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

(– draft November 13, 2016—)

Abstract

According to standard linguistic theory, the meaning of an utterance is the product of a conventional semantic meaning of the used expression and general pragmatic reasoning applied to the context of utterance. This implies that models of the 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 the cultural evolution of language 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. The latter can arise from general cognitive or learning biases, but also from other sources of systematic noise, e.g., as a result of errors in perception. We illustrate the model based on a case study showing that cognitive biases that favor simple semantic representations can prevent the lexicalization of pragmatic inferences. We also show that, technically speaking, it is possible that environmental factors, such as perceptual errors during acquisition, can produce evolutionary outcomes that look as if such cognitive biases are present even if they are not.

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). It 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, an 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 and thereby would have made 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 interesting 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 enrichment 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 meaning evolution abound. There are simulation-based models studying the evolution of meaning 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 meaning evolution, mostly rooted in game theory (Lewis 1969, Wärneryd 1993, Blume et al. 1993, Nowak and Krakauer 1999, Huttegger 2007, Skyrms 2010). Much 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. We would need to look at richer representations of cognizing agents and their communicative interaction.

To fill this gap, we here 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 to appear). Replication and selection is described by the *replicator mutator dynamic*, a general and established model of language evolution (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, such as from inductive learning biases or systematic perceptual errors. The latter is particularly important because neither semantic meanings nor pragmatic usage patterns are directly observable. Language learners have to infer these from observable behavior which is the product of the former. We formalize this acquisition 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 cases, 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 the desired outcome. Additionally, we show that a similar outcome can be achieved without assuming any cognitive biases, simply as an epiphenomenon of systematic disturbances from environmental factors. This formal results highlights the frequently overlooked possibility that channel noise in evolutionary replication can mimic effects of inductive biases.

We see the main contribution of this work as conceptual and technical, not as a definite answer to the question why scalar implicatures emerged. The work here 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 (Steels 2011) [mf: more references?]. 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 the 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. 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. Moreover, even small biases implicit in the acquisition of a language can built 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). In sum, natural languages are pressured for expressivity and learnability. But expressivity and learnability may pull in opposite directions. The 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 modeling the competition 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 update step, (ii) the fitness f_i of each type i, 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 replicator mutator dynamic 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) and subsequent multiplication with a mutation matrix Q of the initial population vector $\vec{x}$:

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

where

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

If the transmission matrix Q is trivial in the sense that $Q_{ij} = 1$ whenever $i = j$, 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. The replicator dynamic is popular and versatile because it can be derived from many abstract processes of biological and cultural transmission and selection (for overview and any 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 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).

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 will be addressed, one by one, in the following.

The replicator equation gives us the means to make these dynamics precise. The proportion of types in a given population is codified in a vector x, where x_i is type i's proportion. As noted above, the fitness of type i is equal to its relative communicative success within this population, $f_i = \sum_j x_j \mathrm{EU}(t_i, t_j)$. The expected communicative success of i and j is simply the average success of i conveying information to j and vice versa: $\mathrm{EU}(t_i, t_j) = [U_S(t_i, t_j) + U_R(t_i, t_j)]/2$. $U_S(x, y)$ and $U_R(x, y)$ are, respectively, $\sum_s P(s) \sum_m S_n(m|s; L) \sum_{s'} R_o(s'|m; L)\delta(s, s')$ and $U_S(y, x)$, for n and o being the reasoning level of x and y, and $\delta(s, s') = 1$ iff $s = s'$ and 0 otherwise. This quantity is symmetric, reflecting the probability of two types' mutual understanding. The average fitness of the population is given by Φ, $\Phi = \sum_i x_i f_i$, serving as a normalizing constant for the discrete replicator equation: $\dot{x}_i = \frac{x_i f_i}{\Phi}$

However, this is not the only challenge learners confront. More central to our explanandum is the issue 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 functional (near-)equivalents, noting in particular that what is systematically conveyed through pragmatics could alternatively be codified lexically. Notwithstanding, lexical meanings that allow for pragmatic modifications often seem to resist the lexicalization of their pragmatic component. The question is why.

We assume an integral part of the answer to lie in the effects of transmission perturbations that arise when linguistic knowledge is acquired by new learners. As shown in the following, such perturbations may take the form of learning biases, but may also stem from extraneous factors such as a noisy perception of the environment.

We model these components using the replicator-mutator dynamics, combining functional pressure on successful communication with effects of transmission perturbations on (iterated) Bayesian learning (Griffiths and Kalish 2007). The semantics-pragmatics distinction and its bearing on production and comprehension are captured by a probabilistic model of rational language use with different degrees of pragmatic sophisitication and different lexica (Frank and Goodman 2012, Franke and Jäger 2014, Bergen et al. 2016). The remainder of this section introduces these components together with the assumptions underlying them. These are: the representation of languages and their use (§2.2), as well as pressures towards expressivity (§2.3) and learnability (§2.4). After laying out the model, we analyze its predictions in a case-study on the lack of lexicalization of scalar implicatures in §3. Additionally, §3.4 shows how the outcome predicted under the assumption of an inductive bias for simplicity in §3.2 can also arise from as a byproduct of the noisy perception of language users and learners. Section §4 discusses the general predictions of the model, as well as the implications drawn from its noisy counterpart.

2.2 Types: Lexica and linguistic behavior

Lexica codify the truth-conditions of a language's expressions. Following Franke and Jäger (2014), a convenient way to represent lexica is by $(|S|, |M|)$-Boolean matrices, where S is a set of states of affairs (meanings) and M a set of messages (forms available in the language).

