

# Metaphor and Linguistic Creativity: Pragmatic Reasoning with Distributional Semantics

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Humans create and interpret novel metaphors, like *Time is a thief* or *My lawyer is a shark*, with relative ease, incorporating world knowledge to determine which aspects of the predicate (*thief*, *shark*) are true of the subject (*time*, *my lawyer*). Here we present a computational theory of metaphor, according to which metaphorical interpretations arise from joint, cooperative reasoning between a speaker and listener. We combine a Bayesian model of this reasoning process with empirically learned word embeddings which are used to provide an underlying representation of word meaning. This allows for open-domain interpretation of predicative and adjectival metaphors. We find a significant preference in human judgments for our model over a system which uses word embeddings without an explicit representation of inter-agent reasoning, providing evidence that reasoning about an informative and relevant speaker is key to understanding non-literal language.

metaphor | informativity | Bayesian pragmatics | distributional semantics

Metaphor presents a compelling theoretical challenge for the understanding of meaning in natural language. On hearing (1) in a context where the subject, Jane, is known to be a journalist, a listener might infer that Jane is not literally a soldier, but rather that she shares certain attributes with soldiers (perhaps determination, endurance, or ruthlessness).

(1) Jane is a soldier

The *pragmatic* view of metaphor, proposed by Grice (1), takes the meaning conveyed by sentence (1) to be the result of joint, cooperative reasoning between a speaker and listener. That is, the speaker has some information about Jane, and wants to communicate some aspects of this information to the listener using the predicate *soldier*. The listener, in turn, jointly infers what Jane must be like and what aspects of Jane are relevant for the speaker.

**Interpreting figurative language** We build on a previous model of metaphor interpretation (2), developed as part of a probabilistic framework for pragmatic reasoning (3), which uses *projection functions* to determine the dimension of the world that the speaker cares about communicating. In this model, a listener jointly reasons about the state of the world (e.g. what Jane is like) and a projection function, corresponding to the aspect of the world the speaker cares to communicate (e.g. Jane's determination). This listener assumes an informative speaker - one whose choice of utterance maximizes the probability of communicating the state of the world - but only up to a projection which dictates the relevant dimension of the world.

This can be used to give an account of predicative metaphors (those of the form *A is a B*) and adjective-noun

(AN) metaphors (like *fiery temper*). However, in order to generate predictions from the model, it is necessary to provide a semantics, specifying the literal meaning of each utterance (for example, that *soldier* literally describes an individual who serves in a military). Previous work has hand-constructed these literal interpretations, restricting the scalability of the models, and their applicability to previously unseen metaphors.

**Our contribution** We develop a model of pragmatic reasoning which uses empirically learned word-embeddings (4, 5) to represent word meanings, obtaining a system capable of interpreting open-domain predicative and adjectival metaphors without the need for hand-specified semantics. This adaptation requires a generalization of projection functions to linear projections in a vector space, and a novel inference algorithm to calculate metaphor interpretations. Constructing this system permits what is to our knowledge the first open-domain evaluation of a Bayesian model of pragmatic reasoning. Evaluated on human judgments, our model significantly outperforms a baseline which uses a word embedding semantics without explicit pragmatic reasoning. This suggests that the information in word embeddings alone is not sufficient to capture the creativity of metaphorical language, but that an explicit model of pragmatic reasoning is also key.

## 1. Overview of metaphor

Metaphor exists in many syntactic forms (6), and has been extensively studied in cognitive science (7–9), linguistics (10, 11) and other disciplines (12, 13).

For present purposes, we focus on metaphors involving copular predicates (e.g. *Jane is a soldier*) and AN noun

### Significance Statement

Linguistic creativity — the ability to combine existing representations to create new meanings — is a distinctive trait of human cognition. Metaphor provides a general vehicle for creative transfer and reuse of concepts. Here, we develop a system for open-domain interpretation of metaphor. Our system integrates world knowledge automatically induced from large text corpora, with reasoning about the social goals of the speaker. The approach provides a general architecture for composing semantic knowledge with social reasoning, providing insight into the origins of linguistic creativity.

