Ray
A Distributed Execution Framework for Emerging AI Applications

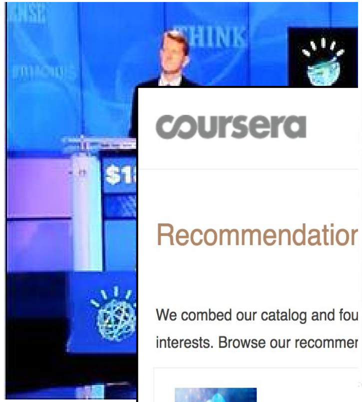
BDD/RISE mini-retreat

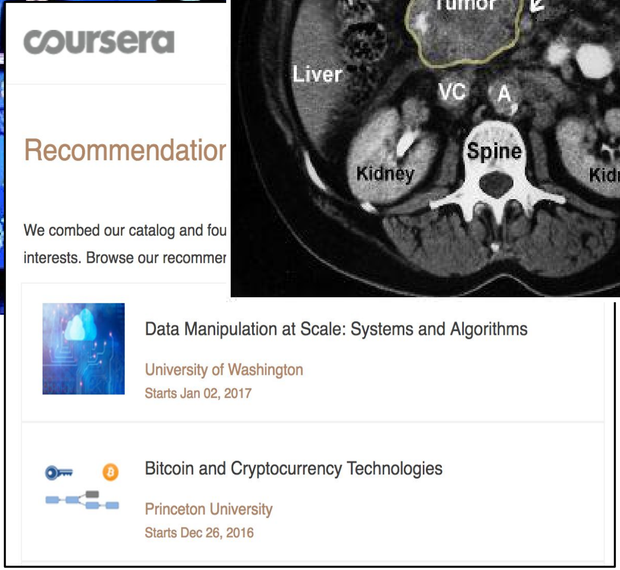
Philipp Moritz

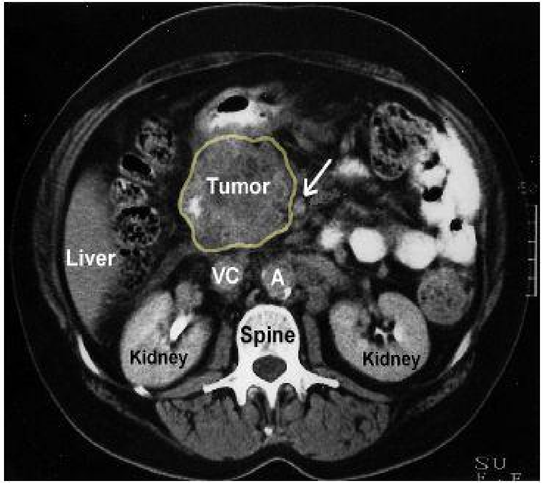

Berkeley
UNIVERSITY OF CALIFORNIA
BERKELEY

Emerging AI applications

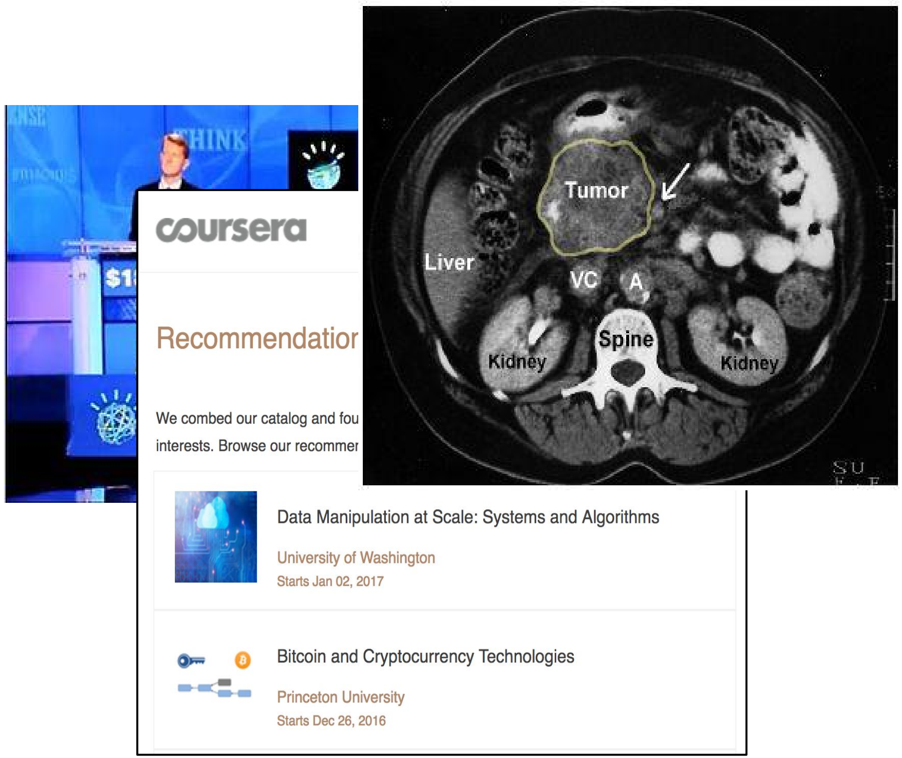
Emerging AI applications

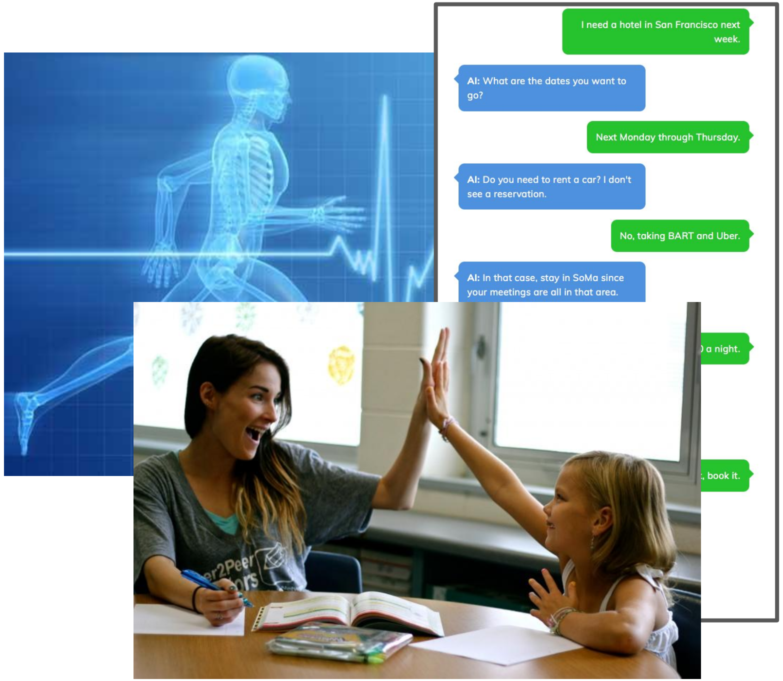




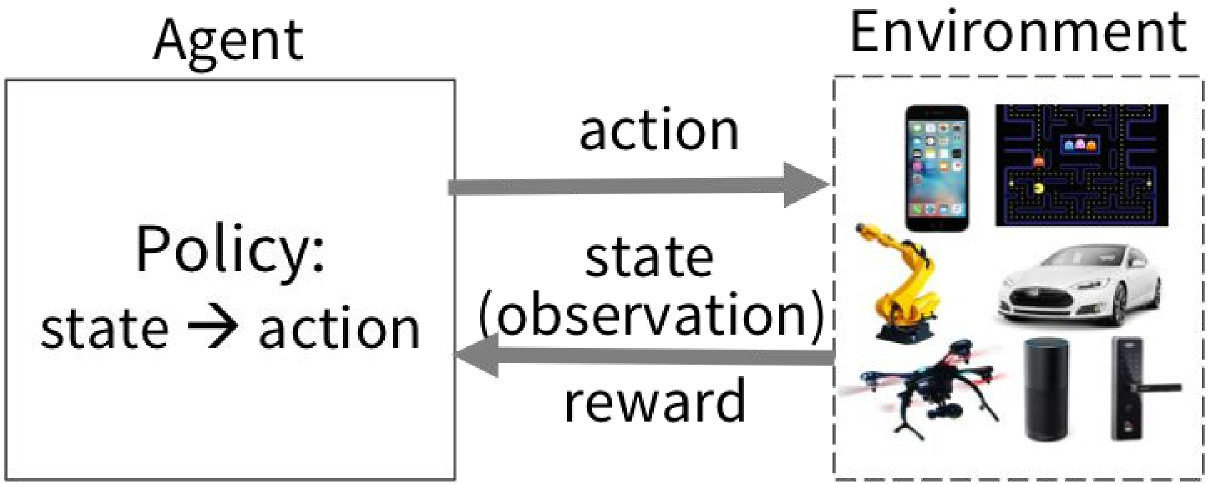


Emerging AI applications





Interacting with an environment



Things that are hard with current distributed systems

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- Reinforcement learning training
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Requirements

- Low latency tasks
- High throughput tasks
- Adapt computation based on task progress
- Complex task dependencies
- Nested parallelism, dynamic task graph construction
- Tolerance of machine failures
- Seamless usage of GPUs and other accelerators

Example: RL training

```
def train(env, hyperparameters):
    policy = initial_policy()
