A Dual-Inheritance Model of Cultural Evolution with Agents

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Abstract

We present an agent-based model of cultural evolution based on dual-inheritance theory. We model populations of interacting and learning agents with vertical transmission of cultural traits indirectly biased by co-evolving preferences for certain external markers, as well as horizontal transmission of cultural traits via model-based, frequency-dependent guided variation. We further analyze the cultural dynamics of these populations over a large number of generations. We present some preliminary results that show biased vertical transmission leading to the emergence of transient clusters of externally and culturally homogeneous agents. We also note that the guided variation mechanism leads to faster drift towards a global monoculture.

1 Introduction & Motivation

Cultural practices structure human conduct in contexts ranging from modes of governance and natural resource management to conflict resolution, power relationships and religious practices. Due to their wide-ranging effects and observed persistence, such practices can serve as either seemingly insurmountable roadblocks or powerful catalysts for problem solving in different areas of life, such as economics, politics or international relations. We can consider the example of climate protection. Global climate change is to a considerable degree driven by specific human-developed natural resource management practices, determined by values, beliefs and social institutions (Tohme 1992). Another area of application is the question of opinion radicalization in social groups. Previous data-driven research has shown that the emergence of specific forms of terrorism is related to differentiation in cultural dimensions and the absence of cultural engagement in individuals (Kluch and Vaux 2015). If we could properly understand the life-cycle of cultural practices, we would be better equipped to solve complex issues in these areas of interest. Here we outline an effort to develop a more powerful explanatory model of the complex long-range dynamics of cultural practices in human societies and present some preliminary results.

The model presented here is embedded in the dual-inheritance theory of cultural evolution, which assumes both horizontal (intra-generational) and vertical (inter-generational) transmission of cultural traits in a population of social actors (Boyd and Richerson 1985). With the help of this model, we wish to address two related questions. First, can persistent cultural clusters emerge solely through vertical transmission of cultural traits indirectly biased by co-evolved preferences for specific external markers? Second, does horizontal transmission in the form of model-based, frequency-dependent guided variation also aid such cultural clustering?

Many decisions that individuals and societies face are largely arbitrary: What does the sequence of characters "tree" signify? When is it appropriate to accept a gift from someone? It often matters more whether the actors can eventually coordinate on a decision, rather than which of the many alternatives is chosen. Under such circumstances it becomes important to the actors knowing which partners to trust to think and act the same way. In this light, the first question then asks whether it is possible for a population of actors to culturally coordinate over many generations if they base their trust in arbitrary markers, and if this is the case, whether the markers can co-evolve into signs of cultural affinity. The second question then asks whether the cultural coordination is more effective if agents can also adjust their own cultural behavior based on the recommendations of actors they deem trustworthy. To determine what kinds of macro-scale phenomena these mechanisms produce in different qualitative types of human societies we develop and analyze an agent-based model where individuals enter into dyadic interactions with others based on co-evolving preferences for external markers and attempt to solve simple coordination problems.

2 Background

In modern anthropology neo-evolutionary theories have discarded several concepts of classical social evolutionism; doing away with notions of social progress and determinism. Neoevolutionism embraced stochasticity and individual decision-making among other driving forces of cultural emergence. Nevertheless, it remained firmly grounded in the Darwinian evolutionary framework (e.g. Sahlins 1960). In the biological sciences, evolutionary explanations of culture emerged under the heading of sociobiology. Wilson (1975) pioneered this approach, taking a strictly genetic view of cultural evolution. These ideas were rejected by many intellectual opponents, claiming them to be biologically deterministic and ehtnocentric (Sahlins 1976, Gould 1981, Lewontin et al. 1984).

Dual-inheritance theories respond to this strain of research and hypothesize that culture is transmitted in human populations both vertically–from generation to generation–by forces that can be modeled with mechanisms similar to biological evolution, as well as horizontally–within generations–by social influence. Boyd and Richerson (1985, 2005) use genetic evolution as a partial metaphor for the evolution of culture, although they point out major differences. Most importantly, genetic evolution drivers such as selection for reproduction,

gene recombination and mutation act on the genotype of individuals, while only indirectly affecting the phenotype. In B&R's model of cultural evolution the phenotype is also affected directly by social forces of cultural transmission. Particularly important in this model are the concepts of biased transmission and guided variation. Biased transmission is based on the notion that the co-evolution of preferences for specific phenotypic variants can drive the selection of certain genetic (or in this case cultural) variants. Guided variation then serves the purpose of transmitting cultural trait variants within a single generation. The process of guided variation depends on an adaptive standard that determines which cultural variants are learned. In our case the chosen adaptive standard is model-based (actors mimic behaviors of preferred model agents) and frequency-dependent (actors mimic behaviors which are encountered more frequently).

Within computational social science, researchers have also contributed towards explanations of cultural dynamics. One of the most influential ABMs of culture is due to Axelrod (1997). A number of agent-based modelers have since revised and extended Axelrod's original model (e.g. Klemm et al. 2003, Parisi et al. 2003, Centola et al. 2007, Flache and Macy 2011).

