1   Polite speech emerges from competing social goals

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9   Abstract

10   Language is a remarkably efficient tool for information transfer. Yet to be polite, speakers

11   often behave in ways that are at odds with this goal, making statements that are inefficient,

12   imprecise, or even outright false. Why? We show that polite speech emerges from competing

13   goals: to be informative, to be kind, and to *appear* to be both of these. We formalize this

14   tradeoff using a probabilistic model of speakers' utterance choice, which predicts human

15   judg- ments with high accuracy. This utility-theoretic approach to speech acts takes a step

16   towards explaining the richness and subtlety of social language.

17   *Keywords:* keywords

18   Word count: X

Polite speech emerges from competing social goals

20   We don't always say what we're thinking. Although "close the window!" could be

21 sufficient, we say "can you please...?" or "would you mind...?" Rather than telling an

22 uncomfortable truth, we lie ("Your dress looks great!") and prevaricate ("Your poem was so

23 appropriate to the occasion"). Such utterances are puzzling for standard views of language

24 use, which see communication as the transfer of information from a sender to a receiver

25 (Bühler, 1934; Frank & Goodman, 2012; Jakobson, 1960; Shannon, 1948). On these views,

26 transfer ought to be efficient and accurate: The speaker should choose a succinct utterance

27 to convey what the speaker knows (Grice, 1975; Searle, 1975), and the information

28 transferred should be accurate and truthful to the extent of the speaker's knowledge. Polite

29 speech – like the examples above – violates these basic expectations about the nature of

30 communication: It is typically inefficient and underinformative, and sometimes even outright

31 false. Yet language users, including even young children, spontaneously produce requests in

32 polite forms (Axia & Baroni, 1985; e.g., Clark & Schunk, 1980), and speakers use politeness

33 strategies even while arguing, preventing unnecessary offense to their interactants

34 (Holtgraves, 1997). So why are we polite?

35   Theories of politeness explain deviations from optimal information transfer in language

36 by assuming that speakers take into account social, as well as informational, concerns. These

37 concerns are sometimes expressed as sets of polite maxims (Leech, 1983) or social norms (Ide,

38 1989), but the most influential account of politeness relies on the notion of "face" to

39 motivate deviations (Brown & Levinson, 1987; Goffman, 1967). On this theory, interactants

40 seek to be liked, approved, and related to ("positive face") as well as maintain their freedom

41 to act ("negative face"). If the speaker's intended meaning contains no threat to the

42 listener's face, then the speaker will choose to convey the meaning in an explicit and efficient

43 manner (putting it "on the record"). As the degree of face-threat becomes more severe,

44 however, a speaker will choose to be polite by producing more indirect utterances. Both

45 inefficient indirect speech and untruthful lies in communication are then the result of

46 speakers' strategic choices relative to possible face threats.

47 The face-based framework for polite language use provides an intuitive and appealing
48 explanation of many types of polite speech, but it does not precisely define how competing
49 communicative goals trade off with one another. For example, it is unclear when face-saving
50 should be prioritized over helpful information transfer, and when the desire to save face will
51 motivate statements that are outright false ("Your cake is delicious!") versus indirect ("It
52 could use a bit of salt"). Concretely, such theorizing does not constrain how an artificial
53 agent like a robot should go about making polite requests, conveying negative evaluations, or
54 delivering bad news. Further, a mutually-understood notion of face introduces additional
55 complexity: Speakers sometimes may not want to preserve the listener's face genuinely but
56 only to be *seen as* doing so, hence appearing to be socially apt and saving their own face,
57 which may lead to a different decision from that based on genuine desires to be kind or
58 informative. What is needed is a precise theory of these goals and how they trade off.

59 To address these challenges, we develop a utility-theoretic model to quantify tradeoffs
60 between different goals that a polite speaker may have. In our model, speakers attempt to
61 maximize a set of competing utilities: an informational utility, derived via classical, effective
62 information transmission; a social utility, derived by being kind and saving the listener's face;
63 and a self-presentational utility, derived by appearing in a particular way to save the
64 speaker's own face. Speakers then can choose between different utterances on the basis of
65 their expected utility (including their cost to utter, approximated by the length of the
66 utterance). The lie that a poem was great provides social utility by making its writer feel
67 good, but does not inform about the true state of the world. Further, if the writer suspects
68 that it was in fact terrible, the speaker runs the risk of being seen as uncooperative.

69 The utilities are weighed within a Rational Speech Act (RSA) model that takes a
70 probabilistic approach to pragmatic reasoning in language (Frank & Goodman, 2012;
71 Goodman & Frank, 2016): Speakers are modeled as agents who choose utterances by
72 reasoning about their effects on a listener relative to their cost, while listeners are modeled

as inferring interpretations by reasoning about speakers and their goals. This class of models has been effective in understanding a wide variety of complex linguistic behaviors, including vagueness (Lassiter & Goodman, 2017), hyperbole (Kao, Wu, Bergen, & Goodman, 2014), and irony (Kao & Goodman, 2015), among others. More broadly, RSA models provide a instantiation for language of the idea that human social cognition can be approximated via reasoning about others as rational agents who act to maximize their subjective utility (Baker, Saxe, & Tenenbaum, 2009), a hypothesis which has found support in a wide variety of work with both adults and children (e.g., Jara-Ettinger, Gweon, Schulz, & Tenenbaum, 2016; Liu, Ullman, Tenenbaum, & Spelke, 2017).

RSA models are defined recursively such that speakers reason about listeners, and vice versa. By convention this recursion is indexed such that a pragmatic listener L_1 reasons about what intended meaning and goals would have led a speaker S_1 to produce a particular utterance. Then S_1 reasons about a "literal listener" L_0, modeled as attending only to the literal meanings of words (rather than their pragmatic implications), and hence grounds the recursion. The target of our current work is a model of a polite speaker S_2: S_2 reasons about what utterance to say to L_1 by considering the set of utilities described above (Figure 1).

