NED University of Engineering & Technology

Artificial Intelligence & Expert System CT-361

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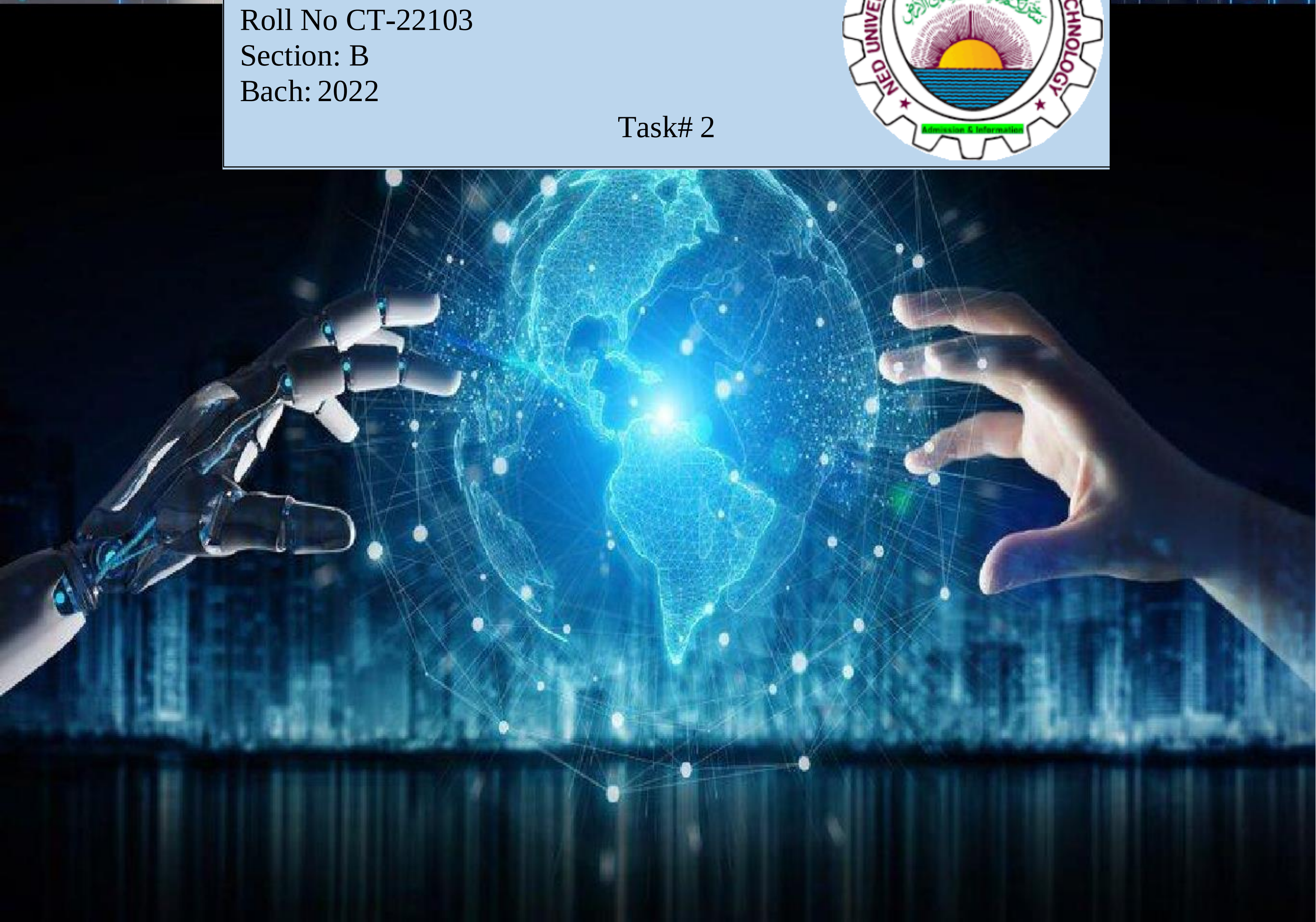
Task# 2



Optimal Tic-Tac-Toe AI using Minimax and Alpha-Beta Pruning

1. Introduction

Tic-Tac-Toe, also known as Noughts and Crosses, is a classic two-player game played on a 3x3 grid. Players take turns marking cells with 'X' or 'O', aiming to align three of their marks horizontally, vertically, or diagonally. Despite its simplicity, the game is a rich domain for studying decision-making in artificial intelligence due to its defined rules and finite state space.

