

AU 342 PRINCIPLES OF ARTIFICIAL INTELLIGENCE

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I. INTRODUCTION

A. Purpose

This homework consists of designing and implementing a program that plays Chinese Checker. It will exemplify the minimax algorithm, and alpha-beta pruning, and the use of heuristic(evaluation/static) functions to prune the adversarial search.

Chinese checkers is a perfect information game for 2 players. A Chinese Checkers board is shown in Figure 1. The goal of the game is to get 10 pegs or marbles from one's starting position to one's ending position as quickly as possible. Starting and ending positions are always directly across from each other on the board, and players are placed as symmetrically as possible around the board. In a two-player game, the players would start at the top and bottom of the board. The goal of the game is moving all marbles from starting point to the star point on the opposite side of the board. Specially, each player has two color marbles. Player 1 at the top of the board has seven red marbles and three green marbles. Player 2 at the bottom of the board has seven blue marbles and three yellow marbles. If all of the red marbles move to the blue marbles' positions and the green marbles move to the yellow marbles' positions, player 1 would win. Player 2 wins by the same rules as player.

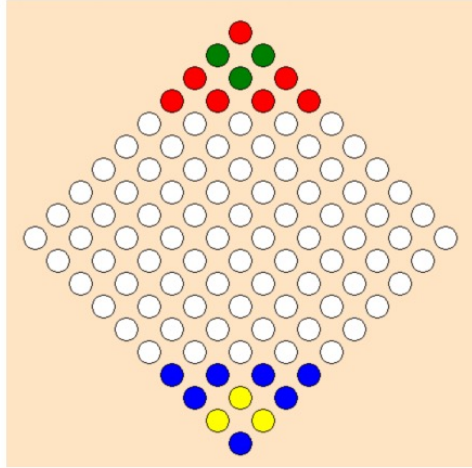


FIG. 1: A Two Player Chinese Checker

The main purpose of this project is to move the marbles of our side as fast as possible to occupy the opponents' original positions with marbles of certain colors in their predetermined right places. The marbles are supposed to move following such rules as below:

- Marbles are moved by stepping to an adjacent position on the board or by jumping over adjacent marbles. One can jump over any player's marbles, or chain together several jumps, but marbles are not removed from the board after a jump. We demonstrate this with a set of consecutive moves in Figure 2.
- Special rules are that every move should be assigned to any marble in one second.
- To prevent illicit competition, if any marble of the player is still in its own triangle, the player is judged to be defeated immediately.
- In case that both sides cannot battle it out after 100 times of iteration, the game ends in a tie.

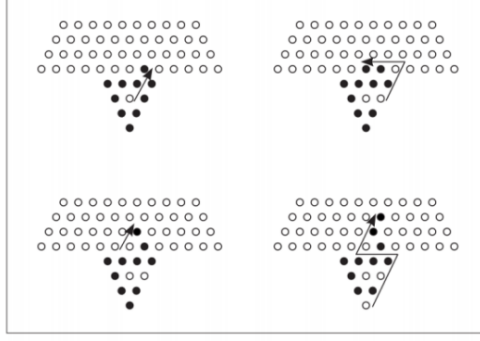


FIG. 2: Move possibilities for Chinese Checker

In this project, we generally apply the minimax algorithm, and alpha-beta pruning, and the use of heuristic functions to prune the adversarial search to our agent. We name our agent `RockMinimaxAgent(agent)`.

B. Environment

There is a minimal amount of equipment to be used in this lab. The few requirements are listed below:

- Windows 10
- Python 3.7
- Pycharm CE

C. Procedure

1. `Estimate_Func(self, state)` is used to evaluate the values of the present board state, in order to calculate the heuristic value.
2. `ALPHA_BETA_SEARCH(self, state)` is composed of the minimax algorithm, and alpha-beta pruning, and the use of heuristic functions to prune the adversarial search.
3. `getAction(self, state)` is used to update next action.

