

Evaluation Heuristics

The purpose of the game is being the last player to play a legal move, so a good heuristic tries to maximize the number of valid moves available to play. It is also very important to try to minimize the opponent's number of available moves, so that the opponent has always less moves than our AI. A good heuristic that combines the previous ones has been shown previously in the course:

$$\# \text{ of player's available moves} - \# \text{ of opponent's available moves}$$

This heuristic works alright, nevertheless it assumes that the number of available moves for both the player and opponent are equally important. It could be the case that prioritizing the opponent's number of available moves could give better results, so I decided to test the `custom_score` function with different variations of the following formula:

$$\# \text{ of player's available moves} - \alpha \times \# \text{ of opponent's available moves}$$

Where α is a parameter that was varied to find the best results. It is important to mention that if the score being evaluated is a leaf node, it returns infinite if the player wins and minus infinite if the opponent wins.

The following table shows the win rates after trying the new score function for different values:

α	Student %
1	56.43
1.5	67.14
2	67.86
2.5	61.43
3	58.57

As seen, the linear combination of the `# of opponent's available moves` for which my `custom_score` function wins the most is when $\alpha = 2$. It is about 11.5% better than the original heuristic where $\alpha = 1$. This means that the AI plays better if `# of opponent's available moves` score doubly as wrong.

Supporting files

```
*****
Evaluating: Student
*****

Playing Matches:
-----
Match 1:  Student  vs  Random    Result: 17 to 3
Match 2:  Student  vs  MM_Null   Result: 10 to 10
Match 3:  Student  vs  MM_Open   Result: 8 to 12
Match 4:  Student  vs  MM_Improved Result: 6 to 14
Match 5:  Student  vs  AB_Null    Result: 13 to 7
Match 6:  Student  vs  AB_Open    Result: 14 to 6
Match 7:  Student  vs  AB_Improved Result: 11 to 9

Results:
-----
Student          56.43%
```

Image 1. Results Alpha equals 1.

```
*****
Evaluating: Student
*****

Playing Matches:
-----
Match 1:  Student  vs  Random    Result: 19 to 1
Match 2:  Student  vs  MM_Null   Result: 17 to 3
Match 3:  Student  vs  MM_Open   Result: 12 to 8
Match 4:  Student  vs  MM_Improved Result: 12 to 8
Match 5:  Student  vs  AB_Null    Result: 11 to 9
Match 6:  Student  vs  AB_Open    Result: 9 to 11
Match 7:  Student  vs  AB_Improved Result: 14 to 6

Results:
-----
Student          67.14%
```

Image 2. Results Alpha equals 1,5.

```

*****
Evaluating: Student
*****

Playing Matches:
-----
Match 1:  Student  vs  Random    Result: 20 to 0
Match 2:  Student  vs  MM_Null   Result: 14 to 6
Match 3:  Student  vs  MM_Open   Result: 10 to 10
Match 4:  Student  vs  MM_Improved Result: 8 to 12
Match 5:  Student  vs  AB_Null    Result: 16 to 4
Match 6:  Student  vs  AB_Open    Result: 12 to 8
Match 7:  Student  vs  AB_Improved Result: 15 to 5

Results:
-----
Student          67.86%

```

Image 3. Results Alpha equals 2.

```

*****
Evaluating: Student
*****

Playing Matches:
-----
Match 1:  Student  vs  Random    Result: 18 to 2
Match 2:  Student  vs  MM_Null   Result: 14 to 6
Match 3:  Student  vs  MM_Open   Result: 7 to 13
Match 4:  Student  vs  MM_Improved Result: 13 to 7
Match 5:  Student  vs  AB_Null    Result: 10 to 10
Match 6:  Student  vs  AB_Open    Result: 13 to 7
Match 7:  Student  vs  AB_Improved Result: 11 to 9

Results:
-----
Student          61.43%

```

Image 4. Results Alpha equals 2,5.

```
*****
Evaluating: Student
*****

Playing Matches:
-----
Match 1: Student vs Random Result: 14 to 6
Match 2: Student vs MM_Null Result: 16 to 4
Match 3: Student vs MM_Open Result: 6 to 14
Match 4: Student vs MM_Improved Result: 8 to 12
Match 5: Student vs AB_Null Result: 14 to 6
Match 6: Student vs AB_Open Result: 10 to 10
Match 7: Student vs AB_Improved Result: 14 to 6

Results:
-----
Student 58.57%
```

Image 5. Results alpha equals 3