Communicative pressures at the semantics-pragmatics interface: Learning biases may prevent the lexicalization of pragmatic inferences

(– draft September 21, 2016—)

Abstract

Certain lexical meanings enable for pragmatic enrichments in a notably productive fashion. This raises the challenge to justify their regular selection, in particular, over alternatives that codify semantically what is conveyed pragmatically. To address this challenge, we propose a general model that integrates iterated Bayesian learning in the replicator-mutator dynamics. This model allows for population-level analyses of the effects of linguistic pressures on probabilistic language users with varied degrees of pragmatic sophistication and distinct languages. We showcase the model's use and predictions in a case study on the (lack of) lexicalization of scalar implicatures. The results suggest simpler semantic representations to be selected for when languages are pressured towards learnability and compression, provided that pragmatic reasoning can compensate for the disadvantage in expressivity that users of such languages otherwise incur.

1 The semantics-pragmatics divide

In linguistic theorizing, it is common to draw a distinction between semantics and pragmatics. Broadly speaking, the former concerns the truth-conditional content of expressions, whereas the latter concerns information beyond literal meanings and their composition. An important consequence of this distinction is that the information conveyed by an utterance is seldom, if ever, solely determined by semantics, but rather in tandem with pragmatics.

Much research at the semantics-pragmatics interface has been aimed at characterizing expressions in terms of either domain, or their interplay. However, an issue that has received little attention is the justification of semantic structure in light of pragmatics. The present investigation seeks to fill this gap by analyzing the effects linguistic pressures have on the selection and pervasiveness of particular lexical meanings under consideration of pragmatic enrichments.

In recent years, similar questions about the emergence and change of linguistic features have lead to a surge in models to address them (see Steels 2015 and Tamariz and Kirby 2016 for recent overviews). Our starting point is given by the overarching argument that has crystalized from accumulated mathematical, experimental and cross-linguistic evidence in this literature: Natural languages need to be well-adapted to communicative needs within a linguistic community, but also need to be learnable to survive their faithful transmission across generations. More succinctly; natural languages are pressured for expressivity as well as learnability.

We build on these insights by modeling these pressures using the replicator-mutator dynamics (see Hofbauer and Sigmund 2003 for an overview). This allows for the inspection of their interaction by combining functional pressure on successful communication with effects of learning biases on (iterated) Bayesian learning (Griffiths and Kalish 2007). The semantics-pragmatics distinction and its effect on production and comprehension is made precise by considering probabilistic models of rational language use in populations with distinct lexica (Frank and Goodman 2012, Franke and Jäger 2014, Bergen et al. 2016).

2 Simplicity, expressivity, and learnability

The emergence and change of linguistic structure is influenced by many intertwined factors, ranging from biological and socio-ecological to cultural (Steels 2011, Tamariz and Kirby 2016). Social and ecological pressures determine communicative needs, while biology determines the architecture that enables and constrains their means of fulfillment. In the following, our focus lies on the latter, cultural factor, wherein processes of linguistic change are understood as shaped by its use and transmission. That is, as a result of cultural evolution.

At latest since Zipf's (1949) rationalization of the observation that word frequency rankings can be approximated by a power law distribution as competing hearer and speaker preferences, the idea that linguistic change is influenced by communicative pressures has played a pivotal role in synchronic and diachronic analyses (e.g. Martinet 1962, Horn 1984, Jäger and van Rooij 2007, Jäger 2007, Piantadosi 2014, Kirby et al. 2015).

As noted above, expressivity and learnability are two major competing pressures. Their opposition becomes particularly clear when considering their consequences in the extreme (cf. Kemp and Regier 2012, Kirby et al. 2015). On the one side, a language with a single form is easy to learn but lacking in expressivity for most purposes. On the other, a language that associates a distinct form with all possible meanings its users may want to convey is maximally expressive but challenging to acquire. The most prominent problem that arises from this tension is that of acquiring a language to express a potentially infinite set of meanings through finite means (Kirby 2002). However, this so-called transmission bottleneck is not the only challenge learners confront.

More important for our purposes is the problem of selecting particular hypotheses out of a potentially infinite space of alternatives compatible with the data learners are exposed to. At the semantics-pragmatics interface this concerns the selection between functionally similar, if not identical, lexical meanings. In the following, we argue an integral part of the answer to be that learners are a priori biased towards simpler, more compressed, lexical representations. This corresponds to the argument that rational learners should prefer simpler over more complex explanations of data (Feldman 2000, Chater and Vitányi 2003, Piantadosi et al. 2012a, Kirby et al. 2015, Piantadosi et al. under review). In linguistics, a drive for simplicity has been argued to underpin speaker preferences for brevity and ease of articulation, as well as to pressure languages towards lexical ambiguity and grammatical compression (Zipf 1949, Grice 1975, Piantadosi et al. 2012b, Kirby et al. 2015). As a broader cognitive principle, the use of simplicity as means to select between hypotheses has a long standing tradition. Crucially, Chater and Vitányi (2003) give a number of compelling arguments for simplicity on both mathematical and empirical grounds.

