Social Learning via Ambiguity

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Abstract

From the Gricean perspective, ambiguity in language is something to be avoided. However, ambiguity seems ubiquitous during conversations. We investigated and modeled how, speakers learn about opinions, preferences, and beliefs of their conversation partners when monitoring their responses. Moreover, we asked the question whether some of us are able to strategically chose ambiguous over unambiguous utterances when the goal is to learn more about the conversation partner, that is, the listener. Accordingly, we ran two main types of experiments online using an enhanced version of the original reference game experiment (Frank & Goodman, 2012) and modeled the recorded response data by modifying and enhancing the Rational Speech Act framework. The resulting model is additionally able to (i) infer Bayesian posteriors of listeners' preferences when analyzing their choice responses to (ambiguous) utterances dependent on the number of options they have, and (ii) choose (ambiguous) utterances by maximizing (or minimizing) expected information gain about the listeners preferences. The modeling results imply that we indeed are able to learn about the listeners' preferences when monitoring their responses to (ambiguous) utterances ($R^2 > 96\%$). Moreover, some but not all of us appear able to strategically chose ambiguous over unambiguous utterances because we want to learn more about the conversation partner, that is, the listener. In this latter case, our model fits the participants' utterance choices revealing two main groups: while the one group acts upon maximizing expected social information gain (expecting to learn more about others'), the other group seems not interested in social learning, effectively even minimizing the expected gain ($R^2 > 91\%$). Overall, we essentially show that when monitoring a conversational partner's responses to our (partially ambiguous) utterances, we socially learn about the partner's inference model, revealing, for example, their preferences, opinions, and beliefs. Moreover, some of us can choose utterances that are expected to yield the highest social information gain about (particular parts of) the partner's inference model.

Keywords: ambiguity; pragmatics; information gain; predictive priors; Rational Speech Act model

1 Introduction

If a speaker and a listener interpret an ambiguous phrase differently, communication between them might fail. On rare occaisions, such communication failure is 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'.

It is not surprising in light of the cases mentioned above (and other more frequent but less severe communication failures) that linguists have treated ambiguity as a bug in the communication system, something to be avoided or explained away (Grice, 1975; Chomsky, 2002); ambiguity hinders the efficient transfer of information between conversation partners. If we look back at the study of ambiguity, we notice that the strategy of ambiguity avoidance is much older than the pronouncements of 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 a special caveat—only God could introduce ambiguity, humans should not. The search for efficient transmission of meaning that lasted over millenia rested on an important assumption: we communicate to transfer knowledge to our conversation partner. However, information-seeking might be not the only communicative task we engage in (Markova & Graumann, 1995), and following instructions–a task commonly used to evaluate the efficiency of communication–is not the only one, and probably not even the most common type of communicative acts (Foppa, 1995) [gcs: not sure what is meant by this last bit].

More recent research has begun to take notice of the efficiency ambiguity affords to 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 it 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 both possible interpretations afforded by an ambiguous utterance. In such cases, recognition of the ambiguity serves as the communicative purpose of the utterance. Wasow, on the other hand, reviews several cases where ambiguity production serves no obvious communicative purpose.

The field of communication sciences views ambiguity as an important communicative tool.In organizational communication—communication that aids production—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 when managers set goals that should stimulate rather than limit future creativity (Mohr, 1983). Ambiguity allows for the expression of ideas that are true of 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). Ambiguous descriptions also allow speakers to avoid conflict (Pascale & Athos, 1981): 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. It is possible that the awareness of a shared code gives rise to the sense of within-group cohesion and social bond between group members. Thus, members of the same group have a sense of high level of mutual understanding.

We will briefly pause here and summarize our current take on ambiguity. As it becomes apparent from descriptions of ambiguity above, different disciplines pack a variety of meanings into this concept. 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, ambiguity aligns closely with underspecification: an utterance is ambiguous when it does not provide every detail about the intended interpretation, 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.

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 the 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, for example, 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 a 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

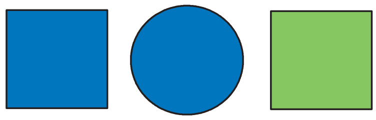

Figure 1: A simple reference game scenario from Frank and Goodman (2012). In the game, speakers choose a single-word utterance to signal one of the objects to a listener. In this scenario, the speaker chooses between the utterances “blue,” “green,” “square,” and “circle.”

