TWO SIGMA

A 24x Speedup for Reinforcement Learning with RLlib + Ray

Raoul Khouri

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@buoy_the_samoyed

Raoul Khouri

Two Sigma

Financial Sciences Company

- Investment management
- Other financial data driven endeavours

  (Insurance, Real Estate, Private Equity, …)

Founded in 2001

- CEOs John Overdeck and David Siegel

~2000 employees (~1000 engineers and ~250 researchers)

Offices in NYC, London, Houston, Tokyo, Shanghai

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Disclaimer

What we will talk about today

Applied research currently includes Reinforcement Learning

Migrated from **Stable Baselines** to **RLlib + Ray**

Lessons learned

Case study of an experiment

The RL Pipeline

Overview of the RL pipeline

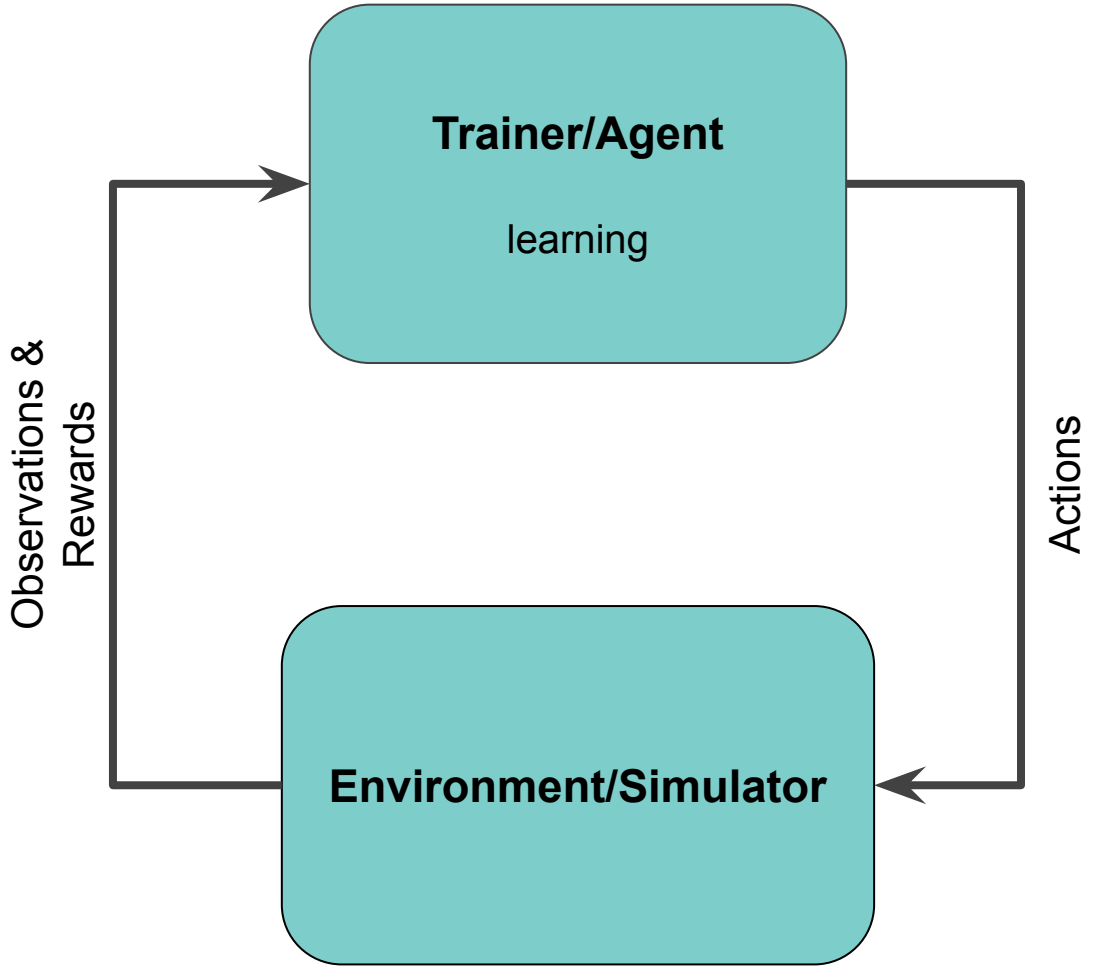
Trainer

- In charge of learning a policy

Environment

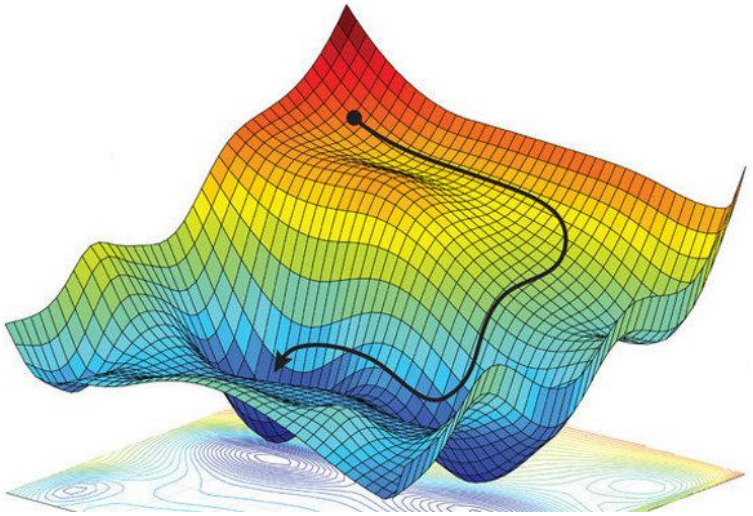
- State machine
- Actions go in
- Observations and rewards come out

Many interactions with the environment needed!

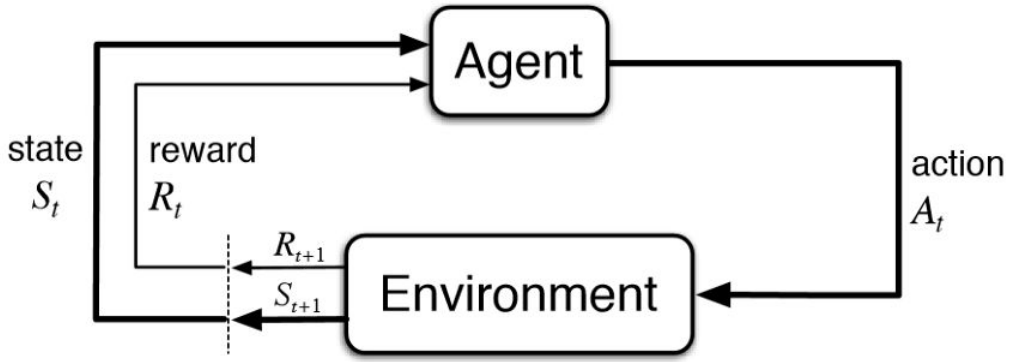


Bottlenecks in the RL pipeline

Learning

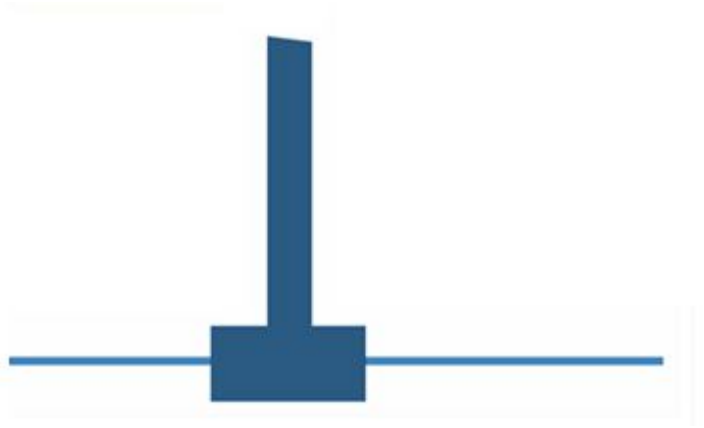


Sampling



[RLlib Scaling Guide]

