

Detection of Sarcasm in Twitter

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**CSCI-GA 3033-008: Statistical Natural Language
Processing - Final Project**



Introduction

Aim

- Given a text, classify it as '*sarcastic*' or '*non-sarcastic*'
- Extract features characterizing sarcasm in natural languages.

Evaluation Metric

Average F-Score

$$F_{avg} = \frac{2 \times rec_{avg} \times prec_{avg}}{rec_{avg} + prec_{avg}} \quad (1)$$



Data Source, Collection Method

Data source

- Data mined from twitter using Twitter Search API.



Andy @IndyAndy_78 · Dec 8

I couldn't be happier right now. 45 min drive to work was doubled and I'll be behind all day. [#sarcasm](#)



The New Yorker @NewYorker · 2h

No matter which party controls Congress after next year's midterms, lawmakers will be forced to revise the G.O.P. tax bill legislation substantially.



Collection

- Queried for [# sarcasm](#) and [# sarcastic](#) tweets. (Labeled sarcastic)
- Queried general tweets of the day - already labeled sarcastic. (Labeled Non Sarcastic)

Preprocessing

- Removed all '#' hashtags, '@' mentions and also urls/images from the tweets.
- Tokenized the data by using NLTK's tokenizer.

Sarcastic:

('if', 'evolution', 'was', 'real', 'why', 'do', 'we', 'still', 'have', 'dumbasses', '?')

Non Sarcastic:

('Great', 'eastern', 'restaurant', 'has', 'amazing', 'Dim', 'Sum', 😊')

Total Data points	380093
Sarcasm	55468
Non Sarcasm	324625
Avg length(Data Pt)	13.5 words*

Table: Data Statistics

Bouzizi et. al. A pattern-based approach for sarcasm detection on twitter

Bouzizi et. al.

- ① **Sentiment Related Features:** Four Features Extracted based on inconsistency between sentiments of words.
 - ① **pw** - Number of positive words.
 - ② **nw** - Number of negative words.
 - ③ **PW** - Number of highly emotional positive words.
 - ④ **NW** - Number of highly emotional negative words.
- ② **Punctuation Related Features**
- ③ **Syntactic and Semantic or Pattern Related Features:** Parts of speech based grammar features.*

Joshi et. al.: Are word embedding-based features useful for sarcasm detection?

Joshi et. al.

- **Idea:**

- Use word embedding based features.
- Compute cosine similarity scores of two word vectors.

- **Unweighted Similarity Features:**

- Maximum score of most *similar* word pair
- Minimum score of most *similar* word pair
- Maximum score of most *dissimilar* word pair
- Minimum score of most *dissimilar* word pair

- **Distance-Weighted Similarity Features:**

Instead of using raw cosine similarity scores of two words, weigh them inversely by the square of the distance between two words and proceed as before.

Example showing feature calculation

Sentence: $word_1, word_2, word_3, \dots, word_n$.

Content Word Sentence: $word_{a_1}, word_{a_2}, word_{a_3}, \dots, word_{a_k}$

	$word_{a_1}$	$word_{a_2}$...	$word_{a_n}$
$word_{a_1}$	-	0.4	...	0.2
$word_{a_2}$	0.7	-	...	0.6
...	-	...
$word_{a_n}$	0.2	0.3	...	-

Table: Similarity Table

	$word_{a_1}$	$word_{a_2}$...	$word_{a_n}$
$word_{a_1}$	-	0.263	...	0.745
$word_{a_2}$	0.732	-	...	0.690
...	-	...
$word_{a_n}$	0.455	0.637	0.177	-