II. CLASS FUNCTIONS

This section will consist of elaborate explanations of the built-in functions in the agent class.

A. Estimation on Concerning Values Dynamically

This part of the laboratory was done for estimate the effects which the possible next actions brought to the overall composition of the board.

In the Estimate.Fun, we assign a weight to common marbles and special marbles respectively. Our early goal is to move all the three special marbles as soon as possible and make them stay put until the game ends. So the special marbles should have larger weights because their coming into right positions is the key factor that determines the winner. So in the heuristic function, we first filter those actions which have counteractive on special marbles and will move common marbles into special marbles' destinations. Then we give a large weight to the special ones to get them faster into their positions.

After all of the special marbles arriving at the destination, we increase the weight of the common marbles and decrease special marbles' to zero. In this part, we first tried to make a rule which stipulates common marbles to move as deep into their domain as possible, and on the edge of the domain, they move towards middle unless middle part is occupied. But we found this single rule is not optimal and sometimes the last two common pegs moving towards one side and without direction of its destination it stuck in one side. We later take the unoccupied destination into account and thus the last several actions are directed by unoccupied destination's column, and finally this rule achieves a better result.

B. Minimax Alpha-Beta Pruning Algorithm

In the minimax algorithm, before we determine each action, we should choose the maximum action from the legal actions. Then for each action, we further consider the possible actions the opponent will take next step. The opponent will probably choose the action which will minimize our score, so we utilize this to make an assumption about what our opponent will take and prevent our next action benefit our opponent.

In the minimax algorithm, we initially write three function: ALPHA_BETA_SEARCH, MAX_VALUE and MIN_VALUE to execute minimax algorithm recursively. But later we also tried use two for loop to execute our algorithm without recursive call. We compared two implementations' time, out of our expectation, their time only has slight difference.

The following is our implementation of MiniMax Algorithm:
Recursive Version:

```
1  def ALPHA_BETA_SEARCH(self, state):
2      v = self.MAX_VALUE(state, -9999, 9999, self.depth)
3      return self.dic[v]
4
5
6
7  def MAX_VALUE(self, state, alpha, beta, depth):
8      if depth == 1:
9          return self.Estimate_Func(state)
10         v = -99999
11         depth -= 1
12         legal_actions = self.game.actions(state)
13         random.shuffle(legal_actions)
14         for action in legal_actions:
15             self.action_list.append(action)
16             v = max(v, self.MIN_VALUE(self.game.succ(state, action), alpha, beta, depth))
17             if depth == 2:
18                 if v in self.dic.keys():
19                     v += self.action_list[0][0][0] - self.action_list[0][1][0]
20                 self.dic[v] = action
21             self.action_list.pop()
22             if v >= beta:
23                 return v
```

```

23     alpha = max(alpha, v)
24     return v
25
26 def MIN.VALUE(self, state, alpha, beta, depth):
27     if depth == 1:
28         return self.Estimate.Func(state)
29     v = 99999
30     depth -= 1
31     legal_actions = self.game.actions(state)
32     random.shuffle(legal_actions)
33     for action in legal_actions:
34         self.action_list.append(action)
35         v = min(v, self.MAX.VALUE(self.game.succ(state, action), alpha, beta, depth))
36         self.action_list.pop()
37         if depth == 2:
38             self.dic[v] = action
39         if v <= alpha:
40             return v
41     beta = min(beta, v)
42     return v