Our Experiment



Financial data

- Lots of data
- Low signal to noise ratio

Experiment taking 7-10 hrs to complete

- **24 CPUs using Stable Baselines**

Learning taking <10% of total time

- **~90%** generating samples

What we tried

GPUs

- Yielded little to no speed up
  - Simulators don’t use GPUs
- GPUs are expensive
- “I got a machine with a larger GPU but I see no speed up.”

More CPUs

- Tried machines with >24 CPUs on **Stable Baselines**
- Little to no speed up

Off-Policy

- Lower solution quality vs on-policy
- Still need many samples due to noisy data

RLlib

Migrating to RLlib

Generic Gym API

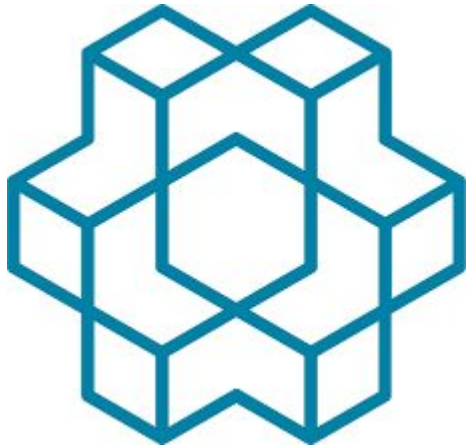
- Easy environment migration

RLlib has a superset of algorithms vs **Stable Baselines**

- Small changes in hyper parameters
- Same solution quality

Tune managed our experiments

~1 week to migrate a project



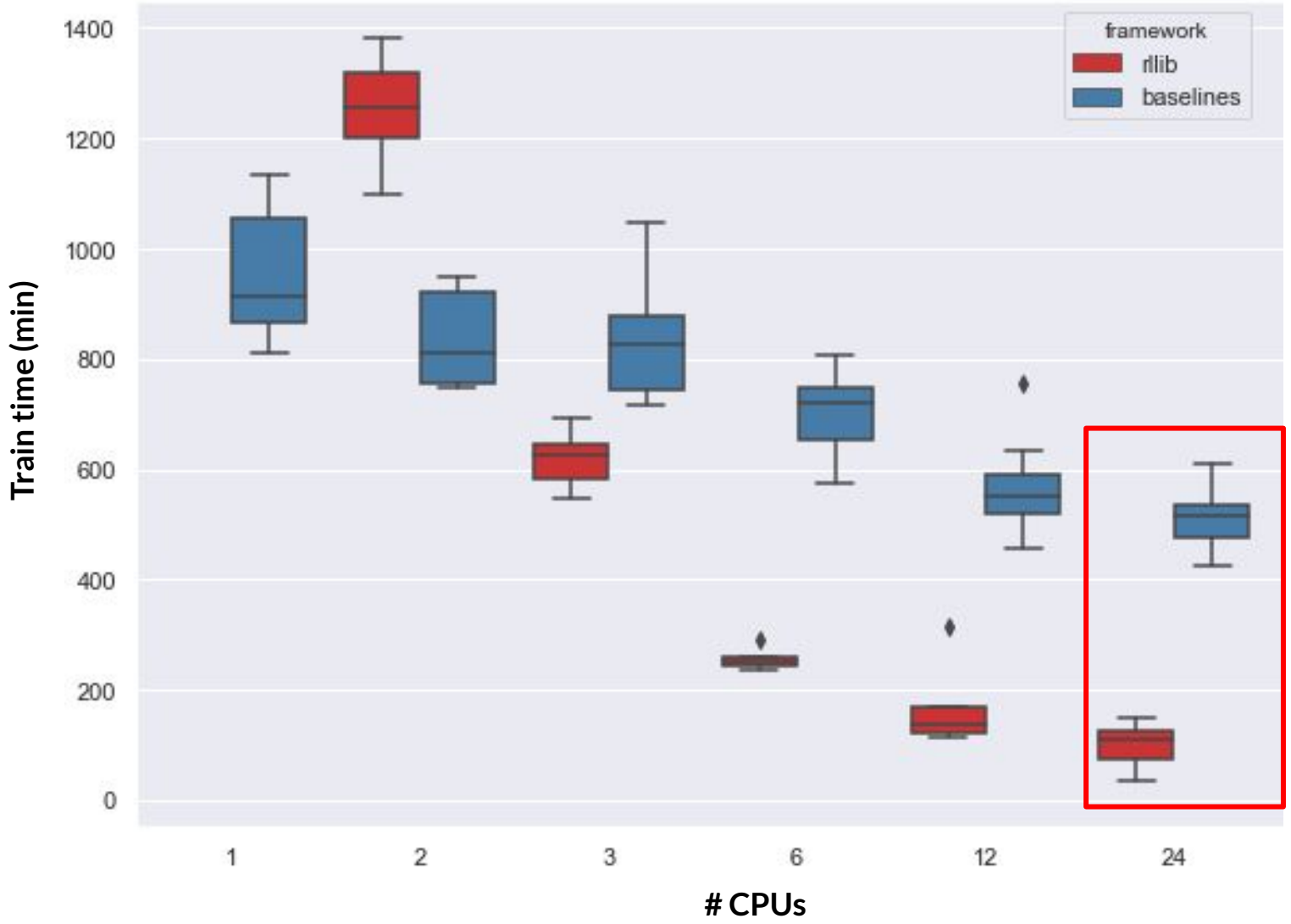
Great community support + **RLlib** examples in the GitHub Repository