We evaluate our model on its ability to predict human utterance choices in situations where polite language use is expected. Imagine Bob recited his poem and asks Ann how well he did. Ann (S_2) produces an utterance w based on the true state of the world s (i.e., the rating truly deserved by Bob's recital) and a set of goal weights $\hat{\phi}$, that determines how much Ann prioritizes each goal. Ann's production decision is softmax, which interpolates between maximizing and probability matching (via λ_{S_2}; Goodman & Stuhlmüller, 2013):

$$P_{S_2}(w|s, \hat{\phi}) \propto \exp(\lambda_{S_2} \cdot \mathbb{E}[U_{total}(w; s; \hat{\phi})])$$

.

What goals must the speaker consider to arrive at a polite utterance? We consider three utilities: informational, social, and presentational. The total utility of an utterance is
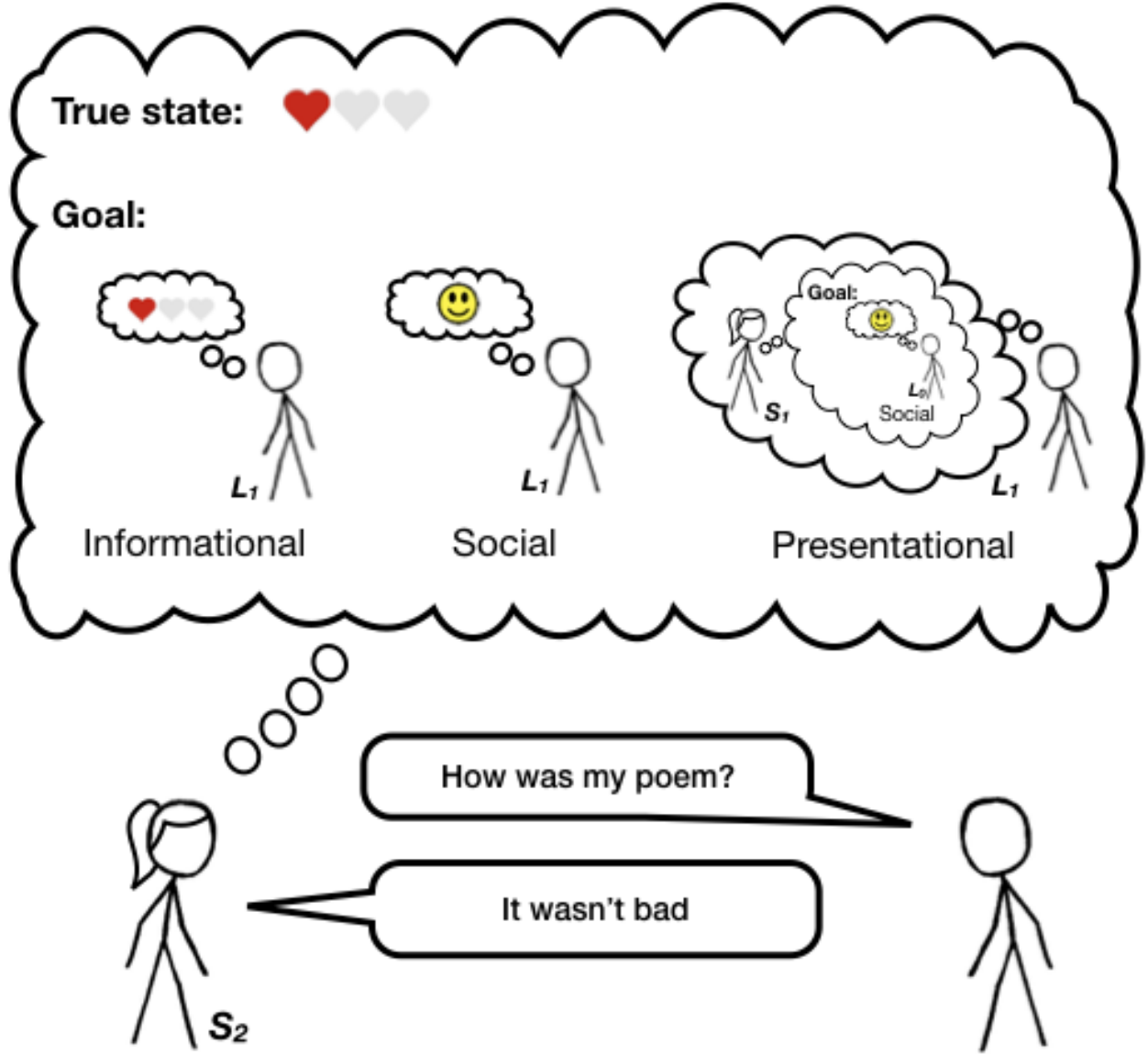
Figure 1. Diagram of the model: The pragmatic speaker observes the true state and determines her goal between three utilities (informational, social, and presentational), and produces an utterance.

98   the weighted combination of the three utilities minus the utterance cost $C(w)$:

$$U_{total}(w; s; \hat{\phi}) = \phi_{inf} \cdot U_{inf}(w; s) + \phi_{soc} \cdot U_{soc}(w; s) + \phi_{pres} \cdot U_{pres}(w; s) - C(w)$$

99   .

The first utility term is a standard *informational utility* (U_{inf}), which represents the speaker's desire to be epistemically helpful. The informational utility captures the amount of information a literal listener (L_0) would still not know about the world state s after hearing the speaker's utterance w (i.e., surprisal): $U_{inf}(w) = \ln(P_{L_1}(s|w))$.

For aspects of the world with affective consequences for the listener (e.g., Bob and his poem recital), we assume speakers produce utterances that make listeners feel like they are in a good state. The second utility term is a *social utility* (U_{soc}), which we define as the expected subjective utility $V(s)$ of the state implied to the listener by the utterance: $U_{soc}(w) = \mathbb{E}_{P_{L_1}(s|w)}[V(s)]$. In our experimental domain, states are explicit ratings, so we use a positive linear value function V to capture the idea that listeners want to hear that they are in a good state of the world (e.g., Bob prefers that his poem was good).

If listeners try to infer the goals that a speaker is entertaining (e.g., social vs. informational), speakers may choose utterances in order to convey that they had certain goals in mind. The third and the most novel component of our model, *presentational utility* (U_{pres}), captures the extent to which the speaker *appears* to the listener to have a particular goal in mind (e.g., to be kind). The speaker gains presentational utility when her listener believes she has certain goals – that she is trying to be informative or kind. Formally,

$$U_{pres}(w) = \ln(P_{L_1}(\phi_{S_1} \mid w)) = \ln \int_s P_{L_1}(s, \phi_{S_1} \mid w)$$

.

