**SARCASM DETECTION FROM USER-GENERATED NOISY SHORT TEXT**

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November 30, 2020  

**ABSTRACT**

Sentiment analysis of social media comments is very important for review analysis. Many online reviews are sarcastic, humorous, or hateful. This sarcastic nature of these short texts change the actual sentiments of the review as predicted by a machine learning model that attempts to detect sentiment alone. Thus, having a model that is explicitly aware of these features should help it perform better on reviews that are characterized by them. Several research has already been done in this field. This paper deals with sarcasm detection on reddit comments. Several machine learning and deep learning algorithms have been applied for the same but each of these models only take into account the initial text instead of the conversation which serves as a better measure to determine sarcasm. The other shortcoming these papers have is they rely on word embedding for representing comments and thus do not take into account the problem of polysemy (A word can have multiple meanings based on the context in which it appears). These existing modules were able to solve the problem of capturing inter sentence contextual information but not the intra sentence contextual information. So we propose a novel architecture which solves the problem of sarcasm detection by capturing intra sentence contextual information using a novel contextual attention mechanism. The proposed model solves the problem of polysemy also by using context enriched language modules like ELMo and BERT in its first component. This model comprises a total of three major components which takes into account inter sentence, intra sentence contextual information and at last use a convolutional neural network for capturing global contextual information for sarcasm detection. The proposed model was able to generate decent results and cleared showed potential to perform state of the art if trained on a larger dataset.

1 **Introduction**

Natural language processing, popularly known as NLP deals in making computers intelligent enough to meaningfully process human language. Some common applications are document topic classification and text summarization. Sentiment analysis is another application in which the goal is to extract a person’s opinion from a piece of text written by them. In recent times, social media has become pervasive in every walk of people’s life. As of late 2019, Facebook has 2.5 billion, Twitter has 321 million monthly active users and Reddit has over 330 million. About 4 petabytes of data is generated every day on Facebook. A little more insight into this figure would show that roughly 4 million likes are generated every minute and close to 350 million photos are uploaded onto Facebook daily. Also, close to 1.42 billion reddit comments are generated across Reddit every month. The sheer number of people involved and their collective activity leads to a vast amount of data being shared between them regarding a wide range of topics. A lot of this information can be of value to many different stakeholders. One example from the recent past is the US elections, wherein a particular political party could gauge people’s sentiment by analyzing online activity. This generation of large amounts of data in a short time becomes too much to handle manually. Hence, social media is the perfect platform to perform any kind of sentiment analysis using NLP. The online Oxford dictionary defines sarcasm as “the use of irony to make or convey contempt”. Merriam-Webster defines it as “a sharp and often satirical or ironic utterance designed to cut or give pain”. Sarcasm is a form of figurative
language whose utterance can alter its sentiment. It is used in daily life to make jokes or at times to criticize people, ideas or events. This ambiguous nature of sarcasm makes it difficult even for humans at times in deciding if the nature of the remark was sarcastic or not.

Given this uniquely confusing nature of sarcasm, it becomes really difficult for NLP based applications such as review summarization and dialogue systems to identify the user’s sentiment. Thus, it is important to have in place a model which is able to classify data as sarcastic or non-sarcastic.

Developing truly conversational speech agents - who can understand all the unique intricacies of the human language - remains one among the most important pending NLP problems of this time. Humans regularly use sarcasm as a crucial part of day-to-day conversation when venting, arguing, or maybe engaging in humorous banter with friends. For an agent to really be conversational, detection of sarcasm may be a must.

Reddit is an online discussion platform, where the community members can post information regarding news, politics, hobbies etc and any other areas of interest. The areas of interests are categorized as subreddits (/news, /politics etc). Understanding sarcasm, which is usually a difficult task even for humans, may be a challenging task for machines. Common approaches for sarcasm detection are supported machine learning classifiers trained on simple lexical or dictionary based features. To date, some research in sarcasm detection has been done on collections of tweets from Twitter, and reviews on Amazon.com. For this task, we have an interest in watching a more conversational medium - comments on Reddit - so as to develop an algorithm which will use the context of the encompassing text to assist determine whether a selected comment is sarcastic or not.

The next section will shed some light on the research that has already happened in this field of sarcasm detection and will also show elaborate some recent advances in the field of natural language processing for sentiment analysis. Then the proposed model will be described by emphasizing on different parts of the model along with their corresponding functioning. The last section will demonstrate how the proposed model was implemented and compared with the existing state of the art modules.