RLlib vs Stable Baselines Experiment Time (20M samples)

Stable Baseline 7-10 Hrs

RLlib 1.5-2.5 Hrs

~4x speed up

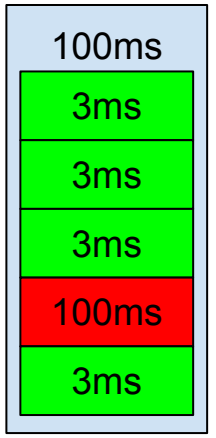


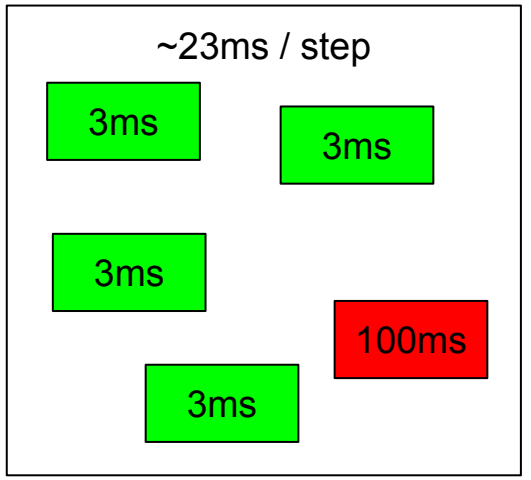
lower is better!

Why does RLlib parallelize better?

