Q-Learning for Connect Four

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This report explores a reinforcement learning method applied to the game Connect Four, using the Minimax algorithm and Alpha-Beta pruning to train an agent to play optimally. Reinforcement learning entails the gradual improvement of decision-making through interaction with the environment. The agent navigates through different states within the game environment, selecting actions to maximize rewards or minimize penalties. The Minimax algorithm is a decision-making algorithm used in two-player games like Connect Four, where one player aims to maximize their score while the other aims to minimize it. Alpha-Beta pruning is an optimization technique for the Minimax algorithm that reduces the number of nodes evaluated in the search tree by eliminating branches that cannot influence the final decision. By continuously learning from its experiences, the agent strives to achieve optimal performance in any given state. This approach aims to develop a proficient Connect Four player capable of making strategic decisions based on past interactions and rewards received during gameplay. Through this process, the agent learns to anticipate opponent moves and devise winning strategies, enhancing its overall gameplay performance over time.

1 Introduction

Connect Four [1] is a game where players select a color and strategically drop tokens into a six-row, seven-column grid, aiming to create a horizontal, vertical, or diagonal line of four of their own tokens. The pieces descend vertically and occupy the lowest available space within the column. Classified as an M,n,k-game (7, 6, 4) with limited piece placement, Connect Four has been solved, meaning the first player can consistently secure victory by executing optimal moves.

The game was created by Howard Wexler, and first sold under the Connect Four trademark by Milton Bradley in February 1974. [1]. Connect Four, despite its apparent simplicity, offers ample opportunity for strategic depth and increased chances of winning. For instance, prioritizing certain slots over others is crucial, with those in the middle holding greater value due to their increased potential for forming four in a row. The game's board layout and rules afford a multitude of potential final board configurations, with players having a range of actions at their disposal to achieve them. Our objective was to employ reinforcement learning to uncover the most effective strategies within the Connect Four Markov Decision Process.

2 Connect Four Rules

The objective of Connect Four is to align four of your checkers in a row while simultaneously blocking your opponent from doing so. However, players must remain vigilant as their opponent can swiftly secure victory. In a typical game scenario, the first player initiates by placing a yellow disc into the central column of an empty board. Subsequently, players take turns dropping their discs into unfilled columns until one player achieves a diagonal alignment of four red discs, clinching victory. Should the board reach full capacity without either player achieving four in a row, the game ends in a draw. The game progresses with each player

Figure 1: Connect Four Board.

strategically dropping discs into unfilled columns, aiming to outmanoeuvre their opponent and secure victory.

3 Literature Review

Scientists have proven that if the first player places his piece in a central row with perfect play, they can't lose. Likewise, when the first player does not place his first piece in the center column with perfect play, it will always be possible for the second player to draw. However, what is the best course of action in such a situation? There are a few complicated calculations involved.

A game tree can be built to calculate the optimal choice each time. Let's say player A gets a chance to move. Player A has seven possible actions (see equation one) that he or she can take. Every node from the parent state that results from choosing one of these actions is what makes up a game tree. Player B can then do $7 - C$ actions from these states, resulting in $7 - C$ distinct states and the formation of a subtree. This goes on until a decision is made that ends the game; because there are no more subtrees, this stage is known as a leaf. By allocating values to the leaves and computing the whole game tree, the optimal course of action can be determined by propagating values from the nodes and leaves all the way up the tree to the present state. The game tree may be calculated quite easily. However, there may be very serious run-time problems that prevent utilizing a game tree to determine the optimal course of action. Think about the scenario in which there are numerous moves left in the game before a winner is declared. Calculating n moves with 7 columns entails storing around 7^n game states. We observe that when more motions need to be calculated, the run-time grows exponentially. As a result, more effort is now being put into developing algorithms that can determine the optimal course of action rapidly and with minimal memory usage.

