The Role of Modularity in Stabilizing Cultural Evolution: Conformity and Innovation in an Agent-Based Model

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Abstract

In this paper I discuss the role and sources of innovation in generating culture, and also the role of modularity in preserving it. I also discuss the extent to which biological selection can underly cultural evolution and the interaction between these. Finally I present two sets of pilot experiments mostly as 'intuition pumps' to explore the problem of cultural stability and change. The first models the impact of noisy transmission and modularity on cultural stability. The second looks at the impact on a culture if a biologically-adaptive variant of one cultural trait is present.

Introduction

Innovation is a topic of great interest in the study of cultural evolution. How do new behaviours and ideas come to be established in a culture? The reason for this interest is obvious — culture is after all an amalgamation of past innovations, so the study of innovation is also the study of the origins of culture. However, the emphasis on novelty that the term "innovation" elicits may not be the most useful perspective for truly understanding culture origins. For evolution, the main challenge is *preserving* useful traits. The most essential characteristic of life is its capacity to reproduce — diversity and increasing complexity, while also fascinating, occur in other materials as well.

How difficult is preserving culture? Sperber & Hirschfeld (2004; 2006) argue that due to the noise inherent in the social transmission of behaviour, only a modular model of learning and mind can explain cultural stability. They propose the massive modularity hypothesis (Samuels 1998; Carruthers 2005) as an alternative to the current emphasis on imitation as a source of culture.

In this paper I examine the Sperber & Hirschfeld argument in terms of reasoning from our knowledge of information and of computation. I then examine the conditions necessary for stabilising cultural transmission in the face of noise using an agent-based model. Next, I extend the original model to a situation where a more adaptive solution is available for one of the culture's modules, and examine the conditions by which the culture can innovate or adapt to embrace that solution, including looking at the impact on other strands of the culture. The results are intriguing and not yet fully analysed — I present them here as pilot work in an exciting area of study.

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Terms and Concepts: Cultural Evolution and Innovation

Whether culture can (like life) be usefully thought of as an evolutionary system is still a matter of debate (Aunger 2000; Richerson & Boyd 2005). While acknowledging this, in the present paper I will not address that controversy directly, but rather just assume an evolutionary perspective towards culture. Indirectly, to the extent that this work provides a useful perspective for explaining and predicting cultural change, it can be viewed as evidence for the hypothesis that culture evolves.

Taking then the selectionist perspective, innovation might be usefully viewed as mistakes in the cultural replication and preservation process that happen to persist. Of course this perspective is a simplification. There may well be intelligent search performed by some individual 'carrier' of the culture that is the root cause of some specific 'defect in replication', and any particular variation in culture may actually convey a *biologically*-adaptive benefit. However, taking a meme's-eye view of innovation may help us understand the processes that underly it (Dawkins 1976).

I take it as given that *some* cultural variation happens as a result of blind chance and copying errors. For the sake of simplicity therefore, this will be the only sort of 'invention' I model here. I presume that intelligent invention only accelerates the pace of change by making actually adaptive 'errors' more frequent, but otherwise does not substantially change the process. In an effort to keep this paper as clear as possible, I will call any deviation from a culture an invention, and any invention that reliably persists through cultural transmission an innovation. My models show conditions where an adaptive innovation can be made, and conditions where innovations occur even though they have no adaptive impact.

Background: Modularity and Cultural Stability

In this paper I will be decompose the social communication of behaviour into two levels of depth. The rote replication of end effector positions or end effects I will call 'imitation'. By 'imitation' I do *not* necessarily mean a full transfer of behaviour. This latter would imply that two agents have communicated not only actions but a model between them, such that they have the same understanding of the role of the actions they imitate, and the goals they might meet with those actions. One of my main departures from Sperber & Hirschfeld is that I believe that this shallow sort of imitation can be an integral part of cultural transmission.

Sperber & Hirschfeld (2004; 2006) argue that due to the unreliability of both performing actions and perceiving others' acts, reliable cultural transmission is exceedingly unlikely. Giving evidence based on the known degradation of signal experienced in simple transmission chains of spoken sentences (the party game of Telegraph [USA] or Chinese Whispers [UK]), they draw doubt on the current emphasis on imitation. Imitation is limited to mere replication of apparent behaviour, and that is in turn limited by constraints in our ability to perceive other's actions, or indeed to execute our intended actions perfectly. Sperber & Hirschfeld insist that what matters is the deep transfer of mental models from one mind to another, not the shallow imitation of expressed behaviour.

How can this deep model be recovered from limited perceptual information? Sperber & Hirschfeld see no way, and use this implausibility as evidence that some information must come from elsewhere. They suggest this missing information is the information encapsulated in modules. Modules under standard massive modularity may have both genetic and explicitly-learned components. Thus extra information is available to compliment the shallow information available from perception and imitation.

