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Nonliteral Language Understanding for Number Terms

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**Abstract**: One of the most puzzling and important facts about communication is that people do not always mean what they say; speakers often use imprecise, exaggerated, or otherwise literally false descriptions to communicate experiences and opinions. Here we focus on the nonliteral interpretation of number words, in particular hyperbole (interpreting unlikely numbers as exaggerated and conveying affect) and pragmatic halo (interpreting round numbers imprecisely). We provide a computational model of number interpretation as social inference regarding the communicative goal, meaning, and affective subtext of an utterance. We show that our model predicts humans’ interpretation of number words with high accuracy. Our model is the first computational model that quantitatively predicts a range of nonliteral effects in number interpretation, and our modeling framework provides a theory nonliteral language understanding more generally.

**Main Text:**

Imagine someone describing a new restaurant where she recently dined. She says, “It took 30 minutes to get a table.” She likely meant that she waited approximately 30 minutes. Suppose she says: “It took 32 minutes to get a table.” This is more likely to mean *exactly* 32 minutes. Now, suppose she says: “It took a million hours to get a table.” She probably meant that the wait was shorter than a million hours, but importantly she thinks it took much too long. One of the most puzzling and important facts about communication is that people do not always mean what they say--a crucial part of a listener’s job is to understand an utterance even when its literal meaning is false. The ubiquity of nonliteral language and the ease with which people are able to interpret it present a puzzle for research on language understanding. Although there is a rich body of literature examining the psychological effects of using and processing nonliteral language (*1-4*), there has been little work on building formal models that predict the quantitative details of these effects or explain the computational basis of nonliteral language understanding.

Many linguists and psychologists have traditionally viewed communication as an interaction between rational and cooperative agents (*5, 6*). A recent body of work formalizes these views by modeling pragmatic language understanding as probabilistic inference over recursive social models. These Rational Speech Act models are able to quantitatively explain a range of phenomena in human pragmatic reasoning (*7, 8, 9, 10*). At the core of these models, a listener and speaker recursively reason about each other to arrive at pragmatically enriched meanings. Given an intended meaning *m,* a speaker *Sn* reasons about a listener *Ln-1* and chooses an utterance *u* based on its informativeness (*9*):

The listener *Ln* then reasons about *Sn* and uses Bayes’ Rule to infer the meaning *m* given utterance *u*:

The recursion begins with a naïve listener, L0, who interprets *u* literally. This framework crucially predicts that it is never optimal for a speaker to choose an utterance whose literal meaning directly contradicts her intended meaning. However, this is precisely the case in nonliteral language. For example, “Juliet is the sun” conveys that Juliet is a beautiful woman and not, in fact, the sun, and “It took a million hours to get a table” conveys that the wait time was long but not, in fact, a million hours. This suggests that speaker and listener must consider additional factors that enable nonliteral communication.

Previous work has revealed people’s reasons for using figurative language: often to convey emotion or emphasis (*1*). Here we propose that nonliteral language understanding relies on considering these alternative communicative goals during interpretation. A speaker’s goal may be to maximize the informativeness of her utterance along one dimension of meaning but not another, which makes it possible for a literally false utterance to be optimal as long as it is informative along the target dimension. We introduce a model in which the listener is uncertain about the speaker’s communicative goal and performs joint inference on both the goal and the intended meaning. The speaker is now modeled as

*Sn* (*u* | *g***s,a**) (

where is a function that denotes whether a communicative goal is satisfied (see Supplementary Materials for details). Importantly, the interpretation space has multiple dimensions and different communicative goals will be satisfied by different aspects of the inferred meaning. Since speakers often use language to express subjective opinions and emotions, we explore the case where the interpretation space has two dimensions: the state of the world and the speaker’s affect. Considering these two dimensions, the listener performs joint inference on both the goal and the meaning:

This formulation of language understanding as joint inference of the communicative goal, state of the world, and affective subtext of an utterance provides a computational model of nonliteral number word interpretation. We focus on number words for two reasons: first, despite their flexible and nonliteral usages in everyday language, numbers have precise literal meanings that can be easily formalized, unlike more complex concepts such as “Juliet” or “the sun.” Second, number words can be systematically manipulated on a continuous scale to yield quantitative predictions. We aim to model two particular well-known phenomena regarding number interpretation: hyperbole and pragmatic halo. Hyperbole is a figure of speech that uses exaggeration to create emphasis and express emotion. While hyperbolic utterances are literally false, listeners can successfully infer the intended meaning; such indirect communication is readily understood and serves many purposes (*1, 11-13*). Pragmatic halo refers to people’s tendency to interpret simple number expressions imprecisely and complex number expressions precisely (*14*). While this effect has been formalized via game theory as a rational choice given different utterance costs and a notion of pragmatic slack (*15, 16*), our model uses alternative communicative goals (to be precise or imprecise) coupled with differential utterance costs to model this effect.

