

### Custom Heuristic Evaluation

I implemented the following three custom heuristic functions:

1. Compound - the average number of moves that my legal moves will afford me (one play into the future) after they are played. Average Win Rate: 61.8%
2. Adversarial Compound - same as Compound Effect, except the average moves are found for both my player and my opponent, and subtracted from one another, like in Improved ID. Average Win Rate: 60.4%
3. Adversarial Only - only evaluate the number of moves that my opponent will have next time, and use the negative of that value as my heuristic. Average Win Rate: 64.6%

After four runs of tournament.py (shown below), at least one of my heuristics beats or ties the Improved ID heuristic. While the results vary significantly (addressed later), it seems that the Compound and Adversarial Only heuristics perform the best, on average tying in which one beats Improved ID more often (however, the average win rate over all the tournaments is higher for Adversarial Only). Adversarial Compound underperforms in three of the four tests. While “looking ahead” one move, as done in heuristics 1 and 2, seems like an interesting technique (and perhaps a promising one with some revision), it might be too convoluted in its current form. Iterative deepening is responsible for looking at deeper levels in the search tree. Looking a level lower and taking the average of the available moves as a heuristic degrades performance because, many of the legal moves might result in very little successive available moves, reducing our heuristic value. This is nonsensical because minimax of alpha beta pruning would not choose those moves in the first place, so there is no reason to evaluate them in this manner. Perhaps evaluating only a few high performing moves instead would prove advisable.

The Adversarial Only approach seems to perform well because, similar to the Improved heuristic, it takes the opponent’s available moves into account. However, in this case, we only evaluate the opponent’s moves and not our own, creating a fully adversarial AI that only focuses on destroying the opponent. This seems to work because, if you can reduce your opponent’s options dramatically, then it doesn’t matter how many options you have as long as it’s marginally more than theirs. Perhaps adding in a fraction of our available moves would improve performance even further, since it is still advisable to ensure that we have enough moves left. Other reasons this approach wins are essentially due to the reasons the others failed.

Interestingly enough, the tournament.py test produced very, very differing results, even for the baseline Improved ID player. It seems that with only 60 games (240 with running the test 4 times), we do not have a statistically relevant enough dataset to deterministically choose the superior heuristic. In such a Monte Carlo simulation, it is generally required to run many more iterations to produce stable results.

NOTE: the custom functions were reorganized in the code in order of performance.

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Playing Matches										
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Match #	Opponent	AB_Improved		AB_Custom		AB_Custom_2		AB_Custom_3		
		Won	Lost	Won	Lost	Won	Lost	Won	Lost	
1	Random	8	2	8	2	10	0	7	3	
2	MM_Open	5	5	6	4	5	5	8	2	
3	MM_Center	8	2	6	4	8	2	6	4	
4	MM_Improved	7	3	5	5	9	1	7	3	
5	AB_Open	5	5	5	5	3	7	5	5	
6	AB_Center	6	4	5	5	7	3	6	4	
7	AB_Improved	5	5	4	6	4	6	8	2	
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Win Rate:		62.9%		55.7%		65.7%		67.1%		

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Playing Matches										
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Match #	Opponent	AB_Improved		AB_Custom		AB_Custom_2		AB_Custom_3		
		Won	Lost	Won	Lost	Won	Lost	Won	Lost	
1	Random	8	2	10	0	6	4	7	3	
2	MM_Open	7	3	6	4	6	4	5	5	
3	MM_Center	5	5	6	4	6	4	7	3	
4	MM_Improved	3	7	6	4	8	2	7	3	
5	AB_Open	5	5	5	5	3	7	8	2	
6	AB_Center	6	4	4	6	3	7	4	6	
7	AB_Improved	5	5	4	6	5	5	5	5	
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Win Rate:		55.7%		58.6%		52.9%		61.4%		

*****										
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	8	2	7	3	8	2	
2	MM_Open	7	3	7	3	8	2	6	4	
3	MM_Center	8	2	8	2	8	2	9	1	
4	MM_Improved	6	4	6	4	5	5	6	4	
5	AB_Open	6	4	5	5	6	4	4	6	
6	AB_Center	5	5	6	4	5	5	8	2	
7	AB_Improved	5	5	6	4	5	5	4	6	
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Win Rate:		65.7%		65.7%		62.9%		64.3%		

*****										
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	8	2	8	2	7	3	
2	MM_Open	5	5	7	3	8	2	8	2	
3	MM_Center	7	3	9	1	7	3	7	3	
4	MM_Improved	8	2	6	4	6	4	7	3	
5	AB_Open	6	4	6	4	4	6	4	6	
6	AB_Center	6	4	7	3	6	4	5	5	
7	AB_Improved	5	5	4	6	3	7	8	2	
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Win Rate:		65.7%		67.1%		60.0%		65.7%		