Notes on cultural evolution of emergent group-level traits applied to bifurcation of political language and conceptualization

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Matthew Turner

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1 Introduction

This paper explores some issues in language use as a group-level trait. I begin with a motivation below: I think a verbal model articulated by George Lakoff is promising, but lacks a serious theoretical social science foundation. I believe a formal model of cultural group selection that accounted for emergent group formation could provide the necessary foundation for Lakoff's verbal model. Since Lakoff's model is about the distribution of concepts in individuals' heads, it's necessary to have a representation of concepts, and I suggest one that I think could work in an emergent group-level trait framework. I continue on to explore the iterated learning model for the evolution of language, and evaluate it in comparison with a fledgling formal model of group language use as an emergent group-level trait.

1.1 Motivation

What causes members of a population to interpret the same word in different ways? The case of a word having multiple meanings is technically known as polysemy. Language has the problem of persistent underdeterminism because the world around us is constantly changing. If the world to which our language ultimately refers is changing faster than language, language can't express everything in the world. However, language changes more rapidly than genes. In this way, languages can fit the mold of biology, but better language can serve as a basin of attraction for genetic evolution. In other words, language/communication evolves culturally towards optimality given a particular biological machine. However, this biological machine encoding will self-optimize for the language family that is used among the population it encodes. Language is a clumsy way to talk about language, is it not?

Language also seems to be a social marker: we identify who to work with based on the language they speak (Smaldino, Flamson, & Mcelreath, 2017). The purpose of this review is to identify the linkages between language evolution and the cultural evolution of groups and group-level traits.

In the political realm, polysemy of words like *justice*, *liberty*, and *freedom* is unavoidable. George Lakoff has suggested bifurcation of political opinion and conceptualization in the United States is due to the human tendency to think of the nation as a family. He argues "conservatives" and "progressives" don't share the same conception of the family prototype. Lakoff claims the progressive family prototype is that of a "nurturant parent family," where parent roles are not gendered and corporal punishment is not used or accepted. On the other hand, in Lakoff's model, conservatives conceptual prototype of the family is supposed to be a "strict father family." In the strict father family the father has ultimate and unquestioned sovereignty over all other members of the household. Violence is to be used to protect that sovereignty (Lakoff, 1996). While the details of this model are questionable on a number of grounds, the general idea that concepts are interrelated, interdependent, and hierarchical has about a forty-year history in cognitive science, starting perhaps with Rosch (1975). I am inspired by Lakoff's work to better understand this conceptual bifurcation, and to express his ideas in the language of *The Cultural Evolution of Emergent Group-level Traits* as expressed by (Smaldino, 2014).

I think Lakoff's hypothesis could be addressed and formalized using the appropriate cultural evolutionary theory. One important question cultural evolutionary theory could answer is, What is the direction of causality, if there is one, in the case of conceptual bifurcation in Unites States politics? That is, were there first progressives and conservatives, or were there first differences of family conceptualization, and in either case how do these concepts interact? Lakoff (2014) provides a framework to develop a neurological understanding of conceptual bifurcation, which could assist in further development of the psychological underpinnings of any cultural evolutionary model.

One successful approach to modeling language evolution is the iterated learning model. One issue is that language evolution dynamics are lost as solutions are found only for equilibrium distributions of language types (Smith & Kirby, 2008). Of course in biology a being in equilibrium is dead! Therefore I suggest an approach to studying the dynamics of iterated learning that I hope will have applications to quantifying and modeling the evolution of language away from equilibrium. New measures for "polarization" can define what a group is, within a certain tolerance. Information theory will help us quantify the difference between clusters.

