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Reinforcement Learning to Simulate Groups of Agents.

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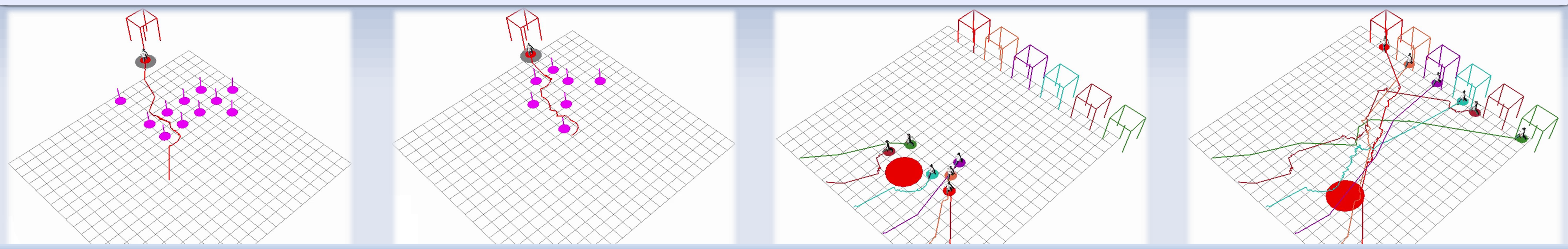
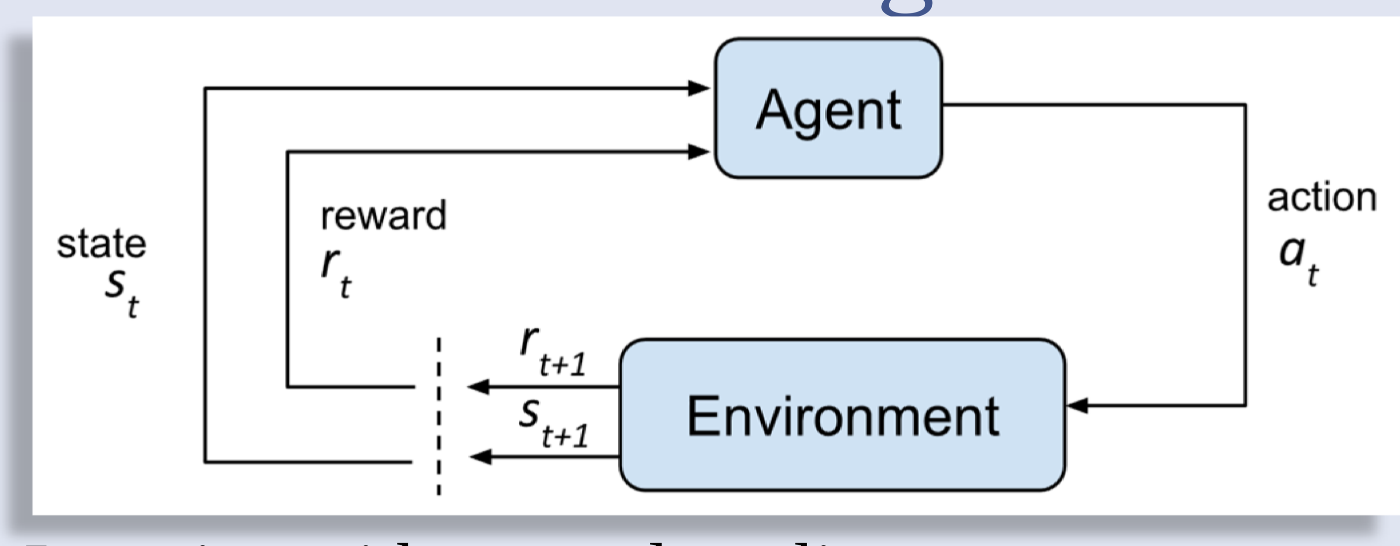


This poster present a Reinforcement Learning (RL) approach for crowd simulation. We train an agent to move towards a goal while avoiding obstacles. Once one agent has learned, its knowledge is transferred to the rest of the members of the group by sharing the resulting Q-Table. This results in individual behavior leading to emergent group behavior. We present a framework with states, actions and reward functions general enough to easily adapt to different environment configurations.

RL for one agent



- Q-Learning with ε-greedy policy

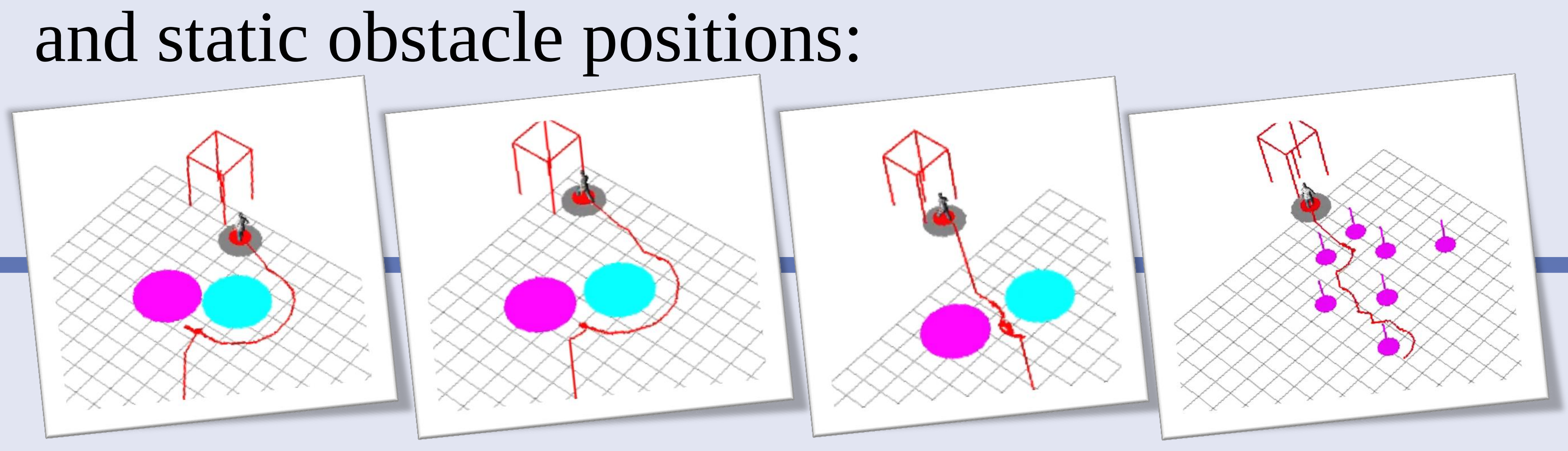
$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_{t+1} + \gamma max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$$

