Tracing the cultural evolution of meaning at the semantics-pragmatics interface

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Abstract

According to standard linguistic theory, the meaning of an utterance is the product of conventional semantic meaning and general pragmatic reasoning applied to the context of utterance. This implies that models of cultural evolution of meaning should likewise take into consideration that observable language use is a complex interaction of semantic representations and pragmatic use. To this end, we present a game theoretic model of cultural language evolution where communicative pressures work on abstract semantic representations and pragmatic patterns of use. Our model traces two evolutionary forces and their interaction: (i) fitness-based pressure towards communicative efficiency and (ii) systematic transmission perturbations when linguistic knowledge is transferred from one agent to another. We illustrate the model based on a case study showing that learning biases that favor simple semantic representations can prevent the lexicalization of pragmatic inferences as long as mutual reasoning counteracts a loss in expressivity otherwise incurred by the adoption of such semantics.

1 Introduction

What is conveyed usually goes beyond what is said. A request for a blanket can be politely veiled by uttering "I'm cold." The temporal succession of events can be communicated by the order in which conjuncts appear as in "I traveled to Paris and got married." An invitation can be declined by saying "I have to work." An influential explanation of the relation between the literal meaning of expressions and what they are intended and interpreted to convey is due to Grice (1975), who characterizes pragmatic use and interpretation as a process of mutual reasoning about rational language use. For instance, under the assumption that the speaker is cooperative and relevant, "I have to work" may be interpreted as providing a reason why the speaker will not be able to accept the invitation, going beyond its literal meaning. Some of these enrichments are rather *ad hoc*. Others show striking regularities, such as the use of ability questions for polite requests ("Could you please . . . ?"), or certain enrichments of lexical meanings such as *and* to mean *and then*.

A particularly productive and well studied class of pragmatic enrichments are scalar implicatures (Horn 1984, Hirschberg 1985, Levinson 1983, Geurts 2010). Usually, the utterance of a sentence like "I own some of Johnny Cash's albums" will be taken to mean that the speaker does not own all of them. This is because, if the speaker had them all, he could have used the stronger word *all* instead of *some* in his utterance, thereby making a more informative statement. Scalar implicatures, especially the inference from *some* to *some but not all*, have been studied extensively, both theoretically (e.g., Sauerland 2004, Chierchia et al. 2012, van Rooij and de Jager 2012) as well as experimentally (e.g., Bott and Noveck 2004, Huang and Snedeker 2009, Grodner et al. 2010, Goodman and Stuhlmüller 2013, Degen and Tanenhaus 2015). While there is much dispute in this domain about many details, a position endorsed by a clear majority is that a word like *some* is underspecified to mean *some and maybe all* and that the enrichment to *some but not all* is part of some regular process with roots in pragmatics.

If this majority view is correct, the question arises how such a division of labor between semantics and pragmatics could have evolved. Models of language evolution abound. There are simulation-based models studying the evolution of language in populations of communicating agents (Hurford 1989, Steels 1995, Lenaerts et al. 2005, Steels and Belpaeme 2005, Baronchelli et al. 2008, Steels 2011, Spike et al. 2016) and there are mathematical models of language evolution, mostly coming from game theory (Lewis 1969, Wärneryd 1993, Blume et al. 1993, Nowak and Krakauer 1999, Huttegger 2007, Skyrms 2010). Much of this work has focused on explaining basic properties such as compositionality and combinatoriality (e.g., Batali 1998, Nowak and Krakauer 1999, Nowak et al. 2000, Kirby and Hurford 2002, Kirby 2002, Smith et al. 2003, Gong 2007, Kirby et al. 2015, Verhoef et al. 2014, Franke 2016), but little attention has been paid to the interaction between conventional meaning and pragmatic use. What is more, many mathematical models explain evolved meaning as a regularity in the behavior of agents which maps objective states of the world to observable signals. There is no room in such a purely extensional approach to address the semantics-pragmatics division directly. Instead, we would need to look at richer representations of cognizing agents and their communicative interaction.

To fill this gap, we spell out a model of the co-evolution of conventional meaning and pragmatic reasoning types. The objects of replication and selection are pairs of lexical meanings and general types of pragmatic behavior, which we represent using state-of-the-art probabilistic cognitive models of pragmatic language use (Frank and Goodman 2012, Franke and Jäger 2016, Goodman and Frank 2016). Replication and selection are described by the *replicator mutator dynamic*, a general and established model of evolutionary change in large and homogeneous populations (Hofbauer 1985, Nowak et al. 2000; 2001, Hofbauer and Sigmund 2003, Nowak 2006). The approach allows us to study the interaction between (i) evolutionary pressure towards communicative efficiency and (ii) possible infidelity in the transmission of linguistic knowledge, caused by factors such as inductive learning biases and sparse data to learn from. Considering transmission of linguistic knowledge is important because neither semantic meanings nor pragmatic usage patterns are directly observable. Instead, language learners have to infer these unobservables from the observable behavior in which they result. We formalize this process as a form of Bayesian inference. Our approach thereby contains a well-understood model of iterated Bayesian learning (Griffiths and Kalish 2007) as a special case, but combines it with functional selection, here formalized as the most versatile dynamic from evolutionary game theory; the replicator dynamic (Taylor and Jonker 1978). Section 2 introduces this model.

Section 3 applies this model to a case study on scalar implicatures. We discuss a setting in which the majority view of underspecified lexical meanings and pragmatic enrichments emerges if selection and transmission infidelity are combined. In particular, we show that inductive learning biases of Bayesian learners that favor simpler lexical meanings can lead to this outcome.

We see the main contribution of this work as conceptual and technical, not as a definite answer to the question why scalar implicatures emerge. It rather demonstrates how current probabilistic cognitive modeling of language use and evolutionary modeling can be fruitfully combined to study the co-evolution of semantics and pragmatics side-by-side. Reversely, the approach taken here may be seen as a first step towards giving an evolutionary rationale for empirically successful probabilistic models of language use that embrace the majority view of the division of labor between semantics and pragmatics. Section 4 elaborates on these points.

2 Model

2.1 Expressivity and learnability at the semantics-pragmatics interface

The emergence and change of linguistic structure is influenced by many intertwined factors. These range from biological and socio-ecological to cultural ones (Benz et al. 2005, Steels 2011, Tamariz and Kirby 2016). Social and ecological pressures determine communicative needs, while biology determines the architecture that enables and constrains the means by which they can be fulfilled. In the following, our focus lies on cultural aspects, wherein processes of linguistic change are viewed as shaped by language use and its transmission, i.e., as a result of a process of cultural evolution (Pagel 2009, Thompson et al. 2016).

