UNIVERSITY OF CALIFORNIA

Los Angeles

Collective Cultural Evolution:

Innovator emergence in language diffusion chains

A thesis submitted in partial satisfaction of the

requirements for the degree Masters of Science

in Biology

by

Shyla L Hardwick

2018

ABSTRACT OF THE THESIS

Collective Cultural Evolution:

Innovator emergence in language diffusion chains

by

Shyla L Hardwick

Master of Science

University of California, Los Angeles, 2018

Professor Peter Nicholas Nonacs, Chair

Cultural transmission of language evolves in a way that increases transmitability. Over generations languages become more adaptive—increasingly structured and less liable to transmission error. However, the underlying mechanisms of this process are largely unmapped. Here, we survey an iterated learning model and individual language trajectories longitudinally. Language variation of individuals over multiple diffusion chains unveils individual adjustments as structure emerges. A behavioral archetype, "Great Innovators", emerges and displays diffusion chain fitness effects. Our results reveal a mechanism of language change in a social environment and exhibit how language evolution adheres to coordination rules.

The thesis of Shyla L Hardwick is approved

Greg A Bryant

Noa Pinter-Wollman

Peter Nicholas Nonacs, Committee Chair

University of California, Los Angeles

2018

Table of Contents

Table of Figures

1.Introduction

A central tenet of communication is the transmission of information from one individual to another. In human systems, language is a well-documented communication scheme (2) centered on the exchange of words in a web of interactions (5). Words are the products and conveyers of cultural evolution and language learners often reverse engineer information with unlimited heredity (3). Humans have studied the evolution of language for centuries yet are just beginning to understand how to explore language evolution in an experimental setting (1,10,11). Now, using computer software and human participants (1), we can assay trajectories of new words from existing forms in relation to context (1,9).

Experimentally, the cultural transmission of language is surveyed through a method called iterated learning (2). Iterated learning is a process of diffusion in which one individual learns behavior by observing another individual who learned the behavior previously. The learning output of one becomes the input for another's learning task. Through iterated learning transgenerational adaptations in the form and function of words occur (1,10,11). This learning process is analyzed through agent-based simulation, mathematical models, and laboratory experiments yet its underlying mechanisms have proven difficult to unearth (1,7,6,9,10).

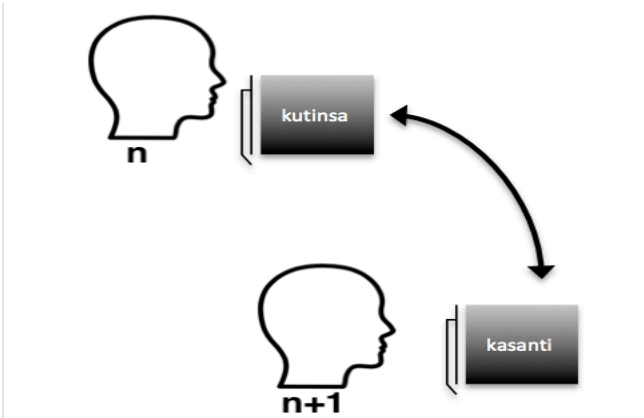

Figure 1- Example of iterated learning model One generation (n, n+1) of an iterated learning diffusion chain experiment. Two boxes show one transgenerational step of a single word. String changes from “kutinsa” to “kasanti”.

Language experts often view language as an information sharing system based on cultural inheritance. Studies indicate that iterated learning language systems exhibit quantifiable heritable variation (1,2,9,10) and hypothesize an “invisible hand process” molds these heritable modifications(4,5,2). Iterated learning models (figure 1.) are orchestrated by chains in which one individual transmits information to another, while the other individual tries to accurately reproduce the information to the next generation. In a traditional diffusion chain model, information transferred from one individual to another individual marks one generation. As generations progress, languages become less subject to between-individual transmission error (1,10,11). It is evident these trends are an inherent feature of cultural inheritance (10) but are the tendencies resulting from transmission of language due to design without a designer or are there other mechanisms at play as structure emerges and diffuse transgenerationally? Here, we attempt to answer this question by assaying data collected from an iterated learning transmission chain model.

