Factory Manipulation with Cooperative Multi-agent Reinforcement Learning

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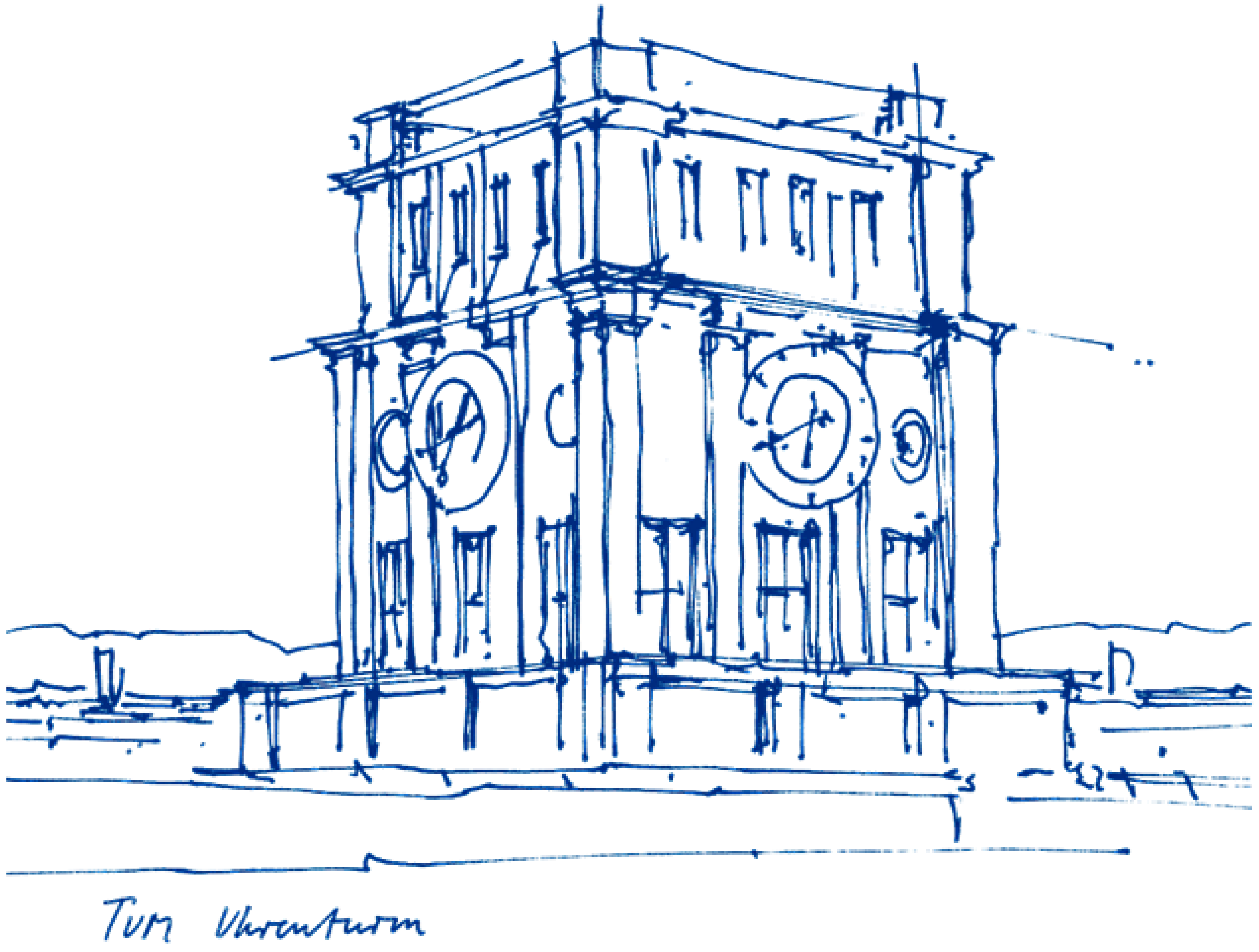
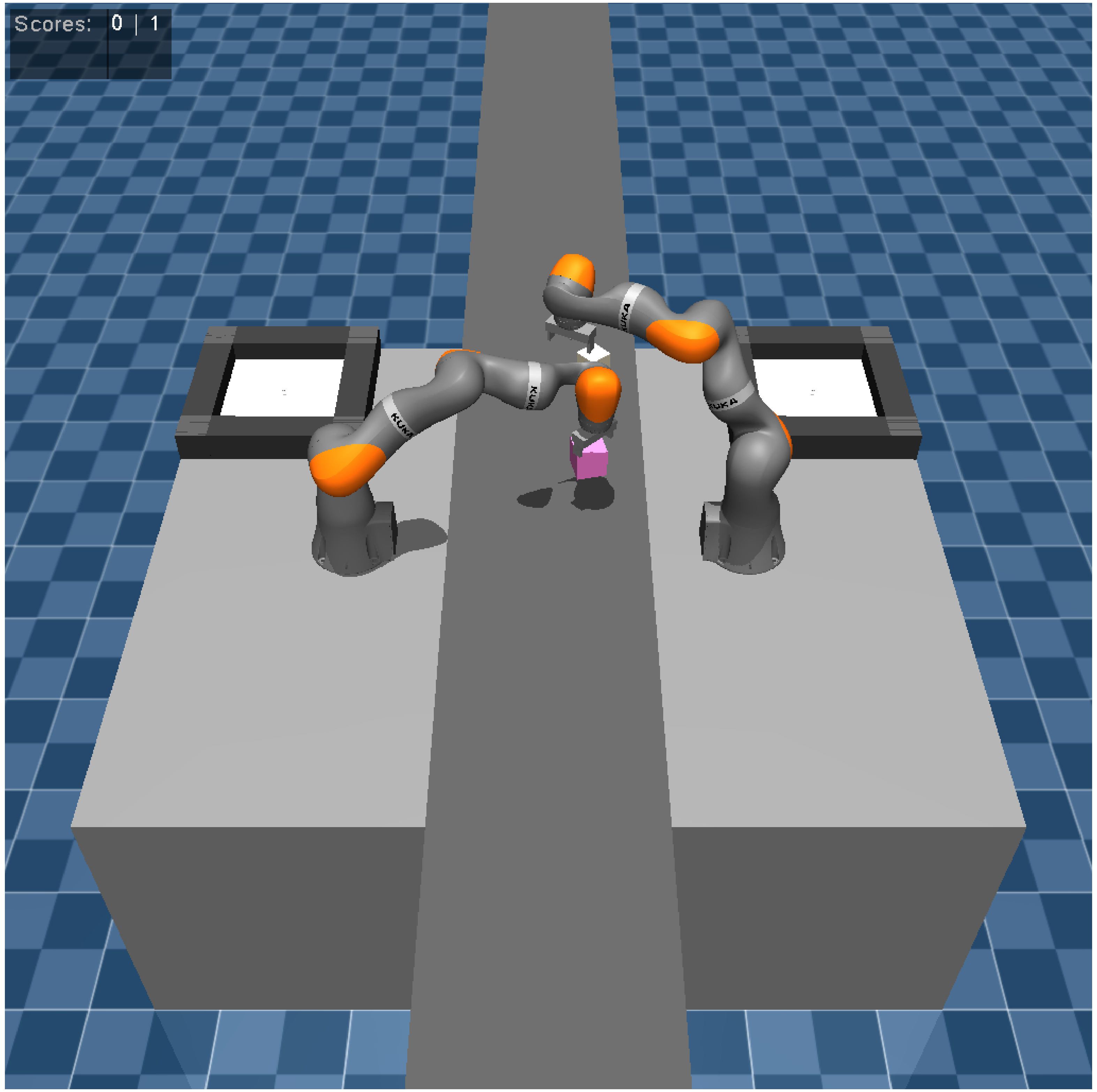
(Team 7)



