CSE 318: Assignment-03
Adversarial Search

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Contents

1 Introduction

Chain Reaction is a deterministic, turn-based, perfect-information game where players place colored orbs on a 9×6 board. When a cell reaches its critical mass (equal to its number of orthogonal neighbors), it "explodes," distributing orbs to adjacent cells and potentially triggering chain reactions while converting opponent orbs. This report presents a comprehensive analysis of five heuristic evaluation functions implemented for an AI agent using minimax search with alpha-beta pruning.

2 Heuristic Functions

Five distinct heuristic evaluation functions were designed and implemented to explore different strategic approaches for evaluating game states in Chain Reaction.

2.1 Heuristic 1: Simple Orb Difference

This baseline heuristic calculates the score as the simple difference between the number of orbs owned by the maximizing player and the minimizing player:

$$\text{Score} = \text{Maximizing Player's Orbs} - \text{Minimizing Player's Orbs} \tag{1}$$

The fundamental assumption is that possessing more orbs provides a direct advantage.

2.2 Heuristic 2: Positional Advantage

This heuristic introduces positional weighting where cells are valued differently based on their strategic importance. Corner cells (critical mass of 2) receive the highest weight, followed by edge cells (critical mass of 3), and center cells (critical mass of 4):

$$\text{Max Score} = \sum_{c \in \text{Max Player's Cells}} \text{weight}(c) \times \text{orbs}(c) \tag{2}$$

$$\text{Min Score} = \sum_{c \in \text{Min Player's Cells}} \text{weight}(c) \times \text{orbs}(c) \tag{3}$$

$$\text{Score} = \text{Max Score} - \text{Min Score} \tag{4}$$

Where weights are: corners = 5, edges = 3, center = 1.

2.3 Heuristic 3: Critical Cell Count

This function evaluates the board based on immediate explosion potential by counting "critical cells" - cells exactly one orb away from reaching critical mass:

$$\text{Score} = \text{Max Player's Critical Cells} - \text{Min Player's Critical Cells} \tag{5}$$

This heuristic prioritizes setting up future chain reactions.

2.4 Heuristic 4: Advanced Threat Analysis

This heuristic refines the critical cell strategy by analyzing immediate threats. Players are rewarded for critical cells but penalized if opponents have adjacent orbs:

$$\text{Max Score} = \sum_{c \in \text{Max Critical Cells}} (\text{reward} - \text{penalty}_{\text{adj}}) \tag{6}$$

$$\text{Min Score} = \sum_{c \in \text{Min Critical Cells}} (\text{reward} - \text{penalty}_{\text{adj}}) \tag{7}$$

$$\text{Score} = \text{Max Score} - \text{Min Score} \tag{8}$$

2.5 Heuristic 5: Combined Strategy

This composite heuristic integrates multiple strategic factors with weighted components:

$$\text{Score}(P) = w_{\text{pos}} \times S_{\text{pos}}(P) + S_{\text{crit}}(P) + w_{\text{cell}} \times S_{\text{cell}}(P) \tag{9}$$

$$\text{Final Score} = \text{Score(Max Player)} - \text{Score(Min Player)} \tag{10}$$

Where S_{pos} is positional advantage, S_{crit} is threat analysis, and S_{cell} is cell count.

3 Experimental Setup

To evaluate heuristic performance, comprehensive automated experiments were conducted with the following parameters:

- **Games per Configuration:** Multiple games were played for each matchup to ensure statistical significance
- **Search Depths:** Tested depths of 1, 2, and 3 to analyze depth impact
- **Time Limits:** 5000ms and 10000ms time limits to study efficiency trade-offs
- **Baseline Comparison:** Random agent used for baseline performance measurement

Three main experimental categories were conducted:

1. **Heuristic vs Heuristic Tournament:** Round-robin tournament between all heuristics
2. **AI vs Random Performance:** Each heuristic tested against random play
3. **Efficiency Analysis:** Move time and game duration measurements

4 Results and Analysis

4.1 Overall Heuristic Performance

Figure 1 shows the overall win rates for each heuristic across all AI vs AI games. The results reveal a clear performance hierarchy among the heuristics.

