Bayesian inference in dialogue

Abstract

An utterance is referentially ambiguous if it has several potential referents. Observing how listeners make choices among those referents can reveal not only the reasoning process but also their hidden beliefs and preferences. We asked subjects to observe how one of the objects is chosen following a possibly ambiguous utterance, and then infer what preferences of the listener made her pick that particular object. We modify the traditional one-shot reference games by extending the scenarios to a round of 4-trial games. We model the inference process within the Rational Speech Act framework implementing learning over multiple trials, where posteriors from previous trials carry over the next trial as priors. The model can accurately predict the human learning trajectory, and it outperforms a model that assumes no accumulation of knowledge.

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

Introduction

Social interactions rely on speakers being able to simulate the listener's thinking process, and the listener reasoning about why the speaker chose to say the things she did. For communicative behavior to be adaptive, interlocutors need to continuously update predictive models of each other. These models include, among other things, understanding the state of each other's knowledge, beliefs and preferences. During conversation, we actively seek to update the information state not only about the world but also about each other. Such interpretation of communicative behavior fits within a broader perspective on active inference as a core principle on which the human mind operates (Friston et al., 2015; Hohwy, 2013; Clark, 2016). In this paper, we adopt the predictive mind perspective as it applies to social interactions.

We argue that ambiguity omnipresent in communication provides a learning platform where conversation partners can gain better understanding of each other. This work presents a considerable departure from a classic view on ambiguity that treats it as an inconvenient side effect of a language system (Grice, 1975; Chomsky, 2002). Within that paradigm, ambiguous utterances prevent an accurate transfer of information between interlocutors and therefore obscure communication.

Despite the apparent negative consequences associated with the use of ambiguous utterances, agents rarely avoid ambiguity even in situations where it would be communicatively appropriate (Wasow, 2015; Ferreira, 2008). Instead, speakers rely on listeners to fill in the missing information and find an interpretation that is the most coherent within the current discourse. Piantadosi, Tily, and Gibson (2012) show via statistical modeling that ambiguity is an essential product of an efficient communication system: it allows to reuse lightweight pieces of language instead of giving a fully specified description of a situation. Ambiguous descriptions save the effort on the speaker side while relying on the listener's ability to interpret the ambiguous utterances within context.

We propose that ambiguity of reference creates a space of alternatives, and choosing of one of those alternatives becomes a meaningful event in itself. This idea is consistent with the attribution theory which captures the human ability to interpret each other's behavior as driven by motives, intentions and goals (Jones & Davis, 1965; Kelley, 1967; Kelley & Stahelski, 1970). In a naturalistic conversation, where speakers take turns, ambiguous utterances open interpretation spaces and the resulting interpretation choices dynamically and mutually reveal individual opinions, beliefs, and preferences.

Making an inference about those individual predispositions requires the speaker to reason pragmatically about the listener. We use the paradigm of references games, as developed in Frank, Goodman, Lai, and Tenenbaum (2009), to model this choice process, and test whether human subjects are able to infer what properties of objects determined a particular course of events. In the course of a classic reference game, a speaker wants to signal a particular object to the listener, and to do that the speaker is allowed to use one-word utterances to refer to one of the objects (e.g. Frank & Goodman, 2012). The task of the listener is to infer which of the available objects is the most likely referent. The listener reasons about the process that generated the utterance, assuming that the speaker uses the utterance that is the most efficient to signal a particular object. For example, consider a scenario in Figure 1.

Suppose a speaker produces a single-word utterance "blue" – meaning: choose a blue object – creating referential ambiguity for the listener, that is, offering a choice between a blue square and a 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? If the listener's choice was driven by purely pragmatic considerations modeled in Frank and Goodman (2012), the listener should have selected the blue square, since if the speaker had intended to refer to the circle, she could have used a more efficient utterance "circle". Since she did not say "circle" she must have referred to the square. Yet, in our situation, the listener did pick the circle following the utterance "blue". Perhaps there is another choice strategy that the listener is using: the circle might be more salient to the listener, 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

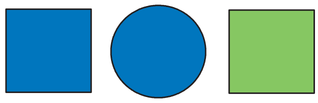

Figure 1: A simple reference game scenario from Frank and Goodman (2012). In the game, speakers are confronted with a collection of objects, which determine the current scenario S, where $S = \{solid\ blue\ square, solid\ blue\ circle, solid\ green\ square\}$ in the depicted example. A speaker may choose a single-word utterance u to signal one of the objects $s \in S$ to a listener. In the shown scenario, the following set of utterances is available: $U = \{$*"solid"*, *"blue"*, *"green"*, *"square"*, *"circle"*$\}$.

the listener.