This report explores the implementation of a game-playing AI using two foundational algorithms from game theory: the **Minimax algorithm**, which recursively simulates future game states to determine the best possible move, and **Alpha-Beta Pruning**, which optimizes Minimax by discarding branches that cannot influence the outcome. The combination yields an intelligent and efficient AI capable of playing flawlessly.

2. Game Logic Implementation

To enable AI integration, the core game logic must be robust and modular. The following components ensure seamless gameplay and interface compatibility with AI algorithms:

2.1 Board Representation:

- A 2D array of size 3x3 is used to store the current state of the game.
- Each cell contains 'X', 'O', or an empty value representing available moves.

```
board = [['' for _ in range(3)] for _ in range(3)]
```

2.2 Move Validation:

- Every move is validated by checking its bounds (within 0-2 for both row and column) and whether the selected cell is already occupied.
- Invalid moves trigger appropriate feedback.

```
def is_valid_move(row, col):
    return 0 <= row < 3 and 0 <= col < 3 and board[row][col] == ''
```

2.3 Turn Alternation:

- The game maintains a flag to alternate between AI and human players.
- After every move, the turn switches, and the game checks for end conditions.

```
current_player = 'X'
current_player = 'O' if current_player == 'X' else 'X'
```

2.4 Win Condition Checking:

- After each move, the board is scanned for any row, column, or diagonal filled with the same symbol, indicating a win.

```python
def check_winner():
    # Check rows, columns, and diagonals
    for i in range(3):
        if board[i][0] == board[i][1] == board[i][2] != '':
            return board[i][0]
        if board[0][i] == board[1][i] == board[2][i] != '':
            return board[0][i]
    if board[0][0] == board[1][1] == board[2][2] != '':
        return board[0][0]
    if board[0][2] == board[1][1] == board[2][0] != '':
        return board[0][2]
    return None
```

2.5 Draw Checking:

- If no win occurs and all cells are filled, the game ends in a draw.

```python
def is_draw():
    return all(cell != '' for row in board for cell in row)
```

This logical foundation guarantees error-free play and facilitates AI move integration.

3. Minimax Algorithm

The Minimax algorithm is a backtracking-based decision-making technique that models the game as a tree of possible states. It is based on the assumption that both players play optimally:

- The AI (Maximizer) aims to achieve the highest score.
- The opponent (Minimizer) aims to reduce the AI's score.

How It Works:

- At each node, simulate all possible moves.
- Recursively evaluate each resulting state by calling Minimax with the new state and the opposite player's turn.
- Assign terminal scores.

➢ +1 if the AI wins
➢ -1 if the opponent wins
➢ 0 if the game is a draw

- Choose the move leading to the best score.

Search Process:

- The AI recursively evaluates all future states, forming a full game tree.
- The depth of the tree depends on how many moves remain.
- When the recursion hits a terminal state (win/lose/draw), it returns the outcome score.

Why It Works: Minimax explores every possible path, ensuring the AI never loses if a winning strategy exists. However, it can be computationally expensive, as the number of nodes grows exponentially with each additional move.