The idea that language is an adaptation to serve a communicative function has played a pivotal role in synchronic and diachronic analyses at least since Zipf's (1949) explanation of word frequency rankings as a result of competing hearer and speaker preferences (e.g., in Martinet 1962, Horn 1984, Jäger and van Rooij 2007, Jäger 2007, Piantadosi 2014, Kirby et al. 2015). If processes of selection, such as conditional imitation or reinforcement, favor more communicatively efficient types of behavior, languages are driven towards semantic expressivity (e.g., Nowak and Krakauer 1999, Skyrms 2010). But pressure towards communicative efficiency is not the only force that shapes language. Learnability is another, as natural languages need to be learnable to survive their faithful transmission across generations. Clearly, an unlearnable code will not make it past the one happy fellow who invented it. Importantly, even small biases implicit in acquisition can build up and have quite striking effects on an evolving language in a process of iterated learning (Kirby and Hurford 2002, Smith et al. 2003, Kirby et al. 2014).

While natural languages are pressured for both expressivity and learnability these forces may pull in opposite directions. Their opposition becomes particularly clear when considering the extreme (cf. Kemp and Regier 2012, Kirby et al. 2015). A language with a single form-meaning association is easy to learn but lacking in expressivity. Conversely, a language that associates a distinct form with all possible meanings a speaker may want to convey is maximally expressive but challenging to acquire.

An elegant formal approach to capture the interaction between expressivity and learnability is the *replicator mutator dynamic* (Hofbauer 1985, Nowak et al. 2000; 2001, Hofbauer and Sigmund 2003, Nowak 2006). In its simplest, discrete-time formulation, the RMD defines the frequency x'_i of each type i in a population at the next time step as a function of: (i) the frequency x_i of each type i before the step, (ii) the fitness f_i of each type i before the step, and (iii) the probability Q_{ji} that an agent who wants to imitate, adopt, or learn the type of an agent with type j ends up acquiring type i:

$$x'_i = \sum_j Q_{ji} \frac{x_j f_j}{\sum_k x_k f_k} \,. \tag{1}$$

The RMD consists of two components: fitness-based selection and transmission biases. This becomes most transparent when we consider an equivalent formulation in terms of a step-wise application of the discrete-time replicator dynamic (Taylor and Jonker 1978) on the initial population vector $\vec{x}$ and its subsequent multiplication with a mutation matrix Q:

$$x'_i = (\mathrm{M}(\mathrm{RD}(\vec{x})))_i \,, \tag{2}$$

where

$$(\mathrm{RD}(\vec{x}))_i = \frac{x_i f_i}{\sum_k x_k f_k} \quad \text{and} \quad (\mathrm{M}(\vec{x}))_i = (\vec{x} \cdot Q)_i = \left(\sum_j x_j Q_{ji} \right)_i .$$

If the transmission matrix Q is trivial in the sense that $Q_{ji} = 1$ whenever $j = i$, the dynamic reduces to the replicator dynamic. The replicator dynamic is a model of fitness-based selection in which the relative frequency of type i will increase with a gradient proportional to its average fitness in the population. This dynamic is popular and versatile because it can be derived from many abstract processes of biological and cultural transmission and selection (for overview and several derivations see Sandholm 2010), including conditional imitation (e.g., Helbing 1996, Schlag 1998) or reinforcement learning (e.g., Börgers and Sarin 1997, Beggs 2005). If fitness f_i is the same for all types i, the replicator step is the identity map $(\mathrm{RD}(\vec{x}))_i = x_i$ and the dynamic reduces to a process of iteration of the transmission bias encoded in Q. In this way, the process in (1), equivalently (2), contains a model of iterated learning (Griffiths and Kalish 2007). [MF: should we include a simple example here? I have an example from a lecture ready at hand; it's a simple coordination game in a one-population setting.] [TB: Yes, I think most readers would appreciate it. We can always cut it out again if the reviewers prefer more compression.]

Where our goal is an application of this dynamic to the case of co-evolution of semantic meaning and pragmatic use, we need to fix what the relevant types are, how fitness is measured and how the mutation matrix is computed. These issues are addressed, one by one, in the following.

2.2 Types: Lexica and linguistic behavior

Types are what cultural evolution operates on. In standard applications of evolutionary game theory, types correspond to ways of acting in a game, e.g., either cooperating or defecting in a prisoner's dilemma. [MF: maybe good to refer back to the example from before if there was one?] [TB: Yes!] For our present purpose, types are identified by their cognitive make-up. Since we are interested in the question under which conditions processes of cultural evolution will favor specific divisions of labor between lexical meaning and pragmatic use, a type is a pair consisting of a lexicon and a pragmatic strategy.

Lexica codify the truth-conditions of expressions. A convenient way to represent lexica is by $(|S|, |M|)$-Boolean matrices, where S is a set of states (meanings) and M a set of messages (forms available in the language). For example, suppose that there are two relevant world states $S = \{s_{\exists\neg\forall}, s_{\forall}\}$. In state $s_{\exists\neg\forall}$ Chris owns some but not all of Johnny Cash's albums while in $s_{\forall}$ Chris owns them all. Suppose that there are two messages $M = \{m_{\text{some}}, m_{\text{all}}\}$ where m_{some} is short for a sentence like *Chris owns some of Johnny Cash's albums* and m_{all} for the same sentence with *some* replaced by *all*. Lexica for this case would assign a Boolean truth value, either 0 or 1, to each state-message pair. The following two lexica exemplify the distinction between a lexicalized upper-bound for *some* in L_{bound} and the widely assumed logical semantics with only a lower-bound in L_{lack}.

$$L_{\text{bound}} = \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array} \qquad L_{\text{lack}} = \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \end{array}$$

We distinguish between two kinds of pragmatic behavior. *Literal interlocutors* produce and interpret messages literally, being guided only by their lexica. *Pragmatic interlocutors* instead engage in mutual reasoning to inform their choices. Recent probabilistic models of rational language use (Franke 2009, Frank and Goodman 2012, Franke and Jäger 2016, Goodman and Frank 2016) capture different types of pragmatic behavior in a reasoning hierarchy. The hierarchy's bottom, level 0, corresponds to literal language use. Pragmatic language users of level $n+1$ act (approximately) rational with respect to level-n behavior of their interlocutors. (3) and (4) define probabilistic behavior of literal hearers and speakers respectively: [MF: is it a problem that S denotes speakers and the set of states?] [TB: I think that's fine. $S_n(\cdot \mid \cdot)$ is not used beyond this section. Otherwise we can, e.g., relabel M as F(orms) and use M(eanings) instead of S(tates). I'm fine with either option.]