Problem Setting

- Gym env based on MuJoCo (Howell et al. 2022)
  - 2 or more robot arms (8 DOF each)
  - basket in reach for each arm
  - conveyor belt with increasing speed
  - cubes transported on conveyor belt
  - score = number cubes in baskets
- episode ends if either:
  - arm hits the env (incl. other arms)
  - cube is missed by all arms
- conventional pre-programming-based approaches too inflexible and tedious → use of MARL (cp. Pérez-Francisco et al. 1998, Bozma and Kalalıoğlu 2012, Yu et al. 2017, Han et al. 2020)



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Multiple robot arms cooperating to maximise efficiency in factory manipulation task

(PnP along conveyor belt as representative and important special case)

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s.t. *communication cost too high to broadcast joint states in real time*
$\Longrightarrow$ true **multi-agent reinforcement learning** (due to partial observability)

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- roadmap: incremental approach

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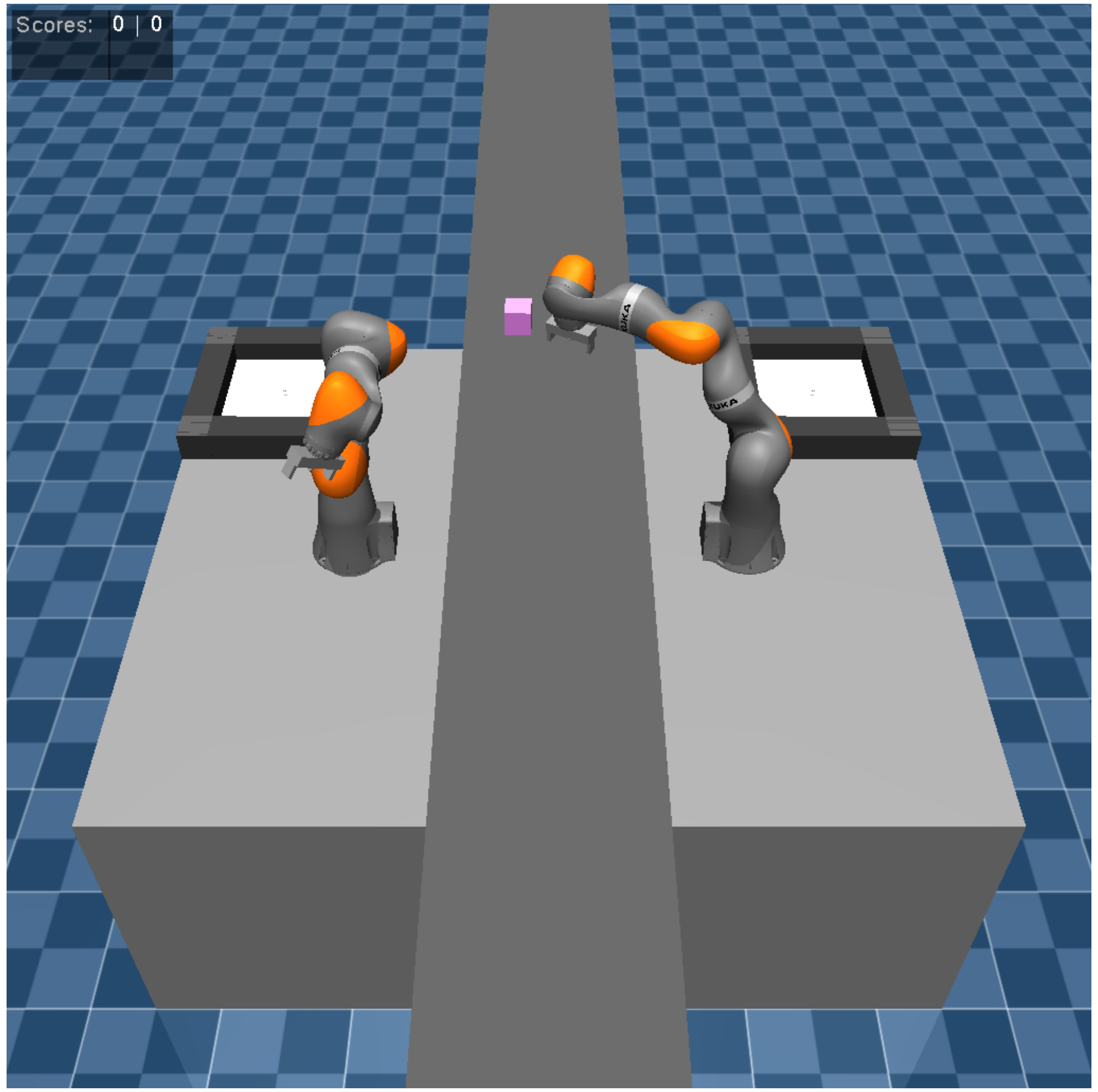
Reward Design