We next show that our framework for pragmatic inference makes quantitative predictions for a number of nonliteral effects in language understanding. Given that knowledge of a domain’s prior distribution drives hyperbolic interpretations, we predict that the same number word used in different domains will elicit different interpretations. We test our model on number words that refer to the prices of three types of everyday items: electric kettles, watches, and laptops. We selected these items because they have distinct prior price distributions, which we measured empirically by asking participants to rate the probability of various prices for the three items (see Experiment 3a in Supplementary Materials). We also obtained an affect prior by asking participants to rate the probability of a speaker thinking that an item is too expensive given a price state (see Experiment 3b). The speaker can say, “The electric kettle cost *u* dollars,” where this utterance is either “round” (divisible by 10 and less costly) or “sharp” (not divisible by 10 and more costly). A formal description of these model assumptions is in Supplementary Materials.

Using the price and affect priors measured for each of the three items, we obtained the full posterior meaning distribution predicted for each utterance (see Figure S1). Figure 1 summarizes this distribution into different types of interpretations. The first three are model interpretations regarding the price state: *exact* (e.g., “1000” interpreted as 1000), *fuzzy* (e.g. “1000” interpreted as 1001 or “1001” interpreted as 1000), and *hyperbolic* (e.g. “1000” interpreted as “100”). Utterances whose literal meanings are less likely given the price prior are more likely to be interpreted hyperbolically (e.g. “1000” is more likely to be interpreted hyperbolically for electric kettles than laptops), which shows the model captures a basic feature of hyperbole. Round utterances such as “500” and “1000” are interpreted less exactly than their sharp counterparts, which shows the model captures pragmatic halo. On the affect dimension, *affective* interpretation refers to the probability that an utterance conveys that the price is too expensive. Utterances whose literal meanings are associated with higher affect priors (such as “10000” and “10001”) are more likely to be interpreted as conveying affect, which shows the model predicts the affective subtext of hyperbole.

To build intuition for these predictions, consider a pragmatic listener who recursively reasons about a speaker and analyzes her choice of utterance. The pragmatic listener hears “10,000 dollars” and knows its literal meaning is extremely unlikely. However, given that the speaker reasons about a literal listener who interprets “10,000 dollars” as actually meaning the object costs 10,000 dollars and is too expensive, “10,000 dollars” is an optimally informative utterance if the speaker’s goal is to communicate that the kettle is too expensive (without concern for the actual price). Since the pragmatic listener uses this information to perform joint inference on the speaker’s communicative goal and the meaning of the utterance, he infers that “10,000 dollars” is likely to mean less than a 10,000 dollars but that the speaker thinks it is too expensive (i.e. strong affect).

We conducted Experiment 1 to evaluate model predictions about interpreted price. Participants read scenarios in which a buyer produces an utterance about the price of an item he just bought, for example: “The electric kettle cost 1000 dollars.” Participants then rate the likelihood that the item actually cost *s* dollars for *s* S (see Experiment 1 in Supplementary Materials). Figure S2 shows participants’ interpretation distributions across all utterances. We found that participants were more likely to interpret utterances as hyperbolic when their literal meanings have lower probabilities under the item’s prior price distribution (F(1, 10) = 44.06, p < 0.0001). To examine the halo effect, we computed the difference between the probability of an exact interpretation and the probability of a fuzzy interpretation for each utterance. This difference is significantly smaller for round numbers than for sharp numbers (F(1, 4)=16.31, p < 0.05), which indicates that round numbers tend to be interpreted less precisely than sharp numbers. These results match the model’s qualitative predictions for hyperbole and halo. To quantitatively evaluate the model’s fit, we compared model and human interpretation probabilities across all utterances and show that model predictions are highly correlated with human interpretations of number words (r=0.974, p<0.0001) (Figure 2A).