$$H_0(s \mid m; L) \propto pr(s) L_{sm} \tag{3}$$

$$S_0(m \mid s; L) \propto \exp(\lambda \, L_{sm}) \tag{4}$$

According to (3), a literal hearer's interpretation of a message m as a state s depends on her lexicon and her prior over states, $pr \in \Delta(S)$. For simplicity, in the following this prior is assumed to be uniform. A literal interpreter with lexicon L_{bound} from above would assign $s_{\exists\neg\forall}$ a probability of $H_0(s_{\exists\neg\forall} \mid m_{\text{some}}; L_{\text{bound}}) = 1$ after hearing m_{some}, while a literal interpreter with lexicon L_{lack} would assign $s_{\exists\neg\forall}$ probability $H_0(s_{\exists\neg\forall} \mid m_{\text{some}}; L_{\text{lack}}) = 0.5$. As usual in probabilistic pragmatics models, speaker behavior 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 behavior that is increasingly in line with expected utility maximization. Expected utility of a message m in state s for a level $n+1$ speaker is here defined as $H_n(s|m; L)$, the probability that the hearer will assign to or choose the correct meaning. Put differently, how likely the hearer is thought to infer s when sent m. The formulation in (4) also allows false messages to be sent with a small positive probability in analogy to the definition of pragmatic speakers in probabilistic pragmatic models. This is also necessary to guarantee a mutation matrix with only positive entries (see below). If $\lambda = 1$ a literal speaker with either lexicon L_{bound} or L_{lack} produces m_{some} in $s_{\exists\neg\forall}$ with probability $S_0(m_{\text{some}} \mid s_{\exists\neg\forall}; L_{\text{bound,lack}}) \approx .73$. The probability of producing m_{some} in $s_\forall$ is $S_0(m_{\text{some}} \mid s_\forall; L_{\text{bound}}) \approx .27$ for L_{bound} and $S_0(m_{\text{some}} \mid s_\forall; L_{\text{lack}}) = .5$ for L_{lack}. By contrast, if $\lambda = 20$, a literal speaker with either lexicon produces m_{some} in $s_{\exists\neg\forall}$ with probability $S_0(m_{\text{some}} \mid s_{\exists\neg\forall}; L_{\text{bound,lack}}) \approx 1$. But the probability of producing m_{some} in $s_\forall$ is $S_0(m_{\text{some}} \mid s_\forall; L_{\text{bound}}) \approx 1$ for L_{bound} whereas it is still $S_0(m_{\text{some}} \mid s_\forall; L_{\text{lack}}) = .5$ because m_{some} is semantically associated with both states by L_{lack}.

Pragmatic behavior of level $n+1$ is similar to its literal counterparts but uses the interpretation or production behavior of a level-n player instead of the lexical meaning:

$$H_{n+1}(s|m; L) \propto pr(s) S_n(m|s; L) \tag{5}$$

$$S_{n+1}(m|s; L) \propto \exp(\lambda \, H_n(s|m; L)) \tag{6}$$

Particularly important to our purpose is the fact that players of a level greater than 0 using L_{lack} can come to *pragmatically* associate m_{some} with $s_{\exists\neg\forall}$ over $s_\forall$ in contrast to their literal counterparts. Intuitively, this is so because hearers reason a speaker to convey $s_\forall$ with m_{all}, as this has a higher chance of leading to mutual understanding than using underspecified m_{some}. Therefore they will expect m_{some} to be more strongly associated with $s_{\exists\neg\forall}$ than with $s_\forall$ as it is already possible to clearly convey the latter state with a different message. The converse reasoning pattern holds for the speaker. In this way, two distinct lexical conventions such as L_{bound} and L_{lack} can give rise to similar observable linguistic behavior.

2.3 Fitness & fitness-based selection based on expressivity

Most evolutionary dynamics assume that the proportion of type i in a population will increase or decrease as a function of its relative fitness f_i. In the context of language evolution, fitness is frequently associated with expressivity, i.e., the ability to successfully communicate with other language users from the same population (e.g., Nowak and Krakauer 1999, Nowak et al. 2000; 2002). Under a biological interpretation, the assumption is that organisms have a higher chance of survival and reproduction if they are able to share and receive useful information via communication with peers. Under a cultural interpretation, the picture is that agents themselves strive towards communicative success and therefore occasionally adapt or revise their behavior to achieve a higher communicative success (see Benz et al. 2005:§3.3 for discussion).

The replicator equation gives us the means to make the ensuing dynamics precise, without necessarily committing to a biological or cultural interpretation. As above, the proportion of types in a given population is codified in a vector $\vec{x}$, where x_i is type i's proportion. The fitness of type i is its average expected communicative success, or *expected utility* (EU), given the frequencies of types in the current population:

$$f_i = \sum_j x_j \mathrm{EU}(t_i, t_j)\,.$$

The expected utility $\mathrm{EU}(t_i, t_j)$ for type i when communicating with type j is the average success of i when talking or listening to j. Assuming that agents are speakers half of the time this yields:

$$\mathrm{EU}(t_i, t_j) = {}^1\!/\!_2\, \mathrm{EU}_S(t_i, t_j) + {}^1\!/\!_2\, \mathrm{EU}_H(t_i, t_j)\,,$$

where $\mathrm{EU}_S(t_i, t_j)$ and $\mathrm{EU}_H(t_i, t_j)$ are the expected utilities for i as a speaker and as a hearer when communicating with j, defined as follows, where n_i and n_j are type i's and j's pragmatic reasoning types and L_i and L_j are their lexica:

$$\begin{aligned}
&\mathrm{EU}_S(t_i, t_j) = \sum_s P(s) \sum_m S_{n_i}(m \mid s; L_i) \sum_{s'} R_{n_j}(s' \mid m; L_j)\delta(s, s') \\
&\mathrm{EU}_H(t_i, t_j) = \mathrm{EU}_S(t_j, t_i)
\end{aligned}$$

As usual for cooperative communication, $\delta(s, s') = 1$ iff $s = s'$ and 0 otherwise.

2.4 Learnability

Languages are shaped not only by functionalist forces towards greater expressivity. Another important factor is the fidelity by which language is transmitted. Among others, linguistic production can be prone to errors, states or messages may be perceived incorrectly, and multiple languages may be compatible with the data learners are exposed to. These sources of uncertainty introduce variation in the transmission of linguistic knowledge from one generation to the next. In particular, learning biases in the iterated transmission process can influence language evolution substantially.

In biological evolution, where types are expressed genetically, transmission infidelity comes into the picture through infrequent and mostly random genetic mutations. However, an agent's lexicon and pragmatic reasoning behavior is not inherited genetically. They need to be learned from observation. Concretely, when agents of type j want to adopt or imitate the linguistic behavior of type i, they observe the linguistic behavior of type i and need to infer what their type is from that. Iterated learning is a process in which languages are learned repeatedly from the observation of linguistic behavior of agents who have acquired the language from observation and inference before as well. In the simplest case there is a single teacher and a single learner. After sufficient training the learner becomes a teacher and produces behavior that serves as input for a new learner. Due to the pressure towards learnability it exerts, iterated learning generally leads to simpler and more regular languages (see Kirby et al. 2014 and Tamariz and Kirby 2016 for recent surveys).