- α defines the learning rate
- γ defines the discount rate (0→maximize immediate reward, 1→takes future rewards into account)

Q-learning with ε-greedy policy provides a balance between exploration (high ε) and exploitation (low ε) of knowledge.

Learning set up:

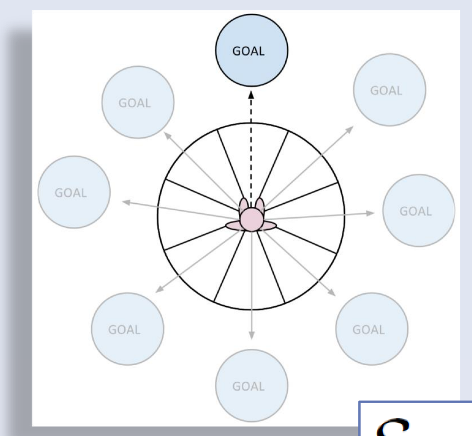
- One agent learning with 2000 episodes
- Several randomly generated configurations of goal and static obstacle positions:



Problem definition

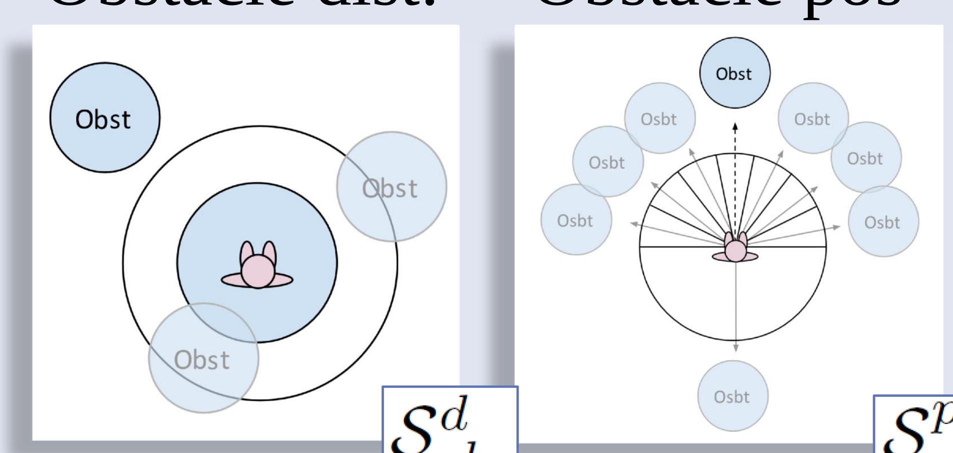
State:

goal pos



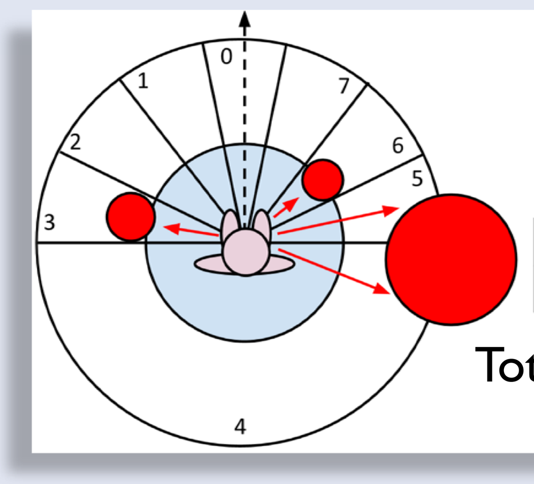
S_{goal}

Obstacle dist: Obstacle pos



S^d_{obs} S^p_{obs}

Obstacle occupancy code:



Angle Interval	0	1	2	3	4	5	6	7
Code	0	0	0	2	1	1	2	0

Total: 52,488 states

S_{obs}

Reward:

$$r(s_t, a_t) = r_g + r_o$$

- Angle towards the goal:

$$r_g^{cos}(t) = cos(\angle(\overrightarrow{v_a}, \overrightarrow{w_a}))^3$$

- Occupancy code:

$$r_o(t) = \begin{cases} 0, & \text{if } d_o > \tau_2 \\ -\sum_{i=0}^{|S^d_{obs}|-1} \frac{10}{10^{(o[i]-1)*2}}, & \text{otherwise} \end{cases}$$

Negative reward increases as the number of occupancy codes with values higher than 0 increase.

Results:

Knowledge transfer to groups of agents: Agents move towards their goal successfully handling moving obstacles and other agents despite learning with static obstacles.