Sarcasm Detection using Embedded Emojis

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***Abstract*—The figurative nature of sarcasm makes it an often-quoted challenge for sentiment analysis. Sarcasm has an implied sentiment, but may not have a corresponding surface sentiment. Embedded sarcasm is where sentences have an embedded incongruity in the form of words and phrases themselves, without the necessity of any contextual information. Emojis express emotions and can also express relationally useful roles in conversation. They are culturally and contextually bound, and are open to reinterpretation and misinterpretation. Therefore, our problem lies at the junction of interpretation of emojis embedded in a sentence, and the exploitation of the same to infer any sarcastic intent associated with the otherwise sentimentally ambiguous sentence.**

***Index Terms*—Sarcasm Detection, Sentiment Analysis, Emoji Interpretation, Natural Language Processing, Machine Learning**

I. Introduction

Natural Language Processing (NLP) is one of the most important domains in artificial intelligence. It acts as a platform between a computer and human languages. It helps in making the machine understand, analyze and interpret the data. It helps in querying the datasets and providing an answer. It helps not only in understanding the text or speech but also the context behind it. It works for structured and unstructured data. The linguistic structure depends on various factors like social context, regional dialects, slang etc. NLP is facing a few challenges in this field. Sentiment Analysis is one of the important fields in NLP which deals with analyzing the context.

Sentiment Analysis is the process of analyzing the opinions expressed by the writer and determining the attitude towards the topic. It is used to classify the polarity of a document or an opinionated text. The intensity of the text can also be further classified by Sentiment Analysis. Several analyses can be performed using sentiment analysis. These analytics can be used to determine and retrieve various levels of sentiment. The analysis process is examined on various individual entities i.e., by words or phrases in the document. It provides a quick understanding of the writer's attitudes. It is sometimes known as opinion mining where it speaks about a particular entity and discusses feedback. Several data pre-processing and classification techniques are used in Sentiment Analysis. Sentiment words convey a positive or a negative meaning. There are a few key challenges faced by Sentiment Analysis such as Entity named recognition, Anaphora recognition, parsing, sarcasm detection and many others.

The Free Dictionary defines sarcasm as a form of verbal irony that is intended to express contempt or ridicule. The figurative nature of sarcasm makes it an often-quoted challenge for sentiment analysis. Sarcasm has a negative implied sentiment, but may not have a negative surface sentiment. A sarcastic sentence may carry positive surface sentiment (for example, 'Visiting dentists is so much fun!'), negative surface sentiment (for example, 'His performance in Olympics has been terrible anyway' as a response to the criticism of an Olympic medalist) or no surface sentiment (for example, the idiomatic expression 'and I am the queen of England' is used to express sarcasm). Since sarcasm implies sentiment, detection of sarcasm in a text is crucial to predicting the correct sentiment of the text.

The challenges of sarcasm and the benefit of sarcasm detection to sentiment analysis have led to interest in automatic sarcasm detection as a research problem. Automatic sarcasm detection refers to computational approaches that predict if a given text is sarcastic. Thus, the sentence 'I love it when my son rolls his eyes at me' should be predicted as sarcastic, while the sentence 'I love it when my son gives me a present' should be predicted as non-sarcastic. This problem is difficult because of nuanced ways in which sarcasm may be expressed.

However, sarcasm must be distinguished from humble bragging, as in the case of the sentence 'I am having such a terrible holiday lying on the beach in the sunshine'. Sarcasm and humble bragging are both situations where words are used to imply a sentiment that is different from their popular sentiment. Unlike humble bragging, a sarcastic sentence always has an implied negative sentiment because it intends to express contempt, as given in the definition. However, to the best of our knowledge, past work does not typically distinguish between humble bragging and sarcasm, and treats humble bragging as sarcasm.

Starting with the earliest known work which deals with sarcasm detection in speech, the area has seen wide interest from the sentiment analysis community. Sarcasm detection from text has now extended to different data forms and techniques. This synergy has resulted in interesting innovations for automatic sarcasm detection.