We explore simpler comparison models to show that each component of the proposed model is responsible for capturing effects observed in the human data. Figure 2B compares predicted interpretations of the utterance “The electric kettle cost 1000 dollars” given considerations of different communicative goals. A model that only considers the goal of communicating the price precisely interprets the utterance entirely literally. A model that considers a speaker whose goal may be to communicate precisely or imprecisely interprets the utterance as meaning either 1000 or 1001. A model that considers a speaker whose goal may be to communicate the precise price state or her affect prefers price states with higher prior probabilities. Finally, a model that considers the full range of goals produces interpretations that demonstrate both hyperbole and halo effects that closely match humans’ interpretations. This suggests that reasoning about a speaker's communicative goals is crucial for the nonliteral interpretation of number words. Figure 3A shows probabilities of an utterance being interpreted hyperbolically by humans, the full model, and a version of the model that takes a uniform price prior for each item type. The full model faithfully captures the human data, while the “lesioned” model fails to differentiate among hyperbole effects for the three item domains. This confirms the hypothesis that people use their knowledge of a domain’s prior distribution to infer hyperbolic interpretations. Figure 3B shows the halo effect in humans, the full model, and a version of the model where the costs of utterances are uniform. The full model replicates humans’ pragmatic halo effect, while the simpler model does not distinguish between round and sharp utterances. This suggests that people consider utterance costs when inferring exact versus fuzzy interpretations.

We conducted Experiment 2 to examine how people infer affective subtext in hyperbolic and literal utterances. Participants read scenarios in which a speaker bought an item that cost *s* dollars and tells her friend that it cost *u* dollars, where *u* *s*. They then rate how likely it is that the buyer thinks the item was too expensive (see Experiment 2 in Supplementary Materials). Results showed that utterances *u* where *u* > *s* are rated as significantly more likely to convey affect than utterances where *u* = *s* (F(1, 25) = 9.592, p < 0.01). This confirms the hypothesis that listeners infer affective subtext from hyperbolic utterances. To measure the model fit quantitatively, we compared model and human interpretations of affect for each of the 45 items where *u* *s*. While there is a significant amount of noise in the human judgments (average split-half correlation is 0.833), the model predicts human interpretations of the utterances’ affective subtext significantly better than chance (r=0.772, p < 0.00001), capturing most of the reliable variation in these data. Figure 4A shows probabilities of inferring affective subtext given a price state and a literal or hyperbolic utterance for humans, the full model, and a version of the model that uses uniform affect priors. The human data shows that higher actual price states are associated with higher probability of affect. Within the same price state, hyperbolic utterances are interpreted as conveying more affect than literal utterances. Both effects are replicated by the full model, but not by the “lesioned” model. This shows that the rhetorical effect of hyperbole is driven in part by prior knowledge of affect associated with different prices.

We have presented the first computational model of nonliteral language understanding that quantitatively predicts humans’ interpretation of number words. Our model and behavioral results show that complex patterns in nonliteral number interpretation depend on the listener's prior knowledge, consideration of communicative efficiency, and reasoning about the speaker's communicative goal. Our model’s quantitative predictions closely match humans’ judgments of hyperbole, a complex phenomenon previously beyond the scope of computational models. These advances result in an innovative formal framework that explains nonliteral language understanding more broadly, suggesting extensions to phenomena such as irony and metaphor. We believe that this framework significantly advances the flexibility and richness of formal models of language understanding, such that some day probabilistic models will explain *everything* (hyperbolically speaking).

References and Notes:

1. R. M. Roberts, R. J. Kreuz, Why do people use figurative language?. *Psychological Science*. **5(3)**, 159-163 (1994).
2. S. Dews, E. Winner, Obligatory processing of literal and nonliteral meanings in verbal irony. *Journal of Pragmatics*. **31(12)**, 1579-1599 (1999).
3. S. Glucksberg, *Understanding figurative language: From metaphors to idioms*. (Oxford Univ. Press, 2001).
4. R. Gibbs, *Figurative language.*(The MIT encyclopedia of the cognitive sciences, 1999), pp. 314-315.
5. H. P. Grice, *Logic and conversation*. (1975), pp. 41-58.
6. H. H. Clark, *Using language*(Vol. 4). (Cambridge Univ. Press, 1996).
7. M. C. Frank, N. D. Goodman, Predicting pragmatic reasoning in language games. *Science*. **336(6084)**, 998-998 (2012).
8. N. D. Goodman, A. Stuhlmüller, Knowledge and implicature: Modeling language understanding as social cognition. *Topics in cognitive science*, **5(1)**, 173-184 (2013).
9. L. Bergen, N. D. Goodman, R. Levy, That’s what she (could have) said: How alternative utterances affect language use. *In Proceedings of the thirty-fourth annual conference of the cognitive science society* (2012).
10. G. Jäger, C. Ebert, Pragmatic rationalizability. *In Proceedings of sinn und bedeutung*. 13, 1-15 (2009).
11. M. McCarthy, R. Carter, “There's millions of them”: hyperbole in everyday conversation. *Journal of pragmatics*. **36(2)**, 149-184 (2004).
12. R. W. Gibbs, Irony in talk among friends. *Metaphor and symbol*. **15**(1-2), 5-27 (2000).
13. R. W. Gibbs Jr, J. O’Brien, Psychological aspects of irony understanding. *Journal of pragmatics*. **16**(6), 523-530 (1991).
14. P. Lasersohn, Pragmatic halos. *Language*, 522-551 (1999).
15. H. Bastiaanse, The rationality of round interpretation. *In Vagueness in communication.* 37-50 (2011).
16. M. Krifka, Approximate interpretation of number words: A case for strategic communication. *Cognitive foundations of interpretation*. 111-126 (2007).
17. R. S. Sutton, A. G. Barto, *Reinforcement learning: an introduction*, *Vol. 1, No. 1*. (Cambridge: MIT press, 1998).