R.C.G. and L.B. designed the model, planned the experiment, performed analyses, and wrote the manuscript. R.C.G. carried out the experiment.

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phrases (e.g. *fiery temper*). We refer to the predicated or modified noun (*Jane, temper*) as the *target* of the metaphor and the predicate or adjective (*soldier, fiery*) as the *source* (see (14) for the more general sense of these terms).

For a given metaphor, only certain properties of the target are described by the source. For instance, (2), said of a sleeping dog, could convey that it is unresponsive, but said of a large alert dog, could convey that it is heavy.

(2) The dog is a rock.

Examples like (2), and more generally the ability to interpret novel metaphors, suggest that metaphors cannot be explained merely as fixed conventional phrase meanings. The benefit of the pragmatic view of metaphor is the ability to explain the interpretation of novel metaphors in a way which takes into account an underlying semantics (e.g. the conventional meanings of *dog* and *rock*).

## 2. A Bayesian model of metaphor interpretation

The Rational Speech Acts framework (RSA) provides an elegant and practical way of formalizing pragmatic reasoning (3). In this framework, listeners and speakers are represented as conditional probability distributions. Speakers are represented as distributions over possible utterances given worlds, and listeners as distributions over possible worlds given utterances. The most basic version of RSA (3) is incapable of interpreting metaphors, due to the strict assumption that the speaker's utterances are literally true. To address this, Kao et al. (2) propose a model  $L_1^Q$ , shown in (5), which in turn is defined in terms of  $S_1$  (4) and  $L_0$  (3).

$$(3) \quad L_0(w|u) \propto \llbracket u \rrbracket(w) \cdot P_L(w)$$

$$(4) \quad S_1(u|w, q) \propto \sum_{w'} \delta_{q(w)=q(w')} \cdot L_0(w'|u)$$

$$(5) \quad L_1^Q(w, q|u) \propto S_1(u|q, w) \cdot P_L(w) \cdot P_{L_Q}(q)$$

**The literal listener**  $L_0$  represents a model of a listener that, given an utterance  $u \in U$ , updates their belief about the world  $w \in W$  by filtering out all worlds that are semantically incompatible with  $u$ . The term  $\llbracket \cdot \rrbracket$  is a function  $U \rightarrow (W \rightarrow \{0, 1\})$ , representing the semantics of the language.  $P_L(w)$  is the prior probability of world  $w$ .

**Projections** Functions  $q \in Q$  formalize the notion of picking a particular *aspect* or *dimension* of  $w$ . Formally, they are functions  $W \rightarrow D$ , for some set  $D$ .

**The informative speaker**  $S_1$  has a state  $w$  they want to communicate to the listener  $L_0$ , and prefers utterances  $u$  which maximize the probability that  $L_0$  assigns to  $w$ , up to the dimension of  $w$  specified by  $q$ .  $\delta_{a=b}$  is an indicator function, and is equal to 1 if  $a = b$ , and equal to 0 otherwise. If  $q$  is the identity function, then  $S_1(u|w) \propto L_0(w|u)$ , and  $S_1$  is thus a model of a speaker who prefers to choose the most informative utterance available.

**The pragmatic listener** The full model,  $L_1^Q$ , hears an utterance  $u$ , and jointly infers values for  $w$  and  $q$  by reasoning about  $S_1$ . The key dynamic is that the listener may hear an utterance  $u$  and infer a pair  $(w, q)$  where  $u$  is semantically incompatible with  $w$  (i.e.  $\llbracket u \rrbracket(w) = 0$ ); this will occur when  $u$  conveys

effectively some feature of world  $w$  as determined by  $q$ .  $P_{L_Q}(q)$  is the prior probability of projection  $q$ .

$L_1^Q$  functions as a model of metaphor interpretation. For instance, using the metaphor in (6), the listener infers both a state  $w$  (representing what John is like) and a feature  $q$  (representing which aspects of John are relevant).

