Adaptive Structure, Cultural Transmission & Language:

Investigating a Population Dynamic in Human Iterated Learning

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Abstract

Over the past 20 years the study of language evolution has made significant leaps towards becoming a serious scientific endeavour. One recent leap is the investigations of cultural transmission in the laboratory, particularly in the realm of iterated learning. However, the research is still very much in its infancy, with human iterated learning experiments still only using single individuals in a chain. Yet as we know, language is manifestly embedded within the social environment, and as such is subject to complex population dynamics. This current thesis expands on human iterated learning by expanding the population to two individuals (polyadic) per generation, which in turn introduces variability in the input. By comparing this modification with single individual populations (monadic), and previous experiments, an empirical framework is developed that can enhance our understanding of population dynamics and the emergence of adaptive structure.

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Chapter One

Introduction

The influence of linguistics upon Charles Darwin's theory of evolution by natural selection is well documented (Croft, 2008). Yet in the 150 years since the publication of *On the origin of species* (Darwin, 1859) biological evolution has made significant leaps forward, while research into the evolution of language remained comparatively stagnant. In the last two decades, however, discerning the evolution of language has become a much sought endeavour. As such, a vast number of explanations are emerging that offer a plethora of choice, but little in the way of consensus. In particular, language structure is a hot topic of interest, with perhaps the most popular theory of its origins stemming from the generative tradition (Chomsky, 1957) and their emphasis on language universals and domain-specific language acquisition devices.

The current state of play is slightly more nuanced, thanks to a growing body of literature offering an alternative theoretical spine from a wide variety of disciplines. In particular, there a consensus is emerging in which language is not only a conveyer of cultural information, but it is itself a socially learned and culturally transmitted system (Kirby, Cornish & Smith, 2008). This perspective opens up a new avenue to investigate the design features of language: that cultural, as opposed to biological, evolution is fundamental in understanding these features (Smith & Kirby, 2008).

In the second chapter, this dissertation will initially consider the design features of human language and how we ended up with a communication system of open-ended expressivity. This then leads into the various positions across linguistics in discussing language universals, language acquisition and natural selection, with the main emphasis being a transition from considering language as solely a *biological problem* to a problem that will only be solved through inclusion of socio-cultural factors. Chapter three extends upon the proposition that culture and language should be studied together, arguing that in fact language is a culturally transmitted product. In looking at the literature into Iterated Learning, this dissertation will review literature regarding the origins of adaptive structure, and how population dynamics can inform human iterated learning experiments. Chapter four then, outlines how we can adapt current human iterated learning experiments, namely by introducing variability in the input. Lastly, Chapter five will report the results from the experiment – discussing this in the context of currently available literature.

Chapter Two

Background

2.1. Language as unique form of communication

2.1.1. Design features of language

Taken as a whole system, language is distinct from any other non-human animal communication known. Of this we are almost certain, and yet when we examine other animal communicative systems there appears to be certain design features they share with humans. These purported similarities and differences were probed by Hockett (1960), who, through his investigations into language, offers a useful heuristic for seeing spoken[1] language as being composed of 13 design features[2] (see table 1).

Design Feature	Description
1) Vocal-auditory channel	"The vocal-auditory channel has the advantage – at least for primates – [in] that it leaves much of the body free for other activities that can be carried on at the same time." (Hockett, 1960, pg. 6).
2) Broadcast transmission and directional reception	"A linguistic signal can be heard by any auditory system within earshot, and the source can normally be localized by binaural direction-finding." (ibid).
3) Rapid Fading	"The rapid fading of such a signal means that it does not linger for reception at the hearer's convenience." (ibid).
4) Interchangeability	"In general, a speaker of a language can reproduce any linguistic message he can understand, whereas the characteristic courtship motions of the male and female stickleback are different, and neither can act out those appropriate to the other." (ibid).
5) Total feedback	"Again, a speaker of a language hears, by total feedback, everything of linguistic relevance in what he himself says." (ibid).
6) Specialization	"[…] refers to the fact that the bodily effort and spreading sound waves of speech serve no function except as signals." (ibid).
7) Semanticity	"[…] there are relatively fixed associations between elements of messages (e.g. words) and recurrent features or situations of the world around us" (ibid).
8) Arbitrariness	"[...] the ties between the meaningful message elements and their meanings can be arbitrary" (ibid).
9) Discreteness	"Human vocal organs can produce a huge variety of sound. But in any one language only a relatively small set of ranges of sound is used, and the differences between these ranges are functionally absolute." (ibid).

[1] Hockett strictly specified that only spoken languages display all thirteen of the features, as opposed to other human language systems such as writing and sign.
[2] Hockett & Altmann (1968) actually add three additional design features (Prevarication, Reflexiveness, and Learnability).

10) Displacement	"Man is apparently almost unique in being able to talk about things that are remote in space or time (or both) from where the talking goes on." (ibid).
11) Productivity	"[language provides] the capacity to say things that have never been said or heard before and yet to be understood by other speakers of the language" (ibid).
12) Traditional Transmission	"Human genes carry the capacity to acquire a language, and probably also a strong drive towards such acquisition, but the detailed conventions of any one language are transmitted extragenetically by learning and teaching." (ibid).
13) Duality of Patterning	"The meaningful elements in any language (e.g. words).constitute an enormous stock. Yet they are represented by small arrangements of a relatively very small stock of distinguishable sounds which are in themselves wholly meaningless." (ibid).

Table 1. *Hockett's (1960) design features of language.*

This essentially allows us to compare the abilities of humans and other species to see the demarcation lines. For instance, the research by von Frisch (1967) into honeybee (*Apini Apis*) communication demonstrates how they are able to use a specific signal (the particular dance employed) to relay a specific spatial location outside of the hive. Perhaps most surprisingly, this example demonstrates that honeybees are capable of processing *semantic* content[3] (by matching the dance *signal* with a food source *meaning*), among other aspects, including *transmission*, *displacement* and *productivity*, all of which are crucial in the understanding the uniqueness of human communication.

In fact, throughout the animal kingdom there are many instances of certain design features being utilised by a wide array of species (see Kirby & Smith, 2008). Incidentally, this leads us to the most insightful aspect of Hockett's paper: that the uniqueness of human communication can be identified through just three particular design features (*semanticity*, *productivity* and *traditional transmission*). As already touched upon, all three of these features are fairly ubiquitous throughout the animal kingdom. However, human language is truly distinct in that it is a combination of these three features. In particular, the semantic capacity of humans is far more powerful and productive than anything else seen in the animal world, which according to Hockett is because it is underpinned by four additional design features: *arbitrariness, duality of patterning, recursion* and *compositionality*[4].

[3] Albeit within very narrow motivational limits: the semantic content refers to food, and nothing else.
[4] As Smith & Kirby note, *recursion* and *compositionality* are only implicated in Hockett's account under the concept of *productivity*, rather than being explicitly mentioned. Recursion is basically the ability to embed *identical* phrases inside of each other, whilst compositionality is defined as an expression that is determined through its structure and the meanings of its constituent elements (see Smith & Kirby, 2008).

As Smith & Kirby (2008) note, "The combination of these four subsidiary features results in a system that is productive and semantic." (pg. 3592). Duality of patterning enables us to generate a vast number of basic units of communication from just a small set of sounds (phonemes). These basic units are then, through recursion, combined in an open-ended fashion, despite there being no meaningful connection between the phonemes used and the message sent – it is arbitrary. By knowing the meaning of these basic elements, and the method through which they are combined, a human is able use this compositional structure to interpret novel utterances (ibid).

Thus far, the overarching sentiment relies on the view of language being a unique and unusual communication system due to a particular combination of features, and the robustness with which they are utilised. Even more obvious is that these design features are hallmarks of a system designed for open-ended expressivity. However, "the fact that human language makes good design sense in various ways does not explain how language came to have these properties." (ibid, pg. 3593). Instead, the question we need to be investigating as linguists is: how did these features of language come to be this way?

2.2. Why is language this way?

2.2.1. Language Universals, Language Acquisition & Natural Selection

One answer to this question appeals to the idea of humans having an array of specialised organs geared towards the production, reception and comprehension of language. For some features, particularly the physical capacity to produce and receive multiple vocalizations, there is ample evidence for specialisation: a descended larynx (Lieberman, 2003), thoracic breathing (MacLarnon & Hewitt, 1999), and several distinct hearing organs (Hawks, in press). Given that these features are firmly in the domain of biology, it makes intuitive sense to apply the theory of natural selection to solve the problem: humans are specially adapted to the production and reception of multiple vocalizations[5].

In his 1980 book *Rules and Representations*, Noam Chomsky extends this notion further, arguing that humans also contain specialised mental organs, or modules, for acquiring language. Tracing the history[6] of this argument stems initially from the widespread assumption of generative grammar that all languages are essentially the same in structure, but differ in their sound systems and vocabularies (Evans & Levinson, 2009). To quote Pinker (1994), "According to Chomsky, a visiting

[5] I use the term *vocalisation* as opposed to language because humans may have evolved these adaptations for other functional reasons, such as singing or laughing (Lieberman, 2003). Conversely, Hauser & Fitch (2003) debate the role of the vocal tract being a language-specific adaptation, citing comparative data with other species that suggests a "[...] descended larynx is not necessarily indicative of speech." (pg. 165).

[6] A fascinating study in itself, with the initial roots of Chomsky's thought stemming from the early work of the Ancient Indian Sanskrit grammarian Pāṇini (http://www.hinduonnet.com/fline/fl1825/18250150.htm).

Martian scientist would surely conclude that aside from their mutually unintelligible vocabularies, Earthlings speak a single language." (pg. 232).

Such reasoning also led to the adoption of natural language being composed of a formal language, where a generative grammar will apply a certain set of rules in sentence formation, regardless of its meaning (Chomsky, 1957). For instance, it is often argued humans organise phrases into hierarchical structures, such that in natural languages "[...] the *noun phrases* and the *verb phrase* within a clause typically receive their grammatical role (e.g., subject or object) by means of hierarchical relations rather than through the bare linear order of words in a string [my emphasis]" (Musso *et al.*, 2003, pg. 774). This relationship can be broken down into even smaller segments (which Chomsky distinguished as *substantive universals*), with noun phrases, for instance, consisting of a *determiner* preceding a *noun* (Chomsky, 1957). Importantly, Chomsky (1957) claims these rules exist without the need for interaction in other linguistic domains. Take for example his now famous phrase of "*Colourless green ideas sleep furiously.*" (ibid, pg. 15). Despite being syntactically correct, it is argued the sentence as a whole is semantically meaningless.

The last major point in explaining the innatist position comes from child language acquisition. Specifically, Chomsky's poverty of the stimulus conundrum: how are children able to acquire a fully expressive language, despite receiving noisy and incomplete amount of input data (Chater & Christiansen, in press)? In opposition to Skinner's (1967) concept of verbal behaviour, and the behaviourist tradition more generally, Chomsky claims the universal properties of languages are explained by a genetically encoded language acquisition device (LAD), which contains a set of discreet, preconfigured rules that are then brought to the task of learning.

Even with these general considerations, the conceptual basis of UG varies quite substantially across different traditions, ranging from *Principles and Parameter Theory* (Chomsky & Lasnik, 1993), the *Minimalist Program* (Chomsky, 1995) and *Simpler Syntax* (Pinker & Jackendoff, 2009). Without becoming entangled in the debate between these strains of thinking (for a good overview, see Christiansen & Chater, 2008), the important point to take away is that the mechanisms for acquiring language are innately encoded by neurobiological constraints. Still, even if we take for granted the innatist perspective in explaining the structure and acquisition of language, an additional explanation is required to understand how this putative language module arose in the first place.

Of the many biological explanations in linguistics (see Gould and Lewontin's exaptation/spandrel (1979) notions of language evolution), a highly influential hypothesis is that of Pinker & Bloom (1990), which claims the language module displays all the hallmarks of being an adaptive trait, and as such it “[...] would be natural, then, to expect everyone to agree that human language is the product of Darwinian natural selection. The only successful account of the origin of complex biological structure is the theory of natural selection” (ibid, pg. 707).

Under this assumption our minds are very much like organs, consisting of functionally specialised machinery known as a *module* (see Cosmides & Tooby, 1997; Pinker, 2002). Like our hearts and livers, which evolved to pump blood and detoxify blood respectively (Cosmides & Tooby, 1997), our brain contains neural circuitry specialised for a whole host of specific processes, including certain design features of language. For instance, Pinker (2003) views compositionality as being functionally advantageous, and as such would have been biologically selected for as it offers a reproductive pay-off (also see Nowak, 2000). Yet what about those feature which do not appear to be functionally advantageous? Indeed, even Chomsky (2005) himself claims many features of language are arbitrary, arguing some abstract properties of UG may actually impinge upon the communicative efficacy of language.

There are many explanations for how arbitrary properties of language may become hardwired into our biological makeup, most notably via the *Baldwin effect*: “[where] characteristics that are initially learned or developed over the lifespan can become gradually encoded in the genome over many generations, because organisms with a stronger predisposition to acquire a trait have a selective advantage” (Christiansen & Chater, 2009, pg. 1015). Computational modelling by Christian & Chater (2009) and Smith & Kirby (2008) offer some counter arguments to the plausibility of the Baldwin effect moulding a language-specific module, with the central thrust of their claims being the rate at which language changes: language is a moving target, and is arguably too fast for any biological adaptation to arise. Still, there are instances where fluctuating environmental systems fall into relatively stable patterns, which allow adaptive genetic processes to work (Barton, 2007; Hawks *et al.*, 2007). Such arguments are used to explain links between cultural rates of change and biology (Hawks *et al.*, 2007). So, why can we not make the same claims about language? For instance, Lieberman *et al.* (2007) show the rate of regularisation correlates with verb frequency, with “the slowest-changing words... replaced at rates comparable to the fastest-changing genes.” (Fitch, 2008, pg. 374).

Regardless of whether or not biological evolution *could* account for a language-specific module, the question is whether it *did* happen. We can indirectly investigate these claims by asking another question: are these features of language accounted for by processes outside of biology?

2.2.2. Beyond Biology: Socio-cultural factors

As we have already touched upon in this chapter: under the stewardship of Pinker, Chomsky and others, the origin, evolution and acquisition of language is primarily seen as a biological question to be answered. Whilst it is certain that biology plays a role in the evolution of language, its exact purpose is still contentious in light of a whole host of arguments emerging from research into cognitive, developmental, cultural and social traditions. Not only are the foundations of language universals (Evans & Levinson, 2009), natural language as a formal language (Deacon, 1997) and poverty of the stimulus (Pullum & Scholz, 2002), being challenged at both a theoretical and empirical level, but the recent resurgence of social and cultural factors in explaining language structure (Smith & Kirby, 2008; Lupyan & Dale, in press), language change (Kirby, 2000) and language acquisition (Chater & Christiansen, in press) are providing independent and alternative theories in our understanding.

Considering the cultural and social influences of language is hardly new. Early work by the likes of Franz Boas (1911), Edward Sapir (1924) and Benjamin Whorf (1956) laid the groundwork for what would be later known as *linguistic relativity*: the view of language being inextricably intertwined with culture (Everett, 2009). Meanwhile, the development of sociolinguistics (Labov, 1966) and pragmatics (Grice, 1975) acknowledged that social dimensions influence linguistic behaviours (for introduction, see Tomasello, 2003). However, these early explorations into language and culture either could not counter the challenges of the cognitive revolution, or simply never gained any significant traction with which to begin.

As already suggested, recent work over the past two decades is beginning to provide a significant and realistic alternative to the generative tradition. Looking at the structural properties of language is clearly a good place to highlight this distinction, given the recent mainstream attention received by Daniel Everett's investigations into the Pirahã people (Everett, 2004; 2009). According to some accounts (ibid), this Amazonian hunter-gatherer tribe lack relative clauses and grammatical recursion in their language – the latter being a key component of one recent conception of UG (Chomsky, Hauser & Fitch, 2004). Although specific claims over the exact dimensions of the Pirahã language are still being disputed (see, Nevins *et al.*, 2007 and Everett, 2007), Everett's broader claims against language universals is receiving continuing support (Grace, 2002; Tomasello, 2003a) and empirical evidence (Wray & Grace, 2007; Evans & Levinson, 2009).

In moving from the view of absolutes (*all languages must have aspect X*) to statistical (*most languages are likely to have aspect X*) (see Evans & Levinson, 2009), it is easy to see how the argument from generative linguistics begins to fall down: without linguistic universals, there is no need for an innately-constrained universal grammar device[7]. After all, "[...] such a property could be due to properties of other mental capacities – memory, action control, sensory integration, etc. Second, it could be due to overall design requirements of communication systems." (Evans & Levinson, 2009, pg. 24).

In highlighting the differences in structure across the spectrum of languages, the renewed emphasis of socio-cultural linguists is to explain these differences. Lupyan (in press), and others (Wray & Grace, 2007), have reported a distributional pattern of structures across the world's languages, with "strong relationships between linguistic factors related to morphological complexity and demographic/socio-historical factors such as the number of language users, geographic spread, and degree of language contact." (Lupyan & Dale, in press, pg. 2). Specifically, both Wray & Grace (2007) and Lupyan & Dale (in press) make a distinction between two types of instances in which languages are learned and used: *exoteric* and *esoteric* niches. An exoteric niche contains languages with a large variety of speakers, thus a pressure is asserted on the communal language to be suited for communication between strangers (Lupyan & Dale, in press). English, Swahili and Hindi are all examples of languages emerging from exoteric niches, in that they are more likely to "(1) be non-native speakers or have learned the language from non-native speakers, (2) use the language to speak to outsiders – individual from different ethnic and/or linguistic backgrounds" (ibid, pg. 7). Conversely, *exoteric niches* are composed of languages like Tatar, Elfdalian and Algonquin (ibid). All of these languages belong to relatively small populations – individuals are part of a tightly knit community, based on a shared cultural and social identity.

