A Computational Model of Linguistic Humor in Puns

Abstract

Humor plays an essential role in human interactions. However, its precise nature remains elusive. While research on natural language understanding has made significant advancements in recent years, there has been little direct integration of humor research with computational models of language understanding. In this paper, we propose two information-theoretic measures—ambiguity and distinctiveness—derived from a simple model of sentence processing. We then test these measures on a set of puns and regular sentences and show that they correlate significantly with human judgments of funniness. Our model is one of the first to integrate general linguistic knowledge and humor theory to model humor computationally. We present it as an example of a framework for applying models of language processing to understand higher-level linguistic and cognitive phenomena.

Introduction

Love may make the world go round, but humor is the glue that keeps it together. Our everyday experiences serve as evidence that humor plays a critical role in human interactions and composes a significant part of our linguistic, cognitive, and social lives. Previous research has shown that humor is ubiquitous across cultures (Martin, 2010; Kruger, 1996), increases interpersonal attraction (Lundy, Tan & Cunningham, 1998), helps resolve intergroup conflicts (Smith, Harrington & Neck, 2000), and improves psychological wellbeing (Martin, Kuiper, Olinger & Dance, 1993). However, the cognitive basis of humor remains largely a mystery. By providing a formal model of linguistic humor, we aim to shed light on the precise properties of sentences that make us laugh.

Many theories of humor have been proposed since Plato and Aristotle (see Attardo, 1994 for review). A leading theory posits that incongruity, loosely characterized as the presence of multiple incompatible meanings in the same input, may be critical for humor (Koestler, 1964; Veale, 2004; Forabosco, 1992; McGhee, 1979; Martin, 2007; Hurley, Dennett, & Adams, 2011; Vaid & Ramachandran, 2001). However, despite consensus on the importance of incongruity, its precise definitions differ across informal analyses of individual jokes, making it difficult to empirically test the role of multiplicity of meaning in humor on a larger scale. On the other hand, most work on computational humor focuses either on joke-specific templates and schemata (Binsted, 1996) or surface features and properties of individual words (Mihalcea & Strapparava, 2006; Kiddon & Brun, 2011; Reyes, Rosso & Buscaldi, 2012). While these approaches are able to identify and produce humorous stimuli within certain constraints, they fall short of testing a more general cognitive theory of humor.

In this paper, we build upon theories of humor and language processing to formally measure the multiplicity of meaning in puns. Philosopher Henri Bergson described puns as sentences “in which two ideas are expressed, and we are confronted with only one

series of words." Puns provide an ideal test bed for our purposes because they are by definition humorous sentences with multiple meanings. Here we focus on phonetic puns, defined as puns containing words that sound identical or similar to other words in English. The following is an example:

(1) "The **magician** got so *mad* he *pulled* his **hare** out."

The phonetic form of this sentence generates two "ideas," or meanings:

(1a) The magician got so mad he performed the trick of pulling a rabbit out of his hat.
(1b) The magician got so mad he pulled out the hair on his head.

At the most basic level, the humor in this pun relies on the fact that the word "hare" is phonetically confusable with its homophone "hair." However, the following sentence contains the same phonetically ambiguous word, but is clearly not a pun:

(2) "The hare ran rapidly across the field."

A critical difference is that "hare" and "hair" are both probable meanings in the context of sentence (1), whereas "hare" is much more likely in sentence (2). From this informal analysis, it seems intuitive that ambiguity of meaning is an important criterion for puns. However, another example shows that ambiguity alone is insufficient. Consider the sentence:

(3) "Look at that hare."

This sentence is also ambiguous between "hare" and "hair," but is unlikely to elicit chuckles. A critical difference between (1) and (3) is that while each meaning is strongly supported by distinct groups of words in (1) ("hare" is supported by words in bold; "hair" is supported by words in italics), both meanings are weakly supported by all words in (3). This suggests that in addition to ambiguity, distinctiveness of support is also an important criterion for humor. These insights on the roles of ambiguity of sentence meaning and distinctiveness of support motivate our formal measures of humor.

