Lexical Features of Sarcasm in Twitter and the Google Books Database

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Introduction

- Sarcasm: figurative language where the intended meaning is the opposite of the literal meaning
- Sarcasm has primarily been studied in terms of pragmatics (e.g., Kreuz, 1996), but lexical features may serve as important discriminating cues.
- An obstacle to studying sarcasm is determining sarcastic intent. One solution is to use corpora such as Twitter (Davidov et al., 2010; González-Ibáñez et al., 2011) and books (Kreuz & Caucci, 2007) where sarcastic intent can be explicitly marked by authors.

Goal: Extend previous work by comparing specific lexical features of sarcastic and non-sarcastic (control) statements in corpora where sarcastic intent is explicitly marked

Hypothesis: Sarcastic statements will differ from control statements on features that reflect asymmetry of affect, hyperbole, and use of interjections

Corpora

Twitter

- Description: Micro-blogging service where users can post short messages (tweets) containing searchable annotations (hashtags)
- Collected 969 tweets marked with the #sarcasm hashtag
- Each sarcastic tweet was paired with an earlier tweet from the same user that was not marked as sarcastic

Google Books Database

- Description: Database of over 15 million scanned books allowing full-text searches and previews
- Collected 110 quotations marked by the phrase "said sarcastically" (39 from Kreuz & Caucci, 2007)
- Each sarcastic quotation was paired with an earlier quotation from the same speaker that was not marked as sarcastic

Analyses

Linguistic Inquiry and Word Count (LIWC)

- Positive emotion, negative emotion, and interjections*

Part of Speech (POS) Tagger Word Counts

- Stanford POS Tagger v3.0.4
- Adjectives (JJ), adverbs (RB), adverb + adjective and adjective + adjective co-occurrences, and interjections (UH)

Compared LIWC scores and POS tagger counts of the sarcastic and non-sarcastic (control) statements in each corpus

*This was a custom dictionary of 161 interjections created by the researchers

Figure 1: Example Sarcastic and Control Tweet Pair

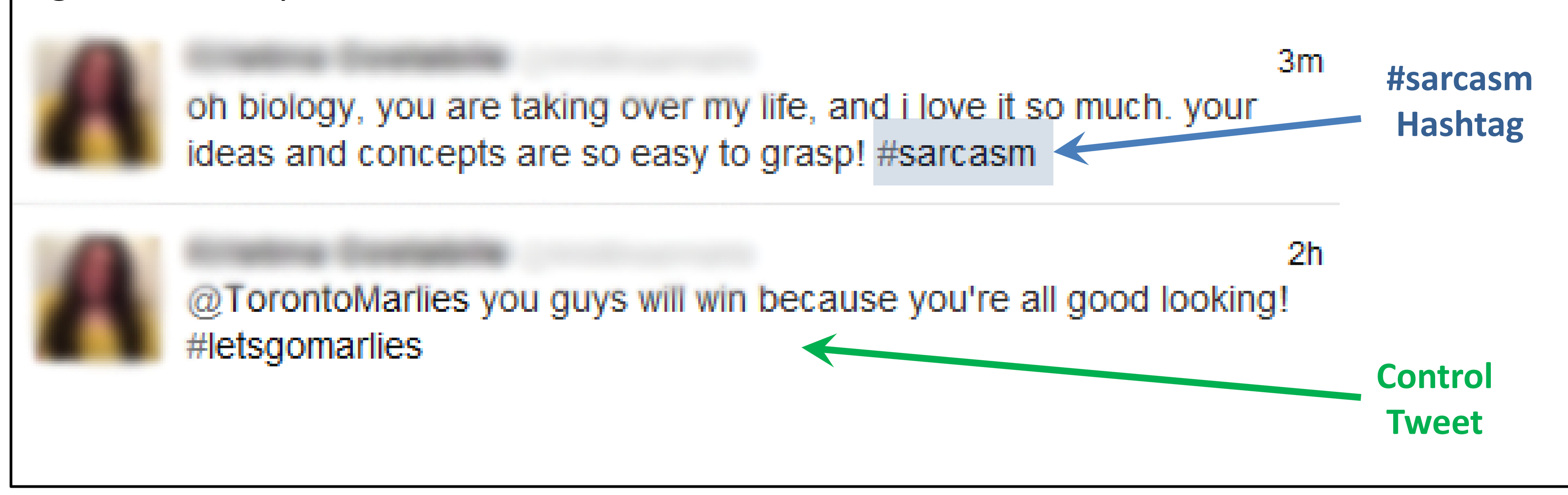

Figure 2: Example Sarcastic and Control Quotation Pair from Google Books Database (excerpt from "Summer Rental" by Mary Kay Andrews)

