Tell Me Everything You Know:
A Conversation Update System for the Rational Speech Acts Framework

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Abstract

The Rational Speech Acts (RSA) framework has been applied to an increasing number of linguistic phenomena. Despite its promise as a model of conversational reasoning, it has rarely been used to model more than a single conversation turn. I propose a system for conversation update in the RSA framework that allows iterative simulations of production and comprehension. I explore three key issues: how to simulate the Common Ground; how to update the Common Ground and participant belief states; and how to select observations.

1 Introduction

The Rational Speech Acts framework (RSA) (Frank and Goodman, 2012) has been used to model an increasing number of linguistic phenomena in recent years.[1] Bayesian approaches like the RSA are based on three fundamental assumptions about language users: (1) that they behave **rationally**; (2) that they reason **recursively** about each other's behavior; and (3) that they **adapt**: they update their linguistic models as they encounter new evidence.

Despite this last assumption, the RSA framework has mainly been used to model a single conversation move: the production or interpretation of a single utterance.[2] Although intuitively, the posterior distribution calculated by RSA models of production and comprehension could be used to update the conversation state, there is no existing model of how this should be done.

I propose a system for conversation update in the RSA framework that allows iterative application of Bayesian reasoning in production and comprehension. I explore three key issues: (1) how to model the Common Ground; (2) how to update the Common Ground and the beliefs of the conversation participants; and (3) how to sample observations.

2 The Rational Speech Acts framework

The Rational Speech Acts model is a pragmatic framework where speakers and listeners use Bayesian inference to reason about each other's linguistic behavior. In production, the speaker samples a world to observe and reasons about which utterance is most likely to communicate the world to their listener. The speaker achieves this goal by simulating how the listener will interpret each potential utterance. In comprehension, the listener's goal is to infer the observed world given the speaker's utterance. The listener reasons about the speaker's meaning by simulating their production process.

Although this recursive reasoning process is potentially infinite, most RSA models focus on the levels shown in Figure 1: the Pragmatic Listener, the Pragmatic Speaker, and the Literal Listener.[3]

The **Pragmatic Listener** represents the actual listener. Given an utterance, they reason about the observed world using Bayes' rule: they calculate the utterance's likelihood given each world, $p(u|w)$, using a mental model of the speaker (the Pragmatic Speaker), discounted by their prior belief in the world, $p(w)$.

The **Pragmatic Speaker** serves as both the actual speaker and the listener's mental model of the speaker. The speaker samples a world and picks an utterance based on its normalized utility, calculated by a simplified mental model of the listener (the

*Many thanks to Alex Göbel, Rodica Ivan, and the reviewers of SCiL for their very helpful comments and suggestions.

[1] Among others, hyperbole (Kao et al., 2014); irony (Cohn-Gordon and Bergen, 2019); politeness (Yoon et al., 2016); implicature (Bergen et al., 2012; Degen et al., 2015; Potts et al., 2016; Bergen et al., 2016); and social meaning (Cohn-Gordon and Qing, 2018).

[2] Hawkins et al. (2015) model question and answer pairs; Smith et al. (2013) and Brochhagen et al. (2016) simulate word learning with multiple generations of learners.

[3] At each step, the probabilities are renormalized; I omit the softmax terms from the model in Figure 1 for readability.

Proceedings of the Society for Computation in Linguistics (SCiL) 2021, pages 244-253.
Held on-line February 14-19, 2021

Literal Listener

$$p(w|u) \propto p(u|w)p(w)$$
$$\propto [[\mathrm{u}]]^w p(w)$$

Pragmatic Speaker

$$p(u|w) \propto p(w|u)p(u)$$
$$\propto LitList(w,u)p(u)$$

Pragmatic Listener

$$p(w|u) \propto p(u|w)p(w)$$
$$\propto PragSpeak(u,w)p(w)$$

Figure 1: Basic RSA model (Bergen et al., 2012)

Literal Listener). The more likely a listener is to recover the speaker's intended meaning from an utterance, the higher its utility.

The **Literal Listener** reasons literally about the speaker's intended meaning. It calculates the posterior probability $p(w|u)$ by taking into account the probability of the utterance given the world, $p(u|w)$, and the prior probability of the world, $p(w)$. Unlike the Pragmatic Listener, the Literal Listener does not reason about the speaker, but just assumes that an utterance's probability given a world is equal to its truth in that world.