2. Results

In each diffusion chain some individuals contribute more changes in linguistic form than others. We define these individuals as Greatest Innovators (GI) and quantify change in linguistic forms per diffusion chain per locale of GI. We define locale as position in a diffusion chain of length 10. Additionally, we find within the well-documented language evolution process, in which string-picture pair correlation leads to transgenerational fidelity (1,11,13), innovators emerge and influence diffusion chain on the basis of the social location.

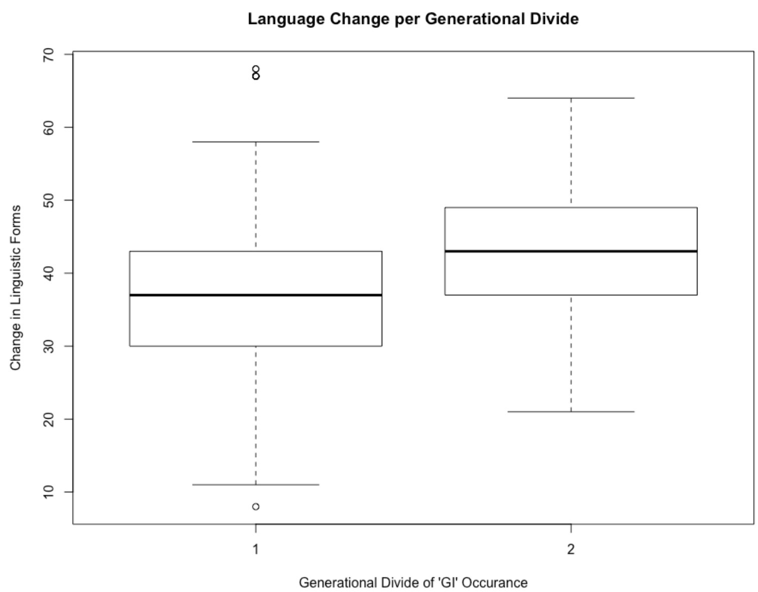

Figure 2 - Language Change per Generational Divide When innovators occur in first stage of diffusion chain (n=1 to 5) diffusion chains undergo less language change overall.

3. Methods

3.1 Data Acquisition

We analyzed data from iterated learning diffusion chains recorded on Amazon Mechanical Turk (1). Diffusion chain models allow observation of natural language change as words are transmitted from generation to generation. Data collected included 240 participants randomly sorted into 24 transmission chains. Each chain was 10 generations long. There were two training set sizes of 12 and 15 string picture pairs (1). Participants were asked to learn a novel language (picture-string pairs). After being trained on a picture paired with an alien string of characters the participant's goal was to reproduce the language. Each chain was initialized with a randomized string for each picture. After initial learning (n) the output was passed to the second individual in the chain (n+1). There were two rounds of learning and participants were tested on language sets in their entirety. The distance between a learners test set and corresponding output quantified language change. The experiment used (1) was modeled after a well-defined experimental approach to the origins of structure in human language (9,10,13).

3.2 Language Change

We used Levenshtein distance to edit each diffusion chain (14). The mean string distance between words gauge language structure.

3.3 'Greatest Innovator' analysis

We defined most innovative individuals within diffusion as those that make most changes to the language within the span of 10 generations. GI locale is widely distributed across generations (Figure 3.)

