Analysis

Isolation: Heuristic functions

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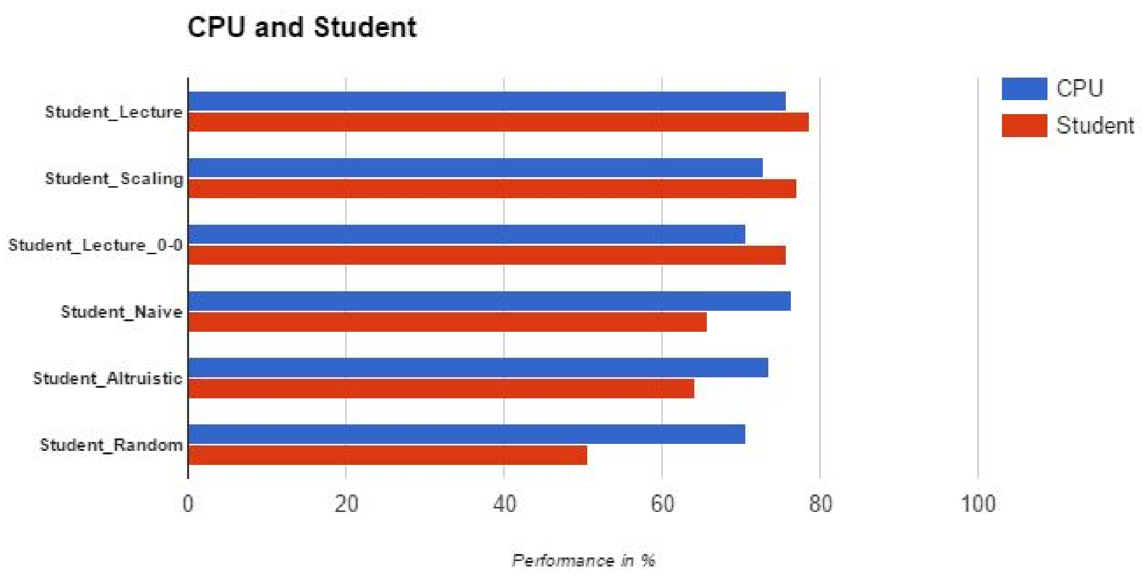
Overview

This graphic shows the performance of the different scoring functions.



The following data was used to create the graphic.

Function	CPU	Student
Student_Lecture	75.71	78.57
Student_Scaling	72.86	77.14
Student_Lecture_0-0	70.71	75.71
Student_Naive	76.43	65.71
Student_Altruistic	73.57	64.29
Student_Random	70.71	50.71

Comparison of scoring functions

This chapter illustrates the different custom scoring functions that were evaluated and compared against each other and shows the tournament result aligned to the specific function.

I tried a hand full of scoring functions and documented my findings in this document.

Random scoring function (center)

The player stars at the center when he has the first move.

The first test was done with a scoring function that returned random values for every node. As expected, the agent performed worse. In the lecture it was stated, that an optimal agent will always outperform an agent that uses no strategy or a non-optimal strategy.

```
*************************
 Evaluating: ID_Improved
*************************

Playing Matches:
----------
  Match 1: vs    Random       Result: 19 to 1
  Match 2: vs    MM_Null      Result: 15 to 5
  Match 3: vs    MM_Open      Result: 12 to 8
  Match 4: vs MM_Improved     Result: 10 to 10
  Match 5: vs    AB_Null      Result: 18 to 2
  Match 6: vs    AB_Open      Result: 15 to 5
  Match 7: vs AB_Improved     Result: 10 to 10

Results:
----------
        70.71%
```

