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Evolution in Mind: Is the Cultural Evolution of Cognitive Mechanisms Analogous to that of Cultural Skills?

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Abstract

Recent proposals within evolutionary psychology have suggested that the distinctive cognitive abilities of humans have evolved culturally as opposed to biologically (Heyes, 2018). This hypothesis makes the prediction that the evolution of cognitive variants (literacy) is an analogous process to that of the evolution of cultural artefacts and cultural behaviours (hunting with kayaks). However, despite correlative and experimental evidence that human psychology indeed varies according to exposure to cultural transmission, this prediction remains unsupported due to methodological constraints. These previous methods have proven capable of exploring cognitive variant transmission over a single generation (learning to read), but the above prediction requires a direct comparison of these two forms of cultural evolution over multiple episodes of transmission, and with a demonstrated selective process for successful variants. It is clear that this aim is difficult to achieve with human participants, and therefore that agent-based simulation could provide a pragmatic initial exploration.

In this project, I revisit a recognised model of cultural artefact and behavioural skill evolution, and determine whether the addition of cognitive variants reproduces analogous results. An agent-based model (ABM) is first rederived from Henrich's (2004) formal mathematical model of cultural evolution, and tested against the predictions of the original formal model. With this comparative target ABM produced, the effects of switching cultural skill traits to cognitive variants is then assessed. The qualitatively similar outputs of the two ABMs do indeed provide further support for some of the key principles of Heyes' (2018) proposal.

Contents

1	Introduction	3
1.1	<i>Cultural Evolutionary Psychology: The Test of a Fledgling Paradigm</i>	6
2	Literature Review	8
2.1	<i>The Origins of a Cultural Evolutionary Psychology</i>	8
2.2	<i>Cognitive Variants are Socially Transmitted Neurobiological Modifications</i>	14
2.3	<i>The Cumulative Cultural Evolutionary Process</i>	20
3	The Agent-Based Models	27
3.1	<i>Henrich's Formal Model</i>	29
3.2	<i>ABM 1: Henrich's Model Rederived</i>	34
3.3	<i>ABM 2: Cognitive Variant Model</i>	39
4	Simulation Results	46
4.1	<i>Validating ABM 1</i>	46
4.2	<i>Selection is Essential</i>	48
4.3	<i>Skill/Architecture Complexity and Demography</i>	52
5	Discussion	55
5.1	<i>Analogous Forms of Cultural Evolution?</i>	55
5.2	<i>Trouble in Tasmania: Acknowledging Limitations of the ABM Assumptions</i>	61
6	Conclusion	65
7	Appendices	66
7.1	<i>Appendix a: Boolean Truth Tables</i>	66
7.2	<i>Appendix b: Data</i>	68

7.3	Appendix c: R Markdown Scripts	68
7.4	Appendix d: Required Resources of Project	68
8	Bibliography	69

List of Figures

1	Forming New Neurocognitive Mechanisms	16
2	ODD Protocol for ABM Description	28
3	Gumbel Distribution	32
4	ABM 1	36
5	ABM 2	41
6	Neural Computation	43
7	Comparing Henrich's model and ABM 1	47
8	ABM 1 and Indirect Bias	49
9	ABM 1 _{sub} , ABM 2, and Indirect Bias	51
10	Demography and Trait Complexity in ABMs 1 & 2	53
11	Boolean logic	67

1 Introduction

The human brain and the processes of mind that it gives rise to, have been heralded as the most complex natural phenomenon yet discovered within the empirically known universe (Fischbach, 1992). Indeed, in comparing the faculties of our species against those of other taxa, nonhuman animals do not appear to spontaneously imagine abstract symbol-based economies, construct arbitrary social institutions, build upon the accumulated discoveries of prior generations, communicate using syntactical language, or significantly alter the dynamics of the entire planetary biosphere (Calcagno and Fuentes, 2012; Fuentes, 2016). Whether emphasising these differences necessarily predisposes researchers to the traps of human exceptionalism or not, such undeniable complexity comes with fundamental questions as to why the human mind is the way that it is, and how it became what each contemporary individual intuitively knows it to be (Finlay and Workman, 2013).

For nearly four decades now, a resounding answer to these long-standing queries has traditionally emanated from the field of evolutionary psychology (Cosmides and Tooby, 2013). This answer holds that the mechanisms underlying the distinctively human aspects of mind have steadily emerged, like so many complex biological phenomena, via the evolutionary process of natural selection (Darwin, 1859). Consistent with this Darwinian approach to the mind, many conservative evolutionary psychologists abide by three principle assumptions about human cognitive evolution:

- 1) The brain has been selected for the adaptive function of information processing, much akin to the human-designated function of digital computers.
- 2) In conjunction with the computational metaphor described in the first assumption, the information-processing programs situated within the brain are predicted to be computational adaptations. That is, information-processing

algorithms selected for solving the particular selective pressures experienced by human ancestors in deep evolutionary time.

3) Variance in the reproductive fitness and survival consequences of possessing particular programs, in turn, results in the differential genetic inheritance of competing program variations. Over successive generations, this process of biological evolution and genetic inheritance effectively accounts for the collective suite of cognitive adaptations present within the architecture of the contemporary human mind.

Equipped with these three assumptions, the field of evolutionary psychology has developed into a comprehensive and highly successful research paradigm. To date, studies have reported upon cognitive mechanisms adapted to the domains of mate choice, social exchange, language, causality, macroscopic physics, inanimate object manipulation and reasoning, folk biology (zoological and botanical knowledge), and folk psychology (generating inferences about the mental states of other agents to predict agent behaviour) (Buss and Schmitt, 2019; Cosmides, 1989; Pinker, 1991; Leslie, 1994; Atran, 1998; New et al., 2007; Kinzler and Spelke, 2007).

Nevertheless, over the last decade, the wider encompassing discipline of evolutionary biology has begun to increasingly consider a more inclusive body of theory regarding the mechanisms of phenotypic inheritance (Laland et al., 2015). Under this recent ‘extended evolutionary synthesis’ movement, inheritance by the way of DNA sequence transmission has come to stand parallel to three additional inheritance pathways, each of equal import to the processes of evolution: epigenetic inheritance, ecological inheritance, and cultural inheritance (Danchin et al., 2011). Each is likely to have had an influence upon the development of our species’ cognitive proclivities. For in highlighting evidence for each, non-genetic markers transmitted through the germline by epigenetic inheritance, appear to influence the personality and psychological

health of following generations (Masterpasqua, 2009). Environments that are experience-rich and stimulating, and which can be transmitted across generations by ecological inheritance, promote early cognitive development in human children (Tucker-Drob and Paige Harden, 2012). And, moving towards what will be the fundamental enquiry of this thesis, children appear to acquire certain cognitive abilities by way of their cultural traditions that they would otherwise not innately possess (Dehaene and Cohen, 2007; Li et al., 2013). Each of these inheritance pathways, a collective violation of the third assumption presented above, represent an opportunity for the expansion of the scope of evolutionary psychology, if it can be systematically demonstrated that each contribute to the evolution of cognitive mechanisms.

The recent work of the social and cognitive psychologist, Cecilia Heyes (2012 and 2018), exhibits great potential for just such an expansion with regard to the cultural inheritance pathway, and how it may have contributed, and may indeed continue to contribute, towards human cognitive evolution. This work proposes that the differential cultural inheritance of cognitive mechanisms can additionally account for the architecture of the distinctly human mind; an approach that Heyes (2018:16) refers to as ‘cultural evolutionary psychology’. At the corner stone of this novel paradigm lies what can be referred to as the ‘cognitive gadgets hypothesis’; a postulation that the information-processing programs of the human mind can evolve culturally, just as culturally-acquired behaviours and artefacts (‘gadgets’) do according to established cultural evolutionary theory (Creanza et al., 2017). It will be the central objective of this dissertation to evaluate whether, in principle, the cognitive gadgets hypothesis (hereafter CGH) can indeed account for the evolution of cognitive phenotypes within culturally-endowed populations.

1.1 *Cultural Evolutionary Psychology: The Test of a Fledgling Paradigm*

In seeking to evaluate the viability of a cultural evolutionary psychology, there are multiple assumptions that require empirical investigation. For instance, Clarke and Heyes (2017) hold that the individual cognitive biases that perform the processes of cultural selection required for cultural microevolution, also evolve culturally. Furthermore, Heyes (2018) also considers that multilevel selection processes, like cultural group selection, additionally influence the cultural selection of cognitive mechanisms. Nonetheless, assumptions such as these necessarily supervene upon the core assumption of the CGH, and this renders the scrutinisation of the CGH as the focal concern of this dissertation before further progress can be made.

Much of the available evidence taken to support the central premise of the CGH currently relies upon identifying the social transmission of psychological processes from one individual to another, as well as the associated neurological changes that accompany this transmission. For example, the transmission of literacy, imitation (i.e. matching the topography of other's actions), and folk psychology, have each been key areas of research focus for these early experimental and correlative studies (Dehaene et al., 2015; Heyes and Frith, 2014; Cook et al., 2014). Essential though these studies are in verifying the occurrence of cultural inheritance, alone, such methodology fails to evaluate the remaining microevolutionary components of cultural evolution needed to support the CGH. For if the cultural evolution of cognitive mechanisms is indeed analogous to that of behavioural skills and artefacts, both should respond analogously to established and relevant principles of cultural microevolution across multiple episodes of transmission, not just a single transmission episode (Mesoudi, 2016). Fortunately, several principles of cultural microevolution are assumed, formulaically, within a single formal mathematical model of cumulative cultural skill evolution derived by Henrich

(2004) (but also see Henrich and Boyd [2002:103] for an earlier rendition). As such, the structure of this model provides ideal grounds for testing the CGH.

In this dissertation, I endeavour to assess whether the cultural evolution of behavioural skills and cognitive mechanisms are indeed microevolutionarily analogous with respect to four predictions. The approach I take is a modular one, beginning with the structure of Henrich's (2004) model, and then progressively deriving two analogous agent-based simulation models (ABMs) from this original model within the computer software environment and programming language of R. The design of the first ABM is based upon the formal model directly, and checked against the predictions of the formal model for comparative validity. The second maintains the overall design and closely emulates the assumptions of the first, but instead of cultural skills, incorporates cognitive variants and their additional assumptions into the ABM. These four predictions are then comparatively tested in both ABMs through adjustable parameters and qualitatively inspecting the output. The project should be conceptualised as an initial proof of principle pilot analysis for more advanced modeling, and demonstrates that the CGH is open to empirical analysis using this method within a 5 month period. Code for the ABMs and their design is accessible by [html link](#), included within the appendix of this dissertation for the replicability of results.

The following literature review establishes the essential necessity of testing the CGH, and draws upon data from various fields to identify instances of cognitive variant transmission. Predictions for testing the CGH are then derived from findings that have been made within the study of cultural evolution.

2 Literature Review

2.1 *The Origins of a Cultural Evolutionary Psychology*

In the approximately 80-60,000 years since anatomically modern humans (*Homo sapiens*) dispersed from Africa, we have demonstrated ourselves to be a truly eurybiomic species in our capacity to not only survive but thrive in nearly every terrestrial habitat upon the globe's surface (Klein, 2009). Achieving such a precocious feat, given that our ancestors originated within a tropical African ecology, has traditionally been attributed by practitioners of evolutionary psychology to the possession of a highly abundant and sophisticated suite of cognitive adaptations, or 'modules', that permitted humans to intuitively process and flexibly overcome the physical, energetic and social demands of entering novel ecosystems (Tooby and DeVore, 1987; Spelke, 2003; Pinker, 2010). These psychological modules, it is argued, exhibit particular information processing principles selected for under Darwinian natural selection, which function in providing adapted responses towards the recurrent fitness challenges that were faced by the hominin ancestors of contemporary humans (Cosmides and Tooby, 2013). A given module's computational complexity and its functional competence in processing a specific set of stimuli encountered within the hominin ancestral environment (known as the Environment of Evolutionary Adaptedness or EEA) are therefore understood to be steadily accreted over evolutionary time through the process of differential genetic transmission with modification.

The result of this elaborate evolutionary process is hypothesised to be a multicomponent brain, composed of distinct computational programs, innately adapted towards processing information of differing ontological domains (social phenomena, natural history phenomena, physical phenomena, artefactual phenomena and the like) and providing outputs that on aver-

age maximized the reproductive fitness of their possessors within the EEA (Boyer and Barrett, 2005). Proponents of this perspective, collectively known as the ‘Santa Barbra School’ of evolutionary psychology, thus emphasise an innate ‘domain-specific’ cognitive aptitude of humans to devise specialised solutions for and causal models of environments, by flexibly deploying various combinations of the computational strategies afforded by this modular suite of cognitive adaptations (Spelke, 2003; Pinker, 2010). Furthermore, under this ‘Santa Barbara model of mind’, cultural behaviour, which is usually defined as socially transmitted and maintained information amongst a group, is construed as either the evoked output of cognitive modules towards domain-specific stimuli, constrained in diversity by the innate structuring of modules, or external superficial representations that are simply mapped onto the corresponding tokens that comprise the internal computational architecture of a module proper (Cosmides and Tooby, 1992; Sperber, 1996:110; Jackendoff, 2006).

In the decades since the inception of the Santa Barbara perspective of evolutionary psychology however, diverse findings collated from across the fields of evolutionary anthropology, developmental psychology, computational neuroscience and artificial intelligence (AI), have resulted in a revision of this central tenant of genetically specified modularity by many researchers in the discipline (Bolhuis et al., 2011; Heyes, 2012; Barrett et al., 2014; Bjorklund and Ellis, 2014). This newly emerging understanding of human psychology and its evolution challenges the Santa Babara model of mind in at least three respects, thereby paving the way for the extension of evolutionary psychological theory.

First, the way in which the brain is presumed to process information has changed radically within the fields of neuroscience and AI since the initial development of evolutionary psychology, and this has had important implica-

tions for interpreting how natural selection acts upon its functions (Bolhuis et al., 2011). Cognitive science and AI of the 1970s, prior to when evolutionary psychology was founded, based models of intelligence upon symbolic AI and expert systems; information-processing softwares that implemented explicit syntax and if-then rules within their architectures (Marr, 1982; Bolhuis et al., 2011). Such explicitly designed systems were thus imported into the then fledgling field of evolutionary psychology, as domain-specific architectures like these with pre-specified algorithms were known to operate with great speed and processing efficiency within computers that process information serially, one clocking cycle at a time (Barrett et al., 2014). Using expert systems as a metaphor for the hominin mind during the EEA is indeed superior under these assumptions compared with underdetermined domain-general cognition, as learning to process information in a potentially unlimited range of ways exponentially slows serial processors to a degree perceived as deleterious to organism fitness (Cosmides and Tooby, 1992:102).

