Game-Theoretic Coalition Formation Using Genetic Algorithm and Agent-Based Model

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Problem

This paper utilizes inverse generative social sciences (a genetic algorithm), and agent-based modeling and simulation (ABMS) approaches, to dissect the dynamics of coalition formation across a spectrum of different coalition sizes illustrating the intricate patterns that emerge.

Various techniques have been employed to gain deeper insights into coalition formation tendencies and structures [?]. However, the relationships between coalition sizes and the ultimate formation of the coalition structure have not been explored in the field of agent-based modeling.

Introduction

Understanding coalition formation is crucial for enhancing our understanding of social and behavioral dynamics [?].

- Coalition formation helps to better understand the emergence of power structures and collective decision-making processes within human societies and organizations.
- The study of coalition formation informs strategies for conflict resolution and cooperation by identifying factors that drive the formation of alliances and comprehending the dynamics of conflicts.
- Investigating coalition formation sheds light on social influence and the diffusion of ideas, offering valuable insights into opinion formation, the emergence of social norms, and the spread of information through social networks.

Background

Comparing various game sizes within the context of coalition formation holds importance for several compelling reasons.

1. It allows us to understand how the size of a game influences the dynamics of coalition formation.
2. Comparing different game sizes helps us assess the scalability and generalizability of coalition formation strategies.
3. It also provides insights into the trade-offs and challenges associated with coalition formation in complex systems.

The methods employed to analyze the problem are inverse generative social science (genetic algorithm), cooperative game theory, and agent-based models.

Inverse Generative Social Science (IGSS) aims to determine agents' behaviors in an agent-based simulation by matching the simulation outputs with provided real-world datasets [?].

Genetic Algorithm (GA) employs stochastic processes to select and mutate a population of potential solutions represented as chromosomes, composed of ordered genes that influence behavior and determine fitness [?]. GAs iterate through generations, repeatedly evaluating and evolving chromosomes to find the most optimal solution. While GAs have been applied in ABMS for parameter exploration, their application in the context of Inverse Generative Social Science (IGSS) is relatively limited.

Cooperative game theory (CGT) studies the behavior of players when they cooperate to form coalitions [?]. Two main questions cooperative game theory answers are:

1. What coalitions will form?
2. How to fairly divide the payoff among coalition members given their contributions to the coalition?

Agent-based simulation of strategic group formation technique simulates the behavior and interactions of individual agents within a given system [?]. This approach allows us to study the emergence of complex phenomena and understand the collective behavior that arises from the interactions of autonomous agents.

Methodology

The methodology incorporates developing a hybrid agent-based model using cooperative game theory [?]. Next, the IGSS approach was applied to perform computational experiments and generate the necessary data [?]. The overview of the steps employed to conduct the experiments and generate the data is presented in Table 1.

	Overview of coalition formation analysis
1	Define the list of games to be considered;
2	Specify the fitness criteria for evaluating the coalition formations;
3	Utilize a genetic algorithm to improve sub-models;
4	Perform a batch run for simulation run, for each game;
5	Record the average number of coalition suggestions from each batch run and game;
6	Analyze the average coalition formation suggestions required;
	Evaluate the quality of the analysis based on the fitness criteria;
	Identify patterns, and trends, that contribute to successful coalition formations.

Metric for evaluation of coalition formation is the suggested mean of the mean, presented in Eq. 1.

