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)
    new_state.board[i, j] = self.symbol  # current player choose to
play at (i, j) pos
    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)
    # Check rows and columns for a win
    # Efficiently check rows and columns for a win
    for i in range(BOARD_ROW):
        if np.all(self.board[i, :] == self.board[i, 0]) and
self.board[i, 0] != 0:
            self.winner = 1 if self.board[i, 0] == 1 else 2
            self.end = True
            return self.end

    for j in range(BOARD_COL):
        if np.all(self.board[:, j] == self.board[0, j]) and
self.board[0, j] != 0:
            self.winner = 1 if self.board[0, j] == 1 else 2
            self.end = True
            return self.end

    # Efficiently check diagonals for a win
    if np.all(np.diag(self.board) == self.board[0, 0]) and
self.board[0, 0] != 0:
        self.winner = 1 if self.board[0, 0] == 1 else 2
        self.end = True
        return self.end

    if np.all(np.diag(np.fliplr(self.board)) == self.board[0,
BOARD_COL - 1]) and self.board[0, BOARD_COL - 1] != 0:
        self.winner = 1 if self.board[0, BOARD_COL - 1] == 1 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):
    all_states = {}  # is a dict with key as state_hash_value and
value as State object.
    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:
      result = 'player2'
    return result
```

Policy

```
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
```

```python
    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 item in self.history:
      hash_value = item.hash_value
      action = item.action
      current_value = self.state_action_value[hash_value][action]
      updated_value = current_value + reward # Ensure values don't go
negative
      self.state_action_value[hash_value][action] = updated_value

    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
```

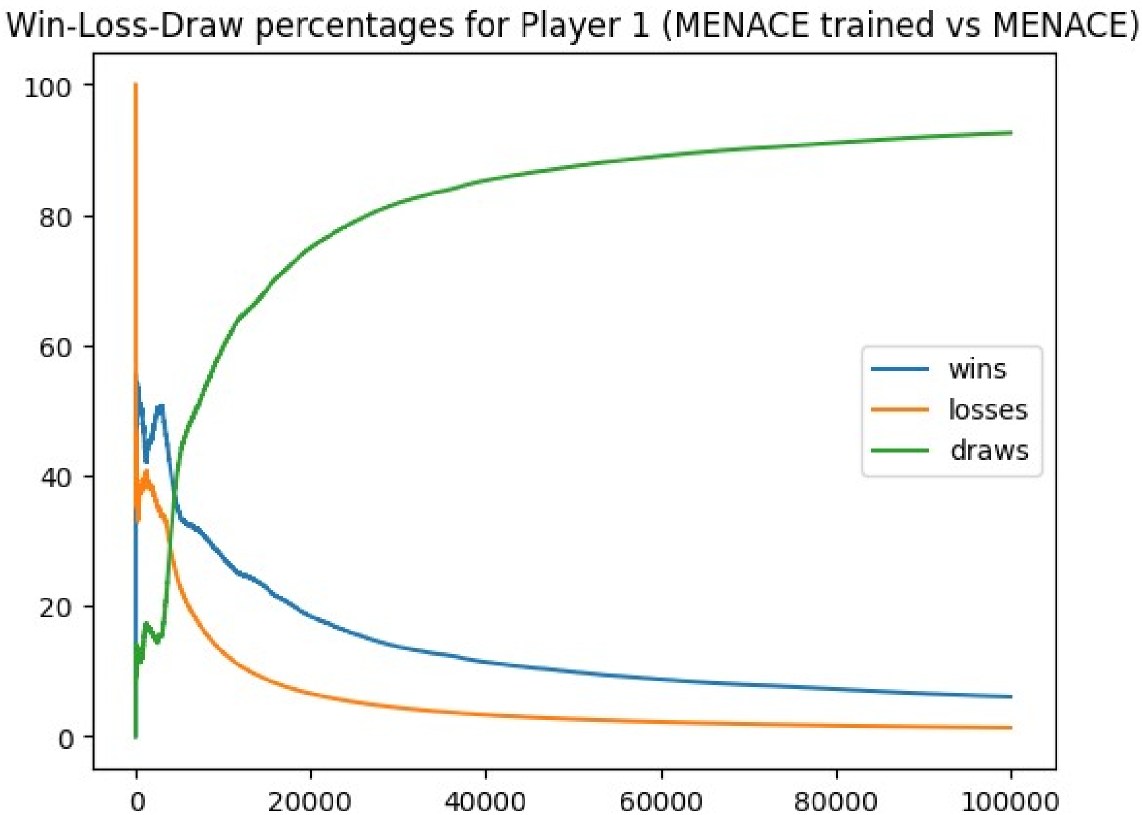
Game Board