In a modified version of reference games, we created situations where a speaker picks an utterance and watches a simulated listener choose one of the objects. The task of the participant is to infer what preferences of the listener made her pick that particular object. In order to avoid an impression that the choice of an object might be random, we allow 4 consecutive trials that focus on the preferences of one particular person. Participants then track the object choices and update their understanding of the listener's preferences across a series of trials. We hypothesize that subjects use a Bayesian learning process: they take into account their existing priors of the listener's preferences as the accumulate more evidence.

Modeling

The recursive interactions between the speaker and the listener are modeled wihin the Rational Speech Act (RSA) framework (Frank & Goodman, 2012; Goodman & Stuhlmüller, 2013; Franke & Jäger, 2016; Goodman & Frank, 2016, cf. a game-theoretic approach of recursive reasoning in Franke, 2009. The model formalizes a state space, or scenario, S in the form of a particular set of objects (e.g. Figure 1) and the corresponding utterance space U. The utterance space contains all possible utterances which correspond to object features that are present in a particular scenario S.

At the base of the reasoning process, there is a hypothetical, naïve literal listener L_0, who hears an utterance $u \in U$ and attempts to infer the object $s \in S$ 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 by:

$$P_{L_0}(s \mid u) \propto [\![u]\!](s), \tag{1}$$

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

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

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 scenario S, which is determined by the log-likelihood of this particular object choice $U_{S_1}(u;s)$:[2]

$$U_{S_1}(u;s) = \log(P_{L_0}(s \mid u)). \tag{2}$$

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

$$P_{S_1}(u \mid s) \propto \exp(\alpha \cdot U_{S_1}(u;s)). \tag{3}$$

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 the utterance choice of speaker S_1. In other words, L_1 reasons about which object s would have been most likely led S_1 to utter u given the scenario S:

$$P_{L_1}(s \mid u) \propto P_{S_1}(u \mid s) \cdot P(s). \tag{4}$$

Frank and Goodman (2012) tested the predictions of RSA against behavioral data from reference games, as in Figure 1. They found a strong correlations between model predictions and behavioral data in both cases, confirming the validity of their model of pragmatic reasoning in reference games (see also Qing & Franke, 2015 for a fuller exploration of the modeling choices).

Pragmatic social inference RSA model

Our model builds on the vanilla version of RSA, modifying the listener's state prior $P(s)$ and enhancing the reasoning process towards a social component, yielding a *pragmatic social inference RSA* model (PSIRSA). 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 introduce two more modifications to the original version of RSA. First, our model relies of fewer layers of reasoning. Recently, it has been shown that even in the original, simpler reference games, fewer layers of reasoning often perform

[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.

equally well or better than more complex RSA-based models (Sikos, Venhuizen, Drenhaus, & Crocker, 2019). Accordingly, simplePSIRSA removes the reasoning about alternative utterances and allows the pragmatic speaker to directly tap into the (expected) interpretation of L_0, augmenting the literal listener's choice likelihoods with the feature-preference-dependent object prior $P(s \mid f)$:

$$P_{L_0}(s \mid u, f) \propto [\![u]\!](s) \cdot P(s \mid f). \tag{5}$$

The pragmatic speaker $S_{1\text{-simp}}$ then reasons directly about the modified literal listener L_0:

$$P_{S_1}(f \mid u, s) \propto P_{L_0}(s \mid u, f) \cdot P(f). \tag{6}$$

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 simplifies the reasoning process accordingly:

$$P_{S_1}(u) \propto \sum_{s:\ [\![u]\!](s)=1} P_{L_0}(s|u, f)\ \exp(\lambda \cdot \mathrm{KL}(P(f)\ ||\ P_{S_1}(f \mid u, s))). \tag{7}$$

Second, we model reasoning as an iterative process where a learner accumulates and updates her understanding of another person's beliefs over a set of trials. A learner starts with a flat prior over possible feature preferences and infers posteriors upon hearing an utterance and observing an object. Then the model passes the obtained posterior distribution of preferences as prior for the next trial, implementing the Bayesian learning process.