Which reward should we use?

1st intention: reward of **1 if block is thrown in the basket**, else 0

- highly sparse reward
  → **learning very hard**
- nearly random behaviour overpowers base policy



Reward Design

Which reward should we use?

2nd intention: reward increases **monotonically** with **progress to target**

Desirable Incentives:

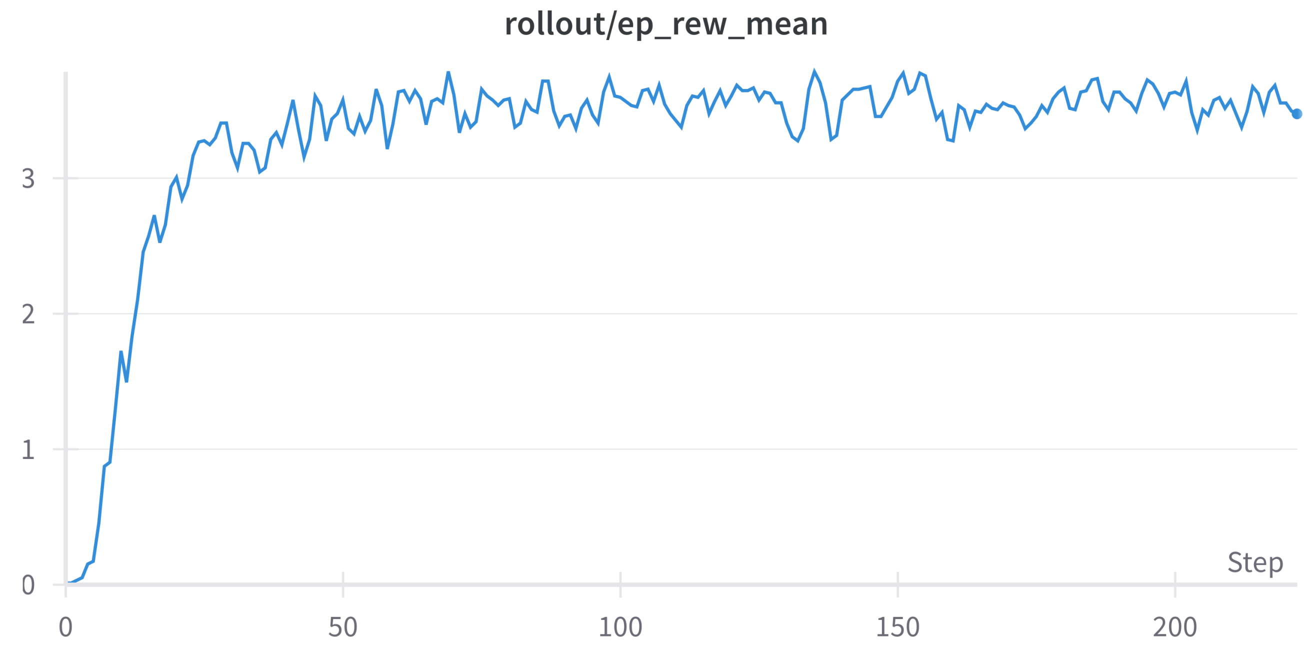
- I_0: Reward cubes put into basked
- I_1: Punish large deviation from base policy
- I_2: Reward vicinity to closest cube
- I_3: Punish distance to other robot arms
- I_4: Reward grasping while very close to cube
- I_5: Reward vicinity to basket with grasped cube
- I_6: Reward relaxing grasp over basket

