Computational Model for Understanding Emotions in Sarcasm: A Survey

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Abstract

Sarcasm is generally associated with a negative emotion. The question is *which negative emotion- anger, sadness, disgust, any other?* This paper presents a methodology of detecting the exact emotion(s) in a sarcastic sentence. Sarcasm arises from contextual incongruity in a sentence and bears a surface sentiment which is different from the intended sentiment. While the surface sentiment may be positive, the intended sentiment is negative. Thus the underlying emotion recognition task becomes one of the most difficult parts of the conundrum. Previous works have extensively studied sentiment and emotion in language, while the relationship between sarcasm and emotion has been largely unaddressed. In this paper, we investigate various challenges and techniques for Sarcasm Detection, Emotion Analysis and relationship between them.

1 Introduction

Sarcasm is a very sophisticated linguistic articulation where the sentential meaning is often disbelieved due to the linguistic incongruencies or differences in implied and surface sentiment. While incongruity is the key element of sarcasm, the intent could be to appear humorous, ridicule someone, or express contempt. Thus sarcasm is often considered a very nuanced, creative, or intelligent language construct which poses several challenges to both detection and generation.

Detecting emotions and sarcasm is crucial for all services involving human interactions, such as chatbots, e-commerce, e-tourism and several other businesses. We hypothesize that sarcasm affects the emotion associated with a conversation and thus this paper aims to study the emotions, arousal and valence in sarcastic sentences. Valence measures the positive or negative affectivity. Arousal measures the intensity of the emotion associated (Cowie and Cornelius, 2003). Research studying the impact of sarcasm on sentiment analysis (Maynard and Greenwood, 2014) showed that sarcasm often has a negative sentiment, but the associated emotions have not been studied. For tweet analysis, NLP researchers have tried to detect sarcasm and perform sentiment analysis together (Poria et al., 2016), while some try to improve sentiment analysis performance using sarcasm detection (Bouazizi and Ohtsuki, 2015).

2 Emotion Analysis from Text

According to (Tripathi et al., 2016), in order to understand emotions, we look at literature from psychology that describes different properties of emotions. In the first subsection, we look at properties of emotions while in the second subsection, we look at Plutchik wheel of emotions.

2.1 Properties of Emotion

(Tripathi et al., 2016) defined four key properties of emotions:

1. **Antecedent**: The antecedent is the event or situation that causes a given emotion. It acts as a trigger to the emotion. For example, in case of surprise, the antecedent can be a unexpected gift.

2. **Signal**: The signal is the physiological method that a human uses to express an emotion. A signal is generated when a person expresses a specific emotion. For example, in case of surprise, your mouth opens wide.

3. **Response**: The response is the expected, conventional reaction to an emotion. A re-

sponse is generated when a person understands a given emotion in another person. If a person sees another person happy because of his achievements, he congratulates him.

4. **Coherence**:Coherence indicates that a given emotion has similar antecedents, signals and responses across different living beings. Simply put, similar things are likely to make a dog and a human sad (antecedents), both dog and human are likely to express sadness in similar ways (signals), etc.

2.2 Plutchik Wheel of Emotions

The Plutchik wheel (Plutchik, 1991) of emotions allows us to understand relationships between different basic and complex emotions in terms of a complex structure as a wheel. One peculiar problem that arises in the task of emotion analysis is that cognitive psychologists do not seem to agree on the number of basic emotions in humans. The idea of 'basic' emotions is similar to the concept of primary colors in color theory that is, once we decide on the set of basic emotions, all other emotions can then be considered as combinations of these basic emotions.

Figure 1: Plutchik's wheel of Emotions: 3D representation showing 8 primary emotions in the center circle with their intensity variants and combinations forming 32 emotions.

3 Sarcasm from a Linguistic Perspective

Sarcasm is a very sophisticated linguistic articulation where the sentential meaning is often disbelieved due to the linguistic incongruencies or differences in implied and surface sentiment. While incongruity is the key element of sarcasm, the intent could be to appear humorous, ridicule someone, or express contempt.