As an example in a hand-constructed setting, we could take John to be fully characterized by two features, whether he is vicious and whether he is aquatic, so that a state  $w$  is a value (true or false) for both of these predicates. The projections  $q \in Q$  are then the functions mapping a state to its value on viciousness ( $q_{vicious}$ ) or aquaticness ( $q_{aquatic}$ ) respectively. Further, we assume that *shark* is semantically compatible only with the state in which John is both vicious and aquatic.

(6) John is a shark.

On hearing (6), the prior belief that John is not literally an aquatic animal leads  $L_1^Q$  to conclude that the speaker cares about conveying the viciousness dimension (i.e. has projection  $q_{vicious}$ ), and that John is vicious. See (2) for quantitative examples.

Importantly,  $L_1^Q$  can do more than simply using prior knowledge to interpret literally false statements in a flexible way. It is also capable of reasoning about alternative utterances: for instance, suppose we add a third property, *quickness*, so that *shark* is compatible only with the state in which John is quick, aquatic and vicious, and also add a third utterance, *dolphin*, compatible only with John being quick, aquatic and *not* vicious.

In this second example, when  $L_1^Q$  hears *shark*, it infers that John is more likely vicious than quick. This is because a speaker who wanted to communicate that John is vicious would only be able to use the utterance *shark*, whereas a speaker who wanted to communicate that John is quick would be able to choose between either *shark* or *dolphin*. The utterance *shark* is therefore more likely to have been produced by the speaker trying to communicate John's viciousness.

$L_1^Q$  can model AN metaphors in a similar way. For a phrase like *John's fiery temper*, the listener infers the features of John's temper that would explain why the speaker modified it with *fiery*.

## 3. Distributional Semantics

*Word embeddings*, or *distributional semantic models*, provide a representation of word meanings that can be learned from large corpora of language data. In these models, word meanings are mapped to points in a high-dimensional vector space, such that words with similar meanings are mapped to nearby points in the space. The embeddings can be obtained either by dimensionality reduction of a word co-occurrence matrix (5) estimated from a corpus, or by extracting the weights of a statistical model (4, 15, 16) trained on a separate task. In both cases, word embeddings provide a way to empirically obtain fine grained connotations of lexical items (4), and have been used effectively in a number of NLP tasks (17–19).

Metaphor is an obvious candidate for approaches that use distributional semantics: a wide variety of attempts have been made to leverage the information inherent in pre-trained word vectors for the detection, interpretation and paraphrase of metaphor (see (20) for an overview of proposed systems).

We hypothesize that, while the information in high quality word embeddings captures important aspects of meaning, a cognitively realistic model of metaphor interpretation should also incorporate pragmatic reasoning, of the sort formalized in the RSA framework. We now explain how the  $L_1^Q$  model described above can be combined with a distributional model of word meaning.

#### 4. Bayesian pragmatics with distributional semantics

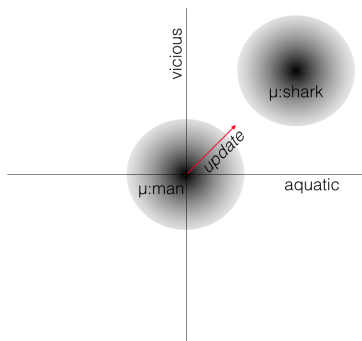
We now introduce a *vector* interpretation of  $L_1^Q$ . Importantly, this requires no modification to equations (3-5). The crucial difference is that our state space  $W$  is now not just a set, but a vector space, so that elements  $w \in W$  are vectors. A word embedding maps words to vectors ( $E : U \rightarrow W$ ). For our application of the model, we assume the set of utterances  $U$  is a set of adjectives.

**The listener's prior** To define a prior distribution  $P_L$  over the vector space  $W$ , we use a multivariate spherical Gaussian distribution  $P_N$ , which can be parametrized by a vector  $\mu$  for the mean and a single scalar  $\sigma$  (the covariance matrix is assumed to be  $\sigma^2 I$ ). We define the prior over projections  $P_{LQ}$  to be uniform (the set of projections is discussed below).