3 Principles of conversation update

I take the goal of conversation to be information-sharing (Lewis, 1979): participants pool their information together in the Common Ground.[4]

I model an individual's knowledge state as a distribution over worlds, where the probability of each world reflects the participant's degree of certainty about whether the world is the actual one. Given this representation, conversation is a process where participants contribute information from their own beliefs in order to reduce their shared uncertainty.

In the following sections I lay out some desired characteristics of a conversation update system.

3.1 Cooperative contributions

One desired characteristic of a conversation update system is that it should capture cooperative behavior by participants. Grice (1975) lays out four maxims that define cooperative behavior: Quantity, Quality, Relation, and Manner. A cooperative speaker is informative, clear, truthful, and relevant.

The existing RSA framework partially captures cooperative behavior: relevant, truthful, and clear utterances are preferred because they improve the likelihood of the listener understanding the utterance. However, the basic RSA model cannot guarantee true informativity, since it cannot assess the novelty of information. A conversation update system should prefer utterances that contribute new information, while maintaining the RSA's preference for true, relevant, and unambiguous utterances.

3.2 Common Ground development

The Common Ground represents the shared beliefs of the conversation participants (Stalnaker, 2002). I model the Common Ground as a distribution over worlds reflecting the state of the conversation. Because the goal of conversation is to share information, the Common Ground should become more settled as the conversation proceeds. One way to measure this is to calculate the **entropy** of the Common Ground: the average uncertainty about which world is real. In a successful conversation, the entropy of the Common Ground should decrease.

In addition, the Common Ground should resist contradictions. Once an assertion has been accepted into the Common Ground, participants should resist later updates that would contradict it.

3.3 Belief consistency and convergence

In a successful conversation, participants are able to learn from each other. This should lead their beliefs to become more similar (convergence). However, we do not always believe everything that we are told: listeners should be less willing to believe claims when they contradict their own beliefs. Thus, a model of conversation should allow participants to update their beliefs based on how they assess the information that has been shared.

4 Conversation update in the Rational Speech Acts framework

In this section, I describe a basic model for conversation update in the RSA. I will model conversations with two participants, A and B, who take turns. A **conversation move** consists of the production or interpretation of a single utterance, simulated as a single application of the basic RSA model of production or comprehension.

[4] As Coppock (2018) points out, this is not the only goal of conversation. An alternative is **perspective alignment** (Fuchs, 2020): in this view, participants want the Common Ground to mirror their beliefs. However, this view is less compatible with the RSA framework, which assumes that speakers make positive contributions (contributions increase the probability of a world). I return to this alternative view in Section 8.

Set Bel_A and Bel_B
CG = Uniform(worlds)
Set Speaker to A and Listener to B
while *true* **do**
  obs = sample(Bel_S)
  u = PragSpeak(obs,CG)
  posteriors = PragList(u,CG)
  CG = UpdateCG(posteriors,CG,lr)
  Switch Speaker and Listener
end

Figure 2: Basic RSA conversation update model

In order to track multiple conversation moves, we must represent the current state of the conversation: the Common Ground. Here we can build on prior work: the Common Ground has been incorporated into previous RSA models (Goodman and Stuhlmüller, 2013; Goodman and Lassiter, 2014; Qing et al., 2016), though I will propose a different formulation in Section 5.

The current speaker's goal is to communicate a possible world from among a set of candidates for the real world.[5] In order for participants to volunteer new information, we must also have representations of each of their private belief states, and a method for selecting contributions from them.

In order to move a conversation forward, each contribution must be used to update the conversation state. Minimally, this entails a mechanism for updating the Common Ground. To model participants who learn from each other, it also entails a mechanism for updating their private belief states.

The update process should take into account both the previous state of the conversation and the new information. I propose that the previous state is updated with the posteriors from the basic RSA model, discounted by a learning rate.[6]

The proposed conversation algorithm is shown in Figure 2. In the next sections, I explore various ways of implementing these components. To illustrate how each component affects the model's predictions, I use example scenarios from the MutualFriends dataset (He et al., 2017). Each world is a tuple of features of an individual, such as their major and their location preference (Figure 3).

[5] As Qing et al. (2016) argues, this is equivalent to assuming a maximal Question Under Discussion.

