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 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 coming from 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 2016). Replication and selection is 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, such as from inductive learning biases or systematic perceptual errors. Considering transmission of linguistic knowledge is important because neither semantic meanings nor pragmatic usage patterns are directly observable. Language learners have to infer these unobservables from the observable behavior in which they result. 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 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 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 capturing 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 update, (ii) the fitness f_i of each type i before the update, 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) 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

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

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. 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 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.]

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.

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?] For our purposes here, 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 truth value for each state-message pair. The following two lexica exemplify the distinction between a lexicalized upper-bound for *some* in L_4 and the widely assumed logical semantics with only a lower-bound in L_5. [MF: can we not give these guys more mnemonic names?]

$$L_4 = \begin{array}{c c} & \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{array}{c} s_{\exists\neg\forall} \\ s_\forall \end{array} & \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array} \qquad L_5 = \begin{array}{c c} & \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{array}{c} s_{\exists\neg\forall} \\ s_\forall \end{array} & \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \end{array}$$

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?][MF: Literal speaker definition had α but that has no effect if we have Boolean semantics; I left this out.]

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

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

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_4 from above would assign $s_{\exists\neg\forall}$ a probability of $H_0(s_{\exists\neg\forall} \mid m_{\text{some}}; L_4) = 1$ after hearing m_{some}, while a literal interpreter with lexicon L_5 would assign $s_{\exists\neg\forall}$ probability $H_0(s_{\exists\neg\forall} \mid m_{\text{some}}; L_5) = 0.5$. A literal speaker chooses any true message for a state with equal probability and prefers a true message over a false one. The formulation in (4) allows also false messages to be sent with a small positive probability in analogy to the definition of pragmatic speakers in probabilistic pragmatic models. This is necessary to guarantee a mutation matrix with only positive entries (see below). A literal speaker with lexicon L_4 or L_5 produces m_{some} in $s_{\exists\neg\forall}$ with probability $S_0(m_{\text{some}} \mid s_{\exists\neg\forall}; L_{4,5}) \approx .73$. The probability of producing m_{some} in $s_{\forall}$ is $S_0(m_{\text{some}} \mid s_{\forall}; L_4) \approx .27$ for L_4 and $S_0(m_{\text{some}} \mid s_{\forall}; L_4) \approx .5$ for L_5. [MF: I realize that the probability of producing a false message for literal speakers is actually rather high. That's iffy because our pragmatic types are able (given favorable parameter values) to perform much better. That means that we implicitly have engineered in a possible fitness advantage of pragmatic types! Should we do something about this? Use definition $S_0(m \mid s; L) \propto L_{sm} + 0.001$? Make sure we only look at parameters for pragmatic types that make them not much better than the literal guys?]

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:

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

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

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 is here defined as $H_n(s|m; L)^{\alpha}$. The probability $H_n(s|m; L)$ is the probability that the hearer will assign to or choose the correct meaning. The transformation with α allows to differentiate theoretically interesting speaker production behavior. To see this, notice that for two states and two messages (the minimal scenario we will investigate), the possible values for $H_0(s|m; L)$ are restricted to zero, 0.5 and one. Consider the case of H_0 with L_5, which assigns the following probabilities to states after hearing messages:

$$H_0(m \mid s; L_5) = \begin{array}{c c} & \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \end{array} \\ \begin{array}{c} m_{\text{some}} \\ m_{\text{all}} \end{array} & \begin{bmatrix} 0.5 & 0.5 \\ 0 & 1 \end{bmatrix} \end{array}$$

A level-1 speaker's utilities are then:

$$\begin{array}{c c} & \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{array}{c} s_{\exists\neg\forall} \\ s_{\forall} \end{array} & \begin{bmatrix} 0.5^{\alpha} & 0^{\alpha} \\ 0.5^{\alpha} & 1^{\alpha} \end{bmatrix} \end{array}$$

As the soft-max choice rule is sensitive to differences in utilities, no matter what λ is we will get $S_1(m_{\text{some}} \mid s_{\exists\neg\forall}; L_5) = S_1(m_{\text{all}} \mid s_{\forall}; L_5)$ if $\alpha = 1$. This means that we cannot distinguish pragmatically deviant choices (selecting a less informative message instead of a more informative one), from semantically deviant choices (selecting a false message instead of a true one). If $\alpha > 1$ pragmatically deviant choices will get less likely than semantically deviant choices; if $\alpha < 0$ it is the other way around. In sum, parameter λ regulates the overall tendency to avoid pragmatically or semantically deviant choices, α further distinguishes between pragmatically and semantically deviant behavior. Variation in α is only necessary for the technical extension to environmental transmission noise in Section XYZ. [MF: I would suggest to just give the intuitive summary here and have a little appendix paragraph with the example. What do you say?]

