Examining the language of humour versus sarcasm/irony in tweets

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Abstract
Humour is the tendency of experiences to provoke laughter and provide amusement. Most people understand humour and can laugh or smile at something like a joke or pun. If one can understand a joke or pun, he is considered to have sense of humour.
On the other hand, sarcasm is the caustic use of words, often in a humorous way, to mock someone or something. How to tell if someone is being sarcastic? Unlike humour, sometimes it can be challenging especially if you can't hear the tone of someone's voice while he is being sarcastic. Or if you don't have the context in which someone is being sarcastic.
So, if humans sometimes have problems detecting sarcasm and even understanding humorous joke, is computer able to detect them and distinguish one from another? With use of machine learning and deep learning computer can learn to detect humour and sarcasm and even distinguish them.

Keywords
Machine Learning, Deep Learning, Humour, Sarcasm, Social media, Twitter

1. Introduction

Figurative language is one of the most difficult topics facing Natural Language Processing. It stands for a way of expressing oneself that does not use a word's realistic or strict meaning. Unlike literal language, figurative language takes advantage of various figures of speech such as metaphor, sarcasm, irony, ambiguity and so on, to project more complex meanings. Traditional NLP tools do not consider how words can be used playfully. Hence, figurative language use on social media, which we are focusing on, and especially the use of sarcasm and irony, in witty and inventive ways, pose significant challenges to these approaches.

The research described in this paper is focused on analysing two popular domains of figurative language, humour and irony. Humour is the tendency of experiences to provoke laughter and provide amusement. Most people understand humour and can laugh or smile at something like a joke or pun. If one can understand a joke or pun, he is considered to have sense of humour. On the other hand, sarcasm is the caustic use of words, often in a humorous way, to mock someone or something. How to tell if someone is being sarcastic? Unlike humour, sometimes it can be challenging especially if you can't hear the tone of someone's voice while he is being sarcastic. Or if you don't have the context in which someone is being sarcastic. So, if humans sometimes have problems detecting sarcasm and even understanding humorous joke, is computer able to detect them and distinguish one from another? With use of machine learning and deep learning computer can learn how to detect humour and sarcasm and even distinguish them.

In this paper, we are focused on describing a model for recognizing these phenomena in social media, such as “tweets”. Our dataset consists of around 5 million tweets, 1 million sarcastic tweets, 1 million ironic tweets, 1 million humorous tweets and 2 million are serious, real talk tweets.

The remainder of this paper is organised as it follows. In the next section the dataset is described. The subsequent sections present related work, used methodology and results of the conducted survey. The ultimate section provides a discussion and theoretical and practical implications, limitations, issues, suggestions and future research.

1.1 Used dataset

Dataset for the paper is made of tweets containing one of four hashtags. Hashtags that the tweets were filtered by were #irony, #sarcasm, #humour and #realtalk. First hashtag represents the data portion for ironic tweets, second for sarcastic tweets, third for humorous tweets and the last hashtag represents non-ironic datasets. To extract the data Python library snscrape was used. After extracting the data all hashtags were removed, as well all tweets containing external URL-s and tweets containing less than 3 words, because they would just bring unnecessary noise.

All together five million tweets were extracted. One million for #irony, one million for #sarcasm, one million for #humour and two million for #realtalk. That makes 40% of 5 million tweets sarcastic/ironic, 20% humorous, and 40% of the data serious tweets.

Figure 1: Dataset description

Hashtag tweets were filtered by	Number of tweets containing hash tagged dataset
#sarcasm	1,000,000
#irony	1,000,000
#humour	1,000,000
#realtalk	2,000,000

2. Related work

Irony and sarcasm are subtle figures of speech that can be traced back to ancient Greece, even preceding the philosopher Socrates, who used irony to illustrate his views (Lee and Katz, 1998). Smith (n.d.) draws upon definitions and explanations given by socio-psycholinguists such as Fowler (1965), Kreuz and Glucksberg (1989) and Gibbs (2000), to finally arrive at this definition; “Irony and sarcasm are used to portray meanings that differ from the literal meaning of an utterance; many times, this can be an opposite or hyperbole”. Sarcasm unlike irony is an aggressive and often hostile type of humour (Norrick, 2003). Specifically, Norrick (ibid.) classified conversational humour into four types: (1) jokes, (2) anecdotes, (3) wordplay and (4) irony, while sarcasm and mockery do not fall under any of these four categories as they can be found across all four. The Oxford English Dictionary defines “irony” as “the funny or strange aspect of a situation that is very different from what you expect” and “sarcasm” as “a way of using words that are the opposite of what you mean in order to be unpleasant to somebody or to make fun of them" (OED, 2020). Although irony and sarcasm are very closely related, they are hence distinctly different, with sarcasm being a more aggressive form of humour.

