Computational Sarcasm Processing: A survey

Kriti Gupta Pushpak Bhattacharyya
Indian Institute of Technology Bombay, India
{kriti,pb}@cse.iitb.ac.in

Abstract

Sarcasm is "a sharp, bitter, or cutting expression" used to convey contempt or to mock. Sarcasm is mainly distinguished by the modulation of pitch with which it is spoken and is largely context-dependent. Prevalence of sarcasm is one of the main challenges in sentiment analysis. Therefore, automatic processing of sarcasm has been widely explored in the past decade. Processing sarcasm using computational approaches is known as Computational Sarcasm Processing. Sarcasm processing has four major sub-domains: Sarcasm Detection, Sarcasm Generation, Sarcasm Interpretation and Sarcasm Target Identification. In this paper, we will summarize the past work that has been done in these sub-domains. We will discuss the persisting issues, the datasets available as well as the various approaches reported.

1 Introduction

Sarcasm is a mode of satirical wit depending for its effect on bitter, caustic, and often ironic language that is usually directed against an individual.[1] Sarcasm processing interests the sentiment analysis community due to the property that sarcastic texts have implied meaning opposite to the literal meaning. One of the initial works done in the domain of computational sarcasm processing was by Tepperman et al. (2006). Sarcasm emanates from incongruity which becomes apparent as the sentence unfolds. Joshi et al. (2015b) presented a computational system that harnesses context incongruity as a basis for sarcasm detection.

Over the years, a lot of research has been done in the domain of Sarcasm Detection which aims to classify if a given piece of text is sarcastic. However, other domains like Sarcasm Target Identification, Sarcasm Interpretation and Sarcasm Generation are very less explored. This is mostly because of lack of labelled data in these domains and this has motivated the need to explore the unsupervised approaches.

Detection of sarcasm is of great importance and beneficial to many NLP applications,such as sentiment analysis, opinion mining and advertising.

Wallace (2015) presents a survey of linguistic challenges of computational irony. Joshi et al. (2016a) present a summary of previous works in automatic sarcasm detection. The major limitations of these works are: (i) the survey is either very long or (ii) it is primarily focused only on approaches for automatic sarcasm detection. However in this survey we will cover all the sub-domains of sarcasm processing.

The rest of the paper is organised as follows. We first talk about the linguistic perspective of sarcasm in section 2. Then we give a step-by-step overview of the past approaches, starting with the problem definitions in section 3. Section 4 describes the available datasets. The approaches along with their reported performance are discussed in section 5 and 6. We finally conclude the paper in section 7.

2 Linguistic study of sarcasm

The computational approaches to sarcasm use the linguistic theories as their foundation. Grice (1975) states that sarcasm is a form of metaphorical language in which the intended meaning is the opposite of the literal meaning.

2.1 Sarcasm vs Irony

Sarcasm and irony are closely related to each other. Sarcasm and irony are similar in that both are forms of reminder, yet different in that sarcasm

[1] https://www.merriam-webster.com/

conveys ridicule of a specific victim whereas irony does not. The remark ”What a sunny day!” uttered during a severe thunderstorm would be sarcastic if it brought to mind a specific weather forecaster’s prediction that it would be a sunny day, whereas it would be ironic if it brought to mind a wistful desire for sunny weather Lee and Katz (1998). The sarcasm-versus-irony classification problem has been reported in past work. Wang (2013) present a linguistic analysis to understand differences between sarcasm and irony. According to them, aggressiveness is the distinguishing factor between the two. Sulis et al. (2016) present a set of classifiers that distinguish between sarcasm and irony.

2.2 Sarcasm formulation

Ivanko and M. (2003) 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, 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’. For example- Given that a student hasn’t done his assignment, if the teacher says, ”Wow, you have done a great job”, then the sentence is sarcastic and the 6-tuple would be as follows:
S = teacher
H = Student
C = Student has not done his assignment
u = Wow, you have done a great job”
p = the student did a good job
p’ = the student didn a bad job.