People used to implementing artificial learning systems and / or familiar with the mathematics or logic of learning will probably find the above arguments somewhat unsatisfying. After all, random noise will cancel itself out if enough information is gathered, and something that is not random is also not noise, but rather some sort of signal which might be useful. In general though I think Sperber & Hirschfeld are correct, but that their model could use further clarification and completeness. Where does the extra information they postulated as coming from modules *itself* originally come from? Biological evolution, cultural evolution and individual learning are all forms of learning. Therefore taken fundamentally as sources of information and knowledge, their power is essentially identical (Wolpert 1996b; Best 1999). Thus to some extent the Sperber & Hirschfeld argument is overly compartmentalised. To say that the extra information required to make sense of the noisy social transmissions *comes from* modules is still to beg a question of how the modules themselves have come to support this process.

Although they are not completely explicit about it — in fact, they are almost explicitly agnostic on the topic (Sperber & Hirschfeld 2004, p. 41) — it seems likely Sperber & Hirschfeld are implying that some of what we commonly call 'human culture' is genetically encoded. This is problematic if we take the simple information-centred definition of culture I ordinarily favour: that culture is all behaviour acquired from conspecifics by non-genetic means (Bryson & Wood 2005; Richerson & Boyd 2005). However, if we instead take a more ordinary-language view of culture as the aspects of behaviour such as language and social organisation which seem to vary between peoples, then the idea of a genetic component becomes more sensible. There is relatively little controversy for example that *some* aspects of linguistic competence must be genetic, though others are clearly learned by individuals from their own or another culture (Fitch 2005). From what we understand of the Baldwin effect, we should not even be surprised if things that first evolve as cultural variation could over time become at least partially genetically entrenched (Hinton & Nowlan 1987; Baldwin 1896).

Modularity and Learning

What Sperber & Hirschfeld really propose then is that the automatic or implicit learning of culture from imitation cannot in itself account for all the richness of human culture. Although they acknowledge a possible complimentary role for imitation-driven cultural transmission, their own emphasis is on complex mental models underpinning human behaviour. This process in turn requires the explicit transfer of abstract / symbolic knowledge. Symbols in themselves contain almost no information, but cultural participants who understand them have high-information-content associations, or *grounding*, for them. Under the Sperber & Hirschfeld model, grounding encoded in modules contains most of the information necessary for the newly acquired behaviour.

This notion of the role of modules is quite similar to one I have proposed in the context of artificial intelligence (Bryson 2000; 2001). In this work I extended the model of modular organisation of intelligence known as Behavior Based Artificial Intelligence (BBAI) (Brooks 1991) to include module-based learning. The original insight of BBAI was that real-time intelligence is best decomposed into behaviour modules. 'Best' in this context means

- responsive to the demands of an unpredictable and rapidly changing environment,

- robust to the difficulties of both sensing and control, and
- easily and reliably developed by programmers and roboticists.

Under standard BBAI, the purpose of a behaviour module is to perform some action or provide some capacity for its agent. It consists therefore of instructions for whatever control is necessary for those actions, but also of whatever perception is necessary to guide those actions. This tight coupling of sensing to action is a hallmark of BBAI. It simplifies the problem of building intelligence by restricting the problems worked on to a minimum set of capacities each with only the most essential detail to reliably execute its tasks. The strength of the approach was not only argued but also demonstrated in the first robots able to move autonomously at animal-like speeds (Horswill 1993; Brooks 1990).

My extension to BBAI stems from the observation that perception is more than just sensing. At any one instant, sensing provides just too little information to successfully disambiguate the correct next action. Animals address this problem through systems of memory ranging from integrating recent signals through conventional ideas of memory (e.g. map learning) and on through genetically provided biases (Carlson 2000; Rao 1999). My extension of BBAI is to argue that just as behaviour modules should contain the dedicated and specialised sensing necessary for their actions, they should also contain the dedicated and specialised memory necessary for both perception and control. One advantage of this modularisation of learning is that specialised representations can be chosen that facilitate the particular sort of learning that each module needs. This increases the probability that the individual agent will learn and act successfully (Bryson 2001; Wolpert 1996a).

Bootstrapping Culture: The Law of Large Numbers

From the above review it should be obvious that I strongly support the idea that modules can and almost must support all learning[1]. This includes the individual learning that underlies cultural transmission and evolution. However, we must consider the full process of internalising information to guide behaviour, from evolution through development and learning. We also need to account for cultural transmission in the non-human species in which it has been observed (Whiten *et al.* 1999; van Schaik *et al.* 2003; Perry & Manson 2003; Kenward *et al.* 2006). Even ants might be thought of as having minor cultural differences between colonies, since their members both determine and learn new nest locations in a distributed, social manner (Franks & Richardson 2006).