3.1 Types of Sarcasm

(Joshi et al., 2016) discusses about 4 types of Sarcasm:

1. **Propositional**: In such situations, the statement appears to be a proposition but has an implicit sentiment involved. For example 'Your plan sounds fantastic!'. This sentence may be interpreted as non-sarcastic, if the context is not understood.

2. **Embedded**: This type of sarcasm has an embedded incongruity in the form of words and phrases themselves. For example 'John has turned out to be such a diplomat that no one takes him seriously'. The incongruity is embedded in the meaning of the word 'diplomat' and rest of the sentence.

3. **Like-prefixed**: Like-phrase provides an implied denial of the argument being made. For example, 'Like you care!' is a common sarcastic retort.

4. **Illocutionary**: This kind of sarcasm involves non-textual clues that indicate an attitude opposite to a sincere utterance. For example, rolling one's eyes when saying 'Yeah right'.

3.2 Representation of Sarcasm

(Joshi et al., 2016) represent sarcasm as a 6-tuple consisting of (S, H, C, u, p, p') where: S = Speaker, H = Hearer/Listener, C = Context, u = Utterance, p = Literal Proposition, and p' = Intended Proposition. The tuple can be read as 'Speaker **S** generates an utterance **u** in Context **C** meaning proposition **p** but intending that hearer **H** understands **p**'.

4 Datasets

In this section, we describe datasets for computational sarcasm. We classify them into categories based on different domains:

4.1 Emotion Analysis

Most of the works in Emotion Analysis have been on short text like tweets from twitter,news headlines,etc.(Tripathi et al., 2016) discusses that the most common short text used in emotion analysis research is news headlines Strapparava and Mihalcea (2007; Bellegarda (2010), followed by microblogs Aman and Szpakowicz (2007a; Chaffar

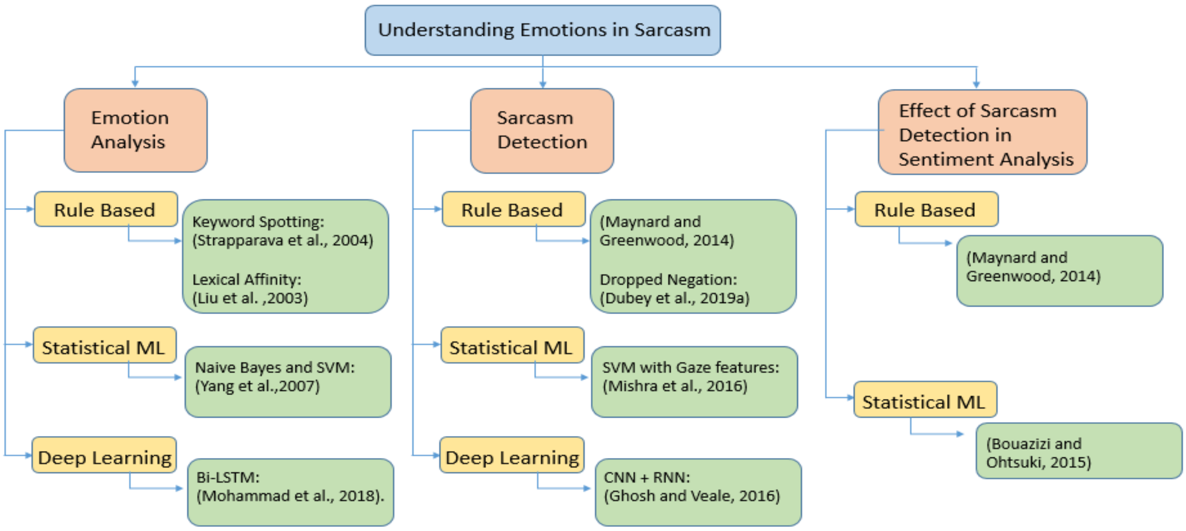

Figure 2: Literature and Approaches in a Nutshell

and Inkpen (2011). There have been few works that analyze long text for emotions. The most notable among these is Liu et al. (2003), who work with emails. Alm (2008) work on children's stories, but instead of treating one story as a large data sample, they break it down into sentences. The annotations is done for each sentence separately. (Zadeh et al., 2018),(Busso et al., 2008),(Poria et al., 2018),(Chen et al., 2018) are the multimodal datasets for emotion analysis task.