Given these differing *linguistic niches*, Lupyan and Dale's main proposal is that the morphological features of a language are the product of adaptation to learning constraints and the communicative requirements of the speaker population. Therefore, a language being subjected to a greater number of outside learners, for instance, via colonization or large-scale migration, is thus under a greater pressure to become learnable – and subsequently simplifies its morphology and increases its productivity of existing grammatical patterns (ibid). Languages in exoteric niches also become more analytical, which according to Wray & Grace (2007) increases their compositionality in that "meanings of expressions can be determined from their composition, because the system approximates a one-to-one relationship between forms and meanings." (pg. 9). Furthermore, Wray & Grace (2007) claim given the dynamics of these niches, language must have originally evolved in esoteric communities. On the basis of these assertions, Carstairs-McCarthy (2005) notes: "It therefore becomes an open question whether what linguists take for granted as grammatical

[7] Even though this does not necessarily mean there is no such device.

universals (even such fundamental features as recursion) may be not biologically based but rather cultural add-ons, resulting from millennia of increasingly exoteric language use." (pg. 508).

2.2.3. Domain-general cognitive constraints

Given the arguments presented thus far, it is becoming increasingly indisputable that socio-cultural factors are at work in accounting for linguistic structure. Suffice to say, this certainly weakens the position of language being purely a cognitive phenomenon, yet it does not completely rule out the possibility of an innate acquisition devise being responsible for the structural properties of language. One such problem in removing the dependency on solely biological explanations is the *logical problem of language acquisition*: that children become competent users of language, despite having an incomplete and noisy input (Kirby, 1999; Chater & Christiansen, in press).

According to Chater & Christiansen, an alternative to the competing views of adaptationists and non-adaptationists is that the "fit between the neural mechanisms supporting language and the structure of language itself is better explained in terms of how language adapted to the human brain, rather than vice versa." (2009, pg. 3). Specifically, they adopt the general view of language being a product of multiple constraints; an evolving system, with features of language emerging from repeated processes of acquisition and transmission across continuous generations of language users (see Deacon, 1997; Kirby & Hurford, 2002; Tomasello, 2003; Christiansen & Chater, 2008).

Working from this basis, Christiansen & Chater make two important points concerning the cognitive acquisition of language. First, language is shaped by a range of domain-general cognitive features, including: *perceptuo-motor*[8], *learning and processing mechanisms*[9], *constraints from thought*[10], and *pragmatic constraints*. Second, and perhaps more importantly, they outline two induction scenarios facing a child – coordination with others (C-induction) and understanding and manipulating the natural world (N-induction) – arguing that C-induction is easier and more likely to be the process by which a child acquires language (ibid).

The utility of C-induction with language is appropriately characterised by coordinating our predictions with others in the speech-community. What is crucial is not which "phonological, syntactic or semantic regularities children prefer, when confronted with linguistic data; it is that they prefer the same linguistic regularities – each generation follows in the footsteps of the last." (ibid, pg. 8). But even if we take the position of language adapting to our mind, it is essentially adapting to

[8] The constraints arising from our motor and perceptual machinery, most notably the seriality of our vocal tract causes a sequential ordering of language.
[9] Learning, processing and memory all place constraints on our ability to acquire a language.
[10] According to Christiansen & Chater, "The structure of mental representation and reasoning must, we suggest, have a fundamental impact on the nature of language" (pg. 6).

a mind of imperfect construction, or as Marcus (2008) puts it, our language mechanisms were "[...] built, rapidly, on a haphazard patchwork of mechanisms that originally evolved for other purposes." (pg. 122).

Therefore, the cognitive architecture underlying the processing of language is likely to be the product of natural selection and developmental processes. For instance, pre-linguistic features such as sequential processing (Christiansen & Delvin, 1997) and working-memory (Fiebach *et al.*, 2005) undoubtedly influence our processing of language, yet it is unlikely these features were *exclusively selected* for language – rather, they are domain-general and probably selected on their functional flexibility (Chater & Christiansen, in press). This somewhat moves away from a common delineation offered by Kirby & Hurford (2002), with language sitting at three complex, dynamical systems: biological evolution, cultural transmission, and individual learning. As Ferdinand & Zuidema (2008) highlight, this tripartite separation is partially misleading "[...] because it implies that evolution acts directly on learning as an adaptive system. This view essentially deletes cognition from the picture, because it is the embodied cognitive agent that ultimately roots its high-level process of language induction within the biologically evolved wet-ware that is the true processor of language." (pg. 3). Still, Kirby & Hurford's central tenant remains: language is not solely a biological problem to probe, but rather a conundrum comprised of many factors.

2.2.3. Language as a complex adaptive system

Thus far, the argument laid out is that the constraints of language arise from two systems: "the embodied cognitive agent and the socio-cultural system in which these agents communicate with one another." (Ferdinand & Zuidema, 2008, pg.2). Amalgamating these perspectives of language being shaped by human interaction and domain-general cognition is a strong argument for moving away from the static system of grammatical principles embodied by the generativist position, and towards a new paradigm of language being a *complex adaptive system* (CAS) (Beckner *et al.*, 2009).

First coined by Holland (1998), CAS are like other complex systems[11] in that they exhibit emergent properties as a result of multiple interconnected elements. What differentiates CAS is its ability to adapt: these systems can learn from past experiences, and subsequently change their behaviour as a result (ibid). Such instances of CAS are found throughout nature, from social insects and ecosystems to immune systems and cellular mechanisms (Ahmed, Elgazzar & Hegazi, 2005). More importantly, these adaptive systems are used to explain the properties of human social endeavours, including: stock markets, communities and political parties (ibid).

[11] Such as chaotic and non-linear systems.

Language displays all the hallmarks of being a CAS: "(1) The system consists of multiple agents (the speakers in the speech community) interacting with one another. (2) The system is adaptive, that is, speakers' behavior is based on their past interactions, and current and past interactions together feed forward into future behavior. (3) A speaker's behavior is the consequence of competing factors ranging from perceptual mechanics to social motivations. (4) The structures of language emerge from interrelated patterns of experience, social interaction, and cognitive processes." (Beckner *et al.*, 2009, pg. 3).

Critically, this view places the existence of language at two inter-dependent junctures, consisting of an idiolect (the individual language user) and the communal language (the community of users). Both of these aspects are emergent, with an idiolect emerging from each individual's use of their language through interactions with other individuals enmeshed in the community, and the communal language being the product of the interactions of all the idiolects (ibid).

These two distinct but connected levels provide a myriad of features and explanations in truly understanding language as a whole, dynamic system. For instance, the inherent diversity between individuals dictates that there is no idealised notion of a speaker-hearer, with each individual's unique linguistic experience resulting in heterogeneous idiolects (Weinreich, Labov, & Herzog, 1968; Bybee, 2006). But this is not all – language is in a constant state of flux at both the level of communal and idiolect (Beckner *et al.*, 2009); it adapts through an upward spiral of competing factors (see speaker-listener conflict: Chater & Christiansen, in press); small phenotypic differences in humans (vocal tract control, shared attention, memory capacity, etc) can build up and result in a *phase transition* (Elman, 2005); the immersion, sensitivity and dependency of language users in social networks (Lupyan, in press); and the view of language being a form of cultural adaptation to both the human mind (Christiansen & Chater, 2008) and the transmission vector (Cornish, Tamariz & Kirby, in press).

2.4. Summary

The literature thus far can be summarised as follows:

- Language is made up of many design features, with the powerful combination of *semanticity*, *productivity* and *traditional transmission* being the fundamental features in distinguishing human language from other forms of communication (Hockett, 1960);
- Although these features result in a communication system of open-ended expressivity, the central question dogging researchers is: how did these features of language come to be this way?;

- This question elicits a whole host of answers, with those coming from a generative position generally opting for biological explanations; specifically that humans are born with a language acquisition device (Chomsky, 1980). Furthermore, some scholars (Pinker & Bloom, 1980) claim the only viable explanation for the existence of this language device is through the theory of natural selection;
- However, a large body of literature offers a whole host of counter claims against the existence of language universals (Evans & Levinson, 2009), poverty of the stimulus (Pullum & Scholz, 2002) and natural language being a formal, computational system (Deacon, 1997);
- Heeding these apparent flaws in generativist explanations, alternative approaches are gaining traction: e.g. emphasising the role of socio-cultural factors (Luypan & Dale, in press) and the influence of domain-general cognitive constraints (Chater & Christiansen, in press);
- Finally, in moving away from language being viewed as a static, monolithic entity, the position taken by this dissertation is that language is a complex adaptive system, comprised of many interlocking parts (Beckner *et al.*, 2009).

Seeking a solitary exposition for language is not a fruitful, or even possible, task. That so many features are intertwined in an inextricable system is something to see as liberating, instead of disparaging. For instance, by exploring language through socio-cultural and domain-general cognition, a picture emerges where language is adapting to the vast linguistic environment in which it is being learned and used (Lupyan & Dale, 2009). As such, some of the features of language may be explained via multiple constraints stemming from "different learnability and communication pressures." (ibid, pg. 18). Languages then, not only undergo a process of gradual drifting until they become mutually unintelligible, they also adapt in response to any significant pressures that are present. Our role as linguists is to see what constraints play a significant role in shaping the features of language? Two obvious candidates are culture and the transmission vector, from which we can pose this question: how does cultural transmission influence, and interact with, language?

Chapter Three

Language as a culturally transmitted product

3.1. Culture as an evolutionary system

3.1.1. Variation, Fitness & Inheritance

Humans are immersed in culture from birth. It is so fundamental to our experience, and what it means to be *human* itself, yet many attempts to explain our behaviour frequently begets biology as the answer. But first, what exactly is *culture*? A generally accepted definition places culture as "information[12] capable of affecting individuals' behaviour that they acquire from other members of their species through teaching, imitation, and other forms of social transmission" (Richerson & Boyd, 2005, pg. 5).

Like the evolution of biological organisms, culture too can be viewed as following three Darwinian principles (1859): *variation, differential fitness,* and *inheritance* (Mesoudi & Whiten, 2008). It is an evolutionary system subject to the *selective* and *non-selective* forces (Cavalli-Sforza & Feldman, 1981; Boyd & Richerson, 1985) Darwin wrote about in *The Origin of Species*: that there is a vast amount of *variation* within a species, which he argued led to *selection* for particular traits, and that these traits were then *inherited* by successive generations. When looking at the spread of culture, Mesoudi *et al.* (2004) claimed there was evidence for all three of these processes. For instance, of the 6-8000 languages spoken throughout the world (Evans & Levinson, 2009) there is a considerable amount of *variation*. Meanwhile, cultural *selection* is taking place at many levels and is the result of many factors, including cognitive constraints in memory, attention and expression (Mesoudi, Whiten & Laland, 2006). Lastly, Mesoudi, Whiten & Laland (ibid) identify the *inheritance* "of successful cultural traits has been demonstrated in numerous studies of transmission of skills and beliefs in traditional societies... and in studies of social learning in children." (pg. 331-2).

Thanks to the early works of cultural evolutionists, researchers are not only drawing cursory parallels with biological evolution; they are actively using mathematical models derived from population genetics (see Richerson & Boyd, 2005) to investigate the inheritance of cultural traits and the role social learning plays in enhancing the overall fitness of a population by allowing "[...] learned improvements to accumulate from one generation to the next" (Boyd & Richerson, 1994, pg. 134). Known as *cumulative cultural evolution* (Caldwell & Millen, 2008) or the *ratchet effect* (Tomasello,

[12] *Information* is a catchall term for ideas, knowledge, beliefs, values, skills, and attitudes (see Mesoudi, Whiten & Laland, 2006).

1999), this process “[...] requires not only creative invention but also, and just as importantly, faithful social transmission that can work as a ratchet to prevent slippage backward – so that the newly invented artifact or practice preserves its new and improved form at least somewhat faithfully until a further modification or improvement comes along.” (Tomasello, 1999, pg. 5).

3.1.2. Cultural Transmission

Just as Darwin struggled when conceptualising an adequate method of inheritance from one generation to another (Mesoudi & Whiten, 2004), those studying cultural evolution arguably have an even greater task to provide an explanation of the transmission vectors. Unlike genetic transmission, we are still only beginning to understand the relative impacts of horizontal (peer-to-peer transmission), oblique (parent generation to non-kin offspring) and vertical transmission (from parent to offspring) (see Cavalli-Sforza & Feldman, 1981; Greenhill *et al.*, 2009); the varying ways in which culture is transmitted (Henrich & Boyd, 2002); the role of population dynamics (Boyd & Richerson, 1985); and, interactions between cultural transmission, individual learning and genetics (Aoki et al. 2005).

Nonetheless, cultural transmission is a vital aspect of cultural evolution – yet our poor understanding probably stems from the varying ways in which culture is transmitted (Mesoudi, 2004).

Memes are frequently held as a catchall solution to being *the* cultural transmission particulate, with the study of *memetics* being an analogous concept to genetics. First coined by Dawkins (1976), the term meme[13] was a way of extending the idea of replicator-centred evolution into the realm of culture – that replicators are universal. Since then, memetics has been picked up and expanded upon by several researchers (see Dennett, 1995; Blackmore, 1999; Aunger, 2000), which rests on a common assumption that “cultural knowledge is stored in brains as discrete packages of semantic information, comparable to how biological information is stored as genes. Once expressed in behaviour or artifacts, these packages of learned information can be replicated in the heads of other individuals through social learning.” (Mesoudi, Whiten & Laland, 2006, pg. 342).

However, the concept of *memes* is a fuzzy term, and some researchers argue against the need for any one particulate being responsible for all forms of cultural transmission (Mesoudi, Whiten & Laland, 2006). As Mesoudi (2004) argues, the lack of understanding as to the transmission particulate, assuming it even exists in a particulate form, is not necessarily an insurmountable problem for those wishing to study cultural evolution. We are still very capable of understanding the roles of population dynamics and the interactions between genes and culture (ibid).

[13] Meme is merely a unit of cultural inheritance, analogous to gene (Mesoud, Whiten & Laland, 2006).

Much of the early advances in population genetics pre-empted Watson and Crick's unveiling of the structure of DNA – and the subsequent explosion in molecular biology. Mathematical models by Fisher (1930), Wright (1931) and Haldane (1932) laid the groundwork for unifying Darwinian natural selection with Mendellian inheritance, which defined evolution as the change in the frequency of alleles in a population (Barton *et al.*, 2007). More importantly, under the assumptions set out in the Hardy-Weinberg principle (Barton *et al.*, 2007), population models can investigate evolutionary processes, such as natural selection and random genetic drift. As such, allele or genotype frequencies "in successive generations can be tracked mathematically to simulate the process of evolution, often to find out whether a particular genetic trait can invade and spread through a population, and if so, to explore the possible evolutionary consequences of this invasion." (Mesoudi, Whiten & Laland, 2006, pg. 336).

Co-opting population genetic methods for the study of culture often fall within the realm of two areas: cultural evolution and *gene-culture coevolution* (Mesoudi, Whiten & Laland, 2006). Already touched upon above, models of cultural evolution focus exclusively on the demographic processes of culture – highlighting the obvious parallels between cultural and biological evolution, whilst also accounting for aspects that "will generate evolutionary dynamics with no obvious parallel in biology." (ibid, pg. 337). Meanwhile, gene-culture coevolution, also known as *dual inheritance theory* (DTI), attempts to unify both biological and cultural evolution within one theoretical framework. By considering both the transmission of genes and culture, DTI offers principles under which the selection certain cultural traits (be they adaptive or maladaptive) can interact with the selection of genetic traits, and vice versa (ibid).

All of these examples point towards culture being an evolutionary system in its own right. Perhaps more importantly, however, is that like language, not all change in culture is the result of genetic drift. Rather, both systems are adaptive: they are shaped in response to their environment. Thus, considering the dynamic interplay between both of these evolutionary systems is imperative.

3.2. Cultural Transmission and Language

3.2.1. Investigations into language, evolution & culture

Having established that both culture (§3.1) and language (§2.2.3) are evolutionary systems, the main question to now ask is: how can evolution and culture inform our understanding of language?

Insights into the role of cultural transmission and language can come from a variety of perspectives. Historical linguistics, for instance, has readily adopted Dawkins' concept of the *replicators* in applying selection to language change (see Croft, 2006; Ritt, 2004). Mufwene (2001) moves away from the memeticist approach, and offers a model of language change where instead of focusing on *linguemes* as the vital replicators, he argues it is in fact the "survival, spread, or extinction of a language is dependent on the survival, spread, or extinction of its host speakers" (Croft, 2008, pg. 223). Furthermore, Mufwene (2001) emphasises the role of populations, arguing that languages can be treated as a species in themselves – populations of idiolects existing inside a speaker-hearer environment. Essentially, his central thesis is that languages are *parasitic* in their nature, with humans being potential hosts for infection with multiple, and at times, competing, idolects (ibid).

