

Isolation Heuristic Analysis

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Definition

I defined three heuristics `custom_score()`, `custom_score_2()` and `custom_score_3()`. All heuristics are given by the difference between the number of legal moves of active player and inactive player. The general formula of the heuristics H

$$H = a \times N_{\text{active}} - b \times N_{\text{inactive}}$$

where a and b are two parameters that $a + b = 1$; N_{active} is the number of legal moves of the active player, while N_{inactive} is of the inactive player. For the three heuristics, I set a and b as

- `custom_score()`: $a = 0.05$, $b = 0.95$. The number of legal moves of the inactive player dominates the heuristic. The player tends to consider the move that the opponent has fewer moves.
- `custom_score2()`: $a = 0.5$, $b = 0.5$. The numbers of legal moves of both the active player and the inactive player have the same contribution to the heuristic. Player will maximize the number of its own moves while minimize the number of the opponent's moves.
- `custom_score3()`: $a = 0.95$, $b = 0.05$. The number of legal moves of the active player dominates the heuristic. The player tends to play the move that maximize the possibility of its own moves.

The following is an example of the implementation of `custom_score()`

```
def custom_score(game, player):
    if game.is_loser(player):
        return float('-inf')
    if game.is_winner(player):
        return float('inf')
    # number of possible moves for active player and inactive player
    act_moves = len(game.get_legal_moves(player))
    inact_moves = len(game.get_legal_moves(game.get_opponent(player)))

    return float(0.05 * act_moves - 0.95 * inact_moves)
```

Result

I set the parameter `NUM_MATCHES` , number of matches against each opponent, to be 20 in the `tournament.py` , so in total, each heuristic has 40 matches with each predefined heuristics.

The result is

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	36	4	35	5	33	7	27	13
2	MM_Open	25	15	29	11	29	11	30	10
3	MM_Center	29	11	31	9	33	7	28	12
4	MM_Improved	27	13	23	17	27	13	23	17
5	AB_Open	19	21	23	17	21	19	20	20
6	AB_Center	24	16	23	17	23	17	27	13
7	AB_Improved	19	21	19	21	23	17	20	20

Win Rate:		63.9%		65.4%		67.5%		62.5%	

Figure 1: `tournament.py` results with 40 matches each and 150ms time limit.

We can find that

- the win rates of all players are around 65%.
- the player `AB_Custom_2` with heuristic `custom_score2()` outperforms the baseline player `AB_Improved` . `AB_Custom_2` plays the best against all opponents.

Recommendation

I would recommend `custom_score2()` because it has the best win rate. It consider the active and inactive player equally. And it is simple enough to explain and it is fast to compute.

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***** Playing Matches *****									
Match #	Opponent	AB_Improved		AB_Custom		AB_Custom_2		AB_Custom_3	
		Won	Lost	Won	Lost	Won	Lost	Won	Lost
1	Random	86	14	85	15	82	18	87	13
2	MM_Open	67	33	67	33	68	32	69	31
3	MM_Center	79	21	73	27	82	18	75	25
4	MM_Improved	66	34	69	31	63	37	66	34
5	AB_Open	53	47	54	46	55	45	51	49
6	AB_Center	58	42	56	44	63	37	61	39
7	AB_Improved	50	50	57	43	55	45	55	45

Win Rate:		65.6%		65.9%		66.9%		66.3%	

Figure 2: `tournament.py` results with 100 matches each and 150ms time limit.