Following Griffiths and Kalish (2007) we model language acquisition as a process of Bayesian inference in which learners combine the likelihood of a type producing the witnessed learning input with prior inductive biases. Experimental and mathematical results on iterated learning suggest that the outcome of this process reflects learners' inductive biases (e.g., Kirby et al. 2014). In a Bayesian setting these biases can be codified in a prior $P \in \Delta(T)$, which reflects the amount of data a learner requires to faithfully acquire the language of the teacher (cf. Griffiths and Kalish 2007:450). The extent of the prior's influence has been shown to heavily depend on the learning strategy assumed to underlie the inference process. On the one hand, early simulation results suggested that weak biases could be magnified by exposing learners to only small data samples (e.g., in Brighton 2002). On the other, Griffiths and Kalish's (2007) mathematical characterization showed that iterated learning converged to the prior, i.e., that the resulting distribution over languages corresponds to the learners' prior distribution and is not influenced by the amount of input given to them. This difference in predictions can be traced back to differences in the selection of hypotheses from the posterior. Griffith & Kalish's convergence to the prior holds for learners that sample from the posterior. More deterministic strategies such as the adoption of the type with the highest posterior probability, so-called *maximum a posterior estimation* (MAP), increase the influence of both the prior and the data (Griffiths and Kalish 2007, Kirby et al. 2007). In the following, we use a parameter $l \geq 1$ to modulate between posterior sampling and the MAP strategy. When $l = 1$ learners sample from the posterior. The learners' propensity to maximize the posterior grows as l increases.

Let D be the set of possible data that learners may be exposed to. This set D contains all sequences of state-message pairs of length k, e.g., $\langle\langle s_1, m_1\rangle, \ldots, \langle s_k, m_k\rangle\rangle$. As k increases, learners have more data to base their inference on and so tend to recover the true types that generated a given sequence with higher probability. The mutation matrix Q of the replicator mutator dynamics in (1) can then be defined as follows: Q_{ji} is the probability that a learner acquires type i when learning from an agent of type j. The learner observes a length-k sequence d of state-message pairs, but the probability $P(d \mid t_j)$ with which sequence $d = \langle\langle s_1, m_1\rangle, \ldots, \langle s_k, m_k\rangle\rangle$ is observed depends on type j's behavior:

$$P(d = \langle\langle s_1, m_1\rangle, \ldots, \langle s_k, m_k\rangle\rangle \mid t_j) = \prod_{i=1}^{k} S_{n_j}(m_i \mid s_i; L_j)\,,$$

where, as before, n_j is j's pragmatic reasoning type and L_j is j's lexicon. For a given observation d, the probability of acquiring type i is $F(t_i \mid d)$, so that:

$$Q_{ji} \propto \sum_{d \in D} P(d \mid t_j) F(t_i \mid d)\,.$$

The acquisition probability $F(t_i \mid d)$ given datum d is obtained by probability matching $l = 1$ or a tendency towards choosing the most likely type $l > 1$ from the posterior distribution $P(\cdot \mid d)$ over types given the data, which is calculated by Bayes' rule:

$$F(t_i \mid d) \propto P(t_i \mid d)^l \;\text{ and}$$
$$P(t_i \mid d) \propto P(t_i) P(d \mid t_i)\,.$$

2.5 Model summary

Expressivity and learnability are central to the cultural evolution of language. These components can be modelled, respectively, as replication based on a measure of fitness in terms of communicative efficiency and iterated Bayesian learning. Their interaction is described by the discrete time replicator mutator dynamics in (1), repeated here:

$$x'_i = \sum_j Q_{ji} \frac{x_j f_j}{\sum_k x_k f_k} \, .$$

This equation defines the frequency x'_i of type i at the next time step, based on its frequency x_i before the step, its fitness f_i and the probability that a learner infers i when observing the behavior of a type-j agent. Fitness-based selection can be thought of as biological (fitness as expected relative number of offspring) or cultural (fitness as likelihood of being imitated or repeated). The types that the dynamic operates on are pairs consisting of a lexicon and a pragmatic use pattern. A type's expressivity depends on its communicative efficiency within a population while its learnability depends on the fidelity by which it is inferred by new generations of learners. The learners' task is consequently to perform a joint inference over types of linguistic behavior and lexical meaning.

3 Scalar implicatures

Scalar implicatures are a particularly well-studied type of conventional pragmatic inferences. They 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 "Chris owns all of Johnny Cash's albums", it would also be true that "Chris owns some of Johnny Cash's albums". However, while weaker expressions such as *some* are truth-conditionally compatible with stronger alternatives such as *all*, this is not what their use is normally 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 stronger alternatives do not hold because the speaker used a weaker alternative instead. In this way, "Chris owns some of Johnny Cash's albums" is strengthened to convey that he owns some but not all albums. A bound that rules out stronger alternatives is thusly not codified in the lexical meaning of weak alternatives but instead pragmatically supplied.

As noted earlier, this kind of strengthening is captured by the linguistic behavior of pragmatic types introduced in §2.2: A pragmatic hearer who reasons about the use of a message involving a weak scalar alternative will associate it more with a state in which stronger alternatives do not hold. This is so because a rational speaker would use a more informative message when in such a state. Conversely, a pragmatic speaker will reason about her interlocutor's expected interpretation and use the messages at her disposition accordingly.

Our initial question about the division of labor between semantics and pragmatics can be narrowed to the case of scalar implicatures by asking for a justification for the lack of lexical upper-bounds in weak scalar alternatives. That is, we ask why lexical meanings that lack upper-bounds and convey it pragmatically are regularly selected for over alternatives such as that of codifying the bound semantically. More poignantly, would it not serve language users better if weak(er) expressions such as *warm*, *or*, *some* and *big* were truth-conditionally incompatible with stronger alternatives such as *hot*, *and*, *all* and *huge*? This question is particularly striking considering the number of expressions that license such inferences across natural languages.

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 with a broader range of applicability by allowing them to 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 'Chris owns some of Johnny Cash's albums' but she does not know whether he owns all, then the use of *some* lacking an upper-bound succinctly conveys her uncertainty. 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 this is preferred over expressing it overtly through longer expressions, e.g., by saying *some but not all* explicitly. Importantly, although morphosyntactic disambiguation may be dispreferred due to its relative length and complexity (Piantadosi et al. 2012b), it allows speakers to enforce an upper-bound and 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 that lexicalizes two expressions for each weak scalar expression – one with and one lacking an upper-bound. We see four conditions along this functionalist explanation that may pressure languages for English-like semantics over this alternative. First, contextual cues are very reliable. Second, morphosyntactic disambiguation is seldom necessary. Third, morphosyntactic disambiguation is only marginally dispreferred. Fourth, larger lexica are costly. Overall, neither condition seems convincing as a pivotal explanatory device for such a widespread phenomenon. The first two conditions put a heavy burden on the ability to retrieve contextual cues to a degree that seems unlikely to undercut the benefit of unambiguous communication. It is likely that human language users are very good at retrieving cues from context, but to stipulate that they are so good as to undercut the benefit of safe communication provided by this hypothetical alternative strikes us as too strong of an assumption. As for the third and fourth condition, these seem mostly like technical solutions without a proper empirical basis.

