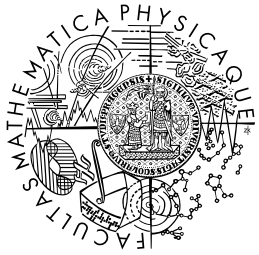

FACULTY
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BACHELOR THESIS

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Artificial Intelligence for Quoridor game

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Supervisor of the bachelor thesis: Mgr. Klára Pešková, Ph.D.
Study programme: Computer Science
Study branch: Artificial Intelligence (AI)

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Dedication.

Title: Artificial Intelligence for Quoridor game

Author: Devyanshu Koirala

Department: Department of Software and Computer Science Education (KSVI)

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Abstract: Quoridor presents a challenging terrain for strategic decision-making, making it a suitable testing ground for various AI algorithms. This thesis explores the implementation and evaluation of three distinct AI algorithms, namely A*, Minimax with Alpha-Beta Pruning, and Monte Carlo Tree Search (MCTS), within the realm of Quoridor gameplay.

The research begins with a comprehensive overview of the Quoridor game, its rules and strategies. Subsequently, we delve into the theoretical foundations and practical implementation details of the aforementioned AI algorithms and conduct a thorough evaluation in an effort to determine the best one in this context.

Keywords: Quoridor Artificial Intelligence AI Board Game

Contents

Introduction

Artificial Intelligence (AI), over the past decade, is becoming an integral part of many elements of modern world. In fact, in the recent years, it has become an the main point of evolution and revolution in many of the technologies and industries. From assisted or autonomous driving (**?**), chat bots **?** to gaming **?**, AI has been a major revelation in evolving the existing technologies to generating new industry space with the plethora of new use cases.

AI has brought a revolutionary transformation to the gaming world, pushing the boundaries of what's achievable in both single and multiplayer gaming experiences. In recent years, AI has taken center stage with its remarkable accomplishments in mastering age-old games such as Chess, Go, and many others. AI-driven games now offer users the opportunity to hone and enhance their skills, providing varying difficulty levels and offering optimal moves to guide players through each step if desired.

Strategy games are a genre of gaming that require planning, often involving various tactics, decision making and execution while under various constraints (e.g., resources). Some of the examples of popular strategy games are Chess, Go, Shogi, Starcraft, etc. Strategy games are unique compared to many other genres of games in the sense that it requires a selection of an optimal move among a subset of sub-optimal moves based on a plan. In many scenarios, the size of the subset of sub-optimal moves depends on exploration of the game space, simulation and prediction of sequence of the player's and the opponent's moves all while managing certain resources efficiently.

AI, due to its suitability towards solving problems involving complex decision making, taking into account sequences of the player's and the opponents possible moves (e.g., game space), outcome prediction or position evaluation all while considering the available resources, have been deemed particularly effective in playing the strategy games. The history of the use of AI in strategy games goes back to the last few decades. One of the initial marked impact of AI in the strategy gaming came in 1997 when IBM's Deep Blue **?** defeated World Chess Champion Garry Kasparov. The influence of AI in stratey games was more prominent with the rise and involvement of AI into the real-time strategy (RTS) games such as Warcraft and StarCraft **?** and implementation of Monte-Carlo tree search (MCTS) in the strategy games such as Go **?**. Recently, DeepMind's Alpha Go for Go, Alpha Zero for Chess **?** and AlphaStar for StarCraft **?** have widened the gap between the AI and human intelligence even further.

Designed by Mirko Marchesi, Quoridor stands out as an engaging strategic board game that is played between two or four players. The game is playes on a square grid board where the objective of this game is for each player to move their pawn to the opposite side of the board. This game introduces a fascinating twist where a player, in addition to trying to move their pawn through the square grid, additionally have an option to place walls on the grid locations strategically to obstruct the opponent's path. This strategy compels the player to think of their traversal strategy while predicting the opponents strategy as well. Despite its seemingly simple rules, Quoridor demands a unique blend of strategic foresight and the ability to anticipate the moves of opponents and outmaneuver

the opponent.

Compared to some other strategy games such as Chess and Go, Quoridor has not been extensively studied in the literature. In **?**, the author developed an agent for playing Quoridor using genetic algorithm to optimize the weights. The authors in **?** study the complexity of the algorithm also develop a Quoridor playing agent based on Minimax algorithm. The authors conclude that Quoridor has a similar state-space and game tree complexity as that of the games such as Chess. Likewise, the authors in **?** developed an MCTS approach for Quoridor. Recently, in **?**, the authors performed an analysis of the game for a miniature 5 by 5 board.

