Learning about Others: Pragmatic Social Inference through Ambiguity Resolution

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Abstract

Grice's maxim of manner postulates that ambiguity should be avoided to maximize clarity. Nonetheless, ambiguity is ubiquitous during conversations. It has been suggested that some ambiguity may be useful for efficiency reasons in cases when clarity is not affected. Here we investigated whether disambiguations of ambiguous utterances yield another, socially-relevant benefit. In particular, we asked if responses to ambiguous utterances can reveal parts of the internal model of the interpreter. More concretely, we asked if speakers (i) can use responses as a source of information to infer unknown preferences of their conversation partner, and (ii) are able to strategically chose ambiguous utterances over unambiguous utterances for learning about their conversation partner's preferences. We ran two web-based experiments using a modified version of the original reference game framework (Frank & Goodman, 2012) and modeled the recorded data by modifying the vanilla Rational Speech Act model. The data and modeling results confirm both points. Participants were able to infer Bayesian posteriors of listeners' preferences when analyzing their choice of objects in situations of referential ambiguity. Moreover, nearly 40% of the speakers were able to strategically choose ambiguous over unambiguous utterances in an epistemic, goal-directed manner, maximizing expected information gain about the listeners' preferences. Surprisingly, an equally-large number of participants seemed to minimize expected information gain by systematically choosing unambiguous utterances. Our results thus show that ambiguity resolution can reveal aspects of the knowledge, preferences, and beliefs of conversation partners, and that some of us are able to strategically use (ambiguous) utterances to gain knowledge about these aspects.

Keywords: ambiguity; pragmatics; information gain; event-predictive cognition; Rational Speech Act models; social intelligence

1 Introduction

Active inference—that is, the anticipatory, goal-directed, and epistemic invocation of behavior—is closely linked to the predictive mind perspective (Friston et al., 2015; Hohwy, 2013; Clark, 2016). The anticipatory nature of the human mind reveals itself in many domains. With respect to planning and executing manual sensorimotor interactions, it has been shown that we anticipate future events and event boundaries, revealing anticipatory active inference processes (Belardinelli, Stepper, & Butz, 2016; Belardinelli, Lohmann, Farnè, & Butz, 2018; Friston et al., 2015; Hayhoe, Shrivastava, Mruczek, & Pelz, 2003; Lohmann, Belardinelli, & Butz, 2019). In the language domain, predictive active inference processes seem to continuously unfold (Christiansen & Chater, 2016), compressing information into event-like units of thought (Gärdenfors, 2014). For example, listeners predict the semantic category of upcoming words (Federmeier & Kutas, 2002), as evidenced by neurophysiological data. Comprehension of sentences relies not only on the ability of listeners to anticipate subsequent words based on their transitional probabilities, but also takes into account the structural properties of sentences, revealing an even more abstract level of predictions (Levy, 2008). Dynamic language models show that complex, event-predictive structures guide ambiguity resolution during comprehension and likely also constrain ambiguity generation during language production (Elman & McRae, 2019).

When systematic abstractions become relevant, event-predictive processes seem to be at play, compressing sensorimotor experiences, including language, into event-predictive encodings (Butz, 2016, 2017). Various disciplines associated with cognitive science suggest that our predictive minds develop event-compressive, predictive encodings, which interact with action, including language production and comprehension, essentially determining thought itself in a highly active, epistemic, goal-directed manner (Baldwin & Kosie, 2019; Shin & DuBrow, 2019; Elsner & Adam, 2019; Storchak, Ehlis, & Fallgatter, 2019; Knott & Takac, 2019; Ünal, Ji, & Papafragou, 2019; Stawarczyk, Bezdek, & Zacks, 2019). Here, we reveal socially epistemic comprehension and utterance productions, while observing and generating social event-predictive interactions.

In two main studies, we show how speakers update predictive models of the listener's preferences and beliefs when watching social event interactions, such as when offering a few objects to choose from and observing the object choice of the conversation partner. We thus show that humans can interpret behavior of other people as driven by their motives, intentions, or personal characteristics. Conceptually, this idea goes back to the attribution theory (Jones & Davis, 1965; Kelley, 1967; Kelley & Stahelski, 1970). More recently, Shafto, Goodman, and Frank (2012) developed a Bayesian model of learning that formalizes the process of inferring others' knowledge about the world based on their actions and goals. They argue that efficient learning is possible if we assume that agents' actions are driven either by physical (non-social) or communicative goals, but are crucially not random. The authors show that giving a communicative goal of an agent allows the observer to draw a stronger inference concerning the underlying hypothesis. The model predicts that learners use knowledge of agents' goals to evaluate how knowledgeable they are, and, as a consequence, how much a learner can trust their actions to be informative about a hypothesis.

While our model also pursues Bayesian inference—that is, psychological reasoning—we do not focus on the inference of the actor's knowledge—that is, on *learning from others* (Shafto et al., 2012). Rather, we focus on *learning about others*, learning about actors' preferences when observing their disambiguating behavioral responses. We explore interpretive choices and the potential strategic, socially epistemic usage of ambiguous utterances in anticipation of actors' responses. To formalize our hypothesis, we adapt the Rational Speech Act model framework, reliably modeling the involved, probabilistic interpretation processes and socially epistemic action choice. Interestingly, the modeling work reveals good interpretive abilities but also strong individual differences when the task is to choose (ambiguous) utterances strategically for gaining social knowledge.

In the following, we first review how different disciplines approach ambiguity in natural language and communication, and provide a computational background on referential ambiguity resolution. In Section 3, we develop computational models that are able to infer the preferences of an agent that led her to a particular choice of objects, as well as a model that predicts which utterances are most useful to create the possibility of learning about the preferences of the conversation partner. Sections 4 and 5 give the results of behavioral experiments and modeling performance. Section 6 concludes that participants were indeed able to use observable behavior of others to infer their prior beliefs, and hypothesizes why the ability to intentionally create epistemic situations can be found only in part of the population.

2 Ambiguity in natural language

2.1 Theoretical approaches

If a speaker and a listener understand an ambiguous utterance differently, communication between them might fail. On rare occasions, such communication failure can even be deadly: Pinker (2015) alludes to the Charge of the Light Brigade during the Crimean War as an example of a military disaster that was caused by vague orders. He also mentions how poor wording on a warning light was responsible for the nuclear meltdown at Three Mile Island. Finally, citing Cushing (1994), Pinker describes how the deadliest plane crash in history resulted from pilots and air traffic controllers arriving at different interpretations of the phrase "at takeoff".