To define this term, the speaker has a weighting of informational vs. social goals to convey (ϕ_{S_1}) and must consider the beliefs of listener L1, who hears an utterance and jointly infers both the speaker's utilities and the true state of the world:

$$P_{L_1}(s, \hat{\phi}|w) \propto P_{S_1}(w|s, \hat{\phi}) \cdot P(s) \cdot p(\hat{\phi})$$

.

¹²² This presentational utility is higher-order in that it can only be defined for a speaker

¹²³ thinking about a listener who evaluates a speaker (i.e., it can be defined for S_2, but not S_1).

¹²⁴ Finally, more complex utterances incur a greater cost, $C(w)$ – capturing the general

¹²⁵ pressure towards economy in speech. In our work, utterances with negation (e.g., "not

¹²⁶ terrible") are assumed to be slightly costlier than their equivalents with no negation (inferred

¹²⁷ from data; see Supplementary Information).

¹²⁸ Within our experimental domain, we assume there are four possible states of the world

¹²⁹ corresponding to the value placed on a particular referent (e.g., the presentation the speaker

¹³⁰ is commenting on): $S = s_1, ..., s_5$. We further assume a uniform prior distribution over

¹³¹ possible states of the world. The set of utterances is {*terrible*, *bad*, *good*, *amazing*, *not*

¹³² *terrible*, *not bad*, *not good*, and *not amazing*}. We implemented this model using the

¹³³ probabilistic programming language WebPPL (Goodman & Stuhlmüller, 2014).

¹³⁴ Intuitively, if Bob's performance was good, Ann's utilities align toward a positive

¹³⁵ utterance. By saying "[Your poem] was amazing," Ann is simultaneously being truthful,

¹³⁶ kind, and appearing both truthful and kind. If Bob's performance was poor, however, Ann is

¹³⁷ in a bind: Ann could be kind and say "It was great", but at the cost of conveying the wrong

¹³⁸ information to Bob if he believes her to be truthful. If he does not, he might infer Ann is

¹³⁹ "just being nice", but is uninformative. Alternatively, she could say the truth ("It was bad"),

¹⁴⁰ but then Bob would think Ann didn't care about him. What is a socially-aware speaker to

¹⁴¹ do? Our model predicts that indirect speech – like "It wasn't bad" – helps navigate Ann's

¹⁴² dilemma. Her statement is sufficiently vague to leave open the possibility that the poem was

¹⁴³ good, but her avoidance of the simpler and less costly "It was good" provides both an

¹⁴⁴ inference that the performance was mediocre and a signal that she cares about Bob's feelings.

¹⁴⁵ We made a direct, pre-registered test of our model by instantiating the example above

¹⁴⁶ in an online experiment ($N = 202$). Participants read scenarios in which we provided

¹⁴⁷ information on the speaker's (Ann's, in our example) feelings toward some performance or

¹⁴⁸ product (e.g., poem recital; *true state*), on a scale from zero to three hearts (e.g., one out of

three hearts). For example, one trial read: "Imagine that Bob gave a poem recital, but he

didn't know how good it was. Bob approached Ann, who knows a lot about poems, and

asked"How was my poem?" We also manipulated the speaker's *goal* across trials: to be

informative ("give accurate and informative feedback"); to be *kind* ("make the listener feel

good"); or to be *both* informative and kind simultaneously. We hypothesized that each of the

three goals will represent a tradeoff between the three utilities in our model (see

Supplementary Information). In a single trial, each scenario was followed by a question

asking for the most likely utterance by Ann. Participants selected one of eight possible

utterances, by choosing between *It was* vs. *It wasn't* and then among *terrible, bad, good,* and

amazing.

Our primary behavioral hypothesis was that speakers describing bad states (e.g., Bob's

performance deserved 0 heart) with goals to be both informative and kind would produce

more indirect, negative utterances (e.g., "It wasn't terrible"). Such indirect speech acts serve

to save the listener's face while also conveying a vague estimate of the true state. This

prediction was confirmed: a Bayesian mixed-effects model predicting negation as a function

of true state and goal yielded an interaction such that a speaker with both goals to be

informative and kind produced more negation in worse states compared to a speaker with

only the goal to be informative ($M = -1.33$, [-1.69, -0.98]) and goal to be kind ($M = -0.50$,

[-0.92, -0.07]). Rather than eschewing one of their goals to increase utility along a single

dimension, participants chose utterances that jointly satisfied their conflicting goals by

producing indirect, polite speech.

Next, to connect the behavioral data to our model, we inferred the parameters of the

RSA model (e.g., the speaker's utility weights in each goal condition; see Supplementary

Information) via a Bayesian data analysis (M. D. Lee & Wagenmakers, 2014). To

approximate the semantics of the words as interpreted by the literal listener L_0, we obtained

literal meaning judgments from an independent group of participants (N=51). Predictions

