Understanding the Sarcastic Nature of Emojis with SarcOji

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Abstract

Identifying sarcasm is a challenging research problem owing to its highly contextual nature. Several researchers have attempted numerous mechanisms to incorporate context, linguistic aspects, and supervised and semi-supervised techniques to determine sarcasm. It has also been noted that emojis in a text may also hold key indicators of sarcasm. However, the availability of sarcasm datasets with emojis is scarce. This makes it challenging to effectively study the sarcastic nature of emojis. In this work, we present SarcOji which has been compiled from five publicly available sarcasm datasets. SarcOji contains labeled English texts which all have emojis. We also analyze SarcOji to determine if there is an incongruence in the polarity of text and emojis used therein. Further, emojis' usage, occurrences, and positions in the context of sarcasm are also studied in this compiled dataset. With SarcOji we have been able to demonstrate that frequency of occurrence of an emoji and its position are strong indicators of sarcasm. SarcOji dataset is now publicly available with several derived features like sentiment scores of text and emojis, most frequent emoji, and its position in the text. Compilation of the SarcOji dataset is an initial step to enable the study of the role of emojis in communicating sarcasm. SarcOji dataset can also serve as a go-to dataset for various emoji-based sarcasm detection techniques.

1 Introduction

Sarcasm detection has piqued significant interest in various research communities, be it linguistics, psychology, or computational. Identifying sarcasm requires context and background which become a challenge for computational models (Ghosh et al., 2017). Joshi et al. (2017) identify three approaches to sarcasm detection, viz., rule-based, statistical (feature and learning-based), and deep-learning approaches. They also identify issues with these approaches. For instance, if we deal with the sentiment (read polarity) as a feature, it may mislead a classifier because the surface sentiment might be different from the intent. They also note that in general sarcasm datasets are skewed in favor of non-sarcastic sentences.

Joshi et al. (2015) talk about *Explicit Incongruity* where words of both positive and negative polarities are present in a sarcastic text. While *Implicit Incongruity* may be expressed through an implied sentiment. Many researchers have incorporated context and exploited context incongruity for sarcasm detection tasks (Joshi et al., 2015), (Ghosh et al., 2017), (Ghosh and Veale, 2017), (Joshi et al., 2018), (Hazarika et al., 2018), (Jena et al., 2020). But we opine that context may not always be available in real-world scenarios. For instance, in (Razali et al., 2017) it is noted that apart from text and context outside the target, other modalities, too, are important for sarcasm detection; especially when the research trend is to use deep learning networks in sarcasm detection tasks. Such classifiers need features that can be extracted by exploring other modalities. Grover (2021) discussed how interest in learning emoji embeddings and using emojis for sentiment classification has evolved in the past few years. This work also discussed the need to explore the role of emojis to uncover complex and nuanced expressions of sarcasm and irony. On the other hand, many works have attempted to incorporate mixed or opposite polarities in sentences to detect sarcasm, (J and Ravikumar, 2019), (Tewani, 2019). Apart from lexical features, researchers are also attempting to explore other features like slang, emoticons, emojis, reviews, etc. for sarcasm detection (Sundararajan et al., 2021). In this work we focus on emojis to understand if and how they contribute to expressing sarcasm. We set to answer the following questions.

1. Is there any incongruence between the polarity of emojis and that of text they occur with?

2. Are there any specific emojis that users tend to use with sarcastic texts?

3. Is there a relationship between the intensity (frequency) of emojis used in the text and underlying sarcasm?

4. Is there a relationship between the position of occurrence of an emoji and the sarcastic nature of the text?

Therefore we compile from various benchmark and emoji datasets to create a labeled Sarcasm Dataset - SarcOji. SarcOji has text records, all with emojis. These records are augmented with derived features like sentiment scores of text and emojis. Sentiment analysis tools like SentiWordNet (Esuli and Sebastiani, 2006), (Baccianella et al., 2010), VADER (Hutto and Gilbert, 2014), TextBlob [1], and Emoji Sentiment Ranking (Kralj Novak et al., 2015) are used to compute sentiment scores. We compute sentiment scores to extract text and emoji polarities. Moreover, these numerical features may be useful in training machine or deep learning classifiers for sarcasm detection. We also capture the most frequent emoji in the text along with its frequency and position of occurrence for an in-depth analysis of emoji usage in sarcastic texts.
The rest of the paper is organized into four sections. In Related Work, various experiments and studies on emojis and sarcasm are discussed. In the Methodology section, we elaborate on the compilation of the SarcOji dataset from five publicly available sarcasm datasets. We also discuss our mechanism to determine incongruence between the sentiment of text and emojis and determine the position of the most frequent emoji in the text. In the subsequent section, we report our observations and inferences from the SarcOji dataset. In the last section, we conclude and identify directions for future work in utilizing emojis for sarcasm detection.

