

Heuristic Analysis

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Heuristic 1: Random

For this heuristic, I simply chose a random value. I wanted to see, mainly as an experiment, how well it would perform against other agents. Turns out, that it has been outperforming all other agents that it has competed against.

```
if game.is_loser(player):  
    return float("-inf")  
  
if game.is_winner(player):  
    return float("inf")  
  
return random.random()
```

Heuristic 2: Ratio

For this algorithm, I wanted the score to be based on a ratio of “my moves” over “total moves”. It would seem reasonable, that higher scores would lead to better overall results. So far, the testing shows this heuristic is promising - as it is beating the “Improved” model fairly consistently.

```
if game.is_loser(player):  
    return float("-inf")  
  
if game.is_winner(player):  
    return float("inf")  
  
own_moves = len(game.get_legal_moves(player))  
opp_moves = len(game.get_legal_moves(game.get_opponent(player)))  
return float(own_moves / (own_moves + opp_moves))
```

Heuristic 3: Distance

For my final heuristic, I wanted to know how the distance between the two opposing players would contribute or correlate to a win or loss. My thought was the further away, the more “mobile” a player could be. However, my results show that it essentially ties with the “Improved” model.

```
if game.is_loser(player):
    return float("-inf")

if game.is_winner(player):
    return float("inf")

y1, x1 = game.get_player_location(player)
y2, x2 = game.get_player_location(game.get_opponent(player))
d = (((y2 - y1) ** 2) + ((x2 - x1) ** 2)) ** 0.5
return float(d)
```

Performance Benchmark

Below are the benchmarks for my three heuristics. The random comes out first, followed by the ratio and finally the distance metric is third. However, it's important to note that all three heuristics are a considerable improvement over the “Improved” model. Overall, I'm happy with these initial results. In the future, I'd like to think about combining some type of ensemble (aggregate) model that could use the best characteristics of each.

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.

Playing Matches

Match #	Opponent	AB_Improved		AB_Custom		AB_Custom_2		AB_Custom_3	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	Random	9	1	10	0	9	1	10	0
2	MM_Open	6	4	7	3	9	1	5	5
3	MM_Center	8	2	10	0	10	0	8	2
4	MM_Improved	4	6	6	4	6	4	6	4
5	AB_Open	6	4	7	3	6	4	6	4
6	AB_Center	7	3	8	2	6	4	7	3
7	AB_Improved	4	6	8	2	7	3	6	4
Win Rate:		62.9%		80.0%		75.7%		68.6%	