Ray API: Tasks & Actors

DS 5110/CS 5501: Big Data Systems

Spring 2024

Lecture 6a

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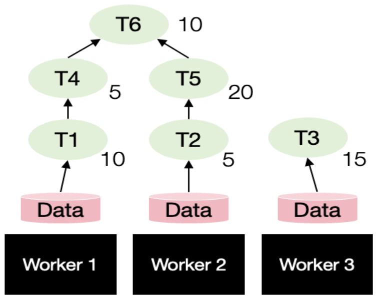
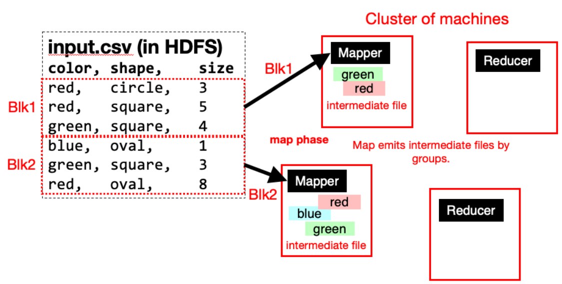
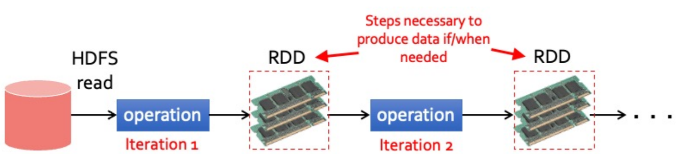
A recap of big data systems covered so far...



Dask: Exposes APIs that automatically parallelize Python analytics programs to a cluster of workers



MapReduce: Developers program Map and Reduce to implement batch processing applications



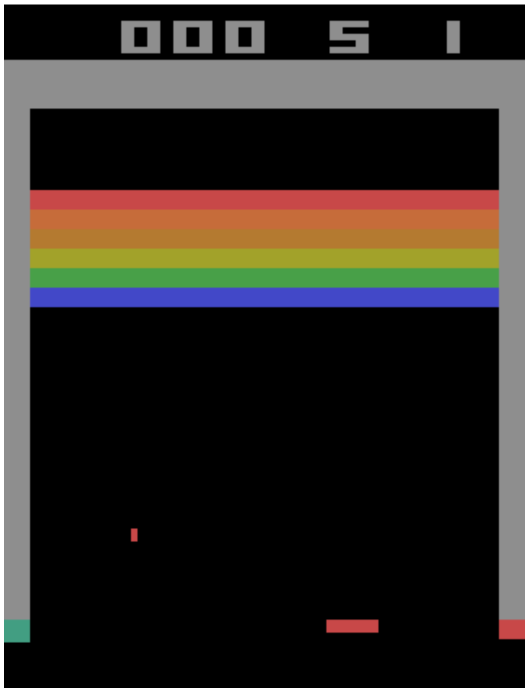
Spark: Based on MapReduce, but with extensive perf optimizations and a much richer set of programming APIs

Ray is different from all the others that we covered...

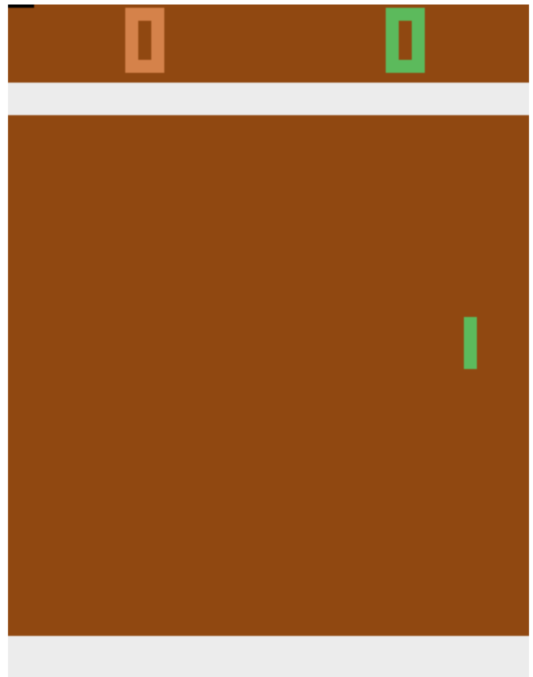
Learning objectives

- Know the unique requirements of RL applications and the motivation behind Ray
- Understand the difference of Ray tasks and actors