The remainder of this section introduces the individual components of the model in more detail, as well as the assumptions underlying them. These are: (i) languages and their use, (ii) pressures towards expressivity and learnability, regulated by the replicator and mutator dynamics, respectively, as well as (iii) a bias towards simpler semantic representations, codified as a language learner's prior. After laying out the model, we discuss its application to the lack of lexicalization of scalar implicatures.

2.1 Languages and linguistic behavior

Lexica codify the truth-conditions of a language's expressions, i.e., its semantics. A convenient way to represent such lexica is by $(|S|, |M|)$-Boolean matrices, where S is a set of states of affairs, or meanings, to convey and M a set of messages of the language (Franke and Jäger 2014). For instance, the following two lexica fragments determine the truth-conditions of two messages, m_1 and m_2, for two states, s_1 and s_2:

$$L_a = \begin{array}{c} \\ s_1 \\ s_2 \end{array} \begin{array}{c} \begin{array}{cc} m_1 & m_2 \end{array} \\ \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \end{array} \qquad L_b = \begin{array}{c} \\ s_1 \\ s_2 \end{array} \begin{array}{c} \begin{array}{cc} m_1 & m_2 \end{array} \\ \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \end{array}$$

In words, according to lexicon L_a, m_1 is true of state s_1 as well as of s_2. In contrast, message m_1 is only true of s_1 in L_b. Otherwise, the two languages are truth-conditionally equivalent.

To make the distinction betweeen semantics and pragmatics precise, we distinguish between two kinds of linguistic behavior. *Literal interlocutors* produce and interpret messages literally. That is, their linguistic choices are guided by their lexica only. In contrast, *pragmatic interlocutors* engage in mutual reasoning to inform their choices. For instance, a rational speaker of L_a who reasons about her addressee should use m_1 to signal state s_1 given that m_2 is already unambiguously associated with state s_2. Analogously, should rational hearers expect their interlocutors to reason along these lines, they will interpret ambiguous m_1 accordingly. Note in particular that according to this strenghtening of m_1, L_a is indistinguishable from L_b in terms of expressivity if its users are pragmatic reasoners.

Following models of rational language use such as Rational Speech Act models (Frank and Goodman 2012) and their game-theoretic counterparts (Benz et al. 2005a, Franke 2009, Franke and Jäger 2014), this kind of signaling behavior is captured by a hierarchy over reasoning types. The hierarchy's bottom, level 0, corresponds to literal language use. Pragmatic language users of level $n + 1$ behave rationally according to (expected) level n behavior of their interlocutors. The behavior of literal and pragmatic hearers of a language L is given by their respective selection functions in (1) and (3). Mutatis mutandis for the speaker functions in (2) and (4).

$$H_0(s|m; L) \propto pr(s)L_{sm} \tag{1}$$
$$S_0(m|s; L) \propto \exp(\lambda\ L_{sm}) \tag{2}$$
$$H_{n+1}(s|m; L) \propto pr(s)S_n(m|s; L) \tag{3}$$
$$S_{n+1}(m|s; L) \propto \exp(\lambda\ H_n(s|m; L)^{\alpha}) \tag{4}$$

According to (1), a literal hearer's interpretation of a message m as a state s depends on her lexicon and her prior over states, $pr \in \Delta(S)$. The literal speaker's choice in (2) is regulated by a soft-max parameter λ, $\lambda \geq 1$ (Luce 1959, Sutton and Barto 1998). As λ increases, choices made in production are more rational in that higher values lead to more deterministic in line with expected utility maximization.

For the most part, pragmatic behavior mirrors its literal counterpart. As described above, their difference lies in that level $n + 1$ speakers/hearers reason about level n hearer/speaker behavior instead of solely relaying on their lexicon. That is, they reason about how a rational level n interlocutor would use or interpret a message and behave according to these expectations. Additionally, pragmatic production is further regulated by a parameter α which controls the tension between semantics and pragmatics, $\alpha \in (0, 1]$. Lower values lead to more literal production, whereas higher values lead to stronger pragmatic behavior.

The combination of a lexicon with its use, i.e., a particular level of linguistic sophistication, yields a type t. Types are the basic units on which our population dynamics operate.

2.2 Replication & expressivity

Communicative efficiency, or expressivity, has received particular attention from investigations using evolutionary game theory (Nowak and Krakauer 1999, Nowak et al. 2000; 2002). Under this view, a type's success in communication confers it a higher fitness relative to less successful ones. As a consequence they replicate more than other types, increasing their proportion in the population. This association of a type's communicative success within a population with changes in the types present in it creates a feedback loop that pressures the population towards greater expressivity. The replicator equation gives us the means to make these dynamics precise.

