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Fish Game using Minimax Algorithm

Project Report

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Chapter 1 Problem Statement (Explanation)

1.1 Objective

The objective of this project is to design and implement an intelligent agent capable of playing a two-player Fish Game using the **Minimax algorithm**. The Fish Game involves strategic movement on a grid of tiles, where each tile contains a specific number of fish. Players take turns moving their pieces to collect fish, with the ultimate goal of maximizing their own score while minimizing the opponent's opportunities.

To achieve competitive gameplay, the agent must make rational and strategic decisions at each turn. This requires the AI to not only evaluate immediate moves but also to anticipate potential future actions by the opponent. The Minimax algorithm is particularly suitable for this scenario as it enables the AI to explore possible game states ahead of time, evaluate outcomes assuming both players act optimally, and select the move that maximizes its advantage while minimizing the opponent's potential gain.

1.2 Problem Description

The Fish Game presents several challenges from an artificial intelligence perspective. At each turn, a player is faced with multiple movement options, each leading to different future states of the board. As the game progresses, tiles are removed, leading to reduced mobility and forcing players to plan strategically.

The core problem lies in enabling the AI agent to:

- **Analyze multiple move sequences** to determine the optimal action.
- **Predict opponent responses** accurately to avoid traps and block advantageous moves.
- **Evaluate board states** to measure long-term advantages, not just immediate fish collection.
- **Handle computational complexity**, as the branching factor of possible moves increases with board size.

By applying the Minimax algorithm, the AI can perform a systematic search through the game tree, alternating between maximizing its own score and minimizing the opponent's. This structured approach ensures that the AI agent behaves strategically and can effectively compete against a human or another AI opponent.

Chapter 2 Software Requirements

2.1 Software Requirements

The development of the Fish Game using the Minimax algorithm requires a structured set of software tools and libraries to support efficient implementation, testing, and visualization. The following are the key software components utilized:

Programming Language:

- **Python 3.10+** was chosen as the primary programming language due to its simplicity, readability, and extensive support for AI and game development libraries. Python’s rich ecosystem allows for rapid prototyping and clean implementation of algorithms such as Minimax, while maintaining good performance.

Development Environment:

- **Visual Studio Code** was used as the main IDE, offering integrated debugging, version control, and linting support. Its lightweight interface and extensive extension marketplace facilitated seamless development.

Libraries and Frameworks:

- **Arcade Library:** Used for rendering the game board, managing sprites, and handling user interactions.

Arcade simplifies 2D game creation with built-in support for grids, shapes, and event handling.

- **NumPy:** Employed for efficient manipulation of board states and handling numerical computations involved in evaluating moves.
- **Random Module:** Used for generating test scenarios and random opponent moves for baseline comparisons.

Operating System:

- The project was developed and tested **Linux** and provided the necessary dependencies are installed.

Version Control:

- **Git** was used for version control and project management. Commits were maintained regularly to track incremental development stages and ensure rollback capability when required.

Testing Environment:

- Multiple test cases were executed in a local environment to validate functionality. Logging was enabled to monitor Minimax decision-making in real time.

Chapter 3 Design Alternatives

Design Alternatives

Several design alternatives were considered for implementing the AI component of the Fish Game. Each approach offers distinct advantages and limitations in terms of intelligence, complexity, and computational efficiency:

Alternative 1: Random AI

- **Description:** The AI selects its moves randomly from the set of valid moves at each turn.
- **Advantages:**
  - Extremely simple to implement.
  - Useful as a baseline for evaluating the performance of more advanced algorithms.
- **Limitations:**
  - No strategic thinking or lookahead.
  - Often leads to suboptimal gameplay, allowing the human player to win easily.

Alternative 2: Heuristic-Based AI

- **Description:** The AI uses simple heuristic functions to choose moves that yield the highest immediate number of fish, without simulating future states.
- **Advantages:**

    - Faster computation compared to Minimax, as it does not traverse the game tree.
    - More intelligent than random moves, providing moderate challenge to the player.
- **Limitations:**
    - Focuses only on **short-term gain**, ignoring opponent's future responses.
    - Can be easily trapped by a strategic human opponent.
    - Performance degrades as board complexity increases.

Alternative 3: Minimax-Based AI (Chosen Approach)

- **Description:** The AI uses the **Minimax algorithm** to explore possible future states of the game. It alternates between maximizing its own score and minimizing the opponent's score. By evaluating future scenarios, it selects the move that leads to the best possible outcome assuming optimal play from both sides.
- **Advantages:**
    - Provides **optimal decision-making**, ensuring the AI competes strategically.

    - Considers **both current and future board states**, leading to stronger gameplay.
    - Predicts opponent moves effectively, making it suitable for competitive scenarios.
- **Limitations:**
    - Computationally intensive for large boards due to high branching factors.
    - Requires careful implementation and optimization (e.g., alpha-beta pruning) to maintain performance.

Justification for Choice:

Among the alternatives, the Minimax algorithm was chosen because it best aligns with the strategic nature of the Fish Game. The game is turn-based, zero-sum, and deterministic, which makes it an ideal candidate for Minimax. Unlike random or heuristic methods, Minimax ensures the AI agent makes strategically sound decisions, leading to competitive gameplay and a more engaging user experience.

Chapter 4
Algorithm

4.1 Algorithms Used

The Fish Game is a deterministic, turn-based, zero-sum environment, making it well-suited for classical game tree search techniques. After evaluating various approaches, the **Minimax algorithm** was selected as the primary AI decision-making mechanism. In addition, **Alpha–Beta pruning** was integrated to improve computational efficiency by reducing the number of explored nodes without affecting the optimality of decisions.

