Tic-Tac-Toe with MiniMax Algorithm

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Abstract

This paper entails the challenges of making an artificial intellegent program face off against humans in a game of Tic Tac Toe and my implementation to make a program do so.

Introduction

Tic Tac Toe has been a game played by a majority of people throughout many generations. Tic Tac Toe contains a 3x3 grid where the players alternate between picking a sqaure in the grid with a unuiqe symbol; usually one individual has an X to place on their turn while the other places an O on there selected spot. The goal of the game is to get 3 symbols in a row whether it be horizontally, diagonaly, or vertically. As soon as a player gets three in a row, the game is over with the winner defined as the player that was able to get three symbols in a row. There is a possibility that no one wins after there are no available choices for a player to pick resulting the game to be a draw. Tic Tac Toe was one of the starting points for primitive AI. A computer must make rational decisions when playing the game in order to beat the opponent. Developed as one of the very first video games [1], computer scientists were able to acomplish implementing an AI that can interactively challenge humans to the game of Tic Tac Toe. With the advancement of computing power, new and evolving methods of making an artificial opponent has come forth. To demonstrate some of the progress human beings have made towards making a worthy opponent, I will be implementing an AI that uses the MiniMax algorithm that decides the best possible moves to challenge an opponent.

Background

Since the dawn of video games, AI has been needed to challenge the player and keep them hooked to the game. As a matter of fact, Tic Tac Toe was one of the first video games created on the ESDAC computer with an AI capaable of defeating oponents [2]. The evolution of AI techniques continues to advance. Alot of the newer game theory algorithms and artifial intelligence algorithms devised can still be applied to Tic Tac Toe just like they can be applied to multiple games like chess or go. This makes the selection of picking a method for a Tic Tac Toe AI difficult because the wide varieties of implementation others have carried out. Computer scientists will always continue improving the teqniques used to solve the problem, which shows true for the way of improving the AI behind Tic Tac Toe video games.

Challenges

The game of Tic Tac Toe is easy at a glimpse, but making a computer go through the same thought processes that humans go through before a decision gets complex quickly. Cosidering there are 9 spots that can be filled with an X, O, or Blank spot, there are 39 = 19,683 possible states [3]. This of course, is not including the restrictions of the number of symbols that can be placed in an turn by turn scenario. An AI must be able navigate through all possible states and simultatiously play in a way that gets it to a subset where the state results in a win for the AI. The entity most know all possible states as its playing or must be able to dynamically choose what to do based on the current state of the board.

Method of Implementation

MiniMax Algorithm

The minimax algorithm has been in the game industry for quite some time and can be applied to other strategic games like chess or go [4]. The minimax algorithm finds optimal decisions to take by maximizing its chances of winning by minimizing the oponents chances of winning. In other words, it looks ahead and sees what possible moves its opponent can make, and makes a decision that minimizes the damage the oppenent can do. Roopali Garg and Deva Prasad Nayak prove the application of minimax being useful for tic tac toe by fully implementing it and demonstating the computer either ending up in a draw state or beating the human opponent. Since the game of Tic Tac Toe isn't as complex as something like chess or go, The minimax algorithm is the way to go. With the memory capabilities we have today, the second the opponent makes a decision, our program will be several steps ahead of them. Also, since we only have a couple months to complete this model and a lot of effort has to also go into making a playable game, it's only appropriate to consider this method since it is doable in such a short time frame opposed to doing something complex like a genetic neural network with double transfer functions which would take the construction of a nueral net alongside training it. Lets not forget that the minimax algorithm takes a whole lot less of the resources compared to the other methods of implementation.

Implementing MiniMax with Tic Tac Toe

I wrote my playable implementation of MiniMax with python. Python's portability makes the showcase of my code as easy as possible to demonstrate on different environments without the hassle of making sure the environment has the correct requirements beforehand. The board I'm using for this program is made up of 3 seperate lists within a list. Each list within the list represents the 1st,2nd, and 3rd row of a Tic Tac Toe game board. The program consists of first initializing the board with the computer taking the first move. It's proven that the corners are the highest advantaged first move, so to make this AI unbeatable, I initialized the computers first move as the top left corner [5]. From there, the opponent playing the program is to make a move. I have the moves you can make as a pair of co-ordinates where 0,0 is taken by the computer, 1,1 is the center of the board 2,2 is the bottom right corner, and so on. The players move looks like so:

```
['X', '-', '-']
['-', '-', '-']
['-', '-', '-']
Enter your move (x, y)
```