2 Related Work

Emojis are now one of the preferred modalities in sentiment analysis tasks. There have been many resources that are publicly available for use to identify emoji sentiments and the sense in which emojis are used. But, these resources do not holistically capture the sarcastic nature of emojis. The Emoji Sentiment Ranking (ESR) by Kralj Novak et al. (2015) computes the sentiment of 751 popular emojis from the sentiment of the tweets where these emojis are used. In this work, it is also reported that the emojis with high sentiment scores (negative or positive) occur towards the end of the tweet and on average, an emoji occurs at a two-thirds length of a tweet. But ESR does not capture the sentiment of the latest emojis which makes it difficult to fully utilize its strengths.
A machine-readable emoji inventory linking emoji Unicode representations with their English meanings is presented in EmojiNet (Wijeratne et al., 2017a). This inventory contains different senses (noun, verb, adjective), etc. in which an emoji can be used. EmojiNet can be used in the disambiguation of emoji senses and identifying similarities between emojis. While this is a very powerful resource for emoji disambiguation, how these senses can be used to determine sarcasm is yet to be explored.
Wijeratne et al. (2017b) compiled the EmoSim508 dataset with similarity scores of 508 pairs of emojis. In this work, EmojiNet was used to extract word descriptions of emojis and learn emoji embeddings. Several experiments have been carried out to observe emoji usage across social media and how can they be used to capture sarcasm.
Zhao et al. (2018) analyzed emoji usage on social media and observed that 70% of emojis occurred towards the end of the tweets, while only 2.6% are used at the beginning. Thompson et al. (2016) conducted experiments with 51 participants and found that emoticons were used more in sarcastic texts. They also reported that tongue and wink face are strong indicators of sarcasm. Garcia et al. (2022) report that emojis can help both young and older adults discern sarcasm. Miller et al. (2017) refute the previous hypothesis that emojis when placed with textual context may reduce miscommunication. They concur that surrounding text does not reduce emoji ambiguity and attribute this result to possible sarcasm.
Many researchers have conducted experiments to incorporate emojis in sarcasm classification tasks. Felbo et al. (2017) built a large text corpus with emojis to learn emotional content, sarcasm, and sentiment detection in texts. They created a pre-trained model called DeepMoji. But the success of DeepMoji heavily relied on tweets and their length. Wang et al. (2021) used the speaker's prior probability of sarcasm and embedded emojis to recognize

[1] https://buildmedia.readthedocs.org/media/pdf/textblob/latest/textblob.pdf

sarcasm. Rustagi et al. (2022) integrate emojis, ratings, and reviews to enhance sarcasm classification tasks. Tewani (2019) uses polarity of texts, emojis, and hashtags to classify sarcasm on a small dataset of 650 tweets.

There have been different approaches to understanding emoji usage, emoji sense, and incorporating emojis to detect sarcasm, but we are yet to come across a study that attempts to investigate whether popular emojis used with sarcasm or if they are indeed incongruent with the surrounding text or does their position or frequency matter when sarcasm is expressed?

We now move ahead to describe the compilation and analysis of a dedicated sarcasm dataset with emojis - SarcOji.

3 Methodology

In this section, we describe the various sources from which the SarcOji dataset was compiled. We further list down steps to mine frequent emojis used in the dataset and how sentiment scores of the text, as well as emojis, were computed using different tools.

3.1 Data Collection

For compiling SarcOji datasets 5 publicly available Sarcasm datasets were utilized, viz.

1. Sarcasm Dataset harvested from Twitter by Ghosh and Veale (2016).

2. Dataset compiled by Subramanian et al. (2019) to detect sarcasm using emojis. The dataset is compiled from Twitter and Facebook posts.

3. Oprea and Magdy (2019) curated a Dataset for intended sarcasm by asking Twitter users to provide links to their sarcastic (1) and non-sarcastic (3) tweets. For the sarcastic tweet user also provided information on why it was sarcastic and a non-sarcastic rephrase of the same message.