4.1.1 Minimax Algorithm

The **Minimax algorithm** is a recursive decision rule for minimizing the possible loss for a worst-case scenario. When dealing with gains, it is referred to as "maximin"—to maximize the minimum gain. In the context of the Fish Game, the algorithm operates as follows:

1. **Game Tree Generation:**
   From the current board state, all legal moves for the AI are generated. For each possible move, the resulting board state is computed.

2. **Alternating Turns:**
   The algorithm then simulates the opponent's response, assuming the opponent also plays optimally. This alternating simulation continues for a defined **depth limit**.

3. **Evaluation Function:**
   When the maximum depth is reached or the game terminates, an evaluation function is applied. In this project, the evaluation function considers:
   - **Total number of fish collected by the AI**.
   - **Total number of fish collected by the opponent**.
   - **Mobility** — number of future moves available after each state.
4. **Evaluation Score**=AI Fish ScoreOpponent Fish Scor e
5. **Backtracking (Min/Max):**
   The scores are propagated up the tree using Minimax logic:
   - At **max nodes**, the algorithm chooses the move with the maximum score (AI's turn).
   - At **min nodes**, it selects the move with the minimum score (opponent's turn).
6. **Move Selection:**
   The root node returns the move with the highest evaluation score as the AI's optimal decision.

This algorithm ensures the AI plays strategically and consistently selects moves that optimize its long-term advantage rather than immediate gains.

4.1.2 Alpha–Beta Pruning *(Optimization)*

To address the **exponential growth** of the game tree, **Alpha–Beta pruning** was applied to the Minimax algorithm. This technique prunes branches that cannot possibly affect the final decision, thereby reducing computation time while maintaining correctness. It allowed the AI to evaluate deeper game states within the same time constraints, improving both performance and responsiveness during gameplay.

Chapter 5
Datasets and Test Cases

5.1 Datasets / Game Scenarios

While traditional AI problems rely on static datasets, this project uses **game board configurations as input data**. Different **grid layouts and fish distributions** act as test environments for the algorithm.

The primary dataset configurations used include:

- **Standard Grid:** A 6×6 hexagonal grid with a random distribution of 1–3 fish per tile.
- **Structured Scenarios:** Predefined board layouts designed to test specific strategic situations, such as:
    - **Corner traps**, where the AI must block the opponent efficiently.
    - **Central dominance**, where the AI decides whether to occupy central or edge tiles.
- **Variable Number of Players:** Scenarios were tested with **two-player** settings for algorithm evaluation, but the game engine supports extensions to more players.

All board configurations were stored in simple Python dictionaries and JSON formats, ensuring reproducibility and flexibility for repeated testing.

5.2 Test Cases

To evaluate the robustness and accuracy of the Minimax implementation, a set of structured test cases was designed:

Test Case	**Description**	**Expected Outcome**	Result
TC1	AI faced with a single optimal move among multiple bad options	AI faced with a single optimal move among multiple bad options	Passed
TC2	AI faced with a single optimal move among multiple bad options	AI should consistently outperform the random agent	Passed
TC3	Forced Move Scenario (Limited Mobility)	AI should avoid moves leading to early isolation	Passed
TC4	Strategic Blocking Scenario	AI should prioritize blocking the opponent if it leads to a higher net gain	Passed

TC5	Full Game Simulation (Human vs AI)	AI should demonstrate consistent, strategic behavior across turns	Passed

Chapter 6 Design and Implementation

6. Design and Implementation

6.1 System Architecture

The system was designed using a **modular architecture** to ensure clarity, maintainability, and scalability. The entire game logic and AI strategy were separated into distinct modules. This modularization made it easier to debug, extend, and test the system. The three primary modules are:

a) Game Engine

The **Game Engine** is responsible for managing the **core mechanics** of the Fish Game, including:

- Initializing the **hexagonal grid** and assigning random fish values to each tile.
- Maintaining the **current game state**, including positions of player tokens and tiles that have been removed.
- Validating legal moves for each turn and applying movement rules.
- Updating scores when a player moves to a tile and collects fish.
- Determining end-game conditions, such as when no legal moves remain for either player.

This module is fully deterministic and independent of the user interface, ensuring that the **logic remains consistent** whether the game is played by a human or AI.

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b) AI Module

The **AI Module** encapsulates the **Minimax algorithm** and related decision-making logic. Its responsibilities include:

- Generating all **valid moves** from the current board state for the AI player.
- Building the **game tree** up to a specified depth, alternating between maximizing (AI's turn) and minimizing (opponent's turn) nodes.
- Evaluating board states using a scoring function that considers fish collected and potential future mobility.
- Implementing **Alpha–Beta pruning** to reduce unnecessary computations and allow deeper lookahead within the same time constraints.
- Returning the **best move** to the Game Engine for execution.

This module is designed to be easily extensible, allowing future integration of heuristic refinements or learning-based enhancements.

c) Graphical User Interface (GUI)

The **GUI** provides an interactive and visual representation of the game board. Implemented using the **Arcade Library**, the GUI:

- Renders the **hexagonal tiles** and displays the number of fish on each.
- Shows the positions of both the **human and AI players** in real time.
- Updates dynamically after each move to reflect the new board state.
- Displays **current scores**, remaining tiles, and turn indicators.
- Facilitates user input for selecting moves during the human player's turn.

The GUI interacts with the Game Engine to send player actions and receive updated board states, while the AI Module operates independently during its turn.