However, following contemporary advances in computational neuroscience and machine learning within AI, the nervous system is currently understood to both operate by executing a magnitude of processes in parallel, thereby mitigating maladaptive conceptions of domain-general cognition, and operate by storing the algorithms needed for processing information in a distributed, inexplicit format across highly modifiable networks, thus disputing the argument that experience simply evokes responses rather than significantly remodeling algorithms according to experience (McClelland and Rumelhart, 1986). Using such modern and neurobiologically inspired models of cognition alternatively suggests that natural selection could have acted significantly on cognitive mechanisms that were not domain-specific, and further that the content of cultural information is not simply mapped onto preexisting tokens or ‘circuits’, but instead plays a fundamental role in generating cognitive phenotypes from both initial domain-general and domain-specific states

(Karmiloff-Smith, 1992).

The second source of challenge for the Santa Barbaran model of mind has emanated from the findings of developmental and comparative psychology. Rather than uncovering richly specified and informationally encapsulated modules, the structures of the mind formed by genetically guided development have been found to be more like primitive axioms, which calibrate social learning towards environmental inputs that co-structure the more complex emergent cognitive systems of mature adults (Tucker and Luu, 2012; Bjorklund and Ellis, 2014). Nowhere is this more salient than in the domain of human linguistic grammar, once thought to be the bulwark of evolved modular programs that richly specified a hypothesised architecture of deep phrase structure rules, ‘x-bar theorems’ and case forms (Jackendoff, 1977). These complex nativist models of grammar have since been reduced to a single posited cognitive operation called ‘Merge’, which takes informational elements, including lexemes and sentences, and combines them into recursively higher order nested units, the combinatorial rules of which can be set by the idiosyncrasies of a learned language (Hauser et al., 2002; Bolhuis et al., 2014).

Indeed, there are ethnolinguistic groups that do not seem to use the Merge operation in the typically recursive fashion to structure their grammars; notably the Brazilian Pirahã and Riau Indonesian speaking communities (Everett, 2005; Sakel and Stapert, 2010; Jackendoff and Wittenberg, 2017). By contrast, in samples of ethnolinguistic groups that do utilise syntactical recursion, diffusion tensor imaging reveals a negative correlation between the frequency of grammatical errors made by children below the age of seven years, and the development of white matter tracts connecting known language areas of the cerebral cortex that remain undeveloped in nonhuman primates (Brauer et al., 2010). Amalgamated together, these findings imply that the species-specific genetically inherited programs of language specify

critical periods of plasticity and guided attention, which ‘assume’ the presence of culturally inherited information (here the instruction to generate the Merge operation) provided by the local social environment (Arbib, 2009; Levinson, 2003). Acknowledging this has led to the introduction of cultural evolutionary theory into formally biological studies of language evolution (Arbib, 2009).

Finally, and most significantly, some of the most distinctive cognitive capacities of *Homo sapiens* have manifested too recently within our species’ evolutionary history to be the products of gradually accreted genetic evolution during a putative EEA alone. Literacy is chiefly among these, as the earliest known systems of true logophonetic writing (scripts containing symbols that represent spoken sounds), only emerged 5200 years ago, following a gradual transition from pictographic and token based systems towards true logophonetic systems between the ninth and fourth millennia B.C. (Schmandt-Besserat, 1977; Downey, 2014). This steady cumulative development of logophonetic writing from less derived forms implies the cultural evolution of a novel skill, concomitant with a *de novo* cognitive capacity to read, developed through successively modified cultural learning regimens (Heyes, 2018).

Consistent with this cultural evolutionary hypothesis, neuroimaging data collected from subjects that have learned to read logophonetic scripts not only demonstrates significant modification of neuroanatomy and activation, but also a displacement of what was thought to be an innately ‘hard-wired’ cortical network for facial recognition to the contralateral hemisphere of the cerebral cortex, as invading cultural skills compete for exapted neural resources (Carreiras et al., 2009; Dehaene et al., 2010). This culturally modified region of the temporo-occipital cortex in the left hemisphere of the brain, referred to as the ‘visual word form area’, remains inactive to orthographic letter

strings in illiterate adult and dyslexic child controls, and projects the signature of a modular cognitive mechanism in its locational specificity across subjects (Monzalvo et al., 2012). Furthermore, in displacing the initial location of facial processing to the right hemisphere, the acquisition of literacy indicates that cultural content constrains the function of innate perceptual mechanisms just as much as innate systems have been hypothesised to conduct cultural diversity towards certain universal ‘attractors’ (Sperber and Hirschfeld, 2004; Downey, 2014). As such, the phenotypic plasticity of the brain can lead to the generation of new neurocognitive mechanisms in response to the transmission of cultural skills from one generation to another and amongst members of a single generation.

Extrapolating across these diverse findings, it becomes apparent that the evolved architecture of the human mind, whilst comprised of multiple computational competencies, may not only be the product of biological evolution suspended in an environment of superficial proximate cultural mappings. The amalgamated evidence rather suggests, contra to the Santa Barbara school, that a critical means of adaptation to novel or fluctuating environments within the human lineage, may have been facilitated by the coevolution of guided neural-developmental plasticity and lineages of culturally transmitted information, with the ultimate function of constructing newly adaptive cognitive phenotypes to the benefit of their possessors (Richerson and Boyd, 2000). Such a suggestion is by no means incompatible with current evolutionary theory. For a plethora of mathematical models have already demonstrated that stochastic environmental variations of the kind that the hominin ancestors of contemporary humans likely faced throughout the plio-pleistocene (5.3 to 0.1 million years ago), directly favour the evolution of elevated phenotypic plasticity, repertoires of cultural information, and the assimilation of advanced learning mechanisms into the genome (Richerson and Boyd, 2000b, Boyd and Richerson, 1989; Henrich and Boyd, 1998; Lande, 2009).

In expanding the scope of evolutionary psychology then, certain domain-specific cognitive mechanisms can additionally be understood as constructed through social interaction and learning during ontogenetic development, whilst their computational complexity and competence is accrued over multi-generational time due to differential acquisition by learners, and accumulated improvement in function due to individual cognitive innovation and social learning error (Heyes, 2018). That is, by the processess of cumulative cultural evolution discussed in the following subsections of this literature review (Mesoudi and Thornton, 2018). This is the aforementioned perspective of ‘cultural evolutionary psychology’ recently proposed by Heyes (2018) to account for the cognitive architecture of the human mind. Indeed, the increasing interdisciplinary integration of cognitive anthropology with cultural neuroscience is beginning to reveal a range of socially transmitted cognitive phenotypes that stand as putative candidates for ‘cognitive variants’; the units under cultural selection within lineages of culturally transmitted cognitive mechanisms.

2.2 *Cognitive Variants are Socially Transmitted Neurobiological Modifications*

The prominent cultural evolutionary theorists Richerson and Boyd (2005:61) have defined culture as “information stored in human brains... transmitted from brain to brain by way of a variety of social learning processes”. Yet, aside from being a specially adapted device for strategically and efficiently acquiring cultural information, the brain is sometimes presented by such theorists as a somewhat inert vessel, or state space, for the beliefs, knowledge, attitudes, institutions, material production skills, behavioural norms, and languages that it comes to contain, retrieve, and transmit (O’Brien et al., 2010; Boyd et al., 2011; Rendell et al., 2011). To the contrary, the encoding

of both consciously explicit and implicit procedural memories significantly alters neuroanatomy and physiology at several scales of organisation, ranging from network to cellular and epigenetic levels (Kandel, 2001).

The use of nonhuman animal models has long demonstrated that the learning of statistical contingencies between pairs of environmental stimuli are accompanied by increased connective branching between neurons involved in processing those stimuli, and increased information exchange across existing connections (referred to as synapses) due to up-regulated quantities of neurotransmitter signalling molecules and their respective receptors at those synapses (Hawkins et al., 1983; Kandel, 2001). Moreover, these modifications have recently been shown to persist for extended periods of time, perhaps even throughout the life history of a given organism, due to inducing evolutionarily conserved molecular signalling cascades within neurons that regulate gene expression through the addition of molecular epigenetic markers to the nucleosome (i.e. the composite structure of genes and the histone proteins around which they are packaged) (Marshall and Bredy, 2016; Levenson and Sweatt, 2006; Kandel, 2012; Landry et al., 2013). As a consequence, these epigenetic changes to protein transcription reorganise neural connectivity and cellular morphology according to patterns of recurrent network activity and repeated use across sensory and affector modalities (see figure 1.). That is, the habitual use of certain cognitive operations alters neural circuitry, and thereby the very computations that occur within nervous tissue (Strauss and Quinn, 1997:90; Downey and Lende, 2012).

In an important sense, what these findings indicate, is that rather than mental content being a kind of computer software stored as information running on immutable hardware, the brain constitutes a unique kind of ‘wetware’, where the boundary between content and mechanism as demarcated entities is far less distinct (Fitch, 2014). With regard to cultural transmission

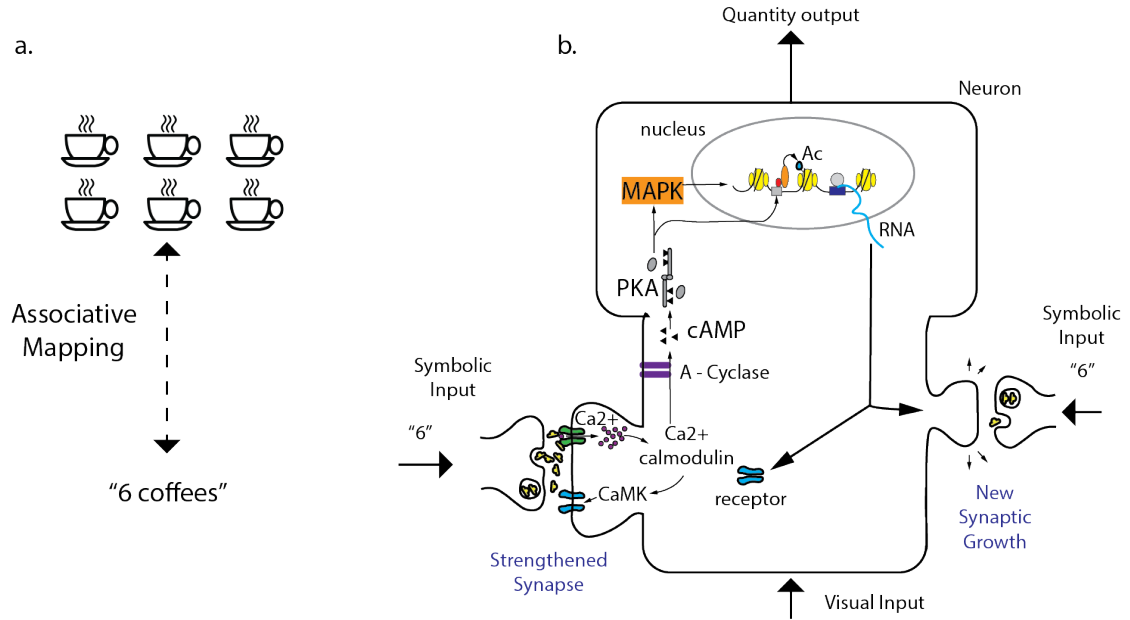


Figure 1: This figure depicts how epigenetic changes to gene packaging result in neuron restructuring, which in turn alters circuit connectivity. a) This particular example shows how this process leads to the formation of a mental association between a given quantity representation and a discrete symbol; an association essential for the cultural acquisition of boundless digital numerical cognition (Dehaene and Cohen, 2007). b) The generation of a new cognitive mechanism is achieved by increasing connectivity between neurons from separate networks. The activation of a neuron involved in representing the symbol “6” at the same time as a continuous quantity neuron, results in an influx of calcium ions into the continuous quantity neuron. Calcium (Ca^{2+}) activates a reaction chain of molecules from Ca^{2+} calmodulin to protein kinase A (PKA). PKA activates transcription factors within the nucleus that bind to the DNA and tag epigenetic acetyl (Ac) markers onto the histone proteins that package the DNA. Ac markers on histones repel each other, which exposes DNA segments for long-term transcription into RNA. The RNA is translated into new receptor proteins that strengthen signal responsiveness at synapses, and also into the components of new synapses that increase connectivity between neurons of separate networks (Alberini and Kandel, 2016). It is these processes that underlie the associations made in a)

from master to apprentice then, not only the acquisition of cultural content, but how that content is algorithmically processed, should be interpreted as an epigenetic selection process for certain neural network configurations underlying cognitive computational capacities within the learner, over alternative forms (Edelman, 1993; Whitehouse, 1996). And, with regard to cultural evolution, it is these alternate neural network configurations and their observable functional properties that comprise the competing cognitive variants under cultural selection at the population level (Cavalli-Sforza and Feldman, 1981:313; Strauss and Quinn, 1997:122). As Heyes (n. d.:7) puts it, the “selectionist view of cultural evolution [applies] not only to beliefs and behaviour (the grist of the mind) but to cognitive mechanisms (the mills)”.

These associative learning processes inherent within the epigenetic workings of neural plasticity, appear to enable the social transmission of more cognitive mechanisms than that suggested with the earlier example of literacy (page 13) alone. Research conducted within the cognitive domain of numeracy has additionally yielded evidence consistent with the social transmission of cognitive variants (Bender and Beller, 2011). Data from comparative mammalian neuropsychology suggests that the human numerical cognitive system comprises both an innate analogue system for estimating quantities via magnitude perception, and a socially-learned digital numerical system for discerning exact integer quantities (i.e. ‘6’, ‘33’) (Feigenson et al., 2004). In the case of the innate analogue system, rodents, nonhuman primates, six-month-old human infants, and adult human populations that lack terms for integers above 5 (e.g. the Mundurukú hunter gatherers of the Amazon basin), have each displayed an ability to discriminate between approximate quantities (Platt and Johnson, 1971; Cantlon and Brannon, 2007; Xu and Spelke, 2000; Pica et al., 2004). Rhesus macaques (*Maca mulatta*) and Mundurukú hunter gatherers are also able to utilise these quantity approximations to perform addition with an accuracy that is dependant upon

the distance between the estimated quantities (smaller distances are difficult to discern) (Cantlon and Brannon, 2007; Pica et al., 2004). Furthermore, the same magnitude coding system, whereby distinct subsets of neurons respond to approximate quantities, appears to exist in bilaterally analogous regions of the intraparietal sulcus (IPS) in both the human and Rhesus macaque cerebral cortex during single-neuron recording and fMRI studies (Piazza et al., 2004; Nieder and Miller, 2004).

