

Transmission perturbations in the cultural evolution of language

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Abstract

Over time, language favors features that can be passed on with high fidelity from one language user to the next. The outcomes of this process are often argued to be influenced by cognitive biases that influence a learner's inductive task. Under this view, cognitive biases are therefore important determinants of linguistic structure. We complement this view by showing how such effects can also arise without assuming any biases but simply as an epiphenomenon of systematic disturbances stemming from environmental factors. To this end, we discuss three case studies in which iterated learning under noisy perception can give rise to (i) vagueness, (ii) meaning deflation, and (iii) a lack of upper-bounds in weak scalar alternatives. We argue these results to underpin the importance of (either cognitive or extraneous) transmission perturbations in the cultural evolution of language and bring attention to the often overlooked possibility that channel noise can mimic effects of inductive biases.

Keywords: noise; biases; iterated learning;

Introduction

Language is shaped by its use and transmission across generations. Linguistic properties therefore need not necessarily arise and stabilize solely due to functional pressure but may also be influenced and selected for by a pressure for learnability. The effects that such iterated learning has on language can be viewed as arising from a combination of general learning mechanisms and inductive cognitive biases (e.g. Griffiths & Kalish 2007, Kirby et al. 2014, Tamariz & Kirby 2016). Proposals of biases that shape language acquisition abound. Some prominent examples are mutual exclusivity (Merriman & Bowman 1989, Clark 2009), simplicity (Kirby et al. 2015), regularization (Hudson Kam & Newport 2005), and generalization (Smith 2011, O'Connor 2015).¹

In the following we show how environmental factors can produce evolutionary outcomes that look as if such cognitive learning biases are present even if they are not. In doing so, we underline the pivotal role of systematic transmission perturbations of linguistic knowledge in language change while showing that such perturbations may stem from other sources, e.g., from learners' noisy perception. [TB: Now mention case studies]

¹Depending on their formulation and the domain(s) they are proposed to apply to, biases may also interact. For instance, a domain-independent bias for simplicity may entail regularization but stand in conflict with mutual exclusivity.

Iterated learning under noisy perception

- Introduction to iterated Bayesian learning. Highlighting predictions of the prior's influence (i) from a technical perspective with respect to sampling to MAP and (ii) conceptual perspective with respect to the claim that laboratory experiments can give us insights into learning priors [TB: For this we can draw directly from what we already had in the other draft]
- Noisy iterated learning. Following what we had before.
- Possibly: functional pressure.

We denote the probability that the teacher (learner) observes state s_t (s_l) when the actual state is s_a as $P_N(s_t | s_a)$ ($P_N(s_l | s_a)$). The probability that s_a is the actual state when the learner observes s_l is therefore:

$$P_N(s_a | s_l) \propto P(s_a) P_N(s_l | s_a).$$

Accordingly, the probability that the teacher observes s_t when the learner observes s_l is:

$$P_N(s_t | s_l) = \sum_{s_a} P(s_a | s_l) P_N(s_t | s_a).$$

Finally, this gives us the probability that a teacher of type t produces a datum that is perceived by the listener as $d = \langle s_l, m \rangle$:

$$P_N(\langle s_l, m \rangle | t) = \sum_{s_t} P_N(s_t | s_l) P(m | s_t; t).$$

Generalize this to a sequence of perceived data d_l and write $P_N(d_l | t)$. Then, the noise-perturbed mutation matrix is defined as:

$$Q_{ij} \propto \sum_{d_l \in D} P(d_l | t_i) F(t_j, d_l), \text{ where } F(t_j, d) \text{ is as before.}$$

