Co-evolution of lexical meaning & pragmatic use

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Abstract

According to standard linguistic theory, the meaning of an utterance is the product of conventional semantic meaning and general pragmatic rules on language use. To investigate how cultural evolution of language plays out under this picture of the semantics-pragmatics interface, we present a game theoretic model of the competition between types of language users, each endowed with a selection of lexical concepts and a particular pragmatic disposition to act on them. Our model traces two evolutionary forces and their interaction: (i) fitness-based pressure towards communicative efficiency and (ii) potential learning biases during the transfer of linguistic knowledge. We illustrate the model based on a case study on scalar implicatures. In this case study learning biases that favor simple semantic representations can boost the evolution of more sophisticated pragmatic reasoning types and so prevent the lexicalization of scalar implicatures.

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;" 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 may convey in context is due to Grice (1975), who characterizes pragmatic use and interpretation as a process of mutual reasoning about rational language use. For instance, under the assumption that the speaker is cooperative and relevant, "I have to work" may be interpreted as providing a reason why the speaker will not be able to accept an 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 convey *and then*.

A particularly productive and well studied class of systematic pragmatic enrichments are scalar implicatures (Horn 1984, Hirschberg 1985, Levinson 1983, Geurts 2010). Usually, the utterance of a sentence like "I own some of Johnny Cash's albums" will be taken to mean that the speaker does not own all of them. This is because, if the speaker owned them all, she could have

used the word *all* instead of *some* in his utterance, thereby making a more informative statement. Scalar implicatures, especially the inference from *some* to *some but not all*, have been studied extensively, both theoretically (e.g., Sauerland 2004, Chierchia et al. 2012, van Rooij and de Jager 2012) as well as experimentally (e.g., Bott and Noveck 2004, Huang and Snedeker 2009, Grodner et al. 2010, Goodman and Stuhlmüller 2013, Degen and Tanenhaus 2015). While there is much dispute in this domain about many details, a position endorsed by a clear majority is that a scalar item like *some* is underspecified to mean *some and maybe all* and that the enrichment to *some but not all* is part of some regular process with roots in pragmatics.

If this majority view is correct, the question arises how such a division of labor between semantics and pragmatics could have evolved and why it would be so pervasive across natural languages. Models of language evolution abound. There are simulation-based models studying the evolution of language in populations of communicating agents (Hurford 1989, Steels 1995, Lenaerts et al. 2005, Steels and Belpaeme 2005, Baronchelli et al. 2008, Steels 2011, Spike et al. 2016) and there are mathematical models of language evolution, mostly coming from game theory (Lewis 1969, Wärneryd 1993, Blume et al. 1993, Nowak and Krakauer 1999, Huttegger 2007, Skyrms 2010). Much of this work has focused on explaining basic properties such as compositionality and combinatoriality (e.g., Batali 1998, Nowak and Krakauer 1999, Nowak et al. 2000, Kirby and Hurford 2002, Kirby 2002, Smith et al. 2003, Gong 2007, Kirby et al. 2015, Verhoef et al. 2014, Franke 2016), but little attention has been paid to the interaction between conventional meaning and pragmatic use. What is more, many mathematical models explain evolved meaning as a regularity in the overt behavior of agents. In contrast, we will here look at language users with a richer cognitive make-up.

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

case, but combines it with functional selection, here formalized as the most versatile dynamic from evolutionary game theory; the replicator dynamic (Taylor and Jonker 1978). Section 2 introduces this model.

Section 3 applies this model to a case study on scalar implicatures. We discuss a setting in which the majority view of underspecified lexical meanings and pragmatic enrichments emerges if selection and transmission infidelity are combined. In particular, we show that inductive learning biases of Bayesian learners that favor simpler lexical meanings can prevent the lexicalization of scalar inferences and lead to the emergence of Gricean-like pragmatic reasoning types. Results of this case study are critically assessed in the light of the assumptions that feed our model in Section 4.

2 A model of co-evolving lexical concepts and pragmatic behavior

2.1 Expressivity and learnability

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

The idea that language is an adaptation to serve a communicative function is fundamental to many 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. Even small learning biases implicit in acquisition can build up and have quite striking effects on an evolving language in a process of iterated learning (Kirby and Hurford 2002, Smith et al. 2003, Kirby et al. 2014).

While natural languages are pressured for both expressivity and learnability these forces may pull in opposite directions. Their opposition becomes particularly clear when considering the extreme (cf. Kemp and Regier 2012, Kirby et al. 2015). A language consisting of a single form-meaning association is easy to learn but lacking in expressivity. Conversely, a language

that lexicalizes a distinct form for a large number of different meanings is highly expressive but challenging to acquire.

2.2 The replicator mutator dynamic

An elegant formal approach to capture the interaction between expressivity and learnability is the *replicator mutator dynamic* (Hofbauer 1985, Nowak et al. 2000; 2001, Hofbauer and Sigmund 2003, Nowak 2006). In its simplest, discrete-time formulation, the RMD defines the frequency x_i' of each type i in a population at the next time step as a function of: (i) the frequency x_i of each type i before the update step, (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) on the initial population vector $\vec{x}$ and its subsequent multiplication with a mutation matrix Q:

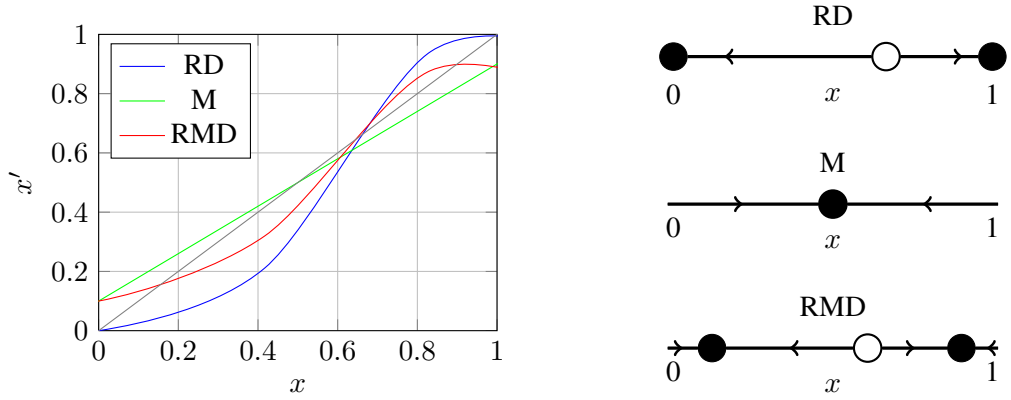
$$x_i' = (\mathrm{M}(\mathrm{RD}(\vec{x})))_i \,, \tag{2}$$

where

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

If the transmission matrix Q is trivial in the sense that $Q_{ji} = 1$ whenever $j = i$, the dynamic reduces to the replicator dynamic. The replicator dynamic is a model of fitness-based selection in which the relative frequency of type i will increase with a gradient proportional to its average fitness in the population. This dynamic is popular and versatile because it can be derived from many abstract processes of biological and cultural transmission and selection (for overview and several derivations see Sandholm 2010), including conditional imitation (e.g., Helbing 1996, Schlag 1998) or reinforcement learning (e.g., Börgers and Sarin 1997, Beggs 2005). If fitness f_i is the same for all types i, the replicator step is the identity map $(\mathrm{RD}(\vec{x}))_i = x_i$ and the dynamic reduces to a process of iteration of the transmission bias encoded in Q. In this way, the process in (1), equivalently (2), contains a model of iterated learning (Griffiths and Kalish 2007).

