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# 人工智能系统 System for AI

# 强化学习系统
System for Reinforcement Learning

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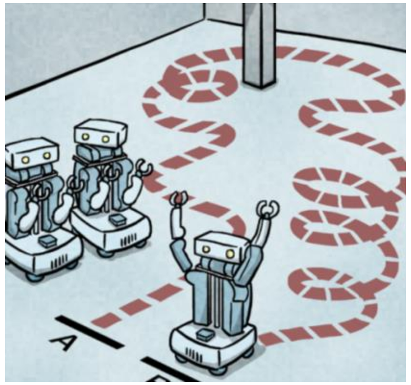
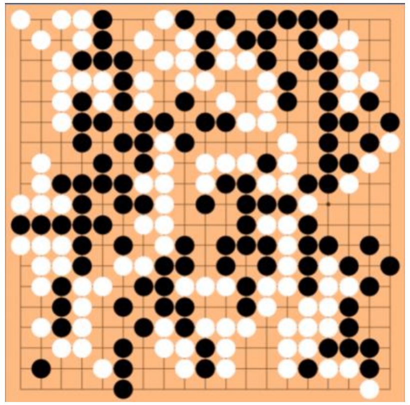
# 真实世界的问题: 在不确定的情况下做正确的序列选择

路径规划

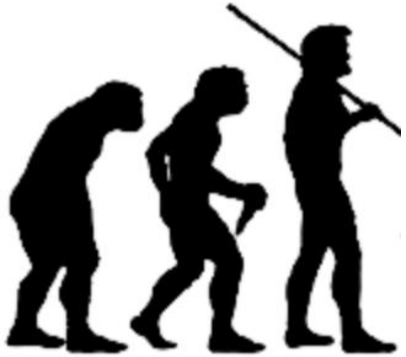



驾驶

打游戏



人类的进化



…

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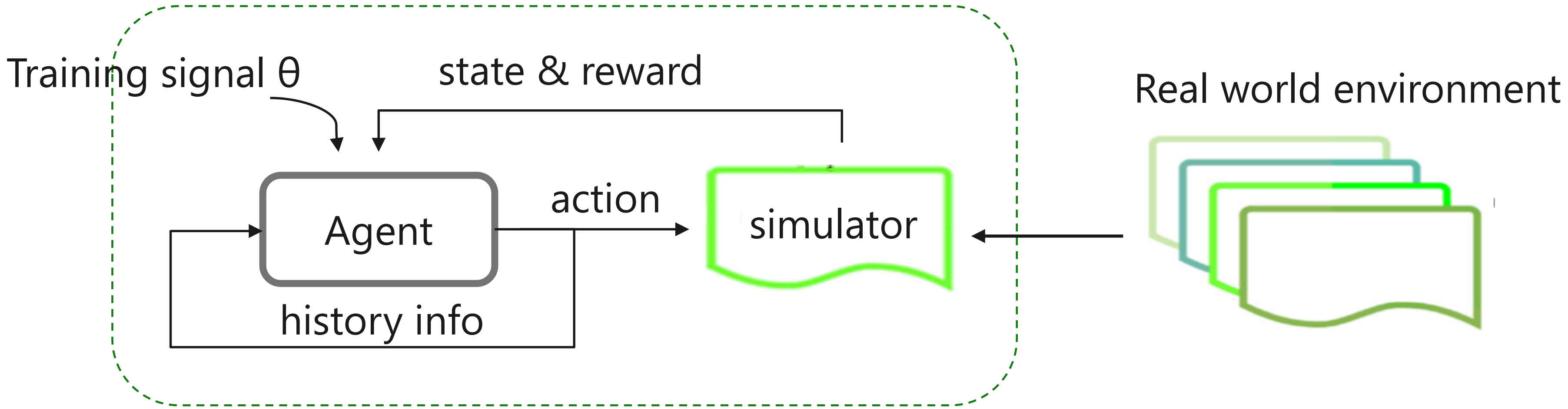
# 强化学习




- *Explore the world (**explore**)*
- *Use experience to guide future decisions (**exploit**)*

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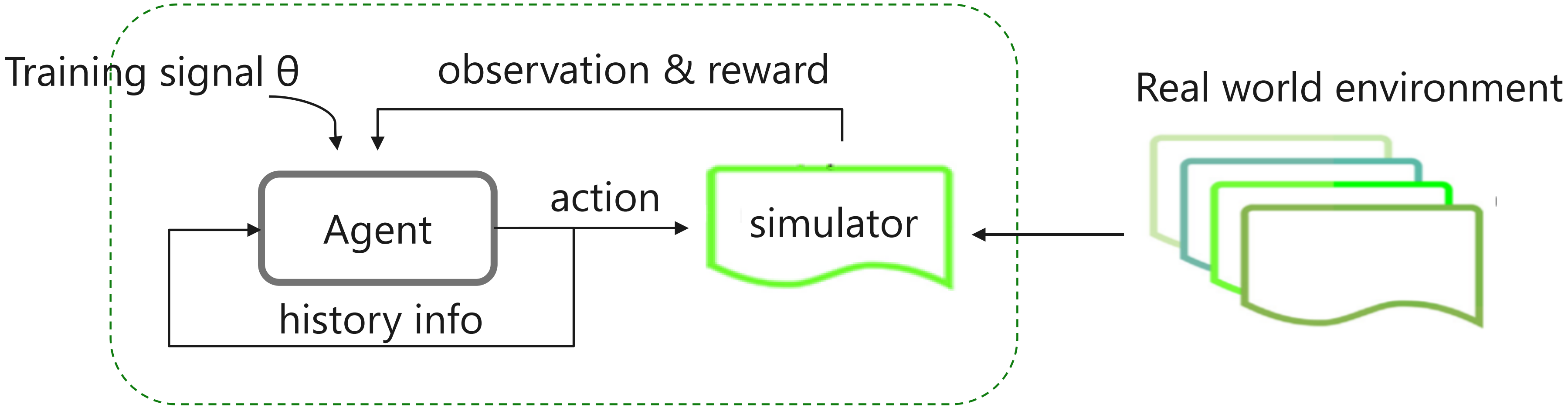
# 强化学习




- Each time step t
  - *Agent takes an **action** $a_t$*
  - *World updates given **action** at , emits **observation** $o_t$ and **reward** $r_t$*
  - *Agent receives **observation** $o_t$ and **reward** $r_t$*

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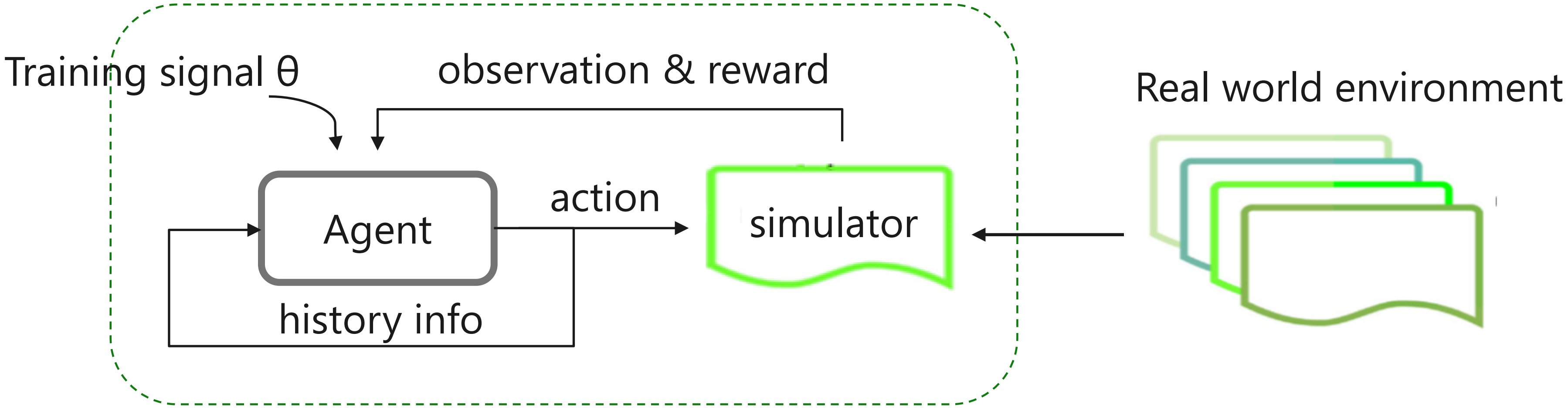
# 强化学习




- ***History*** $h_t = (a_1, o_1, r_1, \ldots, a_t, o_t, r_t)$
- ***Agent*** *chooses action based on history*
- ***State*** *is information assumed to determine what happens next*
  - *Function of history* $s_t = (h_t)$
  - *State* $s_t$ *is* ***Markov*** *if and only if* $p(s_{t+1} \mid s_t, a_t) = p(s_{t+1} \mid h_t, a_t)$
  - *Future is independent of past given present*

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# 强化学习

- **Goal** select actions to maximize total expected future reward
  - *balancing immediate & long-term rewards*

- **Policy** π determines how the agent chooses actions
  - *Deterministic policy*

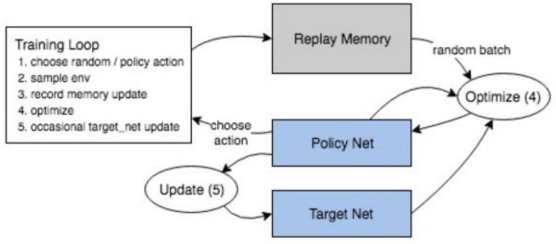
$$\pi(s) = a$$

  - *Stochastic policy*

$$\pi(a|s) = Pr(a_t = a|s_t = s)$$

- **Value function** expected discounted sum of future rewards under a policy π

$$V^{\pi}(s_t = s) = \mathbb{E}_{\pi}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots | s_t = s]$$