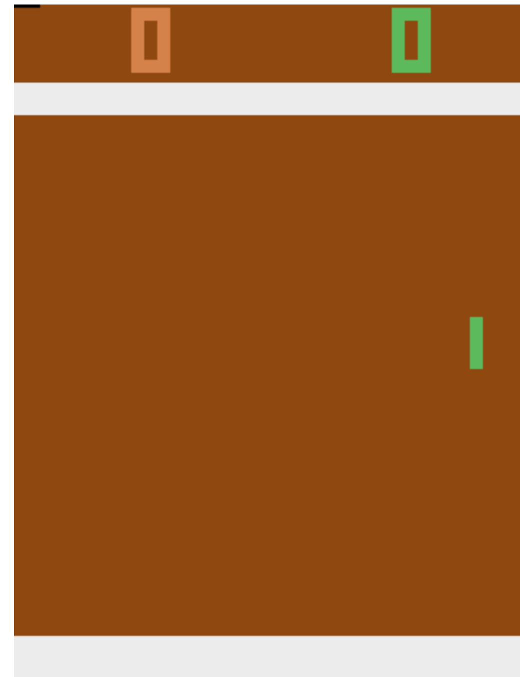
Motivation: Reinforcement learning



Atari breakout



Pong: after 30 mins of training



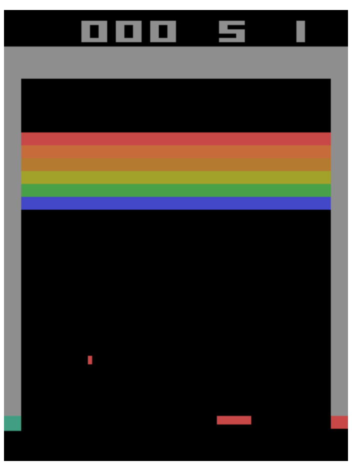
Pong: DQN wins like a boss

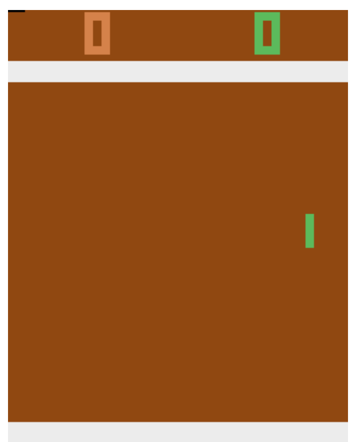
*: Playing Atari with Deep Reinforcement Learning: https://arxiv.org/abs/1312.5602