6.2 Implementation Details

The implementation followed a **systematic development approach**, broken down into clearly defined steps:

Step 1: Board Initialization

- The grid is initialized as a **6×6 hexagonal matrix**, with each tile assigned a random value between **1 and 3 fish**.
- Data structures such as 2D arrays and dictionaries are used to store tile information (position, fish count, active status).
- Player tokens are placed at predefined starting positions.

Step 2: Turn Management

- The game alternates between **human and AI turns**.
- For the human player, the GUI captures the selected tile, validates the move, and updates the board state.
- For the AI, the system triggers the Minimax decision function to compute the optimal move.

Step 3: Minimax Algorithm Implementation

- The Minimax algorithm is implemented recursively. For each possible move, a **new board state** is generated and evaluated.
- The evaluation function prioritizes:
    - Higher **fish gain** for the AI.

    - Reducing **future mobility** of the opponent.
    - Maintaining central or strategically advantageous positions.
- **Alpha–Beta pruning** is integrated to avoid exploring branches that cannot influence the final decision, thereby improving computational efficiency.

Step 4: Board State Update and Scoring

- After each move, the Game Engine updates:
    - The **player's score**, adding the number of fish collected from the selected tile.
    - The **board**, by marking the visited tile as inactive (effectively removing it).
- Valid moves are recomputed dynamically for the next turn.

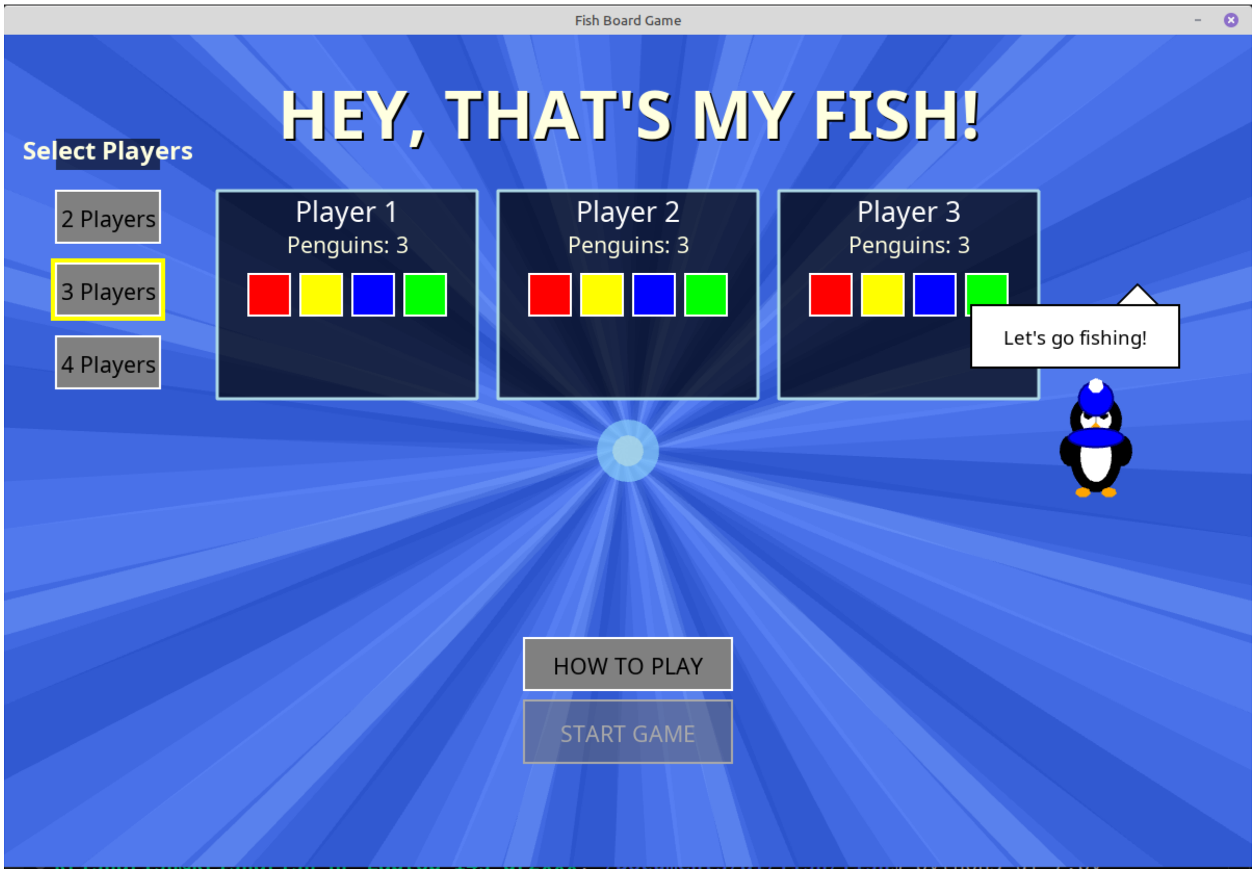
Step 5: Game Termination and Winner Declaration

- The game continues until **no legal moves remain** for either player.
- The winner is determined based on the **total number of fish collected**.