I believe Sperber & Hirschfeld are right to be skeptical of one-shot imitation as a mechanism of social transmission. Essentially, if a single signal can transmit enough knowledge to really alter behaviour, then that knowledge must have been accumulated in a way that is information-equivalent to a symbol anyway (Wood & Bryson 2007). In this case, imitation is not fundamentally different from explicit communication. Also, there is no reason for inheritance in cultural evolution to be limited to one or two parents and a single recombination event (Bryson 2008, p. 89–90). Rather, the more information that can be gathered, the easier it is to detect the salient signal inside the noise and irrelevant detail.

This last point brings me back to the first thing that will make anyone knowledgeable about information theory uncomfortable about the Sperber & Hirschfeld argument. In information theory and statistics in general, we know that the surest way to recover a signal from noisy input is to assume that the true signal, the information, is the most reliable part of the transmission. Everything that is not part of that signal should be randomly distributed with respect to it. Given this situation, by the Law of Large Numbers (in most of its versions) all a learner needs is enough examples to derive the underlying signal by averaging over a large amount of noisy input.

Experiment 1: Stability of Culture with Noisy Transmission

The following experiments demonstrate the above argument, and then move to explore some of its consequences. They are abstract and not yet fully analysed, so at this stage they should probably be thought of as intuition pumps (Dennett 1995). I present a modular model of a culture. The model is agent-based (ABM). It is built in NetLogo, a standard and freely-available ABM development environment (Wilensky 1999). The code for the model is available from the author, and from the author's Web site.

Model

An ABM consists of three parts:

1. an *environment* where the agents are situated and which determines their possible behaviour;
2. *attributes*, also known as parameters or variable state, which describe the agents and what makes them individual; and
3. *behaviour* or intelligence, the actual algorithms which the agents use for control.

[1] Strictly speaking, a homogeneous learning system is Turing-equivalent to a modular one and so therefore could in theory learn anything a modular one can. However, accurate learning is much, much less probable without bias, and therefore will take much longer on average (Wolpert 1996a). For an animal or other real-time system, this means it is less likely to succeed in time to be used.

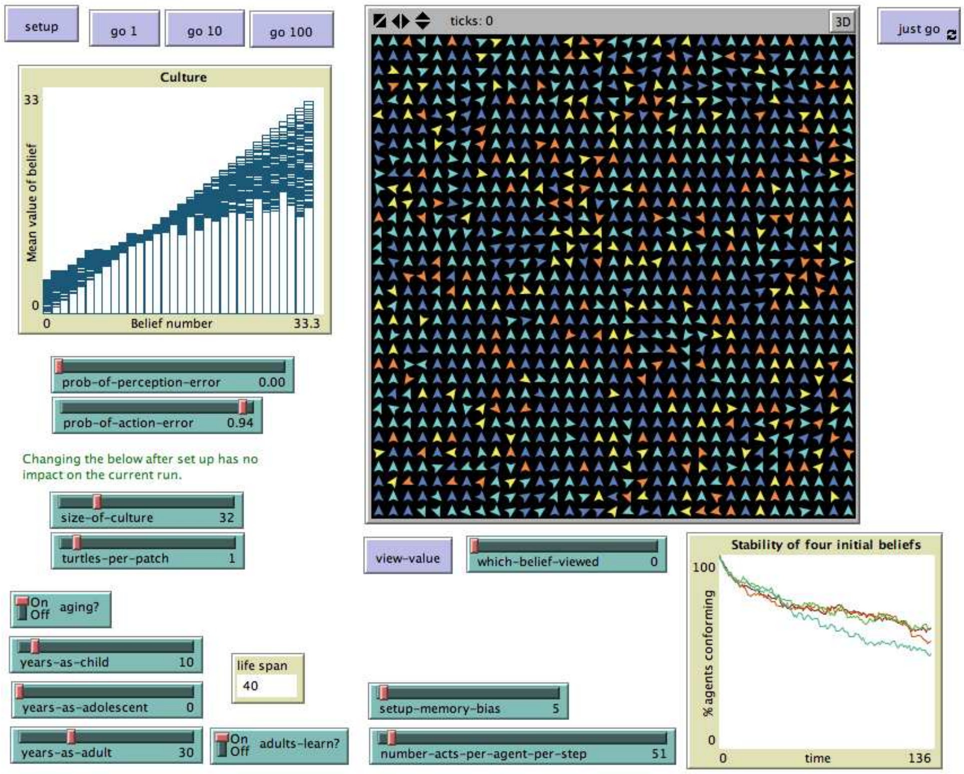

Figure 1: Culture degrading. Notice the presence of subcultures among neighbouring adults.