4. Shared Task on Sarcasm (Twitter and Reddit) dataset at FigLang'2020 (Ghosh et al., 2020). This dataset has been compiled from the self-annotated Reddit corpus of sarcastic texts by Khodak et al. (2017).

5. Intended Sarcasm Dataset in English from iSarcasmEval Task at SemEval'22 Abu Farha et al. (2022). The sarcastic labels of the texts are provided by the text authors. Each sarcastic text is also rephrased by the text author to convey the intended message without sarcasm. The sarcastic texts are additionally labeled by linguists into one of the ironic speech categories like irony, satire, overstatement, understatement, rhetorical question, etc. (Gibbs Jr et al., 2002)

Dataset	Sarcastic	Non-Sarcastic
(Ghosh and Veale, 2016)	18000	21000
(Subramanian et al., 2019)	9260	13070
(Oprea and Magdy, 2019)	2500	2500
(Ghosh et al., 2020)	777	3707
(Abu Farha et al., 2022) (iSarcasmEval SubTask)	867	2601
Total	31404	42872

Table 1: Source Datasets' Statistics

These datasets were used as Ghosh and Veale (2016) , Oprea and Magdy (2019), Ghosh et al. (2020) along with the recent SemEval-2022 Abu Farha et al. (2022) are publicly available benchmark datasets, while Subramanian et al. (2019) is another popular dataset that contains a large number of texts with emojis. Moreover, after combining these datasets we have heterogeneity of sources (Twitter and Facebook) from which data is collected.

To gather as many records as possible we combined records from the train and test sets of the above mentioned datasets. The source datasets' statistics are given in Table 1.

3.2 Data Preprocessing

Before mining this dataset a few preprocessing steps were undertaken, as listed below:

1. Renaming the attributes(column) as Text for text/tweet column and Sarcastic to determine if the Text is sarcastic or not. Since all the datasets came from different sources so their column names, order, and the number of columns differed. We retained only the Text/Tweets and the column specifying their sarcastic nature. Columns like rephrase of sarcastic text, type of sarcasm, etc. were dropped for preparation of SarcOji as we wanted to only focus on how emojis were used with sarcastic texts.

2. The Sarcastic Column was label-encoded to 0,1 for uniformity. The source datasets had

different ways to represent sarcasm, for instance, Sarcastic, Not_Sarcastic, SARCASM, NON_SARCASM. Thus, all the sarcastic texts were label-encoded as 1, and 0 otherwise.

3. All the records where the language source was not English were dropped using the Google Trans API [2]. For example, if the text was “Bonjour", then it was dropped. This was done to ensure that the sentiment scores were computed correctly.

4. The text was also cleaned to remove URLs (HTTP(s), mentions(@), and hashtags (#).

5. The texts that did not contain any emojis were dropped too.

After preprocessing the combined dataset had 29377 labeled records with 11448 sarcastic and 17929 non-sarcastic texts with emojis.

3.3 Mining Frequent Emojis

The next step was to mine the frequent emojis used in the dataset. For every text, the most frequent emoji was found and the emoji and its number of occurrences in the text in consideration were also stored. We also computed the position of the first occurrence of the most frequent emoji in a text. This task can be done using a linear scan of the text and applying regular expressions for Unicode emojis or *advertools* package [3] can also be used. Some examples are shown in Table 2. We use the Python package *emoji* [4] for demojizing emojis to emoji text.

A simple binary search approach to search the first position of emoji with maximum frequency was used and the corresponding algorithm is given in Algorithm 1. We use the first position of the most frequent emoji in a particular text because it is more likely to be associated with a context or with the user’s intent to express an emotion. 0 represents MaxEmoji’s occurrence towards the start of the text, 1 represents its occurrence in the middle, and 2 represents occurrence towards the end of the text.

Algorithm 1 Frequent Emoji Position and Intensity

```
procedure MAXPOSFREQ( text )
    ▷ Computing frequency of the most intense emoji and its first position of occurrence

    MaxEmoji = none
    MaxEmojiNumOccurence = -1
    MaxEmojiPos = -1
    length = len(text)
                ▷ Emoji List can be extracted by emoji Python package, which also gives start position of each emoji

▷ extract all emojis and their counts and store
    emojiDict = {emoji: count}
    emojiList = list of all emojis in text

    MaxEmojiNumOccurence =
                    max(emojiDict.count)
    MaxEmoji = extract first key with
                count as
            MaxEmojiNumOccurence
    startPos = first Occurrence of MaxEmoji
    mid = (length/2)
    if startPos ≥ 0 && startPos < mid/2 then
        ▷ Store 0 for occurrence of the emoji
        towards the start of the text
        maxPos = 0
    else if startPos ≥ mid/2 && startPos < (mid + length)/2 then
        ▷ Store 1 for occurrence of the emoji
        towards the middle of the text
        maxPos = 1
    else
        ▷ Store 2 for occurrence of the emoji
        towards the end of the text
        maxPos =2
                                ▷ end of procedure
```