There are four types of sarcasm:

- Propositional: In such situations, the statement appears to be a proposition but has an implicit sentiment involved.

For example ‘Your plan sounds fantastic!’. This sentence may be interpreted as non-sarcastic, if the context is not understood.
- Embedded: This type of sarcasm has an embedded incongruity in the form of words and phrases themselves. For example ‘John has turned out to be such a diplomat that no one takes him seriously’. The incongruity is embedded in the meaning of the word ‘diplomat’ and rest of the sentence.
- Like-prefixed: A like-phrase provides an implied denial of the argument being made. For example, ‘Like you care!’ is a common sarcastic retort.
- Illocutionary: This kind of sarcasm involves non-textual clues that indicate an attitude opposite to a sincere utterance. For example, rolling one’s eyes when saying ‘Yeah right’. In such cases, prosodic variations play a role.

We shall focus solely on embedded sarcasm.

Many people these days express their opinions on various social websites. People have started to express their emotion in sarcasm. Sarcasm is one of the leading challenges faced in Sentiment Analysis. Sarcasm is an indirect manner of conveying a message. It is basically a bitter expression which is conveyed. Sarcasm can also reflect a state of ambivalence. It contradicts the meaning, in the context which is said. Sarcasm can be expressed in many ways. It can be expressed in speech and text. Sarcasm can be conveyed through various ways like a direct conversation, speech, text etc. In direct conversation, facial expression and body gestures provide the hint of sarcasm. In the speech, sarcasm can be inferred if there is any change in tone.

In text, it is difficult to identify sarcasm compared to other methods, but, it can be conveyed using a capital letter, excessive usage of exclamatory marks, exaggeration, usage of emoticons etc. It can be reflected using rating of stars by using a hyperbole and providing less number of stars. There are various applications of sarcastic text detection. It is used for letting the reviewer know the intent of the writer and the context in which it is said. Sarcasm is more predominant in the places where there are capital letters, emoticons, exclamation marks etc. Sarcasm detection is one of the important tasks in sentiment analysis. In Twitter, it helps to understand the intent behind a tweet. Twitter also acts as a tool for the prediction of Election results. In Amazon and shopping websites, it helps to understand the review of the product. In various social websites, like Facebook, Instagram etc. it helps to understand the opinionated comments. The consumer’s preferences and opinions can be analyzed in order to understand the market behavior for a better consumer experience.

Many refer to sarcastic language as ‘irony that is especially bitter and caustic’. There are two components of this definition: (a) presence of irony, (b) being bitter. Both together are identifying features of sarcasm. For example, ‘I could not make it big in Hollywood because my writing was not bad enough’. An example is sarcastic, because: (a) it contains an ironic statement that implies a writer in Hollywood would need to be bad at writing, (b) the appraisal in the statement is in fact bitter/contemptuous towards the entity ‘Hollywood’.

Social media plays a major role in everyday communication. While images and videos are common in social media sites such as Facebook and Twitter, the text is still dominating the communication. Communication through text may lack non-verbal cues, and emojis can provide richer expression to mitigate this issue. Emojis are a set of reserved characters that are rendered as small pictograms that depict a facial expression. In social media, sarcasm represents the nuanced form of language that individuals state the opposite of what is implied. Sarcasm detection is an important task to improve the quality of online communication. First, it helps us to understand the real intention of the user’s feedback. For example, user reviews can contain examples such as ‘Wow this product is great”, “It is very fast”, “Totally worth it”, etc. These comments, however, are being said in a sarcastic tone. Second, sarcastic posts may influence people’s emotions and reactions to the political campaign. The majority of existing sarcasm detection algorithms focuses on text information. These include identifying the traits of the user from their past activities, responses texts, etc. Most of them have tried to train deep neural network models using the text to analyze sarcasm. To overcome the challenges faced by all of these methods and for better performance, the Emoji can be considered to detect sarcasm. Emojis help us to find the tone of speech, the mood of the user and identify sarcasm in a better way. For example, comments such as, “Wow!! This is beautiful 😛 😛 ”, “You can do this, I trust you 😄 😛 ”, “It’s big proud 😉 ” are examples of sarcastic comments. The above comments without the emoji convey us a different meaning and are taken in the positive sense since it has the keywords “beautiful”, “proud”, “trust”, “wow”. However, with emoji, they strongly help us to identify the sarcasm in the comments. Human thought process and emotions are best conveyed through Emojis and these emotional signals are much stronger than the text. These emotional signals will help the model to learn more accurately about the intention, thought process of the user than by merely looking at the text. In this paper, we address the problem of identifying sarcasm in social media data by exploiting Emojis. In essence, we investigate: 1) how to learn the representation of text and emojis separately; 2) how to take advantage of the emoji signals to improve sarcasm detection performance. In an attempt to solve these two challenges, we propose a novel Emoji-based Sarcasm Detection framework, which captures text and emoji signals simultaneously for sarcasm detection.

