MULTI AGENT REINFORCEMENT LEARNING

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CSE 410 Reinforcement Learning

University at Buffalo
School of Engineering and Applied Sciences

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Multi-Agent Reinforcement Learning (MARL)

- Form of Reinforcement Learning (RL)
  - Agent(s) learn to take actions that maximize a reward derived from the environment
- Includes multiple independent actors (agents)
  - Each agents actions may change the environment
  - Changes to the environment could affect reward for all agents
- Agents may interact to maximize their reward
  - Intentional changes to the environment
  - Direct agent-to-agent communication
  - Cooperation vs competition

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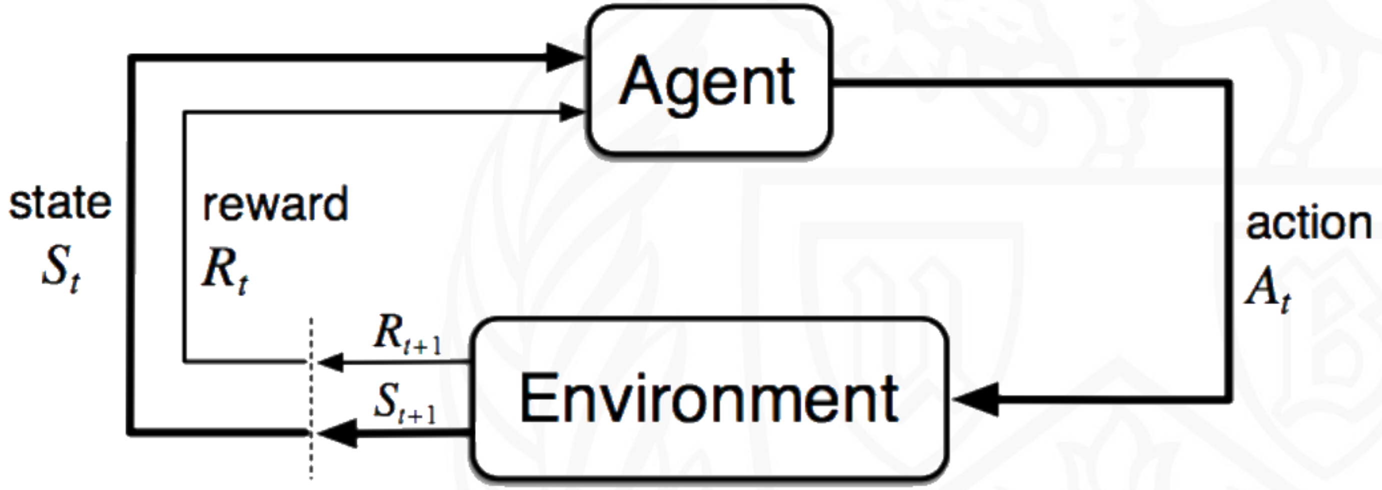
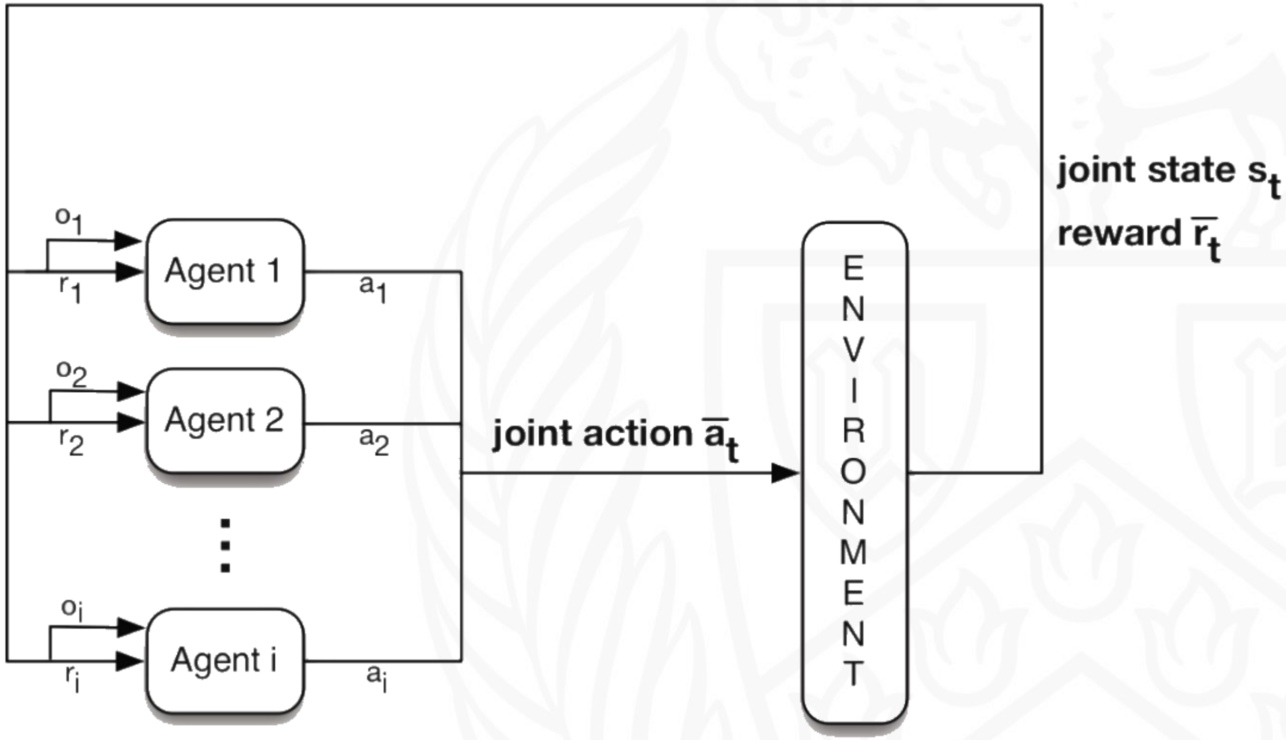
Markov Decision Processes

