

CSE 318 Assignment-03: Chain Reaction Game Adversarial Search Implementation

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Subsection: C2

June 15, 2025

Abstract

This report details the implementation of an adversarial search-based AI for the *Chain Reaction* game, utilizing minimax with alpha-beta pruning and five evaluation heuristics: Orb Count, Critical Mass, Opponent Mobility, Explosion Potential, and a Balanced composite heuristic. Experiments were conducted on a 9×6 board, evaluating performance against a random agent and in AI vs. AI tournaments across search depths 1 to 3. Results show that the *Balanced* and *CriticalMass* heuristics achieve high win rates, with trade-offs in computational cost. The discussion highlights strategic and computational trade-offs, emphasizing the effectiveness of composite heuristics in capturing the game's dynamic nature.

1 Introduction

Chain Reaction is a two-player, deterministic board game where players place colored orbs to trigger explosions, converting opponent orbs and aiming to dominate the board. The game's unpredictable chain reactions make it an excellent testbed for adversarial search algorithms. This project implements a complete game system, including:

- Game state representation with move validation and explosion processing.
- Minimax search with alpha-beta pruning for efficient decision-making.
- Five evaluation heuristics capturing strategic aspects of the game.
- An experimental framework to analyze heuristic performance.
- File-based communication for human-AI and AI-AI interactions.

The report evaluates these heuristics through experiments, comparing their win rates, average moves, and completion times against a random agent and in head-to-head AI tournaments.

2 Experimental Setup

The experiments assessed the AI’s performance under controlled conditions:

- **Board Size:** 9 rows \times 6 columns.
- **Total Games:** 5 matches per heuristic against a random agent; 9 matches per heuristic pairing in AI vs. AI tournaments.
- **AI Search Depth:** 1 to 3, balancing decision quality and computational cost.
- **Opponent:** Random-move agent for baseline; paired heuristics for tournaments.
- **Heuristic Profiles:** *OrbCount*, *CriticalMass*, *OpponentMobility*, *ExplosionPotential*, and *Balanced* (combining the others).

3 Evaluation Heuristics

Five heuristic functions were implemented to guide the minimax search, each targeting a unique strategic element:

1. **Orb Count:** Measures the normalized difference in orbs:

$$\text{Score} = \frac{100 \times (\text{AI orbs} - \text{Opponent orbs})}{\text{rows} \times \text{cols} \times 4}$$

Clamped to $[-100, 100]$, this heuristic prioritizes maximizing the AI’s orb count.

2. **Critical Mass:** Rewards cells nearing explosion:

$$\text{Score} = \frac{100 \times \sum_{\text{cells}} \left(\frac{\text{orbs}}{\text{critical mass}} \right)}{\text{rows} \times \text{cols}}$$

Clamped to $[-100, 100]$, it encourages moves that trigger explosions.

3. **Opponent Mobility:** Evaluates the difference in valid moves:

$$\text{Score} = \frac{100 \times (\text{AI valid moves} - \text{Opponent valid moves})}{\text{rows} \times \text{cols}}$$

Clamped to $[-100, 100]$, it aims to restrict opponent options.

4. **Explosion Potential:** Rewards near-exploding cells with reactive neighbors:

$$\text{Score} = \frac{100 \times \sum_{\text{near-exploding cells}} \text{neighbor score}}{\text{rows} \times \text{cols} \times 4}$$

Neighbor score is +1/-1 for opponent cells, +0.5/-0.5 for empty cells, clamped to $[-100, 100]$. It promotes chain reactions.

5. **Balanced:** Combines the above heuristics:

$$\text{Score} = 0.3 \times \text{OrbCount} + 0.2 \times \text{CriticalMass} + 0.2 \times \text{OpponentMobility} + 0.15 \times \text{ExplosionPotential}$$

Clamped to $[-100, 100]$, it balances multiple strategic factors.