3.4 Extracting Sentiment Scores

To determine if there is incongruence between the sentiment expressed by the text and that of the

[2]https://py-googletrans.readthedocs.io/en/latest/
[3]https://advertools.readthedocs.io/en/master/
[4]https://pypi.org/project/emoji/

Text	MaxEmoji	MaxEmoji#	MaxEmojiPos
“sameee 😂 and im canadian i didnt even know that one of the canadian artists was canadian 😂😂😂	😂	4	0
“6th hour is so boring 😴"	😴	1	2
“she just made my damn night😂😂😂😂😂😂😂 Here I am eating my husband like its so damn normal”	😂	7	1

Table 2: Emoji Occurrences and Positions

emoji sentiment scores were computed for both text and emojis using SentiWordNet, VADER, and TextBlob. The sentiment scores generally fall in the range of [-1,1] where negative scores indicate negative polarity and positive scores indicate positive polarity. Using these scores polarities of both text and corresponding emojis can be identified and compared for incongruence.

SentiWordNet (or SWN) qualifies WordNet synsets in Positive, Negative, and Objective labels by using numerical scores. VADER is a parsing rule-based model that is popularly used for sentiment analysis tasks. It uses lexical features, grammar, and syntax conventions of the language that express the intensity of sentiment. TextBlob is a Python library that contains many natural language processing tools. We used Python’s NLTK interface [5] for all these three tools. We also used these tools to extract emoji scores of the emojis corresponding to the text. The emojis were demojized and their text description was passed to each of the above tools to compute emoji scores. In case an emoji was intense (i.e. more than one occurrence) its sentiment score was computing using the following methods.

1. On experimentation it was observed that appending *!* to a text increases the sentiment score of the text in direction of its polarity. Therefore, we appended *!* to the emoji text its Freq-1 times. i.e. if 😂 was used 3 times in a text, its demojized text along with intensity was “laughing with tears of joy!!"

2. SWN takes into account the number of PoS tags. These scores are added to compute the sentiment score of a sentence. When multiple emojis are used in a text, the demojized text of an emoji was concatenated as many times an emoji appeared with the text record in consideration. For instance 😂 appeared 3 times in a text, then the emoji text used to compute the sentiment score using SWN was "laughing with tears of joy laughing with tears of joy laughing with tears of joy".

The emoji sentiment scores were computed for all emojis in the text and added together to derive the final score of the emojis. We also computed the sentiment score of only the maximum occurring emoji using the above methods.

Emoji Sentiment Ranking (ESR) also gives the emoji sentiment score but it may not cater to recent emojis that have been added to the Unicode Consortium of emojis [6]. But these emojis may occur in SarcOji or any other text on social media. Thus, it was a challenge to apply ESR to all emojis. But, we observed that most of the frequent emojis in SarcOji texts were face emojis. Since, ESR also lists a large number of face emojis with their respective sentiment scores we used ESR, for computing the sentiment score of the most frequent emoji in the text. Sentiment scores of texts and emojis are computed as given in algorithm 2.

3.5 SarcOji Dataset

SarcOji Dataset is now available on github[7]. It comprises 5190 Facebook posts and 24187 Twitter tweets. The ‘Sarcastic’ labels for ‘Text’ from which the following features are derived as discussed as follows