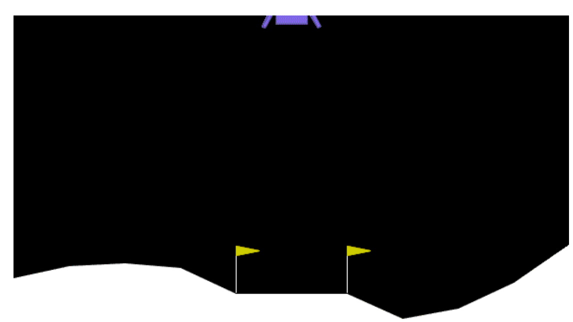
RL application pattern

- Process inputs from different sensors (sources) in parallel & real-time

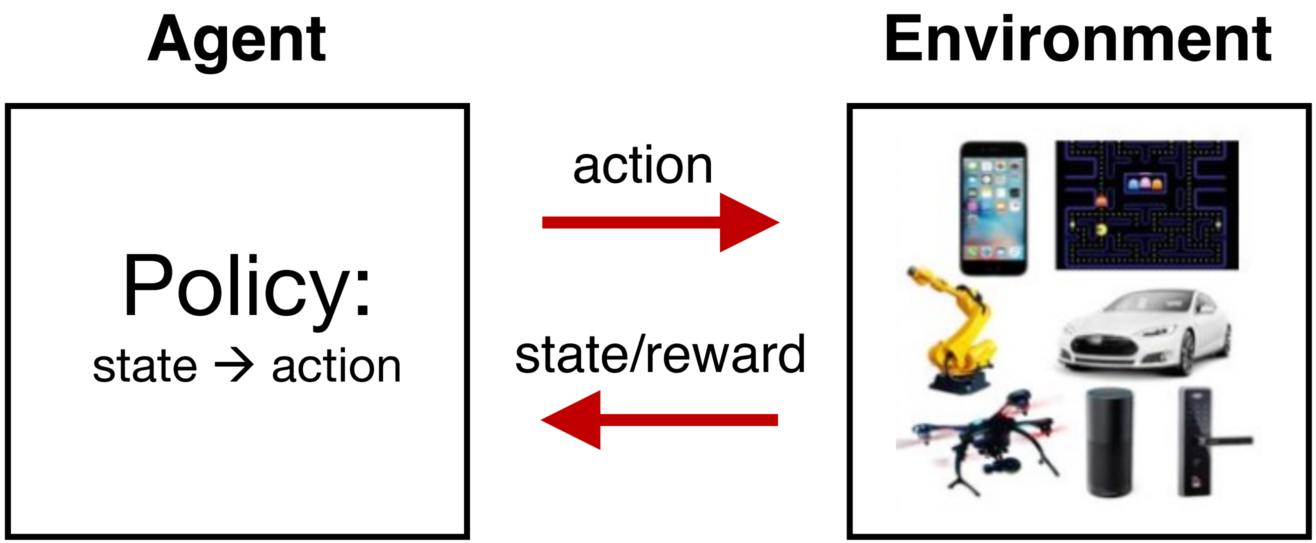
- Execute large number of simulations, e.g., up to 100s of millions



