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A Computational Model of Nonliteral Language Understanding in Number Words

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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 computationally model 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 introduces rich social meaning to formal models of language understanding.

**Main Text:**

Imagine a conversation with a friend about a new restaurant where she recently dined. Your friend says, “It took 30 minutes to get a table.” You are likely to interpret this to mean she waited approximately 30 minutes. Suppose your friend says: “It took 32 minutes to get a table.” You are more likely to interpret this to mean *exactly* 32 minutes. Now, suppose she says: “It took a million hours to get a table.” You will probably interpret this to mean that the wait was shorter than a million hours, but importantly that 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. As a result, a crucial part of a listener’s job is to understand an utterance even when its literal meaning is extremely unlikely. The ubiquity of nonliteral language and the ease with which people are able to interpret it present a puzzle for language understanding research. 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 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, 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*:

Since the recursion ends with a naïve listener who interprets *u* literally, it is never optimal for a speaker to choose an utterance whose literal meaning directly contradicts her intended meaning, and thus impossible for a listener to infer an intended meaning that contradicts the literal 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 information in order for successful communication to take place. Previous work has revealed reasons for using figurative language, such as to communicate emotion or emphasis (*1*). Here we propose that nonliteral language understanding relies on considering such alternative communicative goals. A speaker’s goal may be to maximize the informativeness of her utterance along one particular dimension of meaning but not another, thus making it possible for a literally false utterance to be optimal as long as it is informative along the target dimension. We introduce a model that considers multiple possible goals. The speaker model is now defined 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 communicative goal has multiple dimensions that can be satisfied by different aspects of the meaning. We explore the case where there are two dimensions: the state of the world and the speaker’s affect. Modeling affect allows us to introduce rich social meanings to a formal model of communication, where language is often used not to describe the world objectively but to express subjective opinions and emotions. Considering these two dimensions, the listener then performs joint inference on both the speaker’s communicative goal and the meaning:

By modeling language understanding as social inference regarding the communicative goal, state of the world, and affective subtext of an utterance, we present 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. There are two particular well-known phenomena regarding number interpretation we aim to model: 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 and regard hyperbole as a signal of interpersonal closeness (*1, 11-13*). Our model posits that prior knowledge about the relevant topic plays an important role in interpreting hyperbolic statements. Furthermore, our model uses alternative communicative goals to capture the intuition that a listener will infer a stronger affective subtext from hyperbolic utterances. 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 show that a Bayesian framework for pragmatic inference that considers uncertainty about communicative goals 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 domains with different prior distributions will elicit different interpretations with the same number word. 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 different prior price distributions, which we measured empirically by asking subjects 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 subjects to rate the probability of a speaker thinking that an item is expensive given a price state (see Experiment 3b). We used the same set of price states for the three types of items, defined as S={50, 51, 500, 501, 1000, 1001, 5000, 5001, 10000, 10001}. We assume that the set of utterances U is equivalent to the set of price states S. A speaker can say, “The electric kettle cost *u* dollars,” for *u* U, and a listener can interpret this to mean that the kettle cost *s* dollars, for *s* S. Each utterance is either “round” (divisible by 10 and less costly) or “sharp” (not divisible by 10 and more costly). A formal description of the model is in Supplementary Materials.

Using the price priors and affect priors measured for each of the three items, we obtained the full posterior meaning distribution predicted by the model 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 basic principles of hyperbole. Round utterances such as “500” and “1000” are interpreted less exactly and more fuzzily 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 affect about the price being 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 captures the affective subtext of hyperbole.

The intuition for how the model understands hyperbole is as follows. A pragmatic listener recursively reasons about a speaker and analyzes her choice of utterance given a state of the world, her affect, and her communicative goal. 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 meaning 10,000dollars and believes that the speaker very likely thinks it is expensive, “10,000 dollars” is an optimally informative utterance if the speaker’s goal is to communicate that the kettle is expensive. The pragmatic listener performs joint inference on the speaker’s communicative goal and the meaning of the utterance. This leads him to infer that “10,000 dollars” is likely to mean less than a 10,000 dollars but that the speaker very likely thinks it is expensive.

