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

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Abstract

Many semantic structures enable for pragmatic enrichments in a notably productive fashion. This raises the challenge to justify their regular selection over alternatives that codify semantically what is conveyed pragmatically. This issue is particularly puzzling under a purely functional perspective. To address this challenge, we propose a general model for the analysis of linguistic pressures that integrates iterated Bayesian learning in the replicator-mutator dynamics. This model allows for population-level analyses of the effects of such pressures on probabilistic language users with varied degrees of pragmatic sophistication and distinct languages. We showcase the model's 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, 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. Under this view, 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. As a consequence, their distinction has played an important role in the field's theoretical and experimental development. However, an issue that has received little attention is the justification of semantic structure in light of pragmatics. That is, the selection and pervasiveness of particular semantics under consideration of the regular informational enrichment provided by pragmatics.

Similar questions have lead to a recent surge of models that aim to analyze the development and selection of linguistic features (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 expressiveness as well as learnability.

We proceed by modeling these pressures using the replicator-mutator dynamics (see Hofbauer and Sigmund 2003 for an overview). This allows us to inspect their dynamics by combining functional pressure on successful communication, effects of learning biases on (iterated) Bayesian 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).

2 Simplicity, expressivity, and learnability

The emergence and change of linguistic structure is influenced by many 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 certain processes of linguistic change are understood as shaped by 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 selection and change are driven 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 key instances of such 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 applications. 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 the tension between learnability and expressivity 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 assume an integeral part of the answer to be that learners are a priori biased towards simpler, more compressed, 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 betweeen hypotheses that fit the data has a long standing tradition. Crucially, Chater and Vitányi (2003) provide strong arguments for a prior towards simpler explanations. **this needs to be expanded**

The remainder of this section introduces the individual components of the model in more technical detail. That is: (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 are taken to codify the truth-conditions of a language's expressions, i.e., its semantics. Given a state of affairs and a lexicon, language users can judge whether an expression is true or false. A convenient way to represent such lexica is by $(|S|, |M|)$-Boolean matrices, where S is a set of states of affairs and M the set of messages in the lexicon (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:

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

In words, according to lexicon L_a, m_1 is true of s_1 as well as 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 solely guided by their lexica. In contrast, *pragmatic interlocutors* engage in mutual reasoning to inform their choices. For instance, given that m_2 is unambiguously associated with state s_1, a rational speaker of L_a who reasons about her addressee should use m_1 to signal state s_2. Analogously, should rational hearers expect their interlocutors to reason along these lines, they will interpret the messages accordingly. Note in particular that according to this sketch of the pragmatic strenghtening of m_1, L_a is indistinguishable from L_b in terms of expressiveness.

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. Language users of level $n+1$ behave rationally according to (expected) level n behavior of their interlocutors. The behavior of literal level 0 and pragmatic level $n+1$ hearers of a language L is is captured 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, weighted by her prior over states, $pr \in \Delta(S)$. The latter plays an important role when hearers face ambiguous messages about which the prior is informative.

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 α increases, choices made in production are more rational; higher values lead to more deterministic expected utility maximizing behavior.

Pragmatic behavior resembles its literal counterpart. As described above, the crucial difference is that level $n+1$ speakers/hearers reason about level n hearer/speaker behavior. 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 more pragmatic behavior.

The combination of a lexicon with its use, i.e., a degree of pragmatic sophistication, yields a type $t \in T$. Accordingly, T contains all all lexica and reasoning level pairings under consideration. Types are the basic units on which our population dynamics operate.