However, these models assume agents possess perfect knowledge of their neighbors' cultural "genotype". Moreover, they only model horizontal transmission of cultural information. Other agent-based models of culture have attempted to circumvent the former shortcoming. Bednar and Page (2007) created models in which agents play several games with different payoff matrices, representing cultural domains. Agents possess limited cognitive capacities and their rule sets for both games are forced to overlap to a certain degree. A different approach to represent agents' indirect inference of others' cultural traits is the use of observable tags. Hales (2000) developed a model in which agents played one-shot prisoner dilemma games only with agents possessing the same tag. Hammond and Axelrod (2006) also made use of tags in their agent-based model of ethnocentrism. Finally, Reynolds (1994, 2008) has developed the class of cultural algorithms, introducing vertical transmission. These models are genetic algorithms in which agents evolve based on their performance against a fitness function and a belief space, which consists of the cultural genotypes of top performers. The rest of the population then acquires traits from this space via an influence function.

It is evident from this concise review that computational cultural models can be useful in exploring cultural dynamics, however none of the existing designs can sufficiently implement the proposed theoretical framework. While each of the computational models reviewed in this section implements a subset of required mechanisms, no one incorporates the full set (see table 1).

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	Vertical transmission	Horizontal transmission	Biased interaction	Limited knowledge
Axelrod	✗	✓	✓	✗
Klemm et al.	✗	✓	✓	✗
Parisi et al.	✗	✓	✓	✗
Centola et al.	✗	✓	✓	✗
Flache & Macy	✗	✓	✓	✗
Bednar & Page	✗	✓	✗	✓
Hales	✓	✗	✓	✓
Hammond & Axelrod	✓	✗	✗	✓
Reynolds	✓	✗	✓	✗
Revay & Cioffi	✓	✓	✓	✓

Table 1: Design comparison of relevant agent-based models of cultural dynamics.

3   Model design

We develop an agent-based model to test and analyze the effects of biased transmission and guided variation on the evolutionary dynamics of the cultural makeup of social actors [1].

The model is based on several assumptions about the behaviors of the individual actors:

1. Individuals interact in dyads, in a number of contexts, in which they seek to successfully coordinate their efforts.

2. Individuals have the ability to categorize others based on their external markers.

3. Individuals will tend to select interaction partners based on external markers that they prefer.

4. Individuals have the ability to assess previous interactions to an extent, and designate preferred markers based on this history.

5. Individuals have the ability to learn to imitate the cultural behaviors and attitudes of other actors, at a certain cost to their well-being. Cultural learning is assumed to be costly because it interferes with other activities such as securing natural resources for survival.

6. Individuals have limited knowledge in the sense that they do not have any concrete information on another actor's cultural attitudes before an interaction takes place.

7. Individuals inherit the external markers and cultural attitudes from their ancestors.

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[1] The model is written in the MATLAB programming language. The code of the model is publicly available at www.openabm.org/model/5243

8. An actor's well-being increases when they are able coordinate with others. It decreases when they are unable to coordinate.

Based on these assumptions, we test the following hypotheses:

- *H1*: Interaction biased by actors' co-evolved preferences for specific external markers, iterated over the course of many generations, is conducive to the emergence of stable clusters marked by the presence of shared cultural attitudes.

- *H2*: Guided variation in the form of model-based, frequency-dependent imitation is conducive to the emergence of stable cultural clusters.

The model consists of a large number of agents that are activated in discrete time steps and a mechanism for repopulating the simulation with new generations of agents at equally spaced intervals. The model is then instantiated in several versions. In the first version the agents possess the following attributes:

1. **Indicator:** A set of observable external markers, which can be physiological (e.g. skin tone), material (e.g. clothing) or immaterial (e.g. accent). By design they are always known to other agents. Indicators are represented as integer scalars on a categorical scale. The range is given as a parameter.

2. **Preferences:** A mental list of indicators that each agent uses to determine with whom they would prefer to interact. The size of the list is limited by the agent's memory parameter. It can be updated throughout an agent's life based on experience from past interactions. Preferences are represented as integer vectors.

3. **Cultural Traits:** A list of traits which represent different dimensions of social life (e.g. language, gift-giving). Every agent possesses one of many possible variants in each trait (e.g. 'English', or 'always bring a gift to a dinner party'). Trait variants can change during an agent's lifetime through learning. Each trait variant is represented as an integer scalar on a categorical scale. The range is given as a parameter.

4. **Fitness:** A measure of the agent's ability to coordinate with others. Fitness is represented as an integer scalar on a cardinal scale.

It is important to note that we do not assume any initial relationship between the external markers and the cultural variants. On the other hand, one of the objectives of the model is to determine whether any relationship between them can co-evolve in the system.