```
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)
```

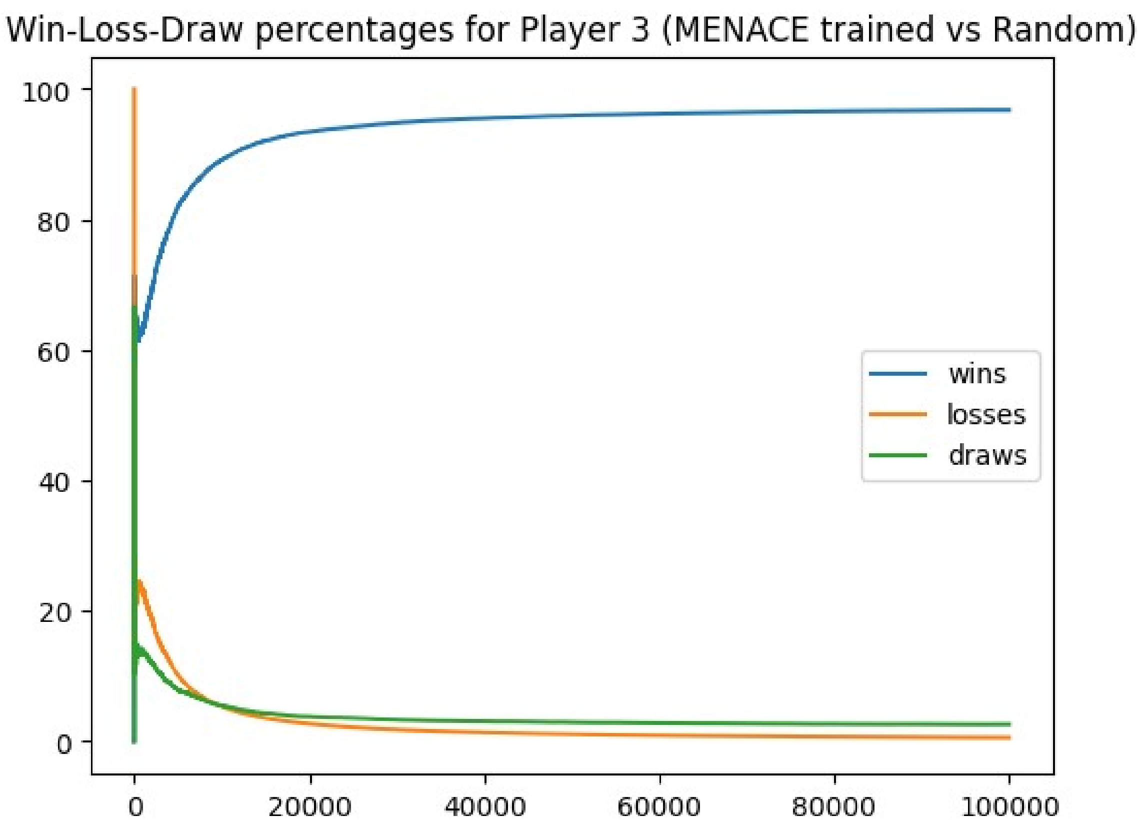
```
    result = self.env.winner
    return result
```

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()
```




```
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)
```

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

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

Question

What can you infer from the above series of experiments?

ENTER ANSWER HERE

MENACE trained vs MENACE (Player 1):

1. Initially, there is significant volatility in the win, loss, and draw rates, which is typical in the early stages of learning where the policy is still exploring the state space.
2. Over time, the win rate gradually increases while the loss rate decreases, suggesting that the MENACE policy is learning and improving its strategy from playing against an opponent with a similar learning approach.
3. The draw rate significantly increases after the initial phase and stabilizes, indicating that as both MENACE players learn and improve, it becomes more difficult for either player to

secure a win, leading to more draw outcomes. This could be because both players are avoiding losing moves and reaching a strategic equilibrium.

MENACE trained vs Random (Player 3):

1. The win rate for the MENACE player quickly escalates (`within 20000 epochs`) to nearly 100%, while the loss and draw rates plummet to nearly 0%. This indicates a rapid learning curve when playing against a non-strategic, random opponent.
2. The MENACE policy appears to capitalize effectively on the lack of strategy in the random player, quickly learning to exploit the random player's moves to secure wins.
3. The consistency of wins against the random player suggests that the MENACE policy can reliably learn and apply winning strategies in a less competitive environment.

Conclusion:

```
The MENACE policy gets better at playing Tic-Tac-Toe the more it
plays. When playing against another player like itself, it starts to
end in a draw more often because they both become good at not losing.
When playing against a random player that doesn't really have a
strategy, the MENACE policy wins almost all the time because it learns
how to take advantage of the random moves.
```