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

(– draft September 14, 2016—)

Abstract

Certain semantic structures enable for pragmatic enrichments in a notably productive fashion. This raises the challenge to justify their regular selection over alternatives that codify semantically what is conveyed pragmatically. This issue is particularly puzzling under a purely functional perspective. To address this challenge, we propose a general model for the analysis of linguistic pressures that integrates iterated Bayesian learning in the replicator-mutator dynamics. This model allows for population-level analyses of the effects of such pressures on probabilistic language users with varied degrees of pragmatic sophistication and distinct languages. We showcase the model's predictions in a case study on the (lack of) lexicalization of scalar implicatures. The results suggest simpler semantic representations to be selected for when languages are pressured towards learnability, provided that pragmatic reasoning can compensate for the disadvantage in expressivity that users of such languages otherwise incur.

1   The semantics-pragmatics divide

In linguistic theorizing, it is common to draw a distinction between semantics and pragmatics. Broadly speaking, the former concerns the truth-conditional content of expressions, whereas the latter concerns information beyond literal meanings and their composition. Under this view, the information conveyed by an utterance is seldom, if ever, solely determined by semantics, but rather in tandem with pragmatics.

Much research at the semantics-pragmatics interface has been aimed at characterizing expressions in terms of either domain, or their interplay. As a consequence, their distinction has played an important role in the field's theoretical and experimental development. However, an issue that has received little attention is the justification of semantic structure in light of pragmatics. That is, the selection and pervasiveness of particular semantics under consideration of the regular informational enrichment provided by pragmatics.

Similar questions have lead to a recent surge of models that aim to analyze the development and selection of linguistic features (see Steels 2015 and Tamariz and Kirby 2016 for recent overviews). Our starting point is given by the overarching argument that has crystallized across this literature: Natural languages need to be well-adapted to communicative needs within a linguistic community, but also need to be learnable to survive their faithful transmission across generations. More succinctly; natural languages are pressured for expressiveness as well as learnability.

1

We proceed by modeling these pressures using the replicator-mutator dynamics (see Hofbauer and Sigmund 2003 for an overview). This allows us to inspect their dynamics by combining functional pressure on successful communication, effects of learning biases on (iterated) Bayesian learning (Griffiths and Kalish 2007), and probabilistic models of language use in populations with distinct lexica (Frank and Goodman 2012, Franke and Jäger 2014, Bergen et al. 2016).

2 Simplicity, expressivity, and learnability

The emergence and change of linguistic structure is influenced by many factors, ranging from biological and socio-ecological to cultural (Steels 2011, Tamariz and Kirby 2016). Social and ecological pressures determine communicative needs, while biology determines the architecture that enables and constrains their means of fulfillment. In the following, our focus lies on the latter, cultural factor, wherein certain processes of linguistic change are understood as shaped by use and transmission. That is, as a result of cultural evolution.

At latest since Zipf's (1949) rationalization of the observation that word frequency rankings can be approximated by a power law distribution as competing hearer and speaker preferences, the idea that linguistic selection and change are driven by communicative pressures has played a pivotal role in synchronic and diachronic analyses (e.g. Martinet 1962, Horn 1984, Jäger and van Rooij 2007, Jäger 2007, Piantadosi 2014, Kirby et al. 2015). As noted above, expressivity and learnability are two key instances of such competing pressures. Their opposition becomes particularly clear when considering their consequences in the extreme (cf. Kemp and Regier 2012, Kirby et al. 2015). On the one side, a language with a single form is easy to learn but lacking in expressivity for most applications. On the other, a language that associates a distinct form with all possible meanings its users may want to convey is maximally expressive but challenging to acquire.

The most prominent problem that arises from the tension between learnability and expressivity is that of acquiring a language to express a potentially infinite set of meanings through finite means (Kirby 2002). However, this so-called transmission bottleneck is not the only challenge learners confront. More important for our purposes is the problem of selecting particular hypotheses out of a potentially infinite space of alternatives compatible with the data learners are exposed to. At the semantics-pragmatics interface this concerns the selection between functionally similar, if not identical, lexical meanings. In the following, we assume an integeral part of the answer to be that learners are a priori biased towards simpler, more compressed, representations. This corresponds to the argument that rational learners should prefer simpler over more complex explanations of data (Feldman 2000, Chater and Vitányi 2003, Piantadosi et al. 2012a, Kirby et al. 2015, Piantadosi et al. under review). In linguistics, a drive for simplicity has been argued to underpin speaker preferences for brevity and ease of articulation, as well as to pressure languages towards lexical ambiguity and grammatical compression (Zipf 1949, Grice 1975, Piantadosi et al. 2012b, Kirby et al. 2015). As a broader cognitive principle, the use of simplicity as means to select betweeen hypotheses that fit the data has a long standing tradition. Crucially, Chater and Vitányi (2003) provide strong arguments for a prior towards simpler explanations. **this needs to be expanded**