The social context is crucial when interpreting sarcastic comments (Katz and Lee, 1993). Ducharme (1994) states that sarcasm promotes "group solidarity", while Gibbs (2000) finds that sarcasm is used to "vent frustration", a tool that Twitter is often used for. For instance, Kim et al. (2011) found that Twitter users bonded over expressing sympathy, worry and frustration. Most psycholinguists agree that a sarcastic utterance typically has a target. Davidov et al. (2010) found that because of Twitter's context-poor and unstructured nature, it is not always possible to easily identify the targets sarcastic comments are aimed at. Text-based user generated content (UGC) is potentially quite limiting to sarcasm detection, at least compared to other modes of communication such as video or spoken language, where visual and acoustic cues significantly help distinguish such utterances, for instance speech features including speech rate, and other contextual cues including laughter (Cheang and Pell, 2009; Tepperman et al., 2006). Parde and Nielsen (2018) have shown that using sarcastic tweets (the #sarcasm hashtag) and enriching training datasets with additional annotated Amazon product review data can slightly improve the performance of automated sarcasm detection. Amazon-based sarcasm detection is more accurate than detection on Twitter, primarily due to longer messages.

Although irony and sarcasm are distinct from each other, what we observed from the computational research literature is that sarcasm and irony are occasionally bundled together and used interchangeably. The reasons for this may be varied, but include some conceptual misunderstandings, similar characteristics (e.g., frequent use of hyperbole), and hence similar automated detection approaches being applicable. Also, more pragmatic considerations may play a role, such as the challenge of human annotators consistently differentiating between irony and sarcasm, hence lack of example cases of irony and availability of labelled datasets for the usually "data hungry" computational machine learning methods. In this section, we provide a brief overview of some prior work that specifically dealt with irony detection.

Reyes et al. (2009) was among the first to discuss the importance and principles behind detecting irony in condensed text. Sarmento et al. (2009) developed a model, also based on pattern detection to locate positive and negative sentiment in Portuguese newspapers – finding that the only problems arising in their system were due to the automatic misinterpretation of irony. Carvalho et al. (2009) created an automatic system for detecting irony relying on emoticons and special punctuation in online newspaper comments. Reyes and Rosso (2011) developed a model that represents irony in Amazon customer reviews by integrating "different linguistic layers" (i.e., from simple n-grams to affective content). They (ibid.) point out the importance of correctly identifying irony because of its use in expressing opinions but acknowledge the difficulty in finding a solution to detect it, admitting that it is unrealistic to rely on a single technique or algorithm. They (ibid.) also found that hashtags were one-way tweeters use in order to avoid being taken literally. They annotated tweets with the hashtag #irony and compared them to tweets that were not ironic. Barbieri and Saggion (2014) attempt to detect irony on Twitter using the same datasets that Reyes et al. (2013) prepared. They also measure word use frequency and apply supervised ML methods; their model included word frequency, style, adjective/adverb intensity and sentence structure. They also looked at sentiments, synonyms and ambiguities in order to "distinguish irony from as many different topics as possible" (ibid.: 66). The researchers only tested their model in controlled experiments using basic linguistic tools such as WordNet,6 and acknowledge the primary problem of disambiguation of meaning is an open problem. Barbieri et al. (2014a) concluded that the more meanings a word has, the more likely it is to be used ironically. They also found that web users often use figurative comparisons as a means to express ironic opinions.

Main paper we will refer to is Hipson et al. (2021). In that paper they examine difference between solitude and loneliness in tweets, like our paper. Dataset contains 19,277,359 tweets from the Twitter API containing any of the following key terms: “solitude,” “lonely” (“loneliness,” “lonesomeness”), and “alone” (“aloneness”). Dataset does not contain duplicate tweets, tweets that contain less than three words or external URLs. Talking about the analytic plan, they used only words that were mentioned in tweets over 500 times to reduce noise arising from words that are used less often.

