Does Punctuation Matter? An Empirical Analysis of Sentiment Tools

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Abstract. In the written text, punctuation is a replacement of the prosody in the speech; it is the most important sign of emotional coloring. In our paper, we explored the role of three popular models which include VADER, TextBlob and a BERT-based model in addressing changes in sentiment on the basis of punctuation alone. We created a distinct set of sentences having variant punctuations and annotated each with human sentiment scores to give a direct basis of comparison. The findings revealed that the BERT model was better than the others in the classification of positive and neutral sentiments, however, all the models failed to recognize nuanced emotional changes that occurred because of punctuation like exclamation points and ellipses, especially in the detection of subtle emotions like sarcasm. In general, our research highlights the necessity of including punctuation-sensitive mechanisms to reflect human perception more closely.

Keywords: Sentiment Analysis, Punctuation, Stylistic Cues, Emotion Detection

1 Introduction

Sentiment analysis is a relatively new method that has been integrated into Natural Language Processing (NLP) [1]. Traditional NLP pipelines are becoming more and more problematic due to the use of abbreviations, emoticons, and punctuation [2]. It supports the applications such as social media sentiment monitoring to handling feedback on customers on large scale [3]. The values are the best manifested on microblogs and web forums, where short, informal bursts of feelings and opinions constantly circulate between users.

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The modern architectures such as BERT are made to capture rich semantics in the word patterns, but it is restricted by a naive approach to a significant element of written language : punctuation marks [4]. Pre-processing is often used in most workflows; all it does is strip off the punctuations, leaving sentences as lists of words with less context. This may make their effect even. For example, "I'm fine." reads as an utterance bound up in itself, but "I'm fine..." suggests doubt or reluctance, and "I'm fine!!!" indicates strength or even temperance. These hints are unconsciously picked by people but people who have been trained to remove punctuation tend to overlook the difference completely.

It has already been demonstrated that non-standard writing characteristics, including the lengthening of words (e.g., "soooo good") [5] or the use of emoticons [6, 7], are strongly correlated with sentiment in informal text. Punctuation is of this family of cues. Characteristics like ellipses, exclamation points, and interrogative clauses usually have emotive force, and serve as an alternative to intonation or stress in written language. Their contribution is even more important in short form such as tweets, in which a small number of marks can change the entire tone of a message, occasionally including such nuances as sarcasm.

This paper is an analysis of the effectiveness of current sentiment analyzers to capture such shifts. Our sentences are built into a dataset of base sentences systematically altered with the help of punctuation, each variant marked with sentiment by human readers. Using this dataset, we consider three popular tools, namely VADER, TextBlob, and a particular BERT-based classification model ('cardiffnlp/twitter-roberta-base-sentiment-latest'). Using model outputs in comparison with where such systems do not succeed, we find where they fail, and what their failing tells about their treatment of punctuation. We find that there is a need for punctuation-sensitive methods of sentiment analysis, not as an adornment but as a fundamental constituent of the manner in which emotional sense is conveyed.

2 Literature Review: The Role of Punctuation in Automated Sentiment Analysis

2.1 Punctuation as a Communicative Device

Punctuation isn't just about structure; it is a communicative device. It sets the tone, controls the rhythm, and in text-only contexts, it is often the main replacement for the prosody (sound patterns) of speech [8]. In contrast to spoken language, where emotional meaning is added by the use of pitch, stress, and timing, digital text is strongly dependent on signs such as exclamation points, ellipses, and question marks to add emotional color [9]. Let us use a simple example: "Sure." may sound neutral or dismissive, whereas "Sure!" conveys enthusiasm, and "Sure...?" suggests doubt. These minor changes show exactly why punctuation is imperative to reading sentiment [10].

2.2 Empirical Evidence from Communication Studies

Studies keep on showing that punctuation shifts how we perceive meaning [8, 11]. Adding pauses with periods between words (e.g., "No. Just. Stop.") showcases negative emotions like disgust or frustration feel stronger. Brody and Diakopoulos [5] had noted that elongation of words (e.g., "soooo good") and repetition of exclamation points enhance positive affect. Likewise, Carvalho et

al. [6] and Liebrecht et al. [11] stated that punctuation marks are important indicators of irony and sarcasm. More importantly, Sidi et al. [12] cautioned that these indicators can also be deceptive: repeated punctuation can showcase a positive or an urgent point to the senders, but the recipients may see it negatively, viewing the sender as amateurish. All these findings clearly show that punctuation is not ornamental but semantic.