$$(7) \quad P_L(w) = P_N(w | \mu = E(\text{target}), \sigma = \sigma_1)$$

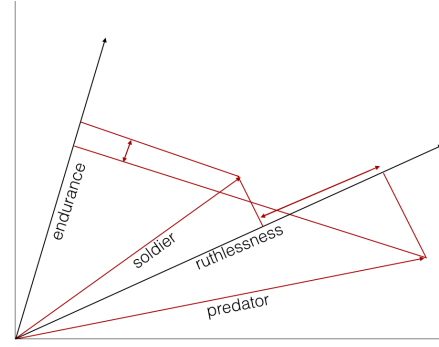
We can view the prior  $P_L$  as representing uncertainty over the position of the entity or concept that the target noun (e.g. *man* in “The man is a shark”) represents. The goal of the speaker is to convey a position in the space to the listener, and the goal of the listener is to infer what this position is. In this sense, the speaker and listener are playing a spatial reference game (21), in an abstract word embedding space. Our vector semantics bears comparison to the *conceptual space* semantics of (22), as well as the proposal for metaphor comprehension of (23).

The prior distribution places more probability mass on points closer to its mean. By setting the mean of the prior as  $E(\text{target})$ , we encode the listener's assumption that the meaning the speaker wishes to communicate is in the neighborhood of the source noun.  $\sigma_1$  is a hyperparameter which determines the extent of the listener's prior uncertainty.



**Fig. 1.** Illustration of literal listener  $L_0$  given *The man is a shark*, with  $\overrightarrow{man} = (0,0)$  and  $\overrightarrow{shark} = (1,1)$ .  $L_0$ 's prior is centered at  $\overrightarrow{man}$ , and is updated towards  $\overrightarrow{shark}$ .

**The semantics** Word embedding spaces allow us to compare the similarity of words (e.g., a noun and an adjective) according to different measures of distance in the space. However, they



**Fig. 2.** In this hand-constructed 2D example, vectors for  $\overrightarrow{soldier}$  and  $\overrightarrow{predator}$  are projected onto subspaces given by  $\overrightarrow{endurance}$  and  $\overrightarrow{ruthlessness}$ . Soldiers have greater endurance than predators, while predators are more ruthless.

do not provide a means of categorically determining the compatibility of that adjective and noun, as previous pragmatic models have required (described in Section 2). We observe, however, that the definition of  $L_0$  in (3) only mathematically requires that the semantics  $[\cdot]$  be a function  $U \rightarrow (W \rightarrow \mathbb{R})$ . We can define such a function as follows, with  $\sigma_2$  as a hyperparameter:

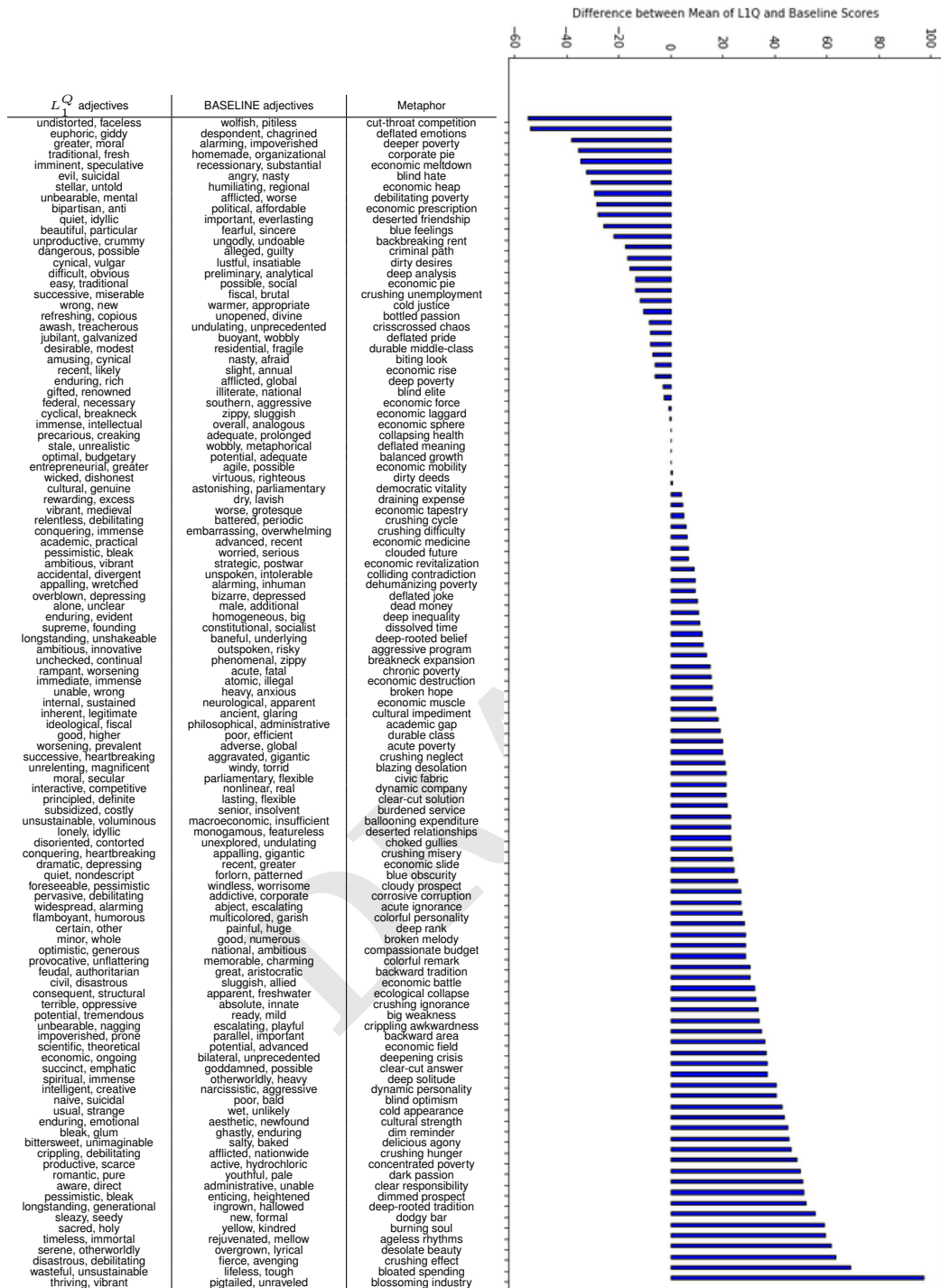
$$(8) \quad [u](w) = P_N(w | \mu = E(\text{source}), \sigma = \sigma_2)$$

The value of  $[u](w)$  is a real number which decreases with the Euclidean distance between  $u$  and  $w$ . The advantage of defining the semantics in this way is that both the prior of  $L_0$ , shown in (7), and the likelihood, in (8), are Gaussian distributions, which allows for a closed form solution of  $L_0$ , described in *Materials and Methods*.

**Projections** Finally, we need to supply a notion of a projection function  $q$  that is defined on our vector space, and to specify a set  $Q$  of such projections. For this, we use linear projections along a vector (or hyperplane)  $v$  capturing the degree to which each  $w$  extends along  $v$ , ignoring orthogonal dimensions. Geometrically, this amounts to dropping a line from an input vector  $w$  at a right angle onto  $v$ , as depicted in figure 2. These projections exploit the linear structure of the word embedding space (5), though see (24, 25) for potential caveats.