2.3 Types of Sarcasm

Camp (2012) distinguishes four subclasses of sarcasm, individuated in terms of the target of inversion. (i) Propositional: When the text appears to be a proposition but has an implicit sentiment involved. For example- This phone should have been a paper weight. This sentence may be interpreted as non-sarcastic, if the context is not understood. (ii) Embedded: This type of sarcasm has incongruity embedded within the sentence. For example- I love being ignored. The congruity is embedded within the sentence by the presence of two opposite polarity words, love and ignored. (iii) Like-Prefixed: This form of explicit sarcasm prefixes the relevant sentence with ‘Like’ or ‘As if’ and employs a sneering tone. For example- Like that’s a good idea. (iv) While speaking ironically, a speaker does not undertake a genuine illocutionary speech act; rather, she mentions or pretends or ‘makes as if to say’ something, in order to express an evaluative attitude towards an associated thought or a perspective, and thereby draw attention to some discrepancy between how things are and how they should be. For example- changing the pitch, rolling of eyes etc.

2.4 Incongruity as a feature

Incongruity is defined as the state of being incongruous (i.e., lacking in harmony; not in agreement with principles). Incongruity is an essential component of sarcasm, and the possibility of incongruity in different degrees is at the heart of sarcasm. Ivanko and M. (2003) state that sarcasm/irony is understood because of incongruity. They studied the relationship between context incongruity and sarcasm processing (by humans). Riloff et al. (2013) identifies sarcasm that arises from the contrast between a positive sentiment referring to a negative situation. The incongruity within a sentence can be due to sentiments expressed within the sentence or due to the semantics of the sentence. Joshi et al. (2015b) has classified sentiment incongruity into two: (i) Explicit sentiment incongruity, where the incongruity arises due to two opposite sentiment polarity words being present within the sentence. For example- I love being ignored. (ii) Implicit sentiment incongruity, when incongruity occurs without the presence of sentiment words of both polarities. For example- I love this paper so much that I made a doggy bag out of it. The word ’love’ has positive sentiment and the clause, I made a doggy bag out of it carries a sentiment opposite to the word ’love’. Semantic incongruity can be explained using an example, ”A woman needs a man like a fish needs a bicycle.” Joshi et al. (2016d) shows that word vector-based similarity/discordance is indicative of semantic similarity which in turn is a handle for context incongruity.

2.5 Sarcasm as a dropped negation

Irony/sarcasm is a form of negation in which an explicit negation marker is lacking. That is, even though the sentence doesn’t explicitly contain the negative marker ’not’, the sentence is negative. For example,the sarcastic sentence ‘Being awake at 4 am with a headache is fun’ is equivalent to the non-sarcastic sentence 'Being awake at 4 am with a head-ache is not fun'. Dubey et al. (2019a) uses this idea to convert sarcastic sentences to their non-sarcastic interpretations.

3 Problem Definition

We will now look at the problem of sarcasm processing as discussed in the past work. We will explore four sub-domains, namely, Sarcasm Detection, Sarcasm Generation, Sarcasm Target Identification, and Sarcasm Interpretation. The field of Sarcasm Detection has been widely explored whereas other areas are relatively new.

3.1 Sarcasm Detection

Most approaches in the past have formulated Sarcasm Detection as a classification problem where given a piece of text, the aim is to predict whether the text is sarcastic or not. So, the sentence, "I love being ignored." should be predicted as sarcastic while the sentence, "I love being acknowledged." should be predicted as non-sarcastic. Other reported formulations include, detecting sarcasm dialogue as a sequence labeling task, as presented by Joshi et al. (2016c), where sarcasm labels are hidden variables which are to be predicted. Ghosh et al. (2015) modelled sarcasm detection as a sense disambiguation task. They stated that a word may have a literal sense and a sarcastic sense.

3.2 Sarcasm Generation

Sarcasm Generation is formulated as a task of automatic generation of sarcastic texts. Joshi et al. (2015a) defines sarcasm generation as the task of producing sarcastic sentences as a response to the user input which may or may not be sarcastic. They present a sarcasm generation module (SarcasmBot) for chatbots and mention that integrating a sarcasm generation module allows existing chatbots to become more 'human'. Abhijit Mishra (2018) proposes a framework which takes a literal negative opinion as input and translates it into a sarcastion version.