2.3 Punctuation in Sentiment Analysis Models

Regardless of its importance, sentiment analysis models vary significantly in their punctuation behavior.

2.3.1 VADER

VADER [13] was built specifically to handle the punctuation cues found in social media. It has a set of rules (or heuristics) that boost sentiment scores whenever it sees exclamation points or repeated symbols, and it also accounts for capitalization [14]. For example, “great!!!” has a higher positive rating than “great”, representing an effort by VADER to mimic human reading. Research confirms that the accuracy of VADER decreases when punctuation is eliminated [14], which shows the extent to which the system relies on punctuation. Though simple, this open, rule-driven design provides VADER with some benefits, especially in short and informal texts where punctuation is highly influential.

2.3.2 TextBlob

TextBlob, takes a lexicon-based approach with statistical smoothing, so it isn’t very sensitive to punctuation [15]. Unlike VADER, it lacks explicit heuristic rules for punctuation. Instead, any impact punctuation has on the sentiment score is incidental, derived merely from token associations in the training corpus (e.g., if “!!!” appeared frequently alongside positive adjectives). Consequently, TextBlob tends to underestimate the intensity of expressive text, treating punctuation as noise rather than a semantic amplifier.

2.3.3 BERT

BERT [16] is a more complicated case. Being a transformer, it tokenizes punctuations marks and appends them into its input embeddings. This theoretically would imply that punctuation should have an impact on the output of the model. In fact, Ek et al. [17] discovered that BERT pays little attention to punctuations not necessarily important. It can be very lacking in the change of meaning with placements; such as the distinction between ”Let’s eat, grandma” and the meaning behind ”Let’s eat grandma” is different [4]. They noted that swapping punctuation changes sentence representation in BERT insignificantly. This implies that this model has not had the experience of learning the practical role of these symbols. Lamprou et al. [18] even remarked that the embeddings of BERT are closer to human brain activity in the event that punctuations are removed. This may mean that the model may even ignore punctuations in favor of noise. To address this, more recent

hybrid models[19] are making attempts to incorporate punctuation to the attention mechanisms and achieve superior performance in the short-text sentiment analysis.

In the entirety of the research, one can see a very misaligned connection in this that although humans are very dependent on punctuation to convey emotion, conventional NLP tools do not take advantage of punctuation. Systems such as VADER operate on rule-based and hard-coded heuristics, which is effective in non-scholarly and casual writing [14]. The hybrids based on lexicon, such as TextBlob, do not pay much attention to these marks, thus they lose the emotional intensity. Even more intricate models of deep learning such as BERT, where punctuations are treated as tokens, do not tend to understand the pragmatic value of such symbols [4, 17]. This disconnect gives us the reason as to why we must also consider punctuation in a systematic manner, otherwise the emotion color that punctuation creates can be overlooked or misunderstood by sentiment analyzers.

3 The Linguistic Role of Punctuation in Sentiment

Punctuation is typically considered to be an adjunct of language, a collection of signs that contain text and make it more easily readable. But it performs many other functions than clause separation. In written speech, rhythm, emphasis, and even the emotive impact of a message can be directed by punctuation [9], a literal analog of intonation in speech [8]. Nonetheless, most sentiment analysis systems underemphasize punctuation, considering it as a secondary fact or omitting it altogether. Such simplistic treatment of a basic component of written language, punctuation, usually limits its effectiveness.

Ignoring these hints may deprive meaning and lead to a hollow interpretation of sentiments. Various marks serve various functions. One obvious intensifier is the exclamation mark. “This is good,” says positivity, but “This is good!” brings excitement and “This is horrible!” magnifies frustration [14]. A mark of doubt is minor. In social media posts, it often means doubt or sarcasm [20]; “you really enjoyed that?” implies doubt instead of mere inquiry [21].

Ellipses tend to suggest uncertainty or something that is to be imagined: ”It was an interesting movie...” has a reservation, the plain sentence does not. The symbols complicate its interpretation even more. Irony, a sheer reversal of the feeling, may be demonstrated in the quotation marks [6]. A review that says that a movie is brilliant can imply the opposite, and this is particularly a problem with systems that are largely reliant on the examination of single words. On the contrary, parentheses dilute or narrow down. A positive note, such as The food was excellent (at least at a roadside diner) is a caveat.

