Could 40% mean 10%? Adding an additional layer of uncertainty to the RSA framework

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Introduction: Rational Speech Acts (RSA; [1]) is a probabilistic framework in which speakers maintain uncertainty over listeners' interpretation of utterances, and listeners maintain uncertainty over speakers' intended meanings. This explicit representation of uncertainty in RSA has been successfully used to model the differences in people's use and interpretation of uncertainty expressions in English such as *might* and *probably* [2]. However, recent work has suggested that there are limitations to the vanilla RSA framework: participants used uncertainty expressions differently when describing uncertainty in different event types (e.g. gumball machines vs. election predictions) [3]. Since the vanilla RSA model does not differentiate between event types, it fails to capture this empirical difference. We propose a general mechanism for adding an additional layer of speaker uncertainty about event probabilities, which allows us to capture the difference in [3]. We use this mechanism to implement two hypotheses about the types of uncertainty over event probabilities, Perception-Uncertainty and Discounting-Uncertainty. Our models suggest that Discounting-Uncertainty better accounts for data from [3]. We verify this with a new experiment.

Model modification description: In [3] participants were presented with images of election predictions or gumball machines, and asked to select an utterance from 3 choices: might, probably, and bare-not. A vanilla RSA model of this data models a *Pragmatic Speaker* (PS) who picks an utterance based on a state (e.g., image with 40% gumballs). The PS generates a matrix S that maps states to utterance probabilities (e.g., $S_{might,\ 40\%}$ is the probability of using *might* to describe an image with 40%). Since PS takes the probability in the image at face value, they sample an utterance directly from this matrix. In our model, we model the uncertainty over the states participants intend to communicate with a matrix M that maps observed states to intended states (e.g., $M_{40\%,10\%}$ is the probability that PS intends to communicate 10% when observing a state of 40%). PS multiplies M and S before sampling an utterance (Fig 1).

Types of uncertainty: We hypothesize at least two sources of uncertainty over the intended states: Perception-Uncertainty where PS is uncertain about their perception of probability in the image (e.g., machines with 40% and 50% purple gumballs look similar); and Discounting-Uncertainty where PS discounts low-probability events (cf. [4]).

Testing model predictions: We simulated 1000 participants by sampling an utterance threshold (from distributions in [2]) and used these to generate the S matrix. Then, we generated three sets of predictions by multiplying S with the participant-specific Perception-Uncertainty (M^P), Discounting-Uncertainty (M^D), and No-Uncertainty matrices (M^I) (Fig 1). For each observed state, we compare the highest probability empirical and model predicted utterances to compute accuracy. Compared to No-Uncertainty, we found that Discounting-Uncertainty improved accuracy for the election but decreased the accuracy for gumball conditions. This is consistent with [4] who argue that people discount low probabilities only for high-impact events. Additionally, Perception-Uncertainty and No-Uncertainty generated the same predictions, suggesting that the observed differences in [3] were unlikely to be driven by participants' uncertainty in perception. To test this, we ran an experiment where we replaced the image stimuli from [3] with text descriptions (Fig 3), thus removing perception uncertainty.

Text experiment: We recruited 120 participants from Prolific (excluded 12). Following [3] we fit separate mixed logistic regression models for each utterance (Tab1). Even with perception uncertainty removed, the difference between gumball and election conditions from [3] still persisted (albeit smaller): participants selected *might* more frequently in the gumball condition and *not* more frequently in the election condition (Fig 4). This validates our hypothesis that the difference in [3] was not just because of perception uncertainty.

Conclusion: We proposed a mechanism to add uncertainty to the existing RSA framework. We showed that this accounts for puzzling data from [3] and provides a way to test new hypotheses.

References:
[1] Frank, M. C., & Goodman, N. D. (2012). Predicting pragmatic reasoning in language games. Science, 336(6084), 998-998.
[2] Schuster, S., & Degen, J. (2020). I know what you're probably going to say: Listener adaptation to variable use of uncertainty expressions. Cognition, 203, 104285.
[3] Wang, A., Anderson, C., & Prasad, G. (2025). To know what you might say, I will probably need to know the event type.
[4] Sundh, J. (2024). Human behavior in the context of low-probability high-impact events. Humanities and Social Sciences Communications, 11, 902.