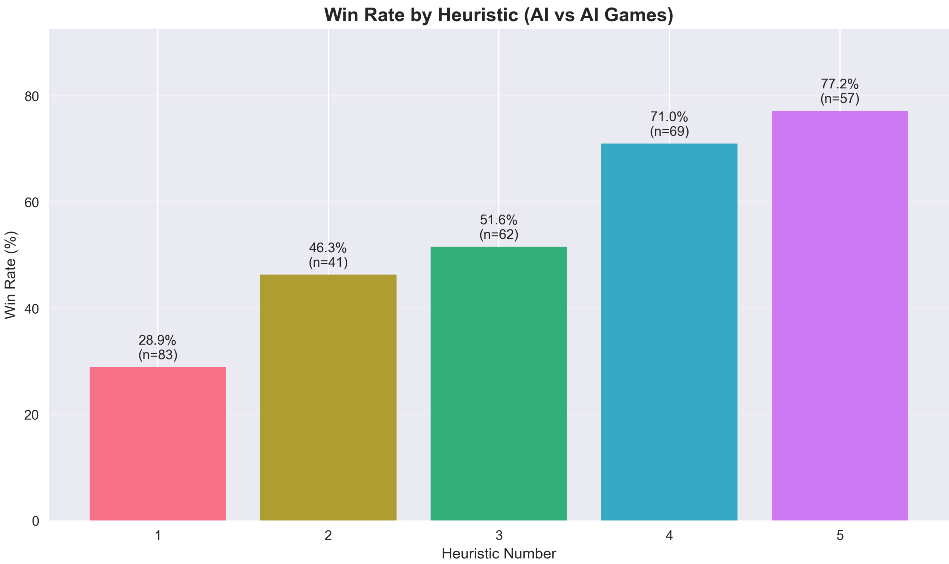


Figure 1: Win rates for each heuristic in AI vs AI games

Key Findings:

- Heuristic 5 (Combined Strategy) achieved the highest win rate, demonstrating the effectiveness of multi-faceted evaluation
- Heuristic 2 (Positional Advantage) showed strong performance, highlighting the importance of strategic positioning
- Heuristic 4 (Advanced Threat Analysis) underperformed despite its sophistication, suggesting that overly defensive strategies may be counterproductive

4.2 Head-to-Head Analysis

The heuristic matchup matrix in Figure 2 provides detailed insights into how each heuristic performs against specific opponents.