# 单机异步的DQN的例子

initialize env

initialize policy

*training loop*

Rollout data

Update policy

```python
def cartpole():
    env = gym.make(ENV_NAME)
    score_logger = ScoreLogger(ENV_NAME)
    observation_space = env.observation_space.shape[0]
    action_space = env.action_space.n
    dqn_solver = DQNSolver(observation_space, action_space)
    run = 0
    while True:
        run += 1
        state = env.reset()
        state = np.reshape(state, [1, observation_space])
        step = 0
        while True:
            step += 1
            #env.render()
            action = dqn_solver.act(state)
            state_next, reward, terminal, info = env.step(action)
            reward = reward if not terminal else -reward
            state_next = np.reshape(state_next, [1, observation_space])
            dqn_solver.remember(state, action, reward, state_next, terminal)
            state = state_next
            if terminal:
                print "Run: " + str(run) + ", exploration: " + str(dqn_solver.exploration_rate) + ", score: " + str(step)
                score_logger.add_score(step, run)
                break
            dqn_solver.experience_replay()
```

Policy model

Policy inference

Policy update

```python
class DQNSolver:

    def __init__(self, observation_space, action_space):
        self.exploration_rate = EXPLORATION_MAX

        self.action_space = action_space
        self.memory = deque(maxlen=MEMORY_SIZE)

        self.model = Sequential()
        self.model.add(Dense(24, input_shape=(observation_space,), activation="relu"))
        self.model.add(Dense(24, activation="relu"))
        self.model.add(Dense(self.action_space, activation="linear"))
        self.model.compile(loss="mse", optimizer=Adam(lr=LEARNING_RATE))

    def remember(self, state, action, reward, next_state, done):
        self.memory.append((state, action, reward, next_state, done))

    def act(self, state):
        if np.random.rand() < self.exploration_rate:
            return random.randrange(self.action_space)
        q_values = self.model.predict(state)
        return np.argmax(q_values[0])

    def experience_replay(self):
        if len(self.memory) < BATCH_SIZE:
            return
        batch = random.sample(self.memory, BATCH_SIZE)
        for state, action, reward, state_next, terminal in batch:
            q_update = reward
            if not terminal:
                q_update = (reward + GAMMA * np.amax(self.model.predict(state_next)[0]))
            q_values = self.model.predict(state)
            q_values[0][action] = q_update
            self.model.fit(state, q_values, verbose=0)
        self.exploration_rate *= EXPLORATION_DECAY
        self.exploration_rate = max(EXPLORATION_MIN, self.exploration_rate)
```

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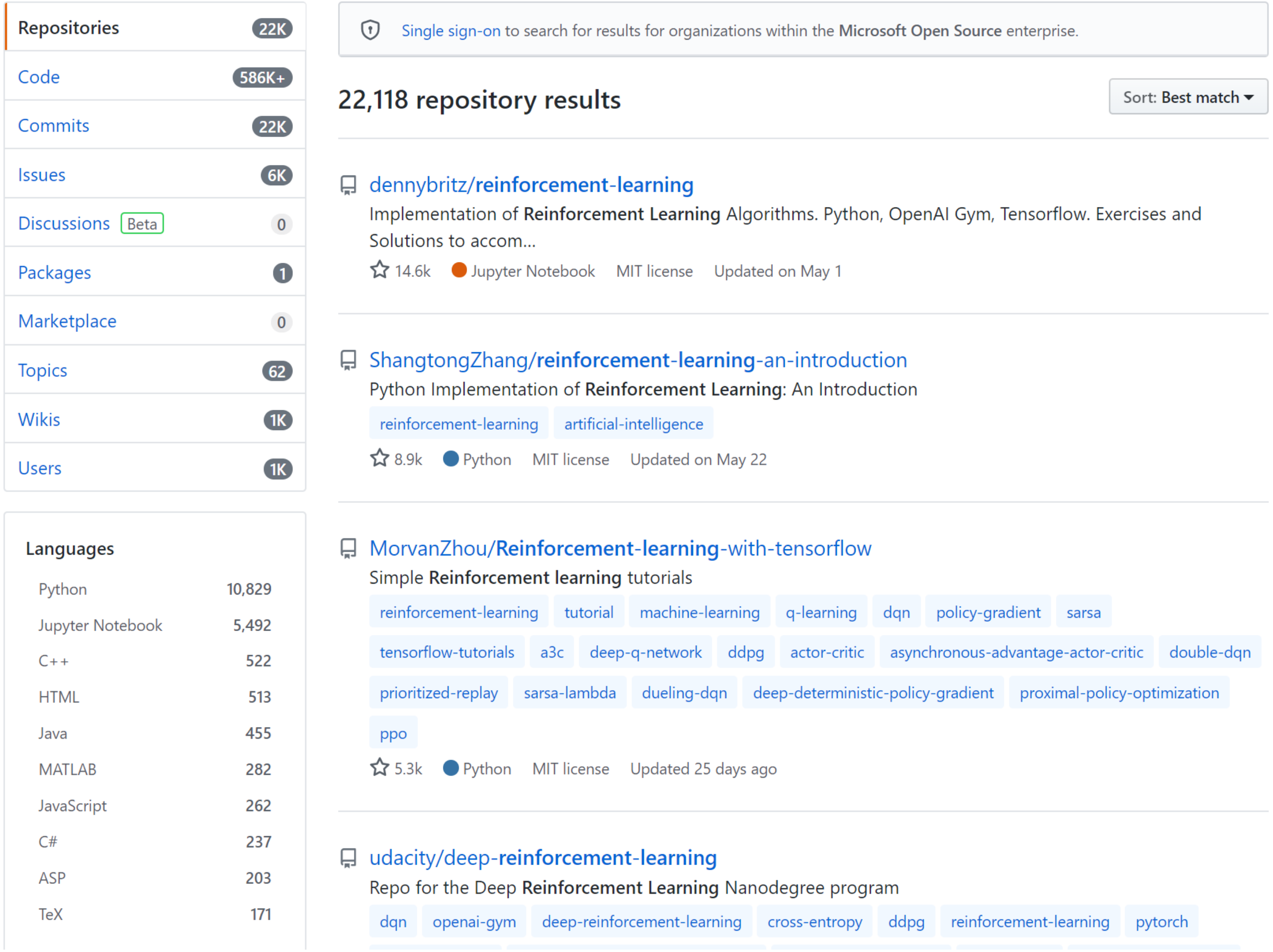
强化学习和机器学习有什么差别?

强化学习系统面临什么和机器学习系统不一样的挑战?

# 大量难以复用的强化学习代码库



# 为什么不能复用这些存在的代码库呢？

# 算法上的一点差别可能会极大影响结果

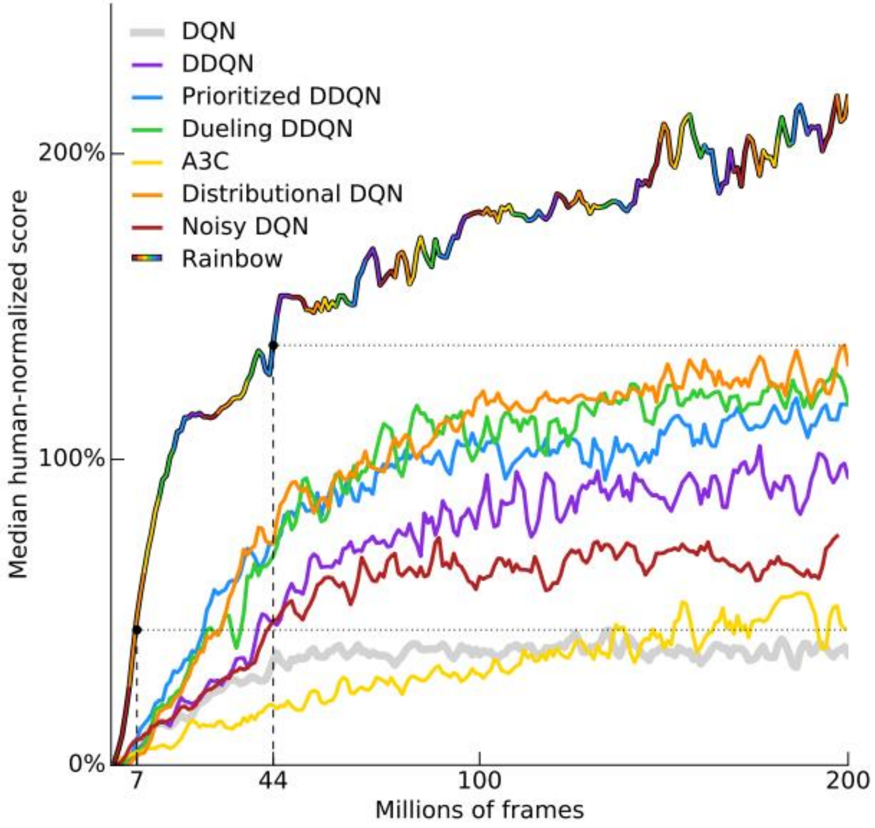
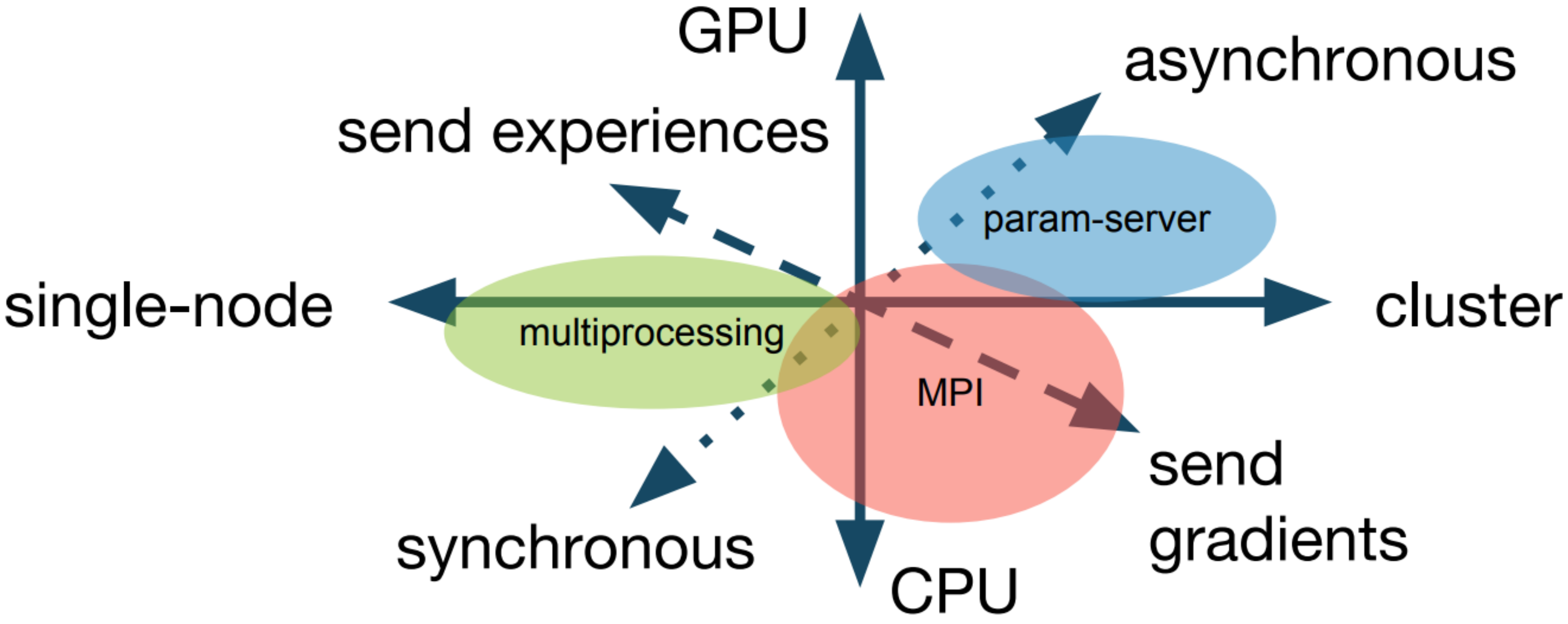