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**Fig. 1**. Each vertical panel column shows the probabilities of different kinds of interpretations given utterances about an item.



**Fig. 2.** (A) Scatterplot with model predictions (x-axis) and average human responses (y-axis) for 300 data points (3 Items 10 Utterances 10 Price States). (B) Humans’ interpretation of an utterance (rightmost panel) and model predictions given different communicative goals. A model that considers both affect and precision goals (3rd panel from the left) closely matches human data.



**Fig. 3.** (A) Probability of hyperbolic interpretation across utterances and items. The leftmost panel shows human data (error bars are standard errors). A full model that uses empirical price priors matches human data; a model that uses uniform price priors does not distinguish among item types and shows weaker hyperbole effects. (B) Bias for exact interpretation for round/sharp utterance types. Humans have a significantly stronger bias for exact interpretations of sharp utterances. A full model that assigns higher costs to sharp numbers matches human data; a model that uses uniform utterance costs does not.



**Fig. 4.** (A) Scatterplot with model predictions of affect (x-axis) and human responses (y-axis) for 45 data points (3 Items 15 Utterance-Price state pairs where *u* *s*). (B) Probability of inferring affect given a price state and a hyperbolic or literal utterance. Humans infer higher probability of affect given higher price states and higher affect given hyperbolic utterances. A full model that uses empirical affect priors matches human data; a model that uses uniform affect priors predicts neither affect across price states or the rhetorical effect of hyperbole.

Supplementary Materials:

Materials and Methods:

**Model.** Here we describe our model in detail. Let *u* be the utterance a speaker utters. Let *m* be the meaning that is known to the speaker. *m* has two dimensions, one concerning the actual price state *s*, and one concerning the speaker's affect *a*. Given the set of price states S and set of affect states A, the set of possible meanings M is given by M = S X A. We denote each possible meaning as *ms,a*, where *s* S and *a*  A={0, 1} (0 means no affect and 1 means with affect).

Let *g* be the communicative goal, which also has two dimensions, one concerning the price state, and the other concerning the speaker's affect. We denote each communicative goal as *g***s,a**where **s** 2S and **a** 2A. The goal *g***s,a**is a function *g***s,a**: M {0,1}, such that *g***s,a**(*ms,a*) = 1 if and only if *s* **s**, *a* **a**. Thus, a goal specifies a subset of price states and affects, and a meaning satisfies this goal if it belongs to this subset. We assume that there are two types of price-related goals: the speaker either wants to communicate the price state exactly or approximately. Exact goals are represented by subsets that consist of a single price state, i.e. **s**={*i*} (for some *i* S), and approximate goals are represented by subsets that consist of the price states within a distance of 1 of some state, i.e. **s**={*j | j S, |j-i|* 1}.

The prior probability of a price state *s* is taken from an empirically derived price prior PS(*s*), and the probability of an affect *a* given a price state *s* is taken from an empirically derived conditional affect prior PA(*a*|*s*) (see Experiments 3a and 3b). The probability distribution PG(|*ms,a*) over goals given that the speaker knows meaning *ms,a* is defined to be uniform over goals consistent with *ms,a*, i.e. uniform over goals *g***s,a**such that *g***s,a**(*ms,a*) = 1. This is equivalent to assuming that the speaker either wants to communicate their meaning exactly or approximately.

A literal listener *L0* provides the base case for recursive social reasoning between the speaker and listener. *L0* interprets an utterance u literally without taking into account the speaker's communicative goals:

*L0* (*ms,a* | *u*) = (1)

The speaker *Sn* is assumed to be a rational planner who optimizes the probability that the listener will infer a meaning *m* that satisfies her communicative goal while minimizing the cost of her utterance. *Sn* chooses utterances according to a softmax decision rule that describes an approximately rational planner (*17*):

*Sn* (*u* | *g***s,a**) (2)

where the constant captures the degree of optimality of the speaker (we used =1 in the model simulations described).