Whilst these above studies imply an evolutionarily conserved homology for innate magnitude estimation within the primate order, the digital numerical system appears to be restricted to post-agricultural human societies that more regularly deploy culture-specific counting sequences (Premack and Premack, 2005). In such societies, the acquisition of the signed, verbalised or written symbols of a counting sequence, results in the associative recognition by the human subject of the ‘cardinality principle’; the knowledge that the last symbol represented when counting a set relates by association to the discrete number of elements nested within an object set (Merkley and Ansari, 2016). That this associative learning of numeracy and cardinality results in neurobiological modifications, Bugden and colleagues (2012) have found that arithmetic competence in math fluency tests among 8-9 year old humans correlates positively with left hemisphere-biased IPS activity in fMRI scanners when subjects compare symbolic numeral quantities. Similar findings have also been reported from an earlier study that additionally demonstrated increasing co-activation of the left IPS with the left temporo-occipital visual cortex among 8-19 year olds, which correlated with the age and educational experience of the subject (Rivera et al., 2005). Taken together, these results suggest that an associative mapping is formed between arabic numeral representations of the visual system and the numerical quantities of the innate analogue system, in order to form a digital numerical mechanism, much like that illustrated in figure 1 (Dehaene and Cohen, 2007).

Evidence for the existence of distinct ‘variants’ of the digital numeracy mechanism comes from the diversity inherent within the ethnomathematical record. Some populations, like the Yupno of Papua New Guinea, utilise an anatomical body location for each integer (a one-dimensional system with an upper limit), while yet others use recursive recombinations of a base and a power (theoretically unbounded two-dimensional systems), such as arabic numerals where the primary counting cycle ends at base 10, or Mayan that once used a base 20 system (Bender and Beller, 2011).

More recently, additional evidence has accumulated that points towards the social transmission of cognitive variants dedicated to action imitation and folk psychology; both of which are mechanisms that support high fidelity social learning and therefore cultural evolution itself. Historically, the literature regarding these mechanisms has described both as species-specific to *H. sapiens*, and dependent upon genetically inherited and derived neural substrates (Gallese et al., 1996; Heyes and Frith, 2014). Nevertheless, new neuroimaging and transcranial electromagnetic stimulation methods have demonstrated that experience and artificial cortical activity induction can significantly alter supposedly innate neural circuit connectivity in areas that are homologous with nonhuman primates during imitation and action training experiments (Ferrari et al., 2005; Stout et al., 2011; Catmur et al., 2011). Furthermore, whilst studies focusing on preverbal infants have typically concluded that 7-month-olds can represent the belief states of other agents, neuroimaging has revealed that entirely separate neurological systems mediate such folk psychological tasks between adults and preverbal infants (Heyes and Frith, 2014). These findings imply that associative learning at the very least contributes to imitation and folk psychology in as of yet neglected ways (Cook et al., 2014; Heyes and Frith, 2014). And, although such studies are currently not as abundant as those for numeracy or literacy, they similarly suggest

that human subjects come to possess similar neurobiological modifications and cognitive phenotypes to those of their models following social learning contexts.

Nonetheless, as important as the above evidence is for identifying the cultural inheritance of putative cognitive variants, inferring the occurrence of single transmission episodes is necessary but not sufficient for empirically verifying the presence of a hypothesised underlying cultural evolutionary process. Such an endeavour requires direct engagement with the findings and tenants of the cultural evolutionary literature. This literature boasts a burgeoning combination of formal theory, laboratory experimentation, and field observation, and investigates both microevolutionary processes of selection and marcoeolutionary relationships of common cultural ancestry. However, the following subsection will focus upon those aspects of cultural microevolution and cumulative cultural evolution most relevant to testing the CGH (see Mesoudi [2016] for a thorough review of the field).

2.3 *The Cumulative Cultural Evolutionary Process*

The study of cultural evolution principally explores the distribution of human cultural traits amongst a population (Richerson and Boyd, 2005). That is, the concepts, behaviours and artefacts that can be learned from others via non-genetic means of transmission (imitation, observation, inference, apprenticeship, and communication), and that change in form and rates of adoption over time (Mesoudi, 2011; Sterelny, 2011). In this regard, cultural evolution can be described as a Darwinian process in that variable traits are differentially transmitted according to differing rates of successful adoption, albeit not a neo-Darwinian process, in that Mendelian laws of particulate inheritance or random mutation are not a default assumption in either theory or practice, and this is evident from the earliest work of the field (Mesoudi,

2011).

Beginning in the 1970s, the theoretical biologists Cavalli-Sforza and Feldman (1973) began to co-opt and modify the methodology of population genetics to produce both mathematical and conceptual models of the change of cultural trait frequencies over time. This extension of methods was intuitive and appropriate, for certain cultural dynamics, including cultural selection, innovation and transmission, are conceptually analogous, if somewhat divergent in certain respects, to natural selection, mutation, and transmission in population genetics (Creanza et al., 2017). For example, the social transmission of cultural traits (arrow making), or variants of a given trait (fledged or unfledged arrows), includes the vertical transmission vector of parents to offspring similar to population genetics, but also oblique transmission from non-parental adult generations to subsequent generations, and horizontal transmission among peers within a contemporaneous generation (Feldman and Cavalli-Sforza, 1975). The existence of these additional transmission pathways is well supported, as even among hunter-gatherer societies, subjects often have the opportunity to learn tool production techniques from potentially over 1000 unrelated individuals from neighbouring bands over their life times (Hill et al., 2014). These early models also quickly identified that, whereas certain cultural traits are similar to discrete gene-like entities, such as awareness of a qualitative item of knowledge, other cultural traits are best described as quantitative and continuous, such as tolerance towards aggression in ‘cultures of honor’, or skill when producing an artefact (Feldman and Cavalli-Sforza, 1975; Nisbett and Cohen, 1996; Henrich and Boyd, 2002).

It was in building upon this early pioneering work on social transmission pathways, that the anthropologist and biologist Boyd and Richerson (1985), began to critically advance the concept of cultural selection by modeling how the psychological properties of individuals results in the biased trans-

mission and persistence of particular cultural traits. These models included the propensity of individuals to acquire the cultural traits of successful others, or those with perceived statuses of prestige (referred to as indirect bias) (Boyd and Richerson, 1985:chapter 8); to preferentially acquire those traits that are most frequent within a population, commonly referred to as conformist bias (chapter 7); or to retain cultural traits based upon the compatibility of their content with the constraints of human psychology (direct bias) (chapter 6). This work was essential for the growing theoretical study of cultural evolution, for it established that, consistent with what evolutionary biologists would refer to as a ‘process of microevolution’, cultural traits have differential adoption fitness under the process of cultural selection dependent upon their frequency, content, and capacity to increase the perceived success of their bearers (Dobzhansky, 1937). Furthermore, in producing clear theoretical predictions about the conditions of human selectivity for certain traits, the study of cultural evolution was able to later incorporate the methods of experimental psychology and field ethnography, in practically testing the presence of these biased selection mechanisms in living human populations (Mesoudi, 2016).

Although both laboratory and field research currently support the presence of these predicted cultural selection biases in living human subjects, the role of such microevolutionary processes in the cultural evolution of cognitive mechanisms is yet to be directly addressed. Of particular importance should be indirect bias for learning cognitive phenotypes from exposure to successful models or communities of models, as success (which can be measured as living to old age, net resource returns, income, educational attainment etc.) can be an index of adaptive trait possession under variable ecological conditions (Henrich and McElreath, 2007). At least where material and behavioural cultural traits are concerned, laboratory experiments already indicate that participant attention is attuned to the success of others, and results in the

preferential copying of these subject's traits. For example, in a setup where participants could choose the length, width and thickness dimensions of virtual projectile points within a virtual hunting environment, Mesoudi and O'Brien (2008a) found that participants preferentially observed and copied the projectile point designs of the group member with the highest caloric returns. This bias result has been reproduced cross-culturally in mainland China and the UK (Mesoudi et al., 2015.) Similarly in field reseach, Henrich and Henrich (2010) have reported that Fijian women often cite *yalewa vuku* (elderly women that are perceived to be successful and experianced) as the source of their knowledge regarding adaptive food taboos that prevent the ingestion of marine dietary toxins during critical periods of pregnancy and lactation.

As such, the above literature already suggests that cognitive variants could, at least in principle, be transmitted along with behavioural skills in an indirectly biased manner constitutive of cultural selection. However, most important, indirect bias for successful traits should be an essential analogous process for the CGH, for it is critical to cumulative cultural evolution; the means by which cultural traits accumulate modifications and adaptiveness to local environmental challenges over time (Tomasello et al, 1993).

According to Mesoudi and Thornton (2018), cumulative cultural evolution typically occurs when: 1) an individual produces new behavioural patterns by modifying existing traits; that are 2) socially transmittable to others; where 3) this social diffusion increases the performance of the average individual within the population as a proxy of inclusive or cultural fitness; and where 4) this entire process reiterates across multiple episodes of transmission leading to the accumulation of functional modifications to a given trait over time. For example, in Mesoudi and O'Brien's (2008a) virtual hunting task, the average group design of projectile points became increasingly

optimal for hunting following biased social learning episodes. Modeling has also demonstrated that in the absence of selective social learning for successful trait variants, cumulative cultural evolution reduces to variant drift whereby traits do not accumulate increasingly adaptive functional properties over time (Vaesen, 2012). It is clear then, that both cumulative cultural evolution and indirect bias would be essential for cognitive mechanism evolution, as computational architectures would need to be constructed via the accumulation of successful modifications (i.e. new cognitive operations and procedures) within social transmission chains, just as projectile point designs improve over time following iterations of indirect-biased transmission.

Finally, if the cultural evolution of cognitive mechanisms is analogous to cumulative cultural evolution with indirect bias, then other extended factors in the literature that are known to influence cumulative cultural evolution should similarly influence cognitive mechanism evolution. Several publications suggest that population size and the difficulty of learning particular traits (trait complexity) interact to impact the rate of cumulative cultural evolution (Henrich, 2004; Powell et al., 2009; Lycett and Norton, 2010).

Using formal mathematical modeling, Henrich (2004) has argued that a decline in population size among Tasmanian foragers of the late Pleistocene-early Holocene can account for the loss of complex traits from the Tasmanian archaeological record. A critical land bridge that existed between Tasmania and Australia, and the social networks that it likely permitted, vanished beneath increasing sea levels during the end of the last glacial maximum 12-10,000 years ago (ya), and the ratio of simple stone tools to more demanding bone tools depreciated from 3:1 7,000ya to 15:1 4,000ya, before disappearing from the archaeological record entirely. It can also be inferred from the reduced association of fish remains with human artefacts, that fishing technology also followed suit. Henrich's (2004) model predicts this loss, as in

smaller populations, the social learning error involved in acquiring complex cultural traits, can overcome the probability that individuals will produce beneficial modifications that others can selectively learn from. Conversely, when effective population sizes increase, the probability that modifications will occur outweighs mistakes made when learning, and rates of accumulation can increase. Powell and colleagues (2009) have used the latter outcome to explain the onset of complex symbolic and technological developments, like shell beads, during the Eurasian Upper Palaeolithic 45,000ya. By analogy then, relatively more complex computational architectures should require larger population sizes for more rapid cognitive mechanism evolution to take place.

To summarise the cited research, if the cultural evolution of cognitive mechanisms and cultural trait skills are microevolutionarily analogous, as held by the CGH, then the current literature suggests the following predictions:

Prediction 1) Both forms of evolution should be similarly affected by the selection-like process of indirect bias for certain cognitive or cultural skill variants across multiple episodes of transmission.

Prediction 2) Both forms of evolution should demonstrate a cumulative increase in trait function across multiple transmission episodes; i.e. both cultural skills and cognitive mechanisms should accumulate competence at achieving a particular function over time on average (cumulative cultural evolution).

Prediction 3) For the cumulative evolutionary process of prediction 2 to occur, the selection-like process of prediction 1 must be present.

Prediction 4) Both forms of evolution should be similarly influenced by other

factors that are recognised under cultural evolutionary theory, such as the influence of both population size and trait-learning complexity upon the rate of cumulative evolution.

It is these predictions that will be assessed in order to test the cognitive gadgets hypothesis. The following section methodically lays out the means with which to achieve this using agent-based modeling. It begins with specifying Henrich's (2004) formal model, and then builds upon these formal assumptions.

3 The Agent-Based Models

In the field of cultural evolution, when a theoretical approach is selected as the preferred research method, it is common to utilise mathematical modeling (McElreath and Henrich, 2006). Simulation with mathematical models can be ideal, both when there are ethical and practical constraints to experimental manipulation, and when formalisation provides a more precise definition of a complex system of behaviour than language and human intuition can achieve alone (Fischer and Kronenfeld, 2011). It is for precisely these two reasons that Henrich's (2004) model (see literature review) can be of great use for testing the four predictions of the CGH addressed above. The conceptual principles of the model formalise these four predictions within its parameters and assumptions, and its simulation of human populations negate the need for the ethically questionable and methodologically daunting manipulation of human cognitive development across several generations. Nevertheless, when describing cognitive mechanisms that exhibit if-then rules, thresholds, and that vary in their computational operation over time, modeling with the required differential equations can become impractical and cumbersome, and it is in such cases that agent-based modeling is an ideal methodology (Bonabeau, 2002).

Agent-based models are computational simulations that describe the behaviour of programmable rule-following automata, known as 'agents', and are used to examine how agent interactions yield emergent phenomena at the population level (Anderson, 2014). In this sense, agents are individual elements of a simulated system that can be assigned states, properties, and behaviours, and that could equally represent particles in a three-dimensional space, or biological organisms (Wilensky and Rand, 2015). ABMs are intended to be simplified and abstract representations of a certain aspect of reality, and although the social sciences are often critical of reductionist ab-

Overview	Purpose
	State variables and scales
	Process overview and scheduling
Design concepts	Design concepts
Details	Initialization
	Input
	Submodels

Figure 2: *Standardised ODD Protocol for ABM Description. Image from Grimm et al (2006:117)*

stractions, ABMs derive their usefulness precisely from the increased causal understanding that they yield between assumptions and conclusions relative to the complexity of reality itself (Smaldino, 2017). Even with such simplifications however, the emergent outputs of ABMs are often sensitive to structural details of design, and thus precise standardised forms of description are essential for the reproduction of models (Fachada et al, 2015).

Here, I use the standardised O.D.D. (Overview, Design concepts, Details) protocol of Grimm et al. (2006) (figure. 2) to present the ABMs, and use formal representation where possible. The model code scripted in R Markdown has been made available in the appendix, as are the raw outputs. Over the following subsections, I provide a summary of Henrich’s (2004) model, and then describe both ABMs.

3.1 *Henrich's Formal Model*

Henrich's (2004) model is primarily an oblique transmission model, whereby a pool of individuals at various timesteps represent cultural generations. Generation one consists of a population of N individuals, each identifiable as $i = 1, \dots, N$, and wherein each possesses a continuous variable: z_i . This z -value captures the degree of enskillment that a particular individual i has attained with a particular cultural trait composed of socially-acquired elements, be it making a fishing spear of appropriate length, knowing all the rituals required for a shamanic healing practice, or how to correctly assist a mother during childbirth.