*Figure 2. 6 tricks in DQN will performs different performance from rainbow paper.*

# 强化学习的执行策略多种多样，底层可使用的通信框架各式各样



# 不同的强化学习算法结构差异很大

| Algorithm Family | Policy Evaluation | Replay Buffer | Gradient-Based Optimizer | Other Distributed Components |
|---|---|---|---|---|
| DQNs | X | X | X | |
| Policy Gradient | X | | X | |
| Off-policy PG | X | X | X | |
| Model-Based/Hybrid | X | | X | Model-Based Planning |
| Multi-Agent | X | X | X | |
| Evolutionary Methods | X | | | Derivative-Free Optimization |
| AlphaGo | X | X | X | MCTS, Derivative-Free Optimization |

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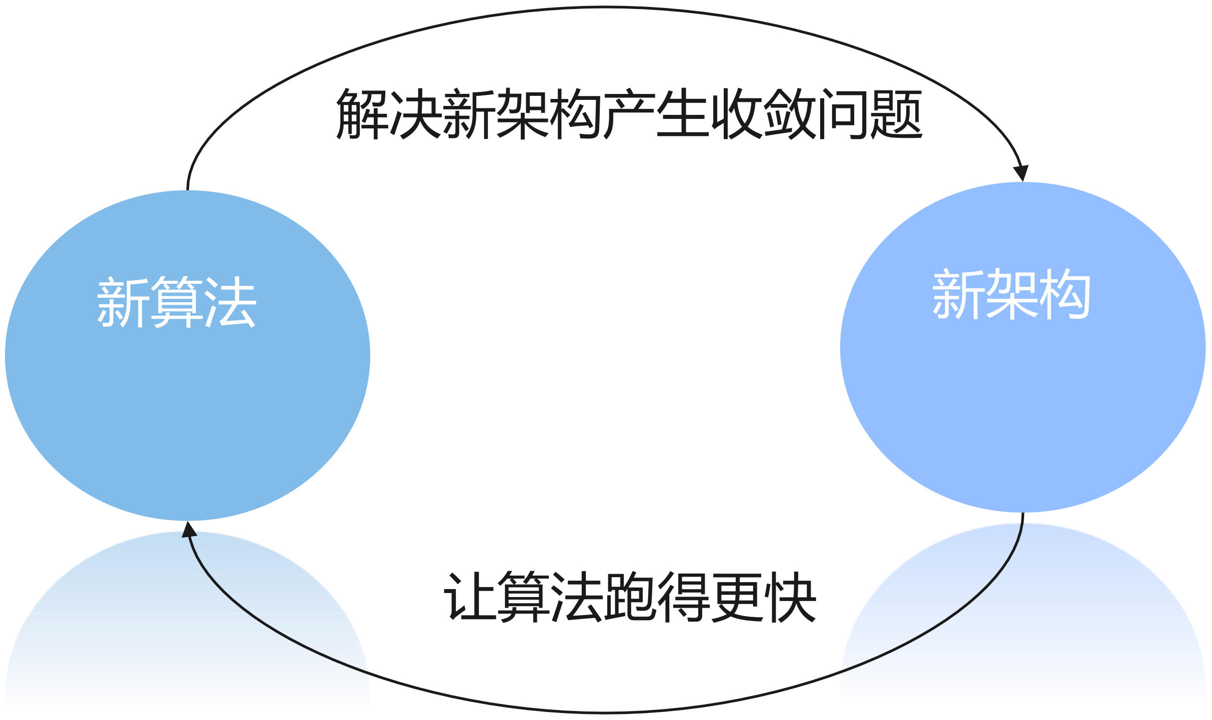
# 强化学习算法和分布式架构互相影响



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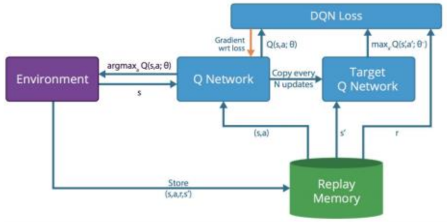
# 强化学习算法和分布式架构互相影响

2013 — 2015 — 2016 — 2018 — 2018 — ?

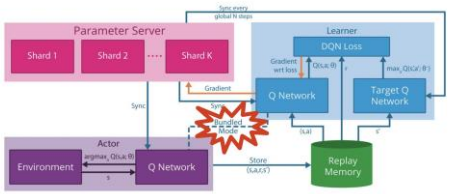
**DQN**

Playing Atari with Deep Reinforcement Learning (Mnih 2013)



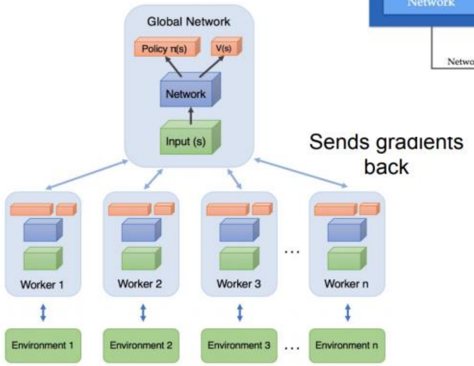

**GORILA**

Massively Parallel Methods for Deep Reinforcement Learning (Nair 2015)



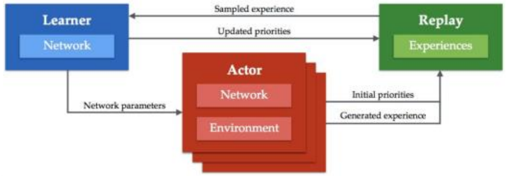

**A3C**

Asynchronous Methods for Deep Reinforcement Learning (Mnih 2016)



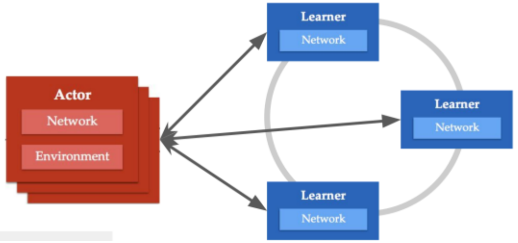

**Ape-X**

Distributed Prioritized Experience Replay (Horgan 2018)




**IMPALA**

IMPALA: Scalable Distributed Deep-RL with Importance Weighted Actor-Learner Architectures (Espeholt 2018)