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 (for more on RSA as a framework, see also 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. We begin by walking through our modeling assumptions. We then present our models in full detail, and test the behavioral predictions of our models against human data in a series of web-based experiments. We conclude with a discussion of the significance of our findings for understanding ambiguity in natural language, and relate the findings to current theories of predictive coding and active inference.

2 Model

2.1 Full pragmatic model

We begin with the vanilla RSA model of Frank and Goodman (2012). The recursive social reasoning inherent to the RSA modeling framework gets cashed out as various layers of inference. At the base, there is a hypothetical, naïve literal listener L_0 who hears an utterance u and infers the state of the world s that u is meant to describe, that is, the object that may be referred to by the utterance. L_0 performs this inference by conditioning on the literal semantics of u, $[\![u]\!]$. L_0 thus returns a uniform distribution over those states s that can be truthfully described by u:

$$P_{L_0}(s|u) \propto [\![u]\!](s).$$

One layer up, the speaker S_1 observes some state s and chooses an utterance u to communicate that state to L_0. S_1 chooses utterances on the basis of their utility for signaling s to L_0, $U_{S_1}(u;s)$. The speaker's utility maximizes the probability that L_0 would arrive at the correct s on the basis of u, $P_{L_0}(s|u)$, while minimizing the cost of u itself, $C(u)$:

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

S_1 chooses utterances in proportion to their utility:

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

At the top layer of inference, the *pragmatic* listener L_1 infers s on the basis of some observed u. The result is a distribution over likely states s; 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 choose the u that was observed:

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

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 generate predictions 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 generate predictions from L_1. Finding extremely high 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).

Our model builds on the vanilla version of RSA above by allowing for uncertainty around the listener's state prior, $P(s)$. In that sense, the model belongs to the family of models known as uncertain RSA (Goodman & Frank, 2016). We have in mind a scenario where a listener might have a preference for a certain object feature (e.g., blue things, squares, circles, etc.), and these preference will influence their object choice. With this in mind, the speaker produces an utterance u, observes the listener's referent choice s, and, on the basis of that choice, infers the preferences f the listener might have had when making the choice. We use the same L_0 and S_1 from the vanilla model. However, we now parameterize L_1's state prior so that it operates with respect to a given feature preference $P(s|f)$:

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

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

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

We also model the reasoning process by which a speaker selects the best utterance to learn about the preferences of the listener. 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, $P_{S_2}(f|u,s)$, deviate from the uniform prior, the more the speaker will have learned about the listener's preferences. We can thus model this reasoning in the light of expected information gain, which can be equated with the attempt to maximize the KL divergence between the speaker's flat prior and the expected posterior of the listener's feature preferences f, integrating over all hypothetically possible state observations s:

$$P_b(u) \propto \sum_{s:\ [\![u]\!](s)} \lambda \cdot \mathrm{KL}(P(f), P_{S_2}(f|u,s)) - C(u).$$

We now have two sets of predictions from our model to check: first, the pragmatic speaker's inference about the listener's feature preferences on the basis of their object choice; and second, the pragmatic speaker's strategic utterance selection in the light of the anticipated information gain about the listener's preferences considering their possible object choices. Below, we present two experiments that test these predictions against human behavior.

2.2 Simplified pragmatic model

As an alternative, we also test a model that relies on fewer layers of reasoning. It involves an enhanced literal listener that now inlcudes prior preferences over states:

$$P_{L_0}(s|u,f) \propto [\![u]\!](s) \cdot P(s|f).$$

Sikos, Venhuizen, Drenhaus, and Crocker (2019) demonstrate that simpler reasoning models perform as well or better than more complex models in contexts where the predictions of the simple and full models diverge. In those situations, a literal listener layer enhanced with salience outperformed the full RSA model. And what is particularly striking, salience alone was a better predictor of human performance than the RSA suggesting that participants engaged in shallower reasoning than the original RSA models suggested.

3 Experiment 1: Inferring preferences

Our first task is to check the predictions of our S_2 layer: having observed that a listener selects some object s in response to an utterance u, what are the most likely preferences the listener had when making their choice?

3.1 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.