    for _ in range(1000):
        trajectories = [rollout(policy, env) for _ in range(K)]
        policy.update(trajectories)
    return policy


def rollout(policy, env):
    # alternately evaluate policy and simulate env
```

Example: RL training

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def rollout(policy, env):
    # alternately evaluate policy and simulate env

while True:
    train(env, random_hyperparameters()):
```

Example: RL training

```
@ray.remote
def train(env, hyperparameters):
    policy = initial_policy()
    for _ in range(1000):
        trajectories = ray.get([rollout.remote(policy, env) for _ in range(K)])
        policy.update(trajectories)
    return policy

@ray.remote
def rollout(policy, env):
    # alternately evaluate policy and simulate env

while True:
    train.remote(env, random_hyperparameters()):
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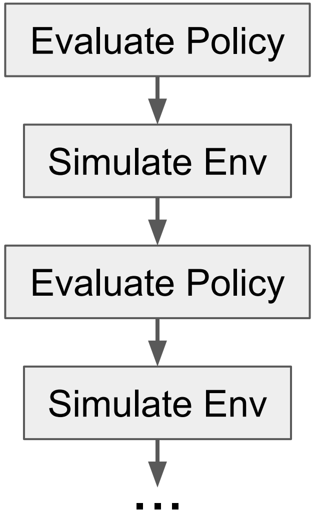
Example: simulators on CPUs, policies on GPUs



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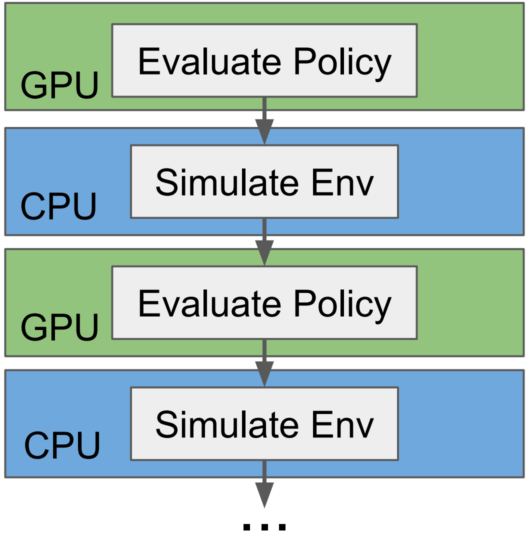