3.3 Sarcasm Target Identification

Sarcasm Target Identification is formulated a task of identifying the target of ridicule in a sarcastic text. For example- "Love when you don't have two minutes to send me a quick text." Here, you is the target of ridicule. Joshi et al. (2018) presents Sarcasm Target Identification as a classification task where each word in the text is classified if it's the target or not. For example- "Tooth-ache is fun", the target is 'tooth-ache'.

3.4 Sarcasm Interpretation

Sarcasm interpretation is formulated as the generation of a non-sarcastic version of the text conveying the same message as the original sarcastic text. This is based on the theory of Sarcasm as dropped negation. Peled and Reichart (2017)), Dubey et al. (2019a) model sarcasm interpretation as a monolingual machine translation task. They define the purpose of the sarcasm interpretation task as the capability to generate a non-sarcastic utterance that captures the meaning behind the original sarcastic text.

4 Datasets

In this section, we will give an overview of the datasets used for experiments in computational sarcasm processing. These datasets can be classified on the basis of their languages as well as their lengths. With the advent of social media platforms like Twitter, Facebook, Reddit etc., data for a lot of researches is being collected from them. This is because a lot of people actively use such platforms and thus, there's plenty of data available. Since, people can freely express their opinions on such platforms, a lot of user generated data on these platforms is sarcastic. This has specially attracted sarcasm processing community to collect datasets to train systems for computational sarcasm. **Short text** is characterized by situations where the length is limited. Twitter is a platform which allow users to post short texts upto 280 characters called tweets. The most popular choice of datasets for computational sarcasm are tweets because of the availability of the Twitter API, short length of tweets and the popularity of Twitter as a social media platform. All these factors makes Twitter an ideal platform for collecting datasets for computational sarcasm. These tweets can be collected manually or by using hashtag-based supervision. The hashtag-based approach is considered to be more reliable due to the assumption that the author knows the best about the sarcasm embedded within the text. Also, this approach is much easier and faster than the manual collection. González-Ibáñez et al. (2011) use hashtag based approach to collect sarcastic tweets. Riloff et al. (2013), Maynard and Greenwood (2014), Mishra et al. (2016a) introduce datasets containing tweets for sarcasm classification. Dubey et al. (2019b) introduce two datasets containing tweets for Numerical Sarcasm Detection. Some Reddit based datasets for sarcasm detection also exist. Khodak et al. (2018) introduce Self-Annotated Reddit Corpus (SARC). It is a large self- annotated corpus for sarcasm research and for training and evaluating systems for sarcasm detection. It is self-annotated in the sense that a comment is considered sarcastic if its author marked it with the /s tag. Joshi et al. (2018) present a manually annotated dataset of tweets for sarcasm target identification. Abhijit Mishra (2018) present an unlabelled sarcasm corpus for sarcasm generation. Peled and Reichart (2017) present a parallel corpora of 15000 sarcastic tweets with their non-sarcastic interpretation for the task of automatic sarcasm interpretation. **Long text** includes the data downloaded from the discussion forums, reviews and book snippets. Joshi et al. (2018) present a manually annotated dataset of book snippets for sarcasm target identification. Reyes and Rosso (2014) created a dataset of movie reviews, book reviews and news articles marked with sarcasm and sentiment. Buschmeier et al. (2014) and Tsur et al. (2010) present a dataset of 1254 and 66000 Amazon reviews for sarcasm detection. Walker et al. (2012) presents the Internet Argument Corpus (IAC), a set of 390,704 posts in 11,800 discussions extracted from the online debate site 4forums.com. Joshi et al. (2016d) create a dataset consisting of quotes on GoodReads which describes itself as 'the world's largest site for readers and book recommendations'.

