Signaling under uncertainty
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Chapter 5

Evolution of Ambiguity

Each city receives its form from the desert it opposes.

Italo Calvino, Invisible Cities

In Chapter 3 we showed that semantic ambiguity can be functionally advantageous provided that interlocutors’ (beliefs about) contextual information agrees, leading to successful disambiguation; or that they interact multiple times so that speakers come to anticipate receivers’ interpretative behavior when faced with ambiguous signals. The extent to which this advantage crystallizes was shown to depend on the context(s) in which interaction takes places. More precisely, on the objective distributions over states that govern these contexts. A central assumption that this analysis built on was that conventionalized form-meaning associations enabled for the exploitation of ambiguity in the first place. That is, we assumed that interlocutors based their signaling behavior on lexica in which preferred messages are semantically associated with two or more states. The present chapter seeks to fill the gap covered by this assumption by elucidating whether and when conventional semantic meaning that enables for functional ambiguity exploitation evolves. We do so by considering not only horizontal but also vertical change, using the model from Chapter 4.

Our results suggest that semantic ambiguity can indeed evolve if there is functional pressure for efficient information transfer and pressure for learnability. However, this only happens if the world is such that communication and learning take place in a mixture of contexts, each governed by a different state distribution. In particular, for ambiguous semantics to survive their faithful transmission across generations, communication needs to take place in informative contexts in which different states are frequent. This is necessary for naïve learners to receive sufficient evidence that a signal is semantically associated with multiple states. Should communication instead take place in a homogeneous world in which only a single state is frequent, or in one in which no state is frequent relative to others, then unambiguous semantics conventionalize.
5.1 The Evolution of Ambiguity: A Puzzle to be Explained?

As mentioned in Chapter 3, much work on the emergence and stability of linguistic conventions has focused on conditions under which unambiguous signaling emerges (e.g., Lewis 1969, Steels 1998, Skyrms 2010; see Spike et al. 2016 for a recent review). By contrast, investigations of pragmatic inference in terms of rational language use standardly take as their starting point some kind of semantic underspecification (e.g., Franke and Jäger 2016a, Goodman and Frank 2016); or they consider other factors that introduce uncertainty over meaning. For instance, a noisy channel (Bergen and Goodman 2015). After all, a shared one-to-one form-meaning mapping in an environment that allows for noiseless communication leaves little to no room for pragmatic refinement.

How can these two strains of research be consolidated? One the one hand, language use can come to exploit ambiguity through pragmatic reasoning. On the other hand, work on language emergence tells us that the association of multiple states with a single message is “bad news” (Skyrms 2010:68); at least when communicative success hinges on distinguishing these states, and players have at least as many messages available as there are states.

On a general level, this apparent contrast is easy to dispel. Work on the emergence and transmission of language usually explains evolved meaning as a regularity in the overt behavior of agents, abstracting from complex interactions between semantic conventions and pragmatic use. That is, a distinction between semantics and pragmatics is seldom, if ever, drawn. This means that this line of research should not be viewed as explaining regularities in underlying relationships of form and semantic meaning, but rather as explaining regularities in the overt linguistic behavior of members of a population (Lewis 1969); call them signaling strategies or pragmatic language use. Once an interaction between semantic meaning and factors that influence how it is deployed in context are factored in, the bad news about ambiguity need to be qualified: an outcome is suboptimal only if language use, operating over semantic meaning, gives rise to uncertainty over states. Under this view, the apparent tension between these two strains of research disappears.¹

In short, ambiguous signaling behavior, but not necessarily ambiguity at the semantic level, is functionally disadvantageous and puzzling from an evolutionary perspective. In Chapter 3 we surveyed many functional advantages ambiguity can confer, such as smaller vocabularies; greater signal compression; reuse of preferred

¹Of course, if no information beyond conventional semantic meaning is at play then semantics is directly reflected by overt signaling behavior. One may argue this to be true of particular natural language phenomena, or of certain cases of non-human signaling. However, it should be relatively uncontroversial to argue for a distinction between semantics and pragmatics where contextual information or mutual reasoning are involved, as in context-driven disambiguation (Chapter 3) or in certain pragmatic inferences (Chapter 4).
forms that are easier to produce or parse; or coordination on novel meaning, for example, in the form of metaphors. What we then want to understand is under which conditions ambiguous semantic conventions evolve and stabilize provided that actual signaling behavior can sometimes turn ambiguity to its advantage.

In light of the synchronic functional advantages of ambiguity, the main challenge we face concerns vertical change. This challenge can be framed as follows. Linguistic knowledge needs to survive its faithful transmission across generations, being iteratively passed on to naïve learners. These learners need to infer unobservables, such as semantic meaning, from the overt linguistic behavior of their teachers. If patterns of language use are not to be functionally disfavored, they have to exhibit (a tendency toward) unambiguous signaling in a given context. This gives rise to the following tension: it is functionally advantageous to signal unambiguously but this can disadvantage the acquisition of ambiguous semantics since the overt behavior that learners witness may not suggest underlying ambiguity.

This chapter’s goal is twofold. First, we want to complement our analysis of signaling with ambiguous messages from Chapter 3 by elucidating under which conditions lexica that allow for functional ambiguity exploitation evolve. Second, we want to explore the predictions of our model from Chapter 4 by applying it on a different question; looking at a different type space, as well as a different inductive bias; and to analyze the influence that communication and learning in different contexts have on language evolution at the semantics-pragmatics interface.

Section 5.2 summarizes the model from Chapter 4 and introduces the setup we focus on. Section 5.3 shows our main results. We discuss them in Section 5.4 and conclude in Section 5.5.

### 5.2 Model Summary and Setup

As before, we model the interaction between functional pressure and learnability using the replicator-mutator dynamic (Hofbauer 1985, Nowak et al. 2000; 2001, Hofbauer and Sigmund 2003, Nowak 2006). The discrete RMD, defined in (4.1) and repeated below, describes change in an infinite population $\vec{x}$ as a function of (i) the frequency $x_i$ of each type $i$ before the update, (ii) the fitness $f_i$ of each type $i$, and (iii) the probability $Q_{ji}$ that a learner witnessing overt behavior of type $j$ will end up with type $i$ (see Section 4.2 for details and discussion).

$$x_i' = \sum_j Q_{ji} \frac{x_j f_j}{\sum_h x_h f_h}.$$  
(5.1)

The fitness of type $i$ is defined as its expected utility in the population. Intuitively, fitness indicates how well a type communicates with members of her community. The transmission matrix $Q$ codifies transition probabilities. These give the fidelity
with which a type is passed on to the next generation of signalers. $Q_{ji}$ is the probability of type $i$ being acquired when learning from type $j$.