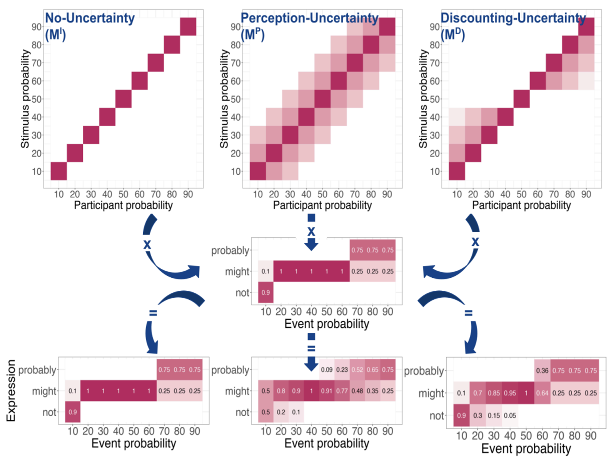

Figure 1: Using the new framework to generate predictions. Top row: uncertainty matrices (degree of uncertainty differ by participant); middle row: pragmatic speaker: bottom row: predictions.

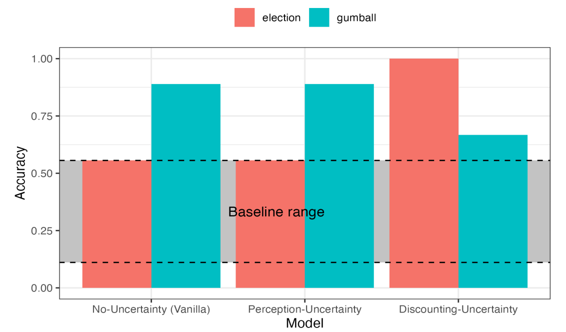

Figure 2: Model experiment results (aggregated over simulated participants). Gray area indicates the range of random baseline performance (baseline 1: fill uncertainty matrix with random values ranging [0, 1]; baseline 2: shuffle uncertainty matrix). No-Uncertainty and Perception-Uncertainty generated identical predictions.

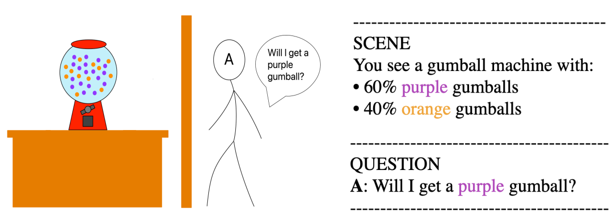

Figure 3: Sample trials from Image experiment [3] (left) and our Text experiment (right).

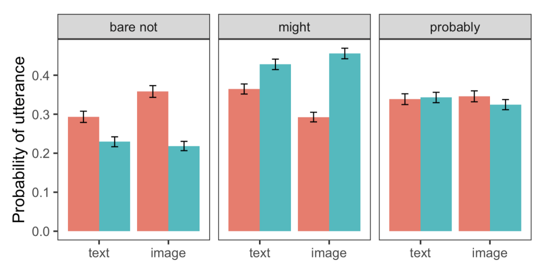

Figure 4: Aggregated mean probability of utterances (Image data is from [3]). Error bar indicates 2 SE.

prob ~ Stimulus * Event +
(1 + Event | partid)

Stimulus: Text (0) vs. Image (1)
Event: Election (0) vs. Gumball (1)

Coefficient	**Not**	**Might**	**Probably**
Stimulus	0.48***	-0.25**	0.16
Event	-0.59***	0.44***	0.02
Event : Stimulus	-0.61***	0.78***	-0.25*

Tab 1: Details about statistical analyses. Note: the main effect of Event is the difference between Gumball and Election for Text experiment because Text is the baseline class for Stimulus.