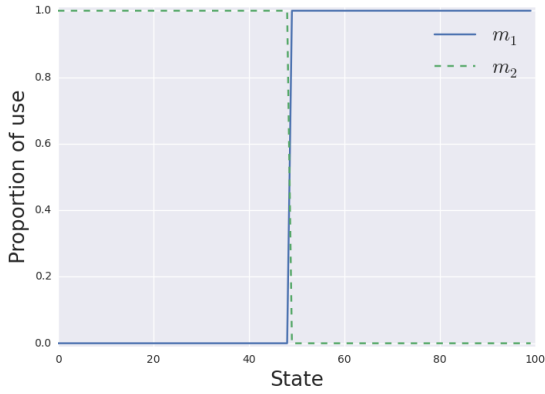
In words, it may be the case that learner and/or teacher do not perceive the actual state as what it is. They are not aware of this, and produce/learn as if what they observed was the actual state. In particular, the learner does not reason about noise when she tries to infer the speaker's type. She takes what she observes a state to be as the actual state that the teacher has seen as well and infers which type would have most likely generated the message to this state. This can lead

to biases of inferring the “wrong” teacher type if the noise makes some types err in a way that resembles the noiseless behavior of other types. That is, such environmental factors can, in principle, induce transmission biases that look as if there was a cognitive bias in favor of a particular type, simply because that type better explains the noise.

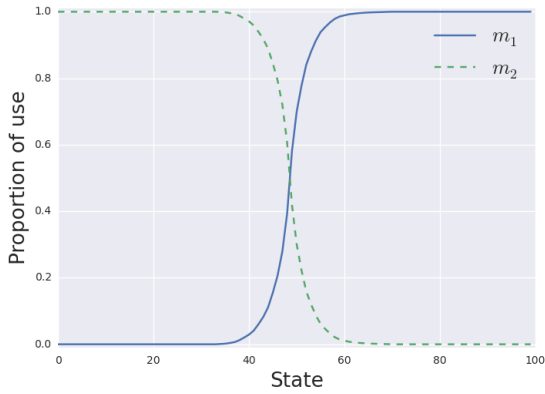
Applications

Vagueness

Main result. Noisy transmission perturbs initially crisp/clear linguistic distinctions, giving rise to vagueness. See Figure 1. Stabilization of the linguistic system around a particular threshold depends on functional considerations which are not modelled here but see Franke & Correia to appear.



(a) Initial “crisp” population



(b) Second “vague” generation

Figure 1: Noisy iterated learning with $\sigma = 0.4$, $k = 20$ and 100 sampled production sequences per parent (posterior sampling)

Setup.

- $S = [0, 99]$
- $|M| = 2$

- There is one signaling behavior per threshold θ and one threshold per state, i.e., 100 types.
- $P(m_1|s, t) = 1$ iff $s \geq \theta_t$, otherwise $P(m_2|s, t) = 1$.
- $P(s_{\text{perceived}}|s_{\text{actual}})$ is the probability density of getting $s_{\text{perceived}}$ from $\text{Normal}(s_{\text{actual}}, \sigma)$
- Data generated by teachers is sampled without noise to get a representative sample. But actual likelihoods of producing the data used to compute Q are subjected to noise as above (as specified above)
- Learners are not aware of noise (as specified above)
- No replication.

Deflation

Main result. Asymmetric and noisy perception can capture meaning deflation. See Figure 2.

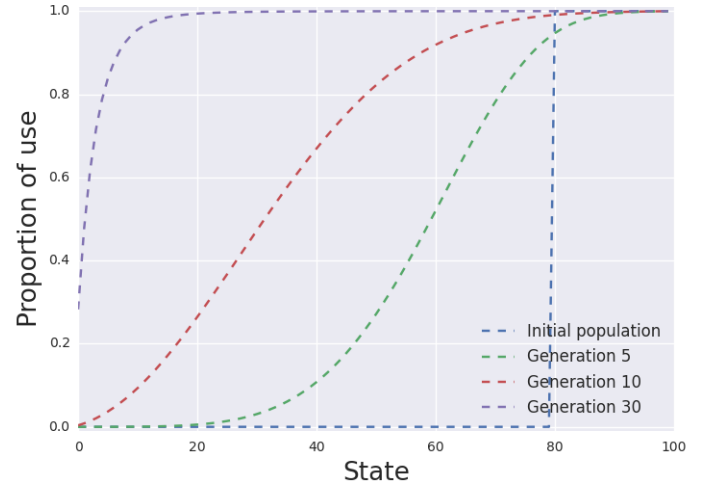


Figure 2: Noisy iterated learning with $\sigma = 0.4$, $k = 30$ and 300 sampled production sequences per parent (posterior sampling)