# 小结

大量难以复用的强化学习代码

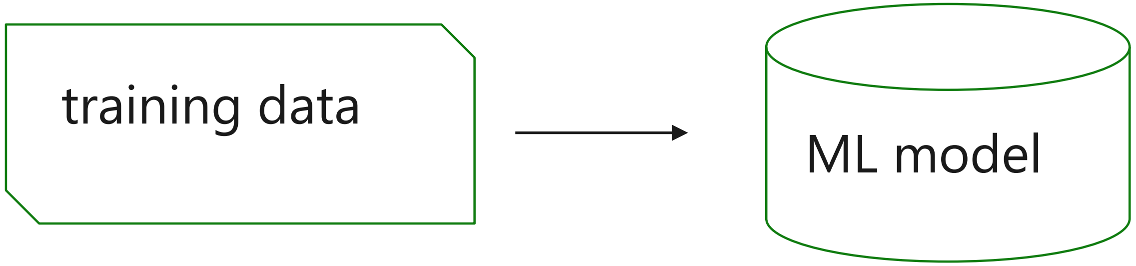
↓

可扩展性的强化学习框架

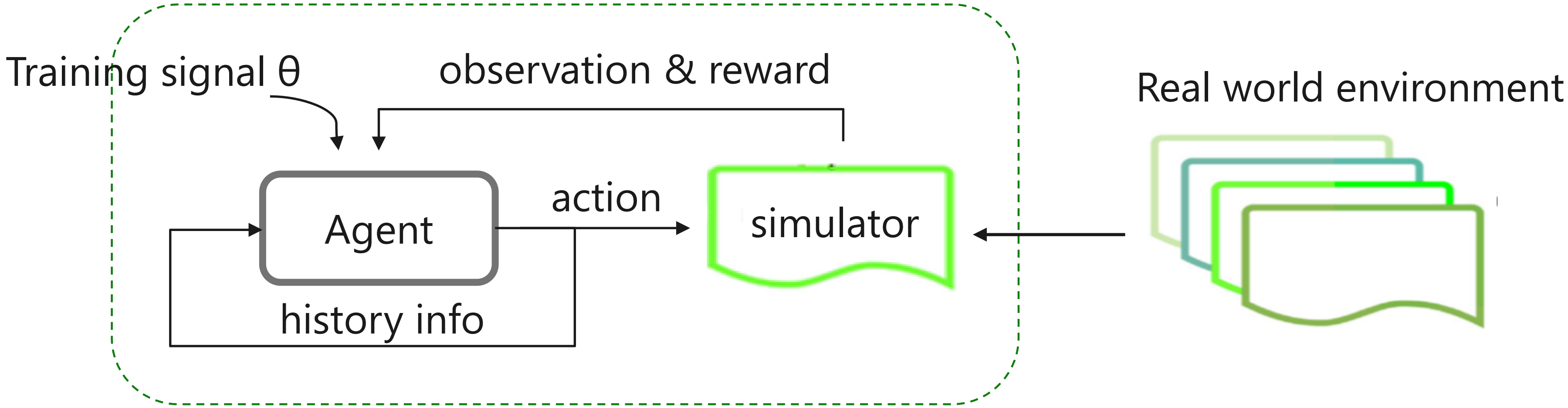
- 具有良好的强化学习算法的抽象接口
- 可以跨深度学习平台使用（e.g. tensorflow/pytorch）
- 可以支持各种物理执行模式（e.g. GPU/CPU vs Sync/Async）
- 支持不同的分布式架构

# 强化学习需要实时采集数据

一般的机器学习




强化学习
- 循环地采集数据去学习
- 可以自己决定采集什么数据



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# 采集数据的效率是收敛的关键！

可能面临的问题

- 和环境交互的效率低下，环境返回的结果时间较长
- 分布式rollout数据可行，但代码难写

↓

- 支持复杂环境的并发采集
- 提供简单的分布式代码的编程方式

# Apex框架让worker分布式地rollout data

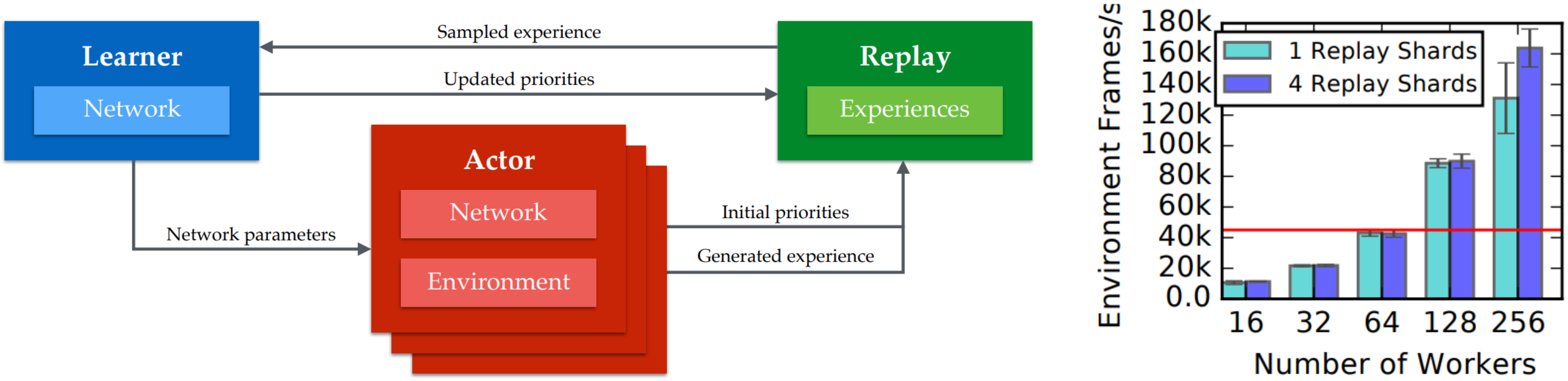


*Figure1. Apex architecture, multiply actors to rollout data in their own environment.*

# 强化学习训练需要切换context

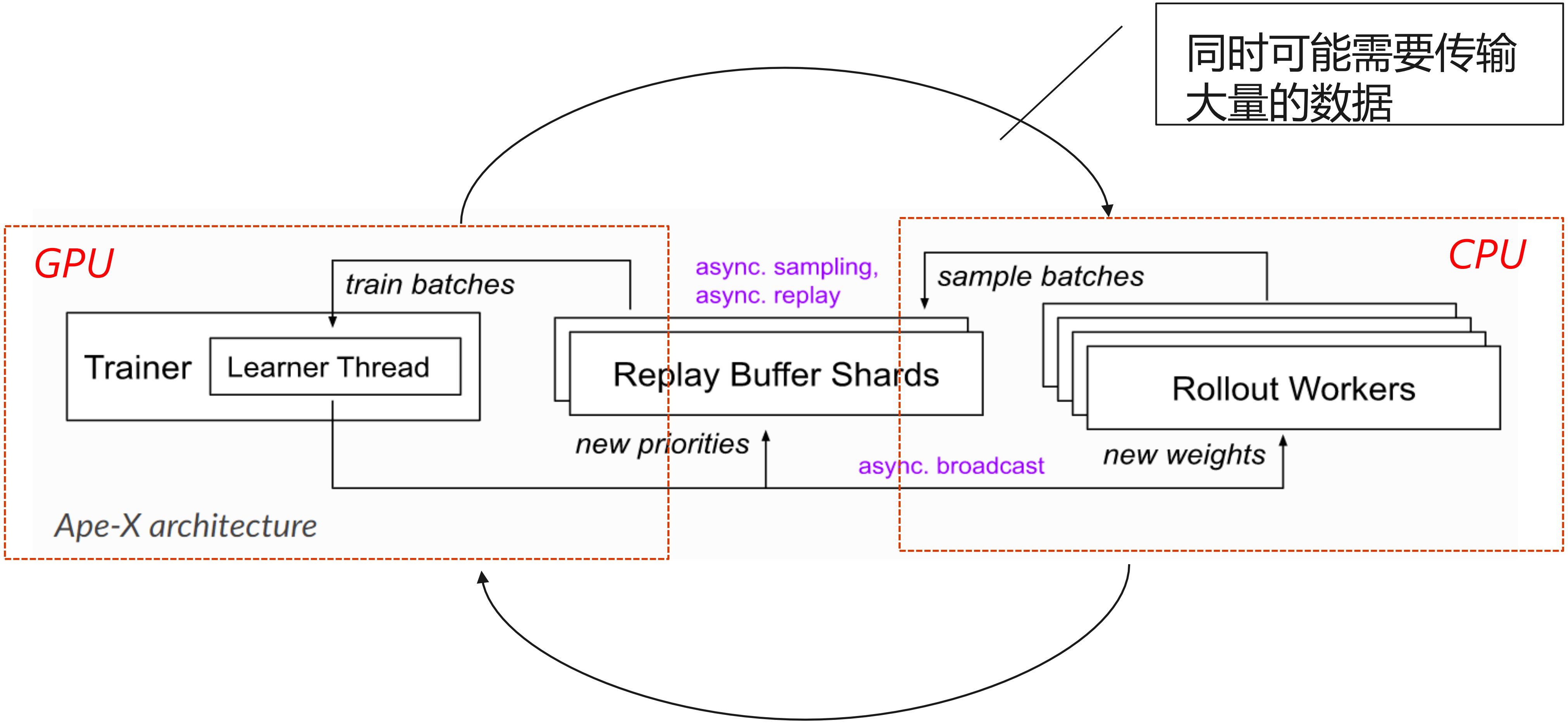


*Figure 3. Context switch in Apex architecture*

# 强化学习训练需要切换context

- 需要在不同的context（GPU/CPU）间不停的切换
- 同时需要传输大量的数据

↓

- 支持高性能的通信框架
- 优化数据的预处理
- 优化数据的传输

# 当前的强化学习平台

此照片，作者:

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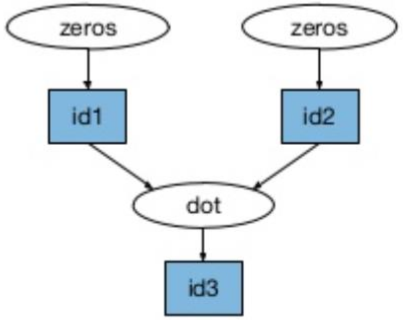
# 案例研究: Ray and RLlib