We distinguish between two kinds of linguistic 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. Following models of rational language use such as Rational Speech Act models (Frank and Goodman 2012) and their game-theoretic predecessors, the Iterated Best/Quantal Response models (Franke 2009, Franke and Jäger 2014), these behaviors are captured by a reasoning hierarchy. The hierarchy's bottom, level 0, corresponds to literal language use. Pragmatic language users of level $n + 1$ behave rationally according to expected level n behavior of their interlocutors. (3) and (5) specify the behavior of literal and pragmatic hearers of a language L. Their speaker counterparts are given in (4) and (6).

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

$$S_0(m|s; L) \propto \exp((L_{sm})^\alpha) \tag{4}$$

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

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

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 across hearers. The behavior of literal speakers, given in (4), is regulated by a parameter α which controls the sensitivity to which speakers prefer one signal over another based on its expected communicative success.

Pragmatic behavior is similar to its literal counterparts. Their difference lies in that level $n+1$ speakers/hearers reason about level n hearer/speaker behavior instead of solely relaying on their lexicon. That is, they reason about the way a rational level n interlocutor would use or interpret a message, and behave according to these expectations. Speaker behavior is further influenced 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.

We call the combination of a lexicon with its use, i.e., a level in the reasoning hierarchy, a *type*. These are the basic units on which the model's dynamics operate.

2.3 Expressivity

Expressivity has received particular attention from investigations using evolutionary game theory (e.g. Nowak and Krakauer 1999, Nowak et al. 2000; 2002). Under this view, a type's ability to convey and interpret information successfully confers it a higher fitness, a measure that is relative to the success of other types in the population. In the simplest models, fitness directly translates into the proportion of types present in the population after a generational turnover. This association of communicative success within a population with changes in the proportion of 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 codified in a vector x, where x_i is type i's proportion. As noted above, the fitness of type i is equal to its relative communicative success within this population, $f_i = \sum_j x_j \mathrm{EU}(t_i, t_j)$. The expected communicative success of i and j is simply the average success of i conveying information to j and vice versa: $\mathrm{EU}(t_i, t_j) = [U_S(t_i, t_j) + U_R(t_i, t_j)]/2$. $U_S(x, y)$ and $U_R(x, y)$ are, respectively, $\sum_s P(s) \sum_m S_n(m|s; L) \sum_{s'} R_o(s'|m; L)\delta(s, s')$ and $U_S(y, x)$, for n and o being the reasoning level of x and y, and $\delta(s, s') = 1$ iff $s = s'$ and 0 otherwise. This quantity is symmetric, reflecting the probability of two types' mutual understanding. The average fitness of the population is given by Φ, $\Phi = \sum_i x_i f_i$, serving as a normalizing constant for the discrete replicator equation: $\dot{x}_i = \frac{x_i f_i}{\Phi}$

Under its biological interpretation, the replicator dynamics capture the idea of fitness-relative selection whereby fitter types produce more offspring, leading to their propagation in subsequent generations. Many aspects of language are subject to transmission and change that can be likened to such biological processes. Amongst others, replication can be construed as modelling language acquisition, as e.g. in Nowak et al. 2002, but also as a process of horizontal adaptation in a single generation (see Benz et al. 2005:§3.3 for discussion).

In their series of papers on language evolution, Nowak and colleagues did not only consider expressivity but also recognized the central role of the fidelity by which language is transmitted. Among others, linguistic production can be prone to errors, states or messages may be percieved incorrectly, and multiple languages may be compatible with the data learners are exposed to. These sources of uncertainty introduce variation in their transmission from one generation to the next which can be likened to mutation to the effect that a type's offspring may adopt a different type than that of its parent as a result of transmission perturbations. Importantly, this variation should be relative to the learnability of a type under these perturbations (instead of, e.g., being a constant that is equal across all types as in Nowak et al. 2002). For this purpose, we turn to a different strand of research in cultural evolution: iterated learning.

2.4 Learnability

Iterated learning is a process in which the behavior of one individual serves as learning input for another. This learner, upon acquisition of this behavior, then goes on to produce behavior that serves as input for a new learner. This process can be thought of as a progression through chains of parents and children; the parent produces linguistic data from which the child infers a language. The latter, now a parent, goes on to produce data for a new generation of learners. Following Griffiths and Kalish (2007) we model iterated learning as a repeated process of Bayesian inference in which learners combine the likelihood of a type producing the received learning input with prior inductive biases.

Due to the pressure towards learnability it exherts, iterated learning generally leads to simpler and more regular languages (see Kirby et al. 2014 and Tamariz and Kirby 2016 for recent surveys). Importantly, experimental and mathematical results have been taken to suggest that the outcome of this process reflects learners' inductive biases. In a Bayesian setting these biases can be codified in a prior $P \in \Delta(T)$, which can be thought of as the amount of data a learner would require in order to adopt a language (cf. Griffiths and Kalish 2007:450). Or, in our case, a combination of a lexicon and its use. The extent of the prior's influence has been shown to heavily depend on the learning strategy assumed to underly 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., 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 parametrize the posterior by $l \geq 1$. In doing so, we obtain a range of learning strategies between posterior sampling and MAP. When $l = 1$ learners sample from the posterior and the learners propensity to maximize the posterior grows as l increases.