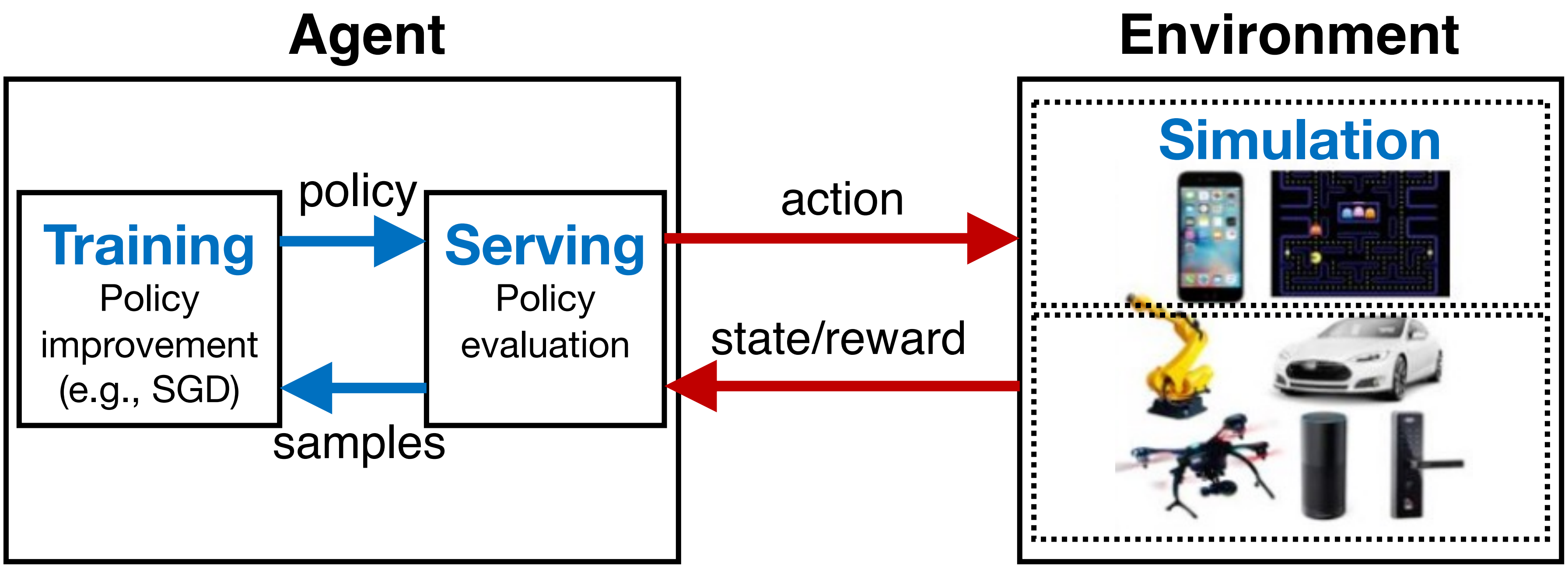




RL setup

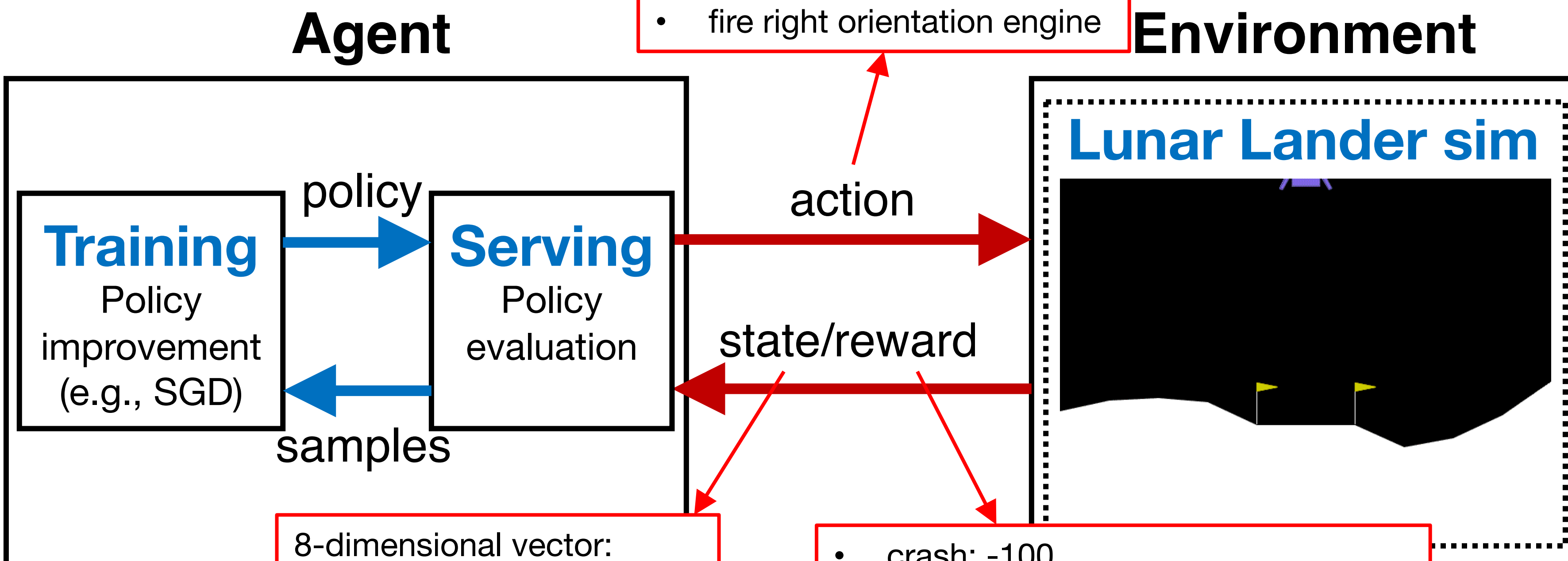

Agent
Environment
Policy:
state → action
action
state/reward

RL setup zoomed in



RL setup zoomed in (Lunar Lander)

