**Speedy AI for 4 in a Row**

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**Game Introduction**

This game is a 2-Player game. Each player will drop a piece (“X” for player1,”O” for player2) on the 8x8 board. To win the game requires four pieces with same mark in a row, a column, or a diagonal. This is a game with “perfect information”, that is every player has the information about everything on the board, like where is each piece, where can I drop next piece, etc. Given this environment, we can implement an informed algorithm to find the best move. Also it’s a two player game, so it’s similar to Nim game in the sense that a winning for one player is the losing move for another player. This feature makes the MIN-MAX algorithm able to work on solving this problem.

**Initial idea and approach**

We did this because this requires the basic AI search algorithm to make the game AI able to play like an intelligent being. To do this the basic search algorithm is better with DFS, BFS won’t work because it doesn’t know what the winning move is. Therefore we need a heuristic function to evaluate each possible move then decide which the best move is. To achieve this we can do A\* search, and MIN-MAX search. Then we need to consider the time complexity of these possible algorithms. The number of possible tiles for each move is 64, so the branch number is 64, and therefore the time complexity is, d is the depth of the search tree. When the depth goes to 4, the number of nodes would be expanded in worst case is 16777216. This would take a very long time. So there are two possible way to enhance the running speed, one is to use iterative-deepening A\* search with a relatively small depth to reduce the nodes our algorithm will look at. But by make a constraint on the depth, it might overlook winning move sometimes. This is a time V.S. best solution trade off; it still can make a good move but not always the best one defined by our heuristic function. Another one is MIN-MAX search with Alpha-Beta prune, by ignoring the move that is worse than current best move, the running speed can be tremendously increased.

**Heuristic function**

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 to the AI alone, and its worth to the adversary. The value of 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.

**Depth First search Algorithm**

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 move 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.

**Observation on initial IDA algorithm**

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.

**Solution 1: reduce the branch factor**

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.

**Solution 2: adjust the search tree depth and prune**

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.

**Space complexity analyzes:**

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.

**Running time analyzes:** To compare the difference on running time, we have tested three different kind of AI:

1. BasicAI: IDA search with depth set to 1.
2. AdvAI: IDA search with larger depth.
3. AdvAI2: IDAsearch with larger depth and alpha-beta prune.

For each AI we calculated the average running time to make the comparison. First for the BasicAI, the average running time is smaller than 0.2s. It’s really fast but it does not plan well because it only looks at immediate values. As for the AdvAI, the average running time is 2~10s when depth is 3, and 100~150s when depth is 4. It almost matches the  estimation. Then for the AdvAI2, the average running time is 0.2s when depth is 3, and 5~10s when depth is 4. So we can see the alpha-beta prune makes the IDA search find a solution about 30 times faster.

**Observation on the intelligence of our AI:**

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 to 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.

**Some limitation:**

After completing the AI and analyzing the win rate results against other AI and against humans, we were able to realize issues with our AI. The AI we created was very good at attempting to win the game and strategizing its own winning strategy plan. However it was not very good at stopping enemy players early on. This could have been probably fixed by improving our utility function and reevaluating costs so that it would be even more beneficial to block early. Our AI was able to see that some moves were better if they happened to block the enemy player, however it would not go out of its way to block another. The AI evaluated that it was more advantageous to continue its winning chain than to go out of its way and attempt to block the opponent early on. Noting how our AI did not see the benefits of blocking early on in the game, a future improvement to the AI would be to create a new utility function that saw these benefits early on. Moves that continued a chain should redistribute values so that moves to block early would seem more advantageous.

The other limitation we noticed with our AI was that searches weren’t very deep. The timing constraint we put on our AI allowed it only to go up to depth five using iterative deepening even with pruning. A human player could easily evaluate advantageous board positions up to a higher depth value. Our AI however would waste time on searching all nodes from initial set of children at level one up to the same level of depth. Some bad nodes were still evaluated even when a better winning strategy existed. The AI could also not learn from previous modes and use this knowledge to evaluate better moves. This could probably be improved by having better pruning so that better nodes are evaluated further. By pruning away more bad nodes, the better nodes could possibly be evaluated past depth five in order to determine the more ideal move.

**Conclusion:**

Upon completion of our AI, we were able to draw several conclusions on characteristics of our AI. The depth value didn’t seem to matter as much early on in the game, since there are few pre-existing moves on the board early on. However a large depth value is required in order to evaluate the best move it was ideal to have depth increase as much as possible in order to find the most ideal move. Iterative deepening depth first search is a good choice because it allows depth to fluctuate based on the timing limitations and increase as much as is feasible. Good moves are not always the most obvious moves and it was known that planning moves ahead is necessary for victory. This is because moves that lead to obvious victory would be blocked by the opponent and the AI would behind in achieving victory. More depth in searches and more planning would allow the AI to perform better in later stages of the game, where the best moves are not as obvious. We also noticed that the AI was horrendously slow without any pruning. Going beyond depth three was impossible given the timing constraints and deeper searches could not be achieved. The branching factor for 4 in a row was huge and the moves of the AI would take too long to evaluate all 64 children. The speed up gained from alpha beta pruning is necessary in order to plan out better moves. Lastly we noted that having deep searches was not enough for achieving victory; a good utility function was also necessary. A utility that was too simple would be unable to determine if a good move was more ideal. If two good moves were evaluated to have the same value, the AI would be unable to determine which of the two was actually more ideal. Obvious winning moves could easily be blocked by the opponent and the AI should be improved to value more non-obvious moves that led to multiple winning strategies. Having a more complicated AI that evaluates the strength in non-trivial winning conditions and the importance of blocking is important to creating a good utility function. Otherwise deep searches will not be very effective if good moves and bad moves were evaluated to have the same value. All in all, we realized there were many important factors in achieving an AI that was both competent and could perform in a reasonable amount of time. It was important to plan moves ahead with long searches as well making sure the searches completed on time by pruning away nodes.