Overview, Design Concepts & Details: Centrality & Environmental Impact Model

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This document outlines the model using the Overview, Design concepts and Details (ODD) protocol for ABMs [1][2][3].

1 Purpose and patterns

The paper aims to clarify the influence of social networks on common pool resource outcomes. Social networks are a crucial component of systems where different stakeholders come together to deal with natural resource problems. The structural patterns of relations of a social network can have significant influence on how actors behave [4]. Previous work has developed a framework for modelling eco-evolutionary games, involving myopic agents and dynamic incentives through an evolving resource state [5]. Behavioral economics studies the decision-making process of actual humans. In the paradigm of bounded rationality, humans are goal-oriented utility maximisers with the computational abilities and access to information actually possessed by humans [6][7][8]. Building on previous work, [9] include a forecasting agent type to the model in a first attempt to bridge the gap between the myopic agent and computational abilities informed by behavioral economics. The purpose of the model is to study the role of information access through social networks. Heterogeneous information generates diverging agent behaviors. Moreover, we consider that agents with access to more information might also have a more considerable impact on the environment.

2 Entities, state variables, and scales

The model comprises two types of entities: agents and an environment. The model does not contain collectives or spatial entities. Agents represent common pool resource users, such as fishermen or factories affecting a lake's pollution levels. The total number of agents is denoted as P and depends on the modelled resource. Agents possess four state variables. First, the memory ledger tracks the most recent strategies chosen by all other agents. Second, previous observations is a list of values regarding the average extraction level in the population. These values are created as snapshots from the memory ledger whenever an agent acts. The third state variable is an agent's perception of the current environmental state. The fourth state variable is the heuristic an agent employs to form expectations. This heuristic may be an adaptive, contrarian, trend-chasing, or anchoring-and-adjustment rule. The combined behavior of all agents determines the average extraction level, which influences the change in the environmental state. The state variable z_t represents the weighted average extraction in the agent population in period t, taking on positive real values in the range $[0, 1]$. An agent's weight in the average of z depends on their network degree and the inequality of environmental impact parameter ν. z is a dynamic state variable that changes states discretely.

The environment represents the common pool resource. Agents' utilities depend on the resource state. The model contains a single environment. The environmental state is dynamic and denoted as n, a positive real number in the range $[0, 1]$. State changes in the environment are discrete.

Simulations of the model do not pertain to any spatial and temporal scales. For instance, if the agents represent fishers and the environment represents a fish population, the spatial extent could be a lake, the timescale might correspond to a fishing season, and each generation could represent a fishing expedition. The spatial and temporal extent and resolution may vary across different contexts. The model runs for $T = 40000$ periods. With 1000 agents that translates to forty generations, enough for the model to reach a steady state.

3 Process overview and scheduling

The model is designed to capture the result of feedback effects in common pool resources. An agent is randomly selected to act each period to approximate continuous time model behavior. The probably of being selected in a round is constant at $\frac{1}{P}$ and does not depend on the number of past selections. A turn comprises seven processes: four concerning agents' decision-making (observation, heuristic selection, expectation formation, and payoff evaluation), one for updating the average extraction level, one for updating the resource state, and one for all agents to update their perception of the resource state. The heuristic selection process does not occur during the first two generations since performance evaluations require at least two prior realizations of the average extraction level.

The scheduling of events per turn is as follows:

1. Agent i executes their *observation* submodel, updating their memory ledger state variable.
2. Agent i executes their *update heuristic* submodel.
3. Agent i executes their *expectation formation* submodel.
4. Agent i executes their *payoff evaluation* submodel, determining their extraction level.
5. The average extraction level is updated for the extraction of agent i.
6. The environment executes their *evolution* submodel, updating its state for the new average extraction level.
7. All agents execute their *update perception* submodel, adjusting their perception of the environmental state.

4 Design concepts

This section discusses the eleven design concepts characterizing ABMs: basic principles, emergence, adaptation, objectives, learning, prediction, sensing, interaction, stochasticity, collectives, and observation. The design concepts *learning* and *prediction* are discussed together because of their overlap in the context of the model.

4.1 Basic principles

The model addresses a classic problem of ecology and economics, known as the tragedy of the commons. This predicament arises due to misaligned incentives that lead agents to exploit common pool resources excessively. The model integrates two basic principles to address this issue effectively:

a dynamic common pool resource model and the presence social networks that influence agents' boundedly rational decision-making.