3.2 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, or 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 possessed 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., "green" in Figure 2) and the listener's choice appeared with a dotted orange outline (e.g., the leftmost 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). Participants completed a series of 15 trials. Objects and utterances were chosen as detailed above, with the constraint that 10 trials were potentially informative with respect to listener preferences and 5 trials were uninformative with respect to listener preferences (e.g., observing that the listener chose one of three identical objects).

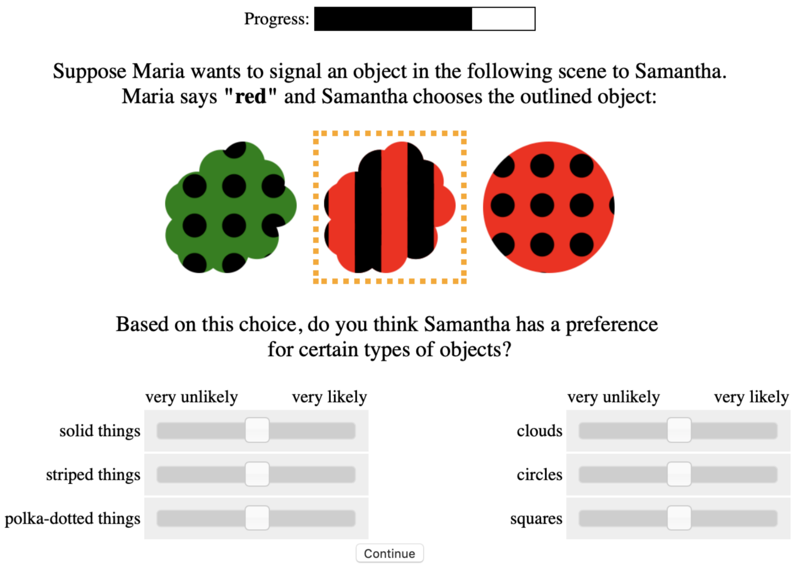

Figure 2: A sample trial from *Experiment 1: Inferring preferences*.

3.3 Results

3.3.1 Models with global optimization

To compare RSA model predictions to the human data, we identified all distinguishable cases in the light of the ambiguity of the chosen utterance and the possible object choices, essentially binning the data of all stimuli for which the extended RSA model yields equal preference-estimate posteriors; there were 48 scene types in our stimuli. For all scene types, the actual feature values and objects in a scene were reordered according to the specific preference inference involved. Thus, after reordering, the results of the individual slider values for individual scenes in each scene type could be averaged for both the participant data and the model predictions.

We will look at the model performance for one of the types of stimuli from a sample trial (Figure 2) in Figure 3. In that trial, participants saw that the middle object was chosen following the utterance *red*. There are two potential referents for this description: a red striped cloud and a 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 object vs dotted ones. From this trial, we cannot learn anything about the preference for solid things or squares, so we expect the subjects to leave the sliders in the middle non-adjusted. The barplot in Figure 3 shows that indeed when faced with a combination of objects from Figure 2, both human subjects and the models assign high slider values to clouds and striped things, and low values of the sliders to circles and dotted things.

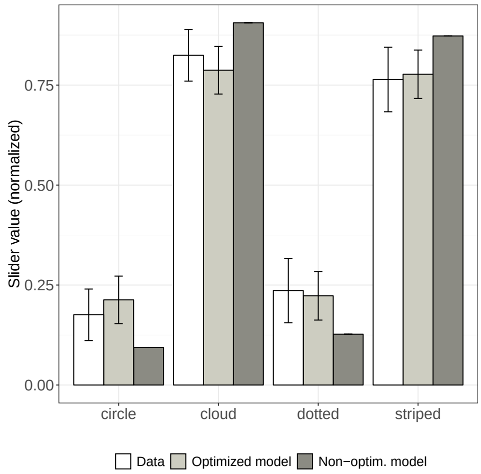

Figure 3: Model predictions and human data for one of the classes of stimuli *Experiment 1: Inferring preferences*.

In this plot we show two types of models: an optimized and a non-optimized one. We performed two types of optimization: at the individual level and at the global group levels. We first present the globally-optimized versions of the model (Figure 4). We fit 3 parameters (2 for the simple model) to assess reasoning strategies individual speakers employ. For the full RSA model, the first is the soft-max scaling parameter α in the S_1 layer of the model, where the default value is typically set to $\alpha = 1$. This parameter controls how likely S_1 is to maximize utility when choosing utterances.