2 Literature Review

The main aim of this sections is to describe different works that have already happened in the field of sarcasm detection and to also give an overview on the recent advances in natural language processing for sentiment analysis. We will first start by describing the previously done work chronologically to showcase different techniques that have already been used to tackle sarcasm detection problems. Recently there have been a lot of advances in the field of natural language especially in language modeling, so next we will try to cover all the new types of language models that have which can be used to solve the problem of sarcasm detection. At the end of this section we will try to introduce our model and how it tries two major limitations of the existing models.

Joshi, Aditya, Vinita Sharma, and Pushpak Bhattacharyya. (2015) [1] presented a computational system that harnesses context incongruity as a basis for sarcasm detection. They used explicit and implicit incongruity features. They used four kinds of features: (a) Lexical, (b) Pragmatic, (c) Implicit congruity, and (d) Explicit incongruity features. They trained their classifiers for different feature combinations using LibSVM with RBF kernel. Precision (P), Recall (R) and F-score for performance evaluation. They introduced inter-sentential incongruity for sarcasm detection, which expanded the context of a discussion forum post by including the previous post in the discussion thread.

Amir, Silvio, et al. (2016) [2] proposed a model to automatically learn and then exploit user embeddings(contextual features of speaker), to be used in concert with lexical signals to recognize sarcasm. The user embeddings required only the text from the speaker’s previous posts. Their model did not require extensive manual feature engineering.

Ghosh, Debanjan, Alexander Richard Fabbri, and Smaranda Muresan.(2017) [3] mainly solved two specific problems: (1) can the conversation context used for sarcasm detection and (2) to realize what parts of the context was responsible for sarcasm. to deal with the primary issue, they investigate both SVM models with linguistically-motivated discrete features and a number of other sorts of LSTM networks(Conditional LSTM network and LSTM networks with sentence level attention on context and reply) which will model both the context and therefore the sarcastic reply. to deal with the second issue, they presented a chemical analysis of attention weights produced by the LSTM models attentively.

They used twitter as their main data source.

Ghosh, Aniruddha, and Tony Veale. (2017) [4] showed significant gains using neural architecture in sarcasm detection accuracy when knowledge of the speaker’s mood at the time of production could be inferred. They show that the mood exhibited by a speaker over tweets leading up to a new post is as useful a clue for sarcasm as the topical context of the post itself. They build CNN-LSTM model by adding input features for the psychological profile of the author and the context of the tweet to those for the tweet itself. The text input layer was initialized with embeddings from Google’s Word2Vec model. The state of mind of the speaker at utterance-time, the values awi(i = 1...11) for each Si are concatenated with the feature vector of & Si in the merge layer. The concatenation layer after BiLSTM combines the feature maps of the source and context (tweets (Sj & Si)) along with a vector of awi(i = 1...11) for the author Ui.

Prasad, Anukarsh G., et al. (2017) [5] compares various classification algorithms such as Random Forest, Gradient
Word embeddings which helps in giving the same word different vector representations based on its context. ELMO is a model which can be given as input to the existing deep classification modules. Introduction of attention mechanisms also played a crucial role in generating state of the art results.

Performance of these models further increased after the introduction of latest language models like Word2Vec, GloVe and BERT. These language modules helped in encoding contextual information into word embeddings. From the literature review we can say that most of the earlier methods for sarcasm detection used simple classification models like SVM, decision trees, logistic regression etc and mainly concentrated on the feature extraction part. Features which they used were also of different types like semantic features, user based features and context based features.

Sarcasm is complex to detect and mostly requires contextual information to identify sarcasm. Introduction and advances in the field of natural language processing made it easier for using deep recurrent neural networks like LSTMs and Bi-LSTM to capture inter-sentence contextual information, which then increased performance of sarcasm detection models. Performance of these models further increased after the introduction of latest language models like Word2Vec, GloVe, ELMO and BERT. These language modules helped in encoding contextual information into word embeddings which can be given as input to the existing deep classification modules. Introduction of attention mechanisms also played a crucial role in generating state of the art results.

These modules were able to solve the problem of capturing inter sentence contextual information but not the intra sentence contextual information. So we propose a novel architecture which solves the problem of sarcasm detection by capturing intra sentence contextual information using a novel contextual attention mechanism.