The extensive literature on the tragedy of the commons shares two crucial issues. First, current efforts consider a static environment, failing to capture its full range of nonlinearities. Recent research has addressed this gap by investigating natural resources in a dynamic context [5][9], emphasizing the importance of the first basic principle. Second, prevailing models assume agents possess rational expectations or are myopic in their decision-making. While extensive literature challenges the assumption of perfect rationality [10][11][12][13][14][15][16][17][18][19][20], the myopic agent, studied by evolutionary game theory, knows little if anything about the game they are playing [9]. Bounded rationality, which emerges in between myopic and rational agents [21][6][7][8], acknowledges the limited access to information faced by real humans. The social networks that underlie the information sharing between common pool resource users [22][23] can significantly influence how actors behave, justifying the second basic principle.

4.2 Emergence

The model dynamics exhibit two emergent properties. First, skewness of the degree distribution generated by the Barabasi-Albert degree distribution may lead to the overrepresentation of globally rare network states in the local neighborhoods of many agents, generating a majority illusion [24].

Second, an above-FIE outcome results when the correlation between degree and strategy is positive at the critical point of the simulation, while a below-FIE outcome results when the correlation between degree and strategy is negative at the critical point of the simulation. The dispersion between these two outcomes increases in the skewness of the degree distribution because of a more significant majority illusion. As the model's inequality of impact parameter increases, globally rare network states become more central to the model's behavior, dispelling the majority illusion. The model dynamics undergo a phase transition from bistability at low values of the inequality of impact parameter to the FIE at values of the inequality of impact parameter above its critical point.

4.3 Adaptation

Agents exhibit adaptive behavior through strategic decision-making. They choose between extracting from the resource with low effort (L) or high effort (H). Agents respond to two stimuli: the environmental state and their expectations regarding the other users' strategic decisions. This decision is a form of direct objective seeking. Agents estimate the utility associated with high- and low-effort extraction and choose the alternative with the highest objective measure value.

4.4 Objectives

In real-world systems, agents' payoffs depend on their actions relative to the population and the environmental state. Consequently, the payoff functions driving agents' adaptive behavior consider dependencies in the previous environmental state n_{t-1}, expectations regarding the other users' strategic decisions z_t^e, and an interaction $n_{t-1}z_t^e$:

$$\begin{aligned} \pi_t^H(n_{t-1}, z_t^e) &= \alpha + \gamma_1^H z_t^e + \gamma_2^H n_{t-1} + \gamma_3^H n_{t-1} z_t^e \\ \pi_t^L(n_{t-1}, z_t^e) &= \gamma_1^L z_t^e + \gamma_2^L n_{t-1} + \gamma_3^L n_{t-1} z_t^e \end{aligned} \tag{1}$$

In Equation 1, the parameters α, γ_1^H, γ_2^H, and γ_3^H influence the incentive to extract with high effort, while the parameters γ_1^L, γ_2^L, γ_2^L, and γ_3^L shape the incentive to extract with low effort. These parameters collectively define the incentive structure of the model. The difference between these two payoffs $\Delta\pi_t = \pi_t^H - \pi_t^L$ guides agents' decision-making, creating a significant role for the differences between the parameters shaping the incentive structure $\gamma_1^d = \gamma_1^H - \gamma_1^L$, $\gamma_2^d = \gamma_2^H - \gamma_2^L$, and $\gamma_3^d = \gamma_3^H - \gamma_3^L$.

The payoff functions extend [5]. However, in this paper's discrete-time framework, the average extraction level z_t is unavailable during decision-making since it is determined after agents have chosen their strategies. Consequently, payoffs are contingent upon the environmental state before decision-making and agents' expectations regarding the average extraction level post-decision-making.

Since the utility difference is defined as $U_t^d = \pi_t^H - \pi_t^L$, it is better to extract with high effort when $U_t^d > 0$ and with low effort when $U_t^d < 0$.

Furthermore, to capture the uncertainty in their information (see Subsection 4.8), agents consider the possibility of their information being incorrect, which can lead them to choose a strategy with a lower utility. This process is modelled using a sigmoid function that takes the utility difference as input and outputs the probability of choosing high-effort extraction:

$$P_H(U_t^d) = \frac{1}{1 + \exp -\frac{\sqrt{d_i}}{\sigma} U_t^d} \tag{2}$$

In Equation 2, d_i represents the network degree of agent i (see Subsection 4.6). The parameter σ scales the slope of the sigmoid. As the absolute value of the utility difference U_t^d increases or as their network degree rises, agents are more inclined to choose the strategy with the higher utility.