Learning is here defined as a process of (iterated) Bayesian learning in which a learner infers a type from the observable behavior of her parent/teacher (Griffiths and Kalish 2005; 2007). The value of $Q_{ji}$ depends on two factors. First, it depends on the probability $P(d \mid \tau_j)$ of witnessing datum $d$ when learning from type $j$. This is the likelihood that a teacher of type $j$ produces particular messages when in particular state. Second, $Q_{ji}$ also depends on the probability $F(\tau_i \mid d)$ that the learner infers witnessed datum $d$ to have been generated by type $i$: $F(\tau_i \mid d) \propto P(\tau_i \mid d)^\gamma$ where $P(\tau_i \mid d) \propto P(\tau_i)P(d \mid \tau_i)$. The learning prior, $P(\tau_i) \in \Delta(T)$, codifies inductive biases that the learner may bring to the task. The combination of the prior with the likelihood of type $i$ producing $d$ yields the learner’s posterior. The posterior, in turn, is regulated by parameter $\gamma \geq 1$ which controls whether learners sample from it, $F(\tau_i \mid d)^1 = P(\tau_i \mid d)$, or whether they instead have a tendency to maximize the posterior. This tendency grows as $\gamma$ increases.

On the one hand, a fitness differential between types leads to the selection of fitter types. In linguistic terms, this amounts to a pressure for successful and efficient communication. On the other hand, if $Q_{ji} \neq 1$ for $j = i$, then the transmission of linguistic knowledge from one generation to the next is perturbed. This can have striking effects on an evolving linguistic system. In particular, if the faithfulness to which a type is passed on depends on its learnability, as assumed here, then types are also pressured for being inferable from overt and possibly sparse linguistic input.

The fitness of a type depends on the company it keeps and the context(s) of interaction in which communication takes place. A type may be well equipped to communicate with some types but may fail to do so when interacting with others. Moreover, it may be better equipped to communicate some states than others. If the distribution over states that governs a context (dis)favors certain states, then this may also affect a type’s fitness. In Chapter 4 we tacitly considered a single and uniform objective distribution over states. In this chapter, we analyze how variation in a distribution over state distributions, i.e., variation in the frequency in which agents find themselves in different contexts, can affect the evolution of ambiguous semantics. We first introduce this idea and its consequences in general terms. The type space we inspect by simulation is introduced afterward.

### 5.2.1 Contexts and objective state distributions

Our analysis of ambiguity in Chapter 3 showed that the functional (dis)advantage semantic ambiguity confers depends on the context of interaction and the distribution over states $P^*$ that governs it. In the extreme, if there are two states $s_1$ and $s_2$ but $P^*(s_1) = 1$ then it is irrelevant whether an ambiguous but preferred message could be used to signal state $s_2$. Senders would never find themselves
5.2. Model Summary and Setup

in this state. Drawing from Chapter 3, we want to inspect how the contexts in which communication takes place influence the kind of semantic conventions a population adopts.

There are two straightforward ways in which the influence of state frequencies could be inspected in detail. The first is to consider a single distribution $P^*$ that changes over time. The second is to consider a distribution over state distributions, $C \in \Delta(P^*)$, which regulates the frequency in which agents find themselves in a context governed by a particular $P^*$. The second alternative is what we assume in the following. It has the advantage of not having to define a rate of contextual change and additionally allows us to easily inspect how the frequency in which communication happens in certain contexts affects the evolution of ambiguity.

In terms of fitness, we simply need to add $C$ to the computation of expected utility (cf. definitions (4.9) and (4.10) for unique $P^*$).

For discrete $C$ and $S$, the expected utility of type $i$ communicating with type $j$ as a speaker, $EU_{\sigma}(\tau_i, \tau_j)$, and as a hearer, $EU_{\rho}(\tau_i, \tau_j)$, are defined as follows:

$$EU_{\sigma}(\tau_i, \tau_j) = \sum_{P^*} C(P^*) \sum_s P^*(s) \sum_m \sigma_{n_i}(m \mid s; \mathcal{P}; L_i)$$

$$\sum_{s'} \rho_{n_j}(s' \mid m; pr^j; L_j) \left( \delta(s, s') - c_\sigma(m) \right); \quad (5.2)$$

$$EU_{\rho}(\tau_i, \tau_j) = \sum_{P^*} C(P^*) \sum_s P^*(s) \sum_m \sigma_{n_j}(m \mid s; \mathcal{P}; L_j)$$

$$\sum_{s'} \rho_{n_i}(s' \mid m; pr^i; L_i) \delta(s, s'), \quad (5.3)$$

where, as before, $n_i$ and $n_j$ are type $i$’s and type $j$’s pragmatic reasoning types, $L_i$ and $L_j$ are their lexica, $pr^i$ and $pr^j$ are their subjective priors over states, and $\mathcal{P}$ is the sender’s belief about the receiver’s prior over states (see below for a review on how signaling behavior is defined). As before, fitness is defined as:

$$f_i = \sum_j x_j EU(\tau_i, \tau_j), \quad (5.4)$$

where

$$EU(\tau_i, \tau_j) = \frac{1}{2} EU_{\sigma}(\tau_i, \tau_j) + \frac{1}{2} EU_{\rho}(\tau_i, \tau_j). \quad (5.5)$$

In terms of learning, we will assume that learners are aware of the context in which the linguistic input they receive is produced. To this end, we need to

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2Differently from Chapter 4 but following the motivations for ambiguous signaling given in Chapter 3, messages are assumed to carry some cost for senders in this chapter.
distinguish between a context of interaction and the distribution over states that governs this context. The former is what learners witness, together with the state and message produced in this context. More precisely, where before the learners’ input was $k$-length sequences of $(s, m)$-pairs, now learners observe sequences of indexed $(s, m)_c$-pairs with $c \in C$ being the context in which $m$ was observed to signal $s$. In short, language use is situated in context and learners are aware of this.