Table: Distance Weighted

$$S_{i,j} = \cos(v[word_{a_i}], v[word_{a_j}])$$

$$S'_{i,j} = S_{i,j} / |(i - j)^2|$$

$$\cos(u, v) = u \cdot v / \|u\| \|v\|$$

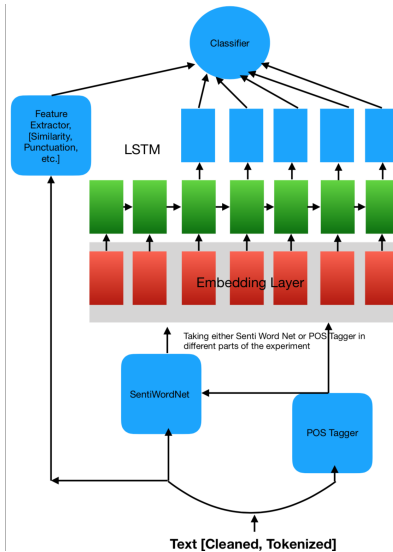
Proposed Solution

Motivation behind our contribution

- Learn more from syntactic features (POS tags) and their sequence.
 - Improve from the hard coded features from POS tags as done previously.
- Utilise sequence modeling for predicting sarcasm with sequence of sentiments.

Implementation

- Trained 2 LSTM's - 1 on sequence of sentiments, and one one sequence of POS Tags.
- Pulled the final layer output of the LSTM, augmented this output with precomputed baseline features and trained classifier over this new feature set.



Results

Results with Linear Kernel SVM Classifier (Sarcastic to Non-Sarcastic Test Class Ratio - 1 : 50)

Model / Features	Precision (%)		Recall (%)		F Score Average
	S	N-S	S	N-S	
Hacky Features	2.935	98.48	46.10	69.64	0.5405
Embeddings	2.068	98.25	55.58	47.60	0.508
Bouzizi et. al.	3.159	98.67	55.14	66.35	0.5540
Joshi et. al.	3.210	98.64	52.43	68.52	0.5529
Sentiment LSTM	3.423	99.03	70.14	60.60	0.5744
POS LSTM	4.132	99.18	72.02	66.73	0.5921
Sent + POS LSTM	4.322	99.22	73.37	67.66	0.5971
ALL FEATURES	4.674	99.24	72.93	70.38	0.6024

S → Sarcastic class

N-S → Non-Sarcastic class

Results

Results with XGBoost Classifier (Sarcastic to Non-Sarcastic Test Class Ratio - 1 : 50)

Model / Features	Precision (%)		Recall (%)		F Score Average
	S	N-S	S	N-S	
Hacky Features	3.163	98.78	60.86	62.91	0.5590
Embeddings	3.103	98.91	68.09	57.67	0.5632
Bouzizi et. al.	3.512	98.87	62.33	65.91	0.5693
Joshi et. al.	3.894	99.08	68.84	66.97	0.5860
Sentiment LSTM	3.481	99.03	69.88	61.43	0.5757
POS LSTM	4.212	99.17	71.56	67.60	0.5932
Sent + POS LSTM	4.455	99.24	73.46	68.63	0.5995
ALL FEATURES	4.818	99.29	74.80	70.58	0.6067

S → Sarcastic class

N-S → Non-Sarcastic class

Results

Results for various Sarcastic to Non-Sarcastic Test Ratios Classifier: Linear Kernel SVM

Sarcastic : Non-Sarcastic	Precision (%)		Recall (%)		F Score Average
	S	N-S	S	N-S	
1 : 50	4.674	99.24	72.93	70.38	0.6024
1 : 9	19.38	96.38	67.11	64.61	0.6436
1 : 3	44.66	88.91	77.82	66.85	0.6898
1 : 1	68.58	74.37	77.82	66.36	0.7128

S → Sarcastic class

N-S → Non-Sarcastic class

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Branch: **master**

Commits on Dec 19, 2017


 Merge branch 'master' of https://github.com/AK101111/Sarcasm-detection
AK101111 committed 6 hours ago


 [3e69f28](#) [Code](#)


 new embeddings
AK101111 committed 6 hours ago


 [5ab7999](#) [Code](#)

Commits on Dec 17, 2017


 Results for Linear SVM
Nish Agarwal committed 2 days ago


 [7c8ac6d](#) [Code](#)

 xgb results added final
AK101111 committed 2 days ago

 [e95cd56](#) [Code](#)

Commits on Dec 16, 2017

 Results Updated
Nish Agarwal committed 3 days ago

 [f7a1248](#) [Code](#)