II. Dataset

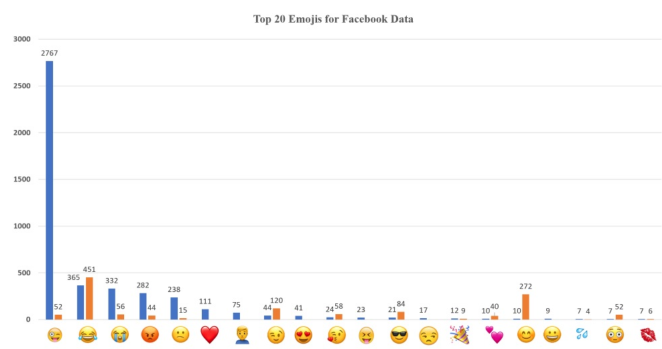
Data was collected from Twitter for a 5-month period and from Facebook for two years from 2015 to 2017 using web scraping in Python 3. The sarcastic pages such as 'sarcasmLOL', 'sarcasmBro' from Facebook and tweets with hashtags, 'sarcasm', 'sarcastic' were taken from Twitter. The statistics of the datasets are:

Datasets	Twitter	Facebook
Sarcasm	6592	2668
Non-sarcasm	10267	2803

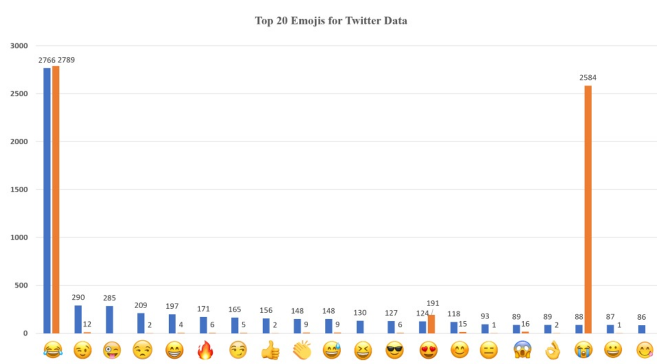
The preprocessing performed was:

- Removal of special characters and punctuations
- Removal of hashtags
- Removal of retweets
- Removed accented characters
- Removal of hyperlinks
- Removed stop words (except negations)
- Remove excess whitespace
- Expand contractions
- Change hashtags to words
- Remove non-english words
- Spell check

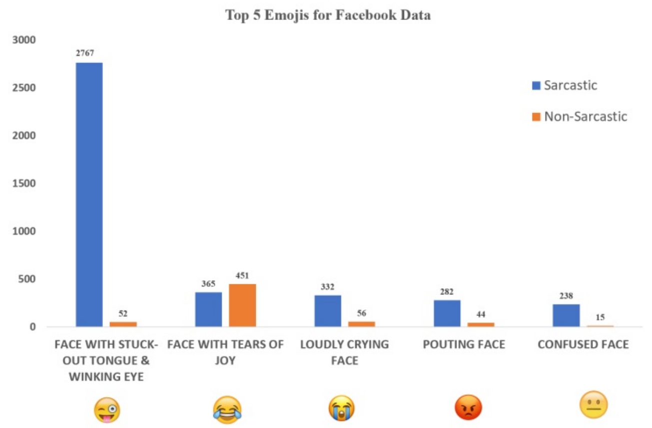
III. Preliminary Analysis of Emoji Usage