The true distribution in context $c$ is $P^*_c$, but $P^*_c$ itself is not accessible to learners. They are only able to distinguish one context from another. The distribution over state distributions $C$ nevertheless has an impact on learning as it affects the data teachers produce. For $k$-length datum $d = \langle \langle s_1, m_1 \rangle_1, \ldots, \langle s_k, m_k \rangle_k \rangle$ we now have that:

$$P(d \mid \tau_j) = \prod_{i=1}^{k} C(P^*_i) \ P^*_i(s_i) \ \sigma_{n_j}(m_i \mid s_i; \mathcal{P}^*; L_j),$$

(5.6)

where, as before, $n_j$ is $j$’s pragmatic reasoning type and $L_j$ is $j$’s lexicon.

To illustrate the effect that the existence of multiple contexts of language use has on learning, consider a situation with two states, $s_1$ and $s_2$, three contexts, $u$, $v$, and $w$, and their respective distributions $P^*_u(s_1) = .9$, $P^*_v(s_1) = 1$ and $P^*_w(s_2) = 1$. Let there be only two types, $i$ and $j$. Both always use message $m$ to signal $s_1$. However, one uses $m'$ and the other uses $m''$ to signal $s_2$, $m' \neq m''$.

If $C(P^*_u) = 1$ then the data they produce will be indistinguishable. Message $m$ is not informative about whether $i$ or $j$ generated the learning input and all that learners witness in this case are sequences of observations of the form $\langle s_1, m \rangle_v$.

Less extremely, if $C(P^*_v) = 1$, then some data sequences may contain messages uttered in $s_2$. These messages can tease $i$ and $j$ apart. The linguistic input that learners receive will be even more informative if $C(P^*_w) > .1$.

The same issue arises for types that use an ambiguous message to signal different states in different contexts. If $C$ is degenerate, their overt linguistic behavior will be indistinguishable from that of a type that uses an unambiguous lexicon. Intuitively, if bat is used to refer to baseball bats in a sports context but to refer to animals in a zoo, there will be little evidence for the ambiguity of bat if communication happens almost exclusively in one of the two contexts.

In sum, the existence of multiple contexts that differ in state frequency not only affects whether or to which degree players find themselves in a context that may be (dis)favorable to their type, communication-wise. It also affects the data that learners witness. Both of these factors are central to the issue at hand given that (i) a functional advantage for semantic ambiguity depends on the distribution over states and consequently it also depends on the frequency in which agents find themselves in a context (Chapter 3), and that (ii) for semantic ambiguity to be faithfully transmitted, overt language use in context needs to suggest that a message is conventionally associated with multiple states.
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5.2.2 Type space

As before, a type is a combination of a lexicon and a disposition to use it to communicate in context. In the following, the latter will correspond to the level-1 behavior of (boundedly) rational language users as they were defined in Chapter 3. We repeat the relevant definitions for player \( i \) below.

\[
\rho^0(s \mid m; pr^i; L) \propto L_{[s,m]} pr^i(s); \tag{5.7}
\]

\[
\sigma^0(m \mid s; L) \propto L_{[s,m]} - c_\sigma(m); \tag{5.8}
\]

\[
\rho^1(s \mid m; pr^i; L) \propto \exp(\lambda \sum_{s'} \sigma^0(m \mid s'; L)pr^i(s')); \tag{5.9}
\]

\[
\sigma^1(m \mid s; P; L) \propto \exp(\lambda(\int P(\theta)\rho^0(s \mid m; \theta; L)d\theta) - c_\sigma(m))). \tag{5.10}
\]

Recall that the level-1 receiver defined in (5.9) results from reasoning about level-0 sender behavior in (5.8). Receiver \( i \)'s tendency to maximize utility from her own perspective grows as \( \lambda \) increases and \( pr^i \) is her subjective prior over states. Such a receiver takes senders to signal following the semantic conventions she holds true, codified in her lexicon \( L_i \), and combines this behavioral expectation with her contextual expectations, codified in \( pr^i \in \Delta(S) \).

The level-1 sender in (5.10) is our generalization of rational sender behavior. This sender reasons about literal level-0 receiver behavior, as defined in (5.7). This reasoning process involves the sender’s beliefs about her addressee’s prior over states \( \mathcal{P} \), with priors parametrized in \( \theta \). Intuitively, if in the context of interaction a rational sender believes her addressee to expect state \( s_1 \) rather than state \( s_2 \), then she may attempt to exploit this expectation by sending a preferred ambiguous message in \( s_1 \), but not in \( s_2 \). As with receiver behavior, \( \lambda \) regulates the strength of the sender’s tendency to maximize utility from her subjective perspective.

In Chapter 3 we saw that, over time, simple adaptive dynamics can lead interlocutors’ priors over states to converge to the true distribution \( P^* \) that governs a context. In the following, we relax the assumption of a non-common prior to allow for a more succinct analysis, abstracting away from proximate causes that lead interlocutors that share a set of semantic conventions to coordinate on ambiguous signals in informative contexts. We assume all types’ priors to correspond to \( P^* \).

Following our setup in Chapter 3, sender \( i \)'s beliefs about her interlocutor’s prior, \( \mathcal{P} \), are Dirichlet distributed with weights for state \( s \) set to \( q \times pr^i(s) + 1 \). As \( q \) increases, so does the sender’s belief that the receiver’s prior is close to her own. In this setup, this is equivalent to the belief that the receiver’s prior is close to true \( P^* \). On the lower end, \( q = 0 \) corresponds to full uncertainty about the receiver’s prior.

For the simulations in Section 5.3 we assume \( \lambda \) and \( q \) to be common as well. The reason for these simplifying assumptions is that we want to trace change
in types’ lexica and the effects the context of interaction has on the evolution of ambiguous semantics, rather than to consider a situation where competition hinges on variation in priors over states, \( q \)-values, \( \lambda \)-values, or reasoning levels. Accordingly, and in contrast to Chapter 4, we assume all types to be level-1 reasoners. Type \( i \) is therefore fully determined by her lexicon \( L_i \).

Turning to the space of lexica that we consider, recall that in Chapter 3 we had a lexicon that specified the truth-conditions of three messages for two states, with \( c_\sigma(m_1) = .4 = c_\sigma(m_2) \) and \( c_\sigma(m_3) = .1 \) as message cost. Following this setup, we consider a space of lexica that is made up of all possible state-message mappings for this 2-states/3-messages game that lexicalize no contradictory message.

