Psych 204: Project Update

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Abstract

What makes a question useful? What makes an answer appropriate? In this paper, we show that a recently proposed probabilistic model of question-answer behavior provides a unifying account of four separate effects from the psycholinguistics and pragmatics literature. For three of these effects, we formulate a pragmatic answerer who is informative with respect to the questioner's underlying goals (or QUD), which are inferred given the context. These simple applications illustrate the role of the QUD in guiding answerer inference. In the final effect we model, the questioner's QUD affects the question they choose to ask; thus, our pragmatic answerer may use the question utterance itself as a signal to help infer the questioner's goals.

Keywords: language understanding; pragmatics; Bayesian models; questions; answers

Introduction

Q:"Are you gonna eat that?" A:"Go ahead."

In this (real life) example, Q strategically chooses a question that differs from her true interest, avoiding an impolite question, yet manages to signal to A what her interests are; A in turn reasons beyond the overt question and provides an answer that addresses Q's interests. This subtle interplay raises two questions for formal models of language: What makes a question useful? What makes an answer appropriate?

Recent work on Rational Speech Act (RSA) models (Frank & Goodman, 2012; Goodman & Stuhlmüller, 2013) has mathematically formalized pragmatic language understanding as a form of recursive Bayesian inference, where listeners reason about speakers who choose utterances that maximize information gained by an imagined listener. In this paper we extend the RSA framework to address simple question-answer dialogs. The immediate challenge in doing so is that the speaker utility in RSA is based on direct information provided by an utterance—since questions don't provide direct information, we must say what utility they do have.

We suggest, following Van Rooy (2003), that the value of a question is the extent to which it can be expected to elicit information relevant to the questioner later in the dialogue. More specifically, for the questioner, the value of a question is the expected information gained about her interests, given the set of likely answers it may provoke. This diverges from regular RSA in that the value of a question depends on information gained by the speaker (rather than listener), and that this information comes later in the (very short) conversation.

To fully specify this questioner we need a model of the answerer, which can serve as both the model assumed by a questioner, and as a model of answer behavior itself. As in previous RSA models, we construct a sequence of progressively more sophisticated answerers. At the most naïve level, the answerer provides a literal answer to the question (without attempting to be informative); at the most sophisticated level, a pragmatic answerer infers the most likely true interests of the questioner, and then informatively addresses those interests. The latter model extends RSA to reason about the topic of conversation, as proposed by Kao, Wu, Bergen, and Goodman (2014) to explain hyperbole; it goes beyond previous work by using the explicit question as a (potentially indirect) cue to this topic.

The rest of this paper is structured as follows. First, we lay out the details of our question-answer model and contrast our approach with some related models (notably the decision-theoretic approach proposed by Van Rooy, 2003). We then proceed to introduce the four scenarios we wish to model and show that the same pragmatic answerer model can qualitatively account for all of the effects observed in these scenarios. We close with a brief discussion of future directions.

Background and Related Work

How should a questioner choose between questions? We start by assuming that the questioner aims to *learn information relevant to a private goal*. In order to choose a question that results in useful information, the questioner reasons about how the answerer would respond, given different possible states of the world; she selects a question that results in an answer that tends to provide goal-relevant information.

More formally, suppose there is a set of world states $\mathcal{W}$, a set of possible goals $\mathcal{G}$, a set of possible questions $\mathcal{Q}$, and a set of possible answers $\mathcal{A}$. These sets are taken to be in common ground between the questioner and the answerer. An informational goal $g \in \mathcal{G}$ is a projection function that maps a world state to a particular feature or set of features that the questioner cares about; this is similar to the notion of a question-under-discussion (Roberts, 1996). We will use the notation $P_g(w)$ to indicate the probability $\hat{P}(g(w))$ of the g-relevant aspect of w under the projected distribution $\hat{P}(v) = \int_{\mathcal{W}} \delta_{v=g(w)} P(w)dw$.

The **questioner** takes a goal $g \in \mathcal{G}$ as input and returns a distribution over questions $q \in \mathcal{Q}$:

$$P(q|g) \propto e^{\mathbb{E}_{P(w^*)}\left[D_{KL}(P_g(w|q,w^*) \,\|\, P_g(w))\right] - C(q)}$$

It trades off the cost of asking a question, $C(q)$, and expected information gain. The cost likely depends on question length, among other factors. Information gain is measured as the Kullback-Leibler divergence between the prior distribution over g-relevant worlds, $P_g(w)$, and the posterior distribution one would expect after asking a question q whose answer reflected true world state w^*:

$$P_g(w|q,w^*) = \sum_{a \in \mathcal{A}} P_g(w|q,a)P(a|q,w^*)$$

This distribution has two components: First, it depends on $P(a|q,w^*)$, a model of the answerer which we will explore shortly. Second, it depends on (the goal projection of) $P(w|q,a)$, an 'interpreter' that specifies the likelihood assigned to different worlds given question and answer pairs.