Not only are concepts in biology being borrowed for analogous processes in linguistics, but so are certain methodological approaches. Phylogenetic methods used to investigate the historical lineage of a species in biology, are now being applied to linguistic phenomena (see Pagel, Atkinson & Meade, 2007; Atkinson *et al.*, 2008). Cavalli-Sforza and colleagues (1988) first brought to light the obvious connections between phylogeny and language history – producing phylogenies to compare human and linguistic populations. Although Cavalli-Sforza *et al.*'s results suggest the distribution of language families largely reflects demographic processes of human populations (such as migration) in pre-history, there is a degree of controversy surrounding their use of language families not "generally accepted among historical linguists" (Croft, 2008, pg. 225).

Despite the initial disputes over the data used in Cavalli-Sforza *et al.*'s study, the application of phylogenetic trees has become widespread across studies in linguistics and culture. Notable studies using linguistic phylogenies include: the explore population movements in the Pacific (Gray *et al.*, 2009); how languages evolve in punctuational bursts (Atkinson *et al.*, 2008); and, to investigate how the frequency of word-use predicts rates of lexical evolution (Pagel, Quentin & Meade, 2007). Furthermore, one paper by Greenhill and colleagues (2009) examines the role of different dimensions of transfer, asking: how influential is horizontal transmission in cultural phylogenies? Even though some critics (see Gould, 1987) argue horizontal transfer is ubiquitous throughout culture, the current study by Greenhill *et al* claim "[...] that phylogenetic influence is remarkably robust to even high levels of borrowing... [and] while reticulation may be common in cultural evolution, it does not necessarily invalidate a phylogenetic approach." (ibid, pg. 6).

The theoretical and technical applications of biology have wider implications in understanding the fundamental foundations of language and its relationship with socio-cultural, cognitive and behavioural aspects. Given the vast quantity of literature in this area, ranging from that of linguistics (Chomsky, 1993; 1995; Deacon, 1997; Bickerton, 2003; Hurford,) and animal behaviour (Dunbar & Shultz, 2007; Premack, 2007) to neurophysiology (Arbib, 2005) and computational modelling (Batali, 1998; Kirby, 2002), there are an even greater range of opinions as to how language evolved (for an extensive overview and introduction into all these areas, see Bickerton, 2007).

One view to gain a significant foothold in the past decade stems from the idea of language being the product of symbol-manipulation and symbol-relations (Deacon, 1997). Under this view, language acquisition takes a central role, as Deacon explains: "Human children appear preadapted to guess the rules of syntax correctly, precisely because languages evolve so as to emobody in their syntax the most frequently guessed patterns. The brain has coevolved with respect to language, but languages have done most of the adapting" (ibid, pg. 122). As already outlined in the previous chapter (see section on *domain-cognitive constraints*), these views have received substantial support from the theoretical literature. However, one of the most prevalent methods of investigating language and culture is via computational modelling.

3.2.2. Iterated Learning Model

If we accept that language is not only a conveyer of cultural information, but it is itself a socially learned and culturally transmitted system (Kirby, Cornish & Smith, 2008), then an individual's linguistic knowledge is the result of observing the linguistic behaviour of others (Hurford, 1990; Smith & Kirby, 2008). This well attested process of language acquisition is often termed *Iterated Learning*, and it opens up a new avenue to investigate the design features of language: that cultural, as opposed to biological, evolution is fundamental in understanding these features (Smith & Kirby, 2008).

Much of the literature regarding Iterated Learning focuses on a computational modelling approach, where "the central idea behind the ILM [Iterated Learning Model] is to model directly the way language exists and persists via two forms of representation" (Kirby & Hurford, 2002, pg. 123). These two forms consist of an I-Language (the internal representation of language as a pattern of neural connections) and an E-Language (the external representation of language as sets of utterances) (Chomsky, 1986). This cycle of continued production and induction is used to understand how the evolution of structure emerges from non-linguistic communication systems (e.g. Batali, 1998; Kirby, 1999; Kirby, 2001; Kirby & Hurford, 2002; Zuidema, 2003; Smith, 2005) and how language changes from one form into another (Niyogi & Berwick, 2007; Reali & Griffiths, 2009).

To briefly summarise, these models contain a single agent who is taught an initial random language (consisting of mappings between meanings and signals). The output of the agent is then used to teach the next generation, and so on. After numerous generational turnovers of teachers and observers, some of these models provide an intriguing insight into the emergence of linguistic phenomena such as *compositionality* and *regularity* (Kirby & Hurford, 2002). Consistently, these models are used to offer an alternative to biological accounts (e.g. Pinker & Jackendoff, 2009) in explaining the emergence of linguistic features, yet in some instances they also directly counter the role biological evolution plays in moulding a putative LAD (e.g. Smith & Kirby, 2008).

3.2.3. The role of transmission and biases

A common theme running through a wide array of these Iterated Learning studies emphasises language as being a compromise between two factors: "the biases of learners, and other constraints acting on language during their transmission." (Smith, 2009, pg. 697). What is perhaps fundamental to this view is encapsulated in the second constraint: that the transmission is a mediating force in the shaping of language. For instance, Kirby & Hurford (2002) show how the infinite expressivity found in languages is a result of the finite set of data presented during acquisition. With this *transmission bottleneck* restricting the amount of data presented, learners must generalise in order to learn the data, but not to the extent where the language is one signal for all possible meanings. Tempering maximal expressivity with generalisation provides an adequate explanation for recursive compositionality (see Kirby & Hurford, 2002), without appealing to the need for an intricately specified LAD. As Zuidema (2003) succinctly put it: "the poverty of the stimulus solves the poverty of the stimulus".

That the transmission and biases work in tandem in forcing languages to adapt suggests we cannot rely solely on cognitive explanations. To further investigate this relationship between transmission and biases, and due to criticisms concerning the bias towards a *minimum description length* (see Vogt, 2005a), recent models of iterated learning are frequently run with Bayesian agents (Griffiths & Kalish, 2005; Kirby & Smith, 2007; Dediu, 2009; Smith, 2009; Ferdinand & Zuidema, 2009). Essentially, by using Bayes' theorem the role of learners is to select a hypothesis h on the basis of its posterior probability when exposed to data d:

$$P(h|d) = \frac{P(d|h)P(h)}{\sum_h P(d|h)P(h)}$$

$P(d|h)$ provides a statistical likelihood of the data d being produced under a certain hypothesis h, with $P(h)$ equalling the prior probability of each hypothesis. When applied to models of language and iterated learning, both hypotheses are considered to be the set of possible grammars, whilst the data consists of sets of utterances required to induce a language (Smith, 2009). Importantly, the prior probability distribution over grammars is the learning bias, which may be domain-specific or domain-general (ibid).

A critical component of Bayesian learning, and still a point of contention, largely stems from two papers (Griffiths & Kalish, 2005; Kirby, Dowman & Griffiths, 2007) investigating the role of prior biases. Griffiths & Kalish show that if agents select a grammar with a probability proportional to its posterior probability, then the stationary distribution is merely a reflection of the prior distribution (Smith, 2009). By *sampling* from the posterior, the agents will revert to the prior regardless of any influence the transmission vector may assert, which as Smith (2009) states: "this suggests a transparent relationship between the prior bias of learners and the observed distribution of languages in the world: the typological distribution exactly reflects the biases of learners." (pg. 698).

Kirby *et al* (2007), however, demonstrate that Griffiths & Kalish's result was because the agents were *samplers* as opposed to another type of hypothesis selection: *maximum a posterior* (MAP selection, or maximisers). Instead of sampling from the posterior, maximisers choose the hypothesis with the highest posterior probability (Ferdiand & Zuidema, 2008). As such, MAP selection offers a more muddied picture of the relationship between learner biases and typological distributions, in that the distribution of languages will "reflect the ordering of hypotheses in the prior, but differences in prior probability are magnified, such that the a priori most likely hypothesis is overrepresented in the stationary distribution." (Smith, 2009, pg. 698). This invariably leads to a situation where different priors can result in the same stationary distribution, and by varying the transmission factors (amount of data presented, the noise between signals and meanings etc) convergence is not always towards the prior (ibid).

3.2.3. Iterated Learning and population dynamics

In the ILMs discussed, each generation consists of a single individual. This limitation breeds two further problems: 1) only vertical transmission is modelled; and, 2) there is little variability in the input. First, by negating peer-to-peer (horizontal) learning, ILMs ignore a potentially vital mechanism in language acquisition (Swarup & Gasser, 2009). For instance, Harris (1998) claims the children of immigrants tend to more readily adopt the language and accent of their home country; the basis of which being that children identify with their peers (classmates etc), rather than their parents.

Investigating horizontal transfer are several computational models (Batali, 1998; Vogt, 2005a; 2005b; Swarup & Gasser, 2009), which highlight how population dynamics play a pivotal role in accounting for the emergence of highly structured languages. Vogt (2005), for instance, uses the iterated learning model to investigate *symbol grounding*, which is simply the notion that "the symbol may be viewed as a structural coupling between an agent's sensorimotor activations and its environment." (Vogt, 2002, pg. 429). Using a *discrimination games* framework, in which a pair of speakers and hearers are presented with a "context of a few geometrical shapes which differ in their shapes and colors [sic]" (Swarup & Gasser, 2009, pg. 217), Vogt creates a scenario whereby a speaker selects a particular shape, and then describes it to the hearer. By comparing three aspects, based on whether the speaker's chosen shape is revealed to the hearer before (*observational game*) or after (*guessing game*) communication, and the transmission dynamic (vertical versus horizontal), Vogt (2005a;2005b) reaches three general conclusions: 1) Single hearer-speaker dynamics in the *observational* condition converge on a compositional language; 2) increasing a population size to three agents results in compositionality being stable in just the *guessing* condition, with agents in the observational condition resulting in their compositional language being replaced by a *holistic* language; and, 3) the inclusion of peer learning in the model consistently produces stable compositional languages across both conditions, without the need for a transmission bottleneck.

But what about our second criticism: that the ILM fails to account for variability in the input. When acquiring a language, children are not learning from a solitary source – they are being exposed to a whole host of sources and learning environments. With this in mind, claims for *increased learnability* being the result of an *evolutionary pressure* (see Smith, 2006) are limited: "An evolutionary pressure is always manifested through variation (creation of alternatives with differing fitness) and selection (fitness-based elimination of some alternatives)." (Swarup & Gasser, 2009, pg. 217). Niyogi & Berwick (2009) pick up on such limitations, and contrast the ILM with their own *Social Learning* (SL) paradigm, where each individual learner is exposed to data from multiple sources within a population. Using historical data, they show that their SL model "more faithfully replicates the dynamics of the *evolution* of Middle English [my emphasis]" (ibid, pg. 1), which is taken as evidence that IL is deficient in two fundamental aspects: (1) it cannot explain language stability over time, and (2) its linear dynamics do not account for phase transitions (ibid).

Regardless of Niyogi & Berwick's specific criticisms concerning language change, they do raise an important point about learning from multiple sources. Yet this point is not an inherent weakness of Iterated Learning process, as suggested by the authors, but it is instead a weakness of the single agent models. Indeed, this is position taken by three recent papers (Dediu, 2009; Smith, 2009; Ferdinand & Zuidema, 2009) which examine population dynamics in the context of Bayesian and iterated learning.

Smith (2009), for instance, looks at the implications for a Bayesian learner learning from two different sources of grammar. Called the *two-grammar model*, agents at each generation are exposed to data produced by multiple individuals. As already discussed, the findings of Griffiths and Kalish (2007) and Kirby *et al.* (2007) highlight differences resulting from single teacher-learner chains of *samplers* and *a posteriori maximisers*: to reiterate, the former converges to the prior genetic bias, while the dynamic is more complex for learners utilising the latter maximising strategy. By introducing diversity into the model, Smith's main result is that, after cultural evolution has run its course, and regardless of whether or not agents are *maximisers* or *samplers*, each grammar "is no longer the same as the prior distribution. Rather, one language predominates, with the winning language being determined by the starting proportions of the two grammars and their prior probability." (pg. 699).

However, as Smith concedes, the model does not really expand much beyond previous Bayesian ILMs, other than introducing multiple individuals into a vertically transmitted chain. Ferdinand & Zuidema (2009) and Dediu (2009) create relatively complex and dynamic models that not only consider population size, but population heterogeneity: agents in a population do not always have the same genetic biases. For example, Ferdinand & Zuidema introduce a great deal of variability into their model, including "the prior, hypothesis structure, bottleneck size, hypothesis choice strategy, population size, and population heterogeneity in terms of different priors per agent." (2009, pg. 1788). After replicating the results from previous single chain, or to use their term, *monadic*, Bayesian ILMs (specifically, Griffiths & Kalish, 2005; Kirby, Dowman & Griffiths, 2007), their main results in *polyadic* (multi-agent) populations is that by just increasing the population size to 2, the "sampler model's stationary distribution does not strictly mirror the prior." (Ferdinand & Zuidema, 2009, pg. 1790). This is true regardless of whether the population is heterogeneous or homogeneous, but it also means the differentiation between *sampler* and *maximiser* models is not as distinct as in monadic chains. In fact, both polyadic maximisers and polyadic samplers tend to behave similarly to monadic maximisers, with heterogeneous agents' hypotheses choices converging "as they are allowed to share more and more data, despite having fixed and different priors from each other." (ibid, pg. 1789).

In contrast to both Ferdiand & Zuidema (2009) and Smith (2009), Dediu (2009) finds that by enlarging the population to two agents, and adding heterogeneous biases, the apparent differences between *samplers* and *maximisers* are diluted. Furthermore, in the case of chains consisting of both *sample* and *maximiser* pairs, the results tend to mirror those found in single chains of *samplers*: convergence towards the prior. Lastly, on the basis of a previous study (Dediu, 2008), Dediu then shows how in general, non-Bayesian heterogeneous "learners with very different genetic biases do converge on a common language." (pg. 2).

It seems all three authors tend to converge on the somewhat diplomatic suggestion that it is too early to draw any strong conclusions concerning the interplay between biases and cultural transmission. Despite the conflicting results regarding the prior biases, with Dediu claiming agents do tend to converge towards the prior whilst Ferdiand & Zuidema (2009) and Smith (2009) find the opposite, the general consensus supports "the view that the process of cultural transmission plays a very important mediating role" (Dediu, 2009, pg. 9).

3.3. Experimental studies into the origin and evolution of language structure

3.3.1. Diffusion chain experiments

Up to this point, the literature pertaining to iterated learning comes from computational models of human communication, and is therefore inherently limited in the conclusions drawn in relation to real human population. Of course, the general point of modelling is to abstract away from the subject matter – focusing on the aspects deemed important (Hurford, 2005). But as Bickerton (2003) notes, "Powerful and potentially interesting although this approach is, its failure to incorporate more realistic conditions (perhaps because these would be difficult to simulate) sharply reduces any contribution it might make toward unravelling language evolution. So far, it is a classic case of looking for your car-keys where street-lamps are" (pg. 522).

Instead, recent approaches to language evolution (see Kirby, Cornish & Smith, 2008) focus on uniting two apparently disparate strands of research: mathematical/computational modelling and experimental studies. The latter is somewhat lacking in regards to cultural and linguistic evolutionary research, with perhaps the closest experimental paradigm to iterated learning coming from the field of social psychology, in particular the use of *serial transmission (diffusion) chains* (Mesoudi & Whiten, 2008). Originally created by Barlett (1932) to investigate the role of memory, *diffusion chains* are comparable to the children's game of *Chinese whispers*: here, some sort of cultural material (usually a sentence or phrase) is passed along a linear chain of individuals (see figure 1), until it reaches the final person. At this point, the sentence or phrase is normally different to its original incarnation, having accrued errors due to repeated retellings.

Early experiments by Barlett and examined a whole host of material, from Native American folktales to descriptions of sporting events (see Mesoudi & Whiten, 2008). Interestingly, in each of these studies the original material retained its overall meaning once reaching the end of the chain, but through repeated retellings along successive participants, the material also displayed two consistent factors of change: 1) the material became much shorter in length, and 2) the material lost much of its original detail (ibid). Barlett also observed what he believed to be evidence for memory being *reconstructive* (see Mesoudi & Whiten, 2008), with cultural material becoming distorted through a process of conforming to pre-existing mental schemas[14].

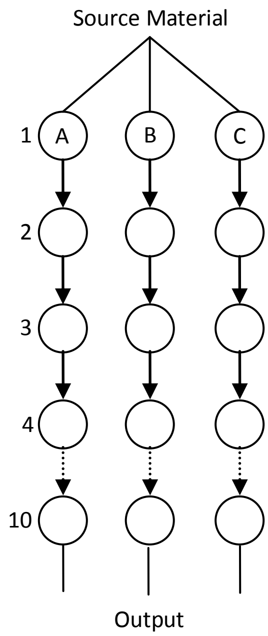

Figure 1. An example of a linear diffusion chain.

Recent studies using diffusion chains have further supported Barlett's claims of *generalisation* (Mesoudi & Whiten, 2004), whilst also investigating his claims of *assimilation*, such as pre-existing gender stereotypes (Bangerter, 2000) and prior cognitive biases (Reali & Griffiths, 2009). The chains have also been adapted to investigate foraging techniques of chimpanzees and children (Horner *et al.*, 2006), the transmission of social learning techniques in chimpanzee tool use (Hopper *et al.*, 2007), and observing the establishment of a wild-type song culture in zebra finch (Fehér *et al.*, 2009).

The general findings of all these studies demonstrate that humans of all ages, non-human primates, and even non-human animals are all capable of high-fidelity cultural transmission – and this can be studied empirically. Yet, to apply this framework for human language, another set of experimental literature needs to be considered, namely: artificial language learning and constructed communication systems.

