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Interpreting Metaphor: Distributional Semantics for Bayesian Pragmatics

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ABSTRACT

Humans interpret metaphors, like *Life is a journey* or *My lawyer is a shark*, with relative ease, incorporating contextual knowledge to determine which aspects of the predicate (*journey, shark*) are true of the subject (*life, my lawyer*). One theory of the process underlying metaphor interpretation is introduced by (Grice, 1975): a listener reasons about a cooperative and informative speaker (who in turn reasons about the listener) to update their beliefs about the subject and the dimensional of meaning that the speaker is trying to convey.

This reasoning process can be modeled in the *Rational Speech Acts framework* (Frank & Goodman, 2012) as a nested inference, where listeners and speakers are Bayesian agents, who make inferences about the state of the world, and the optimal utterance, respectively. However, previous instantiations of these models have required a hand-specified semantics, restricting the generality of the model and the scope of empirical investigation into the effectiveness of pragmatic reasoning for metaphor interpretation.

We present a method to combine empirically learned word embeddings with a Rational Speech Acts model of metaphor. This allows us to interpret arbitrary predicative and adjectival metaphors without manually stipulating the denotations of the words they contain. We find a significant preference in human judgments for our model over a comparable word embedding model without explicit pragmatic reasoning.

INTRODUCTION

Metaphor presents a compelling theoretical challenge for the understanding of meaning in natural language. For instance, on hearing (1) in a context where the subject, Jane, is known to be a consultant, 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 Gricean view on metaphor takes the meaning conveyed by (1) in a given context to be the result of a process of *pragmatic reasoning*, about a speaker who is trying to communicate truthfully, informatively, and relevantly. That is, the listener attempts to jointly deduce what Jane must be like and what aspect of Jane is plausibly relevant, such that the speaker would have chosen the predicate *soldier* over other alternatives.

Modeling metaphor Obtaining metaphorical interpretations for utterances like (1) is within the scope of a formalization of Gricean reasoning, the *Rational Speech Acts* framework (Goodman & Stuhlmüller, 2013). This framework models pragmatic interpretation and production of language via probabilistic models of speakers and listeners, who reason about each other in a nested fashion, with the assumption of cooperativity and a shared semantics.

Kao, Bergen, and Goodman (2014) extend the framework by introducing a new model, L_1^Q, which is able to interpret metaphors. It does so by the mechanism of *projection functions*[1] which dictate the dimension of the world that the speaker cares about communicating. This, in turn, allows for a model of a listener which jointly determines the state of the world (e.g. what Jane is like) and the aspect of the world the speaker cares to communicate (e.g. Jane's determination). Crucially, this listener assumes an informative speaker: one whose choice of utterance maximizes the probability of communicating the world w to the speaker's model of the listener, up to the projection q .

This model provides an account of predicative metaphors (those of the form *A is a B* like (1)) and adjectival metaphors (like *fiery temper*). However, in order to generate predictions from the model, it is necessary to manually construct a semantics for the words involved. This makes empirical validation of the model difficult, because of the bias introduced by the hand-chosen semantics.

Our contribution We adapt the model proposed by Kao et al. (2014) to a distributional semantics, where the denotations of words correspond to points in an abstract, and empirically determined, vector space. Such *word embedding* spaces are a core NLP tool, and have been shown to represent various notions of semantic similarity via the geometry of the space.

Adapting the L_1^Q model to allow for denotations of this kind requires us to introduce a new semantics, to generalize the notion of a projection to a vector space, where it amounts to a linear projection, and to develop an approximate inference algorithm to calculate the now continuous posterior distribution of L_1^Q.

By doing so, we obtain a model capable of interpreting arbitrary predicative and adjectival metaphors, without the need for a hand-specified semantics. This allows us to assess to efficacy of the Gricean view of metaphor (as formalized in L_1^Q), by evaluating our model on human judgments. In particular, we show that our model significantly outperforms a baseline which uses a distributional semantics without explicit pragmatic reasoning.

OVERVIEW OF METAPHOR

Metaphor exists in many syntactic forms, and generally eludes easy definition. For present purposes, we focus on copular predicates (of the form: *A is a B*, like *Jane is a soldier*) and AN noun phrases (of the form [adjective noun] like *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 (Lakoff & Johnson, 1980) for the more general sense of these terms).

[1] These are often referred to in RSA literature as *Questions under Discussion*.

For a given metaphor, only certain properties of the source are described by the target, and which these are depend on the metaphor and the context. For instance, (2) likely conveys that the bread is like a rock with respect to hardness, while (3) likely conveys that the sleeping dog is like a rock with respect to its responsiveness. However, we could also imagine a context in which the dog is very heavy, so that a more natural inference is that it is like a rock with respect to its weight.

(2) The bread is a rock.

(3) The sleeping dog is a rock.

While certain metaphors are conventional - comparing someone to a lion tends to connote bravery - examples like (3) suggest that the interpretation of a metaphor is contextually dependent. The benefit of the Gricean view of metaphor is the ability to explain this dependence on context, in a way which takes into account an underlying semantics (e.g. the conventional meanings of *bread*, *dog* and *rock*).