The data learners are exposed to is described by a set D containing sequences of state-message pairs, e.g., $\langle \langle s_i, m_v \rangle, ... \langle s_j, m_w \rangle \rangle$. These are sequences of language use witnessed by learners, the length of which we denote by k.

We combine the above with the replicator dynamics by codifying iterated learning in a transition matrix Q, where Q_{ij} indicates the probability that a child of a parent of type i adopts type j. This quantity is proportional to the probability of i producing the learning data and that of inferring j given the data:

$$Q_{ij} \propto \sum_{d \in D} P(d|t_i)F(t_j, d), \text{ where } F(t_j, d) \propto P(t_j|d)^l \text{ and } P(t_j|d) \propto P(t_j)P(d|t_j).$$

2.5 Model summary

Drawing from past research, we argued that expressivity and learnability are central to the cultural evolution of language. We propose these components to be modelled respectively as communicative efficiency-relative replication and (iterated) Bayesian learning. Taken together their interaction is described by the replicator-mutator dynamics (Hofbauer and Sigmund 2003):

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

The units that the dynamics operate on are a combination of a lexicon and a degree of pragmatic sophistication determining its use. We call this combination a type. A type's expressivity depends on its communicative efficiency within a population while its learnability depends on the fidelity by which it is inferred by new generations of learners. The learners' task is consequently to perform a joint inference over types of linguistic behavior and lexical meaning. With this model at hand we turn to the analysis of the lack of lexicalization of productive pragmatic inferences in a case study on scalar implicatures.

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 '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 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, 'Some students came to class' is strengthened to convey that some but not all students came to class. A bound that rules out stronger alternatives is thusly not codified in the lexical meaning of weak alternatives but instead pragmatically supplied.

This kind of strengthening is captured by the linguistic behavior of pragmatic types introduced in §2.2: A pragmatic hearer who reasons about a speaker's use of a message involving a weak scalar alternative will associate it more strongly with upper-bounded states than with ones in which stronger alternatives hold because these alternatives already unambiguously convey the latter states. Conversely, a pragmatic speaker will reason about her interlocutor's expected interpretation and use the messages at her disposition accordingly.

Our initial question can now 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, why they are regularly selected for over other 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 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 'Some students came' but she doesn't know whether all came, 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 hypothesis 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 representation, i.e., 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. Note however that we do not represent the contrast between lexical representations explicitly. Instead, the bias is directly encoded in the learners' prior over types. In principle this difference could be made precise with an adequate representational language, e.g., through measures over representational complexity such as minimal description length. There is a growing effort to develop such empirically testable representational languages. For instance, the so-called *language of thought* has been put to test in various rational probabilistic models that show encouraging results (see e.g. Katz et al. 2008, Piantadosi et al. under review; 2012a and references therein). We think that our assumption is well-warranted as a working hypothesis and decide against such an enrichment at present in order to focus on the effects of linguistic pressures predicted the model instead.

3.1 Analysis

We analyze the model's predictions in populations of types with two signaling behaviors; literal and pragmatic. The former correspond to level 0 reasoners who only take their lexica into consideration and the latter to level 1 reasoners. 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.

The space of possible lexica is given in Table 1. These $(2, 2)$-Boolean matrices are the simplest ones that allow us to make the contrast between the presence or abscence of an upper-bound and the use of scalar implicatures precise. One may think of the state corresponding to the first row of any such lexicon as a "some but not all"-state and the second as an "all"-state. The literal meaning of weak scalar expressions such as English *some* then corresponds to a message true of both rows in these fragments. While there are 16 possible $(2, 2)$-lexica, a number of them are identical both in terms of expressivity and the learning bias. The competition between such types is determined by the initial configuration of a population. However, this can be obscured when averaging across simulations. We focus on this smaller representative subset as simulations conducted with the full space confirm that the general results reported here do not hinge on this choice.

Lexica L_1 to L_3 are not optimal for communication because they assign the same state to all their messages. This failure to be able to associate a single form to a state inevitably leads to a communicative disadvantage in their use. L_4 and L_5 are our target lexica. They codify upper-bounded semantics for the message corresponding to the first matrix's column and a lack thereof, respectively. Lastly, L_6 is similar to L_5 in that two messages are true of the same state but differs from it in assigning upper-bounded semantics to the first column's message.

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

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

Table 1: Space of possible lexica.

Combining a linguistic behavior with each of these 6 lexica yields a total of 12 distinct types. Note in particular that a type that has conventionalized upper-bounds to realize a (quasi-)partition of the relevant semantic space, such as L_4, will produce speaker behavior that is *almost* indistinguishable from that of a language that lacks upper-bounds, but with pragmatic users, such as L_5. Almost, because there may be slight differences between the probability with which speakers would (erroneously) use a semantically false description and the probability with which speakers would (erroneously) use a pragmatically suboptimal description. Due to this possibly marginal difference between pragmatic L_4 and L_5, the selection of one type over the other is expected to mainly depend on their transmission to new learners. Things are less clear for literal L_5 contrasted with literal/pragmatic L_4 as the former has a learning advantage under the inductive bias but is expected to fare worse in communicative terms.

The dynamics are initialized with an arbitrary distribution over types, constituting the population's first generation. The results for each parameter setting were obtained from 1000 independent runs, each consisting of 20 generations. This corresponds to a developmental plateau after which no noteworthy change was registered. As specified in §2.4, the learning matrix Q can be obtained by considering all possible state-message sequences of length k. Given that this is intractable for large k, matrices were approximated by sampling 10 sequences from each type's production probabilities and a type's children being exposed only to this subset.