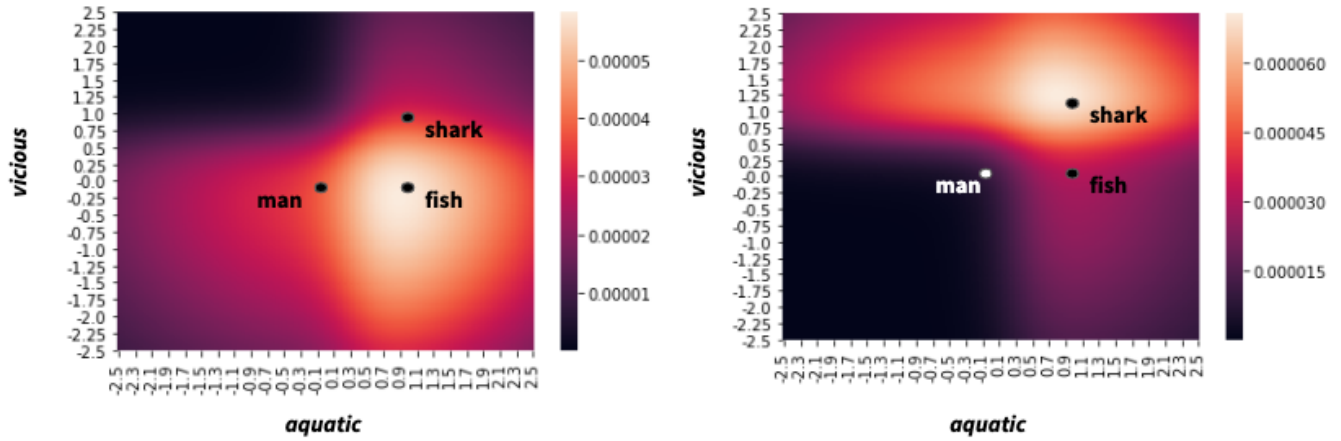
In practice, we restrict ourselves to projections along a vector, rather than a larger subspace. To obtain a set  $Q$  of projections, we first note that since word meanings are vectors in  $W$ , any word parametrizes a linear projection  $q$ . For instance, we can think of the word *vicious* as defining a *viciousness* projection, which measures how far other points in the space fall along *vicious*. We choose  $Q$  as a set of gradable adjectives, so that the projection of a noun onto  $v$  amounts to asking: to what extent does the noun have property  $v$ ? Figure 4 provides a visualization of the  $L_1^Q$  posterior in a simple two-dimensional case corresponding to the example discussed in section 2.

**Interpreting the output of  $L_1^Q$**  The *Materials and Methods* describes how to calculate the interpretation of a metaphor  $u$  given these assumptions. In particular, it shows how to compute  $L_1^Q(w, q|u)$ , the joint distribution over states and projections after hearing a metaphor  $u$ . Unlike points  $w \in W$ , projections  $q \in Q$  are readily interpretable, since they correspond to adjectives, describing the aspect of the metaphorical adjective or predicate that is inferred to be relevant. For



**Fig. 3.** The 109 metaphors used in the experiment, and baseline and  $L_1^Q$  interpretations. Bar positions indicate difference between judgments of  $L_1^Q$  and baseline proposals, averaged across participants and across both proposals of each model. Bars right of center indicate a preference for the pragmatic model, showing that for roughly 75% of the metaphors, the  $L_1^Q$  interpretation is preferred.





**Fig. 4.** Heatmaps visualizing the  $L_1^Q$  marginal posterior over states in a hand-constructed, two-dimensional case. The listener hears *The man is a fish* in the left panel, and *The man is a shark* in the right. The set of utterances  $U = \{man, shark, fish\}$ . For simplicity, the set of QUDs  $Q$  consists of orthogonal vectors, one along the x-axis (*aquatic*) and one along the y-axis (*vicious*). After hearing *fish*, the listener has lower uncertainty along the aquatic dimension, and higher uncertainty along the vicious dimension (left panel); after hearing *shark*, the situation is reversed (right panel).

this reason, we use the marginal posterior over  $Q$  to generate predictions from the model. The top two  $L_1^Q$  marginal posterior projections  $q$  for each metaphor, which we use in our experiment, are shown in the leftmost column of Figure 3.

## 5. Experimental Evaluation

In order to evaluate whether pragmatic reasoning results in metaphor interpretations that better capture human judgments, we designed an experiment comparing  $L_1^Q$  interpretations of metaphors to a baseline model which uses word embeddings but no pragmatic reasoning.

**Experimental Design.** In the experiment, each participant was shown a series of 12 adjectival metaphors, selected randomly from a total of 109. For each metaphor, they were asked to rate four candidate interpretations of the metaphor on a slider bar. These four candidate interpretations consist of the best and second best adjective generated by  $L_1^Q$ , and similarly for a baseline model. The baseline model selects adjectives without pragmatic reasoning, using a standard procedure from the word embeddings literature (see *Materials and Methods*). An example is shown in Figure 5.