A BAYESIAN MODEL OF METAPHOR INTERPRETATION

The Rational Speech Acts framework (RSA) provides an elegant and practical way of formalizing Gricean pragmatics as nested Bayesian inference (Frank & Goodman, 2012).

In this framework, listeners and speakers are represented as conditional probability distributions. Speakers are distributions $P(U|W)$ over possible utterances given worlds, and listeners distributions $P(W|U)$ over possible worlds given utterances, where W is the set of possible states, and U is the set of utterances available to a speaker. The most basic version of RSA, for example (Frank & Goodman, 2012), is incapable of interpreting metaphors, due to the strict adherence to truth observed by the speaker. To address this, Kao et al. (2014) proposes a model L_1^Q, defined in (6).

(4) $L_0(w|u) \propto [\![u]\!](w)P_L(w)$

(5) $S_1(u|w,q) \propto \sum_{w'} \delta_{q(w)=q(w')} * L_0(w'|u)$

(6) $L_1^Q(w,q|u) \propto S_1(u|q,w) * P_L(w) * P_{L_Q}(q)$

The literal listener L_0 represents a model of an agent that, given an utterance $u \in U$ updates their belief about the world $w \in W$ strictly in accordance with the semantics $[\![\cdot]\!]$. This semantics, typically a function $U \to (W \to \{True, False\})$, represents the conventional association between states w and utterances u which the speaker and listener take as given.

Projections Functions $q \in Q$ formalize the notion of picking a particular *aspect* or *dimension* of w. Formally, they are surjective functions out of W.

The informative speaker S_1 has a state w they want to communicate, and reasons about L_0, preferring utterances u which maximize the L_0 posterior probability on w, up to the aspect of w specified by q. If q is the identity function, $S_1(u|w) \propto L_0(w|u)$, and is thus a model of a speaker who prefers to choose the most informative utterance available.

The pragmatic listener L_1^Q jointly infers values for w and q. 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. $[\![u]\!](w) = 0$) but where u conveys some aspect of w as determined by q.

We can view L_1^Q as a model of metaphor interpretation as follows, with the example of (7). Suppose that the goal of the speaker is to communicate a state w, representing what John is like. To this end, they choose a predicate u, here *shark*. Conversely, the goal of the listener on hearing (7) is to infer w as well as the *aspect* of w that the speaker cares about.

(7) John is a shark.

To make this precise, and derive predictions from L_1^Q, five things must be provided: a set W of states, a set U of utterances, a set Q of projections, a prior P_L representing the listener's uncertainty over W, and a semantics $[\![\cdot]\!]$ (We assume throughout that the prior P_{L_Q} over Q is uniform.). Jointly, we say that these determine an *interpretation* of L_1^Q.

One possible interpretation, similar to what is provided by Kao et al. (2014), treats points in the state space W as n-tuples of truth values, corresponding to Boolean properties $w \subset P$. We refer to this as a *set theoretic* interpretation of L_1^Q. We give a very simple example below, for $P = \{\text{vicious}, \text{non-human}\}$:

- $W = \{(\text{vicious} = T, \text{non-human} = T), (\text{vicious} = T, \text{non-human} = F), (\text{vicious} = F, \text{non-human} = T), (\text{vicious} = F, \text{non-human} = F)\}$
- $P_L = W = \{(\text{vicious} = T, \text{non-human} = T) : 0.075, (\text{vicious} = T, \text{non-human} = F) : 0.675, (\text{vicious} = F, \text{non-human} = T) : 0.025, (\text{vicious} = F, \text{non-human} = F) : 0.225\}$
- $U = \{\text{shark}, \text{silence}\}$
- $Q = \{q_{vicious}(\lambda(x, y) : x), q_{non-human}(\lambda(x, y) : y)\}$

We assume a semantics $[\![\cdot]\!]$ in which *shark* is compatible only with $(\text{vicious}, \text{non-human})$, and *silence* is compatible with every state. Note that the projections map each tuple to its value at a single property. In theory, for larger n-tuples of properties, a projection could map to multiple properties, representing a speaker who wishes to communicate multiple aspects of the state w. We return to this point in our concluding discussion. The results of L_1^Q hearing *shark* are shown in figure 1. The key fact to note is that the prior belief that John is not literally an animal leads L_1^Q to conclude that the speaker cares about conveying the viciousness dimension (i.e. projection $q_{vicious}$), and that John is vicious.

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 further assume a third properties, *speed*, so that shark is compatible only with $(\text{vicious} = T, \text{non-human} = F, \text{quick} = T)$, and a third utterance, *hummingbird*, compatible with only $(\text{vicious} = F, \text{non-human} = T, \text{quick} = T)$.