- Typical RL problem
- Characterized by a Markov Decision Process (MDP)
- MDP Parameters
  - S – set of possible states in the environment
  - A – set of possible actions the agent can take
  - R – reward function
  - P – state to state transition probability based on action



Stochastic Games

- Combination of MDP with a repeated game
  - Agents must account for actions of other agents
- Stochastic Game Parameters
  - $\mathcal{N}$ agents
  - A_i - action set for agent i
  - A – combined action
    - $a_1 \times a_2 \times \cdots \times a_n$
  - R – rewards function for A



MARL Challenges

- Moving Target
  - Reward for each agent can be affected by actions of other agents
  - Agent’s action change over time
  - Action-reaction loops can cause rewards to fluctuate
- Reward attribution
  - Which action(s) from which agent(s) led to states with large rewards
  - Impossible to maximize each agent independently
- Curse of dimensionality
  - More agents can increase observation and action spaces
  - Complexity grows exponentially with space and state dimensions

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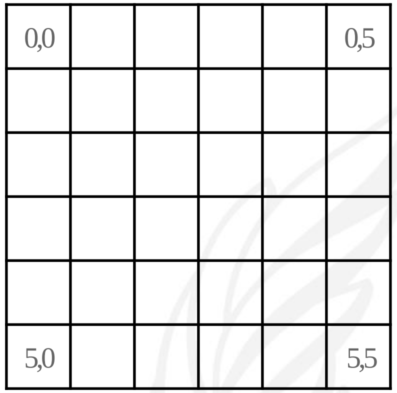
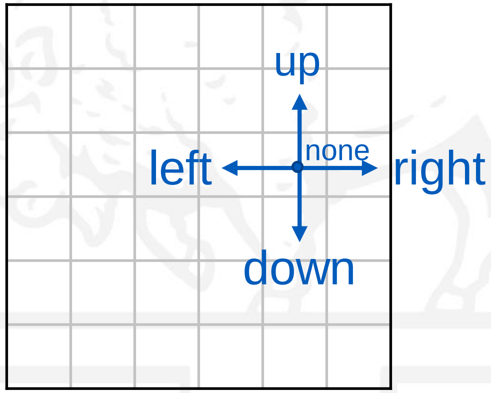
Multi Agent Grid-World

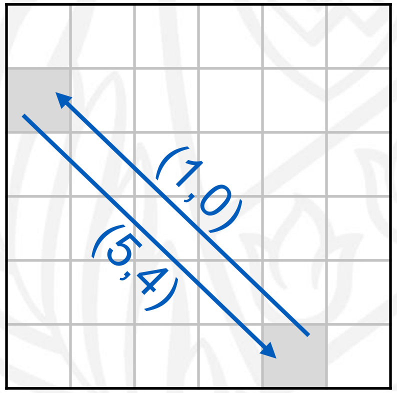
- Square grid-world of size $s \geq 6$
- Support n agents, $n \in 2,3,4$
  - Process n actions per timestep
  - Return n unique rewards
- Observation space
  - Current agent position $[row, col]$
- Action Space
  - 5 possible actions
  - Move up/right/down/left, don’t move
- Enable agent-to-agent communication
  - Agents should be able to share their location with other agents