4.5 Learning and prediction

Agents' adaptation to the strategic decisions of the other resource users changes over time because of a learning process. Agents respond to the other users' strategic behavior by forming expectations regarding their future decisions. They form expectations using the HSM [20][25], described in the *expectation formation* submodel in Subsection 7.4. The HSM is a form of explicit prediction. Evolutionary selection or performance-based reinforcement learning based upon relative performance governs the individual choice of heuristics. Hence, the impact of each rule changes over time, and agents switch to more successful rules. The *update heuristic* submodel in Subsection 7.3 describes the updating rule. Adopting this learning model is vital because it provides a description of human decision-making that aligns with results from the lab and field in behavioral economics.

4.6 Sensing

Agents observe the strategic decisions of all users with whom they have a social tie. Social ties are determined through the Barabasi-Albert algorithm. Each agents tracks what all agents are doing. This memory can be thought of as a ledger kept by all agents with an entry for each agent. Entries that correspond to an agent j that agent i has social tie with change during the simulation, as the actions of agent j are observed by agent i. The starting the value of this entry is 0, indicating low effort, because the starting value of z equals 1 in all simulations. The starting value in agent i's ledger for an agent k with whom agent i has no social tie is NaN. This value does not change during the simulation. Whenever agent i acts, they take a snapshot of this ledger and compute the average extraction level in the population. They do not consider their own action when computing this average. Presumably, agent i acts many times throughout the simulation, resulting in many observations. They use these observations to form expectations on the population's future behavior. Each period t, all agents update their perception of the resource state using the average in their memory ledger updated in period t. Contrary to the average used for expectations formation, the average agents use for resource updating does consider their own action.

4.7 Interaction

Agents engage in three forms of interaction. First, agents share information locally through an information-sharing network. Second, agents interact directly through the average extraction level since the incentive structure in the payoff functions may reward or punish coordinating strategies with the other users. This interaction occurs at the population scale. Third, the model exhibits mediated interaction through the resource. Interaction through the resource is global. All three forms of interaction occur during every agent's turn in every period of the simulation.

4.8 Stochasticity

Stochasticity in the model is present in three categories: initialization, information uncertainty, and the HSM. First, the initialization of one variable is random: the initial heuristic adopted by each agent. An equal probability assigned to each of the four heuristics. By incorporating stochasticity, the model avoids outcomes driven by initial conditions.

Second, network generation is based on the Barabasi-Albert algorithm, generating a different network topology in every simulation run. The network introduces limitations to agents' access to information. Agents account for these limitations by using a sigmoid in their decision-making process that outputs the probability of extracting with high effort. A draw from a uniform distribution then determines whether high-effort extraction occurs. This stochastic element accounts for the uncertainty in the decision-making process due to limited information.

Third, the HSM contains two stochastic components. Agents cannot update their heuristic in every generation. Instead, each agent has a probability ρ of being able to update their heuristic. A draw from a uniform distribution decides whether this occurs. Furthermore, past performance governs the probability of being selected for the four heuristics, dividing the probability domain into four accordingly sized intervals. A draw from a uniform distribution decides which heuristic is selected.

4.9 Collectives

The model features no collectives.

4.10 Observation

Data collection in the model occurs at the agent and aggregate levels. At the agent level, the perceived utility of extracting with high and low effort and the index of the acting agent are collected for all agents in each round per simulation. At the aggregate level, the degree of all agents and the skewness of the degree distribution are saved per simulation. The prevalence of the heuristics and the resource state level are collected in all rounds of the simulation. Analyses consider the distribution of outcomes at the simulation level. Hence, no measures of central tendencies are used. No virtual scientist techniques are used in the data collection.

5 Initialization

The model contains two types of initialization: at the aggregate and agent levels. At the aggregate level, I parametrize the initial values of the resource state to examine its impact on the model dynamics. The initial extraction level is initialized at $z = 1$. Furthermore, the initialization of the information-sharing network uses Barabasi-Albert generation procedure. A new network is generated each simulation.

At the agent level, the heuristics employed in the first two generations are randomized. Furthermore, agents' memories are initialized with values of 0 where social ties exist and values of NaN otherwise.

No elements of the initialization use site-specific data, as the model studies the role of bounded rationality in a general common pool resource setting.

6 Input data

The model does not use input data to represent time-varying processes.

7 Submodels

This section discusses the submodels in the model.