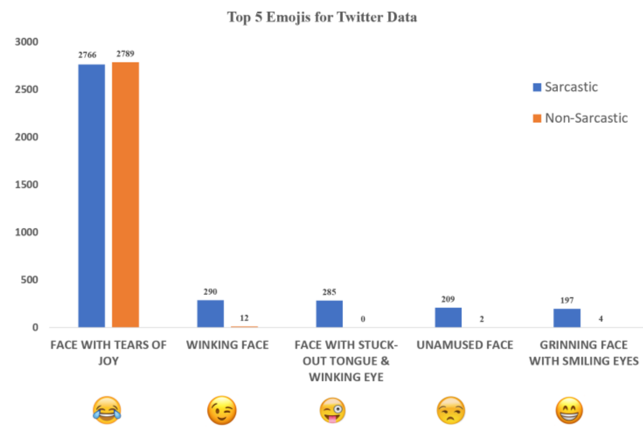
(a) Comparison of top 20 Emojis for Facebook data.



(b) Comparison of top 20 Emojis for Twitter data.



(c) Comparison of top 5 Emojis for Facebook data.



(d) Comparison of top 5 Emojis for Twitter data.

Emojis serve as a medium for us to express certain opinions that can't be expressed by our voice or body language. Emojis are the major contributing factor to the improvement in accuracy of our model because the neural network learns the connection between text and emojis. This analysis is performed to research in depth about the types of emojis used across the comments in the Twitter and Facebook data set. This gives us a clear picture of the most frequently used emojis in both sarcastic as well as non-sarcastic comments which in turn helps us to rank emojis based on their count of occurrences in the comments. The top 20 and top 5 emojis used in our Twitter/Facebook data are visualized through the graphs. The following insights are obtained from the graphs:

- On comparison of emojis used across entire Facebook and Twitter data, the usage of Face with tongue out emoji is the highest (2.7K) among the sarcastic comments. The Face with tears of Joy, Loud crying face (2.6K), Grinning and Pouting face are the three specific emojis that are most frequently used with non-sarcastic comments.
- The number of other emojis used in sarcastic comments like winking face, the smirking face is found to be uniformly distributed across the Twitter data whereas emojis such as the loud crying face, pouting face, the confused face is observed to be uniformly distributed for the Facebook data.
- The usage of Face with stuck out tongue emoji is the first highest for Facebook data and third highest for Twitter data. However, the face with tears of joy emoji is being increasingly used in both sarcastic and non-sarcastic comments across the platforms.
- It is also clearly observed that the amount of Face with tongue out emoji in sarcastic comments is very high which is nearly 54 times its usage in non-sarcastic comments for Facebook data. For twitter non-sarcastic comments, the count of this emoji is in-fact zero. This proves the fact that most of the comments having this emoji are clearly being sarcastic in nature.

IV. Feature Extraction

The emojis are tokenized and seperated from the text. The final vectorized data is train-test split.

A. Word2Vec

The text portion's features are extracted using Word2Vec.

Word2vec is a group of related models that are used to produce word embeddings. These models are shallow, two-layer neural networks that are trained to reconstruct linguistic contexts of words. Word2vec takes as its input a large corpus of text and produces a vector space, typically of several hundred dimensions, with each unique word in the corpus being assigned a corresponding vector in the space. Word vectors are positioned in the vector space such that words that share common contexts in the corpus are located close to one another in the space.