Another important thing stated in this paper is that Twitter does not provide demographics about its users through its API, but they came to some data trough Pew Survey. In this survey they reported that 32% of Twitter users were between the ages of 13–17, 38% were between 18–29, 26% were between 30–49, 17% were between 50–64, and 7% were 65+.

The interest in automatically processing matters related to figurative language is not new in NLP. They are current hot topics in NLP due to the advances in areas such as sentiment analysis and opinion mining, trends discovery, or electronic commerce even though the computational approaches which deal with more abstract uses of figurative language tend to be more restricted. For instance, regarding automatic irony processing, the research described by Utsumi (1996) was one of the first attempts to computationally formalize irony. Although such approaches have proved that both humour and irony can be handled in terms of computational means, it is necessary to improve the mechanisms to represent their characteristics, especially, to create a feature model capable of symbolizing as possible, both linguistic and social knowledge in order to describe deeper and more general properties.

3. Methodology

Dataset for the paper is made of tweets containing one of four hashtags. Hashtags that the tweets were filtered by were #irony, #sarcasm, #humour and #realtalk. First hashtag represents the data portion for ironic, second for sarcastic tweets, third for humorous and the last hashtag represents a dataset of serious tone. To extract the data Python library snscrape was used. After extracting the data all hashtags were removed, as well all tweets containing external URL-s and tweets containing less than 3 words, because they would just bring unnecessary noise.

All together five million tweets were extracted, prefiltering. One million for #irony, #sarcasm and #humour and two million for #realtalk. That makes two thirds of sarcastic, ironic or humorous tone, and one third serous.

Figure 1: Dataset description after filtering

Hashtag tweets were filtered by	Number of tweets containing hash tagged dataset
#sarcasm	987,372
#irony	951,536
#humour	804,962
#realtalk	1,963,425

After getting data from tweets, process of checking word co-occurrence was conducted. As tweets were extracted by hashtags there wasn't specific word for which word co-occurrence was checked. Instead, a simple matrix and network were created to see which are the most common words and most common pairs of words for each dataset. Important to say is that before all that, removal of stop words was run on datasets and words were tokenized, so we could have clean sentences. Next thing was making word co-occurrence matrix using sklearn. Results were visualized with software Gephi. Co-occurrence matrix gives information on which words co-occur the most often with one another in tweets containing same hashtag.

Word co-occurrence was then used for valence, arousal and dominance (VAD) analysis and emotion analysis. VAD analysis is conducted using NRC VAD lexicon to determine valence, arousal and dominance factor for co-occurring words from tweets. Lexicon is a collection of words and their coefficient between 0 and 1 that determines how much does the word correspond with valence, arousal and dominance. For emotion analysis NRC Emotion lexicon was used containing set of words that have a score of 0 if they do not correspond to the emotion or 1 if they do. For analysis only words that appeared at least 100 times were used, to reduce the noise from the dataset. Linear regression was performed in the analysis using co-occurrence matrix as an independent variable when making decision between two terms, and one of the VAD dimensions or one of the chosen emotions as the dependant variable. Analysis was performed for each combination of hashtag datasets.

