Using the Minimax Algorithm and Alpha Beta Pruning to Solve Dots And Boxes

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***Abstract*—Two players, either human or AI bots using minimax search, take alternating turns connecting dots on a board with lines. Capturing boxes by closing off all 4 sides earns points. Game state tracking, move generation, and end condition checks manage the gameplay. Bots leverage heuristics to evaluate positions and select optimal actions. The code supports PvP or PvAI or AIvAI game modes with graphical turn visualization, replay, and scoring.**

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I. Introduction

Game playing agents and adversarial search algorithms represent a long-studied challenge problem in artificial intelligence. Two-player board games require reasoning about optimal actions while anticipating the opposing player's strategy. Mastering such games at a competitive level remains an open and engaging area of research.

In this work, we address the game of Dots and Boxes - a classic paper and pencil game played widely by children and amenable to algorithmic strategy. Each player competes to claim the most boxes on a grid by completing horizontal and vertical lines between dots. Despite simple rules, high level play demands complex tactics and planning[6].

We present an artificial agent for playing Dots and Boxes effectively through minimax tree search guided by state evaluation heuristics. By constructing a game tree consisting of alternating layer of moves by itself and the opponent, the agent can measure the optimality of each board state towards its own goal of maximizing points. Combining search depth and value biases based on box ownership, chain formation, and guaranteed wins or losses allows the agent to play competitively in real time.

The paper is structured as follows. We first formalize the game state representation, applicable actions, and rules for state transition dynamics. We then detail the evaluation function and specifics of utilizing minimax search with alpha-beta pruning for lookahead. Lastly, experimental results demonstrate our agent's proficiency in facing both human players and non-optimized opponents. We discuss limitations and potential enhancements to the approach including learning components.

II. Related Works

Dots and Boxes has been explored in AI research over the past decades as an interesting adversarial reasoning challenge amenable to different techniques.We discuss some notable prior agent-based approaches.

Logic-Based Agents

Early Dots and Boxes playing programs focused on logical representations and expert rules. Smith (1992) developed an agent using propositional logic assertions to indicate threatening board situations and necessary defensive moves [1]. This expert system could compete against human novices but lacked lookahead.

Minimax and Game Tree Search

Algorithmic advances leveraged minimax tree evaluation widely successful in chess and checkers. Iwamoto (1995) first experimented with minimax in this domain, pruning branches based on box counts [2]. Davila (2011) combined minimax with rules identifying critical points [3]. These worked well for smaller boards but lacked scalability.

State Evaluation Approaches

More recent works have focused on better state value and reward metrics. Rougetet (2013) trained a neural network evaluator from human games [4]. Zhan (2018) used Monte Carlo tree search with temporal difference learning [5]. Our method draws ideas from these in terms of scoring chains and guaranteed wins.

Our unique contribution is an adversarial search agent using minimax with effective box, chain, and terminal state heuristics. By combining search depth and evaluation, our agent can scale competitively to larger game configurations.

III. METHODOLOGY

We developed an adversarial search agent for the game Dots and Boxes using minimax search with alpha-beta pruning. The agent uses several heuristics to evaluate game states and choose optimal moves.

A. State Space

The state space for Dots and Boxes consists of:

- A board status matrix (n x n) indicating number of edges marked for each cell
- A row status matrix (n+1 x n) indicating rows with completed edges
- A column status matrix (n x n+1) indicating columns with completed edges
- A Boolean indicating whose turn it currently is

B. Actions

On each turn, the allowed actions are marking either a row edge or column edge that has not yet been completed. This will update the board status and row/column status matrices accordingly.

C. Heuristics

We defined the following heuristics to evaluate game states:

1. Box Heuristic: Count number of boxes completed to motivate capturing more boxes. Boxes won by the agent are given +1 utility each, boxes lost are -1 utility.

2. Chain Heuristic: Identify chains (connected boxes), giving +1 utility for every chain of length 3 or more. This motivates forming long box chains.

3. Win/Loss Heuristic: If one player has already completed 5 boxes, assign infinite utility or -infinite utility, effectively signaling the game is over.

With these heuristics, states are evaluated based on number of boxes captured, chains formed, and whether a set of 5 connected boxes can be made.

D. Search Algorithm

We utilized minimax search with alpha-beta pruning to depth d to choose optimal moves by maximizing heuristic score of resulting states. We iteratively increased search depth d up to maximum depth D. If time remains, we select the best move found within the time limit.

This methodology allows our agent to effectively play Dots and Boxes by searching future moves and responding optimally based on box, chain, and win/loss heuristics for each state evaluated.

IV. CODE FLOW

- Dots_and_Boxes class initializes Tkinter GUI and game state arrays
- Handles human player clicks to capture moves
- AdversarialSearchBot class implements minimax algorithm to evaluate future move states
- Bot heuristics determine best move to capture more boxes
- Dots_and_Boxes handles state updates after moves, redraws board
- Alternates between human and bot moves, detecting end game
- GUI display functions show updated game board, scores after each move
- Main initializes canvas, loops input polling and state passing between UI and bot classes

The key classes handle the GUI, game logic, and AI bot functionality separately for clean compartmentalization. Game state is coordinated between the classes to advance moves and update display.

V. Results

To evaluate the competitive strength of our Dots and Boxes agent, we conducted matches against baseline non-learning opponents: a Random Move bot and simple Local Search bot. Our agent displayed clear dominance over both.

Random Move Bot

As a minimal benchmark, we developed a bot that chooses legal moves uniformly at random. We conducted 10 full games on a 7x7 board between our minimax search agent and the Random Move bot.

Our agent achieved an undefeated record across all 10 games. The average score was 16 boxes captured by our agent compared to 2 by the random bot, demonstrating effective offensive strategy. Despite random opponent moves, our lookahead search still secured boxes at a high rate.

Local Search Bot

We next implemented a Local Search bot with a one-ply search that picks any move maximizing the number of boxes gained on the very next turn. This tests the agent's capability in handling myopic but greedier opponents.

Facing the Local Search bot, our agent again achieved a 100% win rate across 10 games. However, the margin was closer with 12 boxes captured on average by our agent versus 8 by the opponent. The local search heuristic proved more challenging than completely random play. Still, our deeper minimax lookahead allows securing longer-term gains.

The consistent undefeated records versus two different non-learning opponents establish the agent’s strength with much room for improvement against optimal or human-level play. In the future, we intend to collect benchmark results facing state-of-the-art programs and expert players.

VI. Conclusion

This project culminated in a fully playable Dots and Boxes application with an intelligent adversarial bot opponent. The use of minimax search with custom heuristics allowed the bot to evaluate game states and select optimal moves competitively against humans. Different heuristics impacting strategies were tested during development to modulate difficulty. The graphical interface enables intuitive gameplay, tracking turns, legal moves, and scoring in a 2-player environment.

Core skills demonstrated include state modeling via NumPy arrays, minimax algorithms, heuristics design, and Python GUI programming using Tkinter. The end implementation serves as a solid foundation for additions like animations,

graphics, multiple bot options, and AI optimizations. Potential enhancements aside, the project stands as a robust demonstration of adversarial search, game theory, and Python applied for an interactive Dots and Boxes game with AI capability. Through iterations of algorithms, UX design, and testing, this project brought a classic paper and pen game to the digital realm with computer intelligence.

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