The proportion of types in a given population is captured by a vector x, where x_i is type i's proportion in the population. The fitness of a type i, f_i, is given by its expected utility in this population, $f_i = \sum_j x_j \mathrm{EU}(t_i, t_j)$. That is, its fitness is the sum of its expected communicative success with other types weighted by the latter type's population share. The expected utility of i and j is obtained by considering the expected utility of speaker i interacting with hearer j, and vice versa: $\mathrm{EU}(t_i, t_j) = [U_S(t_i, t_j) + U_R(t_i, t_j)]/2$. $U_S(x, y)$ and $U_R(x, y)$ are respectively $\sum_s P(s) \sum_m S_n(m|s; L) \sum_{s'} R_o(s'|m; L)\delta(s, s')$ and $U_S(y, x)$ for n and o being the reasoning level of x and y, and $\delta(s, s') = 1$ iff $s = s'$ and 0 otherwise.[1] This quantity is symmetric, reflecting the probability of two types' mutual understanding. Lastly, the average fitness of the population is captured by Φ, $\Phi = \sum_i x_i f_i$. This term serves as a normalizing constant for the (discrete) replicator equation; $\dot{x}_i = \frac{x_i f_i}{\Phi}$

Under its biological interpretation, the replicator equation captures the idea of fitness-relative selection whereby fitter types produce more offspring, leading to their propagation in subsequent generations. In analogy to this kind of replication, many aspects of natural language are subject to processees of transmission and change across varied time-spans. For example, the replicator equation can be understood as a learning across generations as e.g. in Nowak et al. 2002, but also as a process of horizontal adaptation (see Benz et al. 2005b:§3.3 for discussion). In the following, we take the latter view in assuming that interlocutors adapt their lexica and their use to that which works best within their population. It should be stressed, however, that the model itself is compatible with either view.

Nowak et al. did not only consider replication, but also recognized the important role of the variation that is introduced by a language's transmition across generations, construed as mutation. Due to this process, the offspring of a type may end up adopting a different type than that of its parent. Crucially, in this work mutation rates were modelled as begin independent from a type. This means that the variation introduced by generational turnovers did not depend on factors such as the relative learnability of a type. To address the issue of selecting a particular type over (near) functional equivalents, we turn to a different strand of research in cultural evolution: *iterated learning*.

2.3 Mutation & learning

Iterated learning is a process in which the behavior of one individual serves as learning input for another, who's behavior subsequently serves as input for a new learner, and so on. For linguistic purposes this process can be thought of as chains of parents and children, where the parent produces linguistic data from which the child infers a language. The latter, now a parent, goes on to produce linguistic data for a new generation of naïve learners. Following Griffiths and Kalish (2007) we model learning as a process of Bayesian inference in which learners combine the likelihood of a type producing the learning data with prior inductive biases. They then select a

[1] Note that the definition of $U_R(\cdot, \cdot)$ implies equal sender and receiver payoff in an interaction. This need not be so in the general case but suffices for our application.

type to adopt from the resulting posterior distribution.

Due to the pressure towards learnability it exherts, iterated learning generally leads to simpler and more regular languages (surveys of empirical data and models are given in Kirby et al. 2014 and Tamariz and Kirby 2016). Importantly, experimental and mathematical results suggest the results of this process to reflect learners' learning biases, codified in the following as a prior $P \in \Delta(\mathcal{T})$. A way to think about this bias is as the amount of data a learner would require in order to adopt a language – or, in our case, a combination of a lexicon and a signaling behavior (cf. Griffiths and Kalish 2007:450). Crucially, the extent of the prior's influence has been shown to strongly depend on the learning strategy assumed to underly the inference process. While simulation results suggested that weak biases could be magnified by exposing learners to only small data samples (Brighton 2002), the mathematical characterization provided by Griffiths and Kalish (2007) showed that, instead, iterated learning converged to the prior. That is, the distribution over languages in a population or, from an individual's perspective, the likelihood of learning a language corresponds to the learners' prior distribution, irrespective of the amount of input given to learners. This divergence in predictions can be traced back to differences in the selection of hypotheses from the posterior. On the one extreme, Griffith & Kalish's convergence to the prior holds for learners that sample from the posterior. On the other, more deterministic strategies such as the selection of the type with the highest posterior probability, so-called *maximum a posterior estimation* (MAP), increase the prior's influence (Griffiths and Kalish 2007, Kirby et al. 2007). In the following, we parametrize the posterior, $P(t_i|d)^l$, to obtain a range of learning strategies that live in the range between posterior sampling and MAP, $l \geq 1$. When $l = 1$ learners sample from the posterior. As l increases towards infinity, the learners' tendency maximize the posterior increases.