The remainder of this section introduces the individual components of the model in more technical detail. That is: (i) languages and their use, (ii) pressures towards expressivity and learnability, regulated by the replicator and mutator dynamics, respectively, as well as (iii) a bias towards simpler semantic representations, codified as a language learner's prior. After laying out the model, we discuss its application to the lack of lexicalization of scalar implicatures.

2.1 Languages and linguistic behavior

Lexica are taken to codify the truth-conditions of a language's expressions, i.e., its semantics. Given a state of affairs and a lexicon, language users can judge whether an expression is true or false. A convenient way to represent such lexica is by $(|S|, |M|)$-Boolean matrices, where S is a set of states of affairs and M the set of messages in the lexicon (Franke and Jäger 2014). For instance, the following two lexica fragments determine the truth-conditions of two messages, m_1 and m_2, for two states, s_1 and s_2:

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

In words, according to lexicon L_a, m_1 is true of s_1 as well as s_2. In contrast, message m_1 is only true of s_1 in L_b. Otherwise, the two languages are truth-conditionally equivalent.

To make the distinction betweeen semantics and pragmatics precise, we distinguish between two kinds of linguistic behavior. *Literal interlocutors* produce and interpret messages literally. That is, their linguistic choices are solely guided by their lexica. In contrast, *pragmatic interlocutors* engage in mutual reasoning to inform their choices. For instance, given that m_2 is unambiguously associated with state s_1, a rational speaker of L_a who reasons about her addressee should use m_1 to signal state s_2. Analogously, should rational hearers expect their interlocutors to reason along these lines, they will interpret the messages accordingly. Note in particular that according to this sketch of the pragmatic strenghtening of m_1, L_a is indistinguishable from L_b in terms of expressiveness.

Following models of rational language use such as Rational Speech Act models (Frank and Goodman 2012) and their game-theoretic counterparts (Benz et al. 2005a, Franke 2009, Franke and Jäger 2014), this kind of signaling behavior is captured by a hierarchy over reasoning types. The hierarchy's bottom, level 0, corresponds to literal language use. Language users of level $n+1$ behave rationally according to (expected) level n behavior of their interlocutors. The behavior of literal level 0 and pragmatic level $n+1$ hearers of a language L is is captured by their respective selection functions in (1) and (3). Mutatis mutandis for the speaker functions in (2) and (4).

$$H_0(s|m; L) \propto pr(s)L_{sm} \tag{1}$$

$$S_0(m|s; L) \propto \exp(\lambda\, L_{sm}) \tag{2}$$

$$H_{n+1}(s|m; L) \propto pr(s)S_n(m|s; L) \tag{3}$$

$$S_{n+1}(m|s; L) \propto \exp(\lambda\, H_n(s|m; L)^{\alpha}) \tag{4}$$

According to (1), a literal hearer's interpretation of a message m as a state s depends on her lexicon, weighted by her prior over states, $pr \in \Delta(S)$. The latter plays an important role when hearers face ambiguous messages about which the prior is informative.

The literal speaker's choice in (2) is regulated by a soft-max parameter λ, $\lambda \geq 1$ (Luce 1959, Sutton and Barto 1998). As α increases, choices made in production are more rational; higher values lead to more deterministic expected utility maximizing behavior.

Pragmatic behavior resembles its literal counterpart. As described above, the crucial difference is that level $n+1$ speakers/hearers reason about level n hearer/speaker behavior. That is, they reason about how a rational level n interlocutor would use or interpret a message and behave according to these expectations. Additionally, pragmatic production is further regulated by a parameter α which controls the tension between semantics and pragmatics, $\alpha \in (0, 1]$. Lower values lead to more literal production, whereas higher values lead to more pragmatic behavior.

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

2.2 Replication & expressivity

On a population level, expressiveness, or communicative efficiency, has received particular attention from investigations using evolutionary game theory (Nowak and Krakauer 1999, Nowak et al. 2000; 2002). Under this view, successful communication confers a higher fitness to some types relative to less successful ones. As a consequence, types with a higher fitness replicate and spread through the population, whereas the proportion of communicatively less efficient types decreases. This association of a type's communicative success within a population with changes in the types present in it creates a feedback loop that pressures the population towards greater expressivity. The replicator equation gives us the means to make these dynamics precise.