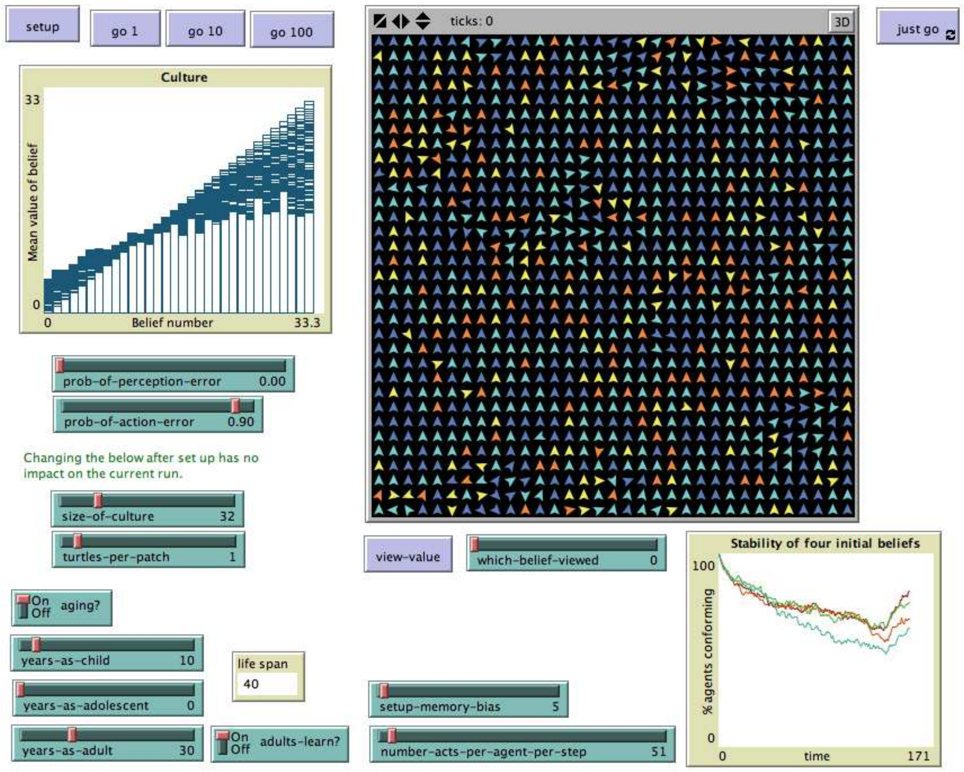

Figure 2: Culture recovering. The probability of generating incorrect actions has been reduced just 4%.

We find models easiest to communicate if we describe each of these in turn (Bryson, Ando, & Lehmann 2007).

Environment The first model has a very simple environment. It is entirely social, with no intrinsic reward provided for any behaviour. Space is described as a torus — really, a square but the left and right edges connect, as do the top and bottom, so that the code and statistics do not have to deal with exceptional agents that live at the edge of their world. Agents occupy every possible location in the grid; each has eight neighbours it can observe.

Agent Attributes Agents have three types of attributes (Bryson, Ando, & Lehmann 2007):

1. *static parameters* which vary only between experimental conditions,
2. *run-dependent parameters* which vary per run and often per individual but are fixed at the beginning of the run, and
3. *dynamic parameters* which change within a single agent's lifetime.

Besides having eight neighbours, the most fundamental static parameter in this model is the agents' modules. All agents have the same number of modules. Although the exact number of modules is run-dependent, how they operate is static. Each module is very simple — it essentially corresponds to a context the agent may find itself in. Each agent has a single behaviour that it currently expresses in that context; *which* behaviour among many possible is learned socially (see algorithm below). For convenience in visualisation (but not in explication) there are exactly as many possible behaviours for each context / module as there are modules.

Since the agents acquire their behaviour socially, they need to be able to keep track of what behaviour they have seen. Thus each agent has associated with each module a memory. The size of this memory is the same as the number of possible actions. The agent remembers how many times it has seen each action it has witnessed in each context. Thus the content of this memory is a dynamic parameter.

Besides the contents of its memory, the only other dynamic parameter of an agent is its age. At the very beginning of a simulation, age is assigned randomly to each agent from the full range of possible values. Subsequently, any new agent starts with age 0.