Types of RL parallelization

- Vectorized environments
  - Efficient inference
  - Everything must step together
    - If large variance in step time this can be very inefficient!
    - We call this the **“lock-step”** issue
  - Constrained to this by many RL libraries
- Batched rollouts
  - Slower inference
  - Sync at end of rollouts
    - requires much less waiting
    - avoids the **“lock-step”** issue





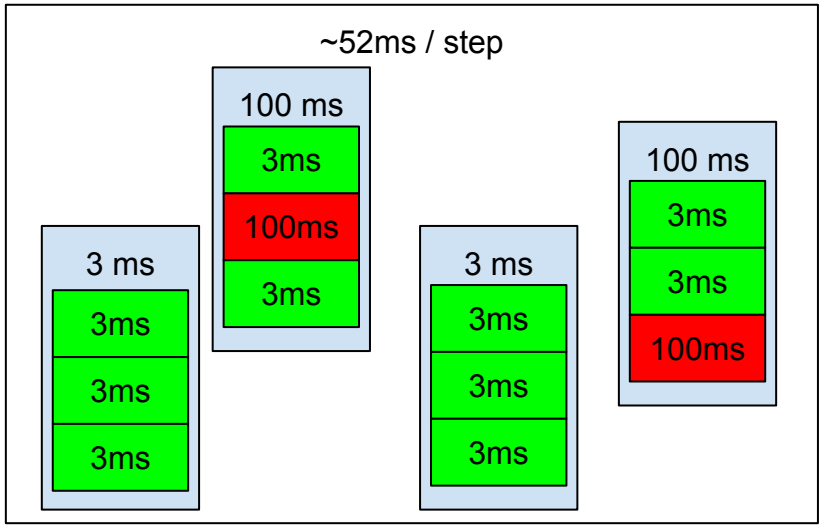
The “**lock-step**” issue is what caused our **Stable Baselines** experiments to not parallelize well.

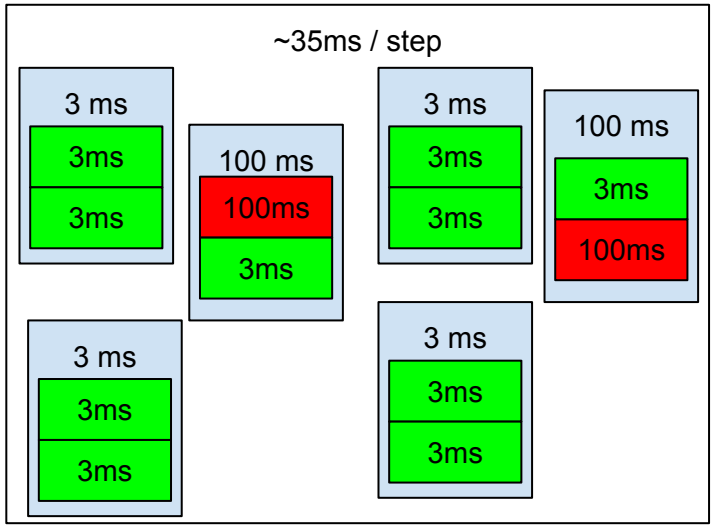
The RLlib Solution to Parallelization

Hybrid Solution

- rollout workers -> batched rollouts
- envs per worker -> vectors

Very customizable!

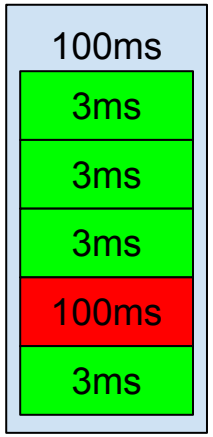




Diagnostic of our Experiment

	Overall Performance		Sampling Performance		
	Sampling	**Optimizing**	**Reset**	**Inference**	**Step**
Stable Baselines (Vectorized)	150s	**13s**	**100ms**	**0.8ms**	24ms
RLlib (Batched)	**20s**	**13s**	**100ms**	1ms	**3ms**

Wasting 6 hours here!