Observation Space



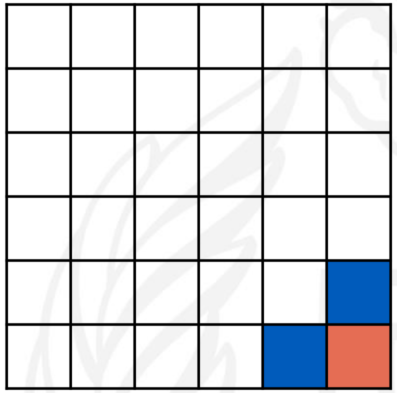
Action Space



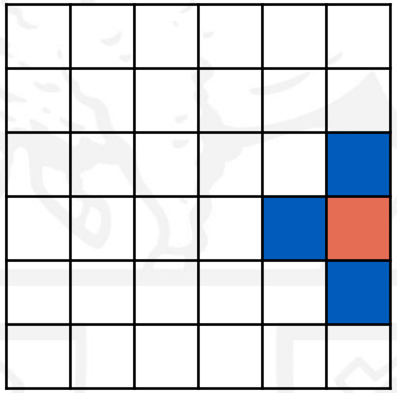
Agent Communication

Task: Enemy Containment

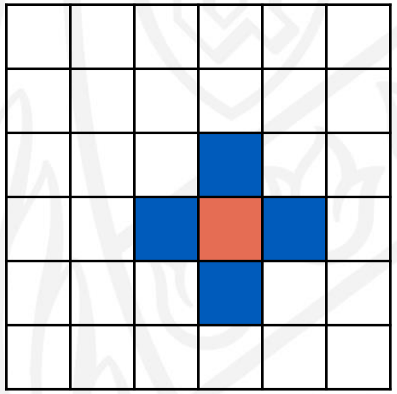
- n agents coordinate to "contain" a static enemy
  - View environment as city streets
  - Location of enemy is neighborhood infected with a virus
  - Agents learn the best location to place testing stations
- Enemy is contained when surrounded on all sides, game terminates
- Reward Function
  - -2 if $d_{t+1} \geq d_t$
  - -1 if $d_{t+1} < d_t$
  - 0 if $d_{t+1} = 1$