Instead, the systematicity and typological spread of scalar implicatures together with the observation that monomorphemic expressions that lexically rule out stronger alternatives are unattested across languages (Horn 1984:252-267, Horn 1972, Traugott 2004, van der Auwera 2010) suggests that other forces may be at play. In what follows we investigate the predictions of our model under the assumption that the lack of lexicalization of scalar inferences may be accounted for by the relative representational simplicity of lexical meanings lacking an upper-bound over those that explicitly codify it. This difference is reflected in a learning bias towards more compressed lexical representations. That is, in a preference of learners for simpler over more complex explanations of the data they witness (Feldman 2000, Chater and Vitányi 2003, Piantadosi et al. 2012a, Kirby et al. 2015, Piantadosi et al. under review). While we do not want to argue that functional aspects as the ones discussed above do not play a role, we do see a clear benefit in exploring whether matters of transmission biases would not give us additional explanatory leverage.

3.1 Analysis

The dynamics are initialized with an arbitrary distribution over types, constituting a population's first generation. In the following we report the outcome of their development under different parameters and pressures after 50 generations. This ensures that these outcomes correspond

$C \rightarrow_2 C \wedge C$	$X \rightarrow_1 \{A, B\}$
$C \rightarrow_2 \neg C$	$X \rightarrow_1 X \cap X$
$C \rightarrow_1 X \subseteq X$	$X \rightarrow_1 X \cup X$
$C \rightarrow_1 X \neq \emptyset$	
$C \rightarrow_1 X = \emptyset$	

Table 1: Toy grammar in a set-theoretic LOT with weighted rules.

to developmental plateaus after which no noteworthy change is registered. As specified in §2.4, the mutation matrix Q can be obtained by considering all possible state-message sequences of length k. Given that this is intractable for large k, the sets of data learners are exposed to are approximated by sampling 250 k-length sequences from each type's production probabilities.

We begin setting the stage by defining the learning prior and the set of types under consideration. Drawing from our preceding discussion, functional pressure on successful communication combined with learning pressures in the form of a bias against upper-bounds may lead to the selection of L_{lack}-like semantics. However, it is instructive to first inspect the effect of these pressures in isolation. We therefore first showcase the effects that expressivity and learnability have on their own before turning to those resulting from their combination.

3.1.1 Inductive learning bias against semantic complexity

There is a growing effort to develop empirically testable representational languages that allow for the measure of semantic complexity. For instance, so-called *languages of thought* (LOT) have 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; 2012a and Piantadosi and Jacobs 2016 for recent discussion). At its core, a LOT defines a set of operations and composition rules from which lexical meaning can be derived. As a first approximation and for the sake of concreteness, we follow this approach to make the preference of learners for simpler semantic representations precise and define the complexity of a representation as a function of its derivation cost in a weighed generative LOT.

Our toy grammar of concepts is given in Table 1. This grammar uses basic set-theoretic operations to form expressions which can be evaluated as true or false in different world states such as $s_{\exists\neg\forall}$ or $s_{\forall}$ (see below). Applications of generative rules have a cost attached to them. (Alternatively, a probability.) Here we simply assume that Boolean combinations of concepts are more complex than atomic concepts and that otherwise each rule application adds the same cost unit.

The prior probability of a type is just the prior probability of its lexicon. The prior of a lexicon is a function of the complexity of the lexical representations in its image set. As motivated above, lexica that use simpler concepts are *a priori* more likely. A simple way of defining such priors over lexica is:

$$P(L) \propto \prod_{c \in Im(L)} P(c) \text{ , with } \qquad P(c) \propto \max_{c'} Compl(c') - Compl(c) + 1 \,,$$

where $Compl(c)$ is the complexity of the minimal derivation length of each concept. There are other more sophisticated ways to define priors over lexica (see, e.g., Goodman et al. 2008, Piantadosi et al. 2012a) but the key assumption here, common to all of them, is that simple

intuitive name	$s_\emptyset$	$s_{\exists\neg\forall}$	$s_\forall$	least complex formula	complexity
"all"	0	0	1	$A \subseteq B$	3
"some but not all"	0	1	0	$A \cap B \neq \emptyset \wedge A \neq \emptyset$	8
"some"	0	1	1	$A \cap B \neq \emptyset$	4
"none"	1	0	0	$A \cap B = \emptyset$	4
"none or all"	1	0	1	$\neg(A \cap B \neq \emptyset \wedge A \neq \emptyset)$	10
"not all"	1	1	0	$\neg(A \subseteq B)$	5

Table 2: Available concepts and their minimal derivation length

representational expressions should be favored and complex ones disfavored. More generally, we should stress that these details – from generative grammar to complexity measure – are stipulated and should therefore be regarded as an illustratory instantiation of our general assumptions instead of as strong empirical claims.

3.1.2 Lexica, signaling behavior & types

We consider a state space with three states $S = \{s_\emptyset, s_{\exists\neg\forall}, s_\forall\}$. This space can be thought of as a partition of possible worlds into cells where none, some or all of the As are Bs, for some arbitrary fixed predicates A and B. Eight concepts can be distinguished based on their truth or falsity in three world states, six of which are not contradictory or tautological. These are listed with mnemonic names in Table 2 together with their complexity according to the grammar given in Table 1.

A lexicon L is a mapping $M \to C$ from messages to concepts. With three messages there are $6^3 = 216$ possible lexica. Of these, three kinds of lexica are of particular relevance. First, lexica that assign the same concept to more than one message. Such lexica lack in expressivity but may be favored by the learning bias. Second, lexica that conventionalize upper-bounds to realize a (quasi-)partition of the relevant semantic space. As discussed before in relation to L_{bound}, users of these lexica need not resort to pragmatic reasoning to convey an upper-bound with weak scalar expressions. Instead, this information is already given by the semantics of their lexicon, giving them an advantage in terms of expressivity. Such lexica are expected to be the main contenders to the natural language like semantics that fail to lexicalize an upper-bound. Third and lastly, L_{lack}-style lexica that, paired with mutual reasoning, can convey an upper-bound pragmatically. Overall, there are 6 lexica of the second kind and 6 of the third. The following three lexica exemplify each kind, with L_{all} being a lexicon of the first kind. It is not optimal for communication as it assigns all its messages to the same state, $s_\forall$. This failure to associate a state to single a form inevitably leads to a communicative disadvantage in its use but it an serves illustrative purpose in comparison to our target, L_{lack}, and its competitor L_{bound}, in virtue of being the simplest lexicon complexity-wise.