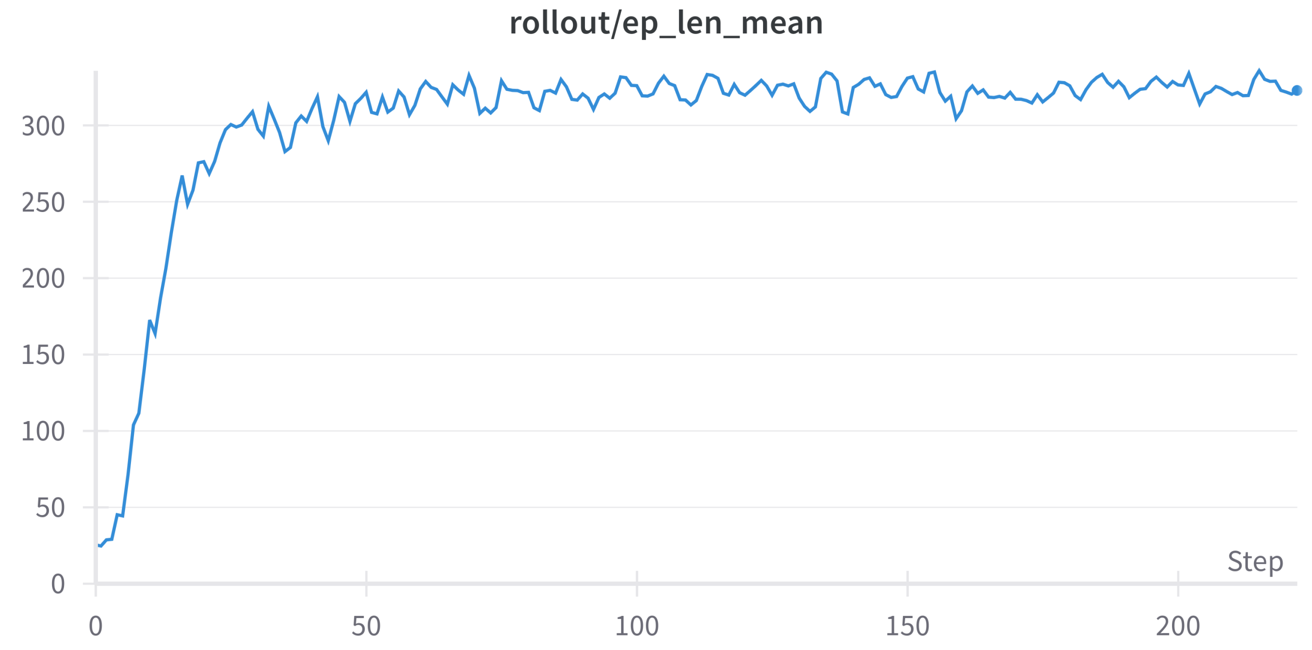
$$r = \sum_{i=0}^{6} \omega_i I_i$$

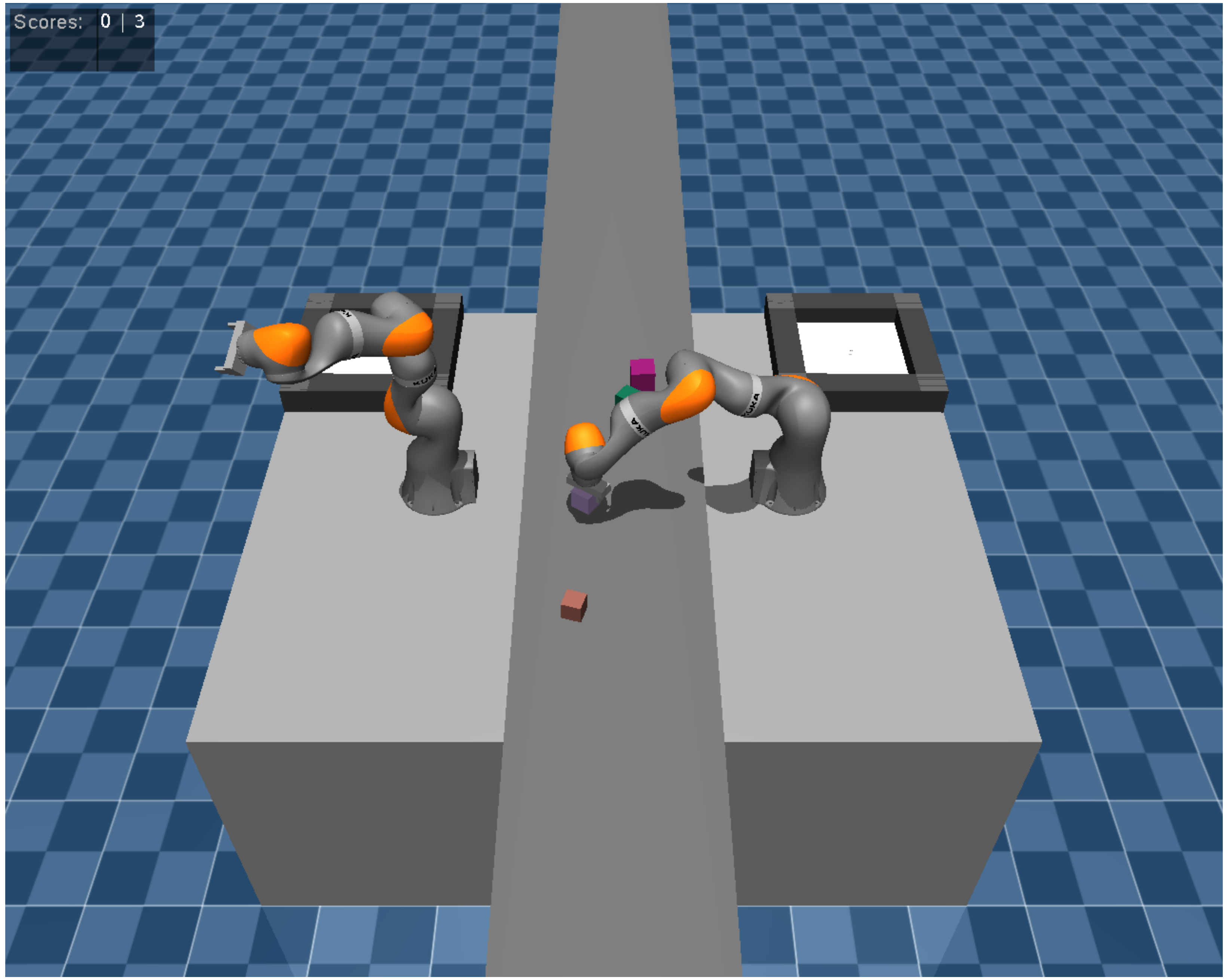
- goal: $\omega_0 >> \omega_i$ for $i \geq 1$
- ideally most $\omega_i = 0$

First Results

PPO for $\omega_0, \omega_1 > 0$ and $\omega_2, \ldots \omega_6 = 0$







learnt RL policy steers IK base policy away from other arm (undesired)

Next Steps

- explore denser reward augmentations
- use other algos/modifications for sparse case
- introduce RL for 2nd arm as well
- construct multi-agent env

TUMultuous

Discussion time!