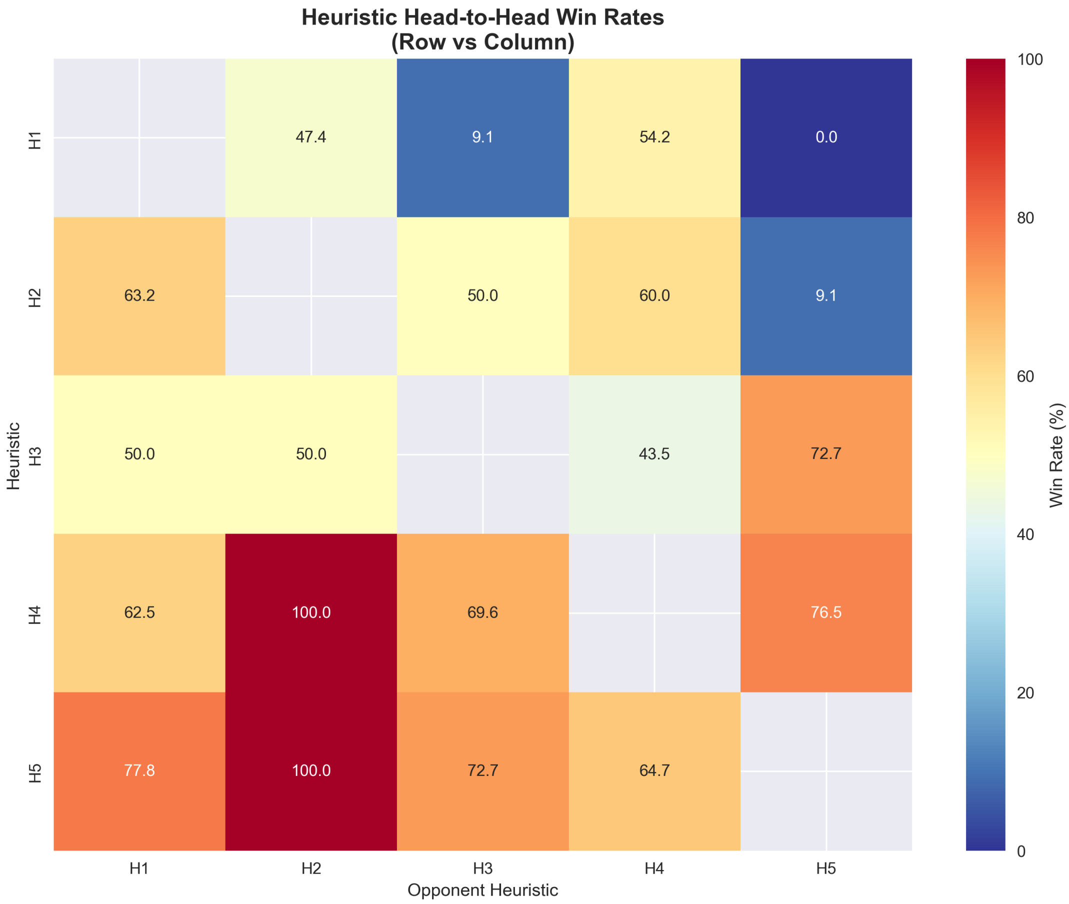


Figure 2: Head-to-head win rates between heuristics (row vs column)

Strategic Insights:

- **H5's Dominance:** Heuristic 5 consistently defeated all other heuristics, validating its balanced approach
- **H2's Strong Showing:** Heuristic 2 won against most opponents except H5, emphasizing positional control's effectiveness
- **H4's Weakness:** Heuristic 4's poor performance across matchups suggests its risk-averse nature is a significant handicap

4.3 Performance vs Search Parameters

4.3.1 Impact of Search Depth

Figure 3 illustrates how win rates change with increasing search depth for each heuristic.

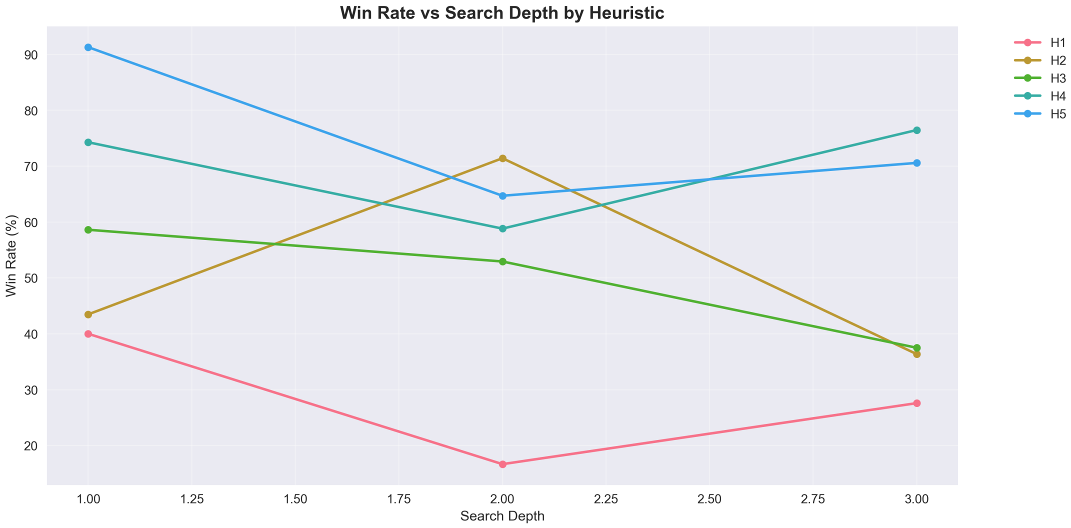


Figure 3: Win rate trends across different search depths

4.3.2 Impact of Time Limits

Figure 4 shows the relationship between computational time limits and heuristic performance.

