Al6101 Reinforcement Learning Assignment

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```
In [1]: from typing import List, Tuple
   import copy
   import numpy as np
   import matplotlib.pyplot as plt
   import pandas as pd
%matplotlib inline
```

The following class defines the grid world environment. The grid world looks like:

0 _1_		_7_ _8_ _9_ _10	0 _11 _12 _13
0 _	. _x_	_x_ _	_
1 _	. x_	_x_	_
2	. _x_ _x_	_x_	_ _x_
3 _	. _x_ _x_		_ _x_ _x_
4 _B_	. _x_		_ _x_ _x_ _G_
5 _A_	. _x_		_ _x_ _x_

```
In [2]: AGENT = 'A'
        BOX = 'B'
        GOAL = 'G'
        DANGER = 'x'
        GRID = ' '
        class CliffBoxGridWorld:
            Cliff Box Pushing Grid World.
            action\_space = [1, 2, 3, 4]
            forces = {
               1: np.array([-1, 0]),
                2: np.array([1, 0]),
                3: np.array([0, -1]),
                4: np.array([0, 1]),
            world width = 14
            world height = 6
            goal pos = np.array([4, 13])
            init agent pos = np.array([5, 0])
            init box pos = np.array([4, 1])
            danger region = [
                [(2, 3), (5, 3)],
                [(0, 6), (3, 6)],
                [(0, 7), (2, 7)],
                [(3, 11), (5, 11)],
                [(2, 12), (5, 12)],
            ]
            def init (self,
                         episode length=100,
                         render=False,
                11 11 11
```

```
The grid world looks like:
         0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
                                |_x_|_x_
    | 1
                                | X | X
                 ___|_x
                             | X | X |
                | X |
                                                    | x | x |
                                X 
                    | X |
                                                    _|_x_|_x_|_G__
    |_5_|_A_|___|_x_|
    # Environment configurations.
   self.episode length = episode length
   self.render = render
   self.agent pos = self.init agent pos
   self.box pos = self.init box pos
    # Visualization.
   if self.render:
        self.world = np.chararray((self.world height, self.world width))
        self.last agent pos = copy.deepcopy(self.agent pos)
        self.last box pos = copy.deepcopy(self.box pos)
       self.world[:] = GRID
       for region in self.danger region:
           A, B = region
           assert A[1] == B[1], "A[1] != B[1]"
            self.world[A[0]:B[0]+1, A[1]] = DANGER
        self.world[self.agent pos[0], self.agent pos[1]] = AGENT
        self.world[self.box pos[0], self.box pos[1]] = BOX
        self.world[self.goal pos[0], self.goal pos[1]] = GOAL
def reset(self):
   Resets the environment.
   Returns:
       The initial state (agent position and box position).
   self.timesteps = 0
   self.action history = []
   self.agent pos = self.init agent pos
   self.box pos = self.init box pos
   return tuple([*self.agent pos.tolist(), *self.box pos.tolist()])
def step(self, actions: int):
   Args: actions (a list of int).
   Returns:
       The next state, reward, done, info.
   self.action history.append(actions)
    # Update the state.
   force = self.forces[actions]
    # check if the agent is near the box
   if np.sum(np.abs(self.agent pos - self.box pos)) == 1:
        # check if box is moved
        if all(self.agent pos + force == self.box pos):
            # check out of boundary
           self.box pos = self. check pos boundary(pos=self.box pos + force, box ha
    # move the agent
   new agent pos = self. check pos boundary(self.agent pos + force)
   if not all(new agent pos == self.box pos):
        self.agent pos = new agent pos
   state = tuple([*self.agent_pos.tolist(), *self.box_pos.tolist()])
```