$n = 2$



$n = 3$



$n = 4$

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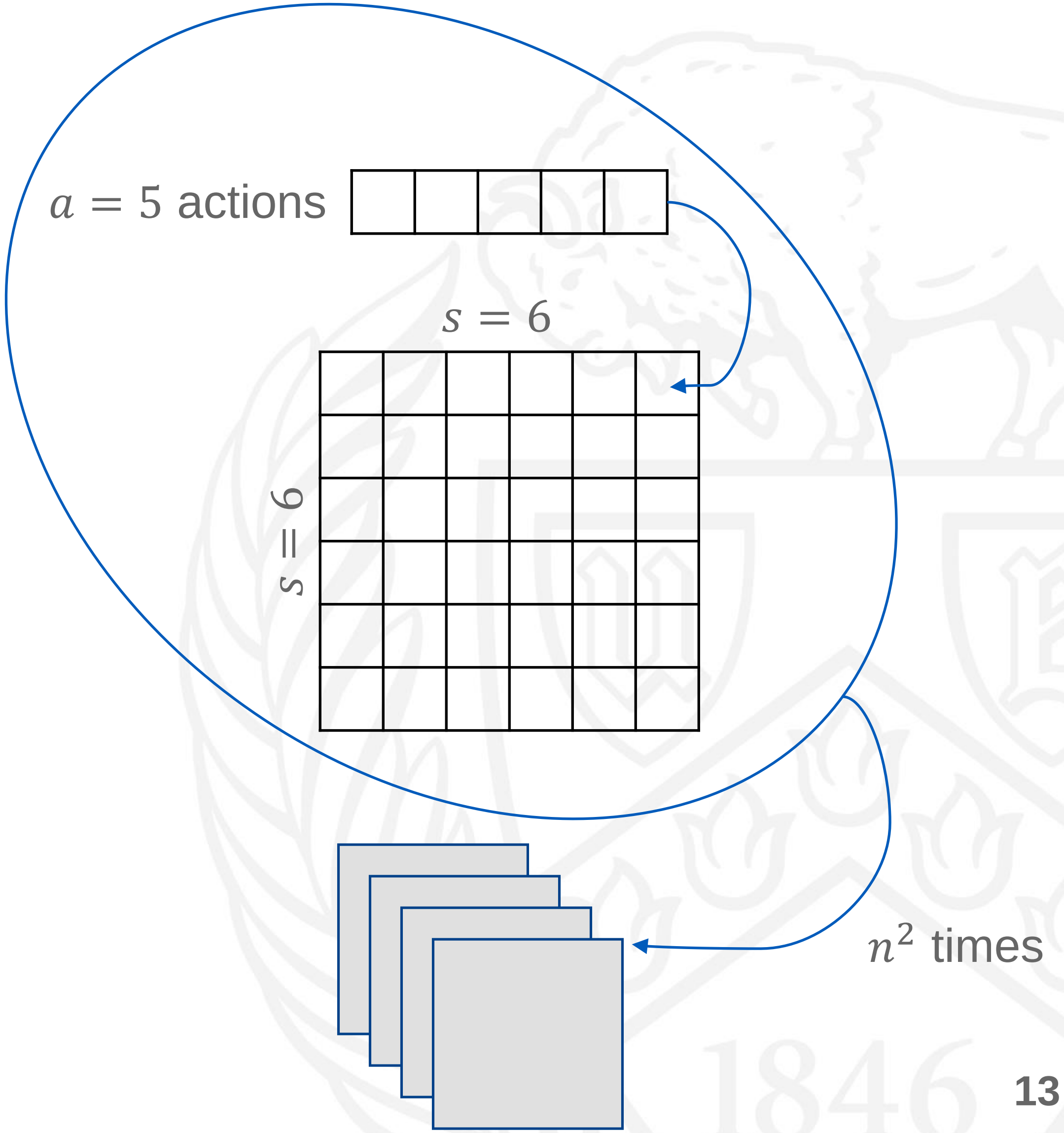
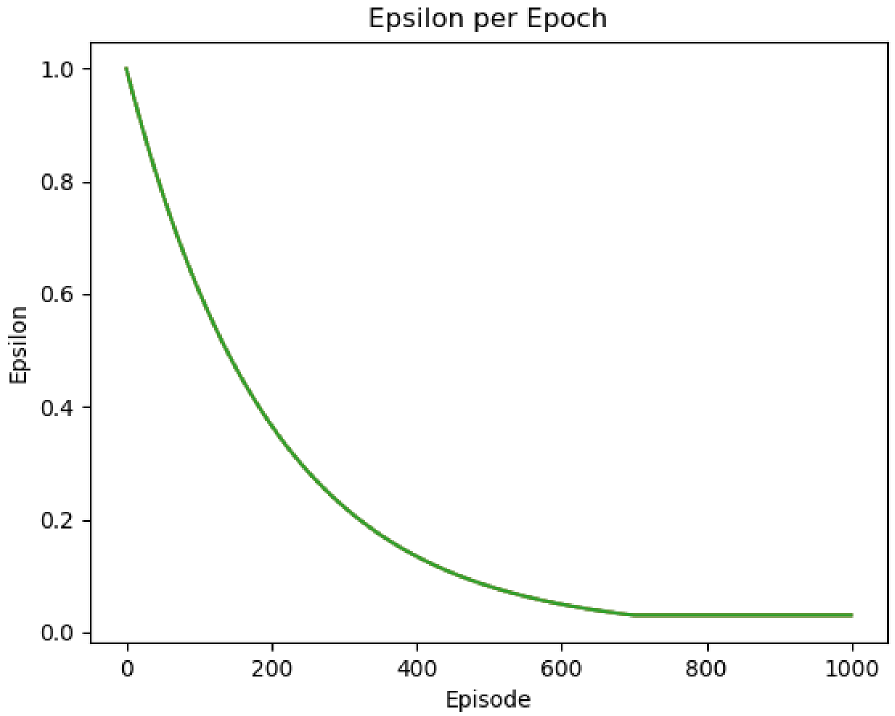
Agents

- Compare performance of two types of agents
  - Tabular Q-Learning (TQ)
  - Deep Q-Network (DQN)
- Agent Inputs
  - Observation: Current location
  - Communication: $n - 1$ other agent locations
- Agent Outputs
  - Next action
- For size s with n agents and a actions
  - Q-table size: $s^2 \times n^2 \times a$
  - DQN input layer of size 2n
    - 2 Dense ReLU layers of size 48