3.2 Transmission bias

Following our assumption of a preference for simple lexical representations, the prior biases learners against lexica in which a message holds true only of the first row, i.e., against messages that lexicalize an upper-bound that rules out the "all"-state. All other semantics are assumed to be a priori equally probable. This is captured by $P(t_i) \propto n - c \cdot r$, where n is the total number of states and r is the number of messages only true of row 1 in t_i's lexicon, $c \in [0, 1]$. Increments in the value of c therefore bring about a stronger bias against languages that lexicalize upper-bounds, i.e., L_2, L_4 and L_6.

According to our hypothesis, 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_5-like semantics. It is instructive to first inspect the effect of these pressures in isolation. For this purpose we focus our attention on three pragmatic types.[1] Pragmatic L_3, a type that is lacking in expressivity but is a priori preferred for its lack of upper-bounds. Pragmatic L_4, a type that is functionally advantageous but biased against. And pragmatic L_5, combining virtues of the latter two.

Expressivity only. The replicator dynamics are sensitive to λ and α as both have a bearing on a type's fitness. The influence of the rationality parameter for is depicted in Figure 1.A. The less expressive L_3 speakers fare the worse and are influenced the least by change in λ. In

[1] Pragmatic reasoning allows language users to refine their (possibly erroneous) choices. Therefore, it is advantageous even for those types that codify an upper-bound lexically.

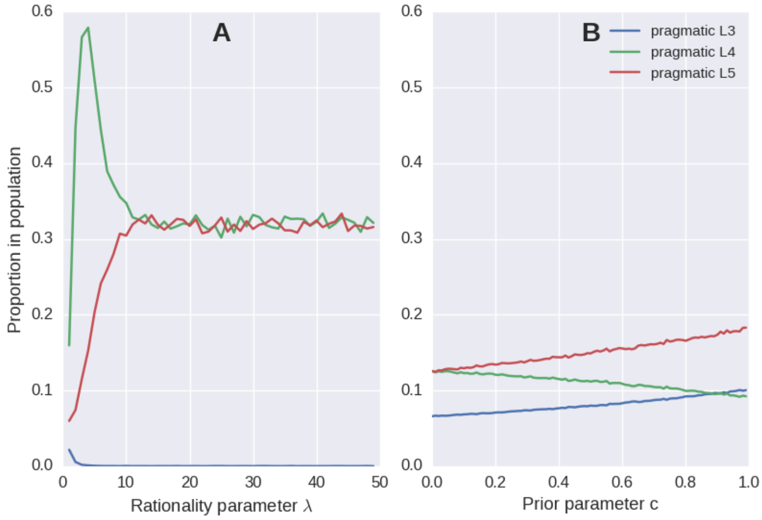

Figure 1: Mean proportions of target types after 20 generations in 1000 populations with only a pressure for expressivity in A ($\alpha = 1$) and only for learnability in B ($\alpha = 1, \lambda = 30, k = 5, l = 1$).

contrast, low values of λ result in a higher proportion of L_4 speakers relative to L_5. This is expected given role of rationality in producing more deterministic behavior in users of L_5-like languages. As the rationality parameter increases, the functional difference between L_4 and L_5 is leveled. Overall, the outcome from only a pressure towards expressivity approximates an even share of pragmatic L_4, L_5 and L_6 types. The latter follows the same trajectory as L_5 in Figure 1.A. This illustrates the problem we started out with: expressivity alone can not differentiate between (near-)functional equivalents to a degree that justifies the systematic prevalence of L_5-like semantics.

Learnability only. The effect of iterated learning with posterior sampling but without a pressure for expressivity is shown in Figure 1.B. In line with our expectations, the share of L_4 speakers decreases as the bias against upper-bounds increases. In turn, this benefits L_3 and, in particular, L_5. However, even a strong bias against lexical upper-bounds leads only to a moderate advantage of L_5 over L_4. More importantly, a pressure only towards learnability can promote functionally defective languages such as L_3.

Inspecting these pressures separately not only showcases the influence of some model components but also highlights some of their broader implications. First and foremost, neither dynamic comes close to converging to a monomorphic population under most parameter configurations. For instance, while L_4 speakers can come to take over a substantial proportion of the population, this only happens in a restricted range of low degrees of rationality. Apart from polymorphy, both pressures make undesirable predictions when considered in isolation. A pressure only towards expressivity leads to the expulsion of communicatively suboptimal L_1, L_2 and L_3 from the population but can not explain the regular selection of L_5-like semantics over either of its functionally similar alternatives. A pressure only towards learnability has a modest but clear effect in differentiating L_5 from these alternatives but fails to rule out functionally suboptimal types such as tautological L_3.