More generally, we combine the replicator dynamics with iterated learning by codifying the latter as a transition matrix Q. Just as in standard mutator dynamics, Q_{ij} indicates the probability of the children of a parent of type i adopting type j. However, to make this process depend on a type's learnbility, this quantity is proportional to the probability of i producing the learning data and that of j given the data.

The elements of the set of learning data D are sequences of length k of state-message pairings. That is, a sequence of observations of language use. Put differently, a datum $d \in D$ contains k members of the set $\{\langle s_i, m_j \rangle \,| s_i \in S, m_j \in M\}$ and D is the set of all such sequences. Having fixed D,

$$Q_{ij} \propto \sum_{d \in D} P(d|t_i) F(t_j, d),$$

where $F(t_j, d) \propto P(t_j|d)^l$ and $P(t_j|d) \propto P(t_j)P(d|t_j)$. Given a type i, $P(d|t_i)$ can be straightforwardly computed based on t_i's production behavior.

2.4 Summary

We argued for expressivity, learnability and simplicity as important pressures that apply on the cultural evolution of language. They are respectively modelled as communicative efficiency-relative replication, iterated Bayesian learning, and a prior that biases learners for compressed lexical meanings. Taken together these evolutionary dynamics are described by the replicator-mutator dynamics (Hofbauer and Sigmund 2003):

$$\hat{x_i} = \sum_j Q_{ji} \frac{x_j f_j}{\Phi}$$

The basic units that the dynamics operate on are a combination of lexica lexicon and their use; a type. A type's expressivity depends on its communicative efficiency within a population while its learnability depends on the fidelity by which it is infered by new generations of naïve learners.

In sum, the innovation of this model lies in its combination of functional pressure on successful communication, effects of learning biases on (iterated) Bayesian language learning Griffiths and Kalish 2007, and probabilistic models of language use in populations with distinct lexica (Frank and Goodman 2012, Franke and Jäger 2014, Bergen et al. 2016). In particular, this synthesis enables for the investigation of the effects of communicative pressures on the semantics-pragmatics interface. In doing so, it links the previously disconnected areas of rational probabilistic language use and cultural evoltion.

3 Lack of lexicalization of pragmatic inferences

With this model, we set out to investigate the prevalence of lexical meanings that allow for regular pragmatic enrichments over other alternatives. A particularly well-studied type of conventional pragmatic enrichment are so-called *scalar implicatures.* These inferences are licensed for groups of expressions ordered in terms of informativity, here understood as an entailment induced order. For instance, *some* is entailed by *all*; if it were true that ‘All students came to class’, it would also be true that ‘Some students came to class’. However, while weaker expressions such as *some* are truth-conditionally compatible with stronger alternatives such as *all*, this is not necessarily what their use is taken to convey. Instead, the use of a less informative expression when a more informative one could have been used can license a defeasible inference that stronger alternatives do not hold (cf. Horn 1972, Gazdar 1979). That is, a hearer who assumes the speaker to be able and willing to provide all relevant information can infer that, since the speaker did not use a stronger alternative, e.g. *all*, this alternative must not hold. In this way, ‘Some students came to class’ is strengthened to convey ‘Some but not all students came to class’. Analogously, a speaker can rely on her interlocutor to draw this inference without having to express this upper-bound overtly, e.g. by stating *some but not all.* In other words, mutual reasoning about rational language use supplies a bound that rules out stronger alternatives pragmatically.

This corresponds to our previous description of the pragmatic use of lexicon L_a, repeated below for convenience. A pragmatic hearer who reasons about a speaker’s use of message m_1 will associate it more strongly with s_1 than with s_2 given that the latter is unambiguously associated with s_2. The strength of this association dependens on the individuals’ degree of rationality λ and their prior over states. Conversely, a pragmatic speaker will reason about her interlocutor’s interpretation and use the messages accordingly.

$$L_a = \begin{array}{c c} & \begin{array}{cc} m_1 & m_2 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \end{array} & \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \end{array} \qquad\qquad L_b = \begin{array}{c c} & \begin{array}{cc} m_1 & m_2 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \end{array} & \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \end{array}$$

Our initial question can now be rephrased in terms of scalar implicatures by asking for justifiations for the lack of lexical upper-bounds in weak scalar alternatives. That is, why semantics such as those of message m_1 in L_a are regularly selected for over the alternative of lexicalizing it as in L_b. More poignantly, would it not serve language users better if weak(er) expressions such as *warm*, *or*, *some* or *big* were truth-conditionally incompatible with stronger alternatives such as, respectively, *hot*, *and*, *all* and *huge*? This question is particularly striking considering the number of expressions that license such inferences across languages (Horn 1972, Horn 1984:252-267, Traugott 2004, van der Auwera 2010).

