CS6700: Reinforcement Learning - Tutorial 1 (MENACE)

Tasks

1. Complete code to determine if there is a winner at a particular state
2. Complete code to update state-action values of a player based on play history
3. Plot win, draw and loss %ages while training MENACE vs MENACE
4. Plot win, draw and loss %ages while training MENACE vs Random policy
5. Report any observations and inferences from the plots in 3 & 4

```
import numpy as np
import matplotlib.pyplot as plt
from typing import NamedTuple
from google.colab import output

SEED = 0
NUM_EPOCHS = 1_00_000

BOARD_COL = 3
BOARD_ROW = 3
BOARD_SIZE = BOARD_COL * BOARD_ROW

"""
Game board and actions are: {q, w, e, a, s, d, z, x, c}

q | w | e
--|---|--
a | s | d
--|---|--
z | x | c
"""
ACTIONS_KEY_MAP = {'q': 0, 'w': 1, 'e': 2,
                   'a': 3, 's': 4, 'd': 5,
                   'z': 6, 'x': 7, 'c': 8}

np.random.seed(SEED)
```

State Definition

```
def print_state(board, clear_output=False):
    if clear_output:
        output.clear()
    for i in range(BOARD_ROW):
        print('-------------')
        out = '| '
        for j in range(BOARD_COL):
```

```
            if board[i, j] == 1:
                token = 'x'
            elif board[i, j] == -1:
                token = 'o'
            else:
                token = ' '  # empty position
            out += token + ' | '
        print(out)
    print('-------------')


class State:
    def __init__(self, symbol):
        # the board is represented by an n * n array,
        #  1 represents the player who moves first (X),
        # -1 represents another player (O)
        #  0 represents an empty position
        self.board = np.zeros((BOARD_ROW, BOARD_COL))
        self.symbol = symbol
        self.winner = 0
        self.end = None

    @property
    def hash_value(self):
        hash = 0
        for x in np.nditer(self.board):
            hash = 3*hash + x + 1   # unique hash
        return hash

    def next(self, action: str):
        id = ACTIONS_KEY_MAP[action]
        i, j = id // BOARD_COL, id % BOARD_COL
        return self.next_by_pos(i, j)

    def next_by_pos(self, i: int, j: int):
        assert self.board[i, j] == 0
        new_state = State(-self.symbol)      # another player turn
        new_state.board = np.copy(self.board)
        # current player choose to play at (i, j) pos
        new_state.board[i, j] = self.symbol
        return new_state

    @property
    def possible_actions(self):
        rev_action_map = {id: key for key, id in
ACTIONS_KEY_MAP.items()}
        actions = []
        for i in range(BOARD_ROW):
            for j in range(BOARD_COL):
                if self.board[i, j] == 0:
```

```
                    actions.append(rev_action_map[BOARD_COL*i+j])
        return actions

    def is_end(self):
        if self.end is not None:
            return self.end

        ### WRITE YOUR CODE HERE ###
        # check 3 rows, 3 columns and both diagonals
        # check if the state is an end state
        # set self.end to be True when the game has ended
        # set self.winner to be 0 (draw), 1 (player 1) or 2 (player 2)

        for i in range(BOARD_ROW):
            if np.all(self.board[i, :] == 1) or
np.all(self.board[i, :] == -1):
                self.winner = 1 if np.sum(self.board[i, :]) > 0 else 2
                self.end = True
                return self.end

            if np.all(self.board[:, i] == 1) or np.all(self.board[:,
i] == -1):
                self.winner = 1 if np.sum(self.board[:, i]) > 0 else 2
                self.end = True
                return self.end

        if np.abs(np.trace(self.board)) == 3:
            self.winner = 1 if np.trace(self.board) > 0 else 2
            self.end = True
            return self.end

        if np.abs(np.trace(np.fliplr(self.board))) == 3:
            self.winner = 1 if np.trace(np.fliplr(self.board)) > 0
else 2
            self.end = True
            return self.end

        # if there is no winner
        # check if there are any available plays
        for x in np.nditer(self.board):
            if x == 0:
                self.end = False
                return self.end

        # declare a draw
        self.winner = 0
        self.end = True
        return self.end
```