We will think of messages as being of the form \( \text{This is an } x \), with a different \( x \) in each state (see below for details on how this changes how the learners’ inductive bias is conceptualized and further motivation). This yields three possible message meanings: either \( s_1 \lor s_2 \), if the message is true in both states; \( s_1 \land \neg s_2 \), if true in \( s_1 \) but false in \( s_2 \); or \( \neg s_1 \land s_2 \), if false in \( s_1 \) but true in \( s_2 \). With three messages there are \( 3^3 = 27 \) lexica, and accordingly 27 types in our type space.

The restriction to non-contradictory messages does not imply that every message is necessarily employed. To see this, consider the following two lexica:

\[
L_t = \begin{bmatrix}
  s_1 & m_1 & m_2 & m_3 \\
  s_2 & 1 & 0 & 1 \\
 & 0 & 1 & 1
\end{bmatrix}
\]

\[
L_{a2} = \begin{bmatrix}
  s_1 & m_1 & m_2 & m_3 \\
  s_2 & 1 & 1 & 1 \\
 & 0 & 1 & 1
\end{bmatrix}
\]

Lexicon \( L_t \) is one of our target lexica. It associates preferred message \( m_3 \) with both \( s_1 \) and \( s_2 \) but also lexicalizes unambiguous messages to signal these states. Lexicon \( L_{a2} \) exemplifies a lexicon with two ambiguous messages: \( m_3 \) and \( m_2 \). Assume that senders strongly believe their interlocutors to expect \( s_2 \). For instance, that it is believed with certainty that \( pr(s_2) = .9 \). In this case, rational users of both lexica alike would use preferred \( m_3 \) when in state \( s_2 \), and unequivocal \( m_1 \) when in state \( s_1 \). Message \( m_2 \) is not used in \( s_2 \) because it is more costly than \( m_3 \). Crucially, the fact that \( m_2 \) is ambiguous in \( L_{a2} \) but unambiguous in \( L_t \) does not need to lead to a difference in their overt signaling behaviors. Whether there is an observable contrast between certain types will depend on the frequency in which they find themselves in contexts that lead them to behave in different ways. That is, it will depend on the distribution over state distributions \( C \).

Our analysis will focus on two kinds of types. The first use lexica with ambiguous \( m_3 \) and unambiguous \( m_1 \) and \( m_2 \), as exemplified by \( L_t \) above. We call these target types because their lexica correspond to the ones we analyzed in Chapter 3: they enable for the use of preferred \( m_3 \) in both states, but also lexicalize unambiguous alternatives that are employed when uncertain about their interlocutors’ contextual expectations. The second kind are unambiguous competitor types that do not lexicalize ambiguous messages. Lexicon \( L_u \), below, illustrates
such a lexicon. There are two target types and six competitor types in total.

\[
L_u = \begin{bmatrix}
m_1 & m_2 & m_3 \\
1 & 0 & 1 \\
0 & 1 & 0 \\
\end{bmatrix} \quad L_{a3} = \begin{bmatrix}
m_1 & m_2 & m_3 \\
1 & 1 & 1 \\
1 & 1 & 1 \\
\end{bmatrix}
\]

Relative to the entire type space, target types are rather conservative when it comes to how much lexical ambiguity they harbor. They are more ambiguous than competitor types. However, other lexica, such as \(L_{a2}\) and \(L_{a3}\), lexicalize more ambiguous messages.

The functional competition between targets and competitors is relatively straightforward. Target types can exhibit more flexible signaling behavior by using preferred \(m_3\) in both states. However, in uninformative contexts they might opt for more costly \(m_1\) and \(m_2\). By contrast, competitor types have a safe unambiguous signaling strategy from the get-to, but are disadvantaged against targets if \(\mathcal{C}\) favors a mixture of distributions over states with both frequent \(s_1\) and \(s_2\). As in Chapter 4, target types and other users of ambiguous lexica will tend to exhibit more stochastic behavior than competitors. Particularly if \(\lambda\) is low.

### 5.2.3 Inductive learning bias

In Chapter 4 learners had to infer the semantic meaning of quantifiers such as *all* or *some*. These meanings were expressed by formulae to explore the effects that an inductive bias that favors simple semantic representations over more complex ones has. In the following we conceptualize the relevant meanings to be inferred from messages as object extensions. The reason for this shift, beyond the fact that lexical ambiguity is a natural and intuitive form of ambiguity, is that it allows us to explore the consequences of a learning constraint often associated with the difficulty of learning ambiguous lexical labels: the mutual exclusivity bias (Markman and Wachtel 1988, Merriman et al. 1989, Clark 2009). In other words, we want to see whether ambiguous semantics of the target type can evolve if they are a priori dispreferred by learners over those that competitor types lexicalize, and do so motivated by a well studied acquisition bias.

Mutual exclusivity refers to a learning constraint that plays an important role in the acquisition of novel linguistic labels. Markman and Wachtel (1988) famously registered it in a series of experiments. For instance, in their first experiment they instructed 3-year-olds to “Show me the \(l\)” where \(l\) was a novel linguistic label. Children had to pick between two objects: one with a name they already knew and one that they did not know the name of. For example, children had to decide whether \(l\) referred to a banana (known name) or a lemon wedge press (unknown name). Overall, Markman and Wachtel found that children show a strong tendency to infer that the novel label applies to the object they do not
know the name of. This tendency has been taken to suggest a learning bias for linguistic labels to be mutually exclusive.

Following Markman and Wachtel’s study, mutual exclusivity has attracted much attention. To name a couple of details under active investigation, there seem to be age differences in how strong this bias is (e.g., Halberda 2003, Bion et al. 2013); it has been suggested that it extends well into adulthood (e.g., Halberda 2006); and mutual exclusivity seems to be stronger in monolingual learners than in plurilingual ones (e.g., Bialystok et al. 2010). These findings have led some to argue the bias to be shaped by a learner’s linguistic experience, being more of a malleable word learning strategy than a fixed preference (Houston-Price et al. 2010).

