CSE 318 Assignment 3: Report on Chain Reaction game

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Introduction

This report presents an evaluation of the **Chain Reaction** game developed for the CSE 318 Assignment-03. Played on a 6×9 grid, the game features two players—Red and Blue—who take turns placing orbs to initiate chain reactions, with the ultimate goal of eliminating all of the opponent's orbs. It evaluates the performances of customized heuristics used in an AI-based version of the game. The game supports four gameplay modes:

- Human vs Human (implemented initially for debugging and testing)
- Human vs AI
- AI vs AI
- AI vs Random Move agent

The AI players operate using the *Minimax algorithm* with alpha-beta pruning, a common adversarial search method that explores possible future moves to determine the optimal action by maximizing AI's advantage while minimizing the opponent's potential. The random agent chooses from the set of legal moves uniformly at random. Human players make decisions manually.

Experimental Setup

The experiments were conducted using the following setup:

- **Search Depth:** Fixed at 3 for all AI moves.
- **AI move Time Limit:** 4 seconds. If an AI exceeds this, a random legal move is chosen instead.
- **Games Played:** Each heuristic played multiple matches against either a human, another AI, or a random agent.
- **Data Recorded:** Heuristic used, number of wins, total games played, win rate, opposing heuristics defeated, duration of each game, and the average duration (in seconds). It is important to note that all data was collected from AI vs AI matches to optimize both author's time and energy.

1 Heuristic Rationales

The following heuristics, implemented in `heuristics.py`, are designed to capture strategic aspects of Chain Reaction. Heuristics 2, 4, 6, and 9 are intentionally designed to favor human players for comparative analysis.

1.1 Core Heuristics

- **h1 (Orb Count Differential)**:
  - **Goal**: Maximize the AI's orb count advantage
  - **Calculation**: $\sum(AI orbs) - \sum(Opponent orbs)$
  - **Purpose**: Fundamental material advantage strategy, has 66.7% win rate. Performs best in early-game when board control is fluid.
- **h3 (Corner Control)**:
  - **Goal**: Dominate corner positions
  - **Calculation**: Base score + 2 for corner cells
  - **Purpose**: Corners provide stable positions with only 2 critical mass points. Our data shows this heuristic achieved 100% win rate (9/9 games).

1.2 Positional Variants

- **h5 (Edge Control)**:
  - **Goal**: Control board edges
  - **Calculation**: Base score + 1 for edge cells (non-corners)
  - **Purpose**: Edges have 3 critical mass points - easier to defend than center but more flexible than corners. But 44.4% win rate proves it to be a mediocre strategy.
- **h7 (Composite Control)**:
  - **Goal**: Combine corner and edge advantages
  - **Calculation**: +2 for corners, +1 for edges
  - **Purpose**: Hybrid strategy that achieved 89% win rate. Optimal balance between stability (corners) and flexibility (edges).

1.3 Specialized Heuristics

- **h8 (Aggressive Dominance)**:
  - **Goal**: Maximize both orb count and positional advantage while punishing opponent's position
  - **Calculation**:
    * Base score + count for owned orbs
    * +1 for edge cells, +2 for corners
    * -1 for opponent's edge cells, -2 for opponent's corners

- **Purpose**: Aggressive strategy that achieved 55.6% win rate. Attacks opponent's strong positions while building own advantage. Game durations averaged 87.08s, indicating balanced pacing between aggression and control. Not as competent as expected.

- **h10 (Adaptive Control)**:
  - **Goal**: Dynamic balance between material and positional advantage
  - **Calculation**:
    - Base score + count for owned orbs
    - +1 for edges, +2 for corners
    - -0.5 for opponent's edges, -1 for opponent's corners
  - **Purpose**: Sophisticated strategy achieving 78% win rate. Less aggressive than h8 but more resilient, with longest average duration (102.00s). Excels in late-game scenarios by maintaining pressure on opponent's strong points.

1.4 Self-Sabotaging Heuristics (Human-Favoring)

- **h2 (Anti-Material)**:
  - **Goal**: Minimize AI's orb count
  - **Calculation**: $-\sum(AIorbs) + \sum(Opponentorbs)$
  - **Purpose**: Benchmark for worst-case performance (22% win rate)
- **h4 (Anti-Corner)**:
  - **Goal**: Avoid corner control
  - **Calculation**: Base score -2 for corner cells
  - **Purpose**: Demonstrates corner importance by achieving 0% win rate when avoided
- **h6 (Anti-Edge)**:
  - **Goal**: Avoid edge control
  - **Calculation**: Base score -1 for edge cells
  - **Purpose**: Shows edges' strategic value (22% win rate when penalized)
- **h9 (Targeted Self-Sabotage)**:
  - **Goal**: Deliberately weaken position while helping opponent
  - **Calculation**:
    - Base score - count for owned orbs
    - -1 for edges, -2 for corners
    - +1 for opponent's edges, +2 for opponent's corners
  - **Purpose**: Human-favored heuristic with only 22% win rate. Particularly weak against corner-control strategies, losing to h3 and h7 consistently. Average duration 74.05s shows games end quickly when AI actively sabotages itself.

