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Speedy AI for 4 in a Row

Introduction

Describe the game

Describe why we are doing this

–Define problem you are solving

–Describe your approach

Our goal is to make a fast algorithm that is still reasonable.

Performance

* Win the game
* Too slow, infeasible time

Environment

* Game board 8x8 grid

Actuator

* Placing tiles on the board

Sensor

* Board stored as matrix for evaluation

Describe GUI and how we capture this. Describe parts of GUI.

Describe Problem/Constraints

Strategic game

* Adversary in Game
* Ideal moves may be blocked

Very large branching factor of moves

* Board size of 64
* Not all moves will contribute anything

Good moves are deep, need to plan ahead

* Because of nature of the game, obvious winning moves are easy to block. AI needs to plan ahead

In implementing our algorithm, we needed to specify a value for each move. Heuristics need to be able to determine which move is more favorable. By comparing the values of several states, the heuristic will be able to evaluate what the next move should be as it seeks to move to a more favorable state and seek to win the game. We created an initial utility function that assigns values to each move, a move being the AI placing a marker of its own color onto a tile, based on the value of tiles. The value of a tile would increase based on the number of nearby tiles with the same marker placed by the AI in previous moves. This would make tiles surrounded by the same marker appear more favorable. A tile’s value would decrease however based on the number of other markers nearby. These tiles would seem to be more favorable for the opponent(s). The utility function we created is (number of own markers in a distance of 3 away on the same row, column, or diagonal) minus (number of enemy markers in a distance of 3 away on the same row, column, or diagonal).

We decided this was a good utility function to use based on the nature of the winning condition of 4 in a row. The game requires a chain of a player’s own markers to win. By making moves close in proximity to the AI’s previous moves, it will be able to better construct a chain of 4 in a row. The utility function was also restricted to only look into tiles of a distance three away because it requires only a chain of four markers to win the game. Including the current move, this will be a chain of four markers. The algorithm will have to evaluate the value of each of its children, children being the resulting board configuration after making a move. The most favorable move for the AI will have the highest positive value and the AI should make the move that will result in that state. A very favorable move for the enemy will be marked by having a very negative value.

We had to make additional adjustments to the utility function; the AI was making moves that seemed good even when there was a winning move in sight. A linear utility function did not prove ideal in all cases. We adjusted the heuristic to assign a value of 1000 for winning moves, this would guarantee that the heuristic will choose winning moves over moves that simply had a high value. The AI would also make some very bad moves that were not nearby any of its own markers. Because a tile’s value was reduced by each nearby marker of the adversary, those tiles did not appear appealing to the AI. The AI would see a very far tile as better because it had a higher value than a nearby tile that was both near its own markers and the opponent’s markers. Each tile was revised to have two values: its worth the AI alone, and its worth the adversary. The value was each state was then recalculated to be the sum of every tiles’ worth to AI minus the sum of every tiles’ worth to the adversary. Moves that would block winning chains from the adversary as well as further a chain for the AI now seemed more beneficial. These moves would increase the tile’s worth the AI and decrease its worth for the adversary, because there is one less neighboring tile for the AI to take advantage of. The caused the AI to prioritize blocking a winning move (a move that has a negative value) which previously did not look like an obvious good move for the AI. A move that helps contribute to a 4 in a row for the AI while blocking the opponent now seems better than a move that only makes a 4 in a row.

The algorithm we chose to implement for AI would use Iterative Deepening Searches with Alpha Beta Pruning. This is a depth first search that has a bounded depth. The depth value was allowed to increase or decrease based on timing requirements. We wanted to record the time for the moves of the AI to ensure that moves were completed within a reasonable amount of time. If there was extra time available in the current search, the depth value would increase and the AI would use a larger depth value for the next iteration of running depth first search. The depth value would be maintained for the duration of the game until it needed to increase or decrease again. If the AI took too long for the current move, then the depth value would decrease and the AI’s next move will search to a smaller depth. We decided a reasonable amount of time for each of the AI’s move should be within five minutes. The algorithm was allowed to adjust the depth value accordingly based on this time limit. Alpha beta pruning was implemented to help speed up searches. Each level of depth first search would alternate placing a move for the current player and a move for the opponent. The move for the player would try to maximize the values of moves possible from the current move while the opponent would attempt to minimize the values. Given that the AI will know the opponent will attempt to make the best move possible and disallow the AI from making good moves, there will be little contribution to searching a branch that the opponent wasn’t going to allow. Alpha beta pruning will allow the AI to prune away the rest of the branch and ignore the remaining children.