Training

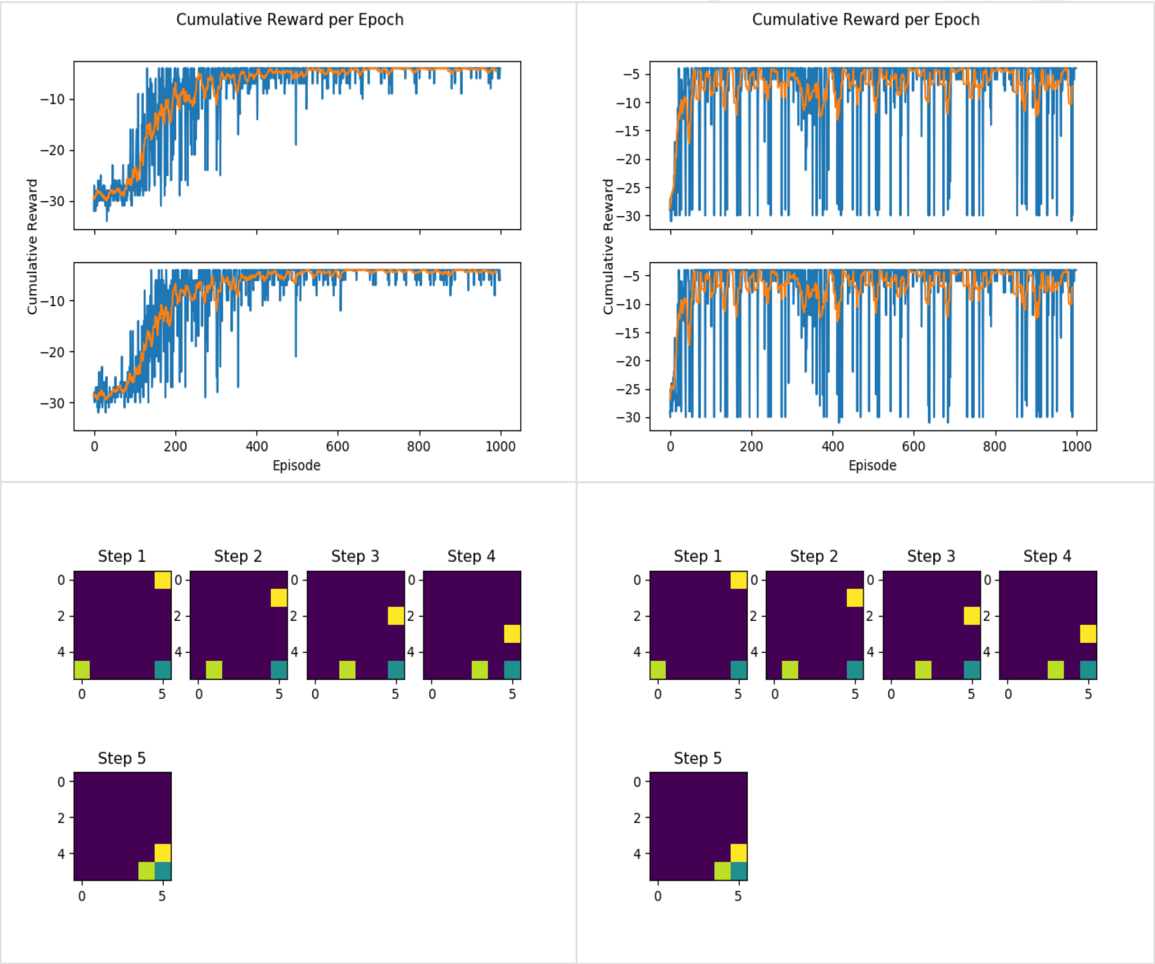
- All agents trained for 1000 epochs
  - $\gamma = 0.95$
  - $\alpha = 0.05$
- Exponential ϵ decay
  - $\epsilon_0 = 1.0$
  - $\epsilon_{min} = 0.03$
  - $\delta = 0.005$
- At each iteration we recorded the score and learned movements for each agent
  - Score = total cumulative reward for one epoch
  - Learned movements recorded with $\epsilon = 0$, greedy



