Q1. MDP

Pacman is using MDPs to maximize his expected utility. In each environment:

- Pacman has the standard actions \{North, East, South, West\} unless blocked by an outer wall
- There is a reward of 1 point when eating the dot (for example, in the grid below, \( R(C, \text{South}, F) = 1 \))
- The game ends when the dot is eaten

(a) Consider the following grid where there is a single food pellet in the bottom right corner (\( F \)). The discount factor is 0.5. There is no living reward. The states are simply the grid locations.

\[
\begin{array}{ccc}
A & B & C \\
D & E & F
\end{array}
\]

(i) What is the optimal policy for each state?

<table>
<thead>
<tr>
<th>State</th>
<th>( \pi(state) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>East or South</td>
</tr>
<tr>
<td>B</td>
<td>East or South</td>
</tr>
<tr>
<td>C</td>
<td>South</td>
</tr>
<tr>
<td>D</td>
<td>East</td>
</tr>
<tr>
<td>E</td>
<td>East</td>
</tr>
</tbody>
</table>

(ii) What is the optimal value for the state of being in the upper left corner (\( A \))? Reminder: the discount factor is 0.5.

\[ V^*(A) = 0.25 \]

(iii) Using value iteration with the value of all states equal to zero at \( k=0 \), for which iteration \( k \) will \( V_k(A) = V^*(A) \)?

\[ k = 3 \text{ (see above)} \]
(b) Consider a new Pacman level that begins with cherries in locations D and F. Landing on a grid position with cherries is worth 5 points and then the cherries at that position disappear. There is still one dot, worth 1 point. The game still only ends when the dot is eaten.

(i) With no discount (\(\gamma = 1\)) and a living reward of -1, what is the optimal policy for the states in this level’s state space?

<table>
<thead>
<tr>
<th>State</th>
<th>(\pi(state))</th>
</tr>
</thead>
<tbody>
<tr>
<td>A, DCherry=true, FCherry=true</td>
<td>South</td>
</tr>
<tr>
<td>A, DCherry=true, FCherry=false</td>
<td>South</td>
</tr>
<tr>
<td>A, DCherry=false, FCherry=true</td>
<td>East</td>
</tr>
<tr>
<td>A, DCherry=false, FCherry=false</td>
<td>East</td>
</tr>
<tr>
<td>C, DCherry=true, FCherry=true</td>
<td>East</td>
</tr>
<tr>
<td>C, DCherry=true, FCherry=false</td>
<td>East</td>
</tr>
<tr>
<td>C, DCherry=false, FCherry=true</td>
<td>East</td>
</tr>
<tr>
<td>C, DCherry=false, FCherry=false</td>
<td>North/East</td>
</tr>
<tr>
<td>D, DCherry=true, FCherry=true</td>
<td>East</td>
</tr>
<tr>
<td>D, DCherry=false, FCherry=false</td>
<td>North</td>
</tr>
<tr>
<td>E, DCherry=true, FCherry=true</td>
<td>East</td>
</tr>
<tr>
<td>E, DCherry=true, FCherry=false</td>
<td>West</td>
</tr>
<tr>
<td>E, DCherry=false, FCherry=true</td>
<td>East</td>
</tr>
<tr>
<td>E, DCherry=false, FCherry=false</td>
<td>West</td>
</tr>
<tr>
<td>F, DCherry=true, FCherry=true</td>
<td>West</td>
</tr>
<tr>
<td>F, DCherry=false, FCherry=false</td>
<td>West</td>
</tr>
</tbody>
</table>

(ii) With no discount (\(\gamma = 1\)), what is the range of living reward values such that Pacman eats exactly one cherry when starting at position A?

Valid range for the living reward is (-2.5, -1.25).

Let \(x\) equal the living reward.

The reward for eating zero cherries \{A,B\} is \(x + 1\) (one step plus food).

The reward for eating exactly one cherry \{A,C,D,B\} is \(3x + 6\) (three steps plus cherry plus food).

The reward for eating two cherries \{A,C,D,E,F,E,D,B\} is \(7x + 11\) (seven steps plus two cherries plus food).

\(x\) must be greater than -2.5 to make eating at least one cherry worth it (\(3x + 6 > x + 1\)).

\(x\) must be less than -1.25 to eat less than one cherry (\(3x + 6 > 7x + 11\)).
Q2. Strange MDPs

In this MDP, the available actions at state A, B, C are LEFT, RIGHT, UP, and DOWN unless there is a wall in that direction. The only action at state D is the EXIT ACTION and gives the agent a reward of \( x \). The reward for non-exit actions is always 1.

(a) Let all actions be deterministic. Assume \( \gamma = \frac{1}{2} \). Express the following in terms of \( x \).

\[
V^*(D) = x \quad V^*(C) = \max(1 + 0.5x, 2)
\]
\[
V^*(A) = \max(1 + 0.5x, 2) \quad V^*(B) = \max(1 + 0.5(1 + 0.5x), 2)
\]

The 2 comes from the utility being an infinite geometric sum of discounted reward = \( \frac{1}{1 - \frac{1}{2}} = 2 \)

(b) Let any non-exit action be successful with probability = \( \frac{1}{2} \). Otherwise, the agent stays in the same state with reward = 0. The EXIT ACTION from the state D is still deterministic and will always succeed. Assume that \( \gamma = \frac{1}{2} \).