Generation upon generation, N acquire their z -values from prior generations via social learning (imitation and reconstructive inference), and it is here that Henrich makes an assumption of indirect-biased learning essential to predictions 1 and 3 of the CGH. Henrich uses the variable f to denote the probability that a particular prior individual (f_i), will be selected as a cultural model due to biased learning attention. The average cumulative change in skill following social learning for a population, $\Delta\bar{z}$, is therefore given by Henrich's adaptation of the Price (1970) equation:

$$\Delta\bar{z} = \underbrace{Cov(f, z)}_{\text{indirect bias}} + \underbrace{E(f\Delta z)}_{\text{learning error}} \quad (1)$$

The first covariance term, $Cov(f, z)$, describes how skill, z , and biased social transmission, f , are positively correlated for each individual i within N , whereby high skill levels result in the individual's z value being more likely to be imitated by following generations. The final term, $E(f\Delta z)$, de-

scribes Henrich’s second assumption of imitation error and is analogous to mutation within Price’s (1970) equation. Each learning attempt is impacted by 1) inaccurate inference about the true value of z_i due to transmission channel noise, and by 2) a high probability of obtaining a z value less than that of a chosen model due to skill complexity. This emphasises that social learning is often imperfect due to compromised imitation fidelity, asocial learning experiments, inconsistent memory fidelity, and even fortuitous error.

Henrich then makes a third simplifying assumption that each individual within N will consistently attempt to copy the most skilled individual, h , to obtain trait skill z_h . Given this assumption that $f_h = 1$, equation (1) reduces to:

$$\Delta \bar{z} = \underbrace{z_h - \bar{z}}_{\text{generational difference}} + \underbrace{\Delta z_h}_{\text{learning error}} \quad (2)$$

which demonstrates that the direction and rate of change in \bar{z} is determined by 1) the difference between the prior generation’s average, \bar{z} , and what will be the new generation’s average, z_h , mediated by 2) the effect of the new generation’s imperfect imitation; Δz_h .

To generate the effect of Henrich’s second assumption of inaccurate z_h imitation, Δz_h , a formalisation of the social learning process is required. Here, Henrich specifies that each individual within N from a new cultural generation will sample a Gumbel probability distribution (a.k.a. the Generalised Extreme Value type-1 distribution) with the mode $m = z_h - \alpha$ and the dispersion β (see figure 3.). The $-\alpha$ parameter captures the difficulty associated with acquiring a skill of given complexity, such that on average, the i th individual acquires a skill value worse than z_h by the amount α . The β dispersion

parameter captures the range of variation within which individuals generate psychological inferences about the culturally learned representational components of their model's z_h skill.

From figure 3, it is clear that there is a low probability that the i th individual will obtain a z_i value greater than z_h . This is reflective of the chance generation of fortuitous error, and the asocial innovation of skill techniques, within the dynamics of cultural evolution (Muthukrishna and Henrich, 2016). Nevertheless, it is also clear that as a population size, N , increases, the chance of sampling from the positive tail end of the distribution and producing a higher z'_h for the next generation to learn from increases. This fact can be approximated with the following equation:

$$\Delta\bar{z} = -\alpha + \beta(\epsilon + \ln(N)) \quad (3)$$

wherein ϵ represents Euler's gamma constant, $\epsilon \approx 0.577$, which, along with the natural logarithm of the population size, $\ln(N)$, approximates the highest values achievable within a sample size N of the Gumbel distribution (see Henrich [2004]:Appendix A for derivation). Here, the $-\alpha$ term works against the process of cumulative cultural evolution, as the low imitative and inferential processing fidelity that the term attempts to capture reduces the rate of, and can even reverse the direction of, $\Delta\bar{z}$. The term $\beta(\epsilon + \ln(N))$ captures how, on average across generations, the effects of variation in inferences about learned skill components, and population size, combine in favour of the adaptive rate of cumulative cultural evolution. As such, the ratio of α/β (social learning error to the range of inferential differences) acts as a rate limiting factor on $\Delta\bar{z}$, with higher ratios acting as an index of cultural skill complexity that demands a larger size of N for cumulative cultural evolution

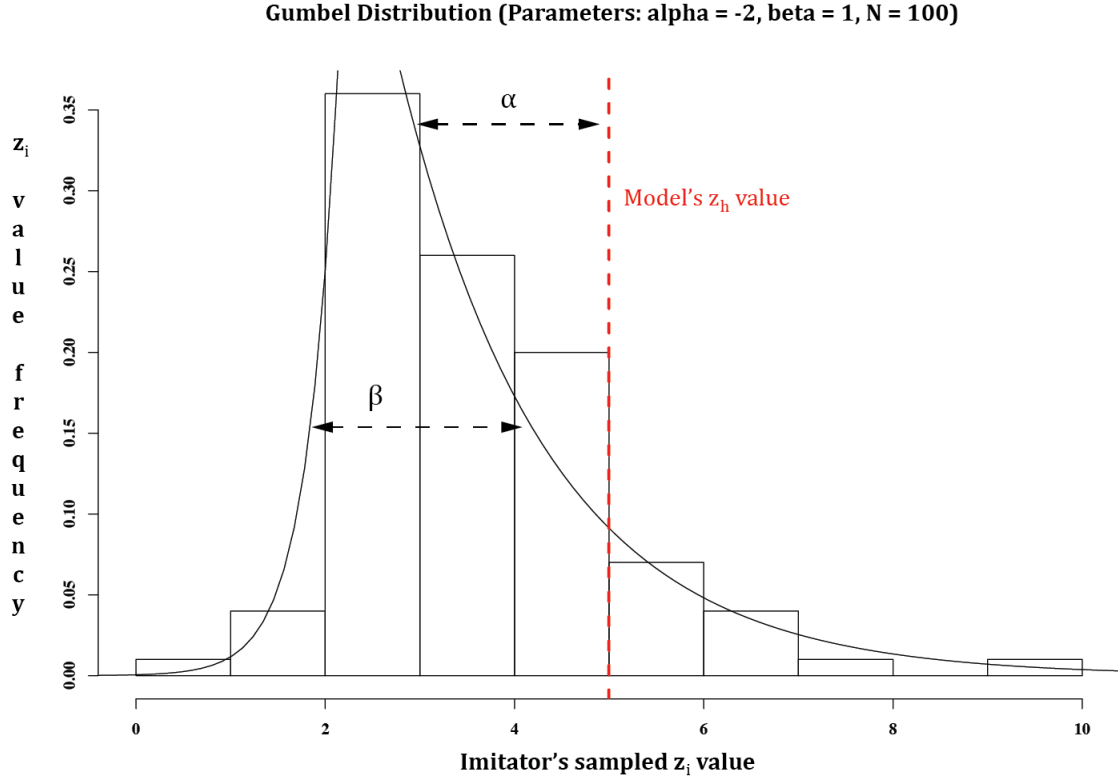


Figure 3: The i th individual within N samples a Gumbel distribution with the parameters $-\alpha$ and β when attempting to copy the z value, 5, of individual h . This histogram of 100 z values produced in R demonstrates the properties of the Gumbel distribution: individuals have a high probability of obtaining z values lower than z_h , due to the mode and asymmetric morphology of the distribution. Parameter $-\alpha$ can represent the difficulty of learning this particular skill, whilst β can represent the range of possible inferential interpretations afforded by the constraints of human psychology when imitating said skill.

to be maintained.

Mathematically, the appropriate size of N to maintain a material or behavioural cultural skill of given complexity α/β can be predicted as an N^* threshold for cumulative cultural evolution with the equation:

$$N^* > e^{\left(\frac{\alpha}{\beta} - \epsilon\right)} \quad (4)$$

which is derived by setting $\Delta \bar{z} > 0$ and solving for N in equation (3).

According to Henrich's equation (4), if, for whatever cause, $N < N^*$, culture will not only fail to enter a cumulative regime of increasing enskillment, but will additionally enter a declining regime of maladaptive knowledge loss. Furthermore, skills that are more complex to learn socially (high α/β) will be more sensitive to population size due to their proportionally high N^* threshold.

Equation (4) will be essential in testing ABM 1 for its capacity to reproduce the results of Henrich's (2004) formal model, as it makes clear formal predictions about the threshold N^* that should be observable even in agent-based modeling format. It is also clear that the model assumes indirect bias ($f_h = 1$) and describes the impact of population size on cumulative cultural evolution, and testing these qualities in the ABMs is essential for predictions 1-4.

3.2 ABM 1: Henrich's Model Rederived

Purpose

The purpose of ABM 1 is to simulate a population of agents that transmit cultural trait skills by oblique transmission across generations in a manner consistent with Henrich's (2004) formal assumptions. Like Henrich's model, it does so without reference to environmental variables, and only focuses on populations of individuals.

State variables and scales

ABM 1 consists of 3 hierarchical levels: the agent, the population, and the global set of independent parallel populations. State variables pertain to those variables that characterise the agents of the system, and here include: identity number, cultural trait skill (z), probability of attempting to copy the most successful individual (f_h), probability for a certain degree of learning error ($-\alpha$), range of learning interpretations afforded for that agent (β), and the cultural generation to which that agent belongs (previous or current). The auxiliary variables at the population level are deduced from the number of agents: population size (N). Each independent population, defined as an independent iteration of the model, is determined by the maximum number of iteration runs (r_{max}). These parallel populations, or iterations, are included in order to account for the extra injection of stochastic variation that occurs in ABMs relative to formal equations due to sensitive dependence upon varying agent interactions (Wilensky and Rand, 2015).

Process overview and scheduling

ABM 1 tracks change in \bar{z} for a population across generational time steps t_1 to t_{100} . This range of generations was chosen as it is identical to the protocol of a previous ABM based upon Henrich's formal model from the literature (see Powell et al., 2009). Each generational time step t , N agents within a given population are replaced by another set of N agents, with these new agents

entering a 'current' generational state, and the replaced agents switching to a 'previous' generational state. In accordance with Henrich's equation (2), each current agent attempts to copy the value of z_h from the previous generation, but in addition, may also attempt to learn from another randomly selected agent of the prior generation according to the adjustable probability $f_{noth} = 1 - f_h$, depending upon the indirect bias parameter settings of the model. This entire process is then repeated until generation t_{100} . Figure 4. illustrates this as a flowchart.

Design concepts

1. *Emergence:* Any change in \bar{z} over the t_{100} generations emerges as output from agent interactions and behaviour. The only empirical rules programmed into the model are the generational cycling and learning processes of the agents.
2. *Sensing:* Like Henrich's model, ABM 1 assumes that each agent can sense and compare the cultural skills of agents in the previous generation, and that these perceived skill levels correlate directly with the true skill levels of previous agents.
3. *Interactions:* Similar to Henrich's formal model, oblique social learning for each current agent occurs via sampling a Gumbel distribution with the mode $m = z_h - \alpha$ and dispersion β , and where α and β are adjustable model parameters that apply as state variables to all agents. In cases where indirect bias parameters are set to $f_{noth} > 0$, each current agent i in $N_{current}$ draws a randomly selected value, q , from a uniform distribution with the interval $0 \leq q \leq 1$. If the i th current agent's q value is less than the probability f_{noth} , the agent attempts to learn from a randomly selected previous agent instead of previous agent h . A module within the ABM then completes these social learning actions by computing a series of N Gumbel distributions for the z values of each previous agent, $z_{iprevious}$, wherein each mode is

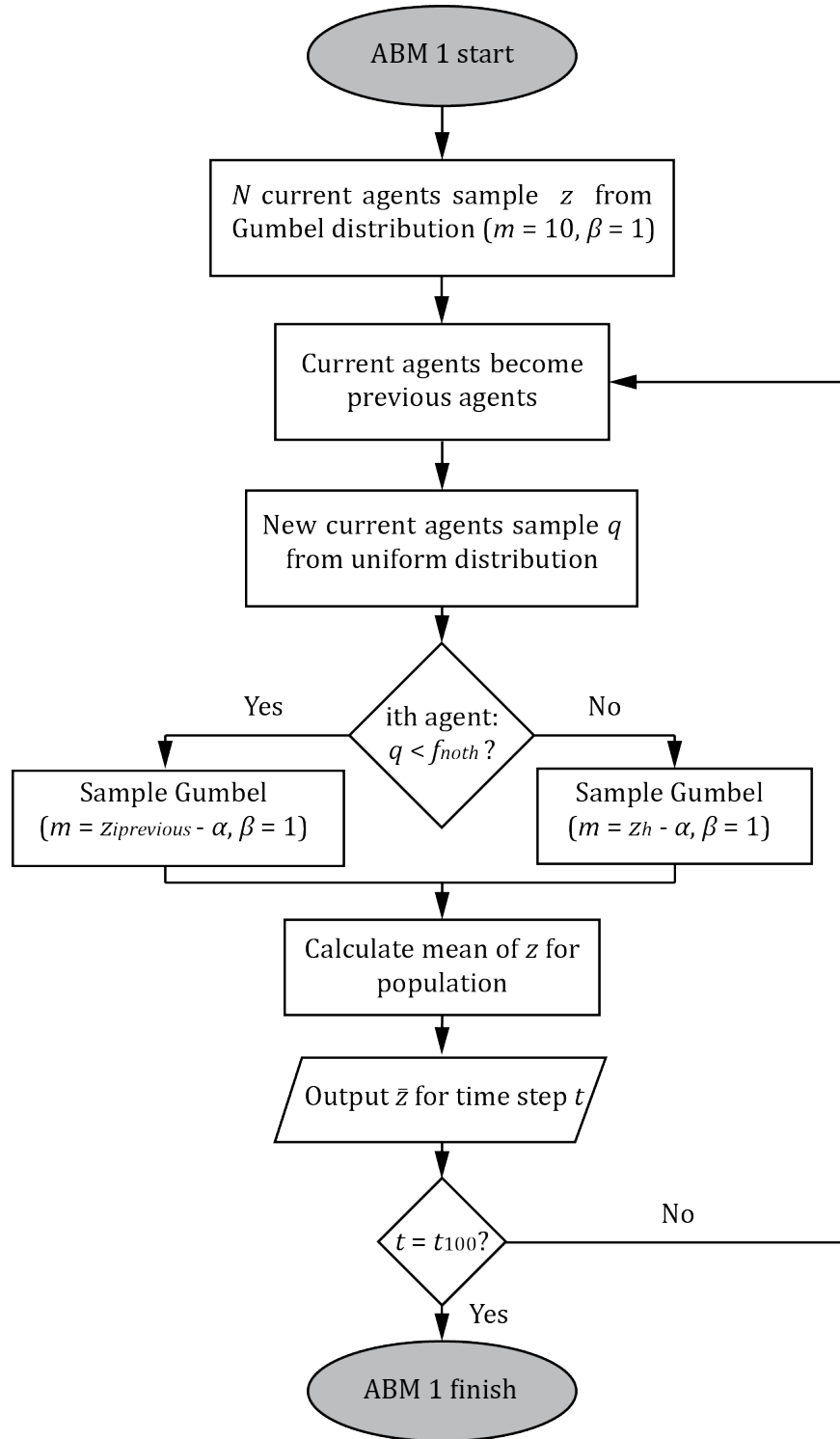


Figure 4: A flowchart depicting ABM 1.