Besides the number of modules, there are a number of other run-dependent parameters:

- Each agent's (X, Y) position in social space. This determines which eight agents are its neighbours.
- The number of 'years' spent as a child and as an adult. The difference is that no one learns socially from children.
- The number of acts performed per 'year'. This in combination with the lifespan and the size of the culture determines how much each agent will experience in its 'life'.
- The probability of a perception error and the probability of an action error. If one agent performs an action error, all of its neighbours will see an unintended behaviour in a particular context. If one agent experiences a perception error, then it is the only agent that's knowledge is affected. In both cases, an error means a value for an action is randomly drawn from all possible acts. For the sake of simplicity, in the experiments discussed here the only probability varied was of action error. This is more likely than perception error to cause perturbations of culture, since it can bias eight neighbours' beliefs the same way.

  This variable is somewhat dynamic, in that it can be varied during the course of a simulation by the experimenter. This allows for a relatively easy search for a threshold value below which the culture is stable an above which the culture degrades. However, nothing the agents do changes this value, so from their perspective it is run-dependent.
- The weight given to the seed culture at the beginning of the simulation. At the beginning of the simulation, all the first generation of agents have their memories set to some initial cultural value for each context. This value is set by the experimenter. If the weight is five, the agents have a memory equivalent to having seen other agents perform that action five times. This parameter has no other role in the simulation after the first generation has died.

For visualisation, the field of agents is visible as a square. The agents are arrow shaped. The agents are coloured to indicate their age: children are light and adults dark. The viewer can be set to examine any one behaviour context for all the agents. The beliefs / chosen action of each agent for that context is then visualised as the angle at which the agent points. The $angle = (360 * i)/N$, where i is the number of this particular context, and N is the number of contexts and therefore also the number of possible beliefs. There is also a chart which shows the what percentage of agents conform to their original beliefs in the seed culture for the first four contexts. Since all contexts are functionally identical, these first four can be treated as a small random sample of modules.

Agent Behaviour On every program cycle, every adult agent chooses one of its modules at random. It then checks its memory for that context and expresses whatever action it has itself most often witnessed in that context. If multiple actions have been seen the same number of times, and this number is the maximum number for all actions, then tied actions are chosen between at random. Assuming there is some Probability of Action Error (PAE), the agent then has a PAE chance of choosing an action randomly from all possible values and expressing it. Otherwise, it expresses its module's true value.

"Expressing an action" in the simulation is manifest as asking all eight of its neighbours to add one count to that action's value, indicating that action has been witnessed once more in that context. If there were a probability of perception error, at this point a random value might be introduced into an individual's memory rather than the act expressed. However it is best practice to limit the number of parameters on a model for simplifying analysis, and since perceptual errors have less impact on culture than action errors I did not manipulate the rate of perception error in the experiments presented here.

When an agent reaches its age limit, it dies. When an agent dies, it is immediately replaced with a new agent of 0 age. This new agent has a completely empty mind. It has the same number of modules as the rest of the agents in the simulation, but every possible value for every module is given 0 weight. Thus its initial actions will be entirely random.

Results

Cultural stability is directly correlated to the number of exposures to an action that an agent is likely to experience for each action in its lifetime. Thus the longer adult life, and the more actions that occur per year, the more stable culture. On the other hand, having more modules decreases the number of actions *per* module, so this is negatively correlated to stability, as of course is the PAE.

The tendency to ignore children's behaviour (which is initially essentially arbitrary) has been proposed as a mechanism of cultural stability.However, because even children after one year are more likely to express their culture's values for any module than any other value, shortening "childhood" — or at least, the period where children do not serve as cultural models — *increases* cultural stability. Of course this is not the only attribute of childhood. If I had modelled it also as a period when more is time devoted to observation of others (perhaps by increasing the neighbourhood size for children), then a longer childhood would have been more beneficial.

Figure 1 shows a run with parameters set such that the culture is fairly stable, but not sufficiently so to stop degradation (forgetting) of the culture. Since we are observing the $i = 0$ context module, the agents conforming to the original culture are pointing straight up. Notice that young agents (the light / yellow agents) may be oriented in any direction since they will not have seen many expressions of behaviour in this context yet. However, where adults (dark / blue agents) are misoriented, they often are so in company. Thus the same mechanisms that largely preserve culture can also serve to form and preserve subcultures.

Figure 2 shows the same simulation in the future. However, just after the previous snapshot, the probability of action error was lowered from 94% to 90%. Notice this does not simply freeze the decline of the culture, but actually results in the initiation of a rapid recovery. This is because the level of conformity to the original culture was still $> 1/N$. If culture had degraded to total chaos, then reducing the PAE would have lead to conformity as well, but not necessarily to the original value. Note also that a culture will never have 100% conformity because of the ignorance of children, but with a low PAE a stable culture will achieve a high level of conformance.