In each time step every agent will seek to interact with another agent. An agent who wishes to initiate an interaction will randomly select one of their preferred indicators and seek out a potential partner with that indicator. If the preference list of the potential partner includes at least one instance of the

initiator's sole indicator the two begin the interaction[2]. The interaction itself consists of randomly selecting a cultural trait and comparing the variants of the agents in that trait. If the variants match, the interaction is considered a success and both agents receive a fitness boost. If the variants do not match, both agents will incur a penalty to their fitness. Moreover, if the interaction is successful the agents will add their partner's indicator to their preferences. At the same time the agent will clear the least recent preference, as it will now consider it out-dated.

After a set number of time steps in which each agent is activated, the population is processed by an evolutionary algorithm. The algorithm first selects a subset of the agent population based on their fitness. This is done by fitness-proportionate, or roulette-wheel selection. That is, if an agent A has a fitness that is k times the fitness of agent B, then agent A has a k times higher probability of being selected. The probabilities are normalized so that they sum to unity. A single agent can be selected multiple times. After the subset of these "parent" agents has been identified, "offspring" agents who inherit their parents' attributes are created. This represents primary socialization during the course of which offspring acquire indicators as well as cultural trait variants and preferences by imitating their parents. After the offspring have been created, their attributes are randomly mutated with small probability. This represents the often imperfect socialization process, as offspring often differ from their parents in the details of their cultural makeup. Finally, the original population is removed from the system and the newly created offspring make up the new generation of agents. The size of the population is kept constant.

The design of the agent architecture and the interaction mechanism in this first version of the ABM is motivated by B&R's (1985) model of biased transmission. Here, the agent's cultural genotype (consisting of its cultural trait variants and its preferences) as well as the phenotype (the indicator) are vertically transmitted from generation to generation. The transmission of the cultural traits is effectively biased by the agent's preferences. However, the preferences will also face selection pressure [3]. In a subsequent version of the model a mechanism for horizontal transmission is added, representing forces of guided variation (Boyd and Richerson 1985). This calls for the inclusion of additional agent attributes:

1. **Learned Traits:** Cultural trait variants that the agent has encountered through learning. An agent retains a certain number (given by its memory size) of variants of each trait encountered in learning experiences. The lists are used to strategically update agent's own cultural trait variants.

2. **Learning Frequency:** The number of times the agent will learn during its lifetime. The learning frequency is also inherited from parent agents.

In this iteration agents will, apart from standard interactions, also attempt

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[2]If there is no agent in the population with the chosen preferred indicator, then no interaction takes place and the agent is punished as if it were an unsuccessful interaction.

[3]Selection pressure is expressed in terms of the relative reproductive disadvantage of one phenotype over another in a given environment.

to "learn" new trait variants in random time steps from other agents. Once the learning algorithm is activated, the ego agent will again randomly select one of its preferred indicators and seek out a potential alter with the given indicator. A random cultural trait is selected and the ego copies the alter's variant on that trait and stores it as one of its learned variants for the given trait. At the same time the ego will clear the least recent learned variant, as it will now consider it out-dated. Both agents then incur a penalty to their fitness, regardless of outcome. Finally, the ego then assesses its list of learned variants associated with the selected trait and chooses the most commonly appearing variant in the list to become its own trait variant.

In the following sections we analyze the performance of the base model, and we test its sensitivity to the following parameters and additional features:

1. Agent memory size (Model *I*)

2. Exploration rate (Model *II*) [4]

3. Range of cultural trait and indicator variants (Model *III*)

4. Guided variation (Model *IV*)

4 Results

We first comment on the behavior of the base model (Model *I* with memory size m=1). In this model we instantiate a population of 100 agents who each possess one of 10 possible variants in a single cultural trait. Each agent also possesses one of 10 possible indicators. The indicators and trait variants are assigned randomly from a uniform distribution. Each successful interaction adds 1 point to the agents' fitness, an unsuccessful one results in a subtraction of 1 point from their fitness. The agents have a memory size of 1. Because agents are initialized with fictional memories, they will only interact with the same types of agents throughout the simulation and never change preferences (because any successful interaction will have already taken place with the agent's preferred type of partner). There is no exploration. The simulations last for 100 generations, each generation consisting of 20 rounds[5]. Figures 1(a),(b) show fan plots [6] of the dynamics of the best performing trait variants and indicators over time. We observe that the variability between runs is quite large: in

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[4]The exploration rate will define the probability of an agent being forced to interact with a random partner regardless of its preferences. In the original specification of the model the diversity of an agent's preferences can only decrease over time. Once a certain type of agent is eliminated from its preferences it may never interact with it again. In reality, circumstances might sometimes force actors to interact with unwanted partners. This can lead to increasing the diversity of the agents' preferences over time.

[5]A round consists of n random agent activations, where n is the population size.

