heuristic_analysis.md

Heuristic Analysis

Introduction

This document describes the comparison and analysis of several parameterised heuristics in their performance in playing Knight Isolation. The evaluation method is running a tournament agains several benchmark players. Each match starts with a randomly initialized game board, and each player pair with get to play the game twice as 1st player and 2nd player respectively for the match to be fair.

The custom players are defined in game_agent.py

The benchmark players are defined in sample_players.py

The tournament is run by tournament.py (a number of revisions are made to the original file in order to run more than three custom players)

Github: https://github.com/dingran1019/aind-2017may/tree/master/Isolation

Benchmark players

- Random: player that selects next move randomly without tree search
- MM_Open: player use minimax for search and score moves based on the number of available next moves
- MM_Center: player use minimax for search and score moves based on distance to center
- MM_Improved: player use minimax for search and score moves based on own number of available moves minus opponent's number of available moves
- AB_Open: same as MM_Open but has alpha-beta pruning and iterative deepening
- AB_Center: same as MM_Center but has alpha-beta pruning and iterative deepening
- AB_Improved: same as MM_Improved but has alpha-beta pruning and iterative deepening

Custom players

All custom players will use alpha-beta pruning and iterative deepening by default.

1. Diff_Agg_{*aggressiveness*}

This set of players call game_agent.score_differential_open_move() with parameter aggressiveness.

```
score = number_of_own_open_moves - aggressiveness * number_of_opponent_open_moves
```

Here we will study the following cases

- aggressiveness = 0: this is equivalent to the AB_Open case
- aggressiveness = 1: this is equivalent to the AB_Improved case
- aggressiveness = 2.5: more aggressive case
- aggressiveness = 0.5: less aggressive case
- aggressiveness = 1e6: this is similar to setting score = - number_of_opponent_open_moves, i.e. soley focused on chasing opponent out of open moves

2. TV_Diff_V1 and TV_Diff_V2

These two players are time-variant (TV) differential score. The players have a aggressiveness setting based on the stage of the game (calculated by the percentage of blank positions on the board). TV_Diff_V1 uses aggressiveness of 2.5 in the first half of the game and aggressiveness of 0.5 in the second half of the game. TV_Diff_V2 is exactly the opposite.

3. LA_Diff_{*aggressiveness*}

This set of players call game_agent.score_look_ahead_differential_move() with parameter aggressiveness. Instead of looking at the available next moves, we look one step further.

For this player, we scan aggressiveness = 0, 0.5, 1, 2, 1e6. The aggressiveness has the same meaning as explained in Diff_Agg_{*aggressiveness*} section.

4. Wall and corner aware player

Out of curiosity, I implemented a variant of what was described here https://github.com/arjunmitrareddy/Artifical-Intelligence---Isolation-Game-Agent/blob/master/game_agent.py

The function is game_agent.score_wall_corner_aware_differential_open_move()

Results and discussions

Due to the close scores in some of the player pairs a large number of matches were executed to reduce the random fluctuations seen in tournament with a small number of matches (20~50).

The results from a tournament of 19600 matches (7 benchmark players x 14 custom players x 200 matches) are summarized below.