from the full polite speaker model showed a very strong fit to participants' utterance choices
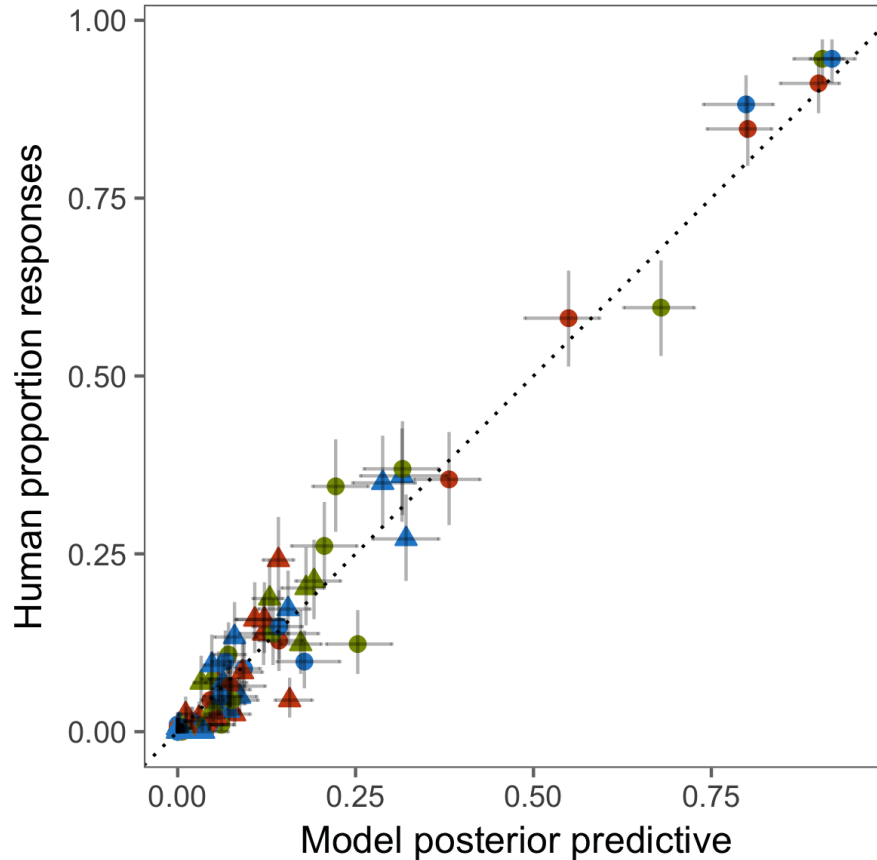
Figure 2. Full distribution of human responses vs. model predictions. Error bars represent 95% confidence intervals for the data (vertical) and 95% highest density intervals for the model (horizontal).

$(r^2(96) = 0.97$; Figure 2).

We also compared the predictions of our model to its variants containing subsets of the three utilities in the full model. Both the variance explained and the marginal likelihood of the observed data were the highest for the full model (Table 1). Only the full model captured the participants' preference for negation in the condition in which the speaker had both goals to be informative and kind about truly bad states, as hypothesized (Figure 3). All three utilities – informational, social, and presentational – were required to fully explain participants' utterance choices.
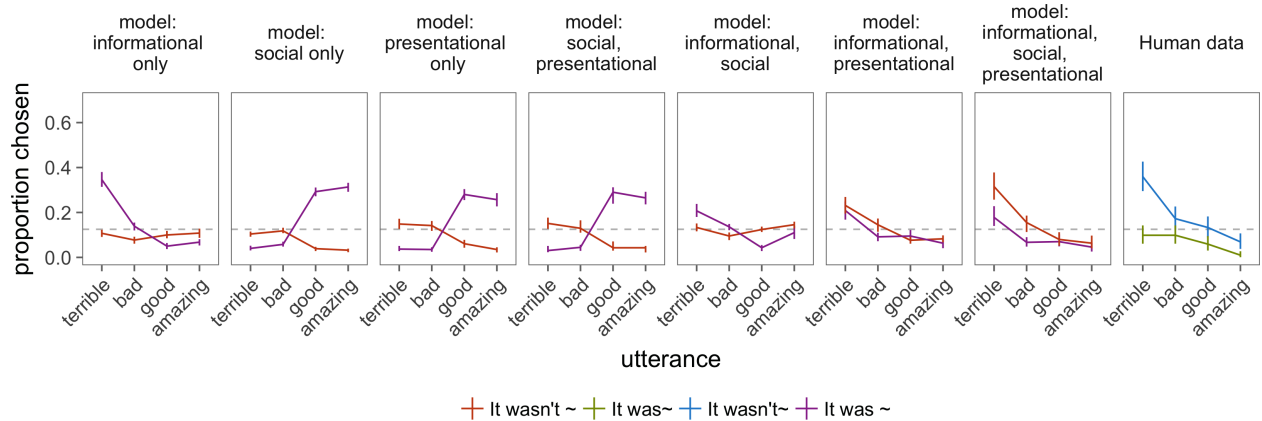
Figure 3. Comparison of predictions for proportion of utterances chosen by pragmatic speaker from possible model variants (left) and human data (rightmost) for average proportion of negation produced among all utterances, given true state of 0 heart (on a scale of 0 to 3) and speaker with both goals to be informative and kind. Gray dotted line indicates chance level at 12.5%.

184   The utility weights inferred for the full model (Table 2) provide additional insight into

185   how polite language use operates: *Being kind* requires equal weights on all three utilities,

186   indicating that Gricean informativity needs to be part of language use even when it is

187   explicitly not the goal. *Being informative* pushes the weight on social utility close to zero,

188   but the weight on *appearing kind* stays high, suggesting that speakers are expected to

189   manage their own face even when they are not considering others'. *Kind and informative*

190   speakers emphasize informativity slightly more than kindness. In all cases, however, the

191   presentational utilities have greatest weight, which may suggest that appearing honest and

192   kind is more important than actually being so! Overall then, our condition manipulation

193   altered the balance between these weights, but all utilities played a role in all conditions.

194   Politeness is a puzzle for purely informational accounts of language use. Incorporating

195   social motivations can provide an explanatory framework, but such intuitions have been

196   resistant to formalization or precise testing. To overcome this issue, we created a

197   utility-theoretic model of language use that captured the interplay between competing

Table 1

Comparison of variance explained for each model variant and log Bayes Factors quantifying evidence in favor of alternative model in comparison.

Model	Variance explained	log BF
model: informational, social, presentational	0.97	–
model: informational, presentational	0.96	-11.14
model: informational, social	0.92	-25.06
model: social, presentational	0.23	-864
model: presentational only	0.23	-873.83
model: social only	0.22	-885.52
model: informational only	0.83	-274.89

198 informational, social, and presentational goals. A preregistered experimental test of the

199 model confirmed its ability to capture human judgments, unlike comparison models that

200 used only a subset of the full utility structure.

201 　　　To precisely estimate choice behavior, our experiment abstracted away from natural

202 interactions in a number of ways. Real speakers have access to a potentially infinite range of

203 utterances to manage the tradeoffs in our experiment ("It's hard to write a good poem",

204 "That metaphor in the second stanza was so relatable!"). Under our framework, each

205 utterance will have strengths and weaknesses relative to the speaker's goals, though

206 computation in an unbounded model presents technical challenges (perhaps paralleling the

207 difficulty human speakers feel in finding the right thing to say in a difficult situation; see

208 Goodman & Frank, 2016).

209 　　　For a socially-conscious speaker, managing listeners' inferences is a fundamental task.

210 Inspired by the theory of politeness as face management (Brown & Levinson, 1987), our

211 model takes a step towards understanding it. Our work extends previous models of language

Table 2

Inferred phi parameters from all model variants with more than one utility.

