



Multi-agents experiments

Based on MADDPG

MADDPG

Multi-Agent Deep Deterministic Policy Gradient [1]

- Challenge: multi-agent environment are **non stationary**
- MADDPG proposes **centralized** training but **decentralized** execution
- Extends other Actor-Critic Policy Gradient Methods (eg: DDPG[2]): shared replay buffer for Critics
- Like DDPG, made for **continuous control**
- For each agent: 2 networks: **Actor** and **Critic** (in a *running* and *target* versions)

[1] "Multi-Agent Actor-Critic for Mixed Cooperative-Competitive Environments", R. Lowe et al, 2017.

[2] "Continuous Control With Deep RL", T. Lillicrap et al, 2015.

- **Centralized training:**

- Critic $Q(o, a) \rightarrow v$, for an observation o (a state) and an action a , give a value v used to train the Actor net.
- Critics **share** their information during **training**.
- *"How good is an action given that state?"*

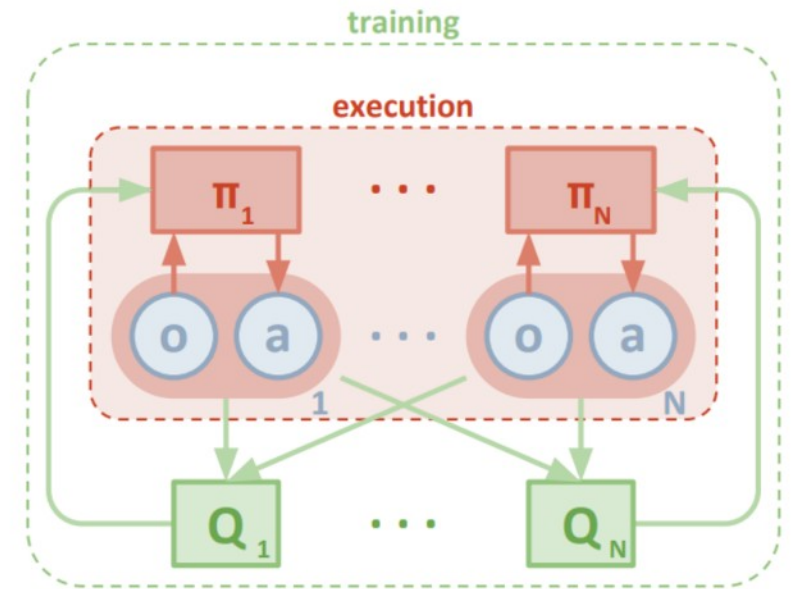


Figure 1: Overview of our multi-agent decentralized actor, centralized critic approach.

- **Decentralized execution:**

- Actor $\pi(o) \rightarrow a$, for an observation o , gives an action a
- Trained of the Critic
- Actors use **only local** information at **exec. time**
- *"What the best action given that state?"*