```

Non-recursive Version:

```

2     i = -1
3     index = 0
4     last_index = 0
5     alpha = -999999999999
6     player = state[0]
7     for action in legal_actions:
8         i += 1
9         if player == 1:
10             if action[1][0] > action[0][0]:
11                 legal_actions.remove(action)
12                 i -= 1
13                 continue
14             else:
15                 if action[1][0] < action[0][0]:
16                     legal_actions.remove(action)
17                     i -= 1
18                     continue
19             beta = 999999999999
20
21         player = state[0]
22         state[1].board_status[action[1]] = state[1].board_status[action[0]]
23         state[1].board_status[action[0]] = 0
24         state1 = (3 - player, state[1])
25         legal_actions1 = self.game.actions(state1)
26         state[1].board_status[action[0]] = state[1].board_status[action[1]]
27         state[1].board_status[action[1]] = 0
28         random.shuffle(legal_actions1)
29         if state[1].board_status[action[0]] == player + 2 and (action[1] == (5, 1) or action[1] == (5, 2)):
30             legal_actions.remove(action)
31             i -= 1
32             continue
33         if action[0] in self.list2:
34             if state[1].board_status[action[0]] == player + 2:
35                 legal_actions.remove(action)
36                 i -= 1
37                 continue
38         if action[1] in self.list2:
39             if state[1].board_status[action[0]] == player:
40                 legal_actions.remove(action)
41                 i -= 1
42                 continue
43         if action[0] in self.list2 and state[1].board_status[action[0]] == player:
44             index = i
45             break
46         if action[0] not in self.list2 and action[1] in self.list2 and state[1].board_status[
47             action[0]] == player + 2:
48             index = i
49             break
50         for action1 in legal_actions1:
51             player2 = state1[0]
52             if player2 == 1:
53                 if action1[1][0] > action1[0][0]:
54                     continue
55                 else:
56                     if action1[1][0] < action1[0][0]:
57                         continue
58             heuristic = Estimate.Func(state, action, player, action1, player2)
59             beta = min(heuristic, beta)
60             if heuristic <= alpha:
61                 break
62         if alpha < beta:
63             last_index = index
64             index = i
65             alpha = beta
66         final_action = legal_actions[i]
67         print(legal_actions[i])
68         if self.last_action is not None and final_action[1] == self.last_action[0]:
69             final_action = legal_actions[last_index]
70         self.last_action = final_action
71         print(final_action)
72         self.action = final_action

```

C. Get the Optimal Next Step

In the simple getAction function, we update next step chosen from the results selected by the minimax alpha-beta-pruning algorithm. In the first a few steps, we apply greedy search algorithm to get the marbles move faster and disturb the rival's choice. After that, we just update the action by rule. Additionally, we set a limit to the time every iteration of action takes. If it fails to reach the globally optimal solution in the limited time, a locally optimal solution will take place of it.

```

1 def Estimate_Func(self, state):
2     value = float(0.0)
3     weight2 = 1
4     player = state[0]
5     board = state[1]
6     player2 = player
7     if player == 2:
8         player2 += 1
9
10    state[1].board_status[self.action_list[1][0]] = state[1].board_status[self.action_list[1][1]]
11    state[1].board_status[self.action_list[1][1]] = 0
12    state[1].board_status[self.action_list[0][0]] = state[1].board_status[self.action_list[0][1]]
13    state[1].board_status[self.action_list[0][1]] = 0
14
15    pos = state[1].getPlayerPiecePositions(player)
16    pos1 = set((row, col) for (row, col) in pos if state[1].board_status[(row, col)] == player)
17    pos2 = set((row, col) for (row, col) in pos if state[1].board_status[(row, col)] == player + 2)
18    pos1 = list(pos1)
19    pos2 = list(pos2)
20    unoccupied_common_des = set(self.list[player2]).difference(pos1)
21    unoccupied_special_des = set(self.list[player2 + 1]).difference(pos2)
22
23    if state[1].board_status[self.action_list[0][0]] == player + 2:
24        weight = 10
25        if len(unoccupied_special_des) == 1:
26            weight = 11
27        if len(unoccupied_special_des) == 0:
28            weight = 0
29        if self.action_list[0][1] in self.list[player2 + 1]:
30            if self.action_list[0][0] in self.list[player2 + 1]:
31                value -= 10000000000
32                weight = 0
33            else:
34                value += 10000000000
35        if self.action_list[0][0] in self.list[player2 + 1]:
36            value -= 10000000000
37            weight = 0
38    else:
39        weight = 1
40        if self.action_list[0][0] in self.list[player2 + 1]:
41            if self.action_list[0][1] in self.list[player2 + 1]:
42                value -= 10000000
43            else:
44                value += 10000000
45        if len(unoccupied_special_des) == 0:
46            self.count = 0
47
48    if player == 1:
49        if (self.action_list[0][1][0] - 2) > self.action_list[0][0][0]:
50            value -= 5000 * weight
51        if self.action_list[0][0][0] < self.action_list[0][1][0]:
52            weight *= 5
53        if self.action_list[0][1] in unoccupied_common_des:
54            weight *= 5
55
56        value += 1000 * (self.action_list[0][0][0] - self.action_list[0][1][0]) * weight - 200 * (
57            self.action_list[1][0][0] - self.action_list[1][1][0])
58        value += weight2 * 150 * (self.action_list[0][0][0] - 4)
59    else:
60        if (self.action_list[0][0][0] - 2) > self.action_list[0][1][0]:
61            value -= 5000 * weight
62        if self.action_list[0][1][0] < self.action_list[0][0][0]:
63            weight *= 5
64        if self.action_list[0][1] in unoccupied_common_des:
65            weight *= 5
66        value += 1000 * (self.action_list[0][1][0] - self.action_list[0][0][0]) * weight - 200 * (
67            self.action_list[1][1][0] - self.action_list[1][0][0])
68        value += weight2 * 150 * (16 - self.action_list[0][0][0])
69
70    return value