$$
\begin{array}{c}
\\ \\ s_\emptyset \\ s_{\exists\neg\forall} \\ s_\forall
\end{array}
\begin{array}{c}
\underline{L_{\text{all}}} \\
\begin{array}{ccc} m_{\text{none}} & m_{\text{some}} & m_{\text{all}} \end{array} \\
\left[\begin{array}{ccc} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{array}\right]
\end{array}
\quad
\begin{array}{c}
\underline{L_{\text{bound}}} \\
\begin{array}{ccc} m_{\text{none}} & m_{\text{some}} & m_{\text{all}} \end{array} \\
\left[\begin{array}{ccc} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array}\right]
\end{array}
\quad
\begin{array}{c}
\underline{L_{\text{lack}}} \\
\begin{array}{ccc} m_{\text{none}} & m_{\text{some}} & m_{\text{all}} \end{array} \\
\left[\begin{array}{ccc} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{array}\right]
\end{array}
$$

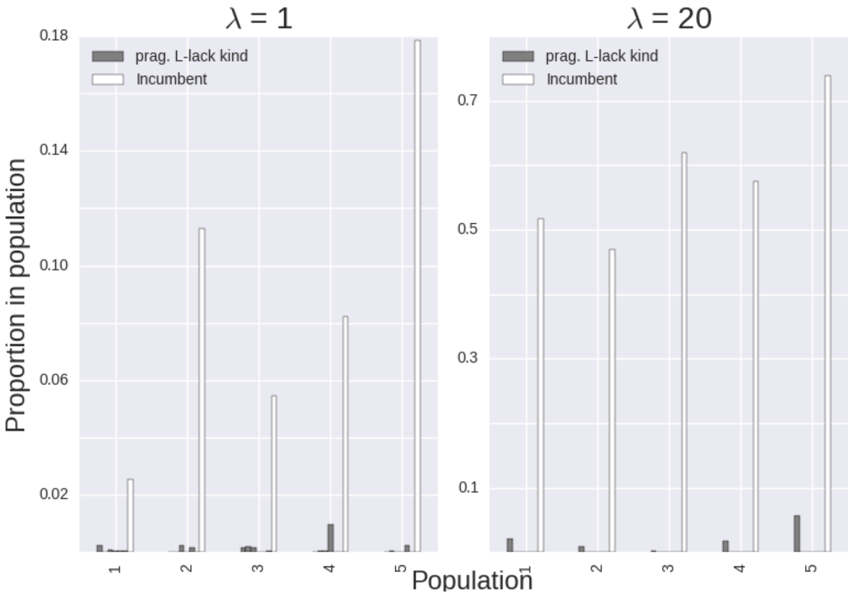

Figure 1: Proportion of pragmatic L_{lack}-style types and incumbent types in 5 independent populations after 50 generations under only a pressure for expressivity.

As we consider the full space of possible lexica, some assign the same concept to more than one message, as L_{all}, or lexicalize the same meanings but associate them with different messages, as the 6 L_{lack}-style lexica. The main results reported in the following do not hinge on the inclusion of these lexica but this an unaltered space does better illustrate the influence of the linguistic pressures at hand.

Lastly, recall that types are a combination of a lexicon and a manner of language use. We analyze the model's predictions in populations of types with one of the two signaling behaviors introduced earlier; literal or pragmatic. The former correspond to level 0 reasoners and the latter to ones of level 1. Higher level reasoning is not required to derive scalar implicatures from the lexica we consider here, nor do they leave room for substantial pragmatic refinement. Accordingly, there are 432 types in this model.

3.1.3 Expressivity only

The replicator dynamic is sensitive to λ as it influences signaling behavior and thereby has a bearing on a type's fitness. This influence is showcased in Figure 1, which depicts the proportion of pragmatic L_{lack}-style speakers in 5 independent populations after 50 generations, as well as that of the type with the highest proportion in a population, the incumbent. As is to be expected, less expressive types do not fare well under pressure for communicative success and those able to convey states less equivocally fare better. This difference increases with λ as it promotes more deterministic linguistic behavior, widening the gap in expressivity between types. Importantly, high values of λ alone do not lend a justification to the systematic prevalence of a division of labor between semantics and pragmatics that we set out to explain. An inspection of 1000 independent populations with $\lambda = 20$ shows a similar outcome to that hinted at by Figure 1: Pragmatic L_{lack} types only make up 11 cases of incumbency, corresponding to a mean proportion of 0.003 across populations. By contrast, 913 incumbents were L_{bound}-style users with close to an even share

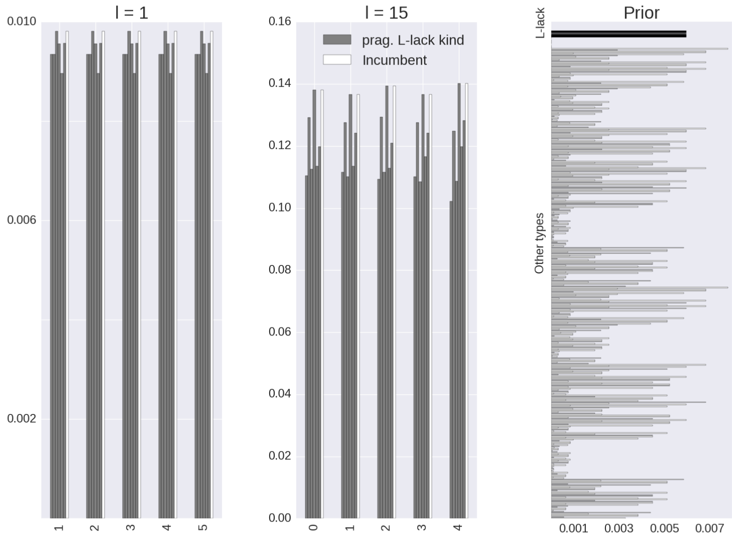

Figure 2: Proportion of pragmatic L_{lack}-style types and incumbent types in 5 independent populations after 50 generations under only a pressure for learnability ($\lambda = 20, k = 5$). The types' prior probability is shown in the right-most plot.

between literal (454) and pragmatic types (459), corresponding to a mean proportion of about 48% together. Overall, incumbents of any type make up 50% of the mean outcome. This shows the strong dominance of L_{bound}-like semantics over other alternatives when only expressivity is at stake.

3.1.4 Learnability only

The effect of iterated learning without a pressure for expressivity using posterior sampling ($l = 1$) and a stronger tendency towards posterior maximization ($l = 15$) is shown in Figure 2 together with the prior over types. The latter illustrates that users of L_{lack} are, while not the most favored types, advantaged by the inductive bias in virtue of the relatively simple semantics they conventionalize. Accordingly, a stronger propensity to maximize the posterior increases their proportion in the population in analogous fashion to increase in λ under the replicator dynamic. However, while replication generally succeeds in driving out competing types of a kind, iterated learning leads to their coexistence as each of these types is passed on to next generations equal faithfulness. Although L_{lack} is not the most favored type by the prior, it is the least semantically complex language in the type space that enables its users to convey each state with a single message when combined with pragmatic reasoning (provided sufficiently high λ). Put differently, it is easier to infer than functionally comparable lexica such as L_{bound} and it is less likely to be mistaken with others because its pragmatic use approximates a one-to-one form-meaning mapping. Consequently, as suggested by Figure 2, in 1000 analyzed independent populations all incumbents were pragmatic L_{lack} users provided sufficient rationality and a tendency towards posterior maximization ($l = 15$, $\lambda = 20$). By contrast, low values of λ and l reflect the inductive bias more directly, favoring functionally deficient but a priori preferred types such as literal L_{all}. In the extreme, all out of 1000 independent populations had this type as incumbent ($\lambda = 1$,$l = 1$).