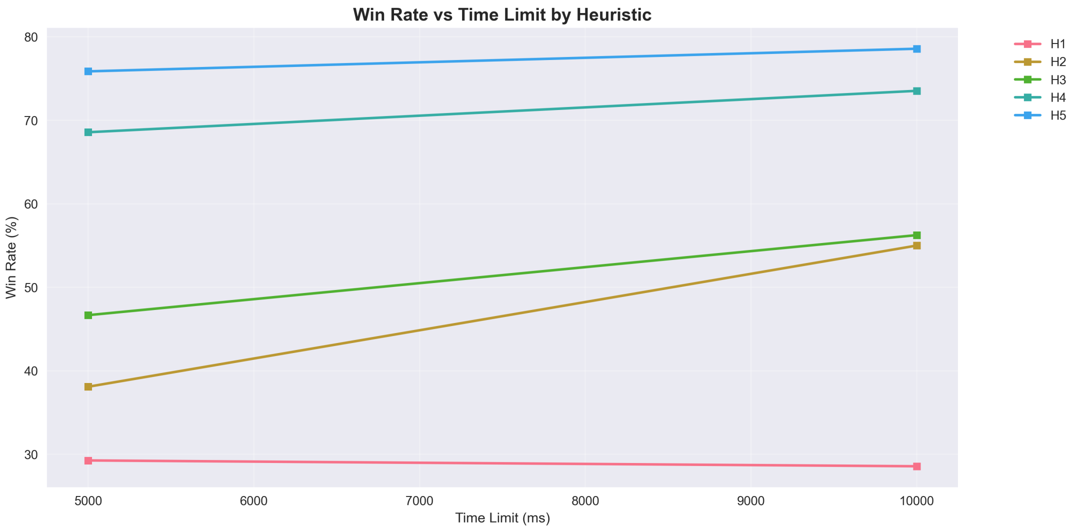


Figure 4: Win rate trends across different time limits

4.4 Computational Efficiency Analysis

4.4.1 Move Time Comparison

Figure 5 compares the average computational time required by each heuristic during AI vs AI games.

