Project #1 Tic-Tac-Toe
CP468-Artificial Intelligence
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Overview

- Implement the Minimax Algorithm: Develop a recursive decision-making process to determine optimal moves in an adversarial game environment.
- Enhance with Alpha-Beta Pruning: Improve efficiency by pruning suboptimal branches in the Minimax decision tree to reduce computational overhead.
- Integrate Gemini API: Use the Gemini API to play against advanced AI agents and evaluate performance under real-time decision-making.
- Compare Algorithm Performance: Measure and compare the execution time, node evaluations, and win rates of Minimax, Alpha-Beta Pruning, and Gemini agents.
- Analyze Scalability: Evaluate how the algorithms perform as game complexity increases, such as moving from 3x3 to larger grids (e.g., 5x5).

Design

<u>Game Representation:</u>

- The Tic-Tac-Toe board is modelled as a 3x3 grid using a 2D list.
- Each cell holds one of three possible values:
  - 'X' for Player 1
  - 'O' for Player 2
  - None or '-' for empty cell

<u>Turn-Based Agent Setup:</u>

- The game alternates turns between two agents:
  - One uses Minimax or Alpha-Beta Pruning
  - The other can be controlled via the Gemini API
- Logic is structured to simulate real-time gameplay decisions.

<u>Heuristics:</u>

- A basic utility evaluation is used:
  - +10 for a win
  - -10 for a loss
  - 0 for a draw
- Heuristics are only applied at terminal states since Tic-Tac-Toe is a simple game.

<u>Recursive Minimax Structure:</u>

- Minimax uses a recursive depth-first approach to simulate every possible future game state.
- The algorithm chooses the move that maximizes or minimizes the player's score depending on whose turn it is.

<u>Alpha-Beta Pruning Optimization:</u>

- Alpha-beta pruning reduces computational time by cutting off branches of the game tree that won't influence the final decision.
- This allows a deeper look ahead within the same time constraints.

<u>Modular Code Design:</u>

- Code is organized into separate modules for:
  - Game logic
  - AI algorithms (Minimax & Alpha-Beta)
  - Gemini API communication
- This modular design improves maintainability and debugging.

Algorithm Analysis

Minimax Algorithm

The Minimax algorithm is a decision-making algorithm used in turn-based, perfect-information games (like Tic-Tac-Toe, Chess, etc.). It explores all possible future moves and chooses the optimal move for the maximizing player while assuming that the opponent plays optimally.

Pseudocode

```
function MINIMAX(board, player, maximizingPlayer):
  if game_over(board):
    return get_utility(board, maximizingPlayer)

  if player == maximizingPlayer:
    best_score = -∞  # Maximizing player wants the highest score
    for move in get_possible_moves(board):
      new_board = apply_move(board, move, player)
      score = MINIMAX(new_board, switch_player(player), maximizingPlayer)
      best_score = max(best_score, score)
    return best_score
  else:
    best_score = +∞  # Minimizing player wants the lowest score
    for move in get_possible_moves(board):
      new_board = apply_move(board, move, player)
      score = MINIMAX(new_board, switch_player(player), maximizingPlayer)
      best_score = min(best_score, score)
    return best_score
```

Logic

1. Base Case: If the game is over, return the utility value:

Win → +1 (for maximizing player)

Loss → -1 (for maximizing player)

Draw → 0

2. Recursive Case:

   - If it's the maximizing player's turn, find the move that gives the highest possible score.
   - If it's the minimizing player's turn, find the move that gives the lowest possible score.

3. The recursion continues until a terminal state (win/loss/draw) is reached.

4. The algorithm propagates the best score back up the tree to determine the optimal move.

<u>Alpha-Beta Pruning</u>

Alpha-Beta Pruning is an optimization of Minimax that eliminates unnecessary calculations. It maintains two values:

- Alpha (α): The best (maximum) score that the maximizing player can guarantee.
- Beta (β): The best (minimum) score that the minimizing player can guarantee.

If at any point Beta ≤ Alpha, further exploration of that branch is pruned (skipped) since it's not beneficial.