4. Results

4.1 Word co-occurrence

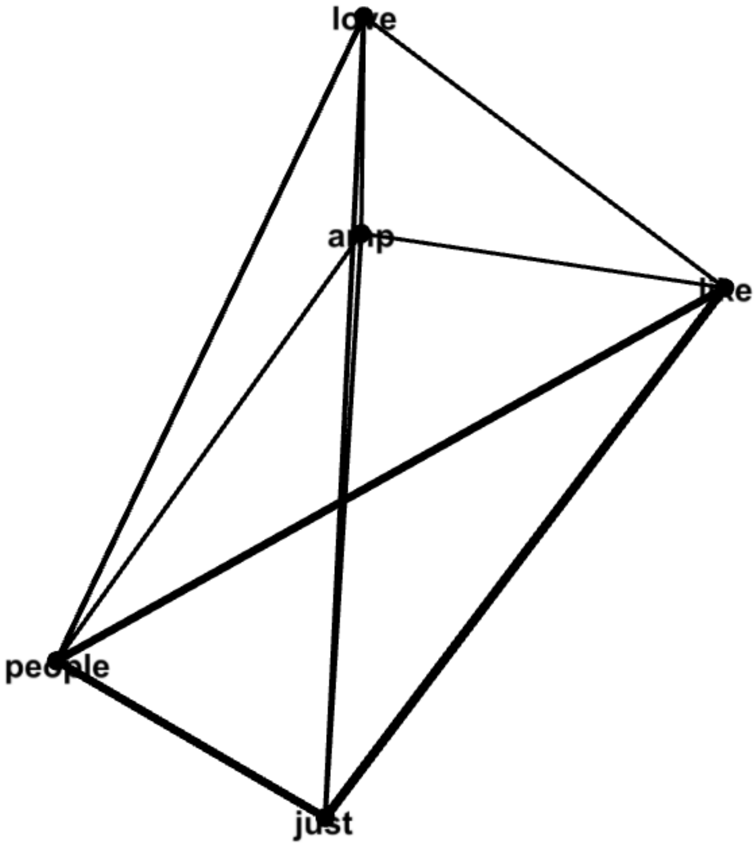
Visualizing co-occurrence matrices gave us results which we interpreted manually. For tweets with hashtag humour most co-occurred words were "joke" and "day", "day" and "did", and "say" and "did". Words "joke" and "day" are usually introduction to some joke like "Joke of the day". Words "day" "did" and "say" are often part of some joke, so they were often occurred in tweets with humour hashtag.

Tweets with hashtag sarcasm most often contain pairs "oh sure" and "oh right". Those phrases are often used in sarcastic context in speech and in tweets. Another interesting pair that we noticed was "Donald Trump", often contained in sarcastic tweets about ex-president of USA.

Further visualizing showed us that tweets with hashtag irony often contain words "people", "just", "like" and "lol". Those words had high co-occurrence ratio between them.

And the last hashtag – real talk showed us that when people are being serious on Tweeter, they usually talk about other people. Most occurred pairs were "people just", "people like" and "people know".

Figure 2: Word co-occurrence matrix for #realtalk



4.2 VAD and emotion analysis

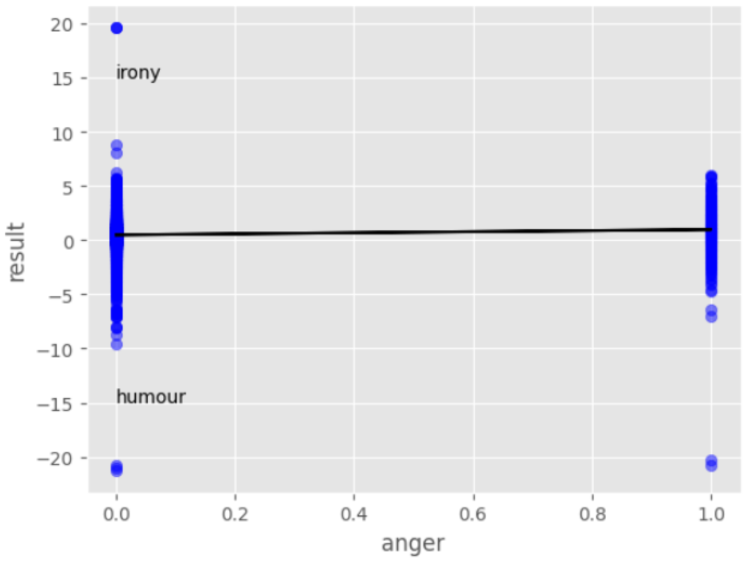
Main task of this paper is to analyse word co-occurrence within given hashtags over three dimensions: valence, dominance, and arousal using NRC Valence Arousal Dominance lexicon (NRC VAD; Mohammad, 2018). The NRC VAD lexicon contains over 20,000 commonly used English words that have been scored on valence (0 for extremely unpleasant, 1 for extremely pleasant), arousal (0 for calm, 1 for active, intense), and dominance (0 for weak, 1 for powerful). Some examples of high and low words for each dimension include high valence for “happy”, low valence for “nightmare”; high arousal for “homicide”, low arousal for “relaxed”; high dominance for “success”, low dominance for “vague”.