2.2 Replication & expressivity

On a population level, expressiveness, or communicative efficiency, has received particular attention from investigations using evolutionary game theory (Nowak and Krakauer 1999, Nowak et al. 2000; 2002). Under this view, successful communication confers a higher fitness to some types relative to less successful ones. As a consequence, types with a higher fitness replicate and spread through the population, whereas the proportion of communicatively less efficient types decreases. 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 when interacting in this population. That is, its fitness is the sum of its weighted expected communicative success, $f_i = \sum_j x_j \text{EU}(t_i, t_j)$. The expected utility of i and j is obtained by considering the expected utility of speaker i interacting with hearer j, and vice versa: $\text{EU}(t_i, t_j) = [U_S(t_i, t_j) + U_R(t_i, t_j)]/2$. $U_S(x, y)$ 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] 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 biological replication, many aspects of natural language are subject to processees of 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 and assume that interlocutors adapt their language's semantics and how it is used to that which works best within their population. In contrast to the effect of language acquisition from a generation to the next, this means that expressivity exherts its pressure on the current members of a linguistic community.

Nowak & et al. did not only consider replication, but also recognized the relevance of variation introduced by a language's transmition across generations, construed as mutation. As a consequence, the offspring of a type may end up adopting a different type than their parents. However, in this work mutation rates were construed as independent from a type. That is, the variation introduced by generational turnovers did not depend on a the relative learnability of a type based on learning data or learning biases. Therefore, 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. In linguistic terms, this process can be construed by chains of parents and children, where the

[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.

parent produces linguistic data from which the child infers a language. The latter then 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 type from the resulting posterior distribution according to their learning strategy.

A central result of iterated learning is that this it leads to simpler and more regular languages due to the pressure towards greater learnability it exherts (surveys of experimental 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 the learners' learning biases, codified as a prior $P \in \Delta(\mathcal{T})$. This bias can be thought of 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).

However, the extent of the influence of the prior on the dynamics was shown to depend on assumptions about the strategy employed by learners. 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 corresponded to the learners' prior distribution – irrespective of the amount of input given to learners. The divergence between these predictions crucially depends on the assumed learning strategy. On the one extreme, Griffith & Kalish's prediction 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.

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 to posterior maximization increases.

More generally, we combine the replicator dynamics with iterated learning by codifying the latter as a transition matrix Q, where Q_{ij} indicates the probability of the children of a parent of type i adopting type j. This, in turn, is proportional to the probability of i producing the learning data and that of j given the data. That is, the learner's task is to perform a joint inference over lexica and signaling behavior.

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

So far, we have argued for expressivity, learnability and simplicity as central pressures that apply on the cultural evolution of language. The dynamics we propose model them as fitness-relative replication, mutation based on iterated Bayesian learning, and a prior that biases learners for compressed lexical meanings, respectively. Taken together the 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 these pressures apply to are a combination of semantics, i.e., a lexicon, and its use. The expressivity of these types depends on their communicative efficiency within a population. Their learnability depends on the fidelity by which they can be infered by a new generation of learners based on production data. In particular, learners perform a joint inference on types of linguistic behavior and lexical meaning. This process is influenced by the learners' preference for simpler lexical representations, codified as a learning bias.

Summarize novelties & advantages 1. Advantage of connection between two strands of research 2. Simple and general mean field dynamics

Possibly put reference to Kalish in EVOLANG7, Spain, on selection + iterated learning, and our CogSci

3 Lack of semantic upper-bounds in lexical meaning

We set out to investigate the prevalence of lexical meanings that allow for regular pragmatic enrichments over other potential alternatives. A particularly well-studied type of conventional pragmatic enrichment are so-called *scalar implicatures* (cf. Horn 1972, Gazdar 1979). 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. 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 (*all*), this alternative must not hold. In this way, 'Some students came to class' is strengthened as conveying '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*. Put differently, mutual reasoning about rational language use supplies a bound that rules out stronger alternatives pragmatically.

Note that 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 the latter state. The strength of this association being dependent on their degree of rationality λ and their prior over states. Conversely, a pragmatic speaker will reason about her interlocutors interpretation and use the messages accordingly.

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

We can now rephrase our initial question in terms of scalar implicatures: Why is the lack of lexical upper-bounds in weak scalar alternatives, as m_1 in L_a, 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 classes of expressions that license such inferences across languages (Horn 1972, Horn 1984:252-267, Traugott 2004, van der Auwera 2010).