Given that ambiguity can hinder the efficient transfer of information between conversation partners, it is not surprising that linguists have treated the possibility for ambiguity as a bug in the communication system (Grice, 1975; Chomsky, 2002). The attitude towards ambiguity has been quite different in other disciplines, in part because the term itself can refer to multiple phenomena. For linguistic research, a word is ambiguous if it can have two separate meanings even in the absence of context, simply as a linguistic sign. In that sense, the word "bat" is ambiguous between a winged mammal and sporting implement. In organizational communication—communication that aids production—ambiguity aligns closely with underspecification: an utterance is ambiguous when it does not provide every detail about the intended meaning, leaving room for the listener to interpret it. In the case of referential ambiguity, an ambiguous utterance may apply to several possible referents in a scene. For example, a pronoun can be referentially ambiguous if there are multiple potential antecedents in the context. It is the latter type of ambiguity that we are concerned with in this paper.

If we look back at the study of ambiguity, we notice that the strategy of ambiguity avoidance is much older than the pronouncements by modern linguists. Greek and Latin rhetoricians believed that a skillfully-written text allows for a perfectly accurate and lossless transmission of meaning to the listener or reader (Ossa-Richardson, 2019); such a text avoids ambiguities.

Still, despite the teachings of classical philologists, authors continued to create ambiguous texts and readers were faced with the challenge of interpreting them. The Bible is one of the most significant of such texts. In the sixteenth century, the Catholic church responded to the Reformation by proposing that the Bible can contain multiple meanings—Ossa-Richardson (2019) equates these meanings with multiple paths that lead readers to God. In a sense, this proposal contained one of the first acknowledgments of the virtue of ambiguity, though with an important caveat: only God could introduce ambiguity, humans should not.

The search for efficient transmission of meaning has rested on an important assumption: we communicate to transfer knowledge to our conversation partner. It is the efficiency of this transfer that many recent experiments were designed to evaluate. To be more precise, communication was considered efficient if an experimental participant could follow instructions precisely. Yet, ordering actions and following instruction are probably not the most common types of communicative acts (Foppa, 1995), and information-seeking might not be the only communicative task in which we engage (Markova & Graumann, 1995)

More recent research has begun to take notice of the efficiency ambiguity affords us: by relying on context to fill in missing information, we can reuse lightweight bits of language rather than fully specifying the intended message (Levinson, 2000; Piantadosi, Tily, & Gibson, 2012; Wasow, 2015). Viewed in this way, ambiguity serves as a feature—not a bug—of an efficient communication system. This reasoning accords with years of psycholinguistic research documenting that speakers readily produce ambiguous utterances (see Ferreira, 2008, for an overview). Along related lines, Wasow (2015) reviews a large body of evidence and concludes that ambiguity is rarely avoided, even in situations where its avoidance would be communicatively appropriate. This observation stands at odds with the Gricean maxim to avoid ambiguity (Grice, 1975). However, even Grice recognized a case of strategic ambiguity where it could be the intention of the speaker to communicate more than one possible interpretation afforded by an ambiguous utterance. In such cases, recognition of the ambiguity serves as the communicative purpose of the utterance. Wasow (2015), on the other hand, reviews several cases where ambiguous production serves no obvious communicative purpose.

The field of communication sciences views ambiguity as an important communicative tool. In organizational communication, ambiguity has traditionally stood in opposition to clarity. However, as Eisenberg (1984) notes, clarity is not necessarily a communicative goal in all conversations. Speakers may prefer to remain ambiguous to leave room for the listener's perspective. This freedom is important in communication between managers and their employees, particularly when managers set goals with the intention of stimulating creativity (Mohr, 1983). In addition, ambiguity allows the somewhat general expression of ideas that are true for a group of people. For example, consider company slogans or vision statements, where the language must be vague enough to allow every member of the audience to relate to a company's avowed aims (Carmon, 2013). Accordingly, Pascale and Athos (1981) show that interlocutors often employ utterances that allow for a range of interpretations and do not enforce a particular viewpoint.

Eisenberg (1984) further specifies that ambiguity does not necessarily stand in opposition to clarity. In communication with close friends, for instance, interlocutors can use incomplete phrases or vague referential expressions and nevertheless resolve the ambiguity in accordance with the speaker's intention through the use of restricted codes—shared knowledge and beliefs. The participants may not even perceive the utterances as ambiguous in such situations. We believe that the experience of shared codes gives rise to the sense of within-group cohesion and social bonding between group members. As a result, members of the same group can be expected to sense a high level of mutual understanding when ambiguous and vague utterances are resolved in accordance with the group's prior beliefs, preferences, and knowledge. In this paper, we thus focus on the effects of resolving, or anticipating the resolution of, ambiguous utterances, modeling the involved probabilistic inference processes.

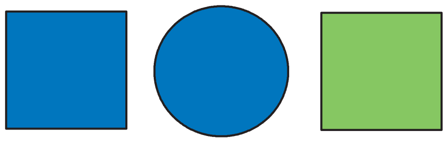

Figure 1: A simple reference game scenario from Frank and Goodman (2012). In the game, speakers are confronted with a collection of objects. The speaker chooses a single-word utterance to signal one of the objects to a listener.

2.2 Computational modeling

In search of the communicative purpose of ambiguous language, the current work identifies an additional benefit in using such language: the *extra* information we gain from observing how our listeners resolve ambiguity. We propose that language users learn about each other's private knowledge by observing how they resolve ambiguity. If language does not do the job of specifying the information necessary for full interpretation, then listeners are left to draw on their opinions, beliefs, and preferences to fill in the gaps; by observing how listeners fill those gaps in, speakers learn about the opinions, beliefs, and preferences of their listeners. In a dynamic, naturalistic conversation, speakers can take turns choosing ambiguous statements in order to leave room for their parter to fill the missing information in, thereby revealing opinions, beliefs, and preferences.

By way of illustration, take the scenario in Figure 1. Suppose a speaker produces the single-word utterance "blue" in an attempt to signal one of the objects to a listener. The utterance is referentially ambiguous; the listener can choose either the blue square or the blue circle. Suppose further that, upon hearing "blue," the listener selects the blue circle. In observing this choice, the speaker learns something about the private thoughts of the listener: what made her select the blue circle instead of the blue square? Perhaps the circle is more salient to the listener, or the listener has a preference for circles, or the listener may believe that the speaker has a preference for circles; there may even be mutual agreement that circles are to be preferred when possible. Importantly, by observing how the listener resolves the ambiguity in reference, the speaker can learn something about the private thoughts of the listener.

However, accessing this added information requires the speaker to reason pragmatically about the pragmatic reasoning of the listener—a higher-order pragmatic reasoning, as it were. In order to select a referent, the listener must interpret the utterance. We follow Frank and Goodman (2012) in treating this interpretation process as active pragmatic, probabilistic reasoning: the listener interprets an utterance by reasoning about the process that generated it, namely the speaker, who selects an utterance by reasoning about how a listener would interpret it. Frank and Goodman model this recursive social reasoning between speakers and listeners within the Rational Speech Act (RSA) modeling framework (cf. Franke & Jäger, 2016; Goodman & Frank, 2016).