3.3.2. Experimental studies of communication

Artificial Language Learning

First devised by Esper (1925), and later expanded to study social transmission (Esper, 1966), Artificial Language Learning (ALL) involves exposing participants to an artificially created, miniature language,

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[14] This mirrors an ongoing debate in Bayesian learning about *converging to the prior.*

which they are then trained, and subsequently tested, on; the goal being to investigate the learning capabilities of individuals. The ALL paradigm is widely used in linguistics, especially when investigation language acquisition and statistical learning abilities of humans (Saffran *et al.*, 1996) and non-humans (Fitch & Hauser, 2004).

For instance, Wonnacott and colleagues (2007) use an ALL to explore two related debates surrounding verb generalisation: 1) how some verb-argument structures tend to generalise to new verbs, whilst other verbs are highly resistant to change; and, 2) how verb-specific and more generalised constraints interact in sentence processing, with emphasis on the role of semantics (ibid). They find that by using languages without semantic cues to verb distribution, learners are quite competent in acquiring "both verb-specific and verb-general patterns, based on distributional information in the linguistic input regarding each of the verbs as well as across the language as a whole" (ibid, pg. 165).

ALL is also useful in expanding upon computational modelling studies, as demonstrated by Christiansen (2000) when, working from a previous connectionist study into word order universals (Christiansen & Devlin, 1997), created two head-ordered languages, with one containing head-last consistent sentences and the other being inconsistent. In tandem with the modelling results, the ALL study confirmed that head-order inconsistency is too hard to learn, which suggests that the underlying processing mechanisms are not necessarily innately constrained with a head-ordering rule, but are rather the result of "non-linguistic constraints on sequential learning and processing" (Christiansen, 2000, pg. 4).

Another area of investigation using ALL is in the emergence and formation of *creoles* from *pidgin* languages (Hudson-Kam & Newport, 2005) – a hybrid language that evolves from its parent pidgin, except it contains a grammar that mirrors the complexity of natural languages (Hall, 1966). Although we can see creoles emerge within a few generations, – such as the development of a new type of sign language in a deaf community of Nicaraguan children (Senghas, Kita & Ozyurek, 2004) and a similar situation in development of the Al-Sayyid Bedouin Sign Language (see Sandler *et al.*, 2005) – these studies fail to "provide us with the experimental control to test our predictions" (Cornish, 2006, pg. 9).

Hudson-Kam & Newport (2005) attempt to address creole formation by exposing both adults and children to two artificial languages, specifically focusing on the role of *regularization*: the process of making irregular forms regular. Importantly, these initial languages contained linguistic features present in pidgins and the early stages of creole formation, such as inconsistent grammatical morphemes – and differed in the presence or absence of a determiner within noun phrases. For the first language (inconsistent condition) the determiner was only present for 60% of the time, whilst it was present 100% in the other language (consistent condition). They found that exposure to consistent grammatical patterns resulted in consistent grammatical patterns for both adults and children. The major finding, however, is that when adults are exposed to inconsistent input, they tend to reproduce these inconsistencies in their output; children on the other hand tend to regularize the language "imposing patterns that were not the same as their input." (ibid, pg. 151).

From these results, Hudson-Kam & Newport claim that, through the regularisation of grammatical patterns, children play a vital role in creole formation. Furthermore, given that children and adults do not learn the inconsistent input in the same manner, with the latter applying a strategy that merely attempts to reproduce consistency or inconsistency, children act as a way to "regularize and stabilize the grammar of an emerging language" (pg. 185).

A more recent study on word learning (Vouloumanos, 2008) investigated the interactions between learning biases and input inconsistency. Specifically, Vouloumanous trained participants on novel word-object pairs consisting of varying frequencies: "some objects were paired with one word, other objects with multiple words with differing frequencies (ranging from 10% to 80%)" (2008, pg. 729). She tested participants by presenting them with two objects while playing a single word, and then asking which of the two objects are best associated with the word. By introducing multiple-referent relations during word learning, Vouloumanous found participants tended to adopt a selection heuristic based on the frequency of the word/object, rather than regularising the inconsistent input. In her conclusion, she argues that the sensitivity to the statistical co-occurrence between words and objects suggests, "[...] learners could entertain overlapping hypotheses about the referents of a word, and assign different likelihoods to each of these candidate mappings" (Vouloumanous, 2008, pg. 739).

Intentional Communication Experiments

Sharing similarities with ALL experiments is a comparatively small body of literature pertaining to experiments into the construction of communication systems (Galantucci, 2005; Selten & Warglien, 2007). A common theme running through each of these experiments is how a novel communication can emerge over a short period of time to solve a particular task (Galantucci, 2005) or just through repeated interaction (Selten & Warglien, 2007).

Selten & Warglien (2007), for instance, use a series of laboratory experiments designed to investigate the inherent costs and benefits of linguistic communication – and how these respective aspects affect the emergence of basic languages in a coordination task. There is no common language available to the participants, with them instead needing to create their own communication system in reference to varying lists of geometrical figures composed of up to three features. Importantly, the communication system is limited, as using letters had a cost attached. By varying number of letters available and the set of figures, the researchers are able to compare different environments – with stable environments resulting in arbitrary codes, whilst "in an environment with novelty, compositional grammars offer considerable coordination advantages and therefore are more likely to arise." (pg.7361).

Although both Selten & Warglien (2007) and Galantucci (2005) show how repeated interactions result in the emergence of compositionality, a vital component of these experiments is that the participants create a system of communication. Thus, the resulting systems are the product of intentional design, and as such cannot tell us much about the actual processes of language, which, as discussed at the start of this chapter, "is an "invisible hand" process leading to phenomena that are the result of human action but not intentional artifacts" (Kirby, Cornish & Smith, 2008, pg. 10681).

3.3.3. Human Iterated Learning

Drawing from these experimental approaches found in diffusion chain (Mesoudi, Whiten & Dunbar, 2006; Marshall-Pescini & Whiten, 2008) and ALL (Christiansen, 2000; Fitch & Hauser, 2004) studies, Kirby *et al* (2008) show that as a consequence of intergenerational transmission "languages transmitted culturally evolve in such a way as to maximize their own transmissibility: over time, the languages in our experiments become easier to learn and increasingly structured." (pg. 10681). In these experiments a subject is exposed to an *alien* language, which is made up of two elements within a finite space: meanings (consisting of a picture with three discernable elements: colour, shape and movement) paired with signals (consisting of a string of letters). Importantly, the subject is only exposed to a set amount of meanings (SEEN items), after which they are then presented with a group of meanings (some SEEN, some UNSEEN) without the corresponding signal – the goal being that they provide a signal (be it the correct version or not). On completion of forming the meaning-signal pairs the experiment is repeated, except this time the new subjects are trained on the data provided by the previous generation. This continues until the experiment is finished, which in the scenario discussed here happened at generation ten (Kirby, Cornish & Smith, 2008).

For their paper, Kirby *et al*. (ibid) run two experiments. The first is essentially identical to the above description, with a set of 27 string-picture pairs being divided into two sets: the SEEN set (14 string-picture pairs) and the UNSEEN set (13 string-picture pairs). In the second experiment however, the SEEN set was filtered before being presented to the next generation:

> "Specifically, if any string labeled more than 1 picture, all but 1 of those string-picture pairs (chosen at random) was moved into the UNSEEN set. As a result, the training data seen by participants in the second experiment consisted of a purely 1-to-1 mapping from strings to pictures, even if the language of the previous generation included 1-to-many mappings." (ibid, pg. 10686).

As already mentioned, the results generally show the languages become increasingly structured coupled with an easing of their learnability. However, the main difference between both experiments is in their expressivity: in experiment one, the languages that emerge have a high degree of ambiguity between the signal-meaning pairs, whilst experiment two manages to bypass this through the introduction of a filter (ibid). In a later paper (Cornish, Tamariz & Kirby, in press), these results are further analysed under a new experimental methodology (see § ... for an in-depth discussion), which investigates this perceived tension between learnability and expressivity. The major finding of this paper is the ability to discover the types of structure that emerged in two of their languages. First, they find one of the languages from the first experiment is clearly the result of *underspecification*: "[...] a reduction in the total number of distinct signals, introducing ambiguity with respect to the meanings" (Cornish, Tamariz & Kirby, pg. 4). Still, this ambiguity is not a random assignment of signals and meanings, but rather a system of consistently structured mappings emerged.

A language from the second experiment, however, is not the result of underspecification. Rather, it appears to be more expressive and communicatively functional, which on the basis of Cornish, Tamariz & Kirby's results suggests it is *compositional*: "whereby the meaning of a given string could be inferred by the meaning of sub-parts of that string (morphemes) and the way they are put together." (ibid, pg. 4). To test this notion, they used an analysis program called *RegMap*, a metric that measures the *systematicity* of a language (see results section for a comprehensive overview).

These results not only tend to confirm the notion recently considered by Christiansen & Chater (2008), whereby language adapts to the user to become learnable – it also has to adapt to brain external constraints found in the transmission itself (Smith, Kirby & Smith, 2008). Therefore, there are essentially two known pressures acting upon language: greater learnability versus expressivity – and it is these competing pressures that allow for structure to emerge over a certain length of time (ibid).

3.4. Discussion

In following on from chapter two, this chapter lays out that the iterated learning paradigm provides a good methodological framework to study the cultural transmission of language (Kirby & Hurford, 2002), investigate the role of biases (Griffiths & Kalish, 2005), and to consider the dynamics of populations (Vogt, 2005b; Ferdinand & Zuidema, 2009). Furthermore, through the amalgamation of diffusion chains (Barlett, 1932), artificial language learning (Christiansen, 2000) and other communication experiments (Selten & Warglien, 2007), we can see how iterated learning can be applied in a laboratory setting (Kirby, Cornish & Smith, 2008).

It is clear from the literature that cultural transmission does influence language given the right settings. The primary setting, or pre-condition, according to Hurford & Kirby (2002) is the *transmission bottleneck*: that the transmission mediates, and subsequently shapes, language. Replicating the results of monadic chains in the laboratory has also proved successful in showing that random artificial languages become increasingly structured, more learnable and, in some cases, compositional.

Yet there are also instances where ILM do not use bottlenecks (Batali, 1998; Vogt, 2005; Swarup & Gasser, 2009), and instead rely on other dynamics to obtain similar results. These studies pose significant challenges to the influence of the transmission bottleneck. They also enable us to delve deeper into the conclusions drawn from human iterated learning, namely: are they constructing compositionality in their experiments? In contrast to the statement put forward by Kirby, Cornish & Smith of their experiment validating “that cultural transmission can lead to the appearance of design without a designer” (pg. 10681), an alternative is they simply designed the system towards converging on compositionality. By adding an artificial bottleneck and then adding a filter, the authors are arguably tweaking the system in the manner of an omnipotent designer. Of course, the theoretical literature somewhat substantiates the inclusion of both an artificial bottleneck (Deacon, 1997) and a filter (reference), in that these processes are analogues of “a pressure to be expressive that would come from communicative need in the case of real language transmission” (Kirby, Cornish & Smith, 2008, pg. 10684).

Still, there is always the possibility of elements within the linguistic environment playing a greater role than the transmission. As already touched upon, these factors may be something like a systematicity bias (Tamariz & Smith, 2008; Brown, 2008). Bayesian population models also demonstrate that other factors – primarily population size and variability in the input (Dediu, 2009; Smith, 2009; Ferdinand & Zuidema, 2009) – influence the relative roles of biases and the subsequent formation of structured languages. All these factors suggest further investigation is warranted into cultural transmission, with us specifically asking: what will happen in the laboratory setting if we introduce a larger population size and variability in the input? It is with this question in which we turn to the next chapter.

Chapter Four

Introducing population dynamics into human iterated learning

4.1. Introducing variability in the input

The desirable conditions when investigating the cultural transmission of language would mirror the complex dynamics of some Bayesian ILMs (Dediu, 2009; Ferdinand & Zuidema, 2009). However, for all of the advantages introduced by working with real people, there is also a manifesto of pitfalls in the comparatively limited resources. To this end, the experiment outlined below will be aimed at introducing variability into human iterated learning through increasing the population size. The central hypothesis in this dissertation is that combining the inputs of several participants will produce a significant impact on the evolution an artificial language over iterated learning.

Given the findings of Kirby *et al.* (2008), it only seems natural that the framework they have developed should be extended to consider different facets of cultural and linguistic phenomena. The initial successes of empirical experimentation through human iterated learning allow us to address the viability of the approach when exposed to two different experimental conditions: *monadic chains* and *polyadic chains*[15]. By performing an experiment, this dissertation will hopefully be investigating new territory whilst being able to analyse the results generated in the context of existing literature. Specifically, I hypothesise the diversity introduced in the input will lead to two findings:

1. The final languages will be significantly more structured and learnable than the initial languages.
2. That the final output of both participants in the polyadic condition will be composed of more similar languages than both participants in the monadic condition.

4.1. Methodology

This section outlines the methodological framework utilised for the experiments in §4.2.

4.1.1. Overview

The experiment adopts a similar methodological approach to that found in Kirby, Cornish & Smith (2008), albeit with modifications to introduce diversity in the input (see §4.1.2 onwards). As such, each experiment consisted of ten generations of learners with each subject being exposed (via a computer) to an artificial alien language, which is a combination of pictures (the meanings) paired

[15] From here on in, I will be using this terminology to describe the single-chain (monadic) and dual-chain (polyadic) experiments.

alongside a string of letters (the signal). After the initial training, the subject moved on to the testing phase where they were presented with the pictures but not the strings. The goal for each subject was to provide the correct response (a string of letters) when presented with the pictures. These responses then became the subsequent input for the next generation. Importantly, participants were not told about the overall aim of the experiment, and were only given verbal and written instructions as to the nature of the task. Participants were instructed to always give response, even in instances when they did not know the response.

As in Kirby, Cornish & Smith (2008), beyond the verbal and written instructions given at the start, no explicit feedback was given to the subjects whilst performing the task. Therefore, each person in the next generation is receiving input solely on the observations, and subsequent productions, made in the previous generation.

4.1.2. Structure of chains

As noted, there were subtle modifications made to Kirby, Cornish & Smith's (2008) methodology to introduce diversity in the input. The first of these modifications was the use of two different experimental conditions across four transmission chains: a *monadic condition* and a *polyadic condition*. In the two monadic chains, initial participants were given the same randomly generated alien language. Their output was then used to train subsequent participants in the chain (*figure 2*) – each generation repeating the process of using the input from the previous generation to train on, and then producing the output for the next generation, and so on. The second experimental condition followed a similar outline, with the initial polyadic generations having received the same randomly generated alien language as the monadic condition. In contrast to the monadic condition, both participants in a single generation of the polyadic condition were exposed to two inputs. In the case of the first generation, this was just two versions of the same generation artificial language, with subsequent generations being exposed to both outputs of the previous generation (*figure 3*).

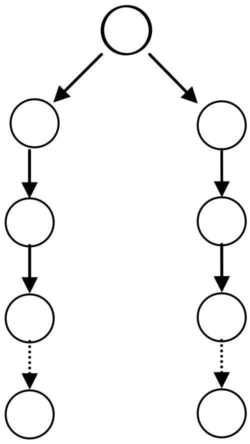


Figure 1: Standard Human Iterated Learning using vertical transmission dynamic

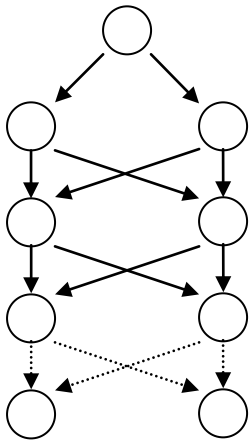


Figure 2: Human Iterated Learning with variability introduced in the input.

4.1.3. Meaning space and initial alien language

Structure of meaning space

The structure of the meaning space is similar to that used in Kirby, Cornish & Smith (2008), with pictures consisting of three dimensions: *motion*, *colour* and *shape* (*table **num***). However, there is a slight difference: the meaning space was reduced from 27 to 18 meanings. This was done on the basis of a pilot study, in which 54 meaning-signal pairs for the polyadic condition[16] was simply too much for participants to handle – and suggested it would take longer for any sort of structure to emerged, which, due to budgetary limitations, is not an aspect I could take liberties. As this experiment needed to compare both monadic and polyadic conditions, it was decided that both meanings spaces would be reduced to 18 distinct meanings: 18 meaning-signal pairs for monadic condition and 36 meaning-signal pairs for the polyadic condition. A *shape* was chosen to be removed on the basis of it being the least salient dimension in previous studies (see Cornish, Tamariz & Kirby, in press).

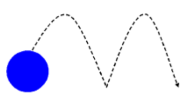
	MOTION	COLOUR	SHAPE	
	spiral	red	triangle	
	bounce	blue	circle	
	horizontal	black		

Table 2: *Table showing the meaning space structure used in both conditions, with an example on either side*.

[16] Remember, the polyadic condition consisted of two inputs, so a meaning space of 27 doubles to 54.

Structure of initial alien language

Unlike the languages in computational ILMs (Kirby & Hurford, 2002), the initial language used in this experiment was not the result of agents inventing a random language – as asking participants to do the same thing could result in any number of issues. Instead, the structure of the initial alien language was produced by a largely similar method to Kirby, Cornish & Smith: a generator was used, which randomly concatenated nine syllables into strings that were three syllables long. These three-syllable strings were then arbitrarily assigned with the 18 meanings. As such, there should be no significant relationship between the signal and meaning elements. The rationale for using only three-syllable instead of two to four syllable strings was for purposes of analysis (for details, see §4.4.).