There are a lot of datasets available in languages other than English. Liu et al. (2014) explore the characteristics of both English and Chinese sarcastic sentences and introduce a set of features specifically for detecting sarcasm in social media. Carvalho et al. (2009) dealt with irony in Portuguese newspapers. Liebrecht et al. (2013) designed a model to detect irony in Dutch Tweets. Andrea Gianti and Caro (2012) collected and annotate a set of ironic examples from a common collective Italian blog. This corpus is also used in Bosco et al. (2013) for the study of sentiment analysis and opinion mining in Italian. Francesco Barbieri and Saggion (2014) present the first system for automatic detection of irony in Italian Tweets. Desai and Dave (2016) collect reviews from movie domain. They collect Hindi sentences which contain '#kataksh' (word for sarcasm in Hindi) from online sources. Liebrecht et al. (2013) collect a dataset of around 78000 Dutch tweets. They collect tweets containing '#sarcasme' marker, which means sarcasm in Dutch with the hashtag prefix. Lunando and Purwarianti (2013) introduce a dataset of Indonesian tweets from various topics like politics, food, movie, etc. Liu et al. (2014) create three datasets containing 3859, 5487, and 10356 comments respectively by crawling topic comments in Chinese language from different online sources.

Recently, cognitive datasets have also gained popularity. Mishra et al. (2017) propose a dataset that contains gaze data along with the text. Schifanella et al. (2016) collect data from three major social platforms that allow to post both text and images, namely Instagram (IG),Tumblr (TU) and Twitter (TW), using their available public APIs. Castro et al. (2019) propose a new sarcasm dataset, Multimodal Sarcasm Detection Dataset (MUStARD), compiled from popular TV shows. MUStARD consists of audiovisual utterances annotated with sarcasm labels. Each utterance is accompanied by its context of historical utterances in the dialogue.

Cross-cultural annotation: The annotation of dataset requires not only good linguistic background but also cultural knowledge. If the annotation is done by someone with different cultural background, it may result in sarcasm not being understood. Joshi et al. (2016b) used two datasets, one consisted of short texts (tweets) and another long texts (discussion forum posts), to analyse the impact of cultural differences on annotation. The datasets were originally labelled by American annotators. Two Indian annotators were asked to annotate the dataset. The difficulties in annotation faced were generally due to unfamiliar words, unknown contexts and unknown named entities.

5 Approaches

In this section, we discuss past approaches to process sarcasm using computational approaches. We categorise these approaches into three: rule-based, statistics-based and deep-learning based approaches.

5.1 Rule-based approaches

Rule-based approaches try to capture sarcasm in text using a set of rules. Riloff et al. (2013) present a bootstrapping algorithm that automatically learns lists of positive sentiment phrases and negative situation phrases from sarcastic tweets. Maynard and Greenwood (2014) propose that hashtag sentiment is a key indicator of sarcasm. Hence, if the sentiment expressed by a hashtag does not agree with rest of the tweet, the tweet is predicted as sarcastic. Dubey et al. (2019b) present a rule-based approach that considers noun phrases in the tweet as candidate contexts, and determines the optimal threshold of a numerical measure to predict sarcasm. Joshi et al. (2015a) implement eight rule-based approaches for generating different types of sarcasm. Depending upon the user input (question type, number of entities etc.), one of these eight rule-based approaches is chosen at run-time to generate a sarcastic reply. Joshi et al. (2018) present a rule-based extractor with nine rules that take as input the sarcastic sentence, and return a set of candidate sarcasm targets. Dubey et al. (2019a) model sarcasm as a form of dropped negation and present a rule-based approach for sarcasm interpretation.

5.2 Statistical approaches

Statistical approaches use mathematical models to infer the relationships between variables and obtain a general understanding of data to make predictions. Tepperman et al. (2006) use decision tree classifier with prosodic, contextual and spectral features to classify sarcasm. Riloff et al. (2013) use a SVM based approach with unigram and bigram features to classify sarcasm. They also combined this with their contrast based approach (discussed earlier) to improve recall further. Buschmeier et al. (2014) use feature set consisting of hyperbole, ellipsis, punctuation, interjections, emoticons, etc. to train a variety of classifiers including linear SVM, logistic regression, decision tree, random forest and naive bayes. Joshi et al. (2015b) use lexical and pragmatic features features based on two types of incongruity: implicit and explicit along with LibSVM and RBF kernel. Joshi et al. (2016d) use a SVM-based approach (SVM-perf) to identify sarcasm using word-embeddings similarity based features. Joshi et al. (2018) present a statistical extractor which uses a classifier that takes as input a word (along with its features) and returns if the word is a sarcasm target. They decompose the task into n-classification tasks, where 'n' is the total number of words in the sentence. This means that every word in input text is considered as an instance, such that the label can be 1 or 0, depending on whether or not the given word is a part of sarcasm target.