We see two main explanations for the lack of upper-bounds in the lexical meaning of weak scalar expressions. The first is that their truth-conditional compatibility with stronger expressions endows them a broader range of application. Scalar expressions occur in contexts in which their upper-bounded reading is absent. This can happen when embedded in downward-entailing contexts, when the speaker is likely uncertain about whether the upper bounded reading is true, or when the distinction between an upper-bounded reading and the simple, only lower-bounded reading, is not relevant. For instance, if for all the speaker knows 'Some students came' but she doesn't know whether 'All came', then the use of *some* succinctly conveys her uncertainty about the latter. This may suggest a functionalist argument for why upper-bounded meanings do not conventionalize: should contextual cues provide enough information to the hearer to identify whether a bound is intended to be conveyed pragmatically, then these means are preferred over expressing it overtly through a longer expression, e.g., by stating 'some but not all' explicitly. Importantly, although dispreferred due to its relative length and complexity, morphosyntactic disambiguation still allows speakers to enforce an upper-bound to override contextual cues that might otherwise mislead the hearer.

In a nutshell, this explanation posits that scalar implicatures fail to lexicalize because, all else being equal, speakers prefer to communicate as economically as possible and pragmatic reasoning enables them to do so. Compare this with a hypothetical language lexicalizes two expressions instead of a single scalar one; one with and one lacking an upper-bound.[2] Should the explanation rest on purely functional grounds, we see four conditions that may pressure languages for English-like semantics over this alternative. First, contextual cues are strongly reliable. Second, morphosyntactic disambiguation is seldom necessary. Third, morphosyntactic disambiguation is only marginally dispreferred. Fourth, larger lexica are costly.

However, these conditions are not convincing in their role as central explanatory devices for such a wide-spread phenomenon. The first two put a heavy burden on the ability to retrieve contextual cues to a degree that seems unlikely to undercut the benefit of . It is likely that human language users are very good at retrieving cues from contexts, but to stipulate that they are so good as to undercut the benefit of safe communication provided by the hypothetical alternative strikes us as too strong of an assumption. As for conditions (3) and (4), these seem mostly like technical solutions, without a proper empirical basis.

Instead, in what follows we investigate the hypothesis that the lack of lexicalization of scalar inferences is driven by the advantage in compression that lexical meanings lacking an upper-bound have over those that explicitly codify it. Note however that we do not represent this contrast in compression between lexical meanings explicitly in lexica. Instead, the bias towards a lack of upper-bounds in weak scalar alternatives is directly encoded in the learners' prior over types.

In principle this difference could be made precise with an adequate representational language, e.g., through measures over representational complexity such as minimal description length. There is a growing effort to develop such empirically testable representational languages. For instance, the so-called language of thought has been put to test in various rational probabilistic models that show encouraging results (see e.g. Katz et al. 2008, Piantadosi et al. under review; 2012b and references therein). We think that our assumption is well-warranted as a working hypothesis and decide against such an enrichment given that the introduction of a larger framework would also require further assumptions and justifications.[3]

In sum, while we do not want to argue that functionalist pressure may not play a role, we do see a clear benefit in exploring whether matters of learnability would not give us additional

[2]The observation that monomorphemic expression that lexically rule out stronger alternatives are unattested across languages has received substantial argumentative support (most prominently in Horn 1984:252-267 but also e.g. in Horn 1972, Traugott 2004, van der Auwera 2010). To the best of our knowledge, this claim stands unchallenged.

[3]T: We could possibly show the length difference of the lexical meanings with and without an upper-bound using a LOT grammar in the appendix. I don't know if it is worth it though.

$$L_1 = \begin{pmatrix} 0 & 0 \\ 1 & 1 \end{pmatrix} \quad L_2 = \begin{pmatrix} 1 & 1 \\ 0 & 0 \end{pmatrix} \quad L_3 = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$$

$$L_4 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad L_5 = \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix} \quad L_6 = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}$$

Table 1: Set of considered lexica.

parameter	explanation	locus
$\lambda \geq 1$	rationality parameter	$S_{n+1}(m\|s; L) \propto \exp(\lambda\, H_n(s\|m; L)^{\alpha})$
$\alpha \in (0, 1)$	semantics-pragmatics tension	$S_{n+1}(m\|s; L) \propto \exp(\lambda\, H_n(s\|m; L)^{\alpha})$
$\|D\|$	learning data produced per parent type	$P(d\|t_j)P(t_i\|d)$
$k = \|d\|$	number of observations per datum	$P(d\|t_j)P(t_i\|d)$
$l \geq 1$	posterior parameter from sampling to MAP	$P(t_i\|d) \propto [P(t_i)P(d\|t_i)]^l$
$c \in (0, 1]$	learning bias for upper-bound lack	$P(t_i)$

leverage.

