Modeling the Co-Evolution of Culture, Signs and Network Structure

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Abstract. We use agent-based simulation to investigate the interplay between the acquisition and transmission of cultural traits, the dynamics of social network structure and the emergence of meaningful signs. We assume agents in our model must cooperate to thrive in their environment and to be successful in doing so, they must synchronize their otherwise selectively-neutral strategies. We further assume that maintenance of social ties is costly, and that agents cannot directly identify the strategies of their counterparts. We show that when cooperation is biased by the possession of arbitrary observable markers, evolutionary dynamics lead to small-world social structures with communities defined by shared culture and the establishment of markers as signs of community membership.

Keywords: agent-based modeling, evolution, culture, social networks

1 Introduction

In this study we investigate the relationship between evolution of culture and the evolution of social network structure. Specifically, we explore the interplay between selectively neutral cultural traits, selectively neutral external markers (or 'tags' as they are referred to elsewhere in ABM literature) and the maintenance of social ties in a context which requires cooperation and coordination of efforts. Humans are cultural organisms: they can acquire and transmit shared sets of values, knowledge and behaviors [1]. Often these attitudes and behaviors are functionally equivalent to their alternatives. For example, distances can be measured in metric or imperial units, and the findings can be communicated effectively, as long as the actors involved share knowledge regarding which system is being used and a familiarity of that system. The only problem would arise, if some of the actors were unaware that one system was being used rather than the other, or if they were unfamiliar with it. More complex tasks, such as large construction projects, often require the collaboration of multiple individuals and their success depends largely on the assumption that all parties involved possess the same set of domain knowledge. Another aspect of culture are sign systems. Languages are the most complex sign systems, but other more rudimentary examples are commonly encountered as well, such as flags representing nations.

Signs can be used to mark the possession of cultural traits, which might be difficult to ascertain directly. For example, an accent might be a sign of the speaker's place or class of origin. Finally, culture has a local character. While generalizing in their nature, cultural systems vary across physical and social space, forming into more or less defined clusters.

We argue that these phenomena are intertwined and have co-evolved over time through the mechanisms of indirectly biased interaction and transmission. Specifically, assuming conditions under which it is (a) necessary to coordinate efforts of multiple actors to solve complex problems, (b) costly to maintain meaningful social connections necessary for cooperation, (c) disproportionately difficult for actors to ascertain possession of cultural traits in others directly and (d) possible for actors to direct their behavior based on the possession of observable markers, we hypothesize that over time such populations will form distinct cultural clusters and meaningful cultural signs will emerge.

To test this hypothesis we build an evolutionary agent-based model that implements the above conditions. In the model, agents each possess a selectively-neutral variant of a cultural trait representing functionally equivalent approaches to solving problems in an abstract domain, and a tag which represents its observable characteristics. The agents are periodically faced with hazards, which can only be averted by successfully coordinating their efforts with another agent. The agents cannot deduce the specific variants of the trait possessed by others, however they may periodically choose to abandon partners or find new ones.

Numerous studies have explored evolutionary dynamics of culture in an agent-based simulation environment [2] and many have approached this from the perspective of cooperation [3–6]. Similarly, the co-evolution of network structure and cooperation has also been explored [7]. Most of these studies use the Prisoner's Dilemma to mode the interplay between individual benefits of defection and group benefits of cooperation, although some have used other games, e.g. the ultimatum game [8]. Here we assume some form of cooperation is necessary for the agents' survival, but we also assume that cooperative behavior is only successful when agents match their strategies, all n of which are equally adept at solving the task at hand. The problem thus becomes an $n \times n$ coordination game with n Nash equilibria. Furthermore, in most previous studies agents' strategies are hidden to their interaction partners, and there have been several models where the connection between hidden traits and tags has been investigated [9–11]. It is common that the tags are "pre-fabricated" signs, in that agents either recognize them as indicators of group membership [9, 11] or are able to learn a pre-existing relationship between the tag and another trait[10]. We take a different approach and attribute the tags randomly and observe whether any signifying quality emerges from the dynamics of the system. It has been hypothesized that indirectly biased transmission—the selection of traits affected by individuals' selection of models on the basis of unrelated attributes—is an important force in cultural evolution and in the emergence of symbolic culture [1]. The role of indirect bias and tags has been studied with mathematical models[1], even on small groups of live subjects [12]. Here we add to the larger field of socioculture by analyzing its effects through an agent-based simulation on a large social network. Although we focus on the selection of collaborators rather than behavioral models, the indirect bias exerted on cultural transmission remains.