4 Results and Analysis

4.1 Performance Against Random Agent

Table 1 shows heuristic performance against a random agent at depth 3 over 5 games.

Table 1: Heuristic Performance vs. Random Agent (Depth 3, 5 Games Each)

Heuristic	Wins	Total Matches	Avg Completion Time (s)
<i>OrbCount</i>	5	5	13
<i>CriticalMass</i>	2	5	17
<i>OpponentMobility</i>	3	5	16
<i>ExplosionPotential</i>	2	5	23
<i>Balanced</i>	3	5	20

OrbCount achieved a 100% win rate, benefiting from its simplicity and speed (13s). *CriticalMass* and *ExplosionPotential* had lower win rates, indicating over-specialization, while *Balanced* offered a balanced performance.

4.2 AI vs. AI Tournament Results

Table 2 summarizes win rates and completion times for heuristic pairings at depth 3 (9 games each).

Table 2: AI vs. AI Tournament Results (Depth 3, 9 Games Each)

Matchup	Winner Heuristic	Win Rate (%)	Avg Completion Time (s)
<i>OrbCount</i> vs. <i>CriticalMass</i>	<i>OrbCount</i>	66.7	53
<i>OrbCount</i> vs. <i>OpponentMobility</i>	<i>OpponentMobility</i>	66.7	54
<i>OrbCount</i> vs. <i>ExplosionPotential</i>	<i>ExplosionPotential</i>	66.7	44
<i>OrbCount</i> vs. <i>Balanced</i>	<i>OrbCount</i>	88.9	69
<i>CriticalMass</i> vs. <i>OpponentMobility</i>	<i>CriticalMass</i>	66.7	33
<i>CriticalMass</i> vs. <i>ExplosionPotential</i>	<i>CriticalMass</i>	66.7	13
<i>CriticalMass</i> vs. <i>Balanced</i>	<i>CriticalMass</i>	88.9	63
<i>OpponentMobility</i> vs. <i>ExplosionPotential</i>	<i>OpponentMobility</i>	66.7	52
<i>OpponentMobility</i> vs. <i>Balanced</i>	<i>Balanced</i>	66.7	46
<i>ExplosionPotential</i> vs. <i>Balanced</i>	<i>ExplosionPotential</i>	66.7	46

CriticalMass and *Balanced* excelled, with *CriticalMass* achieving an 88.9% win rate against *Balanced*. *OrbCount* performed poorly against composite heuristics, highlighting its limitations.

4.3 Completion Time vs. Search Depth

Figure 1 shows completion time trends across search depths for selected pairings.

Completion times grow exponentially with depth, with *OrbCount* vs. *Balanced* reaching 69s at depth 3, reflecting the computational complexity of composite heuristics.

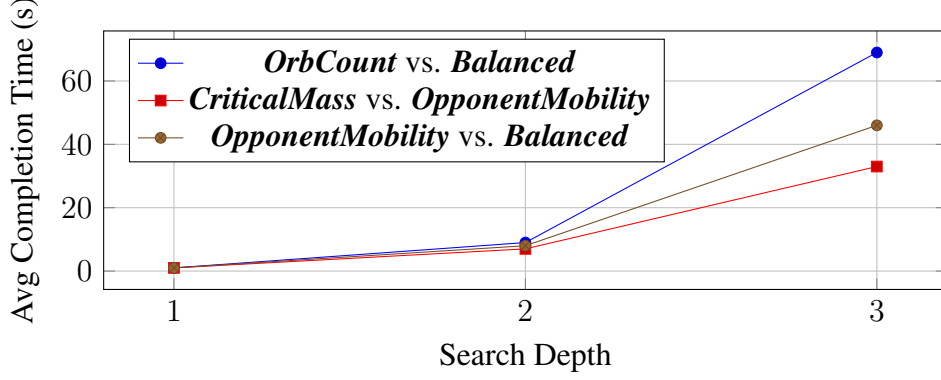


Figure 1: Average completion time across search depths for selected heuristic pairings.