In this second example, when L_1^Q hears *shark*, they infer only that John is vicious, and not fast, even though both are equally likely under P_L. This is because, had the speaker wanted to communicate that John is fast, *hummingbird* would have been a more informative utterance.

todo: note on getting realistic predictions by using large experimentally collected data

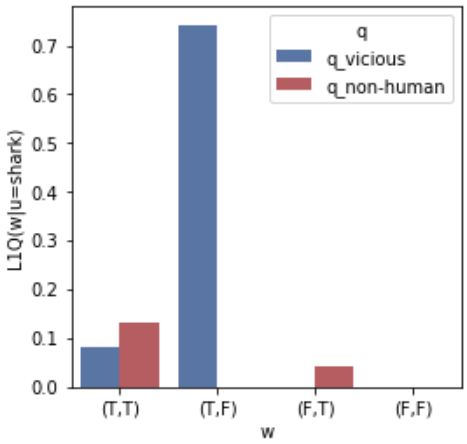


Figure 1: Figure showing the posterior distribution of L_1^Q on hearing *shark*

L_1^Q can also model AN metaphors (the subject of our experiment) in the same way. For example, for a phrase like *fiery temper*, we say that the goal of a listener is to decide what is true of the temper in question given that the speaker has modified it with *fiery*.

DISTRIBUTIONAL SEMANTICS

From a linguistic corpus, it is possible to obtain a mapping from words to points in a high-dimensional vector space that has the property that semantic similarity of a pair of words a and b corresponds to metrics, such as cosine distance, between the vectors $\overrightarrow{a}$ and $\overrightarrow{b}$.

Mappings of this sort, commonly referred to as *word embeddings* or a *distributional model of word meaning*, can be obtained either by dimensionality reduction of a co-occurrence matrix (Pennington, Socher, & Manning, 2014), or by extracting the weights of a statistical model (Devlin, Chang, Lee, & Toutanova, 2018; Mikolov, Sutskever, Chen, Corrado, & Dean, 2013; Peters et al., 2018).

In either case, word embeddings provide a way to empirically obtain fine grained connotations of lexical items (Mikolov et al., 2013), and have been used effectively in a number of NLP tasks (Dai & Le, 2015; Radford, Narasimhan, Salimans, & Sutskever, 2018). They have also been used to compute vectorial representations of phrases and sentences (Coecke, Sadrzadeh, & Clark, 2010; Socher et al., 2013).

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 Shutova (2016) for an overview of proposed systems.). TODO: needs your own citations

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

BAYESIAN PRAGMATICS WITH A DISTRIBUTIONAL SEMANTICS

The set-theoretic interpretation of L_1^Q takes states $w \in W$ to be sets of properties describing the source of the metaphor in question, and projections $q \in Q$ to be surjective functions out of W. The semantics maps utterances to functions from worlds to Boolean values, or equivalently, maps a pair (u, w) to 1 if they are compatible, and 0 otherwise.

We now introduce a *vectorial* interpretation of L_1^Q. Importantly, this requires no modification to equations (4-6). The crucial difference is that our state space W is now not just a set, but a vector space determined by a word embedding E, so that elements $\overrightarrow{w} \in W$ are vectors.[2]. As before, U is a set of adjectives.

The listener's prior In the set-theoretic interpretation of L_1^Q, where W can be finite, a discrete prior P_L over W sufficed. In the present case, where W is necessary infinite (ranging continuously over real-valued vectors), we use a multivariate spherical Gaussian distribution, which can be parametrized by a vector $\overrightarrow{\mu}$ for the mean and a single scalar σ (the value of every diagonal entry of the covariance matrix). As for the prior P_{L_Q} over Q, we take it to be uniform.

We can view P_L as representing uncertainty over the position of the entity or concept that the source noun represents.[3] The goal of the speaker is to convey a position in the space (which they think represents the nature of the source noun's denotation) to the listener, and the goal of the listener is to infer what this position is. In this sense, a spatial reference game is being played (Golland, Liang, & Klein, 2010), in an abstract word embedding space.

$$P_L(w) = P_{\mathcal{N}}(w|\mu = \overrightarrow{source}, \sigma = \sigma_1) \quad (8)$$

The multidimensional Gaussian distribution weights most heavily those points nearest to its mean. By setting the mean of the prior as $E(source)$, we encode the listener's assumption that the meaning the speaker wishes to communicate is in the neighborhood of the source noun. σ_1 is a hyperparameter of the model.

The semantics A word embedding space has no explicit representation of truth. That is to say, while we can compare the similarity of a noun and an adjective according to a variety of metrics, we do not have a means of categorically determining the compatibility of that adjective and noun.

Mathematically speaking, this is not a problem, since the definition of L_0 in (4) requires only that the semantics $[\![\cdot]\!]$ be a function $U \to (W \to \mathbb{R})$. We can define such a function as follows:

$$[\![u]\!](w) = P_{\mathcal{N}}(w|\mu = \overrightarrow{predicate_u}, \sigma = \sigma_2) \quad (9)$$

[2] We note that this generalization is natural, since the set-theoretic interpretation of L_1^Q can be viewed as a special case of the vectorial interpretation, for a vector space over the Boolean field (rather than the real field). That is, consider an n-tuple of Booleans w as a vector of 0s and 1s, with P providing the basis of the space.