For which value of \( x \) does \( Q^*(A, DOWN) = Q^*(A, RIGHT) \)? Box your answer and justify/show your work.

\[ Q^*(A, DOWN) = Q^*(A, RIGHT) \] implies \( V^*(A) = Q^*(A, DOWN) = Q^*(A, RIGHT) \)

\[
V^*(A) = Q^*(A, DOWN) = \frac{1}{2}(0 + \frac{1}{2}V^*(A)) + \frac{1}{2}(1 + \frac{1}{2}x) = \frac{1}{2} + \frac{1}{4}(V^*(A)) + \frac{1}{4}x \quad (1)
\]
\[
V^*(A) = \frac{2}{3} + \frac{1}{3}x \quad (2)
\]
\[
V^*(A) = Q^*(A, RIGHT) = \frac{1}{2}(0 + \frac{1}{2}V^*(A)) + \frac{1}{2}(1 + \frac{1}{2}V^*(B)) = \frac{1}{2} + \frac{1}{4}V^*(A) + \frac{1}{4}V^*(B) \quad (3)
\]
\[
V^*(A) = \frac{2}{3} + \frac{1}{3}V^*(B) \quad (4)
\]

Because \( Q^*(B, LEFT) \) and \( Q^*(B, DOWN) \) are symmetric decisions, \( V^*(B) = Q^*(B, LEFT) \).

\[
V^*(B) = \frac{1}{2}(0 + \frac{1}{2}V^*(B)) + \frac{1}{2}(1 + \frac{1}{2}V^*(A)) = \frac{1}{2} + \frac{1}{4}V^*(B) + \frac{1}{4}V^*(A) \quad (5)
\]
\[
V^*(B) = \frac{2}{3} + \frac{1}{3}V^*(A) \quad (6)
\]
Combining (2), (4), and (6) gives us:

\[ x = 1 \quad (7) \]

There is also a shortcut which involves you noticing that the problem is highly symmetrical such that \( Q^*(A, DOWN) = Q^*(A, RIGHT) \) is the same as solving the equivalence of \( V^*(A) \) in the previous part and the utility of an infinite cycle with reward scaled by half (to account for staying) and discount = 0.5. That leads us to conclude \( 0.5 + 0.5x = \frac{0.5}{1-0.5} = 1 \) so \( x = 1 \)

(c) We now add one more layer of complexity. Turns out that the reward function is not guaranteed to give a particular reward when the agent takes an action. Every time an agent transitions from one state to another, once the agent reaches the new state \( s' \), a fair 6-sided dice is rolled. If the dices lands with value \( x \), the agent receives the reward \( R(s, a, s') + x \). The sides of dice have value 1, 2, 3, 4, 5 and 6.

Write down the new bellman update equation for \( V_{k+1}(s) \) in terms of \( T(s, a, s') \), \( R(s, a, s') \), \( V_k(s') \), and \( \gamma \).

\[
V_{k+1}(s) = \max_a \sum_{s'} T(s, a, s') \left[ \frac{1}{6}(\sum_{i=1}^{6} R(s, a, s') + i) + \gamma V_k(s) \right]
= \max_a \sum_{s'} T(s, a, s')(R(s, a, s') + 3.5 + \gamma V_k(s))
\]
Q3. MDPs: Reward Shaping

PacBot is in a Gridworld-like environment $E$. It moves deterministically Up, Down, Right, or Left, or at any time it can exit to a terminal state (where it remains). If PacBot is on a square with a number written on it, it receives a reward of that size on Exiting, and it receives a reward of 0 for Exiting on a blank square. Note that when it is on any of the squares (including numbered squares), it can either move Up, Down, Right, Left or Exit. However, it only receives a non-zero reward when it Exits on a numbered square.

(a) Draw an arrow in each square (including numbered squares) in the following board to indicate the optimal policy PacBot will calculate with the discount factor $\gamma = 0.5$. (For example, if PacBot would move Down from the square in the middle, draw a down arrow in that square.) If PacBot’s policy would be to exit from a particular square, draw an X in that square.

![Board Diagram]

In order to speed up computation, Pacbot computes its optimal policy in a new environment $E'$ with a different reward function $R'(s, a, s')$. If $R(s, a, s')$ is the reward function in the original environment $E$, then $R'(s, a, s') = R(s, a, s') + F(s, a, s')$ is the reward function in the new environment $E'$, where $F(s, a, s') \in \mathbb{R}$ is an added “artificial” reward. If the artificial rewards are defined carefully, PacBot’s policy will converge in fewer iterations in this new environment $E'$.

(b) To decouple from the previous question’s board configuration, let us consider that Pacbot is operating in the world shown below. Pacbot uses a function $F$ defined so that $F(s, a, s') = 10$ if $s'$ is closer to C relative to $s$, and $F(s, a, s') = 0$ otherwise (consider C to be closer to C than B or A). Let us also assume that the action space is now restricted to be between Right, Left, and Exit only.

![New Board Diagram]

Either left or right from B is correct.

In the diagram above, indicate by drawing an arrow or an X in each square, as in part (a), the optimal policy that PacBot will compute in the new environment $E'$ using $\gamma = 0.5$ and the modified reward function $R'(s, a, s')$.

(c) PacBot’s utility comes from the discounted sum of rewards in the original environment. What is PacBot’s expected utility of following the policy computed above, starting in state A if $\gamma = 0.5$?

(d) Find a non-zero value for $x$ in the table showing $F(s, a, s')$ drawn below, such that PacBot is guaranteed to compute an optimal policy that maximizes its expected true utility for any discount factor $\gamma \in [0, 1)$. 

![Reward Table]

5
\[
\begin{array}{|c|c|}
\hline
F(A, \text{Right, } B) & 10 \\
F(B, \text{Left, } A) & x \\
F(B, \text{Right, } C) & 10 \\
F(C, \text{Left, } B) & x \\
\hline
\end{array}
\]

\[x = \] Any number less than \(-10\) will also work. No other solution is correct.