Since the humor of a sentence depends on its meaning, a formal model of humor requires a formal model of sentence meaning. Meaning (1a) arises if the word "hare" is interpreted as *hare*; meaning (1b) arises if the word "hare" is interpreted as its homophone *hair*. As a result, we can approximate meaning (1a) with the meaning *hare* and (1b) with the meaning *hair.* The sentence-level meanings of a phonetic pun thus directly correspond to the meanings of a single phonetically ambiguous word. Although this is a coarse approximation that captures the "gist" of a sentence rather than its full meaning, it allows us to bypass the largely unsolved problem of formally representing complex sentence meanings.

We derive our measures of humor from a distribution over these approximate sentence meanings. Formally, a sentence is composed of a vector of words $\vec{w} = \{w_1, \ldots, w_i, h, w_{i+1}, \ldots, w_n\}$, where h is a phonetically ambiguous word. The meaning of the sentence

is a latent variable m that we infer. We assume m has two possible values m_a and m_b, where m_a corresponds to the meaning of h, and m_b corresponds to the meaning of the homophone of h. Consistent with a noisy channel approach, we formally construe the task of understanding a sentence as inferring m using probabilistic integration of noisy evidence given by $\vec{w}$. In order to infer the true meaning of a sentence, comprehenders rationally incorporate word-level interpretations to arrive at coherent interpretations at the sentence level. We construct a simple generative model (see Figure) that captures the relationship between the meaning of a sentence and the words that compose it. If a word is a correct observation (should we call this "correct", "meaningful", or "relevant"?), it is sampled based on semantic similarity to the sentence meaning; if the word is irrelevant, or "noise," it reflects the sentence's sequential structure and is sampled from an n-gram model. We propose that the humor in phonetic puns may arise from this assumption of a noisy channel. Because the comprehender maintains uncertainty about the input, it is possible for her to arrive at multiple interpretations of a sentence that are each coherent but incongruous with each other. While our model does not capture deep sentence comprehension, it is sufficiently powerful as a first step for modeling humor in phonetically ambiguous sentences.

Given the words in a sentence, we can infer the joint probability distribution over sentence meanings and the "meaningful" subset of words. This distribution can be factorized as the following:

$$P\left(m, \vec{f} \mid \vec{w}\right) = P(m \mid \vec{w})\, P\left(\vec{f} \mid m, \vec{w}\right)$$

We derive a formal measure of humor from each of the two terms on the right-hand side. Ambiguity is quantified by the entropy of the binomial distribution $P(m \mid \vec{w})$. If the entropy is high, then the sentence is ambiguous because both meanings are similarly likely. Distinctiveness captures the degree to which distributions over meaningful words differ given different sentence meanings. Formally, given one possible meaning m_a and the words $\vec{w}$, we compute $F_a = P\left(\vec{f} \mid m_a, \vec{w}\right)$. Given another meaning m_b and the words $\vec{w}$, we compute $F_b = P\left(\vec{f} \mid m_b, \vec{w}\right)$. Distinctiveness is then quantified by the Kullback-Leibler divergence score between these two distributions, $D_{KL}(F_a \,||\, F_b)$. If the KL score is high, it suggests that the two sentence meanings are supported by distinct subsets of the sentence. Together, ambiguity and distinctiveness constitute a two-dimensional formalization of humor inspired by incongruity-resolution theories. To determine their relationships with human judgments of humor, we empirically evaluate the measures on a set of phonetically ambiguous sentences.

Methods

Measure derivations

Here we describe the derivations for ambiguity and distinctiveness in more detail. We use the entropy of $P(m \mid \vec{w})$ to measure the ambiguity of a sentence. Using Bayes' Rule, $P(m \mid \vec{w})$ is derived as follows[1]:

$$P(m \mid \vec{w}) = \sum_{\vec{f}} P(m, \vec{f} | \vec{w})$$
$$\propto \sum_{\vec{f}} P(\vec{w} | m, \vec{f}) P(m) P(\vec{f})$$
$$= \sum_{\vec{f}} \left(P(m) P(\vec{f}) \prod_i P(w_i | m, f_i) \right)$$