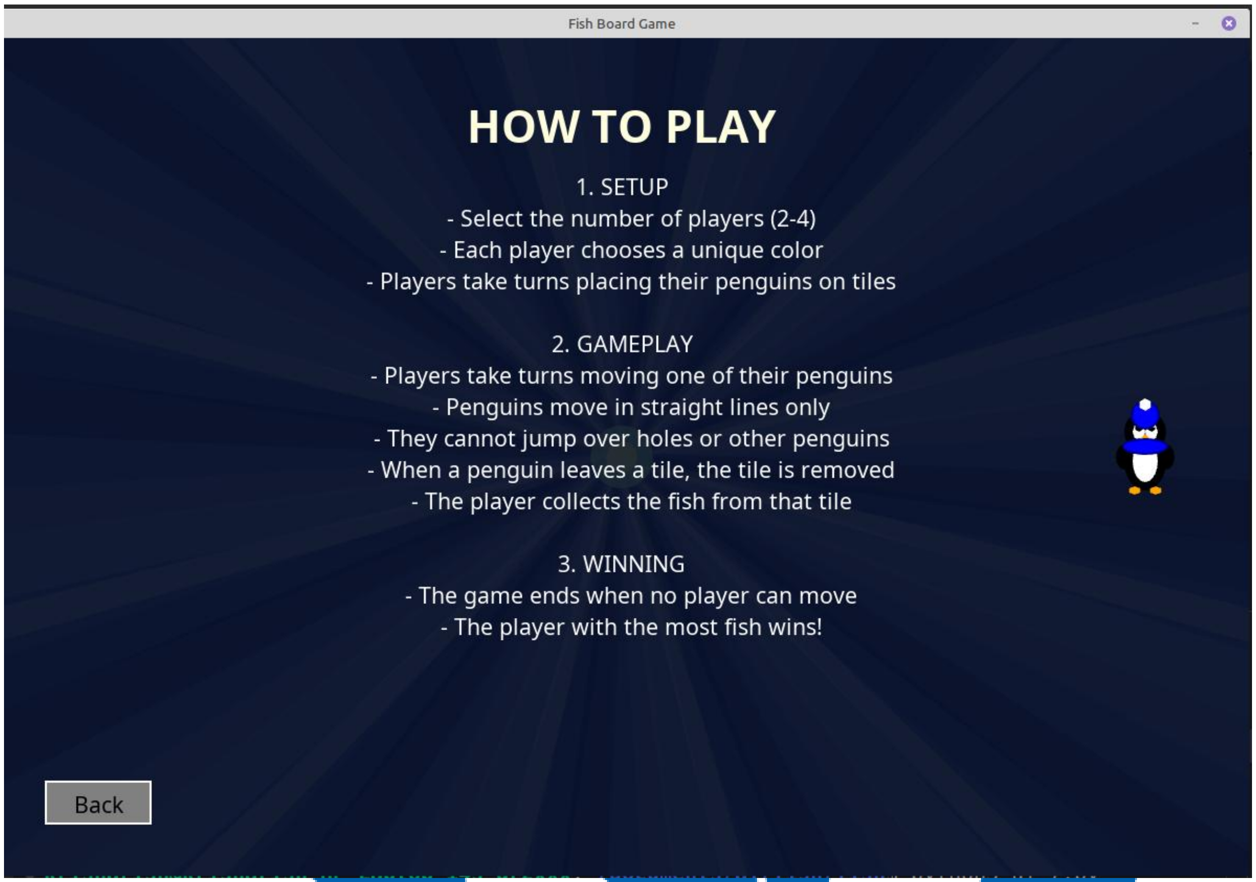
- The GUI displays a final **“Game Over” screen**, announcing the winner and scores.

6.3 Screenshots and Code Snippets

Figure 1 below illustrates the **overall system architecture**, showing the interaction between the Game Engine, AI Module, and GUI