Merriman et al. (1989) suggest a number of functions for mutual exclusivity. For instance, it may aid learners’ word learning process by serving as a heuristic to map labels to objects. On this front its effect is akin to the pragmatic strengthening that results from mutual reasoning about rational language use: if the speaker wanted to refer to the object with the known name she would have used the known label, since she did not, the name must apply to the unlabeled object. Mutual exclusivity may also aid in reorganizing and correcting the semantic conventions a learner entertains. For example, the extension of a known word, say dog, may be corrected upon learning a novel label for an object assumed to fall under its extension, say wolf. Without such a bias, the hypothesis that dog also applies to wolves would remain intact.

The mutual exclusivity bias is evidently not absolute. Children and adults alike do learn and use near-synonyms, such as leaves and foliage, and words below and above the so-called basic-level, e.g., not only dog but also dalmatian and animal. More generally, they come to master multiple ways to refer to an object, be it baseball bat, baseball club, bat, club, or thing.

We implement mutual exclusivity as a learning prior that favors lexica that do not map multiple messages to a single object. For $L \in \{0, 1\}^{\|S\| \times |M|}$ and writing $L_{[ss]}$ for the row in $L$ corresponding to $s$:

$$P(L) \propto \exp(|S| - b \sum_{s \in S} \text{count}(L_{[ss]}));$$

(5.11)

$$\text{count}(L_{[ss]}) = \left\{ \begin{array}{ll} \sum_{m \in M} L_{[s,m]} & \text{if } \sum_{m \in M} L_{[s,m]} > 0 \\ 0 & \text{otherwise.} \end{array} \right.$$  

(5.12)

Parameter $b \in [0; 1]$ regulates the strength of the mutual exclusivity bias. Since types differ from one another only in terms of their lexica, the prior probability of a type is that assigned to its lexicon: $P(\tau_i) = P(L_i)$. If $b = 0$ the prior is flat. For $b > 0$ mutual exclusivity leads to the distinction of four kinds of lexica in our type space. From most to least favored these are: (i) lexica that associate only one state with two messages, such as the competitor lexicon $L_{u*}$, (ii) those that associate two states with two messages each, such as target $L_t$, (iii) those that
associate one state with three messages and one with two, such as $L_{a2}$, and (iv) fully ambiguous lexica that associate all messages with all states, as $L_{a3}$.

Figure 5.1 shows the prior for different values of $b$. As can be read off from these plots, if the prior is not flat then six types fall within the most favored category; 14 fall within the second-most favored category; six into the third-most favored category; and fully ambiguous $L_{a3}$ is alone in the least favored category.

5.2.4 Summary

Our goal is to see whether, and if so under which conditions, ambiguous semantics evolve. Drawing from previous chapters, we focus on the effects that functional pressure and pressure for learnability have, relative to the frequency in which agents find themselves in a context. In particular, we focus on how these factors influence the evolution of ambiguous lexica of the target type, exemplified by $L_t$ above.

The frequency by which players find themselves in context $c_i$, governed by $P_i^* \in \Delta(S)$, is controlled by $\mathcal{E}$. We expect the main contenders of target types to be users of unambiguous lexica of the $L_u$-kind. First, because learners prefer the latter lexica a priori in virtue of associating less messages with the same state. Second, if $\mathcal{E}$ favors either only a (close to) degenerate context, a (close to) uniform one, or a mixture between these two, then $L_u$-style lexica can be functionally advantageous: they do not depend on pragmatics to disambiguate ambiguous
signals, nor is there a functional advantage to associating multiple states with a single message if either (i) contexts do not allow for safe ambiguity exploitation, or (ii) they always favor the same state with high probability (Chapter 3).

5.3 Simulation Results

Our setup involves six parameters: $q$ regulates the degree to which senders believe the receiver’s prior over states to be close to theirs; $\lambda$ regulates how strongly senders/receivers favor messages/interpretations that appear best from their subjective point of view; sequence length $k$ influences how much input learners receive and consequently how faithfully they can identify their teacher’s type (relative to how closely the teacher’s overt behavior resembles that of other types in the population); $\gamma$ modulates the strength of learners’ tendency to maximize the posterior; $b$ controls the strength of the mutual exclusivity bias; and $C$ is the distribution over state distributions which determines how frequently agents find themselves in a particular context.

As in Chapter 4, we begin by inspecting functional pressure and pressure for learnability in isolation in order to gain a better understanding of their effects on this type space. We focus mainly on the influence of $C$ over that of other parameters. As detailed below, $C$ regulates much of the types’ competition and transmissibility. Once its influence is factored in, the effect of the remaining parameters are consistent with the trends reported in Chapter 3 and 4.

Each population is randomly initialized. All reported simulations correspond to population states after 500 update steps. These outcomes correspond to developmental plateaus in which change is, if not absent, then at least very slow. As before, computing $Q$ for large $k$ is intractable. We therefore approximate the mutation matrix by sampling 1000 $k$-length sequences from each type’s production probabilities. For expository ease, we consider only three distributions over states. These are $P_1^*(s_1) = .9$, $P_2^*(s_1) = .1$, and $P_3^*(s_1) = .5$. In words, in context $c_1$ state $s_1$ is much more frequent than $s_2$. Context $c_2$ reversely favors state $s_2$. Context $c_3$ is uniform. To keep our notation simple, we write $C(P_i^*)$ as $C_i$.

Figure 5.2 contains the space that $C$ spans. As exemplified by the five circular nodes in this figure, we will explore our model’s predictions at the points of the 3-simplex in which $C_1 + C_2 + C_3 = 1$.

Drawing from the preceding discussion, we expect that a distribution over state distributions with either high $C_1$, or high $C_2$, or a mixture of only one of the former with $C_3$ will not lead to a prevalence of target types. In such cases, competitor types using $L_u$-style lexica will be as – if not more – functionally advantageous while being easier to learn. By contrast, and in accordance to our analysis in Chapter 3, we expect a distribution $C$ that spreads its probability across contrasting state distributions, $P_1^*$ and $P_2^*$, somewhat evenly to be the most conducive for target types, at least when it comes to fitness-relative replication.
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Figure 5.2: The standard 3-simplex. Edge values range from 0 to 1. \( C \) is degenerate at the three vertices with a node. It is uniform at the simplex’ center.