Good moves are possible by planning ahead and searching deeper into consecutive moves. Iterative deepening will allow the depth to fluctuate and potentially allow the AI to find better moves deeper into the tree. However the branching factor of the game is huge and searching each consecutive moves is very time consuming. Alpha beta pruning will allow the AI to prune away bad children and save time from having to traverse them. This in turn will allow the AI more time to search deeper for good moves and plan further ahead. Planning moves ahead is important because obvious winning moves can easily be blocked by a capable opponent. The opponent is making moves against the AI and is expected to disallow the AI from attempting to win.

After the initial implementation of our algorithm, the algorithm was still very considerably slow. Alpha beta pruning did create a large time reduction for each search. Compared to only having depth first search alone, alpha beta pruning was able to considerably decrease algorithm time by removing expansion of child nodes that were not optimal. However we were still receiving moves taking over five minutes at depth three. Iterative Deepening could not increase depth past three because it was hitting the timing restriction we set for moves taking over five minutes. We wanted to be able to allow depth to increase further through iterative deepening and decided to enhance the algorithm and possibly reduce the branching factor involved in the game. In order to reduce expansion from 64 possible tiles, we first looked into the obvious candidates of illegal moves. A move couldn’t be placed onto a previous move so we were able to reduce the list of possible candidates for expansion. We also wanted to apply the restriction that only viable tiles with good values gain should be candidates for the next move. Because it requires a chain of four moves in a row to win the game, there would be little gain from placing a move that did not build up a chain. Out of the possible 64 tiles that could be expanded, we then limited children to only contain the tiles that were a distance of three away from existing tiles. Including the current existing marker on the board, it would only require three additional markers to create a chain of four and win the game. This enhancement was able to speed up the algorithm significantly in the early stages of the game. Each successive move was able to increase depth further until there became a significant amount of existing markers on the board. The beginning stages of the game will have the possibility of tiles reduced significantly from 64, since there are so few available tiles on the board. However towards the later stages of the game, the branching factor would approach 64 again because the remaining tiles will be viable for being distance three away from an existing marker. The branching factor of searches will eventually become huge again and make searches take significantly long.

Reducing the size of potential children for each branch would give massive speed ups for our algorithm searches. Instead of having to search the entire board of 64 tiles, we reduced the branching factor to a fraction of this. The potential tiles to expand on each level of search are limited to tiles that are distance three away from existing markers. A branching factor of 64 will lead to significant timing hindrances because depth first search is exponential on 64 based on the depth. Reducing the branching factor from 64 will allow depth to potentially be bigger and still meeting timing requirement of searches. With the algorithm speed enhancement, the early portion of a game would allow the AI to search beyond depth two or three and search into depth four and five. However as the game progressed further and each player has placed a significant amount of markers onto the board, more tiles became eligible for being a distance three away from an existing marker. Long games would thus negatively hurt our algorithm because the branching factor of each move would approach 64 again. The depth of each search would slowly drop to three or even two in cases where the AI could not achieve an early victory or loss. In the rare case where the game went extremely long and there number of available spaces of the board has extremely diminished, the AI would be able to make deep searches again because there are few legal moves left on the board. Our speed up enhancements to the algorithm could thus only help the algorithm make wiser moves with deeper planning in the earlier stages of the game. Later stages of the game had to suffer from a huge branching factor and a reduction to the depth of searches.