The current paper builds on the foundational, vanilla RSA model of reference games by introducing uncertainty about the prior beliefs of the listener and modeling a speaker who reasons about these beliefs on the basis of and in anticipation of the observed referent choice.

3 Model

Our model is a modified version of the vanilla RSA model (Frank & Goodman, 2012). It formalizes a state space S in the form of a particular set of objects (cf. the example in Figure 1) and an utterance space U, which consists of the set of possible utterances; when conceived of as a set of single-word utterances, U amounts to the set of all features present in S. Moreover, the model specifies priors or posteriors over referenced objects, object choices, utterance preferences, and utterance choices. For notational convenience, we denote a particular object choice of the listener by $s\ in\ S$. RSA then models a recursive social reasoning processes, incorporating several levels of probabilistic inference.

3.1 Rational Speech Act model (RSA)

At the base of the reasoning process, there is a hypothetical, naïve literal listener L_0, who hears an utterance u and attempts to infer the object s that u is meant to reference. L_0 performs this inference by conditioning on the literal semantics of u, $[\![u]\!](s)$, which returns $true$ (i.e., 1) for those objects that contain the uttered feature and $false$ (i.e., 0) otherwise. As a result, object choice probabilities for the literal listener can be computed:

$$P_{L_0}(s \mid u) \propto [\![u]\!](s),$$

essentially returning a uniform distribution over those objects in S that contain the uttered feature u.[1]

One layer up, the speaker S_1 observes the state S and is assumed to have the intention to refer to a particular object $s \in S$. S_1 chooses an utterance u on the basis of its expected utility for signaling s in the situation S, which is determined by the log-likelihood of this particular object choice $U_{S_1}(u;s)$[2]:

$$U_{S_1}(u;s) = \log(P_{L_0}(s \mid u)).$$

Depending on a "greediness" factor α, the speaker chooses a particular utterance u with a probability that is exponentially proportional to the utility estimates:

$$P_{S_1}(u \mid s) \propto \exp(\alpha \cdot U_{S_1}(u;s)).$$

At the top layer of the vanilla RSA model, the *pragmatic* listener L_1 infers posteriors over s on the basis of some observed utterance u. However, unlike L_0, L_1 updates beliefs about the world by reasoning about the process that *generated* u, namely S_1. In other words, L_1 reasons about the s that would have been most likely to lead S_1 to utter u:

$$P_{L_1}(s \mid u) \propto P_{S_1}(u \mid s) \cdot P(s).$$

Frank and Goodman (2012) tested the predictions of their model against behavioral data from reference games, as in Figure 1. To model production behavior (i.e., which utterance should be chosen to communicate a given object), the authors used the probability distributions from S_1. To model interpretation behavior (i.e., which object the speaker is trying to communicate on the basis of their utterance), the authors generated

[1]Note that the context S is typically not made explicit, but rather treated implicitly in the specification of the model.

[2]The original model in Frank and Goodman (2012) also includes a term for the utterance cost, $C(u)$. We ignore the term here since we assume uniform cost over all utterances.

predictions from L_1. Finding extremely strong correlations between model predictions and behavioral data in both cases, Frank and Goodman have strong support for their model of pragmatic reasoning in reference games (see also Qing & Franke, 2015, for a fuller exploration of the modeling choices).

3.2 Full pragmatic social inference RSA

Our model builds on the vanilla version of RSA presented above, modifying the listener's state prior $P(s)$ and enhancing the reasoning process towards a social component, yielding a full pragmatic social inference RSA model (fullPSIRSA). By changing $P(s)$ to a non-uniform distribution, we essentially model prior beliefs of which object the speaker is more likely to refer to, or—when viewed from a more self-centered perspective—which prior object feature preferences f the listener may have. For example, the listener may like blue things, such that she may be more likely to choose the blue square instead of the green one when hearing the utterance "square" in the scenario shown in Figure 1. As a result, when a pragmatic speaker produces utterance u and observes the listener's referent choice s, the speaker may infer posteriors over possible feature preferences, attempting to explain the observed object choice in this way. We use L_0 and S_1 from the vanilla model, but we now parameterize L_1's state prior such that it operates given a feature preference f:

$$P_{L_1}(s \mid u, f) \propto P_{S_1}(u \mid s) \cdot P(s \mid f).$$

We then model a pragmatic speaker S_2, who updates beliefs about L_1's preferences, $P(f)$. S_2 observes L_1's choice of s given the produced utterance u and then reasons about the likely feature preference f that L_1 used to make the observed choice:

$$P_{S_2}(f \mid u, s) \propto P_{L_1}(s \mid u, f) \cdot P(f).$$

We also model the reasoning process by which a speaker may select the best utterance to learn about the preferences of the listener, essentially striving to maximize expected information gain concerning the listener's feature preferences. Starting with no knowledge of the listener's preferences, S_2 can be assumed to expect a uniform (i.e., flat) feature preference prior $P(f)$. The more the speaker's posterior beliefs about the preferences, $P_{S_2}(f \mid u, s)$, deviate from the uniform prior, the more the speaker will have learned about the listener's preferences. We can thus model this reasoning in light of expected information gain, which can be equated with the attempt to maximize the KL (Kullback-Leibler) divergence between the speaker's flat prior and the expected posterior over the listener's feature preferences f, integrating over all hypothetically possible state observations $s \in S$:

$$P_{S_2}(u) \propto \sum_{s:\ [\![u]\!](s)=1} P_{L_1}(s|u, f)\ \exp(\lambda \cdot \mathrm{KL}(P(f) \mid\mid P_{S_2}(f \mid u, s))),$$

where the factor λ scales the importance of the KL divergence term.

To test our model, we need to evaluate two main predictions of PSIRSA: first, the pragmatic speaker's inference about the listener's feature preferences on the basis of observed object choices in particular situations $P_{S_2}(f \mid u, s)$; second, the pragmatic speaker's strategic utterance selection $P_{S_2}(u)$ in light of the anticipated information gain about the listener's preferences considering the possible object choices. Before presenting the experimental and modeling results, though, we introduce a simplification of fullPSIRSA.