4.2 Sarcasm Detection

In Sarcasm Detection as well, the short text used are mostly in the form of tweets (Riloff et al., 2013),(Ptáček et al., 2014) downloaded from twitter API using hashtag sarcasm as indicator. (Lukin and Walker, 2017) use Internet Argument Corpus for sarcasm detection. (Filatova, 2012) introduce corpus generation and analysis techniques using crowdsourcing. They introduce a dataset of 1254 reviews labelled with sarcasm which can be used for identifying sarcasm on two levels: a document and a text utterance (where a text utterance can be as short as a sentence and as long as a whole document). (Castro et al., 2019) is the first multimodal dataset for Sarcasm Detection problem.

4.3 Effect of Sarcasm on Sentiment Analysis

(Maynard and Greenwood, 2014) (Bouazizi and Ohtsuki, 2015) both used twitter tweets for studying the effect of sarcasm in sentiment analysis.

5 Approaches

Figure 2 describes various approaches (i.e Rule based, Statistical Machine Learning and Deep Learning) used in all different domains like Emotion Analysis, Sarcasm Detection and Effect of Sarcasm in Sentiment Analysis.

5.1 Rule Based Approaches

For **Emotion Analysis**, (Tripathi et al., 2016) discusses the following approaches:

- **Keyword Spotting**: The simplest approach to emotion analysis is spotting word which directly depict emotions. Text is categorised into different categories based on the presence of unambiguous emotion words like distressed,enraged and happy.

- **Lexical Affinity**: It is slightly more sophisticated than keyword spotting. It assigns a probabilistic affinity for a particular word. For example, accident may be assigned a 70 percent probability of indicating a negative effect, as in bus accident". Linguistic corpora is used to train these probabilities. There are two problems with this approach:

  1. The approach works on word-level so it does not consider negations and different word senses.
  2. Lexical affinity probabilities are derived using linguistic corpora and are

,hence, biased towards text of a particular genere

For **Sarcasm Detection**, (Maynard and Greenwood, 2014) perform an analysis of the effect of sarcasm on the polarity of tweets. They have compiled a number of rules for comparing sentiment expressed by a hashtag and rest of the tweet to predict sarcasm. (Riloff et al., 2013) look for contrast between positive verb and negative situation phrase in a sentence. (Bharti et al., 2015) use a phrase-based lexicon generation algorithm. They present a rule-based approach which predicts the sentence as sarcastic if a positive sentence contains a negative phrase. For **Effect of Sarcasm Detection in Sentiment Analysis**, (Maynard and Greenwood, 2014) counts the number of positive and number of negative words. They calculate the ratio of positive is to negative along with specific word weights. They then look at the contrast between the ratio and the hashtag indicators to identify sarcasm in text. If sarcasm is found, then the sentiment of sentence is flipped.

5.2 Statistical Machine Learning Approaches

- For **Emotion Analysis**, the statistical approach is the most common approach of emotion analysis. A large training corpus of annotated text is fed into a machine learning algorithm. The system not only learns the relationship between lexical entities and their valence but about pragmatic features like punctuation. Other approaches involved the use of traditional machine learning algorithms like Naive Bayes and SVM. The use of Conditional Random Fields were also considered for emotion analysis. Another important approach introduces the concept of hierarchical classification to classify weblogs. Prior results show that Support Vector Machines are better in the task of emotion analysis when compared to Naives bayes.

