

Heuristics Overview

While exploring the new to me Isolation game, I tried various heuristics as evaluation functions. Since I am quite familiar with Chess and Computer Chess, although evaluation functions are important in Chess they are not so important as standalone functions. Their most important role is guiding search, initiating extensions or pruning

For evaluation the influence of the various evaluations functions I tested, I used the provided tournament.py

At first I played two round robin tournaments covering all considered heuristics

Tournament Tables for the heuristics used

table 1:

Match	Opponent	AB_Improved		Combined_1		Combined_2		Combined_3	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	Random	37	3	36	4	36	4	35	5
2	MM_Open	29	11	34	6	35	5	31	9
3	MM_Center	36	4	31	9	34	6	36	4
4	MM_Improved	31	9	29	11	30	10	26	14
5	AB_Open	19	21	19	21	16	24	22	18
6	AB_Center	29	11	23	17	23	17	24	16
7	AB_Improved	20	20	22	18	17	23	15	25
Win Rate		71.8%		69.3%		68.2%		67.5%	

table 2:

Match	Opponent	AB_Improved		Distance		Combined_4		Common Moves	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	Random	37	3	36	4	39	1	33	7
2	MM_Open	29	11	28	12	32	8	27	13

3	MM_Center	36	4	34	6	36	4	32	8
4	MM_Improved	27	13	29	11	26	14	22	18
5	AB_Open	23	17	22	18	17	23	15	25
6	AB_Center	20	20	20	20	19	21	20	20
7	AB_Improved	16	24	21	19	20	20	18	18
Win Rate		67.1%		67.9%		67.5%		59.8%	

Statistical Significance of Results.

To make any valid assumptions about the effectiveness of the heuristics, one should play **a lot** of games, because as one can see, even self playing can result in results far away from the expected 50%

This is a very common situation in evaluating chess engines and one can read more [here](#)

To do that evaluation I implemented the function mentioned in the link to evaluate if there is any significance in the results (you can find the function in los.py in the repository)

Of course for any meaningful results much longer matches should be played. For this reason I created 2 tournament matches 1000 games long each , to get some meaningful results for the heuristics.

match 1:

Match	Opponent	Combined_1		Combined_2		Combined_3		Combined_4	
.....	Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	AB_Improved	503	497	504	496	516	484	0	0

match 2:

Match	Opponent	Inv_Distance		Distance		Open_move		Common Moves	
.....	Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	AB_Improved	461	539	0	0	476	524	0	0

Heuristics Reference and performance analysis

1. **Open move score:** Number of legal moves available for the player.
 - **Performance:** fast and simple
 - **ELO Difference:** -16.69
 - **Likelihood of Superiority:** 6.45%
2. **Mobility:** The difference between number of own legal moves - opponent legal moves. This is also used in the tournament.py by the AB_Improved agent

- **Performance:** fast and simple. This is the ID_improved heuristic
 - **ELO Difference:** 0
 - **Likelihood of Superiority:** 0
3. **Common Moves:** This simple heuristic gives a higher score to positions where both players have squares they can both go. It counts the common squares and give that as a score for the position
- **Performance:** slightly slower
 - **ELO Difference:** -61.79
 - **Likelihood of Superiority:** 1.30%
4. **Distance:** This returns the distance between the two players in the board. Trying to stay as far away from the opponent as possible
- **Performance:** fast and simple
 - **ELO Difference:** -13.20
 - **Likelihood of Superiority:** 11.47%
5. **Inverse Distance:** This returns the $1/\text{distance}$ between the two players in the board. Trying to stay as close to the opponent as possible
- **Performance:** fast and simple
 - **ELO Difference:** -27.155
 - **Likelihood of Superiority:** 0.68%
6. **Combined_1:** A linear combination of (1), (2) and (3).
- **Performance:** slightly slower
 - **ELO Difference:** 2.08
 - **Likelihood of Superiority:** 57.52%
7. **Combined_2:** This heuristic gives $(\text{number of legal moves})^2 - \text{number of opponent legal moves}$, when the board is more than half full (that means Its more important to have open moves when the board is full) and $(\text{number of legal moves}) - (\text{number of opponent legal move})^2$ when the board is not , which means I care more about restricting the opponent in the early stages. This gives a slight improvement over AB_Improved and it can be more fine tuned
- **Performance:** much slower than ID_improved
 - **ELO Difference:** 2.08
 - **Likelihood of Superiority:** 57.52%
8. **Combined_3:** Expanding on the previous idea this returns:

```
if moves_to_board >= 0.8: # closer to endgame (most squares are occupied)
    return float(len(own_moves) * 4 - len(opponent_moves))
elif 0.4 <= moves_to_board < 0.8:
    return float(len(own_moves) * 2 - len(opponent_moves))
else:
    return float(len(own_moves) - len(opponent_moves) * 2)
```

which does not change much compare to the previous heuristic

- **Performance**: much slower than ID_improved
- **ELO Difference**: 11.12
- **Likelihood of Superiority**: 84.42%

9. **Combined_4**: This was just a crazy idea as a shot in the dark. In short it calculates the following:

```
score = float(own_moves ** 2 / (1 + opp_moves)) + float(own_moves / (1 + opp_moves ** 2))
```

- **Performance**: fast and simple
- **ELO Difference**:
- **Likelihood of Superiority**:

Summary

The results are summarized in the following graph

Based on the above analysis, the heuristic of choice (based on those shallow depth matches) is because its the only one showing statistically significant evidence of superiority against the reference heuristic