3.1 Preliminaries

The dynamics are initialized with an arbitrary distribution over types. We consider populations with two signaling behaviors, literal or Gricean (level 0 and 1 reasoners), each equipped with one of 6 lexicons. This yields a total of 12 distinct types $t \in T$. As in our examples above, $|M| = |S| = 2$, i.e., lexica are $(2, 2)$-matrices. These are listed in Table 1.

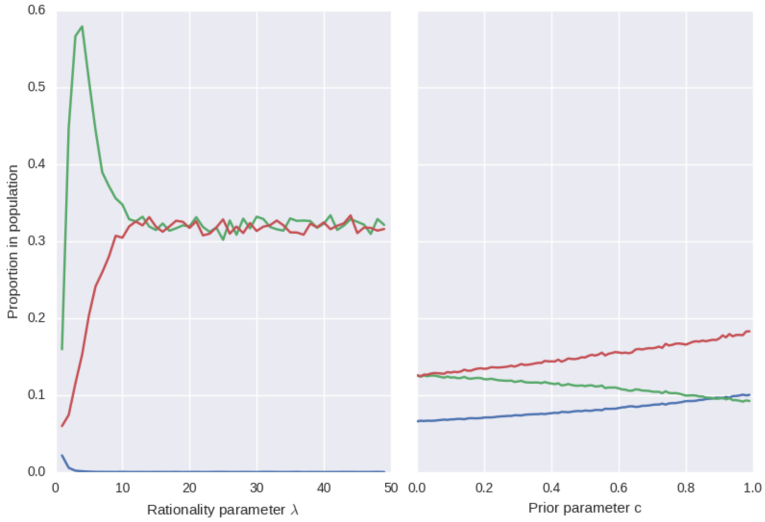
Target lexica....

A language that has conventionalized upper and lower bounds to realize a (quasi-)partition of the relevant semantic space will produce speaker behavior that is /almost/ indistinguishable from that of a language with only the respective upper bounds, but with Gricean speakers. Almost, because there may be slight differences between the probability with which speakers would (erroneously) use a semantically false description and the probability with which speakers would (erroneously) use a pragmatically suboptimal description. explain why only these and not others

Procedural description. At the game's onset we compute Q once based on the sets of sequences D (one for each parent type). Replicator dynamics are computed based on the fitness of each type in the current population as usual. Q is computed anew for each independent run (of g generations) given that it depends on D, which is sampled from production probabilities.

3.2 Model parameters & procedure

1. Sequence length k
2. Pragmatic production parameter α
3. Rationality parameter λ
4. Learning prior over types (lexica); cost parameter c. $p^{\star}(t_i) \propto n - c \cdot r$ where n is the total number of states and r that of upper-bounded messages only true of s_1 in t_i's lexicon (if only s_1 is true of a message, then this message encodes an upper-bound). Then the score for L_1, L_3, L_5 is 2, that of L_4 and L_6 is $2 - c$, and that of L_2 is $2 - 2c$; Normalization over lexica scores yields the prior over lexica (which is equal to the prior over types).



5. Prior over meanings (pr). We assume that $pr(s) = \frac{1}{|S|}$ for all s.
6. True state distribution (P). We currently assume that $P = \frac{1}{|S|}$ but it may be interesting to vary this
7. Learning parameter $l \geq 1$ with 1 corresponding to probability matching, and MAP as l approaches infinity
8. n is the sample of sequences of observations of length k sampled from the production probabilities of each type
9. Number of generations g