5.3.1 Functional pressure only

Players’ signaling behavior depends on \( q \) and \( \lambda \). The value of \( q \), however, only affects senders of types with lexica that allow for the exploitation of ambiguity but also lexicalize unambiguous alternatives. In particular, with sufficiently high \( \lambda \), low \( q \) leads target senders to avoid using preferred \( m_3 \) because they do not believe ambiguous signals to be safe. Instead, if fueled by large enough \( q \) they will use preferred but ambiguous \( m_3 \) in salient states (see Chapter 3). For the remainder, we fix \( q = 40 \) to the effect that target types have a tendency to send \( m_3 \) in \( s_1 \) if in \( c_1 \); in \( s_2 \) if in \( c_2 \); and to avoid ambiguity if in uniform \( c_3 \). This enables us to investigate under which conditions exploitable ambiguity of the target kind emerges.

The influence of \( C \) and \( \lambda \) on expected utility is straightforward. In a world in which \( C_1 \) and \( C_2 \) are high but \( C_3 \) is low, target types have a functional advantage over other types when communicating with other agents of equal type. This difference in expected utility becomes more pronounced the higher \( \lambda \) is. For instance, for \( \lambda = 1 \) and \( C_1 = .45 = C_2 \), \( EU(\tau_i, \tau_i) \) for all types ranges from approximately .5 to .55. The two target types and the six competitor types all come close to the latter value. For the same \( C \) but \( \lambda = 20 \) the expected utility of type \( i \) communicating with others of its type ranges from approximately .76 to .92. Under these circumstances, the two target types alone have the highest expected utility when communicating with their own type, trailed by competitor types. If \( C \) favors either only context \( c_1 \) or context \( c_2 \) then target types do as well as competitors for \( \lambda > 10 \) but worse for lower values. For example, if \( C_1 = .9 \) and \( C_2 = C_3 \). Finally, in a world in which \( c_3 \), governed by a uniform distribution over states, is more frequent than either \( c_1 \) or \( c_2 \), target types lose their functional
advantage. Part of the reason for this is that if players find themselves more often in uniform $c_3$ than in $c_1$ or $c_2$ then using $m_3$ to signal exclusively either one of the states is better than to avoid its use altogether. Moreover, as mentioned above, the use of $L_t$-style lexica carries a risk of misunderstanding that types with unambiguous $m_3$ do not suffer from. If $C$ favors contexts where only $s_1$ or only $s_2$ is frequent, then it is more advantageous to have a lexicon that unequivocally associates $m_3$ with the frequent state.

Taking stock, there are two central things to note in terms of expected utility. First, higher $\lambda$ leads to a starker contrast between types. This is not only true of $\text{EU}(\tau_i, \tau_i)$ nor particular to this type space, but is a more general consequence of the rationality parameter $\lambda$. Low values promote stochastic behavior that blurs differences that some types would exhibit if they had a stronger tendency toward expected utility maximization. Second, as aforementioned, whether target types have a functional advantage depends on $C$. If $C_1$ and $C_2$ are both high, $L_t$-style lexica are particularly advantageous. Conversely, competitors and other types that use $m_3$ only in a single state do better than target types if $C_3$ is higher than at least either $C_1$ or $C_2$; or if a single context is much more frequent than others. This makes intuitive sense. The functional advantage that the exploitation of $m_3$ in both $s_1$ and $s_2$ can confer does not come to bear its fruits if the world is such that players only communicate either $s_1$ or $s_2$, or if the context is uninformative and ambiguity is avoided.

Inspecting only expected utility, and more so only a fragment of it, can be misleading. After all, fitness and replication depend on the population agents find themselves in. Figure 5.3 shows (i) the mean difference between the highest proportion of target types and the highest other type in 1000 independent populations, as well as (ii) the mean difference between the highest proportion of competitor types and the highest other type for $\lambda \in \{1, 5, 20\}$ across values of $C$ (see Figure 5.2). This figure shows that functional pressure alone promotes target types only in the small region in which both $C_1$ and $C_2$ are high, and $C_3$ is very low; and only if $\lambda$ is high. The converse is true of competitor types, who only thrive when $\lambda$ is low and the environment leads to frequent communication in uniform $c_3$. As for the remaining types, none of them comes close to establishing itself in the population under these parameter constellations.

Overall, these results suggest that, for most values of $C$, the functional advantage of target ambiguous lexica is not strong enough to promote either variant of this type. The outcomes in which competitor types come to dominate should also be seen critically. They result from leveraging the erratic signaling behavior effected in other types by low $\lambda$.

5.3.2 Learnability only

As may be intuited from Figure 5.1, which shows the learners’ prior, if $0 < b < 1$ then its particular value only has a slight impact on differences in the learnability
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Figure 5.3: Effects of functional pressure alone across $\mathcal{C}$ for (a) $\lambda = 1$, (b) $\lambda = 10$ and (c) $\lambda = 20$. The upper-row, $L^{df}_t$, shows the mean difference between the highest proportion of target types and the highest other type in 1000 independent populations after 500 replicator steps for (a), (b), and (c). The lower-row, $L^{df}_u$, shows the mean difference between the highest proportion of competitor types and the highest other type in these populations.

between targets and competitors. For illustratory purposes, we focus on $b = .3$ in the following. Main differences in learnability instead come from the posterior parameter $\gamma$ and the distribution over state distributions $\mathcal{C}$. As in Chapter 4 and in somewhat analogous fashion to the effects that $\lambda$ has on signaling behavior, higher $\gamma$ increases differences in the learnability of types. As for $\mathcal{C}$, the fidelity by which target types are transmitted is high relative to that of other types if at least two contexts are highly frequent. For example, if $\mathcal{C}_1 = .45 = \mathcal{C}_2$ target types are transmitted with a fidelity of approximately $.6$ for $\gamma = 1$ and $.98$ for $\gamma = 15$ ($k = 5, b = .3$). Their transmission fidelity is instead low if learners witness data predominantly in a single context. For example, if $\mathcal{C}_1 = .9$ and $\mathcal{C}_2 = \mathcal{C}_3$ then the probability of passing on target types diminishes to approximately $.1$ for $\gamma = 1$ and to almost zero if $\gamma = 15$ ($k = 5, b = .3$). This is expected given that learners that are frequently exposed to only $c_1$ or only $c_2$ have a hard time distinguishing whether their teachers’ lexica are ambiguous. If $b > 0$, this lack of evidence increases the probability that learners acquire unambiguous lexica of the competitor kind. What is more, even without a bias for mutual exclusivity, unambiguous lexica are easier to learn because competitors’ behavior is fairly deterministic compared to that of types with ambiguous lexica. Even if $q$ is high, the latter will occasionally use different messages for the same state in the same context. As before, larger learning sequences (regulated by $k$) allow learners to
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Figure 5.4: Effects of pressure for learnability alone across 'C' with \( \lambda = 20 \) for (a) \( \gamma = 1 \) and \( k = 5 \), (b) \( \gamma = 15 \) and \( k = 5 \), and (c) \( \gamma = 15 \) and \( k = 10 \) \( (b = .3) \). The upper-row, \( L_{df}^{t} \), shows the mean difference between the highest proportion of target types and the highest other type in 1000 independent populations after 500 mutator steps for (a), (b), and (c). The lower-row, \( L_{df}^{u} \), shows the mean difference between the highest proportion of competitor types and the highest other type in these populations.