$m_i = z_{i\text{previous}} - \alpha$. The agent then randomly samples a z value from one of these randomly selected N distributions.

4. *Observation:* At the end of each time step, following learning, the mean of the z scores for the entire generation of current agents is computed to produce the value \bar{z} for a given population. This \bar{z} value is then recorded as model output for all time steps in t_1 to t_{100} . Powell and colleagues (2009:324) have reported stochasticity in their results obtained from an ABM that was similarly based on upon Henrich’s (2004) model. As aforementioned, this stochasticity is common for ABMs. To account for this, Powell et al. (2009:324) computed a further mean over the \bar{z} values of 100 independant model iterations for each given set of input parameters, and the same is done here over 100 independant ‘populations’ ($r_{max} = 100$).

As with other ABMs that have been developed to investigate cultural evolutionary theory with qualitative predictions (Mesoudi and O’Brien, 2008b; Powell et al., 2009), inferential statistical analysis is not required for the output of ABM 1. The model parameters of indirectly biased learning (f_{noth}), trait complexity (α/β), and population size (N), were each systematically adjusted to assess predictions 1-4. As with Powell et al’s (2009) protocol, the output was designated as ‘cumulative cultural evoluton’ if the mean \bar{z} of the final generation was greater than the \bar{z} value of the first when averaging over the 100 populations ($\Delta\bar{z} > 0$).

Initialization

Each model iteration begins with N current agents represented by a data frame of N rows, wherein each agent is equivalent to one row. Each column of cells hold the state variables, like z_i skill, for each agent. Similar to the protocol of Powell et al (2009), the first generation of agents begin with cultural skill values sampled from a Gumbel distribution with the mode $m = 10$

and dispersion β .

Input

Input parameters of the ABM include the probability for indirect biased or unbiased learning (f_{noth}), trait skill complexity (α and β), population size (N), maximum number of generational time steps (t_{100}), and maximum number of independent populations (r_{max}).

Submodels

As discussed with ABM 2, the principle difference in assumptions between ABM 1 and 2 is that, following the literature, cognitive variants appear to conserve architectural similarity following transmission, rather than systematically exhibiting loss of function, as with cultural skill loss following learning with Henrich's assumptions ($-\alpha$). To examine the precise contribution of this particular change of assumptions, a submodel of ABM 1 (ABM 1_{sub}) was produced that utilises the 'normal' Gaussian distribution for all instances where a Gumbel distribution is used in the primary ABM. Henrich's (2004) formal model is robust to this change, with the primary difference being the loss of the $-\alpha$ term (Vaesen, 2012). However, to make the standard deviation (σ) of the Gaussian distribution equivalent to the dispersion β of the Gumbel distribution, the following equation from Vaesen (2012:4) was used, wherein $\beta = 1$:

$$\sigma = \frac{\pi\beta}{\sqrt{6}} \approx 1.28 \quad (5)$$

The modes of the Gaussian distributions in the submodel are either $m = z_h$ in cases of biased social learning, or $z_{iprevious}$ in cases of unbiased learning. All other aspects of ABM 1_{sub} are identical to ABM 1.

3.3 ABM 2: Cognitive Variant Model

Purpose

The purpose of ABM 2 is to simulate populations of agents that transmit variants of a cognitive mechanism in a manner that is sympathetic to Henrich’s (2004) assumptions, whilst also capturing the essence of the literature on the social transmission of cognitive variants. Many of the processes implemented in the model are identical to ABM 1 for comparison.

State variables and scales

The overall structure of ABM 2 is identical to ABM 1, with the exception of six state variable adjustments. Instead of cultural skill (z), each agent exhibits a measurement of error (ζ) associated with their possessed cognitive variant. The higher the value of ζ the greater the number of mistakes a current agent’s cognitive variant makes during a cognitive trial task (described under design concepts). Thus, agent h is the individual in the previous generation with the lowest ζ score. Furthermore, the state variable $-\alpha$ is absent in ABM 2, as in all the cases of cognitive variant transmission surveyed in the literature review, and as held by Heyes (2018), living human subjects appear to gain neurocognitive mechanisms similar to their models following social interaction. State variable β is also replaced by σ , as determined by equation (5), but continues to perform the function of simulating variance in agent learning. Finally, agents possess three additional state variables, I_i , W_{Ji} and θ , that characterise an agent’s cognitive variant (discussed further under design concepts).

Process overview and scheduling

ABM 2 tracks the population average of $\bar{\zeta}$ for r_{max} populations over t_{100} generational time steps. Each time step t , N previous agents are replaced

by N current agents, with these current agents learning from the previous generation. Current agents learn from the previous agent h with the probability f_h , or from a randomly selected previous agent with the probability $f_{noth} = 1 - f_h$. As suggested by findings in the literature, these social learning interactions result in current agents exhibiting neural network modifications (see design concepts) similar to their selected model in the previous generation. The current agents are then presented with a cognitive processing trial that determines the ζ score of the cognitive variant implemented by their neural network. The process is depicted in figure 6.

Design concepts

1. *Sensing:* Like ABM 1, agents of ABM 2 are assumed to be aware of the ζ scores of agents in the prior generation, and capable of identifying the agent with lowest cognitive error ζ_h .
2. *Neural Networks:* The literature regarding cognitive variant transmission suggests that variants are neurobiological modifications within the neural networks of subjects (figure 1). More specifically, one of these modifications hypothesised to be essential to the development of new neurocognitive mechanisms is the epigenetic regulation of receptors at synapses, which adjusts the sensitivity of neurons to informational input. An essential requirement for ABM 2 then is to a) simulate cognition as neural computation, and b) to emulate the effect of changing receptor densities on cognitive processing.

Biological neurons are thought to be the basic units of cognition, owing to their information-processing properties (Kandel et al., 2013). They receive several inputs from other neurons in the form of chemical neurotransmitters binding to their receptors (see figure 7a). They then integrate all these inputs, and if the net sum of the inputs is greater than a particular threshold, they produce all-or-none (binary) electrical potentials that activate neurotransmitter release as output to other neurons (Burkitt, 2006). These chemical

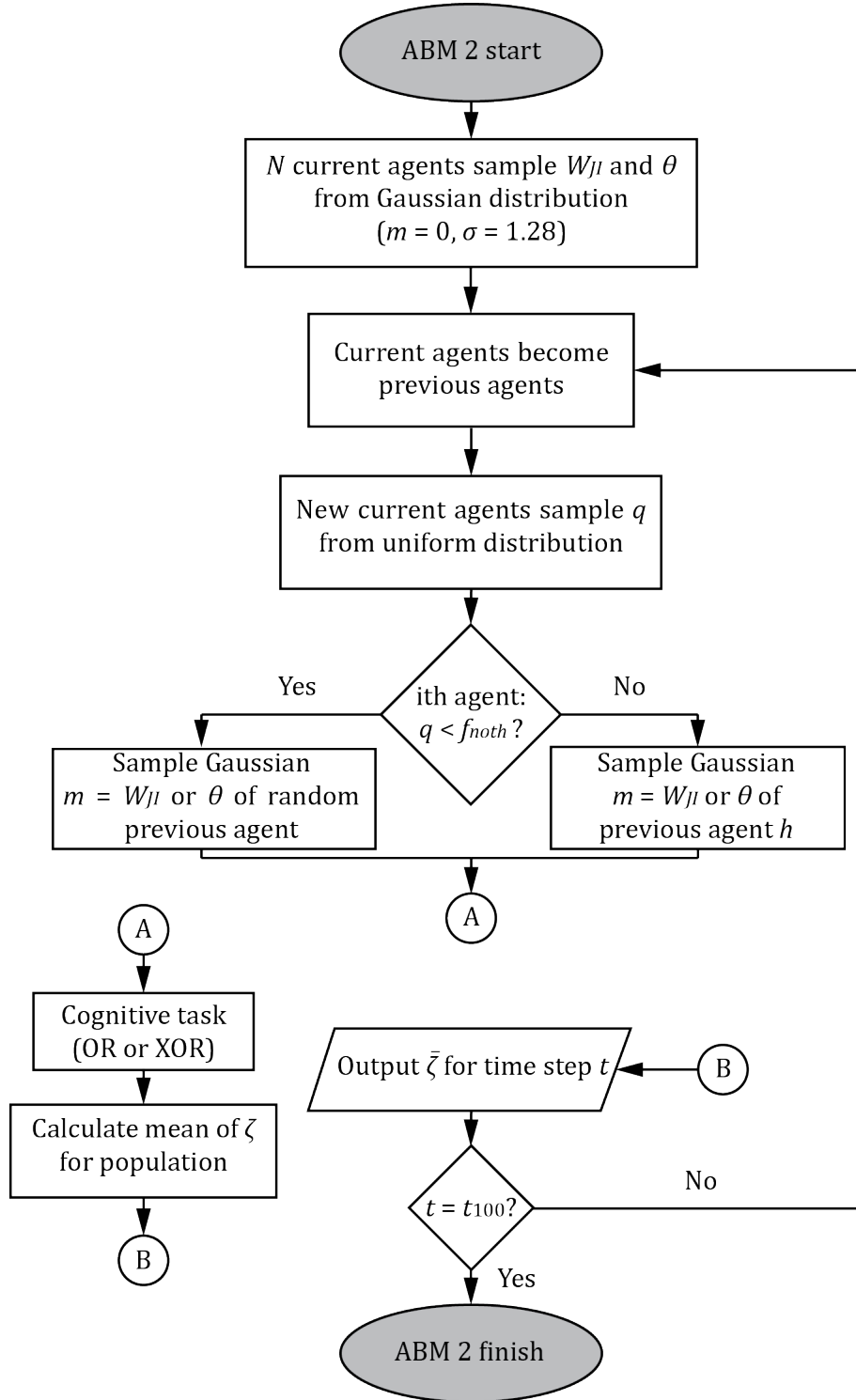


Figure 5: A flowchart depicting ABM 2.

outputs can then excite or repress the electrical activity of further neurons. Such properties enable neurons to compute propositional logic (see below), whilst the quantity of receptors at synapses stores memory and alters the computational properties of the networks in which single neurons participate (McCulloch and Pitts, 1943).

To simulate artificial neural networks with these properties in the agents of ABM 2, the connectionist model developed by McClelland and Rumelhart (1986) was utilised. Within this model (figure 5b), an artificial neuronal unit, J , receives input from I_i input units. Each input unit state, 1 or 0 (TRUE/FALSE), is multiplied by a weighted connection, W_{Ji} , which emulates receptor density at specific synapses. Unit J then uses a sum function over all the input vectors:

$$\mu = \sum_{i=1}^n W_{Ji} I_i \quad (6)$$

Whether unit J then produces an output, O_J , depends upon whether this net sum, μ , exceeds the threshold, θ , of unit J . This is formalised by the following equation:

$$O_J = f(\mu) \quad (7)$$

where f is a Heaviside step function described by the conditional equation:

$$f(\mu) = \begin{cases} 0 & \text{if } \mu \leq \theta \\ 1 & \text{if } \mu > \theta \end{cases} \quad (8)$$

As such, by permitting the state variables W_{Ji} and θ to vary continuously

Neural Computation

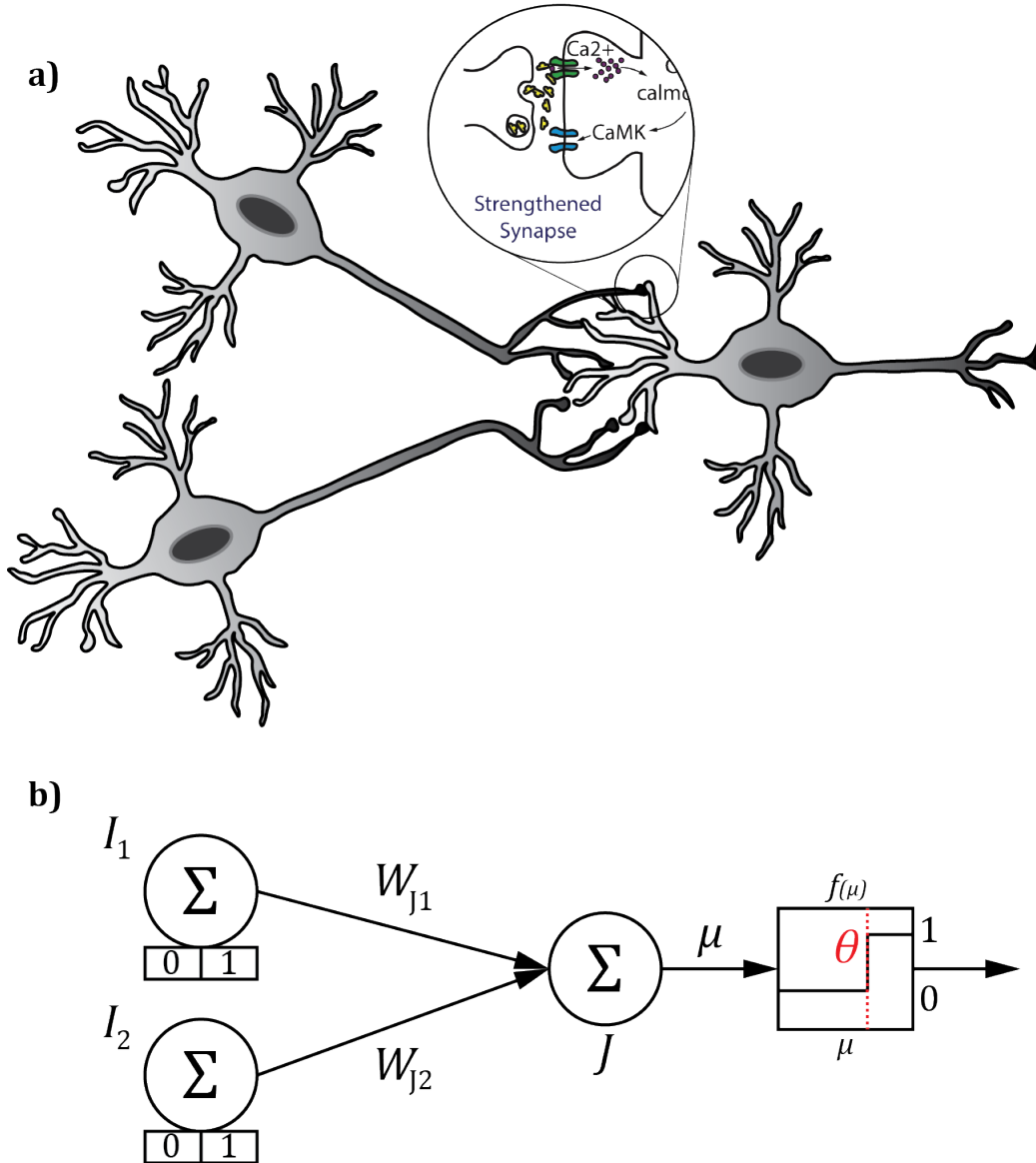


Figure 6: a) A depiction of three biological neurons. b) Three artificial neuronal units.

according to a Gaussian distribution with the standard deviation σ and mode $m = 0$ (where negative values represent repressive synapses and positive represent excitatory synapses), one can at once simulate the epigenetic modification of neural networks and cognitive variant transmission in ABM 2.

