Sarcasm Detection Framework Using Emotion and Sentiment Features

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Abstract

Sarcasm detection is an essential task that can help identify the actual sentiment in user-generated data, such as discussion forums or tweets. Sarcasm is a sophisticated form of linguistic expression because its surface meaning usually contradicts its inner, deeper meaning. Such incongruity is the essential component of sarcasm, however, it makes sarcasm detection quite a challenging task. In this paper, we propose a model, which incorporates emotion and sentiment features to capture the incongruity intrinsic to sarcasm. We use CNN and pre-trained Transformer to capture context features. Our approach outperformed previous state-of-the-art results on four datasets from social networking platforms and online media.

1 Introduction

The world’s use of online communications is expanding quickly as social media has become the most important source of news and public opinion about almost every daily topic. The most popular application of social media analysis is detecting consumer sentiment to help businesses and online merchants to address the needs of their clients, including handling and resolving complaints.

However, not always emotions or sentiment are expressed directly. Frequently social media users tend to make their posts or messages sarcastic in order to have better response from the other users and stimulate the virality of social media content. Moreover, negative sarcastic tweets attract substantially higher social media responses when compared to actual negative tweets [15].

Thus, sarcasm identification in online communications, discussion forums, and e-commerce websites have become essential for fake news detection, sentiment analysis, opinion mining, and hate speech detection. However, sarcasm detection appears to be quite challenging task due to it’s sophisticated nature.

The surface meaning of sarcasm frequently contrasts with the underlying deeper meaning, making it a particularly complex kind of verbal expression. Although, this incongruity is the essential component of sarcasm, the intention may also be to appear humorous, make fun of someone, or show contempt. As
a result, sarcasm is seen as an extremely sophisticated and intelligent language construct that presents a number of difficulties for the perception of emotions.

The following example of a tweet illustrates the above mentioned nuances: “On our 6 am walk, my daughter asked me where the moon goes each morning. I let her know it’s in heaven, visiting daddy’s freedom”.

On the surface, this statement seems to indicate that the speaker is enjoying his morning walk with his daughter and telling her amusing stories. However, close examination of the speaker’s emotion and sentiment reveals that the speaker is unhappy and experiencing some unpleasant emotions at the time of speaking.

This is where incongruity between sentiment and emotions plays an important role. Sentiment, emotion and sarcasm are highly interconnected, and one helps in the understanding of the others. We propose a model, which utilizes sentiment and emotion detection and learns their dependencies related to sarcasm. We hypothesized that learning a pattern of contradiction between surface sentiment and intended sentiment is a key component in sarcasm detection.

2 Related Work

While sarcasm detection is still a relatively new field, it has recently drawn more attention from researchers due to the rapid growth of social media and the need for sentiment analysis therein. A number of approaches have been developed and studied in this regard. In this section, we are going to pay attention to works implementing Transformers, Neural Networks or focusing on a relation between sentiment, emotion and sarcasm.

The research [19] proposed a model based on BERT fine-tuned on related intermediate tasks, such as sentiment classification and emotion detection, before fine-tuning it on the target task. Experimental results on three datasets that have different characteristics showed that the intermediate task transfer learning model outperforms many previous models.

The study [3] proposed two novel deep neural network models for sarcasm detection. Models add to the BERT architecture two components, namely affective feature embedding and contextual feature embedding. The two models are different in the way the two components are combined and the input to the affective feature embedding component.

The paper [8] proposed a neural network semantic model composed of Convolution Neural Network (CNN), followed by a Long Short Term Memory (LSTM) network and a Deep Neural Network (DNN). The proposed model outperforms Support Vector Machine applied to the same dataset.

In the work [2], the authors focus on detecting sarcasm in textual conversation from social media websites and online forums. They developed a model consisting of a multi-headed self-attention module and gated recurrent units. Multi-head self-attention module helps in identifying important sarcastic keywords from the input, and the recurrent units learn long-range dependencies between these keywords to classify the input text more accurately. Proposed
approach achieved state-of-the-art results on multiple datasets from social media 
platforms and online networks.

In the paper [5], authors have also hypothesized that sarcasm is closely 
related to sentiment and emotion. They proposed two attention mechanisms, 
where the first segment learns the relationship between the different parts of the 
sentence, and the second segment focuses within the same part of the sentence 
across the modalities. Finally, representations from both attentions are merged 
for multi-task classification task. The research proved that emotions and sen-
timent help to improve the effect of satire detection, however, the experiments 
were performed on MUSArD dataset [4], which consists of audiovisual utter-
ances accompanied by its context, thus providing additional cues for sarcasm 
detection task.

3 Description of Datasets

We conducted experiments on four benchmark datasets: two Reddit [11] sub-
reddits datasets: SARC/movies and SARC/technology, a subset of Internet 
Argument Corpus-V2 [20] (IAC-V2), and Twitter [18]. All of them have been 
widely used in evaluating sarcasm detection. The details are shown in Table 1.