The major reason for the language being composed of random one-to-one mappings between signals and meanings is that the end result is a language devoid of any noticeable structure at both whole word and syllabic levels. Any structure that does emerge in successive generations then, is the result of some other aspect – and not because of some initial structure that was emphasised at every successive generation.

4.1.4. Participants

A total of 40 participants (23 female, 17 male, mean age = 23, s.d. = 3) were recruited; 20 made up the two monadic chains, and 20 made up the polyadic chains. Criteria for exclusion from study, included: 1) if participants had studied linguistics at university level; 2) they suffered from dyslexia; and, 3) they were not native English speakers. All participants were given an informed consent sheet to sign, and following the alien language task were given a questionnaire to answer (see Appendix I), which on completion resulted in them earning £5 for their participation. One aspect of the questionnaire was a scale of difficulty from one to five: one being easy, and five being very difficult. Across both polyadic and monadic conditions, participants found the task consistently hard – regardless of the specific generation. The mean rating in each condition being 4 (monadic) and 4.46 (polyadic).

4.1.5. Procedure

Using a modified version of the program used in Kirby, Cornish & Smith (2008), the experiment was run on a computer under laboratory conditions. As already mentioned there are two conditions in this study, which are based on the input provided to the next generation in the chain:

- In the ***monadic*** condition, subjects were trained on 18, randomly assigned meaning-signal pairs across two rounds of training. Interspersed between the first and second round of training was a test phase where the participants receive 9 meanings without the corresponding signals. At this point, the participants enter their responses.

- In the ***polyadic*** condition the set up was largely similar, except this time participants were trained on a total 36 meaning-signal pairs. However, when it came to the test phase, participants were only tested a total of 18 meanings. So, the responses of two separate participants (two rounds of 9 each) make up the entire meaning-signal space of the next generation.

Unlike Kirby, Cornish & Smith (2008) there is no artificial bottleneck or filter in this experiment[17]. Given I am investigating the role of populations, by removing the artificial bottleneck and filter this experiment can be contrasted with that of other experiments into human iterated learning.

The amount of exposure to the stimuli was determined by the program, with the participants having an unlimited amount of time to provide an answer during the testing phase. In between each participant, the meaning-signal pairs were rearranged as to avoid introducing any odd bias by having the exact same ordering of meaning-signal pairs for every generation. Below is the exact schedule that participants followed in both experimental conditions:

- Training on 9 (monadic) or 18 (polyadic) meaning-signal pairs;
- Tested on 9 meanings;
- Break;
- Training on the additional 9 (monadic) or 18 (polyadic) meaning-signal pairs;
- Tested on 9 meanings;
- End.

4.3. Learnability & Structure

This section will now outline the results of the experiment.

4.3.1. A decreasing transmission error

When examining the concept of *learnability* in the context of transmission chains, a useful heuristic is to consider the *transmission error* by calculating the mean distance between all the signals in a participant's output and the corresponding signals in the previous generation's output (Kirby, Cornish & Smith, 2008). This gives a measure of the transmission error across all generations, and can be formulised as:

[17] Of course, participants bring their own natural bottlenecks to the task of learning, such as perceptual, memory, processing and other cognitive constraints.

$$E(i) = \frac{1}{|M|}\sum_{m \in M} \mathrm{LD}(s_i^m, s_{i-1}^m)$$

As reported in *Kirby, Cornish & Smith*, "where s_i^m is the string associated with meaning *m* by the participant at generation *i*, LD s_i^m, s_j^m is the normalized Levenshtein distance [...] between strings s_i^m and s_j^m, and the sum is over a set of meanings *M* of magnitude |*M*|." (2008, pg. 10686). Essentially, a decreasing transmission error reflects an increasing amount of inter-generational learnability – as demonstrated in the case of this experiment (see fig.4). To further support the contention of the languages becoming increasingly learnable, a paired t-test shows there is a significant decrease in error between the initial and final generations of the chain (mean decrease 0.561, SD = 0.317; t(2) = 7.2525; *P* = 0.0185).

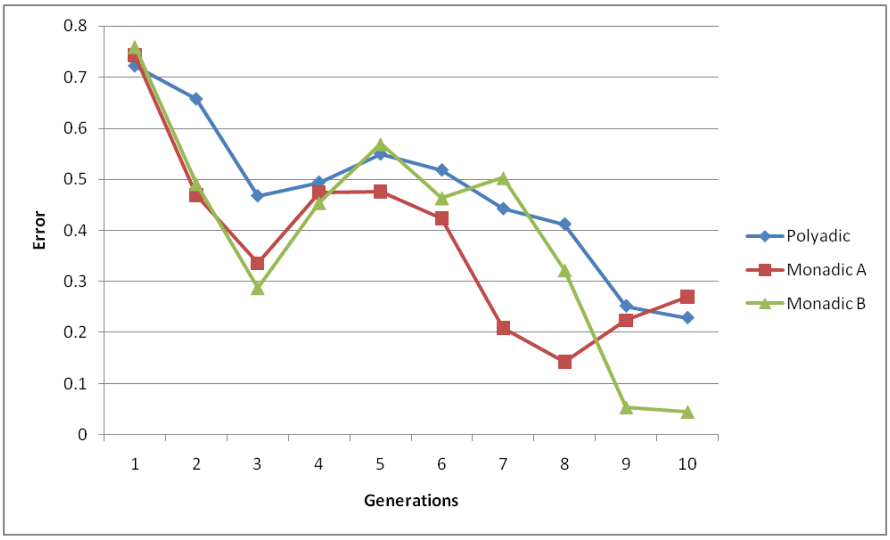


Figure 4. *The transmission error of both monadic and polyadic conditions across 10 generations. The monadic condition consists of two chains (monadic A & monadic B) plotted on the graph, whilst the polyadic plot is an average of score taken from four chain combinations (polyadic A chain, polyadic B chain, polyadic AB chain and polyadic BA chain, see appendix IV). The rationale for plotting the average score instead of two separate chains is because the polyadic condition should be seen as essentially a single chain made up of multiple individuals.*

As suggested by Kirby, Cornish & Smith (2008), this increase in learnability is an example of the languages adapting to become increasingly transmissible. Despite this, a more pertinent question for this dissertation concerns any perceivable differences between the polyadic and monadic chains: namely, does introducing variability in the input decrease the learnability of a language? To investigate, an *Analysis of Variance* (ANOVA) shows that there is no significant difference between the polyadic and monadic groups, as indicated by a one-way ANOVA (d.f.=2; F=1.464; *p* = 0.24).

4.3.2. An increasing structure

Yet how do we explain this increase in learnability? In contrast to Kirby *et al* (ibid), the absence of both a filter and an artificial bottleneck means this experiment is not initially equipped to rule out the possibility of participants using a different heuristic strategy to *generalisation* (such as rote learning) when learning the language. That the participants fail to reproduce the chain faithfully from generation-to-generation is partially indicative of them not wholly relying on rote learning; rather, in later generations at least, the participants appear to rely on a more systematic method – they impose a structural relationship between the signals and meanings.

Quantifying the emergence of an increasingly structured language is computed using a *pairwise distance correlation* (PDC). PDC uses a normalized Levenshtein distance, which calculates the *edit distance* between all pairs of strings in the language, and then the *Hamming distance* for the distances between all pairs of meanings. Next, Pearson's product-moment correlation is applied to these two sets of distances, giving an indication as to which "similar meanings are expressed using similar strings" (ibid, pg. 10686). Lastly, a Monte Carlo sample of 1,000 randomizations is used to give the z score for the veridical correlation (ibid). As fig.5 shows, the languages are gradually evolving to become increasingly structured, with the output of the final generation being significantly more structured than the initial language (mean increase 4.970, SD = 2.046; $t(2) = 10.1552$, $P = 0.0096$).

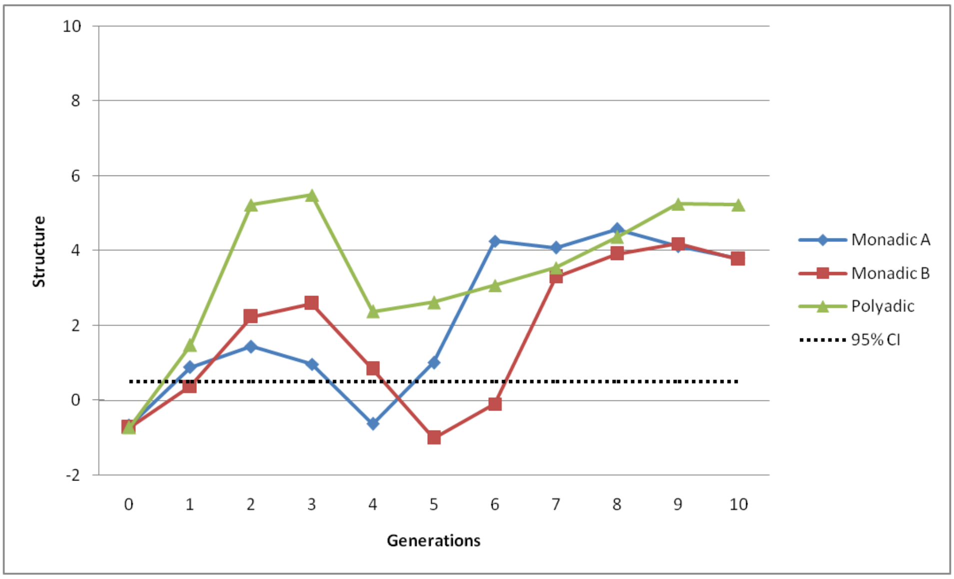


Figure 5. *Measure of structure in both monadic and polyadic conditions across 10 generations. The monadic condition consists of two chains (monadic A & monadic B) plotted on the graph. As with the transmission error, the polyadic plot is an average of score taken from four chain combinations (see appendix IV). The dotted line on the graph gives the 95% confidence interval so that any result above this line is indicative of being a non-random combination of meanings and signals.*

4.3.2. Similarity of languages

Now that we know the structure is increasing across all three groups, the next question to consider is the similarity of strings within the polyadic and monadic conditions. Given the introduction of variability in the input, the expected result is that the two polyadic chains are more similar in their output at the final generation than the two monadic chains. To calculate this, the edit distances of corresponding strings in each condition were calculated. For instance, at generation 10 in the monadic condition, there are two strings (**wannapo** and **wakini**) corresponding to a specific meaning (). By calculating the normalised edit distance of these two strings, the LD equals 0.77. Likewise, the same method is applied to the two corresponding strings (**kimini** and **kiwani**) in the polyadic condition (LD = 0.33). To act as a benchmark against which we can compare both polyadic and monadic conditions, the edit distances of two random languages were calculated and plotted on a graph (figure 6).

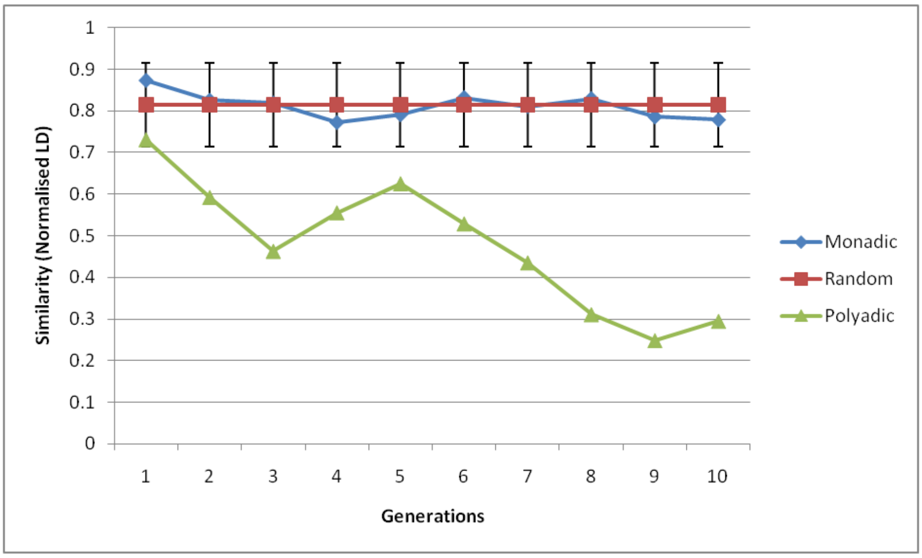


Figure 6. *Similarity measurement of the two polyadic chains, the two monadic chains and two random languages. Error bars on random language plot show the confidence interval of the random language, with a decreasing LD being indicative of increasingly similarity. As you can see, the strings between both monadic chains are no more similar than the randomly generated language. Meanwhile, the strings between the polyadic chains are more similar in their output at almost every generation (the exception being generation 1).*

With the exception of generation 1 the polyadic chains appear to be more similar in their output to that of the monadic chains – which are no more similar than two randomly generated languages.

4.3.4. Summary

The main findings of this section confirm the first of my hypotheses: that both the monadic and polyadic chains are significantly more structured and learnable than the initial language. That these two conditions appear to behave similarly in their development, despite the introduction of variability in the input, is striking. The languages are appearing to adapt to their conditions in almost identical manners, yet there are also noticeable differences. In particular, the confirmation of my second hypothesis – concerning the similarity of output in both conditions – suggests there is a fundamental discrepancy between the two conditions: the two monadic chains drift apart fairly early on in the chain, and remain no more similar than two random languages, whilst the polyadic chains evolve as a single system, with the output of both individuals from generation 2 onwards being much more similar than pure chance.

Another striking feature of this study is the parallels we can draw with other human iterated learning experiments. In contrast to Kirby, Cornish & Smith (2008) this study does not use an artificial bottleneck or filter, yet it achieves comparable results to their first experiment. Naturally, the emergence of structure in a language, despite the absence of these conditions, does not negate their theoretical appeal, largely because the emergence of structure in this experiment does not imply it is *compositional*. So, the obvious question to ask is as follows: what type of structure has evolved in these languages?

4.4. Expressivity of alien language

4.4.1. The signal-meaning space

Having established that both monadic and polyadic chains are becoming easier to learn and increasingly structured, this section will now investigate what type of structure emerged by probing the expressivity of the languages.

As Kirby, Cornish & Smith (2008) highlight, two ways[18] in which a language can converge on a systematic and predictable structure is through either *underspecification* or *compositionality*. First, to gain a greater understanding of the signal-meaning correspondence, we can examine the final generation of each chain and see if there are any obvious patterns. Interestingly, in both conditions the system that emerges appears to be structured around one of the meaning dimensions – motion (see table 2).

[18] Obviously this is not exclusively restricted to underspecification and compositionality. For instance, a form of linguistic categorisation could emerge as an alternative structure.

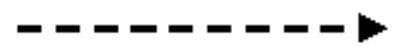
			
Monadic A	wannapo, wanipo, winnipo	wannipe, wanawe, wannapo, wannawe	guhithiko, guithike, guihipikowe, guihikipowe, guihipipo
Monadic B	wakini, wakinini, mahini	miuni, muini, gopoka	gopogo, gopoka
Polyadic A	kimini, kiminni, kiwini, kimiminni	gu, go[19]	guro, gurao, guarmo, guarno
Polyadic B	kiwani, kiwimmi, kimimni, kimmimi	gu, go	guarno, guaro, maro

Table 2. *The correspondence between signals and the motion meaning space at generation 10 in the monadic and polyadic conditions.*

At first glance there does appear to be some sort of consistent structure pertaining to motion, but it is not clear whether this is compositional or not. For instance, in monadic chain A the language shows a consistent structure from generation 6 onwards, but at generation 10 there is not any noticeable compositionality: the sub-parts of a string do not show any specific relationship with a particular motion. Looking across the final generations, specifically when the language is at its most structured (generation 8), and what is immediately noticeable are the hallmarks of systematic structure: the initial segment appears to encode for motion (example 1).

Example 1	Colour	Shape	Motion
wan	Blue (2), black(2), red(2)	Circle(3), triangle(3)	Bounce (6)
wa	Blue(2), red(2), black(2)	Circle(3), triangle(3)	Straight (6)
gu	Blue(2), red(2), black (2)	Circle(3), triangle(3)	Spiral (6)

Example 1. Table looking at the initial segmentation in generation 8 of monadic chain A.

This systematic structure can only be explained by looking at a specific sub-part of a string (the initial segment)[20], and not the whole words. However, neither colour nor shape appears to strongly correspond with any other sub-part, which means only partial compositionality is being achieved. Furthermore, this structure breaks down at generation 10, with the participant not distinguishing between *wan* and *wa* as in previous generations. As a result, it is dubious as to whether or not this particular compositional structure would have continued if new generations were added to the chain – the segmentation does not contain enough distinction (*wan* and *wa* are more closely related than *gu*).

[19] Of particular note is the choice of the string 'go' to describe a representation of forward motion: its length and common occurrence as an English verb may make it highly salient to participants. Hence its consistent prevalence, alongside the closely related 'gu', in successive generations.

[20] It is interesting to note that the segmentation of *wan* and *wa* was not an arbitrary segmentation in order to give the appearance of systematicity. For instance, a word would be segmented *wan* if it was followed by an additional *n*, as in *wannapo* and *wannawe*. So, words such as *wanapo* and *wanawe* were segmented with into *wa*, allowing for the second segment in both instances to be *na*. However, this is an orthographic influence as opposed to phonetic, and probably explains why this particular feature does not remain stable.