The proportion of types in a given population is captured by a vector x, where x_i is type i's proportion in the population. The fitness of a type i, f_i, is given by its expected utility when interacting in this population. That is, its fitness is the sum of its weighted expected communicative success, $f_i = \sum_j x_j \mathrm{EU}(t_i, t_j)$. The expected utility of i and j is obtained by considering the expected utility of speaker i interacting with hearer j, and vice versa: $\mathrm{EU}(t_i, t_j) = [U_S(t_i, t_j) + U_R(t_i, t_j)]/2$. $U_S(x, y)$ and $U_R(x, y)$ are respectively $\sum_s P(s) \sum_m S_n(m|s; L) \sum_{s'} R_o(s'|m; L)\delta(s, s')$ and $U_S(y, x)$ for n and o being the reasoning level of x and y, and $\delta(s, s') = 1$ iff $s = s'$ and 0 otherwise.[1] Lastly, the average fitness of the population is captured by Φ, $\Phi = \sum_i x_i f_i$. This term serves as a normalizing constant for the (discrete) replicator equation; $\dot{x}_i = \frac{x_i f_i}{\Phi}$

Under its biological interpretation, the replicator equation captures the idea of fitness-relative selection whereby fitter types produce more offspring, leading to their propagation in subsequent generations. In analogy to biological replication, many aspects of natural language are subject to processees of change across varied time-spans. For example, the replicator equation can be understood as a learning across generations as e.g. in Nowak et al. 2002, but also as a process of horizontal adaptation (see Benz et al. 2005b:§3.3 for discussion). In the following, we take the latter view and assume that interlocutors adapt their language's semantics and how it is used to that which works best within their population. In contrast to the effect of language acquisition from a generation to the next, this means that expressivity exherts its pressure on the current members of a linguistic community. For pressures of language learning from one generation to the next, we turn to iterated Bayesian learning as mutator dynamics.

2.3 Mutation & learning

While past research using evolutionary game theory has mostly focused on communicative fitness driven change, the contribution of learning has similarly been argued to be one if not the central force guiding language change. In a nutshell, the iterated learning paradigm models language transmission as chains of parents and children citation IL. Look up which ones they use. The parent produces linguistic data from which the child infers a language to adopt. In the next generation, previous children adopt the role of a teaching parent that will themselves produce data to be learnt by a new generation of naïve learners. The central idea is that this iterated learning process pressures languages towards greater learnability. In this way, linguistic complexity hindering may be reduced, and languages regularized, to overcome to transmission bottleneck.

---

[1] Note that the definition of $U_R(\cdot, \cdot)$ implies equal sender and receiver payoff in an interaction. This need not be so in the general case but suffices for our application.

In our present setup, the learners' task is to perform a joint inference over lexica and signaling behavior. As with the sole replicator dynamics, the mutator dynamics are deterministic. They are codified in a transition matrix Q, where Q_{ij} indicates the probability of the children of a parent of type i adopting type j. This, in turn, is proportional to the probability of i producing the learning data and that of j given the data.

The elements of the set of learning data D are sequences of length k of state-message pairings. That is, a sequence of observations of language use. Put differently, a datum $d \in D$ contains k members of the set $\{\langle s_i, m_j \rangle \, | s_i \in S, m_j \in M\}$ and D is the set of all such sequences. Having fixed D,

$$Q_{ij} \propto \sum_{d \in D} P(d|t_i) F(t_j, d),$$

where $F(t_j, d) \propto P(t_j|d)^l$ and $P(t_j|d) \propto P(t_j)P(d|t_j)$. Given a type i, $P(d|t_i)$ can be straight-forwardly computed based on t_i's production behavior. However, the above involves two crucial aspects that require a more detailed discussion: the posterior parameter l and the learning prior $P \in \Delta(\mathcal{T})$.

Posterior parametrization. Crucially, the posterior is parametrized by l, $l \geq 1$. When $l = 1$ learners sample from the posterior. As l increases towards infinity, the learners tendency to posterior maximization increases.

Learning prior.

2.4 Summary

3 Discussion

(II) Sequences and atomic observations. Before, the set of all observations was $O = \{\langle \langle s_1, m_i \rangle, \langle s_2, m_j \rangle \rangle \, | m_i, m_j \in M\}$. A member of O encodes that a teacher produced m_i in state s_1 and m_j in s_2, i.e., it encodes one witnessed message for each state. A datum d was a sequence of length k of members of O. Learners witnessed such data sequences.