2 The Cultural Evolution of Emergent Group-level Traits

I will try to argue that language, or, equivalently, internal conceptual relationships, could be considered an emergent group-level trait, as articulated by Smaldino (2014). An emergent group-level trait is, for example, "the music rather than the rock band," or "the sailing ship's voyage rather than the crew positions." Thus, the emergent behavior is the group-level trait. This is distinguished from collective behaviors, such as flocking. Collective behaviors "result from a number of interchangable individuals acting independently." In another example, Smaldino compares a Roman legion to a barbarian horde, suggesting that legioning allows individually-weaker Roman legionnaires to defeat individually-stronger barbarians. Thus, to map this to the Lakoff model, I suppose the emergent group-level trait for conservatives is "conserving" and progressives it's "progressing." In seriousness, though, this model seems to pose some challenges for naming these not-collective-but-emergent-group-level behaviors.

Why, in the theory of the cultural evolution of emergent group-level traits should music or a ship's voyage be the replicator that's "selected for?" In the emergent group-level trait framework, "group-level traits exist fundamentally at the level of groups and can therefore only be defined in those terms." As a first step toward recasting Lakoff's hypothesis, I believe we can identify some combinations of traits that enable the differentiation between progressive and conservative. In this way, being progressive is still the emergent group-level trait. Progressive political action requires not just a single set of trait values, but the interaction of many individuals' traits. The challenge, that I don't see a clear answer to, is how to assign a value to a particular emergent group-level trait, either in an absolute sense or in relationship to other emergent group-level traits.

One challenge I see that I do have an idea how to answer is that of determining how many groups there are at any given time. A preliminary challenge, for applying the theory of Smaldino (2014) to the Lakoff problem, is to determine a representation for concepts of an individual that can combine with other conceptual representations of other individuals to create emergent group-level conceptual systems. There are many ways for the meaning of words to be associated with the meanings of other words. One popular one is a vector space model of word embeddings in a corpus, for example using the word2vec algorithm (Mikolov, Chen, Corrado, & Dean, 2013). Each word appearing in the corpus is assigned a vector based on how often it appears in the same phrase with other words. Leaving out many details, one is left with a data structure in which every row is a $M-$dimensional representation of the word's meaning. Amazingly, using word2vec, one can perform conceptual arithmetic with properly trained models. For example, using the Google News word embeddings provided as part of the code and data accompaniment to Mikolov et al. (2013), the closest vector to the nearest word vector to the result of the vector arithmetic `Germany + France - Paris` is `Berlin`. So, I propose that we can represent a collection of concepts as a matrix, or equivalently a flattened vector of the entire conceptual system. Then, assuming we are working with flattened concept vectors, we can define a similarity measure between individuals' conceptual system vectors. Given that, some kind of clustering model could be fit to the points in conceptual space defined by each individual's conceptual system. The distribution within clusters can tell us about how each cluster might generate group-level traits that persist because they have found a way to be self-perpetuating. An oustanding question: mustn't this self-perpetuation still act through increasing individual payoffs?

3 Iterated learning models of language evolution

Iterated learning is meant to model the interaction between biological biases towards certain types of language and the cultural evolution of language. The iterated learning model (ILM) is a specialized Markov model. In a Markov model, the future state depends on only the previous state of the system, a property known as the Markov property. a population is split into N subpopulations, with the percentage of the i^{th} subpopulation denoted p_i. For iterated learning of language, p_i is said to be the fraction of the population speaking language i. When we want to include time dependence, we add a t index after a comma, $p_{i,t}$. The difference equation for the prevalence of each subpopulation is

$$p_{i,t+1} = \sum_{j=1}^{N} Q_{ji} p_{j,t} \tag{1}$$

Q_{ij} is the transition matrix. We could write this more compactly in matrix-vector notation as $p_{t+1} = Qp_t$, where p_t is the vector of all $p_{i,t}$. In ILM Q is assumed to be time independent; when the transition matrix is time independent, the Markov chain is labelled *homogeneous* (Griffiths & Kalish, 2007, p. 445). The ILM further assumes that the transition matrix has exactly one eigenvalue of unit magnitude (Griffiths & Kalish, 2007, p. 446). Briefly, this means that there exists a *stationary state* p^* such that $p^* = Qp^*$. In other words, no iteration needs to be done to find the final state of the system, one needs only to find the first eigenvector of Q, and it turns out to be p^*. An alternative, intuitive definition is

$$p^* = \lim_{t\to\infty} Q^t p_{t=0} \tag{2}$$

for any valid distribution $p_{t=0}$, i.e. $\sum_i p_{i,t=0} = 1$. In other words, we could equivalently find the stationary state if we iterated as defined in Equation 1 until $|p_{t+1} - p_t|$ had decreased to below some tolerance.

