Polite speech emerges from competing social goals

Abstract

Language is a remarkably efficient tool for information transfer. Yet to be polite, speakers often behave in ways that are at odds with this goal, making statements that are inefficient, imprecise, or even outright false. Why? We show that polite speech emerges from competing goals: to be informative, to be kind, and to *appear* to be both of these. We formalize this tradeoff using a probabilistic model of speakers' utterance choice, which predicts human judg- ments with high accuracy. This utility-theoretic approach to speech acts takes a step towards explaining the richness and subtlety of social language.

Keywords: Politeness; computational modeling; commmunicative goals; pragmatics

Word count: 3500

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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).

Table 1

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 2

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

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 used for similar models in this model class: $\lambda_{S_2} \sim Uniform(0, 20)$. Finally, we incorporate the literal semantics data into the RSA model by maintaining uncertainty about the semantic weight of utterance w for state s, for each of the states and utterances, and assuming a Beta-Binomial linking function between these weights and the literal semantics data (see *Literal semantics task* above). We infer the posterior distribution over all of the model parameters and generate model predictions based on this posterior distribution using Bayesian data analysis (Lee & Wagenmakers, 2014). We ran 4 MCMC chains for 80,000 iterations, discarding the first 40,000 for burnin. Negation cost and speaker optimality parameters are shown in Table 2.

Supplemental Figures

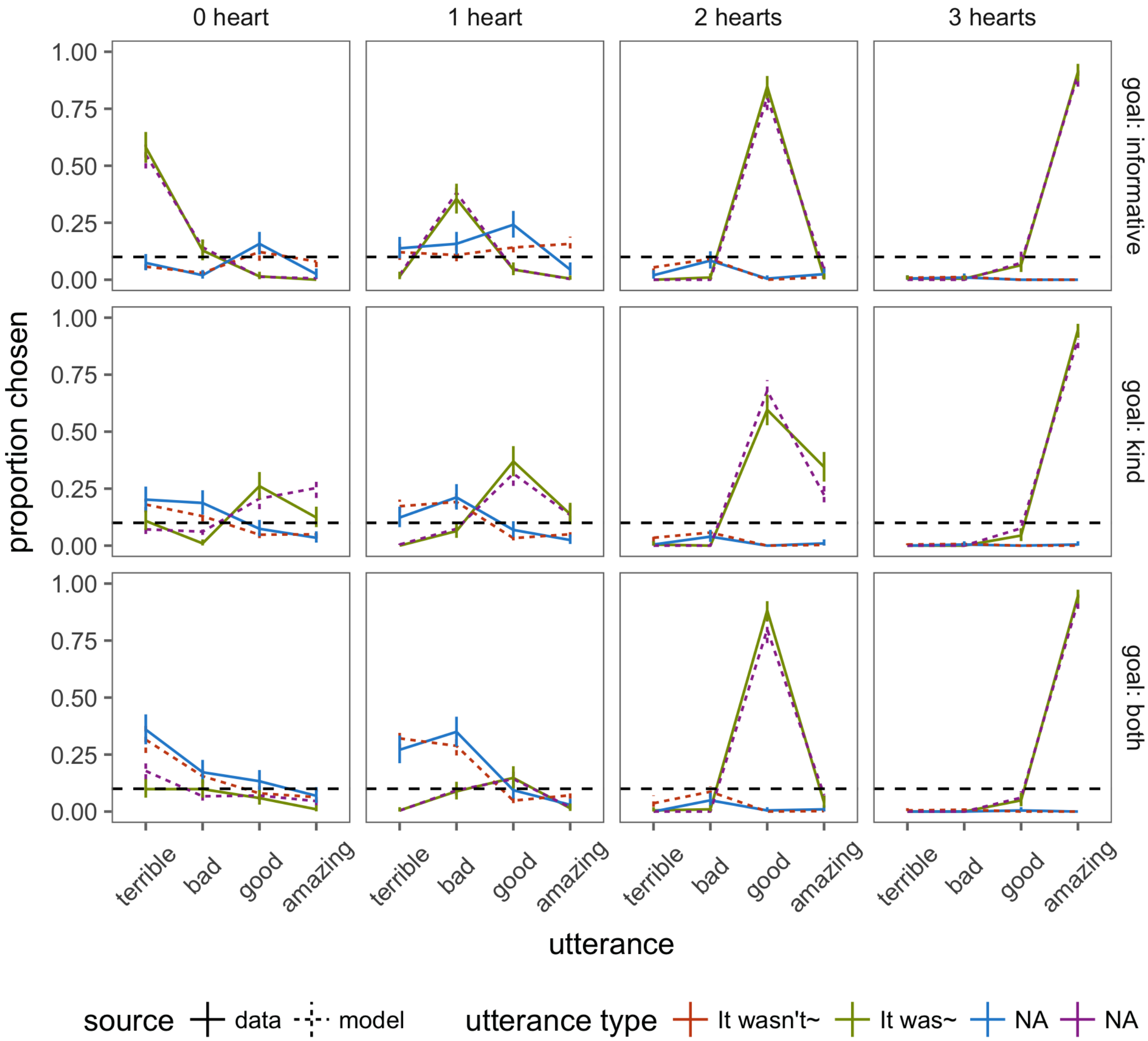

Figure 1. Experimental results (solid lines) and fitted predictions from the full model (dashed lines) for speaker production. Proportion of utterances chosen (utterance type – direct vs. indirect – in different colors and words shown on x-axis) given the true states (columns) and speaker goals (rows). Error bars represent 95% confidence intervals for the data and 95% highest density intervals for the model. Black dotted line represents the chance level.