- For **Sarcasm Detection**, (Mishra et al., 2016) propose a different approach and augment the feature vector with cognitive features extracted from eye movement patterns of human readers. They use a set of gaze-based features such as average fixation duration, regression count and skip count. (González-Ibáñez et al., 2011) state that incorporating sentiment and emoticon related features also improve the performance of sarcasm detection systems. Past work using the described features commonly use variants of Support Vector Machines (SVM). Naive Bayes and ensemble methods like Bagging, Boosting etc., have also been reported in the past.

- For **Effect of Sarcasm in Sentiment Analysis**, (Bouazizi and Ohtsuki, 2015) uses the following feature set:
  - Sentiment-Related features
  - Punctuation-Related features
  - Syntactic features
  - Pattern-Related features

  They then use these features to train Naive Bayes, Support Vector Machine (SVM), and Maximum Entropy classifiers.

5.3 Deep Learning Approaches

- For **Emotion Analysis**, The dataset used is the dataset available for SemEval2018 Task 1C (Mohammad et al., 2018). The goal of the model is that it should predict multiple emotions given a sentence. The input sentence consists of words and each word is mapped into a d- dimensional vector space. In order to represent the sentences, Bidirectional Long Short Term Memory (Bi- LSTM) is used to process each word. For the final layer, the MultiLayer Perceptron (MLP) is applied followed by a hidden layer which is normalised using Softmax layer to obtain probabilistic values for all emotion classes.

- For **Sarcasm Detection**, (Ghosh and Veale, 2016) propose a semantic model which is a combination of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) for sarcasm detection. They show an improvement over recursive SVM by using their approach. (Poria et al., 2016) propose a novel CNN based architecture to detect sarcasm. (Amir et al., 2016) propose a novel CNN-based architecture to learn additional context in the form of form of user embeddings and use that for sarcasm detection.

6 Reported Results

Following are the results:

Table 1: Results for Statistical Approaches in Emotion Analysis. F-Scores Reported

Papers	Naive Bayes	Support Vector Machine
Aman and Szpakowicz (2007b)	72.08	73.89
Bellegarda (2010)	59.72	71.69

Table 2: Recall of negative tweets in Sentiment Analysis before and after adding sarcasm-related features

Classifier	Naive Bayes	SVM	Max Entropy
Before	83.9	85.7	82.3
After	85.9	92.0	83.8

7 Conclusion

This paper presented datasets, approaches, performance values as reported in the past work in Emotion Analysis, Sarcasm Detection and Effect of Sarcasm in Emotion Analysis. We presented basics of emotion analysis, a linguistic perspective of sarcasm and brief explanation of effect of sarcasm in sentiment analysis. We observed that rule-based approaches are useful to get an insight into the problem. We also observed that Sarcasm itself posses challenges for emotion and sentiment analysis due its sophisticated linguistic articulation. 2 shows that when we use the information of sentence being sarcastic or non-sarcastic, the sentiment analysis result improved.

References

[Amir et al.2016] Silvio Amir, Byron C. Wallace, Hao Lyu, and Paula Carvalho Mário J. Silva. 2016. Modelling context with user embeddings for sarcasm detection in social media.

[Bharti et al.2015] Santosh Kumar Bharti, Korra Sathya Babu, and Sanjay Kumar Jena. 2015. Parsing-based sarcasm sentiment recognition in twitter data. In *2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pages 1373–1380. IEEE.

[Bouazizi and Ohtsuki2015] Mondher Bouazizi and Tomoaki Ohtsuki. 2015. Opinion mining in twitter how to make use of sarcasm to enhance sentiment analysis. In *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015*, pages 1594–1597.

[Busso et al.2008] Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeannette N Chang, Sungbok Lee, and Shrikanth S Narayanan. 2008. Iemocap: Interactive emotional dyadic motion capture database. *Language resources and evaluation*, 42(4):335.

[Castro et al.2019] Santiago Castro, Devamanyu Hazarika, Verónica Pérez-Rosas, Roger Zimmermann, Rada Mihalcea, and Soujanya Poria. 2019. Towards multimodal sarcasm detection (an _obviously_ perfect paper). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, 7.