We approximate $P(m)$ as the unigram frequency of the words that represent m. For example, $P(m = hare)$ is approximated as $P(m =$ "hare"). We assume a uniform prior probability over all subsets of the words being semantically meaningful, which means $P(\vec{f})$ is a constant. $P(w_i | m, f_i)$ depends on the value of the indicator variable f_i. If $f_i = 1$, w_i is semantically meaningful and is sampled in proportion to its relatedness with the sentence meaning m. If $f_i = 0$, then w_i is generated from a noise process and sampled in proportion to its probability given the previous two words (including function words). Formally,

$$P(w_i | m, f_i) = \begin{cases} P(w_i | m) & \text{if } f_i = 1 \\ P(w_i | bigram_i) & \text{if } f_i = 0 \end{cases}$$

We estimate $P(w_i | m)$ using measures described in Experiment 2 and compute $P(w_i | bigram_i)$ using the Google Ngrams corpus. Once we derive $M = P(m \mid \vec{w})$, we compute its information-theoretic entropy as a measure of ambiguity:

$$Amb(M) = -\sum_{k \in \{a,b\}} P(m_k | \vec{w}) \log P(m_k | \vec{w})$$

We next turn to the distribution over indicator variables $\vec{f}$ given a sentence meaning to compute the distinctiveness of words supporting each sentence meaning. Using Bayes' Rule, we derive the following:

$$P(\vec{f} | m, \vec{w}) \propto P(\vec{w} | m, \vec{f}) P(\vec{f} | m)$$

Since $\vec{f}$ and m are independent, $P(\vec{f} \mid m) = P(\vec{f})$, which is a constant. Let Let $F_a = P(\vec{f} \mid m_a, \vec{w})$ and $F_b = P(\vec{f} \mid m_b, \vec{w})$. We compute the Kullback-Leibler divergence score $D_{KL}(F_a \mid\mid F_b)$ as a measure of distinctiveness:

[1] For simplification, our model disregards function words. Each w_i in $\vec{w}$ is a content word.

$$Dist(F_a||F_b) = \sum_i \ln\left(\frac{F_a(i)}{F_b(i)}\right) F_a(i)$$

We then implement and test these measures using the following two experiments.

Experiment 1

We collected 435 sentences consisting of phonetic puns and regular sentences that contain phonetically ambiguous words. We obtained the puns from a website called "Pun of the Day" (http://www.punoftheday.com), which at the time of collection contained over a thousand puns submitted by users. We obtained 40 puns where the ambiguous item is a single phonetically ambiguous word that has an identical homophone. Since only a limited number of puns satisfied this criterion, a research assistant generated an additional 25 pun sentences based on a separate list of homophone words, resulting in a total of 65 identical-homophone puns. We selected 130 corresponding non-pun sentences from an online version of Heinle's Newbury House Dictionary of American English (http://nhd.heinle.com). 65 of the non-pun sentences contain the ambiguous words observed in the pun sentences; the other 65 contain the alternative homophones. To test whether our measures generalize to sentences that do not contain words that are perfectly phonetically ambiguous, we collected 80 puns where the phonetically ambiguous word sounds similar (but not identical) to other words in English, as well as 160 corresponding non-pun sentences. Table shows an example sentence from each category.

Homophone	Type	Example
Identical	Pun	The magician was so mad he pulled his hare out.
Identical	Non-pun	The hare ran rapidly across the field.
Identical	Non-pun	Some people have lots of hair on their heads.
Near	Pun	A dentist has to tell a patient the whole tooth.
Near	Non-pun	A dentist examines one tooth at a time.
Near	Non-pun	She always speaks the truth.

We obtained funniness ratings for each of the 435 sentences. 93 subjects on Amazon's Mechanical Turk rated the 195 sentences that contain identical homophones. Each subject read roughly 60 sentences in random order, counterbalanced for the sentence types, and rated each sentence on funniness and correctness. 158 subjects on Mechanical Turk rated the 240 near homophone sentences. Each subject read 40 sentences in random order, counterbalanced for the sentence types, and rated each sentence on funniness. We z-scored the ratings and used the average z-scored ratings across subjects as human judgments of funniness.

Experiment 2

As described in the measure derivations, computing ambiguity and distinctiveness requires the conditional probabilities of each word given a sentence meaning. However, this value is difficult to obtain reliably through traditional topic models trained on corpora due to data sparsity. As a result, we decided to measure it empirically.