Word co-occurrence was also analysed using the NRC Emotion Lexicon Mohammad and Turney (2010) to identify anger, disgust, joy, positive and negative words. The NRC Emotion Lexicon contains over 14,000 commonly used English words with binary ratings corresponding to whether the word reflects the emotion label or not. For example, the word abnormal has a score of 1 on the disgust and negative label but 0 everywhere else.

First two hashtags we analysed were *#realtalk* and *#humour*. While there was no significant difference in co-occurrence for valence, some are noticeable in arousal and dominance analysis. For lower arousal, tendency for words to co-occur with *humour* increases and as arousal increases, co-occurrence decreases. Same goes for dominance, lower dominance means lower co-occurrence for *realtalk* hashtag. Also, *humour* is more likely to co-occur with words that are connected to joy and positivity.

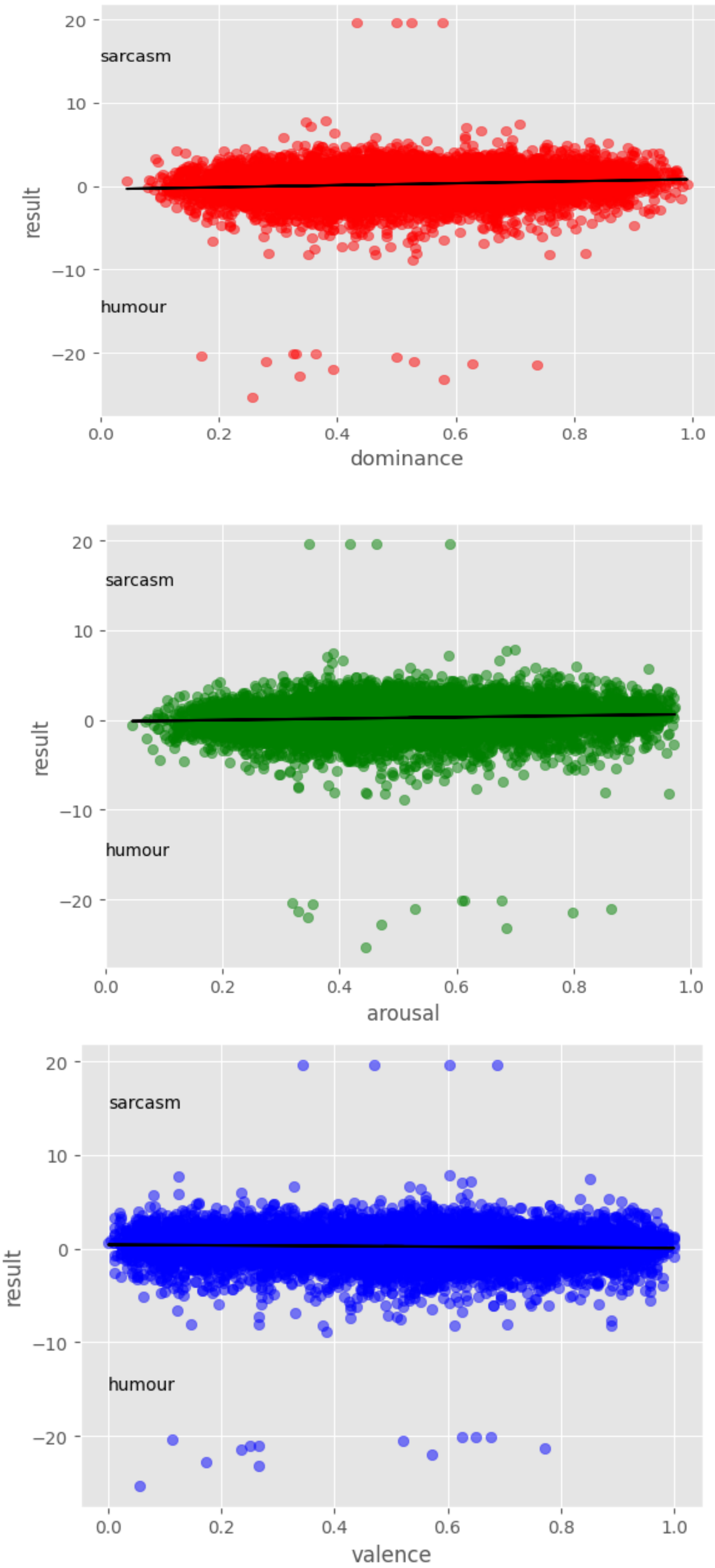
Secondly, we analysed *#humour* and *#irony.* For higher valence words equally co-occur in both datasets, but as valence decreases likelihood of word to co-occur with irony rises. That means that less pleasant words more often occur in tweets that contains *#irony*. On the other hand, when arousal and dominance rise tendency of words to occur in tweets with *irony* hashtag also rises. If we talk about emotions, it is noticeable that irony is significantly associated with words that are related to disgust, anger and negative emotions (Figure 3.). With these results we can notice that people often express their dissatisfaction.

