Analysis of the Application of Heuristics to Evaluate Non-Terminal States in the Game of Isolation

Choosing the Winning Move, Without Being Able to Look Ahead Indefinitely

To chose the best next move we consult a game search tree for a zero-sum game such as Isolation.

The tree ultimately should be evaluated to reach terminal end states. Terminal states can be accurately evaluated taking into account if they represent a win, loss or draw. From there it is an easy task to backup the win or loss up the tree, so that a decision can be made to follow a path towards a win.

However the search tree of even such a small game of Isolation becomes big quickly; making it infeasible to search all possible moves.

As a consequence we restrict the search to a defined depth per move. When reaching the defined maximum depth without reaching terminal nodes, we do not know if this path would eventually to a win, loss or draw. In lieu of this hard information we need to apply a heuristic that should approximate the anticipated result.

For the remainder we will discuss some common characteristics and then some specific scenarios and their relative differences.

Common Characteristics

Movement Patterns

FIXME: As a general rule, we do not take into account future movements in our value function. Instead the search takes care of that.

Partitions

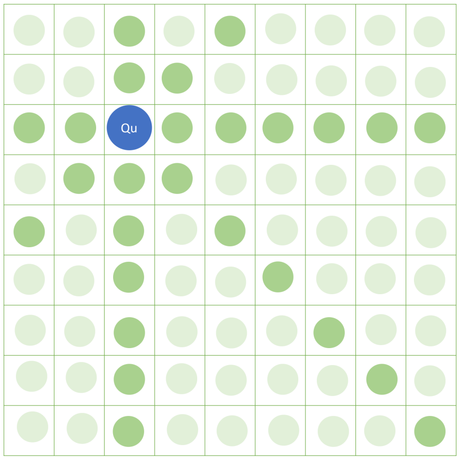
The lectures talked about a game of Isolation that is based on the movement patterns of the Queen in Chess.

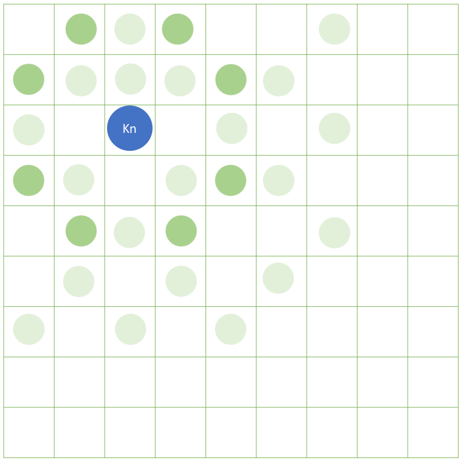
However the actual game of Isolation that we are now supplying heuristics for is based on the Knight Chess figure.

The difference is noteworthy, because it was mentioned the major factor to lookout for was partitioning. However this is not really all that important anymore as the Knight can jump over barriers and the movement patterns is less linear than the Queen's.

As a consequence an evaluation function would need to burn a lot of CPU checking individual moves of a Knight instead of just measuring reachable spaces by the Queen.

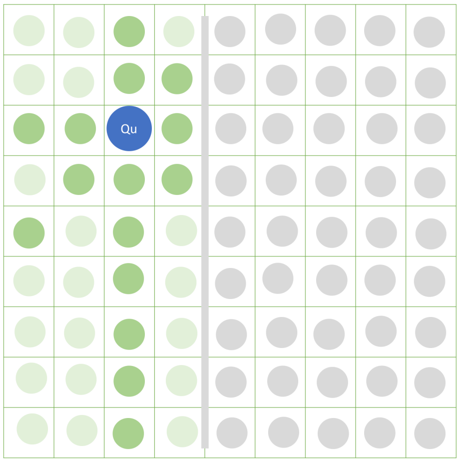
Have a look at the Queen (Qu) in comparison to the Knight (Kn). They both start from the blue position, can reach the dark green boxes with the first move and the light green boxes with the second move:

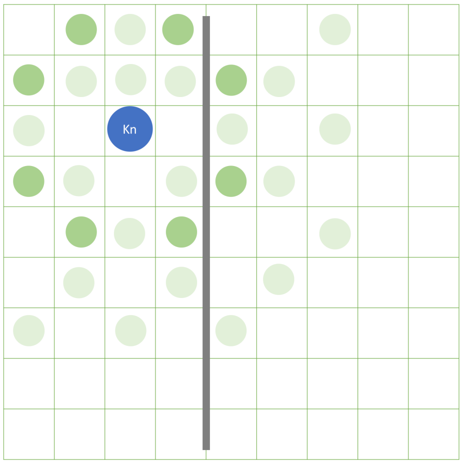




From the starting positions depicted above the Queen could reach any box within two moves. Whereby the Knight cannot dominate a comparable area as he is limited in its reach.

However this explains why introducing a barrier[1] has a much greater impact for the Queen.





[1]The introduced partition is just symbolic. It is simplified in the way to be in between boxes, but a true partition in the game would be built by prior moves, so it would occupy the boxes.

Without the barrier the Queen was able to reach 80 boxes within two moves after the initial placement. After the partition is introduced the Queen loses 45 boxes (~56%). In the above diagram the loss is marked in grey.

Prior to introducing the partition the Knight was able to reach 28 boxes within two moves. It is still able to do so after the introduction of the partition as s/he can jump across any obstacles, as long as the target box is not occupied.

Taking a closer look it is more complicated, as the partition occupies boxes itself too, but the overall pictures remains the same: A contiguous line of previously occupied boxes forms a barrier that may partition the board for a Queen. Not so for a Knight, as s/he can jump.

In conclusion, occupied boxes are relevant no matter what movement patterns, but partitions do not form easily for Knights and therefore are not valuable features to look for.

Centrality

We saw that looking for partitions does not seem fruitful. Also, given the movement pattern of a Knight, just counting blank spaces would not be all that helpful. This also implies that the importance of placing the initial move in the center is limited as well.

However even a Knight can be boxed in. Without burning the extra CPU cycles to map out all possible moves, it is still interesting to understand that the edges of the board automatically limit the possible moves of the player. Therefore - all other factors being equal - a more central position is preferable.

This is only relevant for the move at hand, but not for the moves prior to that. Furthermore "all other factors being equal" becomes less and less true over the course of a game. So decaying the value of centrality seems like a good idea.

Comparing Different Heuristics

In the following sections heuristics are described that were evaluated against the provided ID_Improved scoring method. Agains this baseline relative strengths are gathered.

The baseline evaluates the difference of legal moves left to the the two players.

The results are expressed as absolute differences to the score of the baseline evaluation method.

With the default `NUM_MATCHES=5` in `tournament.py` the variance of the results varied by test run in the same order of magnitude as the expected changes. Using `NUM_MATCHES>10` resulted in an acceptable level of variance. Also the relative differences to the baseline ID_Improved seemed more stable as the absolute *values. The results are still very sensitive to other workloads running on the same machine.*