Example. Consider a simple coordination game. Agents are of two types: positive and negative. If agents of different type play with each other, they obtain a payoff of 0. If negative meets



(a) Update functions: the population state x is mapped onto x' in one update step

(b) Phase portraits for RD, M and RMD: unstable rest points are hollow, attractors are solid.

Figure 1: Example

negative, each receives a payoff of 1. If positive meets positive, they get a payoff of 2. A population state is completely characterized by the proportion x of negatives. The fitness of negatives in population state x is $f_n(x) = x$, that of positives is $f_p(x) = 2 - 2x$. The average fitness is $\Phi(x) = xf_n(x) + (1-x)f_p(x) = 3x^2 - 4x + 2$. Without mutation, the replicator dynamic will then update x to $RD(x) = {}^{x^2}/_{\Phi(x)}$. The update function $RD(x)$ of the replicator step is plotted in Figure 1a as the blue line. Rest points, for which $RD(x) = x$, are at $x = 0$, $x = 1$ and $x = {}^2/_3$. The former are attractors as nearby points converge to them. Points near $x = {}^2/_3$ move towards 0 or 1. This is schematically pictured in the topmost phase portrait in Figure 1b.

Adding mutation changes the dynamic and its rest points. Let's assume that $Q_{ji} = .9$ when $j = i$. The update effect of mutation alone is $M(x) = .9x + .1(1-x) = .8x + .1$ and is plotted as the linear green line in Figure 1a. It has only one stable rest point at $x = 0.5$ (see Figure 1b). If we first take the replicator step and then the mutation step in sequence, we obtain the replicator mutator dynamic $RMD(x) = M(RD(x)) = {}^{.9x^2-.2x+.2}/_{3x^2-4x+2}$, which is plotted in red in Figure 1a. The rest points are at $x = .121$, $x = .903$ and $x = .609$. The former two are attractors (see Figure 1b).

2.3 Fitness & learnability of lexical meanings & pragmatic strategies

Moving beyond an abstract example, our goal is to apply the RMD to investigate the co-evolution of lexical concepts and pragmatic behavior. To do so, we need to fix three things: (i) what the relevant types are, (ii) how fitness derives from communicative success and (iii) how the mutation matrix is computed. These issues are addressed, one by one, in the following.

2.3.1 Types: Lexica and pragmatic strategies

Types are what evolution operates on. They define an agent's fitness, usually through a payoff accrued in single interactions with other agents. Often types can be identified as the possible acts in a game, e.g., either cooperating or defecting in a prisoner's dilemma. In other cases, they may be thought of as general properties of an agent that influences her fitness, such as being positive or negative in our previous example (whatever that means). For our present purposes, types are identified more concretely by specific assumptions about their cognitive make-up. Since we are interested in the evolutionary competition between different lexical concepts and ways of using them in communication, a type is here defined as a pair consisting of a lexicon and a pragmatic strategy.

Agents play signaling games, in which the speaker wants to communicate a world state s with a message m to a hearer who receives m but does not know s (e.g. Lewis 1969, Skyrms 2010). A lexicon associates each message with a (possibly fuzzy) set of states. A pragmatic type maps a lexicon onto a probabilistic speaker rule (a probabilistic choice of message for each state) and a probabilistic listener rule (a probabilistic choice of state for each message). There are many ways of making these general notions more concrete. Here is what we will assume in the remainder of this paper.

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

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

Pragmatic types define dispositions of produce and interpret messages given a lexicon. We distinguish between two kinds of pragmatic types. *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

(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, as in Equations (3) and (4). Pragmatic language users of level $n+1$ act (approximately) rational with respect to level-n behavior of their interlocutors, as in Equations (5) and (6).

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

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

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

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

According to (3), a literal hearer's interpretation of a message depends on her lexicon and her prior over states, $pr \in \Delta(S)$, which is here assumed flat, for simplicity. Literal interpreters thereby choose an arbitrary true interpretation for each message. Pragmatic hearers, defined in (5), use Bayes rule to weigh interpretations based on a conjecture about speaker behavior. Speaker behavior is regulated by a soft-max parameter λ, $\lambda \geq 0$ (Luce 1959, Sutton and Barto 1998). As λ increases, choices approximate strict maximization of expected utilities. Expected utility of a message m in state s for a level $n+1$ speaker is here defined as $H_n(s|m; L)$, the probability that the hearer will assign to or choose the correct meaning. For literal speakers, utility only tracks truthfulness. Literal speakers choose any true message with equal probability but may send false messages as well with a probability dependent on λ.

Here are some concrete examples. [MF: please double-check the numbers!] A literal interpreter with lexicon L_{bound} assigns $s_{\exists\neg\forall}$ a probability of $H_0(s_{\exists\neg\forall} \mid m_{\text{some}}; L_{\text{bound}}) = 1$ after hearing m_{some}, while a literal interpreter with L_{lack} has $H_0(s_{\exists\neg\forall} \mid m_{\text{some}}; L_{\text{lack}}) = 0.5$:

$$H_0(\cdot \mid \cdot, L_{\text{bound}}) = \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{c} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array} \qquad H_0(\cdot \mid \cdot, L_{\text{lack}}) = \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{c} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \end{array} \\ \begin{bmatrix} .5 & .5 \\ 0 & 1 \end{bmatrix} \end{array}$$

If $\lambda = 1$ literal speaker behavior looks like this:

$$S_0(\cdot \mid \cdot, L_{\text{bound}}) \approx \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} .73 & .27 \\ .27 & .73 \end{bmatrix} \end{array} \qquad S_0(\cdot \mid \cdot, L_{\text{lack}}) \approx \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} .73 & .27 \\ .5 & .5 \end{bmatrix} \end{array}$$

If $\lambda = 20$, literal speakers will choose with less slack:

$$S_0(\cdot \mid \cdot, L_{\text{bound}}) \approx \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array} \qquad S_0(\cdot \mid \cdot, L_{\text{lack}}) \approx \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} 1 & 0 \\ .5 & .5 \end{bmatrix} \end{array}$$

Pragmatic hearers of level 1 have the following probabilistic interpretation behavior for $\lambda = 1$:

$$H_1(\cdot \mid \cdot, L_{\text{bound}}) \approx \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{c} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \end{array} \\ \begin{bmatrix} .73 & .27 \\ .27 & .73 \end{bmatrix} \end{array} \qquad H_1(\cdot \mid \cdot, L_{\text{lack}}) \approx \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{c} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \end{array} \\ \begin{bmatrix} .59 & .41 \\ 0.35 & 0.65 \end{bmatrix} \end{array}$$

For $\lambda = 20$, there wil less slack again: Pragmatic listeners of level 1 have the following probabilistic interpretation behavior for $\lambda = 1$:

$$H_1(\cdot \mid \cdot, L_{\text{bound}}) \approx \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{c} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array} \qquad H_1(\cdot \mid \cdot, L_{\text{lack}}) \approx \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{c} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \end{array} \\ \begin{bmatrix} 0.67 & 0.33 \\ 0 & 1 \end{bmatrix} \end{array}$$