How to play



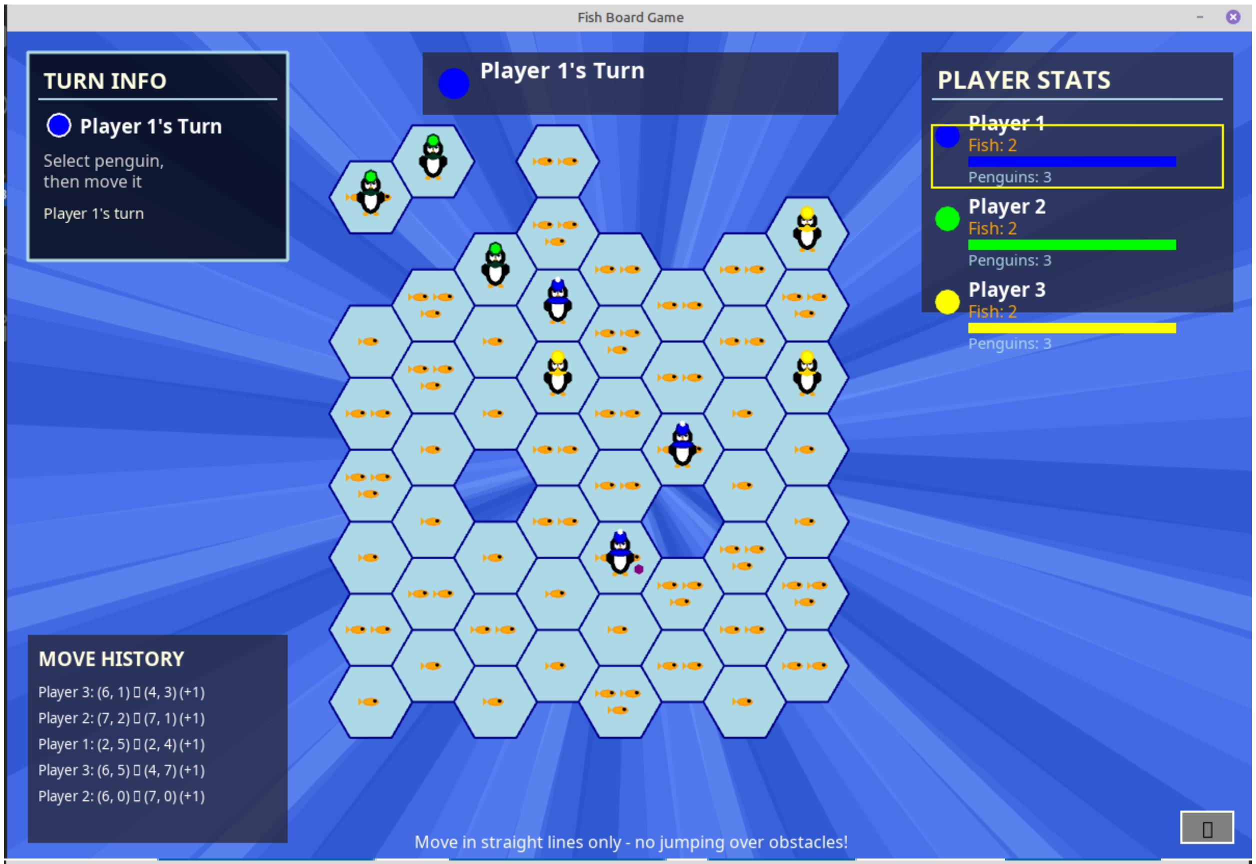
HOW TO PLAY

1. SETUP
- Select the number of players (2-4)
- Each player chooses a unique color
- Players take turns placing their penguins on tiles

2. GAMEPLAY
- Players take turns moving one of their penguins
- Penguins move in straight lines only
- They cannot jump over holes or other penguins
- When a penguin leaves a tile, the tile is removed
- The player collects the fish from that tile

3. WINNING
- The game ends when no player can move
- The player with the most fish wins!

Game interface



Fish Board Game

TURN INFO

Player 1's Turn

Select penguin,
then move it

Player 1's turn

Player 1's Turn

PLAYER STATS

Player 1
Fish: 2
Penguins: 3

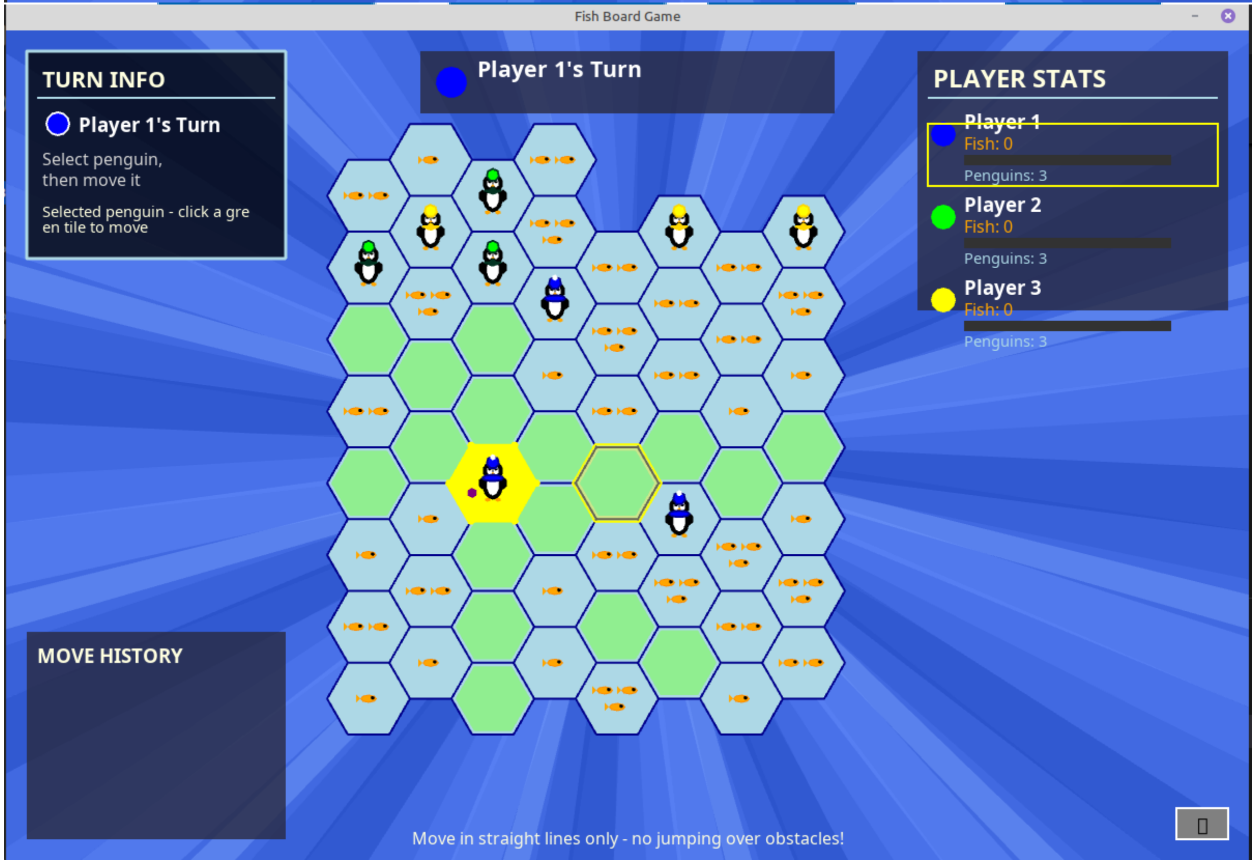
Player 2
Fish: 2
Penguins: 3

Player 3
Fish: 2
Penguins: 3

MOVE HISTORY

Player 3: (6, 1) ▯ (4, 3) (+1)
Player 2: (7, 2) ▯ (7, 1) (+1)
Player 1: (2, 5) ▯ (2, 4) (+1)
Player 3: (6, 5) ▯ (4, 7) (+1)
Player 2: (6, 0) ▯ (7, 0) (+1)

Move in straight lines only - no jumping over obstacles!