Still, as previously mentioned, participants could just be rote learning, rather than inferring structure through generalisation. For instance, from generation 9 to generation 10 (monadic B) there is an almost perfect replication of the entire language[21], which is indicative of the language being highly learnable. Yet this perfect replication also includes *gopoka* corresponding with a *straight* motion – in contrast to the general trend of *gopoka* encoding a *spiral* motion. Given this discrepancy is replicated at generations 8, 9 & 10, then it is almost certain that, for this particular signal at least, participants are rote learning the correspondence.

The polyadic condition also shows a similar adaptation to the meaning space; in that the language appears to have converged upon a systematic method for encoding motion. However, a clear difference between the polyadic and monadic chains are the rules that emerged to reach this adaptive solution. The system is generally noisier and vaguer than either of the monadic chains at generation 10, with *gu*, for instance, encoding both a straight and spiral motion. As participants relayed in their questionnaire responses, the method of distinguishing between these two *gu*(s), and the motion it is encoding for, is through length. So, when participants see a *spiral* motion, then they know the word is going to begin with *gu* followed by additional syllables: e.g. *gu*-***ar***-***mo***. If, on the other hand, the motion is *straight*, then the word is either *gu* or *go* – without any additional syllables.

4.4.2. The evolution of signals

The second step in examining expressivity is to show how each of the languages developed their structure by devising a coalescent tree (see fig.4, 5 and 6). Commonly used in evolutionary biology (Barton, 2007), and more recently in linguistics (Cornish, Tamariz & Kirby, in press), coalescent trees represent descent across generations.

As all three trees show (fig.), the general trend is that the frequency of distinct strings (numbers in brackets) decreases, whilst the transmission fidelity increases – more strings are perfectly replicated at later generations (as indicated by thick black lines). This is evident in the disparity between the initial and final generations, where in the former, there are very few instances of whole strings being stably reproduced; instead, it is the sub-components of a string that are transmitted and recombined with other sub-components. For instance, the appearance of the form *mahini* at generation 7 (monadic chain B) may be the consequence of a blending between *manini* and *wahini*.

In fact, coalescent trees allow us to trace the genealogy of a language to observe changes “that are well attested in cases of natural language change” (Cornish, Tamariz & Kirby, in press, pg. 7). Looking

[21] The exception being *miuni* undergoing metathesis into *muini*.

across all three chains, and there are instances of single segment replacements (gupoki into gopoki), reductions (gowaki into waki), metathesis (miuni into muini), and as already mentioned, blends (wikinini & wahini into wakini & wakinini).

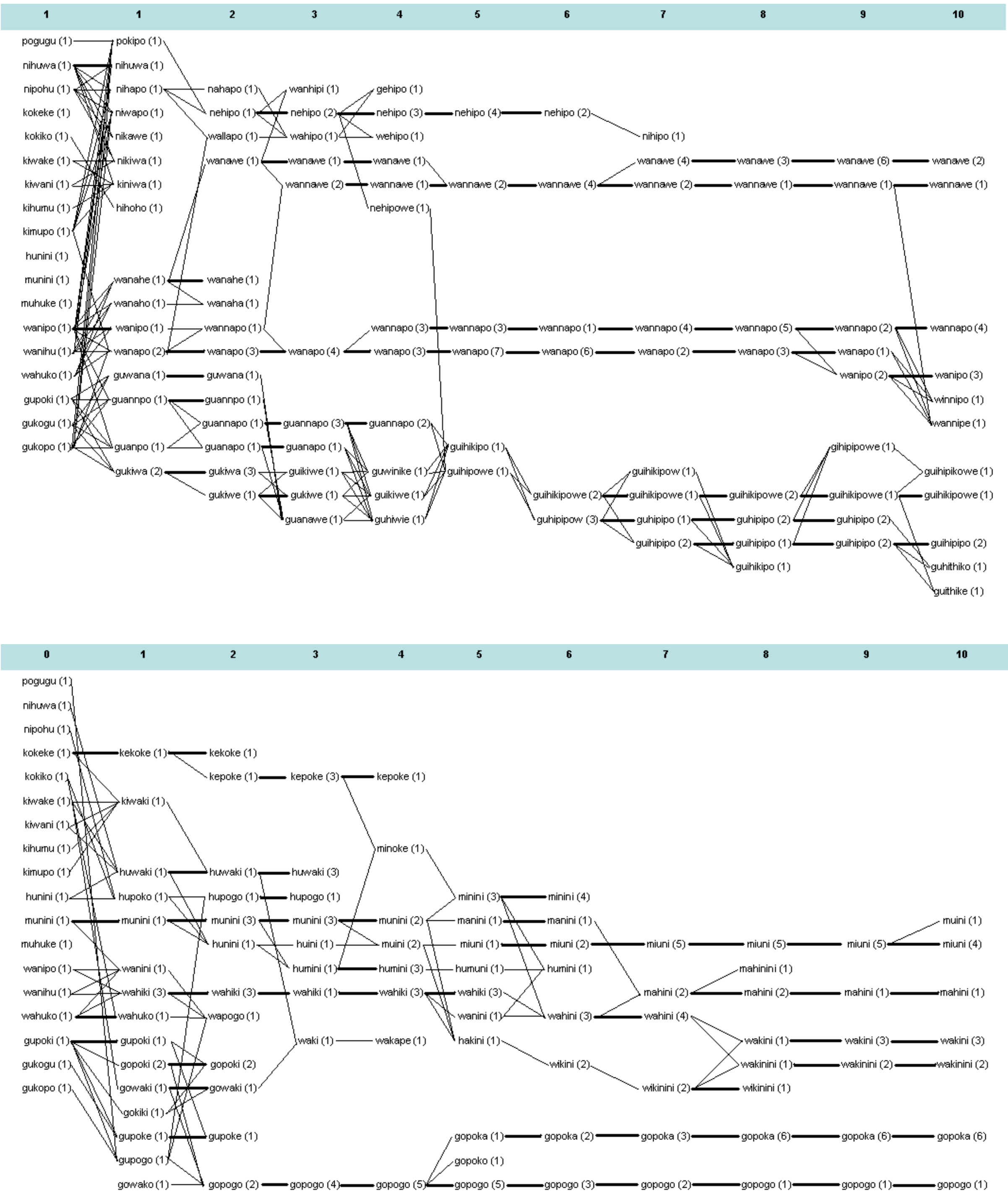


Figure 7. *Coalescent trees showing signal lineages for all 18 items over generations of monadic A (top) and monadic B (bottom). Notice that the tree is for whole signals instead of sub-segments, given that both languages produced in these conditions are not decomposable. Columns correspond to generations; thin lines show possible relationships between signal elements; and, thick lines indicate a perfect replication of the whole signal. Numbers shown in brackets correspond to frequency information (the number of times that signal was produced at a specific generation).*

When examining the monadic chains more closely, the obvious observation is the gradual reduction in the number of distinct signals, and an increase in the frequency of words more closely related through descent. These two observations are not arbitrarily connected, but rather, when combined, it becomes clear why learnability increases: the reduction in the number of distinct words results in less diversity, which in turn narrows the statistical likelihood of *de novo* strings arising. Subsequently, the system becomes more stable and, as the reduction is systematic in the monadic chains, the final generations exhibit a clear and learnable structure.

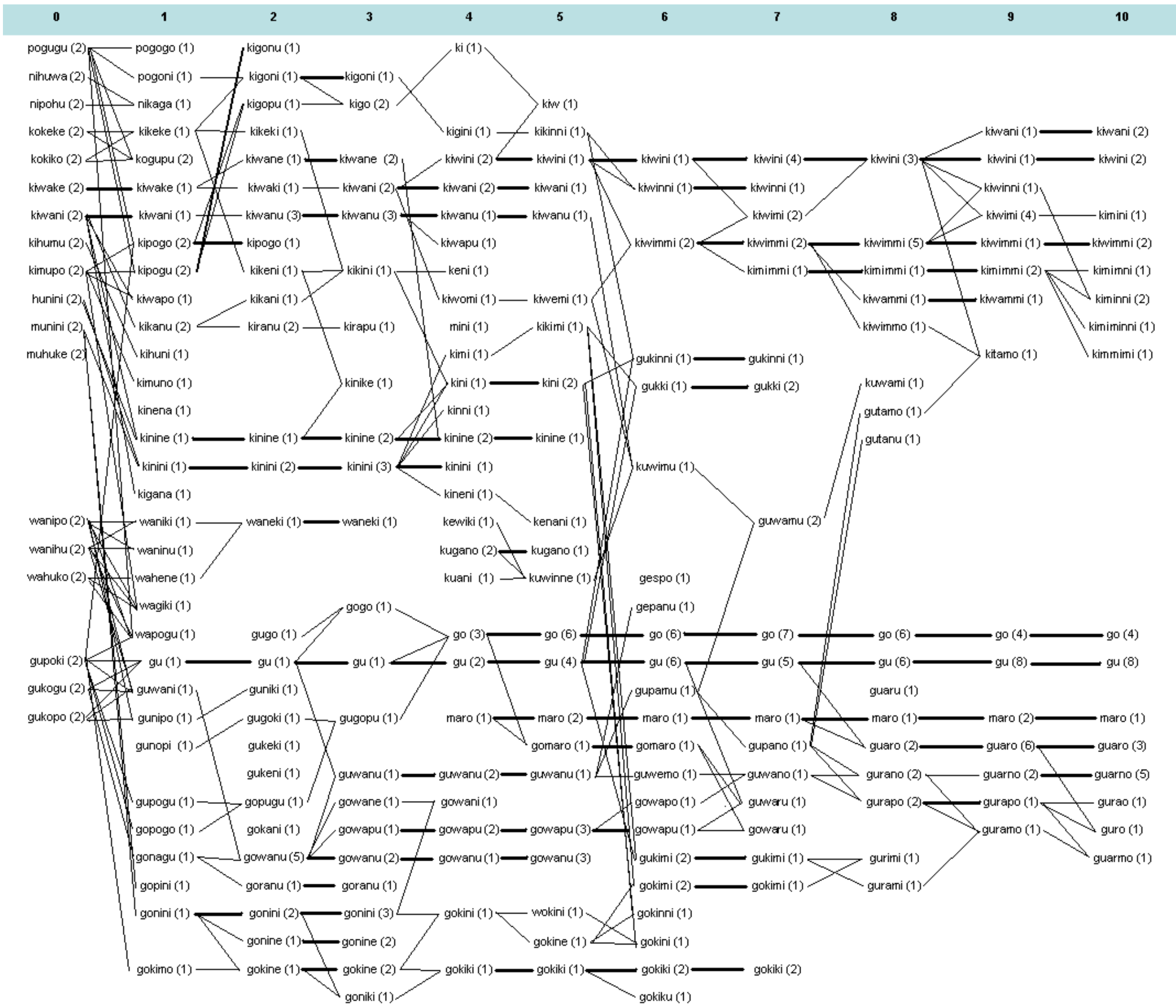


Figure 8. *Coalescent trees showing signal lineages for all 36 items over generations of polyadic condition. Notice that the tree is for whole signals instead of sub-segments, given that both languages produced in these conditions are not decomposable. Columns correspond to generations; thin lines show possible relationships between signal elements; and, thick lines indicate a perfect replication of the whole signal. Numbers shown in brackets correspond to frequency information (the number of times that signal was produced at a specific generation). Notice how the number distinct strings decreases across generations, with both chains converging upon increasingly similar strings/signals.*

As in the monadic chains, the polyadic coalescent tree is an example of a non-compositional system – there is no apparent parsimonious segmentation that consistently corresponds to each of the meaning dimensions. Conversely, the polyadic condition initially increases the number of distinct signals, and only after this initial increase does it begin to decrease – but only to levels not much different to generation 0 (see table). But why do the participants at the first generation end up producing 31 distinct meanings after being exposed to just 18, whilst generation 8 manage to slightly decrease their number to 16?

Generation	0	1	2	3	4	5	6	7	8	9	10
Polyadic Chains	18	31	26	23	27	22	22	18	16	15	16

Table 3. Number of distinct signals at each generation in the polyadic condition. Notice that at both generation 0 and generation 7 there are 18 distinct signals, which almost doubles in the first generation but decreases in the eighth generation. In both instances the total number of distinct signals at each generation are the product of two individuals.

As you can see, both groups of participants were exposed to 18 distinct signals, yet for some reason the later generations are able to decrease the number. In fact, at their sub-component level, the 18 signals at generation 0 display less variation in their number of syllables (10), than those at generation 7 (21). Instead, the reason for this disparity, as suggested by the coalescent tree, is due to the ordering of the sub-components into a more consistent structure. For instance, the number of distinct signal elements beginning with gu at the generation 0 (3) is far less than at generation 7 (7). What this suggests is that the sub-components are ordering themselves in a systematic manner, with certain signal aspects aligning themselves with a particular motion. A brilliant example is the word *maro*. Originally introduced at generation 4, *maro* was perfectly transmitted right through to generation 10, yet the actual frequency of the word remained around 1 per generation. However, the specific sub-component, *ar*, was far more influential and salient in its spread – going from a single appearance at generation 4 to eleven times in generation 10. Therefore, the alignment of *ar* always corresponds to a *spiral* motion by generation 10, which means the word *maro* will also always correspond to this particular motion.

4.4.3. Investigating regularity of mappings in alien languages

As previously mentioned, distinguishing between underspecification and compositionality is difficult to infer from PDC – all we know is that a correlation exists between the meaning structure and signal spaces. To quantify whether or not compositionality has emerged in the languages, a program named *RegMap* (short for *reg*ularity of the *map*ping) is used, which measures the confidence that a particular signal element encodes a specific meaning element is needed (Tamariz & Smith, 2008). Specifically, *RegMap* is "an information-theoretical metric that combines the conditional entropy of meanings given signals and of signals given meanings and normalizes the result to make it comparable across systems of different sizes" (Cornish, Tamariz & Kirby, in press, pg. 8). For any given meaning element (M) and signal segment (S), the *RegMap* is defined by the equation below:

$$\text{RegMap} = \sqrt{\left(1-\frac{H(S|M)}{\log(s)}\right) \times \left(1-\frac{H(M|S)}{\log(m)}\right)}$$

Very simply, $H(X|Y)$ – the *conditional entropy*, which in itself is a method of quantifying the remaining uncertainty of a variable (Y) on the assumption that the value of variable X is a known – is the Shannon entropy (Shannon, 1948), except $p(x)$ is replaced with $p(x|y)$ (Cornish, Tamariz & Kirby, in press). $H(S|M)$ applies to comprehension, in that it is the conditional entropy of the signal segment given the meaning feature; the level of uncertainty about a particular meaning when the segment is a known quantity. Conversely, $H(M|S)$ is the uncertainty about the signal when the meaning is known – and this relates to production (ibid). As such, "The logs of *m* and *s* normalise the values between 0 and 1; *m* is the number of different meaning values (e.g. triangle, circle, square for shape); *s* is the number of different segment variants in the relevant segment position." (ibid, pg. 8). By subtracting the remaining entropies from 1, we can ascertain the level of confidence as opposed to uncertainty (ibid).

Below are the *RegMap* values for the initial, middle and final signal and meaning elements of both polyadic and monadic conditions across 10 generations (figures n). The data fed into *RegMap* consists of strings broken down into three syllables (for instance, *ki-wa-ni*); the rationale being that in Cornish, Tamariz & Kirby their compositional language adapted to the meaning space at the level of the signal elements: for instance, if *ki-wa-ni* was compositional, each syllable may correspond to a different meaning (shape (*ki*), colour (*wa*) and motion (*ni*)). These segmented values are then paired with a meaning space, which consists of numbers corresponding to a specific meaning (e.g. 1=blue, 4=wavy, 7=circle etc). Lastly, to determine the significance of the *RegMap* values, a Monte-Carlo analysis was employed, consisting of 1,000 randomisations of the correspondences between meanings and signals (see table 4).