Pseudocode

```
function ALPHA_BETA_MINIMAX(board, player, maximizingPlayer, α, β):
  if game_over(board):
    return get_utility(board, maximizingPlayer)

  if player == maximizingPlayer:
    best_score = -∞
    for move in get_possible_moves(board):
      new_board = apply_move(board, move, player)
      score = ALPHA_BETA_MINIMAX(new_board, switch_player(player), maximizingPlayer, α,
β)
      best_score = max(best_score, score)
      α = max(α, best_score)
      if β ≤ α:
        break  # Beta cutoff (prune)
    return best_score
  else:
    best_score = +∞
    for move in get_possible_moves(board):
      new_board = apply_move(board, move, player)
      score = ALPHA_BETA_MINIMAX(new_board, switch_player(player), maximizingPlayer, α,
β)
      best_score = min(best_score, score)
      β = min(β, best_score)
      if β ≤ α:
        break  # Alpha cutoff (prune)
    return best_score
```

Logic

1. Alpha (α) represents the best choice for the MAX player.
2. Beta (β) represents the best choice for the MIN player.
3. If at any point:
    - The minimizing player finds a move worse than what the maximizing player can already guarantee, the rest of the branch is ignored.

- The maximizing player finds a move better than what the minimizing player can allow, the rest of the branch is ignored.

4. This significantly reduces the number of nodes that need to be explored.

Gemini API

<u>Integration</u>

1. API Key Configuration

```
import google.generativeai as genai
genai.configure(api_key="YOUR_API_KEY")
```

- The API key is required to authenticate requests.
- Replace YOUR_API_KEY with a valid Gemini API key.

2. AI Agent Function (gemini_algo)

```
def gemini_algo(board, player)
```

- The function gemini_algo() acts as the AI agent.
- It first fetches possible moves using functions.get_possible_moves(board).
- A fallback move (best_move) is selected in case of API failure.

3. Board Representation for Gemini API

```
  symbols = {0: " ", 1: "X", 2: "O"}
   board_desc = "\n".join("|".join(symbols[cell] for cell in row) + "\n" + "-" * (board_size * 2 -1)
      for row in board
   )
```

- The board state is converted into a readable format using symbols (X, O, and spaces).
- It is structured as a multi-line string representing the Tic-Tac-Toe board.

4. Constructing the Prompt for Gemini API

```
  prompt = f"""You are Player {symbols[player]} in a {board_size}x{board_size} Tic-Tac-Toe game.
Current Board (0-based indices):
{board_desc}
Valid moves: {possible_moves}
Return ONLY the zero-based row and column as two numbers between 0-{board_size-1},
formatted exactly like: 'row,column' with no other text.
Examples of valid responses: '0,1' or '{board_size-1},{board_size-1}'"""
```

- The **prompt clearly instructs** Gemini to:
    1. Identify the current player.
    2. Analyze the board state.
    3. Return a move in **'row,col'** format **without any extra text**.

5. Sending the Request to Gemini API

```
model = genai.GenerativeModel('gemini-2.0-pro-exp')
 response = model.generate_content(prompt)
```

- Uses genai.GenerativeModel('gemini-2.0-pro-exp') to interact with Gemini.
- Sends the prompt and retrieves the AI's response.

6. Parsing Gemini's Response

```
def parse_gemini_response(text):
    clean_text = re.sub(r'[^0-9,]', '', text)
    matches = re.findall(r'\d', clean_text)

    if len(matches) >= 2:
        return int(matches[0]), int(matches[1])
    raise ValueError("Invalid response format")
```

- Removes any unwanted characters from the response.
- Extracts numbers representing the row and column indices.
- Ensures that the response is properly formatted.

7. Validating the AI Move

```
row, col = parse_gemini_response(response.text)

 if not (0 <= row < board_size and 0 <= col < board_size):
    raise ValueError("Move out of bounds")

 if not functions.is_valid_move(board, row, col):
    raise ValueError("Invalid move")

 return (row, col)
```

- Ensures the AI-generated move is **within the board bounds**.
- Calls functions.is_valid_move(board, row, col) to verify move legality.
- Returns the move if valid; otherwise, an exception is raised.

2. Handling Errors and Fallback Mechanism

```
except Exception as e:
    print(f"Gemini error: {str(e)[:50]}... Using fallback move.")
    return best_move
```

- If the Gemini API response is invalid or an error occurs, the agent falls back to a **preselected move** from possible_moves.

Agent Configuration and Execution

1. Tracking API Calls

```
def get_gemini_calls():
  return _gemini_calls
```

- The number of API calls is tracked globally using `_gemini_calls`.

2. Game Logic Integration

- The AI agent (gemini_algo) is used within the game framework along with Minimax and Alpha-Beta Pruning strategies.
- The final move selection process depends on the **game settings** (e.g., AI vs. AI, Human vs. AI).