[3] Note that this prior does not represent lexical uncertainty over the meaning of the subject word, but rather uncertainty over what the entity or concept that the subject denotes is like.

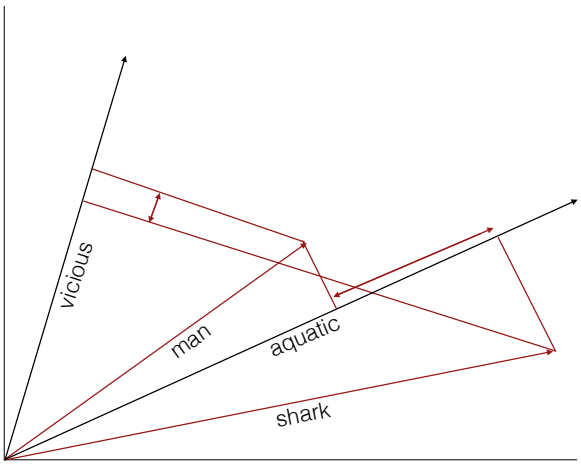


Figure 2: In this example, the vectors for *vicious* and *aquatic* each parametrize a QUD mapping all the points in the space (such as *man* and *shark*) to new points. These new points can be thought of as the positions of *man*, *shark* and so on in a new space which cares only about the position of the points with respect to the *vicious* vector.

The result of this definition is that the value of $[\![u]\!](w)$ is a real number which scales quadratically with the Euclidean distance between u and w. TODO: confirm

The advantage of defining a semantics in this way is that both the prior of L_0, shown in (8) and the likelihood, namely the semantics shown in (9), have the form of Gaussian distributions, which allows for a closed form solution of L_0. As with the definition of the prior in (8), the semantics introduces a hyperparameter, namely σ_2.

Projections Finally, we need to supply an 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[4] along a vector (or hyperplane) $\overrightarrow{v}$. This is a linear transformation from W to the subspace given by $\overrightarrow{v}$, which captures the degree to which $\overrightarrow{w}$ extends along a vector (or hyperplane) $\overrightarrow{v}$, and ignores orthogonal dimensions. Geometrically, it can be thought of as dropping a line from an input vector $\overrightarrow{w}$ at a right angle onto $\overrightarrow{u}$, as is depicted in figure 2.

As in the set-theoretic interpretation, we restrict ourselves to projections to a single dimension, i.e. projections along a vector, rather than a hyperplane. However, we no longer have an obvious set of projections Q, corresponding to an explicit set of properties P. This is because the basis vectors of a word embedding space such as GloVe or Word2Vec do not correspond to easily interpretable attributes of the words in the space.

[4] To see why this is the natural analogue of the projection functions used in the set-theoretic interpretation of L_1^Q, note that when viewed as vectors in a vector space over the Boolean field, projection functions are precisely linear projections. Alternatively, note that in either case, projections q are idempotent maps $(W \to W)$.

To obtain such a set Q, we first note that since the denotations of words are vectors in W, any word parametrizes a linear projection q. For instance, we can think of the word *vicious* as parameterizing a *viciousness* projection, which measures how far the denotations of all other points in the space fall along $\overrightarrow{vicious}$.

As such, we can specify Q as a set of words. In general, it makes sense to choose a set of gradable adjectives, so that the projection of a noun n onto $\overrightarrow{v}$ amounts to asking: to what extent is n v?

INFERENCE

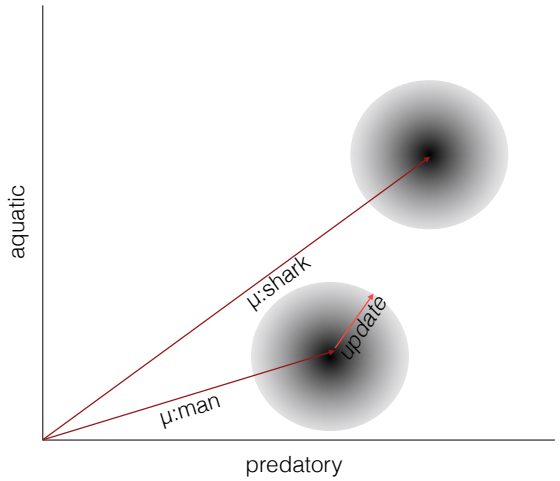


Figure 3: 2D Visualization of L_0

Calculating the posterior of L_1^Q given an utterance u is far more difficult in the vectorial interpretation than the set-theoretic one. Because $P_L(w)$ is now a continuous distribution, inference by enumeration is no longer possible, and either analytic or approximate methods are required. We employ a mix of the two; the L_0 and S_1 posteriors can be calculated analytically, while L_1^Q requires us to develop an approximate inference algorithm[5]. We describe this algorithm in parts, working up from the L_0.