(III) Observations as production. Instead of taking the space of all possible sequences of length k into consideration, we take sample from O k-times according to the production probabilities of each type; $P(o = \langle s, m \rangle \, | t_i) = P(s)P(m|s, t_i)$. n such k-length sequences are sampled for each type. As a consequence, the data used for computing Q_i is not the same as that used for j ($i \neq j$).

(IV) Parametrized learning The proportion of players of type i, x_i, is initialized as an arbitrary distribution over T. $p^\star \in \Delta(T)$ is learning a prior over (player) types dependent only on the lexicon of the type.

- $Q_{ij} \propto \sum_d P(d|t_i) \, P(t_j|d)$, where $P(t_j|d) \propto [P(t_j)P(d|t_j)]^l$, d is a sequence of observations of length k of the form $\langle \langle s_i, m_j \rangle, ... \langle s_k, m_l \rangle \rangle$, and $l \geq 1$ is a learning parameter.

- For parental learning (standard RMD): $\dot{x}_i = \sum_j Q_{ji} \frac{x_j f_j}{\Phi}$

Symmetrized expected utility. With $P \in \Delta(S)$ (uniform so far; $P = pr$):

- $U(t_i, t_j) = [U_S(t_i, t_j) + U_R(t_i, t_j)]/2$

- $U_S(t_i, t_j) = \sum_s P(s) \sum_m P_S(m|s; t_i) \sum_{s'} P_R(s'|m, t_j) \, \delta(s, s')$, where $\delta(s, s')$ returns 1 iff $s = s'$ and otherwise 0

- $U_R(t_i, t_j) = U_S(t_j, t_i)$

4 Lack of semantic upper-bounds in lexical meaning

Note that this corresponds to the description of scalar implicatures given above: Reasoning about the alternatives at the speaker's disposition can pragmatically strengthen an expression's literal meaning by ruling out stronger alternatives not mentioned.

A particularly well-studied type of conventional pragmatic enrichment are so-called *scalar implicatures* (cf. Horn 1972, Gazdar 1979). These inferences are licensed for groups of expressions ordered in terms of informativity, here understood as an entailment induced order. For instance, *some* is entailed by *all*; if it were true that 'All students came to class', it would also be true that 'Some students came to class'. However, while weaker expressions such as *some* are truth-conditionally compatible with stronger alternatives such as *all*, this is not necessarily what their use is taken to convey. Instead, the use of a less informative expression when a more informative one could have been used can license the inference that the stronger alternative does not hold. That is, a hearer who assumes the speaker to be able and willing to provide all relevant information can infer that, since the speaker did not use a stronger alternative (*all*), this alternative must not hold. In this way, 'Some students came to class' is strengthened as conveying 'Some but not all students came to class'. Analogously, a speaker can rely on her interlocutor to draw this inference without having to express the bound overtly, e.g. by stating *some but not all*. In summary, mutual reasoning about rational language use supplies an upper-bound that rules out stronger alternatives pragmatically.

We can now rephrase our initial question in terms of scalar implicatures: Why is the lack of lexical upper-bounds in weak scalar alternatives regularly selected for over the alternative of lexicalizing it? This question is particularly striking considering the number of classes of expressions that license such inferences across languages (Horn 1972, Horn 1984:252-267, Traugott 2004, van der Auwera 2010).

For instance, truth-conditionally, *Bill read five books* does not set an upper-bound to the amount of books that Bill read; he may have read six, seven, or more books. However, the (defeasible) inference that *Bill read no more than five books* may be drawn on pragmatic grounds. After all, if Bill had read, for example, six books, and had the speaker known this, she would have said so. In this manner, what is conveyed (pragmatically) can go beyond what is (literally) said.

Prima facie, it is puzzling that *Bill read five books* does not semantically rule out its more informative or "stronger" alternatives. More poignantly, would it not serve language users better if weak(er) expressions such as *warm, or, some* or *big* were truth-conditionally incompatible with stronger alternatives such as, respectively, *hot, and, all* and *huge*? After all, analogously to the example sketched above, this is what a pragmatically enriched interpretation yields; an upper-bound that rules out these alternatives through a so-called scalar inference (Horn 1972, Gazdar 1979). The present investigation focuses on the lack of lexicalization of such upper-bounds in natural languages. That is, we seek to provide an explanation for the selection of the particular semantics of scalar expressions, which in turn hinges on the semantics-pragmatics distinction for what is ultimately conveyed to interlocutors. However, once a distinction between semantics and

pragmatics is drawn, similar questions can be posed for other types of pragmatic inferences, such as ignorance and manner inferences.