2 Methodology

We initialize agents on nodes of a random network. An agent can interact with others that connect to it via an edge. Each agent possesses one of 10 possible tags and one of 10 possible variants of a cultural trait. The tag and trait variables are categorical. While the tags are visible to the other agents, the trait variants are initially unknown to them. Moreover, each agent possesses a tag preference matrix. For each tag T an agents stores two values. The first, τ_T^+, represents the salience of positive experiences related to tag T, while τ_T^- represents the salience of negative experiences. This salience is expressed in form of a real-valued number from the interval $(-\infty, \infty)$. In each round every agent randomly selects one of its neighbors, and the two interact. The interaction consists of the two agents playing a coordination game: they compare their trait variants and if they match, they both receive one point towards their score; if the variants do not match, both agents deduct one point from their score. After each interaction the agents update their tag preference matrix. Assuming that the interaction was positive, the salience τ_T^+ for the neighbor's tag T is modified as follows:

$$\tau_T^+ = \ln\left[\sum_i^n t_i^{-d}\right] \approx \ln\left[\frac{1}{n-d} t_n^{-d}\right]$$

Here t_i is the time elapsed since the i-th relevant experience, n is the total number of such experiences and d is the rate of decay. An equivalent update applies to negative experiences. The quantity is very sensitive to recent experiences, while the importance of older experiences progressively decays with time. This representation is based on the ACT-R model of agent cognition [13]. Due to the computational infeasibility of the above relationship for large n, we implement a widely-used approximation [13]. In line with convention, we use $d = \frac{1}{2}$ [14]. Because we assume that maintaining social relationships is costly the agents pay a constant link maintenance cost c per round per link. After each round of interaction the agents can choose to cut ties with certain agents or create new ones. Each agent possesses a positive threshold value τ^+ and a negative threshold value τ^-. First it identifies any neighbors with tags whose negative salience exceeds τ^- and it cuts ties with them. It then searches the remaining population of agents and identifies all agents with tags whose positive salience exceeds τ^+. If there are any such agents, it randomly samples a subset of them and attempts to create a new link. The link will attach only if the preference is mutual and if the updated node degree does not exceed the average degree of the initial network. To prevent the network from reaching a degenerative state, we force the agents to maintain at least one connection at all times.

After a predetermined number of steps the population is evaluated and a subset of parents is selected. The parents reproduce to create offspring before they are removed from the population, so that only the offspring remain. Selection is based on agents' scores accumulated throughout the current generation. For each node two parents are selected via a tournament of size 3, chosen randomly from the set of the node's neighbors and the current occupant of the node. The parents recombine their phenotypes to create a single offspring via uniform crossover, i.e. each part of the phenotype is inherited from one of the parents with 50% probability.The inherited phenotype includes the tag, the trait variant, as well as the tag preference matrix and the salience thresholds. Mutation is applied to each part of the phenotype with 1% probability; random resetting is used for categorical variables, while Gaussian perturbations are used for real-valued variables. The population size is kept constant. Because the tag preference matrix is inherited in its final form, as it was molded throughout parents' lives, the model implements a Lamarckian version of evolution in which acquired characteristics are passed on to subsequent generations.

To control for the effects of biased interaction we introduce two other model configurations. In the second configuration, we eliminate the plasticity of the tag representation matrix. Thus, agents preferences for the individual tags are set at birth and they do not change throughout their lives as a result of interaction. This implementation is closer to a purely "genetic" model of bias.

