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Assignment 2: Revised Prisoner's Dilemma Model

Github Repo: https://github.com/zhian21/MACS_40550_A2

Background

The original Prisoner's Dilemma agent-based model investigates the impact of various activation schemes on cooperation and defection dynamics. It tracks the number of cooperating agents over time and uses a single learning strategy, where agents mimic the behavior of their highest-scoring neighbor. In contrast, the present model exclusively uses the simultaneous activation scheme and introduces two additional learning strategies—*copying the most frequent behavior and copying randomly.* These changes recognize that individuals may learn in diverse ways, not strictly by emulating the top performers. The model further introduces flexibility by varying the pay-offs for different behaviors as well as the initial distributions of behaviors. In short, the revised model is designed to achieve three key objectives: (1) to investigate the interplay and collective impact of diverse learning strategies on behavior shift, (2) to evaluate how different pay-off structures influence strategy effectiveness, and (3) to understand the emergence and sustainability of behavioral patterns when subjected to conditions that closely simulate complex social interactions and variable incentives.

Design Concepts

In the modified Prisoner's Dilemma agent-based model:

- **Who**: Each agent is an individual participant in the Prisoner's Dilemma, situated within a grid-based simulation environment.
- **Does What**: Agents adapt their behaviors by emulating their immediate neighbors, choosing between cooperation or defection based on a certain strategy.
- **How**: Agents' decision-making processes are governed by a simultaneous activation scheme, where all agents update their behaviors at the same time based on the following learning strategies:

- *Copying the highest-scoring neighbor*: Agents evaluate their immediate neighbors and adopt the behavior of the one with the highest score. However, if agents find that they themselves have the highest score, they retain their current behavior.
- *Copying the most frequently observed strategy*: Agents evaluate the behaviors of their neighbors and adopt the one that is most common. If there's a tie for the most frequent behavior, they choose randomly among the tied behaviors.
- *Copying randomly*: Agents randomly adopt behaviors from one of their immediate neighbors.

Details

Agent Parameters

Agents in the model are initialized with the following parameters:

- Unique ID: An integer identifier unique to each agent within the simulation.
- Strategy: A string that dictates the decision-making approach the agent will use, selected from one of the three learning strategies.
- Initial Cooperation Probability: A float indicating the likelihood of an agent to initially cooperate (default 0.5).

Model Parameters

The model is initialized with a set of parameters, each accompanied by a default value:

- Payoff Matrix: This includes:
    - payoff_CC (default: 1): Payoff for both agents cooperating.
    - payoff_CD (default: 0): Payoff for an agent cooperating while the other defects.
    - payoff_DC (default: 2): Payoff for an agent defecting while the other cooperates.
    - payoff_DD (default: 0): Payoff for both agents defecting.
- Strategy Ratios: The ratios for the distribution of strategies among the agents are predefined as follows:
    - equal: All strategies are equally distributed among the agents (1/3, 1/3, 1/3).
    - more_majority: A higher proportion of agents use *Copying the most frequently observed strategy* (0.5, 0.25, 0.25).
    - more_best: A higher proportion of agents use *Copying the highest-scoring neighbor* strategy (0.25, 0.5, 0.25).

- more_random: A higher proportion of agents use *Copying randomly* strategy (0.25, 0.25, 0.5).

Data Collection

The model employs a DataCollector object to gather data throughout the simulation. The collected data points include:

- The number of agents employing each strategy.
- The average accumulative score per strategy, which reflects the payoff effectiveness.
- The total number of agents currently cooperating or defecting.

Conclusions

The model executes a batch run, varying initial cooperation probabilities, payoff matrices, and strategic ratios across two iterations limited to 50 steps each.

Influence of Strategy Ratios on Cooperative Behavior

Under the original Prisoner's Dilemma model conditions, Figure 1 indicates that the 'more_majority' ratio is highly effective in promoting cooperation, highlighting conformity to the majority as a significant factor in steering social groups toward collaborative outcomes.