```
# Calculate the rewards
   done = self.timesteps == self.episode length - 1
    # the distance between agents and box
   dist = np.sum(np.abs(self.agent pos - self.box pos))
   reward = -1 # -1 for each step
   reward -= dist
    # if agents or box is off the cliff
   if self. check off cliff(self.agent pos) or self. check off cliff(self.box pos):
        reward += -1000
        done = True
   if all(self.box pos == self.goal pos):
       reward += 1000
       done = True
   reward -= np.sum(np.abs(self.box pos - self.goal pos))
   if self.render:
        self. update render()
   self.timesteps += 1
   info = {}
   return state, reward, done, info
def print world(self):
   Render the world in the command line.
   if len(self.action history) > 0:
       print(f'Action: {self.action history[-1]}')
   print(self.world)
def check pos boundary(self, pos, box hard boundary: bool = False):
   Move the given position within the world bound.
   if pos[0] < 0:
       pos[0] = 0
   if pos[0] >= self.world height:
       pos[0] = self.world height - 1
   if pos[1] < 0:
        pos[1] = 0
   if pos[1] >= self.world width:
       pos[1] = self.world width - 1
   if box hard boundary:
        if pos[0] == 0:
            pos[0] += 1
        elif pos[0] == self.world height - 1:
            pos[0] = self.world height - 2
        if pos[1] == 0:
           pos[1] += 1
   return pos
def check off cliff(self, pos):
   .....
   Check if the given position is off cliff.
   for region in self.danger region:
       A, B = region
        assert A[1] == B[1], "A[1] != B[1]"
        if A[0] \leftarrow pos[0] \leftarrow B[0] and pos[1] == A[1]:
            return True
```

```
return False
def update render(self):
   Update the render information.
   if not all(self.last agent pos == self.agent pos):
           pos = self.last agent pos
           if (pos[0] != self.goal pos[0]) or (pos[1] != self.goal pos[1]):
                self.world[pos[0], pos[1]] = GRID
   if not all(self.last box pos == self.box pos):
       pos = self.last box pos
       if self.world[pos[0], pos[1]].decode('UTF-8') not in {AGENT}:
            self.world[pos[0], pos[1]] = GRID
   if (self.agent pos[0] != self.goal pos[0]) or (self.agent pos[1] != self.goal po
        self.world[self.agent pos[0], self.agent pos[1]] = AGENT
   self.world[self.box pos[0], self.box pos[1]] = BOX
   self.last box pos = copy.deepcopy(self.box pos)
   self.last agent pos = copy.deepcopy(self.agent pos)
```

Q-learning Agent

Q-learning is a value-based method that uses a Q- table to record the estimated Q-values for various actions in different states. The Q-table is initialized prior to exploring the environment. As the agent interacts with the environment, it updates the Q(s, a) values using the Bellman equation, allowing the agent to continually learn and improve its under- standing of the environment. The Q-function continues to be updated until it reaches convergence or the specified number of iterations

```
class QAgent:
In [3]:
            def init (self, env, num episodes, epsilon=0.1, alpha=0.1, gamma=0.99):
                self.action space = env.action space
                self.q table = dict() # Store all Q-values in a dictionary
                # Loop through all possible grid spaces, create sub-dictionary for each
                for agent x in range(env.world height):
                    for agent y in range(env.world width):
                        for box x in range(env.world height):
                             for box y in range(env.world width):
                                 # Populate sub-dictionary with zero values for possible moves
                                 self.q table[(agent x, agent y, box x, box y)] = \{k: 0 \text{ for } k \text{ in } \}
                self.env = env
                self.num episodes = num episodes
                self.epsilon = epsilon
                self.alpha = alpha
                self.gamma = gamma
                self.action_seq = [] # Initialize empty action sequence list
                self.total action seq = [] # Initialize empty action sequence list
                self.max agent seq = []
            def act(self, state):
                """Returns the (epsilon-greedy) optimal action from Q-Value table."""
                if np.random.uniform(0,1) < self.epsilon:</pre>
                    action = self.action space[np.random.randint(0, len(self.action space))]
                else:
                    q values of state = self.q table[state]
                    maxValue = max(q values of state.values())
                    action = np.random.choice([k for k, v in q values of state.items() if v == m
                return action
```