The primary objective of this thesis is to construct a well-structured framework and user-friendly interfaces that seamlessly integrate AI algorithms into the Quoridor game. The development of AI algorithms customized to Quoridor's unique rule set will not only enhance our understanding of the game's intricate nuances but also facilitate the creation of an intuitive interface for simulating these AI agents. Furthermore, a comprehensive evaluation will be conducted to identify the top-performing AI agent.

In addition to this, the project will encompass the creation of a user-friendly interface that empowers players to engage with an AI opponent of their choice, thereby bolstering the game's accessibility and inclusivity.

0.1 Acknowledged Works

Quoridor, being a widely popular game, has attracted a fair number of attention from the research community, resulting in successful AI agent developments. Some of the notable works include:

- **Mastering Quoridor (?)** The writer implements and assesses various algorithms like Negamax, Alpha-beta negamax among others. Additionally, they utilized a genetic algorithm to refine the weights within a linear weighted evaluation function, employing 10 distinct features suggested by the author, some of which include player's position towards their goal side, the opponent's position towards their respective goal, the remaining count of walls available to the player, etc.

In sharp contrast to the aforementioned paper, our thesis takes a distinctly different path by delving deeply into the architectural aspects of AI. Our approach emphasizes abstraction to the greatest extent possible, with an eye on facilitating seamless integration into a broad spectrum of games. We prioritize creating an interface that is adaptable to diverse game environments, setting our research apart from the game-specific focus of the prior works.

1. Description

The game begins with an NxN chess-like board where each square represents a potential position for the game pieces. It contains grooves that runs between the squares where players can place their walls. Each player is represented by a pawn represented by a character label that start on opposite sides, with their pawns located at the center of their respective edge. The primary objective is to be the first player to move their pawn to the row of squares on the opposite side of the game board avoiding any walls deterring its path to the goal while strategically placing walls to deter opponents from reaching their goal squares.

Walls are a fundamental element of the game, allowing players to strategically block their opponent's path and influence the course of the game. Each wall spans across two cells and occupies exactly four cells either horizontally or vertically, effectively creating a barrier between them. At the beginning, each player starts with a set number of walls that they can use during their turn.

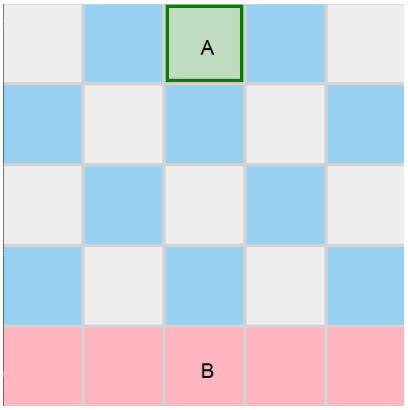


Figure 1.1: A 5x5 game board

As seen in figure **??**, In the beginning, player A starts at cell (2, 0) and player B starts at cell (2, 4). A's goal is to reach the cells highlighted in pink. The gray areas between the cells are grooves for wall placement.

1.1 Notation

There are no official notations for this game. However, some popular ones recognized by the Quoridor community include **Glendenning's Notation** ((**?**)) and the **Quoridor Strats Notation** ((**?**)).

Let $R = \{a, ..., i\}$ and $C = \{1, ..., 9\}$

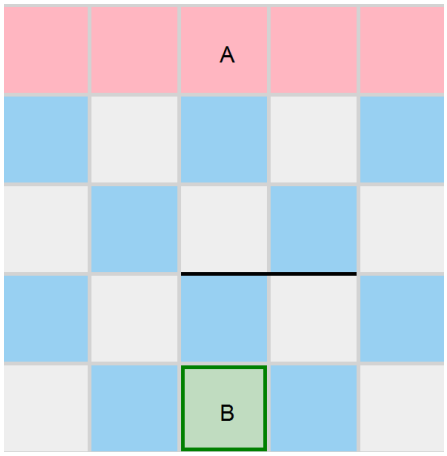
Both notations follow the same principle of labelling each cell by C_{ij} where $i \in R$ and $j \in C$.