Table 1: Statistics of the experimental data.

| Datasets           | Train          |          | Test          |          |
|-------------------|----------------|----------|----------------|----------|
|                   | Sarcast        | Non-     | Sarcast        | Non-     |
|                   |                | sarcastic|                | sarcastic|
| SARC/movies       | 2,533          | 2,707    | 641            | 669      |
| SARC/technology   | 2,738          | 1,815    | 677            | 462      |
| IAC_V2            | 2,616          | 2,600    | 644            | 660      |
| Twitter (Ptacek et al., 2014) | 22,323 | 25,785 | 5,648 | 6,379 |

3.1 Reddit

Khodak et al. [11] collected SARC, a corpus comprising of 600,000 sarcastic com-
ments on Reddit. We use two subreddits: SARC/movies and SARC/technology 
for sarcasm detection. The subreddits contain news and discussions concerning 
films and development, application and related issues of technology, respectively.

3.2 Internet Argument Corpus

Internet Argument Corpus (IAC) [20] is collected from online political debates 
forum. IAC-V2 [1] is the subset of the Internet Argument Corpus. IAC-V2 
divides sarcasm into three sub-types, (i.e., general sarcasm, hyperbole, and 
rhetorical questions). We use the largest subset (general sarcasm) in our ex-
periments.
3.3 Twitter

We use Twitter dataset provided by Tomáš Ptáček [18], who collected a self-annotated corpus of tweets with the \#sarcasm hashtag. We used English balanced version.

4 Proposed Method

4.1 Overview of the Proposed Approach

The model consists of four blocks: Sarcasm Pre-Trained Transformer (SarcPTT), Emotion Detection Pre-Trained Transformer (EmoDPTT), Sentiment Detection Pre-Trained Transformer (SentDPTT), and CNN block. EmoDPTT and SentDPTT are used as feature extractors and are not trainable during model fitting. Other modules (CNN and SarcPTT) are trainable. The detailed overview of the blocks is presented in the following subsections.

The general flow is presented in Figure [1]. The input text is tokenized via transformer tokenizer \{CLS, T_1, ..., SEP\} and is passed through SarcPTT. The output of this step is a last hidden state, but only vector representation $V_{CLS}$ of the first token (CLS) is used for further processing. After that, the output is passed through Fully Connected Network and new vector $V_i$ is obtained.

The non-trainable blocks (EmoDPTT and SentDPTT) are used as feature extractors. After passing the input text tokenized via transformer tokenizers \{CLS_e, T_1, ..., SEP_e\} and \{CLS_s, T_1, ..., SEP_s\} respectively) through the models, the following features are obtained:

- EmoDPTT vector representation of the first token of the last hidden state: $U_{CLS}$;
- Probability distribution of dimension 28 of EmoDPTT labels, e.g., amusement, relief, disgust, neutral, etc.: \{EL_1, EL_2, ..., EL_28\};
- SentDPTT vector representation of the first token of last hidden state : $S_{CLS}$;
- Probability distribution of dimension 2 of SentDPTT labels, i.e., positive and negative sentiments \{SL_1, SL_2\}.

Similarly to the SarcPTT output, text representations were passed through Fully Connected Networks, and new vectors were obtained: $S_i$ and $U_i$. Probability distributions of labels were concatenated and passed through Fully Connected Network, producing vector $D_i$ as output.

For passing data through CNN block, the input text $T = \{W_1, W_2, ..., W_N\}$ was tokenized using nltk library\[^1\] where each $W_i$ represents a tokenized word. The text $T$ was passed through CNN, and text representations were obtained as

\[^1\] https://www.nltk.org/
vector $C$. Vector $C$ was passed through Fully Connected Network, transforming it into vector $C_l$.

As a final step, all the output feature vectors $V_l, U_l, D_l, S_l, C_l$ were concatenated and passed through Fully Connected Network and Softmax transformation, obtaining the prediction.

We made our code available at GitHub\footnote{https://github.com/Wittmann9/SarcasmTuneUntrainableSentEmo}.

We merged all training parts of the datasets and then we pre-trained RoBERTa model on it using masked language modeling objective.

As an emotion feature extractor, we used BERT model\footnote{https://huggingface.co/bhadresh-savani/bert-base-go-emotion} pre-trained on GoEmotions dataset \cite{6} on multi-label (28) emotion classification task. The input

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Proposed architecture of the model.}
\end{figure}
text was passed through this model and corresponding vector representation of CLS token of the last hidden state was obtained, as well as labels’ distribution.