```
def learn(self):
   """Runs Q-learning algorithm to learn optimal policy."""
   rewards per episode = []
   for episode in range(self.num episodes):
       # Initialize variables for storing state and action sequences
       action seq = []
       state = self.env.reset()
       total reward = 0
       done = False
       while not done:
           action = self.act(state)
           next state, reward, done, = self.env.step(action)
            # Update Q-Table using Q-Learning algorithm
           old qvalue = self.q table[state][action]
           next max = max(self.q table[next state].values())
           new qvalue = (1 - self.alpha) * old qvalue + self.alpha * (reward + self
           self.q table[state][action] = new qvalue
           # Update total reward and current state
           total reward += reward
           state = next state
           action seq.append(action)
            self.action seq = action seq # Append action to the action sequence list
        self.total action seq.append(action seq)
       rewards per episode.append(total reward)
       max reward = max(rewards per episode)
       index max reward = rewards per episode.index(max reward)
        self.max action seq = self.total action seq[index max reward]
    #print(rewards per episode)
   print('Maximum reward =', max reward)
   print('Episode of maximum reward achieved =', index max reward)
   print('Action sequence of maximum reward =', self.max action seq)
   return rewards per episode
```

Training Q-learning Agent

```
In [4]: env = CliffBoxGridWorld()
    agent = QAgent(env, epsilon=0.01, alpha=0.1, gamma=0.99, num_episodes=15000)
    rewards = agent.learn()

Maximum reward = 642
    Episode of maximum reward achieved = 6225
    Action sequence of maximum reward = [4, 1, 1, 1, 3, 1, 4, 4, 4, 4, 4, 1, 4, 2, 2, 2, 3, 2, 4, 4, 4, 4, 4, 2, 4, 1, 1, 1, 3, 1, 4, 4, 4, 1, 4, 2, 2, 2]
```

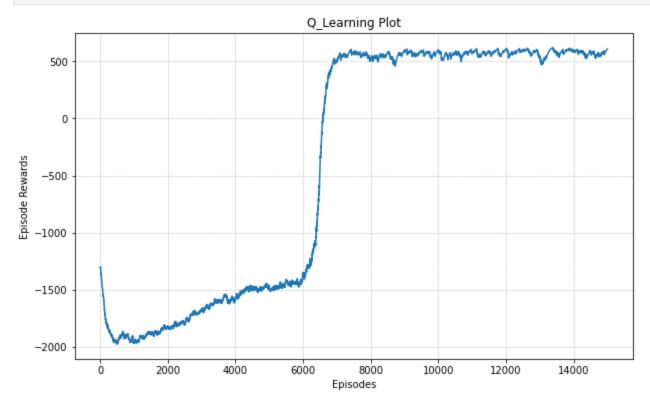
Q-Learning Episodes vs Episode Rewards Curve

It can be observed from the plot below that the q-learning agent converge nicely at the maximum reward of 642 by about episode 7000

```
In [5]: # Smooth plot
  weight = 0.99
  last = rewards[0]
  smoothed = []
  for v in rewards:
      smoothed_val = last * weight + (1 - weight) * v
      smoothed.append(smoothed_val)
```

```
last = smoothed_val

# Plot the learning curve
plt.figure(figsize=(10, 6))
plt.plot(smoothed)
plt.xlabel("Episodes")
plt.ylabel("Episode Rewards")
plt.title('Q_Learning Plot')
plt.grid(linestyle='--', linewidth=0.5)
plt.show()
```



Q-learning V_table Visualization

Finding the 'V' for the agent

```
In [6]:

v_table = {}

for state_, actions_ in agent.q_table.items():
    v_table['('+','.join(map(str, state_))+')'] = list(actions_.values())
    df = pd.DataFrame.from_dict(v_table).transpose()
    df['state'] = list(df.index)
    df['Agent_Position'] = df['state'].apply(lambda x:x[1:5].rstrip(','))
    df_group = df.groupby('Agent_Position')[[0, 1, 2, 3]].mean()

df_group['V'] = df_group[[0, 1, 2, 3]].mean(axis=1)
    df_group[['agent_x', 'agent_y']] = df_group['Agent_Position'].str.split(',', expand=True)

# showing the data frame in terms of x and y coordinate of agent, and 'V'
    df_group = df_group[['agent_x', 'agent_y', 'V']]
    df_group
```

Out[6]:	ut[6]:		agent_y	V
	0	0	0	-38.931412
	1	0	1	-39.317577
	2	0	10	-30.111324

3	0	11	-26.464634
4	0	12	-20.204145
•••			
79	5	5	-37.677345
80	5	6	-37.081845
81	5	7	-35.447405
82	5	8	-34.693796
83	5	9	-28.446331

84 rows × 3 columns

Presentation of V_table in the template of the Cliff Box Grid World

It can be observed from the grid view of the 'V' that the obstacles 'V' are all zero, which by intuition make sense.