5.3 Deep-learning based approaches

Ghosh and Veale (2016) propose a neural network model composed of Convolution Neural Network(CNN) and followed by a Long short term memory (LSTM) network and finally a Deep neural network(DNN). Poria et al. (2016) use CNN-SVM (i.e., when the features extracted by CNN are fed to the SVM). The approach uses pre-trained convolutional neural network for extracting sentiment, emotion and personality features for sarcasm detection. Zhang et al. (2016) use a bi-directional gated recurrent neural network to capture syntactic and semantic information over tweets locally, and a pooling neural network to extract contextual features automatically from history tweets. Schifanella et al. (2016) propose a framework to detect sarcasm that integrate the textual and visual modalities. The method adapts a visual neural network initialized with unigrams as textual input and parameters trained on ImageNet to multimodal sarcastic posts. Hazarika et al. (2018) propose a ContextuAl SarCasm DEtector (CASCADE), which adopts a hybrid approach of both content- and context-driven modeling for sarcasm detection in online social media discussions. Since the sarcastic nature and form of expression can vary from person to person, CASCADE utilizes user embeddings that encode stylometric and personality features of users. Yi Tay (2018) classify the data using convolutional neural networks (CNN), recurrent neural networks (RNN) and a blend of these techniques to improve accuracy. Dubey et al. (2019b) propose a CNN based approach and an attention based model to detect sarcasm due to numbers. Abhijit Mishra (2018) present a framework that employs reinforced neural sequence to sequence learning and information retrieval and is trained only using unlabeled non-sarcastic and sarcastic opinions. Son et al. (2019) propose a deep learning model to detect sarcasm called sAtt-BLSTM convNet that is based on the hybrid of soft attention-based bidirectional long short-term memory (sAtt-BLSTM) and convolution neural network (convNet) applying global vectors for word representation (GLoVe) for building semantic word embeddings.

6 Reported performance

Table 1 summarises the performance reported by the past approaches. The performance in these works is calculated using different metrics and are on different datasets, hence, they are not directly comparable.

7 Conclusion

This paper presented the various problem definitions available in the domain of computaional sarcasm processing. We presented a linguistic perspective of sarcasm and discussed existing linguistic theories. We explored the various datasets available in the domain. We observed that rule-based approaches are useful to get an insight into the problem. The rule-based approaches convey the crux of the sarcasm detection problem, namely, incongruity. The feature-based approaches uncovers the indicators i.e., features of such sarcasm. However, a recent trend indicates that current state of the art models are deep learning-based that incorporate additional context beyond target text. We also looked at some language dependent approaches for sarcasm detection. Finally, we presented a comparison of past works along different dimensions, reported their performance.