Finally we devise a "baseline" configuration, one which does not include any tag-related bias. In this case the agents do not possess the tag preference matrix, they do, however, display some ability to maximize their interaction utility. The agents only remember their last interaction that took place. If that interaction was negative, the agent will cut ties with the partner in question. If the last interaction was positive, the agent, emboldened by its recent success, will create an additional connection to a randomly selected agent.

3 Results

Figure 1 shows the differences in evolutionary dynamics using the three different model configurations with a single choice of parameters. Here, we initialize a population of 1000 agents on a random network with average degree $\langle k \rangle = 8$, link maintenance cost $c = 0.16$ and 10 rounds of interaction per generation, for 100 generations. Sub-figures 1(a),(b) illustrate the distribution of tags and trait variants over time. We observe that in the case with no bias the trait distribution is by far the most skewed, in fact drifting away towards a single variant. The tag distribution is fairly similar in all cases, remaining only moderately skewed. This is to be expected in the unbiased case, as there is no selective pressure exerted on the tags. In the biased configurations, this requires further investigation.

We then introduce a measure of tag "entropy". Based on Shannon's Entropy [15] it measures the (un)predictability of specific states. In this case we measure how well the tag "alphabet" encodes different trait variants. We write:

$$E_j = -\sum_i p_i \ln p_i \quad \text{and} \quad \overline{E} = \frac{1}{N} \sum_j \frac{E_j}{n_j}.$$

Here i iterates over the set of trait variants, p_i is the probability of encountering the i-th variant in the current tag, j iterates over the set of tags, E_j is the entropy of the j-th tag, N is the cardinality of the tag set and finally, we use the size of each tag sub-population, n_j, to normalize and obtain the average metric entropy, $\overline{E}$. Figure 1(c) shows tag entropy results for different model configurations. While the Lamarckian configuration is able to evolve into a state with low entropy, where each tag more or less faithfully encodes for a specific cultural trait variants, the unbiased configuration shows even lower values of entropy. This is surprising at first glance, as the tags are an afterthought in the unbiased model with no real significance. However, it is important to note, that this is a result of the drift in trait variants. It is then easy for every tag to encode a specific variant, as there is only a single one present in the population.

We thus further analyze the interplay of tags and cultural traits by measuring the modularity of the agent networks in terms of both attributes. Network modularity measures how neatly the network decomposes into communities defined on the possession of a shared attribute [16] and is defined as:

$$Q = \frac{1}{2m} \sum_{vw} \left[A_{vw} - \frac{k_v k_w}{2m} \right] \delta(c_v, c_w).$$

Here m is the edge count of the network, v, w are nodes, A refers to the adjacency matrix, k_v and k_w are the degrees of the nodes, c_v and c_w are the attributes of the nodes, and δ refers to the Kronecker delta function. Figures 1(d),(e) show that the the biased versions of the model produce communities that are well defined by both their tags and the trait variants that they share. Such communities do not appear in the unbiased configuration.

To better elucidate the situation we visually tracked the changes in the social networks of the agents over the course of the simulations. Figure 2 shows illustrative snapshots of the network evolution. We observe that in the beginning, the networks become very sparse in both cases and social interaction thus becomes minimal. This changes as the simulation progresses, and the differences between the two model versions becomes clear. In the unbiased model a single giant component emerges; meanwhile the Lamarckian bias creates a network organized into clear communities marked by possession of distinct tags and trait variants. Moreover, each tag locally strongly correlates with a single trait variant. The presence of clearly defined clusters suggests the small-worldness of these networks. To confirm this we compute the average clustering coefficients and the average path lengths of the networks. Watts and Strogatz [17] assign "small-world" properties to networks if they have significantly lower path lengths yet comparable clustering coefficients as a regular lattice of the same size and average degree as the target network. Figures 1(f),(g) show these measures, and we observe that while all three configurations show significantly shorter path lengths than regular lattices, the Lamarckian configuration demonstrates significantly higher clustering coefficients than the other two. This indicates a small-world quality of the networks under the Lamarckian model, while the other versions produce networks that are more random in nature.