Environment

```
class Env:
    def __init__(self):
        self.all_states = self.get_all_states()
        self.curr_state = State(symbol=1)

    def get_all_states(self):
        # is a dict with key as state_hash_value and value as State
object.
        all_states = {}

        def explore_all_substates(state):
            for i in range(BOARD_ROW):
                for j in range(BOARD_COL):
                    if state.board[i, j] == 0:
                        next_state = state.next_by_pos(i, j)
                        if next_state.hash_value not in all_states:
                            all_states[next_state.hash_value] =
next_state
                            if not next_state.is_end():
                                explore_all_substates(next_state)
        curr_state = State(symbol=1)
        all_states[curr_state.hash_value] = curr_state
        explore_all_substates(curr_state)
        return all_states

    def reset(self):
        self.curr_state = State(symbol=1)
        return self.curr_state

    def step(self, action):
        assert action in self.curr_state.possible_actions, f"Invalid
{action} for the current state \n{self.curr_state.print_state()}"
        next_state_hash = self.curr_state.next(action).hash_value
        next_state = self.all_states[next_state_hash]
        self.curr_state = next_state
        reward = 0
        return self.curr_state, reward

    def is_end(self):
        return self.curr_state.is_end()

    @property
    def winner(self):
        result_id = self.curr_state.winner
        result = 'draw'
        if result_id == 1:
            result = 'player1'
        elif result_id == 2:
```

```python
            result = 'player2'
        return result
```

Policy

```python
class BasePolicy:
    def reset(self):
        pass

    def update_values(self, *args):
        pass

    def select_action(self, state):
        raise Exception('Not Implemented Error')

class HumanPolicy(BasePolicy):
    def __init__(self, symbol):
        self.symbol = symbol

    def select_action(self, state):
        assert state.symbol == self.symbol, f"Its not {self.symbol}
symbol's turn"
        print_state(state.board, clear_output=True)
        key = input("Input your position: ")
        return key

class RandomPolicy(BasePolicy):
    def __init__(self, symbol):
        self.symbol = symbol

    def select_action(self, state):
        assert state.symbol == self.symbol, f"Its not {self.symbol}
symbol's turn"
        return np.random.choice(state.possible_actions)

class ActionPlayed(NamedTuple):
    hash_value: str
    action: str


class MenacePolicy(BasePolicy):
    def __init__(self, all_states, symbol, tau=5.0):
        self.all_states = all_states
        self.symbol = symbol
        self.tau = tau

        # It store the number of stones for each action for each state
        self.state_action_value = self.initialize()
        # variable to store the history for updating the number of
stones
```

```
        self.history = []

    def initialize(self):
        state_action_value = {}
        for hash_value, state in self.all_states.items():
            # initially all actions have 0 stones
            state_action_value[hash_value] = {
                action: 0 for action in state.possible_actions}
        return state_action_value

    def reset(self):
        for action_value in self.state_action_value.values():
            for action in action_value.keys():
                action_value[action] = 0

    def print_updates(self, reward):
        print(
            f'Player with symbol {self.symbol} updates the following
history with {reward} stone')
        for item in self.history:
            board = np.copy(self.all_states[item.hash_value].board)
            id = ACTIONS_KEY_MAP[item.action]
            i, j = id//BOARD_COL, id % BOARD_COL
            board[i, j] = self.symbol
            print_state(board)

    def update_values(self, reward, show_update=False):
        # reward: if wins receive reward of 1 stone for the chosen
action
        #         else -1 stone.
        # reward is either 1 or -1 depending upon if the player has
won or lost the game.

        if show_update:
            self.print_updates(reward)

        # for every state-action in history
        # use reward to update the state-action values
        # WRITE CODE HERE
        for state_action in self.history:
            self.state_action_value[state_action.hash_value]
[state_action.action] += reward

        self.history = []

    def select_action(self, state):  # Softmax action probability
        assert state.symbol == self.symbol, f"Its not {self.symbol}
symbol's turn"
        action_value = self.state_action_value[state.hash_value]
        max_value = action_value[max(action_value,
```

```
key=action_value.get)]
        exp_values = {action: np.exp((v-max_value) / self.tau)
                      for action, v in action_value.items()}
        normalizer = np.sum([v for v in exp_values.values()])
        prob = {action: v/normalizer for action, v in
exp_values.items()}
        action = np.random.choice(list(prob.keys()),
p=list(prob.values()))
        self.history.append(ActionPlayed(state.hash_value, action))
        return action
```