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

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

Results:
----------
Student             50.71%
```

Simple scoring function (center)

The player stars at the center when he has the first move.

This improved scoring function simply returns the number of possible steps at the given node. As it does not put the opponent into consideration it is not surprising that the player lost against the computer agent. However, the score has increased related to the random scoring function, as moves are avoided that don't offer many next possible steps.

<pre>************************* Evaluating: ID_Improved ************************* Playing Matches: ---------- Match 1: vs Random Result: 20 to 0 Match 2: vs MM_Null Result: 19 to 1 Match 3: vs MM_Open Result: 13 to 7 Match 4: vs MM_Improved Result: 13 to 7 Match 5: vs AB_Null Result: 15 to 5 Match 6: vs AB_Open Result: 15 to 5 Match 7: vs AB_Improved Result: 12 to 8 Results: ---------- 76.43%</pre>	<pre>************************* Evaluating: Student ************************* Playing Matches: ---------- Match 1: vs Random Result: 18 to 2 Match 2: vs MM_Null Result: 19 to 1 Match 3: vs MM_Open Result: 13 to 7 Match 4: vs MM_Improved Result: 8 to 12 Match 5: vs AB_Null Result: 12 to 8 Match 6: vs AB_Open Result: 11 to 9 Match 7: vs AB_Improved Result: 11 to 9 Results: ---------- Student 65.71%</pre>

Lecture scoring function (center)

The player stars at the center when he has the first move.

This test used the scoring function from the lecture, where situations that offer many moves to the opponent are penalized.

The factor besides the result illustrates the factor which was used to get to this result. Increasing the factor should put more pressure on the opponent as moves are prefered that reduce the number of possible moves from the opponent. It however seems that there is an upper bound on the factor. When increasing the factor after this bound, there is no more effect. This is intuitive as after the factor increases to a size above *myOwnMoves*, the delivered result will always be the same - only the absolute values will differ.

`` ************************* Evaluating: ID_Improved (factor 2) ************************* Playing Matches: ---------- Match 1: vs Random Result: 20 to 0 Match 2: vs MM_Null Result: 18 to 2 Match 3: vs MM_Open Result: 17 to 3 Match 4: vs MM_Improved Result: 11 to 9 Match 5: vs AB_Null Result: 17 to 3 Match 6: vs AB_Open Result: 11 to 9 Match 7: vs AB_Improved Result: 12 to 8 Results: ---------- 80.00% 75.71% 75.00% 77.86% ```	``` ************************* Evaluating: Student (factor 2) ************************* Playing Matches: ---------- Match 1: vs Random Result: 19 to 1 Match 2: vs MM_Null Result: 18 to 2 Match 3: vs MM_Open Result: 16 to 4 Match 4: vs MM_Improved Result: 12 to 8 Match 5: vs AB_Null Result: 19 to 1 Match 6: vs AB_Open Result: 14 to 6 Match 7: vs AB_Improved Result: 12 to 8 Results: ---------- Student 69.29% (factor 1.5) Student 78.57% (factor 2) Student 76.43% (factor 3) Student 77.14% (factor 5) ```

Altruistic scoring function (center)

The player stars at the center when he has the first move.

This scoring function assumes that situations where the enemy has more moves could lead to a winning situations. The idea was to prefer moves that still provide some space for the opponent. The evaluation shows that this scoring function performs comparable to the naive scoring function.

<pre>************************* Evaluating: ID_Improved ************************* Playing Matches: ---------- Match 1: vs Random Result: 17 to 3 Match 2: vs MM_Null Result: 20 to 0 Match 3: vs MM_Open Result: 15 to 5 Match 4: vs MM_Improved Result: 13 to 7 Match 5: vs AB_Null Result: 16 to 4 Match 6: vs AB_Open Result: 12 to 8 Match 7: vs AB_Improved Result: 10 to 10 Results: ---------- 73.57%</pre>	<pre>************************* Evaluating: Student ************************* Playing Matches: ---------- Match 1: vs Random Result: 18 to 2 Match 2: vs MM_Null Result: 16 to 4 Match 3: vs MM_Open Result: 11 to 9 Match 4: vs MM_Improved Result: 9 to 11 Match 5: vs AB_Null Result: 15 to 5 Match 6: vs AB_Open Result: 12 to 8 Match 7: vs AB_Improved Result: 9 to 11 Results: ---------- Student 64.29%</pre>

Lecture scoring function (0,0)

The player stars at the coordinate (0,0) when he has the first move.

This test used the scoring function from the lecture, where situations that offer many moves to the opponent are penalized.

The change of the starting position should evaluate if the starting position has a major effect or not, as the set of moves in this variant of isolation is strongly constrained compared to original isolation.

The performance was comparable to the scoring function from the lecture, but performed a little bit worse. This could however be an effect of randomness.

<pre>************************* Evaluating: ID_Improved ************************* Playing Matches: ---------- Match 1: vs Random Result: 19 to 1 Match 2: vs MM_Null Result: 19 to 1 Match 3: vs MM_Open Result: 11 to 9 Match 4: vs MM_Improved Result: 14 to 6 Match 5: vs AB_Null Result: 16 to 4 Match 6: vs AB_Open Result: 11 to 9 Match 7: vs AB_Improved Result: 9 to 11 Results: ---------- 70.71%</pre>	<pre>************************* Evaluating: Student ************************* Playing Matches: ---------- Match 1: vs Random Result: 19 to 1 Match 2: vs MM_Null Result: 18 to 2 Match 3: vs MM_Open Result: 11 to 9 Match 4: vs MM_Improved Result: 14 to 6 Match 5: vs AB_Null Result: 15 to 5 Match 6: vs AB_Open Result: 14 to 6 Match 7: vs AB_Improved Result: 15 to 5 Results: ---------- Student 75.71%</pre>

Adapting scoring function (center)

The player stars at the center when he has the first move.

The idea of this scoring function is to give the opponent more space at the beginning of the match. Moves that offer more space to the opponent are penalized more and more while the game progresses. So when we get close to the end game, the enemy should not get possibilities to evolve his game, for free.

The performance of this scoring function was comparable to the scoring function used in the lecture.

$$score(move) = ownMoves - \frac{0.25 * numberOfMaxMoves}{numberOfMovesPerformed} * opponentMoves$$

As the performance is very close, I would avoid this function due to the highly increased complexity compared to the lecture scoring function.

<pre>************************* Evaluating: ID_Improved ************************* Playing Matches: ---------- Match 1: vs Random Result: 20 to 0 Match 2: vs MM_Null Result: 18 to 2 Match 3: vs MM_Open Result: 14 to 6 Match 4: vs MM_Improved Result: 15 to 5 Match 5: vs AB_Null Result: 16 to 4 Match 6: vs AB_Open Result: 11 to 9 Match 7: vs AB_Improved Result: 8 to 12 Results: ---------- 72.86%</pre>	<pre>************************* Evaluating: Student ************************* Playing Matches: ---------- Match 1: vs Random Result: 20 to 0 Match 2: vs MM_Null Result: 20 to 0 Match 3: vs MM_Open Result: 16 to 4 Match 4: vs MM_Improved Result: 16 to 4 Match 5: vs AB_Null Result: 16 to 4 Match 6: vs AB_Open Result: 13 to 7 Match 7: vs AB_Improved Result: 7 to 13 Results: ---------- Student 77.14%</pre>

Strategic scoring function

This function will adapt the evaluation of a gamestate depending on the state of the game. Therefore different scoring functions will be used and selected based on a metric, which uses the number of moves performed to decide in which stage the game is.

In the first **10%** of the moves, the player will select the moves that provide the most possible further steps and completely ignores the enemy. Based on this function, the moves will probably try to move around in the center area.

The next **70%** of the game, the scoring function from the lecture will be used with a factor of two. This should apply pressure on the enemy and chose moves that are better for player and worse for the opponent.

The last **20%** of the moves, a longest path heuristic is used that prefers situations that lead to a longer path for the player than for the opponent. This will be very inefficient but as the search depth in the end phase of the game will be limited, it is a reasonable metric. Performing this in the beginning of a game would make no sense as the search space is too big.

This function did perform the highest score so far (80.36%) - but only in a single tournament. Other results were comparable to the scoring function from the lecture or significantly worse, depending on the used scaling factors.

Conclusion

It turns out that besides the correct implementation of the algorithms, that enable the player to evaluate the search space in a directed manner, the scoring function (heuristic) is very important and will have a significant impact on the outcome of a game.

Scoring functions that penalize situations that could be advantageous for the opponent, perform better than scoring functions that completely ignore the opponent.

The complexity of the scoring function and its performance do not correlate with each other. A good scoring function could be super simple and effective at the same time whereas a complex, multi-factor function could perform much worse if it takes the wrong factors into consideration.

I selected the **heuristic from the lecture** because of the following reasons:

Performance

When I interpret the game results related to a specific scoring function as the result, that is **at least** able to be reached, then the comparison shows that this function perfomed better than the other functions.

When I look at all the tournaments that I evaluated that the opponent has a median score of approximately **73%**. The scoring function from the lecture has a medium score of approximately **77%**. It did never reach the highest score of **80.36%** in a single tournament but is more stable in terms of success.

Simplicity