- Emojis: List of emojis in the text
- MaxEmoji: Most frequent emoji in the text

[5] https://www.nltk.org/

[6] https://home.unicode.org/emoji/

[7] https://github.com/VanditaGroverKapila/SarcOji

Algorithm 2 Computing Text and Emoji Sentiment Scores

```
procedure SENTIMENT SCORES( cleanText, EmojiInfo)
  ▷ EmojInfo contains EmojiDict, MaxEmoji, MaxEmojiOccurence
      ▷ CleanText is text without any emojis, hyperlinks, mentions, or hashtags ▷ Compute sentiment scores for text using all the tools
    textVaderScore = vader(cleanText)
    textTextBlobScore = TextBlob(cleanText)
    textSWNScore = SWN(cleanText)

    esrMaxEmojiScore = esr(MaxEmoji)
    i = 0
    ScoreDict =
    {vader:0, textBlob:0 swn:0}
    for emoji in EmojiDict do
        emojiF = EmojiDict[emoji].count

  ▷ demojize is available in Python package
  that converts emoji to text

        emojiText = demojize(emoji)

        if emojiF ≥ 2 then
            Intensifier = !^(emojiF−1)
            concatIntensifier = Concatenate
                                    emojiText
                                    emojiF-1
                                    times
            exemojiText = emojiText
                                  (concat with)
                                  Intensifier
            semojiText = emojiText
                                (concat with)
                              concatIntensifier
      ▷ Computing sentiment scores of emoji
      Text using SWN, Vader, and TextBlob

            vaderEmojiScore =
                        vader(exemojiText)
            textBlobEmojiScore =
                        textBlob(exemojiText)
            sentiEmojiScoreI =
                    sentiWordnet(exemojiText)
            sentiEmojiScoreC =
                  sentiWordnet(semojiText)
            sentiEmojiScore =
                      max(sentiEmojiScoreI,
                      sentiEmojiScoreC)
            Update ScoreDict
                                      ▷ end of procedure
```

Type	Number of Texts	Emoji Per Post	Intense Posts*
Sarcastic	11448	2.156	41.44%
Not Sarcastic	17929	1.526	22.98%

Table 3: SarcOji Dataset Statistics

- MaxEmojiNumOccurence: Frequency of MaxEmoji in the text.
- MaxEmojiPos: Position of MaxEmoji at Left, Middle, Right (0,1, or 2 respectively) from the text.
- TextSWN: Text sentiment score using SentiWordNet
- TextVader: Text sentiment score using VADER
- TextTextBlob: Text sentiment score using TextBlob
- EmojiSWN: Combined sentiment score of all emojis using SentiWordNet
- EmojiVader: Combined sentiment score of all emojis using VADER
- EmojiTextBlob: Combined sentiment score of all emojis using TextBlob
- MEmojiWN: Sentiment score of MaxEmoji using SentiWordNet
- MEVader: Sentiment score of MaxEmoji using VADER
- METB: Sentiment score of MaxEmoji using TextBlob
- ESR: Sentiment score of MaxEmoji using Emoji Sentiment Ranking

4 Observations and Inferences

In this section, we discuss some important Observations and Inferences after an in-depth analysis of the SarcOji dataset.

4.1 SarcOji Dataset Statstics

Table 3 provides the statistics for the compiled SarcOji dataset.[8]

The percentage of positive, neutral, and negative texts and emojis in SarcOji are reported in Figures 1 and 2.

[8]*Posts with >1 emojis

Text Type	Sent	SWN Text %	SWN Emoji %	VADER Text %	VADER Emoji %	TextBlob Text %	TextBlob Emoji %
Sarcastic	+ve	35.48	33.35	46.38	44.22	43.57	29.14
	neu	46.41	55.62	33.19	45.12	41.39	63.02
	-ve	18.11	11.03	20.42	10.66	15.03	7.83

Figure 1: Sentiment Distribution in Sarcastic Texts

Text Type	Sent	SWN Text %	SWN Emoji %	VADER Text %	VADER Emoji %	TextBlob Text %	TextBlob Emoji %
Non Sarcastic	+ve	33.56	27.88	41.81	37.16	40.17	23.41
	neu	44.97	45.75	30.16	29.17	39.29	44.88
	-ve	21.43	26.38	28.03	33.67	20.53	31.71

Figure 2: Sentiment Distribution in Non-Sarcastic Texts

It is observed from Figures 1 and 2 that in general there are more positive texts in sarcastic set. Also, the positive emojis are significantly more in the sarcastic set as compared to non-sarcastic texts. It is also important to observe that the neutral texts dominate in both sarcastic and non-sarcastic sets, which might make it difficult to determine incongruence.

4.2 Incongruence

To determine if there is incongruence between the polarity of text and the polarity of emojis we compare their sentiment scores. We consider incongruence when

- Polarity of text is +ve (>0) and that of emoji is -ve (<0)
- Polarity of text is -ve (<0) and that of emoji is +ve (>0)

Before comparing the sentiment scores for polarity, all the sentiment scores outside the range [-1,1] were normalized using a maximum absolute value scalar.
Sentiment scores computed by all methods for text and emojis are compared and reported in Table 4, 5, 6. All the numbers are reported in percentages.