The second parameter scales the softness of individual feature preferences f_i. This parameter controls the shape of each of the possible feature preferences f_i that S_2 considers. Preference softness increases with γ: a value of $\gamma = 0$ specifies a hard preference, that is, the listener will always choose the object that contains the preferred feature value if possible. We assume $\gamma = 0$ as the default model value. On the other hand, $\gamma \to \infty$ specifies a uniform feature value preference, that is, no actual preference. As a result, a large value of γ approximates a uniform-prior model.

Finally, we allow for the possibility of noise in our human data introduced by participants not following instructions. The parameter β when above 0, allows subjects to consider objects that do not pass the semantic filter of the literal listener. As β increases, speakers disregard instructions and assign non-zero probabilities to objects that do not correspond to the utterance; at zero, speakers fully obey instructions and only consider objects with the named property (e.g. only red objects following the utterance *red*).

We hypothesized that participants may either go through all the layers of pragmatic reasoning, and additionally calculate the prefrences that lead to particular object choice. The last layer of this model S_2 returns a posterior distribution over inferred feature preferences f after observing a listener selecting an object in response to an utterance.

In a simpler model, the object choice is driven only by a L_0 semantics enhanced with priors over feature preferences. Upon hearing an utterance *blue* a participants assigns equal probabilities to all blue objects in a scene, and the actual choice of object signals a preference of other feature values that object has. For example, picking a blue circle rather than a blue square is driven by a prefrence for circles.

Both, the simple and the full models provide a good fit to the data (simple model: $p < 0.001$, $r^2 = 0.86$; full model: $p < 0.001$, $r^2 = 0.86$) suggesting that participants are indeed able to infer the feature preferences that lead to a choice of an object. We can also see that the simple model fits the data just as well as the full more complex model.

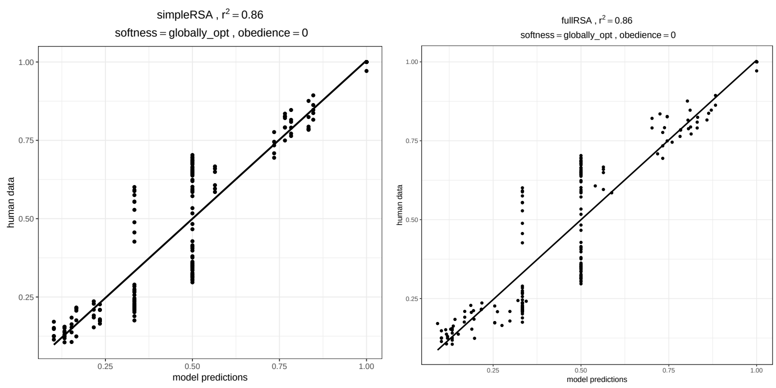

Figure 4: Average human data from Experiment 1 plotted against the predictions of the β-optimized RSA model; both models $r^2 = 0.86$, 95% CI [0.80 0.90].

3.3.2 Individually-fitted models

Model fit improves when fit two parameters on individual level, i.e. calculating a parameter estimate for each participant. Individual-level modeling allows 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 population as a whole (Franke & Degen, 2016).

We optimized α and γ in the light of the KL divergence between the individual participants' slider value choices and the corresponding model predictions:

$$\mathrm{KL} = \sum_{i=1}^{n} P(f_i'|u,s)(\log(P(f_i'|u,s) - \log(P(f_i|u,s)),$$

where $P(f_i'|u,s)$ specifies a participant's normalized slider value settings, that is, empirical estimates of the feature preference posterior given an object scene and a particular utterance u and object choice s; $P(f_i|u,s)$ specifies the respective model prediction value. Since no conclusions can be drawn concerning feature values that are not present in the scene, we ignored the respective feature preference estimates. By minimizing KL divergence between the empirical and model-predicted preferences for each participant, we maximize the model fit to the individual participants' data. We can then use the KL divergence values to perform the likelihood ratio test for nested models relying on G^2-statistic (Lewandowsky & Farrell, 2011).

