

# Automatic Sarcasm Detection: A Survey

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## ABSTRACT

The task of predicting sarcasm in a text is how we can define Automatic sarcasm Detection. Sarcasm detection is a very important step towards sentiment analysis when we also take into consideration the challenges we face while detecting sarcasm in a text that contains a sentiment. The community of sentiment analysis pays a lot of interest towards speech based features in sarcasm detection. So far, there have been three milestones in this research: first being pattern extraction that is semi supervised, second one being hashtag based supervision and third where we need to use the context which lies beyond the target text. The following paper will throw light upon the approach, problems faced, trends and data sets in sarcasm detection.

(i)

## 1. INTRODUCTION:

As definition of sarcasm [1] goes by: “the use of irony to mock or convey contempt”. Sarcasm has a figurative nature which makes it a big challenge when considering sentiment analysis [3]. The implication is negative whereas the way in which it is said is positive which makes it quite difficult to analyze because of which automatic sarcasm detection became a research problem. Henceforth, automatic sarcasm [2] detection is the process of predict if a text is sarcastic or not by using computational approaches. This sector has witnessed a lot of interest from the Natural Language processing experts too and this problem is considered hard because there are various ways in which sarcasm can be expressed. It has also been expressed in forms such as tweets, reviews, TV series dialogues, movies etc. and is analyzed by approaches such as semi supervised, supervised and rule based because of which we’ve reached to several interesting innovations. The goal of this paper will be to analyze the past work in the subject of computational sarcasm detection and to make the new researchers be familiar with the dynamics of it.

## 2. RELATED STUDY OF SARCASM

There are a lot of studies going on about sarcasm detection. We’ll first go through the linguistic studies in sarcasm before looking at the approaches for automatic sarcasm detection. Following are the representations that have been proposed so far:

- i. Sarcasm happens in various dimensions which are failed expectation, tension, in the presence of a victim and insincerity.

- ii. The different type of sarcasm are propositional, embedded[4][5], Like prefixed and illocutionary which can be explained as follows:

- Propositional: Appears to be non-sentimental but the sentiment is implicitly implied.
- Embedded sarcasm: In the form of phrases and words, the sarcasm is embedded inside.
- Like prefixed: Implied and direct denied of the proposition that has been made.

- iii. Cautionary: Involves the clues which are not textual and which convey an attitude which is different from a sincere dialogue.

### THE 6-TUPLE-REPRESENTATION:

Sarcasm as defined by Ivanko and Pexman consists of 6 tuples namely  $\langle S, H, C, u, p, p' \rangle$

Wherein, S=Speaker, H=Hearer, Listener

C = Context, u = Utterance

P = Literal Proposition and p' = Intended Proposition

This can be read as ‘Speaker S generates an utterance u in Context C meaning proposition p but intending that hearer H understands p’. This can be understood using the following example. If a boss tells the employee, “You’ve done a great job!” and the employee knows that (s)he has not completed the project in time, the employee would know that it is a sarcasm. Referring to the 6-tuples given above, the properties of this sarcasm would be:

S: Boss, H: Employee

C: The employee has not completed his/her project.

u: “You’ve done a great job!”

p: You have done a good job at the project.

p’: You have done a bad job at the project.

- iv. SITUATIONAL DISPARITY THEORY: When there is a situational disparity between text and the actual context, there exists sarcasm according to the theory proposed by Wilson.

- v. NEGATION THEORY: When an explicit meaning marker is not present, it is an irony as defined by Giora. A negation is intended when using sarcasm/irony without the use of the word “not”.

There are certain challenges which are very typical to sarcasm which include the following parameters:

- A. Having a common idea of the subject.
- B. Knowing the context which constitutes ridicule.
- C. Speaker and listener context

### 3. PROBLEM DEFINITION:

Let us look at how this problem of sarcasm detection has been defined and dealt with earlier in the past phases. Most common method being classification wherein the aim is to predict if the text is sarcastic or not. For an example, if we need to know the relationship between irony, humor and sarcasm, we'll consider the label names with these particular names itself and give the pair wise classification performance for these. Some other formulations that have been received which suggest the definition of sarcasm detection as a sequence of labelling the tasks for a particular dialogue. Every utterance being an observed unit in a sequence whereas the sarcasm variables are the ones whose values are to be predicted. Hence, sarcasm detection is a sense disambiguation task as said which states that a statement is capable of having a literal sense and a sarcastic sense as well. We need to detect the actual implied sense in order to detect irony/ ridicule/ sarcasm.