Move M and Wall W are denoted algebraically, where

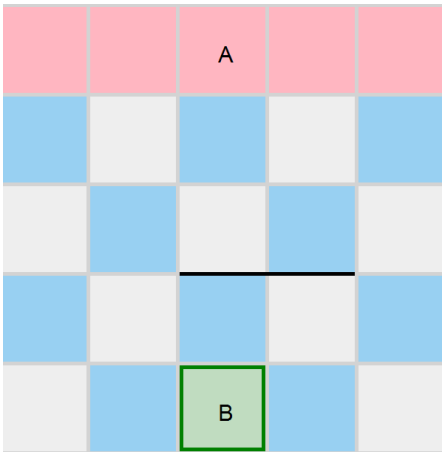
$M(C_{ij}) = ij$ where $i \in R$ and $j \in C$,

$W(C_{ij}) = ijD$ where $i \in R$, $j \in C$ and $D \in \{h, v\}$

The difference between the two notations is the way the walls are represented.



(a) Glendenning's Notation: **c3h**



(b) Quoridor Strats Notation: **c4h**

Figure 1.2: Notation differences

As seen in Figure **??**, the difference lies in the point of reference of the wall. In **Quoridor Strats Notation**, each wall coordinate is represented by the lower-left cell the wall follows along, whereas in **Glendenning's Notation**, each wall is represented by the upper-left cell the wall follows along.

Even though they are widely used, they are very easy to get confused with since they have the same wall representations, and unless specified explicitly, it is difficult to tell which representation is being used.

This is why I have decided to use a different representation for walls. Instead of vertical and horizontal wall with respect to a cell, we define a direction explicitly.

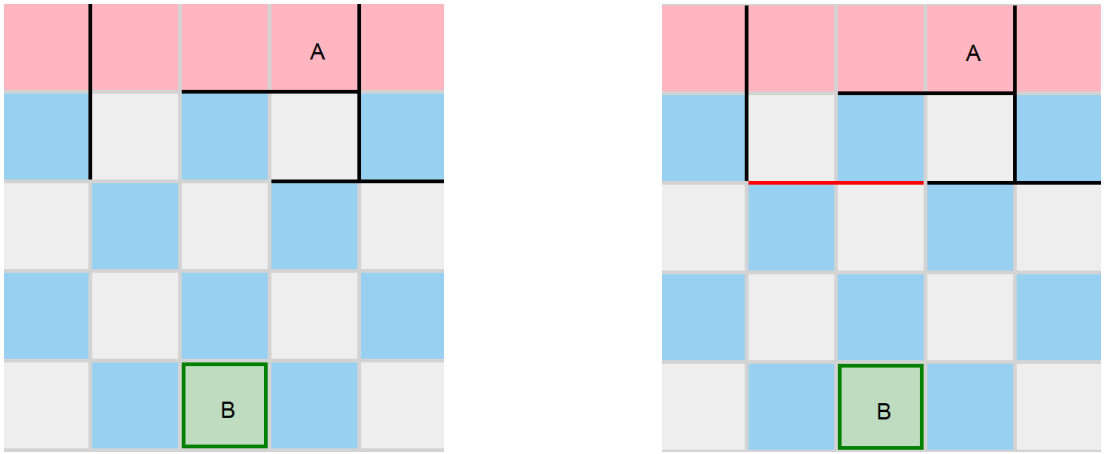
$W(C_{ij}) = ijD$ where $i \in R$, $j \in C$ and $D \in \{N, S, E, W\}$

Looking back at Figure **??**, the walls can now be represented by **c4N**, i.e. a Northern wall from the cell C_{c4}.

1.2 Rules

1.2.1 Wall placement rules

- Walls cannot be placed diagonally.
- A placed wall must not completely block any player's path to victory. Each player must have at least one path to victory *(See figure* **??***)*
- A placed wall cannot intersect any of the previously placed walls.
- Walls cannot be placed along the edges of the board. Walls must be placed to create a barrier for exactly 4 cells
- Every player possesses a limited supply of walls, and once they exhaust these walls, they are unable to place any additional ones. Consequently, the player is only allowed to maneuver their pawn on the board.



(a) Valid game state

(b) Invalid game state

Figure 1.3: Example of an invalid wall placement

The game state represented by Figure **??** shows the situation after 5 turns, with it currently being player B's turn to move. Since both **A** and **B** have viable paths to their respective goal rows and all walls have been placed according to the rules (see *Section* **??**), the game state shown in Figure **??** is considered valid.

However, player B disrupts the rules by placing the red wall, violating the specified wall-placement rules (see *Section* **??**), consequently rendering the game state represented by Figure **??** invalid.

