Inequality and the Emergence of Social Stratification

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ABSTRACT

In this work, we investigate whether differential (unequal) resource access promotes social stratification (the partitioning of a population into hierarchical groups based on socioeconomic factors). We achieve this by conducting scenario experimentation with NeoCOOP, an ABM that utilizes a Cultural Algorithm to simulate the evolution of resource sharing preferences in an artificial society. By varying the agents' initial resource sharing beliefs, the intensity of differential access, and the frequency at which the agents experience environmental stress. We find that while social stratification does increase when differential access increases, the effect is attenuated at the extremes with agents instead favouring an increase in selfish behaviour across the social strata. We also show that the severity (magnitude) of social stratification is most prominent in societies with initially selfish agents regardless of the intensity of differential access. Interestingly, our results also suggest that heterogeneous populations (agents with greater diversity of resource sharing beliefs) exhibit emergent social stratification to a lesser degree than homogenized populations (even in populations where agents are initialized to be altruistic).

CCS CONCEPTS

• **Computing methodologies** → **Agent / discrete models**; *Artificial life*; • **Applied computing** → Anthropology.

KEYWORDS

Agent-Based Modelling, Artificial Life, Cooperation, Cultural Algorithm, Differential Access, Social Stratification

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1 INTRODUCTION AND RELATED WORK

Various research endeavours, across numerous research fields, have shown a strong relationship between differential access (uneven access to material goods such as food and land [13]) and social stratification (the partitioning of a population into hierarchical groups based on socioeconomic factors such as wealth [10]). A limitation of the state-of-the-art is that social stratification is studied within systems in which it has already emerged. This leaves the underlying conditions under which social stratification emerges open to investigation. An endeavour which Agent-based Models (ABM) are uniquely qualified to address [8]. In this work, we investigate whether differential resource access promotes social stratification under varying degrees of environmental stress and initial agent resource sharing belief distributions. We achieve this by conducting scenario experimentation with a modified version of *NeoCOOP* [7], an ABM that utilizes a Cultural Algorithm (CA) to simulate the evolution of resource sharing preferences in an artificial society.

Based on the Ember et al.'s [11] investigation into the resource sharing behaviours of societies in the Standard Cross-Cultural Sample (SCCS) and Angourakis et al.'s [1] study on the emergence of cooperation and the maintenance of common-pool resources, we hypothesize the following:
H1: Regardless of the agent's initial resource sharing beliefs, stratification will emerge (and increase) as differential access increases. This trend will be most prominent for scenarios in which environmental stress is frequent due to the agents preferring to secure resources for themselves as opposed to sharing with others.
H2: The magnitude of social stratification (the degree to which agents prefer sharing resources with their peers as opposed to their subordinates) will be most prominent is societies that start with a population of selfish agents regardless of the degree of differential access. This is because an altruistic population will find it more challenging to evolve selfish gene values.

2 METHODOLOGY

In this work we utilize a modified version of NeoCOOP (*Neolithic Agent Cooperation Model*), an iterative ABM that simulates evolving altruistic and selfish behaviour in a Neolithic inspired artificial society. For a full description of the model, see Gower-Winter and Nitschke [6] or the ODD+D Description [9] of the model which is included with the model's source code available at: https://github.com/BrandonGower-Winter/NeoCOOP.

In *NeoCOOP*, an agent represents a single *household h* which is formally defined as a 5-tuple: **Resources:** The amount of resources the agent has. **Load:** The amount of resources the agent has donated to other households over the course of the simulation. **Conformity:** The degree to which an agent accepts cultural influence. **Peer Transfer:** Probability an agent accepts a resource transfer request from a peer agent. **Subordinate Transfer:** Probability an agent accepts a resource transfer request from a subordinate agent.

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Unlike most cooperation-based ABMs, *NeoCOOP* allows agents to make decisions based on their social status and the social status of the agents they are interacting with. We define *social status* as the sum of an agent's available *resources* and *load*. To facilitate social stratification, we use the self-organization scheme described by Chliaoutakis and Chalkiadakis [3] whereby a relationship type can be determined for every agent pair by comparing their social status. In this work, agents are considered to be from the same settlement, thus who they can form a relationship with is unrestricted.