[6] As discussed by Qing and Franke (2015), an alternative is to update only the probability of the world with the highest probability according to the Pragmatic Listener.

Ina world: [Astronomy, Student, Indoors]
Katie world: [Astronomy, Student, Outdoors]
Nancy world: [German, Student, Outdoors]
Sally world: [German, Student, Indoors]

Figure 3: MutualFriends example

Production Model
Literal Listener
$p(w|u) \propto [[\text{u}]]^w CG(w)$
Pragmatic Speaker
$p(u|w) \propto LitList(w,u)p(u)$
Comprehension Model
Literal Listener
$p(w|u) \propto [[\text{u}]]^w CG(w)$
Pragmatic Speaker
$p(u|w) \propto LitList(w,u)p(u)$
Pragmatic Listener
$p(w|u) \propto PragSpeak(u,w)CG(w)$

Figure 4: Shared Common Ground RSA

5 The Common Ground

The Common Ground represents the current state of the conversation: the shared beliefs that the conversation participants have developed by pooling information. The basic RSA model implicitly incorporates the Common Ground via the prior distribution over worlds, shared between the speaker and listener (Bohn et al., 2019). I develop this into an explicit representation by creating separate distributions for the Common Ground and for the private beliefs of each conversation participant.

The Common Ground has been modeled explicitly in the RSA framework in previous work. Qing et al. (2016) treat the Common Ground as a set of worlds whose members can vary. In their system, the Pragmatic Listener jointly reasons over the Common Ground and the speaker's intended meaning; the posterior distribution over the Common Ground represents uncertainty over its membership, not over the probabilities of each world.

Treating the Common Ground as a set whose members can vary is consistent with the update by set intersection approach commonly used in formal semantics. However, I pursue a different approach: I represent the Common Ground as a

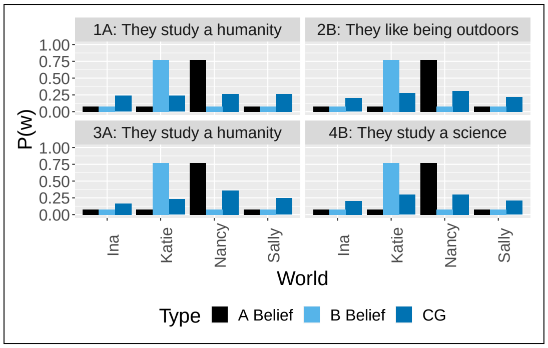

Figure 5: 4 moves with Shared Common Ground

full distribution over worlds and relax the assumption that the world set is monotonically decreasing. The advantage of this approach is that it allows the Common Ground to be directly substituted in for the world priors in the basic RSA model, allowing the proposed conversation update system to be easily adapted to any existing RSA model.[7]

5.1 A Shared Common Ground

Having created distributions to represent the participants' beliefs and the Common Ground, we can incorporate them into the RSA model. Conversation participants cannot access each other's beliefs, but they can access each other's public commitments: the Common Ground. In production, the Pragmatic Speaker can use the Common Ground as a model of the listener's prior beliefs. In comprehension, the Pragmatic Listener can use the Common Ground in its model of how the speaker samples observations and its model of the speaker's model of the listener.[8] The Shared Common Ground RSA model is shown in Figure 4.

5.1.1 Shared Common Ground results

The Shared Common Ground model allows us to simulate how new information is incorporated into the discourse context. First, consider a case where A and B hold different beliefs. In the Mutual-Friends dataset, a world is a person with certain features (Figure 3). In this example, A thinks the person is Nancy, while B thinks it is Katie.

As shown in Figure 5, the Common Ground is initially uniform (empty), but begins to favor the Nancy and Katie worlds as A and B share information.[9] Thus, the Shared Common Ground meets the most basic criteria of a conversation update model: it tracks information across discourse turns.

Production Model

Literal Listener

$p(w|u) \propto [[\text{u}]]^w CG_S(w)$

Pragmatic Speaker

$p(u|w) \propto LitList(w,u)p(u)$

Pragmatic Listener (for CG update)

$p(w|u) \propto PragSpeak(u,w)CG_S(w)$

Comprehension Model

Literal Listener

$p(w|u) \propto [[\text{u}]]^w CG_L(w)$

Pragmatic Speaker

$p(u|w) \propto LitList(w,u)p(u)$

Pragmatic Listener

$p(w|u) \propto PragSpeak(u,w)B_L(w)$

Figure 6: Approximate Common Ground RSA

5.2 Approximating the Common Ground

The Shared Common Ground model presented above assumes that participants access a shared representation of the Common Ground. While this is a convenient assumption, it may not be realistic, since it assumes that the listener is always successful (always assigns highest probability to the speaker's intended world).