Free parameter optimization

We fit the model parameters at the group and individual levels by optimizing the KL divergence between the data and the model predictions:

$$\mathrm{KL}(P_{data}(f \mid u, s)\ ||\ (P_{model}(f \mid u, s)), \tag{8}$$

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 $P_{S_{1\text{-simp}}}(f \mid u, s)$.

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

$$P(s \mid f) \propto \begin{cases} 1+\gamma, & \text{if } s \text{ contains } f \\ \gamma, & \text{otherwise} \end{cases}, \tag{9}$$

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, consider a scenario in Figure 2, where the listener picked a striped object following the utterance "circle". If her $\gamma = 0$, she should adjust the "striped" slider to 1 and set other sliders to 0 if we assume she has not previously learned anything about the relative ranking of the other values. If her $\gamma = 0$, the model predicts that she sets the "striped" slider to 0.75 and the other slider values to 0.25. In that case, we can say that her preferences became softer, i.e. less categorical. We use $\gamma = 0$—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.

Experiment

The experiment is designed to address three questions: first, whether speakers are able to pick ambiguous utterances that could create a potentially informative learning situation. In such a situation, the listener's object choice would reveal his preferences. Second, we ask whether participants are able to infer the preferences of the listener. Finally, we are interested in whether participants are able to use the information about listener preferences that they accumulated over previous trials.

Participants

We recruited 100 participants with US IP addresses through Amazon.com's Mechanical Turk crowdsourcing service. Subjects were compensated for their participation. On the basis of a post-test demographics questionnaire, we identified 98 participants as native speakers of English. 3 participants reported that they did not understand the instructions or were confused by the task. As a result, the data from 95 participants were included in the analysis. We obtained a confirmation from all the subjects that they agree to participate in the study.

Design and methods

We presented the subjects with a series of reference game scenarios modeled after Figure 1 from Frank and Goodman (2012). Each trial consisted of 2 parts, as shown in Figure 2. The experiment participant played the role of a speaker. Her task first was to find out a certain type of preferences of the listener, either related to color of objects, their pattern

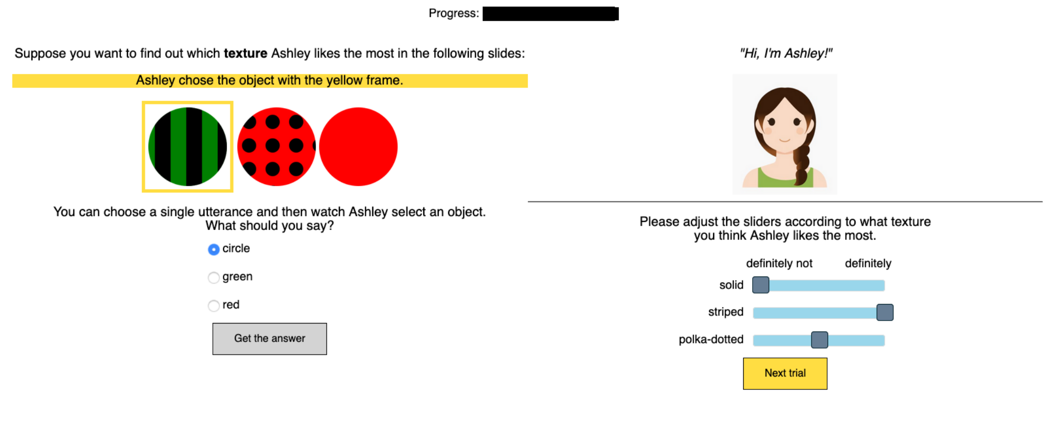

Figure 2: A sample trial. Each trial portrays a listener. The speaker (experiment participant) produces an utterance to refer to one of the objects. The listener picks the object with the orange dotted outline. The experiemtn participants then evaluates what preferences of the listener may have led her to the particular object choice, specifying their inference by adjusting the sliders for each of the features.

or shape. Listener names and what particular feature preferences we need to infer (color, shape or pattern) were chosen randomly in each block but remained constant within a block. Participants completed a series of 4 blocks each containing 4 trials.