7.1 Observation

The observation submodel determines the average extraction level agents perceive. It uses two data arrays: the memory ledger with observed actions and the weights an agent allocates to each of these observations. The memory ledger contains a NaN value at the entries corresponding to agents with whom no social tie exists. Moreover, when forming expectations about the population's average behavior, there is a NaN value at the entry corresponding to a self-link. The other entries of the memory ledger contain the most recent action chosen by the agents with whom a social tie exists.

The array of weights is calculated using the degrees of all agents with whom a social tie exists and the inequality of impact parameter. If d_j is the degree of agent j and A_{ij} equals 1 if agent i has a social tie with agent j and 0 otherwise, then the values of the array of weights at entry j equals:

$$W_j = \frac{A_{ij} d_j}{\sum_k^P A_{ij} d_k} \tag{3}$$

The perceived average extraction level is the sum of the element-wise product of the memory-ledger and the array of weights.

7.2 Update perception

Agents update their perception of the environmental state employing the actual law of motion, outlined in subsection 7.6. This law of motion uses the previous perception of the environmental state and the observed strategic decisions. Agents update their perception of the resource states each round. Agents do not observe all other users, which may result in a potentially distorted perception of the environmental state.

The assumption that agents have access to the environmental law of motion allows deviations from the FIE to be attributed to cognitive constraints instead of a lack of knowledge on the functioning of the resource.

7.3 Update heuristic

The probability that agent i chooses heuristic h in generation t follows a discrete choice model with asynchronous updating:

$$P_{i,t}(h) = \rho h_{i,t-1} + (1-\rho) \frac{\exp(\phi f_{h,t-1})}{\sum_{j=1}^4 \exp(\phi f_{j,t-1})} \tag{4}$$

The parameter $0 < \rho \leq 1$ represents the inertia in switching as subjects change strategies only occasionally. The value $h_{i,t-1}$ equals one if agent i used heuristic h in generation $t-1$ and zero otherwise. The parameter $\phi \geq 0$ quantifies the intensity of choice, reflecting individuals' sensitivity to differences in strategy performance. A forecasting heuristic's fitness f is evaluated using quadratic forecasting errors, consistent with earnings in experiments.

$$f_{h,t-1} = -(z_{t-1} - z^e_{h,t-1})^2 + \eta f_{h,t-2} \tag{5}$$

The parameter $\eta \in [0, 1]$ represents the strength of agents' memory. This form of memory is distinct from agents' memory in observing other users' strategic decisions.

7.4 Expectation formation

The HSM employs the following heuristics:

- adaptive rule: $z^e_t = \beta_1 z_{t-1} + (1-\beta_1) z^e_{t-1}$,
- contrarian rule: $z^e_t = z_{t-1} + \beta_2(z_{t-1} - z_{t-2})$,
- trend-following rule: $z^e_t = z_{t-1} + \beta_3(z_{t-1} - z_{t-2})$,
- anchoring-and-adjustment rule: $z^e_t = 0.5(z^{ave}_{t-1} + z_{t-1}) + (z_{t-1} - z_{t-2})$.

The adaptive rule is an exponentially weighted average of all previous observations. The contrarian and trend-following rules extrapolate the most recent observation using the last observed change in the average extraction level. The contrarian and trend-chasing rules differ in the sign of the β coefficient. Whereas the contrarian rule uses a negative coefficient, the trend-chasing rule employs a positive coefficient. The anchoring-and-adjustment rule uses the average of the memory sample average and the last observation as an anchor. It extrapolates the last observed change in the average extraction level.

7.5 Payoff evaluation

The payoff evaluation submodel begins by computing the utility difference between extracting with high and low effort, as described in Equation **??**. Since the utility difference is defined as $U^d_t = \pi^H_t - \pi^L_t$, extracting with high effort is better when $U^d_t > 0$ and extracting with low effort when $U^d_t < 0$. Second, agents incorporate the possibility of incorrect information and may choose an action with a lower perceived payoff. The sigmoid in Equation 2, which takes as input the utility difference and outputs the probability of choosing high-effort extraction, models this process.

7.6 Evolution

The environment n evolves according to the following law of motion, which captures the qualitative dynamics of decaying and renewing resources [5]:

$$n_t = n_{t-1} + \epsilon(z_t - n_{t-1}) \tag{6}$$

The law of motion dictates that the environment closes a share $\frac{\epsilon}{P}$ of the gap between n_{t-1} and z_t every period. The state variable z_t denotes the fraction of agents extracting with low effort. The parameter ϵ denotes the relative speed of environmental to strategic dynamics. Environmental dynamics are slower than strategic dynamics, i.e., $0 < \epsilon < 1$.

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