```
In [16]: # create a 6x14 array of NaN values
         grid = np.empty((6, 14))
        grid[:] = np.nan
         # fill in the grid with the V values from the dataframe
         for , row in df group.iterrows():
           x = int(row['agent x'])
            y = int(row['agent y'])
             grid[x, y] = round(row['V'], 2)
         # create a dataframe from the grid
         grid df = pd.DataFrame(grid, columns=range(14), index=range(6))
         # set format for V values
         grid df = grid df.style.format("{:.2f}")
         # add borders and show row/column indices
         grid df = grid df.set table styles([
             {"selector": "th", "props": [("border", "lpx solid #ccc"), ("text-align", "center")]
             {"selector": "td", "props": [("border", "1px solid #ccc"), ("text-align", "center")]
             {"selector": "th.row heading", "props": [("background-color", "transparent"),]}
         1)
         # display formatted grid of v table
        print('V table Visualization')
        display(grid df)
```

V table Visualization

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	-38.93	-39.32	-39.80	-37.75	-33.89	-44.51	0.00	0.00	-41.71	-30.93	-30.11	-26.46	-20.20	-16.49
1	-31.63	-30.82	-32.17	-41.92	-36.60	-43.60	0.00	0.00	-38.03	-23.32	-22.88	-22.87	-32.19	-17.33
2	-35.12	-31.17	-42.79	0.00	-42.38	-44.70	0.00	0.00	-39.77	-25.62	-22.80	-40.08	0.00	-30.02
3	-38.24	-32.12	-43.18	0.00	-42.91	-43.18	0.00	-48.01	-33.66	-28.79	-37.37	0.00	0.00	-32.47
4	-38.79	-32.82	-42.27	0.00	-41.20	-30.67	-40.94	-28.66	-28.00	-29.62	-38.21	0.00	0.00	-31.42
5	-34.93	-32.86	-46.04	0.00	-45.23	-37.68	-37.08	-35.45	-34.69	-28.45	-38.33	0.00	0.00	-31.05

Q-learning Policy Visualization

Below is the presentation of policy of the agent following the action sequence taken for the maximum reward, which is 642.

As observed shown below, the agent is travelling correctly with the action sequence = [4, 1, 1, 1, 3, 1, 4, 4, 4, 4, 1, 4, 2, 2, 2, 3, 2, 4, 4, 4, 4, 4, 4, 4, 1, 1, 1, 1, 3, 1, 4, 4, 4, 1, 4, 2, 2, 2]

```
In [8]: env = CliffBoxGridWorld(render=True)
  state = env.reset()
  env.print world()
  done = False
   rewards = []
  step = 0
  while not done:
    action = agent.max action seq[step]
    state, reward, done, info = env.step(action)
    rewards.append(reward)
    print(f'step: {env.timesteps}, state: {state}, action taken: {agent.action seq[actio
    env.print world()
    step += 1
  print(f'rewards: {sum(rewards)}')
  print(f'action history: {env.action history}')
   [b' ' b' ' b' ' b' ' b' ' b' ' b' x' b'x' b' ' b' ']
   step: 1, state: (5, 1, 4, 1), action taken: 3, reward: -14
  [b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' ' b' ' b' ' b' ' b' x' b'x' b' ']
   step: 2, state: (4, 1, 3, 1), action taken: 1, reward: -15
  Action: 1
   [b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' x' b' ' b' ' b' ' b' ' b' ' b' x' b' ']
   step: 3, state: (3, 1, 2, 1), action taken: 1, reward: -16
   step: 4, state: (2, 1, 1, 1), action taken: 1, reward: -17
  Action: 1
   [b' ' b'B' b' ' b' ' b' ' b' ' b' x' b' x' b' ' b' ' b' ' b' ' b' ' b' ' b' ']
```