Using a minimax algorithm, which reduces the maximum losses for a player, is one of the other options. This is achieved by disregarding all other options and believing that the opponent would choose the best course of action. This ensures the best possible outcome for the player while drastically lowering the number of states that must be calculated. Still, it takes some time, particularly in the game's early stages. In this case, alpha-beta pruning—a method that eliminates the need to take into account numerous subtrees—comes into play. It entails determining if the values in a subtree could potentially alter the action that the tree is currently indicating. If no value in the subtree has the potential to alter the action, it is not computed and is disregarded.

4 Problem Description

Our project endeavours to uncover the most effective strategy for playing Connect Four based on a given game board. We define an optimal playing strategy as the sequence of moves that maximizes the likelihood of winning a single game of Connect Four.

4.1 A. Action Table

In Connect Four, the action space is relatively limited, with each player having a maximum of seven potential actions available at any given state. An action is defined as placing a piece into one of the seven columns on the board. The number of actions a player can take is contingent upon the occupancy of the columns; thus, the calculation of possible actions at a specific state account for the current fullness of the columns on the board.

Actions Possible = 7 - C (1) C = Number of full columns at current state (2)

4.2 State Space

In Connect Four, the state space significantly surpasses the action space in complexity. A state represents the configuration of the board with placed pieces visible to a player. Depending on whether a player starts the game or joins as the second player, the board will have an even or odd number of pieces, respectively. Estimating the upper bound of possible states involves considering that each position on the 6×7 board can be vacant, occupied by player one's piece, or player two's piece, resulting in a rough calculation of 3^{42}. However, this simplistic calculation overlooks the fact that certain board configurations are invalid due to gravitational constraints and game rules. For a more accurate estimate, a computer program has determined a lower bound of approximately 1.6×10^{13} possible positions.

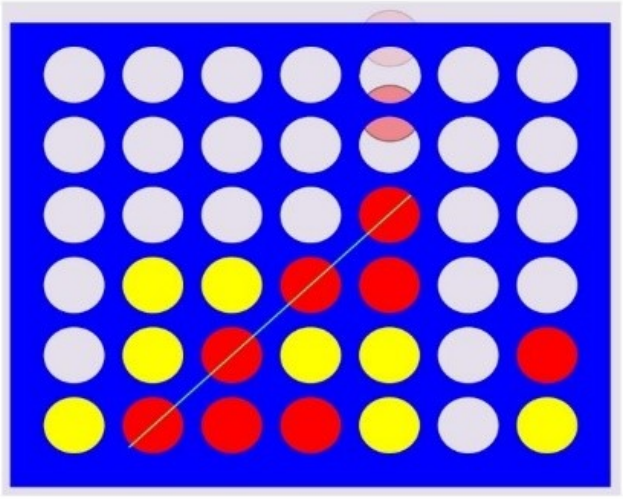

Figure 2: Winning Position.

5 Minmax Algorithm and Alpha Beta Pruning

The Minimax algorithm [**?**]. is a fundamental technique used in game theory and artificial intelligence, particularly in two-player, zero-sum games such as chess, Go, and Connect Four. Its primary goal is to determine the optimal strategy for a player by simulating all possible moves and their outcomes recursively. The algorithm operates on the premise of alternating turns between maximizing the player's advantage and minimizing the opponent's advantage. Starting from the current game state, it explores all possible moves available to the player and evaluates potential future states by assuming that both players make optimal decisions. This exploration continues down the game tree until a terminal state is reached, which could be a win, loss, or draw, or until a specified depth limit is reached. Despite its effectiveness in finding optimal strategies, the Minimax algorithm can be computationally expensive, especially in games with large state spaces and deep game trees. To address this challenge, Alpha-Beta pruning is employed as an optimization technique. Alpha-Beta pruning enhances the efficiency of the Minimax algorithm by eliminating branches of the game tree that cannot influence the final decision. It achieves this by maintaining two bounds, alpha and beta, which represent the best possible scores that the maximizing and minimizing players can guarantee, respectively. During the recursive search, if it is determined that a certain branch (or subtree) of the game tree cannot possibly lead to a better outcome than an already examined branch, that branch is pruned. This pruning mechanism significantly reduces the number of nodes that need to be evaluated, thereby speeding up the search process without compromising the accuracy of the final decision.