With $\lambda = 1$, pragmatic speakers of level 1 will have:

$$S_1(\cdot \mid \cdot, L_{\text{bound}}) \approx \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} .73 & .37 \\ .37 & .73 \end{bmatrix} \end{array} \qquad S_1(\cdot \mid \cdot, L_{\text{lack}}) \approx \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} .62 & .38 \\ .38 & .62 \end{bmatrix} \end{array}$$

For high $\lambda = 20$, pragmatic speakers of level 1 give us:

$$S_1(\cdot \mid \cdot, L_{\text{bound}}) \approx \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array} \qquad S_1(\cdot \mid \cdot, L_{\text{lack}}) \approx \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array}$$

It is important to note that pragmatic agents of level 1 using L_{lack} associate m_{some} preferentially with $s_{\exists\neg\forall}$, in contrast to their literal counterparts of level 0. This association is not perfect, and usually less strong than what agents with a lexicalized upper bound in L_{bound} can achieve, even without pragmatic reasoning. Higher oder iteration of reasoning types leads to stronger associations of m_{some} and $s_{\exists\neg\forall}$ also for the hearer. Still, the case study presented in Section 3 will consider speaker and hearer behavior at levels 0 and 1, as the latter are the simplest pragmatic reasoning types which show a tendency to communicatively attuned pragmatic enrichment. Using only level 1 reasoning types is therefore a conservative choice that works against the fitness-based selection of pragmatic language use for a notion of fitness based on communicative efficiency, which is introduced next.

2.3.2 Fitness & fitness-based selection based on expressivity

Under the replicator dynamic 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 usually associated with expressivity, i.e., the ability to successfully communicate with other language users from the same population (e.g., Nowak and Krakauer 1999, Nowak et al. 2000; 2002). Under a biological interpretation the assumption is that organisms have a higher chance of survival and reproduction if they are able to share and receive useful information via communication with peers. Under a cultural interpretation the picture is that agents themselves strive towards communicative success and therefore occasionally adapt or revise their behavior to achieve higher communicative success (see Benz et al. 2005:§3.3 for discussion).

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

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

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

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

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

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

$$\mathrm{EU}_H(t_i, t_j) = \mathrm{EU}_S(t_j, t_i)\,.$$

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

2.3.3 Learnability

Languages are shaped not only by functionalist forces towards greater expressivity. Another important factor is the fidelity with which linguistic knowledge is transmitted. Among others, linguistic production can be prone to errors, states or messages may be perceived incorrectly, and

multiple languages may be compatible with the data learners are exposed to. These sources of uncertainty introduce variation in the transmission of linguistic knowledge from one generation to the next. In particular, learning biases in the iterated transmission process can influence language evolution substantially.

In biological evolution, where types are expressed genetically, transmission infidelity comes into the picture through infrequent and mostly random genetic mutations. However, an agent's lexicon and pragmatic reasoning behavior is likely 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 overt linguistic behavior of type i and need to infer the covert type that most likely produced the visible behavior. Iterated learning is a process in which languages are learned repeatedly from the observation of linguistic behavior of agents who have themselves acquired the language from observation and inference. In the simplest case there is a single teacher and a single learner. After sufficient training the learner becomes a teacher and produces behavior that serves as input for a new learner. Due to the pressure towards learnability it exerts, iterated learning alone generally leads to simpler and more regular languages (see Kirby et al. 2014 and Tamariz and Kirby 2016 for recent surveys).

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

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

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

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

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

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

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

2.4 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 dynamic in (1), repeated here:

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

This equation defines the frequency x_i' of type i at the next time step, based on its frequency x_i before the step, its fitness f_i, and the probability that a learner infers i when observing the behavior of a type-j agent. Fitness-based selection is here thought of not as biological (fitness as expected relative number of offspring) but cultural (fitness as likelihood of being imitated or repeated) evolution, since 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.

The model has three parameters: λ regulates the degree to which pragmatic speakers choose messages that maximize the chance of communicative success; k is the number of observations for each language learner; l regulates where the learners' inference behavior lies on a spectrum from probability matching to choice of the most likely parent type.

3 Case study: scalar implicatures

The model of the previous section formalizes the evolutionary competition between different pairs of lexical concepts and ways of using them. This section looks at a case study on scalar implicatures. It engages in a following formal thought experiment to address the question: if a population of language users could freely combine different lexica with different pragmatic strategies, what are conditions under which the majority view of scalar implicatures could have evolved?

Recall that the majority view is that scalar implicatures are non-lexicalized pragmatic enrichments. Scalar implicature triggers like *some*, *warm* or *may* are semantically weak expressions for which logically stronger expressions are salient, e.g., *all*, *hot* or *must*. For instance, *some* is entailed by *all*. If the sentence "Chris owns all of Johnny Cash's albums" is true, then "Chris owns some of Johnny Cash's albums" is also true. 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). In this way, "Chris owns some of Johnny Cash's albums" is strengthened to convey that she owns *some but not all* albums. According to the majority view, this is a pragmatic inference, not part of the conventional meaning.

In the following we consider a specific application of the model from Section 2 which allows to address the question if or when scalar inferences might (not) lexicalize. We consider what is perhaps one of the simplest non-trivial setups that speak to this matter and reflect on its limitations in Section 4. The setup is introduced in Section 3.1. Section 3.2 describes the simulations and their results.

3.1 Setup

To fill the model from Section 2 with life, we need to specify the sets of states, messages and lexica (Section 3.1.1). Additionally, we want to explore the effects of a learning bias in favor of simple lexical concepts. One way of motivating and formalizing such a bias is introduced below in Section 3.1.2.

3.1.1 States, messages, concepts and Lexica

Consider a state space with three states $S = \{s_\emptyset, s_{\exists\neg\forall}, s_\forall\}$ and think of it as a partition of possible worlds into cells where none, some or all of the As are Bs, for some arbitrary fixed predicates A and B. Eight concepts can be distinguished based on their truth or falsity in three world states, six of which are not contradictory or tautological (see Table 2 below).

A lexicon L is a mapping $M \to C$ from messages to concepts. With three messages there are $6^3 = 216$ possible lexica. Some assign the same concept to more than one message and others lexicalize the same concepts but associate them with different messages. Out of these possible lexica, three kinds are of particular relevance. First, lexica that assign the same concept to more than one message. Such lexica lack in expressivity but may be favored by particular learning biases nonetheless (see below). Second, lexica that conventionalize upper-bounds to realize a one-to-one mapping of messages to states. Finally, lexically that do not lexicalize an upper bound but allow it to be conveyed pragmatically due to the presence of a stronger lexical item. There are six lexica of the second kind and six of the third. The following three lexica exemplify each kind:

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

Lexicon L_{all} is clearly bad for communication: all message and interpretation choices will be equally likely for all types; no information about the observed world state will be conveyed by its users. In contrast, users of L_{bound} can communicate world states perfectly, no matter whether they are literal or pragmatic users. Users of L_{lack} can also communicate information about the actual world state but need pragmatic language use to approximate a one-to-one mapping between message use and states (see Section 2.3.1).