We approximate $P(w_i \mid m)$ using an empirical measure of the semantic relatedness between w_i and m, which we denote as $R(w_i, m)$. We use $R(w_i, m)$ as a proxy for point wise mutual information between w_i and m, defined as follows:

$$R(w_i, m) = \log \frac{P(w_i, m)}{P(w_i)P(m)} = \log P(w_i|m) - \log P(w_i)$$

We assume that human ratings of relatedness between two words $R'(w_i, m)$ approximate true relatedness up to an additive constant z and assume $z = 0$. With the proper substitutions and transformations,

$$P(w_i \mid m) = e^{R'(w_i,m)+z} P(w_i)$$

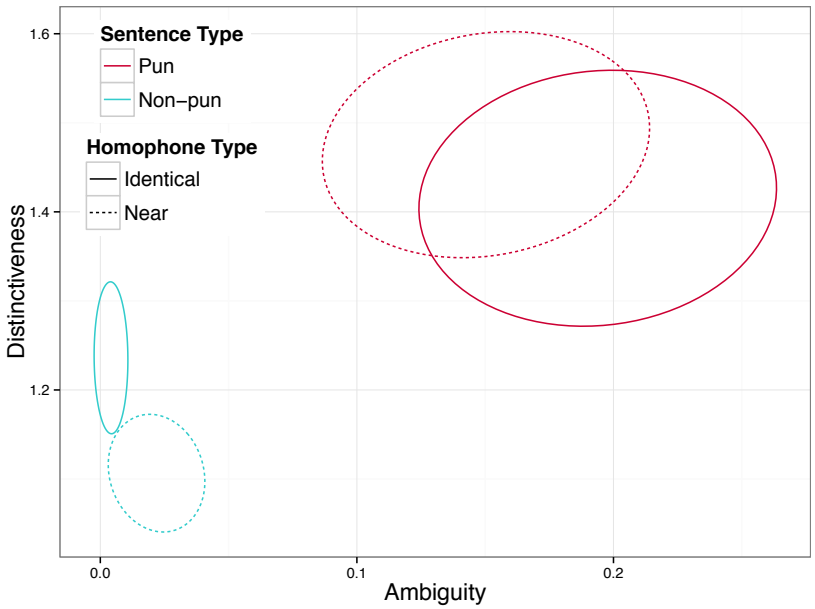
To obtain $R'(w_i, m)$ for each of the words in the stimuli sentences, we recruited 200 subjects on Amazon's Mechanical Turk to rate word pairs on their semantic relatedness. Function words were removed from each of the sentences in our dataset, and the remaining words were paired with each of the interpretations of the phonetically ambiguous word *h* (e.g., for the pun in Table, ["magician", "hare"] is a legitimate word pair, as well as ["magician", "hair"]). This resulted in 1460 distinct word pairs. Each subject saw 146 pairs of words in random order and were asked to rate how related each word pair is using a scale from 1 to 10. The average split-half correlation of the relatedness ratings was 0.916, suggesting that semantic relatedness is a reliable measure. Since it is difficult to obtain the relatedness rating of a word with itself, we used a free parameter r and fit it to data (r=13). We used the average z-scored relatedness measure for each word pair to obtain $R'(w_i, m)$ and Google Web unigrams to obtain $P(w_i)$, thus computing $P(w_i \mid m)$ for all word and meaning pairs.

Results

We computed an ambiguity and distinctiveness score for each of the 435 sentences. Ambiguity was significantly higher for pun sentences than non-pun sentences ($F(1, 433) = 108.4$, $p < 0.0001$), which suggests that our ambiguity measure successfully captures characteristics distinguishing puns from other phonetically ambiguous sentences. Distinctiveness differs marginally significantly across sentence types ($F(1, 433) = 47.1$, $p < 0.1$).