Objects were allowed to vary along three dimensions: color (blue, red, green), shape (cloud, circle, square), and texture (solid, striped, polka-dotted). The speaker's utterance was chosen at random from the properties of the three objects present, excluding the utterances which correspond to the target feature (e.g. texture in Figure 2). All trials contained at least 1 ambiguous utterance. In the first part of the experiment (left side of the screen) the speaker had to pick an utterance and watch the simulated listener select an object. The listener's choices were driven by the literal semantics of the utterance, i.e. only red objects qualified as a possible choice following the utterance "circle". And second, we built in particular distributions of feature preferences giving a priority scale. The listener picked the object that matched the highest value on the scale. For example if the scale was red $>$ green $>$ blue, and all three colors were present in a scene, the listener picked the red object. If only green and blue objects were present and qualified, the listener picked a green object.

In the second part of the trial (right half of the screen in Figure 2), the speaker adjusted the sliders guessing the listener's preferences. Then the experiment proceeded to the next trial with the same simulated listener and the same hierarchy of preferences. The sliders remained in their adjusted positions, so the participant could see what information about the listener's preferences she already obtained.

To compare the model predictions to the human data, we calculated an average value for each slider. We partitioned the data into ambiguity classes, similar to Frank and Goodman (2012). Depending on how many features competitor objects share with the chosen object, we were able to identify 33 ambiguity classes, which group the constellations that have the exact same ambiguity pattern. The ambiguity classes distinguish how many objects are referenced by the utterance, how the referenced objects differ in their two non-uttered features, and how the non-referenced objects differ from the referenced objects and from each other. We excluded combinations that contained identical objects as well as combinations were objects share non of the features, i.e. all objects are unique. As a result, each ambiguity class yields unique model prediction values for the individual features present (with respect to their "ambiguity role" in the particular ambiguity class) in corresponding scenarios S, effectively distinguishing all model-relevant cases.

Results

In this experiment, the task of the participants was to first pick an utterance, then observe the choice of an object and ultimately infer the hierarchy of the listener's preferences. In order to assess whether subjects learned the target ordering of listener preferences, we developed an evaluation score from 0 to 3. The preferences are encoded as pairs. If a hierarchy is $a > b > c$, there are three relations to learn: $a > b$; $b > c$, and $a > c$. A score of 3 is assigned if the relations in all the pair are identified correctly, a score of 0 means that all the relations between feature preferences have been reversed, and values 1 and 2 correspond to 1 and 2 pairs guessed correctly respectively.

Figure 3 reveals that both the model and the human subjects successfully learned the implemented hierarchy of preferences: both got the evaluation scores of 2 and 3 most of the time.

We can now explore how the accuracy of predictions improves over time. We predicted that if learning is iterative and subjects use the information about the preferences that they have already accumulated, we should see higher evaluation scores on subsequent trials. We see in Figure 4 that the line for best evaluation score "3" rises as the trial order increases.

As both Figures 3 and 4 show, in certain cases both the speakers and the model failed to learn the preferences hierar-

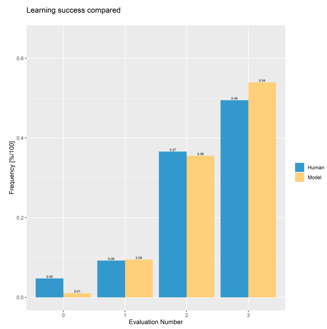

Figure 3: Success of human subjects and the model in detecting the listener preferences

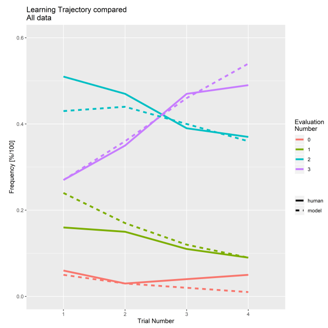

Figure 4: Success of human subjects and the model in detecting the listener preferences

chy. We attribute this effect to different strategies participants used when choosing utterances. Recall, that while every trial contained at least one ambiguous utterance, participants also had a possibility to choose an unambiguous utterance. Unambiguous utterances pick a single object making the learning impossible both for human subjects and for the model (Figure 5). When subjects pick ambiguous utterances, learning curve clearly goes up (Figure 6).

