Heuristic analysis

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Introduction

— sp2

In this project we have to implement an adversarial search agent for playing to the isolation game.

In this version of the isolation game each agent is restricted to L-shaped moves on a square grid of 7 x 7. A time limit is fixed for each player in order to search the best possible move to apply to the next play. The player who has reached the time limit loss the match by forfeits.

Heuristic implementation

```
Heuristic 1 : custom_score increase #own_moves  
The custom_score function try to maximize the own moves.  

""

sp1 = len(game.get_legal_moves(player))

sp2 = len(game.get_legal_moves(game.get_opponent(player)))

m \times sp1 - sp2, with m \in \mathbb{R}

""

Heuristic 2: custom_score_2

reduce #opponent_moves:  
The cutom_score_2 function try to reduce the opponent move
```

sp2 = len(game.get_legal_moves(game.get_opponent(player)))

```
Heuristic 3: custom score 3
```

```
decrease #opponent_moves
```

The custom_score_3 function try to decrease the opponent moves.

```
sp1 = len(game.get_legal_moves())
sp2 = len(game.get_legal_moves(game.get_opponent(player)))
sp1 -m \times sp2, with m \in \mathbb{R}
```

Evaluation of the heuristic implementation

In order to test whether the implementation of the heuristic functions is effective, the tournament module is used.

The functions are tested in competition with the heuristic function improved_score, which is performed by an agent using the alpha-beta search and the iterative deepening search algorithm.

Opponents are materialized by three agents to evaluate different heuristics.

The first agent "Random" does not implement an heuristic function.

The second 'MinMax' agent implements the MinMax search algorithm.

The third agent 'AlphaBeta' implements the alphabeta pruning search algorithm.

Three heuristics are evaluated by MinMax and AlphaBeta, improved, central movement and open movement.

The result of tournament execution is shown in the table below.

In order to choose the coefficient m, I proceed to three tests with the values:

```
Test 1 m = 1,5
Test 2 m = 2
Test 3 m = 3
```

As indicated in the project the most efficient heuristic function has been implemented in "AB_custom" which surpasses the result of "AB_improved" with any coefficient of m.

Coefficient m equal to 1.5

This script evaluates the performance of the custom_score evaluation function against a baseline agent using alpha-beta search and iterative deepening (ID) called `AB_Improved`. The three `AB_Custom` agents use ID and alpha-beta search with the custom_score functions defined in game_agent.py.

		****	******			*			
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Match #	Opponent	AB Improved		AB Custom		AB Custom 2		AB Custom 3	
	00.000.000.000.000	Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	Random	20	0	16	4	20	0	19	1
2	MM Open	15	5	15	5	15	5	12	8
3	MM Center	15	5	20	0	18	2	16	4
4	MM Improved	15	5	15	5	12	8	13	j 7
5	AB Open	12	8	11	9	7	13	10	10
6	AB Center	11	9	14	6	13	7	9	11
7	$AB_\overline{I}mproved$	8	12	11	9	11	9	9	j 11
	Win Rate:	68.6%		72.9%		68.6%		62.9%	

Coefficient m equal to 2

	****	*****	*****	*****	*			
	****				*			
Opponent	AB Improved		AB Custom		AB Custom 2		AB Custom 3	
	Won	Lost	Won	Lost	Won	Lost	Won	Lost
Random	16	4	19	1	17	3	18	j 2
MM Open	19	1	15	5	15	5	16	j 4
MM Center	18	2	19	1	15	5	16	4
MM Improved	15	5	14	6	13	7	15	j 5
	10	10	12	8	12	8	12	i 8
AB Center	14	6	14	6	14	6	10	10
AB_Improved	10	10	10	10	11	9	11	9
Win Rate:	72	. 9%	73	. 6%	69	. 3%	70	.0%
	Random MM_Open MM_Center MM_Improved AB_Open AB_Center AB_Improved	**** Opponent AB_Impulsion Random 16 MM_Open 19 MM_Center 18 MM_Improved 15 AB_Open 10 AB_Center 14 AB_Improved 10	Playing ************************************	Playing Match ******************************* Opponent AB_Improved AB_Cu Won Lost Won Random 16 4 19 MM_Open 19 1 15 MM_Center 18 2 19 MM_Improved 15 5 14 AB_Open 10 10 12 AB_Center 14 6 14 AB_Improved 10 10 10	Playing Matches ****************************** Opponent AB_Improved AB_Custom	**************************************	Playing Matches ************************************	Playing Matches ************************************

There were 4.0 timeouts during the tournament -- make sure your agent handles s

Coefficient m equal to 3

		****	****** Playin			*			
		****	*****			*			
Match #	Opponent	ponent AB Improved		AB Custom		AB Custom 2		AB Custom 3	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	Random	19	1	19	1	18	2	19	1
2	MM Open	12	8	13	j 7	12	8	14	6
2 3	MM Center	17	8 3 5	17	j 3	18	2	19	j 1
4	MM Improved	15	5	15	5	14	6	14	6
4 5	AB Open	9	11	10	10	8	12	11	9
6	AB Center	11	9	13	i 7	9	11	9	11
7	$AB_\overline{I}mproved$	13	7	15	5	12	8	11	9
	Win Rate:	68	. 6%	72	.9%	65	. 0%	69	. 3%

Performance of agents using the implemented evaluation functions

Based on the best of the three tests (done with 1.5 as the coefficient).

Agent	Win Rate
AB_Improved	68.6 %
AB_Custom with m = 1.5	72.9 %
AB_Custom_2	68.6 %
AB_Custom_3 with m = 1.5	62.9 %

Recommendation

I would recommend to use the ab_custom with 1.5 as coefficient, this function try to maximize the player moves.

- 1. AB_custom has increased its success rate by 4.3% compared to the results of the AB_Improved heuristics function.
- 2. The ratio between efficiency and execution time is good.
- 3. It can be implemented simply.
- 4. It confirmed that maximizing the players moves give more chances of winning.