		Colour S1	*Colour* S2	*Colour* S3	*Motion* S1	*Motion* S2	*Motion* S3	*Shape* S1	*Shape* S2	*Shape* S3	*RegMap* (Language)
	1	0.16783	-0.63157	-1.13663	-0.92256	1.005328	2.457363	-0.81884	0.388446	-0.17524	0.951754546
	2	0.002086	-0.98509	-0.43214	0.631733	1.521454	3.078197	-1.46961	-0.55764	0.879176	-1.472333156
	3	0.20167	1.401317	-1.02941	2.614116	1.837374	0.692362	-1.30356	-0.8652	0.543292	-0.313780699
	4	-0.19397	-0.70535	-1.51629	1.811142	0.044413	0.881275	-1.26134	-1.24567	-1.49942	0.853642636
Monadic A	5	-0.31378	1.287951	-0.54215	2.526472	-0.70661	1.444837	1.229012	-0.56337	1.20479	-0.306894568
	6	-1.11029	-0.63054	-1.51902	6.759614	4.487519	4.664548	1.297254	1.966002	1.811256	-1.323276566
	7	-0.60833	0.703662	-0.53284	8.020848	5.679249	1.53482	-0.79834	-0.84216	0.612932	0.639565908
	8	-1.55404	-0.31816	0.408768	8.09361	2.577962	1.439741	-0.17217	0.940028	0.189961	0.468
	9	-0.08451	-1.09282	-1.12547	3.717863	5.966809	5.37316	-1.12167	-1.06841	1.386944	-1.710912007
	10	-1.01473	-0.65398	-0.13793	4.324063	4.011833	2.860041	-0.84459	-1.13771	-0.86232	-0.750909224

		Colour S1	*Colour* S2	*Colour* S3	*Motion* S1	*Motion* S2	*Motion* S3	*Shape* S1	*Shape* S2	*Shape* S3	*RegMap* (Language)
	1	0.147305	1.453449	1.821834	-0.34709	-0.74563	-0.42841	1.159593	-0.96643	-0.12124	-0.519256947
	2	0.660157	-0.81004	-1.44606	1.192103	4.32988	3.007764	-0.29756	0.575842	0.323457	-0.034617171
	3	-2.19151	-1.92616	-1.01138	3.12406	4.941006	4.475433	0.145873	1.920221	0.848782	-0.421405513
	4	-0.14026	-0.41776	-0.097	2.686932	3.578177	2.192115	-1.88396	0.385138	-0.38017	-0.411785243
Monadic B	5	-1.28158	-1.15892	-1.16758	-0.01419	-0.18903	0.500972	-1.29101	1.898251	1.088019	-1.505765838
	6	-0.87779	-0.6995	-0.23086	2.138777	2.513265	0.06739	-0.65242	0.800968	-1.37973	1.459321548
	7	1.974917	2.529767	0.125391	1.958502	2.186402	1.9734	0.57687	-0.02493	0.48807	-0.926541418
	8	-0.81147	0.427063	-0.50055	6.380394	6.185541	5.185014	-0.94821	-1.00628	3.050559	-3.010675803
	9	-1.26464	-0.01576	-0.51228	6.440252	6.276903	5.181803	-1.50284	-0.76968	3.303901	-3.19860506
	10	-0.93884	0.214729	-0.56062	5.832373	5.416575	5.695034	-1.61531	-1.12624	3.244446	-3.092811019

		Colour S1	*Colour* S2	*Colour* S3	*Motion* S1	*Motion* S2	*Motion* S3	*Shape* S1	*Shape* S2	*Shape* S3	*RegMap* (Language)
	1	0.30064	0.638393	1.283215	0.298916	1.28958	0.456507	0.300436	1.774207	0.65799	-0.458749672
	2	-0.9599	-1.57337	-1.12777	-0.95617	5.997138	5.575769	8.825716	0.98147	0.52816	3.381180727
	3	-1.62394	-0.59464	1.141956	-0.35484	-0.07166	2.688043	5.564119	1.015778	0.021357	3.460833867
	4	0.508684	-0.54267	-0.71989	1.530338	3.902569	2.348022	-0.0152	0.538818	1.538305	-1.418426946
Polyadic A	5	1.02254	-0.78878	-1.53526	0.512062	5.243631	2.883852	0.479927	1.445987	0.165867	1.327823269
	6	-0.56281	-1.36771	-1.41482	0.422787	5.625355	4.347909	0.246366	1.629446	-0.1473	1.561269134
	7	1.441907	-0.24771	-1.5262	-0.12908	4.288788	5.760052	1.260371	2.336477	1.739814	1.36564606
	8	-1.605	-0.95836	-1.22815	4.316907	6.971016	5.600324	1.046342	0.567773	-0.03227	-0.34735033
	9	-0.0143	-1.77705	-0.05349	6.379837	6.749911	7.13928	-0.79163	1.893217	0.973211	-1.864002602
	10	-1.02708	-0.64785	-0.93843	7.021849	6.382948	6.777793	-0.64983	0.942612	1.45724	-1.974483955

		Colour S1	*Colour* S2	*Colour* S3	*Motion* S1	*Motion* S2	*Motion* S3	*Shape* S1	*Shape* S2	*Shape* S3	*RegMap* (Language)
	1	-1.20456	1.153753	0.032636	-0.53451	0.252205	-1.71941	4.033044	-0.67661	-1.02526	2.237751531
	2	-1.59137	-0.26354	-1.05546	-1.63129	-0.25288	-0.78546	4.159555	-0.5857	-0.82402	4.266608479
	3	-0.73804	-1.25102	0.21914	-0.74925	4.519162	3.231535	6.61201	2.069303	0.669051	2.20652583
	4	-1.02911	0.071129	-1.56686	-0.12988	4.926678	3.127075	1.364375	0.853006	-0.09732	1.886061386
Polyadic B	5	-0.12992	-0.23199	-1.12343	2.202715	2.95062	2.767656	-1.02815	1.646803	-0.04532	-0.63907539
	6	-0.89595	-1.41789	-0.45485	0.349207	4.901421	4.009297	1.934496	1.299138	1.161164	1.316315037
	7	-0.5095	-1.33984	-0.12102	3.1763	5.643258	5.122513	-0.11594	1.256198	0.270452	-1.0509506
	8	-1.61364	-2.057	-0.28353	6.353086	6.44223	5.023997	-0.65909	1.137868	-1.02094	-0.068667359
	9	-1.86477	-1.52516	-0.05025	6.345999	7.68403	6.911194	1.038453	1.406572	1.202109	-0.083783584
	10	-1.61153	-0.66401	0.074947	6.467852	7.942617	5.527973	0.849453	1.382659	0.822713	-1.189982114

Table 4. The z-scores for the *RegMap* of both monadic and polyadic conditions. Numbers highlighted in blue indicate a p-value significance below 0.5. Numbers highlighted in yellow indicate a p-value significance below 0.05. Notice that in all four chains, motion is consistently encoded as indicated by the highly significant z-scores.

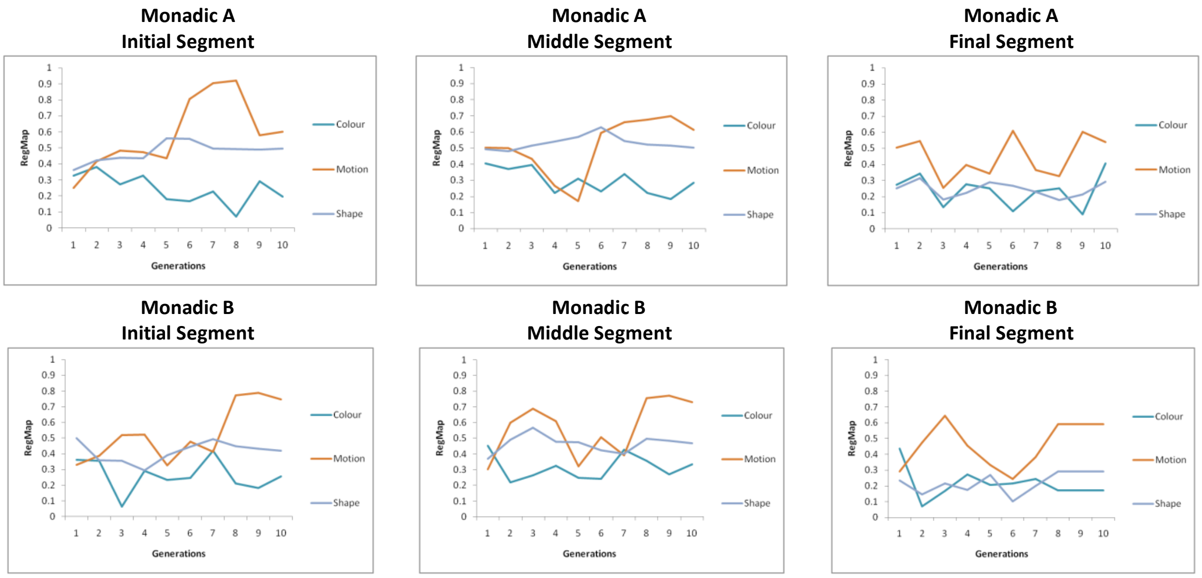


Figure 9. Regularity of the associations between signal and meaning elements of monadic chains A and B, for the initial, middle and final segments. The continuous coloured lines represent *RegMap* values obtained with all nine segment-meaning pairs across ten generations. Notice that in every instance, motion emerges as the meaning dimension with the highest *RegMap* score. This suggests both languages are consistently encoding for motion over colour and shape.

In both the graphs and tables, the general trend of results supports the assertion made throughout this section: in the later generations, motion is being consistently encoded at the initial, middle and final segments (p<0.01). The rate at which motion becomes encoded varies across segmentation and chains, but ultimately all four chains converge upon the same solution. As previously discussed, in Monadic A at generations 6 though to 8 we can see the emergence of an almost perfect mapping between the initial segment and motion. However, at generation 9 the distinction is somewhat lost, even though it retains its significance, as indicated in the table: the z-score of the initial segment drops from 8.09 to 3.72, whilst the final segment goes from 1.44 (non-significant) to 5.37.

Monadic B, on the other hand, is the only chain to record a consistently significant negative *RegMap* score for the entire language (see generations 8, 9 and 10). This is because the *RegMap* is far lower than most of non-significant results, which could be accounted for by chance.

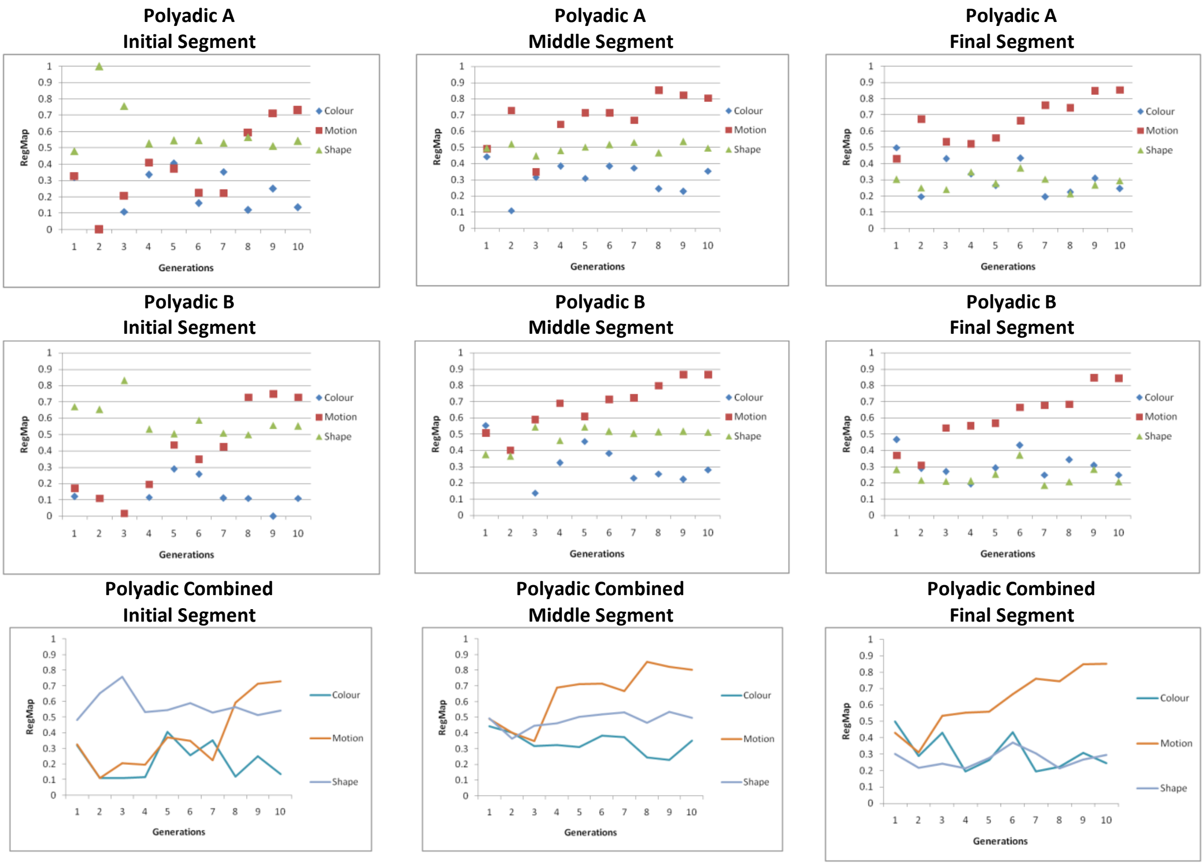


Figure n. Regularity of the associations between signal and meaning elements of polyadic chains A, B and a combination of the best *RegMaps* of both chains for the initial, middle and final segments. Polyadic chains A and B do not have continuous lines because the distinction between chains is arbitrary, with solitary plots representing the *RegMap* values obtained with all nine segment-meaning pairs; likewise for the continuous coloured lines in the polyadic combined graphs. As in the monadic condition, motion emerges as the meaning dimension with the highest *RegMap* score. This suggests the polyadic language is consistently encoding for motion over colour and shape.

Lastly, the polyadic combined graph highlights another common theme of competition: both shape and motion are equally encoded in the initial segment at generation 8, but by generation 9 the conflict is resolved with motion being amplified to dominance.

4.4.3.1. Discussion

In short, the analyses of results outlined above demonstrate the languages in both monadic and polyadic conditions are not compositional. This is in contrast to one of the language families presented in Cornish, Tamariz & Kirby (in press), which converges on compositional system. As you can see in the *RegMap* graphs, most segmentations appear to encode for motion fairly early on in most of the chains. There are some instances where there is competition between meaning dimensions, as seen in the polyadic combined initial segment at generation 8. However, due to the rapid convergence towards stable system early on in all the chains, there is no evolutionary pressure for the languages to become compositional: they are already adequately adapted to their niche. This somewhat validates the use of an artificial bottleneck and filter in other human iterated learning experiments, as participants in this experiment did not need to generalise as there is no unseen set.

Chapter Five

General Discussion

The central position taken by this study is that language is the result of adapting to various niches. It is a complex adaptive system (Beckner *et al.*, 2009), and as such is potentially shaped by dizzying array of factors – one of which being cultural transmission (Smith & Kirby, 2008). Working on this basis, cultural transmission studies are able to investigate through theoretical (Deacon, 1997), experimental (Kirby, Cornish & Smith, 2008) and computational modelling (Kirby & Hurford, 2002) the origin, and subsequent emergence, of structure in language, arguing that the very fact "that language persists through multiple repeated patterns of usage can explain the origins of key structural properties that are universally present in language" (Cornish, Tamariz & Smith, in press, pg. 1). Using these theoretical underpinnings, this study has aimed to further investigate the role of population dynamics in human iterated learning. This section outlines the results of the study, whether or not it supports the hypotheses outlined at the start of this dissertation, how it fits in with the wider literature and lastly, ways in which the methodology can be improved upon for any potential future studies.

5.1. Summary of results

The results of experiments testing both monadic and polyadic conditions can be summarised as follows:

1. In both conditions, the languages on average became more learnable and increasingly structured across the successive generations. This is demonstrated in the replication fidelity of the languages, with the transmission error between generations consistently decreasing, whilst the structure increased.
2. That introducing variability in the input did not hinder or impinge upon the language becoming increasing learnability through the emergence of a systematic structure.
3. As a result, this study has reproduced some of the findings in Kirby, Cornish & Smith (2008) without the need for an artificial bottleneck or filter.
4. Furthermore, by measuring the edit distance between the output of both monadic chains, and then both polyadic chains, the second experimental hypothesis was confirmed: that the polyadic condition will have more similar languages in its final output than the output of participants in the monadic condition.

5. By using coalescent trees, this paper was able to show that in both conditions languages undergo processes commonly associated with natural language change, such as: single segment replacements, reductions, metathesis and blends.
6. As in Cornish, Tamariz and Smith (in press), the results of this study are adapting to a three-element meaning space. However, this is only at a holistic, and not compositional, level.
7. Lastly, all four chains ended up encoding for a single meaning dimension: motion.

The results outlined above offer interesting parallels and dissimilarities with previous studies. With this in mind, the forthcoming section will discuss these results in the context of the broader literature. Specifically, I will consider the notion of the resulting languages being a product of adaptation to the linguistic environment.

5.2. Population dynamics and iterated learning

5.2.1. Adapting to the linguistic environment

The rationale for introducing variability in the input stems from explanatory power of population dynamics in biology (Hawks *et al.*, 2007), culture (Mesoudi, Whiten & Laland, 2006), historical linguistics (Croft, 2006) and recent iterated learning models (Vogt, 2005b; Smith, 2009; Dediu, 2009; Ferdinand & Zuidema, 2009). Interestingly, whilst the particular population variable employed did not hinder the emergence of a systematic language, it also failed to exert any noticeable pressure[22] in actually shaping language development. This is because, in spite of not having an artificial bottleneck or filter, both monadic and polyadic conditions produce languages that are not only increasingly structured and more learnable, but that holistic strings appear to be adapting to encode motion.

Nonetheless, the environment produced by experiment clearly creates pressures that are adequately explained by evolutionary mechanisms of *variation*, *replication* and *selection* when "applied to the mappings between signal and meaning elements" (Cornish, Tamariz & Kirby, in press). Through these respective processes, the linguistic environment forces unstructured mappings between signal and meaning elements to become systematically structured. However, unlike the aforementioned study, it appears the pressures on languages to become learnable are not inclined towards the emergence of compositionality.

[22] The obvious exception being how the signal elements in both polyadic chains became more similar over time, in contrast to the monadic condition: where the signal elements in the two monadic chains are no more similar than two randomly generated artificial languages.

Absence of a bottleneck means absence of compositionality?

But what do these results in the context of transmission bottleneck? That the current experiments failed to produce compositional languages could stem from two possible conclusions. First, by imposing a transmission bottleneck and filter, Kirby, Cornish & Smith (2008) are more accurately mirroring the true dynamic a language learner brings to the task of acquisition: learners must generalise from a sparse, subset of linguistic data. Although this is technically true in accounting for the origins of compositional structure in the laboratory, there are equally compelling alternatives from computational modelling of peer-to-peer learning (Batali, 1998; Vogt, 2005b) and other complex population dynamics (Dediu, 2009). Answering the question of whether or not either one of these scenarios is an accurate reflection of the *actual* pre-linguistic conditions facing our hominid ancestors is currently still within the realm of speculation and conjecture.