When a simulation run is initialized, a limited number of resource patches are generated (100 in this work). These resource patches are assigned to households on a "first come first serve" basis. Each patch contains resources $\in [0, 1]$ that are assigned to it every iteration. Stress is applied to these patches by varying the amount of collectable resources received each iteration according to *sine* waves of different frequencies. Every iteration, agents gather resources from their assigned resource patch. The amount of resources gathered is equal to the full amount of resources available at said patch. These resources are then put into the agent's storage. If an agent does not have an assigned resource patch, it will try to claim one. An agent that does not have an assigned resource patch will not receive any resources during the resource acquisition phase. This is how we introduce differential resource to access to the model. In a simulation with more agents than available resource patches, agents without direct to access to resource patches will be beholden to the cooperative nature of the agents with direct access to resource patches.

Once acquisition is complete, agents determine if they have enough resources to satisfy their needs for the iteration. An agent needs to consume 0.5 resources per iteration to be satisfied. If an agent does not have enough resources, it first asks its authority agents if they would be willing to donate some of their excess resources. For each authority asked, a random value $\in [0, 1]$ is generated and compared to the authority agent's *subordinate_transfer* property. If the generated value is less than the *subordinate_transfer* property, the authority agent is willing to grant donations for that iteration. Whenever a donation is granted, the authority agent has its *load* property increased by the resources donated. If an agent has asked all of its authority agents for resources and it will still go hungry, it then repeats this process for its peer relationships with the donating agent using its *peer_transfer* property to determine if the donation succeeds. If that is still not sufficient, the agent will then ask all of its subordinates for resources. If a subordinate is asked to give any of its excess resources to an authority agent, it does so with 100% certainty.

Agent adaptation is facilitated by a *Cultural Algorithm* (CA) [12] The CA utilizes the agent genotype comprised of the agent's *conformity, peer transfer* and *subordinate transfer* properties described before. The peer and subordinate transfer properties have values constrained $\in [0.0, 1.0]$. Agent fitness is defined by its *social status*. This ensures that selfish and altruistic behaviours are evaluated equally given that high social status can be achieved by both sharing and hoarding resources. The CA executes as follows: every *influence frequency* iterations, agents are influenced in accordance with the *influence rate*. Additionally, agents that will be influenced may instead have one of their genes mutated, using Random mutation [4], in accordance with the *mutation rate* parameter. Pseudocode for this process in included with the Supplementary Materials.

Table 1: NeoCOOP Initialization Parameters

Property	Value
Iterations (M)	10 000
Initial Households	$\in [100, 200, 300]$
L	0.6 [2]
Mutation Rate	0.1
Influence Rate	0.1
Influence Frequency	15
Conformity Range	$\in [0.2, 0.7]$

