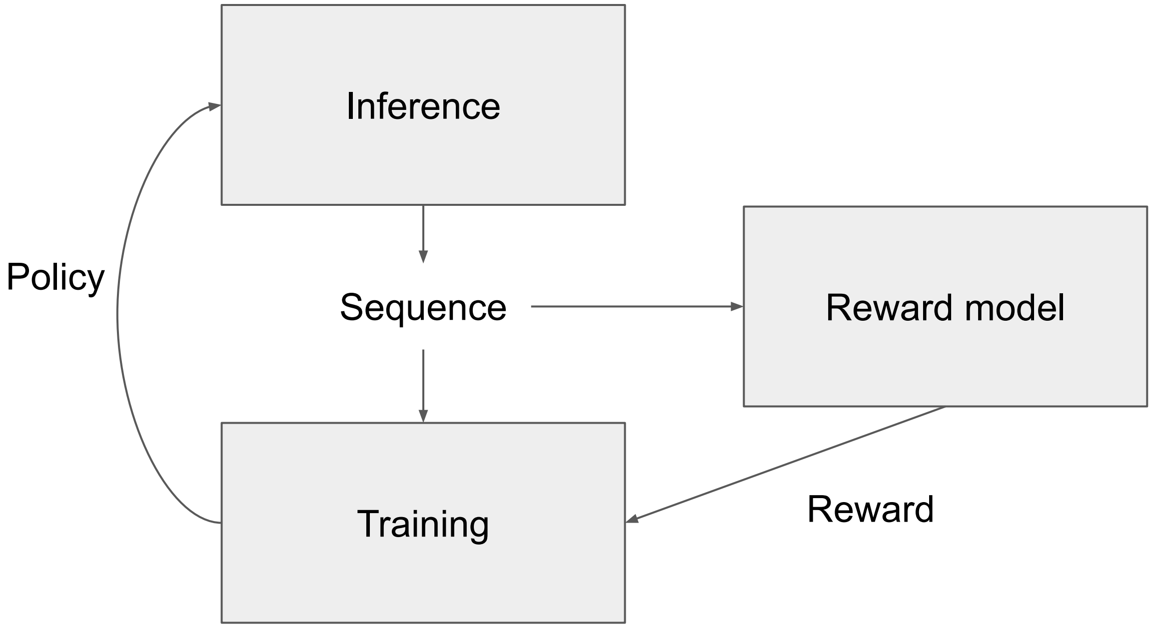


SPMD colocates scheduler with worker 0:

- **Reduces overhead** of metadata transfer
- But **couples** the scheduler and worker

Interoperability: SPMD for composition?

Reinforcement learning (RL) for LLMs requires **composition.**



Interoperability: SPMD for composition?

```
def train(self, …):
  def vllm_generate(...):
    r = vllm_engine.generate.remote(...)
    queue.put(ray.get(r))
  def broadcast_to_vllm(...):
    for param in self.model.weights:
      dist.broadcast(param, 0, group=...)

  threading.Thread(vllm_generate).start()
  for _ in range(training_steps):
    broadcast_to_vllm(...)
    g_vllm_responses = queue.get()
    dist.broadcast(g_vllm_responses, 0)
    ...
```

Inference

Weight syncing

Data transfer

Training

Interoperability: SPMD for composition?

```
def train(self, …):
  def vllm_generate(...):
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    ...
```

- **Tightly coupled** to particular algorithm (e.g., on-policy vs. off-policy)
- Collective ops and groups need to be **manually scheduled**
- **Additional optimizations** are challenging: reducing data movement, elastic scaling, …

SPMD: Single program, multiple data

SPMD: Each accelerator runs a copy of the same program.

```python
# Compose two models A and B
model = modelA if self.rank == 0 else modelB
while True:
  if self.rank == 0:
    inp = torch.rand(N, device="cuda")
    tensor: torch.Tensor = model.execute(inp)
    send(tensor, peer=1)
  else:
    tensor = torch.zeros(N)
    recv(tensor, peer=0)
    output = model.execute(tensor)
```

Does not support:

- Variable-size tensors
- Asynchronous communication
- Failure handling
- CPU metadata + GPU data
- …

SPMD: Single program, multiple data

SPMD: Each accelerator runs a copy of the same program.

```
# Compose two models A and B
```

Improving **extensibility** requires more CPU coordination.
But **performance** requires GPUs to run ahead of CPUs.