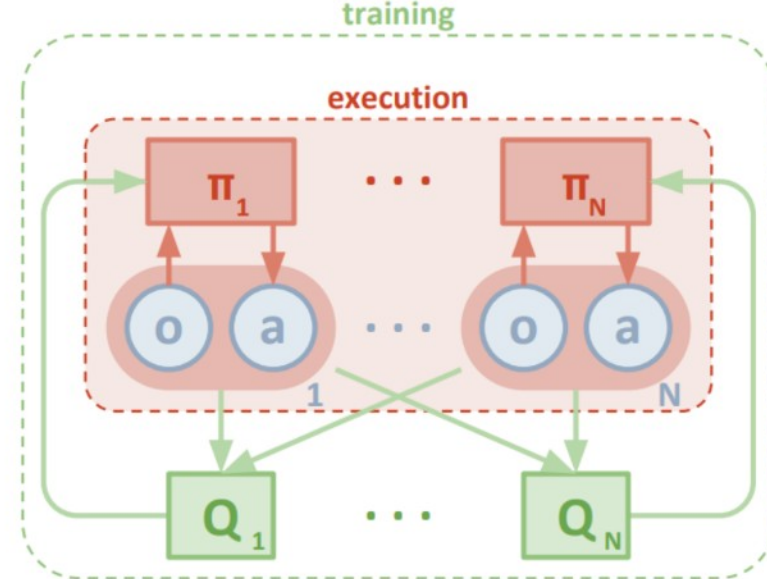
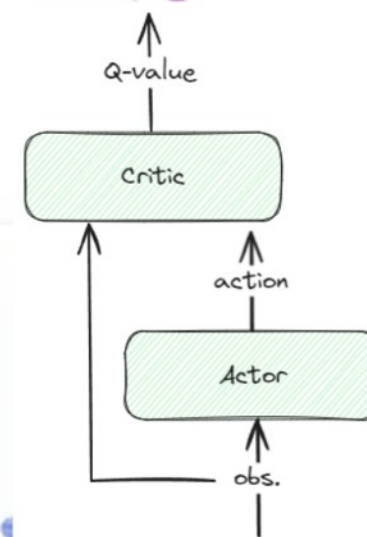
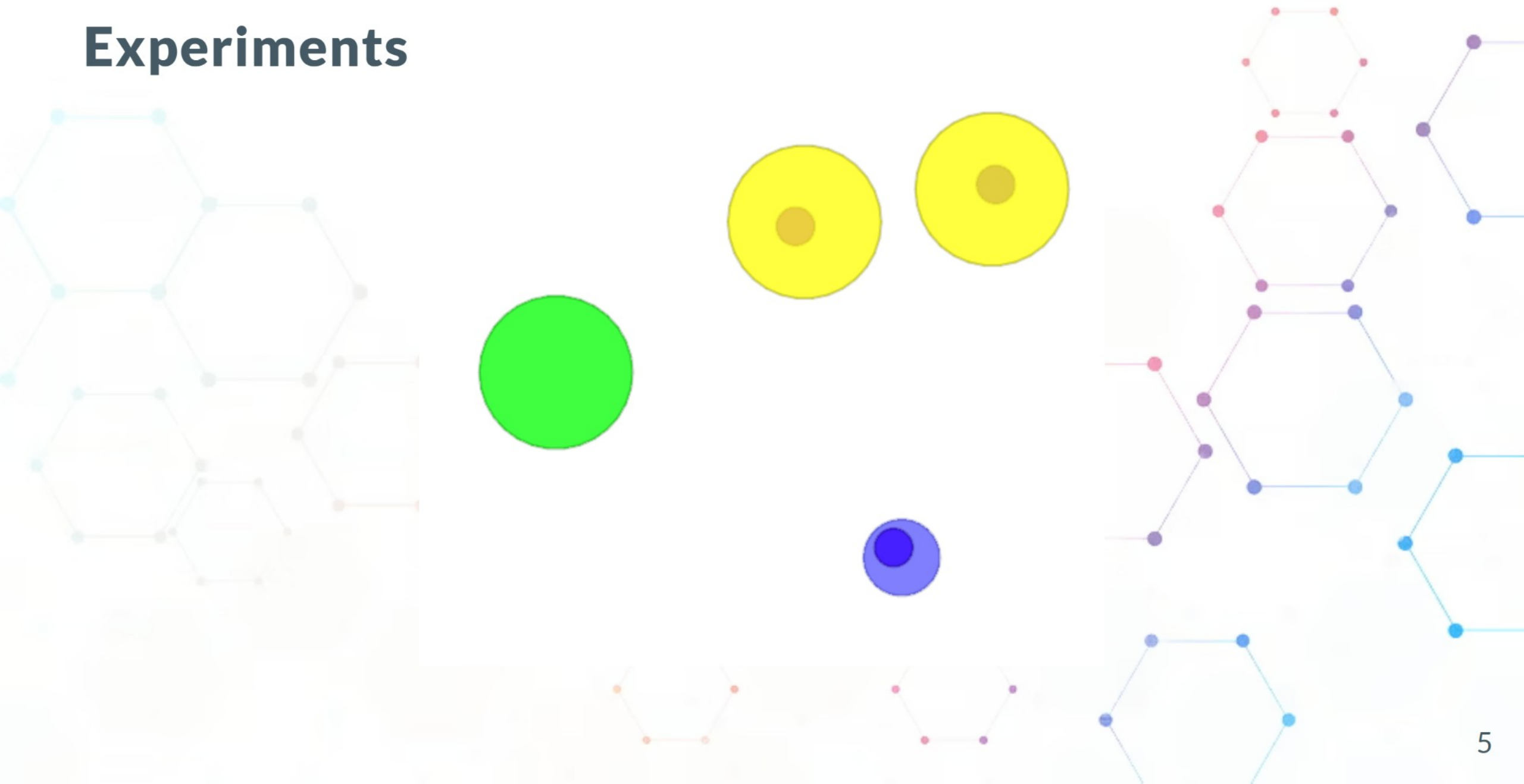