When the “Lock-Step” Issue Matters

Non-uniform time spent in steps or resets:

- **4-5x speed up**

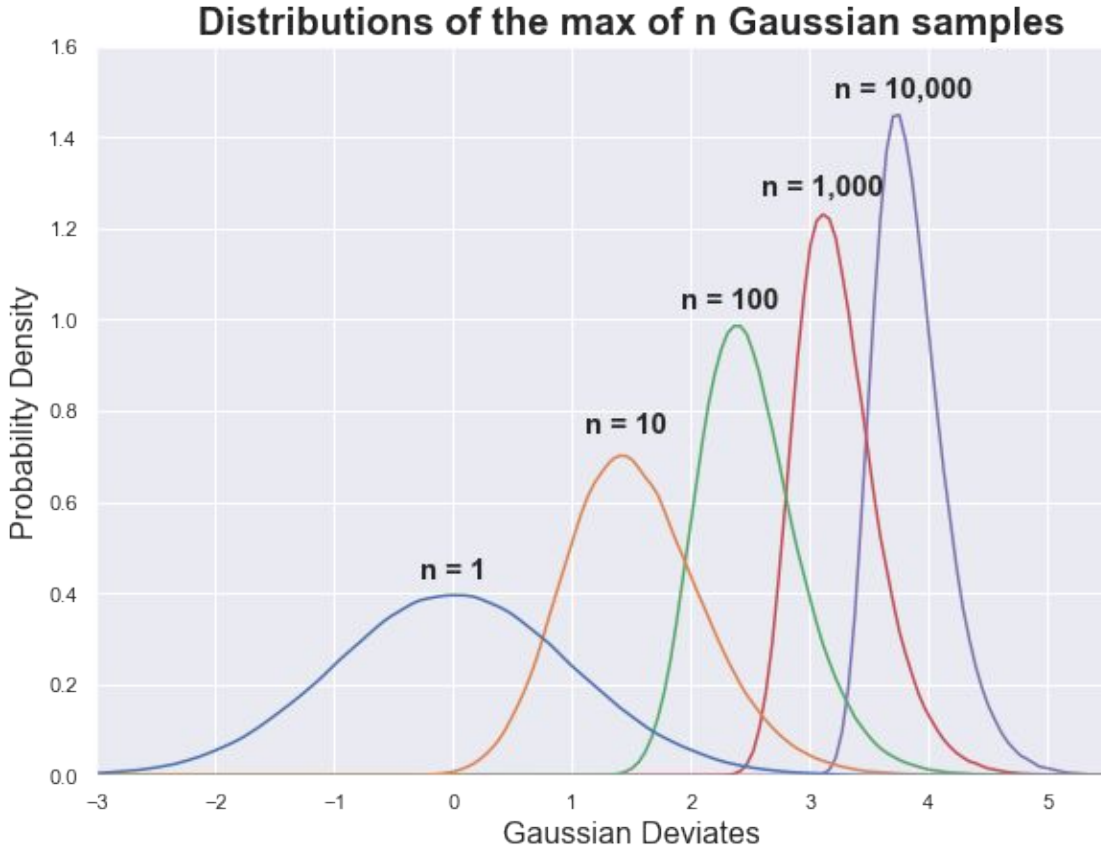
Large parallelization (if inference is marginal):

- **~ 10-50%**

Expected Speed up at 24 CPUs:

$$2\frac{std(step\_time)}{mean(step\_time)}$$

assuming gaussian step/reset variance



RLlib + Ray Clusters

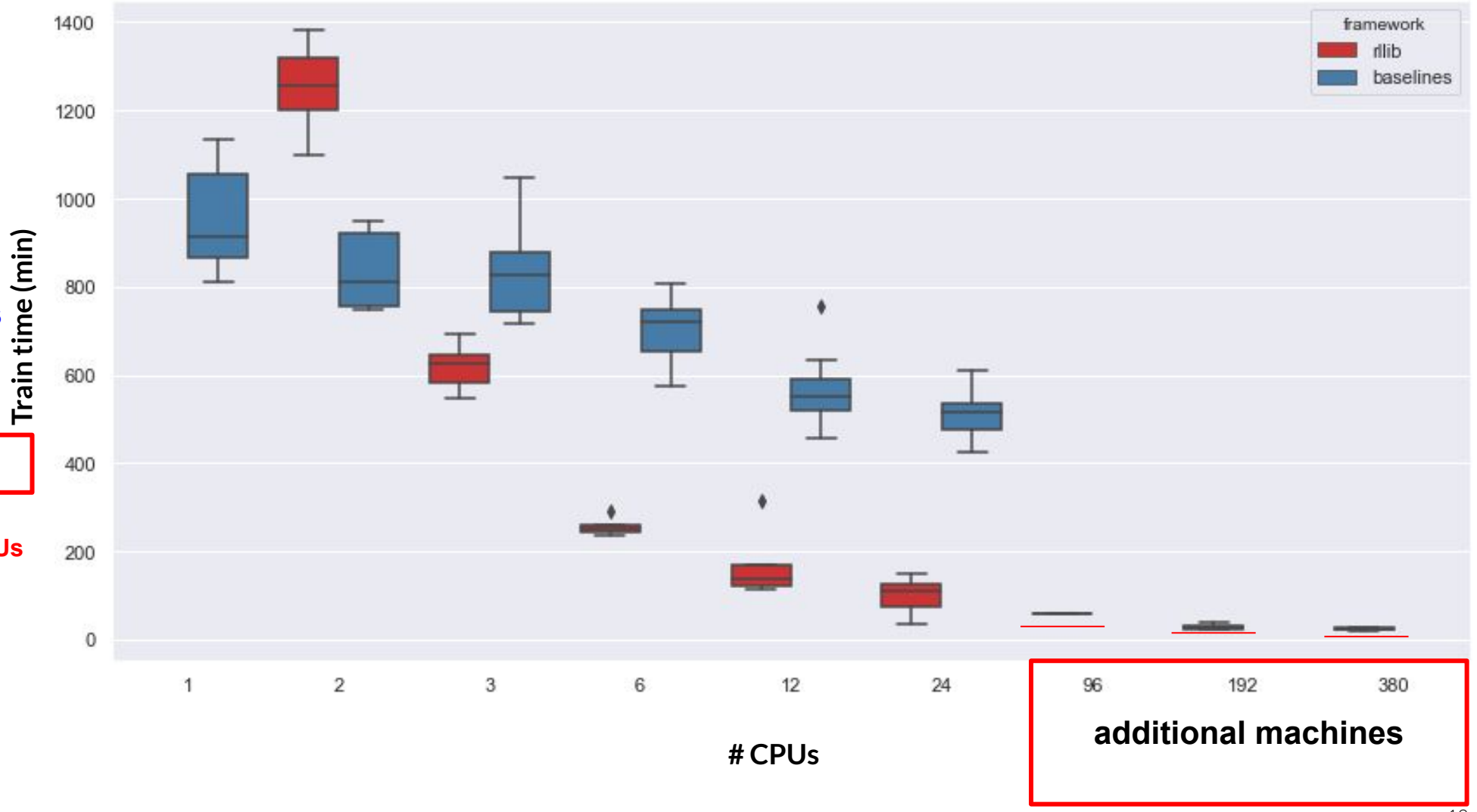
RLlib + Ray vs Stable Baselines Experiment Time (20M samples)