**Analysis.** The results, shown in Figure 3, were analyzed using mixed-effects models with random slopes and intercepts for items and participants. Participants rated four interpretations for each metaphor: the best and second-best interpretations, as output by each of the target and baseline models. Participants rated the target interpretations significantly higher than the baseline interpretations ( $\beta=13.8$ ,  $t=5.3$ ,  $p < 10^{-7}$ ) in a combined analysis. The results were similar when the best target interpretations were compared to the best baseline interpretations ( $\beta=16.4$ ,  $t=4.8$ ,  $p < 10^{-5}$ ) and when the second-best interpretations were compared ( $\beta=11.1$ ,  $t=3.2$ ,  $p < 0.005$ ).

## 6. Discussion

We have shown that it is possible to scale Bayesian pragmatic reasoning to distributional semantics, and using this to obtain

a model of metaphor interpretation. Our evaluation, the first open-domain evaluation of a Bayesian model of pragmatic language interpretation, indicates that the principles of pragmatic reasoning continue to operate at this scale, and are key to obtaining human-like interpretations of metaphors. We see this as an important step towards a cognitively accurate and computationally tractable model of pragmatic language interpretation and production in general.

## Materials and Methods

**Model inference.** We employ a mix of analytic and approximate methods to compute the  $L_1^Q$  distribution. We first present the approach for computing  $L_0$  and  $S_1$  posteriors, which can be done analytically, and then present the approximate inference algorithm for  $L_1^Q$ . The implementation, written in TensorFlow, will be made publicly available.

**$L_0$  Inference** The vector interpretation of  $L_0$  is illustrated in Figure 1, where a ball, corresponding to the prior, is moved in the direction of the point corresponding to the perceived utterance. To calculate  $L_0$  analytically, we make use of Gaussian conjugacy. When the prior  $P_L$  is defined as in Equation 7, and the semantic interpretation is defined as in Equation 8, then conjugacy implies that the listener posterior is given by:

$$(9) \quad L_0(w|u) = P_{\mathcal{N}}(w|\mu = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2} (\frac{E(target)}{\sigma_1^2} + \frac{E(source)}{\sigma_2^2}), \sigma = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2})$$

**$S_1$  Inference** The speaker is defined by Equation 4, which in the continuous case can be rewritten as:

$$(10) \quad S_1(u|w, q) \propto \int_{w'} \delta_{q(w)=q(w')} \cdot L_0(w'|u)$$

Here  $q(w)$  is the projection of state  $w$  onto the subspace spanned by projection vector  $q$ . This integral computes the marginal probability of all states that are projected to the same location as  $w$  along  $q$ . From Equation 9,  $L_0(\cdot|u)$  is a normally distributed random variable, and therefore the projection of this random variable onto a linear subspace is also normally distributed, providing a closed-form solution to  $S_1$ .

**$L_1^Q$  Inference** The  $L_1$  posterior is a joint distribution over one continuous and one discrete random variable. Because of the linear structure of the problem, we are able to devise a near-exact inference algorithm for the marginal distribution over projections in  $Q$ , derived as follows:

$$\begin{aligned}
L_1(q|u) &= \int_{\mathbb{R}^n} L_1(w, q|u) dw = \frac{1}{K} P_{L_Q}(q) \int_{\mathbb{R}^n} P_L(w) S_1(u|w, q) dw \\
&= \frac{1}{K} P_{L_Q}(q) \int_{\mathbb{R}^n} P_L(w_q, w_\perp) S_1(u|w_q, q) dw \\
&= \frac{1}{K} P_{L_Q}(q) \int_{D^\perp} P_L(w_\perp) dw_\perp \int_D P_L(w_q) S_1(u|w_q, q) dw_q \\
&= \frac{1}{K} P_{L_Q}(q) \int_D P_L(w_q) S_1(u|w_q, q) dw_q
\end{aligned}$$

Here  $K$  is a normalizing constant,  $w, q \in \mathbb{R}^n$ , and  $w_q$  is the projection of  $w$  onto the vector  $q$ .  $D$  is the subspace of  $\mathbb{R}^n$  spanned by the vector  $q$ , and  $D^\perp$  is the orthogonal complement of  $D$ . The vector  $w_\perp$  is the projection of vector  $w$  onto the subspace  $D^\perp$ . The final equation is a one-dimensional integral, and can be computed using a discrete approximation. We use a Gaussian approximation, which easily generalizes to the setting of multi-dimensional projections. The constant  $K$  can be found from the constraint  $\sum_q L_1(q|u) = 1$ .