```
def scoring_function_lecture(game, player):

  ownMoves = game.get_legal_moves(player).__len__()
  opponentMoves = game.get_legal_moves(game.get_opponent(player)).__len__()

  return ownMoves - 2. * opponentMoves
```

Efficiency

The function can be executed very efficiently and will therefore not thwart the search too much. This allows a deeper search. All operations execute in the order of `C + O(1)`.

Final Evaluation Match

The final match statistics support my reasoning.

```
*************************
Evaluating: ID_Improved
*************************

Playing Matches:

----------

Match 1: vs   Random      Result: 190 to 10
Match 2: vs   MM_Null     Result: 179 to 21
Match 3: vs   MM_Open     Result: 142 to 58
Match 4: vs MM_Improved   Result: 134 to 66
Match 5: vs   AB_Null     Result: 167 to 33
Match 6: vs   AB_Open     Result: 119 to 81
Match 7: vs AB_Improved   Result: 102 to 98

Results:

----------

ID_Improved        73.79%
```

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

Playing Matches:

----------

Match 1: vs   Random      Result: 189 to 11
Match 2: vs   MM_Null     Result: 189 to 11
Match 3: vs   MM_Open     Result: 154 to 46
Match 4: vs MM_Improved   Result: 135 to 65
Match 5: vs   AB_Null     Result: 173 to 27
Match 6: vs   AB_Open     Result: 126 to 74
Match 7: vs AB_Improved   Result: 115 to 85

Results:

----------

Student            77.21%
```