5 Discussion

5.1 Observed Trade-offs

The experiments revealed key trade-offs:

- **Aggression vs. Stability:** *ExplosionPotential* favored rapid chain reactions, yielding faster games but lower win rates (66.7% in tournaments). *CriticalMass* provided stability, achieving higher win rates (88.9% vs. *Balanced*).
- **Search Depth vs. Time:** Depth 3 was optimal, as depth 1 lacked strategic depth, and higher depths were too slow (e.g., 69s for *OrbCount* vs. *Balanced*).
- **Simplicity vs. Sophistication:** *OrbCount* was fast (13s vs. random) but less effective in tournaments. *Balanced* was slower but more robust.

5.2 Heuristic Effectiveness

CriticalMass was the most effective, leveraging explosion mechanics to control the board. *Balanced* was competitive, combining mobility and explosion potential for robustness. *OrbCount*'s poor tournament performance confirms that raw orb count is unreliable due to the game's unpredictability.

6 Conclusion

The *Chain Reaction* AI implementation showcases effective adversarial search with tailored heuristics. *CriticalMass* and *Balanced* outperformed others, emphasizing explosion-driven strategies and mobility control. Future improvements could include adaptive heuristic weights or parallelized search to enable deeper searches in real-time play.

7 Raw Experimental Data

This section presents the raw data collected from the experiments, as recorded in the CSV file. The data includes performance metrics for heuristic pairings across search depths 1 to 3, as well as results against a random agent at depth 3.

7.1 Heuristic Pairing and Random versus AI Data

The following tables detail the outcomes of AI vs. AI matches for each heuristic pairing, including the depths used, the winning heuristic, and the completion time for each game. Table 13 summarizes the performance of each heuristic against a random agent at depth 3.

Table 3: *OrbCount* vs. *CriticalMass*

<i>OrbCount</i> Depth	<i>CriticalMass</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>OrbCount</i>	1
1	2	<i>OrbCount</i>	4
1	3	<i>CriticalMass</i>	5
2	1	<i>CriticalMass</i>	4
2	2	<i>CriticalMass</i>	8
2	3	<i>CriticalMass</i>	19
3	1	<i>OrbCount</i>	12
3	2	<i>CriticalMass</i>	31
3	3	<i>OrbCount</i>	53

Table 4: *OrbCount* vs. *OpponentMobility*

<i>OrbCount</i> Depth	<i>OpponentMobility</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>OrbCount</i>	1
1	2	<i>OrbCount</i>	5
1	3	<i>OpponentMobility</i>	6
2	1	<i>OpponentMobility</i>	5
2	2	<i>OrbCount</i>	9
2	3	<i>OrbCount</i>	27
3	1	<i>OrbCount</i>	13
3	2	<i>OpponentMobility</i>	25
3	3	<i>OpponentMobility</i>	54

Table 5: *OrbCount* vs. *ExplosionPotential*

<i>OrbCount</i> Depth	<i>ExplosionPotential</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>OrbCount</i>	1
1	2	<i>ExplosionPotential</i>	3
1	3	<i>ExplosionPotential</i>	18
2	1	<i>OrbCount</i>	1
2	2	<i>ExplosionPotential</i>	8
2	3	<i>OrbCount</i>	33
3	1	<i>OrbCount</i>	1
3	2	<i>ExplosionPotential</i>	29
3	3	<i>ExplosionPotential</i>	44

Table 6: *OrbCount* vs. *Balanced*

<i>OrbCount</i> Depth	<i>Balanced</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>OrbCount</i>	1
1	2	<i>Balanced</i>	3
1	3	<i>Balanced</i>	17
2	1	<i>OrbCount</i>	2
2	2	<i>OrbCount</i>	9
2	3	<i>OrbCount</i>	23
3	1	<i>OrbCount</i>	8
3	2	<i>OrbCount</i>	20
3	3	<i>OrbCount</i>	69