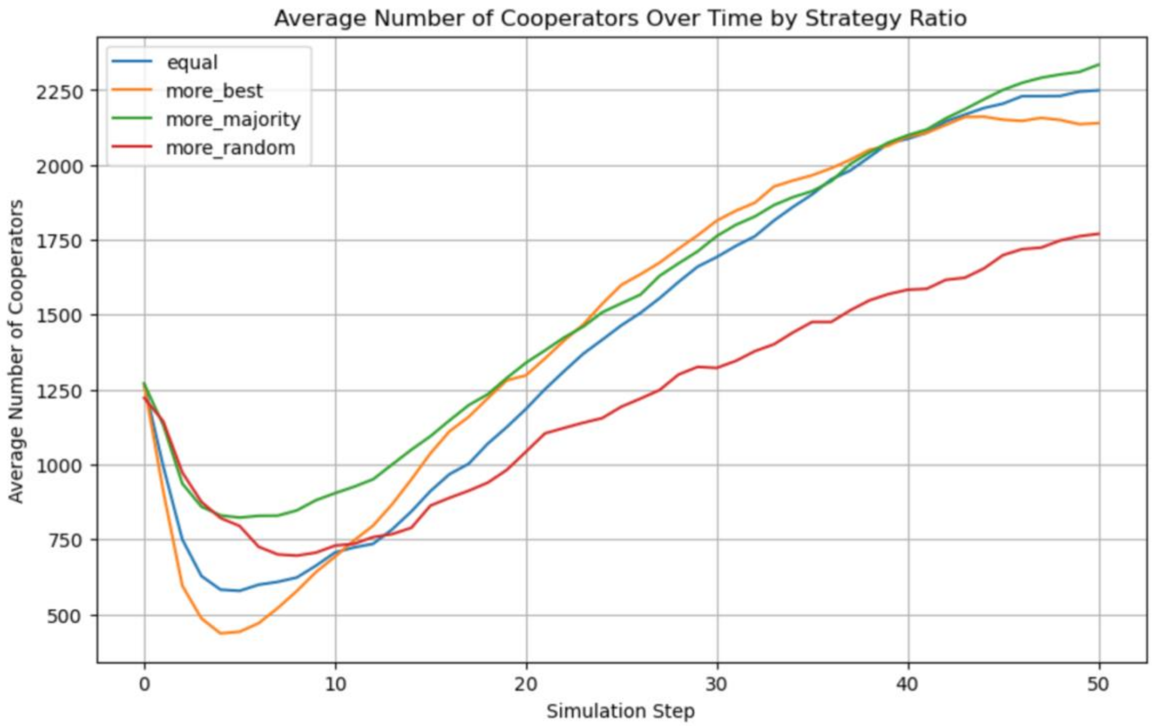

Figure 1. Dynamics of Cooperation. The graph displays the average number of cooperating agents over 50 simulation steps under the original PD model's payoff conditions (CC: 1.5, CD: 0.0, DC: 3.0, DD: 0.0) with an initial cooperation probability of 0.5.

In the scenario where a high level of cooperation is initially set, Figure 2 demonstrates varied dynamics among the different distribution of strategies over time. The 'more_majority' quickly surges in the number of cooperators before reaching a plateau, suggesting that once a majority-based strategy is established, it can sustain a stable level of cooperation. The 'more_best' distribution, after an initial decline, gradually recovers and nearly converges with the 'more_majority' trajectory by the end of the simulation. This indicates that agents employing a strategy that emulates the most successful peers can eventually adapt and thrive even after initial setbacks. On the other hand, the 'more_random' distribution shows a decrease in cooperators, followed by a period of stabilization at a lower level than its counterparts. This suggests a lack of a robust mechanism in 'more_random' for recovering the cooperative population after a decline.

