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“Still Feeling Lucky?” Features of Sarcasm in the Context of Failed Predictions

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Background

With a large portion of communication taking place through e-mail, texts, and other computer mediated forms of communication (CMCs), many cues we take for granted in face-to-face conversation are absent. This presents a potential challenge in communicating various forms of non-literal language. The principle of inferability (Kreuz, 1996) suggests that people will only use irony if they are fairly certain they will be understood appropriately.

Despite the limitations presented by CMCs, however, sarcasm has certainly not disappeared from the digital linguistic landscape. Several studies have explored how sarcasm is signaled in CMC settings (e.g., Hancock, 2004). Further, a rapidly-growing body of literature has attempted to classify sarcastic statements in social media using combinations of features (e.g., via punctuation).

The majority of the sarcasm classification research has used corpora drawn from Twitter (e.g., Kunneman et al., 2014), though other sources have also been used (e.g., Reddit; Wallace et al., 2014). Given the restrictions imposed by Twitter, in particular, such as the 140 character limit (most analyses have analyzed corpora prior to the expansion of this limit) it is unclear how this may generalize to other means of signaling sarcasm (e.g., in text messaging).

Failed predictions are one situation in which sarcasm frequently occurs (e.g., claiming that you feel lucky and subsequently bowl several gutter balls in a row). Eight such scenarios (from Kreuz & Glucksberg, 1989) were presented to participants as part of a previous study (Johnson & Kreuz, 2018), as well as eight fillers (i.e., not involving failed predictions). A balanced set of responses were drawn from this dataset to create the corpus for the current study.

Specifically, we were interested in how various features of sarcasm could be used to classify sarcastic responses. Using features commonly described as signaling sarcasm (e.g., echoes), as well as several linguistic and typographic features, we sought to examine how individuals signaled sarcasm in the context of failed predictions.

Predictions

- Echoes (i.e., references to some antecedent event or statement) will be strong predictors
- Extreme positive adjectives and adverbs should also be common in sarcastic responses
- Specific linguistic features (e.g., punctuation, interjections) may also indicate sarcasm
- Features of the individuals providing the response, as well as those of the recipient (e.g., gender) might also influence sarcasm

Corpus

Sarcasm-Eliciting Scenarios

Provide Completions to 16 Scenarios (8 Intended to Elicit Sarcasm)

Example

Bill and Ann had decided to go bowling. “I’m feeling pretty lucky tonight,” said Bill. A few minutes later, they began their game, and Bill threw several gutter balls in a row. As Bill returned to his seat, Ann called over to him: ___________________________________

Sample Subject Responses

you’re REAL lucky tonight
Still feeling lucky?
Pretty lucky, eh, bill?
You’re a Rockstar!

Method & Analysis

Method

The corpus for this analysis was drawn from responses to the scenarios described above. Importantly, subjects were told to respond to the prompts as they normally would (i.e., no instructions to be sarcastic), as it is unclear how explicit instructions may influence the signaling of sarcasm. In total, 187 sarcastic responses were identified and a prompt-matched set of 187 literal responses were selected. That is, for each scenario, there is an equal number of literal and sarcastic responses. Features were hand-coded by two raters with 93.24% agreement. Disagreements were resolved through discussion.

Using the balanced corpus with these features (*right*), we fit a logistic regression model, using *PROC LOGISTIC* in SAS 9.4. with a binary sarcastic/literal dependent variable. Our model was significant and had good predictive power: Nagelkerke R^2 = .417, Cox and Snell R^2 = .313, Tjur R^2 = .324.

Logistic Regression Analysis of Sarcastic (n = 187) and Literal (n = 187) Responses Using SAS PROC LOGISTIC (Version 9.4)

					Odds Ratio	
Predictor	β	*SE* β	Wald’s χ^2	*p*	Estimate	95% CI
Echo	1.96	0.34	33.72	< .0001	7.12	3.73, 14.08
Label (Jocular)	1.67	0.55	9.06	< .01	5.31	1.87, 16.86
Label (Name)	1.47	0.43	11.80	< .01	4.36	1.92, 10.40
Adjective/Adverb	1.29	0.46	7.85	0.01	3.65	1.50, 9.30
Hyperbole	1.11	0.54	4.16	0.04	3.04	1.05, 9.01
Source[a]	0.89	0.35	6.25	0.01	2.43	1.22, 4.90
Rhetorical	0.72	0.35	4.32	0.04	2.06	1.05, 4.14
Direct	0.34	0.33	1.07	0.30	1.40	0.74, 2.67
Interjection	0.30	0.36	0.69	0.40	1.36	0.66, 2.79
Speaker Gender[b]	0.27	0.30	0.85	0.36	1.31	0.74, 2.36
Consequence	0.14	0.29	0.22	0.64	1.15	0.64, 2.08
Exclamation	0.09	0.35	0.06	0.80	1.09	0.55, 2.20
Frozen Expression	0.05	0.41	0.02	0.90	1.05	0.48, 2.35
Word Count[c]	-0.22	0.04	31.28	< .0001	0.80	0.74, 0.86
Test		χ^2	*df*	*p*		
Overall model evaluation						
Likelihood ratio test		140.42	14	< .0001		
Score test		115.69	14	< .0001		
Wald test		84.84	14	< .0001		

Note. Reference for all variables is feature absent (0) unless otherwise noted. Cox and Snell R^2 = .313, Nagelkerke R^2 = .417, *c*-statistic = .827.

[a] *Reference category: Filler.* [b] *Reference category: Female.* [c] *Note: Fewer words increases likelihood*

Features

Echo: For our analysis, presence of explicit echo of interlocutor’s statement *(e.g., “Still feeling lucky?”)*

Label (Jocular & Name): Use of a jocular name (*e.g., ace*) or explicit use of the interlocutor’s name.

Adjective/Adverb: Use of intensifying adjectives or adverbs (*e.g., amazing, really*)

Hyperbole: Use of hyperbole (*i.e., exaggerated statements not meant to be taken literally*)

Source: Response to one of the failed prediction prompts (*e.g., above*) or literal prompts.

Rhetorical: Use of rhetorical questions (*e.g., “Pretty lucky, eh, bill?”*)

Direct: Was the statement direct (e.g., *you’re a real genius*) or indirect (e.g., *that went well*)?

Interjection: Use of an interjection (e.g., “*Wow!*”)

Speaker Gender: Gender of the speaker

Consequence: Did situation affect speaker (e.g., *car breaking down vs. interlocutor failing exam*)?

Exclamation: Use of an exclamation point

Frozen Expression: Use of frozen expressions

Word Count: Number of words (*fewer words = increased probability*)

Conclusions

Results demonstrate that a number of typographic, contextual, and linguistic features can be used to classify sarcastic responses. However, while many features may contribute to classification, no single feature is indicative of sarcastic intent.

Our findings also suggest that context (e.g., failed predictions) can contribute to classification. Machine learning classification of sarcasm may be improved by including broader conceptualizations of response features (e.g., echoes) in addition to traditional features (e.g., emoticons, bigrams).

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