- do nothing
- fire left orientation engine
- fire main engine
- fire right orientation engine

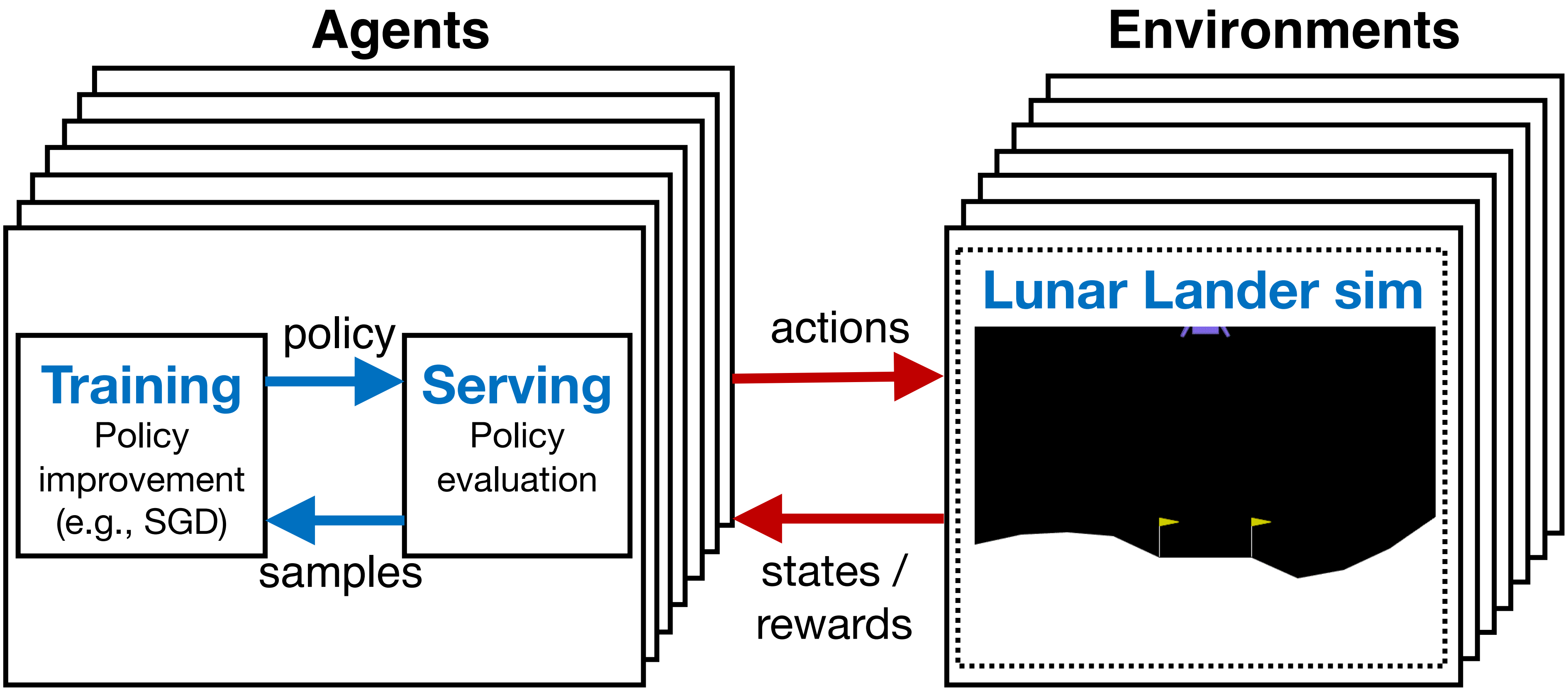


8-dimensional vector:
- coordinates
- linear velocities
- angle
- whether each leg is in contact with ground