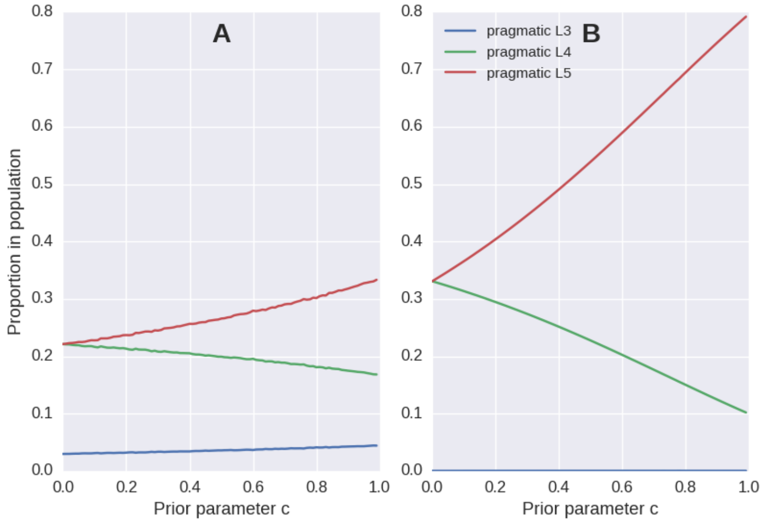

Figure 2: Mean proportions of target types after 20 generations in 1000 populations across bias values $c \in [0, 1]$ with $l = 1$ in A and $l = 3$ in B ($\alpha = 1, \lambda = 20, k = 5$).

Expressivity and learnability. Figure 2 illustrates the effect of the learning bias for posterior sampling (2.A) and slightly more MAP-like learning (2.B) when pressured for both expressivity and learnability.[2] More detailed results for all types across a sample of c-values for $l = 1$ and $l = 3$ are presented in Table 2. These results show that a weak bias is sufficient to lead to a selection of L_5 over L_4. As in the outcomes that only considered learnability, this effect increases with the bias' strength provided L_5 users are pragmatic. Importantly, the addition of a pressure towards expressivity magnifies this effect and dampens the proliferation of functionally suboptimal types advantaged by the learning bias. As stressed above, this indicates 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.

Other than the consideration of both pressures, the resulting proportion of pragmatic L_5 speakers primarily hinges on three factors. First, the degree to which linguistic behavior is deterministic, as it plays a role both for expressivity as well as in producing data that allows learners to discriminate this type from others. Second, the inductive bias, which controls the learners preference for simpler lexical representations. Lastly, the posterior parameter, which magnifies the effects of the learning bias in tandem with replication.

As discussed in relation to Figure 2.A, posterior sampling can lead to the incumbency of pragmatic L_5. However, not even a strong favorable learning bias combined with a pressure for expressivity completely drives out competing types. This is not so for more posterior maximizing behavior. As shown in Figure 3, the range of bias values within which L_5 takes over the population increases with MAP-like learning. In other words, the strength of the learning bias required for a given final proportion of L_5 speakers strongly depends on learners' inferential strategy. As for the effect of the other parameters not mentioned so far, changes in sequence length influence the population in a predictable way: smaller values lead to more heterogeneous populations that reflect the learner's prior more faithfully. Larger ones lead to more pronounced differences amongst equally preferred types. This is due to the fact that the likelihood that a small sequence

[2] Robert suggests to illustrate the effect with a higher l-value. E.g., l = 1 and l = 10

	$l = 1$					$l = 3$				
c	0	.1	.5	.8	.9	0	.1	.5	.8	.9
lit. L_1	.03	.03	.04	.04	.04	0	0	0	0	0
lit. L_2	.03	.03	.02	.01	.04	0	0	0	0	0
lit. L_3	.03	.03	.04	.04	.04	0	0	0	0	0
lit. L_4	.07	.07	.06	.06	.05	0	0	0	0	0
lit. L_5	.04	.05	.05	.06	.06	0	0	0	0	0
lit. L_6	.04	.04	.04	.04	.03	0	0	0	0	0
prg. L_1	.03	.03	.04	.04	.04	0	0	0	0	0
prg. L_2	.03	.03	.02	.01	.04	0	0	0	0	0
prg. L_3	.03	.03	.04	.04	.04	0	0	0	0	0
prg. L_4	.22	.22	.2	.18	.17	.33	.31	.23	.15	.12
prg. L_5	.22	.23	.27	.3	.32	.33	.37	.54	.7	.75
prg. L_6	.22	.22	.2	.18	.17	.33	.31	.23	.15	.12

Table 2: Mean proportions of types in 1000 populations after 20 generations across bias values $c \in [0, 1]$ with $l = 1$ and $l = 3$ ($\alpha = 1, \lambda = 30, k = 5$)

was produced by any type is relatively uniform (modulo prior) compared to that of types with lexica L_1 - L_3 to produce larger sequences with the same state-message combination in contrast to pragmatic speakers of L_4 - L_6, or literal L_4.

3.3 Discussion

Under the assumption of a learning bias for simpler 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 – low λ renders languages that rely on pragmatics to associate one state to one message too prone to communicative failure and more difficult to learn. 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.

While non upper-bounded lexical meanings in weak scalar alternatives are predicted by the literature, it not clear to what extent other types should be present in the final population, if at all. 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.[3] Notwithstanding, 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 3). This empirical issue relates to other two

[3] 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 the "some but not all"-state and not, as with scalar implicatures, the "all"-state. 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 without further restrictions.