### 4. DATASETS:

The various datasets used in sarcasm detection can primarily be divided into three classes: Short text, long text and other datasets.

#### a. Short Text:

There are various platforms available in today's era of social media and there are certain platforms where there is a restriction of word limit and the writer is need to express their views in a few words. One such platform is twitter which is quite a popular and widely used medium. So a simpler approach to deduce the sense of the statement is by manually labelling them wherein we introduce certain tweets and then manually label them if they are sarcastic or not. Then another approach is by using hashtags in tweets which indicate sarcasm wherein we create labelled datasets and is called hashtag based supervision [6].

#### b. Long text:

It includes the reviews and discussions on forum posts and they're also used in sarcasm labelled datasets. Large Datasets from multiple sources such as Twitter, movie reviews, news articles, Amazon reviews, book reviews Netcena etc. are considered to detect the sentiment behind them and then it's calculated how many of them are ironic.

#### c. Other texts:

There are some new datasets which also have been used. For an example, Tepper man etc. used a huge number of call center transcripts to detect if the intention behind all "yea right" was sarcastic or not. In another example, the lexical indicators of sarcasm are also detected by considering certain sarcastic and non-sarcastic excerpts [7].

Some focus on identifying which similes contain irony and search for a pattern. TV show such as friends was also analysed for every utterance of a particular word.

### 5. APPROACHES:

Based on the datasets, we will describe three approaches used for sarcasm detection: rule-based, statistical and deep learning [8].

#### 5.1 Rule-Based Approaches

Rule-based use specific evidences to detect sarcasm. Indicator of sarcasm is used to capture these evidences. There is an error analysis in this approach for every rule.

There are some approaches to this. If someone uses a hashtag opposite to the post, it will be categorized as sarcasm [9]. A negative phrase in a positive post is also an indicator of sarcasm.

#### 5.2 Statistical Approaches

Statistical Approach has two algorithms mentioned below:

- a. Features Used: This approach uses seven sets of features that include adjectives, adverbs, synonyms and others in the target text. The features are classified into two sets: implicit and explicit incongruity-based features.
- b. Learning Algorithm: This approach uses the similarity between the features and the labels. The algorithm used a decision tree in the process that includes different label amongst humor, irony, politics and education [10][11].

#### 5.3 Deep learning-based Approaches

With the popularity of Deep Learning, few approaches are used for automatic sarcasm detection. The similarity between words embedded as features is used for sarcasm detection. This approach reports in huge improvement in performance [12]. It allows to learn user-specific context.

### 5.4 Shared Task

Shared task allows the use of common database among the team members. A dataset of ironic and metaphorical statements is provided with positive, negative and neutral labels.

- a. Some topics are likely to evoke more sarcasm than others. Hashtags are valuable in this algorithm. Based on timestamps and the sequence of tweets, sarcasm is detected.

## 6. VARIOUS ISSUES IN SARCASM DETECTION

The current techniques of sarcasm detection have some of the issues [13]. In this section, we will discuss the three major issues:

**6.1 Issues with Data:** Hashtags can provide a large dataset for supervision, but the quality of the datasets is doubtful. To solve this problem, the pattern is validated based on multiple datasets.

**6.2 Issues with features:** The main question arises here is, if sentiment can be used to detect sarcasm. Sarcasm sentences sometimes mislead the sentiment classifier. However, Sarcasm classifier uses several approaches to use the sentiment. But these approaches need 'surface polarity'.

**6.3 Dealing with Dataset Skews:** Sarcasm is an infrequent phenomenon of sentiment expression. Datasets also reflect this skew. Sarcasm detection is used to work with existing skew. Which results in an error with different contexts.

## CONCLUSION

We've approached certain milestones in sarcasm detection including semi supervised pattern extraction, hashtag supervision and the use of context which is beyond the target text. Certain actions that could be proposed for future include incongruity in numbers, Architectures based on Deep Learning, Culture specific aspects and implicit sentiment detection.

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