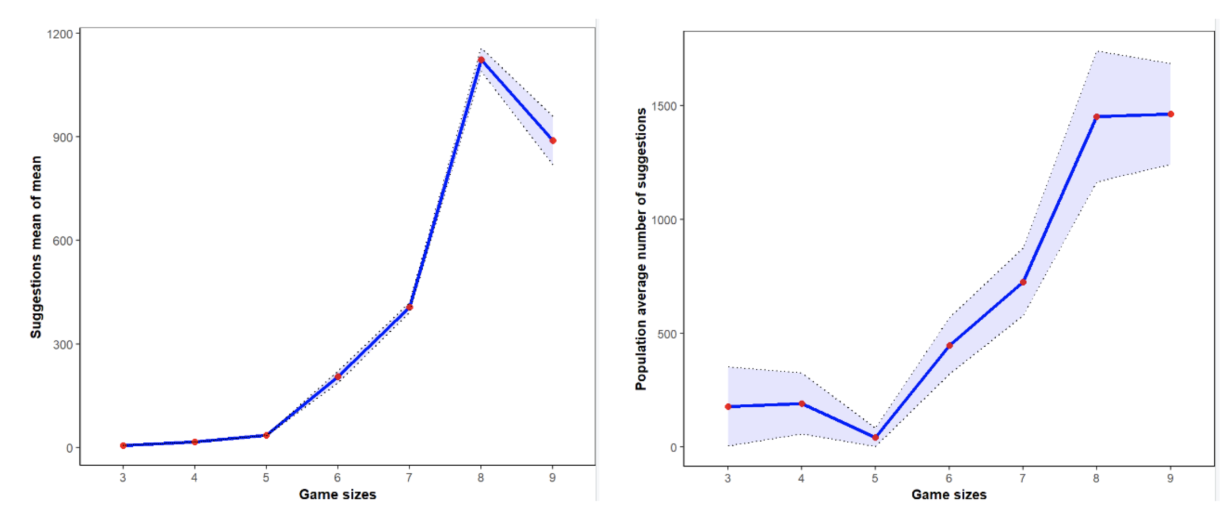
$$SMM = \frac{\sum_{Game=1}^{g} \frac{\sum_{BatchRun=1}^{m} CSC}{m}}{g} \tag{1}$$

Where SMM is the suggestion mean of mean, CSC refers to the coalition suggestion count for a given simulation run, and g refers to the games.

Results

We have analyzed the variation in suggestion means across different:

- Game sizes (Figure 1)
- Time (Figure 2)
- Generations (Figure 3)



(a) Fittest chromosome' suggestion mean of mean (b) Population average of suggestion mean of means