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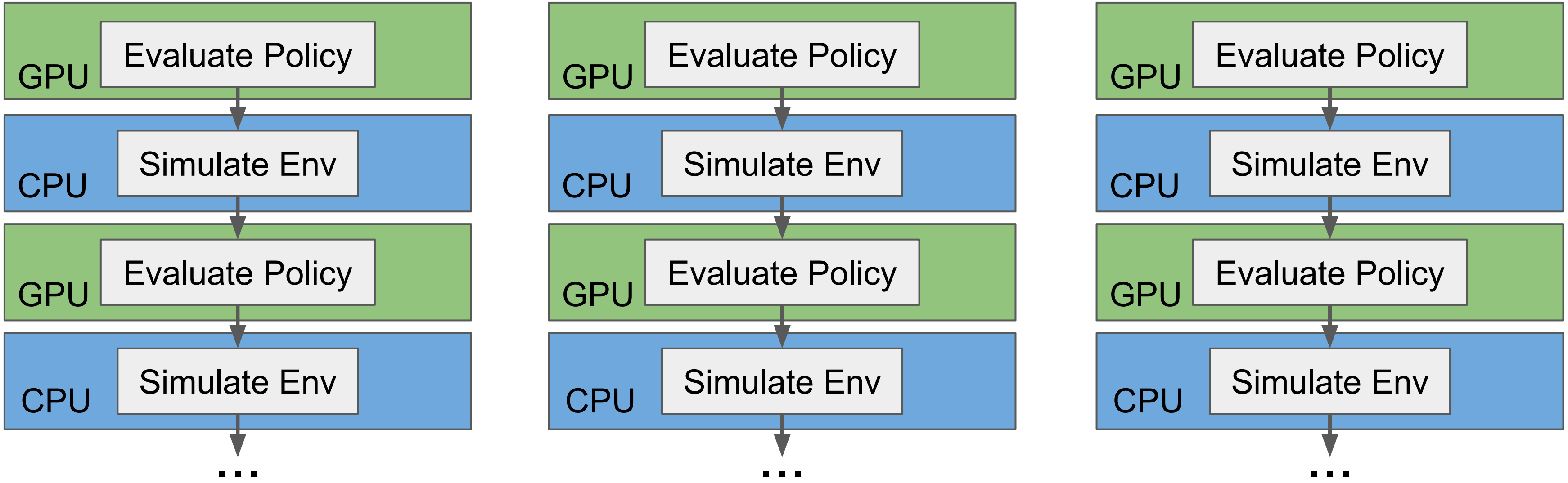
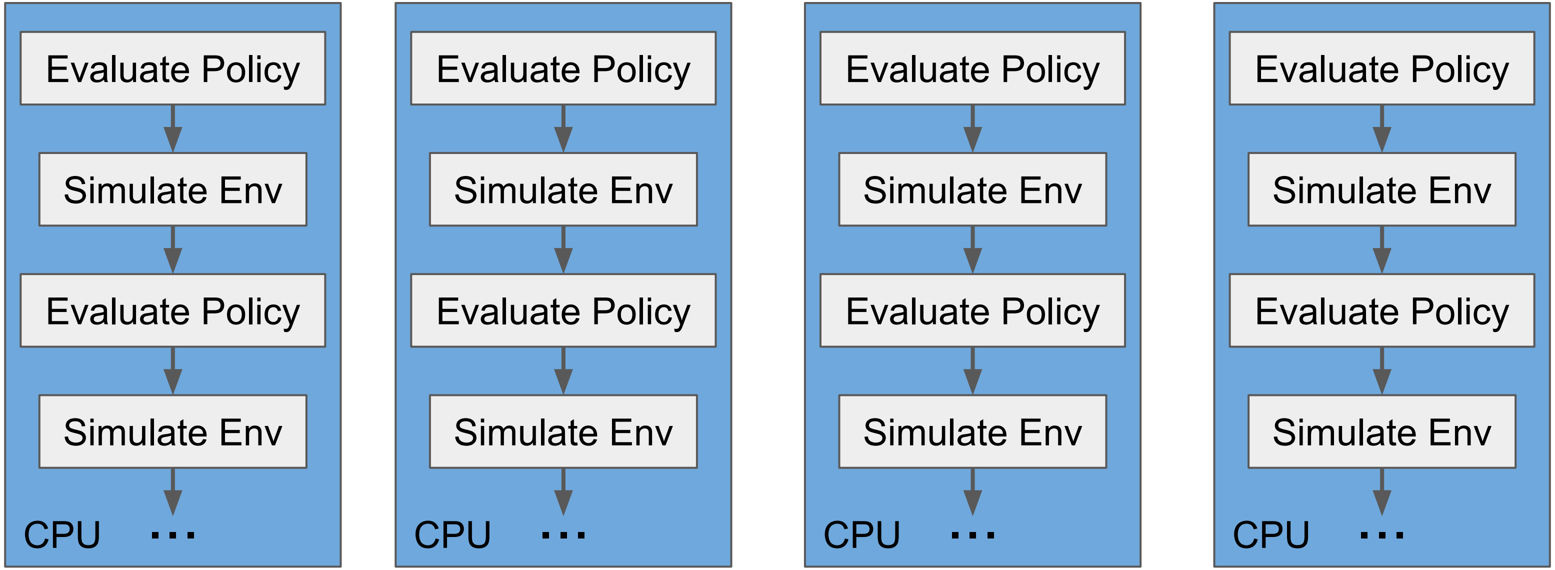


Example: simulators on CPUs, policies on GPUs

Options:

1) **One task per CPU, do everything on CPUs.**
2) One task per GPU (batch policy evaluation on GPU).
3) Many tasks. Policy evaluation on GPUs and simulator on CPUs.



