Battleship agent

Training of an agent capable of playing battleship

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Classes: Ship

- A class to represent a ship in the Battleship game.
- Attributes:
 - size : int → The size of the ship
 - $hits: list \rightarrow A$ list to keep track of the coordinates where the ship has been hit
 - x1, y1, x2, y2: int o The coordinates of the ship's position on the grid
 - orientation : $str \rightarrow The$ orientation of the ship, either 'horizontal' or 'vertical'

Methods:

- place(self, x1, y1, orientation) → Saves the position and orientation of the ship on the grid
- hit(self, x, y, show=False) → Registers a hit on the ship at the given coordinates, return True if the ship
 is completely hit (sunk), False otherwise

Classes: Battleship

A class to represent the Battleship game environment.

Attributes:

- $ships: list \rightarrow A$ list of Ship objects representing the ships in the game
- opponent_grid : numpy.ndarray → A 2D array representing the opponent's grid with ship positions (-1 means sea, 1, 2, 3, ... are the ships' indices+1)
- player_grid : numpy.ndarray → A 2D array representing the player's grid with hits and misses (0 means unknown,
 -3 is a miss, -2 is a hit)
- sunken_ships : list → A list to keep track of the indices of sunken ships

Important methods:

- build_ships(self) → Randomly places ships on the grid. Ships cannot overlap or touch each other
- action(self, x, y, last_action) \rightarrow Performs an action on the player's grid at the given coordinates and return the reward. It also return *True* if the action result is a hit, *False* otherwise

Other important functions

- get_q_values(state) → Retrieves the Q-values for a given state from the Q-table. If the state
 is not in the Q-table, initializes it with random values. The Q-table is implemented as a
 dictionary.
- main → For each episode, the process executes max 1000 steps. At each step, it can either select a random action with a probability epsilon or perform the action with the highest Q-value for the current state (i.e., the player_grid). The Q-table is then updated using the following equation:

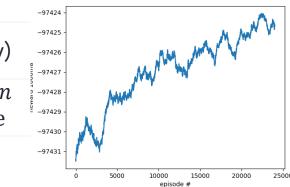
new_q = (1 - LEARNING_RATE) * current_q + LEARNING_RATE * (reward + DISCOUNT * max_future_q) Finally, it saves the average episode reward.

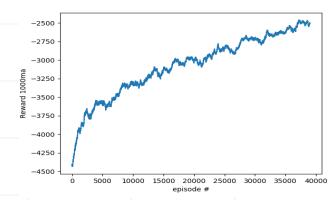
Training parameters

```
SIZE = 4
                                   # grid dimension
HM EPISODES = 40000
                                   # number of episodes
TURN PENALTY = 50
                                   # penalty for each turn
HIT REWARD = 150
                                   # reward for a hit
CONSECUTIVEHIT REWARD = 50
                                   # reward for consecutive hits
                                   # penalty for misses after a hit
CONSECUTIVEMISS_PENALTY = 20
SUNK REWARD = 30
                                   # reward for sinking a ship
MISS PENALTY = 25
                                   # penalty for a miss
ALREADY HIT PENALTY = 200
                                   # penalty for hitting a cell already hit
WIN_REWARD = 1030
                                   # reward for winning
ZEROCELLS REWARD = 20
                                   # reward for each remaining zero cell in the grid
epsilon = 0.5
                                   # exploration rate
EPSILON DECAY = 0.99999
                                   # exploration rate decay
SHOW EVERY = 1000
                                   # how often to show the game
                                   # learning rate
LEARNING RATE = 0.1
DISCOUNT = 0.9
                                   # discount rate
```