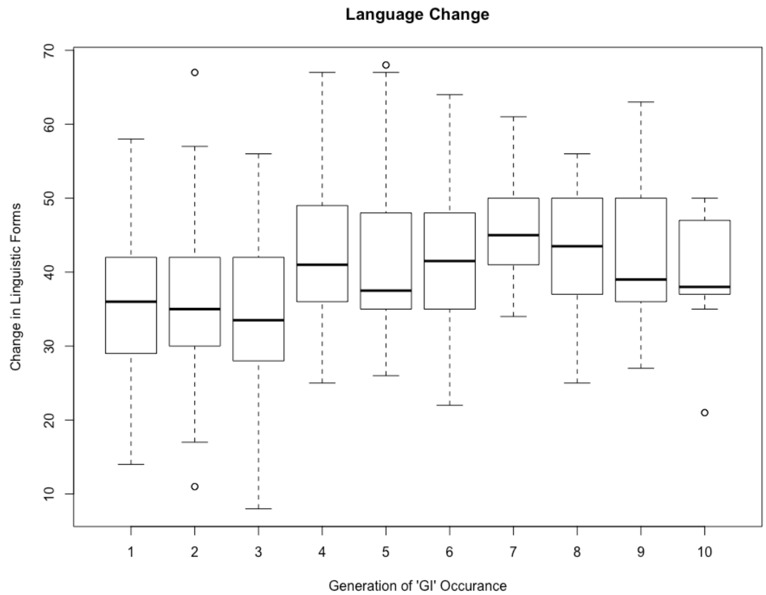

Figure 3 - Change in linguistic forms per diffusion chain in respect to GI locale.

4. Conclusion

Cultural transmission of language evolves in a way that increases transmitability. A between-chain analysis of language change over 24 transmission chains reveals the transgenerational effects behavioral archetype, “Great Innovators”, in the language evolution process. Over generations, language becomes more adaptive— increasingly structured and less susceptible to between-individual innovation. This structure is not unmediated and purely consequential of transgenerational inheritance. Our results reveal a notable mechanism at play that increases transmitability of a language over generations. The emergence of language structure and adaptability in response to selection pressure on faithful transmission signifies how language can be thought of as a process of cultural selection. Here we show “Great Innovators’ exist and impact the language system. Our results aid in unearthing benefits of un-intentional changes in a progressively social environment and show how a distributed system such as language adheres to coordination rules.

References:

1. Beckner, Clay, Janet B. Pierrehumbert, and Jennifer Hay. "The emergence of linguistic structure in an online iterated learning task." *Journal of Language Evolution* 2.2 (2017): 160-176.
2. Centola, Damon, and Andrea Baronchelli. "The spontaneous emergence of conventions: An experimental study of cultural evolution." Proceedings of the National Academy of Sciences 112.7 (2015): 1989-1994.
3. Centola, Damon. "The spread of behavior in an online social network experiment." science 329.5996 (2010): 1194-1197.
4. Chomsky, Noam. "Generative grammar." *Studies in English Linguistics and Literature* (1988).
5. Dorogovtsev, Sergey N., and José Fernando F. Mendes. "Language as an evolving word web." Proceedings of the Royal Society of London B: Biological Sciences 268.1485 (2001): 2603-2606.
6. Dyer, John RG, et al. "Consensus decision making in human crowds." Animal Behaviour 75.2 (2008): 461-470.
7. Gong, Tao, and Lan Shuai. "Computer simulation as a scientific approach in evolutionary linguistics." Language Sciences 40 (2013): 12-23.
8. Gong, Tao, Lan Shuai, and Menghan Zhang. "Modeling language evolution: Examples and predictions." Physics of life reviews 11.2 (2014): 280-302.
9. Kirby, Simon, and James R. Hurford. "The emergence of linguistic structure: An overview of the iterated learning model." Simulating the evolution of language. Springer London, 2002. 121-147.
10. Kirby, Simon, Hannah Cornish, and Kenny Smith. "Cumulative cultural evolution in the

laboratory: An experimental approach to the origins of structure in human language." Proceedings of the National Academy of Sciences 105.31 (2008): 10681-10686.

11. Kirby, Simon, Tom Griffiths, and Kenny Smith. "Iterated learning and the evolution of language." Current opinion in neurobiology 28 (2014): 108-114.
12. Shuai, Lan, and Tao Gong. "Language as an emergent group-level trait." Behavioral and Brain Sciences 37.3 (2014): 274-275.
13. Smith, Kenny, Simon Kirby, and Henry Brighton. "Iterated learning: A framework for the emergence of language." Artificial life 9.4 (2003): 371-386.
14. van der Loo, Mark, et al. "Package ‘stringdist’." (2018).