L_0 Inference Intuitively, the vectorial interpretation of L_0 amounts to the process shown in figure 3, where a ball, corresponding to the prior, is moved in the direction of another point, the received utterance. To calculate L_0 analytically, we make use of Gaussian self-conjugacy, which allows a distribution with a Gaussian prior and likelihood term to be rewritten as a single Gaussian of different parameters.

S_1 Inference Since U remains a finite set of utterances, the S_1 posterior can be computed exactly, as for the set-theoretic interpretation of S_1.

[5] Inference for all our models is implemented in Tensorflow, and will be made publicly available.

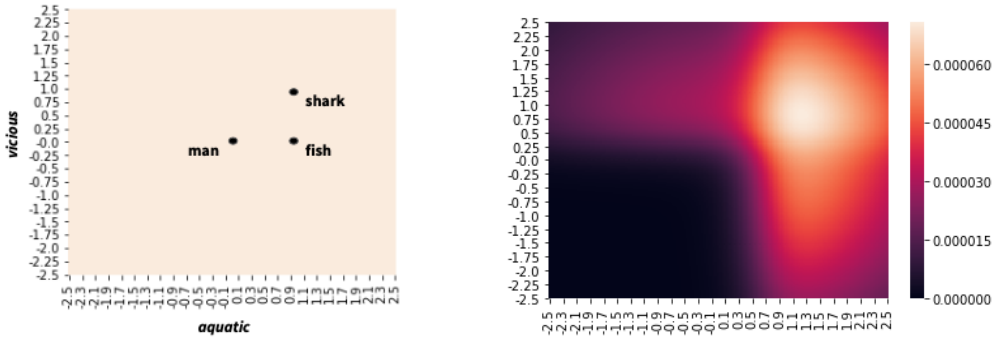


Figure 4: Heatmap visualizing the L_1^Q posterior (right), with the hand-chosen denotations of *man*, *shark*, and *fish* used in this 2 dimensional example (left).

L_1 Definition The L_1 posterior is a joint distribution over one continuous and one discrete random variable. We are unable to use conjugacy to compute it analytically, but equally unable to compute it exactly. However, because of the linear projections q, we are able to devise a near-exact inference algorithm[6] for the marginal distribution over Q, derived as follows:

$$L_1(q|u) = \int_w L_1(w,q|u) = \frac{1}{K}P(q)\int_w P(w)S_1(u|w,q) = \frac{1}{K}P(q)\int_w P(w)S_1(u|w_q,q)$$

$$= \frac{1}{K}P(q)\int_w P(w_q,w^\perp)S_1(u|w_q,q) = \frac{1}{K}P(q)\int_w P(w_q)P(w^\perp)S_1(u|w_q,q)$$

$$= \frac{1}{K}P(q)\int_{w^\perp\in Q^\perp} P(w^\perp)\int_{w_q\in Q} P(w_q)S_1(u|w_q,q) = \frac{1}{K}P(q)\int_{w_q\in Q} P(w_q)S_1(u|w_q,q)$$

Let $K = \sum_{q'}\int_{w'} P(w')P(q')S_1(u|w',q')$. $w, q \in \mathbb{R}^n$, and w_q is the projection of w onto the vector q. In addition, Q is the subspace of $\mathbb{R}^n$ spanned by the vector q, and $Q^\perp$ is the orthogonal complement of Q. The vector $w^\perp$ is the projection of vector w onto the subspace $Q^\perp$. The final equation is a one-dimensional integral, and can be computed using a discrete approximation . The constant K can be found from the constraint $\sum_q L_1(q|u) = 1$. Figure 4 provides an example of the L_1^Q posterior in a simple 2D case, corresponding to the example used for the set-theoretic example in figure 1.

Interpreting results from L_1^Q

We now have an algorithm for approximating the posterior distribution of L_1^Q after hearing a metaphor u. One way of converting this into an interpretable prediction is to examine the marginal distribution over Q, and take adjectives q which have high probability under this distribution to be interpretations of the metaphor u that the model considers likely.

[6] We verify the correctness of this algorithm in the 2 dimensional case by comparison to the exact posterior, which is calculable (up to discretization of the prior) in 2 dimensions.