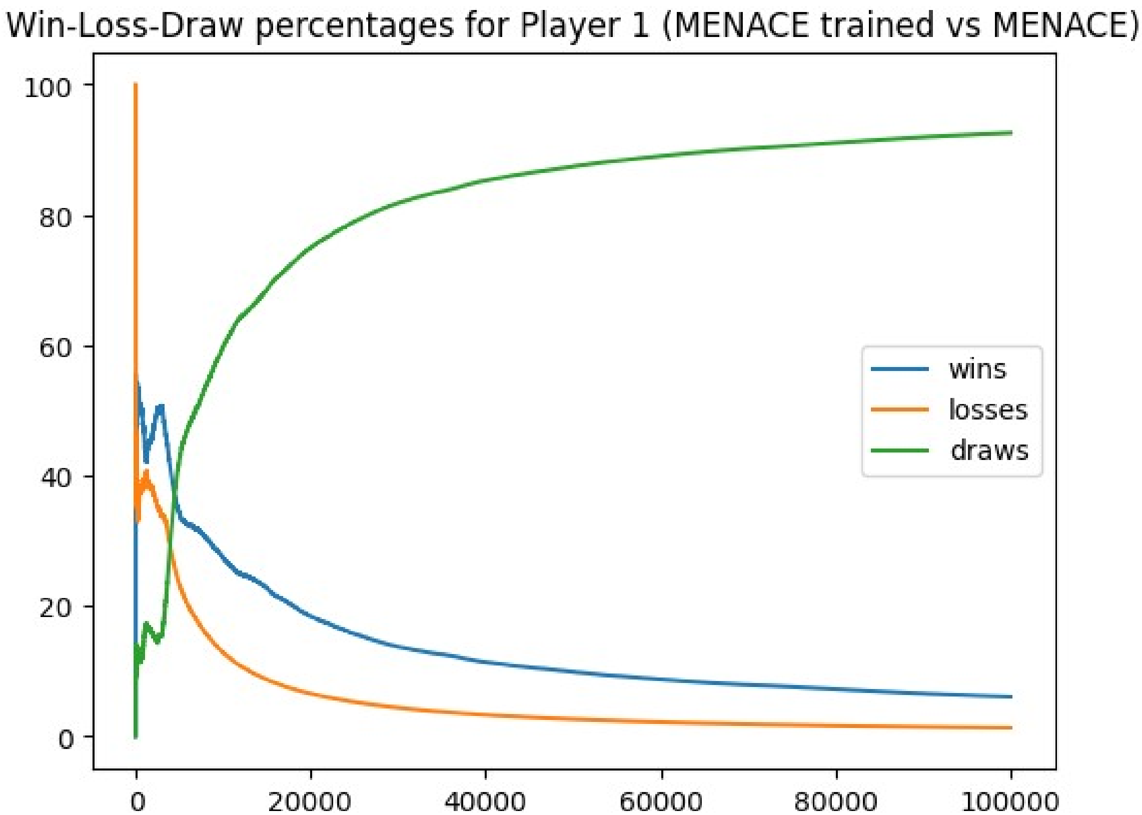
Game Board

```
class Game:
    def __init__(self, env, player1, player2):
        self.env = env
        self.player1 = player1
        self.player2 = player2
        self.show_updates = False
        self.train_results = None

    def alternate(self):
        while True:
            yield self.player1
            yield self.player2

    def train(self, epochs=1_00_000):
        self.train_results = [[], []]
        player1_reward_map = {'player1': 1, 'player2': -1, 'draw': 0}
        for _ in range(epochs):
            result = self.play()

            # if player1 wins add 1 stone for the action chosen
            player1_reward = player1_reward_map[result]
            player2_reward = -player1_reward   # if player2 wins add 1
stone

            self.player1.update_values(player1_reward)
            self.player2.update_values(player2_reward)

            # append results
            self.train_results[0].append(player1_reward)
            self.train_results[1].append(player2_reward)

    def play(self):
        alternate = self.alternate()
        state = self.env.reset()
        while not self.env.is_end():
            player = next(alternate)
            action = player.select_action(state)
```