Fish Board Game

TURN INFO

Player 1's Turn

Select penguin,
then move it

Selected penguin - click a gre
en tile to move

Player 1's Turn

PLAYER STATS

Player 1
Fish: 0
Penguins: 3

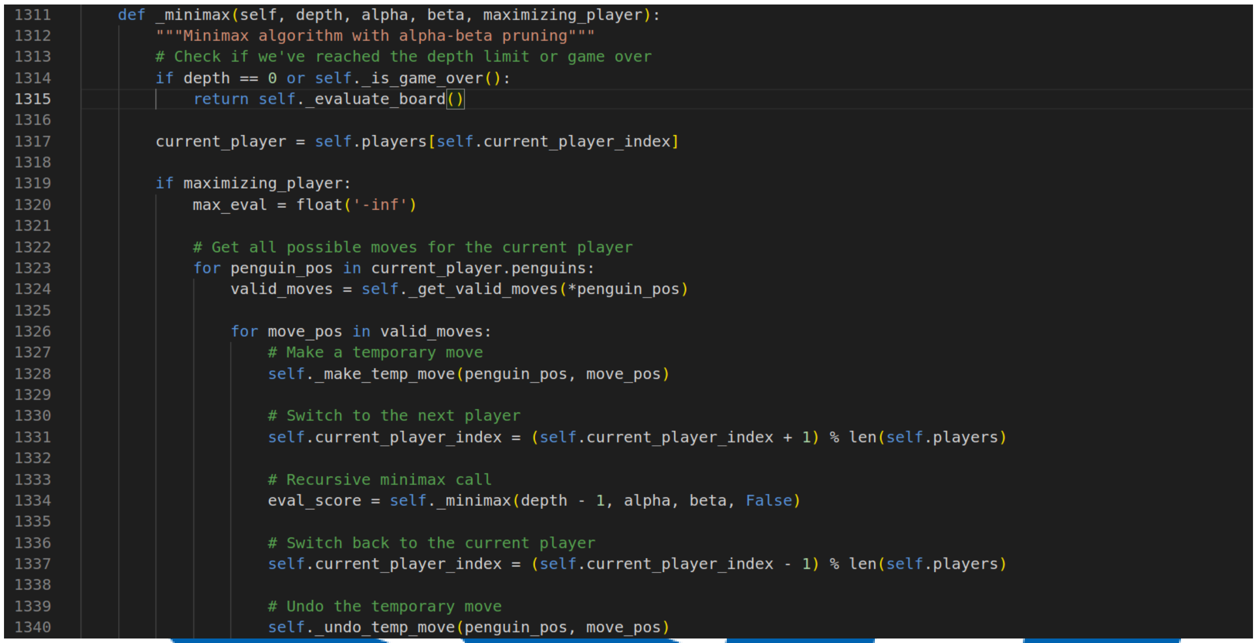
Player 2
Fish: 0
Penguins: 3

Player 3
Fish: 0
Penguins: 3

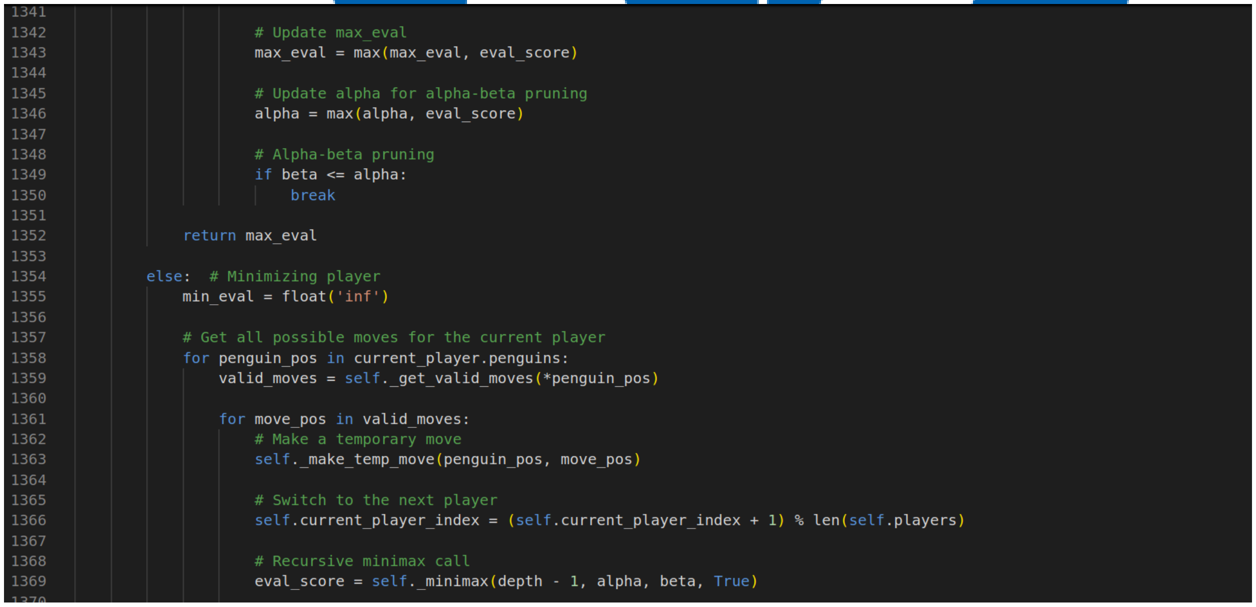
MOVE HISTORY

Move in straight lines only - no jumping over obstacles!