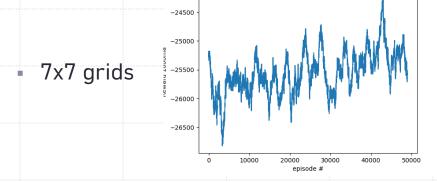
Plots

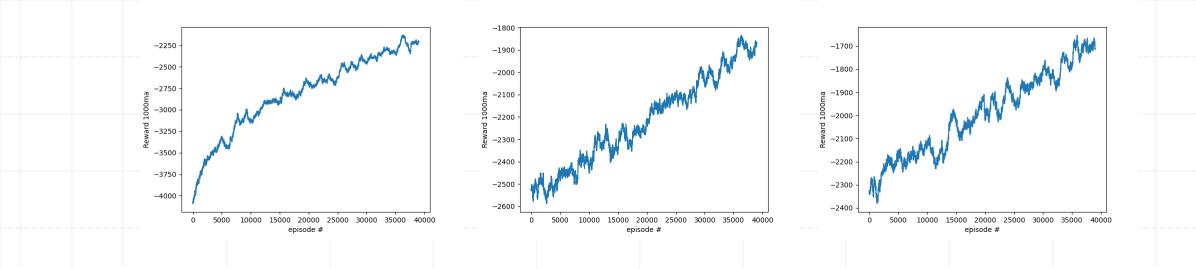
- 1000 rounds (mandatory)
- TURN_PENALTY = $\begin{cases} 0.5 \text{ if not w} \\ 0 \text{ otherwise} \end{cases}$





- More episodes $(25k \rightarrow 40k)$
- Higher ALREADY_HIT_PENALTY (100 → 200)
- Introduced SUNK_REWARD
- Higher TURN_PENALTY (0.5→5)
- Higher WIN_REWARD (1000 \rightarrow 1030)
- Higher MISS_PENALTY (5 \rightarrow 25)
- Introduced ZEROCELLS_REWARD, CONSECUTIVEHIT_REWARD and CONSECUTIVEMISS_PENALTY





- Three consecutive training on the same Q-table
- Higher CONSECUTIVEMISS_PENALTY (15 \rightarrow 20)
- Higher HIT_REWARD ($100 \rightarrow 150$)
- No diagonals contact between ships (less possible states)

BattleshipAgent class

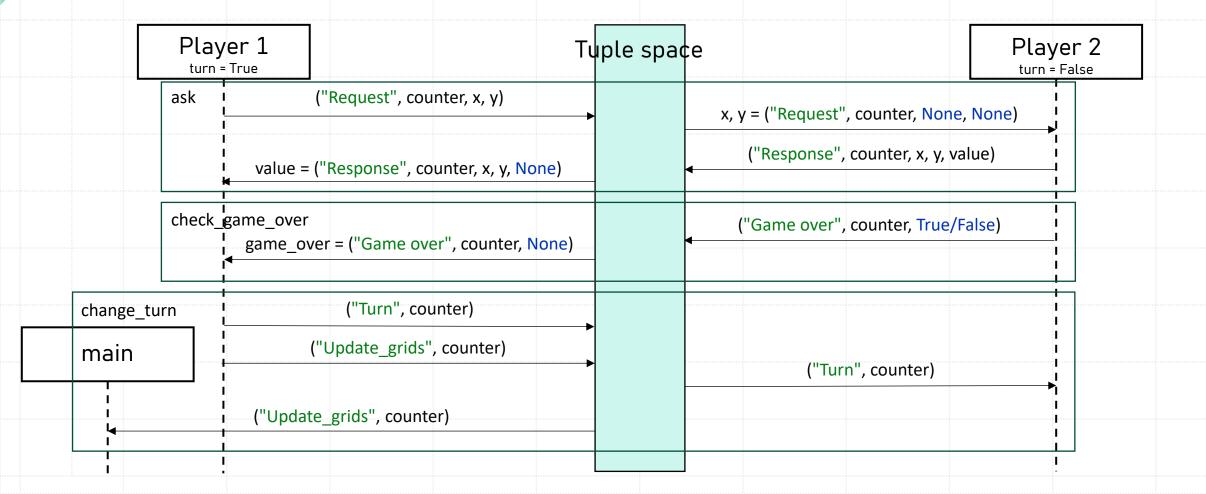
- A class to represent an agent in the Battleship game
- Attributes:
 - $id: str \rightarrow Name of the agent$
 - ts: BlockingTupleSpace → Tuple space for the communication between the agents
 - turn: bool → A flag indicating if it is the agent's turn
 - counter : int → Turn counter
 - $q_{table}: dict \rightarrow The Q-table for storing the Q-values$
 - $grid_size:int \rightarrow Size$ of the gaming grid
 - $ships: list \rightarrow A$ list of Ship objects representing the ships in the game
 - sunken ships: $list \rightarrow A$ list to keep track of the indices of sunken ships
 - done: bool → A flag indicating if the game is over
 - player_grid: numpy.ndarray → A 2D array representing the player's grid with ship positions
 - opponent_grid : numpy.ndarray → A 2D array representing the opponent's grid with hits and misses