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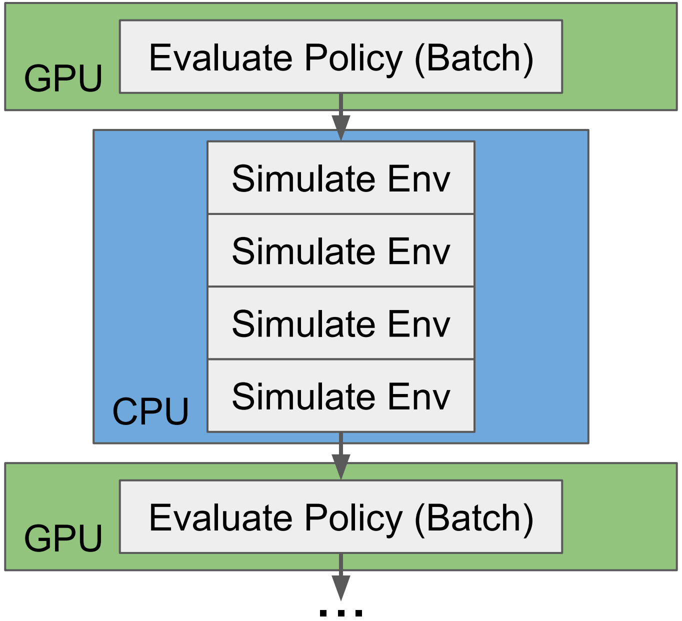

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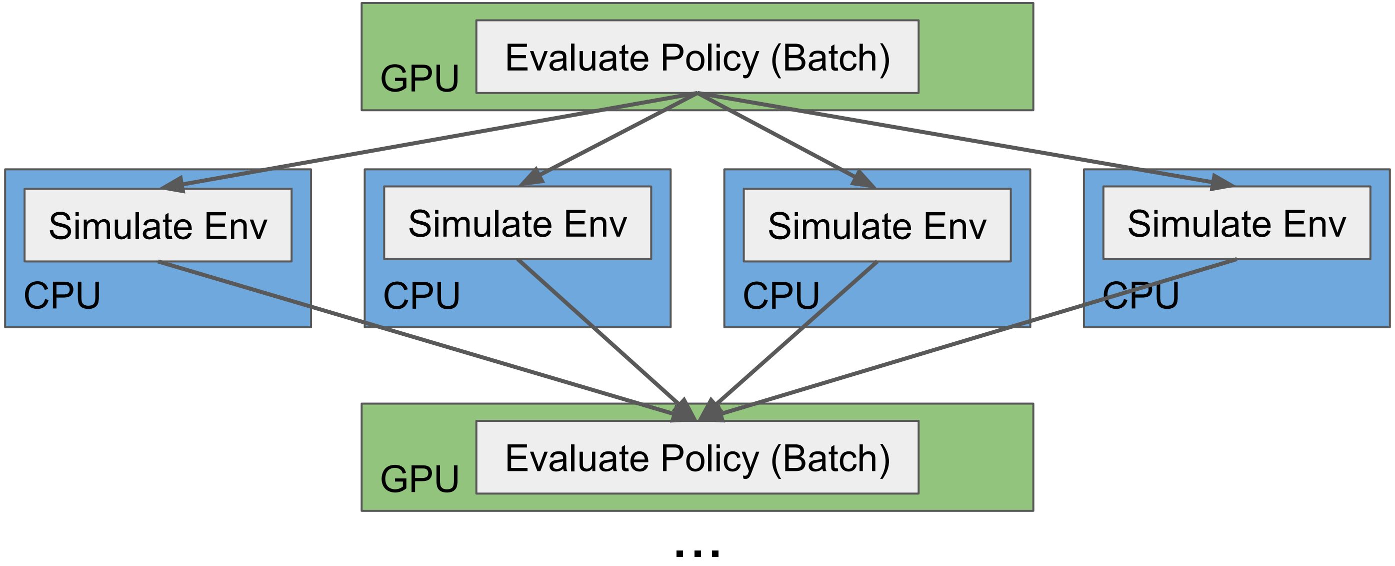

Ray API

Ray API - remote functions

```
def zeros(shape):
    return np.zeros(shape)


def dot(a, b):
  return np.dot(a, b)
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def dot(a, b):
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id1 = zeros.remote([5, 5])
id2 = zeros.remote([5, 5])
id3 = dot.remote(id1, id2)
ray.get(id3)
```

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- Blue variables are Object IDs.

Ray API - remote functions

```
@ray.remote
def zeros(shape):
    return np.zeros(shape)

@ray.remote(num_gpus=2)
def dot(a, b):
  return np.dot(a, b)

id1 = zeros.remote([5, 5])
id2 = zeros.remote([5, 5])
id3 = dot.remote(id1, id2)
ray.get(id3)
```

- **Blue** variables are Object IDs.
- Can specify **GPU** requirements

Ray API - actors

```python
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

c = Counter()
c.inc()  # This returns 1
c.inc()  # This returns 2
c.inc()  # This returns 3
```

Ray API - actors

```python
@ray.actor
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

c = Counter.actor()
id1 = c.inc()
id2 = c.inc()
id3 = c.inc()
ray.get([id1, id2, id3])  # This returns [1, 2, 3]
```