- $S = [0, 99]$
- $|M| = 1$
- There is one type of signaling behavior per threshold θ and one threshold per state, i.e. 100 types.
- $P(m|s, t) = 1$ iff $s \geq \theta_t$, otherwise no message is sent. [TB: I’m pretty confident that adding some error-rate to this behavior wouldn’t change the predictions. I left it deterministic for the time being]
- $P(s_{\text{perceived}}|s_{\text{actual}})$ is the probability density of getting $s_{\text{perceived}}$ from $\text{Normal}(s_{\text{actual}}, \sigma)$

- $P(\theta|d) \propto (\prod_{s \in d} P(m|s, \theta)) \times \text{Binom}(\text{successes} = k - |d|, \text{trials} = k, \text{succ.prob} = \sum_{s'=0}^{\theta-1} P(s'))$, where the latter is the probability of a type not reporting $k - |d|$ events for a total of k events.
- Data generated by teachers is sampled without noise to get a representative sample. But actual likelihoods of producing the data used to compute Q are subjected to noise as above (as specified above)
- Learners are not aware of noise (as specified above)
- No replication. [TB: Not sure how this would work anyway. The higher θ , the less a type communicates. If that's a communicative failure, then these types are even more dispreferred than with only learning. If it's not, then we have the same fitness for each type]

Quantifiers

Main result. Noisy perception of states can mimic cognitive biases. In this case, a bias towards simplicity (no upper-bounds) as analyzed in Brochhagen et al. (2016). Pragmatic inferences stabilize in population as byproduct of noise, as shown in Figure 3. Little changes for small increases of k (10 or 15) or l (e.g. 10 instead of posterior sampling).

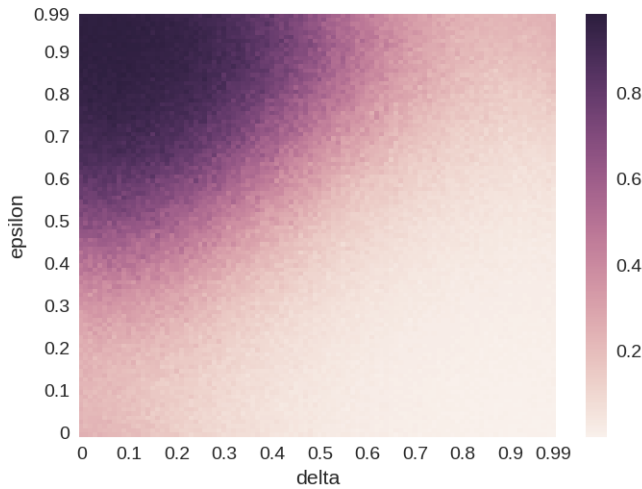


Figure 3: Influence of noise-parameters on the mean proportion of Gricean players with a lexicon lacking an upper-bound after 20 generations with $k = 5, \lambda = 20, \alpha = 1$ and 10 sampled production sequences per parent (posterior sampling).

- $S = \{s_{\exists-\forall}, s_{\forall}\}$
- $|M| = 2$
- There are two lexica, one upper-bounded and one lacking upper-bound, and two signaling behaviors, literal and gricean, for a total of four lexica

- $P(m|s, t)$ is soft-maximizing literal or gricean behavior with α as exponent, using a type's lexicon – as in our other setup [TB: Alternatively, we could go for simple Boolean behavior to keep everything uniform]
- $P(s_{\exists-\forall}|s_{\forall}) = \delta, P(s_{\forall}|s_{\exists-\forall}) = \epsilon$
- Learners are not aware of noise (as specified above)
- No replication

Discussion

[TB: To be specified. Parts can be taken from our previous draft]

Conclusion

Acknowledgments

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