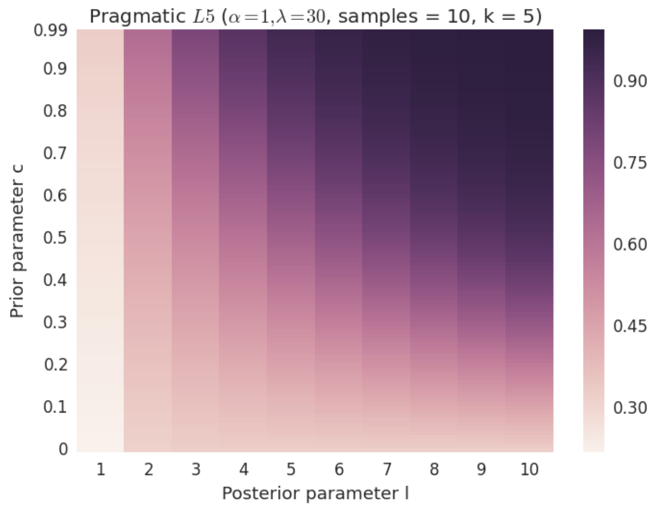

Figure 3: Mean proportion of pragmatic L_5 in 1000 populations after 20 generations ($\alpha = 1, \lambda = 30, k = 5$)

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 could still be computed on-line. This opens a possible venue to address the first question about the expected presence of L_4-like semantics, but further empirical evidence is needed to assess these matters beyond speculation.

3.4 Noisy transmission

The assumption of a learning bias was pivotal in introducing transmission perturbations that differentiate functionally similar types. However, these perturbations need not necessarily arise from inductive biases. As shown in the following, outcomes that are indistinguishable from the ones predicted above can come about through environmental factors such as perceptual errors during production and comprehension as well. We should stress that we do not want to suggest noisy perception to underlie the selection of a lack of semantic upper-bounds in scalar items. Instead, our goal is to stress the role that transmission perturbations play in this process and the cultural evolution of meaning more broadly, as well as to highlight the explanatory potential environmental forces, which have received less attention than their inductive counterparts.

The core components of the model remain as before. All that is required is their adjustment to the possibility of confusing one state with another by language users and learners. Letting ϵ stand for the probability of confusing the first row state with the second, and vice-versa for δ, we denote the probability that the teacher (learner) observes state s_t (s_l) when the actual state is s_a as $P_N(s_t \mid s_a)$ ($P_N(s_l \mid s_a)$). The probability that s_a is the actual state when the learner observes s_l is therefore:

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

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

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

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

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

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

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

In words, it may be the case that learner and/or teacher do not perceive the actual state as what it is. They are not aware of this, and produce/learn as if what they observed was the actual state. In particular, the learner does not reason about noise when she tries to infer the speaker's type. She takes what she observes a state to be as the actual state that the teacher has seen as well and infers which type would have most likely generated the message to this state. This can lead to biases of inferring the "wrong" teacher type, if the noise makes some types err in a way that resembles the noiseless behavior of other types. That is, such environmental factors can, in principle, induce transmission biases that look as if there was a cognitive bias in favor of a particular type, simply because that type better explains the noise.

Apart from changing the mutation matrix in this way, we also need to adapt the calculation of expected utilities, taking into consideration that states are perceived noisily:

$$U_S(t_i, t_j) = \sum_{s_a} P(s_a) \sum_{s_t} P_N(s_t \mid s_a) \sum_m S_n(m|s_t; L) \sum_{s'} R_o(s'|m; L)\delta(s, s')\,.$$

Results. As shown in Table 3, a prevalence of pragmatic L_5 can also arise from noisy transmission without a learning bias for particular types ($c = 0$). In contrast to the outcome predicted by its noiseless counterpart, favourable outcomes for this type concentrate in parameter configurations with $\epsilon > \delta$, $\alpha \geq 5$, $1 < k < 20$ and $l > 3$. As stressed above, we are not concerned with the interpretation of these particular values for the case study at hand, but rather with the technical result that shows that the mere presence of systematic noise in the transmission of strategies can introduce regularization that looks as if the agents have a learning bias. In other words, learning biases are clearly not the only transmission perturbations that shape cultural evolution alongside functional pressure. Environmental and perceptual noise can play a role too.

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

	$l = 5$					$l = 15$				
(ϵ, δ)	(.1,.1)	(.1,.3)	(.3,.1)	(.8,.1)	(.1,.8)	(.1,.1)	(.1,.3)	(.3,.1)	(.8,.1)	(.1,.8)
lit. L_1	.01	.02	.03	.03	.03	0	.02	.02	.01	.01
lit. L_2	.01	.02	.03	.03	.03	0	.02	.02	.01	.01
lit. L_3	.01	.02	.03	.01	.03	0	.02	.02	.01	.01
lit. L_4	.03	.03	.03	.05	.01	.04	.03	.03	.01	.01
lit. L_5	.02	.04	.03	.02	.02	.01	.03	.02	.02	.01
lit. L_6	.02	.03	.04	.03	.05	.01	.03	.04	.01	.02
prg. L_1	.01	.02	.03	.03	.03	0	.02	.02	.01	.01
prg. L_2	.01	.02	.03	.03	.03	0	.02	.02	.01	.01
prg. L_3	.01	.02	.03	.03	.03	0	.02	.02	.01	.01
prg. L_4	.45	.11	.11	.02	.02	.44	.11	.1	.22	.02
prg. L_5	.22	.17	.47	.04	.68	.24	.18	.56	.02	.84
prg. L_6	.22	.48	.17	.69	.04	.24	.52	.16	.84	.02

Table 3: Currently: Mean proportions of types from 50 runs per 100 independently generated Q-matrices per parameter setting after 20 generations across noisy values for ϵ and δ with $l = 5$ and $l = 10$ ($\alpha = 10, \lambda = 20, k = 5$). In principle, we could skip every second row because pragmatic $L5$ and $L6$ mirror each other.