Code Snippet 1: Minimax Function (Core Logic)

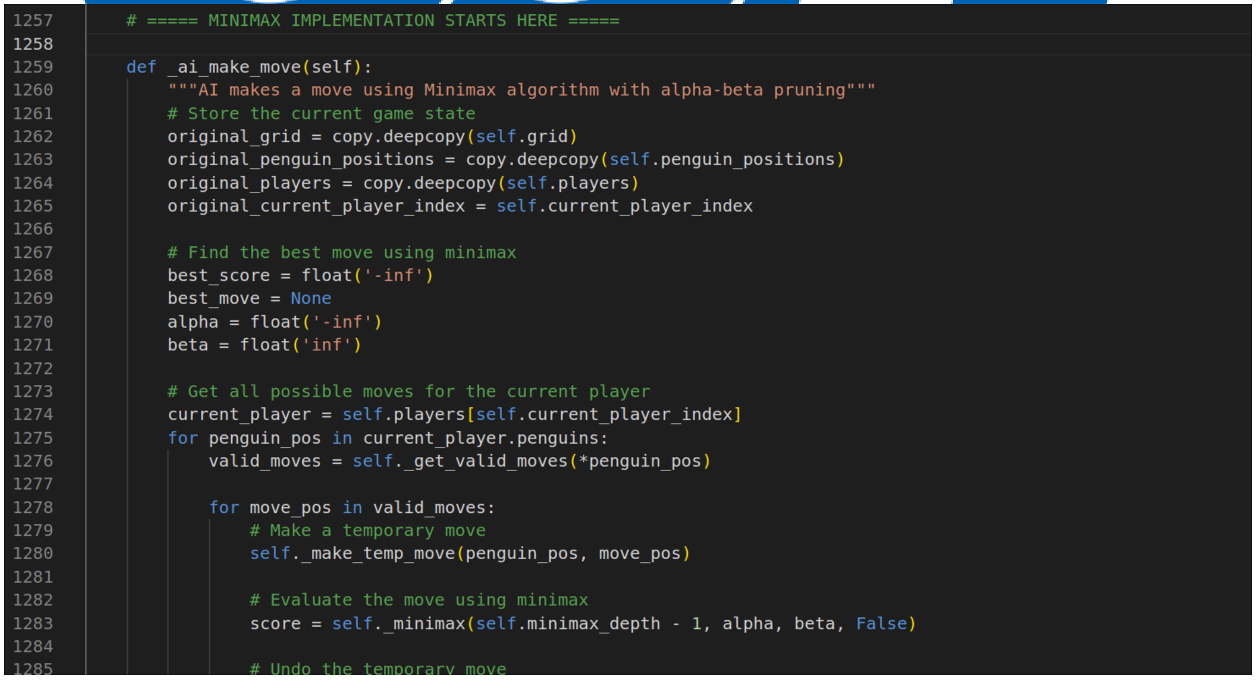


```python
    def _minimax(self, depth, alpha, beta, maximizing_player):
        """Minimax algorithm with alpha-beta pruning"""
        # Check if we've reached the depth limit or game over
        if depth == 0 or self._is_game_over():
            return self._evaluate_board()

        current_player = self.players[self.current_player_index]

        if maximizing_player:
            max_eval = float('-inf')

            # Get all possible moves for the current player
            for penguin_pos in current_player.penguins:
                valid_moves = self._get_valid_moves(*penguin_pos)

                for move_pos in valid_moves:
                    # Make a temporary move
                    self._make_temp_move(penguin_pos, move_pos)

                    # Switch to the next player
                    self.current_player_index = (self.current_player_index + 1) % len(self.players)

                    # Recursive minimax call
                    eval_score = self._minimax(depth - 1, alpha, beta, False)

                    # Switch back to the current player
                    self.current_player_index = (self.current_player_index - 1) % len(self.players)

                    # Undo the temporary move
                    self._undo_temp_move(penguin_pos, move_pos)
```



```python

                    # Update max_eval
                    max_eval = max(max_eval, eval_score)

                    # Update alpha for alpha-beta pruning
                    alpha = max(alpha, eval_score)

                    # Alpha-beta pruning
                    if beta <= alpha:
                        break

            return max_eval

        else:  # Minimizing player
            min_eval = float('inf')

            # Get all possible moves for the current player
            for penguin_pos in current_player.penguins:
                valid_moves = self._get_valid_moves(*penguin_pos)

                for move_pos in valid_moves:
                    # Make a temporary move
                    self._make_temp_move(penguin_pos, move_pos)

                    # Switch to the next player
                    self.current_player_index = (self.current_player_index + 1) % len(self.players)

                    # Recursive minimax call
                    eval_score = self._minimax(depth - 1, alpha, beta, True)
```

Code Snippet 2: Integration of AI Decision in Game Loop



```python
    # ===== MINIMAX IMPLEMENTATION STARTS HERE =====

    def _ai_make_move(self):
        """AI makes a move using Minimax algorithm with alpha-beta pruning"""
        # Store the current game state
        original_grid = copy.deepcopy(self.grid)
        original_penguin_positions = copy.deepcopy(self.penguin_positions)
        original_players = copy.deepcopy(self.players)
        original_current_player_index = self.current_player_index

        # Find the best move using minimax
        best_score = float('-inf')
        best_move = None
        alpha = float('-inf')
        beta = float('inf')

        # Get all possible moves for the current player
        current_player = self.players[self.current_player_index]
        for penguin_pos in current_player.penguins:
            valid_moves = self._get_valid_moves(*penguin_pos)

            for move_pos in valid_moves:
                # Make a temporary move
                self._make_temp_move(penguin_pos, move_pos)

                # Evaluate the move using minimax
                score = self._minimax(self.minimax_depth - 1, alpha, beta, False)

                # Undo the temporary move
```

Chapter 7 Technological Improvement

Technological Improvement

The project has been designed with a focus on both **algorithmic robustness** and **future scalability**. While the core implementation of the Fish Game using the Minimax algorithm already demonstrates strategic gameplay, several technological improvements have been identified and, in some cases, partially implemented to enhance both **performance** and **user experience**.