We conducted Experiment 1 to evaluate model predictions. Subjects 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.” Subjects then rate the likelihood that the item actually cost *s* dollars for *s* S (see Experiment 1 in Supplementary Materials). Figure S2 shows humans’ interpretation distributions across all utterances. We found that humans are more likely to interpret utterances whose literal meanings have low probabilities under the item’s prior price distribution as hyperbolic (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 more approximately than sharp numbers. These results match the model’s qualitative predictions for hyperbole and halo. Quantitatively, 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 lesion various parts of the model to show that each component is responsible for capturing different effects that we observe in the human data. Figure 2B compares model interpretations of the utterance “The electric kettle cost 1000 dollars” given considerations of different communicative goals. A model that does not consider alternative communicative goals interprets the utterance entirely literally. A model that considers a speaker whose goal may be to communicate precisely or imprecisely interprets the utterance as 1000 but also probably 1001. A model that considers a speaker whose goal may be to communicate the precise price state or her affect interprets the utterance hyperbolically and places mass on 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 and 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 in 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 take into account the prior distribution of item prices when inferring 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 lesioned model does not. This suggests that people consider utterance costs when inferring exact versus fuzzy interpretations.

We conducted Experiment 2 to examine humans’ inference of affect subtext in hyperbolic versus literal utterances. Subjects read scenarios in which a speaker bought an item that cost *s* dollars and tells his friend that it cost *u* dollars, where *u* *s*. They then rate how likely it is that the buyer thinks the item was 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. 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 data (average split-half correlation is 0.833), the model significantly predicts human interpretations of the utterances’ affective subtext (r=0.772, p < 0.00001). 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 takes in 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 rhetoric effect of hyperbole is driven by prior knowledge of affect associated with different prices.

We present 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 communication 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. In addition, we also introduced an “affect” dimension to formally model subjective and social aspects of communication. These advances result in an innovative formal framework that explains nonliteral language understanding phenomena using core theories of communication. We believe that this framework marks a significant advancement in the flexibility and richness of formal models of language understanding, such that some day Bayesian models can explain *everything* (hyperbolically speaking).

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**Fig. 1**. Each panel shows the probabilities of a kind of interpretation (exact, fuzzy, hyperbolic, and affective) across utterances. The model interprets sharp utterances more exactly and utterances with unlikely literal meanings more hyperbolically. It also interprets higher utterances as conveying more affect.



**Fig. 2.** (A) Correlation between model predictions and average human responses for the 300 data points (3 Items 10 Utterances 10 Price States). Model predictions and human data are highly correlated for all item types and interpretation kinds, with an overall correlation of r=0.974. (B) The rightmost panel shows humans’ average interpretations of the utterance “The electric kettle cost 1,000 dollars.” Model comparison shows that affect and precision goals are both needed to match human data.



**Fig. 3.** (A) The leftmost panel shows humans’ average probability of hyperbolic interpretation given different utterances and item types. A full model that uses empirical price priors matches human data and produces different interpretations across item types, while a model that uses uniform price prices does not. (B) The leftmost panel shows that humans treat sharp numbers with a significantly stronger bias for exact interpretations. A full model that assigns higher costs to sharp numbers matches human data, while a model that uses uniform utterance costs does not.



**Fig. 4.** (A) Correlation between model predictions of affect and human responses for 45 data points (3 Items 15 Utterance-Price state pairs where *u* *s*), with r=0.772. Error bars are standard error for human responses. (B) The leftmost panel shows humans’ average probability of inferring affect given a price state and a hyperbolic or literal utterance. A full model that uses empirical affect priors matches human data and assigns higher affect to hyperbolic utterances, while a model that uses uniform affect priors does not.

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; such a subset will be referred to as a goal state. We assume that there are two types of price-related goal states: 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.

**Experiment 1: Halo and Hyperbole.** 120 subjects were recruited on Amazon's Mechanical Turk. Each subject 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. Given an utterance *u*, subjects 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 subjects' ratings across price points for each trial to sum up to 1. The average normalized ratings across subjects for each item/utterance pair is shown in Figure S2.

**Experiment 2: Affective subtext.** 160 subjects were recruited on Amazon’s Mechanical Turk. Each subject 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 . Subjects 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.

**Experiment 3a: Price prior.** To obtain people’s prior knowledge of the price distributions for electric kettles, laptops, and watches, 30 subjects were recruited from Amazon's Mechanical Turk. Each subject 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 subjects' ratings across price points for each trial to sum up to 1. The average normalized ratings across subjects 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 subjects were recruited from Amazon’s Mechanical Turk. Each subject 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 error.

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