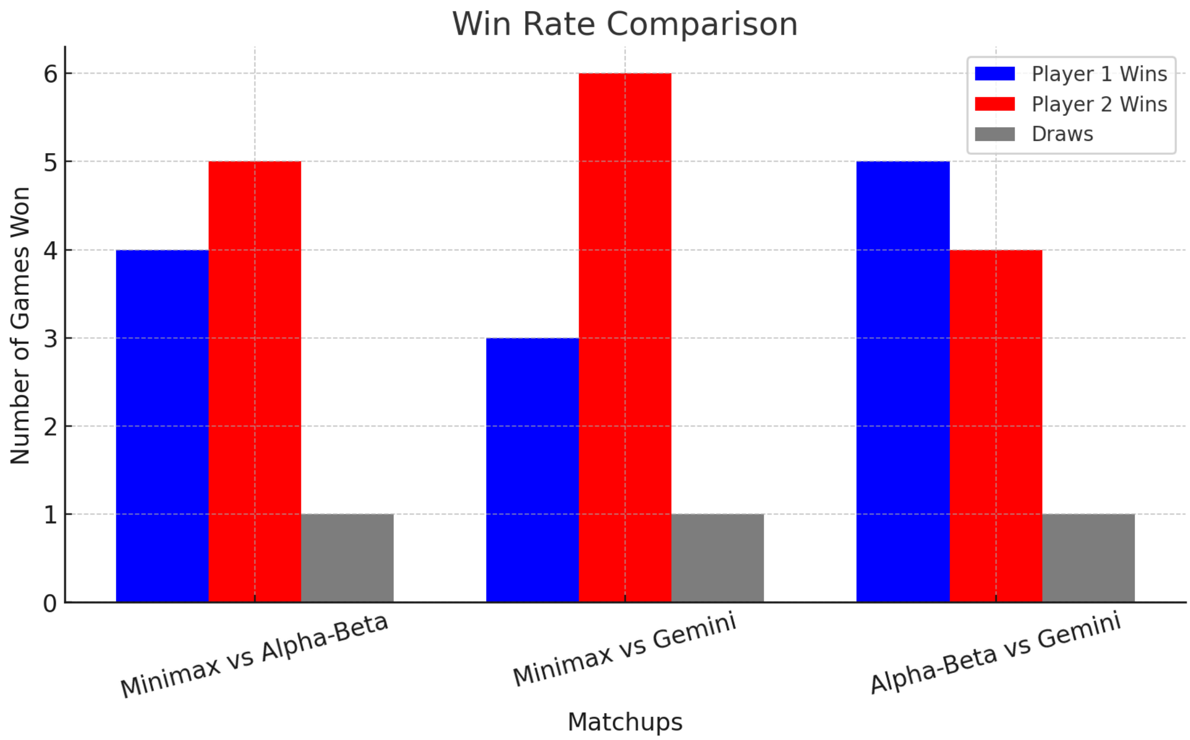
Testing

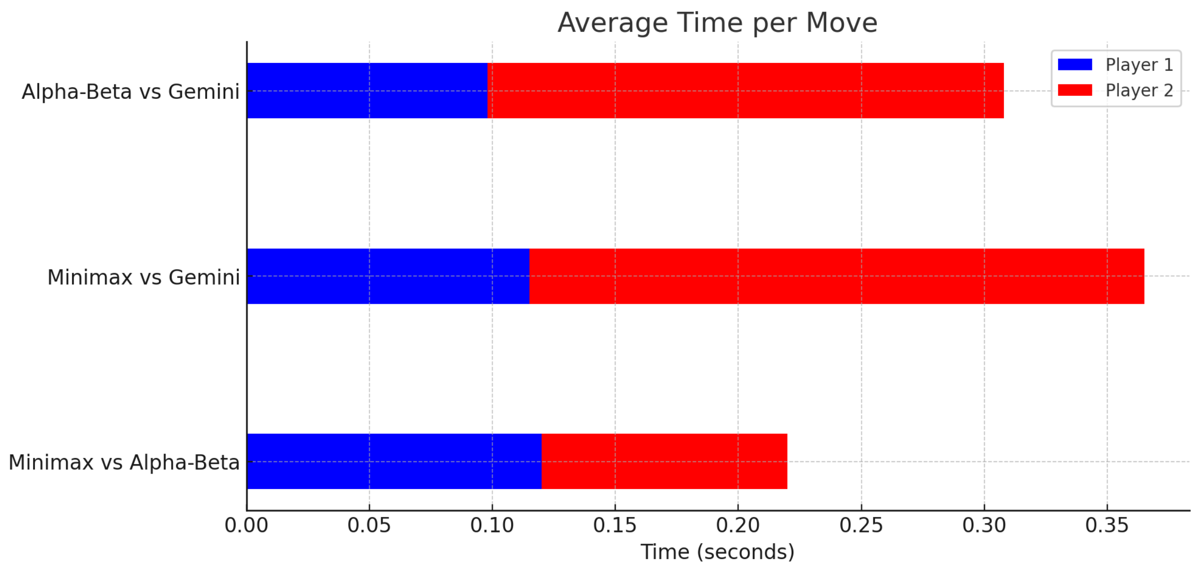
To effectively analyze the **performance results**, we generated tables and graphs to compare:

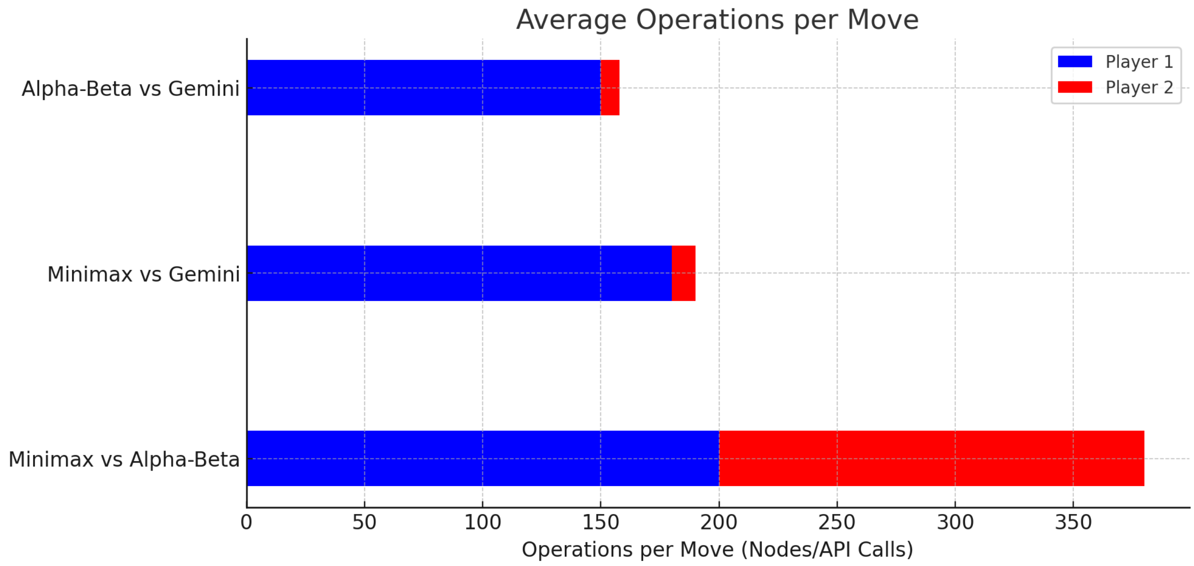
1. **Average Time per Move**

2. **Average Operations (Nodes/API Calls) per Move**

3. **Win Rate Comparisons**


Win Rate Comparison
Number of Games Won
Player 1 Wins
Player 2 Wins
Draws
0
1
2
3
4
5
6
Minimax vs Alpha-Beta
Minimax vs Gemini
Alpha-Beta vs Gemini
Matchups


Average Time per Move
Player 1
Player 2
Alpha-Beta vs Gemini
Minimax vs Gemini
Minimax vs Alpha-Beta
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
Time (seconds)



Here are the visualized **performance results**:

1. **Win Rate Comparison:**
   - Alpha-Beta performs slightly better than Minimax in direct comparison.
   - Gemini-based AI tends to outperform Minimax but is slightly weaker against Alpha-Beta.
   - Draw rates are relatively low.
2. **Average Time per Move:**
   - Minimax and Alpha-Beta have similar response times.
   - Gemini-based AI takes significantly longer, likely due to API calls.
3. **Average Operations per Move:**
   - Minimax and Alpha-Beta process hundreds of nodes per move.
   - Gemini AI makes far fewer API calls, indicating efficient decision-making but at a higher time cost.