Results

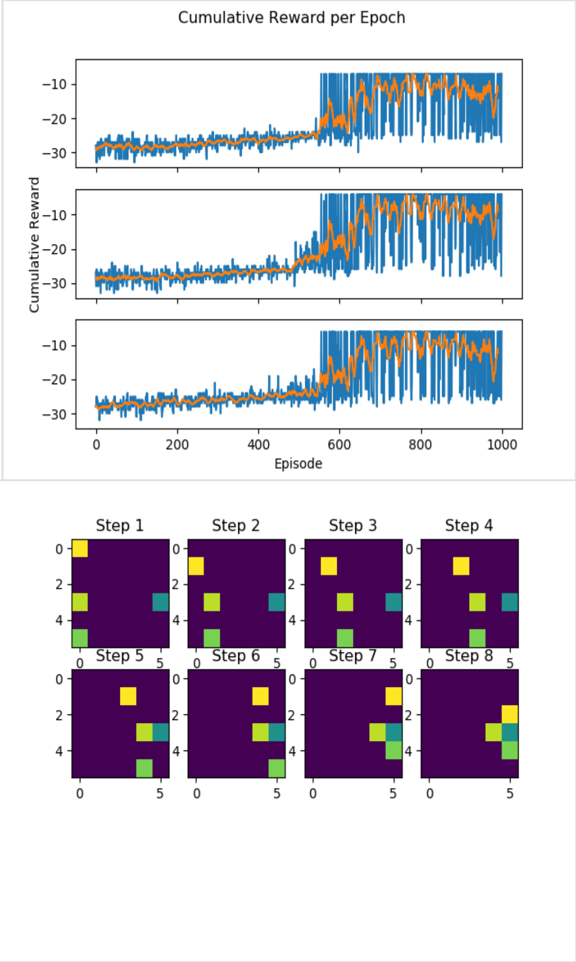
- Results for $n = 2$
- Plots of score with averaging over a sliding window of size 10
- Final learned path
  - Agents shown in yellow and green
  - Enemy shown in blue
- Both TQ and DQN agents converge to the same optimal path
- DQN agents learn much more quickly, but with slightly more noise