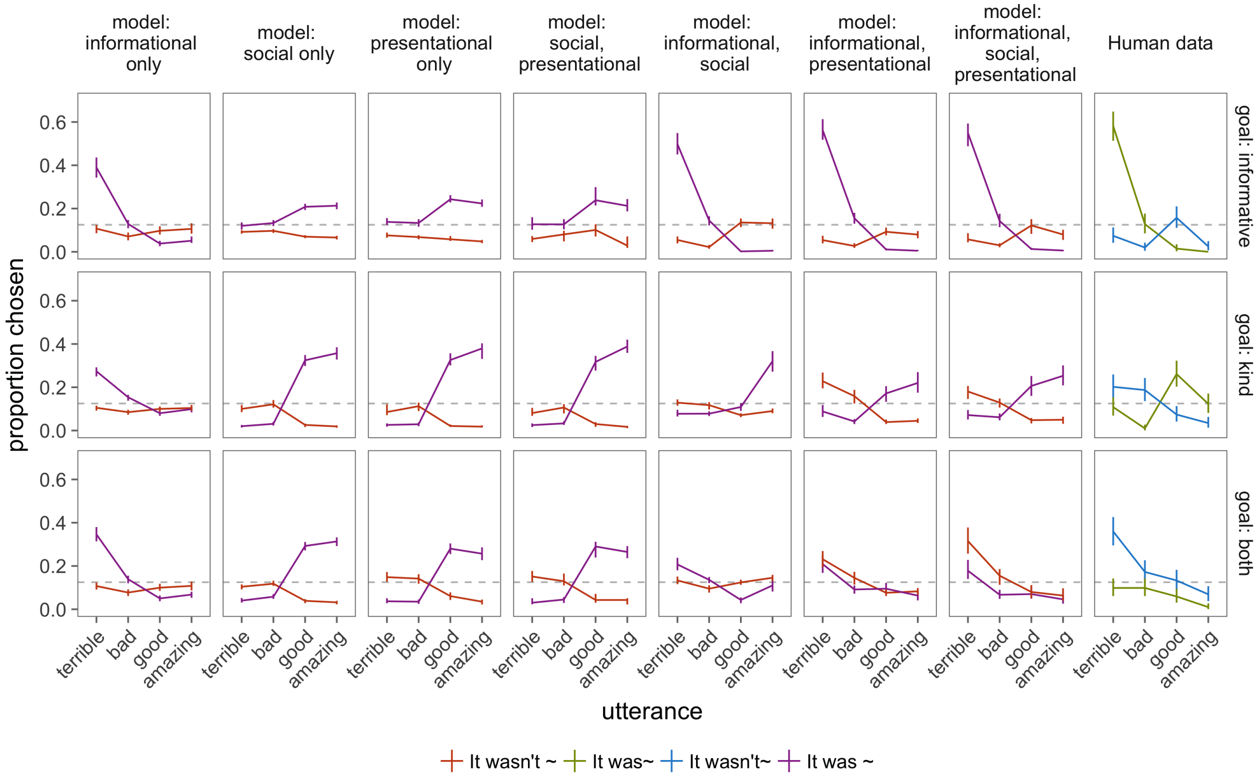

Figure 2. Comparison of predictions for proportion of utterances chosen by pragmatic speaker from possible model variants (left) and human data (rightmost) for average proportion of negation produced among all utterances, given true state of 0 heart and speaker with a goal to be informative (top), kind (middle), or both (bottom). Gray dotted line indicates chance level at 12.5%.

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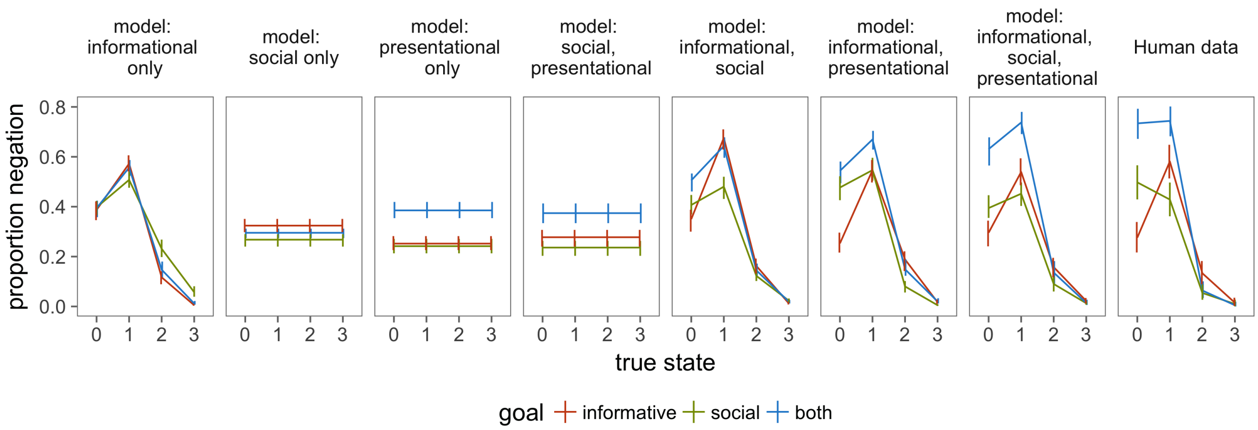

Figure 3. Experimental results (left) and fitted model predictions (right) for average proportion of negation produced among all utterances, given true states (x-axis) and goals (colors).

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