Ray API - actors

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ray.get([id1, id2, id3])  # This returns [1, 2, 3]
```

- State is shared between actor methods.
- Actor methods return **Object IDs**.

Ray API - actors

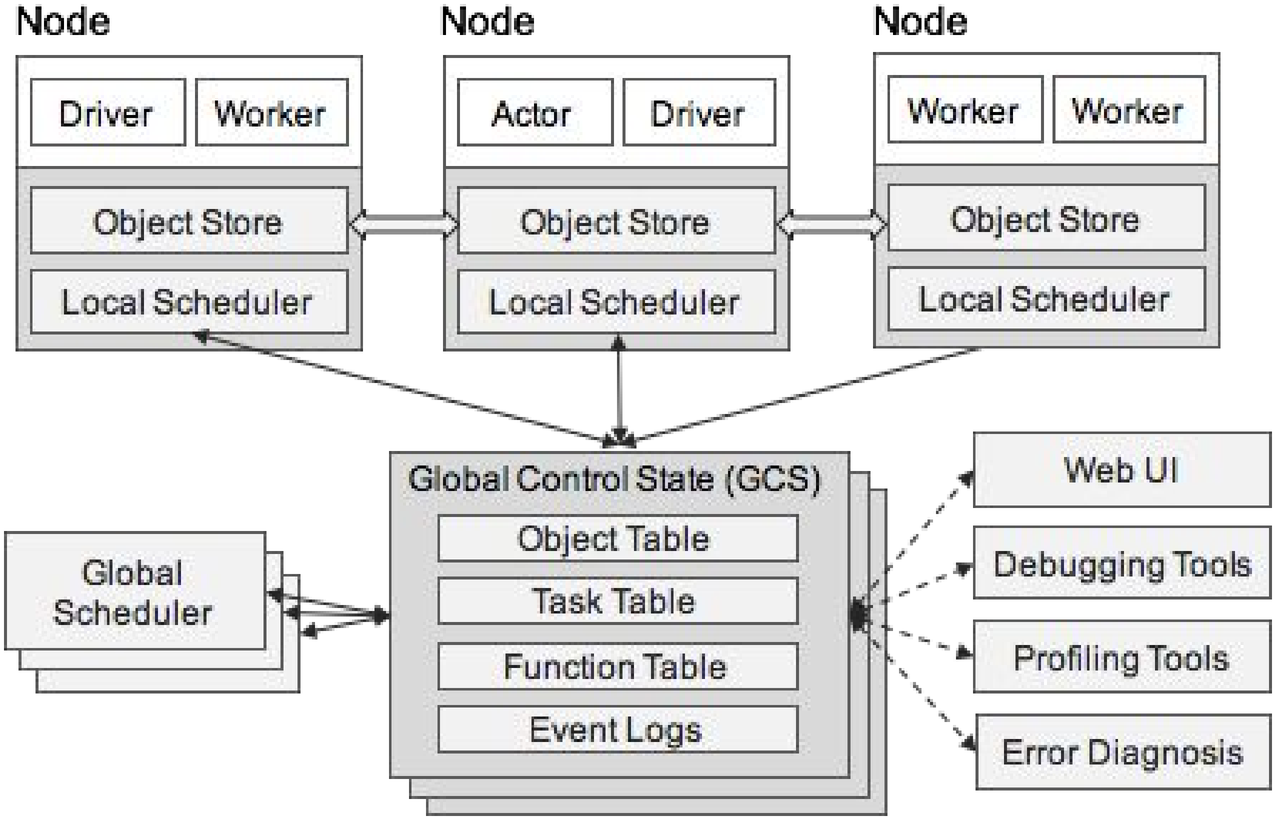
```python
@ray.actor(num_gpus=1)
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