Figure 1: Overview of our multi-agent decentralized actor-critic approach.



Experiments



Summary

Exp.	Desc.	Obs.	Reward	Acc.R.
1	Single agent follows a leader	dx, dy	dist(leader)	240
2	Single agent follows a leader	dx, dy, agent_vel_x/y	idem	310
3	2 agents and a landmark (lk)	idem, lk_dx/dy, lk_is_active	dist(lk or leader)	160
4	2 agents and a landmark + separation	idem	dist(leader_pos - 4 * leader_vel)	150
5	3 agents and 2 landmarks (no sep) 10k it.	idem, target_vel_x/y	dist(lk or target)	410
6	3 agents and 2 landmarks (with alignment) 10k it.	idem	.7 * dist + .3 * cos_sim(d_vel)	300
7	4 agents and 3 landmarks (with align) 25k it.	idem	idem	540
8	idem + separation and alignment (WIP)	idem - agent/target vel + d_vel angle and mag	idem	395

target: leader or previous agent

dx, dy: target_pos - agent_pos

d_vel: agent_vel - target_vel

Observations example (Exp. 8)

```
target_id = agent.id-1

# target distance
target = self.find_agent_by_id(world, target_id)
if target:
    self.fix_agent_vel(target)
    # delta x/y
    d_pos = target.state.p_pos - agent.state.p_pos
    # delta vel
    dv_angle, dv_mag = self.get_angle(target.state.p_vel, agent.state.p_vel)

# agent's goal
lm = self.find_entity_by_name(world, f"Goal {target_id}")
if lm:
    lm_d_pos = lm.state.p_pos - agent.state.p_pos
    lm_act = int(lm.activate == True)

return np.array([d_pos[0], d_pos[1], dv_angle, dv_mag, lm_d_pos[0], lm_d_pos[1], lm_act])
```

Rewards example (Exp. 8)