Model	goal	ϕ_{inf}	ϕ_{soc}	ϕ_{pres}	ϕ_{S_1}
informational, social, presentational	both	0.36	0.11	0.54	0.36
informational, social, presentational	informative	0.36	0.02	0.62	0.49
informational, social, presentational	social	0.25	0.31	0.44	0.37
informational, presentational	both	0.64	–	0.36	0.17
informational, presentational	informative	0.77	–	0.23	0.33
informational, presentational	social	0.66	–	0.34	0.04
informational, social	both	0.54	0.46	–	–
informational, social	informative	0.82	0.18	–	–
informational, social	social	0.39	0.61	–	–
social, presentational	both	–	0.38	0.62	0.55
social, presentational	informative	–	0.35	0.65	0.75
social, presentational	social	–	0.48	0.52	0.66

beyond standard informational utilities to address social and self-presentational concerns. Previous theories of language use have not explained how informational versus social concerns trade off to inform the speaker's utterance choices. Thus, this work represents a key theoretical advance exploring how informational cooperativity interacts with other social goals. By considering utility-driven inferences in a social context (Baker, Jara-Ettinger, Saxe, & Tenenbaum, 2017; Hamlin, Ullman, Tenenbaum, Goodman, & Baker, 2013) where agents need to take into account concerns about both self and others, our approach here could give insights into a wide range of social behaviors beyond speech.

The model presented here relates to other work done in game-theoretic pragmatics. Van Rooy (2003) uses a game-theoretic analysis of polite requests ("Could you possibly take

₂₂₂ me home?") to argue the purpose of polite language is to align the preferences of

₂₂₃ interlocutors. Our notion of social utility U_{soc} and presentational utility U_{pres} is similar in

₂₂₄ that they motivate speakers to signal worlds that make the listener feel good. Van Rooy

₂₂₅ (2003)'s analysis, however, relies on the notion that polite language is costly (in a social way

₂₂₆ e.g., by reducing one's social status or incurring social debt to one's conversational partner)

₂₂₇ but it's not clear how the polite behaviors explored in our experiments (not polite requests)

₂₂₈ would incur any cost to speaker or listener. Our model derives its predictions by construing

₂₂₉ the speaker utility as a collection of possible goals (here, epistemic, social, and presentational

₂₃₀ goals). The speech-acts themselves are not costly.

₂₃₁   In another game-theoretic approach by Pinker, Nowak, and Lee (2008), human

₂₃₂ communication is assumed to involve a mixture of cooperation *and* conflict: indirect speech

₂₃₃ then allows for plausible deniability that is in self-interest but goes against the interest of the

₂₃₄ addressee. In contrast, our work builds on existing classic theories of polite speech as

₂₃₅ primarily cooperative (Brown & Levinson, 1987; Grice, 1975) rather than based on both

₂₃₆ cooperation and conflict. We have shown that a separate notion of plausible deniability may

₂₃₇ not be needed, as indirect speech in our specific case comes from both a goal to be helpful

₂₃₈ and a desire to look good. Our work is able to capture different linguistic nuances involved

₂₃₉ in this process of reasoning about different goals that speakers have.

₂₄₀   By experimenting with different utility weights and value functions, our model could

₂₄₁ provide a framework for understanding systematic cross-cultural differences in what counts

₂₄₂ as polite. For example, following Brown and Levinson (1987), cross-cultural differences in

₂₄₃ politeness could be a product of different weightings within the same utility structure. It is

₂₄₄ also possible, however, that culture affects the value function V that maps states of the

₂₄₅ world onto subjective values for the listener (e.g., the mapping from states to utilities may be

₂₄₆ more complex than we have considered). Our formal modeling approach with systematic

₂₄₇ behavior measurements provides an avenue towards understanding the vast range of

₂₄₈ politeness practices found across languages.

²⁴⁹   Politeness is only one of the ways that language use deviates from pure information

²⁵⁰ transfer. When we flirt, insult, boast, and empathize, we also balance being informative with

²⁵¹ goals to affect others' feelings and present particular views of ourselves. Our work shows how

²⁵² social and self-presentational motives can be integrated with other concerns more generally,

²⁵³ opening up the possibility for a broader theory of social language. Further, a formal account

²⁵⁴ of politeness moves us closer to courteous computation – to computers that can

²⁵⁵ communicate with tact.

²⁵⁶   **Acknowledgments**

₂₆₀   **Methods**

₂₆₁ **Literal semantic task**

₂₆₂   We probed judgments of literal meanings of the target words assumed by our model

₂₆₃ and used in our main experiment. 51 participants with IP addresses in the United States

₂₆₄ were recruited on Amazon's Mechanical Turk. We used thirteen different context items in

₂₆₅ which a speaker evaluated a performance of some kind. For example, in one of the contexts,

₂₆₆ Ann saw a presentation, and Ann's feelings toward the presentation (true state) were shown

₂₆₇ on a scale from zero to three hearts (e.g., two out of three hearts filled in red color; see

₂₆₈ Figure 5 for an example of the heart scale). The question of interest was "Do you think Ann

₂₆₉ thought the presentation was / wasn't X?" and participants responded by choosing either

₂₇₀ "no" or "yes." The target could be one of four possible words: *terrible*, *bad*, *good*, and

₂₇₁ *amazing*, giving rise to eight different possible utterances (with negation or no negation).

₂₇₂ Each participant read 32 scenarios, depicting every possible combination of states and

₂₇₃ utterances. The order of context items was randomized, and there were a maximum of four

₂₇₄ repeats of each context item per participant. For this and the speaker production

₂₇₅ experiment, we analyzed the data by collapsing across context items. For each

₂₇₆ utterance-state pair, we computed the posterior distribution over the semantic weight (i.e.,

₂₇₇ how consistent X utterance is with Y state) assuming a uniform prior over the weight (i.e., a

₂₇₈ standard Beta-Binomial model). Meanings of the words as judged by participants were as

₂₇₉ one would expect (Figure 4).