[6]A fan plot aims to visualize the uncertainty that surrounds repeated simulations of time-series. Each shaded region shows a different percentage of the range of outcomes. The lighter the color, the larger the percentage of the range encompassed within that region.
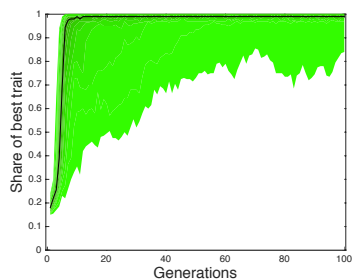
Figure 1: Model I: Statistics for simulations with different agent memory sizes m (100 runs each).
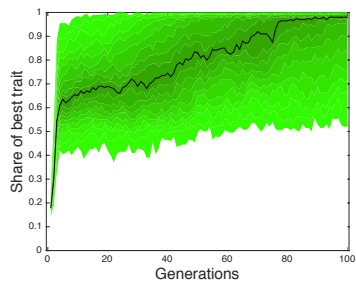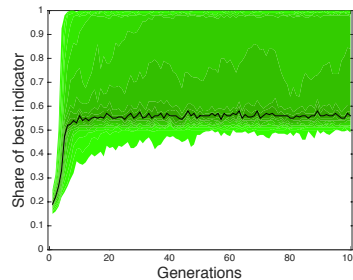
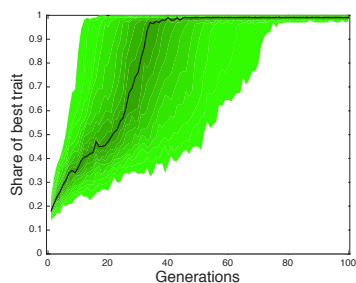

(a) Best trait variant, $m = 1$
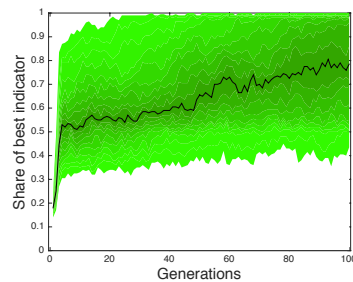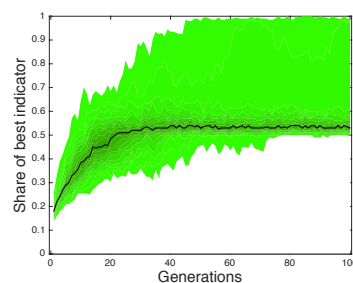
(b) Best indicator, $m = 1$
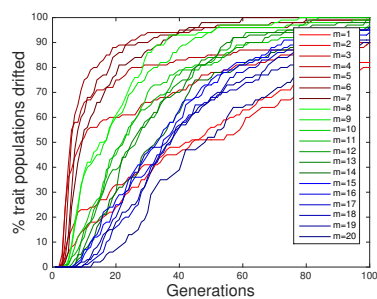
(c) Best trait variant, $m = 5$
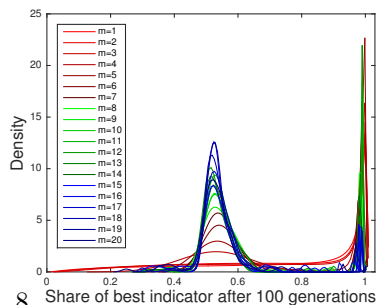
(d) Best indicator, $m = 5$

(e) Best trait variant, $m = 15$

(f) Best indicator, $m = 15$

(g) Trait drift

(h) Indicators after end of run

some runs the trait distribution drifts to a single variant after the first few generations; in a few others there is no clear trend towards a single cultural variant [7]. However, by the end of the last generation a vast majority of runs has drifted to a single trait variant. The indicator distribution also invariably narrows to a considerable degree over time. In a significant number of runs the distribution drifts once again to a single value. In several of the remaining runs the distribution settles into a bimodal state with two more or less equally strong indicators.

4.1   Memory size (Model I)

Figures 1(c)-(h) show the effect of increasing the memory size. At first when the memory size is increased, the agent populations show a trend towards faster drift to a single trait variant. The increases in memory size also lead to higher overall drift rates. However, as the memory size increases even further, specifically when $m > 6$ (or about a third of a generation length), the drift in cultural traits begins to slow down once again and this continues until the maximum memory size of $m = 20$ is reached. The overall drift rates remain high even as the memory length increases continue. The indicator distributions also respond to increasing memory size, albeit in a different way. We observe that as memory size increases, the ratio of agent simulations which result in a bimodal indicator distribution grows substantially larger (see figure 1(h)). In these cases, the population is divided into two groups of roughly the same size marked by two different indicators.

4.2   Exploration rate (Model II)

Figures 2(a)-(h) show the dynamics of the system under different values of the exploration rate, with memory size $m = 5$. We note that small perturbances in the agents' preferences (i.e. low non-zero exploration rates, specifically $e = 0.1$) contribute to a slightly slower drift in the trait variant distribution. On the other hand the low exploration rate is more conducive to drift towards a single indicator. However, as the exploration rate is further increased ($e \geq 0.2$) the drift in cultural traits becomes even faster than in model version I with no exploration. Finally, as the exploration rate nears its limits ($e \approx 1$), thus overriding any agent preferences and rendering indicators irrelevant, the indicator distribution ceases to drift away.