Other hyp The first is that pragmatic reasoning offers a general mechanism to strengthen the meaning of a wide range of expressions when the conditions outlined above hold. Consequently, cases where cooperativity or knowledge are not likely to be given are non-committal to whether stronger alternatives hold. If for all the speaker knows some students came but she does not know whether all came, then the compatibility of some with (possibly) all succinctly conveys the speakers uncertainty about the latter.

Given that scalar expressions occur in contexts in which their upper-bounded reading is absent, one could argue for a func- tional advantage of a lack of semantic upper-bounds: If ex- pressing such a state of affairs is relevant and contextual cues provide enough information for a hearer to discern when a bound is conveyed pragmatically, then doing so is preferred over enforcing the bound overtly through a longer (more com- plex) expression, e.g. by stating some but not all explicitly. That is, all else being equal, speakers prefer to communicate as economically as possible, and pragmatic reasoning enables them to do so. Additionally, this can be contrasted with the hypothetical alternative of lexicalizing two expressions one with and one lacking an upper-bound. Four conditions may pressure language to English-like semantics over this alter- native: (i) contextual cues are very reliable, morphosyntactic disambiguation is either (ii) not frequently necessary or (iii) not very costly, or (iv) having larger lexica is more costly than morphosyntactic disambiguation. In a nutshell (i) and (ii) place a heavy burden on the ability to retrieve contextual cues to a degree that is unlikely to undercut the benefit of safe communication with more expressions. As for (iii) and (iv), these seem mostly like technical solutions without a proper empirical basis.

Our hyp In what follows we investigate the hypothesis that this preference is driven by the advantage in compression that lexical meanings lacking an upper-bound have over those that explicitly codify it.

At present, the contrast in compressability between lexical meanings, however, is not represented as lexica codify the truth-conditions of expressions at a lower level of granularity. 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, 2012 and references therein). We think that our assumption is well-warranted as a working hypoth- esis and decide against such an enrichment given that the introduc- tion of a larger framework would also require further assumptions and justifications.

3.1 Application

Procedural description. The game is initialized with some arbitrary distribution over player types. 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.

Languages. We consider a population of players with two signaling behaviors, literal and Gricean (level 0 and 1 below), each equipped with one of 6 lexicons. This yields a total of 12 distinct player types $t \in T$. $|M| = |S| = 2$, i.e., a lexicon is a $(2, 2)$-matrix. These are listed in Table 1.

$$L_1 = \begin{pmatrix} 0 & 0 \\ 1 & 1 \end{pmatrix} \quad L_2 = \begin{pmatrix} 1 & 1 \\ 0 & 0 \end{pmatrix} \quad L_3 = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$$
$$L_4 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad L_5 = \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix} \quad L_6 = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}$$

Table 1: Set of considered lexica.