₂₈₀ **Speaker production task**

₂₈₁   202 participants with IP addresses in the United States were recruited on Amazon's

₂₈₂ Mechanical Turk. As in the literal semantic task above, we used scenarios in which a person

₂₈₃ (e.g., Bob) gave some performance and asked for another person (e.g., Ann)'s opinion on the

₂₈₄ performance (Figure 5). Additionally, we provided information on the speaker Ann's goal –

₂₈₅ to make Bob feel good, or to give as accurate and informative feedback as possible, or both –
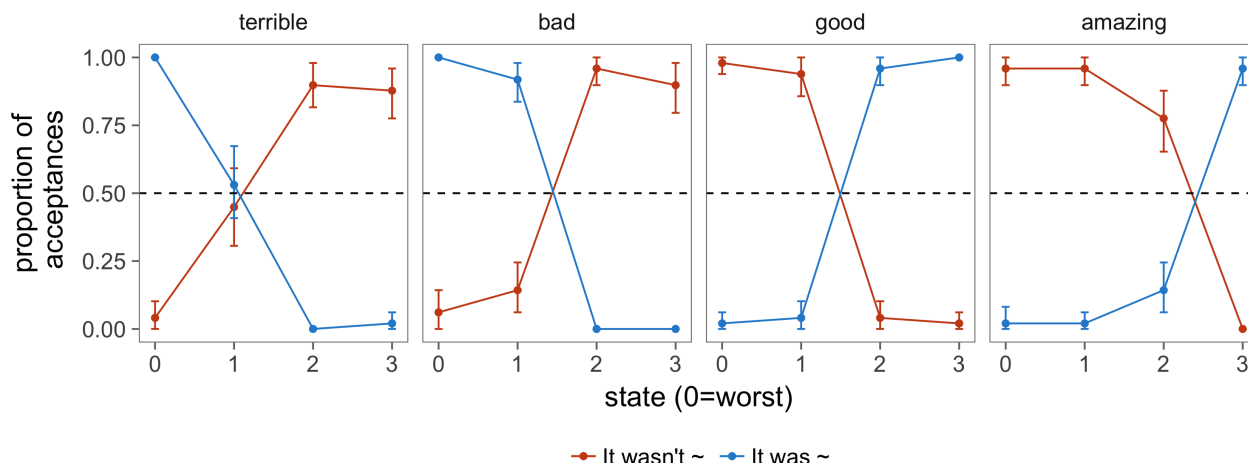
Figure 4. Semantic measurement results. Proportion of acceptances of utterance types (shown in different colors) combined with target words (shown in different facets) given the true state represented on a scale of hearts. Error bars represent 95% confidence intervals.

Figure 5. Example of a trial in the speaker production task.

and the true state – how Ann actually felt about Bob's performance (e.g., two out of three hearts, on a scale from zero to three hearts; Figure 5). Each participant read twelve

scenarios, depicting every possible combination of the three goals and four states. The order of context items was randomized, and there were a maximum of two repeats of each context item per participant. Each scenario was followed by a question that read, "If Ann wanted to make Bob feel good but not necessarily give informative feedback (or to give accurate and informative feedback but not necessarily make Bob feel good, or BOTH make Bob feel good AND give accurate and informative feedback), what would Ann be most likely to say?" Participants indicated their answer by choosing one of the options on the two dropdown menus, side-by-side, one for choosing between *It was* vs. *It wasn't* and the other for choosing among *terrible*, *bad*, *good*, and *amazing.*

Data availability

Our model, preregistration of hypotheses, procedure, data, and analyses are available at https://github.com/ejyoon/polite_speaker.

Author information

Author contributions

All authors designed research and wrote the paper; E.J.Y. and M.H.T. performed research and analyzed data.

Competing interests

The authors declare no conflict of interest.

Supplementary Information

Data analysis

We used R (Version 3.4.3; R Core Team, 2017) and the R-packages *BayesFactor* (Version 0.9.12.2; Morey & Rouder, 2015), *bindrcpp* (Version 0.2; Müller, 2017a), *binom* (Version 1.1.1; Dorai-Raj, 2014), *brms* (Version 2.0.1; Bürkner, 2017), *coda* (Version 0.19.1;

Plummer, Best, Cowles, & Vines, 2006), *directlabels* (Version 2017.3.31; Hocking, 2017), *dplyr*

(Version 0.7.4; Wickham, Francois, Henry, & Müller, 2017), *forcats* (Version 0.2.0; Wickham,

2017a), *ggplot2* (Version 2.2.1; Wickham, 2009), *ggthemes* (Version 3.4.0; Arnold, 2017),

gridExtra (Version 2.3; Auguie, 2017), *here* (Version 0.1; Müller, 2017b), *jsonlite* (Version 1.5;

Ooms, 2014), *langcog* (Version 0.1.9001; Braginsky, Yurovsky, & Frank, n.d.), *lme4* (Version

1.1.15; Bates, Mächler, Bolker, & Walker, 2015), *magrittr* (Version 1.5; Bache & Wickham,

2014), *Matrix* (Version 1.2.12; Bates & Maechler, 2017), *papaja* (Version 0.1.0.9655; Aust &

Barth, 2017), *purrr* (Version 0.2.4; Henry & Wickham, 2017), *RColorBrewer* (Version 1.1.2;

Neuwirth, 2014), *Rcpp* (Eddelbuettel & Balamuta, 2017; Version 0.12.17; Eddelbuettel &

François, 2011), *readr* (Version 1.1.1; Wickham, Hester, & Francois, 2017), *rwebppl* (Version

0.1.97; Braginsky, Tessler, & Hawkins, n.d.), *stringr* (Version 1.3.1; Wickham, 2017b), *tibble*

(Version 1.4.2; Müller & Wickham, 2017), *tidyr* (Version 0.7.2; Wickham & Henry, 2017),

and *tidyverse* (Version 1.2.1; Wickham, 2017c) for all our analyses.

Full statistics on human data

We used Bayesian linear mixed-effects models (`brms` package in R; Bürkner, 2017)

using crossed random effects of true state and goal with maximal random effects structure

(Barr, Levy, Scheepers, & Tily, 2013; Gelman & Hill, 2006).