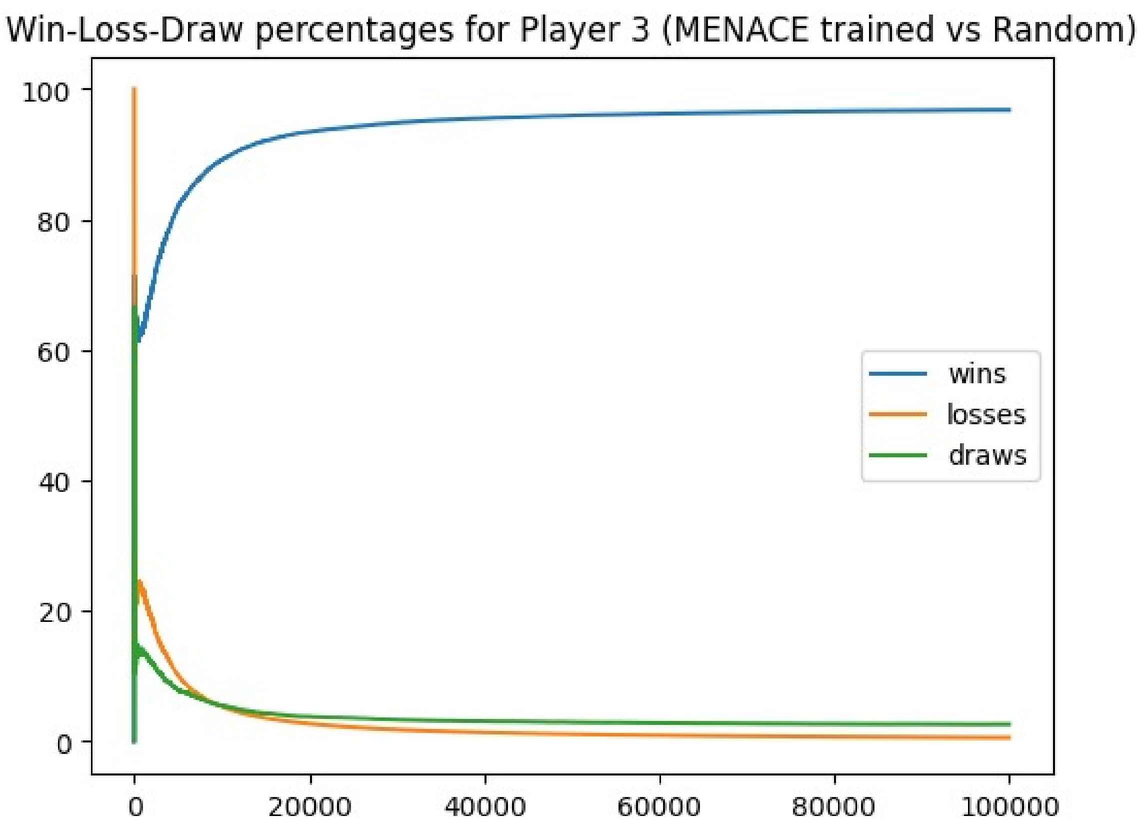
```
            state, _ = self.env.step(action)
        result = self.env.winner
        return result
```