Figure 5 demonstrates that the full model optimized at the individual level for an additional parameter α does not improve the fit compared to the simple model. Since

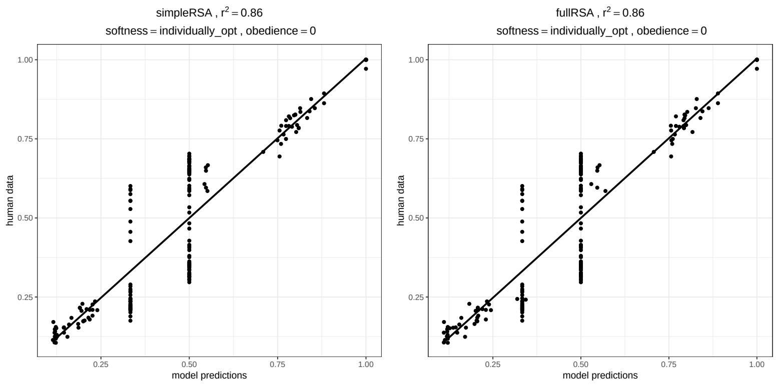

Figure 5: Average human data from Experiment 1 plotted against the predictions of the individually γ-optimized simpe RSA model $r^2 = 0.86$, 95% CI [0.81 0.90] and γ and α optimized full RSA model; $r^2 = 0.86$, 95% CI [0.80 0.90].

two models account for the same amount of variance in the data, we will further proceed with the simple model evaluation.

We plot predictions from the β and γ-optimized model in Figure 6, where a strong positive correlation between the human judgments and model predictions ($r^2 = 0.99, p < 0.001$) can be observed. The likelihood ratio test revealed that a γ and β-optimized model provides a better fit compared to a model optimized only for γ ($G^2 = 237.36, df = 82, p < 0.01$). The more complex model contains 1 additional parameter fitted for each subject giving as 82 degrees of freedom. We additionally check the generalizability of the model by performing cross-validation. We show in Figure 6 that the cross-validated model retains its fit.

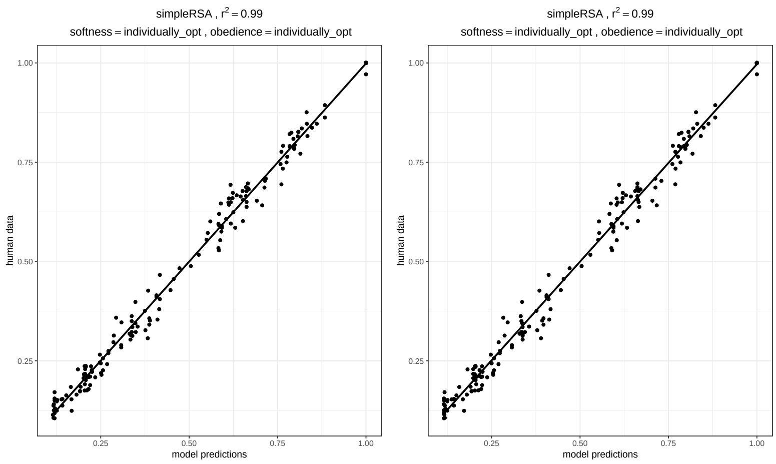

Figure 6: Average human data from Experiment 1 plotted against the predictions of the individually β and γ-optimized simpe RSA model, non-cross-validated (left panel) $r^2 = 0.99$, 95% CI [0.98 1.00] and cross-validated (right panel) $r^2 = 0.99$, 95% CI [0.98 1.01] .

Thus, we find strong empirical support for our extended RSA model of preference inference: speakers are indeed able to use listener behavior to arrive at information about their preferences. The question now turns to whether speakers are aware of the relative utility of different utterances when it comes to this reasoning. In other words, are speakers aware that ambiguous language is potentially more informative?

4 Experiment 2: Choosing utterances

Our next task is to check the predictions of our strategic utterance selection model: given a set of potential referents, which utterance would be most informative with respect to the listener's preferences?

4.1 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.

4.2 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."