Word2vec can utilize either of two model architectures to produce a distributed representation of words: continuous bag-of-words (CBOW) or continuous skip-gram. In the continuous bag-of-words architecture, the model predicts the current word from a window of surrounding context words. The order of context words does not influence prediction (bag-of-words assumption). In the continuous skip-gram architecture, the model uses the current word to predict the surrounding window of context words. The skip-gram architecture weighs nearby context words more heavily than more distant context words. CBOW is faster while skip-gram is slower but does a better job for infrequent words.

B. Emoji2Vec

Emoji2Vec is similar to word2vec, for emoji embeddings. We first extract the emojis from sentences and pass them through certain filters so as to remove redundant characters and retain only the emojis. This is achieved with the help of a python library called Enchant. The embeddings for the filtered list of emojis are retrieved using emoji2vec. These embeddings are then stored in the embedding matrix W along with the word embeddings. The emoji embeddings play a major role in determining sarcasm. These embeddings help us in understanding complex emotions which cannot be derived from words alone. Given a list of sentence vectors Si for every emoji ei there exists an emoji embedding e'i:

ei -> emoji2vec(ei) -> e'i

The extracted features are then combined via summation and multiplication.

V. Classifiers

A. Stochastic Gradient Descent

Stochastic gradient descent (often abbreviated SGD) is an iterative method for optimizing an objective function with suitable smoothness properties (e.g. differentiable or subdifferentiable). It can be regarded as a stochastic approximation of gradient descent optimization, since it replaces the actual gradient (calculated from the entire data set) by an estimate thereof (calculated from a randomly selected subset of the data). Especially in big data applications this reduces the computational burden, achieving faster iterations in trade for a slightly lower convergence rate.

Accuracies obtained are in the range of 95-97 %

B. AdaBoost

AdaBoost, short for Adaptive Boosting, can be used in conjunction with many other types of learning algorithms to improve performance. The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favor of those instances misclassified by previous classifiers. AdaBoost is sensitive to noisy data and outliers. In some problems it can be less susceptible to the overfitting problem than other learning algorithms. The individual learners can be weak, but as long as the performance of each one is slightly better than random guessing, the final model can be proven to converge to a strong learner.

Accuracies obtained are in the range of 96-98 %.

C. MaxEnt

The Max Entropy classifier is a probabilistic classifier which belongs to the class of exponential models. Unlike the Naive Bayes classifier, the Max Entropy does not assume that the features are conditionally independent of each other. The MaxEnt is based on the Principle of Maximum Entropy and from all the models that fit our training data, selects the one which has the largest entropy. The Max Entropy classifier can be used to solve a large variety of text classification problems such as language detection, topic classification, sentiment analysis and more.

Accuracies obtained are in the range of 96-98 %.

D. Hybrid

Based on majority voting from the above three classifiers, classification labels are decided. This gives us the hybrid insight of the classical ML classifier like SGD combined with the probabilistic classifiers like AdaBoost and MaxEnt. This helps push our accuracies even higher.

Accuracies obtained are in the range of 97-99 %.

VI. Interpretation

The Text and Emoji Components are obtained as embeddings using the Word2Vec and Emoji2Vec methods. We test our baseline features, and observe the following:

- Only word embeddings: When we train our model with only word embeddings, we observe that the model struggles to learn sarcastic features in the data since it is difficult to infer sarcasm using only words.
- Only emoji embeddings: When we train our model with only emoji embeddings, we observe that the model performs better than it performed with

word embeddings. This is because emojis are able to convey complex emotions that are essential to detect sarcasm.
- Both word and emoji embeddings concatenated: The word embeddings and emoji embeddings are concatenated horizontally and are given as input to the model. We observe that the model is able to perform considerably better than it did with only word and only emoji embeddings because the model is able to relate complex emotions with the contextual meaning. This enables the model to detect sarcasm more accurately.

VII. Conclusion

Emojis provide a new dimension to social media communication. We study the role of emojis for sarcasm detection on social media. We propose a new deep learning model by introducing an attention layer which helps to model the text and emojis simultaneously for sarcasm detection. The empirical results on real-world datasets demonstrate the effectiveness of the proposed framework.

VIII. Acknowledgements

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