Up to this point, I have just presented some facts about the type of Markov chains assumed to be at work in the ILM. We have covered the "I" in ILM: iteration. Where is "learning"? It is in the values of Q_{ij} themselves. In the iterated learning model of language change, these represent the probability that a speaker of language i at time t will speak language j at time $t+1$. Each speaker is assumed to be exposed to a certain number of utterances, or data, d, at each time step. The learner in this model must decide which language they heard based on this data and choose the language that they believe is most representative of the data they have observed. In terms of probabilities, we modify notation of Equation 4.6 in (Smith & Kirby, 2008) and write

$$Q_{ij} = P(\text{choose } i \text{ at } t+1 \mid \text{speaker of } j \text{ at } t) = \sum_d P_L(\text{choose } i|d)P(d|\text{speaker of } j) \tag{3}$$

The goals of ILM are typically to characterize p^* for some set of parameters. These parameters include the data "bottleneck," or how many example data d a learner sees, i.e. the number of summands in Equation refeq:qij-elements. Learning is parameterized by choice of calculating these probabilities written in Equation 3. Further detail about how these probabilities are calculated is important, but left to the references. The important takeaway is that the dynamics are entirely determined by a time-invariant transition matrix Q. The typical approach is to find a stationary distribution p^* of Q, then analyze how the stationary distribution changes with changes in learning parameters, that eventually result in changes in the calculation of probabilities in Equation 3.

Immediately we can see that this particular approach will not do for emergent group-level traits, or any *emergent* trait for that matter. Any emergence that had occurred happened before the stationary state was reached. Stationary states are in equilibrium, and equilibrium is death! Perhaps Markov chains could be interesting, but it would have to be in the time before a stationary state was reached. Transition matrices could be based on data in the form of expressions of traits. In the Lakoff-inspired concepts model I proposed, traits are vector representations of concepts. Learners could have a similar updating strategy as in ILM. What we gain is the capability to simultaneously track the flow of information within and between groups based on the differences in traits. Given the right dynamics, groups could come into and out of existence. When equilibrium is reached, the groups that remain can be identified as attractor groups.

4 Conclusion

Conceptualizing language use as the exchange of information about individual traits, we have seen the potential of how iterated learning methods could work with the framework of emergent group-level traits. Iterated learning in the limit of $t \to \infty$, as practiced by (Smith & Kirby, 2008), will not reveal emergence. One response from Doebeli & Simon to the target article of (Smaldino, 2014) suggested their model (Simon, Fletcher, & Doebeli, 2013) should be adapted and then adopted as the formal model of cultural evolution of emergent group-level traits. However, this model they suggest is not directly applicable, most importantly because its model only allows parent-child group divergence. An individual may not change groups in its lifetime in this model. Group size change is determined by how many offspring of a parent in group i are born as being in group j. Clearly pre-existing groups that one could be born into are not appropriate for emergent group-level traits. This claim would require that groups and the group-level traits define a group, which I think holds. Simon et al. (2013) do provide an important framework for building increasingly expressive models of group formation, building a deterministic partial differential equation model of group selection from a Markovian model (Simon et al., 2013). This could be important since trying to fit a mixture model to every timestep to identify emergent group-level traits may prove computationally infeasible, especially as N becomes large. All this is still general, there is no payoff function yet defined for the individuals that form groups. While details must be left until later, I think interesting and relevant dynamics can be found using a reinforcement learning approach (Sutton & Barto, 2016) combined with some kind of economics, so that behavior has a payoff landscape to navigate, which could result in emergent groups as evidenced by their group-level traits.

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