Sarcasm Target Identification: Dataset and An Introductory Approach

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Sarcasm Target Identification

Sarcasm is defined as a form of verbal irony that is intended to express contempt or ridicule

Sarcasm Target is the entity or situation being ridiculed in a sarcastic text.

“This mobile phone is amazing - use it as a paperweight”

Target: *“mobile phone”*

Sarcasm Target Identification is the automatic extraction of sarcasm target in a sarcastic text

Applications: Can be used by aspect-based sentiment analysis to attribute negative sentiment to the sarcasm target

In this paper, (a) A sarcasm target dataset, (b) An hybrid (rule-based + statistical) approach for sarcasm target identification

It sounds like aspect-based sentiment analysis. How is it different?

1. **Not simply noun phrase extraction:** *'This phone heats up so much that I strongly recommend chefs around the world to use it as a cook-top'*. The target is '*phone'* and not *'chefs'* or '*cook-top'*
2. **Multiple sarcasm targets:** *'You are as good at coding as he is at cooking'.* The targets are *'you'* and *'he'*
3. ***Absence of sarcasm target as a word:*** *'What a great way to start off the day!'.* The target is not a word in the sentence

Therefore, given a sarcastic text,

We label the sarcasm target as either: (a) subset of words towards which the sarcasm is expressed, or (b) a fall-back label 'Outside'

Sarcasm Target Dataset

224 sarcastic book snippets from Joshi et al (2016) and 506 sarcastic tweets from Riloff et al (2013); three annotators undertake the annotation

	Snippets	Tweets
Count	224	506
Average #words	28.47	13.06
Vocabulary	1710	1458
Total words	6377	6610
Average length of sarcasm target	1.6	2.08
Average polarity of sarcasm target	0.0087	0.035
Average polarity of portion apart from sarcasm target	0.027	0.53

Inter-annotator agreement

50 random instances from each dataset are labeled by two of the three annotators:

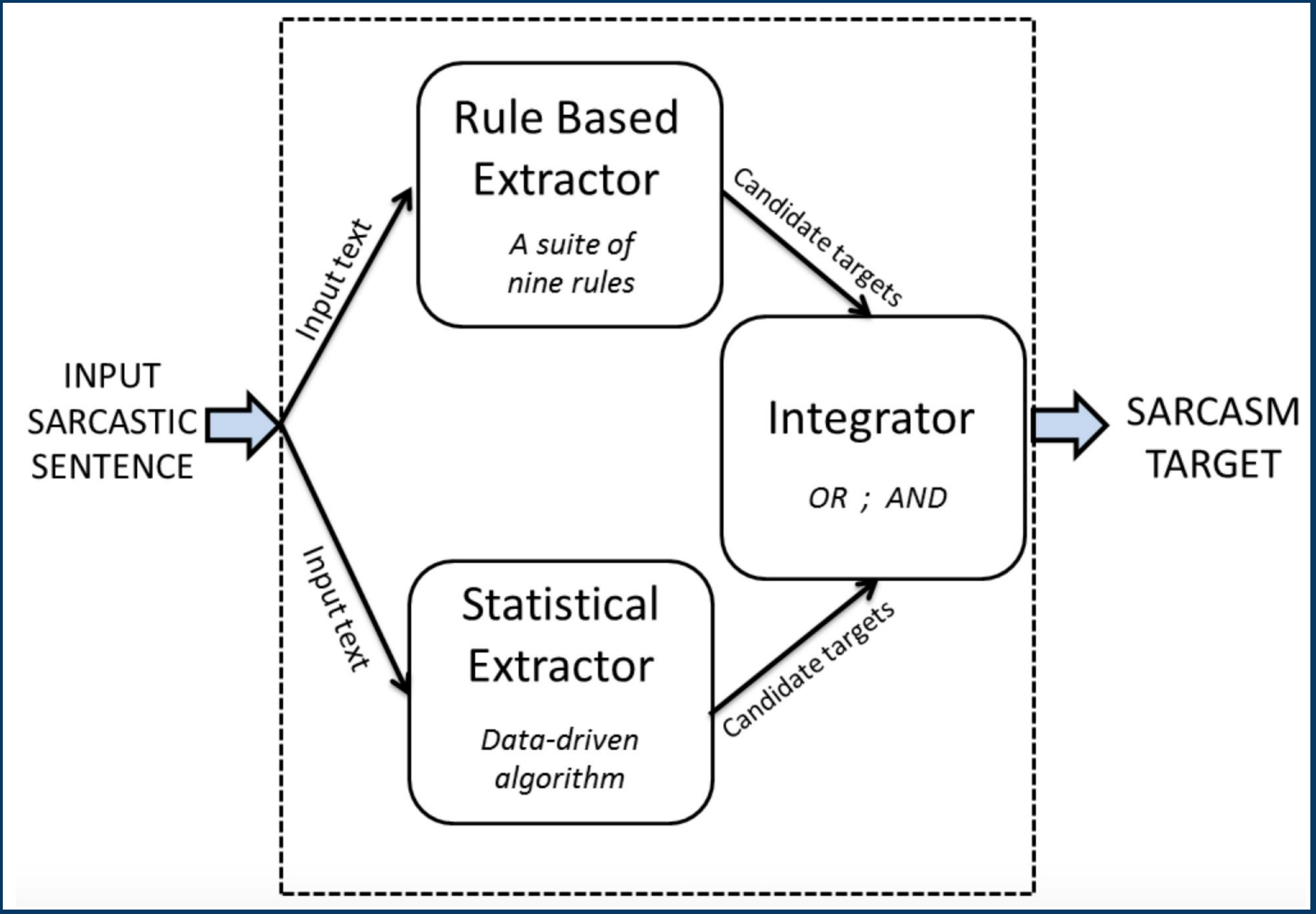
Exact match:

- Book snippets: 28%,
- Tweets: 38%

Partial Match:

- Both: 66%

Sarcasm Target Identification: Introductory Approach



Rule-based Extractor

Rule	Definition	Example
R1	Return pronouns and pronominal adjectives	Love when **you** don't have two minutes to send me a quick text .. ; I am so in love with **my job**.
R2	Return named entities as target	Don't you just love it when **Microsoft** tells you that you're spelling your own name wrong.
R3	Return direct object of a positive sentiment verb	I love **being ignored**.
R4	Return phrase on lower sentiment side of primary verb	So happy to just find out it has been *decided* **to reschedule all my lectures and tutorials for me to night classes at the exact same times**!
R5	Return Gerund and Infinitive verb phrases	**Being covered in hives** is so much fun!
R6	Return nouns preceded by a positive sentiment adjective	Yep, this is indeed an *amazing* **donut** ..
R7	Return subject of interrogative sentences	A murderer is stalking me. Could **life** be more fun?
R8	Return subjects of comparisons (similes)	**He** is as good at coding as **Tiger Woods** is at controversies.
R9	Return demonstrative adjective-noun pairs	Oh, I love **this jacket**!

Statistical Extractor

Note that we convert individual sentences into words. For each word as an instance, we use the following features:

(A) Lexical: Unigrams,

(B) Part of Speech (POS)-based features: Current POS, Previous POS, Next POS,

(C) Polarity-based features: Word Polarity, Phrase Polarity : Sentiment score for the trigram formed by considering the previous word, current word and the next word together (in that order),

(D) Pragmatic features

SVM-Perf (Joachims, 2006)

Results of the Rule-based Extractor

Rule	Overall		Conditional	
	EM	DS	EM	DS
R1	6.32	19.19	8.69	26.39
R2	11.26	16.18	30.32	43.56
R3	**12.45**	20.28	34.24	**55.77**
R4	6.91	13.51	18.42	36.0
R5	9.28	**23.87**	15.36	39.47
R6	10.08	16.91	19.31	32.42
R7	9.88	15.21	32.25	49.65
R8	11.26	11.26	**50**	50
R9	11.46	13.28	43.59	50.51

Dice Coefficient for Tweets

Rule	Overall		Conditional	
	EM	DS	EM	DS
R1	7.14	**32.8**	7.65	35.23
R2	**8.48**	16.7	19.19	37.81
R3	4.91	6.27	16.92	21.62
R4	2.67	11.89	4.38	19.45
R5	1.34	6.39	2.32	11.11
R6	4.01	6.77	8.91	15.02
R7	3.12	10.76	9.46	32.6
R8	4.91	6.78	**35.02**	45.17
R9	4.46	6.94	34.48	**53.67**

Dice Coefficient for Book Snippets

In integrated approach, each rule is weighted by its performance
'Overall' spans all text units in the dataset whereas 'Conditional' is limited to text units which match a given rule

Results of the Integrated Approach

Approach	EM	DC
Baseline 1: All Objective Words	1.38	27.16
Baseline 2: Seq. Labeling	12.26	33.41
Only Rule-Based	9.48	29.13
Only Learning-Based	10.48	31.8
Hybrid OR	9.09	**39.63**
Hybrid AND	**13.45**	20.82

Performance for Tweets

Approach	EM	DC
Baseline 1: All Objective Words	0.0	16.14
Baseline 2: Seq. Labeling	12.05	31.44
Only Rule-Based	9.82	26.02
Only Learning-Based	12.05	31.2
Hybrid OR	7.01	**32.68**
Hybrid AND	**16.51**	21.28

Performance for Book Snippets

Baseline 1: All objective words
Baseline 2: Sequence labeling for opinion target identification, as shown by Jin et al (2009)

Conclusion

We report a sarcasm target dataset, available at:

https://github.com/Pranav-Goel/Sarcasm-Target-Detection

Our introductory approach sets a baseline and also shows why typical opinion target identification may not suffice in case of sarcasm target identification.

References:

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