Figure 3: Plot showing likelihood of words to co-occur with irony and humour hashtags.



Furthermore, examining the difference between *sarcasm* and *humour* brought us more expected results. With the lower valence probability of word co-occurrence increases for sarcasm. For higher valence it was almost equal between *humour* and *sarcasm*. And for dominance and arousal, it was reversed. Arousal and dominance were positively associated with *sarcasm.* (Figure 4.) And for emotions we noticed that sarcasm is slightly more associated to emotions like anger, disgust and negative.

Figure 3: Plot showing likelihood of words to co-occur with sarcasm and humour hashtags.



For *irony* and *realtalk* there weren't many differences. We only noticed that for lower valence likelihood for words to co-occur with *realtalk* rise and that *irony* is less likely to be associated with joy emotion.

For hashtags *realtalk* and *sarcasm* there was bigger difference for dominance than for valence and arousal. It is noticeable that for higher dominance word are more often associated with *sarcasm* than *realtalk*. We also saw that *sarcasm* is often associated with emotions such as anger, disgust and negative. Which again brings us back to fact that people like to express their negative feelings about society through *irony* and *sarcasm.*

And for the last part, we examined *irony* and *sarcasm.* VAD analysis gave us results which showed that irony is more negatively associated to valence, arousal and dominance. Emotion analysis showed us similar results. Only observed difference was that *irony* is slightly more associated to negative emotions.

5. Discussion

Based on the outcomes of our presented analysis we need to highlight primary observations, some related issues, as well as limitations associated with our study, and suggestions for future work.

Examining the language of humour, sarcasm, and irony in tweets is an important task for natural language processing and sentiment analysis, as these linguistic phenomena can often be misinterpreted or misclassified. Understanding the difference between humour, sarcasm, and irony is important for accurately analysing and understanding the sentiment of tweets.

Sarcasm and irony are forms of expression that people often use to convey their negative emotions in a less direct and less confrontational manner. When someone is feeling frustrated, annoyed, or disappointed, they may use sarcasm or irony to indirectly communicate their feelings. For example, if someone is upset about a situation, they might say something like "This is just great" with a heavy dose of sarcasm to express their disappointment. In the case of irony, the speaker may say the opposite of what they actually mean. For example, if someone is upset about poor service at a restaurant, they might say, "Wow, this service is just fantastic." The use of irony in this way allows the speaker to express their negative emotions without directly confronting the source of their frustration. Sarcasm and irony are often used as a defence mechanism or to mask one's true feelings. They allow individuals to communicate their negative emotions in a more subtle way, which can help to avoid direct confrontation or conflict. However, it is important to note that sarcasm and irony can sometimes be misinterpreted and lead to misunderstandings in communication. It is essential to understand the context and tone of the words being used in order to accurately interpret their meaning.

The aim of this study was to investigate the usage of these words in everyday language and to focus on the emotional context in which they appear. A large collection of tweets was gathered, and computational linguistic methods were used to analyse and compare the emotional content of words that co-occur with either humour, irony, sarcasm, or real talk. The primary goal was to examine whether sentiment differs among words that co-occur more strongly among humour versus irony/sarcasm. The visualization of co-occurrence matrices revealed some interesting insights into the words most often used in tweets with different hashtags. The hashtag #humour was associated with the words "joke," "day," "did," and "say." The hashtag #sarcasm was associated with the phrases "oh sure" and "oh right" and when mentioning former president Donald Trump. The hashtag #irony was often used with the words "people," "just," "like," and "lol." The hashtag #realtalk was associated with talking about other people and the most common pairs were "people just," "people like," and "people know."

As we mentioned before, word co-occurrence was analysed over three dimensions (valence, arousal, and dominance) within hashtags #realtalk, #humour, #irony, and #sarcasm.