Diff_Agg_{x} players

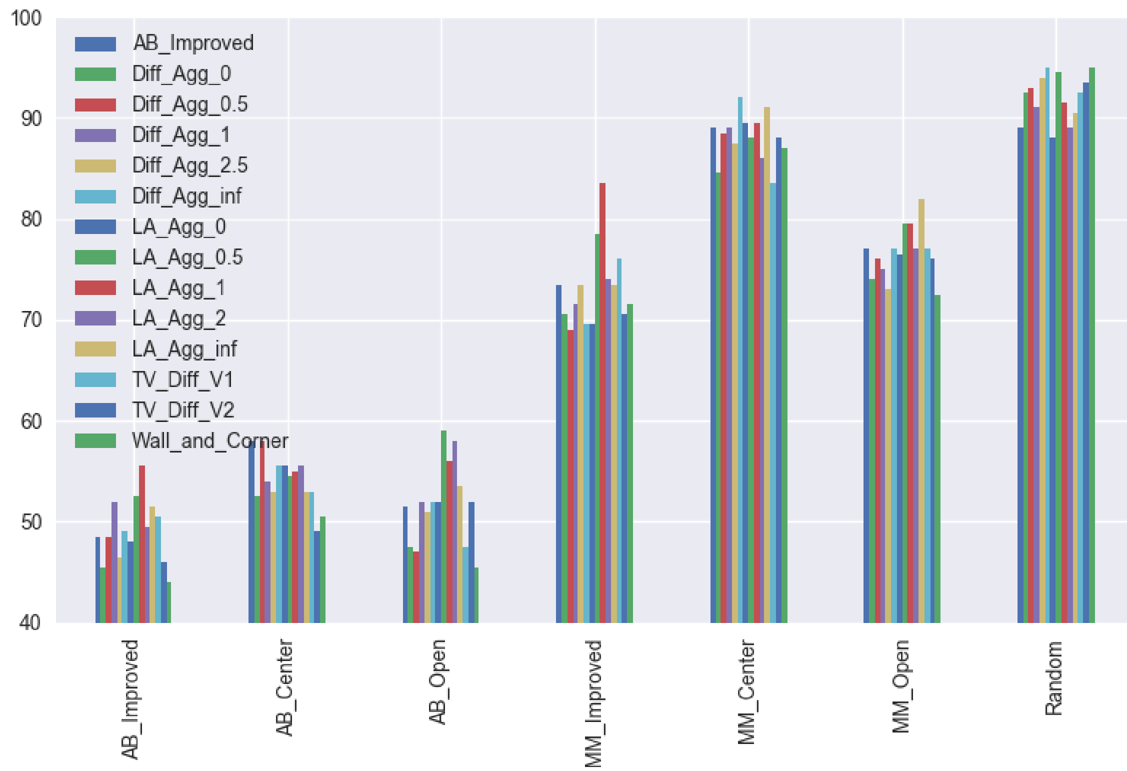
Match #	Opponent	AB_Improved		Diff_Agg_0		Diff_Agg_0.5		Diff_Agg_1		Diff_Agg_2.5		Diff_Agg_inf	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	AB_Improved	97	103	91	109	97	103	104	96	93	107	98	102
2	AB_Center	116	84	105	95	116	84	108	92	106	94	111	89
3	AB_Open	103	97	95	105	94	106	104	96	102	98	104	96
4	MM_Improved	147	53	141	59	138	62	143	57	147	53	139	61
5	MM_Center	178	22	169	31	177	23	178	22	175	25	184	16
6	MM_Open	154	46	148	52	152	48	150	50	146	54	154	46
7	Random	178	22	185	15	186	14	182	18	188	12	190	10
	Win Rate:	69.5%		66.7%		68.6%		69.2%		68.4%		70.0%	

TV_Diff_{x} and Wall_and_Corner players

Match #	Opponent	AB_Improved		TV_Diff_V1		TV_Diff_V2		Wall_and_Corner	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	AB_Improved	97	103	101	99	92	108	88	112
2	AB_Center	116	84	106	94	98	102	101	99
3	AB_Open	103	97	95	105	104	96	91	109
4	MM_Improved	147	53	152	48	141	59	143	57
5	MM_Center	178	22	167	33	176	24	174	26
6	MM_Open	154	46	154	46	152	48	145	55
7	Random	178	22	185	15	187	13	190	10
	Win Rate:	69.5%		68.6%		67.9%		66.6%	

LA_Agg_{x} players

```
Match #    Opponent     AB_Improved    LA_Agg_0     LA_Agg_0.5     LA_Agg_1      LA_Agg_2      LA_Agg_inf
                         Won | Lost   Won | Lost    Won | Lost    Won | Lost    Won | Lost    Won | Lost
   1      AB_Improved    97  |  103   96  |  104   105 |  95     111 |  89     99  |  101   103 |  97
   2       AB_Center     116 |  84    111 |  89    109 |  91     110 |  90     111 |  89    106 |  94
   3        AB_Open      103 |  97    104 |  96    118 |  82     112 |  88     116 |  84    107 |  93
   4      MM_Improved    147 |  53    139 |  61    157 |  43     167 |  33     148 |  52    147 |  53
   5       MM_Center     178 |  22    179 |  21    176 |  24     179 |  21     172 |  28    182 |  18
   6        MM_Open      154 |  46    153 |  47    159 |  41     159 |  41     154 |  46    164 |  36
   7        Random       178 |  22    176 |  24    189 |  11     183 |  17     178 |  22    181 |  19
--------------------------------------------------------------------------------------------------------
           Win Rate:      69.5%         68.4%         72.4%         72.9%         69.9%         70.7%
```



