Sketch:
Transmission perturbations in the cultural evolution of language

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1 Introduction

Language emergence and change are shaped by their use and transmission across generations. The latter process is often viewed as arising from a combination of general learning mechanisms and inductive cognitive biases (e.g. Griffiths and Kalish 2007, Kirby et al. 2014, Tamariz and Kirby 2016). Proposals of biases that shape language acquisition abound. Some prominent examples are mutual exclusivity (Merriman and Bowman 1989, Clark 2009), a simplicity (Kirby et al. 2015), regularization (Hudson Kam and Newport 2005), and generalization biases (Smith 2011, O'Connor 2015).[1] Here, we show how environmental factors can produce evolutionary outcomes that look as if 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. That is, they may not stem from learning biases but from other sources of systematic noise, e.g., as a result of errors in perception. This result highlights the frequently overlooked possibility that channel noise in evolutionary replication can mimic effects of inductive biases.

- Brief overview of the cases we consider

2 Model

- 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]

[1] Depending on their formulation and the domain(s) they are proposed to apply to, some biases entail others. For instance, a domain-independent bias for simplicity can entail regularization (and may conflict with mutual exclusivity).

- Noisy iterated learning. Following what we had before.
- Possibly: functional pressure [TB: I'd leave it out if it's not strictly necessary, we should mention that this also plays a role in the introduction, but no need to introduce the full model we use elsewhere.]

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

$$P_N(s_a \mid s_l) \propto P(s_a)\ P_N(s_l \mid s_a)\,.$$

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

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

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

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

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

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

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.

3 Applications

If we only look at iterated learning, we can skip receiver strategies. In any case, it may be best to assume that a single type's strategy is derived from a single language in order to avoid having too many types.

3.1 Vagueness setup

- $T = [0, 100]$
- $|M| = 2$
- For pure Boolean languages we would have to look at the average language of the population to see vagueness. This gives 100^2 types. [TB: I think this is managable, computation-wise, but would have to test.]
- For probabilistic languages we can say that a single language is vague, but we would have to sample to construct types. [TB: Not really problematic. With only two messages we get a good approximation with far less than 100^2 types from above]
- Production is simply proportional to the truth-value of a message in a teacher's perceived state t_t – no Gricean reasoning or exponential functions.
- Confusability: Either proportional to physical distance e.g. following **?**:9, or, to keep matter uniform to deflation
  t_t Normal(t_a, σ)
  t_l Normal(t_a, σ)

4 Deflation

5 Quantifiers

(III) Inductive bias. A second learning bias that codifies the idea that lexica should be uniform, i.e. be biased towards either lexicalizing an upper-bound for all weaker alternatives in a scalar pair or for none.

(IV) Uncertainty. The other advantage of non-upper bounded semantics lies in being non-committal to the negation of stronger alternatives when the speaker is uncertain. Adding this to the model requires the most changes to our present setup and some additional assumptions about the cues available to players to discern the speaker's knowledge about the state she is in.

(V) More scalar pairs. Taking into consideration more than one scalar pair. Preliminary results suggest that this does not influence the results in any meaningful way without further additions, e.g. by (III).

(VI) More lexica. Not necessary. Preliminary results suggest that considering more lexica has no noteworthy effect on the dynamics (tested with all possible 2x2 lexica).

(VII) State frequencies. Variations on state frequencies. This may have an interesting interaction with (III).

(VIII) Reintroduction of communal learning. One possibility: The probably N_{ij} with which a child of t_i adopts t_j could be the weighted sum of Q_{ij} (as before) and a vector we get from learning from all of the population: $L_j = \sum_d P(d|\vec{p})P(t_j|d)$, where $P(d|\vec{p}) = \sum_i P(d|t_i)\vec{p}_i$ is the probability of observing d when learning from a random member of the present population distribution.

6 Discussion

7 Conclusion

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