```

III. DISCUSSION & CONCLUSION

The goal of this lab was to exemplify the minimax alpha-beta pruning algorithm and inspire us to develop our own AI Chinese Checker game based on the algorithm. By personally comprehend and utilize it, I was illuminated how to use such an adversarial search algorithm to carry out a two-player zero-sum game.

After the two-week laboratory of this project, we finally successfully built a basic conceptual framework of the minimax alpha-beta pruning algorithm. In all fairness, it was not a cinch for us to actually implement the thoughts into our code with a coarse and shallow understanding of the theory. Chances are that we came up with a new possible solution while we were stuck by how to accomplish our settled goal by means of codes, which led to us falling into a dilemma. Also, it was really a difficulty to debug the program.

The basic obstacle we were faced with is the time limit. We were demanded to update the action as soon as possible. It sets a challenge for our algorithm to be simplified in logic, and the search tree should be restricted from unfolding wildly. The alpha-beta pruning algorithm is in application for such a problem. Besides, we added an equative sentence to examine present time of processing. If it times out, a locally optimal solution instead of a globally optimal one is selected to be implemented.

In addition, we totally implemented different search methods into our experiment. Naturally, we used the minimax alpha-beta algorithm with heuristic functions to prune the adversarial search. In the first stance that the marbles moved forward with an average speed, which squandered a large number of iteration times. To deal with the situation, we chose to adopt a so-called 'updated greedy' algorithm that owns a better performance compared to the given simple greedy algorithm. As a result, we had a more powerful control over the marbles forcing them to move in a higher speed and larger vertical leap. Furthermore, it had an additional function in adversarial game to disorganize the rival's rhythm.

After all, we completed the task basically during the two-week laboratory, with a win rate of seventy to eighty percentage. Our best performance are illustrated in Figure 3.

However, many problems remains unsolved within limited time. First of all, we did not handle the 'stuck' situation, which we are supposed to avoid. In our code, we are striving to prevent all marbles from be stuck or blocked. It is flawed that we did not provide an independent function to manage the problem, thus put our marbles in risk. Moreover, to be frank, the heuristic function and the parameters to be designed is just passable. It is regrettable that we did not have enough competence to find the optimal values of the parameters, in which case we are easier to get into a scrape when moving forward, the marbles maybe retreating or jumping repeatedly at times.