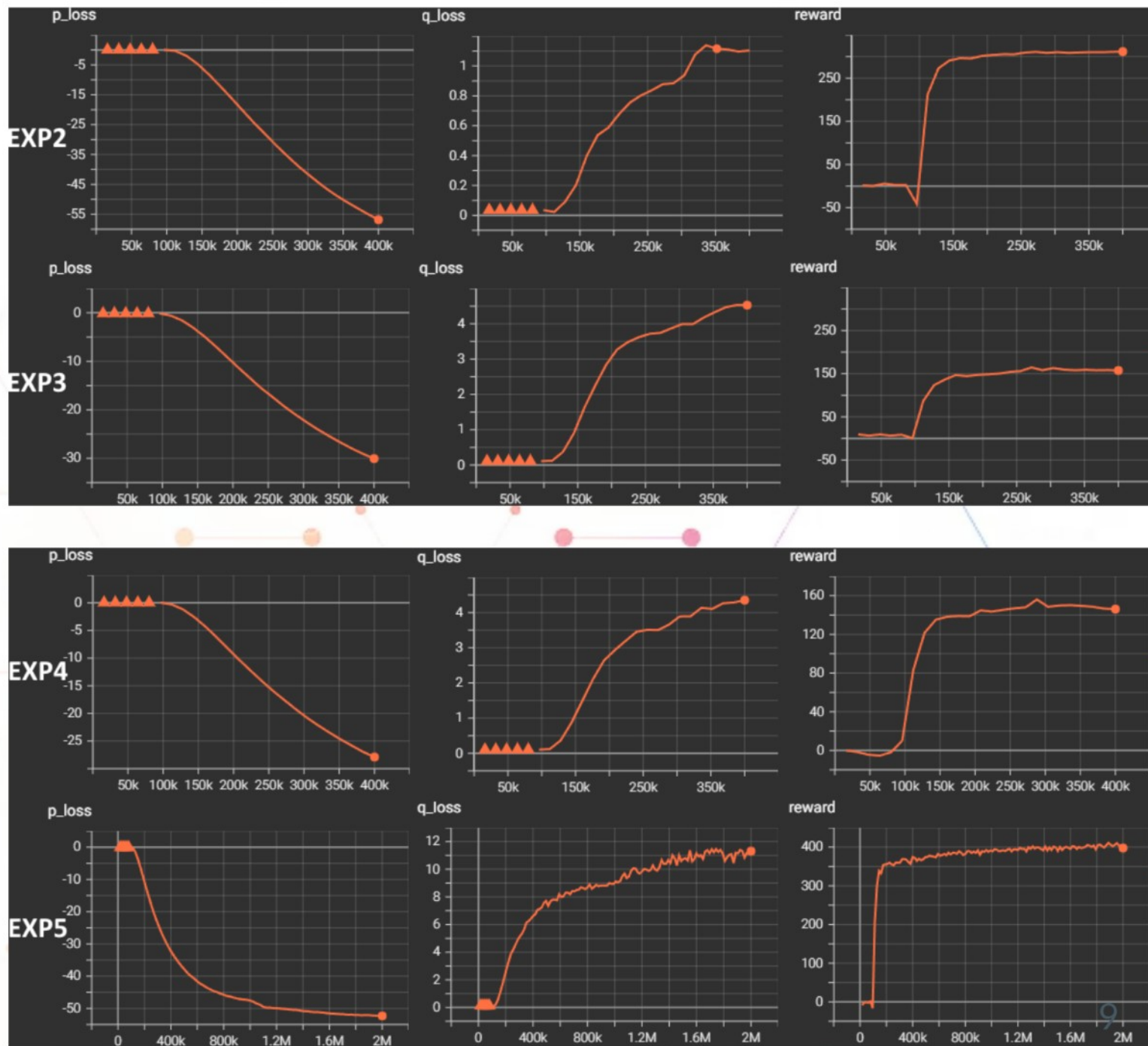
```
target_id = agent.id-1
target = self.find_agent_by_id(world, target_id)

# if the goal is activated, try to get it
landmark = self.find_entity_by_name(world, f"Goal {target_id}")
if landmark and landmark.activate:
    d = dist(agent.state.p_pos, landmark.state.p_pos)
    reward = -math.log(d)

# else follow the leader
else:
    target_pos = self.estimate_target_pos(agent, target)
    d = dist(agent.state.p_pos, target_pos)
    angle, mag = self.get_angle(target.state.p_vel, agent.state.p_vel)
    reward = .7 * -math.log(d) + .15 * -math.log(abs(angle)) + .15 * -math.log(mag)
return reward
```


How does it learn?

- No landmark VS landmark (exp2 vs exp3): 🏠
- Separation (exp4 vs exp5): 🏠
- Single vs multi-agents (exp3 vs exp5): 🐌
- All constraints: 🚀 convergence time and unstability



What went well/wrong

- ⚠ Setup on MacOS
- ⚠ Fix some "bugs" (no blinking landmarks)
- ⚠ Hard to find a good multi-objective reward (distance + separation + alignment)
- ✓ Setup dev. env using VSCode
- ✓ Time management: family time during WE, work, sport, etc.
- ✓ Discovered new algo, multi-agent RL and a new GYM platform!

Next steps

- Finish separation and alignment (5 functions so far)
- Better reward activation:
 - $-\log(x)$,
 - $1/x$,
 - $\text{sigmoid}(x)$,
 - $-x * .5 + 1$, etc
- Obstacles, ...
- Longer trainings, ...



Thank you!