c = Counter.actor()
id1 = c.inc()
id2 = c.inc()
id3 = c.inc()
ray.get([id1, id2, id3])  # This returns [1, 2, 3]
```

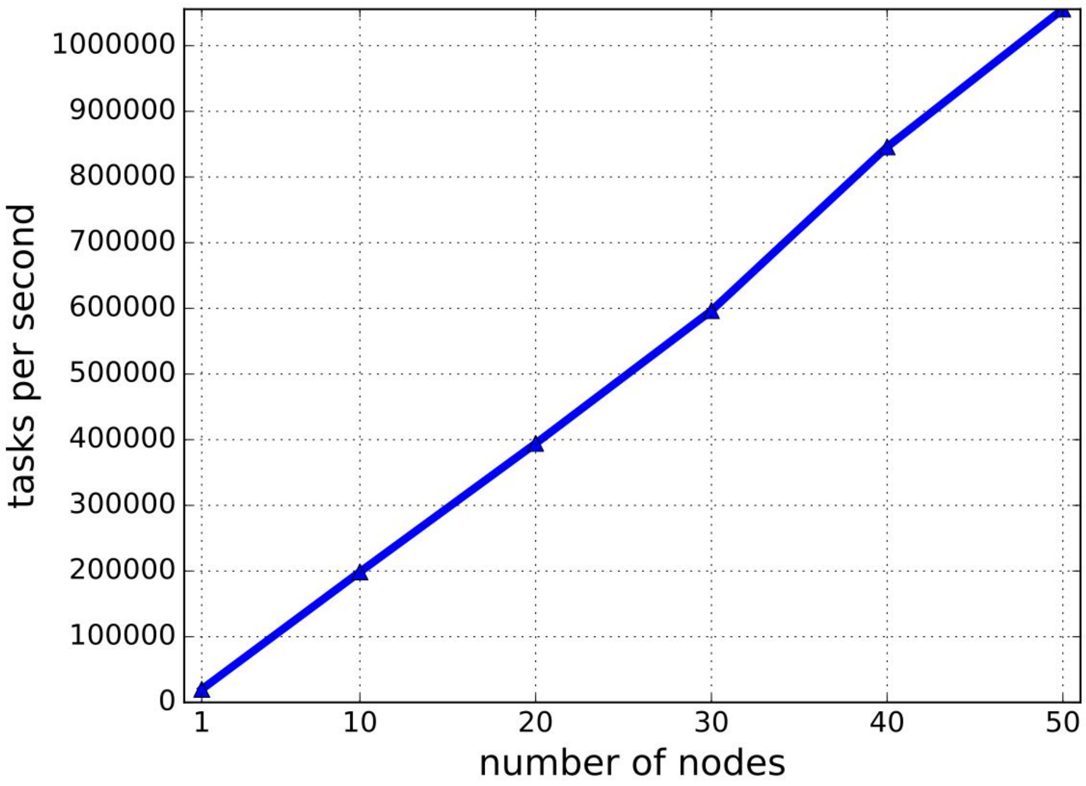
- State is shared between actor methods.
- Actor methods return **Object IDs**.
- Can specify **GPU** requirements

Ray Architecture

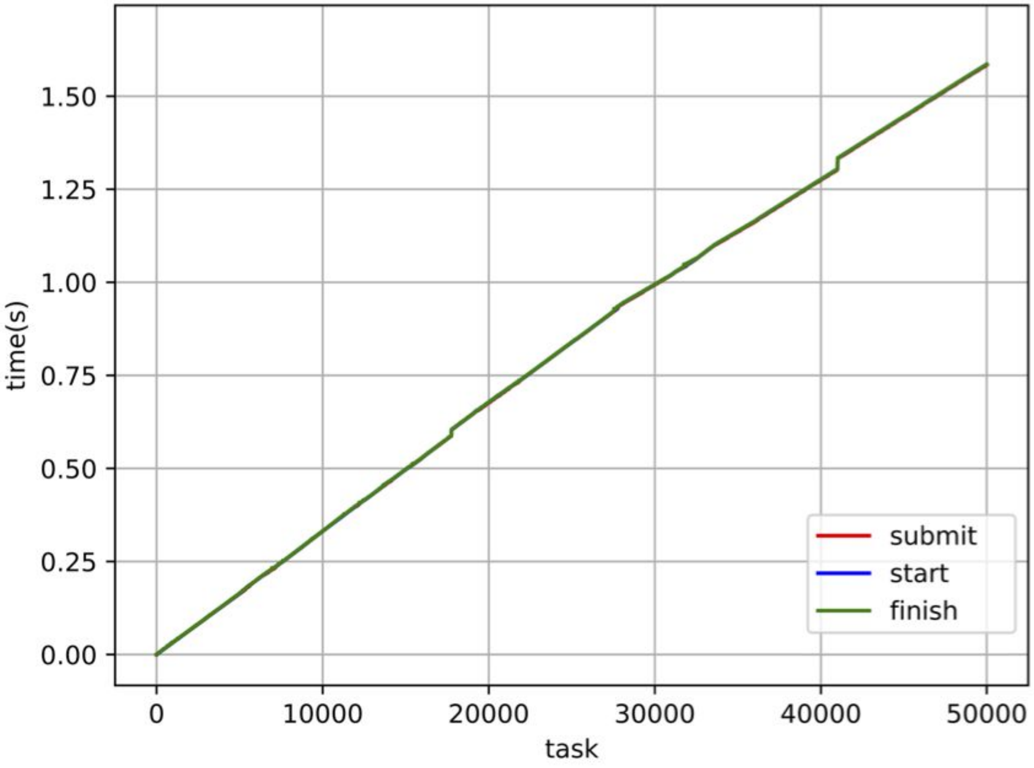
System Architecture



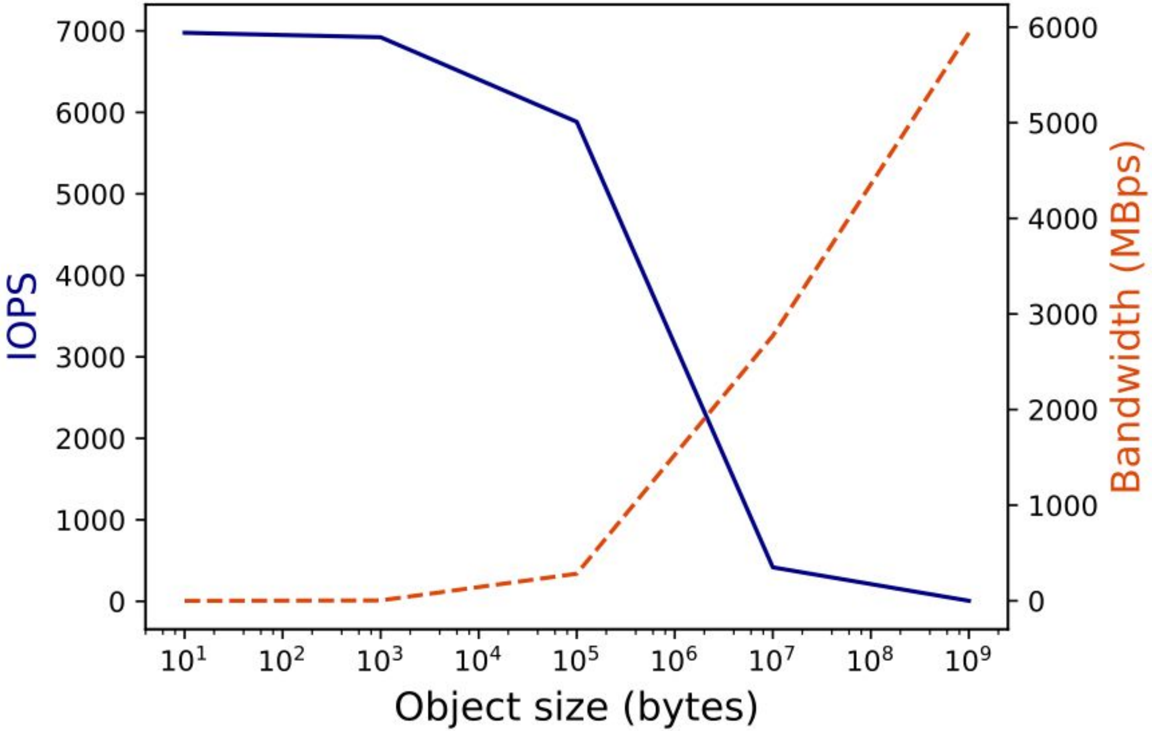
System throughput



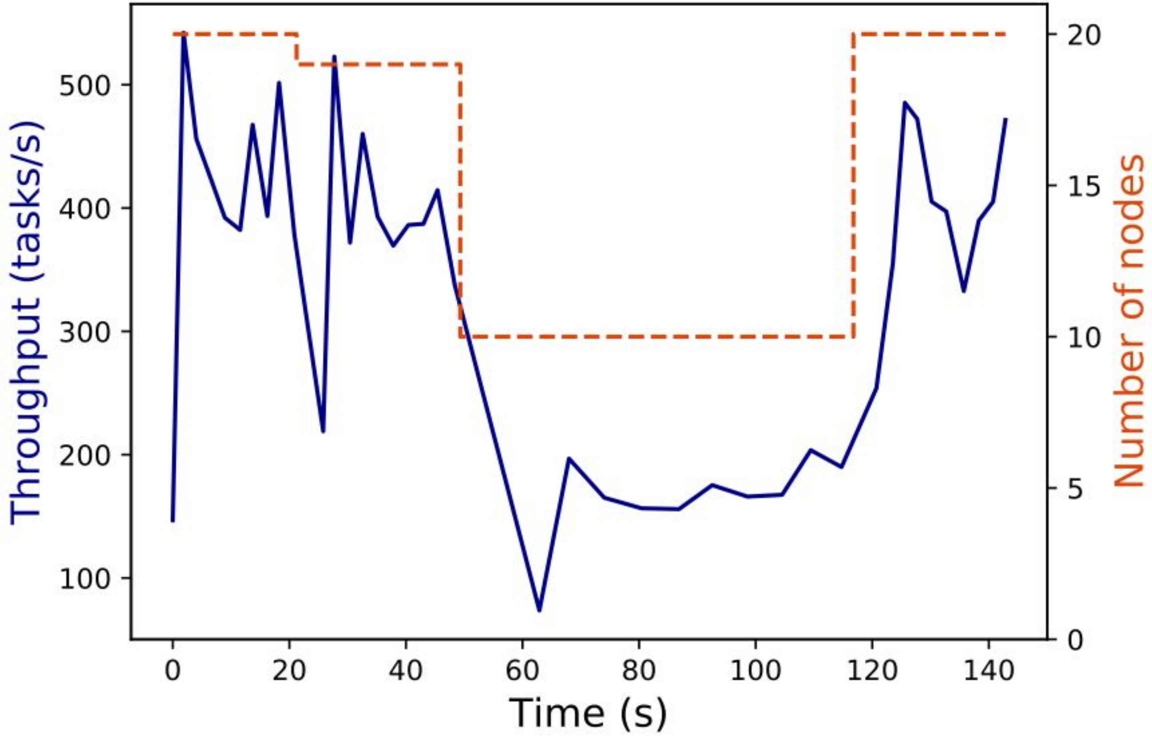
