



## 1. Introduction

### Problem:

- Deep reinforcement learning (RL) has **long training time**
- To reduce RL training time, many parallel **synchronous** and **asynchronous** RL methods have been proposed

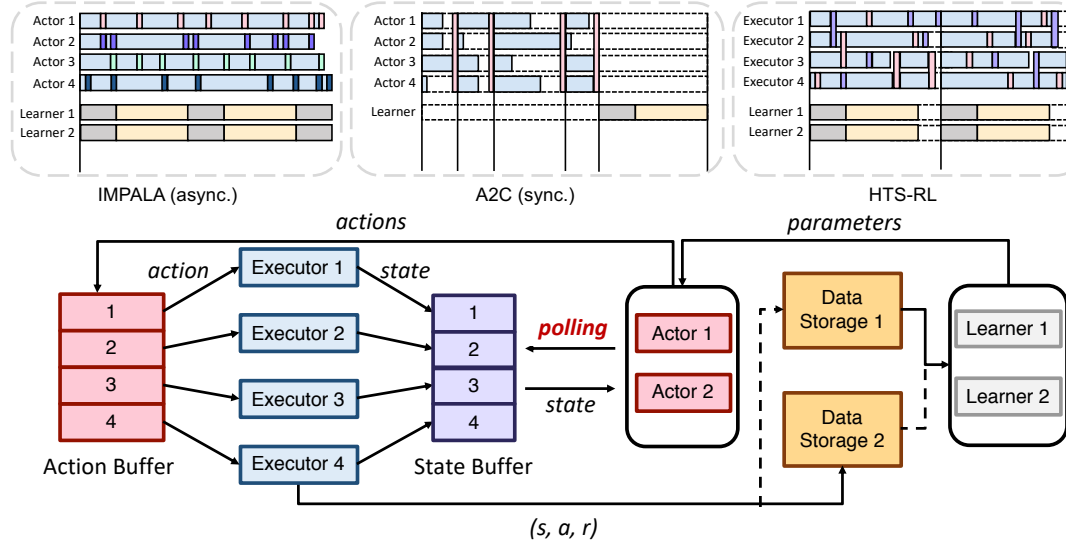
### Challenge:

- **Synchronous** methods:
  - Advantage: data efficiency, training stability, full determinism, reproducibility
  - Disadvantage: **synchronization overhead**
- **Asynchronous** methods:
  - Advantage: high throughput
  - Disadvantage: **low data efficiency, non-determinism, stale-policy issue**

### Ours: High-Throughput Synchronous RL (HTS-RL)

- Combine advantages of synchronous and asynchronous methods while avoiding their disadvantages
- HTS-RL achieves
  - **High-Throughput**
  - **Without sacrificing data efficiency**

## 2. Overview



### Approach

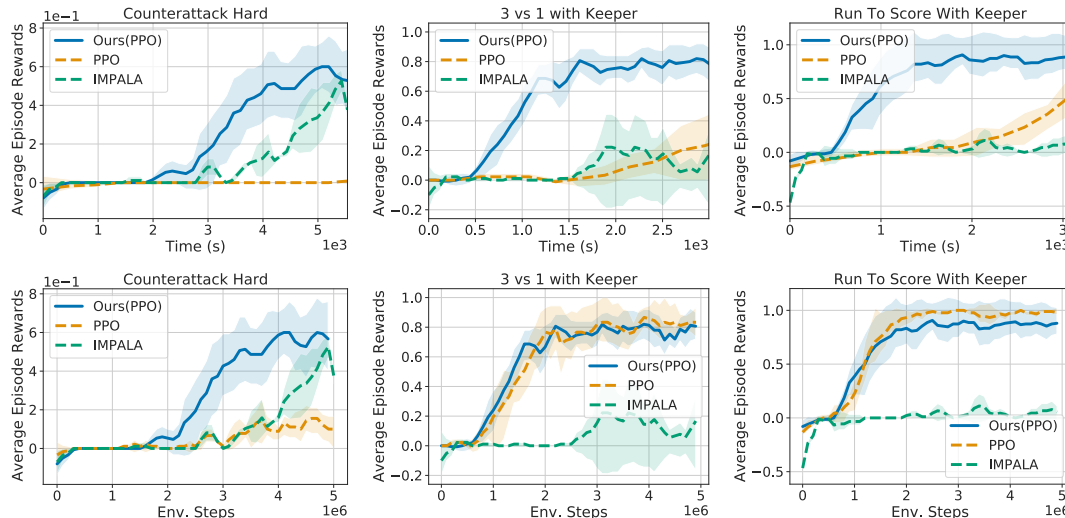
- Three types of processes: actors, executors, and learners
- Concurrent rollout and learning
- Actors and executors interact in an asynchronous manner, which prevents actors from waiting for executors
- Batch synchronization
  - Synchronize all processes every alpha steps
  - Effectively reduces the synchronization overhead
  - Maintain full determinism

<https://ioujenliu.github.io/HTS-RL/>



## 3. Experimental Results (see paper for additional results)

### Comparison of HTS-RL, PPO and IMPALA on GFootball environment



### Required time (min) to achieve average target scores

- Max score = 1 for each task
- Target score: 0.4 / 0.8

Method	IMPALA	PPO	HTS-RL
Empty goal close	1.7/2.6	5.4/15.5	<b>1.0/2.0</b>
Empty goal	8.4/11.7	12.8/19.2	<b>2.0/3.9</b>
Run to score	27.0/34.6	16.2/32.5	<b>6.3/11.4</b>
RSK	52.3/-	51.2/68.2	<b>11.5/18.8</b>
PSK	-/-	70.0/-	<b>38.8/-</b>
RPSK	22.3/25.4	45.2/90.8	<b>13.5/27.1</b>
3 vs. 1 w/ keeper	-/-	67.4/144.2	<b>15.9/25.6</b>
Corner	-/-	-/-	-/-
Counterattack easy	-/-	223.2/-	<b>91.3/-</b>
Counterattack hard	-/-	383.4/-	<b>61.8/-</b>
11 vs. 11 w/ lazy	58.2/-	95.8/260.9	<b>14.4/72.1</b>
Opp.			