Discussion

The idea that a module might take only a few discrete values may seem such an extreme abstraction that it renders the model meaningless. However, we know that animals including humans are extremely inclined to categorise perceptual data. Even in continuous domains such as the light spectrum, humans are far more sensitive to variation near the "boundaries" between named colours than well within them (Harnad 1987). This emphasises the role both Sperber & Hirschfeld and I hypothesise for modules in learning in general, of which social learning is a special case. Through some combination of genetics and experience the agent is assumed to know a set of categories or concepts, which learning facilitates a choice between.

Social learning may also facilitate the discovery of *new* categories and modules by signalling through variations in behaviour a perceptual difference an agent had not otherwise detected (Bates 1999; Bryson 2008). However, module construction is not modelled in the current simulations.

Experiment 2: Innovation

In the first model we already witnessed the formation of subcultures. Since these can be stable for a few years or even generations, they might already be viewed as innovations. In the second set of experiments we observe what happens when one possible value for a culture model is more adaptive than the one currently dominant in the culture. To do this, we have to introduce reproductive variation into the model.

In the previous simulation, reproduction was always at exactly replacement rate. To keep the experiment simple, a mechanism of selective reproduction was chosen that kept a full environment as the *maximum* number of agents. Thus, for the non-adaptive culture values, reproduction was lowered below replacement rate.

Model

The model is largely as described before, with only one exception: reproduction.

Environment The environment is largely unchanged, except that there is now one context which can be differentially rewarded. Which context this is can be set by the experimenter.

Agent Attributes There is one new attribute, a run-dependent parameter reflecting Selective Advantage, SA, described below.

Agent Behaviour One module or context is chosen by the experimenter to be selectively rewarded. For that module, only one value is right or "true". When an agent dies, if it does not hold the correct value, then its probability of being replaced is reduced by SA. On the other hand, if an agent does have the adaptive belief, not only will it certainly reproduce, but also if one of its neighbouring spaces is available, it will create one additional offspring.

Note that because all agents are identical, there is no change in *genetic* distributions due to this advantage. What a parent leaves to its child or children is only its neighbours — its social network.

Results and Discussion

Ironically, my explorations of the parameter space have shown that a culture needs to be strongly disposed towards stability in order for a new tradition to take root. If culture degrades easily, then even when agents stumble on the adaptive subculture they forget it again within a few generations. Obviously, however, it takes considerable disruption for a stable culture to loose its existing values so it can change to the adaptive ones. As the model is currently built, this disruption takes the form of the loss of neighbours and therefore the lower probability of discriminating the cultural values accurately. When one isolated subculture does stumble on the adaptive value and begin refilling the space around it, then the propensity for stability returns.

If the culture parameters are set to a lower level of stability, then the dominant culture can stop dominating earlier, but any new subculture has significantly more difficulty maintaining its value. The adaptive subculture in particular becomes surrounded by juveniles who are relatively open to influence — both to random patterns of other juveniles and to the influence of members of other neighbouring subcultures. Because it will still be disproportionately wide-spread in the culture, the ring of juveniles is particularly vulnerable to invasion by the original, non-adaptive value held by that culture. Since they surround the core of 'true' (adaptive) believers, they will generally sway their behaviour and the true belief is lost.

Another significant factor determining the outcomes for this simulation is the probability of stumbling on the correct answer in the first place. Recall that in all these simulations all behaviours are equally probable for naïve agents. If there are too many possible values for the module that is subject to selection, the agents are unlikely to find the rewarded value in time to save themselves from extinction. If the simulation were changed so that the agents were even slightly more intelligent in their search — for example, if they could remember neighbours that failed to reproduce or succeeded in having two children, this would increase the probability of the correct action being chosen (Hinton & Nowlan 1987).

Although only one module was subject to selective pressure, the cultural norms for other modules also change. This might be because the same agents that are likely to discover the adaptive innovation had a general tendency for invention. Although all the agents have identical programs and are seeded randomly at the beginning of the simulation, the population is not entirely homogeneous. Chance patterns of distribution of age — the only differentiation between agents in the initial population — can lead to some patches of space being more or less likely to deviate from the cultural norm and form a subculture. Due to the policy of reproduction by replacement, age patterns are fairly stable. Another explanation is that change simply occurs due to the drop in cultural stability with the reduction of numbers. However, since the other modules are not having their original culture actively selected against, in some cases they recover their original value after the population stabilises (see chart in lower right of Figure 4).

Another unanticipated result from this experiment was that the pattern of regrowth after the adaptive behaviour was discovered lead to large regions of adjacent age cohorts. This in turn seems to lead to the emergence in many but not all of the module contexts not subject to selection of multiple stable cultures. Figure 4 shows an example of one such. This may have analogues in natural culture, where age cohorts may communicate predominantly internally rather than mixing with other ages. Even where there is a mix of ages, it is possible for age cohorts to focus their social learning attention on their peers.