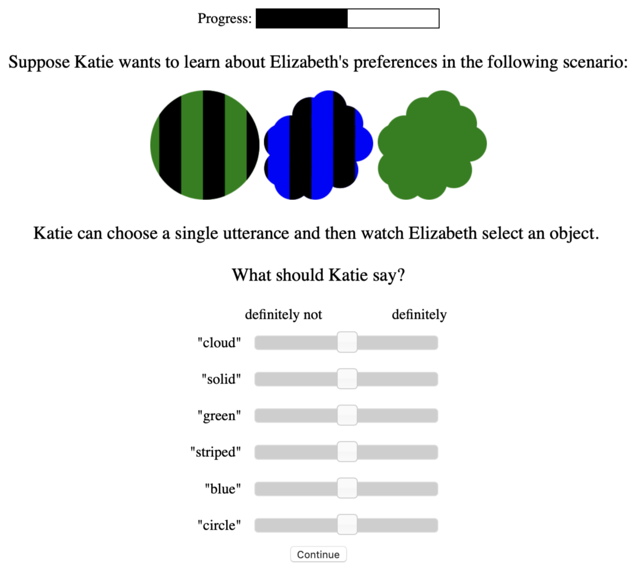

Figure 7: A sample trial from *Experiment 2: Choosing utterances*.

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 7. After observing the objects, participants adjusted sliders to indicate which single-feature utterance the speaker should choose. Potential utterances corresponded to the features of the objects present; depending on the number of unique features, participants adjusted between three and nine sliders, which specified the present feature values. Participants completed a series of 15 trials. As with Experiment 1, objects were chosen at random, with the constraint that 10 trials were potentially informative with respect to listener preferences (as in Figure 7) and 5 trials were uninformative with respect to listener preferences (e.g., observing a set of three identical objects).

4.3 Results

Let us first examine the predictions of the model for the sample trial (Figure 7). Figure 8 shows that in a situation, when there are three possible objects– a striped green circle, a blue striped cloud, and a solid green cloud–uttering things like *cloud*, *striped* or *green* and then watching the person pick an object could let the speaker learn something about the listener's preferences. For example, *green* picks out two objects: a striped green circle and a solid green cloud. Therefore, we could learn whether the listener prefers striped things over solid things, and circles over clouds.

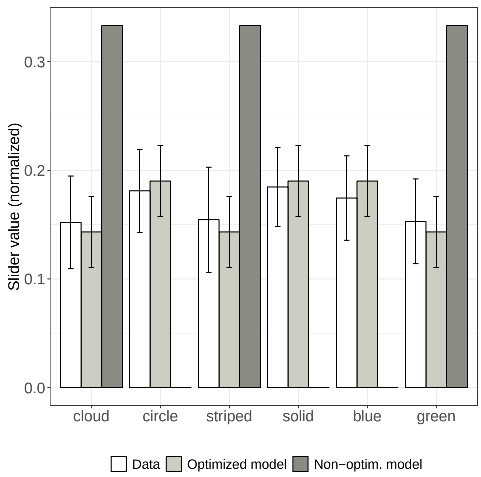

Figure 8: Model predictions and human data for one of the classes of stimuli *Experiment 2: Picking utterances*.

By reasoning the about predictions of S_2, we are able to use our extended RSA model to compute the expected most informative utterance with respect to inferring preferences. In other words, $P_b(u)$ calculates the probability that a speaker would choose u for the purpose of inferring preferences in our reference game scenario.

To generate predictions from $P_b(u)$, a total of four free parameters can be identified. As with the analysis for Experiment 1, we consider different values for α (i.e., speaker's soft-max factor) and γ (i.e., preference softness), and obedience β. We must also set 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, in this case the model would favor unambiguous utterances. Moreover, when $\lambda = 0$, the model collapses to a uniform distribution of utterance choices, thus yielding a nested model to a uniform base model.

As with Experiment 1, we averaged the data and the respective model predictions across specific case bins, 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. After matching the respective actual feature values with the utterance choice relevant within the respectively-binned conditions, we again computed averages over utterance preference values for the respectively-binned trials across participants and across respective model predictions.

Figure 9 shows the model fits of non-parametrized full and simple RSA models, with both models failing to predict the human data. Therefore, we proceed with optimizing free parameters of the models.

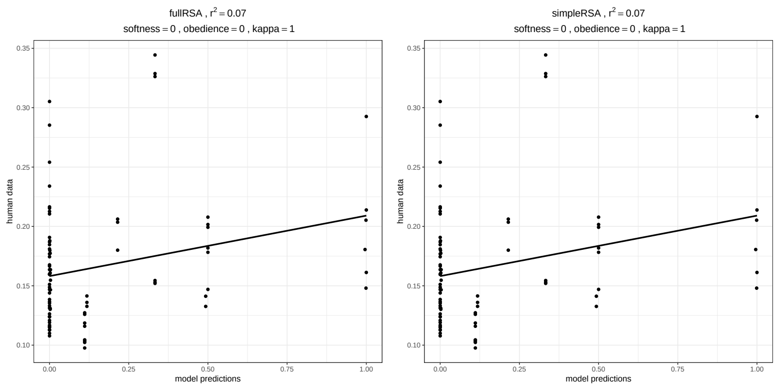

Figure 9: Average human data from Experiment 2 plotted against the predictions of the parameter-free RSA model; both models $r^2 = 0.07$, 95% CI [0.01.23].