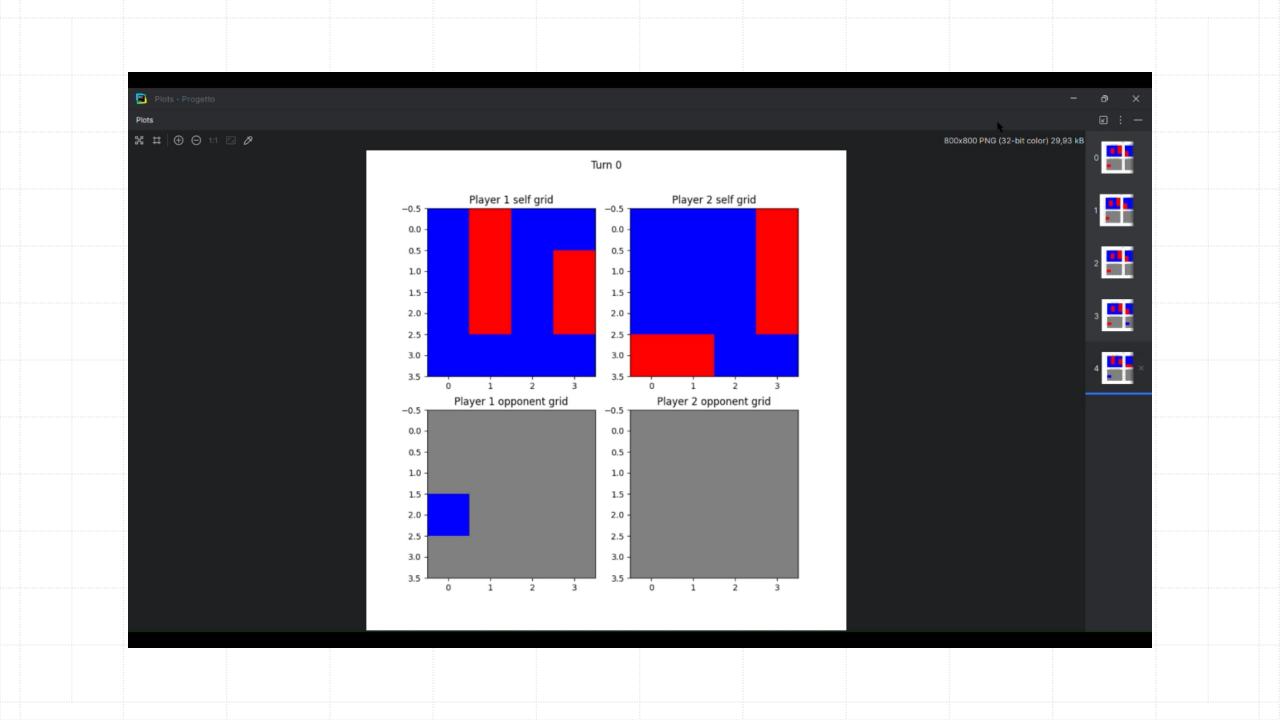
Important methods

- build_ships(self) → Randomly places ships on the grid. Ships cannot overlap or touch each other
- step(self) → Performs a step in the game, either making a move or responding to a request (depending on whether it is its turn or not)
- get_q_values(state) → Retrieves the Q-values for a given state from the Q-table. If the state is not in the Q-table, initializes it with random values. The Q-table is implemented as a dictionary
- choose_action(self) → Chooses an action based on the current state and Q-values. It follows an epsilon-greedy policy
- ask(self, x, y) \rightarrow Sends a request to the opponent and returns the response
- change_turn(self) → Changes the turn to the other player. It is used to synchronize the agents
- loop(self, delay=2) → Runs the game loop until the game is over

The game is played by 2 agents with the same policy (but it can be different). The agents run in two separate threads and they communicate with each other using a simple tuple space.

Communication





Open issues and future deployment

- Efficiency with bigger grids (and so bigger Q-tables)
- Better Q-table representation and implementation
- Improve the policy (number of turns, avoid hitting the same cell twice...)
- Different policies for different agents
- Interface for playing human vs agent

Thank you for your attention