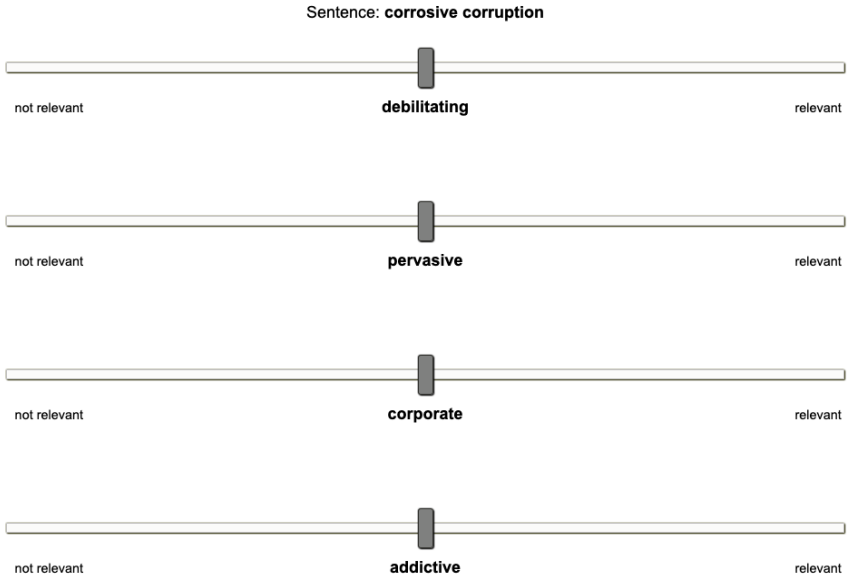


Figure 5: An item in the experiment. Item order, and in-item order of the 4 adjectives from L_1^Q and baseline models is randomized.

For example, on the metaphor, (subject=*man*, predicate=*shark*), the blah with most mass TODO example

EXPERIMENTAL VALIDATION

In order to test our model on human judgments, we design an experiment which compares the L_1^Q interpretations of metaphors to a baseline model which uses word embeddings but no pragmatic reasoning.

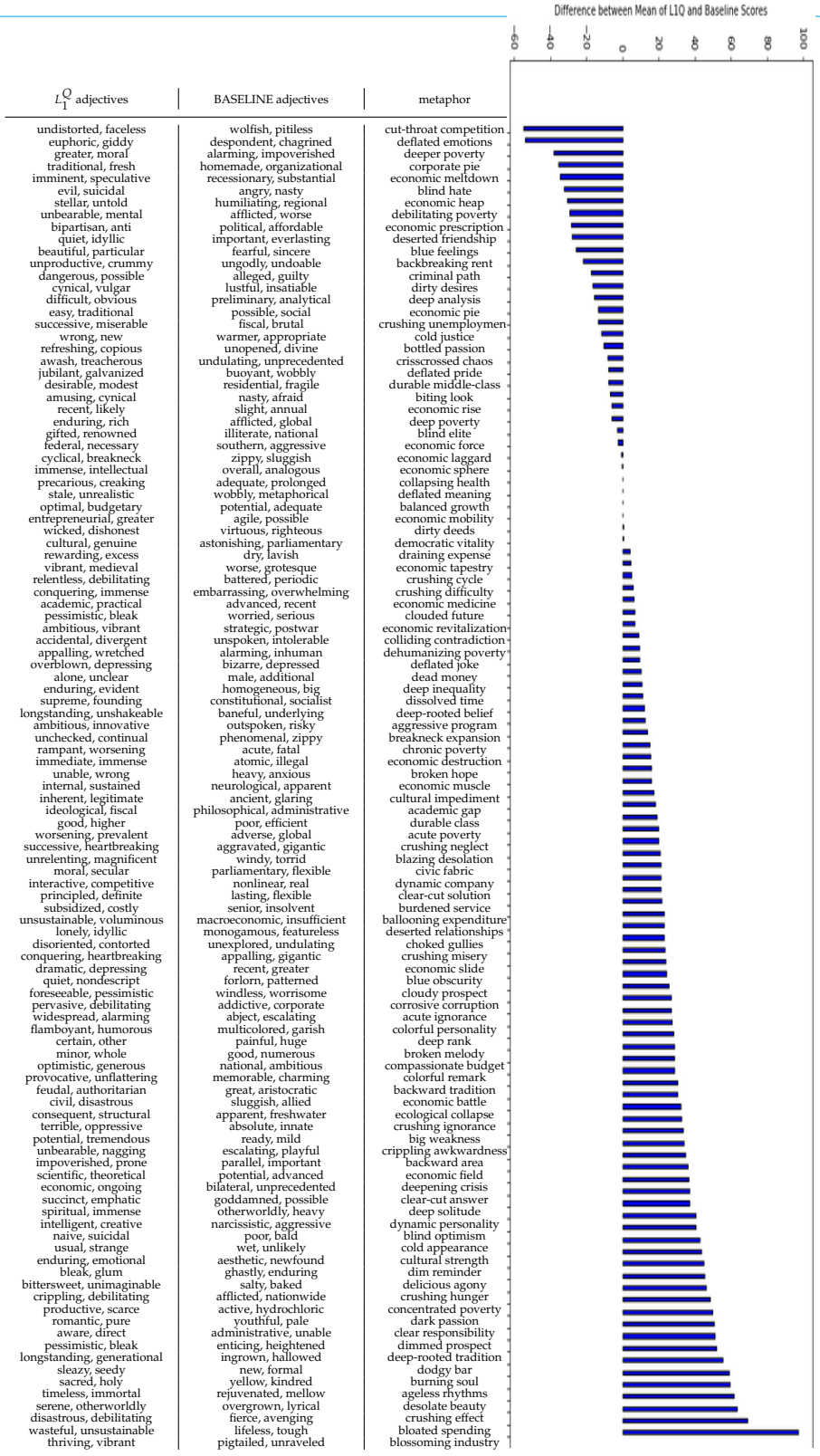
Experimental Design todo: fix alignment stuff

(Tsvetkov, Boytsov, Gershman, Nyberg, & Dyer, 2014) provides a corpus of ∼800 AN metaphors, gathered by human annotators, of which we select ∼100 of the least frequent by bigram count[7] for our experiment, in order to filter out conventionalized metaphors. Our full set of 109 metaphors is shown in figure 6.