- crash: -100
- coming to rest: +100
- each leg with ground contact: +10
- …

*: https://www.gymlibrary.dev/environments/box2d/lunar_lander/

Scaling out the RL setup



RL application pattern

- Process inputs from different sensors (sources) in parallel & real-time
- Execute large number of simulations, e.g., up to 100s of millions
- Simulation outcomes are used to update policy (e.g., SGD/Adam)

RL application requirements

- Need to handle dynamic task graphs, where tasks have:
  - heterogeneous durations (secs to minutes)
  - heterogeneous computations (CPUs vs. GPUs)

- Need to schedule millions of tasks / sec

- Need to make it easy to parallelize ML algorithms (in Python)

Today's AI/ML data system landscape

Distributed systems	Distributed systems	Distributed systems	Distributed systems
Data processing	Model training	Model tuning	Model serving
Spark, Hadoop, Dask, Modin, …	PyTorch, TensorFlow, scikit-learn, …	Optuna, Hyperopt, SigOpt, MLflow, …	FastAPI, Arize, Alibi, Gradio, …

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Emerging AI applications require **stitching** together **multiple** disparate systems

Ad hoc integrations are difficult to manage and program!

Ray ecosystem offers a unified solution

Distributed systems

Data processing

Spark, Hadoop, Dask, Modin, …

Distributed systems

Model training

PyTorch, TensorFlow, scikit-learn, …

Distributed systems

Model tuning

Optuna, Hyperopt, SigOpt, MLflow, …

Distributed systems

Model serving

FastAPI, Arize, Alibi, Gradio, …

Ray AI Runtime (AIR)

Data processing
Ray Dataset

Model training
Ray Training
Ray RLlib

Model tuning
Ray Tune

Model serving
Ray Serve

Ray Core
(remote tasks, actors, scheduling, data sharing, etc.)

Example: Retrieving a data item

```
database = [
  “learning”,
  “Ray”,
  “for”,
  “distributed”,
  “data”,
  “processing”
]
```

```
def retrieve(item_idx):
    time.sleep(item_idx / 10.)
    return item_idx, database[item_idx]
```

```
data = [retrieve(idx) for idx in range(6)]
```

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```
0
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```

```
0, “learning”
```

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1

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1, "Ray"

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```
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    time.sleep(item_idx / 10.)
    return item_idx, database[item_idx]
```

```
              5
data = [retrieve(idx) for idx in range(6)]
```

```
5, “processing”
```

Expect a runtime of around (0+1+2+3+4+5)/10 = 1.5 seconds

Ray API: Remote Ray tasks

```
database = [
  “learning”,
  “Ray”,
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  “distributed”,
  “data”,
  “processing”
]
```

Ray task decorator

```
def retrieve(item_idx):
    time.sleep(item_idx / 10.)
    return item_idx, database[item_idx]