(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 for the longstanding assumption of a divide and interaction between semantics and pragmatics by offering an account of why (certain) pragmatic inferences fail to lexicalize. More generally, we showed that systematic noise in perception can produce outcomes that are indistinguishable from those generated by inductive biases. This adds to Franke and Correia's (to appear) argument that linguistic regularities may arise as a byproduct of noise, rather than through 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 showcased 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 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 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 indistinguishable from those generated by prior learning biases is relevant not for the case study at hand, but more so for the broader project of analyzes of 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 informative about the perturbation assumed to generates 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 from 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 their lack of expressivity in use. That is, the relative advantage in learning 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 indistinguishable from 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.

References

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

Andrea Baronchelli, Andrea Puglisi, and Vittorio Loreto. Cultural route to the emergence of linguistic categories. *PNAS*, 105(23):7936–7940, 2008. doi: doi: 10.1073/pnas.0802485105.

John Batali. Computational simulations of the emergence of grammar. In James R. Hurford, Michael Studdert-Kennedy, and Chris Knight, editors, *Evolution of Language: Social and Cognitive Bases*. Cambridge University Press, Cambridge, UK, 1998.

A.W. Beggs. On the convergence of reinforcement learning. *Journal of Economic Theory*, 122 (1):1–36, 2005. doi: 10.1016/j.jet.2004.03.008.

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

Leon Bergen, Noah D Goodman, and Roger Levy. That's what she (could have) said: How alternative utterances affect language use. In *Proceedings of Thirty-Fourth Annual Meeting of the Cognitive Science Society*, 2012.

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

Andreas Blume, Yong-Gwan Kim, and Joel Sobel. Evolutionary stability in games of communication. *Games and Economic Behavior*, 5(5):547–575, 1993. doi: doi:10.1006/game.1993.1031.

Tilman Börgers and Rajiv Sarin. Learning through reinforcement and replicator dynamics. *Journal of Economic Theory*, 77(1):1–14, 1997. doi: 10.1006/jeth.1997.2319.

Lewis Bott and Ira A. Noveck. Some utterances are underinformative: The onset and time course of scalar inferences. *Journal of Memory and Language*, 51(3):437–457, 2004.

Melissa Bowerman. *Linguistic Typology and First Language Acquisition*. Oxford University Press, 2010. doi: 10.1093/oxfordhb/9780199281251.013.0028.

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

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

Gennaro Chierchia, Danny Fox, and Benjamin Spector. Scalar implicature as a grammatical phenonenon. In Claudia Maienborn, Klaus von Heusinger, and Paul Portner, editors, *Semantics. An International Handbook of Natural Language Meaning*, pages 2297–2332. de Gruyter, Berlin, 2012.

Judith Degen and Michael K. Tanenhaus. Processing scalar implicatures: A constraint-based approach. *Cognitive Science*, 39:667–710, 2015. doi: 10.1111/cogs.12171.

Nicolas Fay and T. Mark Ellison. The cultural evolution of human communication systems in different sized populations: Usability trumps learnability. *PLoS ONE*, 8(8), 2013. doi: 10.1371/journal.pone.0071781.

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

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

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

Michael Franke. The evolution of compositionality in signaling games. *Journal of Logic, Language and Information*, 25(3–4):355–377, 2016. doi: 10.1007/s10849-015-9232-5.

Michael Franke and Jose Pedro Correia. Vagueness and imprecise imitation in signalling games. *British Journal for the Philosophy of Science*, to appear.

Michael Franke and Judith Degen. Reasoning in reference games: Individual- vs. population-level probabilistic modeling. *PLOS ONE*, 11(5):e0154854, 2016. doi: 10.1371/journal.pone.0154854.

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

Michael Franke and Gerhard Jäger. Probabilistic pragmatics, or why bayes' rule is probably important for pragmatics. *Zeitschrift für Sprachwissenschaft*, 35(1):3–44, 2016. doi: 10.1515/zfs-2016-0002.

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

Bart Geurts. *Quantity Implicatures.* Cambridge University Press, Cambridge, UK, 2010.

Tao Gong. *Language Evolution from a Simulation Perspective: On the Coevolution of Compositionality and Regularity.* Chinese University of Hong Kong, 2007.

Noah D. Goodman and Michael C. Frank. Pragmatic language interpretation as probabilistic inference. *Trends in Cognitive Sciences*, to appear. under review.

Noah D. Goodman and Andreas Stuhlmüller. Knowledge and implicature: Modeling lanuage understanding as social cognition. *Topics in Cognitive Science*, 5:173–184, 2013. doi: 10.1111/tops.12007.

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

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

Daniel J. Grodner, Natalie M. Klein, Kathleen M. Carbary, and Michael K. Tanenhaus. "some," and possibly all, scalar inferences are not delayed: Evidence for immediate pragmatic enrichment. *Cognition*, 166:42–55, 2010.

Dirk Helbing. A stochastic behavioral model and a 'microscopic' foundation of evolutionary game theory. *Theory and Decision*, 40(2):149–179, 1996. doi: 10.1007/BF00133171.

Julia Hirschberg. *A Theory of Scalar Implicature*. PhD thesis, University of Pennsylvania, 1985.

Josef Hofbauer. The selection mutation equation. *Journal of Mathematical Biology*, 23:41–53, 1985.