Recall that types are a combination of a lexicon and a manner of language use. We analyze the model's predictions in populations of types with one of the two behaviors introduced earlier;

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

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

literal or pragmatic. The former correspond to level 0 reasoners and the latter to level 1. Accordingly, we consider a total of 432 types. Six are variants of pragmatic language users with L_{lack}-like lexica. We refer to these as *target types*, because they represent lexica and language use that conform to the majority view of scalar implicatures. Twelve types are either literal or pragmatic speakers with lexical of the L_{bound} kind. We refer to these as *competitor types*, because they are expected to be the target types' main competitors in evolutionary competition.

3.1.2 An inductive learning bias for semantic simplicity

There is a growing effort to develop empirically testable representational languages that allow for the measure of semantic complexity. For instance, so-called *languages of thought* (LOTs) have been put to test in various rational probabilistic models that show encouraging results (see, e.g., Katz et al. 2008, Piantadosi et al. view; 2012 and Piantadosi and Jacobs 2016 for recent discussion). At its core, a LOT defines a set of operations and composition rules from which concepts can be derived. As a first approximation and for the sake of concreteness, we follow this approach to motivate and formalize a preference of learners for simpler semantic representations (Feldman 2000, Chater and Vitányi 2003, Piantadosi et al. 2012, Kirby et al. 2015, Piantadosi et al. view). A concept's complexity is a function of its derivation cost in a weighed generative LOT.

Our toy grammar of concepts is given in Table 1. This grammar uses basic set-theoretic operations to form expressions which can be evaluated as true or false in states $s_\emptyset$, $s_{\exists\neg\forall}$ or $s_\forall$ from above. Applications of generative rules have a cost attached to them. Here we simply assume that the formation of Boolean combinations of concepts incurs 2 cost units, while all other rule applications incur only 1 cost unit. Table 2 lists all six concepts relevant here, their truth conditions and the simplest formula that expresses this concept from the grammar in Table 1.

The complexity measure for lexical concepts from Table 2 is used to define a learning bias that favors simpler concepts over more complex ones. The prior probability of a type is just the prior probability of its lexicon. The prior of a lexicon is a function of the complexity of the lexical representations in its image set. Lexica with simpler concepts have a higher prior. One simple

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

Table 2: Available concepts and their minimal derivation cost

way of defining such priors over lexica (and thereby types) is:

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

where $Compl(c)$ is the complexity of the minimal derivation cost of c according to the LOT-grammar (see Table 2). This construal assigns the highest probability the above example for a lexicon of type L_{all}, which only uses the simplest concept "all" for all messages. Lexica of type L_{lack} are less likely, but more likely than L_{bound}.

There are many ways to define priors over lexica (see, e.g., Goodman et al. 2008, Piantadosi et al. 2012) but the key assumption here, common to all of them, is that simple representational expressions should be favored over more complex ones. We should stress that these details – from the generative grammar to its complexity measure – are to be regarded as one convenient operationalization of one general approach to explicating learning biases; this is not a commitment that this general approach is necessarily superior or that, within it, this particular instrumentalization is the single most plausible.

3.2 Simulation results

Recall that there are three parameters: soft-max parameter λ affects how strongly pragmatic speakers favor messages that appear best from their subjective point of view; the bottleneck size k influences how faithfully learners can identify their teacher type; l defines the learners' disposition towards choosing the most likely teacher type from the posterior distribution. We expect that competitor types (types with lexica of the kind L_{bound}) have a fitness advantage over target types (pragmatic agents with lexica of the kind L_{lack}), especially for very low levels of λ. Selection based on fitness alone may therefore not lead to prevalence of target types in the population. On

the other hand, lexica of type L_{lack} are simpler than those of type L_{bound} by the postulated measure from above. This may make them more likely to be adopted by learners, especially when k is low so that different teacher types are relatively indistinguishable based on their behavior and when l is high. Still, lexica of the kind L_{all} are in turn more likely *a priori* than lexica of the kind L_{lack}. Simulation results will shed light on the question whether target types can emerge and for which parameter constellations.

To better understand the workings of a pressure towards communicative efficiency and a pressure towards learnability, we look at the behavior of the replicator and mutator step first in isolation, and then in combination. All simulation runs are initialized with an arbitrary distribution over types, constituting a population's first generation. All reported results are the outcome of 50 update steps. These outcomes correspond to developmental plateaus in which change is, if not absent, then at least very slow. In other words, even if the resulting states do not correspond to an eventual attracting state, they characterize long almost stationary states in which the system remains for a very long time. As specified in §2.3.3, the mutation matrix Q can be obtained by considering all possible state-message sequences of length k. Given that this is intractable for large k, the sets of data learners are exposed to are approximated by sampling 250 k-length sequences from each type's production probabilities.

3.2.1 Replication only: selection based on expressivity and communicative success

As expected, selection based on communicative success is sensitive to λ as it influences signaling behavior, which in turn determines communicative success. This is showcased in Figure 2, which depicts the proportion of target types in 5 independent populations after 50 replicator steps. The plot also shows the proportion of the *majority type*, i.e., the type with the highest proportion in the final population. With low λ many types have very similar behavior, so that evolutionary selection lacks grip and becomes very slow. The result is a very long transition with near stagnancy in a rather homogeneous population with many types. Conversely, higher λ promotes more rational linguistic behavior, widening the gap in expressivity between types and promoting more homogeneous populations. As suggested by Figure 2, the incumbent in most populations is not one of the six pragmatic L_{lack}-style types. That is, a pressure only for expressivity does not lead to a prevalence of target types under any λ-value. For instance, in 1000 independent populations with $\lambda = 20$ only had 11 cases in which the target type was the majority type, corresponding to a mean proportion of 0.003 across populations. By contrast, in 913 cases the majority types had L_{bound} with close to an even share between literal (454) and pragmatic types (459), corresponding to a mean proportion of about $.48$ taken together.

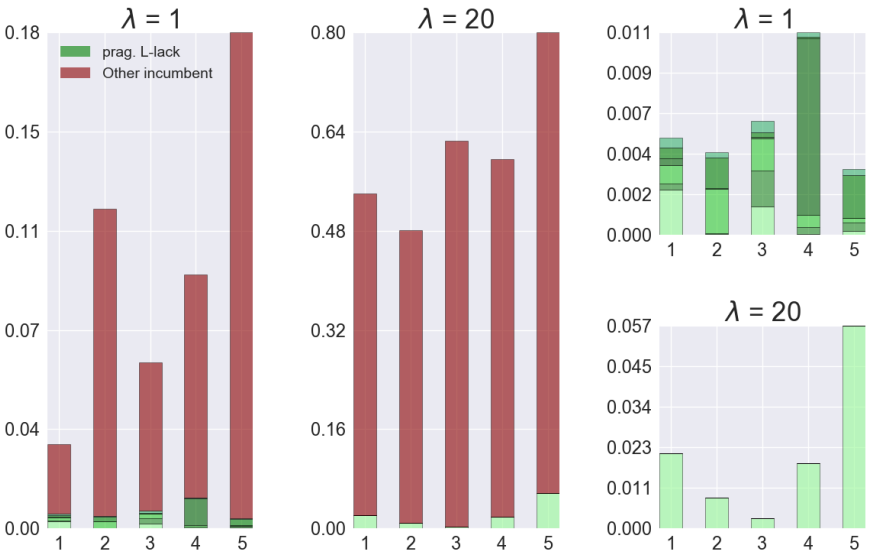


Figure 2: Stacked proportion of pragmatic L_{lack}-style types and incumbent types, when other than pragmatic L_{lack}, in 5 independent populations after 50 generations under only a pressure for expressivity. The right-most plots zoom in on only the proportion of pragmatic L_{lack} types. [MF: not sure if "incumbent" is the right term here; I believe it means "someone who is already there and established" but we mean "type with the highest proportion"; I used "majority type" in the main text; maybe change the plot?]