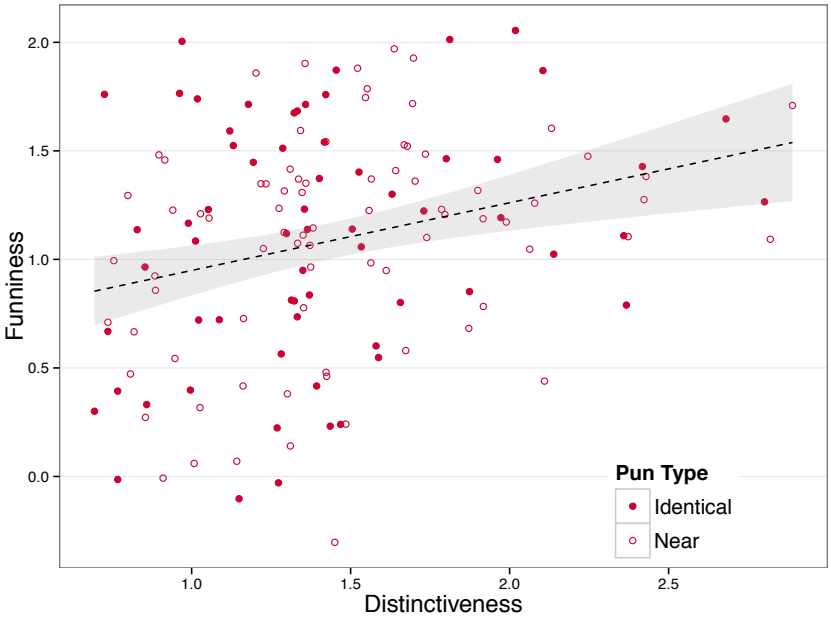
Figure shows the standard error ellipses for the two sentence types in the two-dimensional space of ambiguity and distinctiveness. Although there is a fair amount of noise in the predictors (likely due to simplifying assumptions, the need to use empirical measures of relatedness, and the inherent complexity of humor), we see that pun sentences (both identical and near homophone) tend to cluster at a space with higher ambiguity and distinctiveness, while non-pun sentences score lower on both measures. A linear regression model showed that both ambiguity and distinctiveness are significant predictors of funniness ratings across all 435 sentences. Together, the two predictors

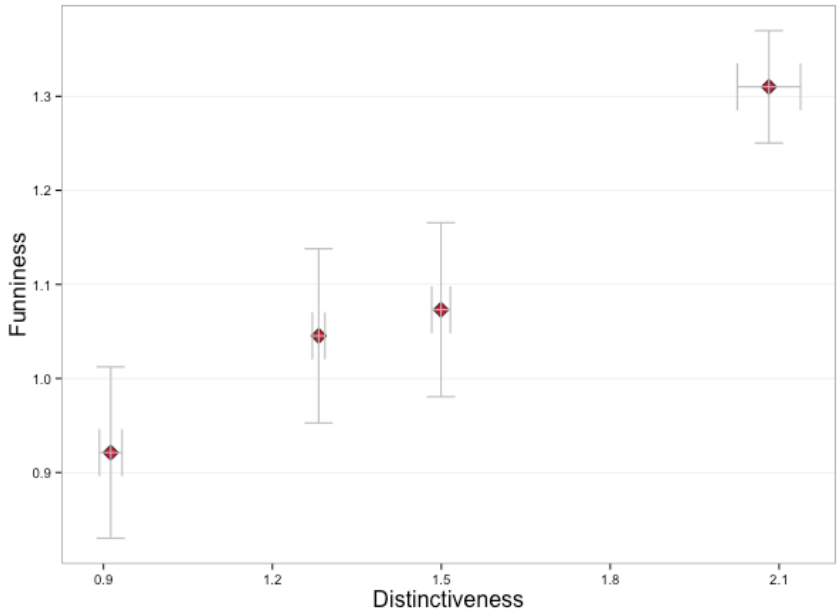
capture a modest but significant amount of the reliable variance in funniness ratings ($F(2,432) = 76.79$, $r = 0.51$, $p < 0.0001$; see Table).



	Estimate	Std. Error	p-value
Intercept	-0.830	0.107	< 0.0001
Ambiguity	1.899	0.212	< 0.0001
Distinctiveness	0.568	0.082	< 0.0001

We now examine the measures' quantitative predictions of funniness within puns only. Ambiguity does not correlate with human ratings of funniness within the 145 pun sentences ($r = 0.03$, $p > 0.05$). However, distinctiveness ratings correlate significantly with human ratings of funniness within pun sentences ($r = 0.28$, $p < 0.001$). This suggests that while ambiguity distinguishes puns from non-puns, distinctiveness separates very funny puns from mediocre ones. (Which figure should we show?)