3 Proposed Model for Sarcasm Detection

This section will give a detailed analysis of the existing language models which will later be used as the embedding layer of the proposed model. After that the architecture of the proposed model will be described.

Recently there has been a lot of research happening in the field of natural processing and mainly in finding a better way of representing words. Word representations play a major role in any text based learning task. Long back people used to use simple TF-IDF representations for representing words. They were very easy to use but at the same time because it was based on the Bag of words model so it was not able to capture the position in text, semantics, co-occurrences in different documents. This problem was solved by Word2Vec based word vectors. Word2Vec vectors showed huge improvement in embedding sub-linear relationships into the vector space of the words but at the same time they were unable to handle out of vocabulary words. Another comparable word representation model is GloVe. GloVe works to fit a giant word co-occurrence matrix built from matrix. GloVe helps in taking into account the semantics and also gives relatively smaller dimension vectors. Word2Vec is a predictive model and GloVe is a count-based model but both lack the capability of solving the problem of polysemy. Polysemy is the capacity of a word or phrase to have multiple meanings. We believe sarcastic comments also in many cases take use of polysemy for intending sarcasm. The word vectors trained by the ELMO model can solve the problem of polysemy. ELMO generates deep contextualized word embeddings which helps in giving the same word different vector representations based on its context. ELMO is a character based language model but Word2Vec and GloVe are word based models. It is claimed that character level
models don’t perform as well as word level models but at the same time word level models face the problem of out of vocabulary words. So to solve this, recently BERT was introduced. BERT’s transformer based sub-words model takes the best of both the world and helps in giving better vector representations. At the same time fine-tuning BERT takes more time compared to other models as BERT contains a total of 12 transformers and 12 self-attention layers. Keeping all these points in mind the following four types of language models will be used later in the experiments for the embedding layer:

- Word2Vec
- GloVe
- ElMo
- BERT

3.1 Proposed Model Architecture

This section will describe the components of the proposed novel architecture in detail. The proposed model called Contextual Attention CNN (CA-CNN) mainly contains three major parts i.e.:

- Two separate bidirectional LSTMs for the parent comment and its corresponding reply comment.
- Our novel contextual attention mechanism.
- A convolutional neural network for classification.

Contextual attention is introduced for capturing the intra sentence attention. This mechanism gathers contextual information between sentences compared to the existing word vectorisation models which captures only character level or word level contextual information. The starting point of this model is the component 1 which takes language model embeddings as input. Then these embeddings for both the comment and reply are passed into two separate Bi-LSTMs for capturing inter-sentence contextual information. Then the output of both the Bi-LSTMs are used for capturing intra sentence contextual information by using the novel contextual attention mechanism which then generates four separate feature maps. These feature maps are concatenated and are passed on to a convolutional neural network for classification.

Figure 1: CA-CNN
classification purposes. For clear understanding, contextual attention inside our complete model is illustrated in Figure 1.

3.1.1 Component 1: Capturing Inter-sentence Contextual Information

The embeddings generated from the language models listed above are fed into two independent Bi-LSTMs, one for the parent comment embeddings and another for the reply comment embeddings. Both the Bi-LSTMs output hidden states of all the LSTM cells along with the final left and right representation of these sentences. The hidden states of parent comment and it’s reply are represented as \([hp1, hp2, \ldots, hpi]\) and \([hr1, hr2, \ldots, hri]\) respectively, final outputs (left and right) for parent comment are represented by \([hpl, hpr]\) and final outputs (left and right) for it’s reply comment are represented by \([hrl, hrr]\).

In general we have used an embedding size of 768 and all the sentences are padded to a size of 100. So this generates an input array shape of \((100, 768)\) for both the sentences (comment as well as reply). Both these embedding arrays are given as input to two separate Bi-LSTMs for capturing inter sentence contextual information of the corresponding sentences. Figure 8, depicts the architecture of this component. The output of this component are the hidden states and the final outputs of both the Bi-LSTMs which will be used to capture the contextual information between the comments and the replies by our proposed novel contextual attention mechanism.

![Figure 2: Component 1: Bi-LSTMs](image)

3.1.2 Capturing Intra-sentence Contextual Information (Our Contribution)

Word embeddings are generated to capture the contextual information within a sentence. We propose contextual attention mechanisms to capture the contextual information between these sentences. Contextual attention leads to production of 4 feature maps i.e. parent comment contexted on reply (right), parent comment contexted on reply (left), reply contexted on parent comment (right), reply contexted on parent comment (left).