3.2.2 Iterated learning only

The effect of iterated learning without a pressure for expressivity using either posterior sampling ($l = 1$) or a stronger tendency towards posterior maximization ($l = 15$) is shown in Figure 3 together with the prior over types. The prior shows that while users of L_{lack} are not the most favored by the inductive bias (compared, e.g., to L_{all}) they are nevertheless more advantaged than others, such as L_{bound}, in virtue of the relatively simple semantics they conventionalize (see Section 3.1.2). Crucially, L_{lack} enables its users to convey each state with a single message when combined with pragmatic reasoning provided sufficiently high λ. This makes it less likely to be confused with other types if the learning data is not too sparse ($k \geq 5$). Put differently, learners have a higher propensity to infer pragmatic L_{lack} when the teacher's type produces very similar data, such as when using L_{bound}. Moreover, L_{lack} is also less likely to be confused with types with different observable behavior because its pragmatic use approximates a one-to-one form-meaning mapping. As a consequence, a stronger propensity to maximize the posterior increases their proportion in the population.

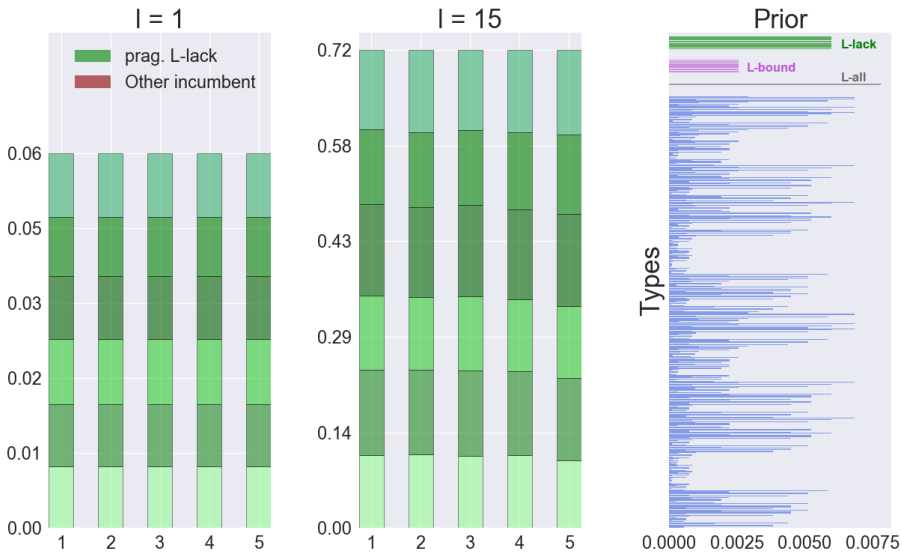


Figure 3: Stacked proportion of pragmatic L_{lack}-style types and incumbent types, when other than pragmatic L_{lack}, in 5 independent populations after 50 generations under only a pressure for learnability ($\lambda = 20, k = 5$). The types' prior probability is shown in the right-most plot. [MF: explain the topmost part of the right plot?!]

However, in contrast to a pressure only for expressivity with high λ (see Figure 2), learnability alone does not succeed in selecting for a single prevalent type. Indeed, all six target types tend to coexist at roughly equal proportion. Each is passed on to the next generation with the same faithfulness and, differently from a pressure for communicative success, they do not stand in competition with each other. In 1000 independent populations all majority types were target types provided, sufficiently high λ [MF: don't understand this proviso: what λ values were used in the 1000 runs? what's sufficiently high?], with each reaching approximately the same proportion of users in the population. As with expressivity only, low values of λ make the differences in observable behavior across types less pronounced and therefore reflect the learners' inductive bias more faithfully, favoring functionally deficient but a priori preferred types such as those that use L_{all}. A pressure for learnability alone may consequently lead to a spread of communicatively suboptimal types that are easier to learn. In the extreme, when $l = 1$ and $\lambda = 1$ all of 1000 independent populations had users of L_{all} as incumbents.

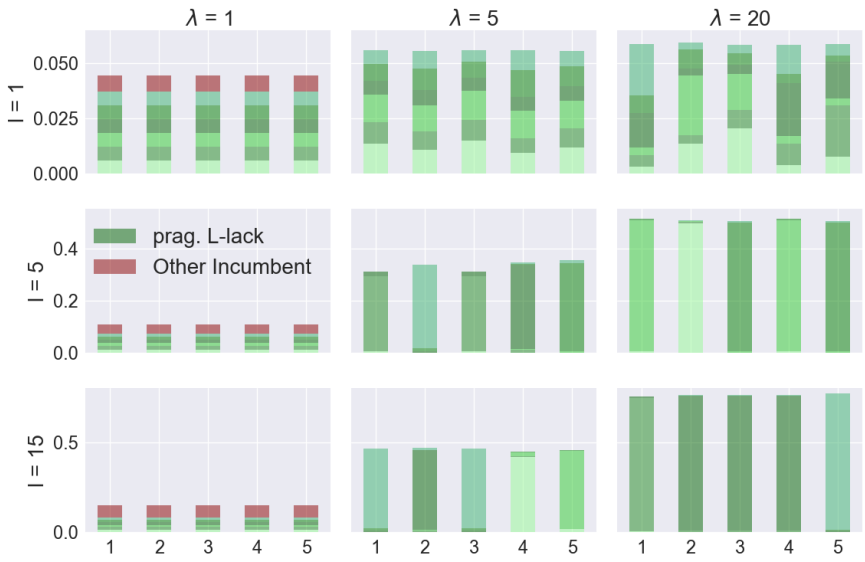


Figure 4: Stacked proportion of pragmatic L_{lack}-style types and incumbent types, when other than pragmatic L_{lack}, in 5 independent populations after 50 generations under both pressures ($k = 5$).

3.2.3 Combining pressures of expressivity and learnability

Pressures for communicative success or learnability are not sufficient on their own to have a single target type dominate the population. When pressured for expressivity, the slight communicative advantage of L_{bound} users leads to the its prevalence. When pressured for learnability, pragmatic L_{lack} is promoted over functionally similar but semantically more complex alternatives such as L_{bound}. However, on its own learnability does not foment the propagation of a single target type across the population.

Figure 4 illustrates the combined effects of both pressures for a sample of λ and l values. These results show that an inductive learning bias for simpler semantics in tandem with functional pressure can lead to the selection of a single target type. The proportion of a single majority target type increases with λ and l. Pressure for communicative success magnifies the effects of iterated learning and dampens the proliferation of types of a kind that are equal in expressivity *and* learnability. A pressure towards learnability favors the transmission of simpler semantics and thereby selects for pragmatic language use.