The first two hashtags analysed were #realtalk and #humor. There was no significant difference in co-occurrence for valence, but differences were observed in arousal and dominance analysis. The likelihood of words co-occurring with the humour hashtag increases for lower arousal but decreases for higher arousal. The same pattern was observed for dominance, with lower dominance resulting in lower co-occurrence for the #realtalk hashtag. Additionally, humour was more likely to co-occur with words related to joy and positivity.

The next hashtags analysed were #humor and #irony. For higher valence words, there was an equal co-occurrence in both datasets, but as valence decreased, the likelihood of a word co-occurring with irony increased. This means that less pleasant words more frequently occurred in tweets containing the irony hashtag. As arousal and dominance increased, the tendency of words to occur in tweets with the irony hashtag also increased. A strong connection was found between irony and words related to disgust, anger, and negative emotions. These results suggest that people often express their dissatisfaction through irony.

The comparison of sarcasm and humour gave results that were expected. The likelihood of word co-occurrence increased for sarcasm with lower valence, while it was almost equal between humour and sarcasm for higher valence. For arousal and dominance, the pattern was reversed, with arousal and dominance being positively associated with sarcasm. Sarcasm was slightly more associated with emotions such as anger, disgust, and negativity.

For irony and real talk, there were not many differences. We only noticed a higher likelihood of word co-occurrence with real talk for lower valence and less association of irony with joy.

A bigger difference was observed for dominance between real talk and sarcasm than for valence and arousal. Higher dominance was more often associated with sarcasm than real talk, and sarcasm was often associated with emotions like anger, disgust, and negativity.

Finally, when we compared irony and sarcasm, VAD analysis showed that irony was more negatively associated with valence, arousal, and dominance. Emotion analysis showed similar results, with the only difference being that irony was slightly more associated with negative emotions.

The only question that arises is, why is this research of our interest? Well, examining the differences between humour, sarcasm, and irony in tweets is useful for several reasons. One of them is understanding social media communication. By analysing the associations between these hashtags and emotions, words, and sentiments, researchers can gain insight into how people use these terms in their social media communication. The other one is sentiment analysis which can provide valuable information for sentiment analysis algorithms. The differences between humour, sarcasm, and irony can help these algorithms to better distinguish between different types of sentiments in social media text. Another reason is marketing and advertising. Understanding the associations between these hashtags and emotions, marketers and advertisers can better target their audience and tailor their messaging to evoke specific emotions. Further, analysing the differences between humour, sarcasm, and irony in social media can provide valuable information for researchers studying public opinion on various topics. By identifying the emotions and sentiments associated with these hashtags, researchers can better understand how people express their views on social media.

Overall, the examination of the differences between humour, sarcasm, and irony in tweets can provide valuable insights that can be applied in various fields, including sentiment analysis, social media communication, marketing and advertising, and public opinion research.

5.1 Limitations and future research

Analysing humour, sarcasm and irony in tweets is a challenging task for natural language processing (NLP) systems due to several limitations. The first one is that words and phrases can have multiple meanings, making it difficult to determine the intention behind them. That is commonly known under the term ambiguity. The second one is that the context in which a statement is made is crucial in determining its meaning. In a tweet, the context is limited to 140 characters, making it challenging for NLP systems to understand the full context of a statement. Furthermore, the sentiment behind a statement can be difficult to determine, especially in cases of sarcasm or irony where the intended sentiment is opposite to the words used. Another limitation in analysing humour, sarcasm and irony are cultural differences. Humour, sarcasm, and irony can vary greatly between cultures, making it challenging for NLP systems to understand their intended meaning in different contexts.

Future research in this field could focus on improving NLP systems' ability to understand context, sentiment, and cultural differences in order to more accurately determine the intention behind a statement. This could be accomplished through increased training data, advanced deep learning techniques, and improved understanding of cultural nuances. Additionally, future research could also focus on developing methods for detecting sarcasm, irony, and humour in a more fine-grained manner, considering the different forms that these can take in different contexts. This could lead to a more nuanced understanding of the underlying mechanisms of these phenomena and could inform the development of better NLP systems for detecting them.

In conclusion, analysing humour, sarcasm, and irony in tweets remains a challenging task for NLP systems, but with continued research and advancements in the field, it is likely that the accuracy of these systems will continue to improve.

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