In practical applications, the Minimax algorithm with Alpha-Beta pruning is widely used in developing game-playing agents capable of strategic decision-making in adversarial environments. By efficiently navigating through the game tree and focusing computational resources on the most promising paths, this approach ensures that the agent can make informed decisions in real-time gameplay scenarios. Moreover, advancements such as heuristic evaluations and iterative deepening further enhance its applicability and performance in complex game scenarios where exhaustive search is impractical. Overall, the combination of Minimax with Alpha-Beta pruning represents a robust framework for developing intelligent agents capable of competitive gameplay and strategic decision-making in various board games and beyond. [2].

6 Algorithm

6.1 Define the State Space

In Connect Four, the state space represents the current configuration of the game board. We can represent the board as a 2D array, where each cell can be empty, occupied by player 1, or occupied by player 2.

6.2 Define the Action Space

Actions represent the columns where a player can drop their piece. In Connect Four, players can drop their piece in any column that is not already full.

6.3 Define Rewards

In Connect Four, the game is won by getting four of our pieces in a row, either horizontally, vertically, or diagonally. We can assign positive rewards for winning, negative rewards for losing, and zero rewards for intermediate states or draws.

6.4 MinMax Algorithm

It operates on the principle of alternating turns between maximizing the player's score and minimizing the opponent's score. This recursive exploration continues until a terminal state (win, loss, or draw) or a specified depth limit is reached in the game tree.

6.5 Alpha Beta Pruning

Alpha-Beta pruning enhances the Minimax algorithm's efficiency by reducing unnecessary computations. It achieves this by maintaining bounds (alpha and beta) that represent the best achievable scores for the maximizing and minimizing players, respectively. During the search, if a branch of the game tree is determined to be irrelevant (i.e., cannot affect the final decision), it is

pruned—meaning further exploration of that branch is halted, saving computational resources.

6.6 Iteration and Training

Repeating the above steps for a large number of episodes or until convergence.

7 Results and Inference

Certainly! Here's the converted paragraph discussing the Minimax algorithm with Alpha-Beta pruning for Connect Four:

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The Connect Four game was implemented using the Minimax algorithm with Alpha-Beta pruning and evaluated for its performance. The results demonstrated that the model could systematically analyze and improve its gameplay strategy over time. Alpha-Beta pruning efficiently balanced exploration and exploitation by reducing unnecessary computations, allowing the model to make optimal decisions based on its learned knowledge of the game state. The training process involved multiple iterations, evaluating metrics such as win rate and average score to gauge the model's progress.

In our analysis of Connect Four with Minimax and Alpha-Beta pruning, we consistently observed a significant advantage for the player who makes the first move. Across all test scenarios, the starting player consistently won the majority of games, showcasing the inherent advantage of optimal play in Connect Four. Although the starting player doesn't win every game due to variations in strategy learning, it consistently outperforms the opponent.

We observed variations in win percentages based on different parameters such as depth of search and heuristic evaluation function, indicating their influence on gameplay outcomes. The depth of search significantly impacted the model's ability to foresee future moves and make optimal decisions, with deeper searches generally resulting in improved performance. Additionally, tuning the heuristic evaluation function to better assess board positions played a crucial role in determining the effectiveness of the Minimax algorithm.