To define the interpreter function, which all agents use to compute the literal interpretation of a question-answer pair, we must assign questions a semantic meaning. We assume that a question is an informational goal that projects from worlds to the answer set $\mathcal{A}$. This is equivalent to the more common partition semantics of Groenendijk and Stokhof (1984), as can be seen by considering the pre-image of such a projection; an answer picks out an element of the partition via $q^{-1}(a)$. The **interpreter** constrains the prior on worlds to the subset of its support that is consistent with the semantics of a question-answer pair[1]:

$$P(w|q,a) \propto P(w)\delta_{q(w)=a}$$

We next describe two different answerer models; the questioner could assume any one of them, leading to two corresponding versions of the questioner model. All answerers take a question $q \in \mathcal{Q}$ and a true world state $w^* \in \mathcal{W}$ as input and return a distribution over answers $a \in \mathcal{A}$. The **literal answerer** simply chooses answers by trading off prior answer probability and how well a question-answer pair conveys the true state of the world to an interpreter:

$$P(a|q,w^*) \propto P(a)P(w^*|q,a)$$

For a fixed question, this is equivalent to the speaker in previous RSA models. The question enters only in specifying the literal meaning of an answer.

The **pragmatic answerer** also evaluates answers with respect to how well they address the informational goal, but doesn't take the question's explicit meaning at face value. Instead, the pragmatic answerer reasons about which goals g are likely given that a question q was asked, and chooses answers that are good on average:

$$P(a|q,w^*) \propto p(a) \sum_{g \in \mathcal{G}} P(g|q)P_g(w^*|q,a)$$

Reasoning backwards from questions to goals is a simple Bayesian inversion of the (explicit) questioner using a prior on goals:

$$P(g|q) \propto P(q|g)P(g)$$

For all of the questioner and answerer models, we can vary how strongly optimizing they are—that is, to what extent they are sampling from the distributions defined above, and to what extent they deterministically choose the most likely element. For any such distribution over utterances, we introduce an optimality parameter α and transform it by $P'(x) \propto P(x)^{\alpha}$.

This concludes our specification of the model space, giving a set of two answerers and two corresponding questioners that reason about them. We have implemented these models in WebPPL, a probabilistic programming language (Goodman & Stuhlmüller, electronic), and runnable code for all reported simulations will be available online at http://hawkrobe.github.io/Q_and_A/. The model predictions shown throughout the rest of the paper are computed using this implementation.

This Bayesian account of question and answer behavior bears some resemblance to recent decision theoretic or game theoretic accounts in linguistics. These theories were a response to early work on question and answer semantics, which focused on the notion of informativeness. In Groenendijk & Stokhof's (1984) theory of question and answer semantics, asking a question induces a partition over the space of possible worlds, where each cell of the partition corresponds to a possible answer. An answer, then, consists of eliminating cells in this partition, and the most useful answers are those that eliminate all relevant alternatives to the true world. However, as van Rooy (Van Rooy, 2003) and others (Ginzburg, 1995) have pointed out, this predicts that *wh*-questions like "Where can I buy an Italian newspaper?" can only be fully resolved by exhaustively mentioning whether or not such a newspaper can be bought at each possible location. Clearly, this is not the case: a single nearby location would suffice. These theories also cannot account for contextual variation in what counts as a useful answer, such as identification questions like "who is X?" (Boër & Lycan, 1975), and to questions like "where are you?" that permit answers at many levels of abstraction (Potts, 2012).

More recent theories have tried to fix these problems by introducing some consideration of the questioner's goals. van Rooy (2003), for instance, formalizes these goals as a decision problem faced by the questioner. A useful answer under this decision theoretic account is one that maximizes the expected value of the questioner's decision problem. A useful question is one that induces a sufficiently fine-grained partition, optimally distinguishing the worlds relevant to the decision problem. While this framework elegantly accounts for the context-dependence and relevance-maximization of question and answer behavior, it assumes that the questioner's decision problem is known *a priori* by the answerer. If this were the case, the act of asking questions would seem irrelevant: why wouldn't the answerer directly tell the questioner which action to take? Nevertheless, while empirical work has almost exclusively focused on *answerer* behavior, van Rooy's approach suggests that the question itself is important in prompting a relevant answer. Our model is an effort to expand on this core idea in a probabilistic framework that also provides an inferential mechanism for the answerer to *infer* the 'decision problem' instead of assuming it.