3. *Cognitive mechanisms:* Cognitive mechanisms are emulated by agent neural networks via trialing their capacity to perform Boolean logic functions. Boolean logic tasks are often used as analogies to cognition in computer simulations of neural network evolution, wherein, over generations, populations of neural networks are selected for correctly computing Boolean logic (Fogel et al., 1990). The two types of trial task used in ABM 2 are the OR Boolean function task and the XOR (exclusive OR) Boolean function task. The XOR function requires a more demanding (complex) computational architecture relative to the OR function, and so is somewhat analogous to a cultural skill with a higher α/β ratio (Fogel et al., 1990).

XOR and OR logical functions have 4 correct solutions for 4 combinations of two binary (0 or 1) inputs (Anderson, 2014). These inputs are fed to the agents by varying the input unit variables (I_i) of their neural networks. The resulting error score, ζ , therefore documents how many mistakes out of 4 an agent’s cognitive variant (comprised of modifications W_{Ji} and θ) makes relative to true XOR and OR logic. The required architectures and correct solutions are displayed in the Appendix.

4. *Interactions:* Current agents select previous agents to learn from following the same principles of ABM 1. However, instead of sampling a Gumbel distribution, the agents acquire similar W_{Ji} and θ values to their selected model. The i th current agent’s values are sampled from Gaussian distributions with the standard deviation σ , and with modes equivalent to the W_{Ji} and θ values of the selected previous agent.

5. *Emergence:* Whilst any change in $\bar{\zeta}$ emerges at the population level from agent interactions over the t_{100} generations, the value ζ also emerges at the agent level from the specific combination of an agent's W_{J_i} and θ values.

6. *Observation:* Similar to ABM 1, the value $\bar{\zeta}$ for each time step represents the average agent ζ score taken over r_{max} populations. If $\bar{\zeta}$ at t_{100} is less than at t_1 , the output is deemed as 'cumulative evolution' ($-\Delta\bar{\zeta} > 0$).

Initialization

As with ABM 1, agents are represented within a dataframe of N rows. Starting W_{J_i} and θ parameters are sampled from a Gaussian distribution with the standard deviation σ and mode $m = 0$, yielding a $\bar{\zeta}$ score of 2 on average.

Input

Inputs parallel those of ABM 1, with the exception of α and β , and with the addition of σ .

Submodels

Two submodels of ABM 2 are used, whereby each contain either the OR or XOR cognitive trial task. These are referred to as the OR and XOR conditions respectively.

4 Simulation Results

4.1 *Validating ABM 1*

The validity of ABM 1 as an adequate comparative target for ABM 2 (in place of Henrich's model) was tested using equation (4) as a criterion. Maintaining β at 1, α/β ratio was increased in intervals of 0.2 between ratios of 4 and 9. N^* was then calculated using (4) as a prediction for the value of N^* that should be observed in ABM 1 for a given α/β ratio if it follows the same assumptions as the formal model ($f_h = 1$). Equivalent α/β ratios were then entered into the ABM and N was increased until the output demonstrated consistent cumulative evolution ($\bar{z} > 10$ at t_{100}) for 5 consecutive sets of 100 iterations. The observed N required for cumulative evolution to occur for a given skill of α/β complexity was then recorded as the observed N^* threshold.

As displayed in figure 7., the observed N^* thresholds for cumulative evolution in ABM 1 approximate the predicted N^* thresholds of Henrich's (2004) formal model. However, the output also demonstrates that the observed N^* values of ABM 1 are increasingly greater than that predicted for larger values of α/β . This indicates that the model is inadequate for testing exact quantitative predictions. Nevertheless, for the qualitative predictions tested in this dissertation, the ABM captures cumulative gain and loss in a manner that is very similar to Henrich's formal model, with the observed N^* values being more conservative rather than below that of the predicted N^* thresholds. For this reason, its use was accepted.

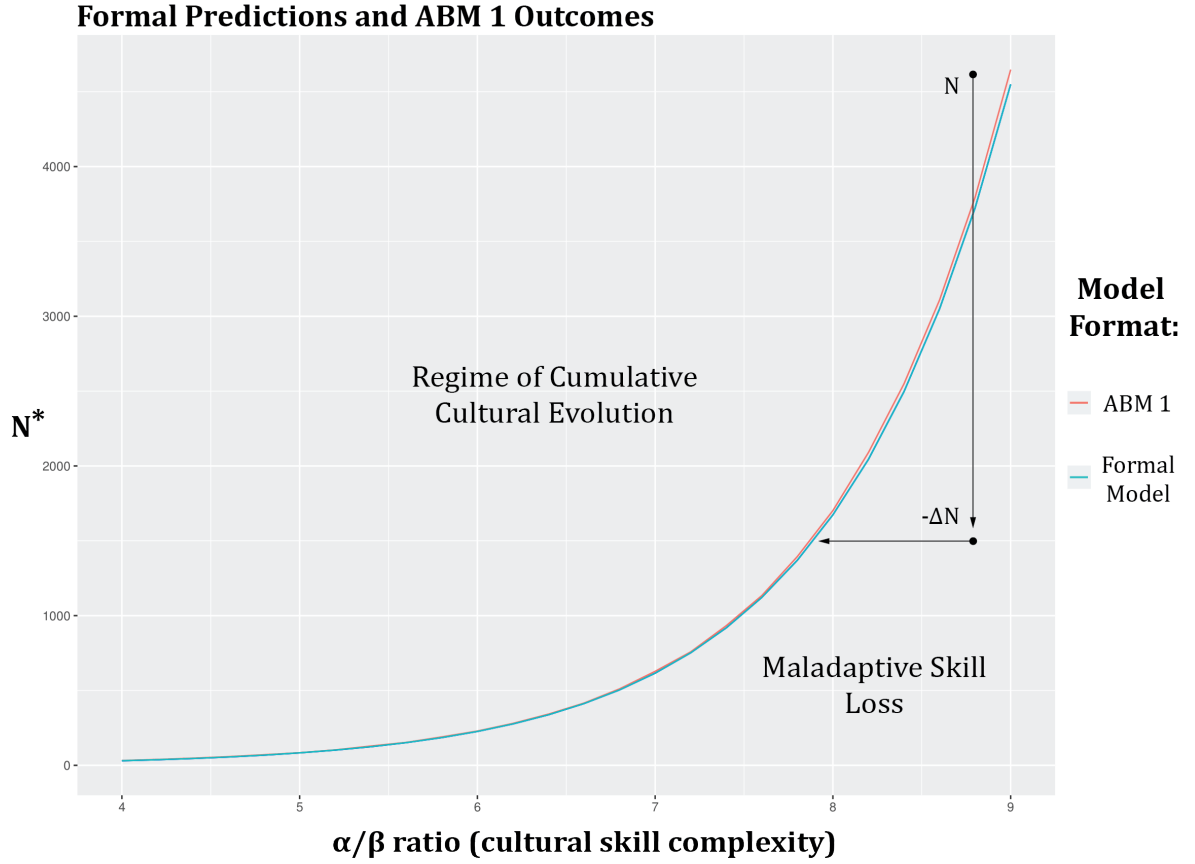


Figure 7: N^* thresholds for various α/β ratios of Henrich's formal model and ABM 1. A loss in population size from $> 4500N$ to $1500N$ results in a loss of skill traits with complexity $\alpha/\beta > 7.9$ in both the formal model and the ABM.

4.2 *Selection is Essential*

Predictions 1-3 specify that cumulative increase in trait function (i.e. increase in skill or decrease in cognitive error) should occur for both cultural skills and cognitive mechanisms when indirect bias is present among agents. To test these predictions, population size and trait complexity parameters were held constant ($N = 100$, $\alpha/\beta = 5$, ABM 2 condition: XOR). The probability that current agents learned from random previous agents, f_{noth} , was then increased from 0 to 1 in intervals of 0.25, and the \bar{z} and $\bar{\zeta}$ values were recorded for each generation between t_1 and t_{100} .

As depicted in figure 8., the output of ABM 1 demonstrates that as f_{noth} increases and indirect bias decreases, cumulative gain in skill over the 100 populations dissolves into dramatic maladaptive loss. As such, in the absence of cultural selection for skillful variants of a cultural trait, learning error during transmission ($-\alpha$) becomes the dominant determinant of cultural evolutionary outcome. This contrasts with the output of ABM 1_{sub}, which indicates that when cultural transmission is lossless and only generates normal copying variation (i.e. exhibits Gaussian rather than Gumbel properties), a lack of indirect bias simply results in skill values grounded at equilibrium (see $f_{noth} = 1$ in figure 9a.). Nevertheless, consistent with ABM 1, cumulative evolution is absent in ABM 1_{sub} without some probability for indirect bias (generation 1: $\bar{z} = 9.99$, generation 100: $\bar{z} = 9.44$). This is because previous agents possessing skill variants are selected as models according to drift (the frequency with which a model is selected is random), but the skill variants themselves are acquired during social learning according to a rule of normal variation.

Output from ABM 2 (figure 9b.) demonstrates the standard learning 'r' curve documented within the learning psychology literature, indicating that agent cognitive variants become cumulatively proficient at computing XOR

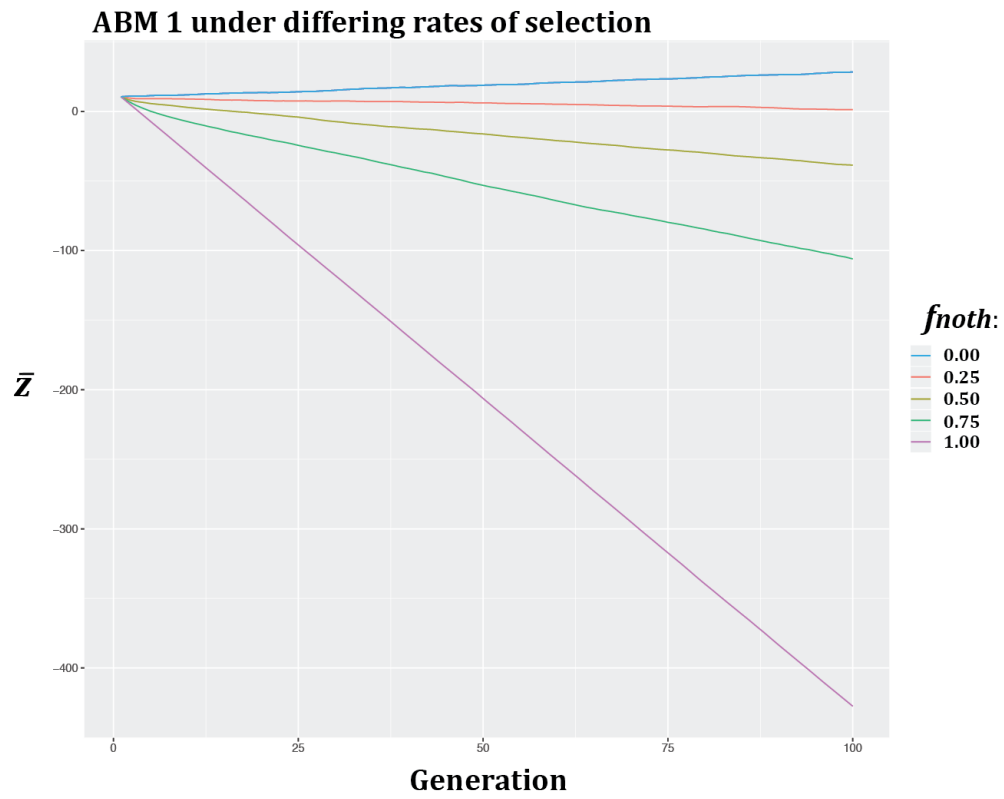


Figure 8: *How cultural skill evolution responds to differing rates of indirectly-biased selection, according to ABM 1.*

logic following generations of indirect-biased learning (Ebbinghaus, 1913). The y -axis of figure 9b. has been inverted to capture how this decrease in error is equal to an increase in function over generations. Like ABM 1_{sub}, under conditions without selective social learning for highly successful cognitive variants ($f_{noth} = 1$), cognitive performance stalls at an equilibrium devoid of cumulative evolution (generation 1: $\bar{\zeta} = 1.99$, generation 100: $\bar{\zeta} = 1.99$). Unique to ABM 2 however, balanced increase in the probability that agents choose random previous agents as models injects useful variation into the W_{Ji} and θ values of agents, and this accounts for the greatest degree of cumulative evolution under $f_{noth} = 0.5$. For controlled increased variation enables a larger search without loss of optimal values within an adaptive landscape, in which the relationship between W_{Ji} and θ values and $\bar{\zeta}$ can be conceptualised as a multidimensional space (Wright, 1932).

Over all three models, all demonstrate that some degree of indirect bias is an essential analogous factor for cumulative evolution (prediction 3). All demonstrate that cumulative increase in function can occur under the analogous conditions in both cultural trait and cognitive mechanism lineages (prediction 2). However, prediction 1 is only partially supported, in that increases in indirect-biased selection are required for cumulative evolution in both ABMs, but only reduces maladaptive loss in ABM 1 (indirect bias has a different effect).