The impact of exploration in Minimax with Alpha-Beta pruning was evident in our experiments. Higher exploration rates often led to more varied outcomes when the algorithm played against itself or different opponents. Increased exploration benefited the model's performance when playing against different strategies, as it allowed for better adaptation and decision-making. However, excessive exploration could lead to suboptimal strategies when playing against itself, where pre-

Algorithm 1 Minimax with Alpha-Beta Pruning for Connect Four

```
function EVALUATE_BOARD(state)
    Implementation of heuristic evaluation function
    return heuristic_value
end function
function MINIMAX(state, depth, alpha, beta, maximizing_player)
    if game_over(state) or depth == 0 then
        return EVALUATE_BOARD(state)
    end if
    if maximizing_player then
        max_eval = −∞
        for move in legal_moves(state) do
            eval = MINIMAX(make_move(state, move), depth - 1, alpha, beta, False)
            max_eval = MAX(max_eval, eval)
            alpha = MAX(alpha, eval)
            if beta ≤ alpha then
                break
            end if
        end for
        return max_eval
    else
        min_eval = ∞
        for move in legal_moves(state) do
            eval = MINIMAX(make_move(state, move), depth - 1, alpha, beta, True)
            min_eval = MIN(min_eval, eval)
            beta = MIN(beta, eval)
            if beta ≤ alpha then
                break
            end if
        end for
        return min_eval
    end if
end function
function FIND_BEST_MOVE(state, depth)
    alpha = −∞
    beta = ∞
    best_move = None
    for move in legal_moves(state) do
        eval = MINIMAX(make_move(state, move), depth - 1, alpha, beta, False)
        if eval ¿ alpha then
            alpha = eval
            best_move = move
        end if
    end for
    return best_move
end function
```

dictability in opponent moves reduced the effectiveness of aggressive exploration strategies.
Overall, the Minimax algorithm with Alpha-Beta pruning proved effective in training the Connect Four model, enabling it to learn and adapt its gameplay strategy effectively against different opponents. Adjustments in exploration rates and depth of search were critical in optimizing performance, highlighting the algorithm's robustness and adaptability in competitive game environments like Connect Four.

8 Future Work and Conclusion

In conclusion, the Connect Four game using Min Max algorithm has been successfully implemented and analyzed. The algorithm was able to learn and improve its performance over time, demonstrating the effectiveness of Alpha Beta pruning for this type of game. The experience replay technique was used to store past observations, actions, and rewards, which helped the model learn from previous experiences. The results showed that the model was able to consistently win against a random player, and the learning curve showed a steady increase in the model's performance over time. The model was also able to learn the optimal actions to take in the game and avoid losing actions.
For future work, there are several areas that can be explored. One area is to implement and compare the performance of other reinforcement learning algorithms, such as Deep Q-Network (DQN) or Monte Carlo Tree Search (MCTS), to see how they perform compared to Q-learning. Another area is to explore different state representations, such as using convolutional neural networks (CNNs) to extract features from the game board, and compare their performance to the current state representation. [3]. Additionally, the model can be further improved by implementing a more sophisticated exploration strategy, such as using a variable epsilon value or using a different exploration policy altogether. The model can also be trained for a longer period of time to see if it can achieve a higher win rate. Using Q-learning and Sarsa, our implementation provides the best possible strategy for the general 2-dimensional game of Connect Four. Future research may focus on figuring out the best approach for different Connect Four iterations.
Developing an optimal strategy for the 3-dimensional version of Connect Four might be an intriguing endeavor. The game's three-dimensional element increases the model's complexity and modifies the rules as well. Comparing the variations in the approaches could be a worthwhile endeavor.
Using a wide range of board sizes while still implementing the best strategy would be conceptually interesting. including boards with varying dimensions, sizes, and shapes. examining and contrasting the several best tactics that are produced in order to spot or detect a trend. The results might then be used for other games or related issues.
In conclusion, the Connect Four game using Q-learning algorithm has been successfully implemented and analyzed, demonstrating the potential of reinforcement learning for building intelligent agents for complex decision-making tasks. With further exploration and improvement, the model can achieve even higher performance and provide a more challenging opponent for human players.

References

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