4.4 Sentiment Detection Pre-Trained Transformer

As a sentiment feature extractor, we used SiEBERT model [9]. It is a fine-tuned on sentiment classification task RoBERTa-large model [13]. The model was trained on 15 datasets from different text sources (reviews, tweets, etc.). We passed the input text through the model and corresponding vector representation of CLS token of last hidden state was obtained, as well as labels’ distribution.

4.5 CNN

We used the CNN architecture following [12], see Figure 2. For processing the input text through CNN, we built a vocabulary dictionary for each dataset separately to create an embedding layer. We used Glove Common Crawl pre-trained vectors (42 billion words version). For words with no pre-trained vectors, we checked their stemmed versions. If no pre-trained embedding were found, random vector was initialized. Then, the input text was encoded into the embedding matrix of shape \((N_W, 300)\), where \(N_W\) is a number of words in the input text and 300 is an embedding dimension.

![Figure 2: CNN block.](https://nlp.stanford.edu/projects/glove/)

We then used convolutions with different filter sizes to extract feature maps from the embedding matrix. Next, we applied the ReLU activation and max-over-time-pooling to reduce each feature map to a single scalar. Then we concatenated these scalars into a vector and obtained vector representations for the texts.

5 Description of Baselines

Since prior studies lack uniform datasets, we run baseline comparison experiments using our datasets and either open source code or reproduced code.

[4]https://nlp.stanford.edu/projects/glove/
5.1 NBOW

Neural bag-of-words (NBOW) baseline takes an average of word vectors in the given text as sentence representation and feeds it into standard logistic regression model. As word vector representations we used GloVe 100-dimensional vectors [16] pre-trained on Wikipedia and an archive of English newswire text named Gigaword 5, the version contains 6 billion tokens.

5.2 CNN

We used CNN configuration following [12]. The overall architecture is as follows. The padded embedded sentences are processed via the CNN cells. Next, the ReLU activation function and Max Pooling are applied. The concatenated outputs from the previous step are processed by linear layers to produce the distribution of the classes.

5.3 CNN-LSTM-DNN

This model [8] is a combination of CNN, LSTM, and DNN. It stacks two layers of convolution and two LSTM layers, then passes the output to a DNN for prediction.

5.4 SAWS

SAWS [14] model proposes a self-attention mechanism of weighted snippets to model the incongruity between sentence snippets.

5.5 ELMo

This model [10] uses character-level vector representations of words, based on embeddings from ELMo [17] language model architecture. Subsequently, word embeddings passed on to a BiLSTM, the output hidden states are max-pooled and fed to the 2-layer feed-forward network. The output of this step is then fed to the final layer of the model, which performs the binary classification.

6 Experiments

We implemented our model using Pytorch Lightning [7] and transformers library [21]. For each dataset, we have experimented with different sets of hyperparameters. The best performing hyperparameters are presented in the Table 2.

7 Results and Discussion

We used precision, recall, macro-weighted F1, and accuracy scores as the evaluation metrics. We emphasized F1 score as the main metric in our analysis. Table 3 reports the results of our method as well as baselines.
Table 2: Best performing hyperparameters for various datasets.

| Parameter     | SARC/movies | SARC/technology | IAC_V2 | Twitter (Ptacek et al., 2014) |
|---------------|-------------|-----------------|--------|--------------------------------|
| max_length    | 18          | 14              | 16     | 16                             |
| max_epochs    | 12          | 30              | 20     | 20                             |
| lr            | $1e(-5)$    | $1e(-5)$        | $1e(-5)$ | $1e(-5)$                      |
| batch_size    | 8           | 4               | 32     | 32                             |

Table 3: Results of the experiments.

| Datasets      | Model        | Precision | Recall | Acc. | F1   |
|---------------|--------------|-----------|--------|------|------|
| SARC/movies   | NBOW         | 0.60      | 0.60   | 0.60 | 0.60 |
|               | CNN          | 0.65      | 0.65   | 0.64 | 0.65 |
|               | CNN-LSTM-DNN | 0.58      | 0.58   | 0.59 | 0.58 |
|               | SAWS         | 0.65      | 0.65   | 0.65 | 0.65 |
|               | ELMo         | 0.72      | 0.57   | 0.68 | 0.64 |
|               | Our Model    | 0.72      | 0.74   | 0.73 | **0.73** |
| SARC/technology | NBOW       | 0.63      | 0.64   | 0.64 | 0.64 |
|               | CNN          | 0.67      | 0.67   | 0.66 | 0.66 |
|               | CNN-LSTM-DNN | 0.65      | 0.58   | 0.56 | 0.61 |
|               | SAWS         | 0.65      | 0.65   | 0.66 | 0.65 |
|               | ELMo         | 0.76      | 0.81   | 0.73 | 0.78 |
|               | Our Model    | 0.77      | 0.84   | 0.75 | **0.80** |
| IAC-V2        | NBOW         | 0.72      | 0.71   | 0.72 | 0.71 |
|               | CNN          | 0.71      | 0.70   | 0.70 | 0.70 |
|               | CNN-LSTM-DNN | 0.63      | 0.75   | 0.65 | 0.68 |
|               | SAWS         | 0.75      | 0.75   | 0.75 | 0.75 |
|               | ELMo         | 0.78      | 0.74   | 0.77 | 0.76 |
|               | Our Model    | 0.86      | 0.84   | 0.85 | **0.85** |
| Twitter       | NBOW         | 0.75      | 0.75   | 0.75 | 0.75 |
|               | CNN          | 0.80      | 0.80   | 0.80 | 0.80 |
|               | CNN-LSTM-DNN | 0.77      | 0.82   | 0.80 | 0.80 |
|               | SAWS         | 0.81      | 0.81   | 0.81 | 0.81 |
|               | ELMo         | 0.83      | 0.86   | 0.85 | 0.84 |
|               | Our Model    | 0.93      | 0.94   | 0.94 | **0.93** |