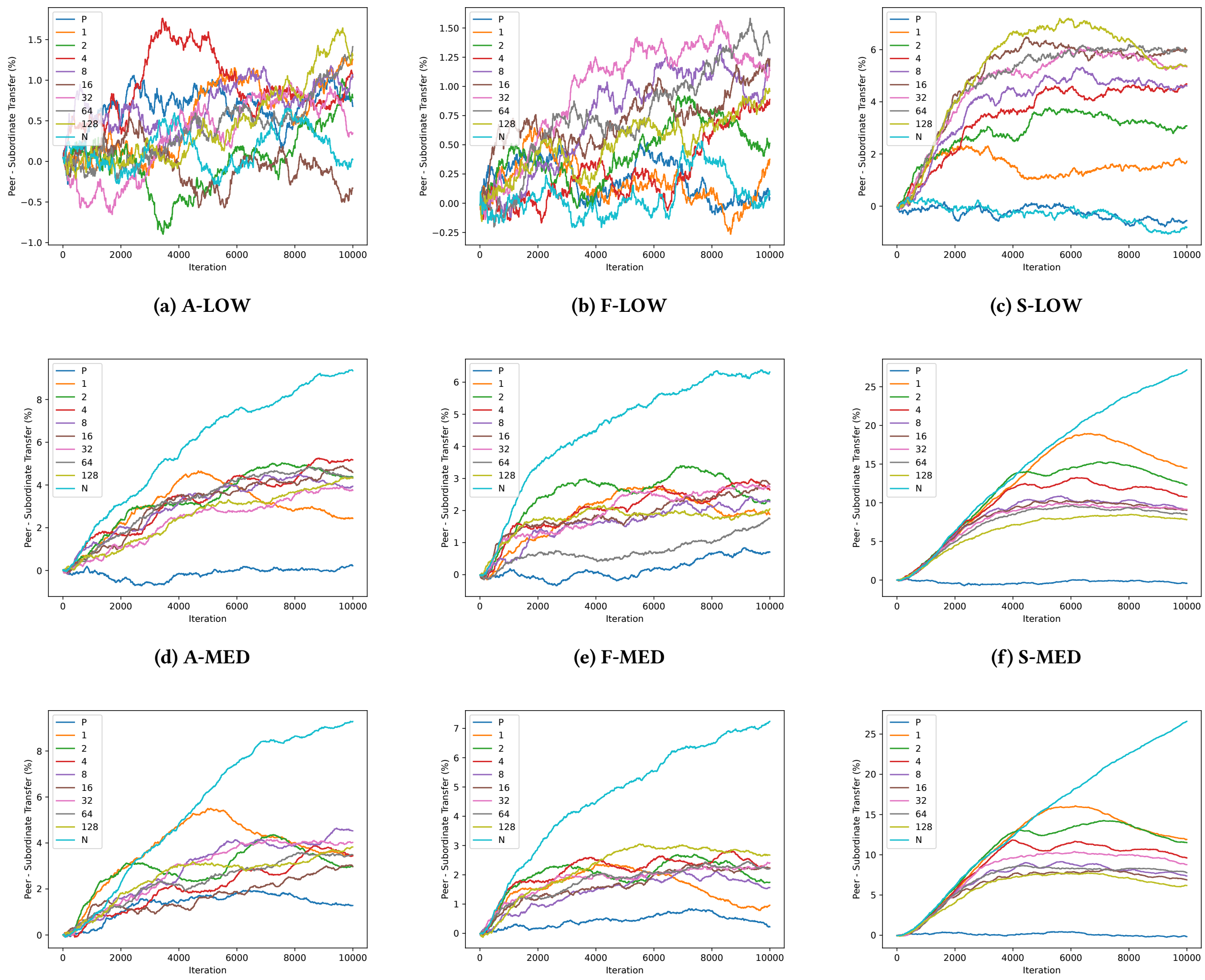
3 EXPERIMENT DESIGN

Given our goal to study the effect environmental stress has on emerging social stratification in societies with differential resource access, our experimental setup was as follows. We first defined the agent's initial resource trading belief distributions denoted as A, S and F. For purely altruistic A initialization, agents have their peer and sub transfer properties initialized to 1.0. For purely selfish S initialization, agent peer and sub transfer properties are set to 0.0. The mixed population F scheme initializes the agents' resources trading beliefs such that half of them follow the A initialization scheme and the other half follow the S initialization scheme. We use differing initialization schemes since the initial resource trading beliefs of an agent population may affect how they evolve over time. We then used the same stress scenarios defined in Gower-Winter and Nitschke [6]. Lastly, we define a set of agent population values to vary the intensity of the differential resource access. We denote these values as $LOW = 100$, $MED = 200$ and $HIGH = 300$. These values represent three distinct conditions where differential access is non-existent, present in half the population and present in a majority of the population respectively.

Using the three initialization schemes, 10 stress conditions [6] and three population categories, 90 scenarios where created. For each scenario, 50 simulations were run to account for model stochasticity for a total of 4500 simulations across all scenarios. Each simulation was run for $M = 10000$ iterations and all other user-defined properties (*Mutation rate, Influence Rate, Influence Frequency* and *Conformity Range*) were parameter tuned (See Table 1) using the same process described in Gower-Winter and Nitschke [7] (with the exception of the load difference L parameter which was taken from Chliaoutakis and Chalkiadakis [2]).

4 RESULTS

The primary take-away from all LOW experiments (See Figures 1a, 1b and 1c) is that stratification of the agents' peer and and subordinate resource transfer properties occurs across all initial belief distributions (to varying degrees) even when differential access is non-existent or low. More specifically, the results show altruistic (A



(a) A-LOW **(b) F-LOW** **(c) S-LOW**

(d) A-MED **(e) F-MED** **(f) S-MED**

(g) A-HIGH **(h) F-HIGH** **(i) S-HIGH**

Figure 1: Plots of the mean difference between the peer and subordinate transfer agent properties for all stress frequencies investigated across all differential access (vertical) and initial belief distributions (horizontal) investigated. A higher value indicates greater stratification. Each subfigure is captioned with its unique identifier. For example subfigure (a) showcases the mean difference between the peer and sub transfer properties for the A-LOW scenarios.

initialization scheme) agents exhibit stratification sporadically and at low magnitudes (a maximum of 1.41%). The mixed population scheme F exhibited similarly low magnitudes of stratification (a maximum of 1.37%) across a wider range of contiguous values (from $f = 4$ to $f = 128$). Lastly, the selfish agents (S initialization scheme) showed the greatest degree of stratification with significant results found across all stress frequencies (except P and N) at greater magnitudes (a maximum of 5.99%).