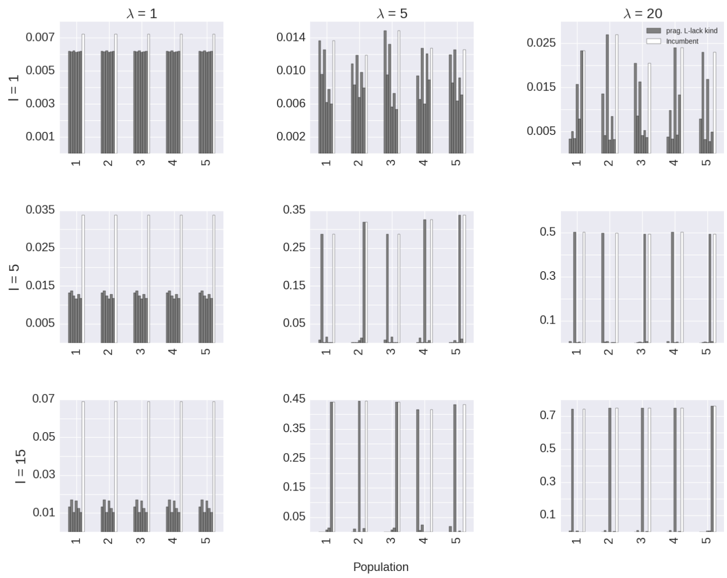

Figure 3: Proportion of pragmatic L_{lack}-style types and incumbent types in 5 independent populations after 50 generations under both pressures ($k = 5$).

3.1.5 Expressivity and learnability.

Inspecting these pressures separately not only showcases the contribution of the model's components but also highlights some of their broader implications. First and foremost, neither dynamic on its own comes close to converging to a monomorphic population of a type of pragmatic L_{lack} speakers. On the one hand, the slight communicative advantage of L_{bound}'s lexicalization of an upper-bound over pragmatic use of L_{lack} leads to the former's selection under a pressure for expressivity. On the other hand, pressure only towards learnability has a modest but clear effect of promoting pragmatic L_{lack} over functionally similar but semantically more complex alternatives such as L_{bound}. However, on its own learnability does not strongly foment the propagation of these types across the population. Furthermore, this pressure alone leads to heterogeneous populations that do not justify the selection of a particular type over others.

Figure 3 illustrates the combined effects of both pressures for a sample of λ and l values. Overall, these results show that an inductive learning bias for simpler semantics in tandem with functional pressure can lead to the selection of L_{lack}-like semantics over L_{bound}. As when each pressure was considered in isolation, this effect increases with λ and l. Importantly and by contrast to the effects of learnability alone, the addition of a pressure towards expressivity magnifies this effect and dampens the proliferation of similar or identical types. As stressed above, this suggests that neither a learning bias nor functional pressure alone but their combination may lead to the lack of upper-bounds in the lexical meaning of scalar expressions in a mostly monomorphic population. [TB: However, not even its combination with a pressure for expressivity completely drives out competing types under this inference strategy. This is not so for stronger posterior maximizing learning. The proportion to which a single pragmatic L_{lack}-style type increases grows with MAP-like learning.]

As before, low λ and l lead to the incumbency of communicatively suboptimal types that learners are biased for, such as L_{all}. An increase in λ leads to the selection and incumbency of

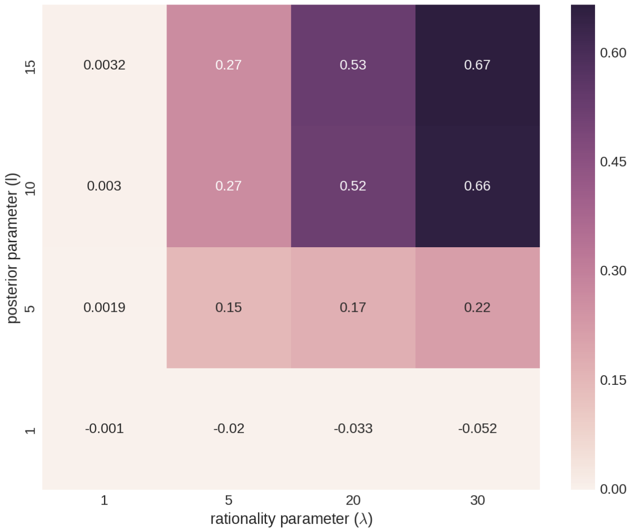

Figure 4: Difference between mean proportion of highest pragmatic L_{lack} type and highest other type in 1000 independent populations after 50 generations under both pressures ($k = 5$).

pragmatic L_{lack} types but does not lead to monomorphic populations if learners sample from the posterior. Finally, a combination of sufficiently rational signaling behavior with some tendency for posterior maximization leads to increasingly monomorphic populations of types that convey upper-bounds pragmatically. A more succinct representation of the difference between the mean of the highest pragmatic L_{lack}-like types and the highest proportion of other types across λ and l values is given in Figure 4.

As for the effect of the sequence length k not mentioned so far, it influences populations in a predictable way: small values lead to more heterogeneous populations that reflect the learner's prior more faithfully. This is due to the fact that the likelihood that a small sequence was produced by any type is relatively uniform (modulo prior). By contrast, larger values increasingly allow learners to differentiate types with different signaling behaviors.

To recapitulate, other than the involvement of both pressures, the resulting proportion of pragmatic L_{lack} speakers primarily hinges on three factors. First, the degree to which linguistic behavior is deterministic. This plays a role both in expressivity as well as in producing data that allows learners to discriminate this type from others. Second, the inductive bias, which leads learners to prefer simpler over more complex semantic representations in acquisition. Lastly, the posterior parameter, as it magnifies the effects of the learning bias in tandem with replication.

3.2 Discussion

Under the assumption of a learning bias for simpler lexical representations, our results suggest that a lack of semantic upper-bounds coupled with pragmatic reasoning can overcome communicative pressures and stabilize in a population. This prediction hinges on three assumptions. First, that language is pressured toward both expressivity and learnability. Second, that language use is relatively deterministic. Lastly, that learners prefer simpler over more complex lexical representations. An important addendum to this third condition being that a combination of rationality in choice and maximization in learning requires a weaker bias towards simplicity. Under these conditions the selection of lexical meanings lacking upper-bounds in populations of pragmatic speakers is robust against parameter perturbations. This outcome is particularly encouraging in light of other advantages a lack of semantic upper-bounds may confer, as discussed at the beginning of Section 3.