Research work	Dataset details	Approach	Performance
		Sarcasm Detection	
Riloff et al. (2013)	Tweets	Hybrid: Bootstrapped lexicon + SVM	F: 0.51
Buschmeier et al. (2014)	Reviews	Hyperbole, emoticons, interjection + Logistic regression	F: 74.4
Joshi et al. (2015b)	Tweets/ Dis-cussion forum posts	Incongruity based features with SVM	F:0.8876, F:0.64
Schifanella et al. (2016)	Tumblr/ Instagram posts	Multimodal features + SVM	Acc: 89.7
Mishra et al. (2016b)	Tweets,Reviews	Cognitive features	F:75.7
Joshi et al. (2016d)	Book snippets	Word embeddings based similarity with SVM-perf	F: 81.19
Ghosh and Veale (2016)	Tweets and reviews	CNN + LSTM + DNN	F: 0.921
Poria et al. (2016)	Tweets	CNN-SVM, pretrained CNNs on sentiment, emotion and personality based features	F: 97.7
Zhang et al. (2016)	Tweets	local + contextual features	Acc: 94.1, F: 90.26
Mishra et al. (2017)	Tweets	CNN + text and gaze features	F: 76.24
Hazarika et al. (2018)	Discussion forums	Hybrid context driven approach using CNN	Acc: 79, F: 86
Yi Tay (2018)	SARC corpus	LSTM-CNN	Acc: 72.425
Son et al. (2019)	Twitter	sAtt-BLSTM convNet	Acc: 97.87
Dubey et al. (2019b)	Tweets having numbers	CNN	0.93
		Sarcasm Target Identification	
Joshi et al. (2018)	Book snippets	Hybrid OR/AND	DS:32.68, DS:21.28
Joshi et al. (2018)	Tweets	Hybrid OR/AND	DS:39.63, DS:20.82
		Sarcasm Generation	
Joshi et al. (2015a)	-	Rule-based generator	Acc: 87.09
Abhijit Mishra (2018)	Tweets and short snippets	Reinforced neural sequence to sequence learning	Acc: 73.3 Fluency: 3.7 Adequacy: 3.8
		Sarcasm Interpretation	
Peled and Reichart (2017)	Parallel Tweet Corpus	monolingual MT	BLEU: 66.96 ROUGE: 69.98
Dubey et al. (2019a)	Parallel Tweet Corpus	monolingual MT	BLEU: 67.96 ROUGE: 68.81

Table 1: Reported performance of past approaches along with the dataset details. Acc: Accuracy, F: F-score, DS: Dice score

References

[Abhijit Mishra2018] Karthik Sankaranarayanan Abhijit Mishra, Tarun Tater. 2018. A modular architecture for unsupervised sarcasm generation. *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*.

[Andrea Gianti and Caro2012] Viviana Patti AndreaBolioli Andrea Gianti, Cristina Bosco and Luigi Di Caro. 2012. Annotating ironyin a novel italian corpus for sentiment analysis. *InProceedings of the 4th Workshop on Corpora for Re-search on Emotion Sentiment and Social Signals*, pages 1–7.

[Bosco et al.2013] C. Bosco, V. Patti, and A. Bolioli. 2013. Developing corpora for sentiment analysis: The case of irony and senti-tut. *IEEE Intelligent Systems*, 28(2):55–63.

[Buschmeier et al.2014] Konstantin Buschmeier, Philipp Cimiano, and Roman Klinger. 2014. An impact analysis of features in a classification approach to irony detection in product reviews. pages 42–49, June.

[Camp2012] Elisabeth Camp. 2012. Sarcasm, pretense, and the semantics/pragmatics distinction. *Nous*, 46(4):587–634, December.

[Carvalho et al.2009] Paula Carvalho, Luís Sarmento, Mário Silva, and Eugénio Oliveira. 2009. Clues for detecting irony in user-generated contents: Oh...!! it's "so easy" ;-). *International Conference on Information and Knowledge Management, Proceedings*, 11.

[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*, pages 4619–4629, Florence, Italy, July. Association for Computational Linguistics.

[Desai and Dave2016] Nikita Desai and Anandkumar D Dave. 2016. Sarcasm detection in hindi sentences using support vector machine. *International Journal*, 7(4):8–15.

[Dubey et al.2019a] Abhijeet Dubey, Aditya Joshi, and Pushpak Bhattacharyya. 2019a. Deep models for converting sarcastic utterances into their non sarcastic interpretation. pages 289–292, 01.

[Dubey et al.2019b] Abhijeet Dubey, Lakshya Kumar, Arpan Somani, Aditya Joshi, and Pushpak Bhattacharyya. 2019b. "when numbers matter!": Detecting sarcasm in numerical portions of text. In *Proceedings of the Tenth Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pages 72–80, Minneapolis, USA, June. Association for Computational Linguistics.

[Francesco Barbieri and Saggion2014] Francesco Ronzano Francesco Barbieri and Horacio Saggion. 2014. Italian irony detection in twitter: a first approach. *In The First Italian Conference on Computational Linguistics CLiC-it 2014 & the Fourth International Workshop EVALITA*, pages 28–32.