We can relax this assumption by using separate Common Ground representations for each participant. The listener updates their Common Ground (CG_L) according to their Pragmatic Listener calculation. The speaker runs a separate Pragmatic Listener calculation to update their own Common Ground (CG_S). This also lets the listener use their own beliefs in their Pragmatic Listener calculation rather than the Common Ground. The Approximate Common Ground model is presented in Figure 6.

5.2.1 Approximate Common Ground results

When the Common Ground is approximate, divergence can arise when the listener's prior beliefs differ from the Common Ground, leading to different speaker and listener Pragmatic Listener outcomes.

For instance, in Figure 7, A believes strongly in Nancy, while B begins with a uniform belief distribution. After B's first turn, A's Common Ground

[7] It also allows discourse corrections to be modeled without backtracking, since worlds can regain probability.

[8] Paralleling Goodman and Stuhlmüller (2013)'s information access, the listener's model of the speaker's knowledge.

[9] I use a learning rate of 0.2; the details of the Common Ground update will be discussed further in Section 6.

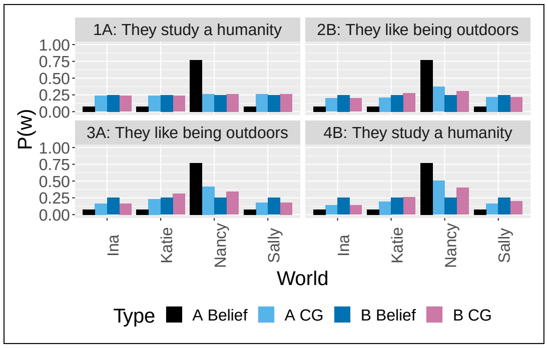

Figure 7: 4 moves with Approximate Common Ground

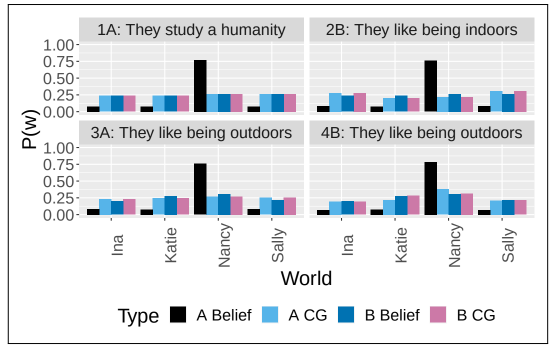

Figure 9: Belief updates (learning rate=0.2)

Set Bel_A and Bel_B
CG = Uniform(worlds)
Set Speaker to A and Listener to B
while *true* **do**
 obs = sample(Bel_S)
 u = PragSpeak(obs,CG_S)
 post_L = PragList_L(u,CG_L,Bel_L)
 CG_L = UpdateCG(post_L,CG_L,lr)
 post_S = PragList_S(u,CG_S,CG_S)
 CG_S = UpdateCG(post_S,CG_S,lr)
 Bel_L = UpdateB(Bel_L,CG_L,post_L)
 Switch Speaker and Listener
end

Figure 8: Belief update conversation model

places more probability on Nancy than B's Common Ground, because of A's prior belief in Nancy.

6 Conversation update

In order to have a multi-turn model of conversation, the output of the RSA production model must be used to update the conversation state. I propose a simple update mechanism: increment the prior probabilities with the posteriors from the Pragmatic Listener, discounted by a learning rate.

It is useful to apply a learning rate for several reasons. First, the Pragmatic Listener calculations can go wrong. Applying a learning rate limits the impact of any one misinterpretation. Second, some meanings are too complex to be conveyed in a single turn. In these cases, it is useful to adopt some information from a single utterance, while preserving some information from the previous distribution.