3.3 Simplified pragmatic social inference RSA

fullPSIRSA assumes a rather deep reasoning process. Recently, it has been shown that even in the original, simpler reference games, fewer layers of reasoning often perform equally well or better than more complex models (Sikos, Venhuizen, Drenhaus, & Crocker, 2019). fullPSIRSA essentially assumes that feature preference inference not only considers the current object choices possible, but also differentiates the choice options further with respect to their pragmatic plausibility. For example, fullPSIRSA includes modeling the fact that when a speaker utters “blue” in the object situation depicted in the example in Figure 1, she is more likely to refer to the blue square than to the blue circle, because in the latter case the utterance choice “circle” would have been unambiguous and thus a better choice for the speaker.

simplePSIRSA removes this reasoning about alternative utterances and allows the pragmatic speaker to directly tap into the (expected) interpretation of L_0, directly augmenting the literal listener’s choice likelihoods with the feature-preference-dependent object prior $P(s \mid f)$:

$$P_{L_{0\text{-simp}}}(s \mid u, f) \propto [\![u]\!](s) \cdot P(s \mid f).$$

The pragmatic speaker $S_{s\text{-simp}}$ then reasons directly about the modified literal listener $L_{0\text{-simp}}$:

$$P_{S_{1\text{-simp}}}(f \mid u, s) \propto P_{L_{0\text{-simp}}}(s \mid u, f) \cdot P(f).$$

As a result, simplePSIRSA ignores any indirect pragmatic reasoning considerations about which object the speaker may refer to given an utterance and a particular object constellation. It simply assumes that all objects may be chosen that match the utterance, modifying these choice options dependent on the feature-preference-dependent object choice priors. The corresponding utterance-selection model also simplifies the reasoning process:

$$P_{S_1\text{-simp}}(u) \propto \sum_{s:\ [\![u]\!](s)=1} P_{L_0}(s|u,f)\ \exp(\lambda \cdot \mathrm{KL}(P(f)\ ||\ P_{S_{1\text{-simp}}}(f \mid u,s))),$$

In the evaluation section below, we compare the modeling performance of fullPSIRSA with simplePSIRSA.

4 Experiment 1: Learning about others’ preferences

Our first task is to check the inferences of the pragmatic speaker having observed that a listener selects some object s in response to an utterance u. Is it possible to draw inferences about the most likely preferences the listener had when making her choice? Can this inference process be modeled by PSIRSA—that is, by recursive, Bayesian generative modeling?

4.1 Participants

We recruited 90 participants with US IP addresses through Amazon.com’s Mechanical Turk crowdsourcing service. Participants were compensated for their participation. On the basis of a post-test demographics questionnaire, we identified 82 participants as native speakers of English; their data were included in the analyses reported below.

4.2 Design and methods

We presented participants with a series of reference game scenarios modeled after Figure 1 from Frank and Goodman (2012). Each scenario featured two people and three objects. One of the people served as the speaker, and the other served as the listener. The speaker asks the listener to choose one of the objects, but in doing so she is allowed to mention only one of the features of the target object. Participants were told that the listener might have a preference for certain object features, and participants were tasked with inferring those preferences after observing the speaker's utterance and listener's object choice.

We followed Frank and Goodman (2012) in our stimuli creation. Objects were allowed to vary along three dimensions: color (blue, red, green), shape (cloud, circle, square), and pattern (solid, striped, polka-dotted). The speaker's utterance was chosen at random from the properties of the three objects present, and the listener's choice was chosen at random from the subset of the three objects that possesed the uttered feature. By varying the object properties, the targeted object, and the utterance, we generated a total of 2400 scenes. Speaker and listener names were chosen randomly in each trial. Participants saw the speaker's utterance in bold (e.g., "red" in Figure 2) and the listener's choice appeared with a dotted orange outline (e.g., the center object in Figure 2). Based on the observed choice, participants were instructed to adjust a series of six sliders to indicate how likely it is that the listener had a preference for a given feature. The sliders specified the six feature values of the two feature dimensions that were not mentioned in the speaker's utterance (e.g., pattern and shape in Figure 2).

Depending on how many features competitor objects share with the target object, we were able to identify 48 ambiguity classes. Ambiguity classes group trials where a model considers a similar number of alternatives that could qualify for the uttered feature. For example, in Figure 2, the utterance "red" picks out two possible objects. If, however, the utterance were "green", only one object would qualify, and no learning about preferencs would be possible. In that case, the model would assign equal probability to the listener's preferring dotted objects, striped objects, clouds, and squares. Once the model establishes that more than one object can be picked, it also needs to consider whether alternative objects share their features with the target object. For example, if both red objects were also striped, the model would not be able to infer any preferences about the pattern. Finally, we also code whether the objects that were not picked are similar in any of their feature values.

Participants completed a series of fifteen trials. Objects and utterances were chosen as detailed above, with the constraint that ten trials were potentially informative with respect to listener preferences and five trials were uninformative with respect to listener preferences (e.g., observing that the listener chose one of three identical objects).

4.3 Results

To compare PSIRSA's predictions to the human data, we calculated an average value for each slider, binning data into 48 ambiguity classes. We excluded the sliders if their corresponding feature value was not present in a scene. For example, for the trial depicted in Figure 2, we excluded the sliders for solid things and squares since none of these are present, and therefore no learning about them is possible.

We fit the model parameters either at the individual level or at the group level by optimizing the KL (Kullback-Leibler) divergence between the data and the model predictions:

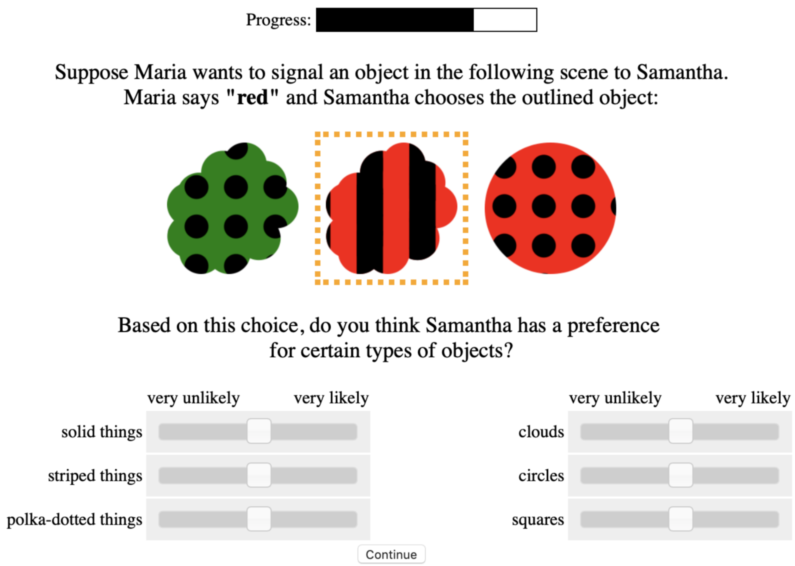

Figure 2: A sample trial from *Experiment 1: Inferring preferences*. Each trial portrays a speaker and a listener: the speaker produces an utterance to refer to one of the objects. The listener picks the object with the orange dotted outline. Participants were tasked with evaluating what preferences of the listener led her to the particular choice of object. They specify their inference by adjusting the sliders for each of the features.

$$\mathrm{KL}(P_{data}(f \mid u,s) \mid\mid (P_{model}(f \mid u,s)),$$

where $P_{data}(f \mid u,s)$ specifies a participant's normalized slider value setting, which offers empirical estimates of the feature-preference posterior given object scene S, a particular utterance choice u, and the consequent object choice s; $P_{model}(f \mid u,s)$ specifies the corresponding model posterior, either $P_{S_2}(f \mid u,s)$ in the case of fullPSIRSA or $P_{S_{1\text{-simp}}}(f \mid u,s)$ in the case of simplePSIRSA. By minimizing the KL divergence between the empirical and model-predicted preference posteriors for each participant, we maximize the model fit to the participants' data. Moreover, we can use the minimized KL divergence values to perform the likelihood ratio test for nested models relying on the G^2-statistic, because the summed KL divergence values are approximately chi-square distributed (Lewandowsky & Farrell, 2011). Individual vs. global-level parameter fitting allows us to explore potential differences between participants, and, more importantly, to evaluate whether the Gricean reasoning strategies apply at the level of individual speakers or only to the population as a whole (Franke & Degen, 2016).