[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.

[Ghosh et al.2015] Debanjan Ghosh, Weiwei Guo, and Smaranda Muresan. 2015. Sarcastic or not: Word embeddings to predict the literal or sarcastic meaning of words. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1003–1012, Lisbon, Portugal, September. 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. pages 581–586, June.

[Grice1975] H. P. Grice. 1975. Logic and conversation. *In Peter Cole and Jerry L. Morgan, editors, Syntax and Semantics*, 3:41–58.

[Hazarika et al.2018] Devamanyu Hazarika, Soujanya Poria, Sruthi Gorantla, Erik Cambria, Roger Zimmermann, and Rada Mihalcea. 2018. CASCADE: Contextual sarcasm detection in online discussion forums. In *Proceedings of the 27th International Conference on Computational Linguistics*, pages 1837–1848, Santa Fe, New Mexico, USA, August. Association for Computational Linguistics.

[Ivanko and M.2003] Stacey L. Ivanko and Penny M. 2003. Context incongruity and irony processing. *Discourse Processes*, 3(35):241–279.

[Joshi et al.2015a] Aditya Joshi, Anoop Kunchukuttan, Pushpak Bhattacharyya, and Mark Carman. 2015a. Sarcasmbot: An open-source sarcasm-generation module for chatbots. 08.

[Joshi et al.2015b] Aditya Joshi, Vinita Sharma, and Pushpak Bhattacharyya. 2015b. Harnessing context incongruity for sarcasm detection. pages 757–762, July.

[Joshi et al.2016a] Aditya Joshi, Pushpak Bhattacharyya, and Mark Carman. 2016a. Automatic sarcasm detection: A survey. *ACM Computing Surveys*, 50, 02.

[Joshi et al.2016b] Aditya Joshi, Pushpak Bhattacharyya, Mark Carman, Jaya Saraswati, and Rajita Shukla. 2016b. How do cultural differences impact the quality of sarcasm annotation?: A case study of Indian annotators and American text. pages 95–99, August.

[Joshi et al.2016c] Aditya Joshi, Vaibhav Tripathi, Pushpak Bhattacharyya, and Mark J. Carman. 2016c. Harnessing sequence labeling for sarcasm detection in dialogue from TV series 'Friends'. pages 146–155, August.

[Joshi et al.2016d] Aditya Joshi, Vaibhav Tripathi, Kevin Patel, Pushpak Bhattacharyya, and Mark Carman. 2016d. Are word embedding-based features useful for sarcasm detection? pages 1006–1011, November.

[Joshi et al.2018] Aditya Joshi, Pranav Goel, Pushpak Bhattacharyya, and Mark Carman. 2018. Sarcasm target identification: Dataset and an introductory approach. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, Miyazaki, Japan, May. European Language Resources Association (ELRA).

[Khodak et al.2018] Mikhail Khodak, Nikunj Saunshi, and Kiran Vodrahalli. 2018. A large self-annotated corpus for sarcasm. *ArXiv*, abs/1704.05579.

[Lee and Katz1998] Christopher Lee and Albert Katz. 1998. The differential role of ridicule in sarcasm and irony. *Metaphor and Symbol*, 13:1–15, 03.

[Liebrecht et al.2013] Christine Liebrecht, Florian Kunneman, and Antal van den Bosch. 2013. The perfect solution for detecting sarcasm in tweets #not. pages 29–37, June.

[Liu et al.2014] Peng Liu, Wei Chen, Gaoyan Ou, Tengjiao Wang, Dongqing Yang, and Kai Lei. 2014. Sarcasm detection in social media based on imbalanced classification. pages 459–471, 06.

[Lunando and Purwarianti2013] Edwin Lunando and Ayu Purwarianti. 2013. Indonesian social media sentiment analysis with sarcasm detection. *2013 International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, pages 195–198.

[Maynard and Greenwood2014] Diana Maynard and Mark Greenwood. 2014. Who cares about sarcastic tweets? investigating the impact of sarcasm on sentiment analysis. pages 4238–4243, May.