Figure 5.4 shows how pressure for learnability alone plays out. As above, this figure shows (i) the mean difference between the highest proportion of target types and the highest other type in 1000 independent populations, as well as (ii) the mean difference between the highest proportion of competitor types and the highest other type in these populations across values of \( C \) for two values of \( \gamma \) and \( k \). As expected, target types do not fare well if there is no functional pressure at play. Competitor types fare better the higher \( \gamma \), \( k \), and – to a lesser degree – \( b \) are, but also fail to take over populations. As stressed in Chapter 4, pressure for learnability alone leads to the coexistence of multiple types, and consequently to highly polymorphic populations (see also Nowak 2006).

5.3.3 Functional pressure and learnability

We ascertained that neither pressure on its own leads to the prevalence of ambiguous target types. Nor does it lead to any other clear victor for that matter. While the expected utility of target types when communicating among themselves is high, functional pressure alone only leads to their selection in a small region.

recover the type of their teacher with greater accuracy. The trends just mentioned nevertheless remain.
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Figure 5.5: Effects of both pressures across $C$ for (a) $\lambda = 1$, $\gamma = 1$ and $k = 5$, (b) $\lambda = 20$, $\gamma = 15$ and $k = 5$, and (c) $\lambda = 20$, $\gamma = 15$ and $k = 10$ ($b = .3$). The upper-row, $L_{df}^{t}$, shows the mean difference between the highest proportion of target types and the highest other type in 1000 independent populations after 500 replicator-mutator steps for (a), (b), and (c). The lower-row, $L_{df}^{u}$, shows the mean difference between the highest proportion of competitor types and the highest other type in these populations.

The upper-row, $L_{df}^{t}$, shows the mean difference between the highest proportion of target types and the highest other type in 1000 independent populations after 500 replicator-mutator steps for (a), (b), and (c). The lower-row, $L_{df}^{u}$, shows the mean difference between the highest proportion of competitor types and the highest other type in these populations.

Figure 5.5 shows the joint effect of both pressures for two values of $\lambda$, $\gamma$ and $k$. As in Chapter 4 the emergence and stability of monomorphic populations is mainly influenced by $\lambda$ and $\gamma$. If rationality is low and learners sample from the posterior (Figure 5.5a), there is not sufficient functional differentiation between types nor high transmission fidelity to allow for a stable and pronounced evolutionary outcome. By contrast, Figure 5.5b already showcases how the distribution over state distributions affects the evolutionary process: the center of the simplex favors near monomorphic populations of target types; its edges, and particularly frequent $c_3$, favor populations composed of unambiguous competitor types. This outcome is more pronounced for higher $k$ because transmission fidelity increases (compare Figure 5.5b and Figure 5.5c).

These results stand to reason in light of our preceding discussion. Target types are easier to transmit in environments that allow them to showcase ambiguity exploitation of preferred $m_3$ to communicate $s_1$ in context $c_1$, in which this state is highly frequent; that of $m_3$ to communicate $s_2$ in context $c_2$ for analogous reasons; and ambiguity avoidance when in uniform $c_3$. The contribution of $c_3$ mainly lies
in allowing learners to tease target types apart from more ambiguous types, while frequent communication in $c_1$ and $c_2$ confers them with a functional advantage over unambiguous competitors (see Figure 5.3). This advantage disappears if $C_3$ is higher than $C_1$ and $C_2$.

In sum, the model predicts the emergence and stability of ambiguous target types, but not under all circumstances. Ambiguous target types evolve only if the world is such that agents find themselves in varied contexts; show a tendency to signal optimally according to their subjective perspective; and show a tendency to adopt the most likely type inferable from the overt behavior of their teachers.

5.4 General Discussion

Lexica that allow for the safe exploitation of preferred messages in informative contexts but lexicalize less ambiguous alternatives used to signal in uninformative ones can evolve and be taken up by a population. This can happen provided that the world is such that communication takes place in a mixture of these contexts. In general terms, this result reflects the fact that flexible types that can react to varied environments are typically favored over those that are narrowly specialized to few environments. Conversely, specialization wins over flexibility when there is little to no environmental variation. This is often true of biological as well as cultural evolution (Christiansen and Chater 2008:493).

These predictions add to the plausibility of our synchronic analysis of ambiguity in Chapter 3. The lexicon we assumed evolves in a mixture of the environments in which we predicted ambiguity exploitation to be functionally advantageous, and iterated communication to lead to coordination even without a common prior. Additionally, they strengthen the approach we followed in Chapter 4, where we argued that understanding phenomena at the semantics-pragmatics interface may require taking functional pressure as well as learnability into consideration. As in the case of scalar implicatures, either pressure on its own fell short from providing a justification for the pervasiveness of the property in question. However, the joint influence of both pressures suggests plausible conditions under which it emerges and stabilizes.

As for the particulars of ambiguity, learnability and in particular mutual exclusivity are important for they keep the transmission of more ambiguous lexica at bay. In this respect, learning plays a regularizing role. While more ambiguous lexica often lead to overt signaling behavior that is indistinguishable from that of target or competitor types, inferring them from the overt behavior of other agents is more difficult; even more so if there is at least a slight bias for mutual exclusivity. The contribution of functional pressure is straightforward and in line with what we have stressed throughout this and past chapters: it puts types in direct competition and promotes monomorphic populations. Under the right contextual conditions, this favors the selection of ambiguous target types and leads to their
prevalence even if disfavored in learning.