Production of all the feature maps follow the same procedure, so explaining one will be enough to give an idea on how contextual attention works. Let’s take an example, in the case of parent comment contexted on reply (right) we first do a dot product of all the hidden states \([hp1, hp2, \ldots, hpi]\) with the final right side output of the reply sentence \([hrr]\), which produces a contextual attention score for all these hidden states. These contextual attention scores are then multiplied by their corresponding hidden states to produce contextually aware representations of these hidden states. These contextually aware hidden state representations are used to create a feature map. In the case of parent comment contexted on reply (left) the contextual attention score are generated by using the final right side output of the reply sentence \([hrl]\) and in the case of reply contexted on parent comment \([hr1, hr2, \ldots, hri]\) are used as hidden states and \([hpl, hpr]\) are used for left and right contextual attention scores respectively. The Contextual attention mechanism is shown in above. These four feature maps represent the total relationship between the comments and replies and can be used for sarcasm detection. In our case because we chose the embedding size to be of 768 dimensions, the CA mechanism led to generation of 4 feature maps of size \((100, 798)\).
3.1.3 Component 3: A convolutional Neural Network for Classification

The above four feature maps are then concatenated (generation a concatenated feature map of shape (100,3072)) and passed to convolutional neural networks(CNN) which contains a total of 6 blocks, each consisting of a convolution layer, a leaky ReLu layer, a batch normalization layer, a regularization layer and a dropout layer. A sigmoid function is used at the end of these 6 blocks for classification purposes. At the end binary cross entropy was used as the loss function of our model. The Figure above depicts the architecture of component 3.

4 Implementation & Results

This section will show how the experiments were conducted, and what were the results. It will start by describing the type of dataset we will be using for experimenting. Then there will be a detailed explanation of the preprocessing steps used for making the data ready to be given as input to different models.
4.1 Dataset

Sarcasm detection may be a complex problem. Sarcasm is usually supported by some quite context and thanks to its contextual nature we believed that we required a parallel dataset which will also provide contextual information about the text to be classified. So it had been decided to use the SARC [9] dataset. This dataset contains 1.3 million Sarcastic comments from the web commentary website Reddit. The dataset was generated by scraping comments from Reddit containing the’s (sarcasm) tag. This tag is usually employed by Redditors to point that their comment is in jest and not meant to be taken seriously, and is usually a reliable indicator of sarcastic comment content. This dataset has balanced and imbalanced (i.e true distribution) versions. (True ratio is about 1:100). The corpus has 1.3 million sarcastic statements, alongside what they skilled also as many non-sarcastic comments from an equivalent source. The info was gathered by Mikhail Khodak and Nikunj Saunshi and Kiran Vodrahalli for his or her article "A Large Self-Annotated Corpus for Sarcasm” [10].

4.2 Data Preprocessing

The dataset contains 3 columns i.e. parent comment (p), parent comment’s reply (r) and a label (l) which shows whether the reply was sarcastic to the parent comment or not. We start by preprocessing our textual data by lower-casing all the sentences, removing unnecessary punctuation’s and stopwords using NLTK. After all this we tokenized all the sentences into a list of words (W1,W2,..........., Wn). Tokens of a parent comment sentence are represented as (W1p,W2p,..........., Wnp) and the tokens of a reply sentence are represented as(W1r,W2r,..........., Wnr). These preprocessing steps are shown in figure above. These steps were required for removing all the unwanted tokens from the sentences. Not all sentences are of the same shape, but at the same time our classification model had a fixed input size. So for the purpose of making the data compatible with the shape of our model input, we paddled all the sentences with special “<PAD>” tokens and made the length of every sentence equal to that of the longest one.

5 Conclusion

In this paper a novel approach was introduced to combat the problem of sarcasm detection by taking into account conversational context as well as contextualized embeddings. The proposed model was able to combat the problem of polysemy by using contextualized language models like ELMO and BERT. In this model a novel attention mechanism was also introduced which helped in taking into account the intra sentence contextual information between reply and comment pair of a Reddit post. To the best of our knowledge this the first time an intra sentence contextual attention mechanism is used to solve the problem of sarcasm detection. The proposed model was able to generate decent results and cleared showed potential to perform state of the art if trained on a larger dataset.

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