1.5 Key Insights from Analysis

- Corner control (h3) proved most effective (100% win rate); dominated all matchups, winning against every other heuristic.
- Composite strategy (h7) offered best balance between aggression and stability.
- Self-sabotaging heuristics (h2,h4,h6, h9) successfully created human-favorable conditions
- Average game duration varied significantly:
  - Fastest: h2 (49.4s)
  - Slowest: h10 (102.00s)
- Adaptive nature of h10 showed increasing effectiveness in longer games (102s avg).
- The gradient from h3 (pure corner) to h10 (adaptive) shows how positional flexibility trades off against win rate.
- Interestingly, Heuristic h4, despite having a 0% win rate, exhibited a higher average game duration than h2. This indicates that h4's corner-avoidant strategy, while ultimately detrimental, delays the AI's defeat relative to h2's aggressive self-sabotage. Such trade-offs highlight that not all weak heuristics fail equally—some prolong the game due to indecisive or inefficient play rather than outright boosting the opponent's advantage.

The following charts below illustrate the key findings based on the collected game statistics.

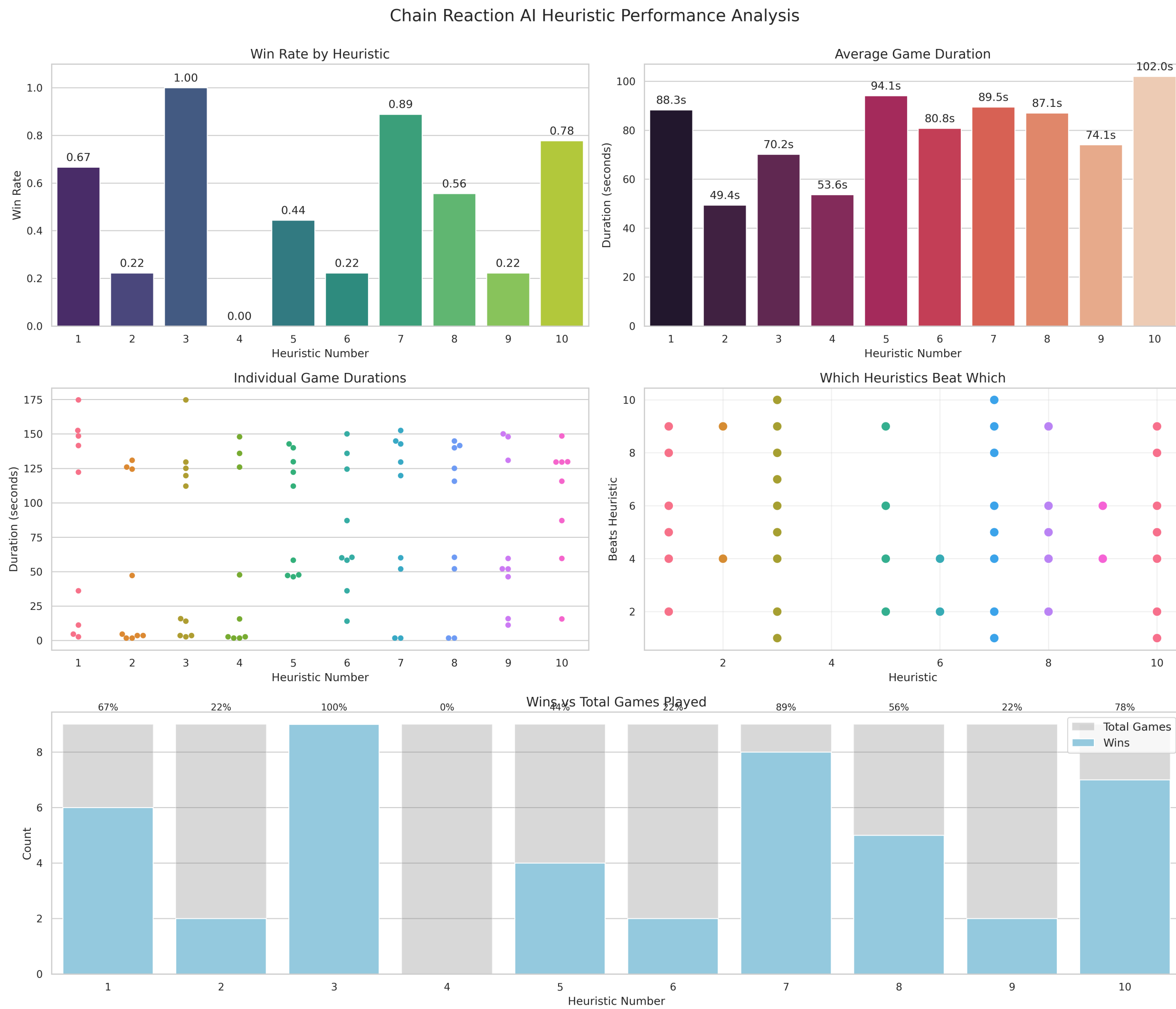

Figure 1: Statistics on performances of Heuristics

Conclusion

The experimental results demonstrate that heuristic design plays a critical role in AI performance in adversarial games like Chain Reaction. Heuristics that align with strategic principles (e.g., prioritizing corners or maximizing orb count) significantly outperform those that deliberately favor the opponent. This study highlights the need for well-structured evaluation methods when designing heuristic-driven game AI.