1.2.2 Player movement rules

- Players are allowed to move their pawn one unit at a time in the North, South, East, or West directions during their turn. Diagonal movements are not allowed.
- **Jump**
  - If an opponent is at to the cell a player intends to move to, the player can jump over the opponent provided there is no wall between them or behind the opponent they intend to jump over. In the latter case, the player can jump to a cell on either side of the opponent's cell, given the cell is accessible from the opponent's cell.
  - Players cannot jump over walls
  - A Player is allowed to jump over multiple opponents as long as they adhere to the aforementioned conditions.

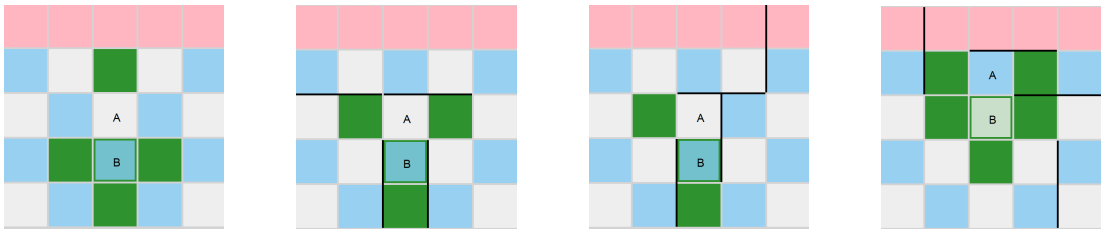


Figure 1.4: Examples of possible moves for player B in the game state

2. Game Analysis

In Chapter **??**, we briefly explored the rules and gameplay mechanics of Quoridor. As we progress, this chapter aims to deepen our understanding by analyzing Quoridor from a theoretical and computational perspective.

In this chapter will classify Quoridor within the realm of strategic games, examine its game tree, state-space and tree complexity, and explore the implications of these factors on gameplay and artificial intelligence application.

2.1 Classification of Quoridor

Quoridor can be characterized as a discrete, deterministic, zero-sum, sequential, game with perfect information (**?**) , and therefore, a combinatorial game (**?**)

2.1.1 Discrete

In every turn, each player has a finite number of moves and wall placements. These are limited by the game state (already placed walls and moved pawns) and the rules of the game. The game-tree of Quoridor has finite number of nodes (e.g **??**)

2.1.2 Deterministic

Quoridor has no random elements or chance involved in the gameplay. Every outcome and situation is a direct result of the players' decisions and strategies. There's no dice rolling, card drawing, or any other mechanism that introduces randomness.

2.1.3 Zero-sum

In Quoridor, when a player makes a move that brings them closer to winning (like advancing their pawn or placing a wall effectively), it inherently puts the opponent at a disadvantage. Therefore, any positive progress for a player translates into a negative impact for their opponent. This reciprocal relationship of gain and loss between the players is what characterizes Quoridor as a **zero-sum** game.

2.1.4 Perfect Information

Every aspect of its gameplay are completely visible and known to all players at all times. This means that the positions of the pawns and the placements of the walls on the board are always in full view, allowing players to make strategic decisions based on the entire state of the game.

2.2 Game-Tree

A game tree for an **abstract strategy game** is a comprehensive graph representing every possible game states and sequence of moves. The nodes of a game tree represent game states, and the edges represent action/move.

Game trees are integral to the framework of **adversarial search problems**, where they are employed to systematically explore and evaluate the possible outcomes of different strategies, and forecast future states of the game based on current and potential moves.

The following depicts a (partial) game tree for the Quoridor game with a board of size 3x3:

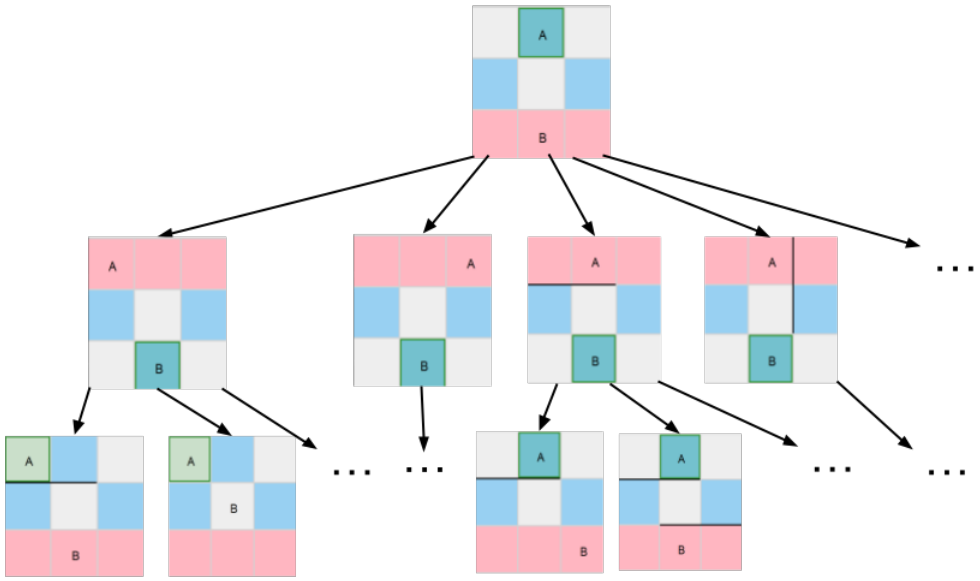


Figure 2.1: A partial game tree for a 3x3 game board.

2.2.1 Branching Factor

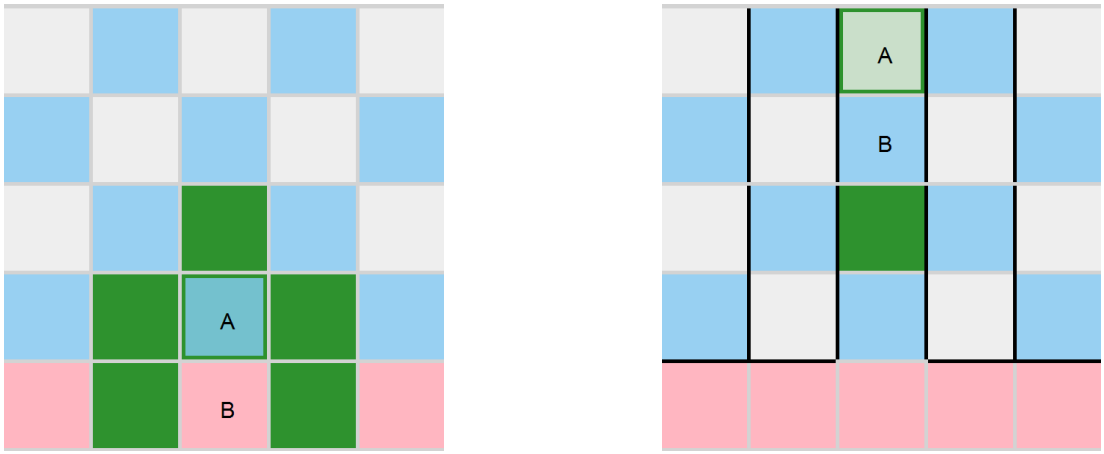
The branching factor of a **Game-tree** is the number of child nodes of each node, or in other words, the number of possible moves a player at their turn can make, given the game state.

In figure **??**, player A makes the first move. A has **3** places to move their pawn to and **8** places to put one of their walls at. So, the root has a **branching factor** of **11**.

The branching factor is greatly influenced by the state of the board in Quoridor, i.e the player locations and walls placed.

As an example, the figure below represents a game states with the maximum and minimum branching factors:

As depicted by Figure **??**, player A has 5 possible places to move their pawn to. No walls have been placed so far, so player A can also place one of their walls in any place.



(a) Maximum : 37 (b) Minimum : 1

Figure 2.2: Branching factor differences

For a board of size NxN with no wall(s) placed, $(N-1)$ walls can be placed in each row (since each wall occupies **2** cell lengths), and there are $(N-1)$ rows for correct horizontal wall placements. Hence, there are $(N-1)^2$ slots for horizontal wall placements, and since the board is NxN, the total slots for both horizontal and vertical wall placements is given by the equation:

$$2 * (N-1)^2 \tag{2.1}$$

Coming back to figure **??**, since the board has no walls placed, we now see that A has $5 + 2 * (5-1)^2 = 37$ possible moves they can perform, ergo, the branching factor of the game state represented by Figure **??** is **37**, which is also the maximum branching factor for board sized 5x5.

However, in Figure **??**, A has no available slot for wall-placement, and the already present walls block A from moving anywhere except for cell **c3**. Hence, the branching factor for the game state represented by Figure **??** is 1.

Average Branching Factor

In sub-section **??**. we saw that the branching factor is not uniform due factors like wall-placements and positioning of the player greatly influencing it.

We, therefore, would like to estimate an average branching factor for boards of different lengths to see if varying board dimension has any affect in the average branching factor.