The main difference between our application of the replicator-mutator dynamic in Chapter 4 and the present chapter concerns the involvement of a distribution over state distributions. Our motivation for its inclusion was to analyze the effects that the context of interaction has on language evolution where it is known to play an important role, as is the case for disambiguation. The connection between ambiguity and frequency is well established. Zipf (1949) already suggested that frequent words show a tendency to be associated with more meanings. Additionally, frequent words are typically short, predictable, and phonotactically unmarked (see, e.g., Dautriche 2015, Dautriche et al. 2017 and references within Chapter 3). Our results square well with this connection but do not support the idea that frequent words will inevitably be ambiguous. Instead, they suggest a qualification: ambiguity survives over time only when multiple meanings associated with a preferred form are frequent and appear in contrasting contexts in which one state is markedly more expected than the other. In our setup, state $s_1$ was frequent and expected in context $c_1$, and state $s_2$ was frequent and expected in context $c_2$. Frequent communication in both contexts is what (i) endows speakers of ambiguous lexica with a functional advantage over unambiguous ones and (ii) allows learners to infer that a message is semantically associated with two states from overt language use. The conclusion that message frequency unconditionally breeds ambiguity does not follow because the functional advantage of semantic ambiguity hinges on receivers being able to correctly infer different states across contexts. Either there are multiple contexts in which this is possible, or there is a single one in which a preferred message may lexicalize to signal the frequent meaning exclusively (see Figure 5.5 and Chapter 3). As shown in Figure 5.4, if a single context with a frequent state is more frequent, then an unambiguous lexicon is also easier to learn. According to our analysis, the relationship between frequency and ambiguity is consequently as follows: a preference for certain forms in language use leads to semantic ambiguity inasmuch as ambiguity is safe to be exploited in use and inferable by learners from their observable behavior. This leads frequent meanings to show a tendency to be associated with a single form if they appear in contrasting contexts, where these meanings tend to be recoverable.

The idea that the true distribution over states can have an impact on an evolving linguistic system has also been explored by Perfors and Navarro (2014), although only within the iterated learning tradition. That is, without a communicative task involving language use (see §4.3 for discussion). Perfors and Navarro’s premise is nevertheless similar to ours: learning can be affected not only by the production and inference algorithms of teachers and learners, but also by the environment in which language is used. Differently from here, they not only assume that $P^*$ affects the frequency in which data is produced but also that the observation of states (without accompanying linguistic material) is informative for the learner. In their own words, “it might be that language carries with it certain assumptions about what events are possible or probable in the
world” therefore “simply observing meaningful events $x$ may bias the learner to prefer some languages over others” (Perfors and Navarro 2014:779). In general terms, I agree with their assessment that the types in a population can be informative about the environment in which linguistic behavior takes place. After all, utility and fitness are functions of $P^*$ and the population. In turn, they shape what types emerge, spread, and stabilize. In this sense, well-adapted types may show traces of the environment in which they emerged. However, the stronger hypothesis that the environment is informative for learners raises two intertwined issues.

First, focusing on learning only, it is an empirical question whether this information is used, or even extractable, by naïve learners who have yet to acquire a type. To the best of my knowledge, this claim has not been sufficiently addressed in the literature to decide one way or another. The good news is that the precision in which Perfors and Navarro’s (2014) and our model are formulated allow for the investigation of this issue in a straightforward matter; by asking about the extent to which learners are aware of $P^*$ prior to or during type acquisition; and, if they are aware at all, whether and how this affects learning.

Second, and more generally, it is doubtful that much can be learned from the environment alone for it to be informative about the types that interact in it. The reason is simply that it is hard, if not impossible, to read off which factor contributes to an evolutionary outcome and to what degree, by observing only the outcome itself. We have already seen that linguistic outcomes can result from non-trivial interactions between pressures that apply on cultural evolution under idealized conditions. Add more realistic complexity to these factors, as well as biological and social influence, and it seems difficult to maintain this hypothesis. As with the first issue, we do not have strong evidence to decide either way, but past and present research suggest caution on this front. We return to this issue in Chapter 6 for a broader assessment of linguistic outcomes, the processes likely to give rise to them, and what models can tell us about these matters.

Another analysis close in spirit is that of Santana (2014) who analyzed the evolution of ambiguity using the replicator(-mutator) dynamic as well. Differently from here, Santana stipulated a fixed mutation rate and assumed contextual information to always be informative about the state in play. That is, based on the contextual information at their disposition, receivers knew with certainty that some states did not obtain at a given interaction. We instead used (iterated) Bayesian learning to model transmission fidelity, assumed a common prior but no information about the particular state in play, and had varied objective state distributions that enabled for ambiguous signals to be exploited in multiple ways. This enabled us to tackle the challenge that the pervasiveness of ambiguity poses in light of the known problems it raises for language acquisition.

Our setup gives room for further analysis and refinement as we focused only on three concrete state distributions rather than on a larger space of distributions. Or, arguably even more naturally, on an infinite one. This choice was mainly
driven by pragmatic considerations about simple setups. On the one hand, it is relatively straightforward to analyze the predictions of, for instance, Dirichlet distributed $\mathcal{C}$. On the other hand, the qualitative results reported above are not expected to be affected by this. However, it would certainly make the analysis and our exposition more complex. We have already discussed the choice to fix $q$ and that of a common prior over states above, as well as that of common parameters such as $\lambda$, $\gamma$ and $k$, together with possible refinements, in Section 4.5. At this point, I should reiterate that these choices are particular to the questions addressed. Different questions or additional empirical evidence might call for a relaxation or refinement of these assumptions (cf. Chapter 3).

### 5.5 Conclusion

This chapter addressed the question under which conditions (un)ambiguous lexical meanings (fail to) lexicalize. In particular, we focused on how variation in the context in which communication and learning take place can affect such evolutionary outcomes. Semantic ambiguity is predicted to evolve when the world is varied, enabling for the relatively safe pragmatic exploitation of preferred messages in contrasting informative contexts. A world that instead favors a single context promotes specialization over flexibility. Preferred messages are then predicted to be semantically associated with single states unambiguously, thereby reducing unnecessary risk introduced by uncertainty in signaling. The same is true of signaling among less rational agents, where specialization in the form of unambiguous lexical conventions safeguards against mistakes.