```
step: 5, state: (2, 0, 1, 1), action taken: 1, reward: -18
Action: 3
step: 6, state: (1, 0, 1, 1), action taken: 1, reward: -17
Action: 1
[b'A' b'B' b' ' b' ' b' ' b' ' b'x' b'x' b' ' b' ' b' ' b' ' b' ' b' ']
[b' ' b' ' b' ' b'x' b' ' b' ' b'x' b' ' b' ' b' ' b' ' b' ' b'x' b' ']
step: 7, state: (1, 1, 1, 2), action taken: 3, reward: -16
Action: 4
step: 8, state: (1, 2, 1, 3), action taken: 3, reward: -15
Action: 4
[b' ' b' ' b' x' b' ' b' x' b' ' b' x' b' ' b' ' b' ' b' x' b' x' b' ']
step: 9, state: (1, 3, 1, 4), action taken: 3, reward: -14
Action: 4
[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' ' b' ' b' ' b' ' b' x' b'x' b' ']
step: 10, state: (1, 4, 1, 5), action taken: 3, reward: -13
Action: 4
[b' 'b' 'b' 'b' 'b'A' b'B' b'x' b'x' b' 'b' 'b' 'b' 'b' 'b' ']
step: 11, state: (0, 4, 1, 5), action taken: 1, reward: -14
Action: 1
[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' ' b' ' b' ' b' ' b' ' b' ' b' ']
step: 12, state: (0, 5, 1, 5), action taken: 3, reward: -13
Action: 4
[b' ' b' ' b' ' b' ' b' ' b' b' b' b' x' b' ' b' ']
```

step: 13, state: (1, 5, 2, 5), action taken: 1, reward: -12

```
Action: 2
step: 14, state: (2, 5, 3, 5), action taken: 1, reward: -11
Action: 2
[b' 'b' 'b' 'b'x'b' 'b'A'b'x'b'x'b' 'b' 'b' 'b' 'b' 'b' ']
[b' 'b' 'b' 'b'x'b' 'b'B'b'x'b' 'b' 'b' 'b' 'b'x'b'x'b'']
step: 15, state: (3, 5, 4, 5), action taken: 1, reward: -10
Action: 2
[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b'x' b' ' b' ' b' ' b' ' b' x' b'
[b' 'b' 'b' 'b'x'b' 'b'A'b'x'b' 'b' 'b' 'b' 'b' 'b'x'b'x'b']
[b' 'b' 'b' 'b'x'b' 'b'B'b' 'b' 'b' 'b' 'b' 'b' 'b'x'b'G']
step: 16, state: (3, 4, 4, 5), action taken: 1, reward: -11
Action: 3
[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' x' b' ' b' ' b' ' b' ' b' ' b' x' b' ']
[b' 'b' 'b' 'b'x'b' 'b'B'b' 'b' 'b' 'b' 'b' 'b'x'b'x'b'G']
step: 17, state: (4, 4, 4, 5), action taken: 1, reward: -10
Action: 2
[b' ' b' ' b' ' b' ' b' ' b' ' b' x' b'x' b' ' b' ' b' ' b' ' b' ' b' ']
[b' ' b' ' b' ' b'x' b' ' b' ' b'x' b' ' b' ' b' ' b' ' b' ' b' ' b' ']
[b' ' b' ' b' ' b'x' b' ' b' ' b'x' b' ' b' ' b' ' b' ' b' ' b'x' b' ']
step: 18, state: (4, 5, 4, 6), action taken: 3, reward: -9
Action: 4
[b' ' b' ' b' ' b'x' b' ' b' ' b'x' b' ' b' ' b' ' b' ' b'x' b'x' b' ']
[b' 'b' 'b' 'b'x'b' 'b'A'b'B'b' 'b' 'b' 'b' 'b'x'b'x'b'G']
step: 19, state: (4, 6, 4, 7), action taken: 3, reward: -8
Action: 4
[b' ' b' ' b' ' b' ' b' ' b' ' b' x' b'x' b' ' b' ' b' ' b' ' b' ' b' ' b' ']
[b' ' b' ' b' x' b' ' b' x' b' ' b' x' b' ' b' ' b' ' b' x' b' x' b' ']
step: 20, state: (4, 7, 4, 8), action taken: 3, reward: -7
Action: 4
[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' x' b' ' b' ' b' ' b' ' b' x' b'
[b' ' b' ' b' ' b'x' b' ' b' ' b'x' b' ' b' ' b' ' b' ' b' ' b'x' b' ']
[b' 'b' 'b' 'b'x'b' 'b' 'b' 'b'A' b'B' b' 'b' 'b'x'b'x' b'G']
step: 21, state: (4, 8, 4, 9), action taken: 3, reward: -6
```