6.1 Belief updates

In Section 5, we saw how the Common Ground is updated. But conversation is not just about advancing the conversation state: it is also about learning new information. Figure 8 shows a conversation update system that includes belief updates. After calculating the posteriors via the RSA Pragmatic Listener, the listener updates their own beliefs according to the posteriors, discounted by a learning rate. The speaker does not update their own beliefs, since they have not gained new information.

6.1.1 Belief update results

To see how the belief updates work, let us return to the scenario explored in Figure 7. Figure 9 shows how both the individual beliefs and the approximations of the Common Ground change over the course of the conversation. Because B has no strong beliefs of their own, their beliefs shift more than those of A, who has a prior belief in Nancy. Since the learning rate is fixed, B's beliefs and Common Ground remain very similar.

If both participants hold different strong views, they will eventually become less certain of their initial positions. If A starts out believing in Nancy and B starts out believing in Katie, both Common Grounds and sets of private beliefs will eventually converge and assign equal probability to Nancy and Katie. Figure 10 illustrates this. While the Common Ground of each participant still reflects a bias towards their initial belief, it assigns high probability to both Nancy and Katie, and each participant's belief in their initial choice has decreased.

6.2 Varying the learning rates

The learning rate can be adjusted to explore conversation dynamics. For instance, the learning rate might be higher for the speaker's Common Ground

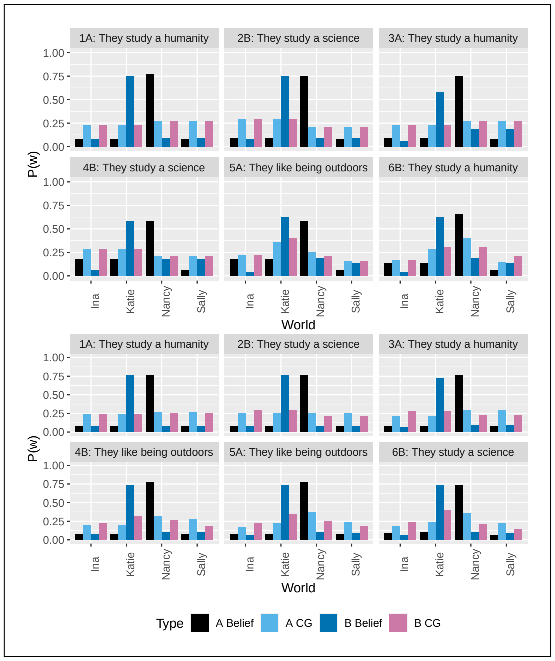

Figure 10: Belief updating with informed speakers (Top: lr=0.2, Bottom: speaker lr=0.2, listener lr=0.05)

update than the listener's, since the speaker may trust their own information more. A skeptical listener is shown in Figure 10 (bottom). Participants may also be more willing to update the Common Ground than their own beliefs; listeners sometimes accept an assertion while privately disagreeing. A lower learning rate for belief updates models this.[10]

6.3 Uncertainty-based updates

Because we have models of both the Common Ground and the listener's private beliefs, another possibility is to allow larger updates when the listener's uncertainty is high. A listener who is uncertain may be more willing to learn from the speaker.

The current uncertainty of the Common Ground and of the participants' individual belief states can be measured using entropy: when the entropy of the listener's belief distribution is high, they are relatively undecided, and should be more willing to learn from their conversation partner.

Figure 11 shows how setting individual learning rates based on the uncertainty of each participant allows uncertain participants to learn from more certain ones. Since the entropy of A's belief distribution is low, A's belief updates are very small, while B starts with a high-entropy belief distribution and applies large belief updates.

7 Making observations

In Section 3, I discussed Grice's Maxims as principles for cooperative speaker behavior that a model of conversation update should strive to capture. The basic RSA model captures these principles in a limited way: the Pragmatic Speaker is truthful and informative in the sense of favoring true and informative utterances for a given world.

However, real speakers not only select utterances to communicate, but decide what information to prioritize. Thus, in a conversation update model, we would like the speaker's observation sampling process to lead to cooperative contributions. In this section, I explore different approaches to the issue of observation selection.

7.1 Weighted sampling

In the simulations presented in Sections 5 and 6, I used **weighted selection**: a meaning is sampled from the speaker's beliefs based on its probability.

Weighted sampling incorporates a pressure towards truthfulness, since if a speaker assigns no probability to a world, it will not be sampled. However, this bias towards truth is unintuitively weak in the probabilistic belief system I have proposed.

