# HEURISTIC ANALYSIS

For an Adversarial Game Playing Agent for Isolation

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### **SYNOPSIS**

The project's goal is to develop an adversarial search agent to play the game of Isolation. This report focuses on the heuristics used for the Alpha-Beta agents.

Isolation is a deterministic, two-player game of perfect information in which players take turns moving their piece on a 7x7 chess-like board. Whenever an agent occupies a space, that space becomes blocked for the remainder of the game. The game ends when an agent is unable to make a legal move and loses the game, with the opponent being the victor.

This project uses a variation of Isolation in which the piece being used behaves like a knight in chess. The agents are allowed to move their piece in an L-shaped movement onto any available space. Movement is blocked at the edges of the board, but players can jump over blocked or occupied spaces.

Lastly, agents have a fixed time limit of 150 milliseconds to search and return an appropriate move. Should the time limit expire during an agent's turn, that agent automatically forfeits the game and the opponent is declared the victor. These rules are implemented in the isolation.py file under the Board class.

### **Custom Heuristics**

#### 1. Custom 1:

Custom 1 focuses on maximizing its available moves while still minimizing the opponent's available moves.

 $\lambda len(own\ available\ moves) - len(opponent\ available\ moves),\ where\ \lambda\ \epsilon\ (1,\ \infty)$ The value of  $\lambda$  used was 1.5

#### 2. Custom 2:

Instead of focusing on its own moves, Custom 2 prioritizes minimizing the opponent's available moves. Maximizing its own moves comes second.

len(own available moves) –  $\lambda$ len(opponent available moves), where  $\lambda \in (1, \infty)$ The value of  $\lambda$  used was 1.5

#### 3. Custom 3:

Similar to Custom 1, but this time the available moves are scaled by the distance from the center of the board to the player's location. This results in moves closer to the center to be prioritized over those closer to the edge of the board.

$$\lambda \frac{\textit{len(own available moves)}}{\textit{own distance to center}} - \frac{\textit{len(opponent available moves)}}{\textit{opponent distance to center}}, \ \textit{where} \ \lambda \ \epsilon \ (1, \ \infty)$$
 The value of  $\lambda$  used was 1.5

#### 4. Custom 4:

Similar to Custom 2 and Custom 3. The goal here is to prioritize minimizing the opponent's available moves and trying to force him to the edges. At the same time we are trying to maximize our available moves while trying to stay closer to the center.

$$\frac{\textit{len}(\textit{own available moves})}{\textit{own distance to center}} - \lambda \frac{\textit{len}(\textit{opponent available moves})}{\textit{opponent distance to center}}, \textit{ where } \lambda \; \epsilon \; (1, \; \infty)$$
The value of  $\lambda$  used was 1.5

### **Evaluating Heuristics**

To evaluate the effectiveness of the different heuristics, tournament.py is used to run a round-robin tournament. Multiple other predefined agents have been added as opponents for the tournament.

Since the performance of time-limited iterative deepening search is hardware dependant, an agent is used as a baseline measurement. This agent is called "ID\_Improved" and it uses Alpha-Beta Search with Iterative Deepening and the "improved\_score" heuristic from sample\_players.py

The following agents are the opponents in the tournament:

- Random: Selects a random action each turn
- MM\_Open: Uses Fixed-Depth Minimax Search with the "open\_move\_score" heuristic
- MM\_Center: Uses Fixed-Depth Minimax Search with the "center\_score" heuristic
- MM\_Improved: Uses Fixed-Depth Minimax Search with the "improved\_score" heuristic
- AB\_Open: Uses Iterative Deepening Alpha-Beta Search with the "open\_move\_score" heuristic
- AB\_Center: Uses Iterative Deepening Alpha-Beta Search with the "center\_score" heuristic
- AB\_Improved: Uses Iterative Deepening Alpha-Beta Search with the "improved score" heuristic
- AB\_Custom: Uses Iterative Deepening Alpha-Beta Search with the "custom\_score" heuristic
- AB\_Custom\_2: Uses Iterative Deepening Alpha-Beta Search with the "custom score 2" heuristic
- AB\_Custom\_3: Uses Iterative Deepening Alpha-Beta Search with the "custom\_score\_3" heuristic
- AB\_Custom\_4: Uses Iterative Deepening Alpha-Beta Search with the "custom\_score\_4" heuristic

### **Results**

Bellow are the final results of the tournament between the four custom heuristics and the baseline agent. Each agent played 500 matches against each opponent. With a match consisting of two games in which each agent takes a turn at going first.

Rank	Agent	Win Rate			
1	AB_Custom_1	65.59%			
2	AB_Custom_2	64.96%			
3	AB_Improved	64.21%			
4	AB_Custom_3	63.27%			
5	AB_Custom_4	63.12%			

Based on the results of the tournament the best agent is AB\_Custom\_1 for the following reasons:

- 1. It achieved the highest win rate out of all the other agents at 65.59%
- 2. It won more than 50% of its games against the other AB\_Custom agents
- 3. It had the highest win rate versus the other opponents in the tournament that were not ranked at 75.20%

### **Appendices**

### A. Appendix: Tournament Results

Opponent	AB_lmp	oroved	oved AB_Custom_1 AE		AB_Custom_2		AB_Custom_3		AB_Custom_4	
	Won	Lost	Won	Lost	Won	Lost	Won	Lost	Won	Lost
Random	932	68	942	58	939	61	932	68	943	57
MM_Open	750	250	769	231	765	235	743	257	730	70
MM_Center	884	116	897	103	876	124	866	134	871	129
MM_Improved	722	278	749	251	756	244	730	270	708	292
AB_Open	514	486	537	463	510	490	518	482	531	469
AB_Center	588	412	618	382	584	416	572	428	579	421
AB_Improved			496	504	513	487	483	517	490	510
AB_Custom_1	501	499			499	501	469	531	469	531
AB_Custom_2	499	501	506	494			503	497	492	508
AB_Custom_3	502	498	527	473	530	470			499	501
AB_Custom_4	529	471	518	482	524	476	484	516		
Win Rate	64.2	64.21% 65.59% 64.96%		65.59%		6%	63.27%		63.12%	