4.3.1 Models with global optimization

We first present results of the globally-optimized versions of PSIRSA (Figure 3). We fit three parameters for fullPSIRSA and two for simplePSIRSA. The soft-max scaling factor α is only relevant for fullPSIRSA; it controls how likely speaker S_1 is to maximize utility when choosing utterances. The default value is typically set to $\alpha = 1$ (i.e., no scaling).

The softness parameter γ regulates the strength of individual feature preferences f:

$$P(s \mid f) \propto \begin{cases} 1+\gamma, & \text{if } s \text{ contains } f \\ \gamma, & \text{otherwise} \end{cases},$$

controlling the choice probability of those objects s that contain feature f compared to those that do not. A value of $\gamma = 0$ models a hard preference choice; in this case, the speaker always chooses one of the preferred objects. On the other hand, when $\gamma \to \infty$, the choice prior becomes uniform over all objects, thus ignoring feature preferences. For example, in the trial shown in Figure 2, there are two objects that fit the utterance $u =$ "red": a red striped cloud and a red dotted circle. When $\gamma = 1$, $P(s_{\text{red striped cloud}} \mid f_{\text{"cloud"}}) = 2/3$, while $P(s_{\text{red dotted circle}} \mid f_{\text{"cloud"}}) = 1/3$, yielding a soft preference for clouds. We assume $\gamma = 0$—that is, hard preferences—as the default model value.

Finally, we allow for the possibility of noise in our human data introduced by participants not following instructions. Parameter β models the possibility that listeners choose objects that do not pass the semantic filter of the literal listener, allowing for non-literal interpretations that result in choosing objects whose features do not match the received utterance u. The computation is equivalent to the softness parameter above, in this case softening the object choices of the literal listener L_0 towards a uniform choice over all objects present. Again, $\beta = 0$ models a hard object choice—that is, full obedience to the uttered instruction u—while $\beta \to \infty$ models a uniform object choice—that is, full ignorance of u.

As Figure 3 shows, both simplePSIRSA and fullPSIRSA with softness (γ) optimized globally provide nearly-identically good fits to the data. simplePSIRSA yields a correlation of $r^2 = 0.8614$ when only softness parameter γ is optimized ($\gamma = 0.2204$ after optimization).[3] When both parameters are optimized globally, a correlation of $r^2 = 0.9789$ is reached ($\gamma = 0.2210$ and $\beta = 0.2693$ after optimization), indicating that participants indeed considered (possibly subconsciously) the option to interpret utterances non-literally. fullPSIRSA yields nearly identical values. Optimizing only the softness parameter γ, a correlation of $r^2 = 0.8576$ is reached ($\gamma = 0.2231$). Optimizing both, α and γ, a correlation of $r^2 = 0.8614$ is reached ($\alpha = 0.1797$, $\gamma = 0.2205$). When optimizing all three parameters, fullPSIRSA yields a correlation of $r^2 = 0.9773$ ($\alpha = 0.2657$, $\gamma = 0.2214$, $\beta = 0.0030$), not quite reaching the correlation of simplePSIRSA, which may be due to some subtle interactions between parameters α and β. Overall, the results show that participants are indeed able to infer the feature preferences that lead to the choice of an object, and, notably, simplePSIRSA models this inference process very well. The higher model flexibility of fullPSIRSA—controlled via parameter α—does not yield any modeling improvement.

4.3.2 Individually-fitted models

We now compare our two model variants further when fitting the parameters to the individual data of each participant separately. We optimized α and γ in light of the KL divergence between the individual participants' slider value choices and the corresponding model predictions for PSIRSA. We then again averaged the individualized model prediction values and participants' slider values with respect to the particular ambiguity classes and calculated correlations between the data and the model.

The full model optimized at the individual level for the additional parameter α does not improve the fit compared to the simplified model (simplePSIRSA: $r^2 = 0.8631$;

[3]All correlations were highly significant, that is, $p < 0.001$, if not stated differently in the text.

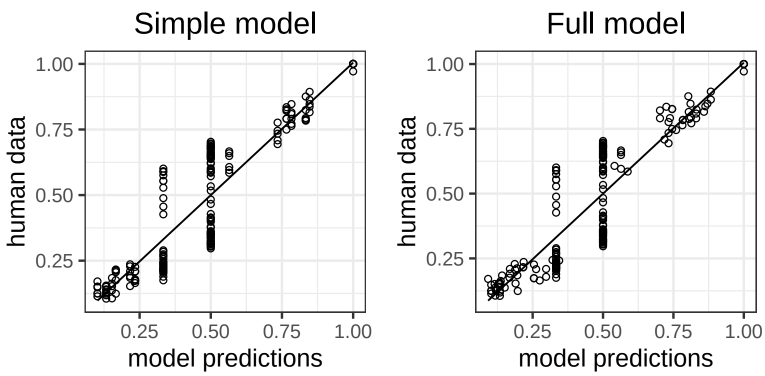

Figure 3: Human data from Experiment 1 plotted against the predictions of simpleP-SIRSA and fullPSIRSA with γ *optimized globally*. Each data point indicates the slider values and model predicted feature preference posteriors for a particular ambiguity class. Left panel: *simple model* ($r^2 = 0.8614$); right panel *full model* ($r^2 = 0.8576$).

fullPSIRSA: $r^2 = 0.8614$). Seeing that both models fit the data nearly equally well (if anything, simplePSIRSA performs slightly better), we will henceforth only consider the predictions of simplePSIRSA. Note further that the individually-fitted parameters do not improve the correlation values much, if at all, when compared to the globally-fitted model.

The model fit improves considerably if we additionally fit the obedience parameter β at the individual level. Here the strongest positive correlation between the human judgments and model predictions ($r^2 = 0.992$) can be observed. The likelihood ratio test revealed that a γ- and β-optimized simplePSIRSA model provides a better fit compared to a model optimized only for γ ($G^2 = 237.36, \mathrm{df} = 82, p < 0.01$). The more complex model contains one additional parameter β fitted for each subject, giving us 82 degrees of freedom. We additionally checked the generalizability of the model by performing leave-one-out cross-validation. Figure 4 shows that the resulting cross-validated model predictions retain the strong correlation ($r^2 = 0.9901$).