(Y axis is win rate in %)

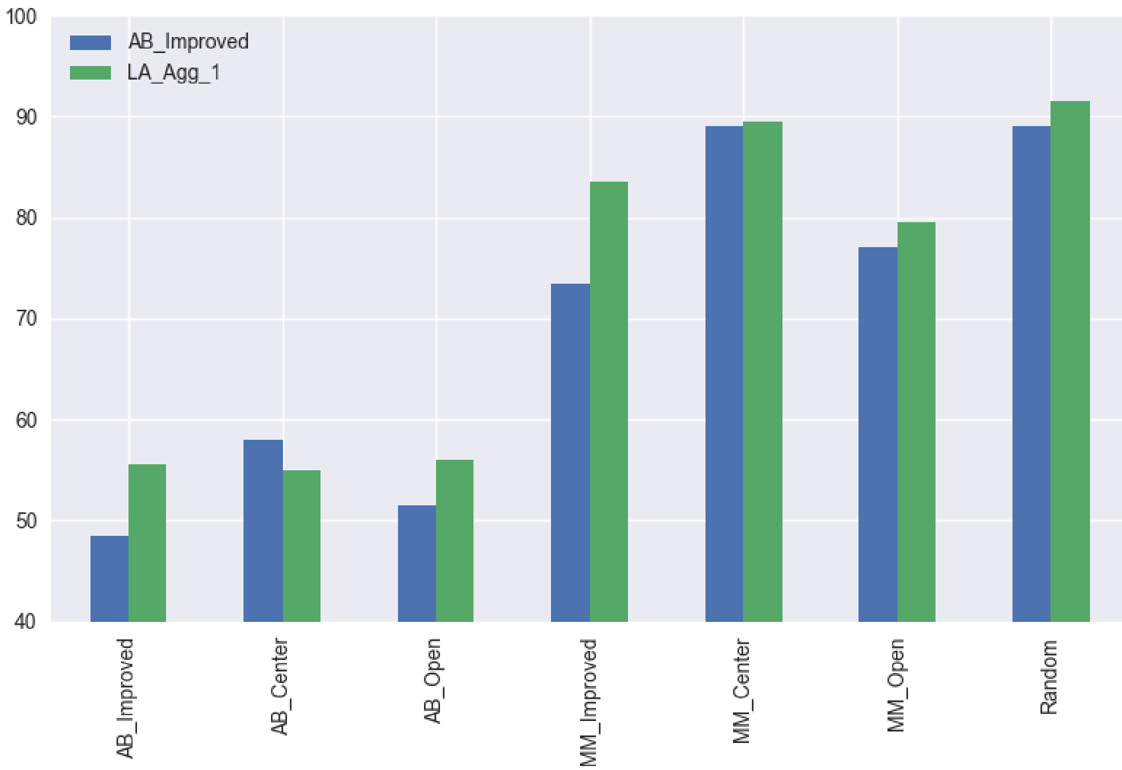
Considering the overall win rates:

- Diff_Agg_{x} did not show significant improvement over AB_Improved (equivalent to aggressiveness=1). With a setting of totally aggressive, i.e. aggressiveness = 1e6 (inf) being slightly better.
- The time-variant players also did not show benefit over AB_Improved either, related to the lack of performance in Diff_Agg_{x}.
- The look-ahead players LA_Agg_{x} consistently outperform AB_Improved with LA_Agg_1 being the best choice.
- The wall and corner aware player did not perform well, at least partially due to high complexity in evaluation.

Overall, I choose LA_Agg_1 as the best heuristic, with the following reasons:

- The overall win rates clearly indicate LA_Agg_1 is the best performing heuristic.
- In addition, several aggressiveness settings under this player family yielded top win rates - somewhat suggesting robustness with this heuristic.
- The look-ahead action in LA_Agg_{x} is intuitive. It is a more complex evaluation compared to Diff_Agg{x} and TV_Diff_{x}, but the look-ahead action proves to indeed add game-play advantage.
- The look-ahead is different than searching one more depth because the board remains unchanged in such look-ahead action. So, the look-ahead of available next-next moves is only an estimate. This turned out to be a good tradeoff in terms of keep computation complexity low enough to go deeper with limited time. This might be the reason wall and corner aware player did not perform well due to overly complex evaluation functions.

Here is a side-by-side comparison to AB_Improved on the win rate versus all the benchmark players



(Y axis is win rate in %)