Clark (1979): Experiment 4

Our model can provide different—sometimes over- or under-informative—answers to the same explicit question, depending on context. For our first illustration, we model Clark's (1979) whiskey study. In this study, researchers called liquor

[1] We should also have a semantic evaluation function that maps an answer utterance to its value in $\mathcal{A}$. For clarity we assume this is a trivial mapping and suppress it.

merchants and opened the conversation with one of two sentences to set context: “I want to buy some bourbon” (the *uninformative* condition) or “I’ve got $5 to spend” (the *five dollar* condition). They then asked, “Does a fifth of Jim Beam cost more than $5?” Merchants gave a literal yes/no answer significantly more often in the latter condition than the former, where an exact price was more common.

When provided with the five dollar context, the merchant inferred that the questioner’s goal was literally to find out whether or not they could afford the whiskey, hence a simple ‘yes’ sufficed. In the uninformative context, however, the merchant inferred that the questioner’s goal was just to buy whiskey, so the exact price was the most relevant response (Clark, 1979).

Our world state is simply the whiskey’s price ($1, $2, ..., $10). There are two possible goals: learning the price of whiskey and learning whether the price is greater than $5. The set of answers includes exact prices as well as “yes” and “no”, with lower cost for “yes” and “no” than the price statements. We model the context sentence as affecting the questioner’s goal prior. When the context is “I’d like to buy some whiskey,” we assume that the the two goals are equally likely. When it is “I only have $5 to spend,” we assume that it is 9:1 in favor of learning whether the price is greater than $5.

Results When the question is “Does Jim Beam cost more than $5?”, the correct Boolean answer is the most probable choice (at probability .44 and .49). Critically, there is a context-dependence for answers to this question: when prefaced with “I’d like to buy some whiskey.”, the correct exact price answer is favored more strongly (at probability .18) than when the context is “I only have $5 to spend.” (probability .11). By contrast, the literal answerer (which has no natural way to account for context) does not make differential predictions in the two situations. This suggests that our pragmatic *answerer* is consistent with human behavior in psychologically interesting situations, passing a first, qualitative, test.

Groenendijk and Stokhof (1984)

For a slightly more complex example, we consider the classic puzzle of *mention-some* and *mention-all* readings of wh-questions, as raised by Groenendijk and Stokhof (1984). Some questions, like “Who is coming to dinner tonight?” are clearly meant to elicit an exhaustive list of the entities that are answers. For other questions, like “Where can I find a bathroom in this building?”, a single answer would be sufficient.

The question “Where can one buy an Italian newspaper?” can be ambiguous between these meanings depending on who is asking: if it is a tourist, they probably just want to know the nearest place, but if it is a businessperson trying to build a newspaper distribution network in town, they likely want the whole list.

Our world state is an object consisting of four cafes in town. Each cafe is assigned two properties: its distance from the speaker and whether or not it sells Italian newspapers. There are two possible goals: learning the identity of the nearest cafe selling a newspaper and learning the identity of *all* cafes selling a newspaper. The set of answers includes all 16 combinations of different cafes (e.g. “cafe 1 and cafe 3” or “cafe 2, cafe 3, and cafe 4”), as well as the answer “none”.

The prior over answer utterances is constructed as follows: there is a 10% chance of saying “none,” as it would be rude. Otherwise, the agent selects one of the four cafes and terminates with probability .5. If the agent does not terminate, they pick another cafe from the list and continue until either terminating or running out of possible cafes. This naturally gives longer answers lower probability, reflecting their higher cost of utterance.

We model the context sentence as affecting the questioner’s goal prior: if they say “I’m new here,” there is a 9:1 chance that they are interested in the closest location with a newspaper; if they say “I’m a businessperson...,” there is a 9:1 chance that they are interested in all of the newspaper locations.

Results

We set the world to be the following :