[Chen et al.2018] Sheng-Yeh Chen, Chao-Chun Hsu, Chuan-Chun Kuo, Ting-Hao K. Huang, and Lun-Wei Ku. 2018. Emotionlines: An emotion corpus of multi-party conversations. *CoRR*, abs/1802.08379.

[Cowie and Cornelius2003] Roddy Cowie and Randolph R Cornelius. 2003. Describing the emotional states that are expressed in speech. *Speech communication*, 40(1-2):5–32.

[Filatova2012] Elena Filatova. 2012. Irony and sarcasm: Corpus generation and analysis using crowdsourcing. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC'12)*, pages 392–398, Istanbul, Turkey, May. European Language Resources Association (ELRA).

[Ghosh and Veale2016] Aniruddha Ghosh and Tony Veale. 2016. Fracking sarcasm using neural network. In *Proceedings of the 7th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pages 161–169, San Diego, California, June. Association for Computational Linguistics.

[González-Ibáñez et al.2011] Roberto González-Ibáñez, Smaranda Muresan, and Nina Wacholder. 2011. Identifying sarcasm in twitter: A closer look. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 581–586, Portland, Oregon, USA, June. Association for Computational Linguistics.

[Joshi et al.2016] Aditya Joshi, Pushpak Bhattacharyya, and Mark James Carman. 2016. Automatic sarcasm detection: A survey.

[Lukin and Walker2017] Stephanie Lukin and Marilyn Walker. 2017. Really? well. apparently bootstrapping improves the performance of sarcasm and nastiness classifiers for online dialogue.

[Maynard and Greenwood2014] Diana G Maynard and Mark A Greenwood. 2014. Who cares about sarcastic tweets? investigating the impact of sarcasm on sentiment analysis. In *LREC 2014 Proceedings*. ELRA.

[Mishra et al.2016] Abhijit Mishra, Diptesh Kanojia, Seema Nagar, Kuntal Dey, and Pushpak Bhattacharyya. 2016. Harnessing cognitive features for sarcasm detection. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1095–1104, Berlin, Germany, August. Association for Computational Linguistics.

[Mohammad et al.2018] Saif Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. 2018. SemEval-2018 task 1: Affect in tweets. In *Proceedings of The 12th International Workshop on Semantic Evaluation*, pages 1–17, New Orleans, Louisiana, June. Association for Computational Linguistics.

[Plutchik1991] Robert Plutchik. 1991. *The emotions*. University Press of America.

[Poria et al.2016] Soujanya Poria, Erik Cambria, Devamanyu Hazarika, and Prateek Vij. 2016. A deeper look into sarcastic tweets using deep convolutional neural networks. *arXiv preprint arXiv:1610.08815*.

[Poria et al.2018] Soujanya Poria, Devamanyu Hazarika, Navonil Majumder, Gautam Naik, Erik Cambria, and Rada Mihalcea. 2018. MELD: A multimodal multi-party dataset for emotion recognition in conversations. *CoRR*, abs/1810.02508.

[Ptáček et al.2014] Tomáš Ptáček, Ivan Habernal, and Jun Hong. 2014. Sarcasm detection on Czech and English twitter. In *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers*. Association for Computational Linguistics, August.

[Riloff et al.2013] Ellen Riloff, Ashequl Qadir, Prafulla Surve, Lalindra De Silva, Nathan Gilbert, and Ruihong Huang. 2013. Sarcasm as contrast between a positive sentiment and negative situation. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, October.

[Tripathi et al.2016] Vaibhav Tripathi, Aditya Joshi, and Pushpak Bhattacharyya. 2016. Emotion analysis from text : A survey.

[Zadeh et al.2018] AmirAli Bagher Zadeh, Paul Pu Liang, Soujanya Poria, Erik Cambria, and Louis-Philippe Morency. 2018. Multimodal language analysis in the wild: Cmu-mosei dataset and interpretable dynamic fusion graph. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2236–2246.