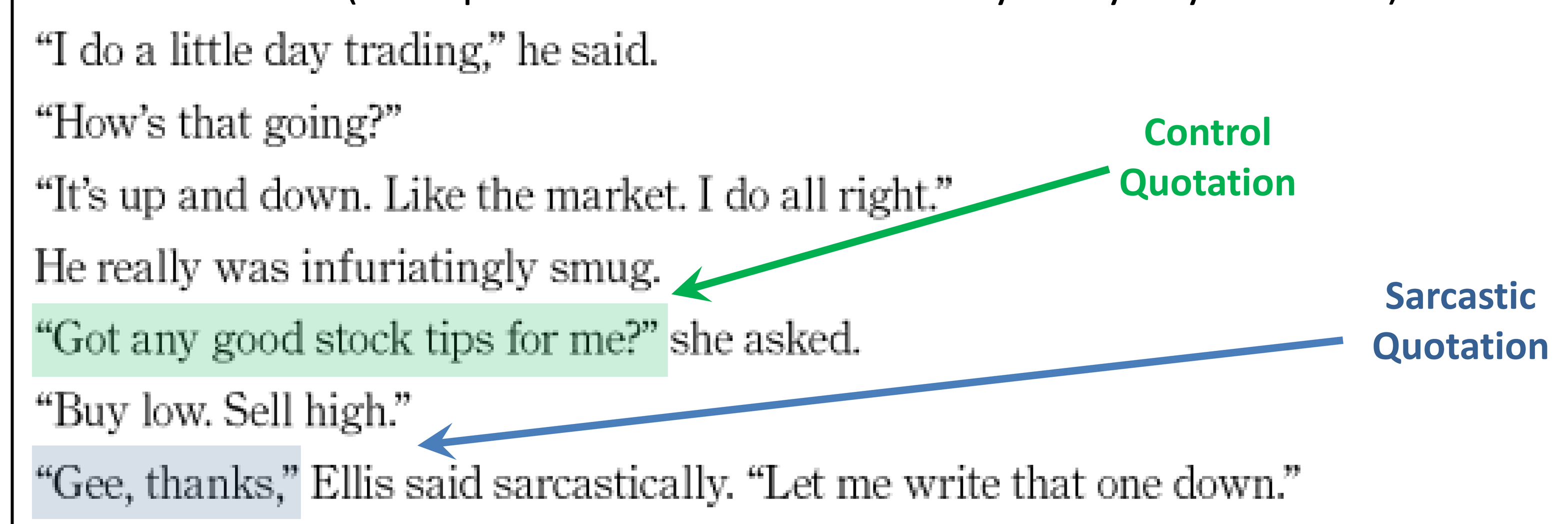
"I do a little day trading," he said.
"How's that going?"
"It's up and down. Like the market. I do all right."
He really was infuriatingly smug.
"Got any good stock tips for me?" she asked.
"Buy low. Sell high."
"Gee, thanks," Ellis said sarcastically. "Let me write that one down."

Table 1: Paired t-tests of Sarcasm vs. Control LIWC Scores

Corpus	LIWC Category	Sarcasm Mean	Control Mean	*t* (S - C)	Sig. (2-tailed)
Twitter	Positive Emotion	10.12	5.82	8.93	< .001
	Negative Emotion	2.04	3.12	-3.72	< .001
	Interjections	1.62	1.18	2.04	.041
Google Books	Positive Emotion	14.57	3.97	4.30	< .001
	Negative Emotion	2.03	3.08	-0.76	.448
	Interjections	4.83	1.25	2.47	.015

Table 2: Paired t-tests of Sarcasm vs. Control POS Tagger Counts

Corpus	POS Type	Sarcasm Mean	Control Mean	*t* (S - C)	Sig. (2-tailed)
Twitter	Adjectives	0.87	0.75	2.90	.004
	Adverbs	0.81	0.75	1.56	.120
	Adverb + Adjective	0.14	0.10	3.07	.002
	Adjective + Adjective	0.04	0.04	0.11	.913
	Interjections	0.10	0.03	5.55	< .001
Google Books	Adjectives	0.52	0.35	1.73	.074
	Adverbs	0.54	0.74	-1.90	.038
	Adverb + Adjective	0.09	0.09	0.00	>.999
	Adjective + Adjective	0.02	0.01	0.58	.566
	Interjections	0.23	0.05	3.59	< .001

Results

LIWC Scores (Table 1)

Positive emotion words were more frequent in sarcastic statements across both corpora.
Negative emotion words were less frequent in sarcastic tweets and equally frequent in sarcastic Google Books quotations.
Interjections were more frequent in sarcastic statements across both corpora.

POS Tagger Counts (Table 2)

Adjectives and adverb + adjective were more frequent in sarcastic tweets.
Adverbs were less frequent in sarcastic Google Books quotations.
Interjections were more frequent in sarcastic statements across both corpora.

Discussion

- Our goal was to use two unique, naturalistic corpora where sarcastic intent was explicitly marked to examine lexical features of sarcastic statements.
- Sarcastic statements in both corpora contained more positive emotion words, but not more negative emotion words. This is consistent with the idea of asymmetry of affect: sarcasm tends to be a positive evaluation of a negative event.
- Interjections were more frequent in sarcastic statements across both corpora, indicating that people may use interjections as lexical cues to sarcasm.
- Results for adjectives and adverbs—potential lexical indicators of hyperbole—were mixed, suggesting that these may not be particularly discriminating features.
- The fact that the emotion word and interjection results converged across two very different corpora suggests that these features are stereotypic of sarcasm and may potentially be useful as discriminating cues in machine learning applications.

References

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