The goal of the algorithm implementation is to be able to make a competent AI for 4 in a row game that can make moves in a reasonable amount of time. Good moves require a considerable amount of time for deliberation for human players and the same can be said for AI. Our implementation of Depth First Search can make better moves with more planning ahead if it had more time to compute the values of moves. It cannot compute the complete game tree within a reasonable amount of time, 64 possible tiles means 64 branches have to be explored to depth 64 is very large. The algorithm will have to make do with making as far a depth as possible given the timing constraints. Going further into the game tree will take up more time, and the Depth First Search was allowed to fluctuate with Iterative Deepening to adjust to timing limitations of the current search. However the time to process each node and its children can be discounted with alpha beta pruning. By pruning away children, the algorithm can save time from exploring bad children and potentially increase depth. Without alpha beta pruning, the algorithm could only maintain going up to depth three at the most; the timing restrictions we set forth helped us notice that the AI did most searches up to depth two. The AI can be very fast if we kept the depth value very low, depths two or three and easily meet the five minute timing requirement we set. However better moves only become apparent by exploring ahead and going deeper into the game tree. The implementation of alpha beta pruning helped us record the AI making searches up to depth four or depth five. Having a constantly changing variable for depth and having enhancements for pruning away nodes makes the AI a very complex algorithm. It can adjust to the current environment and the state of the board configuration and make complex moves that require deliberation and are not obvious conditions for victory. The removal of speedups would have made depths four and five infeasible considering our timing restrictions. We wanted to ensure our AI would be capable of making complex moves that require more look ahead than just the next move, and this was possible with the implementation of alpha beta pruning. The time requirements for a search of up to depth three could be easily met if we allowed for pruning away of children and the reduction of branching. The complexity of the algorithm is also complex because each level of max depth used in iterative deepening will increase in succession. Allowing the algorithm to go up to depth five would usually exceed the five minute timing requirement for the current search. The depth will have to be decreased back to four for the next iteration so that searches can be completed on time. Our goal for the algorithm was for the AI to be able to make non-trivial solutions with deep searches, and we realized this required speed up enhancements to the algorithm because of the large board size involved in 4 in a row.

The space complexity of the algorithm was proportional of the game itself. Each node would save the current 8 x 8 grid of the board and its value worth to both the AI and its adversary. Because of the large branching factor of the involved in 4 in a row, there would be many of these large nodes created at any given time. Each node also requires a significant amount of computation work in order to determine the value of the state as based by our utility function. Since the algorithm is an implementation of depth first search, we do not need to keep a record of every node generated. Once all the children of a node is explored, that node can be cleaned up and its memory given to garbage collection. This will keep the data used by the program compact and not explode exponentially based on the branching factor. However when we have large depth values the amount of children generated from the root to the last level will still be significantly huge. Each node will open up 64 additional children and reaching up to depth five will be 65 \* 5 children nodes in memory simultaneously. We found that on our laptops, we would encounter memory issues and system slowdowns when the depth approached five and beyond. Depth five was not only infeasible based on our five minute timing requirement we set for our AI, but it was difficult to maintain for our systems running the game. Because of space limitations the AI cannot possibly search up to infinity or up to all 64 available tiles. The data structure used to maintain the algorithm was complex in itself and became a potential issue when attempting to search to large depth values.

The AI we designed had to not only be tested for speed and to meet timing requirements, but it also had to be a competent player. The AI should make moves that will draw it closer to victory and eventually attempt to win the 4 in a row game against the adversary. Even with limiting searches to a time restriction, the AI should still be able to win some games and we wanted to measure that the AI was still competent enough. We first compared our AI to a very simple AI that made completely random moves. In this case our AI will win every single game. We then made a created new AI that would make moves with our utility function on the immediate tiles; this is similar to rewriting our AI to evaluate only depth 0 and expand no moves. In this case we noticed our AI would sometimes lose if it happened to make very obvious chains to win. The other AI would immediately block our AI, gain the lead, and win the game. We measured the win rate against the simpler AI and our AI would seem to lose about one in eight games playing. Considering how the simple AI evaluates at depth 0 and moves for that AI take much less than a second to complete, our AI did not seem so good in comparison. Our AI would occasionally exceed the five minute time restriction for making a move when iterative deepening allowed the depth to approach five or more. Having the possibility of losing to an AI that completes moves in less than one percent of the time makes our AI look bad at winning relative to speed. Our AI was using more resources, time and algorithm complexity, for relatively low gain against a faster, simpler AI. We then created another test AI that would evaluate using Iterative Deepening and Alpha Beta pruning but uses our original utility function. This AI would evaluate the value of individual tile values and their worth to max and min, unlike our current AI that evaluated the value of moves to be the sum of values on the entire game grid. This new test AI would thus be able to perform faster compared to our original AI because the computational resources required per move evaluation was significantly lower. However our AI was able to achieve victory on against this new AI in almost all games. The win rate for our AI was around 95 percent against this AI. This goes to show how bad our original utility function was and that a good utility function was necessary for making a capable AI. The AI we used for comparison would make occasional very bad moves, since its utility function evaluated those moves as the best, and give our AI the lead in winning. This new test AI would make quicker moves because it required less time to process a child node, however this speedup did not prove useful if the win rate for the AI was very low. We wanted to make a competent AI that performed well in spite of timing restrictions and we were able to show that it could compete decently well against other AI’s, however it was not guaranteed victory simply because of the fact that it planned moves ahead. Against an AI that did no planning and performed lightning quick moves, our AI still failed to achieve victory in all games.