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world = {'cafe1' : [3, false],
         'cafe2' : [1, true],
         'cafe3' : [3, true],
         'cafe4' : [3, true]}
```

and enumerated over all model executions for both contexts. We find that the highest probability response given the “I’m new here” context is the single location “cafe2,” with probability 0.56. Given the “I’m a businessperson...” context, however, the highest probability response is the conjunction “cafe2 and cafe3 and cafe4,” with probability 0.82. Note that cafe 1 was not assigned any probability in either context because it did not sell Italian newspapers (demonstrating that the pragmatic answerer will not lie), and that the nearest cafe was given precedence in the “tourist” context. Crucially, the only difference between our model of this scenario and the Clark scenario is the set of QUDs, the structure of the world, and the meanings of the answers. The questioner and answerer functions stayed exactly the same.

Gibbs Jr. & Bryant (2008): Experiment 3

The recent study on time-telling behavior by Gibbs Jr and Bryant (2008) is the final example we will address where answerers infer QUDs solely on the basis of context. For background, it has been shown in previous work that people typically round their answers to the nearest 5 or 10 minute interval when asked ‘Do you have the time?”, even when they’re wearing a digital watch (Der Henst, Carles, & Sperber, 2002). Gibbs Jr. & Bryant replicated this result, and then performed a follow-up study where they preceded their question by the context “I have a meeting at 4:00.” They found that the tendency to round times decreased as a function of the time remaining until the stated deadline: when people were asked at 3:40, they would say “It’s 3:45,” but when people were asked at 3:53, they would make their response precise to the minute. They explain this result by appealing to the questioner's goals: while an approximate time is sufficiently informative with respect to most goals, a questioner who is running late to an appointment may have the goal of judging whether to rush, in which case a precise time is needed.

We have not yet implemented this model, but the plan is to represent a world state as the true current time and the time of the questioner's appointment. There are two possible goals: learning the (approximate) time and learning whether to rush. The set of answers is the set of times that could be given (e.g. 3:30, 3:31, ..., 4:00), with higher prior probability for round numbers. Again, this reflects relative cost of utterance ("ten 'til" vs. "three thirty-seven"). Rather than inferring the QUD on the basis of a context sentence provided by the questioner, the probability of the "should I rush?" QUD is a function of the distance between the current time and the appointment time.

Clark (1979): Experiment 5

Our final scenario is a critical test for the questioner component of our model: if our RSA model is correct, the questioner's choice of utterance itself should guide a pragmatic answerer's inferences about likely underlying goals. In a follow-up to the first experiment we modeled in this paper, Clark (1979) tested the inferences the merchant made about the questioner's goals on the basis of their question utterance, without hearing an explicit context sentence. The goal of the questioner was to find out all the kinds of credit cards the merchant accepted, and they could ask questions at different levels of specificity, e.g. "Do you accept Master Charge cards?" or "Do you accept credit cards?" or "Do you accept any kinds of credit cards?" He found that as the noun used in the question became less specific, literal *yes/no* responses were less likely and the alternative (over-informative) response *We accept x, y, z cards.* were preferred.

We have also not yet implemented this model, but the plan is to represent a world state as an object mapping each possible kind of credit card (Visa, Discover, MasterCard) to a boolean value representing whether the establishment will accept that card. There are four possible goals: learning whether or not the establishment accepts (1) Visa, (2) Discover, (3) MasterCard, or (4) learning the exact list of cards that the establishment accepts. The set of answers includes "yes," "no," and all possible lists of the three cards listed above, with "yes" and "no" slightly preferred for their lower cost. Because there is now a decision between different questions that the questioner must entertain, we must also specify a *questioner* prior, which we set to uniform for simplicity.

General discussion

Remarkably, the same questioner and answerer program was able to reproduce patterns of question-answer behavior in four different scenarios. It captured both explicit and implicit context effects as well as effects where the question itself served as a signal about the relevant underlying goals. Note that all of these studies were focused primarily on answerer behavior, allowing us to show that our model of the questioner is consistently used as an submodule of the answerer. However, because questioner behavior was always manipulated as an independent variable, we could not test the questioner model as a stand-alone predictor of human questioning behavior. This reflects a general neglect of questioner behavior in the psycholinguistics literature, and further experiments are needed to test its predictions.

Perhaps the most important formal advance of the models considered here is to move the Rational Speech Act framework beyond interpretation of single utterances (in context), to consider the dynamics of simple dialogs (albeit consisting of a single question and its answer). Doing so requires replacing the immediate motive to convey true information with the more distant motive to provoke useful information from one's interlocutor. On the answerer side, sophisticated inference was required to account for the implicit interests of the questioner. This provides a useful connection to current game-theoretic and decision-theoretic models (Vogel, Bodoia, Potts, & Jurafsky, 2013; Van Rooy, 2003), which also emphasize the importance of goals and speaker beliefs in communication but emphasize less the complex interplay of inference between questioner and answerer.

Humans are experts at inferring the intentions of other agents from their actions (Tomasello, Carpenter, Call, Behne, & Moll, 2005). Given simple motion cues, for example, we are able to reliably discern high-level goals such as chasing, fighting, courting, or playing (Barrett, Todd, Miller, & Blythe, 2005; Heider & Simmel, 1944). Experiments in psycholinguistics have shown that this expertise extends to speech acts. Behind every question lies a goal or intention. This could be an intention to obtain an explicit piece of information ("Where can I get a newspaper?"), signal some common ground ("Did you see the game last night?"), test the answerer's knowledge ("If I add these numbers together, what do I get?"), politely request the audience to take some action ("Could you pass the salt?"), or just to make open-ended small talk ("How was your weekend?"). These wildly different intentions seem to warrant different kinds of answers. By formalizing the computational process by which answerers infer these different intentions, our model framework provides a unifying way to accommodate this diversity.

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