Static, inflexible and fast vs.
Dynamic, flexible and slow

```
tensor = torch.zeros(N)
recv(tensor, peer=0)
output = model.execute(tensor)
```

data

- …

The extensibility problem

SPMD:

→ works well for **codesign** with **one to few static** strategies

→ is difficult to adapt to different **placement** choices

→ discourages **interoperability**, because composition requires changes to each program to implement the global schedule

DAFT: An intermediate representation for distributed GPU programming

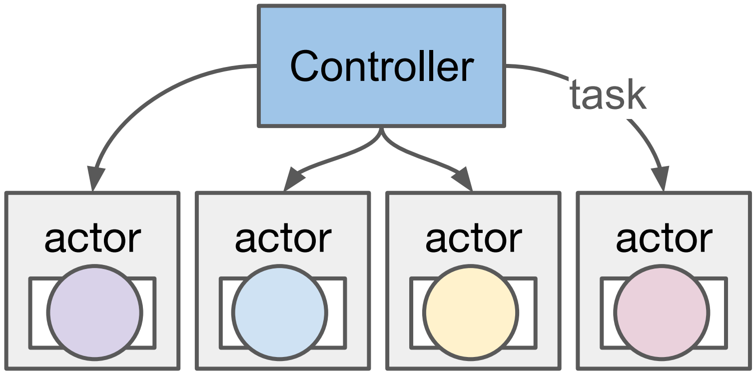
DAFT

Distributed: Program distributed GPUs with a "single controller" program

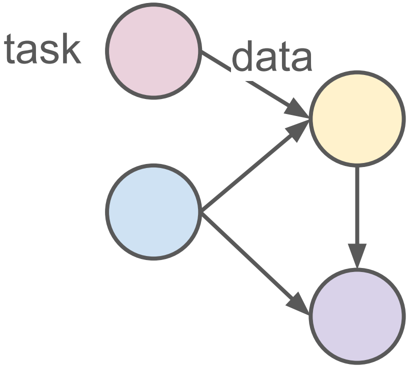
Actors: Stateful and remote workers, wrap any framework

Futures: Async execution, dataflow programming

Tasks: RPC-like interface



Dataflow graph



Related work

- Most other distributed ML control planes based on SPMD or limited MPMD
- Single controller frameworks:
  - Pathways, TensorFlow v1: Tied to XLA compiler
  - RLlib, Hybridflow (veRL): RL-specific
- Previous DAFT systems are CPU-centric: Ray, Ciel, Dask

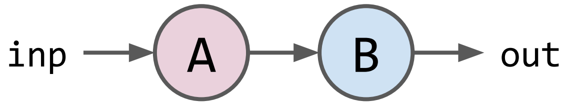
→ **OS** coordinates **CPU** execution and communication

→ **CPU** coordinates **GPU** execution and communication

A DAFT example (using Ray)

```
@ray.remote(num_gpus=1)
class ModelA:
  @ray.method(tensor_transport="nccl")
  def execute(self, input: torch.Tensor) -> torch.Tensor:
    return self.model.execute(input)
```

Dataflow graph



Distributed future: Reference to remote, eventual value

System triggers p2p (or collective communication) operation

A DAFT example (using Ray)

```python
@ray.remote(num_gpus=1)
class ModelA:
  @ray.method(tensor_transport="nccl")
  def execute(self, input: torch.Tensor) -> torch.Tensor:
    return self.model.execute(input)

@ray.remote(num_gpus=1)
class ModelB:
  def execute(self, tensor: torch.Tensor) -> torch.Tensor:
    return self.model.execute(tensor)

A, B = ModelA.remote(), ModelB.remote()
def schedule(A: Actor[ModelA], B: Actor[ModelB]):
  inp: torch.Tensor = torch.rand(N, device="cuda")
  tensor_ref: Ref = A.execute.remote(inp)
  output_ref: Ref = B.execute.remote(tensor_ref)
  out: torch.Tensor = ray.get(output_ref)
```

Already supports:

- Variable-size tensors
- Asynchronous communication
- Failure handling
- CPU metadata + GPU data
- …

DAFT for composition in RL for LLMs

```
# Multi-GPU inference replica.
vllm_workers: WorkerGroup[vllm.LLMEngine]
# Multi-GPU training replica.
train_workers: WorkerGroup[Trainer]

# Single controller program.
def train():
```