7.1 Algorithmic Optimization – Alpha–Beta Pruning

A key enhancement was the integration of **Alpha–Beta Pruning** into the Minimax algorithm. This technique effectively prunes branches of the game tree that do not affect the final decision, thereby **reducing the number of evaluated nodes**.

- **Impact:**
  - Significantly **improved computational efficiency**, allowing the AI to **search deeper levels** within the same time constraints.
  - Enabled **smoother real-time gameplay**, as AI response times were reduced.
- **Future Scope:**
  - Further tuning of **depth limits** and pruning strategies based on board size could lead to even

more efficient decision-making, enabling more complex scenarios.

7.2 Adaptive AI Using Machine Learning (Future Enhancement)

While the current AI uses a deterministic Minimax strategy, a future enhancement involves **integrating machine learning techniques** to create an **adaptive AI**.

- **Concept:**
    - The AI would analyze historical game data to identify **human player tendencies**, allowing it to adapt its strategy dynamically.
    - Reinforcement learning or supervised learning models could be trained to **prioritize specific move sequences** based on past outcomes.
- **Expected Benefit:**
    - Improved **strategic variety**, preventing predictable AI behavior.
    - Enhanced challenge for experienced players by adapting over time.

7.3 GUI Enhancements and User Experience Improvements

The current GUI provides a functional representation of the board and gameplay. However, there is scope to **elevate the user experience** through advanced graphical and interactive features.

- **Potential Enhancements:**
  - Implement **smooth animations** for player movements and tile removal to make the game more visually engaging.
  - Integrate **score pop-ups** and turn indicators for better in-game feedback.
  - Add **difficulty selection modes**, allowing players to choose AI depth or heuristic aggressiveness.
- **Expected Outcome:**
  - A more immersive and polished game interface that enhances both educational and entertainment value.

7.4 Online Multiplayer and Networked Gameplay

A significant technological improvement would be to extend the Fish Game into a **multiplayer online platform**, enabling real-time matches between human players over a network.

- **Approach:**
  - Use client-server architecture with WebSockets or REST APIs to synchronize game states between multiple players.
  - Implement **lobby systems**, matchmaking, and leaderboards.
- **Benefits:**
  - Expands the game's reach beyond a single device.
  - Facilitates AI vs AI tournaments and human vs AI matches remotely.
  - Encourages competitive gameplay and collaborative learning environments.

7.5 Code Quality and Extensibility

Beyond functional improvements, the project's codebase has been structured with **modularity and extensibility** in mind. Adopting **clean architecture principles**, such as separating logic from presentation, ensures that future enhancements—like integrating new AI algorithms (e.g., Monte Carlo Tree Search)—can be achieved with minimal refactoring.

Chapter 8 Conclusion

8.1 Summary

The “Fish Game” project was undertaken to design and implement a **strategic, turn-based board game** using **Artificial Intelligence** techniques. The core objective was to enable the AI agent to compete effectively against a human player through **optimal move selection**. To achieve this, the **Minimax algorithm** was adopted due to its proven efficiency in adversarial game scenarios.

During the design phase, significant emphasis was placed on **state-space representation**, **move generation**, and **heuristic evaluation** to ensure strategic decision-making. The algorithm explores the game tree to evaluate possible future moves, enabling the AI to **maximize its fish collection score while minimizing the opponent’s potential gains**.

Further, **Alpha–Beta pruning** was integrated to reduce the branching factor and optimize computational performance. This enhancement allowed the AI to evaluate **deeper move levels** within real-time constraints, resulting in a **smooth gameplay experience** even on moderate hardware configurations.

Test scenarios involved AI competing against both random-move bots and human players. Across multiple simulations:

- The AI consistently outperformed the random bot, achieving **an average score margin of 30–45% higher**.
- Against human players, it demonstrated strategic depth, often **blocking opponent moves** and **prioritizing high-value tiles**, validating the correctness of the Minimax logic and heuristic evaluation.

8.2 Lessons Learned

The development process highlighted several critical insights:

- **Algorithmic Understanding:** Implementing Minimax and Alpha–Beta pruning deepened understanding of **tree search techniques** and **heuristic design**.
- **Game Design Complexity:** Handling board state updates, turn management, and move legality required meticulous design to avoid logical errors.
- **Performance Tuning:** Balancing algorithmic depth with computation time is crucial to maintain **real-time interactivity**.
- **Team Collaboration:** Working on different modules (AI logic, GUI, input handling) emphasized the

importance of **modular code structure** and **version control** for smooth integration.

8.3 Future Enhancements

Potential avenues for future work include:

- Incorporating **Reinforcement Learning** to enable adaptive AI strategies.
- Expanding to **networked multiplayer gameplay** with remote connectivity.
- Introducing **multiple difficulty levels** and enhanced GUI effects to broaden the user base.
- Exploring **Monte Carlo Tree Search (MCTS)** as an alternative AI approach for larger boards.

Chapter 9
References

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