We already know from equation **??** that the maximum branching factor of the game tree is exponential in order of N and from Figure **??**, we can deduce that the minimum branching factor is 1 (since we can replicate a similar game state for any game state).

To find an estimate of the average branching factor, we use the Algorithm **??**

Algorithm 1: Average branching factor

```
Function AvgBranchingFactor(agent1, agent2, simulations):
    input  : Two agents and number of simulations
    output: Average of averages branching factor
    SumOfAverages ← 0
    for i ← 1 to simulations do
        State ← Initialize()
        GamePossibleMoves ← 0
        GameMovesMade ← 0
        Agents ← [agent1, agent2]
        AgentIndex ← 0
        while State is not Terminal do
            Agent ← Agents[AgentIndex]
            AgentIndex ← (AgentIndex + 1) % 2
            GamePossibleMoves ← GamePossibleMoves +
             Length(State.PossibleMoves())
            Move ← Agent.GetMove(State)
            State ← State.Apply(Move)
            GameMovesMade ← GameMovesMade + 1
        end
        GameAverage ← GamePossibleMoves / GameMovesMade
        SumOfAverages ← SumOfAverages + GameAverage
    end
    return SumOfAverages / simulations
```

We then simulate **1000** games between **Minimax AB** and **Semi-random** agents, each for boards of dimensions 3, 5, 7 and 9, and the results of the average branching factor can be seen in figure **??**

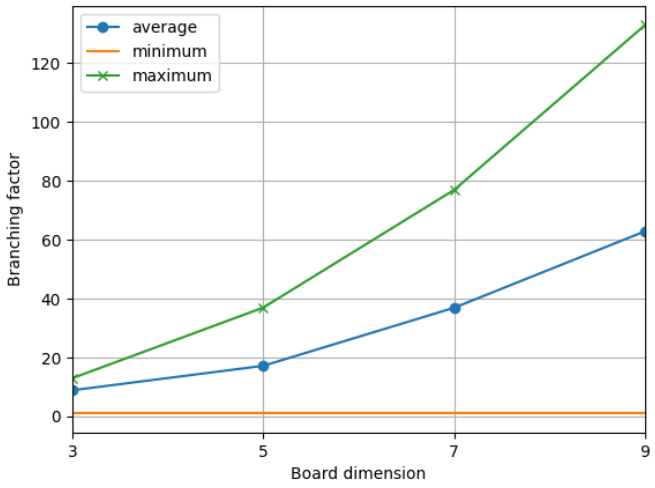


Figure 2.3: Branching factor for boards of different sizes

From figure **??**, like with the maximum branching factor, we can see a similar exponential trend of the average branching factors in order of N. Furthermore, based on only the four dimensions and their averages and maximum branch-

ing factors, the average branching factor seems to be almost half the maximum branching factor

The average branching factor for board of dimension 9x9 was about **62**, which is very close to the value proposed by **?**

2.3 Minimax

The Minimax algorithm is a decision-making algorithm commonly used in two-player, zero-sum games, such as chess, checkers, and tic-tac-toe. Its primary objective is to determine the best move for a player in a given game state by considering the potential outcomes of each move and selecting the one that minimizes the maximum possible gain for the opponent.

A high-level overview of the Minimax algorithm ((ADD PICTURES))

- **Game Tree**
  The algorithm constructs a game tree, where each node represents a possible game state, and the edges represent possible moves. The tree extends to various depths, representing different future moves and their consequences.

- **Evaluation Function**
  It can be computationally expensive for games with a large number of possible moves and deep game trees. For this reason, after a certain depth, a static evaluation function is used to determine the value of that game state. This function assigns a score to the game state, reflecting how favorable it is for the player whose turn it is.

- **Alternating Players**
  The algorithm alternates between two players, maximizing and minimizing. The player who is currently maximizing (MAX) aims to choose moves that maximize their own score, while the player minimizing (MIN) aims to choose moves that minimize the score of the maximizing player.

- **Backtracking**
  As the algorithm traverses the tree, it backtracks and carries information about the values of the nodes up to the root node. The root node's children are the possible moves, and the algorithm selects the move that leads to the highest value for the maximizing player.

- **Pruning**
  To optimize the search process and reduce the number of nodes to evaluate, various pruning techniques are often applied, such as the Alpha-Beta Pruning, which eliminates branches of the tree that are guaranteed not to affect the final decision.

Conclusion

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List of Abbreviations

A. Attachments

A.1 First Attachment