For each dataset, we trained each baseline model and our model. We observed that the basic models (i.e., NBOW, CNN, and CNN-LSTM-DNN) perform poorly compared to other models. Those models simply encode input text to capture local semantic information, which is insufficient to derive global context or recognize incongruity between words.

However, out of three above-mentioned models, CNN showed higher results...
on SARC/movies and SARC/technology subreddit. One of the reasons leading
to such result could be in the relative shortness of texts in those datasets.
The statistics are presented in Table 4. Particularly, median and mean for
SARC/movies dataset ($Med = 10, \mu_i = 12.24$) are significantly lower than median
and mean for IAC-V2 dataset respectively ($Med = 39, \mu_i = 17.61$).

Table 4: Statistics of the datasets.

| Dataets          | Median | Mean   | Variance       | Max  | Min  |
|------------------|--------|--------|----------------|------|------|
| SARC/movies      | 10     | 12.24  | 8.814760348    | 138  | 1    |
| SARC/technology  | 12     | 13.88  | 9.330058949    | 103  | 1    |
| IAC-V2           | 39     | 50.63  | 36.05135226    | 212  | 10   |
| Twitter          | 17     | 17.61  | 6.257155903    | 64   | 1    |

SAWS and ELMo models outperformed basic models. Compared to the pre-
vious baselines, SAWS and ELMo models are built to capture more sophisticated
patterns, such as text fragments incongruity and complex morpho-syntactic fea-
tures. However, the ELMo model is almost always a few points ahead of SAWS,
showing that purely character-based input and subsequently obtained contextual embeddings capture more useful sarcastic information.

For all datasets, our model outperformed all baselines for all metrics and
achieved state-of-the-art performance. The best improvement of the F1 metric
was achieved on IAC-V2 and Twitter dataset. Specifically, the F1 metric is 9%
higher, compared with the previous state-of-the-art version. For SARC/movies
dataset, F1 metric is improved by 8%, and for SARC/technology dataset F1
metric is improved by 2%.

We used different transformer models fitted on emotion and sentiment de-
tection tasks to obtain contextualized and more deep features. This allows the
model to learn complex patterns from different perspectives, e.g. “emotional”
and “sentiment”.

Furthermore, the CNN block of our model utilizes Glove embeddings in order
to capture semantic relationships of words and general context. Our model
shows that modeling dependencies between emotion, sentiment and sarcasm is
an important feature for sarcasm detection task.

Interestingly, all models show its best results on Twitter dataset, and its
performance decreases when the length of the input text is relatively long (IAC-
V2) or short (SARC/movies). It suggests that more ideas should be investigated
for texts of particular length.

8 Conclusion and Future Work

In this paper, we introduced a novel sarcasm detection method, which incorpo-
rates both emotion and sentiment features. Proposed approach contains four
components: Sarcasm Pre-Trained Transformer (SarcPTT), Emotion Detec-
tion Pre-Trained Transformer (EmoDPTT), Sentiment Detection Pre-Trained Transformer (SentDPTT), and CNN block.

EmoDPTT and SentDPTT are used as feature extractors and are not trainable during model fitting. These models are used to highlight the parts of the sentence which provide crucial cues for sarcasm detection. CNN module extracts semantic relationships of words and general context features. SarcPTT is pre-trained on train chunks of datasets, so the model learns sarcasm patterns. The output from each block is passed through a fully-connected network and then through a linear layer to get the final classification score.

Experiments are conducted on four datasets: SARC/movies, SARC/technology, IAC-V2, and Twitter. They show significant improvement over the state-of-the-art models using all evaluation metrics. Our results show that emotion and sentiment features along with contextual knowledge play a crucial role in the performance of sarcasm detection.

Even though our model outperformed all the baselines, all the methods are struggling on too short or too long texts. In our future works we are planning to address this challenge.

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