All in all, this laboratory gave me an insight on how adversarial search algorithm like minimax alpha-beta pruning to be used in games. Through the hands-on practice, we learned to combine theory with practice. And last but not the least, it opens a new world to us of AI algorithms, which we have not heard before. We really appreciate it and derive a good deal of benefit from it.

```
runGame x
2 4 4
2 2
2
1
game 10 finished winner is player 1
In 10 simulations:
winning times: for player 1 is 10
winning times: for player 2 is 0
Tie times: 0
```

(a) Agent as player1

```
runGame x
2 4 2
4 4
2
2
game 10 finished winner is player 2
In 10 simulations:
winning times: for player 1 is 0
winning times: for player 2 is 10
Tie times: 0
```

(b) Agent as player2

FIG. 3: The result of RockMinimaxAgent versus SimpleGreedyAgent

...

IV. ACKNOWLEDGEMENT

We highly appreciate our professor Yue Gao, who gave us an insight into these brand new AI algorithms and provided a perfect platform for us to implement our own algorithm. Besides, we really appreciate the teaching assistants, who gave a hand in the times we were stuck. We are grateful to our classmates, who always gave us inspirations to do with the challenges faced with us.

V. APPENDIX

The following is our code of agent.py:

```

1 import random, re, datetime
2 import math
3 import copy
4
5
6
7 class Agent(object):
8     def __init__(self, game):
9         self.game = game
10        self.dic = {}
11        self.list = [[(1, 1), (3, 1), (3, 3), (4, 1), (4, 2), (4, 3), (4, 4)], [(2, 1), (2, 2), (3, 2)], [(19, 1),
12            (17, 1), (17, 3), (16, 1), (16, 2), (16, 3), (16, 4)], [(18, 1), (18, 2), (17, 2)]]
13        self.last_action = None
14        self.depth = 3
15        self.action_list = []
16        self.count = 0
17
18    def getAction(self, state):
19        raise Exception("Not_implemented_yet")
20
21 class RandomAgent(Agent):
22     def getAction(self, state):
23         legal_actions = self.game.actions(state)
24         self.action = random.choice(legal_actions)
25
26
27 class SimpleGreedyAgent(Agent):
28     # a one-step-lookahead greedy agent that returns action with max vertical advance
29     def getAction(self, state):
30         legal_actions = self.game.actions(state)
31         player = self.game.player(state)
32         # self.action = random.choice(legal_actions)
33         for action in legal_actions:
34             if action[1][0] == 2 or (action[1][0] == 3 and action[1][1] == 2):
35                 if self.game.succ(state, action)[1].board_status[(action[1][0], action[1][1])] == player + 2:
36                     self.action = action
37         if player == 1:
38             max_vertical_advance_one_step = max([action[0][0] - action[1][0] for action in legal_actions])
39             max_actions = [action for action in legal_actions if
40                 action[0][0] - action[1][0] == max_vertical_advance_one_step]
41         else:
42             max_vertical_advance_one_step = max([action[1][0] - action[0][0] for action in legal_actions])
43             max_actions = [action for action in legal_actions if
44                 action[1][0] - action[0][0] == max_vertical_advance_one_step]
45         self.action = random.choice(max_actions)
46
47
48 class RockMinimaxAgent(Agent):
49     def getAction(self, state):
50         player = state[0]
51         board = state[1]
52         self.start = datetime.datetime.now()
53         global count, delta
54         legal_actions = self.game.actions(state)
55         player_status = board.getPlayerPiecePositions(player)
56         self.count += 1
57         if self.count >= 100:
58             self.count = 0
59         if self.game.isEnd(state, 100):
60             self.count = 0
61
62         if self.count <= 10:
63             legal_actions = self.game.actions(state)
64             player = self.game.player(state)
65             board = state[1]
66             flag = 0
67
68             if player == 1:
69                 max_vertical_advance_one_step = -100
70                 max_actions = {}
71                 for action in legal_actions:
72                     if board.board_status[action[0]] == 3:
73                         if action[0] == (2, 1) or action[0] == (2, 2) or action[0] == (3, 2) or action[1] == (1, 1):
74                             continue
75                     else:
76                         if board.board_status[action[0]] == 3 and (
77                             action[1] == (2, 1) or action[1] == (2, 2) or action[1] == (3, 2)):
78                             flag = 1
79                             self.action = action
80                             break
81                     else:
82                         if (action[0][0] < 13):
83                             priority = 1
84                         else:
85                             priority = 0
86                         v = action[0][0] - action[1][0] + priority
87                         if v >= max_vertical_advance_one_step:
88                             max_vertical_advance_one_step = v
89                             max_actions.setdefault(v, []).append(action)
90             else:
91                 if action[1] == (2, 1) or action[1] == (2, 2) or action[1] == (3, 2):