Results $n = 2$

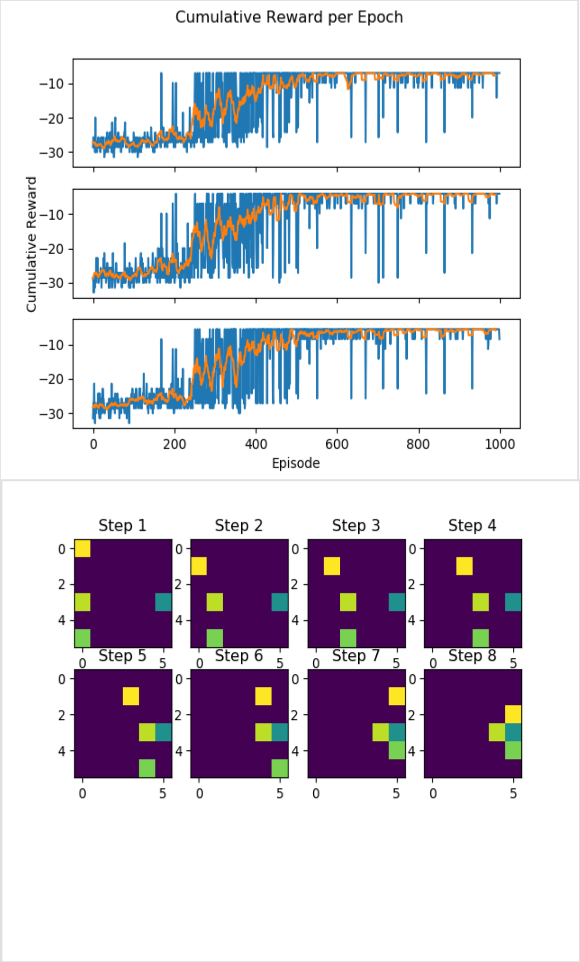


Tabular DQN

Results $n = 3$

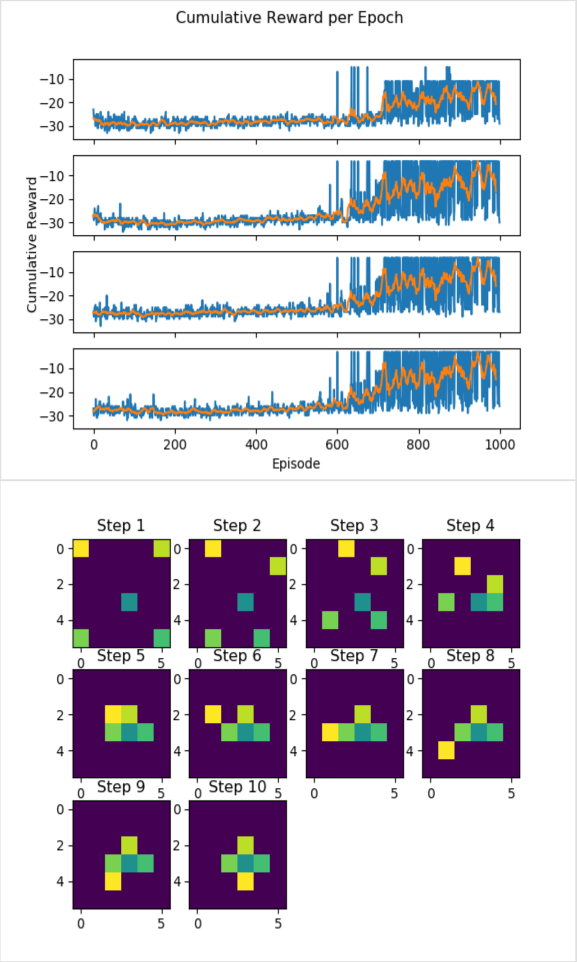


Tabular

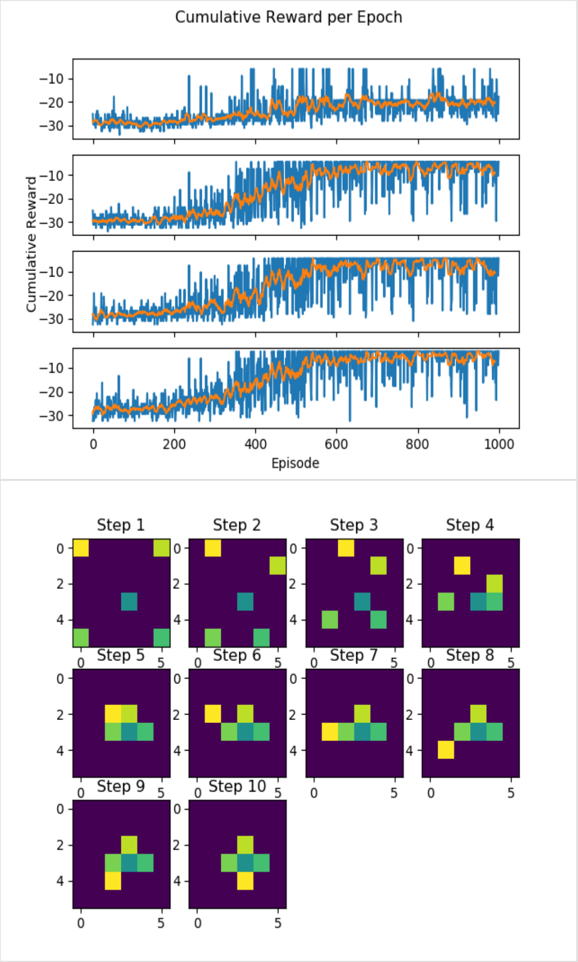


DQN

Results $n = 4$



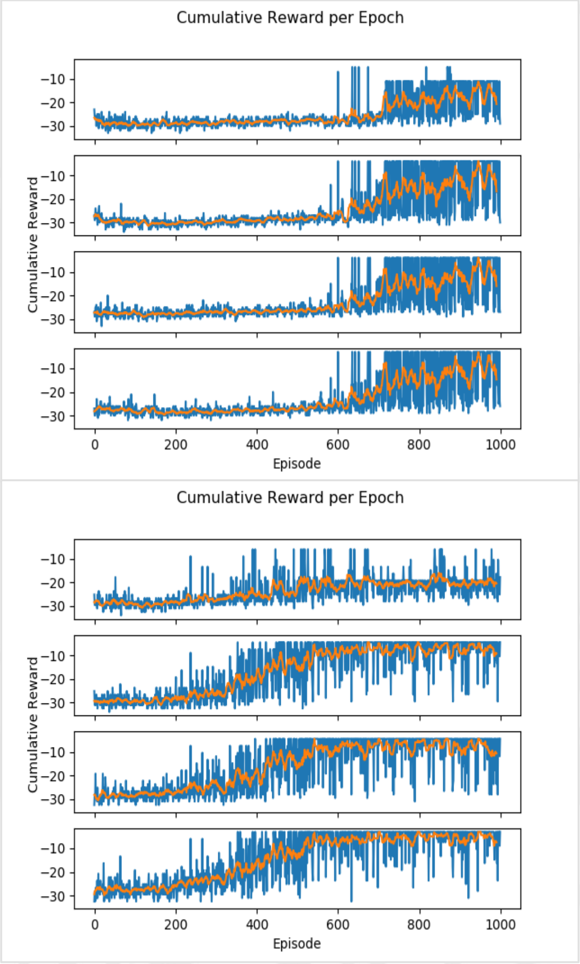
Tabular



DQN

Analysis

- In all cases $n = 2,3,4$ the tabular and DQN agents learned a path from their starting locations to a containment position
- DQN achieved the same paths, but with less training time
  - Scores reach optimal values at earlier epoch
  - Difference of ~400 epochs for $n = 3,4$
- Improvement likely due to curse of dimensionality
  - Tabular agents must visit and learn each of $s^2 \times n^2 \times a$ values independently
  - DQN agents update weights on every iteration
    - Use same weights to predict Q-Values for every state-action pair
    - Allows DQN agents to generalize to unseen states
    - Greatly improves training sample efficiency



TQ an DQN scores, $n = 4$

THANK YOU!
QUESTIONS?