The figures show a run where the PAE was set to what was in the non-selective condition a fairly stable value, particularly given the number of modules in the culture. Figure 3 shows the cultural values for the context / module subject to selective pressure when the number of agents holding the adaptive belief has just begun to outnumber number conforming to the original culture. Figure 4 shows the same run after the population has recovered. This figure observes not the context subject to selection, but one of the other contexts where the values are arbitrary from a selective perspective. This context has now formed multiple sizeable, stable subcultures. Notice the pattern of ages in the agents as indicated by their colour.

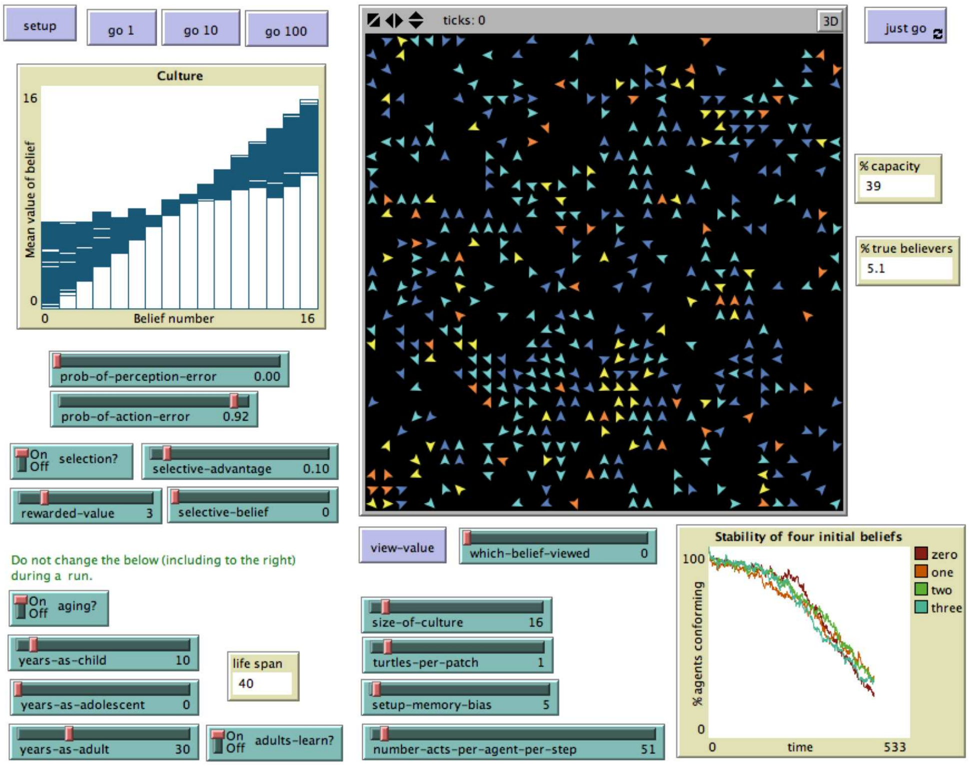

Figure 3: The threshold where an adaptive innovation beginning to dominate a culture.