We again optimized model values with respect to KL divergence estimates between the participant data and the model predictions—in this case for utterance preference distributions. We compared three individually-optimized models to determine which model provides the best linear fit to the data. All the models have similar levels of complexity with one free parameter being optimized. The results indicate that we get the best fit by optimizing the KL-factor ($r^2 = 0.91$; cross-validated optimization $r^2 = 0.89$), with other models capturing less variance in the data: obedience ($r^2 = 0.80$), softness of preferences ($r^2 = 0.81$).

In Figure 10 we compare a KL-factor optimized model (right panel) to a uniform base model (left panel) that assigns equal probability to each utterance available for a particular context. A model with the λ (KL-factor) parameter optimized at the individual level fits the data better than a uniform model (Likelihood ratio test: $G = 268.87, df = 82, p < 0.01$). Optimizing for two parameters (KL-factor and softness) does not further improve the fit neither does optimizing for three parameters.

As with the results of the previous experiment, we were able to distinguish three groups of participants on the basis of the fitted parameter values of λ. The first was a "lazy worker" group of 18 participants whose fitted λ values were close to zero (i.e., $-.02 < \lambda < .02$). 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 non-ambiguous utterances. The third group of again 32 participants yielded more positive values (i.e., $.02 < \lambda < .54$), indicating that these partic-

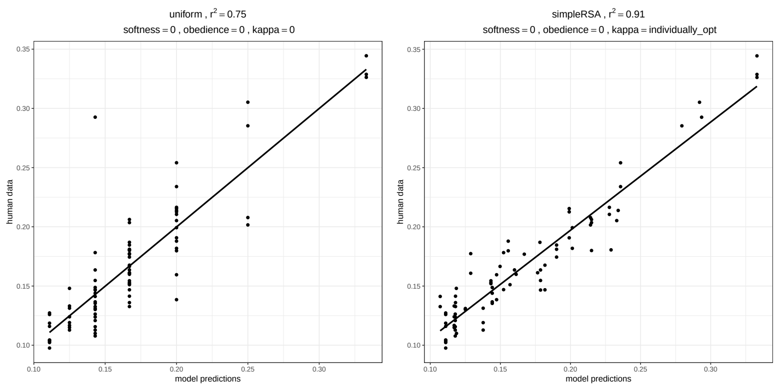

Figure 10: Average human data from Experiment 2 plotted against the predictions of the uniform and simple RSA models; uniform model $r^2 = 0.75$, 95% CI [0.65 0.84], KL-factor optimized $r^2 = 0.91$, 95% CI [0.92 1.06]].

ipants indeed chose the most ambiguous utterance in a rather strategic manner.

5 General discussion

We have found strong support for our model of inferring priors 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, and 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 speakers are able to capitalize on this reasoning to strategically select utterances that are most likely to inform their understanding of the preferences of their listeners, and that the most informative utterances are also the ambiguous ones.

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. Used in this way to inform preferences, ambiguous utterances are closely related to questions, which may ask directly about the relevant preferences. However, ambiguous language provides a ready alternative to asking directly. In normal conversations, a speaker might favor the indirect route afforded by ambiguous utterances, given considerations of politeness and possibly also in an effort to keep the conversation on track.

We note that the analyzed preference prior, viewed from a broader perspective, can be interpreted as the general predictive state of mind of the listener when interpreting the speaker's utterance (Butz & Kutter, 2017). Thus, this state of mind does not only include preferences per se, but all imaginable opinions, beliefs, *and* preferences of the listener. Moreover, during a conversation, this prior will dynamically develop depending on the internal predictive models and the generated utterances and actions of the speaker and listener. This prior depends on the privileged grounds of the conversational partners, and also on the common ground in which the conversation unfolds. Ambiguous utterances are one device for making the privileged ground common knowledge.

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