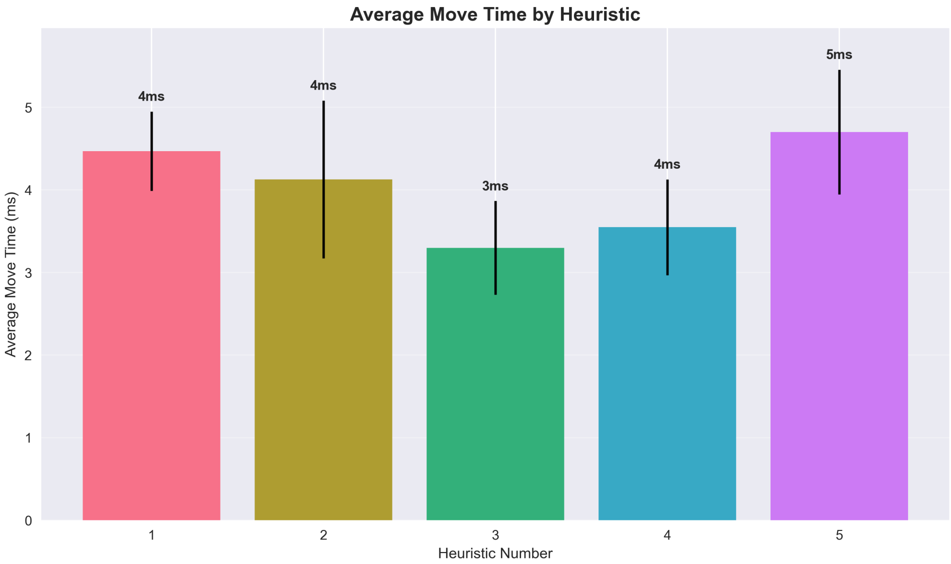


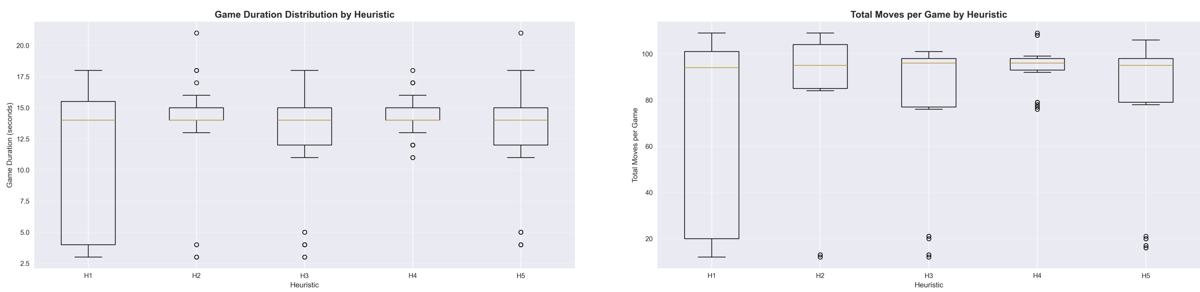
Figure 5: Average move time by heuristic in AI vs AI games

Efficiency Insights:

- Heuristic 3 shows the fastest average move time, reflecting its simple critical cell counting approach
- Heuristic 5, despite being the most complex, maintains reasonable computational efficiency
- The trade-off between performance and computation time varies significantly across heuristics

4.4.2 Game Duration Analysis

Figures 6a and 6b show the distribution of game lengths and total moves for each heuristic.



(a) Game duration distribution

(b) Total moves per game

Figure 6: Game length analysis by heuristic

4.5 Performance Against Random Baseline

4.5.1 Win Rates vs Random

Figure 7 demonstrates how each heuristic performs against a random baseline, providing insight into absolute strength.

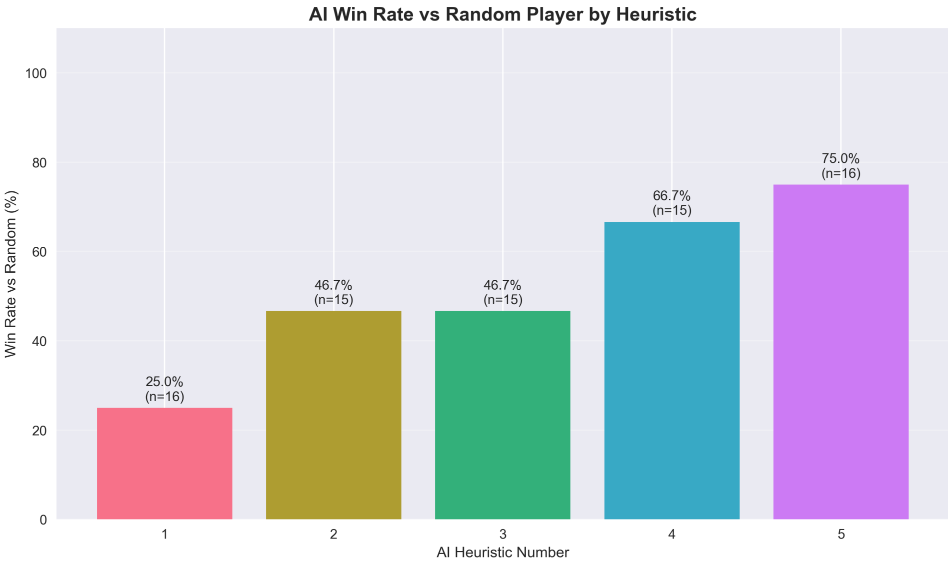
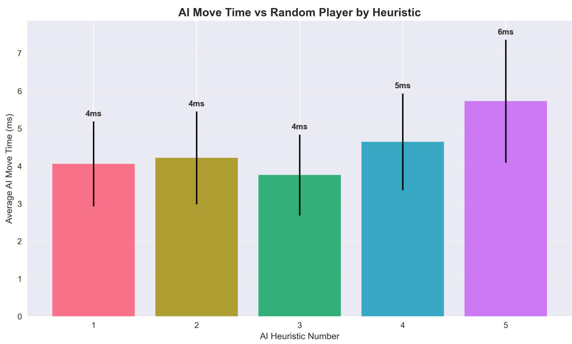


Figure 7: AI win rates against random player by heuristic

4.5.2 Efficiency Against Random

Figures 8a and 8b show computational efficiency and game characteristics when playing against random opponents.