Lastly, the digital punctuation has become more developed and has incorporated emoticons and emojis as a way of expressing a mood. Even a word that is neutral, such as okay, can become either supportive with a smiley face :) or disappointed with a sad face :(. These signals are important to human readers, and it has been shown that even the classifiers perform better when emoticons are present than in their absence

Combined, punctuations have more of an effect than form. They change the tone, sharpen or soften the sentiment, and sometimes even change the intended meaning. Any method of sentiment analysis that overlooks them runs the danger of missing the cues, which make human communication

so emotional.

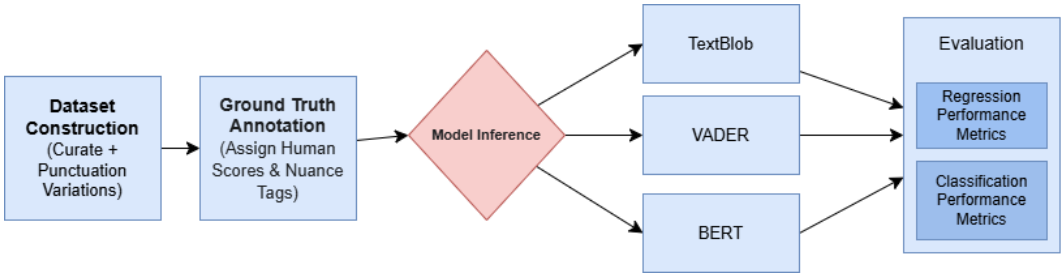


Fig. 1. Overall Workflow of Punctuation-Aware Sentiment Analysis.

4 Models for Evaluation

We selected three popular models with varying architectural philosophies to examine a range of sentiment analysis methods. These include VADER, TextBlob and a BERT-based classifier. In this way, we can compare and contrast a rule-based model, a lexicon-based statistical model, and a modern deep learning architecture.

- **VADER (Valence Aware Dictionary and Sentiment Reasoner):** VADER was chosen as our foundation model since it follows a rule-based framework, which encompasses punctuation heuristics (such as capitalization and exclamation marks), making it theoretically sensitive to the elements that we would be investigating [13].
- **TextBlob:** TextBlob is a hybrid model based on lexicons. Although it lacks clear punctuation rules, its statistical model may have learned certain relevant patterns on the training data (the Movie Review corpus dataset) [15]. It is highly popular; therefore, it serves as a strong benchmark.
- **BERT (Bidirectional Encoder Representations from Transformers):** BERT is a deep learning model. Being a transformer, it processes punctuations as a consecutive input and learns context using large amounts of text [16]. The issue of whether modern architectures can naturally derive the practical role of punctuation without explicit rules is examined by comparing BERT with other models.

By comparing these three models, we can evaluate the way in which various techniques, ranging from hand-crafted rules to deep contextual embedding, address sentiment changes caused by punctuation.

5 Methodology

To test the three types of sentiment models, we developed a methodology that uses a custom-built dataset designed to isolate the effect of punctuation, as well as a comprehensive evaluation protocol.

5.1 Dataset Design and Annotation

Our primary contribution in this project is a new collection of 200 sentences that was designed expressly to evaluate the effects of punctuation on eliciting sentiment. We did not use a large general-purpose corpus but built a specialized one, in which the lexical content is frequently fixed and punctuation is modified.

5.1.1 Dataset Construction

We selected base sentences from general expressions and online reviews. Every base sentence was then systematically manipulated to produce pairs or groups of sentences that are lexically similar but differ in practical and emotional meaning due to punctuation. It is a methodology that was employed in previous experiments to control linguistic effects [4, 8]. Key variations included:

- **Exclamation Marks (!)** to indicate excitement or intensity.
- **Ellipses (...)** to mean hesitation, weariness or sarcasm.
- **Question Marks (?)** to express doubt or rhetorical unbelief.
- **Quotation Marks (” ”)** to show the ironic distance or scepticism.

These specific marks were chosen because they act as the primary prosodic markers in the written text. They are the closest functional equivalents to pitch, stress, and intonation in spoken language. By using these, we ensure that any observed shift in sentiment was driven strictly by the 'tone' encoded in the punctuation, rather than by the changes in word choice. Table 1 presents some of the examples from our dataset, where punctuation changes the subjective ratings of sentiment and nuance.