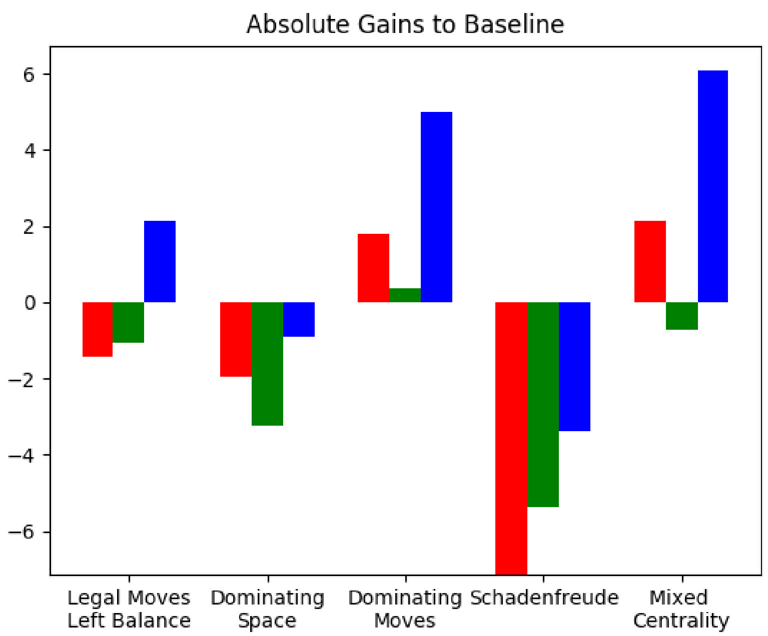


Figure 1: Strengths of Evaluation Methods

Method	Δ
Baseline	—
Dominating Moves	+2.4%
Dominating Space	-2.0%
Schadenfreude	-5.3%
Mixed Centrality	2.5%
Legal Moves Left (Canary)	-0.1%

Gains were averaged over three runs with `NUM_MATCHES=20` and `TIME_LIMIT=500`, everything else were left to the defaults.

Dominating Moves

This heuristic is comparable to ID_Improved as it also takes into account the balance of legal moves left for both players.

However it does not express the balance as difference, but a ratio of move of the player itself vs all moves left (player's moves: M_p and opponent's moves: M_o) and also gives more weight to the opponents moves.

The results are somewhat encouraging - beating ID_Improved consistently - and for the future it would be interesting to experiment with the weights.

$r = \left(\frac{M_p}{1+M_p+3M_o} \right)$

Dominating Space

Calculating the reward based on the relative dominance of the current player with respect to the available space. Expressed as ratio.

Here the current players remaining moves are compared to remaining blank spaces (B). Strictly speaking this is an apples to oranges comparison, because not all spaces may be reachable given the movement pattern - two moves in one direction and one move in another - but this is just one of many heuristics and could be enhanced by changing to a more exact method, when only five spaces are remaining.

This method ignores the opponent's position. It could be extended to run this for the opponent as well and then express it as a balance or ratio.

$r = \left(\frac{M_p}{B} \right)$

Schadenfreude

Calculating the score by putting an emphasis on limiting the other player's inability to move.

The current implementation is laser sharp focused on the opponent only. A more balanced implementation could take the current players possible moves into account as well.

$r = -M_o$

Mixed Centrality

As described above partitions don't play a big role when the movement patterns is that of a Knight. Nevertheless a central position is beneficial, more specifically to stay away from the edges and corners. It reduced the chances of being boxed in yourself and eating up the central space makes life harder for the opponent.

Over time this becomes less relevant and also it becomes more likely for the iterative deepening to come to the end.

To reflect this the value of this metric could be decayed with every move. Doing this should be accompanied by cutting off calculating centrality at all, to save CPU time for iterative deepening.

However in the initial testing the decay didn't seem to have much of an effect, so that it is left out for now. Cutting out the centrality calculation after five moves is still active.

$$\Delta x^2 = \left(x - \frac{width}{2}\right)^2$$

$$\Delta y^2 = \left(x - \frac{height}{2}\right)^2$$

$$r = 1 - \left(\frac{\Delta x^2 * \Delta y^2}{width^2 * height^2}\right)$$

In the diagram below the resulting advisable positions are marked in green, and the positions to avoid in red.

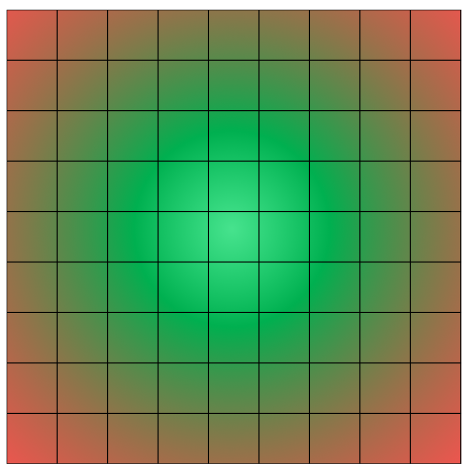


Figure 2: Centrality

Playing with the weights and cutoffs could be interesting for the future.

Legal Moves Left Balance

This is basically the same as the base line and should therefore be zero. It shows that with the current setup the results are not fully reproducible.

Summary

Possibilities are endless at the beginning. Save our breath later on to run to the end instead.

Data

Run <− Link