**Ray** is a **fast** and **simple** framework for building and running **distributed applications**.

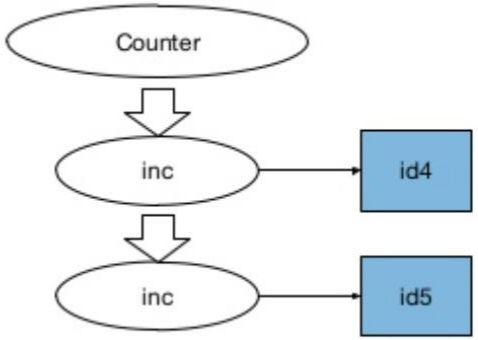
- *Ray provide a task parallel API*

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

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

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




- *Ray provide an actor API*

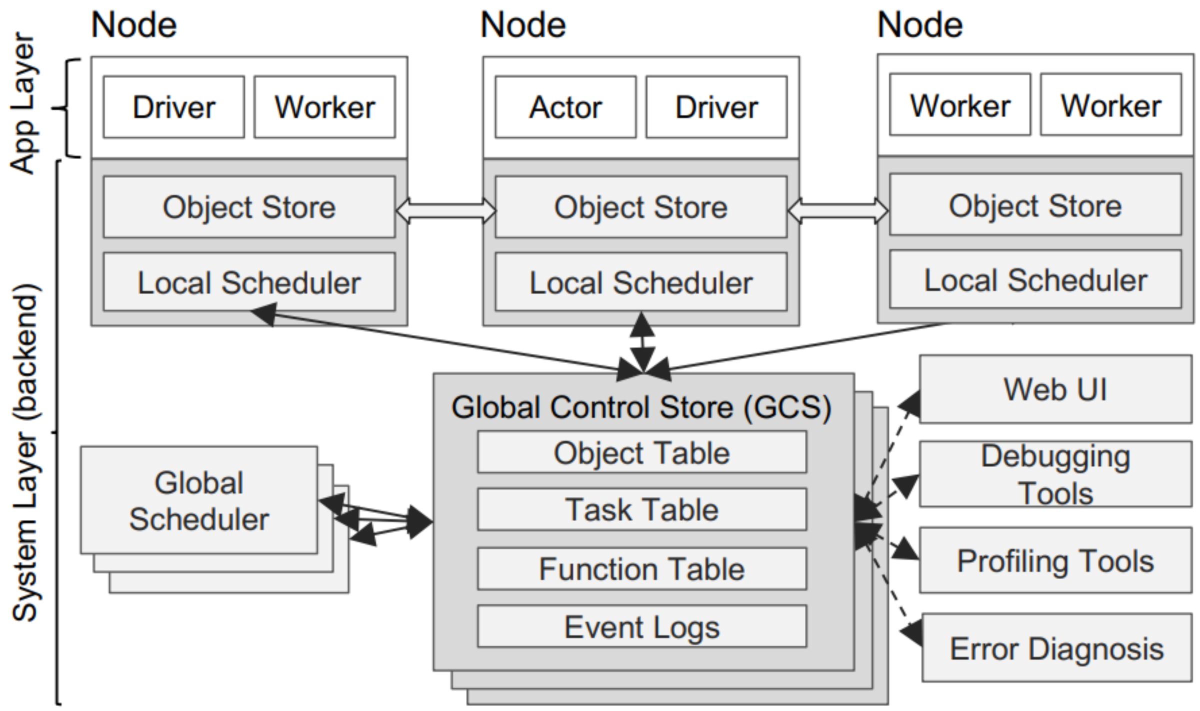
```
@ray.remote(num_gpus=1)
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

c = Counter.remote()
id4 = c.inc.remote()
id5 = c.inc.remote()
result = ray.get([id4, id5])
```




*Github repo: https://github.com/ray-project/ray*

# 案例研究: Ray and RLlib

<u>**Ray** is a **fast** and **simple** framework for building and running **distributed applications**.</u>




- *Faster than Python multiprocessing on a single node*
- *Competitive with MPI in many workloads*

- App Layer
  - Driver - *A process executing the user program*
  - Worker - *A stateless process that executes remote functions invoked by a driver*
  - Actor - *A stateful process that executes*
- System Layer
  - Global Control Store(GCS)
    - *A key-value store with pub-sub functionality*
  - Distributed scheduler
    - *Submitted first to local scheduler*
    - *Global scheduler considers each node's load and task's constraints to make scheduling decisions*
  - Distributed object store
    - *In-memory distributed storage to store the inputs/outputs, or stateless computation.*
    - *Implement the object store via shared memory*
    - *Use Apache Arrow as data formats*

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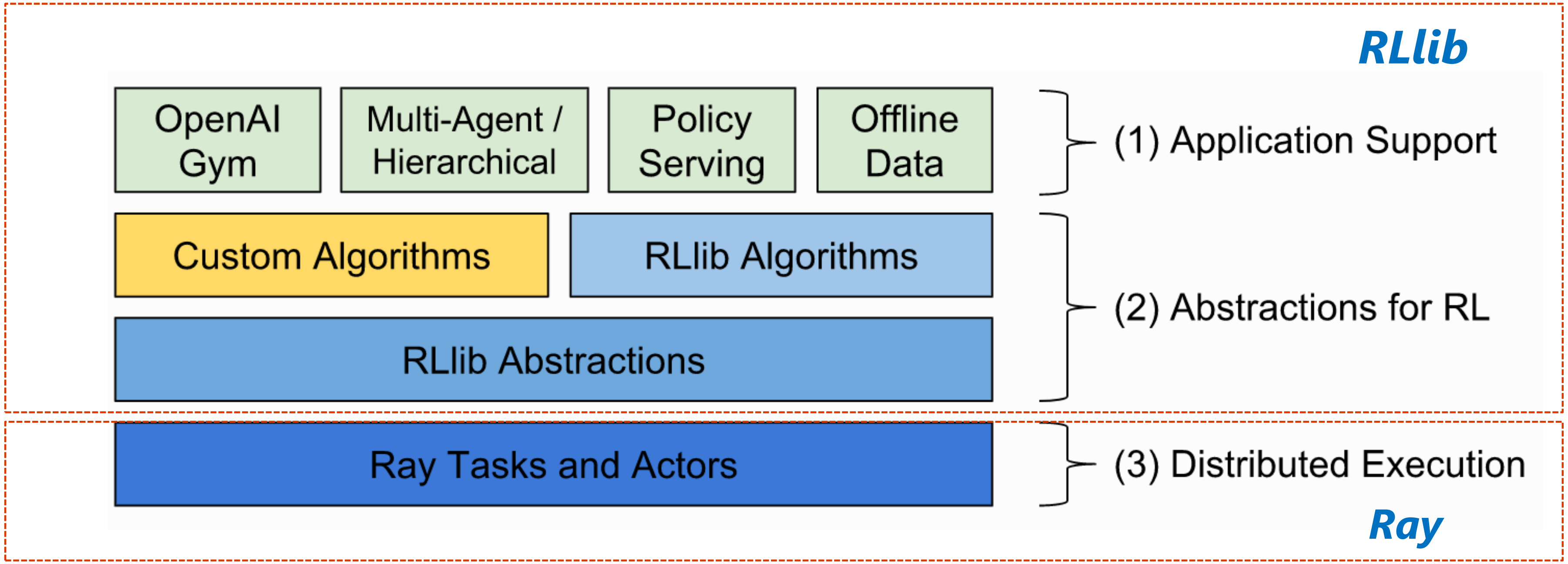
# 案例研究: Ray and RLlib

**RLlib** is an open-source library for reinforcement learning that offers both **high scalability** and a **unified API** for a variety of applications.




*Github repo: https://github.com/ray-project/ray/tree/master/rllib*

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# 友好的分布式编程接口

*Ray's distributed scheduler is a natural fit for the hierarchical control model, as nested computation can be implemented in Ray with no central task scheduling bottleneck.*

```
if mpi.get_rank() <= m:
    grid = mpi.comm_world.split(0)
else:
    eval = mpi.comm_world.split(
        mpi.get_rank() % n)
...
if mpi.get_rank() == 0:
    grid.scatter(
        generate_hyperparams(), root=0)
    print(grid.gather(root=0))
elif 0 < mpi.get_rank() <= m:
    params = grid.scatter(None, root=0)
    eval.bcast(
        generate_model(params), root=0)
    results = eval.gather(
        result, root=0)
    grid.gather(results, root=0)
elif mpi.get_rank() > m:
    model = eval.bcast(None, root=0)
    result = rollout(model)
    eval.gather(result, root=0)
```

a. Distributed control in MPI

```
@ray.remote
def rollout(model):
    # perform a rollout and
    # return the result

@ray.remote
def evaluate(params):
    model = generate_model(params)
    results = [rollout.remote(model)
        for i in range(n)]
    return results

param_grid = generate_hyperparams()
print(ray.get([evaluate.remote(p)
    for p in param_grid]))
```

b. Hierarchical control in ray.