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

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

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

Yi Ting Huang and Jesse Snedeker. Online interpretation of scalar quantifiers: Insight into the semantics–pragmatics interface. *Cognitive Psychology*, 58(3):376–415, 2009.

James R. Hurford. Biological evolution of the saussurean sign as a component of the language acquisition device. *Lingua*, 77(2):187–222, 1989.

Simon M. Huttegger. Evolution and the explanation of meaning. *Philosophy of Science*, 74:1–27, 2007. doi: 10.1086/519477.

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

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

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

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

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

S. Kirby, H. Cornish, and K. Smith. Cumulative cultural evolution in the laboratory: An experimental approach to the origins of structure in human language. *Proceedings of the National Academy of Sciences*, 105(31):10681–10686, 2008. doi: 10.1073/pnas.0707835105.

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

Simon Kirby and James R. Hurford. The emergence of linguistic structure: An overview of the iterated learning model. In A. Cangelosi and D. Parisi, editors, *Simulating the Evolution of Language*, pages 121–148. Springer, 2002.

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

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

Tom Lenaerts, Bart Jansen, Karl Tuyls, and Bart De Vylder. The evolutionary language game: An orthogonal approach. *Journal of Theoretical Biology*, 235:566–582, 2005.

Stephen C. Levinson. *Pragmatics*. Cambridge University Press, Cambridge, UK, 1983.

David Lewis. *Convention: A Philosophical Study*. Harvard University Press, Cambridge, 1969.

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

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

Wim De Neys and Walter Schaeken. When people are more logical under cognitive load. *Experimental Psychology*, 54(2):128–133, 2007.

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

Martin A. Nowak. *Evolutionary Dynamics: Exploring the Equations of Life*. Harvard University Press, 2006.

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

Martin A. Nowak, Natalia L. Komarova, and Partha Niyogi. Evolution of universal grammar. *Science*, 291(5501):114–118, 2001. doi: 10.1126/science.291.5501.114.

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

Mark Pagel. Human language as a culturally transmitted replicator. *Nature Reviews Genetics*, 10:405–415, 2009. doi: 10.1038/nrg2560.

Steven T Piantadosi. Zipf's word frequency law in natural language: A critical review and future directions. *Psychonomic bulletin & review*, 21(5):1112–1130, 2014. doi: 10.3758/s13423-014-0585-6.

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

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

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

Robert van Rooij and Tikitu de Jager. Explaining quantity implicatures. *Journal of Logic, Language and Information*, 21(4):461–477, 2012. doi: 10.1007/s10849-012-9163-3.

William H. Sandholm. *Population Games and Evolutionary Dynamics*. MIT Press, Cambridge, MA, 2010.

Uli Sauerland. Scalar implicatures in complex sentences. *Linguistics and Philosophy*, 27:367–391, 2004. doi: 10.1023/B:LING.0000023378.71748.db.

Karl H. Schlag. Why imitate, and if so, how? *Journal of Economic Theory*, 78(1):130–156, 1998. doi: doi:10.1006/jeth.1997.2347.

Catriona Silvey, Simon Kirby, and Kenny Smith. Word meanings evolve to selectively preserve distinctions on salient dimensions. *Cognitive Science*, 39(1):212–226, 2014. doi: 10.1111/cogs.12150.

Brian Skyrms. *Signals: Evolution, Learning, and Information.* Oxford University Press, Oxford, 2010.

Kenny Smith, Simon Kirby, and Henry Brighton. Iterated learning: A framework for the emergence of language. *Artificial Life*, 9:371–386, 2003.

Matthew Spike, Kevin Stadler, Simon Kirby, and Kenny Smith. Minimal requirements for the emergence of learned signaling. *Cognitive Science*, 2016. doi: 10.1111/cogs.12351.

Luc Steels. A self-organizing spatial vocabulary. *Artificial Life*, 2(3):319–332, 1995. doi: 10.1162/artl.1995.2.3.319.

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

Luc Steels and Tony Belpaeme. Coordinating perceptually grounded categories through language: A case study for color. *Behavioral and Brain Sciences*, 28(4):469–529, 2005. doi: 10.1017/S0140525X05000087.

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

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

Peter D. Taylor and Leo B. Jonker. Evolutionary stable strategies and game dynamics. *Mathematical Bioscience*, 40(1–2):145–156, 1978.

Bill Thompson, Simon Kirby, and Kenny Smith. Culture shapes the evolution of cognition. *Proceedings of the National Academy of Sciences of the United States of America*, 113(16): 4530–4535, 2016. doi: 10.1073/pnas.1523631113.

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

Tessa Verhoef, Simon Kirby, and Bart de Boer. Emergence of combinatorial structure and economy through iterated learning with continuous acoustic signals. *Journal of Phonetics*, 43: 57–68, 2014. doi: 10.1016/j.wocn.2014.02.005.

Karl Wärneryd. Cheap talk, coordination, and evolutionary stability. *Games and Economic Behavior*, 5(4):532–546, 1993. doi: doi:10.1006/game.1993.1030.

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

6 Some thoughts + what may be missing

- The data used in plots and slides should be generated as uniformly as possible. I will do this once we settle for everything else. Any input on this is welcome, but I think it boils down to adjusting the non-noisy simulations a bit to the noisy ones (the number of samples is what mostly diverges). It's also up to debate whether we should run the non-noisy simulations with multiple Qs, as their noisy counterparts.
- The analysis may benefit from further data and less of a qualitative overview of the parameters' effect (e.g. the regression analysis Michael conducted);