Single machine throughput



Object store performance

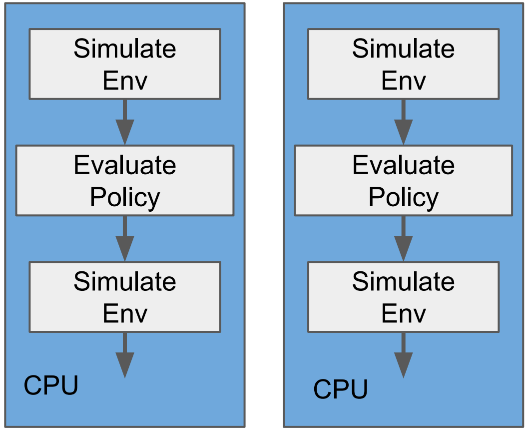


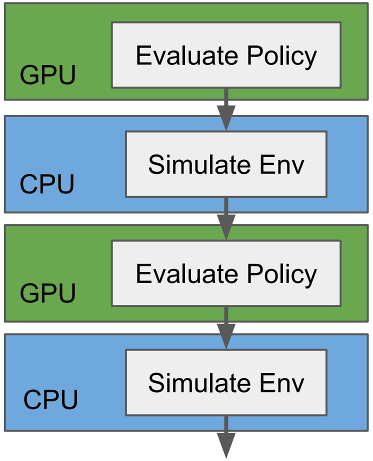
Robustness to node failure

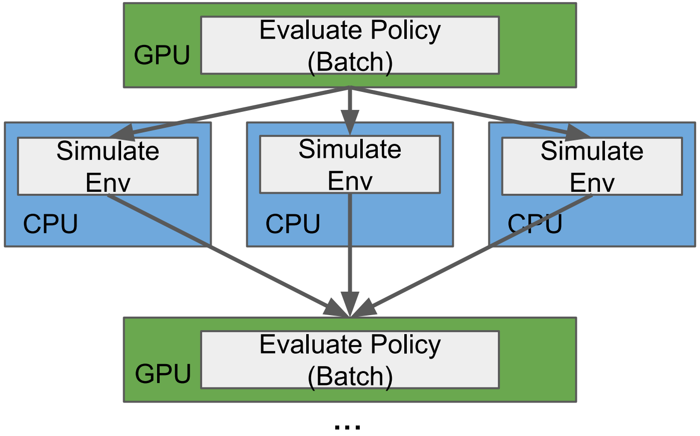


Experiments

Speeding up rollouts for policy gradients







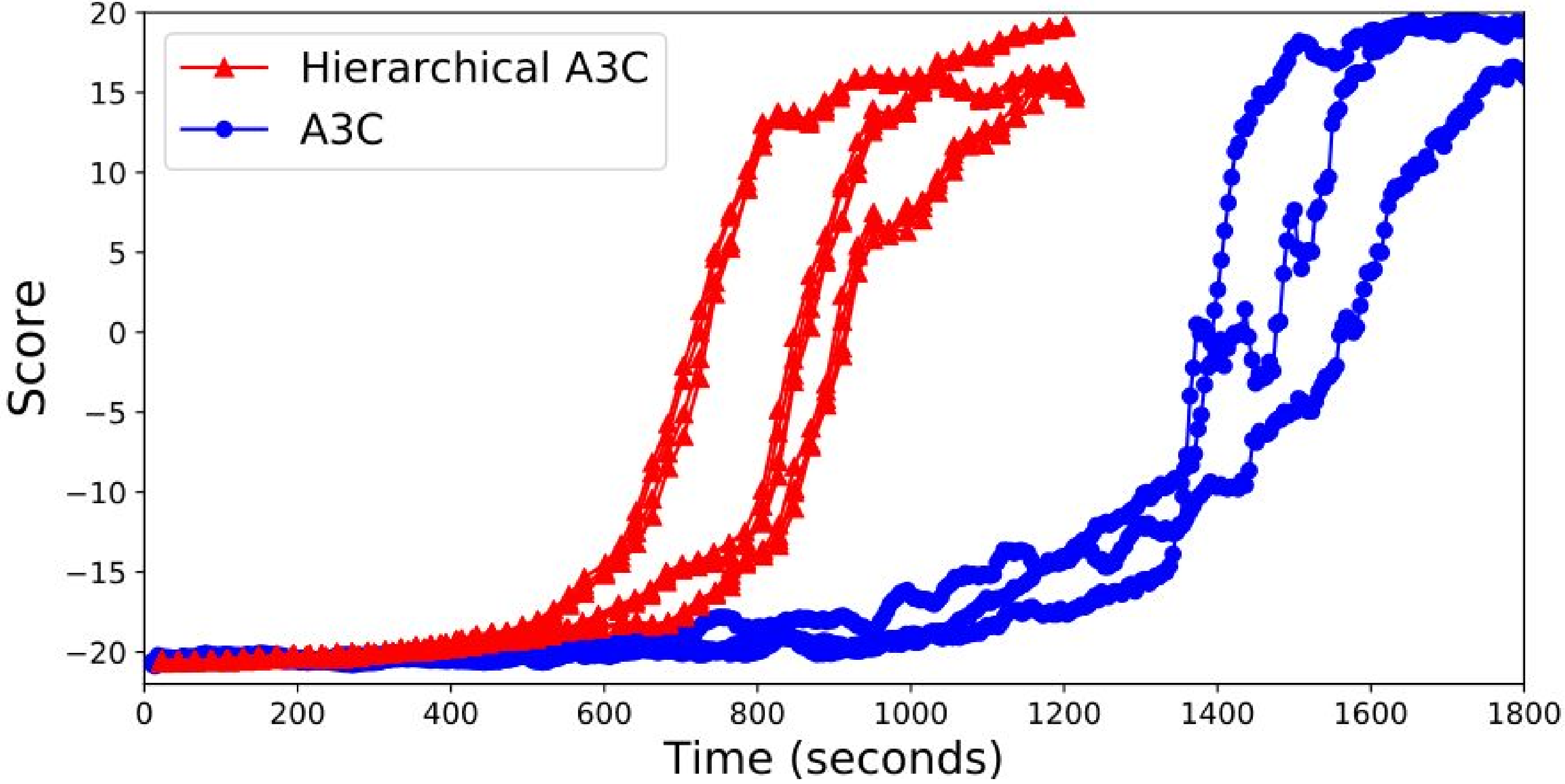
	Parallel Rollouts on CPU	**Policy Evaluation on GPU**	**Fine grained rollouts**
Speedup:	**1.0x**	**1.3x**	**4.1x**

Evolution strategies