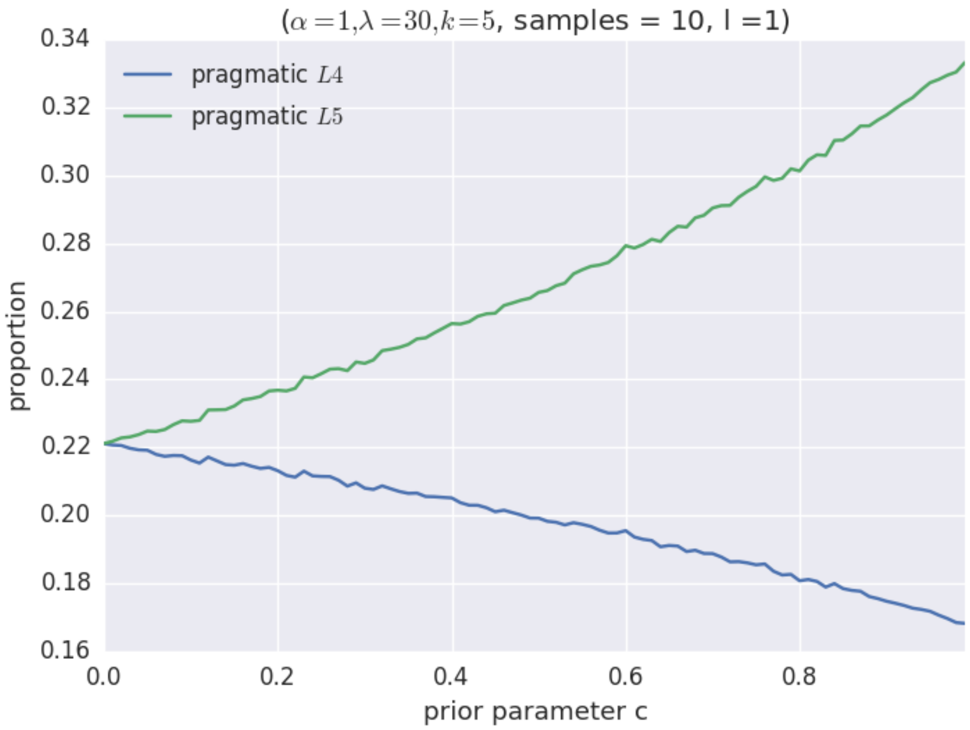
As in the CogSci paper, L_4 (semantic upper-bound for m_2) and L_5 (no semantic upper-bound for m_2) are the target lexica. Gricean L_5 users can convey/infer the bound pragmatically, while literal/Gricean L_4 users do so semantically.

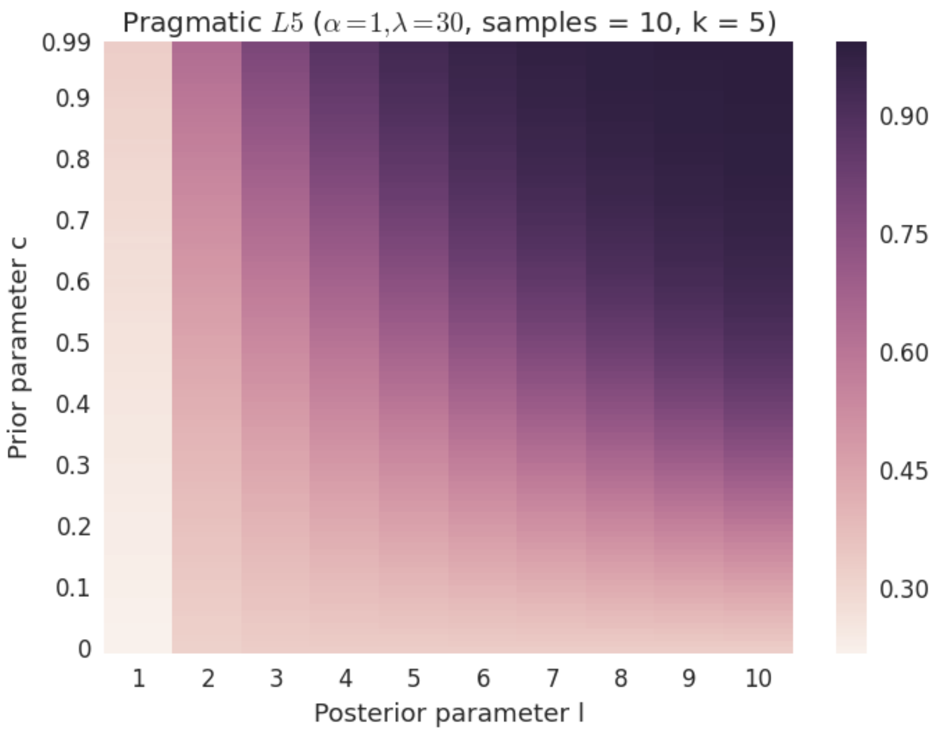
3.2 Model parameters & procedure

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

Possibly put only fitness and only learning in a single plot with shared y axis


($\alpha=1,\lambda=30,k=5$, 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

4 Discussion

5 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.

6 Conclusion

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