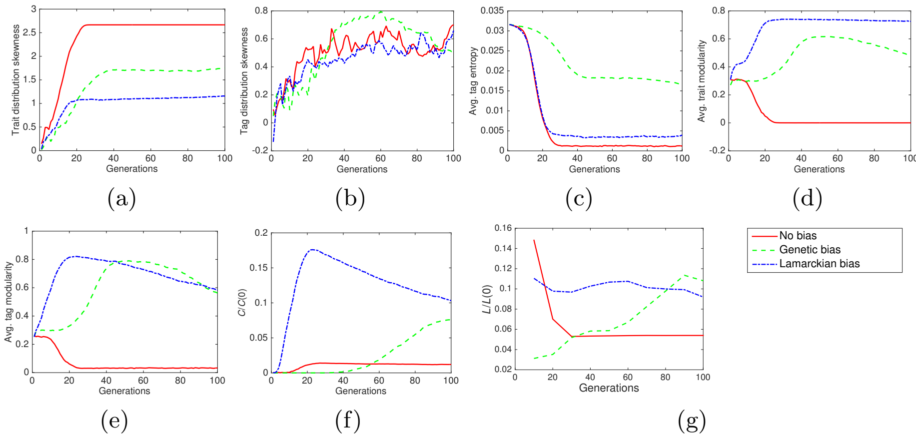

Fig. 1: Model statistics for $\langle k \rangle = 8, c = 0.16$ and $H/V = 10$.

To ascertain how sensitive these outcomes are to the choice of parameters we performed a partial parameter sweep. Namely, we tested the sensitivity with respect to the average degree $\langle k \rangle$ of the initial network, the link maintenance cost c, and the ratio between horizontal interaction frequency and vertical transmission frequency H/V. Figure 3 shows the dependence of some of the measured quantities on the cost and the ratio between interaction and transmission events frequency[1]. We observe that the Lamarckian model demonstrates higher clustering coefficient values than the other configurations across a major part of the parameter space, especially in cases with very low maintenance costs. Similarly, the Lamarckian model shows consistently shorter path lengths, while the other configurations display sensitivity to increasing the generation length (i.e. the genetic bias configuration) or increasing the maintenance cost (i.e. the unbiased model). Moreover, both of the biased versions display consistently higher rates of tag modularity than the unbiased configuration. Once again, this is especially pronounced in low maintenance cost regimes. A similar narrative applies to trait modularity, although it is worth noting, that in high maintenance cost regions the Lamarckian model now performs worse than the unbiased model.

4 Discussion

We have shown that bias can have a significant effect on social network structures in the long run, especially if bias acquired throughout agents' lifetimes is inherited by their offspring and the cost of social tie maintenance is low. In the beginning, the system dynamics are similar in all of the observed cases. Because trait variants and tags are assigned randomly, and the placement of

[1] We have not observed significant effects of changing the average degree, and therefore do not show figures including this parameter.