Experiments

```
env = Env()

# Game 1: train MENACE vs MENACE
# plot win, draw, loss fractions for player 1
player1 = MenacePolicy(env.all_states, symbol=1)
player2 = MenacePolicy(env.all_states, symbol=-1)
game1 = Game(env, player1, player2)
game1.train(epochs=NUM_EPOCHS)

# GAME 2: train MENACE vs RANDOM
# plot win, draw, loss fractions for player 3
player3 = MenacePolicy(env.all_states, symbol=1)
player4 = RandomPolicy(symbol=-1)
game2 = Game(env, player3, player4)
game2.train(epochs=NUM_EPOCHS)

results1 = game1.train_results[0]
wins1, draws1, losses1, tot1 = 0., 0., 0., 0.
fracs1 = [[], [], []]
for i in range(NUM_EPOCHS):
    tot1 += 1
    if results1[i] == 1:
        wins1 += 1
    elif results1[i] == 0:
        draws1 += 1
    else:
        losses1 += 1

    fracs1[0].append((wins1/tot1)*100)
    fracs1[1].append((losses1/tot1)*100)
    fracs1[2].append((draws1/tot1)*100)

plt.plot(range(NUM_EPOCHS), fracs1[0], label='wins')
plt.plot(range(NUM_EPOCHS), fracs1[1], label='losses')
plt.plot(range(NUM_EPOCHS), fracs1[2], label='draws')
plt.title('Win-Loss-Draw percentages for Player 1 (MENACE trained vs
MENACE)')
plt.legend()
plt.show()
```




```python
results2 = game2.train_results[0]
wins2, draws2, losses2, tot2 = 0., 0., 0., 0.
fracs2 = [[], [], []]
for i in range(NUM_EPOCHS):
    tot2 += 1
    if results2[i] == 1:
        wins2 += 1
    elif results2[i] == 0:
        draws2 += 1
    else:
        losses2 += 1

    fracs2[0].append((wins2/tot2)*100)
    fracs2[1].append((losses2/tot2)*100)
    fracs2[2].append((draws2/tot2)*100)

plt.plot(range(NUM_EPOCHS), fracs2[0], label='wins')
plt.plot(range(NUM_EPOCHS), fracs2[1], label='losses')
plt.plot(range(NUM_EPOCHS), fracs2[2], label='draws')
plt.title('Win-Loss-Draw percentages for Player 3 (MENACE trained vs
Random)')
plt.legend()
plt.show()
```




```
# GAME 3: Play against player 1 (MENACE trained vs MENACE)
# See if you can beat this policy!

game3 = Game(env, player1, HumanPolicy(symbol=-1))
game3.play()

result = env.winner
print(f"winner: {result}")

player1_reward_map = {'player1': 1, 'player2': -1, 'draw': 0}
player1.update_values(player1_reward_map[result], show_update=True)
```

```
-------------
| o |   | x |
-------------
|   | x | x |
-------------
|   |   | o |
-------------
Input your position: a
winner: player1
Player with symbol 1 updates the following history with 1 stone
-------------
|   |   | x |
```

```
-------------
|   |   |   |
-------------
|   |   |   |
-------------
-------------
| o |   | x |
-------------
|   |   | x |
-------------
|   |   |   |
-------------
-------------
| o |   | x |
-------------
|   | x | x |
-------------
|   |   | o |
-------------
-------------
| o |   | x |
-------------
| o | x | x |
-------------
| x |   | o |
-------------
```

Question

What can you infer from the above series of experiments?

ENTER ANSWER HERE

```
statement = """
After every series of experiment the AI Learn to play good against
human.
The self play mechanism makes it become more powerful by playing
against itself
The update of the value of the state and action is closely related to
the
Q-Learning approach where we define the Q functions state action value
and the concept of history is needed to improve the strategy to make
it
learn the game more profficiently,
"""

print(statement)
```

```
After every series of experiment the AI Learn to play good against
```

```
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```