Discussion

In order to interpret an ambiguous utterance, listener need to rely on their priors to determine which interpretation is most

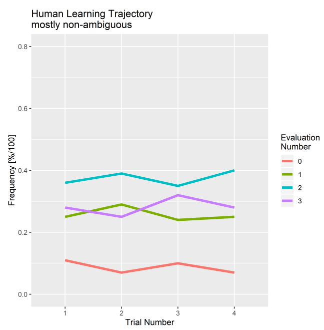

Figure 5: Success of human subjects and the model in detecting the listener preferences

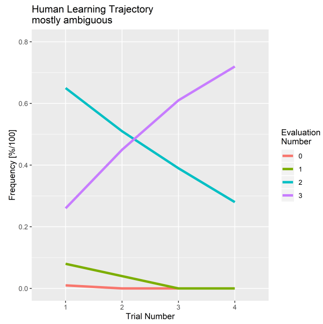

Figure 6: Success of human subjects and the model in detecting the listener preferences

likely. These priors broadly viewed can include personal preferences and beliefs, prior knowledge, and understanding of the current context. Listener choices are in that sense informative about the underlying priors of the listener.

We simulate the ambiguity resolution process with a Bayesian reasoning model that allows accumulation of evidence over a series of trials. We demonstrate that if ambiguous utterance are chosen, the accuracy of guesses improves as a function of trial order, and we faithfully model this process computationally.

References

Chomsky, N. (2002). An interview on minimalism. In A. Belletti & L. Rizzi (Eds.), *On nature and language* (p. 92-161). Cambridge: Cambridge University Press.

Clark, A. (2016). *Surfing uncertainty: Prediction, action and the embodied mind*. Oxford, UK: Oxford University Press.

Ferreira, V. S. (2008). Ambiguity, accessibility, and a division of labor for communicative success. *Psychology of Learning and Motivation: Advances in Research and Theory*, *49*, 209-246.

Frank, M. C., Goodman, N., Lai, P., & Tenenbaum, J. (2009). Informative communication in word production and word learning. In *Proceedings of the annual meeting of the cognitive science society* (Vol. 31).

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

Franke, M. (2009). *Signal to act: Game theory in pragmatics: University of amsterdam phd dissertation.*

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

Friston, K., Rigoli, F., Ognibene, D., Mathys, C., Fitzgerald, T., & Pezzulo, G. (2015). Active inference and epistemic value. *Cognitive Neuroscience*, *6*, 187-214. doi: 10.1080/17588928.2015.1020053

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

Goodman, N. D., & Stuhlmüller, A. (2013). Knowledge and implicature: Modeling language understanding as social cognition. *Topics in cognitive science*, *5*(1), 173–184.

Grice, H. P. (1975). Logic and conversation. In P. Cole & J. L. Morgan (Eds.), *Syntax and semantics 3: Speech acts* (p. 26-40). New York: Academic Press.

Hohwy, J. (2013). *The predictive mind.* Oxford, UK: Oxford University Press.

Jones, E. E., & Davis, K. E. (1965). From acts to dispositions the attribution process in person perception. In *Advances in experimental social psychology* (Vol. 2, pp. 219–266). Elsevier.

Kelley, H. H. (1967). Attribution theory in social psychology. In *Nebraska symposium on motivation.*

Kelley, H. H., & Stahelski, A. J. (1970). Social interaction basis of cooperators' and competitors' beliefs about others. *Journal of personality and social psychology*, *16*(1), 66 – 91.

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

Qing, C., & Franke, M. (2015). Variations on a Bayesian theme: Comparing Bayesian models of referential reasoning. In H. Zeevat & H.-C. Schmitz (Eds.), *Bayesian natural language semantics and pragmatics* (p. 201-220). Springer.

Sikos, L., Venhuizen, N., Drenhaus, H., & Crocker, M. (2019, 04). *Reevaluating pragmatic reasoning in web-based language games.* doi: 10.13140/RG.2.2.30535.14249

Wasow, T. (2015). Ambiguity avoidance is overrated. In S. Winkler (Ed.), *Ambiguity: Language and communication* (p. 29-47). de Gruyter.