Consider a speaker with no strong beliefs. Weighted sampling will lead them to assert beliefs at random, since all worlds are equally likely. This works for a single turn, but since it triggers an update to the Common Ground, it can cascade and lead the Common Ground to flip-flop indefinitely.

This is shown in Figure 12, where A holds a strong belief in Nancy, while B holds no strong beliefs.[11] Unfortunately, B samples Katie and produces an utterance contradicting A's previous claim. Contradictions are not always bad: A and B might legitimately hold different opinions. But in this case, it is just chance that B samples Katie. This is undesirable: if the speaker holds no strong beliefs, they should avoid committing to a stance.

7.1.1 Setting a belief threshold

One solution to this uncooperative behavior is to use uncertainty-based updates, as in Section 6.3. Another is to add a belief threshold to the sampling algorithm. Instead of sampling worlds in proportion to their probability, the **thresholded sampler** filters out low-confidence worlds before sampling.

[10] A possible direction for extending existing RSA models of politeness (Yoon et al., 2016, 2017).

[11] I present results without belief updates for simplicity, but the consequences are worse when this updates A's beliefs.

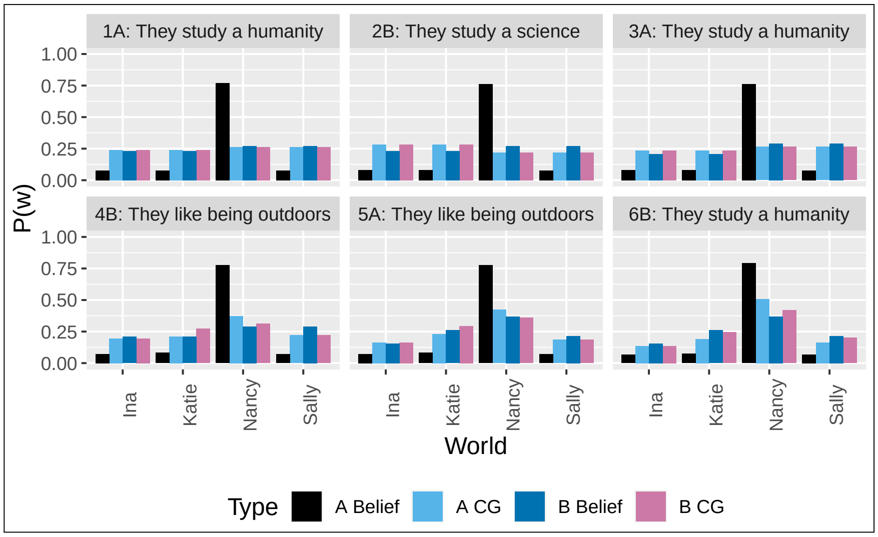

Figure 11: Entropy-based update example

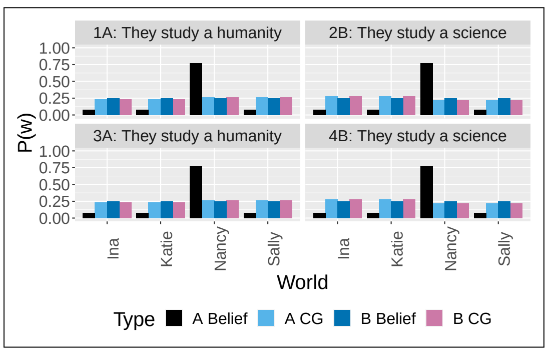

Figure 12: Sampling from a uniform belief distribution leads to flipflopping in the Common Ground

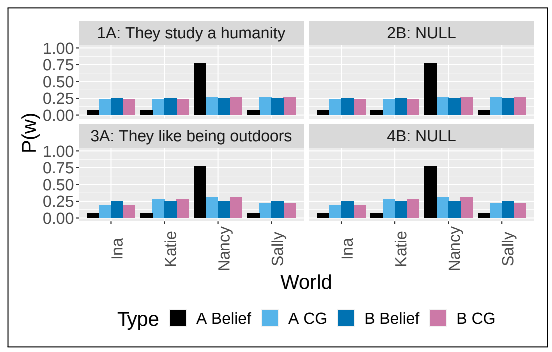

Figure 13: A threshold lets noncommittal speakers pass

If the speaker holds no strong beliefs, the thresholded sampler may not return any world. To avoid this, I introduce a null utterance:[12] when the null utterance is produced, all updates are skipped and the Common Ground is not changed.