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[7] Genetic drift is the change in the frequency of a gene variant in a population due to random sampling of genotypes (Masel 2011). Here we define that a simulation has *drifted* towards a single variant occurs at the first point in time when a single indicator or trait variant reaches a 95% share of the population. Absolute homogeneity (100%) can never be achieved due to random mutation. The value of 95% was chosen because in every run this mark was achieved, the share then never dropped below it again.
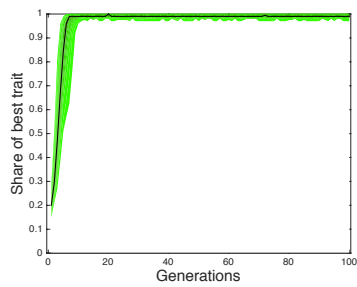
Figure 2: Model II: Statistics for simulations with different exploration rates e (100 runs each).
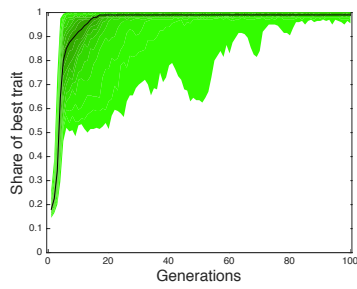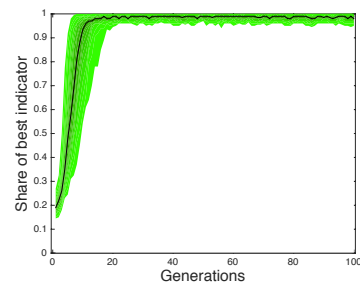

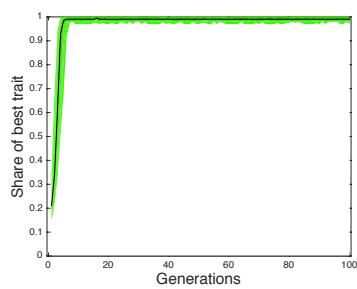(a) Best trait variant, $e = 0.1$
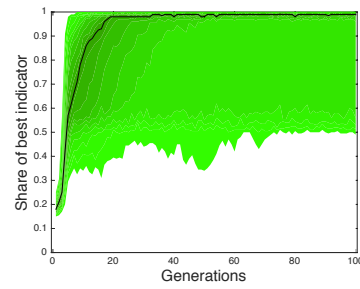
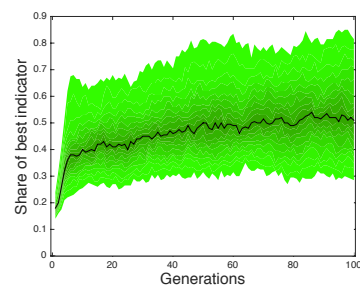(b) Best indicator, $e = 0.1$

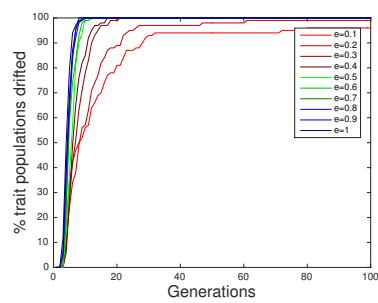(c) Best trait variant, $e = 0.5$

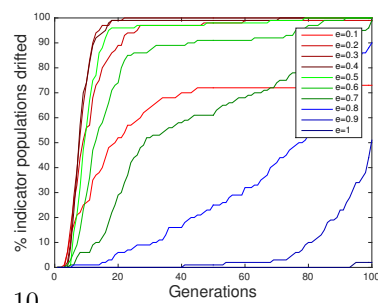(d) Best indicator, $e = 0.5$

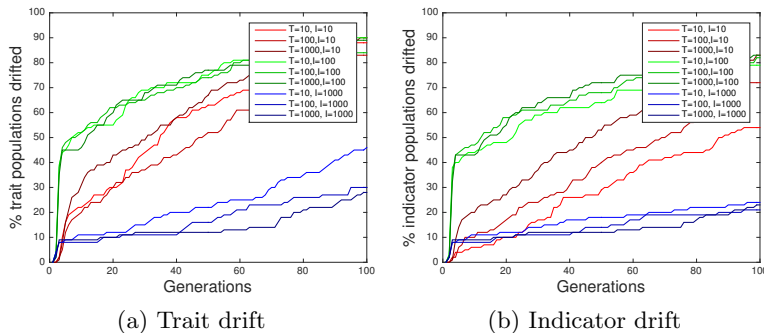(e) Best trait variant, $e = 1$

(f) Best indicator, $e = 1$

(g) Trait drift

(h) Indicator drift

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Figure 3: Model III: Statistics for simulations with different indicator (I) and cultural trait variant (T) ranges (100 runs each).

