



Optimizing Goalkeeper Positioning

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What problem did we address?

- RL in soccer mostly regards outfield play, but what about the goalkeeper..?
- The goalkeeper is arguably the most important position in a soccer team and a goalkeeper's effectiveness comes down to a few key skills:
 - Hands (i.e. catching)
 - Agility (i.e. diving and quickness)
 - Positioning
- Knowing where to be all times puts the goalie in the best position to save a shot from the opposing team
 - Having impeccable positioning can sometimes even make up for subpar catching or agility
- Given the position of an attacker, what is the best position for a goalkeeper to be in?



What RL methods did we use?

- Multi-Armed Bandit
 - Agent has n arms (actions)
 - Observes a state from the environment and will either:
 - Exploit → Pick the current best arm
 - Explore → Pick a random arm
 - Receives a reward based on the optimality of the arm picked
 - Stores *estimated* value of each arm (per state)
 - Essentially a Q-table
 - Updates *estimated* values based on reward and a constant step-size

$$Q_{n+1} = Q_n + \alpha[R_n - Q_n]$$

- Best fit for the structure of the problem
 - Episodic, but each episode is comprised of just one time step



What is the environment?

- Two perpendicular sides of a cube
 - The vertical side (XZ plane) represents the goal
 - The horizontal side or base (XY plane) represents the goal area
- State Space
 - Initial position of the attacker
- Action Space
 - All possible positions the goalie can be in
 - In theory: any position within the goal area
 - In practice: we discretized the goal area into 24x18 matrix (each cell is one square foot)
- Reward Function
 - Save $\rightarrow 0$
 - Goal $\rightarrow -1$



How did we train the agent?

Initialize attacker S , goalkeeper G , and step-size α :

$Q(a, s) \leftarrow 0$

$\alpha \in (0, 1]$

Loop forever:

$P \leftarrow S.\text{newPosition}()$

$G.\text{newPosition}(P)$

$L \leftarrow S.\text{newShotLocation}()$

$R \leftarrow G.\text{saveOrNot}(L)$

$Q(a, P) \leftarrow Q(a, P) + \alpha[R - Q(a, P)]$

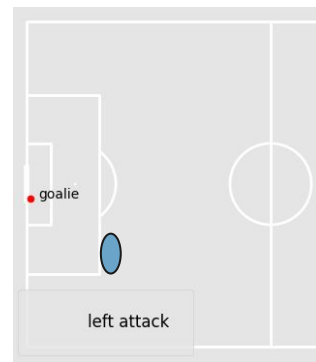
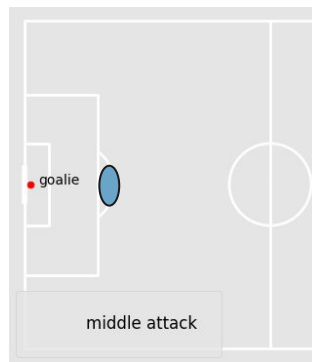
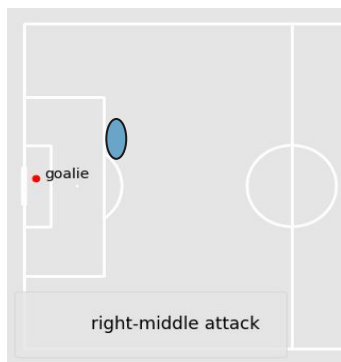
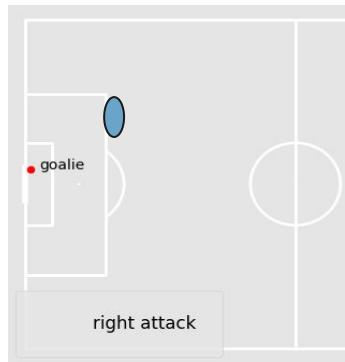


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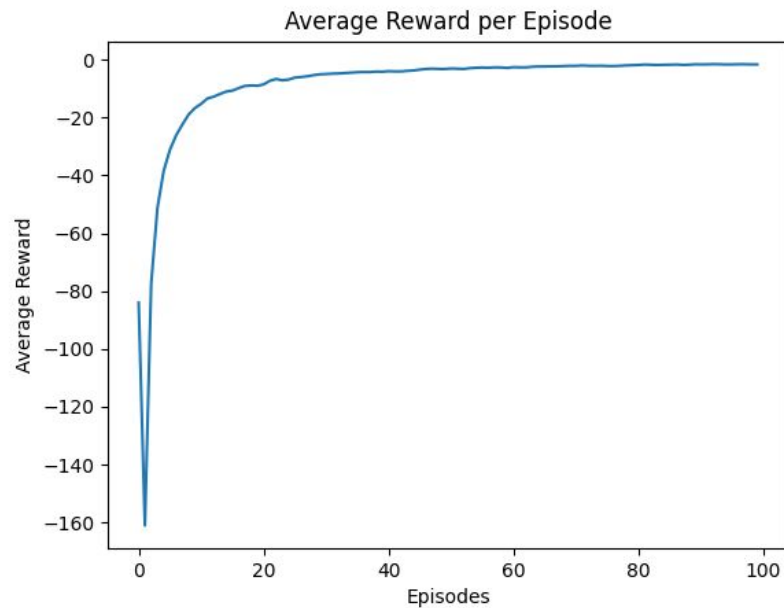
- Attacker position randomized between 5 different locations
 - Each location has its own shot distribution
- Attacker shot location sampled from respective shot distribution
- Goalkeeper picks action (i.e. what position to be in) solely based on attacker position
 - Does not know shot distributions
- Based on Goalkeeper position, *savable area* of goal is calculated and used to assess if shot was saved or not
 - Goalkeeper casts shadow onto goal
 - If Goalkeeper is far out, the shadow increases in width but decreases in height
 - If Goalkeeper is closer to the goal line, the shadow increases in height but decreases in width



What were our results?



What were our results?





Where do we go from here?

- Quick Recap
 - The scope of our project was to optimize goalkeeper positioning
 - Implemented agent as a Multi-Armed Bandit
 - Results clearly show that the agent learned which positions are better (and worse)
- Next steps
 - Extend this experiment to 3D via RoboCup Simulator
 - Expand environment to additionally have more than one attacker or defenders



Thank You!

Any questions?