After the player makes a move, the computer must now pick the best possible next move. To do so, the computer calls the miniMax funtion I have defined. The miniMax funtion starts by checking all possible moves for the current player, which in this case, is the AI. To find each and every possible move the player can make, I parse through the board for any '-' symbols and return a list of co-ordinates representing the moves the player can make.

```
def possibleMoves(board):
    moves = []
    index = 0
    for i in board:
        for j in range(len(i)):
            if i[j] == '-':
                moves.append([j,index])
        index = index +1
    return moves
```

For each possible move, the computer recursively calls the miniMax funtion again and changes the current player to the opponent so the opponent's moves can be calculated. The Function will keep calling itself until the board passed in is in a winning state for either players, or until there is no possible moves left. Once we reach the final states of the recursive calls, the function returns a score of 1 if the computer wins in this state, a -1 if the opponent wins in this state, and a 0 for no winner.Checking the score of the board passed in was fairly straight forward as shown below.

```
def checkScore(board):
    columns = [[],[],[]]
    diagonals = [[],[]]
    for i in board:
        columns[0].append(i[0])
        columns[1].append(i[1])
        columns[2].append(i[2])
    diagonals[0].append(board[0][0])
    diagonals[0].append(board[1][1])
    diagonals[0].append(board[2][2])
    diagonals[1].append(board[0][2])
    diagonals[1].append(board[1][1])
    diagonals[1].append(board[2][0])
    for i in board:
        if i[0] == 'X' and i[1] == 'X'
        \ and i[2] == 'X':
            return 1
        elif i[0] == 'O' and i[1] == 'O'
        \ and i[2] == 'O':
            return -1

    for i in columns:
        if i[0] == 'X' and i[1] == 'X'
        \ and i[2] == 'X':
            return 1
        elif i[0] == 'O' and i[1] == 'O'
        \ and i[2] == 'O':
            return -1

    for i in diagonals:
        if i[0] == 'X' and i[1] == 'X'
        \ and i[2] == 'X':
            return 1
        elif i[0] == 'O' and i[1] == 'O'
        \ and i[2] == 'O':
            return -1
    return 0
```

Each possible move now has a score associated with the state of the board passed in. For the computers prespective, I make the computer only pick states that land the board in either winning or a draw state. For the opponent, the opponent tries to only pick moves that garuantee it's win. The final result returns a list of co-ordinates for the computer to make in its next move. The AI makes the move and the game is back into the player's hands. After each move the player makes, the computer again uses miniMax with the current state of the board to again decide the best course of action for itself. Once the game see's itself in a win state, the player with the consecutive symbols is displayed to the user.

Conclusion

MiniMax proved to be a useful algorithm to apply to traditional Tic Tac Toe. In some cases however, I have seen the AI make some apparently irrational decisions. One pitfall of the MiniMax algorithm is that the algorithm assumes that the opponent will play optimally. When the opponent makes irrational decisions, the computer makes the best move of what it can make out of the situation, which might not be something a human would do. Take this sequence of moves for example:

```
['X', '-', '-']
['-', '-', '-']
['-', '-', '-']
```

```
Enter your move (x, y)
1,0
['X', 'O', '-']
['-', '-', '-']
['X', '-', '-']
Enter your move (x, y)
2,0
['X', 'O', 'O']
['-', '-', '-']
['X', '-', 'X']
```

Here on the second move I made irrational move of placing my symbol on the top right instead of blocking the potential win. Any human with some sense would complete the three 'X's in a row but the MiniMax algorithm makes a defensive move instead. Here you can see how the computer was expecting the opponent to play optimally and had a unusual move as a result of the opponent not playing optimally. Although the AI makes some of these apparently quirky decisions, the outcome always has the AI as the winner since each and every move the computer makes is playing both defensivley and offensively. In the example I gave above, yes the computer did not grab the immediate win, but, instead it made the win it can have in the next moves a garauntee. In the end, I haven't been able to beat my own implementation which is what I was hoping for. The robustness of MiniMax has proven it's worth. My implementation has a corresoponding move almost immediately and has yet to be beaten. Hopefully, the MiniMax algorithm can follow suit once we implement the 3x3x3 game of Tic Tac Toe.

References

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