Encoding motion: adaptation to a perceptual niche?

Another interesting question raised by this study is: how come the languages resulting from the polyadic and monadic conditions converged upon motion?

If it were just the polyadic condition, I might have argued the shared input resulted in participants converging upon the same solution. Although this might be part of the reason, it obviously fails to explain how the two monadic chains also end up encoding the same meaning dimension. Another alternative stems from the variance in the meaning dimension: given its 3x3x2 meaning-space structure, it is not surprising that the deficient meaning dimension (shape) is not consistently encoded. However, if this is the sole reason for the results, then why was colour not consistently encoded for, even though it shared the same number of meaning-spaces as motion? Instead, we can offer another consideration: languages are adapting to a perceptual constraint for motion, rather than colour and shape (Christiansen & Chater, in press). Partly corroborating this suggestion is a recent research paper outlines the role of the human *parietal cortex* in maintaining colour, shape and motion direction[23] in visual short-term memory (Kawasaki *et al.,* 2009). From their *fMRI* results, Kawasaki and colleagues' most relevant finding for this study is that when all three features were presented to participants, only the anterior portion of the parietal cortex showed distinct activity for motion. Basically, this means that in contrast to the posterior parietal cortex which is memory-dependent for all three features, the anterior section of the parietal cortex "plays a special role in the retention of motion direction information" (ibid, pg. 94).

[23] Importantly, this study looked at motion-direction as an iconic representation, as is the case in this dissertation.

Of course, it is hard to infer too much from Kawasaki *et al.*'s findings in relation to this study. Yet if motion is held in visual short-term memory in a distinct manner, then this offers a potential explanation to the results of this study: languages are the products of very similar perceptual environments. Linking in with this notion is Chater & Christiansen's discussion of studies into coordinated learning and *rapid convergence* (Feldman, 1997; Tenenbaum, 1999), which show "that people converge on the same categories incredibly rapidly, given a very small number of perceptual examples... Moreover, when people are allowed to interact, they rapidly align their choice of lexical items and frames of reference, even when dealing with novel and high ambiguous perceptual input" (2009, pg. 10). The level of interaction taking place is obviously limited in this study, given that the only aspect linking participants is that one will observe, and attempt to reproduce, the output of the previous participant. Nonetheless, the present observations certainly provide an impetus for further investigation.

Chapter Six

Conclusion

The current experimental results demonstrate that variability in the input does not hinder the emergence of a systematic and highly learnable language in human iterated learning. Furthermore, we have gained a glimpse at how languages exposed to different population dynamics can still converge on the same adaptive solution. That this structure emerged without the need for an artificial bottleneck or filter has important implications for future research, namely: do we need these conditions for the emergence of compositionality?

As it stands, this experiment was unable to reproduce the results of Kirby, Cornish & Smith (2008) in seeing the development of a systematic and stable compositional language. However, we have only scratched the surface of investigating the role of population dynamics. There is certainly an opening for both horizontal and vertical transmission to be examined in iterated learning. Another potential road to traverse concerns the role of biases and how they impact upon explanatory framework of cultural transmission. Bayesian models are continuing to lead the way in examining the relative roles of the transmission, biases and population dynamics. Yet there is still a significant gap between translating the results in modelling into something we can understand and use to interpret laboratory results.

At the start of this dissertation, I outlined the disparity between research into evolutionary biology and evolutionary linguistics. However, through a strong interdisciplinary framework across the theoretical, mathematical and experimental paradigms, recent decades have certainly seen the study of language evolution close in on its biological forbearer. Even though experiments into this expanding discipline are still in their infancy, it is with that infancy a degree of excitement emerges as to where the field will eventually take us.

Appendices

Appendix I

Questionnaire

1. How difficult would you rate the task of learning the alien language (on a scale of 1 – 5, with 1 being very easy and 5 being very difficult)?

2. How did you go about trying to learn the language?

3. Did you notice any patterns in the labels and meanings?

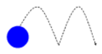
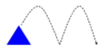
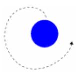
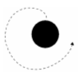
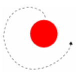
4. How confident were you that you knew the correct label for each meaning?

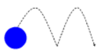
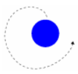
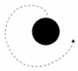
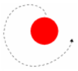
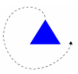
5. Did you recognise all the meanings/ pictures you saw during the testing phase?

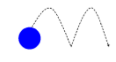
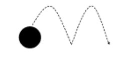
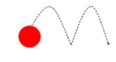
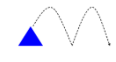
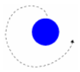
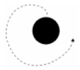
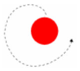
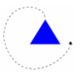
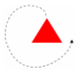
6. If you couldn't remember the exact picture to label correspondence during testing, did you try to use a pattern of some kind?

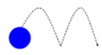
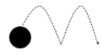
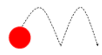
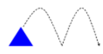
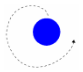
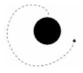
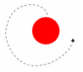
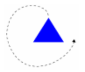
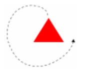
Appendix II

Language families

Gen (Polyadic)	0a	0b	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b
	pogugu	pogugu	pogoni	gu	gonini	gugoki	gonini	gonini	kinni	gokini	gowanu	kini
	nihuwa	nihuwa	pogogo	gopogo	gonine	gugo	gonini	kinini	kinine	gokiki	gokiki	kiwini
	kokeke	kokeke	kikanu	gupogu	gonini	gokani	gokine	gonine	kigini	kiwomi	gokine	kikimi
	kiwake	kiwake	kiwake	kinine	kinine	kikeni	kigoni	kiwani	kiwini	kiwini	guwanu	kinine
	kimupo	kimupo	kiwani	kiwapo	kinini	kikani	kinini	kiwani	kiwani	kikine	wokini	kuwinne
	hunini	hunini	waninu	kinini	kinini	kigonu	kinine	kinine	kinini	kineni	kiw	kikinni
	wanipo	wanipo	kipogo	gunipo	gowanu	gokine	gu	gonine	go	gu	gu	go
	munini	munini	nikaga	guwani	gowanu	guniki	gokine	gogo	kugano	go	go	go
	kokiko	kokiko	kipogo	gonini	gowanu	gu	goranu	goniki	go	keni	go	gu
	gupoki	gupoki	kigana	kimuno	kiwanu	kigoni	kinini	kigo	kimi	ki	gu	gowapu
	gukopo	gukopo	wagiki	kinena	kipogo	kiwaki	kiwane	kikini	mini	kiwani	gu	go
	muhuke	muhuke	wapogu	kipogu	kiwanu	kikeki	kiwanu	kigo	kini	gu	go	kini
	kiwani	kiwani	kihuni	gonagu	gowanu	gukeki	gowapu	gowane	kugano	guwanu	maro	gowanu
	kihumu	kihumu	kogupu	gunopi	goranu	gopugu	guwanu	gowanu	kiwapu	gowani	gomaro	kugano
	nipohu	nipohu	kikanu	gokimo	gowanu	gukeni	gugopu	gowanu	gowapu	gowanu	kiwani	gowapu
	wahuko	wahuko	waniki	kikeke	kiranu	kigopu	waneki	kiwanu	maro	kewiki	kenani	maro
	wanihu	wanihu	kogupu	gopini	kiwanu	waneki	kinike	kiwanu	kuani	guwanu	kiwanu	kiwemi
	gukogu	gukogu	kipogu	wahene	kiranu	kiwane	kirapu	kiwane	gowapu	kiwanu	gowanu	gowapu

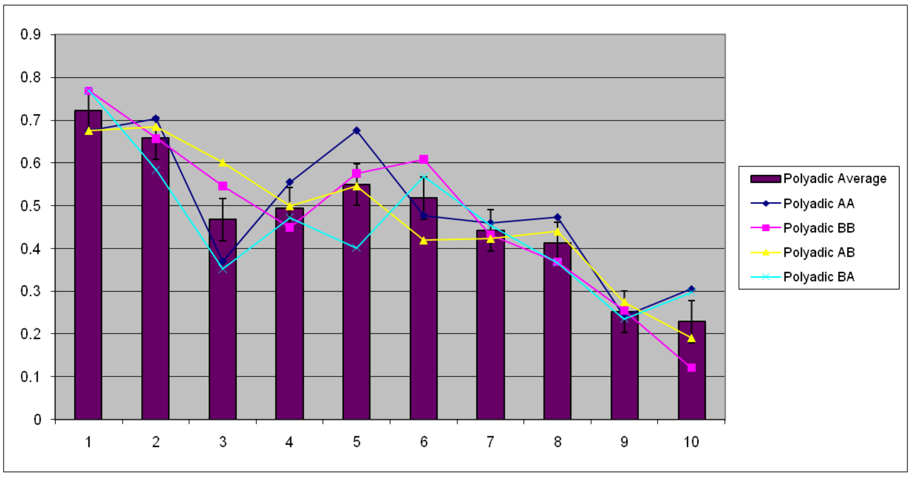
Gen (Polyadic)	6a	6b	7a	7b	8a	8b	9a	9b	10a	10b
	gokimi	gukki	gukki	kiwini	kiwimmi	kiwimmo	kiwini	kiwimi	kimini	kiwani
	gokini	gokiki	gokiki	kiwimi	kiwimmi	kiwini	kiwimmi	kiwimi	kiminni	kiwimmi
	gokinni	kiwini	gokiki	gukimi	kiwini	kiwimmi	kiwammi	kimimmi	kiwini	kiwimmi
	gukinni	kiwimmi	gukki	kiwini	kiwini	kimimmi	kiwani	kiwinni	kiwini	kiwani
	gokiki	kuwimu	gukinni	kiwini	kiwimmi	kiwimmi	kiwimi	kimimmi	kiminni	kimimni
	gokiku	guwemo	kiwimmi	kiwinni	gurimi	kiwammi	kiwimi	kitamo	kimiminni	kimmimi
	gu	go	go	gu	go	go	gu	go	gu	go
	gu	go	go	go	go	go	go	go	gu	go
	gu	go	go	go	go	gu	gu	go	gu	go
	gu	gu	gu	gu	gu	gu	gu	gu	gu	gu
	go	gu	gu	gu	gu	gu	gu	gu	gu	gu
	go	go	go	go	gu	go	gu	gu	go	gu
	gokimi	maro	guwaru	guwamu	gurapo	guaru	guaro	guarno	guro	guarno
	gowapo	gomaro	gowaru	gupano	gurano	guaro	guaro	guaro	gurao	guarno
	gowapu	gepanu	kimimmi	guwamu	gurapo	kuwami	maro	guaro	guarmo	guaro
	kiwinni	gespo	kiwimmi	kiwini	gurano	gutamo	guramo	guarno	guarno	guarno
	gukimi	gupamu	gokimi	guwano	gurami	gutanu	gurapo	guaro	guaro	guaro
	gukimi	kiwimmi	maro	kiwimi	maro	guaro	maro	guaro	guarno	maro

Gen (Monadic A)	0a	1a	2a	3a	4a	5a	6a	7a	8a	9a	10a
	pogugu	nikawe	wanaha	nehipo	wannapo	wannapo	wannawe	wannawe	wannapo	wanipo	wannapo
	nihuwa	nihuwa	guannapo	guannapo	wannapo	wannawe	nehipo	wannapo	wannapo	wannapo	wanipo
	kokeke	wanahe	wallapo	wanhipi	nehipo	wannawe	wannawe	wannapo	wannapo	wanapo	wannapo
	kiwake	guwana	nahapo	wannawe	wannawe	wannapo	wannawe	wannapo	wannapo	wannapo	wanipo
	kimupo	guannpo	guannpo	guannapo	gehipo	nehipo	wannawe	wannawe	wannawe	wanipo	winnipo
	hunini	hihoho	nehipo	nehipo	wanawe	nehipo	wannapo	wannapo	wannapo	wanawe	wanipo
	wanipo	wanapo	wanapo	wanapo	wehipo	wanapo	wanapo	wanawe	wanapo	wannawe	wannipe
	munini	guanpo	guanapo	guanapo	guannapo	nehipo	wanapo	wanawe	wanawe	wanawe	wanawe
	kokiko	wanipo	wanapo	wanapo	wanapo	wanapo	wanapo	wanapo	wanapo	wanawe	wannapo
	gupoki	wanapo	wanapo	wanapo	wanapo	wanapo	wanapo	wanapo	wanawe	wanawe	wannapo
	gukopo	niwapo	gukiwe	guanawe	nehipo	wanapo	wanapo	wanawe	wanawe	wanawe	wannawe
	muhuke	nihapo	wanawe	wanapo	wanapo	wanapo	wanapo	wanawe	wanapo	wanawe	wanawe
	kiwani	gukiwa	gukiwa	gukiwe	guhiwie	wannapo	guihikipowe	guihipipo	guhipipo	gihipipowe	guhithiko
	kihumu	wanaho	wanahe	guannapo	guikiwe	guihikipo	nehipo	nihipo	guhipipo	guihikipowe	guithike
	nipohu	kiniwa	wannapo	wannawe	nehipowe	guihipowe	guihikipowe	guihikipow	guihikipowe	guhipipo	guihipikowe
	wahuko	gukiwa	gukiwa	wahipo	nehipo	wanapo	guhipipow	guihipipo	guihikipowe	guhipipo	guihikipowe
	wanihu	nikiwa	guwana	wanawe	guwinike	wanapo	guhipipow	guhipipo	guihipipo	guihipipo	guihipipo
	gukogu	pokipo	gukiwa	guikiwe	wannapo	nehipo	guhipipow	guihikipowe	guihikipo	guihipipo	guihipipo

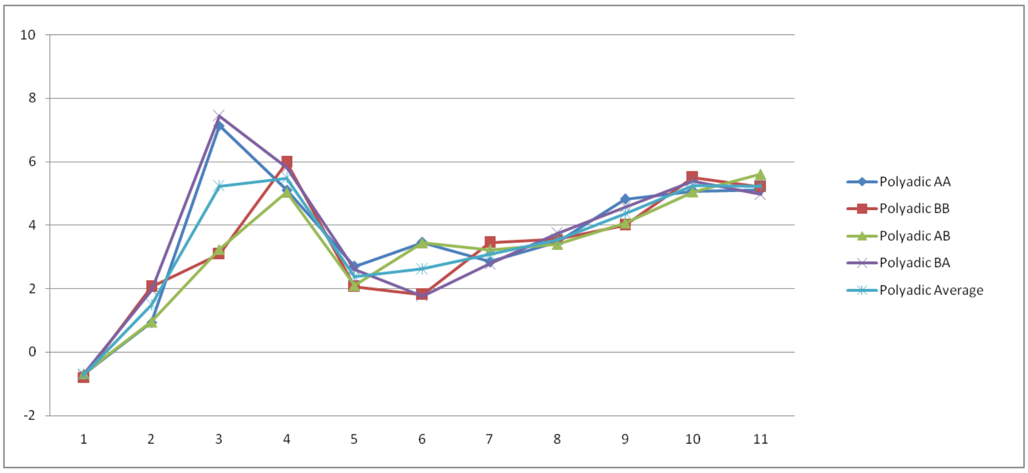
Gen (Monadic B)	0b	1b	2b	3b	4b	5b	6b	7b	8b	9b	10b
	pogugu	gupogo	gowaki	huwaki	wahiki	gopoko	gopogo	mahini	mahini	wakini	wakini
	nihuwa	gowaki	gopogo	huwaki	humini	humuni	wikini	wikinini	wikinini	wakinini	wakinini
	kokeke	wahiki	wahiki	huwaki	wahiki	minini	gopoka	miuni	mahinini	wakini	wakini
	kiwake	kiwaki	wahiki	humini	humini	wahiki	wikini	wahini	mahini	mahini	mahini
	kimupo	wahuko	huwaki	waki	humini	minini	humini	wikinini	wakinini	wakinini	wakinini
	hunini	wahiki	wahiki	wahiki	wahiki	wahiki	minini	gopogo	wakini	wakini	wakini
	wanipo	gokiki	gopogo	gopogo	muini	miuni	minini	miuni	miuni	miuni	miuni
	munini	huwaki	hunini	huini	gopogo	gopogo	miuni	miuni	miuni	miuni	muini
	kokiko	gupoke	gopoki	gopogo	gopogo	wanini	miuni	miuni	miuni	miuni	miuni
	gupoki	gopoki	munini	munini	wakape	hakini	wahini	wahini	miuni	miuni	muini
	gukopo	munini	munini	munini	munini	wahiki	wahini	wahini	gopoka	gopoka	gopoka
	muhuke	gopoki	munini	munini	munini	gopogo	wahini	miuni	miuni	miuni	miuni
	kiwani	gupoki	gupoke	kepoke	minoke	manini	manini	mahini	gopogo	gopogo	gopogo
	kihumu	hupoko	hupogo	gopopo	muini	gopogo	gopogo	gopoka	gopoka	gopoka	gopoka
	nipohu	kekoke	kekoke	kepoke	gopogo	gopoka	minini	gopoka	gopoka	gopoka	gopoka
	wahuko	wanini	gopoki	gopogo	gopogo	gopogo	gopogo	wahini	gopoka	gopoka	gopoka
	wanihu	gowako	kepoke	kepoke	kepoke	gopogo	gopoka	gopogo	gopoka	gopoka	gopoka
	gukogu	wahiki	wapogo	hupogo	gopogo	minini	minini	gopoka	gopoka	gopoka	gopoka

Appendix III

Other graphs



Polyadic Average for Learnability



Polyadic Average for Structure

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