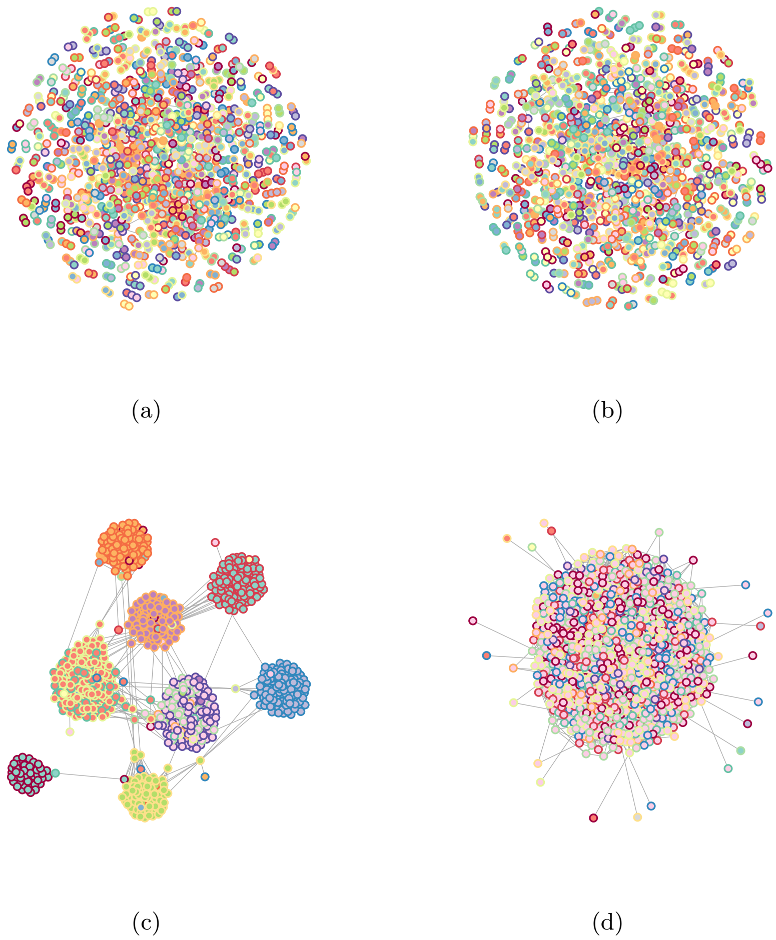

Fig. 2: Visualizations of the agent network in the Lamarckian bias (left) and unbiased (right) configurations after 5, 20 and 100 generations. The border color of a node determines its external marker, while the inner color determines its cultural trait variant. $\langle k \rangle = 8, c = 0.16, H/V = 10$.

agents on nodes is also random, the probability of any agent having a successful interaction is fairly low at the onset. Tie maintenance is costly and therefore in the biased configurations evolution selects for individuals who possess strict preference thresholds, and thus can maximize their utility by minimizing the frequency of social interactions. The same outcome can be observed in the unbiased configuration where agents simply prune their neighborhoods after every failed interaction. This explains why we witness a dramatic decrease in network