# 基于Ray的简单的异步DQN的例子

## Trainer

```python
import ray
from collections import deque
import time
import threading

from dummy import DQN, Repl

@ray.remote
class Trainer:
    def __init__(self):
        self.steps = 0
        self.thread = None
        self.dqn = DQN()
        self.buffer = ReplayBuffer()
        self.worker = None
        self.checkpoint_interval = 5

    def _run(self):
        for _ in range(10000):
            self.steps += 1
            batch = self.buffer.sample()
            self.dqn.train(batch)
            if self.steps % self.checkpoint_interval:
                weight = self.dqn.dump_weights()
                if self.worker is not None:
                    self.worker.update_weights.remote(weig

    def run(self, worker):
        self.worker = worker
        self.thread = threading.Thread(target=self._run)
        self.thread.start()

    def add_transitions(self, trans):
        for row in trans:
            self.buffer.append(row)
```

Remote decorator for run in remote

Start thread for async training

## Actors

```python
import ray
import threading

from dummy import DQN, Env

BATCH_SIZE = 10

@ray.remote
class Worker:
    def __init__(self):
        self.dqn = DQN()
        self.env = Env()
        self.s0 = self.env.reset()
        self.trainer = None

        self.buffer = []

    def _run(self):
        for _ in range(10000):
            a = self.dqn.act(self.s0)
            s1, r, done, _ = self.env.step(a)

            if done:
                self.s0 = self.env.reset()
            else:
                self.s0 = s1
            f.buffer.append((self.s0, a, r, s1, done))

            len(self.buffer) == BATCH_SIZE:
                if self.trainer is not None:
                    self.trainer.add_transitions.remote(self.buffer)
                self.buffer = []

    def run(self, trainer):
        self.trainer = trainer
        self.thread = threading.Thread(target=self._run)
        self.thread.start()

    def update_weights(self, weights):
        self.dqn.load_weights(weights)
```

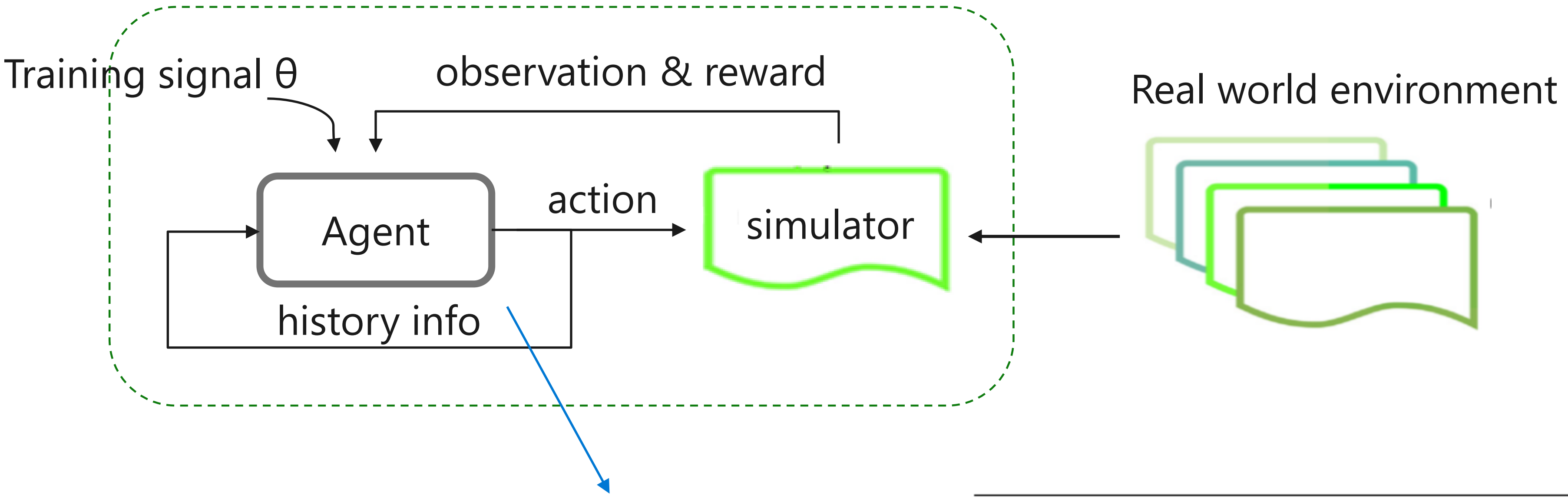
## Run script

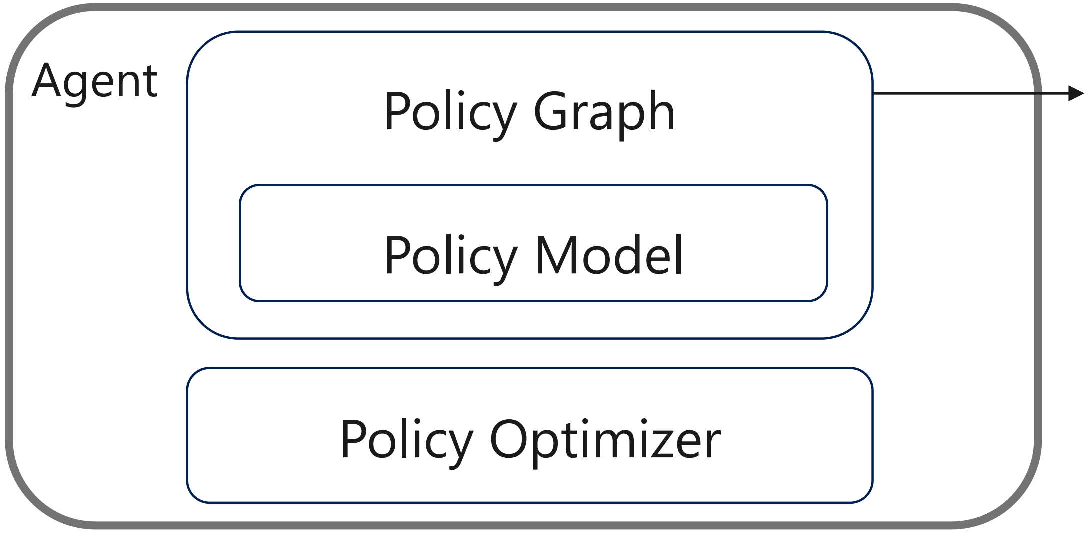
```python
import ray
import time
from trainer import Trainer
from worker import Worker

ray.init()

worker = Worker.remote()
trainer = Trainer.remote()
t1 = worker.run.remote(trainer)
t2 = trainer.run.remote(worker)
ray.get([t1, t2])
time.sleep(100)
ray.shutdown()
```

Init ray

Execute the trainer and actor in remote

# 为了容易使用而设计的模块化算法

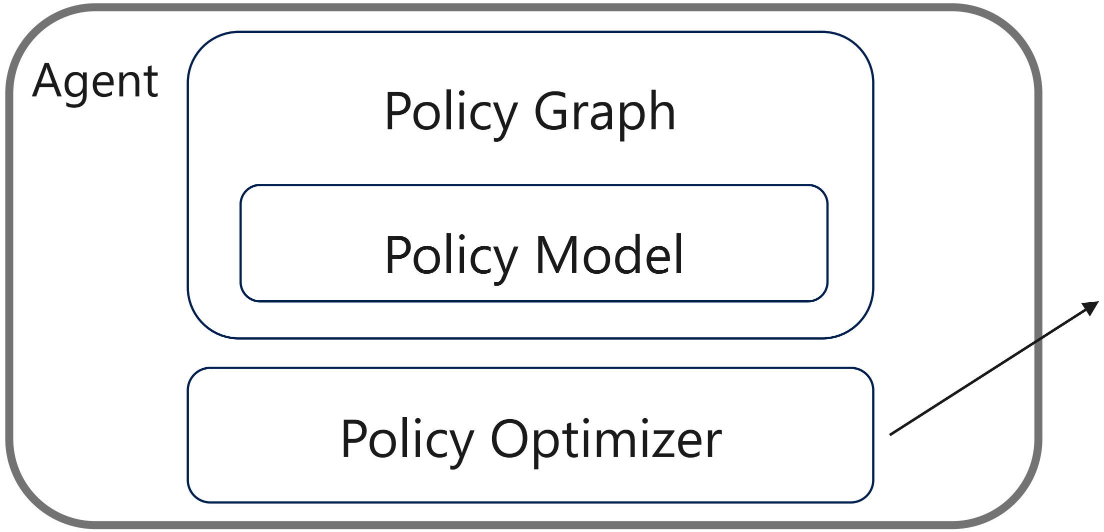



```
abstract class rllib.PolicyGraph:
  def act(self, obs, h): action, h, y*
  def postprocess(self, batch, b*): batch
  def gradients(self, batch): grads
  def get_weights; def set_weights;
  def u*(self, args*)
```

$$\pi_\theta(o_t, h_t) \Rightarrow (a_t, h_{t+1}, y_t^1 \dots y_t^N)$$

# 为了容易使用而设计的模块化算法




<u>**The policy optimizer** is responsible for the performance-critical tasks of distributed sampling, parameter updates, and managing replay buffers.</u>

```
grads = [ev.grad(ev.sample())
    for ev in evaluators]
avg_grad = aggregate(grads)
local_graph.apply(avg_grad)
weights = broadcast(
    local_graph.weights())
for ev in evaluators:
    ev.set_weights(weights)
```

(a) Allreduce

```
samples = concat([ev.sample()
    for ev in evaluators])
pin_in_local_gpu_memory(samples)
for _ in range(NUM_SGD_EPOCHS):
   local_g.apply(local_g.grad(samples)
weights = broadcast(local_g.weights())
for ev in evaluators:
    ev.set_weights(weights)
```

(b) Local Multi-GPU

```
grads = [ev.grad(ev.sample())
    for ev in evaluators]
for _ in range(NUM_ASYNC_GRADS):
    grad, ev, grads = wait(grads)
    local_graph.apply(grad)
    ev.set_weights(
        local_graph.get_weights())
    grads.append(ev.grad(ev.sample()))
```

(c) Asynchronous

```
grads = [ev.grad(ev.sample())
    for ev in evaluators]
for _ in range(NUM_ASYNC_GRADS):
    grad, ev, grads = wait(grads)
    for ps, g in split(grad, ps_shards):
        ps.push(g)
    ev.set_weights(concat(
        [ps.pull() for ps in ps_shards])
    grads.append(ev.grad(ev.sample()))
```