Type	SWN	VADER	TextBlob
Sarcastic	9.79	12.87	7.55
Not Sarcastic	16.49	19.26	14.6

Table 4: Incongruence computed after taking into account all emoji scores

We see more agreement in Table 6 where the emoji sentiment score was computed using ESR for the MaxEmoji. Less incongruence between text and emojis was observed in the sarcastic text as compared to non-sarcastic texts. One of the reasons for this could be that neutral text and emojis are sig-

Type	SWN	VADER	TextBlob
Sarcastic	5.4	11.25	7.33
Not Sarcastic	9.5	18.43	15.11

Table 5: Incongruence computed after taking into account only the MaxEmoji score computed using SWN,VADER, and TextBlob

Type	SWN	VADER	TextBlob
Sarcastic	18.74	21.38	21.4
Not Sarcastic	21.32	22.8	21.8

Table 6: Incongruence computed after taking into account only the MaxEmoji score computed using Emoji Sentiment Ranking

nificantly high in the dataset. Thus, to understand sarcasm it is important to dive into neutral texts and emojis.

4.3 Emojis in SarcOji

In this section we report the emojis that were most used in the compiled SarcOji dataset. The top 25 emojis used in Sarcastic and Non-Sarcastic subsets of SarcOji are reported in Figures 3 and 4 respectively.

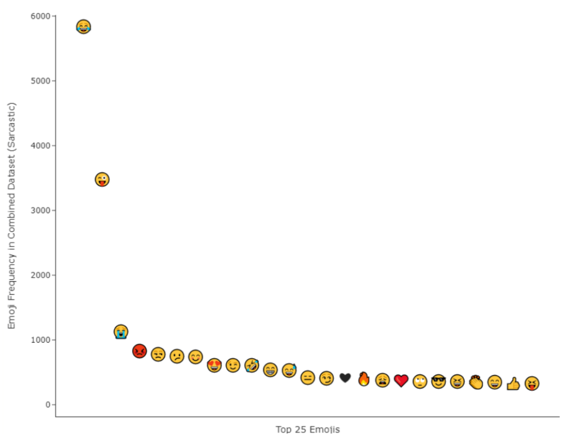

Figure 3: Sentiment Distribution in Sarcastic Texts

Usage in Text	😂	😜	😭	😡	😕
% of occurrence	18.763	***21.75***	2.43	1.05	0.08
Intensity (freq>1)	***50.14***	2.53	41.21	40	33.7

Table 7: Usage of Emojis in Sarcastic Texts

Usage in Text	😂	😜	😭	😡	😕
% of occurrence	19.342	0.45	15.16	13.04	13.02
Intensity (freq>1)	15.325	6.25	6.47	2.35	0.8

Table 8: Usage of Emojis in Non-Sarcastic Texts

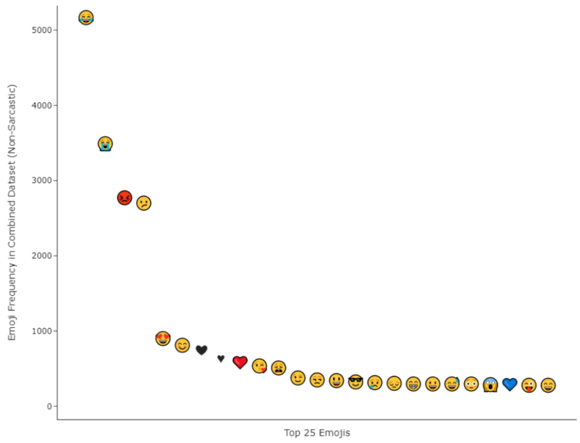

Figure 4: Sentiment Distribution in Non-Sarcastic Texts

😂 is the most popular emoji in SarcOji with 5669 occurences in 11448 sarcastic texts and 5018 occurences in 17929 sarcastic texts. This might be an indication that 😂 is one of the preferred emojis to express sarcasm.

4.4 Usage Patterns of Top Emojis

We further analyze usage patterns of the top-5 emojis of the entire SarcOji dataset in tables 7 and 8.