Model fitting and inferred parameters

In the speaker production task, participants were told the speakers' intentions (e.g.,

wanted to make Bob feel good). We assume that the intention descriptions conveyed some

mixture of weights ϕ_{epi}, ϕ_{soc}, ϕ_{pres}, and ϕ_{S_1} that the speaker was using. We put

uninformative priors on the unnormalized mixture weights ($\phi \sim Uniform(0,1)$) separately

for each goal condition ("wanted to be X"; *kind*, *informative*, or *both*). In addition, the full

model has two global parameters: the speaker's soft-max parameter λ_{S_2} and soft-max

paramater of the hypothetical speaker that the pragmatic listener reasons about λ_{S_1}. λ_{S_1}

was 1, and λ_{S_2} was inferred from the data: We put a prior that was consistent with those

Table 3

Predictor mean estimates with standard deviation and 95% credible interval information for a Bayesian linear mixed-effects model predicting negation production based on true state and speaker goal (with both-goal as the reference level).

Predictor	Mean	SD	95% CI-Lower	95% CI-Upper
Intercept	0.88	0.13	0.63	1.12
True state	2.18	0.17	1.86	2.53
Goal: Informative	0.47	0.17	0.14	0.80
Goal: Kind	0.97	0.25	0.51	1.49
True state * Informative	-1.33	0.18	-1.69	-0.98
True state * Kind	-0.50	0.22	-0.92	-0.07

Table 4

Inferred negation cost and speaker optimality parameters for all model variants.

Model	Cost of negation	Speaker optimality
informational only	1.58	8.58
informational, presentational	1.89	2.93
informational, social	1.11	3.07
informational, social, presentational	2.64	4.47
presentational only	2.58	9.58
social only	1.73	7.23
social, presentational	2.49	5.29

337 used for similar models in this model class: $\lambda_{S_2} \sim Uniform(0, 20)$. Finally, we incorporate

338 the literal semantics data into the RSA model by maintaining uncertainty about the

339 semantic weight of utterance w for state s, for each of the states and utterances, and

340 assuming a Beta-Binomial linking function between these weights and the literal semantics

341 data (see *Literal semantics task* above). We infer the posterior distribution over all of the

342 model parameters and generate model predictions based on this posterior distribution using

343 Bayesian data analysis (M. D. Lee & Wagenmakers, 2014). We ran 4 MCMC chains for

344 80,000 iterations, discarding the first 40,000 for burnin. The inferred values of weight

345 mixtures for each model variant (with different ϕ components) and other parameters are

346 shown in Table 2 and Table 4, respectively.
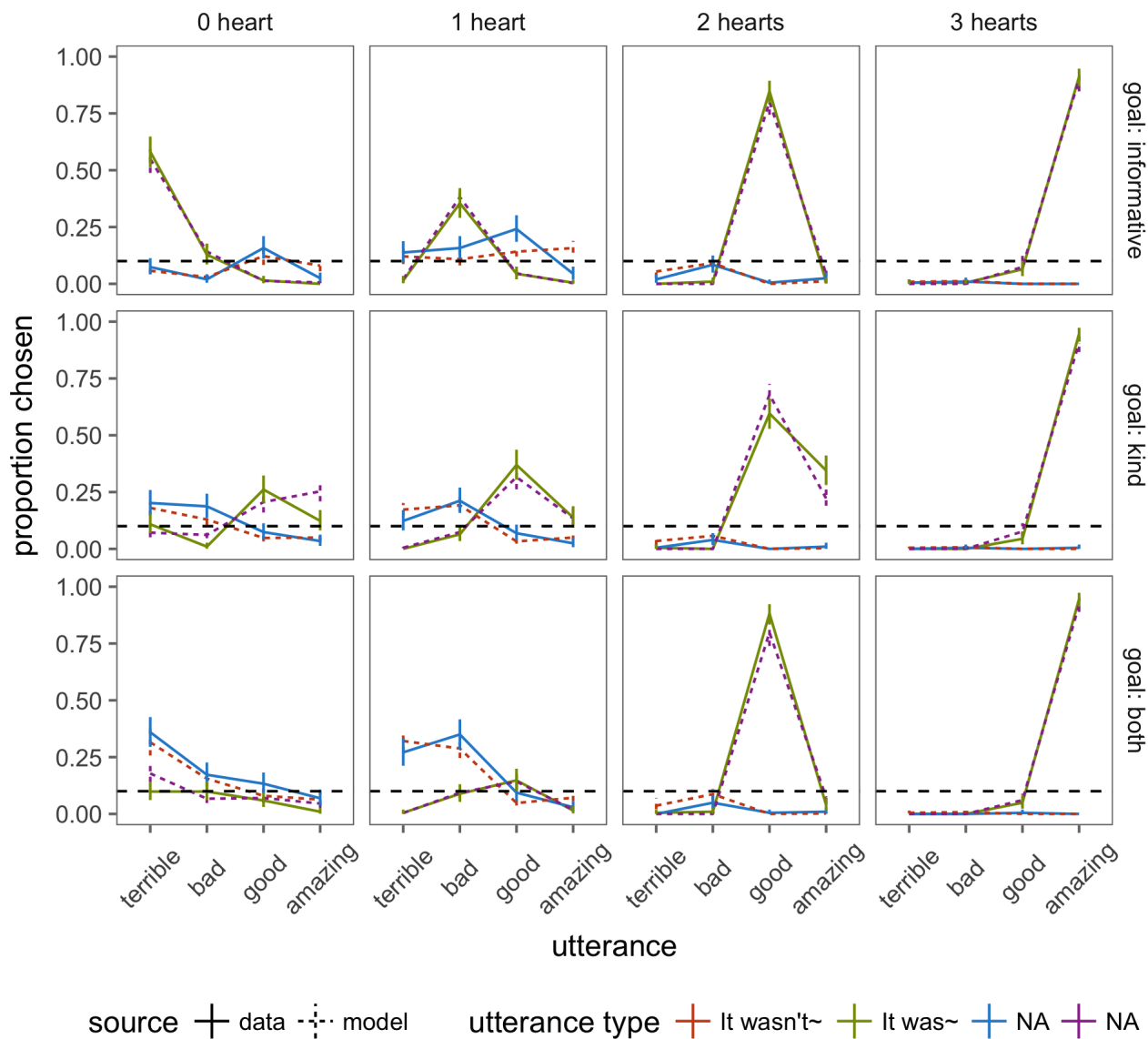
Supplemental Figures