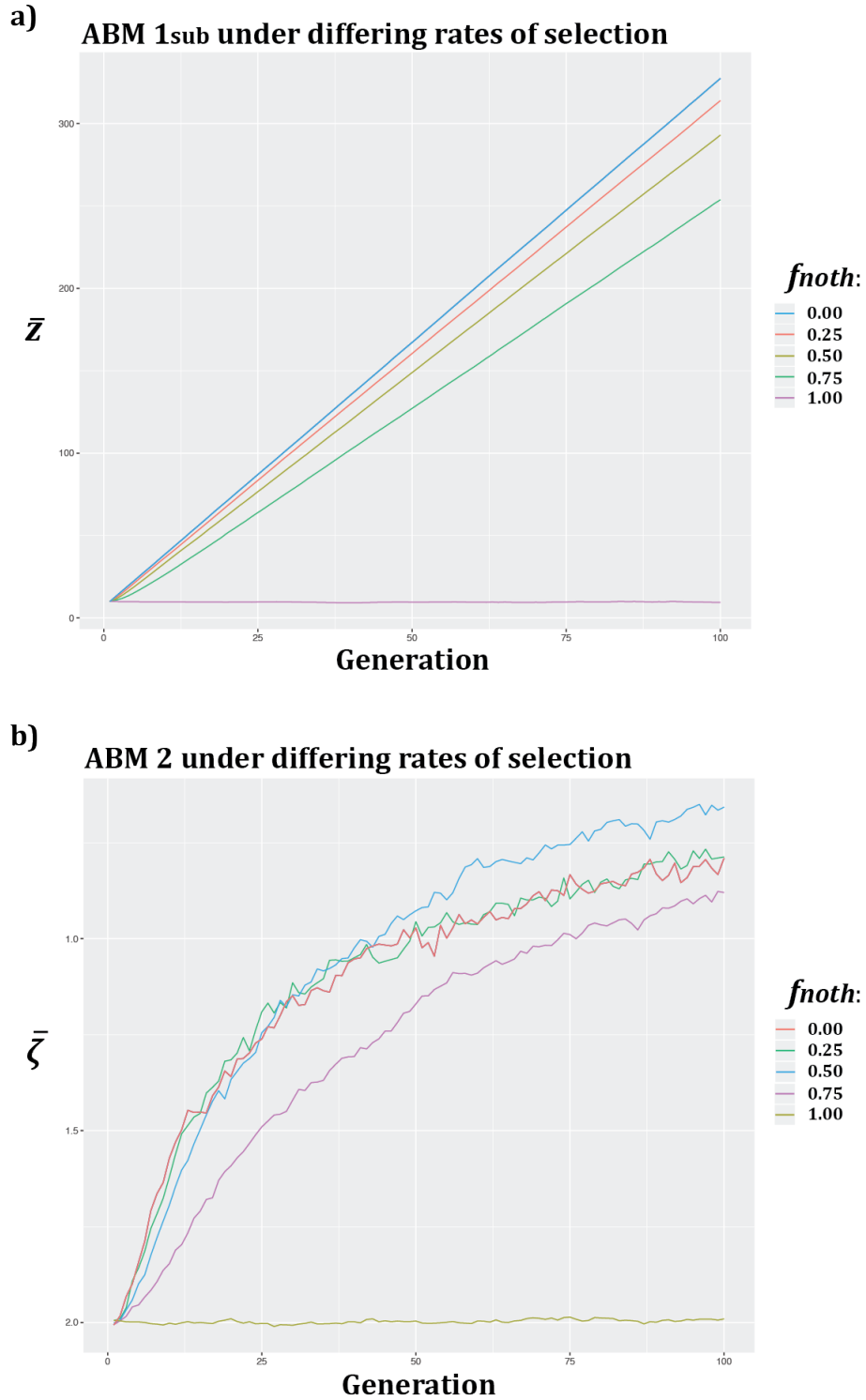


Figure 9: How cultural skill and cognitive variant evolution responds to differing rates of indirectly-biased selection. a) ABM 1_{sub}. b) ABM 2.

4.3 *Skill/Architecture Complexity and Demography*

Prediction 4 states that the influence of population size and trait-learning complexity on the rate of functional cumulation should be similar between the two forms of evolution. To test this prediction, biased learning selectivity was held constant ($f_{noth} = 0$), while population size N was increased for two levels of complexity (ABM 1: $\alpha/\beta = 7$ and $\alpha/\beta = 9$, ABM 2: OR and XOR conditions). The rate of functional accumulation was observed by documenting the values of \bar{z} and $\bar{\zeta}$ after 100 generations as a proxy. It should be noted that population size scales are not identical between models, as rate of cumulative gain begins to steady by $N = 200$ for ABM 2.

For both ABMs, the output (figure 10.) indicates an influence of trait complexity upon the rate of skill and Boolean accuracy gain. Cultural skill traits of relatively lesser social learning complexity ($\alpha/\beta = 7$) exhibit greater rates of gain with equivalent population size than more complex skills ($\alpha/\beta = 9$). This is demonstrated by the difference in skill level after 100 generations at $N = 4600$ between α/β ratios, which is $195.898\bar{z}$. This relationship also holds for cumulative cognitive accuracy gain, wherein variants performing OR logic exhibit a greater level of accuracy gain (i.e. reduction of error) than XOR variants. For example, after 100 generations, OR variants exhibit 1.176 less $\bar{\zeta}$ error with a population size of $N = 5$ than XOR variants (see figure 10b.).

Both ABM outputs also exhibit signature 'r-curve' relationship between skill or cognitive error and increasing population size. However, a critical difference is that this relationship is exclusively of gain in ABM 2 due to the normality assumptions of transmission, where as the relationship includes loss for ABM 1 once N declines below a threshold approximated by the observed N^* values of figure 7. As such, prediction 4 is only partially supported, wherein agent population size can analogously influence the probability that

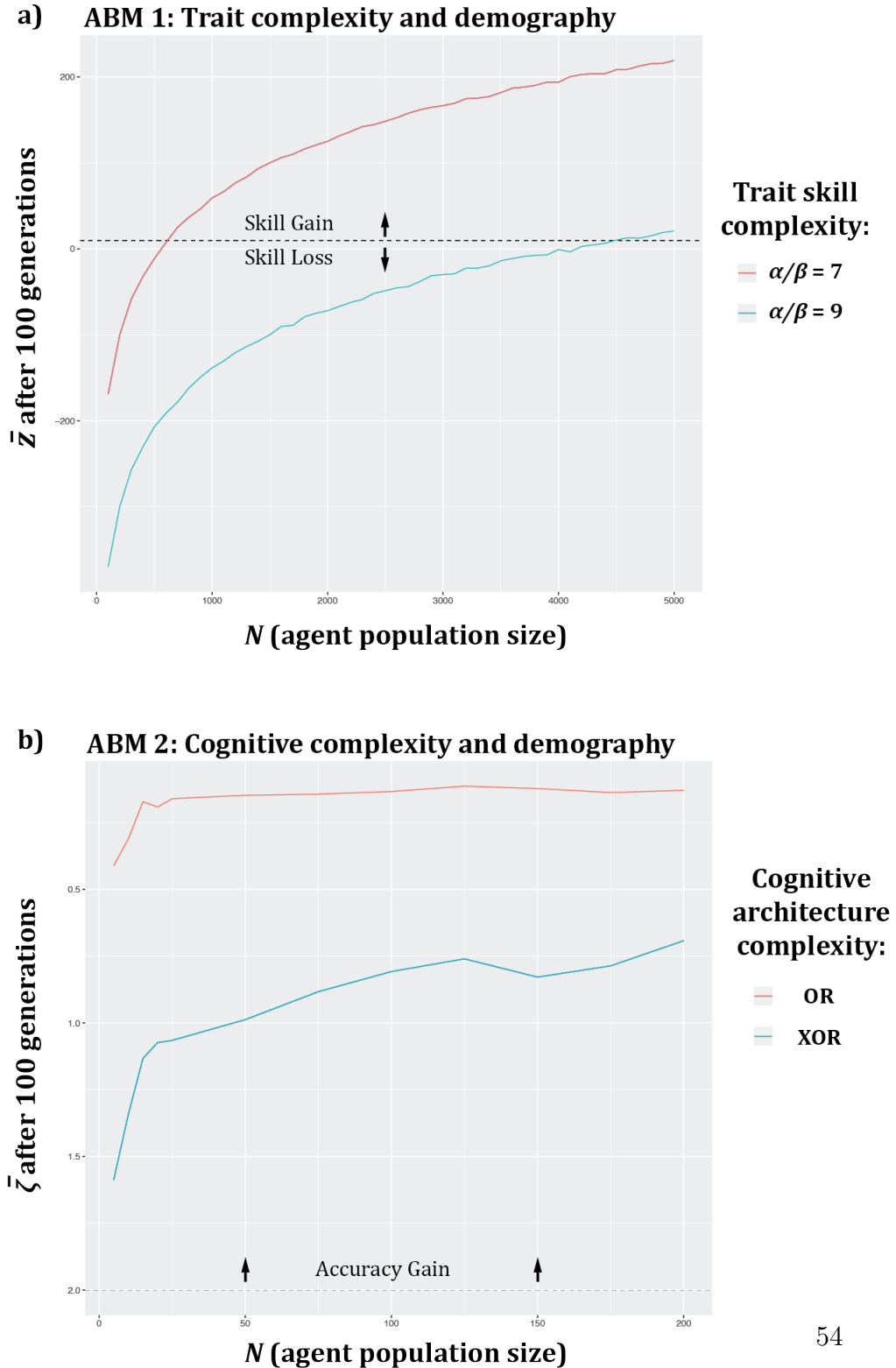


Figure 10: How cultural skill and cognitive variant evolution responds to different population sizes and trait complexities. a) ABM 1. b) ABM 2.

populations will exhibit faster rates of cumulative gain, but not loss.

5 Discussion

5.1 *Analogous Forms of Cultural Evolution?*

Heyes (2018) has argued that cognitive phenotypes can evolve in a manner analogous to the cultural evolution of behavioural skills and artefacts. The output of the two pilot ABMs presented in this dissertation do suggest that cognitive mechanism evolution is, at least in principle, microevolutionarily analogous to cultural skill evolution, but additionally exhibits key differences. As with cultural skill traits, cumulative increase in the functionality of cognitive variants possessed by agents depends upon indirectly-biased cultural selection (predictions 1-3), and is sensitive to effective population size and the complexity of the trait or mechanism architecture in question (prediction 4). Nevertheless, dissimilar to cultural trait skills, loss of functional performance among the cognitive variants possessed by agents does not occur over generations with small population size or with absence of selection; predictions 1 and 4 are only partially fulfilled. Similarity in output between ABM 2 and ABM 1_{sub} indicate that this lack of functional loss is due to modeling assumptions that are based upon findings within the available literature, namely that subjects tend to exhibit similar cognitive variants to their models, both in terms of psychological processing and neuroanatomy, following social learning (Dehaene and Cohen, 2007). This draws attention to the current absence of explicit discussion regarding lossless transmission fidelity within this literature.

The subject of transmission fidelity and iterative copying error has attracted great interest within the both the fields of cultural evolution and experimental archaeology over the previous two decades (Schillinger et al., 2016). At least where artefactual traits are concerned, a plethora of social transmission chain studies have demonstrated that perceptual variation,

compromised memory fidelity, learning context constraints, and complexity involved in different kinds of artefact production methods, each lead to the loss of information regarding the dimensions of artefact size and shape over transmission episodes (Schillinger et al., 2016). The great degree of redundancy that seems to occur during cognitive mechanism transmission therefore seems even more surprising, especially given arguments that non-material traits have to be inferentially reconstructed within the minds of subjects without the tangibility that is afforded by observational imitation when copying material traits (Atran, 2001). It is possible that the interdisciplinary requirements of researching cognitive variant transmission have resulted in transmission redundancy and error being overlooked or postponed for later research proposals. Indeed, agent-based modeling often draws attention to previously implicit assumptions regarding human behaviour and cognition within the social sciences, as the programming of ABMs requires explicit formal specification of these assumptions (Fischer and Kronenfeld, 2011).

Whether cognitive variant transmission intrinsically exhibits less loss of functional information than behavioural or artefactual skill transmission, requires experimental investigation using living human subjects. For now however, why cognitive variant transmission may exhibit greater informational redundancy may be gleaned from the modeling assumptions of ABM 2. Whilst the agent W_{J_i} and θ values of ABM 2 were permitted to vary, the synaptic connections between neuronal units were fixed for this pilot project as a tractability assumption. Therefore variation in learning was constrained around what can be interpreted as a direct bias for certain learning outcomes due to the ‘innate’ properties of agent neural networks (Boyd and Richerson, 1985). This, however, is not the same kind of innately structured variation subscribed to by evolutionary psychologists of the Santa Barbara school, whereby innate neural circuits perform different predetermined cognitive functions under varying ecological conditions; what has been referred

to as 'evoked culture' (Cosmides and Tooby, 1992:116). Rather, this kind of innate bias additionally requires generations of selective oblique transmission in order to accumulate computational competence, and therefore operates in a manner akin to how analogue numeracy mechanisms permit humans to invent, transmit and acquire digital numeracy, or how the visual system becomes exapted through associative learning to acquire symbol-reading proficiency (Dehaene and Cohen, 2007). In these two cases, the mechanisms themselves are not predetermined, but innate structures provide resources for mechanism construction during ontogeny (Heyes, 2018). As such, these innate exaptable resources may possess properties that provide some redundancy during the acquisition of certain cognitive variants, as has been suggested for the transmission of certain cultural beliefs, such as religious representations, by cognitive anthropologists (Atran and Henrich, 2010).

An alternate (but potentially also complimentary) explanation, is that in all the putative cases for cognitive mechanism transmission surveyed from the literature, all occur in either formally scaffolded educational environments (e.g. literacy), or during ritual activities that are common among many human populations (e.g. dancing in synchrony could scaffold imitation) (Ray and Heyes, 2011; Laland et al., 2016). Sterelny (2006:137) has argued that such high fidelity learning environments are themselves the products of cultural evolution, and represent a kind of iterative cultural niche construction that functions to reduce the loss of accumulated knowledge and 'cognitive capital' during oblique social transmission. In pointing this out, Sterelny is drawing upon Niche Construction Theory, a perspective within evolutionary biology that emphasises how organism activities can modify the states and selection pressures of their ecosystems, and how ensuing generations of organisms can then inherit, develop within, and reproduce these engineered ecosystems in a manner that can be fitness enhancing (Laland et al., 2000). In humans, niche-constructing behaviour takes on a particu-

larly cultural bent, whereby behavioural traditions determine the kinds of ecosystem engineering that take place (Laland and O'Brien, 2011). In the case presented by Sterelny (2006) then, cultural niche construction includes the production of learning environments that feature increasingly greater informational redundancy. For example, among many societies, technologies are commonly present within the learning environment for children to interact with, and natural historical information is encoded in repeated bouts of myth, ritual, and accounts of life-time experience (Sterelny, 2006). Similarly, within the context of literacy acquisition, skilled teachers themselves inherit sets of techniques and material reading resources that improve the informational redundancy of print-reading transmission, and these too are likely to be the result of cumulative cultural evolution (Atkinson, 1974).