For all MED scenarios, the agent population is such that half of the agents have direct access to resource patches and the other half do not. Furthermore, MED scenarios are also unique in that under perfect environmental conditions and perfect altruism (unconditional resource sharing), all agents can meet their resource needs. As shown in Figures 1d, 1e and 1f, this does not stop stratification from emerging at a greater magnitudes across all initialization schemes. In fact, with the exception of the $f = P$ for the A and S initialization schemes, significant stratification of the agents' peer and subordinate resource transfer properties was found. Interestingly, the F initialization scheme exhibited the lowest magnitude of stratification (ranging from 0.7% to 6.32%). At first glance, this seems to refute hypothesis H2 suggesting that the agent population's initial beliefs does not affect their capacity to exhibit social stratification. However, by examining the magnitude of stratification that occurred for both the A and S initialization schemes, we see that the predominately selfish societies (S) exhibited greater social stratification (ranging from 7.82% to 27.18%) compared to the predominately altruistic societies (A) whose magnitude of stratification ranged from 2.43% to 9.34%. What this suggests then is that while selfish populations are capable of exhibiting greater degrees of social stratification than their altruistic counterparts, it is in fact population homogeneity that plays a more significant role in determining the magnitude of social stratification. With increased homogeneity leading to greater social stratification.

For all HIGH experiments, the primary results reveal (Figures 1g, 1h and 1i) that while the prevalence of stratification from the MED experiments remains, its magnitude does not increase or decrease consistently across the initialization schemes. For example, stratification across all stress scenarios investigated for $S - HIGH$ shows a decrease in magnitude when compared to $S - MED$. Whereas stratification decreases for $f = P$ to $f = 32$ but increases from $f = 64$ to $f = N$ when compared across $F - MED$ and $F - HIGH$. Furthermore, stratification increased for $f = [P, 1, 8, 32]$ but decreased for $f = [2, 4, 16, 64, 128, N]$ when compared across $A - MED$ and $A - HIGH$. This shows that in the presence of altruistic resource sharing behaviour, the emergence of social stratification exhibits complex non-linear behaviour that is difficult to quantify. Our results indicate that social stratification will appear, but the degree to which it does appear will be hard to predict. This is in contrast to predominately selfish societies where extreme differential access reduces stratification. Interestingly, the cause is not an increase in altruistic behaviour towards subordinates but rather an increase selfishness towards peer agents. In EC terms, fitness values associated with more selfish-leaning agents will be closer to those who prefer to share resources with their peers.

5 DISCUSSION AND CONCLUSIONS

In this work, we investigated whether differential resource access promotes social stratification under varying degrees of environmental stress and initial agent resource sharing belief distributions. We achieved this by conducting scenario experimentation with a modified version of NeoCOOP [6], an ABM that utilizes a Cultural Algorithm (CA) to simulate the evolution of resource sharing preferences in an artificial society. By conducting scenario experimentation and varying the agents' initial resource sharing beliefs, the intensity of differential access, and the frequency at which the agents experience environmental stress. We predicted that social stratification of the agents peer and subordinate resource transfer properties would be positively correlated with differential access. Our results showed that while social stratification does increase when differential access increases, this effect is attenuated in extreme scenarios with the agents instead favouring an increase in selfish behaviour across the social strata. We attribute this phenomena to the principal of "no free riding" in which agents with direct access to resources evolve selfish behaviour to avoid giving out resources to agents who will not reciprocate.

Secondly, we predicted that the magnitude of social stratification (the difference between the peer and subordinate transfer properties) would be most prominent in societies with initially selfish agents regardless of the intensity of differential access. Our results showed that this was the case with the selfish S initialized agents exhibiting the greatest social stratification across all scenarios investigated. Interestingly, our results showed that heterogeneous populations (agents with greater diversity of resource sharing beliefs) exhibit social stratification to a lesser degree than homogenized populations (even in populations where agents were initialized to be altruistic) seemingly agreeing with theoretical notions that some degree of heterogeneity is good for promoting cooperative behaviour across the social strata [5] but, in contrast to other ABM which have shown either neutral or negative correlations with regards to agent heterogeneity and emergent cooperative behaviour. At the very least, our results motivate future research endeavours whereby we will investigate this phenomena more closely by varying the diversity of the agents resource sharing preferences to a greater degree with the overarching goal of attempting to model and understand the underlying conditions that gave rise to social stratification throughout the world and across history.

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