As before, low λ and l lead to the prevalence of communicatively suboptimal types that are a priori favored, such as L_{all}. An increase in λ leads to the selection of target types but does not lead to monomorphic populations if learners sample from the posterior. Finally, a combination of high λ and l, leads to increasing proportions of a single majority target type. The difference

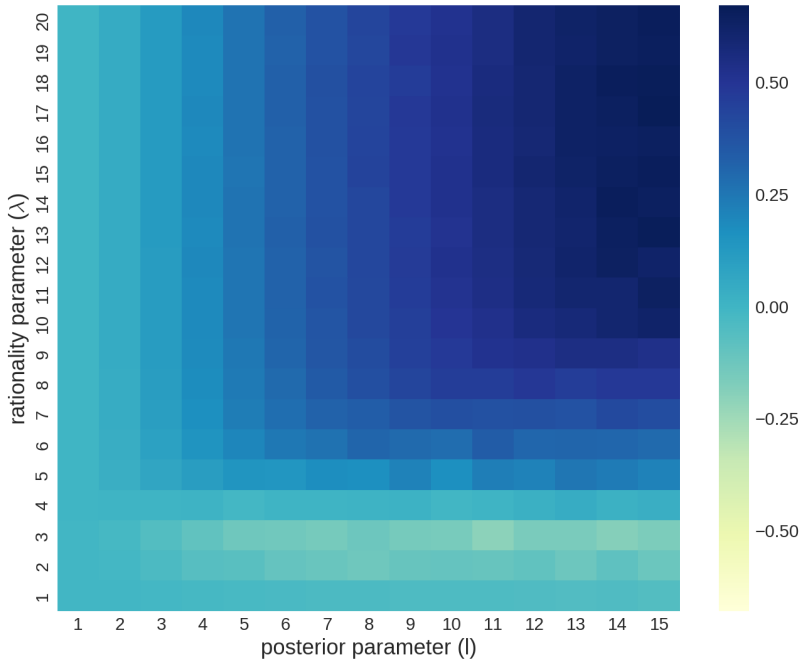


Figure 5: Difference between mean proportion of highest pragmatic L_{lack} type and highest other type in 1000 independent populations after 50 generations under both pressures ($k = 5$). [TB: I will run more simulations with higher λ and l. I'm pretty sure the difference still increases.] [MF: I think it's okay like that] [MF: the coloring is not that easy to decipher here; would a two-dimensional surface be possible and look better?]

between the mean of the highest pragmatic L_{lack}-like type in 1000 independent populations and the highest proportion of other types across λ and l values is shown in Figure 5.

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

To recapitulate, other than the involvement of pressure on both expressivity and learnability, the resulting proportion of pragmatic L_{lack} speakers primarily hinges on three factors. First, the degree, captured by λ, to which agents try to maximize communicative success from their own subjective point of view. Second, the inductive bias, which leads learners to prefer simpler over more complex semantic representations in acquisition. Lastly, the learning behavior, captured by

parameter l, where approximating a MAP strategy magnifies the effects of the learning bias in tandem with replication.

In summary, target types, which represent the majority view of scalar implicatures, can come to dominate the population if three assumptions are met: (i) language is pressured toward both expressivity and learnability; (ii) pragmatic language use is an option; (iii) learners prefer simpler over more complex lexical representations and exhibit a tendency towards the acquisition of the type that best explains the learning data.

4 General discussion

The approach introduced here combines game theoretic 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 reasoning about unobservable lexical representations (Bergen et al. 2012; 2016). This allows a conceptual investigation of the co-evolution of conventional meaning and pragmatic language use. Main contributions of the model are (i) its modular separation of expressivity and learnability on evolutionary trajectories, (ii) the characterization of language learning as a joint inference over pragmatic behavior and lexical meaning, and (iii) the possibility to trace the co-evolution of conventional semantics and pragmatic use.

[MF: can this abstract be shortened (by a factor of .4)?] The interaction of expressivity and learnability in language evolution 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. The degree of mutual understanding of interlocutors central to replication and to our notion of expressivity is absent. That is, while our proposal combines bidirectional horizontal transmission with its vertical and unidirectional counterpart, Kirby et al. only consider the latter's influence. Our reasoning behind the inclusion of the former lies in the empirical and theoretical observation that learnability alone can lead to the selection of functionally defective languages, as showcased by L_{all}. This outcome has been reported in a number of laboratory experiments where subjects learned and subsequently reproduced the language produced by a previous participant over multiple iterations, leading to a proliferation of ambiguous languages that associate many 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 communicatively distinguish meanings more accurately (e.g., Fay and Ellison 2013; for a review of laboratory results under the iterated learning paradigm and further discussion see Kirby et al. 2015, Tamariz and Kirby 2016). It is not evident how to compare

these empirical findings given that they consider distinct meaning spaces, modes of transmission, iterations and feedback given to participants. However, on a general level they may suggest that there is an important difference between a language generating learnable linguistic data and its actual performance as a means of information transfer. That is, we contend that successful information transfer in a linguistic community is central to the adoption of a communication system and that this measure may not be adequately reflected by production alone.

The main result of our case study is that types that correspond to the majority view of scalar implicatures (scalar readings are non-lexicalized pragmatic enrichments) can come to dominate a population. This can happen under the assumption that simpler semantic representations are more likely to be learned (cf. Chater and Vitányi 2003). Pragmatic language use can be recruited indirectly by a preference for simpler lexical concepts. Under this view, semantics and pragmatics play a synergic role: pragmatic use allows maintenance of simpler concepts; pressure towards representational simplicity indirectly promotes pragmatic over literal language use. As a consequence, iterated transmission and use of language lead to a regularization that may explain the lack of lexicalization of systematic pragmatic enrichments.

While the results of this case study are interesting, they also raise a number of critical issues. First of all, while many favorable parameter settings exist which lead to a prevalence of target types, other types are usually represented in non-negligible proportions. This may just be a technical quirk of the mutator step. But there is a related issue of empirical importance. Several experimental studies on scalar implicatures suggest that participants can be classified as either semantic or pragmatic users of, in particular, *some* (e.g. Bott and Noveck 2004, Nieuwland et al. 2010, Degen and Tanenhaus 2015). The former consistently accept *some* where *all* would be true as well, the latter do not. Interestingly, in our simulations when a target type is the majority type an inflated proportion of the population uses compatible lexica with a lexicalized upper bound. [MF: Thomas, please check this; I'm making it up; total conjecture; it might be true but I don't know for sure] In other words, we do find a similar co-existence of semantic and pragmatic types. Whether this analogy has any further explanatory value is an interesting path for future exploration.

Another important issue that is not addressed in the model are potential costs associated with pragmatic reasoning. Here, we simply assumed that literal and pragmatic reasoning strategies exist from the start and are equally costly to apply. In contrast, empirical results suggest that the computation of a scalar implicature may involve additional cognitive effort (e.g. Breheny et al. 2006, Neys and Schaeken 2007, Huang and Snedeker 2009, Tomlinson Jr. et al. 2013). Extensions of the model presented here to include processing costs for pragmatic language use would be interesting future work. It seems plausible that effects of reasoning cost may trade off with the frequency with which a given scalar expression is used. It may be that frequently

drawn scalar implicatures lexicalize to avoid cost, whereas infrequent ones are derived on-line to avoid more complex lexical concepts during acquisition. Such a prediction would lend itself to empirical testing in line with a recent interest in differences between various scalar implicature triggers (van Tiel et al. 2016).