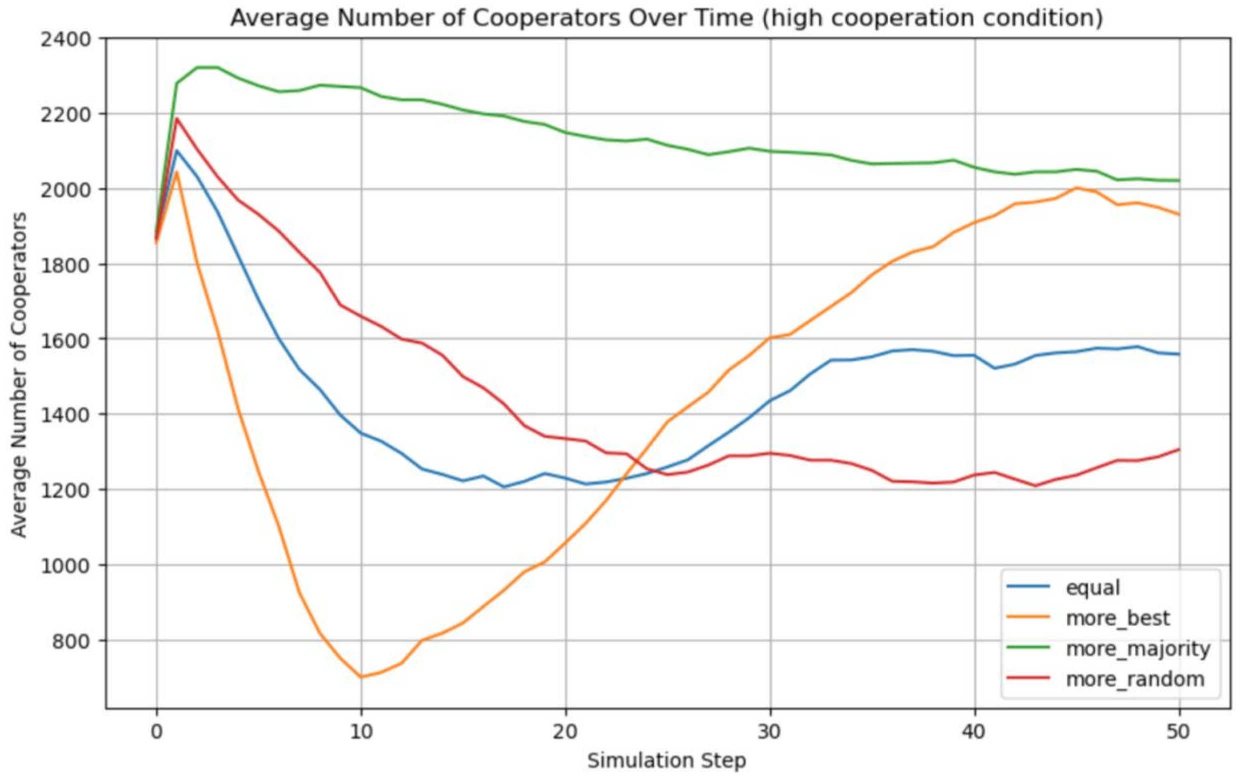

Figure 2. Trajectory of Cooperative Behavior in a High Initial Cooperation Environment. The graph depicts the average number of cooperators under the condition of an initial 75% probability of cooperation among agents.

Strategy Performance

Figure 3 presents a comparison of average scores for the three different strategies, showing negligible differences in their performance with an equal initial distribution of strategies and the original pay-off structure. The convergence in scores suggests that no single strategy significantly outperforms the others, possibly due to the simultaneous activation scheme (i.e., make their moves without foreknowledge of others' moves) or the lack of variation between pay-offs of the behaviors (i.e., the incentives are not great enough).