```
[b' 'b' 'b' 'b'x'b' 'b' 'b' 'b' 'b'A'b'B'b' 'b'x'b'x'b'G']
step: 22, state: (4, 9, 4, 10), action taken: 3, reward: -5
Action: 4
[b' 'b' 'b' 'b'x'b' 'b' 'b' 'b' 'b' 'b'A' b'B' b'x' b'x' b'G']
step: 23, state: (5, 9, 4, 10), action taken: 1, reward: -6
Action: 2
[[b' 'b' 'b' 'b' 'b' 'b' 'b' 'b'x'b'x'b'_'b'_'b'_'b'_'b'_']
[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' x' b' ' b' ' b' ' b' ' b' ' b' x' b' ']
[b' 'b' 'b' 'b'x'b' 'b' 'b' 'b' 'b' 'b' b'B'b'x'b'x'b'G']
step: 24, state: (5, 10, 4, 10), action taken: 3, reward: -5
Action: 4
[b' ' b' ' b' ' b'x' b' ' b' ' b' x' b'x' b' ' b' ' b' ' b' ' b' b' x' b'
[b' ' b' ' b' ' b'x' b' ' b' ' b'x' b' ' b' ' b' ' b' ' b'x' b'x' b' ']
step: 25, state: (4, 10, 3, 10), action taken: 1, reward: -6
Action: 1
[b' ' b' ' b' x' b' ' b' x' b' ' b' x' b' ' b' b' b' b' b' b' x' b' x' b' ']
step: 26, state: (3, 10, 2, 10), action taken: 1, reward: -7
[b' ' b' ' b' ' b' ' b' ' b' ' b' x' b'x' b' ' b' ' b' ' b' ' b' ' b' ']
[b' 'b' 'b' 'b'x'b' 'b' 'b'x'b'x'b' 'b' b'B'b' 'b'x'b'
step: 27, state: (2, 10, 1, 10), action taken: 1, reward: -8
Action: 1
step: 28, state: (2, 9, 1, 10), action taken: 1, reward: -9
Action: 3
[b' 'b' 'b' 'b'x'b' 'b' 'b'x'b'x'b' 'b'A'b' 'b' 'b'x'b'']
[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' ' b' ' b' ' b' ' b' x' b' y']
step: 29, state: (1, 9, 1, 10), action taken: 1, reward: -8
Action: 1
```

[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' ' b' ']

```
step: 30, state: (1, 10, 1, 11), action taken: 3, reward: -7
Action: 4
[b' ' b' ' b' ' b' ' b' ' b' ' b' x' b'x' b' ' b' ' b' A' b'B' b' ' b' ']
step: 31, state: (1, 11, 1, 12), action taken: 3, reward: -6
Action: 4
[b' ' b' ' b' ' b' ' b' ' b' ' b' ' b'x' b'x' b' ' b' ' b' ' b'A' b'B' b' ']
[b' ' b' ' b' ' b' x' b' ' b' ' b' x' b' ' b' ' b' ' b' ' b' x' b' x' b' ']
step: 32, state: (1, 12, 1, 13), action taken: 3, reward: -5
[b' ' b' ' b' x' b' ' b' x' b' x' b' x' b' ' b' ' b' ' b' ' b' x' b' ']
step: 33, state: (0, 12, 1, 13), action taken: 1, reward: -6
Action: 1
step: 34, state: (0, 13, 1, 13), action taken: 3, reward: -5
Action: 4
[b' ' b' ' b' ' b'x' b' ' b' ' b'x' b' ' b' ']
step: 35, state: (1, 13, 2, 13), action taken: 1, reward: -4
Action: 2
[b' ' b' ' b' ' b'x' b' ' b' ' b'x' b' ' b' ' b' ' b' ' b'x' b' ']
step: 36, state: (2, 13, 3, 13), action taken: 1, reward: -3
Action: 2
[b' ' b' ' b' x' b' ' b' x' b' ' b' x' b' ' b' ' b' ' b' ' b' x' b'B']
step: 37, state: (3, 13, 4, 13), action taken: 1, reward: 998
Action: 2
[b' ' b' ' b' ' b' ' b' ' b' ' b' x' b'x' b' ' b' ' b' ' b' ' b' ' b' ']
```