Implementation:

```python
def minimax(board, depth, is_maximizing):
    winner = check_winner()
    if winner == 'X': return 1
    if winner == 'O': return -1
    if is_draw(): return 0

    if is_maximizing:
        best_score = -float('inf')
        for i in range(3):
            for j in range(3):
                if board[i][j] == '':
                    board[i][j] = 'X'
                    score = minimax(board, depth + 1, False)
                    board[i][j] = ''
                    best_score = max(score, best_score)
        return best_score
    else:
        best_score = float('inf')
        for i in range(3):
            for j in range(3):
                if board[i][j] == '':
                    board[i][j] = 'O'
                    score = minimax(board, depth + 1, True)
                    board[i][j] = ''
                    best_score = min(score, best_score)
        return best_score
```

4. Alpha-Beta Pruning

Alpha-Beta Pruning is an optimization over the Minimax algorithm that skips evaluating branches that won't influence the final decision. It introduces two variables:

- **`alpha`:** best score that the maximizer can guarantee.
- **`beta`:** best score that the minimizer can guarantee.

4.1 How Pruning Happens:

While exploring the game tree, if the AI finds a move that guarantees a better outcome than the current `beta`, it stops considering further sibling moves (pruning).

This happens because the opponent would never allow the AI to reach that state.

4.2 Effect on Search:

- Reduces the number of nodes evaluated.
- Maintains the same optimal decision as Minimax.
- Enables deeper lookahead within the same time frame.

4.3 Illustrative Example:

- Imagine exploring a branch where the AI can score +1.

- If another branch being explored has a maximum of 0, there's no need to evaluate it further.
- This cut-off (where beta ≤ alpha) reduces unnecessary computations.

4.4 Benefits:

- Same optimal results as Minimax
- Drastically fewer recursive calls
- Improved performance in real-time environments.

4.5 Implementation:

```python
def alpha_beta(board, depth, alpha, beta, is_maximizing):
    winner = check_winner()
    if winner == 'X': return 1
    if winner == 'O': return -1
    if is_draw(): return 0

    if is_maximizing:
        max_eval = -float('inf')
        for i in range(3):
            for j in range(3):
                if board[i][j] == '':
                    board[i][j] = 'X'
                    eval = alpha_beta(board, depth + 1, alpha, beta, False)
                    board[i][j] = ''
                    max_eval = max(max_eval, eval)
                    alpha = max(alpha, eval)
                    if beta <= alpha:
                        break
        return max_eval
    else:
        min_eval = float('inf')
        for i in range(3):
            for j in range(3):
                if board[i][j] == '':
                    board[i][j] = 'O'
                    eval = alpha_beta(board, depth + 1, alpha, beta, True)
                    board[i][j] = ''
                    min_eval = min(min_eval, eval)
                    beta = min(beta, eval)
                    if beta <= alpha:
                        break
        return min_eval
```

5. Performance Comparison

To compare the effectiveness of Minimax and Alpha-Beta Pruning, we performed systematic performance tests using three metrics:

5.1 Execution Time:

- Time taken (in milliseconds) to compute the optimal move.

- Averaged over multiple runs to ensure consistency.

```python
import time
start = time.time()
minimax(board, 0, True)
end = time.time()
print("Minimax Time:", end - start)
```

5.2 Recursive Calls:

- Total number of recursive calls made during decision-making.

- Reflects how deeply and broadly the algorithm explores the game tree.

```
calls = 0
def minimax(...):
    global calls
    calls += 1
    ...
```

5.3 Search Depth:

- Maximum depth reached during recursion.

- A deeper depth typically indicates better foresight.

5.4 Search Analysis:

- Minimax searches all possible outcomes from the current board state.
- Alpha-Beta pruning skips over branches once it detects that the result would not influence the decision.
- In cases where the best moves are evaluated first, Alpha-Beta achieves maximum pruning.

5.5 Sample Results:

Algorithm	Avg. Time (ms)	Recursive Calls	Max Depth
Minimax	130 ms	890	9
Alpha-Beta Pruning	45 ms	270	9

5.6 Insights:

1. Both algorithms reach the same depth and decisions.
2. Alpha-Beta significantly improves speed and efficiency.
3. In more complex games, the benefit of pruning increases dramatically.