Figure 1. Comparing variation in suggestion means across different game sizes

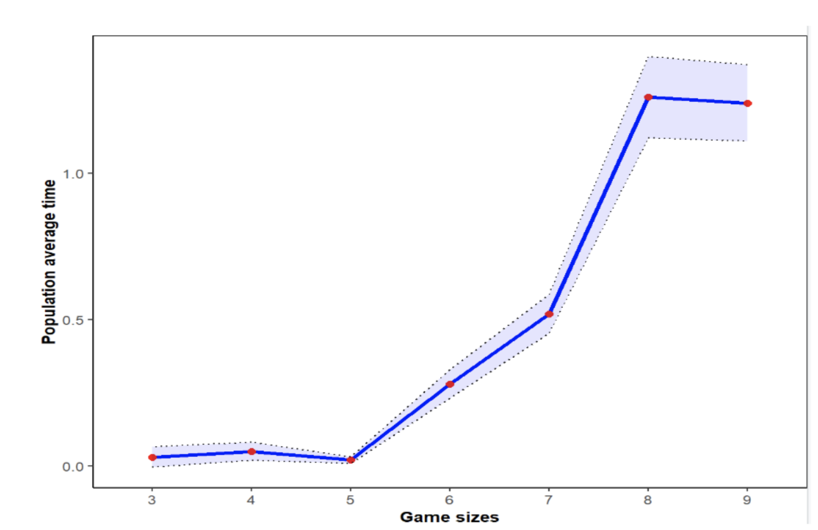
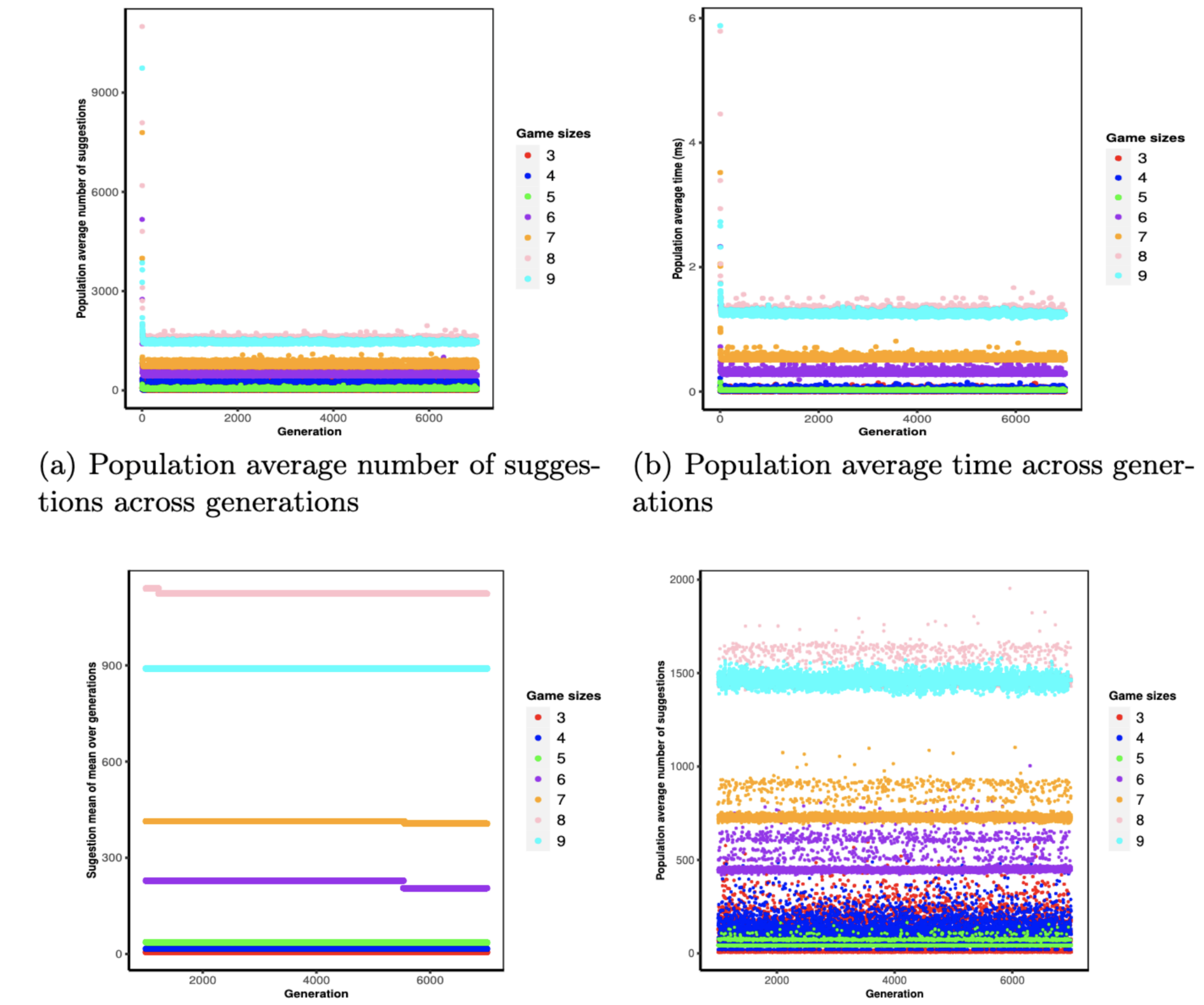


Figure 2. Coalition formation time across different game sizes

Results Cont'd

Initially, we anticipated an increasing trend in the average number of suggestions in the population as the game size increased. However, the graph did not exhibit a consistent upward trend.



(a) Population average number of suggestions across generations (b) Population average time across generations

(c) Population suggested mean of mean: truncated (d) Population average number of suggestions: truncated

Figure 3. Analysis of coalition suggestions across generations

Key findings include:

- The Game size of 5 exhibited a shorter time to reach the solution compared to games with 3 or 4 agents.
- Game size of 9 displayed a slightly shorter time for coalition formation than the game with 8 players.
- The confidence intervals for the Game size of 8 display a slightly wider span compared to the game with 9 players, indicating a slight increase in uncertainty for the estimated value.

Overall the analysis of suggestion outcomes across generations using the genetic algorithm shows a consistent trend in coalition suggestions per generation. There is subtle improved performance observed as generations progress. Larger game sizes generally require a greater number of suggestions. Games with eight players have a higher mean number of suggestions compared to games with nine players.

Conclusion

The computational experiment conducted reveals that, besides game sizes, other factors could significantly impact the time and performance of coalition formation, as indicated by the coalition suggestions and time. The results also indicate the presence of learning in the genetic algorithm; however, it is suggested that increasing the number of generations would yield clearer insights. Additional extensive computational experiments are required to obtain definitive findings from this approach.

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