As Figure 13 shows, this improves the outcome for the scenario discussed in the previous section. Since B holds no beliefs with certainty above threshold, they select the null utterance at each turn. B's utterances no longer cancel out A's, and A's belief in Nancy propagates to the Common Ground.

7.2 Informative selection

The weighted sampler selects observations based on their truth, but does not consider their informativity. But cooperative speakers do not just avoid making false contributions: they also strive to make useful ones. Participants may hold beliefs about many aspects of the world: which are the most important to communicate?

Informativity has two components: relevance and non-redundancy. Since relevance has been addressed by previous work,[13] I concentrate on redundancy. To be non-redundant, a speaker should not repeat previously shared information. This means that an informative sampler must consider what information is already in the Common Ground.

Consider the situation illustrated in Figure 14: B believes that the individual is Katie, and A believes that the individual could be either Nancy or Katie. Since A's prior for Katie is higher, the weighted sampler is likely to select Katie on each of A's turns. This leads A to keep describing Katie, even though

[12]Null utterances are independently motivated by previous work as one solution to a kind of problem that can arise in RSA inference. See Bergen et al. (2016) for further discussion.

[13]Relevance means relation to a Question Under Discussion (Roberts, 1996), which previous work has added to the RSA (Kao et al., 2014; Hawkins et al., 2015; Qing et al., 2016).

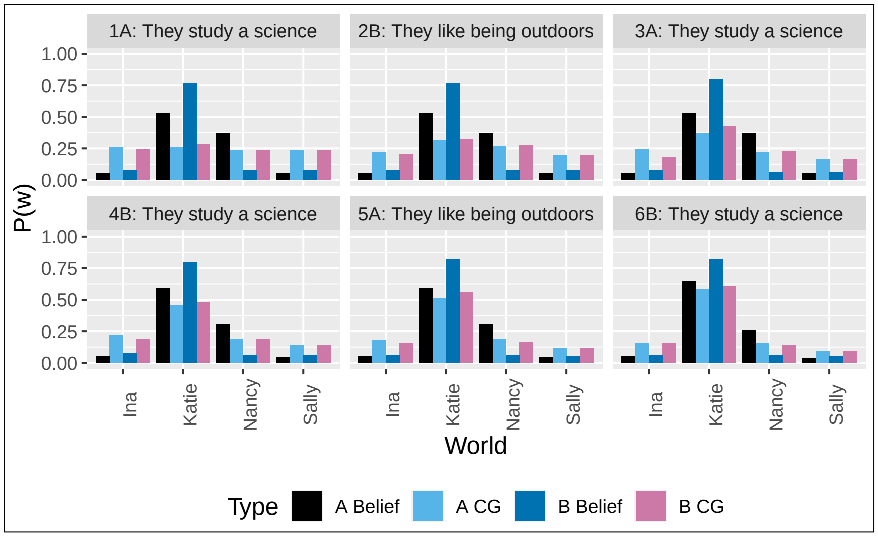

Figure 14: Redundancy with weighted sampling

the Common Ground already favors her.

7.2.1 Difference-based sampling

To incorporate awareness of the Common Ground, I propose an **difference-based** sampler that weights observations based on their potential to contribute new information.

If the goal of conversation is knowledge sharing, success means reducing uncertainty. Since uncertainty is highest when the Common Ground is a uniform distribution over worlds, the best observations are ones that increase the probability of a world.[14] A cooperative speaker should describe the world with the highest update potential: the largest (positive) difference in probability between the speaker's beliefs and the Common Ground. The difference-based sampler weights worlds by this positive probability difference.

In the scenario where A assigns high probability to both Katie and Nancy, difference-based sampling improves A's ability to contribute their beliefs to the Common Ground (Figure 15). Initially, A describes Katie, since her prior is higher. Once Katie has been established as likely in the Common Ground, A switches to describing Nancy.

Although difference-based sampling is intuitively appealing, its simplest form actually exacerbates the problem of noncommittal speakers discussed above. If the speaker has a uniform belief distribution, the only worlds with positive probability differences will be worlds that have been decreased in probability by a previous utterance. With naive difference-based sampling, a noncommittal speaker no longer makes contributions at random; they actively select for contradictions.