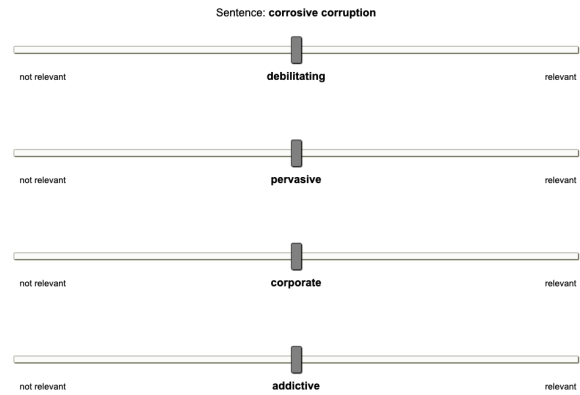
**Experiment.** The aim of our experiment is to determine whether pragmatic reasoning results in better interpretations of metaphors, according to human judgments. We compare against a lesioned model, with a distributional semantics that does not make use of pragmatic reasoning.

**Baseline model** Our baseline model is defined as follows: for a given metaphor of the form  $(a\ n)$ , we take the mean of the adjective word embedding  $E(a)$  and the noun word embedding  $E(n)$ . The two nearest adjectives  $q$  to this mean (measured by cosine distance) are the baseline interpretations for the metaphor. Taking the mean of word vectors is a standard technique for computing phrase and sentence meanings from constituent words (19, 26, 27), while cosine distance is commonly used to find words with the most similar meaning (5).

**$L_1^Q$  hyperparameters** We use the largest available (300 dimensional) GloVe vectors, as our word embedding  $E$ . For each Adjective-Noun metaphor  $(a\ n)$ , we specify  $U$  as a set of 101 alternative utterances, consisting of  $a$  and 100 of the nearest adjectives (by cosine distance) to  $n$ . These adjectives are chosen from the set of the 1425 adjectives with concreteness ranking  $> 3.0$  in the concreteness corpus of (28), to exclude abstract nouns. Similarly, we select a set  $Q$  of projections corresponding to the hundred closest adjectives to the mean of the subject and predicate (the method of adjective choice in the baseline model), and take  $P_{L_Q}$  to be a uniform distribution over  $Q$ .

By tuning on an independent validation set of metaphors, we choose  $\sigma_1 = \sigma_2 = 0.1$ ; all model parameters and features of the architecture were frozen prior to the experiment. Metaphor interpretations are generated by selecting the two projections with highest marginal posterior mass under  $L_1^Q$ . We choose two rather than one since the model tends to distribute most of its probability mass to at least two projections, intuitively reflecting the fact that there is usually more than one good interpretation of a metaphor.

**Experimental Methods** Tsvetkov et al. (29) provide a corpus of  $\sim 800$  AN metaphors, gathered by human annotators, from which we select the least frequent by bigram count (n-gram data from the Corpus of Contemporary American English (30)) to filter out conventionalized metaphors. Our full set of 109 metaphors is shown in figure 3. The data will be made available online. The experiment was run on Mechanical Turk, with 99 native English speakers. Participants who failed to follow instructions on a test item were excluded, leaving 60 participants (analyses remain significant with all participants included). Participants are shown a metaphor, as in figure 5 and asked to judge how relevant each proposed adjective (here, *debilitating*, *pervasive*, *corporate*, *addictive*) is to the metaphorical meaning of the AN phrase. In a test example, they are told to rate *intense* as relevant to *fiery temper* “because a fiery temper is an intense temper” but rate *warm* as irrelevant.



**Fig. 5.** An item in the experiment. Item order, and order of the 4 candidate adjectives are randomized.

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