Our next step was evaluate if our AI could compete competently against human players. We wanted to limit the time for each move when playing against AI to also be five minutes so that we could compare the win rate of the AI relative to speed. While initially playing against our AI, a human player would take moves over five minutes. A new player would take more time to plan moves ahead than a veteran or a time-sensitive AI would. The AI could beat a new player consistently over the course of several games. The players would takes moves sometimes taking only ten seconds and also beyond the five minute time limit. However when we had more competent players play off against the AI, the AI would fail to win in most games. When we initially played against the AI, our moves would take four to five minutes and meet the timing restrictions, and still be able to achieve victory over the AI. Over time as we were able to recognize winning strategies and play them out consistently, we were able to complete moves in less than two minutes and still beat the AI. The AI would occasionally win when as humans we were not being careful and allowed the AI to set up a game state that guaranteed victory despite any possible move we could make. While playing against the AI, its win rate was about ten percent. This seemed considerable bad since we were able to complete moves in half the time that the AI was allowed. In light of the resources that the AI was consuming, this made the AI appear bad compared to players. We noticed in the cases where the AI would lose, the AI was very good at planning its own victory. However the AI neglected to stop us humans when we were setting up a strategy. The AI would only attempt to block in cases where we might achieve immediate victory, however in most cases it wasn’t making moves that would put a considerable hindrance for the enemy to win. If we as humans kept setting up scenarios that led to multiple winning moves, the AI would neglect to stop us in time. The AI was good at trying to set up its own chain of 4 in a row to win the game yet wasn’t as good at stopping a player’s winning strategy. As humans we were able to plan ahead beyond five moves, which the AI seemed limited to in regards to timing restrictions. The AI would evaluate each potential candidate tile to the same depth. However we humans could evaluate more ideal locations to a larger depth and disregard non-deal tile locations. We were also able to remember winning set ups and attempt to recreate them. The AI does not have memory of previous games and we did not design it to learn from past games. These limitations on the AI make it very difficult for the AI to win against humans in the game of 4 in a row. The branching factor of the game itself was very huge and the AI was not allowed the time to evaluate very good winning strategies.

Our AI was able to compete competently against basic AIs but it had trouble against playing other competent human players. Because it was not able to achieve victory in all games, the AI likely will not be able to achieve a high win rate against a brute force or against an optimal algorithm with foresight. However the AI could likely complete moves within a more reasonable amount of time. Unlike brute force we restricted our AI compute only up to a set depth level as determined by iterative deepening. Brute force will require evaluation of nodes up to depth level 64 in order to know all possible winning scenarios. An AI using brute force will likely not meet the timing requirements we set for our AI, so in spite of achieving victory in all scenarios it would be infeasible due to resource constraints. Our AI was able to complete moves within a reasonable time restriction and achieve a considerable win rate.

Problems/Improvements with the Algorithm?

Although the algorithm was very good at trying to win

* Very bad at stopping an opponent from winning if the opponent is going for a not obvious winning strategy plan
  + This could have been fixed by making our utility function more complicated
  + Trying to win appears better than trying to block, didn’t block often
* Human players can search deeper for very good plans and strategies
  + AI was limited to search all strategies to the same depth
  + Searching a bad strategy takes time and the algorithm will not increase depth value when time is wasted

Early in the game, large depth has little deciding factor

* Values do not fluctuate a lot when few pieces on board

Large depth matters more later in the game

* Tile values will differ more as the game progresses
* The best moves are not as obvious
* Allowing depth to fluctuate and potentially increase will help the AI make smarter moves when needed

Alpha beta pruning and branch reduction are necessary

* Branching factor of game is huge
* AI’s moves will take too long when depth increases

Having deep searches is not enough

* Utility function that is too simple makes okay and very good moves seem indifferent
* Making obvious winning moves wasn’t very good. The other player could easily block those moves. Whoever when we increase the depth of the searches, the AI would choose to rather make more tricky moves that allowed multiple winning moves. Being able to plan moves ahead has a large advantage.
* Bad utility function will cause deep searches to be meaningless. If the utility function is not very good, then the good and better moves will have the same values. The AI will think they will have both just as good as the other and will not make the better move. The heuristic needs to be improved to better differentiate between what’s a good move and what is better or else having deep searches will not be as effective.