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 adapt or revise their behavior occasionally 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. 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 type i's average expected communicative success, or *expected utility* (EU), given the current frequencies of types in the current population:

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

The expected utility $\text{EU}(t_i, t_j)$ 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:

$$\text{EU}(t_i, t_j) = {}^1\!/\!{}_2\, U_S(t_i, t_j) + {}^1\!/\!{}_2\, U_H(t_i, t_j)\,,$$

where $\text{EU}_S(t_i, t_j)$ and $\text{EU}_H(t_i, t_j)$ 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:

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

As usual, $\delta(s, s') = 1$ 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 their transmission from one generation to the next. Biases or systematic noise 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. But 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 in the same way before. In the simplest case, there is a single teacher and a single learner. After sufficient training, each 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 received 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 reflect the amount of data a learner requires to faithfully acquire the language of the teacher (c.f. Griffiths and Kalish 2007:450). 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 use a paremeter $l \geq 1$ to modulate between posterior sampling and the MAP strategy. When $l = 1$ learners sample from the posterior and 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 length k of state-message pairs, e.g., $\langle \langle s_1, m_1 \rangle, \ldots, \langle s_k, m_k \rangle \rangle$. The number k

of observations is another model parameters. 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 one 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:

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

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: [MF: check if we need "proportional to" here or whether "equals to" is okay]

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

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 update, 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 of 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 '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

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

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

Table 1: Space of possible lexica.

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.

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.

[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.

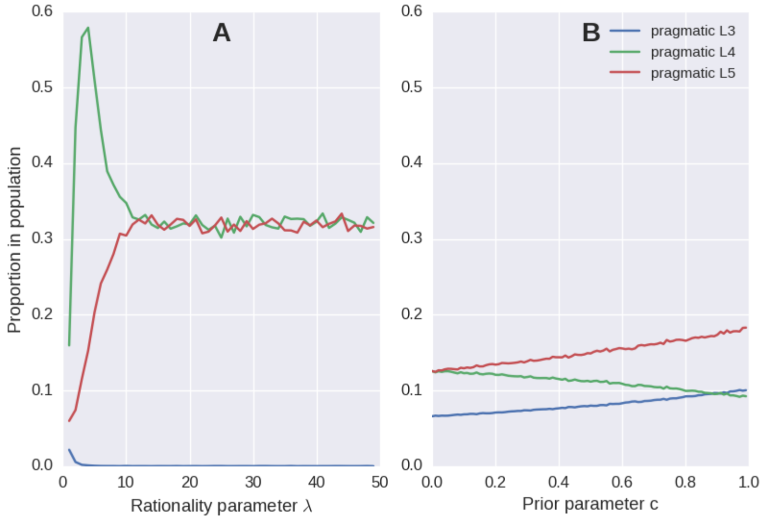

Figure 1: Mean proportions of target types after 20 generations in 1000 populations with only a pressure for expressivity in A ($\alpha = 1$) and only for learnability in B ($\alpha = 1, \lambda = 30, k = 5, l = 1$).

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 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

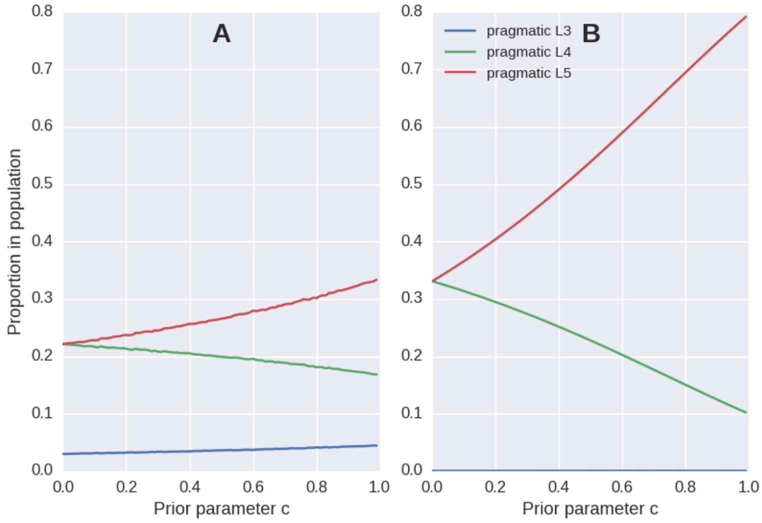

Figure 2: Mean proportions of target types after 20 generations in 1000 populations across bias values $c \in [0, 1]$ with $l = 1$ in A and $l = 3$ in B ($\alpha = 1, \lambda = 20, k = 5$).

types such as tautological L_3.

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

[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 $l = 3$ ($\alpha = 1, \lambda = 30, k = 5$)

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 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

[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.

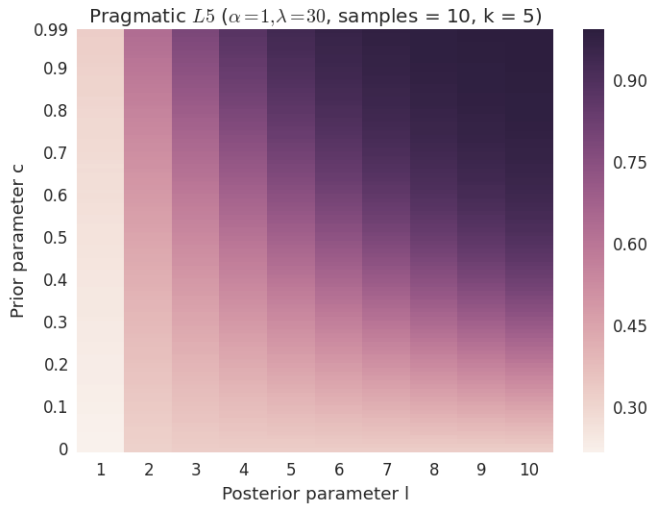

Figure 3: Mean proportion of pragmatic L_5 in 1000 populations after 20 generations ($\alpha = 1, \lambda = 30, k = 5$)

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 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.

	$l = 5$					$l = 15$				
(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.

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 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.

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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);