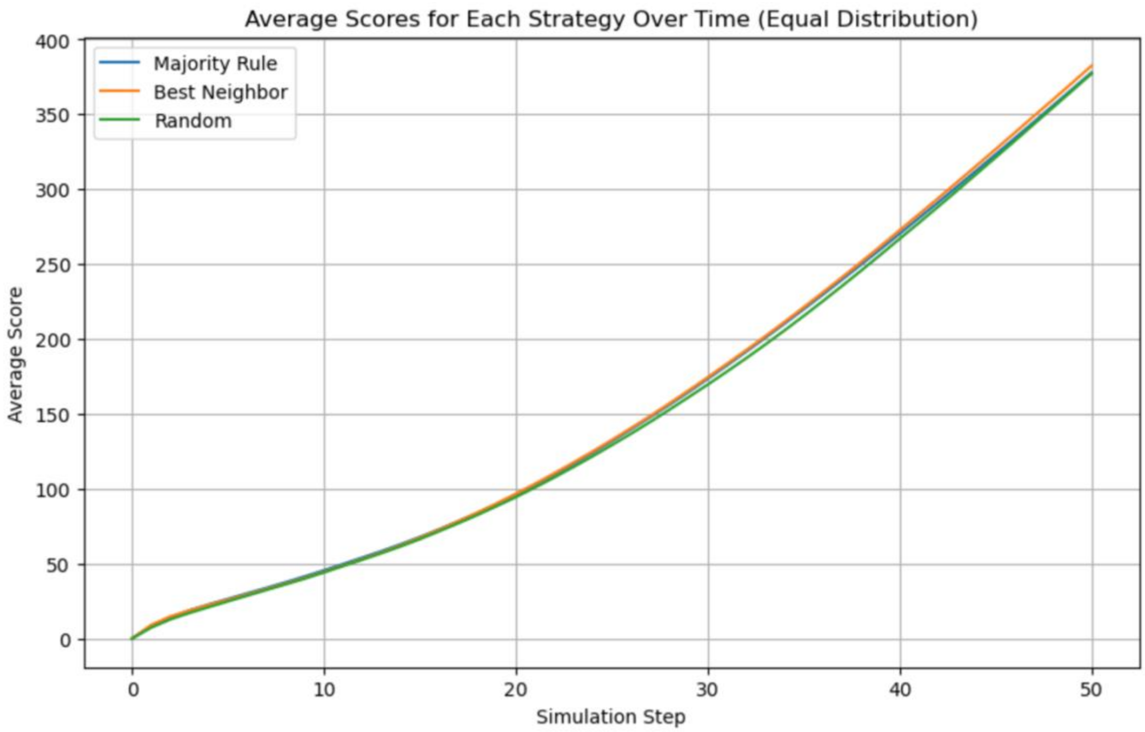

Figure 3. Comparative Efficacy of Learning Strategies. The graph tracks the average scores of the three strategies in a simulation with equal distribution of strategies. Initial conditions were set with a cooperation probability of 0.5 and specific pay-offs (CC: 1.5, CD: 0.0, DC: 3.0, DD: 0.0).

However, when the agents are initialized with a greater variation of pay-offs, such as CC: 0.0, CD: 0.0, DC: 3.0, DD: 0.0, Figure 4 reveals a pronounced advantage for copying the best strategy. Agents employing this strategy swiftly maximize their scores, which then stabilize at a high level. This quick adjustment phase reflects the agility of the strategy in recognizing and adopting the most rewarding interactions.

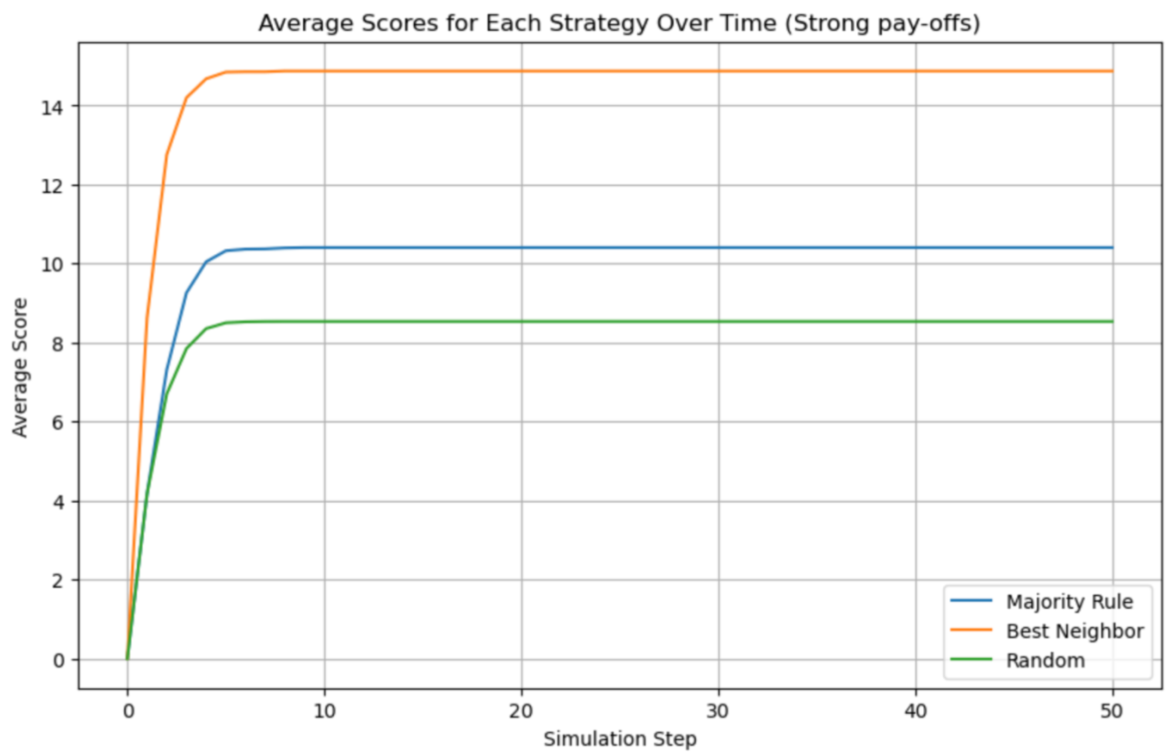

Figure 4. Average scores for different strategies with strong pay-off (CC: 0.0, CD: 0.0, DC: 3.0, DD: 0.0).