(a) Trait drift   (b) Indicator drift

4.3   Indicator and cultural trait variant ranges (Model III)

Figures 3(a),(b) reveal the regimes of the system behavior with different ranges of indicators and cultural trait variants. We observe that both indicator and trait drift is more more common in configurations where either the indicator range does not exceed the population size. Drift rates in both distributions decrease when the range exceeds population size. We also note that the drift rate is more sensitive to the range of indicators than the range of the trait variants. Moreover, the change in drift rates is not monotonic with respect to the indicator range: both the indicator and the trait populations drift at higher rates once the indicator range is increased from 10 to 100, only to see this trend reversed once the range is further increased to 1000.

4.4   Horizontal transmission (Model IV)

Figures 4(a),(b) illustrate the differences in behavior of the agent simulations in situations with and without horizontal transmission of cultural traits. We note that the addition of the horizontal transmission mechanism results in a higher drift rate in the trait variant distribution and overall faster drift times. Moreover, the drift rate towards a single indicator is also higher in the case that includes inter-agent horizontal transmission. The percentage of simulations that result in bimodal indicator distribution remains roughly the same in both cases.

5   Discussion

5.1   Main Results

At its core the evolving system of agents is a simple hill-climber. This is best demonstrated in model version II in the case when $e = 1$. Even when indicators are taken out of the equation and agents attempt to blindly coordinate with random interaction partners, the evolutionary forces of genetic drift weed out

Figure 4: Model IV: Statistics for simulations with and without horizontal transmission (100 runs each).

(a) Trait drift   (b) Indicator drift
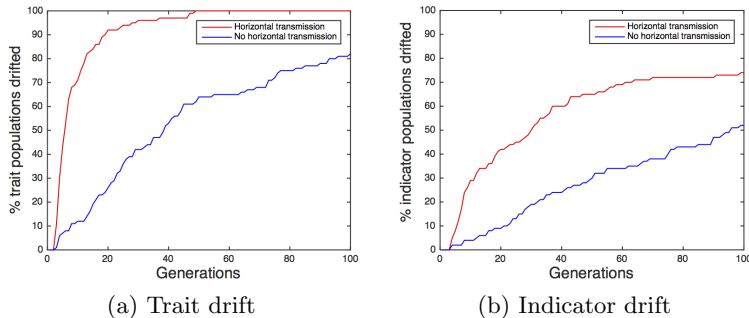
those who are in the minority (i.e. those who have a lower probability of coordination with a randomly selected agent), until eventually a single trait variant spreads into the cultural genotype of the entire population. In this light we can deduce that when the vertical transmission cultural traits is indirectly biased by preferences for specific indicators, it acts as a culturally divergent force, by slowing down the drift in the population-wide trait variant distribution.

In model version I without exploration and a trivial memory size of 1 the average number of interactions during an agent's lifetime as well as the percentage of successful interactions soars very early (see figure 5(a),(b)). After the first few generations nearly every interaction is successful. However, at this stage neither the indicator nor the trait variant distributions have drifted away (see figure 5(c),(d)), and there are numerous unique variants still present in the population. These two facts point to the presence of several distinct indicator-trait variant pair clusters within which agents are able to coordinate with each other. Figure 5(e) shows an example run where this phenomenon occurs. Within these clusters the indicators effectively begin to function as culturally defined signs of socialization, informing agents of suitable interaction partners. In most cases, after this first part of the run where the clusters are established, the indicator and trait variant distributions eventually settle on a single value due to genetic drift (Boyd and Richerson 1985, pp. 271-279).

Agent memory size has proven to affect the behavior of the system. In the low to middle ranges of the memory size parameter the speeds and rates at which indicator and cultural trait drift happen are higher. This is because although the agents get to sample a wider range of the indicator spectrum in the beginning, they are able to keep a high success ratio, thanks to the efficient updating of preferences. Due to these factors the population quickly crystallizes into a single trait variant group with one or two indicators present, skipping the clustering phase altogether (see figure 5(c),(d)). However, in the high end of the memory size spectrum the drift in the trait variant distribution once again decelerates noticeably. This is because it takes the agents longer to flush out ineffective

preferences from their memories. Even if an agent records several successful interactions a large number of unproven or out-dated indicators remain in its list of preferences. This is demonstrated by the very low number of interactions and the low success rates in the early simulation stages of such configurations.

It might seem counter-intuitive that increasing the exploration rate would result into faster drift towards a single trait variant and a single indicator. However, Figure 6(a) shows us that in configurations with higher exploration rates, agents interact significantly more often in the beginning stages of the simulation; resulting in heightened selection pressure. The main difference is that in populations where the indirect bias acting on vertical transmission has a larger effect, the indicators begin to serve as cultural signs for the other agents, thus also becoming a constituent part of the agent culture.