+ Algorithm **decoupled** from worker code
+ **Transparent scheduling** for collectives
+ Reduce data movement by creating different dataflows

Elastic scaling of WorkerGroups

DAFT as an IR for distributed GPUs

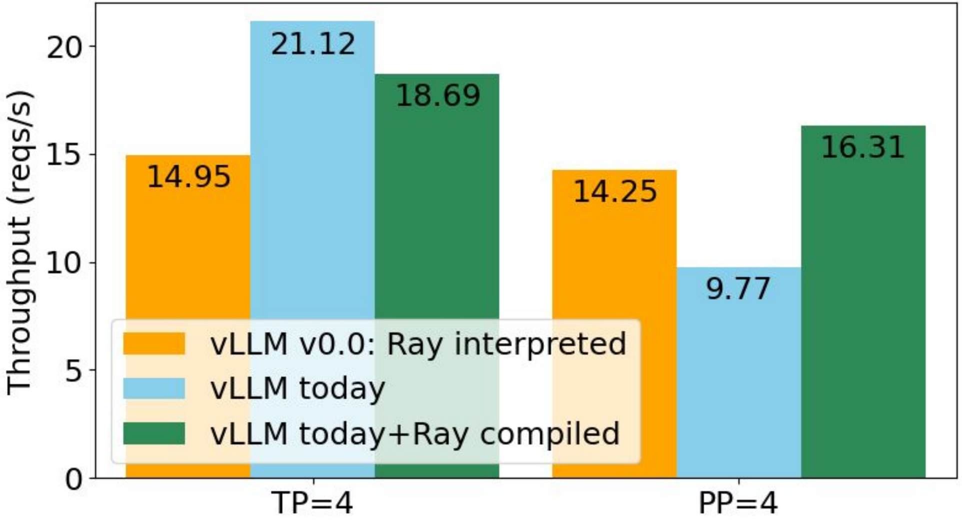
Problem: Dynamic dispatch can add high overheads compared to SPMD.

Solution: Interpreted vs. compiled execution.

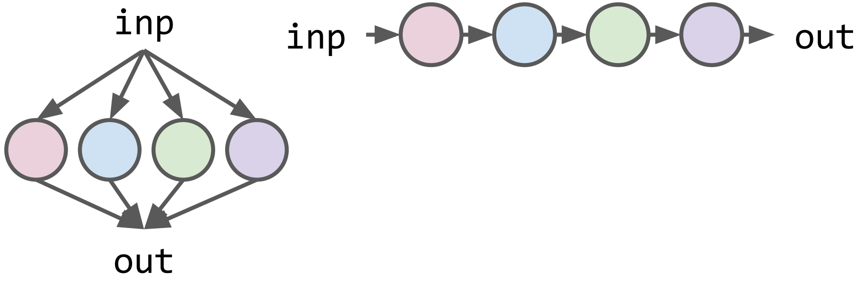
- **Interpreted**: Program executes eagerly, one task at a time
  → For coarse-grained composition, debugging, dynamic failover, …
- **Compiled**: Freeze a dataflow (sub)graph, schedule all tasks in one round-trip
  → For fine-grained GPU orchestration, static control flow

Allow user to **control** tradeoff between **dynamicity vs. system overheads**!

Interpreted vs. Compiled DAFT



DAFT dataflows



Control plane optimizations:

- Reduce communication overhead by using shared memory
- Reduce scheduling overhead by executing multiple tasks in one round trip
- …

Open systems challenges

A distributed tensor runtime

Distributed tensor API	User-controllable distributed strategy
Compiler frontend	Extract non-distributed static tensor subgraphs
Distributed tensor runtime	Apply distributed strategy, plan distributed ops
Interpreted and compiled DAFT	Intermediate representation for distributed GPU programming

Opportunity: Codesigning compilers and distributed systems?

Message passing APIs

An alternative API to DAFT for application composition:

- **Scales** better than single controller
- Best for loosely coupled systems/applications

But there is no good message-passing APIs for distributed GPUs:

- Messages can be executed in any order → **collective operations** may deadlock

And current collective communication libraries are limited :

- Statically declared collective groups
- User must manually schedule calls to the library

Opportunity: A message-passing API for distributed GPUs?

The rise of large models

Models are getting larger.

But also more *complicated*: RL, multimodal models, multi-model routing, heterogeneous resources, …

Performance is important.
But so is **extensibility**!