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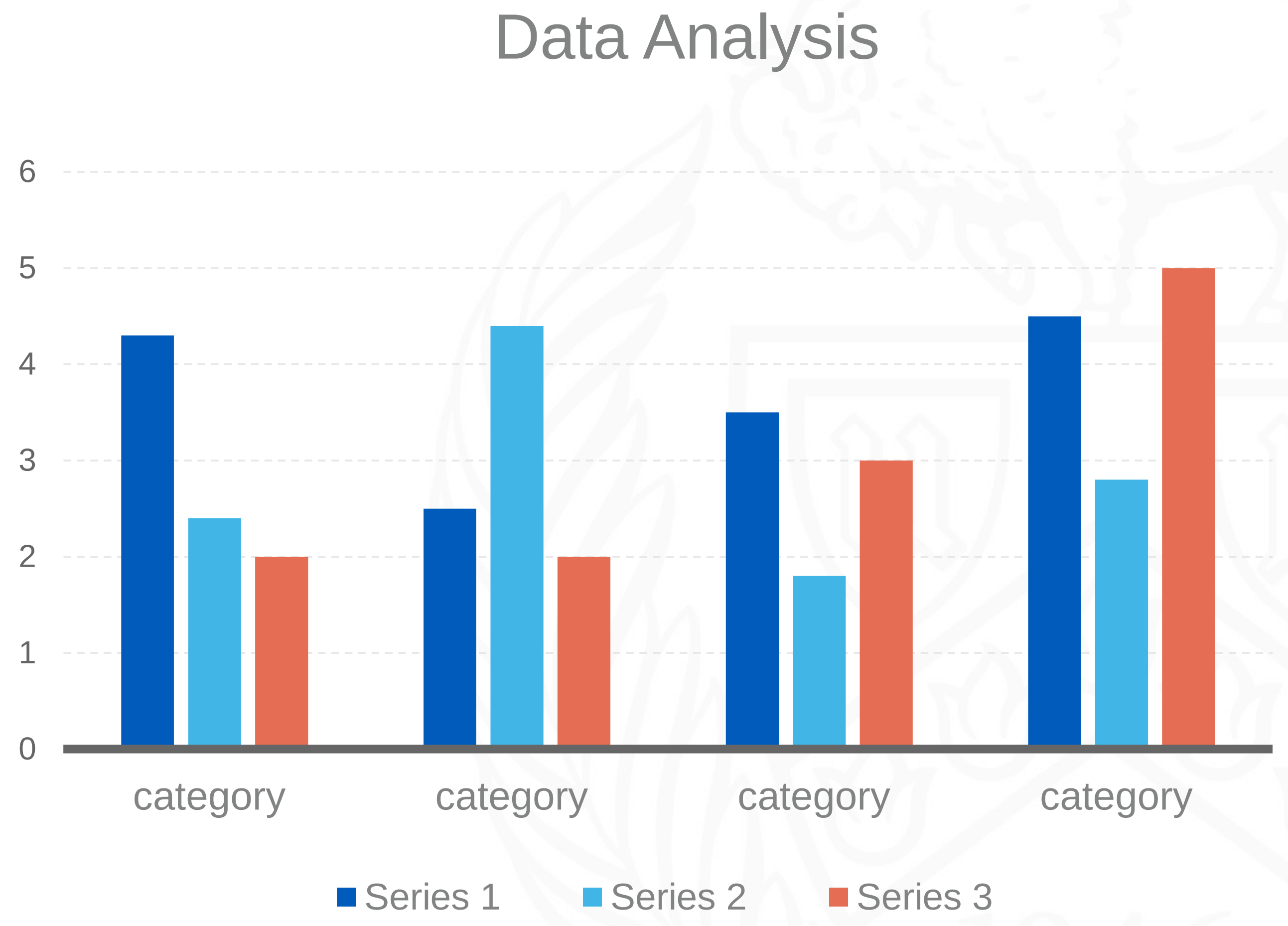

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