Stable Baseline 7-10Hrs

RLlib 1.5-2.5 Hrs

RLlib + Ray ~20 min

~6x speedup with ~16x the CPUs



Other nice things about RLlib + Ray

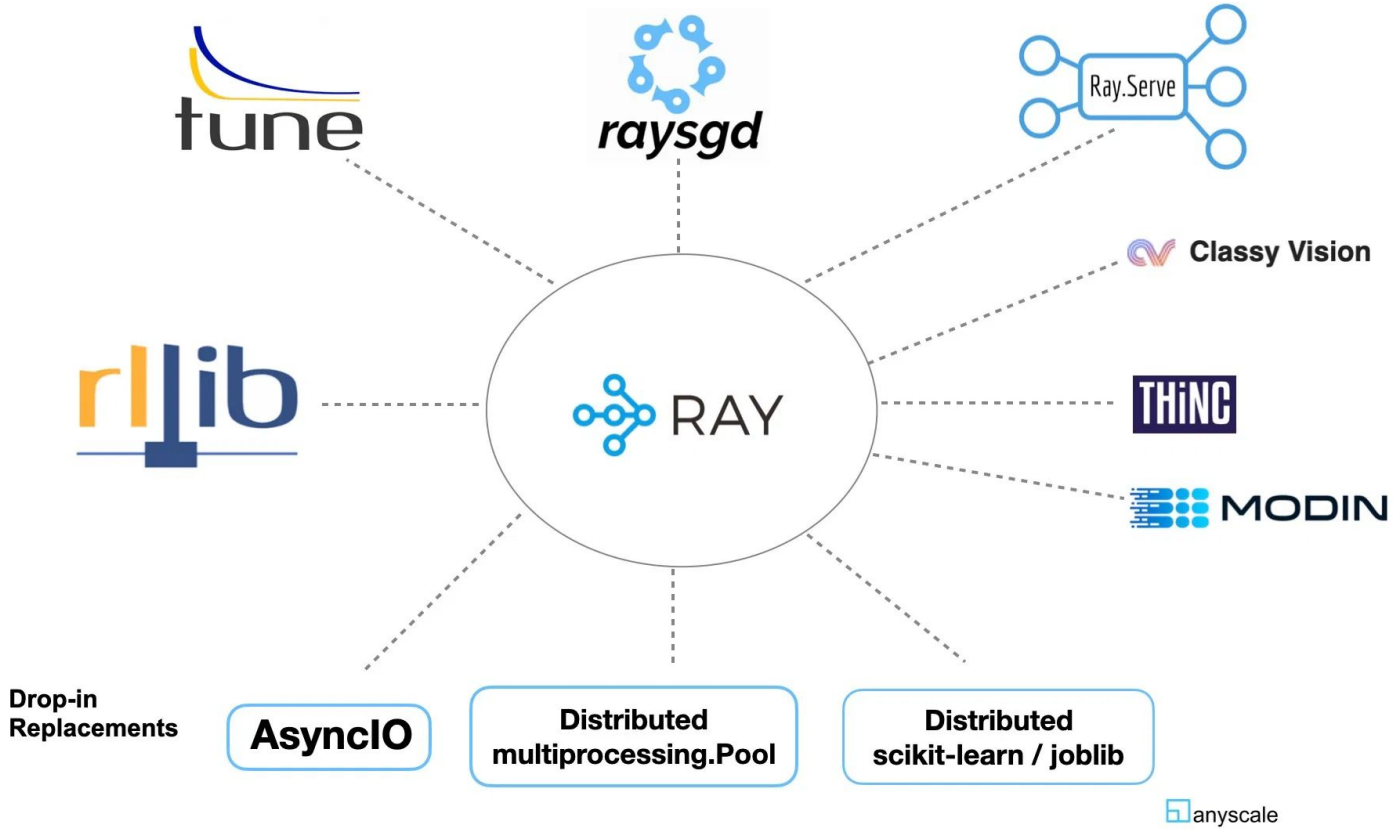
Bonus features

Tune

a. Hyper parameter optimization
b. Experiment management

Large number of supported algorithms in **RLlib**

Ray distributed compute



Conclusion

Stable Baselines -> **RLlib**

- Mileage may vary depending on the experiment
  - 7-10 Hrs -> 1.5-2.5 Hrs ~4x
- Be aware of the environment parallelization!

+ Ray Clusters

- Mileage may vary depending on the experiment
  - 1.5-2.5 Hrs -> **~20 mins** ~6x
- Commodity CPU-only machines are cheap

Together **~24x**

The **Ray** ecosystem is a nice bonus

Questions?