(d) Sharded Param-server

*Figure 4. Pseudocode for four RLlib policy optimizer step methods. Each step() operates over a local policy graph and array of remote evaluator replicas.*

# 支持的强化学习算法

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- High throughput architectures
  - Distributed Prioritized Experience Replay(Ape-X-DQN, Ape-X-DDPG)
  - Importance Weighted Actor-Learner Architecture(IMPALA)

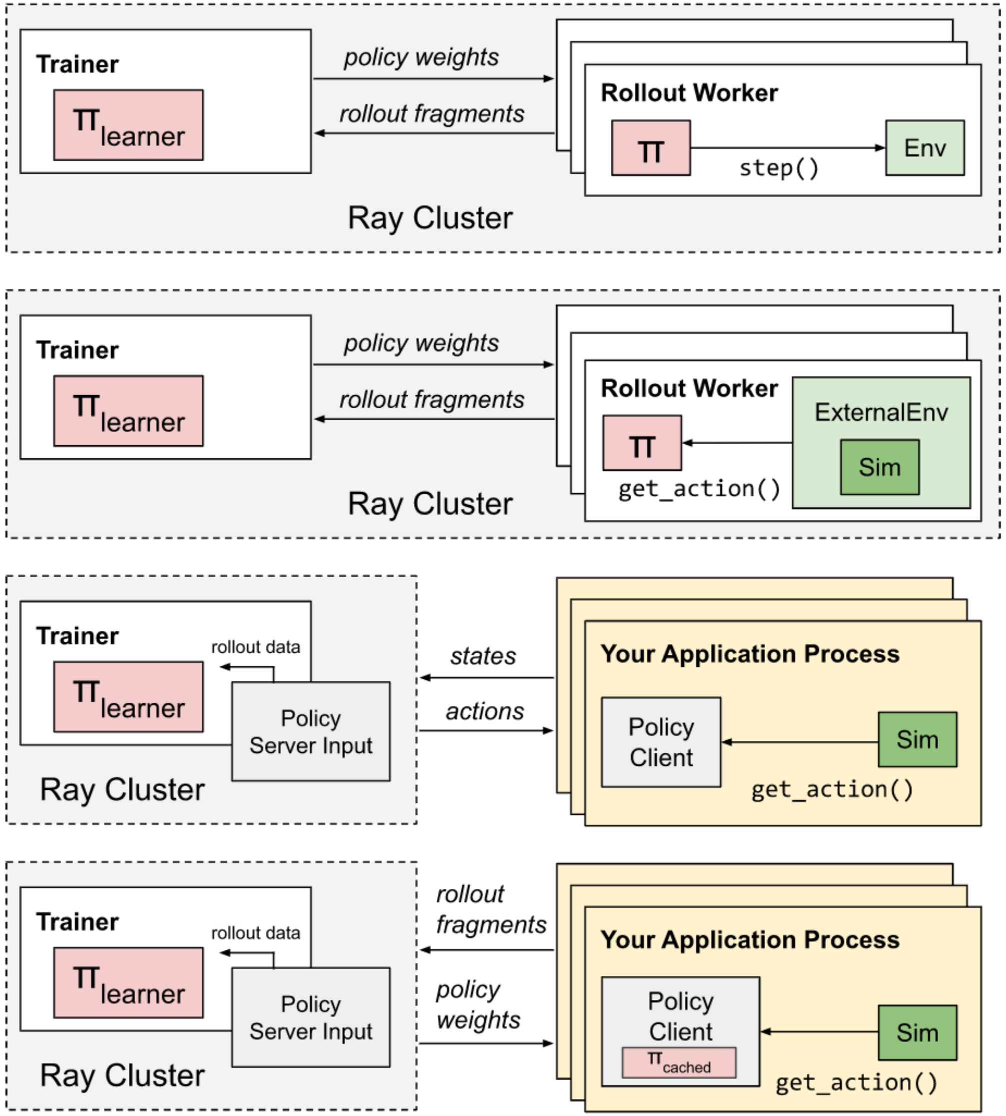
- Gradient-based
  - Advantage Actor-Critic(A2C, A3C)
  - Deep Deterministic Policy Gradients(DDPG, TD3)
  - Deep Q Networks(DQN, Rainbow)
  - Policy Gradients
  - Proximal Policy Optimization(PPO, APPO)
  - Soft Actor-Critic(SAC)
  - Single player AlphaZero

- Derivative-free
  - Augment Random Search(ARS)
  - Evolution Strategies

- Multi-agent
  - Monotonic Value Function Factorization(QMIX, VDN, IQN)
  - MADDPG

```
tune.run(
    "DQN",
    stop={"episode_reward_mean": 100},
    config={
        "env": "CartPole-v0",
        "num_gpus": 0,
        "num_workers": 1,
        "lr": tune.grid_search([0.01, 0.001, 0.0001]),
        "monitor": False,
    },
)
```

# 支持的复杂的环境




(1) Standard environments (e.g., gym.Env, MultiAgentEnv types) are created and stepped by RLlib rollout workers.

(2) External environments (ExternalEnv) run in their own thread and pull actions as needed. RLlib still creates one external env class instance per rollout worker.

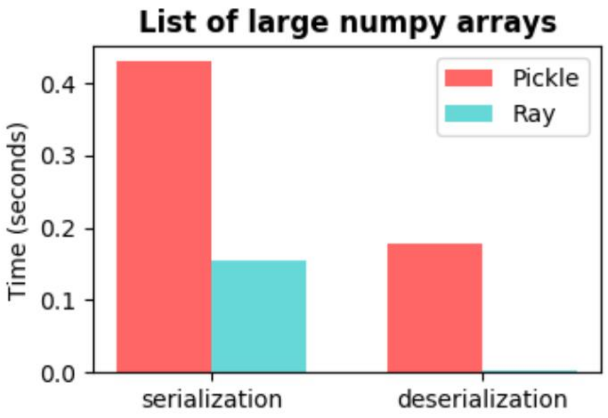
(3) Applications running outside the Ray cluster entirely can connect to RLlib using PolicyClient, which computes actions remotely over RPC.

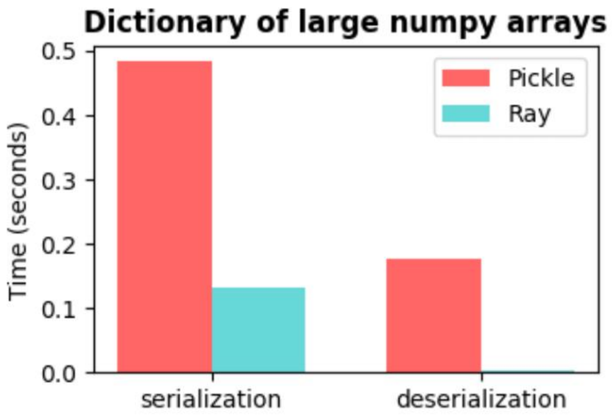
(4) PolicyClient can be configured to perform inference locally using a cached copy of the policy, improving rollout performance.

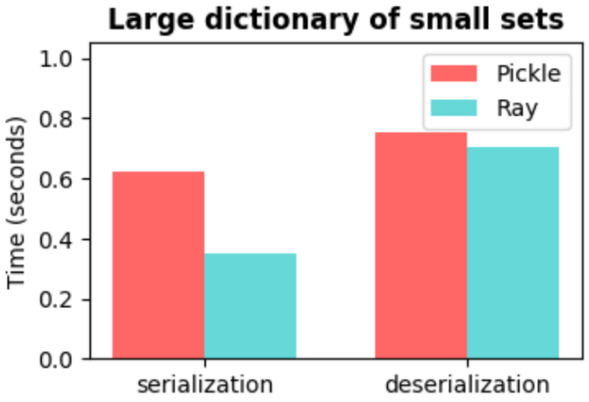
# 快速的序列化和反序列话

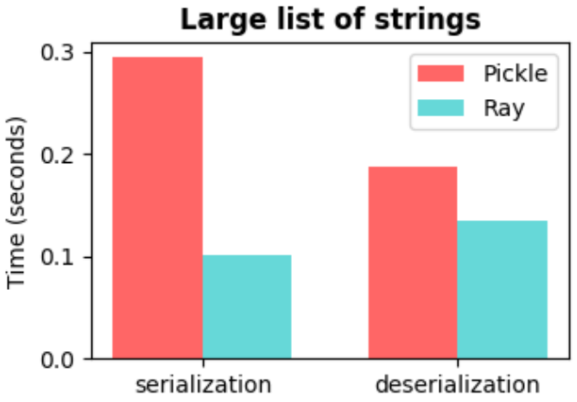
Serialization and deserialization are **bottlenecks in parallel and distributed computing**, especially in machine learning applications with large objects and large quantities of data.