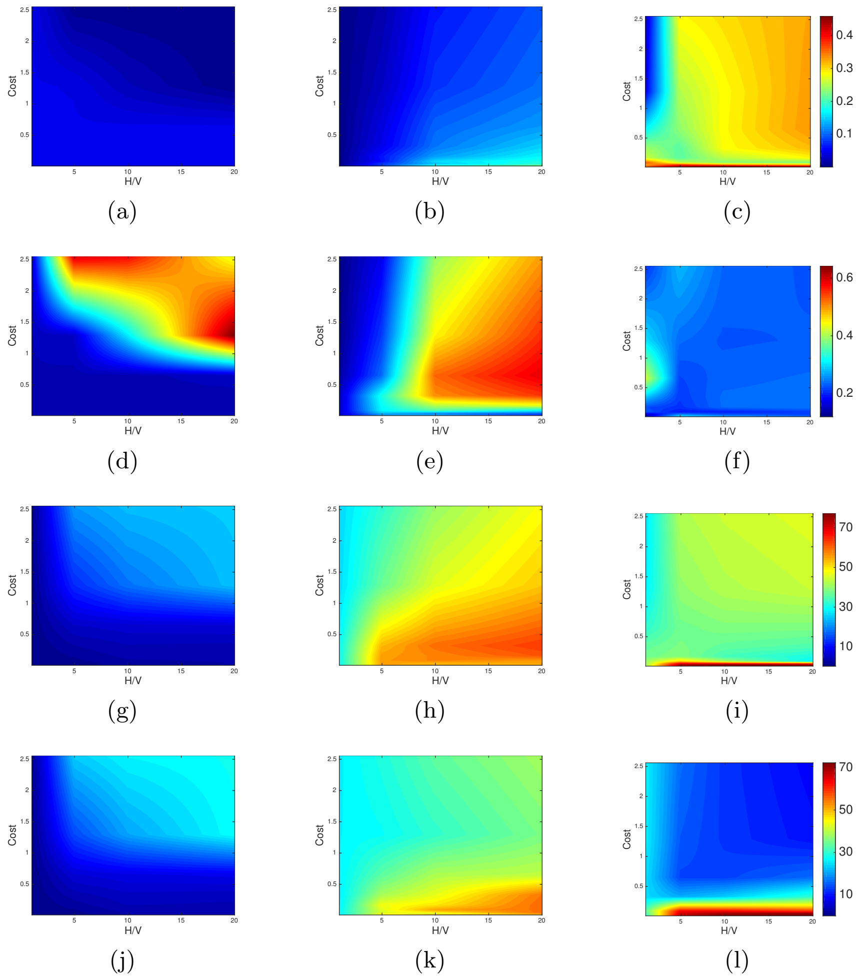

Fig. 3: Model statistics as a function of maintenance cost and interaction/transmission ratio for the unbiased (left), genetic bias (centre), and Lamarckian bias (right). Parts (a)-(c) show the average local clustering coefficients at the end of runs compared to regular lattices. Parts (d)-(f) show average path lengths at the end of runs compared to regular lattices. Parts (g)-(i) show the sum of tag modularity values at the end of each generation. Parts (j)-(l) show the sum of trait modularity values at the end of each generation. $\langle k \rangle = 32$.

density in the beginning stages. After this phase, the dynamics diverge. In the biased versions, sub-populations of agents who are located on fairly small connected components of the network eventually converge on a single trait variant and a single tag. We argue that this is due to drift effects, which become exacerbated in small populations, and most importantly due to kin selection [18]. Because offspring are always born in their parents' vicinity, agents find themselves in neighborhoods which are increasingly homogeneous with respect to agent attributes. If, by chance, the dominant phenotype possesses a high-scoring preference for its own tag, the dynamics are only reinforced. Furthermore, the integrity of the tag group is unharmed by growth, as new links are only made to the already established preferred tags. Because these processes are able to emerge in parallel within the many disjoint network components, this results in the formation of multiple clusters defined by a dominant tag-variant pair. Due to this effect of bias, the tags can become imbued by meaning, transforming into cultural signs representing possession of specific variants. It is worth noting that due to the local nature of network coalescence the meaning is also local: the same variant can be represented by different tags in different clusters, and different variants can be represented with identical tags in separate communities.

The situation is quite different in the unbiased configuration. The lack of distinct tag groups is self-explanatory, however, the absence of trait clustering deserves more attention. We argue that the main driver of the network structure in this case is drift. Without bias, agents attach to others randomly. If a certain trait variant owns a slight edge in frequency, agents possessing that variant will have a better chance of meeting their counterparts. As this trait group grows so does its advantage, attracting and infecting smaller components more easily.

We have also observed that the biased populations were able to evolve into more distinct clusters when the cost of tie maintenance was low. When costs were high the "small-worldness" of the biased networks has diminished and trait variant distributions displayed higher takeover rates. We argue that this is partly because as costs increase the effect of drift surpasses the effect of kin selection. As the maintenance cost becomes high relative to interaction payoffs, mistakes—nearly ubiquitous at the onset—become cruelly punished. This leads to a highly uniform distribution of fitness. Moreover, the high costs lead the agents to hold higher standards, and thus to keep smaller neighborhoods. Both of these facts contribute to higher rates of drift and lower rates of modularity and clustering.

The importance of cultural markers throughout has been documented throughout history. But cultural dimensions are likely important in modern networks of trust as well. Does culture factor in transactions between strangers on web services such as AirBnB or Craigslist? How does large-scale collaboration on open-source software projects emerge? We believe that our model could be applied to such real-world scenarios and validated with the help of empirical data.

While the simulations analyzed for this study have provided insight into the effect of biased interaction on the evolution of network and community structure there are still questions worthy of further investigation. It is natural to ask how exactly and to what degree kin selection affects the dynamics. It is therefore worthwhile to consider designing an experiment in which one would to isolate the dynamics of kin selection and analyze them precisely. Furthermore, we did not attempt to adjudicate the question whether the proposed strategies are evolutionarily viable and robust. In future research we will focus on simulating mixed populations, and identify conditions under which bias-driven strategies can permeate populations from random mutations and resist invasion.

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