A lack of upper-bounded in the lexical meaning of weak scalar expressions constitutes the majority view in the literature. However, it not clear to what extent other types should be present in the final population. It seems reasonable to expect functionally suboptimal types L_1, L_2 and L_3 to be ruled out because they fail to enable their users to communicate effectively. However, this is not true of L_4.[1] The prediction that natural language communities are homogeneous or that a single speaker may entertain L_4-like semantics for one scalar expression and L_5-like semantics for another is not implausible (cf. Franke and Degen 2016). Alternatively, a stronger tendency for posterior maximization has to be assumed (see Figure **??**). This empirical issue relates to other two aspects left undiscussed: disadvantages of pragmatic reasoning and the effect of state frequencies on the fossilization of pragmatic inferences. We tacitly assumed pragmatic reasoning to come at no cost. However, there is experimental evidence that suggests that the pragmatic derivation of upper-bounds costs effort and takes additional processing time (cf. Neys and Schaeken 2007, Huang and Snedeker 2009). This raises the question at which point such usage-based cost undercuts the learnability advantage of simpler semantic representations. Should cost play a role, then its effect is bound to depend on the frequency with which a given scalar expression is used. It is therefore plausible that frequently drawn scalar implicatures might fossilize to avoid cost, while infrequent ones are still derived on-line. This also opens a possible venue to address the preceding question about the expected presence of L_4-like semantics, but further empirical evidence is needed to assess these matters beyond speculation.

4 General discussion

We laid out a model that combines game theoretical models of functional pressure towards efficient communication (Nowak and Krakauer 1999), effects of transmission perturbations on (iterated) language learning (Griffiths and Kalish 2007), probabilistic speaker and listener types of varied degrees of pragmatic sophistication (Frank and Goodman 2012, Franke and Jäger 2014) as well as different lexica (Bergen et al. 2012; 2016). This model generates predictions about lexicalization patterns and, more generally, effects of communicative pressures on the cultural evolution of language.

We argued that the puzzle raised by semantics in light of pragmatics is hard to explain on purely functional grounds and that part of the answer may instead lie in the way transmission shapes the outcome of cultural evolution in tandem with a pressure for successful information transfer. In the realm of inductive biases, we adopted the assumption that simpler semantic representations are more likely to be learned (cf. Chater and Vitányi 2003). Under this view, semantics and pragmatics play a synergic role in that representational simplicity is supplemented by pragmatic reasoning to counteract functional disadvantages otherwise incurred. As a consequence, iterated transmission and use of language lead to a regularization that may explain the lack of lexicalization of systematic pragmatic enrichments. This result is of particular relevance

[1] L_6 presents a special case. In our current setup, it mirrors L_5 in enabling for the pragmatic strengthening of a message that does not codify an upper-bound lexically. However, this is achieved by ruling out $s_{\exists\neg\forall}$ and not, as with scalar implicatures, $s_\forall$. L_6 speakers therefore strengthen a "some"-message to convey something paraphrasable as 'some but not [some but not all]'. The current representation of lexica as Boolean matrices is blind to this anomaly.

for the longstanding assumption of a divide and interaction between semantics and pragmatics. It offers an account of why (certain) pragmatic inferences fail to lexicalize. More generally, we showed that systematic noise in perception can produce outcomes that are similar from those generated by inductive biases.

The main innovations of the model are its modular separation of expressivity and learnability, allowing for their isolated and combined analysis, the learning process involving a joint inference over types of pragmatic behavior and lexical meaning, as well as in its accommodation of different transmission perturbations that go beyond learning biases. The goal to decouple but model both expressivity and learnability has also recently been addressed by Kirby et al. (2015). In contrast to our proposal, Kirby et al. model expressivity as exerting its force only in the production of learning data. This model's expressivity parameter thereby fulfills a similar role to high values of λ in making speaker behavior more deterministic. In this way, it "favors" unambiguous languages. However, the degree of mutual understanding of interlocutors central to replication and to our notion of expressivity is not taken into consideration. That is, while our proposal combines bidirectional horizontal transmission with its vertical and unidirectional counterpart, Kirby et al.'s model only considers the latter's influence. Our reasoning behind the inclusion of the former lies in the empirical and theoretical observation that learnability alone can lead the selection of functionally defective languages, as illustrated by the tautological language L_3 in our analysis. This outcome has been reported in a number of laboratory experiments where the participants' task was to learn and subsequently reproduce the language produced by a previous participant, leading to a proliferation of languages that associated a large number of meanings with a single form (see e.g. Silvey et al. 2014 and experiment 1 in Kirby et al. 2008). In contrast, experiments involving an interactive component have been found to foster languages that enable interlocutors to distinguish meanings more accurately (e.g. Fay and Ellison 2013; for a review of laboratory results under the iterated learning paradigm and further discussion see Kirby et al. 2015, Tamariz and Kirby 2016). It is not evident how to compare these empirical findings given that they consider distinct meaning spaces, modes of transmission, iterations and feedback given to participants. However, we take these results to suggest that there is an important difference between a language generating learnable linguistic data and its actual performance as a means of information transfer. The former solely depends on the mechanism by which speakers associate form and meaning. The latter additionally hinges on the addressee's linguistic experience and her ability to interpret linguistic input based on this experience. In sum, we contend that successful information transfer in a linguistic community is central to the adoption of a communication system and that this measure is not adequately reflected by production alone.

The demonstration that noise can lead to regularized evolutionary outcomes that are similar to those generated by prior learning biases is relevant not for the case study at hand, but more so for the broader project of investigating the cultural evolution of language. On the one hand, the plurality of sources of transmission perturbations admitted by these models paints a cautionary tale for the design of studies that purport to provide explanatory accounts of linguistic phenomena. In particular when the outcome is interpreted as being informative about the perturbation assumed to generate it (cf. Tamariz and Kirby 2016). On the other, and most importantly, it showcases how regularities can arise as a byproduct of systematic noise rather than from standardly assumed inductive biases.

5 Conclusion

The cultural evolution of language is influenced by intertwined pressures. We set out to investigate this process by putting forward a model that combines a pressure toward efficient and successful information transfer with perturbations that may arise in the transmission of linguistic knowledge in acquisition. Additionally, we argued for the necessity of considering the role of pragmatics in investigations on the cultural evolution of meaning. These components and their mutual influence were highlighted in a case study on the lack of lexical upper-bounds in weak scalar expressions that showed that, when pressured for learnability and expressivity, the former drives for simpler semantic representations inasmuch as pragmatics can compensate for lack of expressivity in use. That is, the relative learning advantage of simpler semantics in tandem with a functional pressure in use may offer an answer to why natural languages fail to lexicalize systematic pragmatic inferences.

We also considered an alternate instantiation of the model, which shows that systematic noise in state perception can give rise to evolutionary outcomes that are similar to those predicted by inductive biases. This stresses the fact that that learning and typology are not necessarily close reflections of each other (Bowerman 2010). In particular, language use and environmental factors can play an important role in language change, making them central variables in explanatory accounts of natural language properties.

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