Our case study could be criticized as follows: all it shows is that scalar implicatures do not lexicalize because upper bounds are dispreferred concepts. This criticism would be too superficial and highly unjust. Dispreferred lexical concepts can thrive under evolutionary selection. Lexicalized upper-bounds can dominate a population because they may boost communicative efficiency. But they do not have to. Moreover, even without selective pressure for communicative efficiency, it is not the case that necessarily the types that are most likely *a priori* will dominate. The dynamics of iterated learning are not that trivial. Iterated learning does not necessarily promote the *a priori* more likely type, but tends to promote a type t based on a gradient of how many other types might likely mutate into t, so to speak. Taken together, without an explicit model of the interaction between pressure for efficiency and learnability, it is far from trivial to judge whether or when preferred or dispreferred concepts can be adaptive. This is why a major contribution of this paper is the arrangement of many different ingredients into a joined model of the co-evolution of lexical meaning and pragmatic use.

What is more, it is not that we just assumed a prior disadvantage of lexicalized upper bounds. We tried to motivate and formalize a general assumption about concepts' complexity witha a concrete, albeit provisional proposal. The specification of a learning bias in terms of a "grammar of concepts" can and should be seen critically, however. Much depends on the primitives of such a grammar. For instance, the concept "none or all" is the most complex in Table 2. But consider adding a primitive operation on sets $A \smile B$ which is true if and only if $\neg(A \cap B \neq \emptyset \wedge A \neq \emptyset)$. The concept "none or all" would then be one of the simplest. Clearly, further research, empirical and conceptual, into the role of representational complexity, processing costs and learning biases is needed. The model here makes a clear and important contribution nonetheless: it shows how simplicity of concepts can interact with use and evolutionary selection to show that without pragmatic language users we would not see simpler concepts emerge in what may be a natural way. Future work should also include the possibility that conceptual simplicity may itself be a notion that is subject to evolutionary pressure (c.f. Thompson et al. 2016).

Finally, our case study should not be interpreted as a proposal for a definite explanation of how scalar implicatures evolved. Other factors should be considered eventually even if they will lead to much more complex modeling. One such factor is the observation that non-lexicalized upper bounds allow a broader range of applicability, e.g., when the speaker is not certain as to whether *all* is true. This may suggest an alternative argument for why upper-bounded meanings do not conventionalize based on functional criteria only: 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. 2012), 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. What this alternative explanation does not explain is why functional pressure does not lead to the emergence of different, equally costly lexical items to express different knowledge states of the speaker. Looking at pressure from learnability might come in again. The present work made a first start and gave a framework for exploring exactly these issues systematically.

5 Conclusion

The cultural evolution of meaning is influenced by intertwined pressures. We set out to investigate this process by putting forward a model that combines a pressure toward successful information transfer with perturbations that may arise in the transmission of linguistic knowledge in acquisition. Its objects of selection and replication are pairs of lexical meanings and patterns of language use. This allows the model to trace the interaction between conventional meaning and pragmatic use. Additionally, it takes the challenge serious of neither semantics nor pragmatics being directly observable. Instead, learners need to infer these unobservables from overt data that results from their combination. 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 force drives for simpler semantic representations inasmuch as pragmatics can compensate for lack of expressivity in use. That is, the relative learning advantage of simpler semantics in combination with functional pressure in use may offer an answer to why natural languages fail to lexicalize systematic pragmatic inferences. And, more broadly, to a division of labors between semantics and pragmatics.

References

Baronchelli, A., A. Puglisi, and V. Loreto (2008). Cultural route to the emergence of linguistic categories. *PNAS 105*(23), 7936–7940.

Batali, J. (1998). Computational simulations of the emergence of grammar. In J. R. Hurford, M. Studdert-Kennedy, and C. Knight (Eds.), *Evolution of Language: Social and Cognitive Bases*. Cambridge, UK: Cambridge University Press.

Beggs, A. (2005). On the convergence of reinforcement learning. *Journal of Economic Theory 122*(1), 1–36.

Benz, A., G. Jäger, and R. van Rooij (2005). *An Introduction to Game Theory for Linguists*, pp. 1–82. Palgrave.

Bergen, L., N. D. Goodman, and R. Levy (2012). 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*.

Bergen, L., R. Levy, and N. D. Goodman (2016). Pragmatic reasoning through semantic inference. *Semantics and Pragmatics*.

Blume, A., Y.-G. Kim, and J. Sobel (1993). Evolutionary stability in games of communication. *Games and Economic Behavior 5*(5), 547–575.

Börgers, T. and R. Sarin (1997). Learning through reinforcement and replicator dynamics. *Journal of Economic Theory 77*(1), 1–14.

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

Breheny, R., N. Katsos, and J. Williams (2006). Are generalised scalar implicatures generated by default? An on-line investigation into the role of context in generating pragmatic inferences. *Cognition 100*(3), 434–463.

Brighton, H. (2002). Compositional syntax from cultural transmission. *Artificial Life 8*(1), 25–54.

Chater, N. and P. Vitányi (2003). Simplicity: a unifying principle in cognitive science? *Trends in Cognitive Sciences 7*(1), 19–22.

Chierchia, G., D. Fox, and B. Spector (2012). Scalar implicature as a grammatical phenonenon. In C. Maienborn, K. von Heusinger, and P. Portner (Eds.), *Semantics. An International Handbook of Natural Language Meaning*, pp. 2297–2332. Berlin: de Gruyter.

Degen, J. and M. K. Tanenhaus (2015). Processing scalar implicatures: A constraint-based approach. *Cognitive Science 39*, 667–710.

Fay, N. and T. M. Ellison (2013). The cultural evolution of human communication systems in different sized populations: Usability trumps learnability. *PLoS ONE 8*(8).

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

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

Franke, M. (2016). The evolution of compositionality in signaling games. *Journal of Logic, Language and Information 25*(3–4), 355–377.

Franke, M. and G. Jäger (2014). Pragmatic back-and-forth reasoning. *Semantics, Pragmatics and the Case of Scalar Implicatures.*, 170–200.

Franke, M. and G. Jäger (2016). Probabilistic pragmatics, or why bayes' rule is probably important for pragmatics. *Zeitschrift für Sprachwissenschaft 35*(1), 3–44.

Gazdar, G. (1979). *Pragmatics, Implicature, Presuposition and Logical Form*. New York: Academic Press.

Geurts, B. (2010). *Quantity Implicatures*. Cambridge, UK: Cambridge University Press.

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

Goodman, N., J. Tenenbaum, J. Feldman, and T. Griffiths (2008). A rational analysis of rule-based concept learning. *Cognitive Science: A Multidisciplinary Journal 32*(1), 108–154.

Goodman, N. D. and M. C. Frank (2016). Pragmatic language interpretation as probabilistic inference. *Trends in Cognitive Sciences 20*(11), 818–829.

Goodman, N. D. and A. Stuhlmüller (2013). Knowledge and implicature: Modeling lanuage understanding as social cognition. *Topics in Cognitive Science 5*, 173–184.

Grice, P. (1975). Logic and conversation. In *Studies in the Ways of Words*, Chapter 2, pp. 22–40. Cambridge, MA: Harvard University Press.

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

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

Helbing, D. (1996). A stochastic behavioral model and a 'microscopic' foundation of evolutionary game theory. *Theory and Decision 40*(2), 149–179.