- Goals
  - Very efficient with **large numerical data** (e.g. Numpy arrays and Pandas dataframes)
  - As fast as Pickle for **general Python types**
  - Compatible with **shared memory** (allowing multiple processes to use the same data without copying it)
  - **Deserialization** should be extremely fast (e.g. streaming)
  - **language independent**



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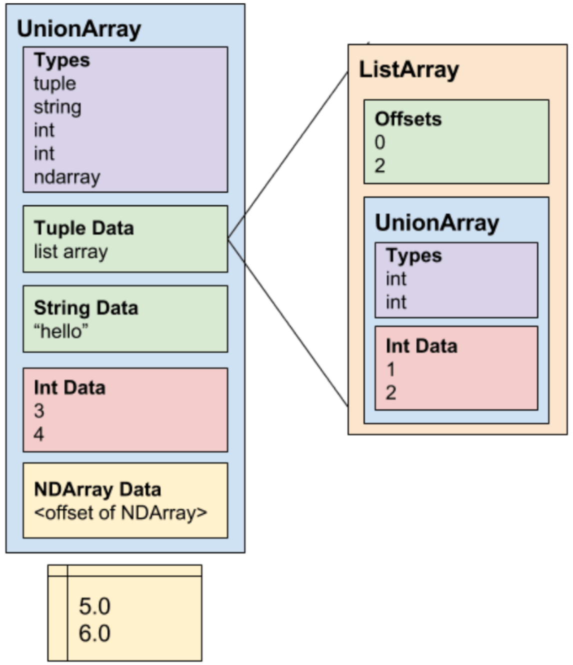
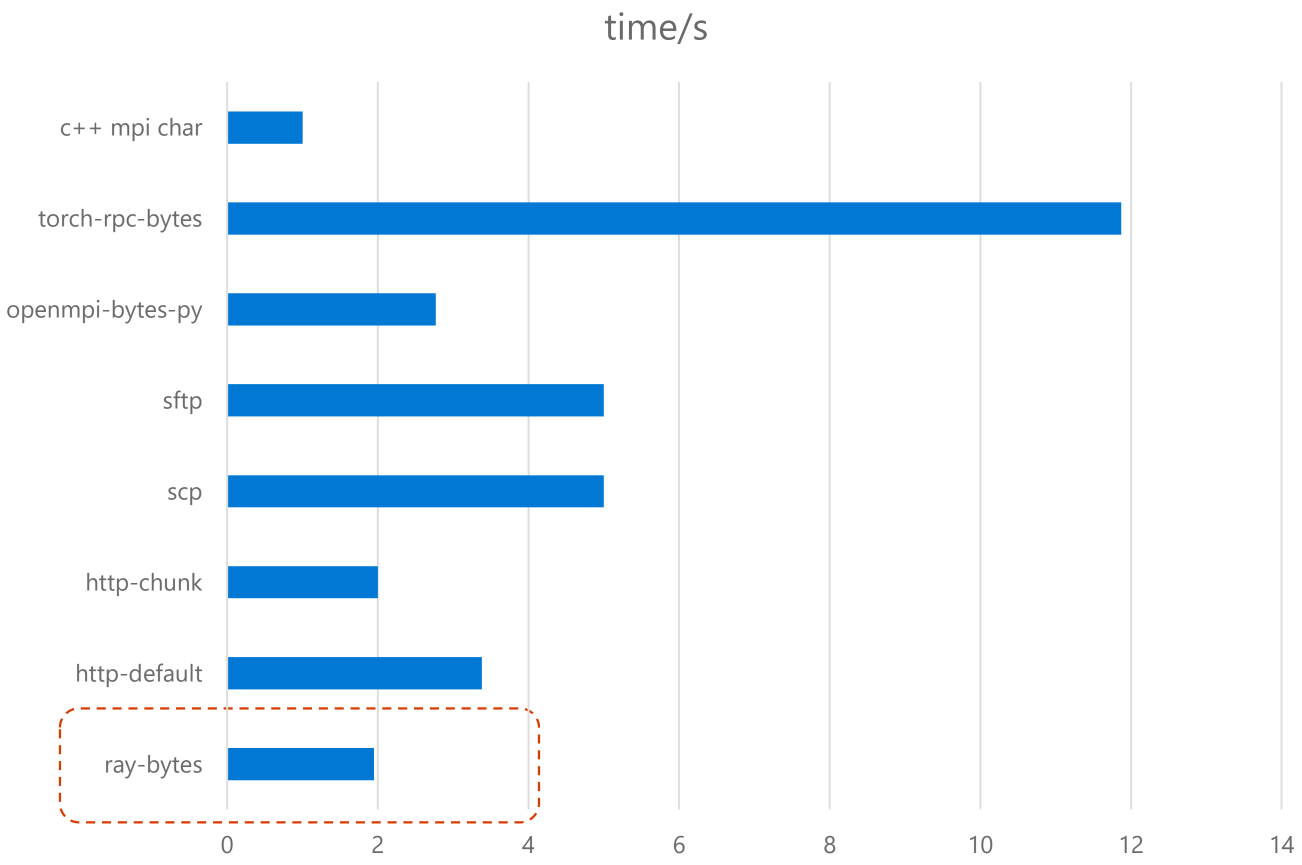
# 快速的序列化和反序列话

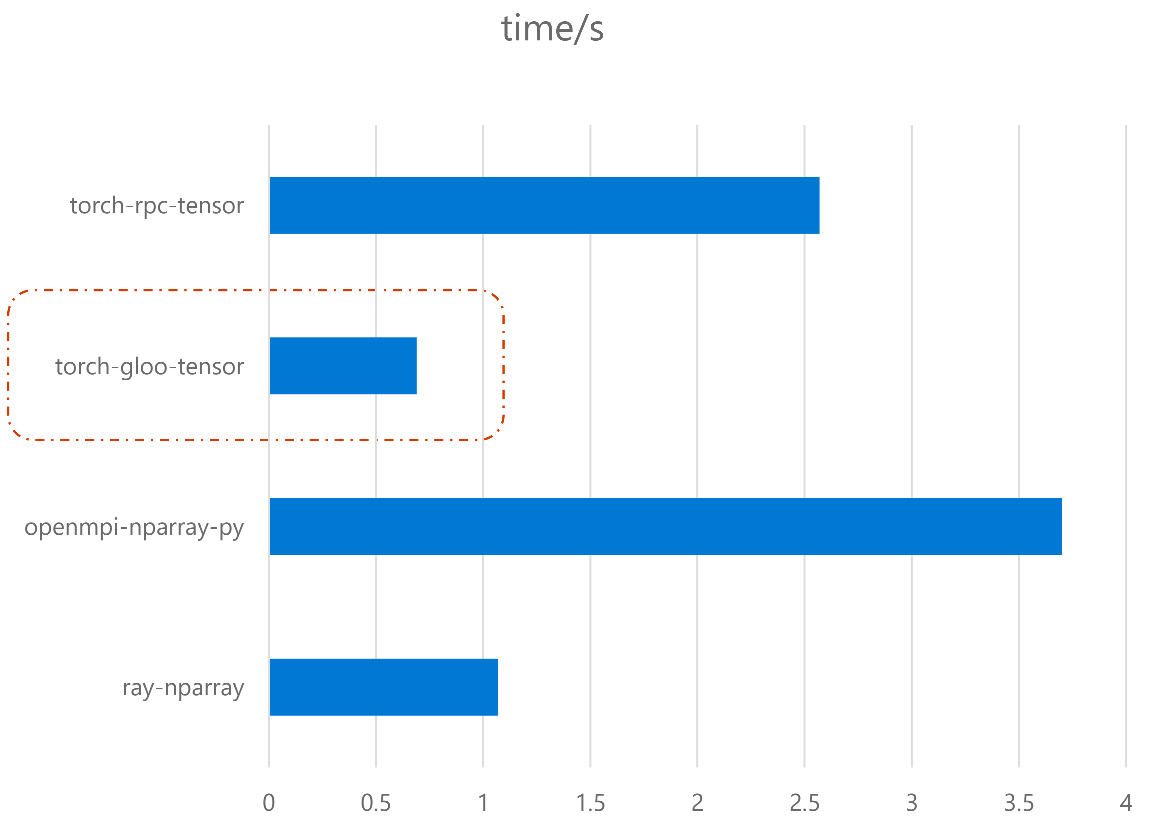
- Making **deserialization** fast is important.
  - An object may be serialized once and then deserialized many times
  - A common pattern is for many objects to be serialized in parallel and then aggregated and deserialized one at a time on a single worker making deserialization the bottleneck
- Deserialization is fast and barely visible
  - **Using only the schema, can compute the offsets of each value in the data blob without scanning through the data blob** (unlike Pickle, this is what enables fast deserialization)
  - Avoid copying or otherwise converting large arrays and other values during deserialization(the savings largely come from the lack of memory movement)

```
[(1, 2), 'hello', 3, 4, np.array([5.0, 6.0])]
```



# 不同通信框架的速度评测




*The speed of transferring 1GB data.*

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# RLlib的小总结

- 优雅而简单的分布式编程语言
- 容错和高并发的分布式框架
- 通用的强化学习接口
- 为python对象优化的高效通信框架

在Rllib上实现一个新的RL算法需要多大的代价呢?

# 强化学习的其他挑战

- 可复现性 *(e.g. SURREAL)*
- 可解释性
- 从少量的数据中学习
- 安全限制
- 实时推理
- …

# 参考资料


- Ray: A Distributed Framework for Emerging AI Applications
- RLlib: Abstractions for Distributed Reinforcement Learning
- DISTRIBUTED PRIORITIZED EXPERIENCE REPLAY
- Rainbow: Combining Improvements in Deep Reinforcement Learning
- SEED RL: Scalable and Efficient Deep-RL with Accelerated Central Inference
- IMPALA: Scalable Distributed Deep-RL with Importance Weighted Actor-Learner Architectures
- Asynchronous Methods for Deep Reinforcement Learning
- SURREAL: Open-Source Reinforcement Learning Framework and Robot Manipulation Benchmark
- Challenges of Real-World Reinforcement Learning
- Apache Arrow https://arrow.apache.org/
- https://wesmckinney.com/blog/arrow-streaming-columnar/
- Modin(speed up the pandas in ray) https://github.com/modin-project/modin
- https://www.zhihu.com/question/377263715
- https://www.slideshare.net/databricks/enabling-composition-in-distributed-reinforcement-learning-with-ray-rllib-with-eric-liang-and-richard-liaw
- https://github.com/deepmind/reverb