The speaker wants to minimize both the cost C(*u*) of the utterance and the surprisal of her goal state. The utility function is therefore defined by:

) = (3)

which combined with equation 2 leads to:

*Sn* (*u* | *g***s,a**) ( (4)

The listener *L*n performs Bayesian inference to guess the intended meaning given the prior *P* and his internal model of the speaker. To determine the speaker's intended meaning, the listener will marginalize over the possible goals under consideration.

(5)

After obtaining a posterior distribution for all possible meanings *m* given an utterance *u*, we performed a Luce choice transformation on the distribution and fit to the behavioral data with . Figure S1 shows the full posterior distributions for all utterances. These model predictions were computed given the assumption that the available utterances for the speaker were identical to those used in constructing the experimental items (described below), and that the available price interpretations for the listener were identical to the possible price responses of the experimental participants.

**Experiment 1: Halo and Hyperbole.** 120 participants were recruited on Amazon's Mechanical Turk. Each participant read 15 scenarios in which a person (e.g. Bob) buys an item (e.g. a watch) and is asked by a friend whether the item is expensive. Bob responds by saying “It cost *u* dollars,” where *u* {50, 50 k, 500, 500 k, 1000, 1000 k, 5000, 5000 k, 10000, 10000 k}, where k was randomly selected from the set {1, 2, 3} for each trial. We will refer to this set of utterances as U. There are a total of 30 possible trial configurations (3 Items X 10 Utterances). Given an utterance *u*, participants rated the probability of Bob thinking that the item was expensive. They then rated the probability of the item costing the following amounts of money: 50, 50 k, 500, 500 k, 1000, 1000 k, 5000, 5000 k, 10000, 10000 k, where k was randomly selected from the set{1, 2, 3} for each trial. We will refer to this set of prices as S. Ratings for each price state were on a continuous scale from “impossible” to “extremely likely”, represented as real values between 0 and 1. We normalized participants ' ratings across price points for each trial to sum up to 1. The average normalized ratings across participants for each item/utterance pair is shown in Figure S2. There are a total of 300 normalized average ratings (3 Items X 10 Utterances X 10 Price States).

**Experiment 2: Affective subtext.** 160 participants were recruited on Amazon’s Mechanical Turk. Each participant read 30 scenarios in which a person (e.g. Bob) buys an item that costs *s* dollars and is asked by a friend whether the item is expensive. Bob responds by saying “It cost *u* dollars,” where *u* U and . Participants then rated how likely Bob thinks the item was expensive on a continuous scale ranging from “impossible” to “absolutely certain,” represented as real values between 0 and 1. The average ratings determine the degree of affect conveyed by an utterance given the actual price state. There are a total of 180 trial configurations (3 Items X 60 { } pairs where ). Since we assume that utterance cost should not affect affective subtext, in the analysis we collapsed round/sharp versions of an utterance and price state such that there are 45 configurations.

**Experiment 3a: Price prior.** To obtain people’s prior knowledge of the price distributions for electric kettles, laptops, and watches, 30 participants were recruited from Amazon's Mechanical Turk. Each participant rated the probability of an electric kettle, laptop, and watch costing *s* dollars, where *s* S. Ratings for each price state were on a continuous scale from “impossible” to “extremely likely”, represented as real values between 0 and 1. We normalized participants ' ratings across price points for each trial to sum up to 1. The average normalized ratings across participants for each item were taken as the prior probability distribution of item prices. These price distributions were used in the model to determine the prior probability of each price state.

**Experiment 3b: Affect prior.** To obtain people’s prior knowledge of the affect likelihood given a price state, 30 participants were recruited from Amazon’s Mechanical Turk. Each participant read 15 scenarios where someone had just bought an item that cost *s* dollars (s S). They then rated how likely the buyer thinks the item was expensive on a continuous scale ranging from “impossible” to “absolutely certain,” represented as real values between 0 and 1. The average ratings for each item/price state pair were taken as the prior probability of an affect given a price state. This was used in the model to determine the prior probability of an affect given each price state.



Fig. S1. Full posterior meaning distribution predicted by the model for each utterance. Each column is an utterance, and each row is an item type. Each panel represents the interpretation distribution given an utterance.



Fig. S2. Full meaning distribution produced by humans for each utterance. Each column is an utterance, and each row is an item type. Each panel represents the interpretation distribution given an utterance. Error bars are standard errors.

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