[Mishra et al.2016a] Abhijit Mishra, Diptesh Kanojia, and Pushpak Bhattacharyya. 2016a. Predicting readers' sarcasm understandability by modeling gaze behavior. page 3747–3753.

[Mishra et al.2016b] Abhijit Mishra, Diptesh Kanojia, Seema Nagar, Kuntal Dey, and Pushpak Bhattacharyya. 2016b. Harnessing cognitive features for sarcasm detection. pages 1095–1104, August.

[Mishra et al.2017] Abhijit Mishra, Kuntal Dey, and Pushpak Bhattacharyya. 2017. Learning cognitive features from gaze data for sentiment and sarcasm classification using convolutional neural network. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 377–387, Vancouver, Canada, July. Association for Computational Linguistics.

[Peled and Reichart2017] Lotem Peled and Roi Reichart. 2017. Sarcasm sign: Interpreting sarcasm with sentiment based monolingual machine translation. *In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*, 1:1690–1700.

[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. pages 1601–1612, December.

[Reyes and Rosso2014] Antonio Reyes and Paolo Rosso. 2014. On the difficulty of automatically detecting irony: Beyond a simple case of negation. *Knowl. Inf. Syst.*, 40(3):595–614, September.

[Riloff et al.2013] Ellen Riloff, A. Qadir, P. Surve, L. Silva, N. Gilbert, and R. Huang. 2013. Sarcasm as contrast between a positive sentiment and negative situation. *Proceedings of EMNLP*, pages 704–714, 01.

[Schifanella et al.2016] Rossano Schifanella, Paloma de Juan, Joel Tetreault, and LiangLiang Cao. 2016. Detecting sarcasm in multimodal social platforms. page 1136–1145.

[Son et al.2019] L. H. Son, A. Kumar, S. R. Sangwan, A. Arora, A. Nayyar, and M. Abdel-Basset. 2019. Sarcasm detection using soft attention-based bidirectional long short-term memory model with convolution network. *IEEE Access*, 7:23319–23328.

[Sulis et al.2016] Emilio Sulis, Delia Hernandez Farias, Paolo Rosso, Viviana Patti, and Giancarlo Ruffo. 2016. Figurative messages and affect in twitter: Differences between #irony, #sarcasm and #not. *Knowledge-Based Systems*, 108, 05.

[Tepperman et al.2006] J. Tepperman, D. Traum, and S. Narayanan. 2006. " yeah right": Sarcasm recognition for spoken dialogue systems. *In Ninth International Conference on Spoken Language Processing*, pages 1838–1841, sep.

[Tsur et al.2010] Oren Tsur, Dmitry Davidov, and Ari Rappoport. 2010. Icwsm - a great catchy name: Semi-supervised recognition of sarcastic sentences in online product reviews. *ICWSM 2010 - Proceedings of the 4th International AAAI Conference on Weblogs and Social Media*, 01.

[Walker et al.2012] Marilyn Walker, Jean Fox Tree, Pranav Anand, Rob Abbott, and Joseph King. 2012. A corpus for research on deliberation and debate. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC'12)*, pages 812–817, Istanbul, Turkey, May. European Language Resources Association (ELRA).

[Wallace2015] Byron C. Wallace. 2015. Computational irony: A survey and new perspectives. *Artificial Intelligence Review*, 4(43):467–483, Apr.

[Wang2013] Po-Ya Angela Wang. 2013. #irony or #sarcasm — a quantitative and qualitative study based on twitter. In *Proceedings of the 27th Pacific Asia Conference on Language, Information, and Computation (PACLIC 27)*, pages 349–356, Taipei, Taiwan, November. Department of English, National Chengchi University.

[Yi Tay2018] Siu Cheung Hui Jian Su Yi Tay, Luu Anh Tuan. 2018. Reasoning with sarcasm by reading in-between. *ACL 2018*.

[Zhang et al.2016] Meishan Zhang, Yue Zhang, and Guohong Fu. 2016. Tweet sarcasm detection using deep neural network. In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pages 2449–2460, Osaka, Japan, December. The COLING 2016 Organizing Committee.