For either account, and indeed both need not be mutually exclusive, the ABMs presented in this dissertation can be modified to test their explanatory validity. In the case of the direct bias account, additionally varying connectivity between agent neuronal units could be achieved by assigning different unit connectivity matrices to agents (i.e. agent 'connectomes'), which then could only be accurately reconstructed by following generations according to some biased probability τ . Comparison between rates of cognitive error reduction or gain ($\Delta\bar{\zeta}$) could then be made under conditions where not only W_{J_i} and θ variables vary, but also where τ additionally varies. If the direct bias account has theoretical explanatory validity, increase in cognitive error greater than generation t_1 should occur over cultural generations with higher probabilities of τ , as agents should struggle to reconstruct the network architectures of prior models without some predetermined neural parameters. And in this sense, τ would represent the relative contribution of some innately specified principles of agent cognitive psychology towards directly-biased cultural learning redundancy.

In the case of the second explanation, the cultural niche construction account proposes that cognitive variant transmission did not exhibit as effective informational redundancy in human prehistory as it does in contemporary populations (Sterelny, 2006). Furthermore, it suggests that redundancy in cognitive variant transmission should co-evolve with culturally transmitted ecological modifications imparted to agent learning environments by cumulative cultural evolution (Sterelny, 2012). This could be examined theoretically by combining ABMs 1 and 2. In this hybrid model, increasing values of \bar{z} for certain cultural traits that modify learning environments would, in turn, reduce a bias for information loss imparted to cognitive variant transmission. The cultural evolution of artefactual and behavioural traits should then precede lossless cumulative cognitive mechanism evolution within this ABM, and end with output similar to ABM 2 after sufficient generational timesteps, if this second explanation is to be supportable.

With regard instead to the observed similarity between ABM outputs, the finding that both cumulative cognitive mechanism evolution and cumulative cultural skill evolution depend upon indirectly-biased social transmission, inevitably follows from the central tenants of Darwin's (1859) theory of evolution by natural selection. For the theory predicts the emergence of organised structures, be they cognitive mechanisms or behavioural skills, as long as three necessary and sufficient criteria are met: 1) a population of definable units must exhibit intrapopulation variation in some variable(s) describing their properties (i.e. individual genetic variation, cultural variation, neurocognitive mechanism variation); 2) these units must then express differential likelihood of being reproduced due to some correlation between their properties and reproductive outcomes (i.e. differential fitness); and 3) correlation is required to exist between unit properties across generations of reproduction (i.e. trait heritability)(Lewontin, 1970). These criteria were met within the ABMs, as although cultural trait skills and cognitive variants

were not precisely replicated, they were related and varied across generations of transmission, and expressed differential cultural fitness under conditions of indirect bias ($f_h > 0$)(Boyd and Richerson, 1985). As such, the reason why both cumulative cultural skill evolution and cumulative cognitive mechanism evolution were analogously dependant upon indirect bias, is that each is, in turn, analogous to cumulative biological evolution with it's dependance upon natural selection.

Finally, the r-shaped relationships that were discovered in both ABMs between agent population size and rate of cumulative evolution, point towards an analogous effect of increased sampling pool size between the two forms of evolution. In Henrich's (2004) formal model, increasing effective population size has two important causal effects upon rates of average skill change. The first is that, assuming that the distribution of cultural skills among the average natural human population is like that of the Gumbel distribution, increasing the number of random draws from the distribution increases the likelihood that a z'_h value greater than z_h is drawn (figure 3.). In other-words, innovations via fortuitous copying error are more likely to occur in larger populations, and therefore skill can accumulate despite learning error (Mesoudi, 2016). Secondly, and resulting from the first effect, increasing the number of z values among the prior generation gives individuals in the current generation a larger pool of models to select from inorder to identify the highest value available (Henrich, 2004). Given that the N^* output of ABM 1 nearly reproduced the predicted N^* output of Henrich's model (figure 8.), increased sampling pool size likely accounts for these findings within ABM 1 also.

In ABM 2 however, the effects of increased sampling pool size occur in more than one dimension of variation. W_{J_i} and θ values are distributed normally among as many dimensions as there are neuronal units and synapses in

an agent’s neural network (Kandel et al., 2013). Furthermore, cultural fitness and cognitive error depends upon the relative distances between these W_{Ji} and θ values (for optimal OR logic: $W_{Ji} > \theta$). Utilising Wright’s (1932) concept of fitness landscapes, in which all the correlations between traits and average fitness are represented spatially, one can hypothesise that larger agent populations may be able to sample the fitness landscape more efficiently for optimal cognitive variants.

Beyond the CGH, these findings regarding population size and computational architecture complexity may also have additional theoretical applications to the Palaeoanthropological literature. For despite anatomically modern humans appearing within the palaeontological record approximately 300,000 years ago, the typical suite of modern behavioural capacities that characterise *Homo sapiens* (e.g. symbolic behaviour) did not increase in consistency within the archaeological record until between 200,000-60,000 years ago (Hublin et al., 2017; d’Errico and Stringer, 2011). Explanations for this discrepancy have oscillated between neurocognitive mutation accounts on the one hand, and cultural evolutionary accounts on the other, with the latter emphasising fluctuations in population size or cultural niche construction (Klein and Edgar, 2002; Powell et al., 2009; Sterelny, 2011). With further development, ABM 2 as presented here, may reconcile these two alternate accounts, with cognitive variants responding to demographic perturbations.

5.2 *Trouble in Tasmania: Acknowledging Limitations of the ABM Assumptions*

Thus far, potential reasons for why the outputs of the two ABMs exhibit differences and similarities have been discussed with relation to the cultural evolutionary and cognitive anthropological literatures. However, analysis of further implications of the findings, should this study be carried out beyond a

pilot stage, can only be made relative to the weaknesses of the ABM assumptions. For Vaesen and colleagues (2016) have rightly argued that model interpretations can only be made in relation to the wider field if their tractability assumptions can be justified. Here, I acknowledge that both ABMs inherit limitations in their potential application to the CGH from two sources; simplifying assumptions transferred from Henrich’s (2004) formal model, and constraints imported from the field of computational neuroscience in modeling cognition according to McClelland and Rumelhart’s (1986) methodology.

Beginning with the limitations imparted by adopting Henrich’s framework, Vaesen et al (2016) have pointed out that Henrich’s model assumes an unrealistic formalisation of indirect bias, whereby, regardless of population size, all agents correctly identify and learn from the most globally skillful individual (h). Vaesen (2012:6) has stated that this simplifying assumption may be excusable for the Tasmanian case study application, as assuming the most extreme form of indirect bias provides the most ‘conservative’ test in the context of investigating cultural skill loss with population size reduction. However, where ABMs like that of Powell et al (2009) have been directly rederived from Henrich’s (2004) assumptions to study gain in cultural complexity, this justification of conservatism no longer applies (Vaesen, 2012). Despite this criticism, ABM 2 is actually more robust against this charge relative to Powell et al’s (2009) ABM, for cumulative gain is most rapid for agent cognitive variants under conditions of weaker selectivity ($f_{noth} = 0.5$). Thus, unlike Powell et al’s model (2009), which fails to replicate gain without strong selectivity (see Vaesen [2012]), gain in ABM 2 can be maintained under conditions of weaker selectivity, which can represent less derived psychological bias mechanisms, or compromised access to the globally best performing previous agent.

In addition to the above assumptions, and with respect to the CGH, it

is also unrealistic to assume that cognitive variants are exclusively acquired via oblique transmission. For in the cases of literacy, folk psychology and imitation, it is observable that simultaneous vertical and horizontal transmission also contribute to cognitive development in important ways (Heyes, 2018). Leaving such details out of the ABMs in this pilot study was a necessary compromise for this dissertation, as basing the ABMs on the structure of Henrich's (2004) formal model enabled the comparison with cumulative cultural skill evolution required to test the CGH. When engaging with agent-based modeling, it is also important to start out with simulating more basic processes, as even basic agent-level interactions can produce complex population-level phenomena that are challenging to interpret (Wilensky and Rand, 2015). As such, additional modeling complexity can be accreted over iterations of later modeling, similar to Cavalli-Sforza and Feldman's (1975) progression from models that treated oblique transmission as the effect of a homogenous group, towards later models where individuals in the prior generation instead possessed independent cultural traits.

Finally, modeling agent cognition with neural networks also imparts limitations, and it is important to recognise these. First, while McClelland and Rumelhart's (1986) approach to modeling cognitive processing with neural networks captures more biological realism than symbolic artificial intelligence (the method preferred by the Santa Barbara school), it still negates much of the complexity of human neurobiology (Fitch, 2014). Second, utilising Boolean logic as an analogy to higher-order cognitive mechanisms similarly reduces the complexity of simulated 'cognitive variants' by orders of magnitude relative to the phenomenon being modeled. Nevertheless, in the former case, Heyes (2010) has embraced the significance of neural-level descriptions of cognitive variant transmission, making it an inseparable aspect of cultural evolutionary psychology. And in the latter, more complex cognitive processes, such as visual object recognition, have been found to be comprised of

small-scale logical conjunctions, like those of Boolean logic simulated within ABM 2 (Kandel et al., 2013). These two counter arguments render the methods and tractability assumptions made in ABM 2 an ideal starting position for later modeling attempts required for further exploring the plausability of cultural evolutionary psychology from a theoretical perspective.

6 Conclusion

It has long been the purpose of evolutionary psychology to identify where organised and competent cognitive structure emerges from prior generations of differential genetic inheritance. However, recent comparative psychological and neuroimaging studies have suggested that cognitive structure can also be inherited by the means of environments of social learning. In this dissertation, I have used agent-based modeling to additionally demonstrate that in assuming such social transmission, microevolutionary processes analogous to those recognised under cultural evolutionary theory, can also produce increasingly organised and competent cognitive structures. This formalisation provides theoretical support to the cognitive gadgets hypothesis; the proposal that human cognitive mechanisms can evolve by the means of cultural evolution, just as behavioural skills, beliefs, values, traditions, and artefacts do. This formalisation also supports the ever-expanding interdisciplinary breadth of evolutionary psychology in acknowledging increasingly inclusive systems of phenotypic inheritance within theory. And finally, the agent-based models draw attention to a salient but possibly overlooked aspect of the newly proposed discipline of cultural evolutionary psychology; that the cases of cognitive variant transmission currently studied exhibit a great degree of informational redundancy relative to many cultural artefacts and representations. As such, the opportunity for future theoretical investigation is exponential, and what it means to possess an evolved human psychology will likely grow in kind.

7 Appendices

In support of open science approaches, the raw output data used to generate the plots of this dissertation, and the model code itself, have each been made available via links in the following appendices. The links provided are to a temporary google drive account bearing only the candidate number as an identifiable signature. As such, only those with access to this dissertation have access to the data and model scripts at this time. Should this study be conducted beyond pilot modeling, this information would be more freely accessible to encourage the independent replication of results and the reproducibility of the findings under different assumptions.

7.1 Appendix a: Boolean Truth Tables

As depicted in figure 11., OR logic produces ‘true’ (1) responses to the following propositional inputs: true and false (1, 0); false and true (0, 1); true and true (1, 1). This can be achieved with a neural network like that shown in figure 6 consisting of only 3 neuronal units. However, XOR logic is more specific and only permits true responses to differing propositional inputs: true and false (1, 0); false and true (0, 1). This greater specificity of XOR logic requires a larger neural network architecture with more simultaneously varying W_{ji} and θ variables (Fogel et al., 1990). This renders the XOR architecture relatively more complex than the OR architecture.

An agent’s ζ score was computed by calculating the difference between the outputs of its neural network and this Boolean truth table.

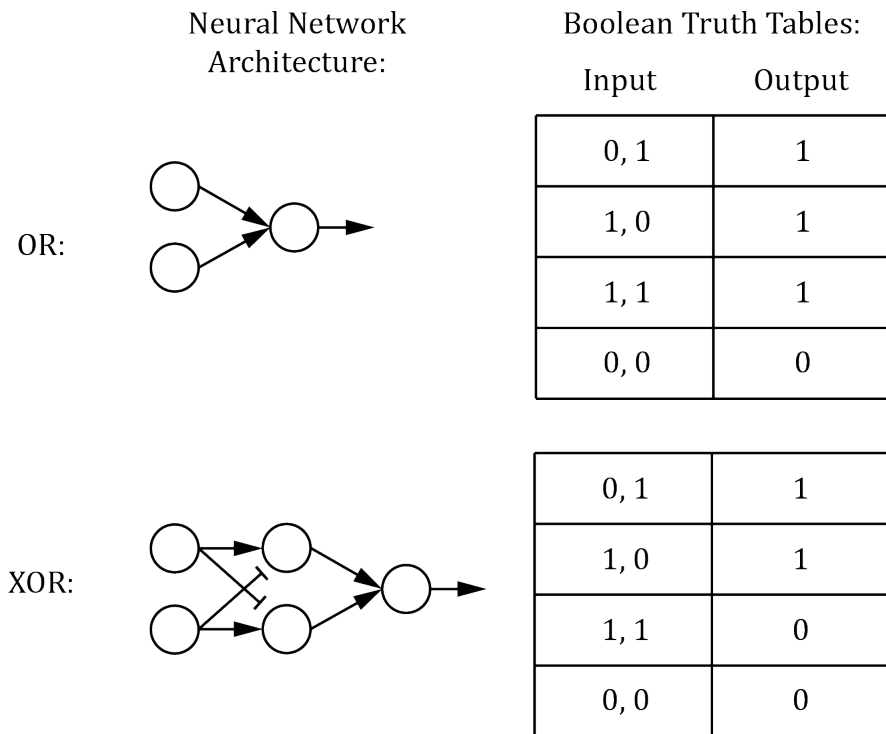


Figure 11: Boolean logic and the required neural architectures.

7.2 Appendix b: Data

Data and Protocols ([click here](#))

7.3 Appendix c: R Markdown Scripts

ABM 1 link ([click here](#))

ABM 2 link ([click here](#))

7.4 Appendix d: Required Resources of Project

The agent-based models used in this dissertation were scripted using the R programming language. As both R and the RStudio graphics environment are open source, there is little monetary cost or constraint for this study. Access to download both is provided below:

R ([click to follow link](#))

RStudio ([click to follow link](#))

Nevertheless, agent-based modeling does incur the cost of computing time, and this is particularly the case with ABM 2. To reduce this cost, online cloud computing can be used, whereby R can be installed into the Ubuntu operating system to wirelessly command hired computing facilities via the internet. For this dissertation, two CPUs (central processing units) were hired from the cloud computing company DigitalOcean for the price of 0.022 US dollars per hour (see rates [here](#)). Over the course of the total project time, the cost of running the ABMs was approximately 10 dollars. However, this monetary cost will vary depending upon how efficient a researcher is in using these facilities.

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