3.3 Analysis

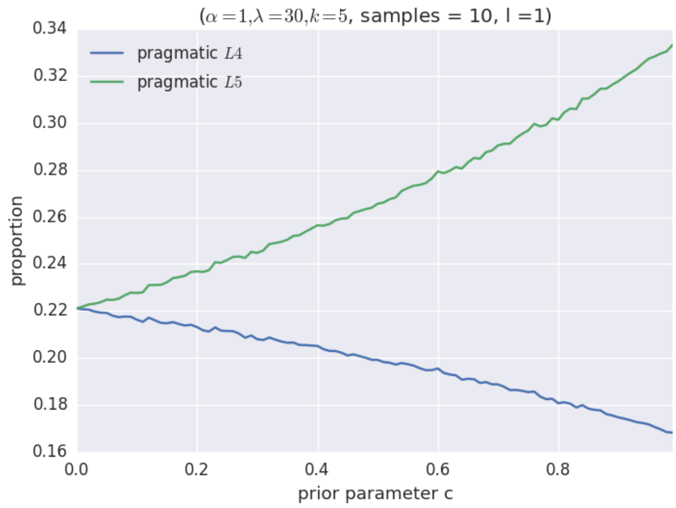
3.4 Discussion

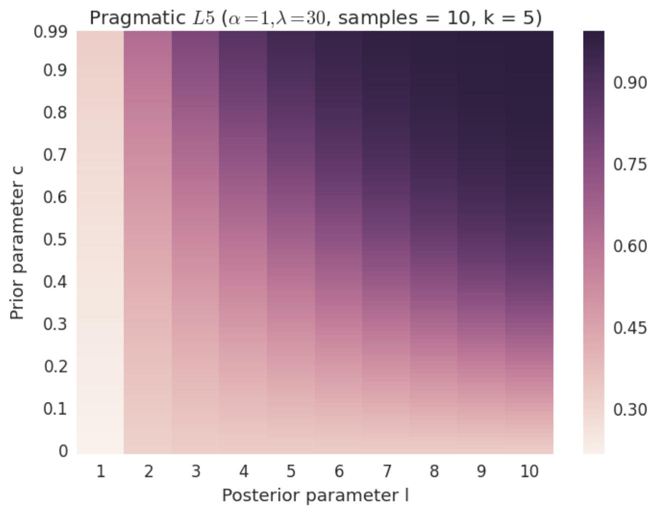
- There is experimental evidence that scalar implicature calculation costs effort and takes additional processing time (Schaeken, Snedeker, ...).

4 General discussion

The model combines:

- game-theoretical models of functional pressure towards efficient communication
- effects of learning biases on (iterated) language learning
- assumptions about particular learning biases (Piantadosi et al. 20XX)
- probabilistic speaker and listener types of various pragmatic sophistication (Frank & Goodman, 2012; Franke & Jger, 2014)
- speaker and listener types with different lexica (Bergen et al. 2012, to appear)


($\alpha=1$,$\lambda=30$,$k=5$, samples = 10, l =1)
pragmatic $L4$
pragmatic $L5$
proportion
prior parameter c
0.34
0.32
0.30
0.28
0.26
0.24
0.22
0.20
0.18
0.16
0.0
0.2
0.4
0.6
0.8


Pragmatic $L5$ ($\alpha=1$,$\lambda=30$, samples = 10, k = 5)
Prior parameter c
Posterior parameter l
0.99
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
7
8
9
10
0.90
0.75
0.60
0.45
0.30

Discussion about expressivity as external to learning (cf. Stadler, replicator-papers by Kenny Smith, Kirby et al 2015). Possibly add appendix with direct comparison between IL and RMD.

Extensions:

(I) Cost for pragmatic reasoning. At least in the CogSci setup the effect of adding cost to pragmatic reasoning is unsurprising: High cost for pragmatic signaling lowers the prevalence of pragmatic types. Lexica that semantically encode an upper-bound benefit the most from this. However, the cost needed to be substantial to make the pragmatic English-like lexicon stop being the incumbent type (particularly when learning is communal).

(II) Negative learning bias. Instead of penalizing complex semantics (semantic upper-bounds) one may consider penalizing simple semantics (no upper-bounds). This is useful as a sanity check but also yields unsurprising results in the CogSci setup: The more learners are biased against simple semantics, the more prevalent are lexica that semantically encode upper-bounds.

(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.

5 Conclusion

References

Luc Steels. *The Talking Heads experiment: Origins of words and meanings.* Language Science Press, 2015.

Monica Tamariz and Simon Kirby. The cultural evolution of language. *Current Opinion in Psychology*, 8:37–43, 2016.

Josef Hofbauer and Karl Sigmund. Evolutionary game dynamics. *Bulletin of the American Mathematical Society*, 40(04):479–520, 2003.

Thomas L. Griffiths and Michael L. Kalish. Language evolution by iterated learning with bayesian agents. *Cognitive Science*, 31(3):441–480, 2007.

M. C. Frank and N. D. Goodman. Predicting pragmatic reasoning in language games. *Science*, 336(6084):998–998, 2012.

Michael Franke and Gerhard Jäger. Pragmatic back-and-forth reasoning. *Semantics, Pragmatics and the Case of Scalar Implicatures.*, pages 170–200, 2014.

Leon Bergen, Roger Levy, and Noah D Goodman. Pragmatic reasoning through semantic inference. *Semantics and Pragmatics*, 2016.

Luc Steels. Modeling the cultural evolution of language. *Physics of Life Reviews*, 8(4):339–356, 2011.

George Zipf. *Human behavior and the principle of least effort.* Addison-Wesley Press, 1949.

André Martinet. *Functionalist View of Language.* Clarendon Press, Oxford, 1962.

Laurence R. Horn. Toward a new taxonomy for pragmatic inference: Q-based and R-based implicature. In D. Schiffrin, editor, *Meaning, Form and Use in Context*, pages 11 – 42. Georgetown University Press, Washington, 1984.

Gerhard Jäger and Robert van Rooij. Language structure: psychological and social constraints. *Synthese*, 159(1):99–130, 2007. doi: 10.1007/s11229-006-9073-5.

Gerhard Jäger. Evolutionary game theory and typology: A case study. *Language*, 83(1):74–109, 2007. doi: 10.2307/4490338.