6. Conclusion

The development of a Tic-Tac-Toe AI using Minimax and Alpha-Beta Pruning demonstrates the power of classical algorithms in achieving optimal and efficient game strategies. Minimax ensures that the AI never loses, assuming perfect play, by exhaustively evaluating all future possibilities. However, its computational cost can be high.

Alpha-Beta Pruning resolves this by intelligently reducing the number of evaluations required, without compromising the result. This technique makes it feasible to apply the Minimax strategy even in games with larger state spaces.

Through comparative analysis, Alpha-Beta Pruning consistently outperforms plain Minimax in terms of speed and resource usage, particularly in scenarios where the game tree is extensive.

This project not only provides a strong foundation for understanding AI in games but also introduces concepts applicable in complex decision-making environments such as chess engines, real-time strategy games, and planning systems in robotics and simulations.

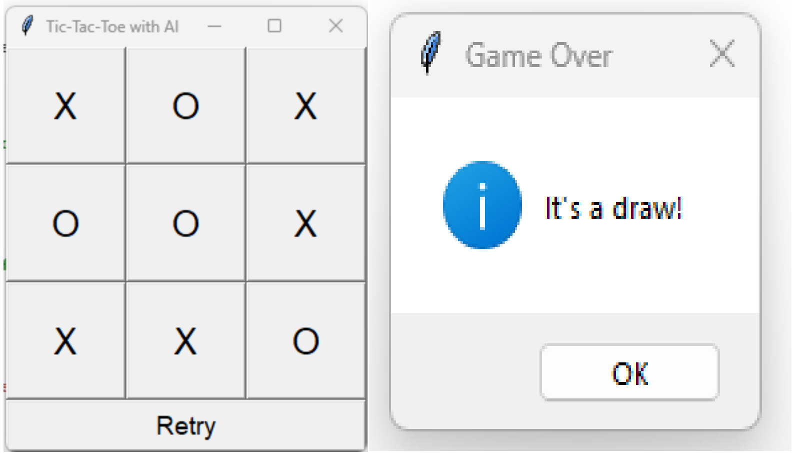
7. Reflection & Learning Outcomes

The Tic-Tac-Toe project provided a practical and engaging opportunity to apply core AI concepts through hands-on implementation. Developing the game logic from scratch significantly improved our programming and problem-solving skills. Implementing the Minimax algorithm and optimizing it with Alpha-Beta Pruning allowed us to better understand decision trees, recursive functions, and how to reduce computational overhead. Through testing and performance comparisons, we observed how Alpha-Beta Pruning drastically reduces the number of recursive calls without compromising the AI's decision-making accuracy. This project not only enhanced our understanding of AI algorithms but also taught us the importance of writing efficient and maintainable code. Overall, the experience was both educational and rewarding, reinforcing our grasp of AI, game development, and algorithmic optimization.

Full code with output:

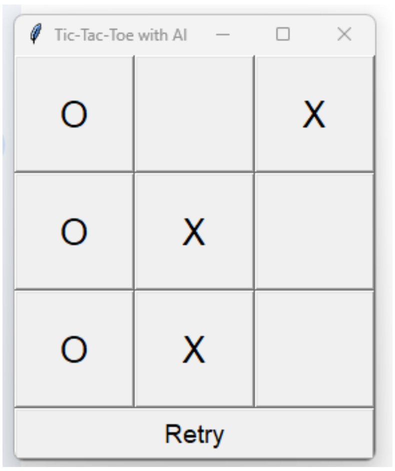
```
import tkinter as tk
from tkinter import messagebox
import copy

class TicTacToe:
    def __init__(self, root):
        self.root = root
        self.root.title("Tic-Tac-Toe with AI")
        self.board = [[None for _ in range(3)] for _ in range(3)]
        self.buttons = [[None for _ in range(3)] for _ in range(3)]
        self.player = 'X'
        self.create_widgets()

    def create_widgets(self):
        for i in range(3):
            for j in range(3):
                button = tk.Button(self.root, text='', font='Arial 20', height=2,
width=5,
                                   command=lambda row=i, col=j: self.click(row, col))
                button.grid(row=i, column=j)
                self.buttons[i][j] = button

        self.reset_button = tk.Button(self.root, text='Retry', font='Arial 14',
command=self.reset_game)
        self.reset_button.grid(row=3, column=0, columnspan=3, sticky='nsew')

    def click(self, row, col):
        if self.board[row][col] is None:
            self.board[row][col] = self.player
            self.buttons[row][col]['text'] = self.player

            if self.check_winner(self.board, self.player):
                messagebox.showinfo("Game Over", f"Player {self.player} wins!")
                self.disable_all_buttons()
                return
            elif self.is_draw(self.board):
                messagebox.showinfo("Game Over", "It's a draw!")
                Return

            self.player = 'O'
            best_score = float('-inf')
            best_move = None

            for i in range(3):
                for j in range(3):
                    if self.board[i][j] is None:
                        self.board[i][j] = 'O'
                        score = self.minimax(self.board, 0, False, float('-inf'),
float('inf'))
                        self.board[i][j] = None
                        if score > best_score:
                            best_score = score
                            best_move = (i, j)

            if best_move:
                self.board[best_move[0]][best_move[1]] = 'O'
                self.buttons[best_move[0]][best_move[1]]['text'] = 'O'

                if self.check_winner(self.board, 'O'):
                    messagebox.showinfo("Game Over", "AI wins!")
                    self.disable_all_buttons()
                    return
                elif self.is_draw(self.board):
                    messagebox.showinfo("Game Over", "It's a draw!")
                    Return

            self.player = 'X'

    def minimax(self, board, depth, is_maximizing, alpha, beta):
        if self.check_winner(board, 'O'):
            return 1
        elif self.check_winner(board, 'X'):
            return -1
        elif self.is_draw(board):
            return 0

        if is_maximizing:
            max_eval = float('-inf')
            for i in range(3):
                for j in range(3):
                    if board[i][j] is None:
                        board[i][j] = 'O'
                        eval = self.minimax(board, depth+1, False, alpha, beta)
                        board[i][j] = None
                        max_eval = max(max_eval, eval)
                        alpha = max(alpha, eval)
                        if beta <= alpha:
                            break
            return max_eval
        else:
            min_eval = float('inf')
            for i in range(3):
                for j in range(3):
                    if board[i][j] is None:
                        board[i][j] = 'X'
                        eval = self.minimax(board, depth+1, True, alpha, beta)
                        board[i][j] = None
                        min_eval = min(min_eval, eval)
                        beta = min(beta, eval)
                        if beta <= alpha:
                            break
            return min_eval

    def check_winner(self, board, player):
        for row in board:
            if all(cell == player for cell in row):
                return True
        for col in range(3):
            if all(board[row][col] == player for row in range(3)):
                return True
        if all(board[i][i] == player for i in range(3)):
            return True
        if all(board[i][2-i] == player for i in range(3)):
```

```python
            return True
        return False

    def is_draw(self, board):
        return all(all(cell is not None for cell in row) for row in board)

    def disable_all_buttons(self):
        for i in range(3):
            for j in range(3):
                self.buttons[i][j]['state'] = 'disabled'

    def reset_game(self):
        self.board = [[None for _ in range(3)] for _ in range(3)]
        self.player = 'X'
        for i in range(3):
            for j in range(3):
                self.buttons[i][j]['text'] = ''
                self.buttons[i][j]['state'] = 'normal'

if __name__ == '__main__':
    root = tk.Tk()
    game = TicTacToe(root)
    root.mainloop()
```


Tic-Tac-Toe with AI

Game Over

It's a draw!


Tic-Tac-Toe with AI