In our experiment, each participant is shown a series of 12 metaphors, selected randomly from the total 109. For each metaphor, they are asked to rate on a slider four adjectives representing interpretations of the metaphor, of which two are selected by L_1^Q and two from a baseline model (details below). An example is shown in figure 5.

The experiment was run on Mechanical Turk, with 99 participants, all of whom are native English speakers. Participants who failed to follow instructions on a test item were

[7] N-grams data from the Corpus of Contemporary American English (Davies, 2011).



L_1^Q adjectives	BASELINE adjectives	metaphor
undistorted, faceless	wolfish, pitiless	cut-throat competition
euphoric, giddy	despondent, chagrined	deflated emotions
greater, moral	alarming, impoverished	deeper poverty
traditional, fresh	homemade, organizational	corporate pie
imminent, speculative	recessionary, substantial	economic meltdown
evil, suicidal	angry, nasty	blind hate
stellar, untold	humiliating, regional	economic heap
unbearable, mental	afflicted, worse	debilitating poverty
bipartisan, anti	political, affordable	economic prescription
quiet, idyllic	important, everlasting	deserted friendship
beautiful, particular	fearful, sincere	blue feelings
unproductive, crummy	ungodly, undoable	backbreaking rent
dangerous, possible	alleged, guilty	criminal path
cynical, vulgar	lustful, insatiable	dirty desires
difficult, obvious	preliminary, analytical	deep analysis
easy, traditional	possible, social	economic pie
successive, miserable	fiscal, brutal	crushing unemploymen
wrong, new	warmer, appropriate	cold justice
refreshing, copious	unopened, divine	bottled passion
awash, treacherous	undulating, unprecedented	crisscrossed chaos
jubilant, galvanized	buoyant, wobbly	deflated pride
desirable, modest	residential, fragile	durable middle-class
amusing, cynical	nasty, afraid	biting look
recent, likely	slight, annual	economic rise
enduring, rich	afflicted, global	deep poverty
gifted, renowned	illiterate, national	blind elite
federal, necessary	southern, aggressive	economic force
cyclical, breakneck	zippy, sluggish	economic laggard
immense, intellectual	overall, analogous	economic sphere
precarious, creaking	adequate, prolonged	collapsing health
stale, unrealistic	wobbly, metaphorical	deflated meaning
optimal, budgetary	potential, adequate	balanced growth
entrepreneurial, greater	agile, possible	economic mobility
wicked, dishonest	virtuous, righteous	dirty deeds
cultural, genuine	astonishing, parliamentary	democratic vitality
rewarding, excess	dry, lavish	draining expense
vibrant, medieval	worse, grotesque	economic tapestry
relentless, debilitating	battered, periodic	crushing cycle
conquering, immense	embarrassing, overwhelming	crushing difficulty
academic, practical	advanced, recent	economic medicine
pessimistic, bleak	worried, serious	clouded future
ambitious, vibrant	strategic, postwar	economic revitalization
accidental, divergent	unspoken, intolerable	colliding contradiction
appalling, wretched	alarming, inhuman	dehumanizing poverty
overblown, depressing	bizarre, depressed	deflated joke
alone, unclear	male, additional	dead money
enduring, evident	homogeneous, big	deep inequality
supreme, founding	constitutional, socialist	dissolved time
longstanding, unshakeable	baneful, underlying	deep-rooted belief
ambitious, innovative	outspoken, risky	aggressive program
unchecked, continual	phenomenal, zippy	breakneck expansion
rampant, worsening	acute, fatal	chronic poverty
immediate, immense	atomic, illegal	economic destruction
unable, wrong	heavy, anxious	broken hope
internal, sustained	neurological, apparent	economic muscle
inherent, legitimate	ancient, glaring	cultural impediment
ideological, fiscal	philosophical, administrative	academic gap
good, higher	poor, efficient	durable class
worsening, prevalent	adverse, global	acute poverty
successive, heartbreaking	aggravated, gigantic	crushing neglect
unrelenting, magnificent	windy, torrid	blazing desolation
moral, secular	parliamentary, flexible	civic fabric
interactive, competitive	nonlinear, real	dynamic company
principled, definite	lasting, flexible	clear-cut solution
subsidized, costly	senior, insolvent	burdened service
unsustainable, voluminous	macroeconomic, insufficient	ballooning expenditure
lonely, idyllic	monogamous, featureless	deserted relationships
disoriented, contorted	unexplored, undulating	choked gullies
conquering, heartbreaking	appalling, gigantic	crushing misery
dramatic, depressing	recent, greater	economic slide
quiet, nondescript	forlorn, patterned	blue obscurity
foreseeable, pessimistic	windless, worrisome	cloudy prospect
pervasive, debilitating	addictive, corporate	corrosive corruption
widespread, alarming	abject, escalating	acute ignorance
flamboyant, humorous	multicolored, garish	colorful personality
certain, other	painful, huge	deep rank
minor, whole	good, numerous	broken melody
optimistic, generous	national, ambitious	compassionate budget
provocative, unflattering	memorable, charming	colorful remark
feudal, authoritarian	great, aristocratic	backward tradition
civil, disastrous	sluggish, allied	economic battle
consequent, structural	apparent, freshwater	ecological collapse
terrible, oppressive	absolute, innate	crushing ignorance
potential, tremendous	ready, mild	big weakness
unbearable, nagging	escalating, playful	crippling awkwardness
impoverished, prone	parallel, important	backward area
scientific, theoretical	potential, advanced	economic field
economic, ongoing	bilateral, unprecedented	deepening crisis
succinct, emphatic	goddamned, possible	clear-cut answer
spiritual, immense	otherworldly, heavy	deep solitude
intelligent, creative	narcissistic, aggressive	dynamic personality
naive, suicidal	poor, bald	blind optimism
usual, strange	wet, unlikely	cold appearance
enduring, emotional	aesthetic, newfound	cultural strength
bleak, glum	ghastly, enduring	dim reminder
bittersweet, unimaginable	salty, baked	delicious agony
crippling, debilitating	afflicted, nationwide	crushing hunger
productive, scarce	active, hydrochloric	concentrated poverty
romantic, pure	youthful, pale	dark passion
aware, direct	administrative, unable	clear responsibility
pessimistic, bleak	enticing, heightened	dimmed prospect
longstanding, generational	ingrown, hallowed	deep-rooted tradition
sleazy, seedy	new, formal	dodgy bar
sacred, holy	yellow, kindred	burning soul
timeless, immortal	rejuvenated, mellow	ageless rhythms
serene, otherworldly	overgrown, lyrical	desolate beauty
disastrous, debilitating	fierce, avenging	crushing effect
wasteful, unsustainable	lifeless, tough	bloated spending
thriving, vibrant	pigtailed, unraveled	blossoming industry