Unsurprisingly, significantly broader ranges of possible indicators and cultural trait variants have resulted in the inability of the agents to coordinate, at least in the time-spans analyzed in this study. As the range of possibilities becomes larger, the probability of encountering an interaction partner with the same trait variant in the beginning of the simulation decreases proportionally. Moreover, the probability of the presence of a preferred indicator for any given agent also decreases with any increase in the indicator range. This results in a much lower number of interactions between agents (see figure 6(b)) which in turn considerably slows down the evolutionary process. The higher sensitivity to the indicator range is explained by the causal precedence that indicator choice takes over trait interactions: for the interaction to take places, one must first find a suitable indicator. At this moment it is unclear what causes the non-monotonic drift rates with respect to increasing the indicator range.

The addition of the horizontal transmission mechanism resulted into cultural trait and indicator drift occurring more rapidly and more often on average. This is despite the fact that learning is costly and thus results into a fitness penalty. Indeed, the average agent fitness is consistently lower. On the other hand, the fitness distribution is more negatively skewed during the first few generations (see figure 7(a),(b)). This exerts higher selection pressure on the under-performing individuals, which in turn triggers a faster drift-away process in the agent population. However, we also observe that the role of horizontal transmission quickly deteriorates as the simulation progresses (figure 7(c)). We hypothesize that this is because selection will initially favor those individuals who do not spend resources on learning. These individuals will then take over the population before any positive effect of learning appears.

## 5.2   Implications for Future Research

We have seen that if dissonance in cultural trait variants is punished and successful coordination is rewarded, while assuming vertical transmission of cultural traits, genetic drift will drive a population of agents toward a single cultural trait variant. When preferences for certain external markers are further assumed the resulting indirect bias on the cultural traits results in slower drift. Moreover, for certain parameter configurations (described in 5.1) this mechanism leads

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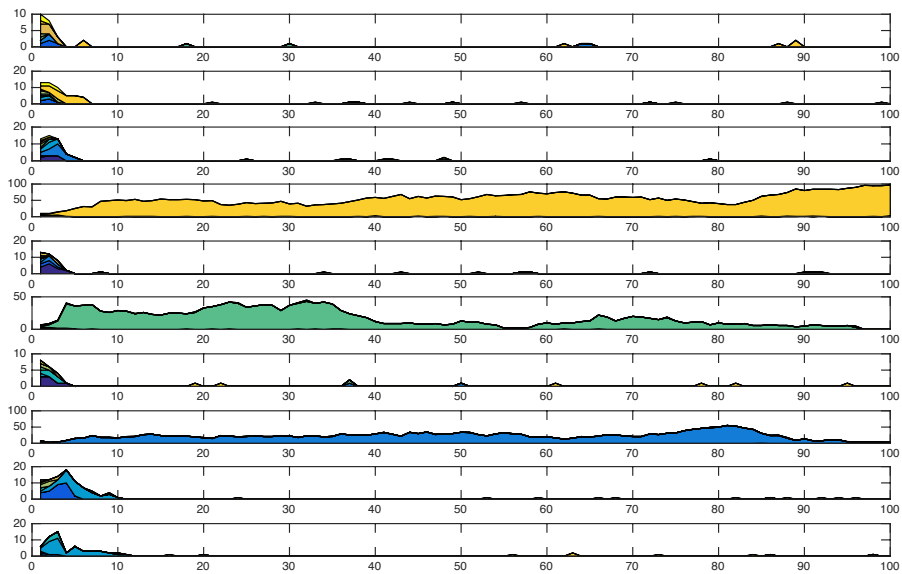Figure 5: Model I: Additional statistics for simulations with different memory sizes m
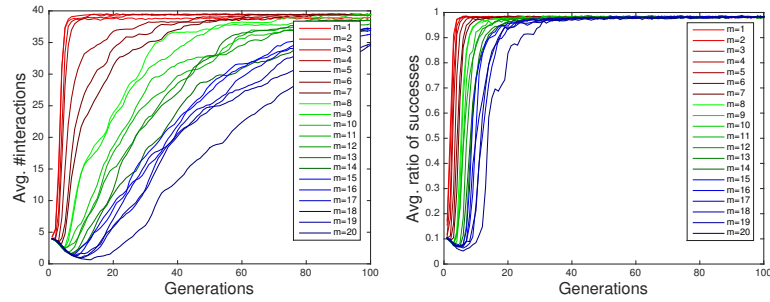
(a) Interactions

(b) Succesful interactions
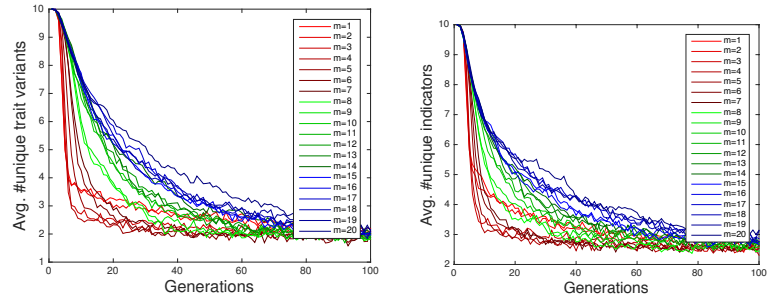
(c) Unique trait variants

(d) Unique indicators

(e) Area graph of trait variant counts in sub-populations sharing the same indicator. Each trait variant is associated with a different color.