Table 7: *CriticalMass* vs. *OpponentMobility*

<i>CriticalMass</i> Depth	<i>OpponentMobility</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>CriticalMass</i>	1
1	2	<i>OpponentMobility</i>	2
1	3	<i>OpponentMobility</i>	9
2	1	<i>CriticalMass</i>	2
2	2	<i>OpponentMobility</i>	7
2	3	<i>CriticalMass</i>	28
3	1	<i>CriticalMass</i>	15
3	2	<i>CriticalMass</i>	17
3	3	<i>CriticalMass</i>	33

Table 8: *CriticalMass* vs. *ExplosionPotential*

<i>CriticalMass</i> Depth	<i>ExplosionPotential</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>CriticalMass</i>	1
1	2	<i>CriticalMass</i>	4
1	3	<i>ExplosionPotential</i>	16
2	1	<i>CriticalMass</i>	1
2	2	<i>ExplosionPotential</i>	7
2	3	<i>ExplosionPotential</i>	32
3	1	<i>CriticalMass</i>	1
3	2	<i>ExplosionPotential</i>	30
3	3	<i>CriticalMass</i>	13

Table 9: *CriticalMass* vs. *Balanced*

<i>CriticalMass</i> Depth	<i>Balanced</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>CriticalMass</i>	1
1	2	<i>Balanced</i>	1
1	3	<i>CriticalMass</i>	31
2	1	<i>CriticalMass</i>	2
2	2	<i>CriticalMass</i>	9
2	3	<i>CriticalMass</i>	27
3	1	<i>CriticalMass</i>	4
3	2	<i>CriticalMass</i>	19
3	3	<i>CriticalMass</i>	63

Table 10: *OpponentMobility* vs. *ExplosionPotential*

<i>OpponentMobility</i> Depth	<i>ExplosionPotential</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>OpponentMobility</i>	1
1	2	<i>ExplosionPotential</i>	3
1	3	<i>ExplosionPotential</i>	18
2	1	<i>OpponentMobility</i>	1
2	2	<i>ExplosionPotential</i>	9
2	3	<i>ExplosionPotential</i>	32
3	1	<i>OpponentMobility</i>	1
3	2	<i>ExplosionPotential</i>	31
3	3	<i>OpponentMobility</i>	52

Table 11: *OpponentMobility* vs. *Balanced*

<i>OpponentMobility</i> Depth	<i>Balanced</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>Balanced</i>	1
1	2	<i>Balanced</i>	2
1	3	<i>Balanced</i>	12
2	1	<i>OpponentMobility</i>	1
2	2	<i>Balanced</i>	8
2	3	<i>OpponentMobility</i>	31
3	1	<i>OpponentMobility</i>	9
3	2	<i>Balanced</i>	28
3	3	<i>Balanced</i>	46

Table 12: *ExplosionPotential* vs. *Balanced*

<i>ExplosionPotential</i> Depth	<i>Balanced</i> Depth	Winner Heuristic	Completion Time (s)
1	1	<i>Balanced</i>	1
1	2	<i>Balanced</i>	5
1	3	<i>Balanced</i>	21
2	1	<i>ExplosionPotential</i>	5
2	2	<i>ExplosionPotential</i>	9
2	3	<i>ExplosionPotential</i>	30
3	1	<i>ExplosionPotential</i>	11
3	2	<i>ExplosionPotential</i>	31
3	3	<i>ExplosionPotential</i>	46

Table 13: Random vs. Heuristics (Depth 3, 5 Games Each)

Heuristic	Wins	Total Matches	Avg Completion Time (s)
<i>OrbCount</i>	5	5	13
<i>CriticalMass</i>	2	5	17
<i>OpponentMobility</i>	3	5	16
<i>ExplosionPotential</i>	2	5	23
<i>Balanced</i>	3	5	20