Besides predicting the funniness of a sentence, the model also reveals the critical features of each pun that make it amusing. For each sentence, we identified the set of words that is most likely to be meaningful given $\vec{w}$ and each sentence meaning m. Formally, we computed $\arg\max_{\vec{f}} P(\vec{f} \mid m_a, \vec{w})$ and $\arg\max_{\vec{f}} P(\vec{f} \mid m_b, \vec{w})$. Table shows a group of identical-homophone sentences and a group of near-homophone sentences. Sentences in each group contain the same pair of candidate meanings for the homophone; however, they differ on ambiguity, distinctiveness, and funniness. Words that are most likely to be

meaningful given sentence meaning m_a are in red; words that are most likely given m_b are in green; and words that are most likely given both meanings are in blue. Qualitatively, we observe that the two pun sentences (which are significantly funnier) have more distinct and balanced sets of meaningful words for each sentence meaning than other sentences in their groups. Non-pun sentences tend to have no words in support of the meaning that was not observed. Furthermore, the colorful words in each pun sentence—for example, the fact that magicians tend to perform magic tricks with hares, and people tend to be described as pulling out their hair when angry—are what one might intuitively use to explain why the sentence is funny. Besides producing quantitative predictions of funniness, the model also provides a natural way to explain which aspects of a pun make it funny.

Discussion

In this paper, we presented a simple model of sentence processing and derived formal measures to predict human judgments of humor in puns. We showed that a noisy-channel model of sentence processing facilitates flexible context selection, which enables a single series of words to express multiple meanings at once. Our work is one of the first to integrate a general model of sentence processing to analyze humor in an intuitive and quantitative manner. To our knowledge, it is also the first computational work to go beyond classifying humorous versus regular sentences and predict fine-grained funniness judgments within humorous stimuli.

Our results contribute to humor theory by providing evidence that different factors may account for separate aspects of humor appreciation. Some humor theorists argue that while incongruity is necessary for humor, resolving incongruity—discovering a cognitive rule that explains the incongruity in a logical manger—is also key (Ritchie, 1999; Suls, 1972). Under this theory, we can construe our measures as each corresponding roughly to incongruity and resolution, where ambiguity represents the presence of incongruous sentence meanings, and distinctiveness represents the degree to which each meaning is strongly supported by different parts of the stimulus. Our results would then suggest that incongruity distinguishes humorous input from regular sentences, while the intensity of humor may depend on the degree to which incongruity is resolved by logical support. Future work could more specifically examine the roles of incongruity and resolution using a similar framework.

Motivated by a growing need for computers to interact with humans in a more natural and engaging manner, researchers in artificial intelligence have applied computational tools to identify and generate humorous input (Mihalcea & Strapparava, 2006). Our work contributes to this literature by incorporating a simple and psychologically driven model of sentence processing to formally capture multiplicity of meaning in sentences. Our measures distinguish puns from regular sentences, correlate significantly with fine-grained humor ratings within puns, and provide an intuitive way for identifying critical features that make a pun funny. This suggests that models of general sentence processing may help derive richer and more explanatory measures of humor.

Although our task in this paper is limited in scope, it is a first step towards developing models that can explain higher-order linguistic phenomena such as humor understanding. Future work may incorporate more sophisticated models of language understanding to consider the time course of sentence processing, deeper semantic representations, and multi-sentence discourse. Besides seeking to understand linguistic humor for its own sake, creative language use can serve as probes for developing models of language processing that account for a wider range of linguistic behavior, and may shed light on how language understanding works more generally. We believe that our work contributes to research in humor theory, computational humor, and language understanding, such that some day we can build robots that make us laugh and understand the appreciation for humor that makes us uniquely human.

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m_a	m_b	Type	Sentence	Amb.	Dist.	Funni.
hare	hair	Pun	The magician got so mad he pulled his hare out.	0.15	1.36	1.71
		Non	The hare ran rapidly through the fields.	$1.43E^{-5}$	1.07	-0.40
		Non	Most people have lots of hair on their heads.	$9.47E^{-11}$	1.55	-0.34
tooth	truth	Pun	A dentist has to tell a patient the whole tooth.	0.1	1.64	1.41
		Non	A dentist examines one tooth at a time.	$8.92E^{-5}$	1.23	-0.45
		Non	She always speaks the truth.	$3.85E^{-10}$	0.72	-0.46