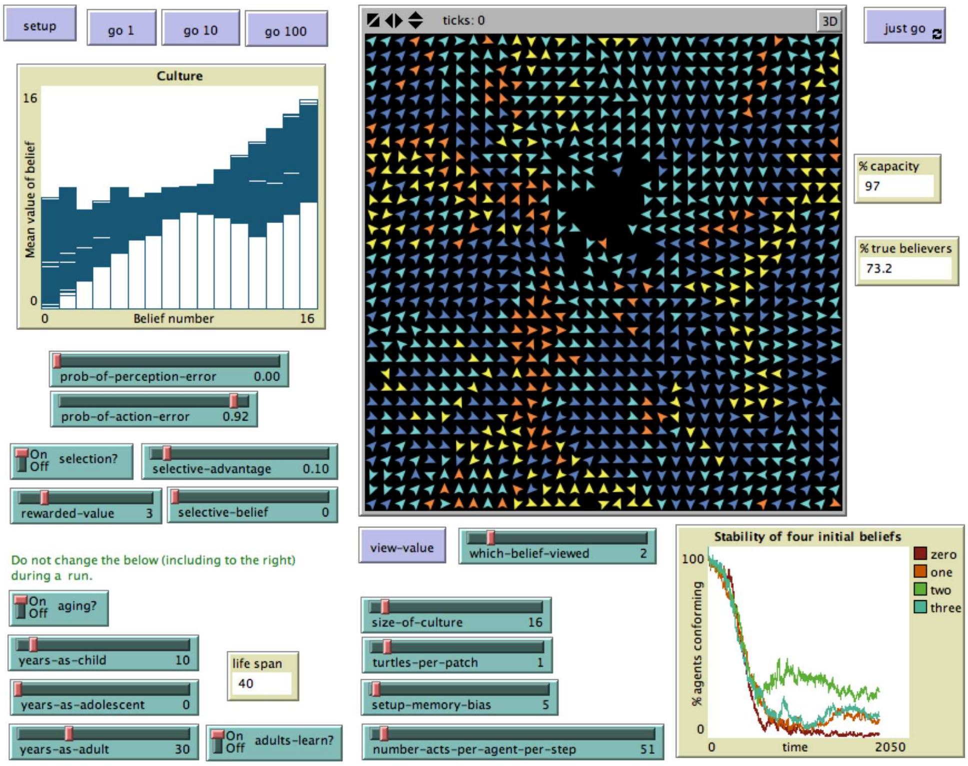

Figure 4: The impact of adaptive selection for new values in one module on the cultural values of another.

Conclusions and Discussion

In this paper I have examined and to a large extent supported the proposal of Sperber & Hirschfeld (2006), while at the same time clarifying some details of how their system might work. The modules they describe utilise information previously acquired either by the species (encoded genetically) or by the individual's learning, which of course may also be channelled by the species through culture.

The model I have presented demonstrates the ability of a culture to be stable in the face of enormous errors in communication. The famous 'poverty of the stimulus' is simulated by the high level of noise in the actions actually generated by the agents. Agents are nevertheless able to derive a signal because of the Law of Large Numbers and the fact the errors are unbiased. In these simulations all behaviour contexts are equally probable and all social demonstrations equally salient. In human culture we know that rare but important cultural behaviours such as rituals tend to be associated with high emotion salience indicators such as music which may assist in emphasising particular memories (LeDoux 1996). For example, in medieval England the relatively boring and seldom-performed but essential task of patrolling the parish boundaries was made salient to young boys by beating them at boundary stones so the boys would remember the stones' locations (Darian-Smith 2002).

The models also show circumstances in which innovations can not only take place but take hold. Strong tendencies towards conformity can give rise to small stable subcultures even in strictly arbitrary environments, as shown in Experiment 1. Experiment 2 explores the conditions necessary for acquisition of a newly-adaptive norm — that is, an action selected by the environment. In addition, it also shows that society-wide displacements of one cultural norm for another can take place for no direct adaptive reason, but simply as a side-effect of the disruption to the society necessary for another, more urgent change in cultural norms. This incidental disruption could be dangerous if a norm that is adaptively-neutral in the current, local environmental context actually held adaptive salience in some larger-scale environmental context, for example in times of a natural disruption such as flooding. On the other hand, if the society is too conservative — that is, makes too few "errors" in behaviour replication, then inventions seldom occur and innovations are never adopted.

One difference between my work and that of Sperber & Hirschfeld —- I do not believe they are correct to assume that identical internal models necessarily underly apparently identical connections between contexts and expressed actions. The conformance demonstrated here is based on shallow imitation. To some extent, it is quite likely that agents with similar brains and similar experiences will wind up forming similar internal models or theories in order to generate similar behaviour. However, it is possible that multiple models would result in the same or at least categorically indiscriminable behaviour. For example, one might obey law due to concerns about an afterlife, due to an elaborate model of the importance of the rule of law and the power of social contagion, or simply because one is evolved to unthinkingly behave like others around you, and most of them are lawful. These three models would be indiscriminable from the perspective only of your observing the law. Similarly, Steels & Kaplan (1999) demonstrates the difference in underlying lexicon models for robots that have "perfectly" learned a shared language. In all circumstances the robots say and reference the same objects, yet the internal representation they require for grounding the terms as mappings to their sensor and motor states vary considerably between robots. Thus model conformance is not a necessary part of social conformance, and may in fact provide a useful source of variation to the populations' inventions.

The simulations I have described beg much further analysis. For example there should be a more thorough exploration of the effects of developmental differences in communication on the adaptation of cultures to new circumstances or to the opportunities of adaptive innovations. Further, the spontaneous emergence of stable subcultures in both sets of experiments might be seen as examples of sympatric speciation — a process normally attributed to sexual selection. Clearly no equivalent of sexual selection takes place here. Although the model is intended to be one of cultural evolution, it might easily be extended to model biological evolution to study this process. Or, one might hypothesise that cultural evolution underlies the beginning of sympatric speciation, and the process is then genetically consolidated. These projects are left as future work.

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