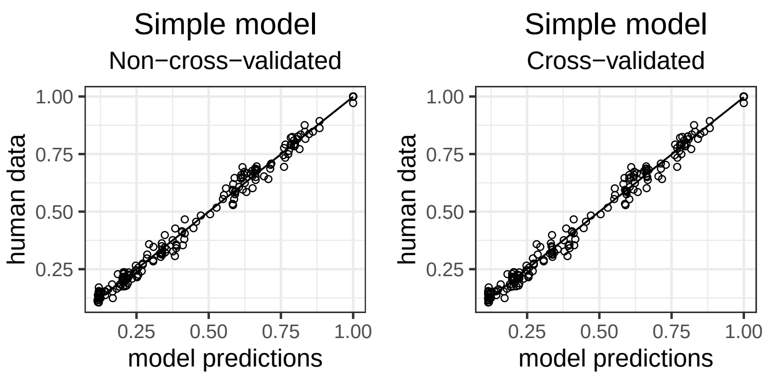

Figure 4: Human data from Experiment 1 plotted against the predictions of the *individually* β- and γ-optimized simplePSIRSA model. Left panel: *non-cross-validated* ($r^2 = 0.992$); right panel: *cross-validated* ($r^2 = 0.9901$).

To appreciate the gains obtained by fitting model parameters, Figure 5 shows the average responses of the human participants and of the individually-, two-parameter-optimized simplePSIRSA model and the non-optimized simplePSIRSA model for the scene type of the sample trial from Figure 2. In that trial, participants saw that the middle object was chosen following the utterance "red". There are two potential referents for this description: the red striped cloud and the red dotted circle. Since the cloud was chosen, we infer that the person who chose this object has a preference for clouds over circles, and for striped objects over dotted ones. Note that we cannot learn anything about the preference for solid things or squares in this trial because these features are not present, thus we ignore the respective slider values. Moreover, we can definitely not learn anything about color preferences because the color was the uttered, thus sliders for those features were not present. As Figure 5 shows, both humans and the models assign high slider values to clouds and striped things, and low values to circles and dotted things. Indeed, even the non-optimized model fits the qualitative pattern of results; optimizing β and γ improves the quantitative fit.

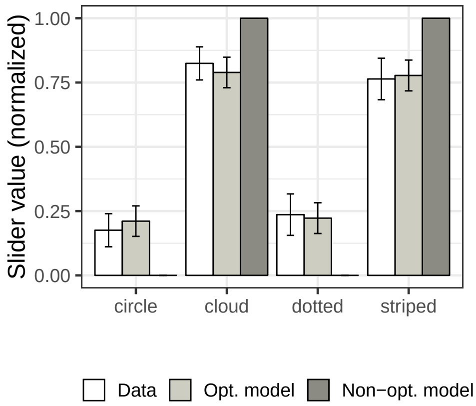

Figure 5: Human data and simplePSIRSA's (individually-, two-parameter-optimized and non-opimized) feature preference posterior estimates for the scenario S shown in Figure 2.

We thus find strong empirical support for simplePSIRSA: speakers are indeed able to use listener behavior to acquire information about their preferences. We fail to find that the fullPSIRSA model predicts the data better. This result suggests that the task in our experiments does not require full-blown pragmatic inference about alternative utterances, in contrast with Frank and Goodman (2012) but in line with Sikos et al. (2019).

The question now turns to whether speakers are able to capitalize on this reasoning when it comes to selecting utterances. In other words, are speakers aware that ambiguous language is potentially more informative?

5 Experiment 2: Choosing utterances to learn about others

Our next task is to check the predictions of our strategic utterance selection model: given a set of potential referents, are participants able to reason pragmatically about the utility of ambiguous utterances in informing listener preferences?

5.1 Participants

We recruited 90 participants with US IP addresses through Amazon.com's Mechanical Turk crowdsourcing service; participants in Experiment 1 were not eligible to participate in Experiment 2. Participants were compensated for their participation. On the basis of a post-test demographics questionnaire, we again identified 82 participants as native speakers of English; their data were included in the analyses reported below.

5.2 Design and methods

Participants encountered a reference game scenario similar to Experiment 1 in which a speaker signals an object to a listener who might have a preference for certain types of objects. However, rather than observing the utterance and referent choice, participants were now tasked with helping the speaker choose an utterance that was "most likely to reveal the listener's color, shape, or pattern preferences."

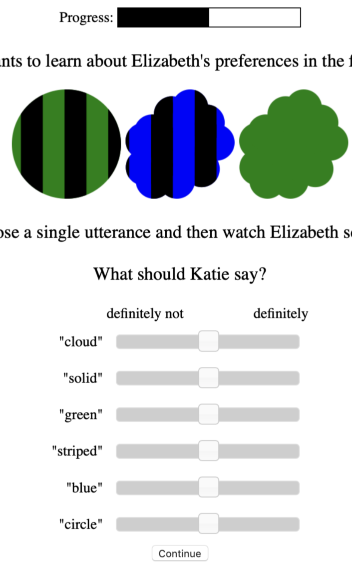

Figure 6: A sample trial from *Experiment 2: Choosing utterances*.

We used the same sets of objects from Experiment 1, which could vary along three dimensions. Each trial featured a set of three objects, as in Figure 6. After observing the objects, participants adjusted sliders to indicate which single-feature utterance the speaker should choose to learn about the preferences of their listener. Potential utterances corresponded to the features of the objects present; depending on the number of unique features, participants adjusted between three and nine sliders. As with Experiment 1, we averaged the data and the respective model predictions across specific ambiguity classes, which include all scenes that yield identical utterance choice options. In this case, 14 distinct conditions can be identified, with a total of 84 slider values to set. Membership within an ambiguity class is defined by how many objects in a scene share each of the features: shape, pattern, and color. If objects share a feature, we also consider whether these objects also share other features. For example, in Figure 6, two green objects differ in shape, making the utterance *green* informative. If, on the other hand, both green objects were clouds, uttering *green* would not allow the speaker to update their beliefs about the listener's shape preferences. In the most extreme case, when all objects share all three features, all utterances are ambiguous since multiple objects can always be picked; but no utterance allows the speaker to learn anything about the listener because the object choice is uninformative. Another extreme case is a situation where all objects are unique and do not share any features. In such a case, any utterance will only pick one object, making learning about preferences impossible unless obedience (β) is not 0—that is, unless listeners have a tendency to disobey the utterance and consider objects that do not satisfy its literal interpretation.

Participants completed a series of fifteen trials. As with Experiment 1, objects were chosen at random, with the constraint that ten trials were potentially informative with respect to the listener's preferences (as in Figure 6) and five trials were uninformative with respect to the listener's preferences (e.g., observing a set of three identical objects).

5.3 Results

By reasoning about the predictions of S_2, we are able to use simplePSIRSA to compute the expected most informative utterance with respect to inferring preferences. In other words, $P_{S_1\text{-simp}}(u)$ calculates the probability that a speaker would choose u for the purpose of inferring preferences in our reference game scenario.