@ray.remote
def retrieve_task(item_idx):
    return retrieve(item_idx)
```

```
obj_refs = [
      retrieve_task.remote(idx) for idx in range(6)
]
data = ray.get(obj_refs)
```

Ray tasks are **decorated Python functions** that can execute **remotely**.

`task.remote()` executes a task remotely asynchronously and immediately returns a `future` (i.e., an object reference, which you need to explicitly ask the result of).

`ray.get(ObjRef)` fetches the computed result of a remote task referenced by `ObjRef`.

Ray API: Remote Ray tasks

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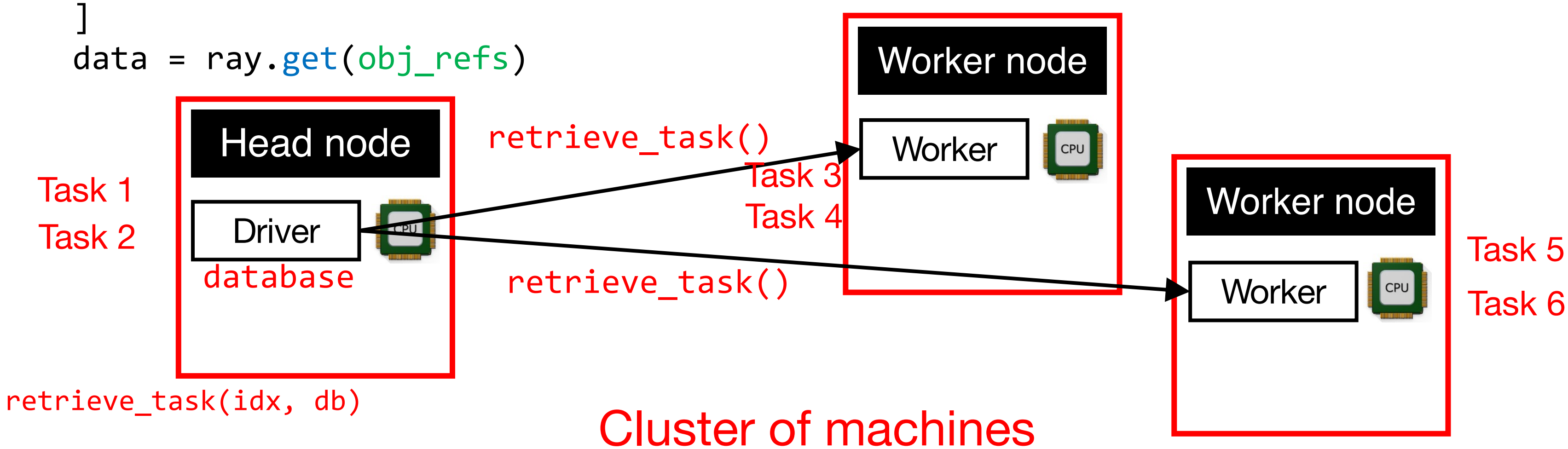

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]
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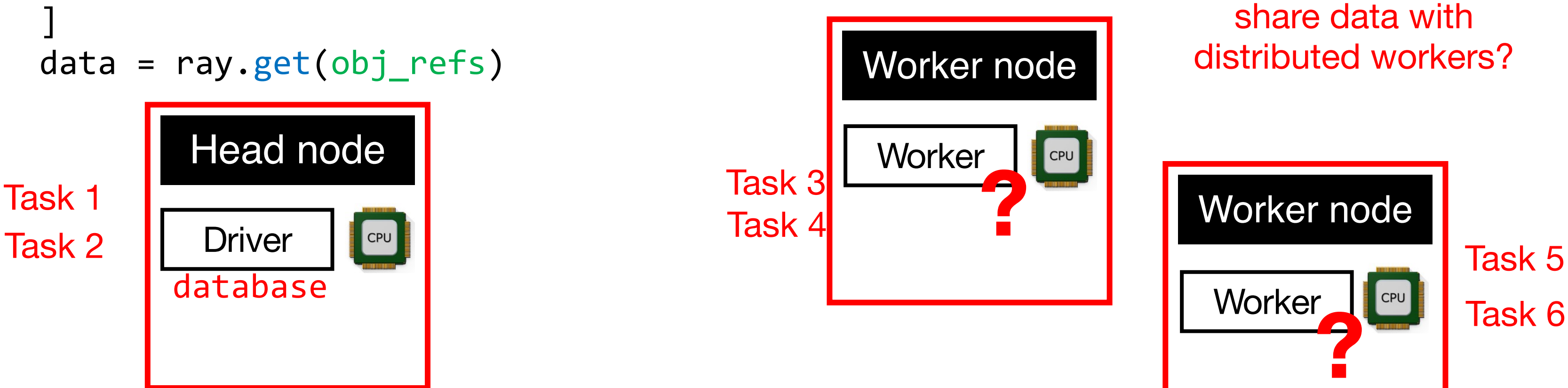
```

Q: How would driver share data with distributed workers?