Figure 6: This figure shows all 109 metaphors used in the experiment, and the corresponding baseline and LL_1^Q proposals, with the height of the bar corresponding to the difference of the mean rating (across users and both proposed adjectives) given to that metaphor under the LL_1^Q model and baseline model. This shows that for roughly 75% of the metaphors, the LL_1^Q interpretation is preferred.

excluded, leaving 60 participants (although this affects results very little, which remain significant without the exclusion).

Baseline model The aim of our experiment is to determine whether pragmatic reasoning results in better interpretations of metaphors, according to human judgments. As such, a natural baseline model to compare against is a model with a distributional semantics that does not make use of the pragmatic reasoning process inherent in L_1^Q.

Our baseline model is defined as follows: for a given metaphor of the form $(a\ n)$, we take the mean of the a and n (or noun and adjective). The two nearest adjectives q to this mean are our baseline interpretations for the metaphor. We use the mean (a weighted sum) in light of the effectiveness of vector addition in deriving representations of phrasal and sentence meanings from constituent words, see (Grefenstette, 2013; Mitchell & Lapata, 2010; Socher et al., 2013). Cosine distance is a standard metric of similarity used for word embeddings (Pennington et al., 2014).

L_1^Q hyperparameters We use the largest available (300 dimensional) GloVe vectors, as our word embedding E. For each AN 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 (Brysbaert, Warriner, & Kuperman, 2014), 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 a validation set of hand-selected metaphors, we choose $\sigma_1 = \sigma_2 = 0.1$ (the variances of the Gaussians used in the prior and semantics respectively). We select the adjectives corresponding to the two projections with highest marginal posterior mass under L_1^Q as the interpretations provided from our model in the experiment.

Analysis The data, shown in figure 6, were analyzed using a mixed-effects model with random slopes and intercepts for items and participants. The target interpretations were rated significantly higher than the baseline interpretations (beta=13.8, t=5.3, $p<0.001$).

DISCUSSION

The significant improvement of L_1^Q over a model with the same semantics but no pragmatic reasoning provides evidence that this reasoning is key to obtaining human-like interpretations of metaphors.

In building a tractable inference algorithm for L_1^Q, we have also shown that the technical challenges in adapting a nested Bayesian model of pragmatics to a continuous setting are not insurmountable. We see this as an important step towards an open domain model of pragmatic language interpretation and production.

One direction of future work we consider to be especially promising is the extension of the system to multidimensional projections, since metaphors can plausibly convey multiple dimensions of meaning at once - in fact, we hypothesize that this is what motivates

their use. We also aim to develop a pragmatic speaker S_2 as a model of metaphor production. More generally, optimization of our algorithm, in line with recent developments in word embeddings (Devlin et al., 2018; Peters et al., 2018) should allow us to handle a broad range of metaphor in natural language.

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