To generate predictions from $P_{S_1\text{-simp}}(u)$, a total of three free parameters can be identified. We consider different values for γ (i.e., preference softness) and obedience β, as well as for the λ parameter, which factors the importance of choosing the expected most informative utterance with respect to the determined KL divergence values. Note that when allowing negative values for λ, negated information gain essentially minimizes expected information gain. Thus, negative values for λ yield a model that favors unambiguous utterances. Moreover, when $\lambda = 0$, the model collapses to a uniform distribution over the available utterances.

Figure 7 shows the model fits of the non-optimized simplePSIRSA and the simplePSIRSA model with all three parameters optimized globally. Again, we optimized values with respect to KL divergence estimates between the participant data and the model predictions—in this case, for utterance preference distributions. Both models fail to predict the human data ($r^2 = 0.0709$, $p = 0.01439$ [gcs: we need another r^2 value (I think Martin is working on this)]).

Seeing that global optimization does not yield good fits, we moved on to individual optimization. We compared three single-parameter-individually-optimized simplePSIRSA models to determine which model provides the best fit to the data. All models have similar levels of complexity, with either softness γ, obedience β, or KL-factor λ being optimized. The results indicate that we get the best fit by optimizing the KL-factor λ ($r^2 = 0.9071$; leave-one-out cross-validated optimization $r^2 = 0.8902$), with other models capturing less variance in the data (β-optimized $r^2 = 0.8039$; γ-optimized

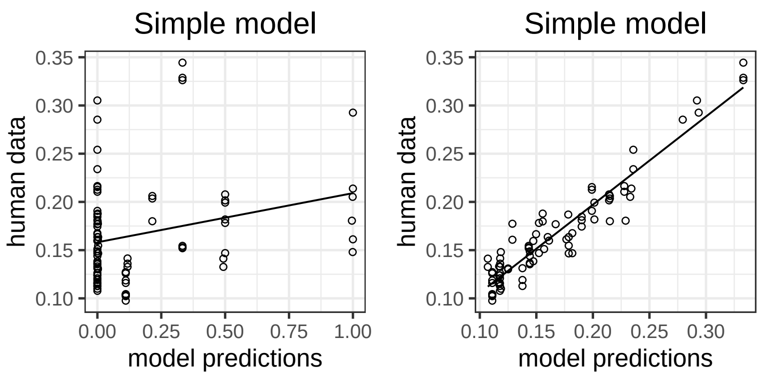

Figure 7: Average human data from Experiment 2 plotted against the predictions of the non-optimized and three-parameter-optimized simplePSIRSA models. [gcs: can we get more informative figure titles that specify non-optimized vs. optimized?] [gcs: it looks like we have the wrong figure on the right side for the globally-optimized model]

$r^2 = 0.8100$). Two- and three-parameter individual optimizations were unstable due to parameter interactions; therefore, we do not report the results for those models.

Unlike for Experiment 1 where even the non-optimized models provided a good linear fit to the data, optimization produces a large effect on the model predictions in Experiment 2. Figure 8 compares individually-optimized vs. non-optimized model predictions against the human behavior for the sample trial in Figure 6. We see that the non-optimized model strongly favors ambiguous utterances: in a situation with a striped green circle, a blue striped cloud, and a solid green cloud, uttering things like *cloud*, *striped*, or *green* (i.e., the utterances that point to more than one object in the scene) and could let the speaker learn something about the listener's preferences. However, Figure 8 shows that human behavior deviates quite strongly from the non-optimized, ambiguity-selecting baseline; once we optimize λ, we are able to capture human behavior in the task.

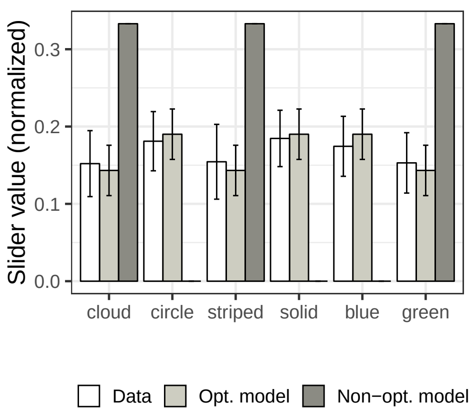

Figure 8: Simple Social Inference model predictions and human data for one of the classes of stimuli *Experiment 2: Picking utterances*. The optimized version of the model is optimized for the KL-factor λ.

In Figure 9, we compare λ-optimized simplePSIRSA (right panel) with a uniform base model (left panel), which assigns equal probability to each utterance available for a particular context. This baseline model essentially has no utterance preferences whatsoever, but reflects the fact that the ambiguity classes distinguish between cases with a different number of utterance choice options (i.e., three to nine). Since simplePSIRSA with $\lambda = 0$ collapses to the baseline model, optimizing the λ parameter in simplePSIRSA is a nested model. When statistically comparing the individually-optimized λ simplePSIRSA model with the baseline model, the likelihood ratio test confirms that individual λ optimizations yield better fits than the baseline model ($G^2 = 268.87, \mathrm{df} = 82, p < 0.01$).

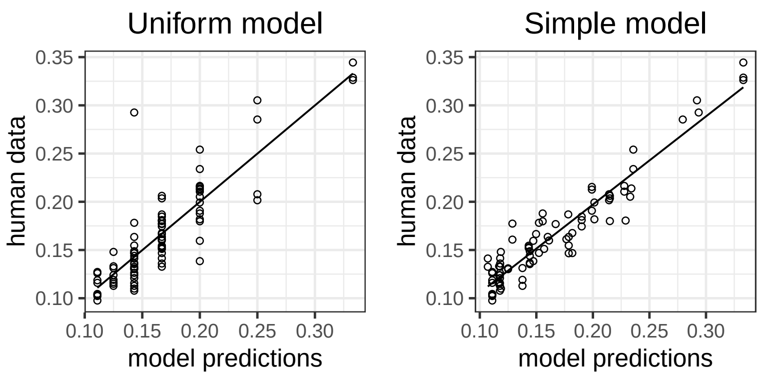

Figure 9: Average human data from Experiment 2 plotted against the predictions of the uniform baseline model and the simplePSIRSA model. Left panel *uniform model* ($r^2 = 0.7497$); right panel *KL-factor λ-optimized model* ($r^2 = 0.9071$).

We were able to distinguish three groups of participants on the basis of the individually-optimized parameter values of λ. The first was a "lazy worker" group of 18 participants whose fitted λ values were close to zero (i.e., $-.02 < \lambda < .02$), indicating that they were randomly selecting utterances. The second group of 32 participants yielded more negative values (i.e., $-7.13 < \lambda < -.02$), indicating that a significant number of participants preferred to systematically choose unambiguous utterances. The third group of again 32 participants yielded more positive values (i.e., $.02 < \lambda < .54$), indicating that these participants indeed chose the most ambiguous utterance in a strategic manner.

