Chain Reaction Game

Student ID: 2105071

1. Minimax Agent Overview

Minimax Algorithm: Minimax is a decision-making algorithm commonly used in two-player games. It assumes that both players play optimally. The AI attempts to maximize its minimum guaranteed score by exploring the game tree up to a certain depth. At each level, it alternates between maximizing its own score and minimizing the opponent's potential score.

Alpha-Beta Pruning: To optimize the Minimax algorithm, we implemented alpha-beta pruning, which eliminates branches of the game tree that cannot affect the final decision. This significantly reduces the number of nodes evaluated, allowing deeper searches in the same computation time.

2. Heuristic Evaluation Functions

2.1. Heuristic 1: Orb Count Differential

Rationale: This heuristic measures the raw numerical advantage in terms of orbs on the board. Since the objective is to eliminate all opponent orbs, maintaining a higher orb count is a basic and intuitive sign of positional strength.

2.2. Heuristic 2: Critical Mass Advantage

Rationale: This heuristic evaluates cells that are close to exploding, assigning higher value to cells that are one orb away from critical mass. These cells are potential chain reaction starters, making them tactically valuable.

2.3. Heuristic 3: Strategic Position Control

Rationale: This heuristic favors control of corners and edges. These positions have fewer neighbors and thus lower critical mass, allowing players to trigger explosions more easily and maintain stable regions on the board.

2.4. Heuristic 4: Orb Conversion Opportunity

Rationale: This heuristic emphasizes the potential to convert opponent orbs by initiating explosions. By focusing on opportunities to weaken the opponent and simultaneously grow the player's influence, it encourages aggressive, game-changing plays.

2.5. Heuristic 5: Weighted Composite Control

Rationale: This heuristic combines the above strategies. By assigning weighted values to orb count, critical cell advantage, board control, and conversion potential, this composite heuristic evaluates the game state from multiple perspectives for better strategic awareness.

3. Experimentation & Analysis

3.1. Experimental Setup

For this initial set of experiments, we evaluated the performance of our Minimax AI agent at a fixed search depth of **2**. Each heuristic configuration played **5 games** against a simple opponent AI, No explicit time limits were imposed per move, as the low depth of 2 generally results in near-instantaneous move calculations. Performance was primarily measured by Win Rate, along with total moves per game and overall game duration.

3.2. Results Summary (Depth 2)

The following table and chart summarize the performance of each heuristic when the Minimax agent searched to a depth of 2.

Table 1: AI Performance Summary by Heuristic (Depth 2, 5 Games Each)

Heuristic	Win Rate (%)	Games Played	Games Won	Games Lost
Orb Difference	100%	5	5	0
Critical Mass Advantage	80%	5	4	1
Strategic Position Control	60%	5	3	2
Orb Conversion Opportunity	80%	5	4	1
Weighted Composite Control	100%	5	5	0

3.3. Discussion of Heuristic Performance and Trade-offs

Based on the preliminary results from Depth 2, several observations can be made regarding heuristic performance:

3.3.1 Which Heuristic Performed Best?

At Depth 2, the **Strategic Position Control** heuristic ("Control Value" in the table) clearly did worst among the 5 heuristic functions.As it prefers corner and edges rather that possiblity of exploding critical cells thats why critical mass and orb conversion oppurtunity performs better than that heuristics.In orb difference heuristics ai agent tries to aquire more orbs so does it performs better than others.And weighted heuristics is the weighted sum of other 4 heuristics giving much more weight to good heuristics and less to others

3.3.2 Trade-offs Observed

Given the fixed Depth 2, the primary trade-off observed here is related to **heuristic quality versus direct win rate**. All heuristics are computationally very fast at this shallow depth, so there isn't a significant trade-off in terms of "Heuristic Complexity vs. Performance Time" yet.

3.3.3 Limitations of Preliminary Analysis:

It's crucial to acknowledge that these are preliminary results from a very shallow search depth (Depth 2) and a small sample size (5 games per configuration). The simple random opponent also limits the insights into true competitive performance. Deeper searches and more extensive testing are necessary to draw more robust conclusions about which heuristic ultimately performs "best" and to properly tune the composite heuristic's weights.