Some interesting observations can be made from Tables 7 and 8.
😂 is in general an emoji with maximum occurrences (frequency) in 18.76% of sarcastic texts. 19.34% of non-sarcastic texts also see 😂 as a MaxEmoji. But, 😂 is more intense in sarcastic texts. In 50% of sarcastic texts, the users have used 😂 more intensely. By intensity, we mean that an emoji is used repeatedly (more than 1 time) with the text in consideration. And in general, apart from 😜, all other emojis are used more intensely in sarcastic texts. It is to be noted that 😜 is the most dominant emoji in sarcastic texts which may

Tool	😂 face with tears of joy	😜 winking face with tongue	😭 loudly crying face	😡 Pouting face	😕 Confused face
SWN	0.25	0.0	0.0	0.0	-0.5
VADER	0.44	0.0	-0.477	0.0	-0.4
TextBlob	0.8	0.0	-0.2	0.0	0.0
ESR	0.221	0.456	-0.093	-0.173	-0.4

Table 9: Sentiment scores of Emojis using various tools

Type	Left	Middle	Right
Sarcastic	13.75	18.88	67.36
Not Sarcastic	6.9	12.76	80.34

Table 10: Position of Occurrence of MaxEmoji (% of the text)

point towards its inherently sarcastic nature. This result is in alignment with (Thompson et al., 2016).

4.5 Sentiment Scores of Emojis

In table 9, the sentiment scores of the top-5 emojis computed using various tools used in this work are reported.

We observe that none of the tools agree with each other when it comes to computing the sentiment scores of the emojis. We also observe that SWN, VADER, and Textblob are computing sentiment scores as 0 for some emojis. This may impact determining the incongruence of text and emoji polarities. ESR is giving a more negative score for 😕 as compared to 😭.
Further work may be required that captures all the emojis (even those added every year). There is a need to build a tool that assigns and regularly updates numerical scores for emojis to identify the sentiment they express. For instance, 😂 may be associated more with a fun component when used non-sarcastically. But it may have a sarcastic connotation when it is used more intensely in a text.

4.6 Position of Occurrence of MaxEmoji

In Table 10 the percentages of texts where the MaxEmoji occurs first is provided. This trend is observed in the top-5 emojis also. The results of the position of emojis in non-sarcastic texts are similar to those reported by (Kralj Novak et al., 2015) and (Zhao et al., 2018) but vary significantly for sarcastic texts.
We can concur that users may use emojis in non-sarcastic texts towards the end to annotate or conclude their text. While in sarcastic texts they use emojis nearer to context.

5 Conclusion and Future Directions

In this work, we compiled a labeled sarcasm dataset SarcOji from five publicly available datasets. SarcOji contains 29377 labeled records with emojis. Sentiment scores were derived using SentiWordNet, VADER, and TextBlob for both text and emojis, and Emoji Sentiment Ranking was used to compute the sentiment score of MaxEmoji. Using this publicly available dataset, researchers can explore the role of emojis in sarcasm detection.
On studying SarcOji no significant incongruence between sarcastic text and corresponding emojis was found. But more exploration is needed to understand the role of seemingly neutral texts and emojis.
It was also observed that sarcastic texts, as well as emojis used with them, are more positive as compared to non-sarcastic texts.
😜 was the most used emoji in the sarcastic text.
😂 was frequently used in both sarcastic and non-sarcastic texts. In the sarcastic texts, 😂 was used more intensely (more occurrences in a single text). In general, the sarcastic subset of SarcOji saw double the number of texts with intense emojis as compared to the non-sarcastic subset. This means that the intensity of emojis used in the text can indicate sarcasm.
In 80% of non-sarcastic texts, the MaxEmoji appeared towards the end of the text. This number was 67.35% for sarcastic texts, while MaxEmoji appeared 18.9% times in the middle and 13.75% times towards the beginning of the text. This hints that emojis in sarcastic texts are more often used with the context.
With this work we have been able to identify that 😂 when used intensely may indicate sarcasm, while 😜 is inherently sarcastic in nature. We were also able to demonstrate that number and position of occurrence of an emoji in the text are strong indicators of sarcasm. Although not much incongruence in the polarity of sarcastic texts and emojis was observed, there is a need to understand the role of seemingly neutral text and emojis in discerning sarcasm.
In the future, existing emoji resources can be augmented to flag the sarcastic nature of emojis which

can enable better training of sarcasm classifiers.

Acknowledgements

We thank all the researchers who have compiled and made Sarcasm datasets publicly and freely available. Compilation of SarcOji would not have been possible without these resources.

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