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Figure 6: Average number of agent interactions per generation for different model versions.
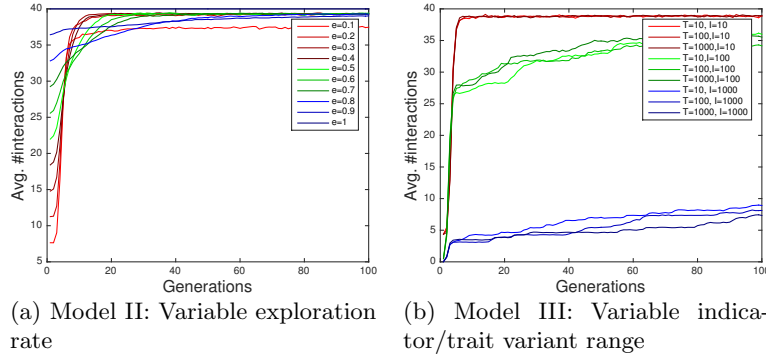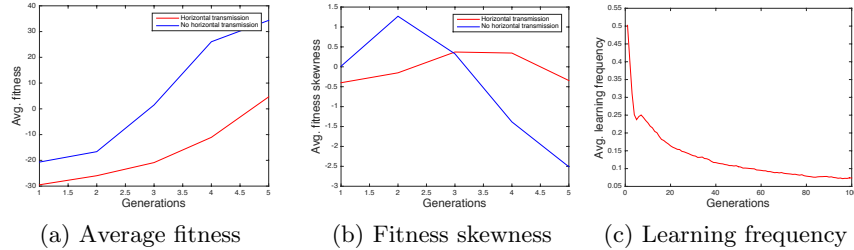

(a) Model II: Variable exploration rate

(b) Model III: Variable indicator/trait variant range

Figure 7: Model IV: Additional statistics for simulations with horizontal transmission.

(a) Average fitness

(b) Fitness skewness

(c) Learning frequency

to the presence of several "cultural clusters" in which all agents share a single indicator-trait variant pair. However in a majority of cases these clusters are unstable, eventually collapsing into a single homogeneous culture. In some cases such clusters remain present throughout the entire simulation. Nonetheless, we hypothesize that in such cases an eventual collapse into a homogeneous culture might also occur at later times. This does not reflect the reality of human cultures well, because we witness persistent clustering (local convergence offset by global diversity) in most cultural domains: the existence of different religions, nation-states, languages, etc.

For this reason future research on cultural evolution should consider additional factors which influence the clustering of population into distinct cultural groups. We propose several features that we wish to implement in subsequent versions of the model:

1. Spatial and network representations

2. Ordinal scales of cultural features

3. n-adic interactions

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4. Homophily

5. Alternative selection and reproduction methods

6. Multiple/dynamic indicators

7. Discovery of new cultural variants and traits

Finally, in this study we have only analyzed the performance of indirectly biased vertical transmission and model-based frequency-dependent horizontal transmission as hypothesized driving forces of cultural evolution. However, we have not discussed the question of how these mechanisms could have evolved themselves and become selected by evolutionary forces as the ultimate drivers of culture formation. In fact, based on the analysis of our model, horizontal transmission did not prove to be advantageous under our assumptions. The costs simply outweighed the benefits before they could show their full effect. It is important to note that the costs and rewards were simply selected to be equal in magnitude. It is difficult to select any other "natural" set of payoffs without further research and validation. However, for the reasons stated above, the sensitivity of the system with respect to different sets of payoffs should be explored in the future.

6   Conclusions

We have developed a model of vertical transmission of cultural traits indirectly biased by preferences for external markers and model-based, frequency-dependent horizontal transmission in populations of interacting and reproducing agents. Based on analysis of preliminary results, we have shown that evolutionary forces of selection and reproduction alone, acting on populations where dissonance in cultural trait variants is punished and coordination rewarded, contributed to a rapid drift toward a homogeneous culture marked by a single trait variant shared by all agents. The addition of the indirectly biased vertical transmission of cultural traits acted as a culturally divergent force. Moreover, in certain parameter value regimes, the indirectly biased vertical transmission mechanism resulted into transient cultural clusters of agents marked by a common indicator-trait variant pair shared by members of the group. This finding is in line with our first hypothesis. This meant that the indicators effectively commenced to serve as cultural signs. However, these clusters were not permanent and in most cases eventually collapsed into homogeneous monocultures. Finally, the addition of model-based frequency-dependent horizontal transmission led once again to more rapid and more common drift events in both the indicator and cultural trait variant distributions. Thus, our second hypothesis that horizontal transmission facilitates cultural clustering has not been supported.

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