Adversarial Game Playing Agent for Isolation – Heuristic Analysis*

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1 Background

The goal was to implement a game playing agent for the variant of the ISOLATION GAME in which players move like Knights instead of Queens in Chess. I implemented a Minimax search algorithm as well as Minimax with Alpha-Beta pruning. After this I tested the implemented agents with three different score evaluation heuristics against several baseline players which were provided. One in particular is useful to work with, namely the baseline agent which uses the `ID_Improved` heuristic from the lectures. In this report we present the results of improving further on this heuristic.

2 Implemented agents and heuristics

The `ID_Improved` heuristic is the following

$$ID\_Improved = \#ownMoves - \#oppMoves \tag{1}$$

The question is can we somehow improve on this heuristic by perhaps, adding some additional information? One additional useful information that comes to mind is the `CenterScore` heuristic which basically measures the distance of the current player's position from the center of the board. Let (x, y) be the position of the player. Let $w = BoardWidth/2$ and $h = BoardHeight/2$. Then the `CenterScore` metric is given by.

$$CenterScore = (x - w)^2 + (y - h)^2 \tag{2}$$

I believe that this additional information is useful for a game agent as the player which is "closer" to the center has more freedom to move. Therefore,

*submitted as part of the Udacity AI Engineer Nanodegree in the following I shall test the intuition that adding this information to an already good heuristic will improve further the playing strength of the agent.

In the following I shall work on incorporating this information in the `ID_Improved` heuristic and do several transformations of it. For a player, let

$$ownScore = \#ownMoves \cdot oppCenterScore$$

and

$$oppScore = \#oppMoves \cdot ownCenterScore$$

The reasoning is that, not only does a player know his number of available moves but also how far is his opponent from the center. If say, the opponent is very close to the center (`CenterScore` is then closer to zero) then that will make some of these moves not very useful since the opponent has a better strategic position on the board. For the improved metric we now define as a difference between these two scores:

$$CustomScore = ownScore - oppScore \tag{3}$$

If we make a step back and try to also improve further on the measurement of ID_Improved we might think of considering the ratio of $ownMoves$ versus $oppMoves$. The intuition is that the player who is better should have more available moves and the player which is worse should have less. In particular we can maximize

$$\frac{ownMoves}{oppMoves} - \frac{oppMoves}{ownMoves}.$$

This is equivalent to maximizing $ownMoves^2 - oppMoves^2$ so that is what we shall use to define `CustomScore2`.

$$CustomScore2 = \#ownMoves^2 - \#oppMoves^2 \tag{4}$$

We now combine `CustomScore2` with `CenterScore` in similar way we obtained `CustomScore`. The intuition is to combine the knowledge of player's position as well as the increase in player's available options and decrease of the opponent's.

$$CustomScore3 = oppCenter \cdot \#ownMoves^2 - ownCenter \cdot \#oppMoves^2 \tag{5}$$

3 Results

In the following table we present the results of playing 200 matches for each of our implemented agent against the test players provided by the testing system.

```
*************************
     Playing Matches
*************************
```

Match #	Opponent	AB_Improved		AB_Custom		AB_Custom_2		AB_Custom_3	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	Random	177	23	185	15	177	23	182	18
2	MM_Open	114	86	141	59	111	89	136	64
3	MM_Center	149	51	169	31	158	42	156	44
4	MM_Improved	109	91	124	76	92	108	130	70
5	AB_Open	106	94	110	90	99	101	132	68
6	AB_Center	88	112	107	93	98	102	126	74
7	AB_Improved	105	95	116	84	99	101	121	79
Win Rate:		60.6%		68.0%		59.6%		70.2%	

There is a question whether using simpler heuristics could perhaps replace our complicated heuristic. Suppose we take the `CustomScore2` heuristic and add a weight to either side of the subtraction in a similar way that was done in the lectures. We can try replacing for `CustomScore` and `CustomScore2` with example

$$CustomScoreImproved = \#ownMoves^2 - 1.6 \cdot \#oppMoves^2 \tag{6}$$

$$CustomScoreImproved2 = 1.6 \cdot \#ownMoves^2 - \#oppMoves^2 \tag{7}$$

respectively. Here the value 1.6 is chosen empirically. The following experiment shows that this simple change to the original metric (4) does improve it in one case for about 2% however it did not outperform `CustomScore3`. In the following `custom_score` is replaced by $CustomScoreImproved$ and `custom_score_2` is replaced by $CustomScoreImproved2$.

```
*************************
      Playing Matches
 *************************
```

Match #	Opponent	AB_Improved		AB_Custom		AB_Custom_2		AB_Custom_3	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	Random	173	27	181	19	172	28	183	17
2	MM_Open	113	87	130	70	121	79	140	60

3	MM_Center	152	48	151	49	154	46	157	43
4	MM_Improved	95	105	115	85	106	94	133	67
5	AB_Open	96	104	106	94	100	100	114	86
6	AB_Center	104	96	92	108	92	108	115	85
7	AB_Improved	98	102	104	96	96	104	112	88
Win Rate:		59.4%		62.8%		60.1%		68.1%	

4 Conclusion

For this assignment, three different heuristics were implemented. Based on the experiment results, the `CustomScore` heuristic was better by about 8% than the `ID_Improved` heuristic. What is interesting to note here is that `CustomScore2` has roughly the same performance as the `ID_Improved`. However, when `CustomScore2` is combined with `CenterScore` to obtain `CustomScore3` heuristic, the performance improves by 10%. It should be noted here that also to estimate the uncertainty in these measurements, we would need to perform this experiment several times and calculate the confidence intervals.

5 Recommended heuristic

I would recommend using the `CustomScore3` heuristic for the following reasons.

1. Based on the experiment results, the heuristic improves on the `ID_Improved` heuristic as well as the other considered heuristics with a Win Rate of roughly 70%.
2. It depends only on the current state of the game and does not involve using any additional memory or move history of the game.
3. It aligns with the intuition that knowing more information, namely the players position should contribute to a better strategy.