Procedural description. The game is initialized with some arbitrary distribution over player types. At the game's onset we compute Q once based on the sets of sequences D (one for each parent type). Replicator dynamics are computed based on the fitness of each type in the current population as usual. Q is computed anew for each independent run (of g generations) given that it depends on D, which is sampled from production probabilities.

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

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

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

Table 1: Set of considered lexica.

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

4.1 Model parameters & procedure

1. Sequence length k

2. Pragmatic production parameter α

3. Rationality parameter λ

4. Learning prior over types (lexica); cost parameter c. $p^\star(t_i) \propto n - c \cdot r$ where n is the total number of states and r that of upper-bounded messages only true of s_1 in t_i's lexicon (if only s_1 is true of a message, then this message encodes an upper-bound). Then the score for L_1, L_3, L_5 is 2, that of L_4 and L_6 is $2 - c$, and that of L_2 is $2 - 2c$; Normalization over lexica scores yields the prior over lexica (which is equal to the prior over types).

5. Prior over meanings (pr). We assume that $pr(s) = \frac{1}{|S|}$ for all s.

6. True state distribution (P). We currently assume that $P = \frac{1}{|S|}$ but it may be interesting to vary this

7. Learning parameter $l \geq 1$ with 1 corresponding to probability matching, and MAP as l approaches infinity

8. n is the sample of sequences of observations of length k sampled from the production probabilities of each type

9. Number of generations g

5 Discussion

6 Extensions

(I) Cost for pragmatic reasoning. At least in the CogSci setup the effect of adding cost to pragmatic reasoning is unsurprising: High cost for pragmatic signaling lowers the prevalence of pragmatic types. Lexica that semantically encode an upper-bound benefit the most from this. However, the cost needed to be substantial to make the pragmatic English-like lexicon stop being the incumbent type (particularly when learning is communal).

(II) Negative learning bias. Instead of penalizing complex semantics (semantic upper-bounds) one may consider penalizing simple semantics (no upper-bounds). This is useful as a sanity check but also yields unsurprising results in the CogSci setup: The more learners are biased against simple semantics, the more prevalent are lexica that semantically encode upper-bounds.

(III) Inductive bias. A second learning bias that codifies the idea that lexica should be uniform, i.e. be biased towards either lexicalizing an upper-bound for all weaker alternatives in a scalar pair or for none.

(IV) Uncertainty. The other advantage of non-upper bounded semantics lies in being non-committal to the negation of stronger alternatives when the speaker is uncertain. Adding this to the model requires the most changes to our present setup and some additional assumptions about the cues available to players to discern the speaker's knowledge about the state she is in.

(V) More scalar pairs. Taking into consideration more than one scalar pair. Preliminary results suggest that this does not influence the results in any meaningful way without further additions, e.g. by (III).

(VI) More lexica. Not necessary. Preliminary results suggest that considering more lexica has no noteworthy effect on the dynamics (tested with all possible 2x2 lexica).

(VII) State frequencies. Variations on state frequencies. This may have an interesting interaction with (III).

(VIII) Reintroduction of communal learning. One possibility: The probably N_{ij} with which a child of t_i adopts t_j could be the weighted sum of Q_{ij} (as before) and a vector we get from learning from all of the population: $L_j = \sum_d P(d|\vec{p})P(t_j|d)$, where $P(d|\vec{p}) = \sum_i P(d|t_i)\vec{p_i}$ is the probability of observing d when learning from a random member of the present population distribution.

7 Conclusion

References

Luc Steels. *The Talking Heads experiment: Origins of words and meanings.* Language Science Press, 2015.

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

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

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

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

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

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

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

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

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

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

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

Steven T Piantadosi. Zipfs word frequency law in natural language: A critical review and future directions. *Psychonomic bulletin & review*, 21(5):1112–1130, 2014. doi: 10.3758/s13423-014-0585-6.

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

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

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

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

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

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

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

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

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

Anton Benz, Gerhard Jäger, Robert Van Rooij, and Robert Van Rooij, editors. *Game theory and pragmatics*. Springer, 2005a.

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

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

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

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

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

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

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

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

S. M. Huttegger and K. J. S. Zollman. Methodology in biological game theory. *The British Journal for the Philosophy of Science*, 64(3):637–658, 2013.

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

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

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

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