```

```

93         continue
94         v = action[0][0] - action[1][0]
95         if v >= max_vertical_advance_one_step:
96             max_vertical_advance_one_step = v
97             max_actions.setdefault(v, []).append(action)
98     else:
99         max_vertical_advance_one_step = -100
100         max_actions = {}
101         for action in legal_actions:
102             if board.board_status[action[0]] == 4: # special pegs
103                 if action[0] == (18, 1) or action[0] == (18, 2) or action[0] == (17, 2) or action[1] == (19, 1):
104                     continue
105                 else:
106                     if board.board_status[action[0]] == 4 and (
107                         action[1] == (18, 1) or action[1] == (18, 2) or action[1] == (17, 2)):
108                         flag = 1
109                         self.action = action
110                         break
111                 else:
112                     if (action[0][0] > 7):
113                         priority = 1
114                     else:
115                         priority = 0
116                     v = action[1][0] - action[0][0] + priority
117                     if v >= max_vertical_advance_one_step:
118                         max_vertical_advance_one_step = v
119                         max_actions.setdefault(v, []).append(action)
120             else:
121                 if action[1] == (18, 1) or action[1] == (18, 2) or action[1] == (17, 2):
122                     continue
123                 v = action[1][0] - action[0][0]
124                 if v >= max_vertical_advance_one_step:
125                     max_vertical_advance_one_step = v
126                     max_actions.setdefault(v, []).append(action)
127         if flag == 0:
128             self.action = random.choice(max_actions[max_vertical_advance_one_step])
129
130     else:
131         action = self.ALPHA_BETA_SEARCH(state)
132         now = datetime.datetime.now()
133         time = str(now - self.start)
134         delta = float(time.split(':')[1]) #
135         print(delta)
136         if self.last_action is not None and self.last_action[0] == action[1]:
137             cnt = 1
138             sorted_d = sorted(self.dic.keys(), reverse=True)
139             while (self.last_action[0] == action[1]):
140                 action = self.dic[sorted_d[cnt]]
141                 cnt += 1
142             self.last_action = action
143             self.action = action
144
145
146 def ALPHA_BETA_SEARCH(self, state):
147     v = self.MAX_VALUE(state, -9999, 9999, self.depth)
148     return self.dic[v]
149
150
151 def MAX_VALUE(self, state, alpha, beta, depth):
152     if depth == 1:
153         return self.Estimate_Func(state)
154     v = -99999
155     depth -= 1
156     legal_actions = self.game.actions(state)
157     random.shuffle(legal_actions)
158     for action in legal_actions:
159         self.action_list.append(action)
160         v = max(v, self.MIN_VALUE(self.game.succ(state, action), alpha, beta, depth))
161         if depth == 2:
162             if v in self.dic.keys():
163                 v += self.action_list[0][0][0] - self.action_list[0][1][0]
164                 self.dic[v] = action
165             self.action_list.pop()
166             if v >= beta:
167                 return v
168             alpha = max(alpha, v)
169     return v
170
171 def MIN_VALUE(self, state, alpha, beta, depth):
172     if depth == 1:
173         return self.Estimate_Func(state)
174     v = 99999
175     depth -= 1
176     legal_actions = self.game.actions(state)
177     random.shuffle(legal_actions)
178     for action in legal_actions:
179         self.action_list.append(action)
180         v = min(v, self.MAX_VALUE(self.game.succ(state, action), alpha, beta, depth))
181         self.action_list.pop()
182         if depth == 2:
183             self.dic[v] = action
184             if v <= alpha:
185                 return v
186             beta = min(beta, v)
187     return v
188
189 def Estimate_Func(self, state):
190     value = float(0.0)
191     weight2 = 1
192     player = state[0]
193     board = state[1]
194     player2=player