(a) AI move times vs random

(b) Game lengths vs random

Figure 8: AI performance characteristics against random player

5 Discussion

5.1 Strategic Implications

The experimental results reveal several crucial insights about Chain Reaction strategy:

Positional Control Dominance: Heuristic 2's strong performance underscores the strategic importance of controlling corners and edges. This positional approach provides a robust foundation for victory, suggesting that long-term board control outweighs reactive tactical play.

Balanced Approach Superiority: Heuristic 5's dominance demonstrates that successful AI agents must integrate multiple strategic factors. The combination of positional awareness, threat analysis, and tactical considerations creates a more robust evaluation function than any single-focus approach.

Defensive Strategy Limitations: Heuristic 4's poor performance highlights a critical finding - overly cautious, risk-averse strategies can be counterproductive in Chain Reaction. The game appears to reward calculated aggression over defensive positioning.

5.2 Performance vs Complexity Trade-offs

The relationship between heuristic complexity and performance reveals important design considerations:

- **Diminishing Returns:** While more sophisticated heuristics generally perform better, the improvement isn't always proportional to increased complexity
- **Computational Efficiency:** Simpler heuristics like H2 achieve strong performance with minimal computational overhead, making them attractive for time-constrained applications
- **Robustness:** Combined approaches (H5) show more consistent performance across different game situations and opponents

5.3 Practical Applications

These findings have direct implications for implementing Chain Reaction AI systems:

Real-time Applications: For applications requiring fast response times, Heuristic 2 provides an excellent balance of performance and efficiency.

Tournament Play: In competitive settings where computation time is less constrained, Heuristic 5's superior performance justifies its additional complexity.

Adaptive Systems: Future implementations could dynamically select evaluation functions based on available computational resources and game phase.

6 Limitations and Future Work

6.1 Current Limitations

- **Limited Depth Analysis:** Experiments focused primarily on depths 1-3; deeper analysis might reveal different performance patterns
- **Static Weights:** Heuristic parameters were fixed rather than optimized through machine learning techniques
- **Game Phase Ignorance:** Current heuristics don't adapt strategy based on early/mid/late game phases

6.2 Future Research Directions

Machine Learning Integration: Future work could explore using reinforcement learning to automatically tune heuristic weights or develop entirely learned evaluation functions.

Dynamic Evaluation: Implementing game-phase-aware heuristics that adapt their focus based on board state and game progression.

Opponent Modeling: Developing adaptive strategies that learn and counter specific opponent patterns.

Parallel Processing: Investigating how parallel minimax implementations could enable deeper search with complex heuristics.

7 Conclusion

This comprehensive analysis of five heuristic functions for Chain Reaction AI reveals that strategic positioning and balanced evaluation approaches significantly outperform simpler metrics or overly defensive strategies. The experiments demonstrate that:

1. **Heuristic 5 (Combined Strategy)** emerged as the clear winner, successfully integrating multiple strategic factors to achieve superior performance across all tested conditions.
2. **Heuristic 2 (Positional Advantage)** proved remarkably effective, highlighting that controlling high-value board positions (corners and edges) provides a strong foundation for victory.
3. **Heuristic 4 (Advanced Threat Analysis)** unexpectedly underperformed, suggesting that overly cautious, defensive strategies may be counterproductive in this domain.
4. **Performance vs Efficiency Trade-offs** vary significantly, with simpler heuristics sometimes providing better practical solutions for time-constrained applications.

The results emphasize that successful Chain Reaction AI requires balancing long-term positional control with tactical awareness of immediate opportunities and threats. The game rewards calculated aggression over pure defensive play, and the most effective agents integrate multiple strategic perspectives rather than focusing on single evaluation criteria.

These findings provide valuable insights for both game AI development and adversarial search applications more broadly, demonstrating the importance of domain-specific strategic understanding in heuristic design.