Figure 6. Experimental results (solid lines) and fitted predictions from the full model (dashed lines) for speaker production. Proportion of utterances chosen (utterance type – direct vs. indirect – in different colors and words shown on x-axis) given the true states (columns) and speaker goals (rows). Error bars represent 95% confidence intervals for the data and 95% highest density intervals for the model. Black dotted line represents the chance level.
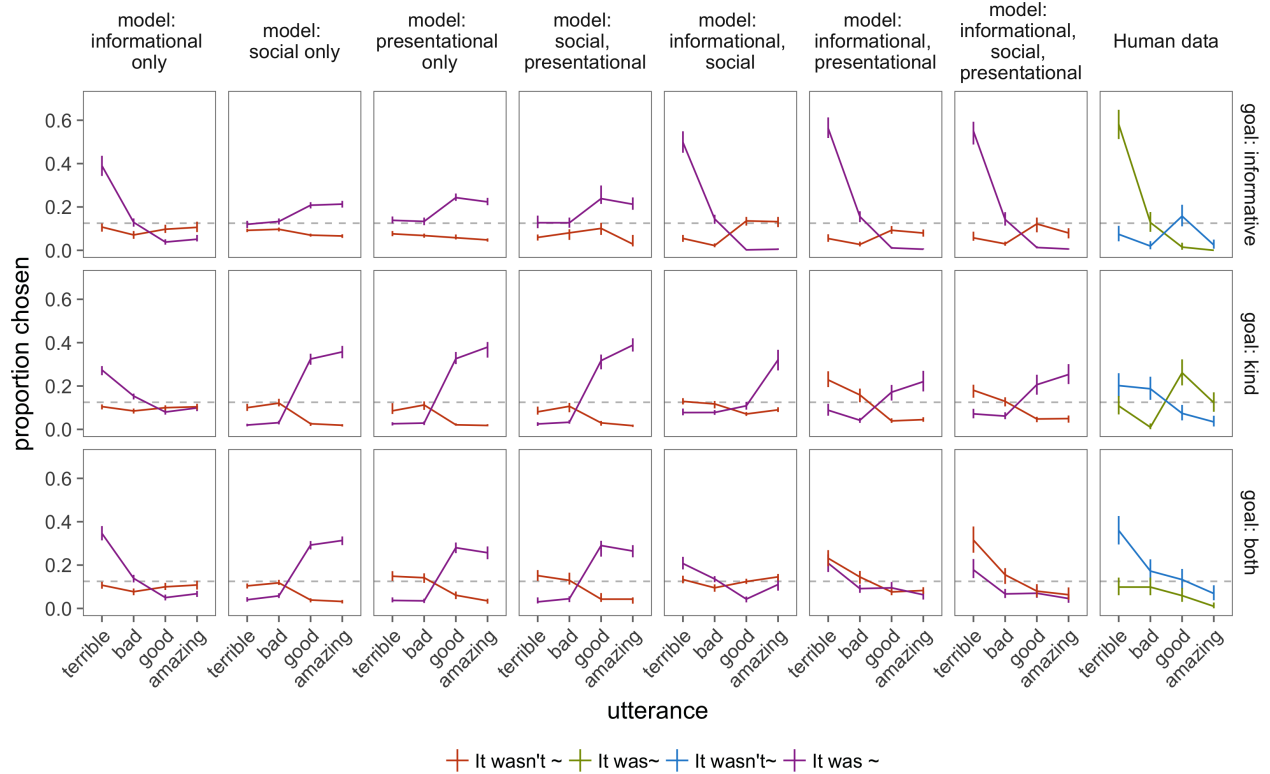
Figure 7. Comparison of predictions for proportion of utterances chosen by pragmatic speaker from possible model variants (left) and human data (rightmost) for average proportion of negation produced among all utterances, given true state of 0 heart and speaker with a goal to be informative (top), kind (middle), or both (bottom). Gray dotted line indicates chance level at 12.5%.

<p style="text-align:center;">**References**</p>

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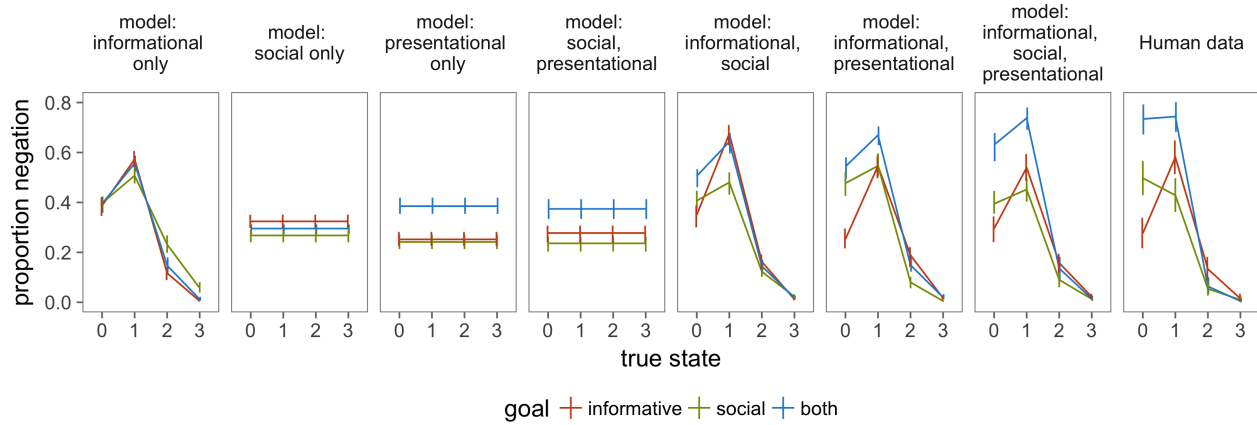
Figure 8. Experimental results (left) and fitted model predictions (right) for average proportion of negation produced among all utterances, given true states (x-axis) and goals (colors).

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