	10 nodes	20 nodes	30 nodes	40 nodes	50 nodes
Reference	97K	215K	202K	N/A	N/A
Ray	152K	285K	323K	476K	571K

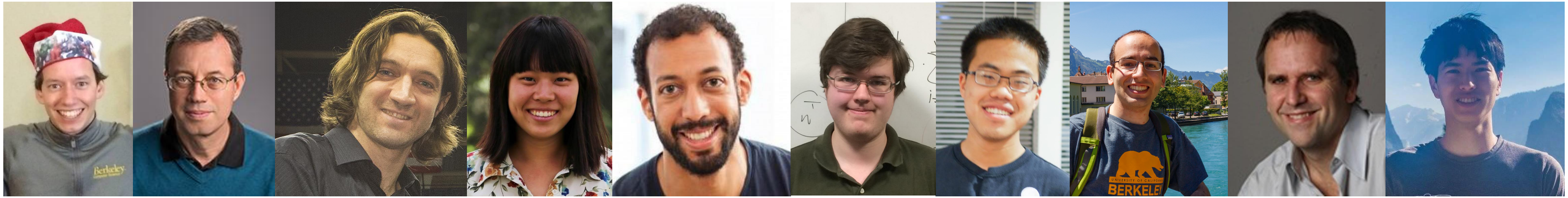
The Ray implementation takes half the amount of code and was implemented in a couple of hours

Hierarchical A3C



Ray is a system for AI Applications

- Ray is open source! https://github.com/ray-project/ray
- We have a pre-release!
- We'd love your feedback.



Philipp Ion Alexey Stephanie Johann William Richard Mehrdad Mike Robert