Cluster of machines

Ray API: Distributed object store

```
database = [
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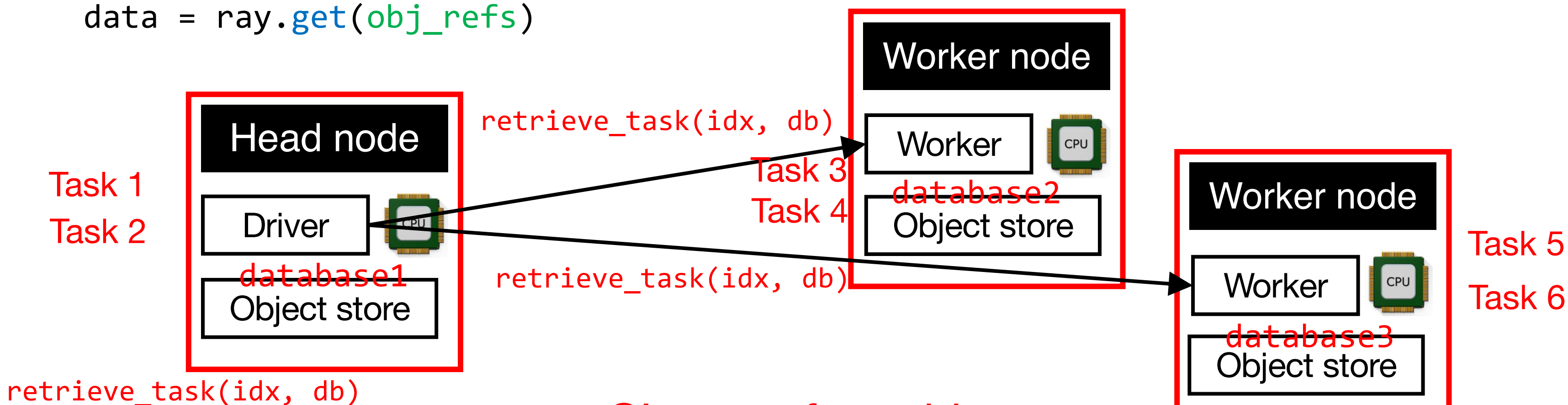
  “for”,
  “distributed”,
  “data”,
  “processing”
]
```

```
@ray.remote
def retrieve_task(item_idx, db):
    time.sleep(item_idx / 10.)
    return item_idx, db[item_idx]
```

Use distributed object store to share data across all workers in the cluster

```
db_obj_ref = ray.put(database)
obj_refs = [retrieve_task.remote(idx, db_obj_ref) for idx in range(6)]
data = ray.get(obj_refs)
```



Cluster of machines

Ray API: Actors

Ray actor class definition

```
@ray.remote
class DataTracker:
    def __init__(self):
        self._counts = 0
    def increment(self):
        self._counts += 1
    def counts(self):
        return self._counts
```

```
database = [
  “learning”,
  “Ray”,
  “for”,
  “distributed”,
  “data”,
  “processing”
]
```

Ray task definition

```
@ray.remote
def retrieve_task_n_track(item_idx, tracker, db):
    time.sleep(item_idx / 10.)
    tracker.increment.remote()
    return item_idx, db[item_idx]
```

Invoke remote actor

```
tracker = DataTracker.remote()
obj_refs = [
       retrieve_task_n_track.remote(idx, tracker, db_obj_ref) for idx in range(6)
]
data = ray.get(obj_refs)
print(ray.get(tracker.counts.remote()))
```

Invoke remote tasks

Ray tasks are decorated Python functions.

Ray actors are decorated Python classes, which encapsulate state.

Actors allows you to run stateful computations on a cluster.

Demo ...