```

```

195     if player==2:
196         player2+=1
197
198     state[1].board_status[self.action_list[1][0]] = state[1].board_status[self.action_list[1][1]]
199     state[1].board_status[self.action_list[1][1]] = 0
200     state[1].board_status[self.action_list[0][0]] = state[1].board_status[self.action_list[0][1]]
201     state[1].board_status[self.action_list[0][1]] = 0
202
203     pos = state[1].getPlayerPiecePositions(player)
204     pos1 = set((row, col) for (row, col) in pos if state[1].board_status[(row, col)] == player)
205     pos2= set((row, col) for (row, col) in pos if state[1].board_status[(row, col)] == player+2)#special pos
206     pos1=list(pos1)
207     pos2=list(pos2)
208     unoccupied_common_des = set(self.list[player2]).difference(pos1)
209     unoccupied_special_des = set(self.list[player2+1]).difference(pos2)
210
211     if state[1].board_status[self.action_list[0][0]] == player + 2:
212         weight=10
213         if len(unoccupied_special_des) == 1:
214             weight=11
215         if len(unoccupied_special_des) == 0:
216             weight=0
217         if self.action_list[0][1] in self.list[player2+1]:#
218             if self.action_list[0][0] in self.list[player2+1]:
219                 value -= 1000000000
220             else:
221                 value+=1000000000
222         if self.action_list[0][0] in self.list[player2+1]:
223             value -=1000000000
224             weight=0
225         else:
226             weight=1
227         if self.action_list[0][0] in self.list[player2+1]:
228             if self.action_list[0][1] in self.list[player2+1]:#
229                 value -= 1000000
230             else:
231                 value+=1000000
232         if len(unoccupied_special_des)==0:
233             self.count=0
234
235     if player==1:
236         if (self.action_list[0][1][0] - 2) > self.action_list[0][0][0]:
237             value -= 5000 * weight
238         if self.action_list[0][0][0] < self.action_list[0][1][0]:
239             weight *= 5
240         if self.action_list[0][1] in unoccupied_common_des:
241             weight *= 5
242
243         value += 1000 * (self.action_list[0][0][0] - self.action_list[0][1][0]) * weight + 200 * (
244             self.action_list[1][0][0] - self.action_list[1][1][0])
245         value += weight2 * 150 * (self.action_list[0][0][0] - 4)
246     else:
247         if (self.action_list[0][0][0] - 2) > self.action_list[0][1][0]:
248             value -= 5000 * weight
249         if self.action_list[0][1][0] < self.action_list[0][0][0]:
250             weight *= 5
251         if self.action_list[0][1] in unoccupied_common_des:
252             weight *= 5
253         value += 1000 * (self.action_list[0][1][0] - self.action_list[0][0][0]) * weight + 200 * (
254             self.action_list[1][1][0] - self.action_list[1][0][0])
255         value += weight2 * 150 * (16-self.action_list[0][0][0] )
256
257     return value
258
259
260
261
262
263
264
265     ### END CODE HERE ###

```