6 General discussion

We have found strong support for PSIRSA, which infers preference posteriors on the basis of ambiguous language. The results of Experiment 1 demonstrate that naïve speakers are able to reason pragmatically about *why* listeners may take the actions they do. The success of our computational model in predicting the observed behavior offers an articulated hypothesis about *how* this reasoning proceeds: when speakers are aware of the ambiguity in their utterances, observing how listeners resolve that ambiguity provides clues to the preferences listeners use when doing so. The results of Experiment 2 demonstrate that at least some speakers are able to capitalize on this reasoning to strategically select ambiguous utterances that are most likely to inform their understanding of the preferences of their listeners. However, this group of ambiguity-selecting participants included only about 40% of the participants. Further experiments with highly similar setups (not reported in detail here) confirmed this trend. In particular, we ran a complementary study with a blocked design where participants first completed preference-inferences trials as in Experiment 1 and then completed utterance-selection trials as in Experiment 2. Even in such an experimental setup, the trend stayed the same. Currently, we are transferring the experimental setup to more naturalistic interaction scenarios. Even in these cases, though, it appears that we still find participants who consistently prefer to choose unambiguous utterances. Two explanations may be warranted and need to be investigated further. First, it may be the case that these participants think overly egocentrically, thus having the intention to signal their own preferences rather than to give options to the listener. Second, it may simply be the case that these participants do not have access to the required deeper reasoning process, and thus prefer to give instructions with predictable outcomes.

Nonetheless, taken together, the results of our experiments and the success of our model in predicting those results indicate that humans are aware of the fact that by observing responses to ambiguous utterances, information about the listener's prior preferences can be inferred—that is, they are able to learn about the hidden model states of others, including preferences but probably also other aspects of beliefs. It should also be noted that ambiguous utterances used in this way to learn about others are closely related to questions, which may ask directly about considered preferences. Ambiguous utterances provide a ready but more subtle, indirect alternative to asking directly. In normal conversations, a speaker might favor the indirect route, given considerations of politeness and possibly also in an effort to keep the conversation open. With ambiguous language, the conversation partner can choose to disambiguate the ambiguous utterance or, alternatively, choose to continue in a different direction or even to change topic.

We note that the analyzed preference prior, viewed from a broader perspective, can be closely related to a part of the event-predictive mind of the listener and the speaker (Butz, 2016; Butz & Kutter, 2017). When interpreting an utterance—in our case, opening up a set of referent choices—the listener's mind infers the current choices and integrates them with her preference priors, implicitly anticipating possible choice consequences. Moreover, the expected information gain term—computing the utterance choice of the speaker—can be equated with the computation of socially-motivated active inference (Butz, 2017; Friston et al., 2015). It causes the model to strive for an anticipated epistemic value that quantifies the expected information gain about the preferences of the listener—that is, expecting a form of social information gain.

More generally, predictive states of mind about others do not only include considerations of the preferences of others, but may also concern all imaginable knowledge, opinions, beliefs, current trains of thought, and preferences of the listener. Moreover, during a conversation, the involved "social" priors will dynamically develop depending on the internal predictive models and the generated utterances, actions, and responses of the speaker and listener. The priors dynamically depend on the privileged grounds of the conversational partners, and also on the common ground in which the conversation unfolds. In that sense, ambiguous utterances are one device for projecting parts of each other's privileged grounds into the common ground.

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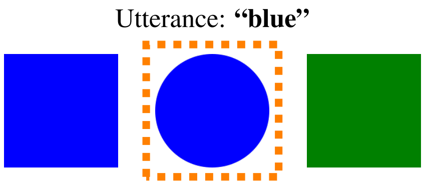
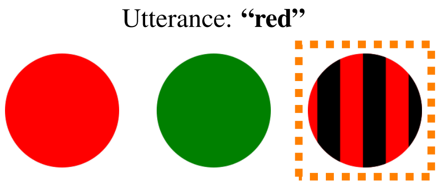
Appendix

Description of ambiguity classes



(a) The objects can differ in shape, texture, and color. The utterance applies to 2 objects which differ in shape: a circle and a square. No clouds are present in the scene, therefore we cannot learn whether the listener likes clouds. All the objects have the same texture – solid, so no learning about texture is possible.

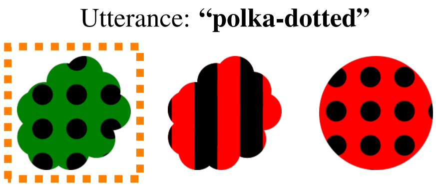


(b) Another combination, here two red objects differ in texture but share shape.

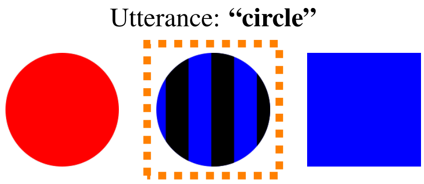
(c) Two solid objects differ in color but share shape.

Figure 10: In all these examples, the utterance picks out two objects. The picked object has one feature for itself. The other two objects share that feature between them. The last feature is shared by all objects.

(a) The objects can differ in shape, texture, and color. The utterance applies to 2 objects which differ in shape and texture: a striped cloud and a polka-dotted circle. Solid objects or squares are absent in the scene, so we cannot learn whether the listener likes squares or solid objects.

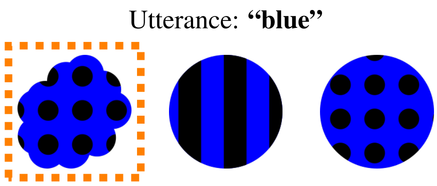


(b) Another combination, here the polka-dotted objects differ in shape and color.

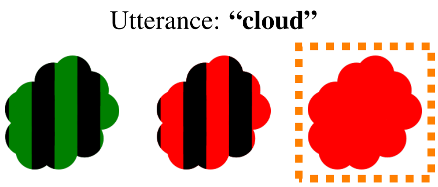


(c) Two circles differ in texture and color.

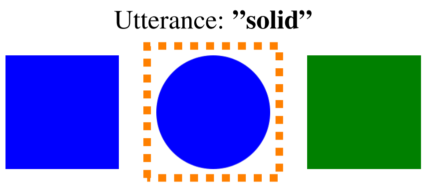
Figure 11: The utterance always picks out two objects and both objects only share that uttered feature. The third object shares one feature with each of those objects.



(a) The objects can differ in shape, texture, and color. The utterance applies to all 3 objects but they differ in shape and texture. Solid objects or squares are absent here, so we cannot learn whether the listener likes squares or solid objects.



(b) Another combination, here all objects are clouds but the picked object shares being red with another object.



(c) All objects are solid, the picked object shares being blue with one object.

Figure 12: Here the utterance picks out all objects. The picked object shares one feature with one other object and has one feature just for itself while the other two objects share it.