Steven T Piantadosi. Zipfs word frequency law in natural language: A critical review and future directions. *Psychonomic bulletin & review*, 21(5):1112–1130, 2014. doi: 10.3758/s13423-014-0585-6.

Simon Kirby, Monica Tamariz, Hannah Cornish, and Kenny Smith. Compression and communication in the cultural evolution of linguistic structure. *Cognition*, 141:87–102, 2015.

C. Kemp and T. Regier. Kinship categories across languages reflect general communicative principles. *Science*, 336(6084):1049–1054, 2012. doi: 10.1126/science.1218811.

Simon Kirby. Learning, bottlenecks and the evolution of recursive syntax. In Ted Briscoe, editor, *Linguistic Evolution Through Language Acquisition*, pages 173–204. Cambridge University Press (CUP), 2002. doi: 10.1017/cbo9780511486524.006.

Jacob Feldman. Minimization of boolean complexity in human concept learning. *Nature*, 407 (6804):630–633, 2000.

Nick Chater and Paul Vitányi. Simplicity: a unifying principle in cognitive science? *Trends in Cognitive Sciences*, 7(1):19–22, 2003. doi: 10.1016/s1364-6613(02)00005-0.

Steven T. Piantadosi, Joshua B. Tenenbaum, and Noah D. Goodman. Bootstrapping in a language of thought: A formal model of numerical concept learning. *Cognition*, 123(2):199–217, 2012a.

Steven T. Piantadosi, Joshua B. Tenenbaum, and Noah D. Goodman. Modeling the acquisition of quantifier semantics: a case study in function word learnability, under review.

Paul Grice. Logic and conversation. In *Studies in the Ways of Words*, chapter 2, pages 22–40. Harvard University Press, Cambridge, MA, 1975.

Steven T. Piantadosi, Harry Tily, and Edward Gibson. The communicative function of ambiguity in language. *Cognition*, 122(3):280–291, 2012b. doi: 10.1016/j.cognition.2011.10.004.

Anton Benz, Gerhard Jäger, Robert Van Rooij, and Robert Van Rooij, editors. *Game theory and pragmatics*. Springer, 2005a.

Michael Franke. *Signal to Act: Game Theoretic Pragmatics*. PhD thesis, University of Amsterdam, 2009.

Duncan R. Luce. *Individual choice behavior: a theoretical analysis*. Wiley, 1959.

Richard S. Sutton and Andrew G. Barto. *Introduction to Reinforcement Learning*. MIT Press, Cambridge, MA, USA, 1998.

M. A. Nowak and D. C. Krakauer. The evolution of language. *Proceedings of the National Academy of Sciences*, 96(14):8028–8033, 1999.

Martin A. Nowak, Joshua B. Plotkin, and Vincent A. A. Jansen. The evolution of syntactic communication. *Nature*, 404(6777):495–498, 2000. doi: 10.1038/35006635.

Martin A. Nowak, Natalia L. Komarova, and Partha Niyogi. Computational and evolutionary aspects of language. *Nature*, 417(6889):611–617, 2002. doi: 10.1038/nature00771.

Anton Benz, Gerhard Jäger, Robert Van Rooij, and Robert Van Rooij, editors. *An Introduction to Game Theory for Linguists*. Springer, 2005b.

Simon Kirby, Tom Griffiths, and Kenny Smith. Iterated learning and the evolution of language. *Current Opinion in Neurobiology*, 28:108–114, 2014. doi: 10.1016/j.conb.2014.07.014.

Henry Brighton. Compositional syntax from cultural transmission. *Artificial Life*, 8(1):25–54, 2002. doi: 10.1162/106454602753694756.

S. Kirby, M. Dowman, and T. L. Griffiths. Innateness and culture in the evolution of language. *Proceedings of the National Academy of Sciences*, 104(12):5241–5245, 2007. doi: 10.1073/pnas.0608222104.

Laurence R. Horn. *On the Semantic Properties of Logical Operators in English*. Indiana University Linguistics Club, Bloomington, IN, 1972.

Gerald Gazdar. *Pragmatics, Implicature, Presuposition and Logical Form*. Academic Press, New York, 1979.

Elizabeth Closs Traugott. Historical pragmatics. In Laurence R. Horn and Gregory Wand, editors, *The Handbook of Pragmatics*, pages 538–561. Blackwell Publishing, 2004.

Johan van der Auwera. On the diachrony of negation. In *The Expression of Negation*, pages 73–110. Walter de Gruyter GmbH, 2010. doi: 10.1515/9783110219302.73.

Yarden Katz, Noah D Goodman, Kristian Kersting, Charles Kemp, and Joshua B Tenenbaum. Modeling semantic cognition as logical dimensionality reduction. In *Proceedings of Thirtieth Annual Meeting of the Cognitive Science Society*, 2008.