Hirschberg, J. (1985). *A Theory of Scalar Implicature*. Ph. D. thesis, University of Pennsylvania.

Hofbauer, J. (1985). The selection mutation equation. *Journal of Mathematical Biology 23*, 41–53.

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

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

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

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

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

Huttegger, S. M. (2007). Evolution and the explanation of meaning. *Philosophy of Science 74*, 1–27.

Jäger, G. (2007). Evolutionary game theory and typology: A case study. *Language 83*(1), 74–109.

Jäger, G. and R. van Rooij (2007). Language structure: psychological and social constraints. *Synthese 159*(1), 99–130.

Katz, Y., N. D. Goodman, K. Kersting, C. Kemp, and J. B. Tenenbaum (2008). Modeling semantic cognition as logical dimensionality reduction. In *Proceedings of Thirtieth Annual Meeting of the Cognitive Science Society*.

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

Kirby, S. (2002). Learning, bottlenecks and the evolution of recursive syntax. In T. Briscoe (Ed.), *Linguistic Evolution Through Language Acquisition*, pp. 173–204. Cambridge University Press (CUP).

Kirby, S., H. Cornish, and K. Smith (2008). 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.

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

Kirby, S., T. Griffiths, and K. Smith (2014). Iterated learning and the evolution of language. *Current Opinion in Neurobiology 28*, 108–114.

Kirby, S. and J. R. Hurford (2002). The emergence of linguistic structure: An overview of the iterated learning model. In A. Cangelosi and D. Parisi (Eds.), *Simulating the Evolution of Language*, pp. 121–148. Springer.

Kirby, S., M. Tamariz, H. Cornish, and K. Smith (2015). Compression and communication in the cultural evolution of linguistic structure. *Cognition 141*, 87–102.

Lenaerts, T., B. Jansen, K. Tuyls, and B. D. Vylder (2005). The evolutionary language game: An orthogonal approach. *Journal of Theoretical Biology 235*, 566–582.

Levinson, S. C. (1983). *Pragmatics*. Cambridge, UK: Cambridge University Press.

Lewis, D. (1969). *Convention: A Philosophical Study*. Cambridge: Harvard University Press.

Luce, D. R. (1959). *Individual choice behavior: a theoretical analysis*. Wiley.

Martinet, A. (1962). *Functionalist View of Language*. Oxford: Clarendon Press.

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

Nieuwland, M. S., T. Ditman, and G. R. Kuperberg (2010). On the incrementality of pragmatic processing: An ERP investigation of informativeness and pragmatic abilities. *Journal of Memory and Language 63*(3), 324–346.

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

Nowak, M. A., N. L. Komarova, and P. Niyogi (2001). Evolution of universal grammar. *Science 291*(5501), 114–118.

Nowak, M. A., N. L. Komarova, and P. Niyogi (2002). Computational and evolutionary aspects of language. *Nature 417*(6889), 611–617.

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

Nowak, M. A., J. B. Plotkin, and V. A. A. Jansen (2000). The evolution of syntactic communication. *Nature 404*(6777), 495–498.

Pagel, M. (2009). Human language as a culturally transmitted replicator. *Nature Reviews Genetics 10*, 405–415.

Piantadosi, S. T. (2014). Zipf's word frequency law in natural language: A critical review and future directions. *Psychonomic bulletin & review 21*(5), 1112–1130.

Piantadosi, S. T. and R. A. Jacobs (2016). Four problems solved by the probabilistic language of thought. *Current Directions in Psychological Science 25*(1), 54–59.

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

Piantadosi, S. T., J. B. Tenenbaum, and N. D. Goodman (under review). Modeling the acquisition of quantifier semantics: a case study in function word learnability.

Piantadosi, S. T., H. Tily, and E. Gibson (2012). The communicative function of ambiguity in language. *Cognition 122*(3), 280–291.

van Rooij, R. and T. de Jager (2012). Explaining quantity implicatures. *Journal of Logic, Language and Information 21*(4), 461–477.

Sandholm, W. H. (2010). *Population Games and Evolutionary Dynamics*. Cambridge, MA: MIT Press.

Sauerland, U. (2004). Scalar implicatures in complex sentences. *Linguistics and Philosophy 27*, 367–391.

Schlag, K. H. (1998). Why imitate, and if so, how? *Journal of Economic Theory 78*(1), 130–156.

Silvey, C., S. Kirby, and K. Smith (2014). Word meanings evolve to selectively preserve distinctions on salient dimensions. *Cognitive Science 39*(1), 212–226.

Skyrms, B. (2010). *Signals: Evolution, Learning, and Information*. Oxford: Oxford University Press.

Smith, K., S. Kirby, and H. Brighton (2003). Iterated learning: A framework for the emergence of language. *Artificial Life 9*, 371–386.

Spike, M., K. Stadler, S. Kirby, and K. Smith (2016). Minimal requirements for the emergence of learned signaling. *Cognitive Science*.

Steels, L. (1995). A self-organizing spatial vocabulary. *Artificial Life 2*(3), 319–332.

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

Steels, L. and T. Belpaeme (2005). Coordinating perceptually grounded categories through language: A case study for color. *Behavioral and Brain Sciences 28*(4), 469–529.

Sutton, R. S. and A. G. Barto (1998). *Introduction to Reinforcement Learning*. Cambridge, MA, USA: MIT Press.

Tamariz, M. and S. Kirby (2016). The cultural evolution of language. *Current Opinion in Psychology 8*, 37–43.

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

Thompson, B., S. Kirby, and K. Smith (2016). Culture shapes the evolution of cognition. *Proceedings of the National Academy of Sciences of the United States of America 113*(16), 4530–4535.

van Tiel, B., E. van Miltenburg, N. Zevakhina, and B. Geurts (2016). Scalar diversity. *Journal of Semantics 33*(1), 137–175.

Tomlinson Jr., J. M., T. M. Bailey, and L. Bott (2013). Possibly all of that and then some: Scalar implicatures are understood in two steps. *Journal of Memory and Language 69*(1), 18–35.

Verhoef, T., S. Kirby, and B. de Boer (2014). Emergence of combinatorial structure and economy through iterated learning with continuous acoustic signals. *Journal of Phonetics 43*, 57–68.

Wärneryd, K. (1993). Cheap talk, coordination, and evolutionary stability. *Games and Economic Behavior 5*(4), 532–546.

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

A notes

- [MF: The text frequently uses the term “expressivity” and “pressure for/towards expressivity”. I have mixed feelings about this. First of all, I don’t know what “expressivity” really is. It seems to relate to a lexicon: how much information can the lexicon convey about the states. But we do not model selection of expressivity, but selection of communicative success relative to the population state. The difference is very pronounced: there can be several maximally expressive lexica with huge differences in their communicatively success or expected utility for a given population state. We only indirectly select for expressivity, and we don’t necessarily select for expressivity of a lexicon. . . . It may be that “expressivity” is very much Edinburgh terminology where exactly the picture of communication success in the current population is missing. I might be wrong though. Possibly, we should introduce this distinction (with this terminology) and use it also in the general discussion to relate our work to those articles from the iterated-learning community that bring in some pressure for “expressivity” but not communicative efficiency (if that is what they do, I don’t know?).]