[14]A reduction in probability is also informative. However, because the RSA treats utterances as assertions that a world is true, this is harder to model.

The solution is as before: we can set a threshold to prevent noncommittal speakers from making low-confidence observations. Thresholded difference-based sampling leads informed speakers to select utterances with the best update potential, while allowing noncommittal speakers to pass.

8 Conclusion

I have presented a conversation update system for the Rational Speech Acts framework. By providing a way to simulate multi-turn conversations, it extends the range of phenomena that can be modeled with the RSA. I hope it will aid future exploration of phenomena that evolve during a discourse, such as perspective prominence (Anderson and Dillon, 2019); adaptation (Schuster and Degen, 2020), and social identity (Cohn-Gordon and Qing, 2018).

The proposed model successfully captures the desired principles laid out in Section 3.

Truthful and informative contributions

For optimally cooperative behavior, the speaker should select observations that lead to truthful and informative contributions. To favor truthful contributions, I introduced a thresholded observation sampling method, which allows noncommittal participants to pass. To favor informative observations, I introduced difference-based sampling, which fa-

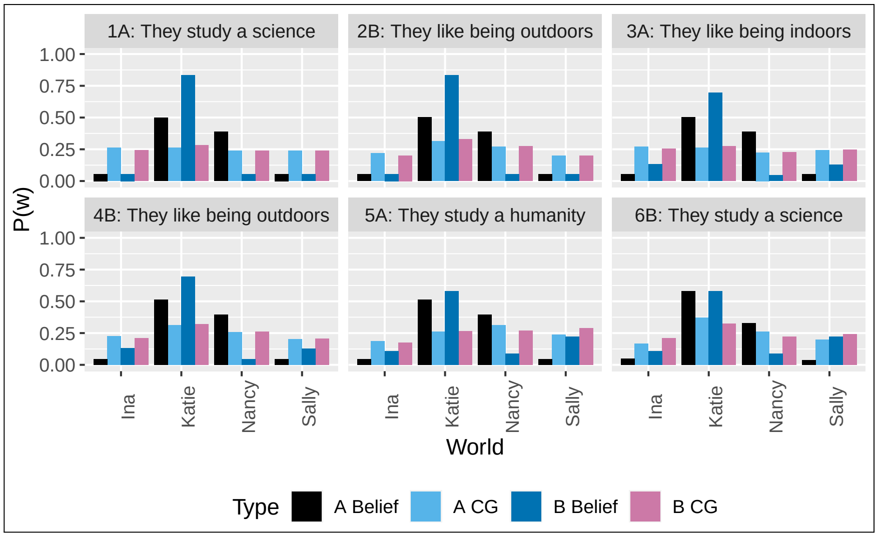

Figure 15: Thresholded difference-based sampling

vors worlds that will lead to a decrease in uncertainty in the Common Ground.

Decreasing uncertainty, avoiding contradiction

Since each update to the Common Ground is based on its prior state, the system shows how participants cooperate in order to reduce their shared uncertainty. However, the system also allows contradictory updates. I have proposed two features to mitigate this: adding a threshold to the observation sampler to prevent participants from making low-confidence observations, and setting the learning rate based on the participant's level of uncertainty. These techniques help ensure that when contradictions occur, they are due to real differences of opinion between the participants.

Belief consistency and convergence

In order to model how participants learn from each other, I have introduced belief updates: as information is shared, participants incorporate it into their beliefs. However, the system does not force participants to believe everything they are told: the update takes into account their prior beliefs, and is discounted by a learning rate, which can be adjusted to reflect their degree of skepticism or uncertainty.

Challenges and Future Directions

I have presented approaches for producing cooperative conversational behavior in the RSA framework. However, the current RSA model may not lead to optimal results, because of its assumption that the speaker's goal is to select the utterance that best describes a single world. This suffices for the one-turn scenarios common in RSA work, but it is too narrow of an objective for multi-turn conversations. If the goal of conversation is to share knowledge, speakers should instead select utterances based on their utility in minimizing the Common Ground's entropy.[15] Reworking the RSA around this objective is a promising direction for future work.

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[15] Alternatively, if the goal is perspective alignment, they should seek to minimize the Kullback–Leibler divergence of the Common Ground and their beliefs.

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