Table 1: Examples of Punctuation-Driven Sentiment Shifts in the Dataset

Type	Sentence	Human Score	Nuance Tag
Genuine	This should be fun!	0.8	Enthusiasm
Sarcastic	This should be fun...	-0.6	Sarcasm/Weariness
Genuine	It was a learning experience.	0.4	Gratitude
Sarcastic	It was... a ”learning experience.”	-0.6	Sarcasm
Genuine	The service here is efficient.	0.6	Satisfaction
Sarcastic	The service here is ”efficient.”	-0.6	Criticism

5.1.2 Ground Truth Annotation

A reliable ground truth was established by manually annotating each of the 200 sentences. Each entry received:

- A continuous Human Score from -1.0 (very negative) to +1.0 (very positive).
- A Nuance Tag summarizing the exact emotional nuance (e.g., *Sarcasm, Enthusiasm, Skepticism*). These labels were subsequently grouped into broader categories: Sarcasm / Irony, Genuine Positive and Genuine Negative, to enable deeper analysis.

This dual annotation allows for both accurate regression analysis and more general categorical analysis.

5.2 Models for Evaluation

The three models chosen to take part in the current study (VADER, TextBlob, and BERT) are explained in Section IV.

5.3 Evaluation Protocol

Performance of each model was evaluated through two approaches.

5.3.1 Regression Analysis

The continuous sentiment scores of the individual models were directly compared to the Human Score. We measured performance using Mean Absolute Error (MAE), which measures the average prediction error; Root Mean Squared Error (RMSE), which highlights larger deviations by assigning greater weight to extreme errors; and R-squared (R^2), which evaluates how effectively the model explains variability in the observed data.

5.3.2 Classification Analysis

To perform a categorical assessment, all continuous scores (both human and model-generated) were transformed to three categories: Positive (score > 0.05), Neutral and Negative (score < -0.05). We then measured Accuracy, Weighted F1-score (to account for class imbalance), and created Confusion Matrices to understand the patterns of errors. We selected a threshold of ± 0.05 rather than a strict 0.0 to define neutrality. This creates a small buffer for noise, ensuring that sentences with barely noticeable sentiment scores are not arbitrarily forced into positive or negative categories. This is a standard way for making the conversion from regression scores to categories more stable.

5.3.3 Nuance-Based Subset Analysis

We divided the dataset into two subsets to differentiate the impact of sarcasm: Standard Sentiment (genuine positive/negative sentences) and Sarcasm/Irony. The F1-score was computed for each subset to assess how well the models handle this type of nuance.

6 Results and Analysis

We have shown that there is a distinct performance difference between the models when used for intensity estimation and categorization tasks, as their performance drops significantly when dealing with sarcastic text.

6.1 Overall Model Performance

6.1.1 Regression Performance: The Challenge of Intensity

Table 2 shows that the values of the R^2 are consistently negative, which highlights the challenge that all three models face as they cannot predict the actual intensity of human feelings nor match human ratings. VADER performs the best in this regard, with the lowest MAE and RMSE, whereas BERT performs the worst, showing the lowest correlation, as indicated by the lowest value of R^2.

Table 2: Overall Regression Performance Metrics

Model	MAE	RMSE	R^2
VADER	0.611	0.750	-0.523
TextBlob	0.645	0.752	-0.530
BERT	0.722	0.922	-1.298

The highly negative R^2 score for BERT (-1.298) requires specific explanation. Unlike VADER and TextBlob, which naturally output a continuous intensity score, the BERT model functions as a probabilistic classifier. It predicts the likelihood of a class rather than an exact position on a scale. When we mapped these probabilities to a linear regression scale, this caused a mismatch. The negative value essentially shows that while BERT is excellent at determining the category of

sentiment (positive vs. negative), its probability confidence does not align linearly with the human intensity scale of -1 to +1.

6.1.2 Classification Performance: BERT's Superiority in Categorization

BERT has the highest accuracy and F1 score because it is illustrated in 3, which is above TextBlob and VADER. It is a sign that although BERT does not effectively predict the degree of sentiment, its contextual comprehension also enables it to detect more abstract categories of sentiment.The confusion matrix analysis suggests that both VADER and TextBlob are very easily misled by positive lexical cues, leading to the misclassifications of a large percentage of actual negative sentences as positive (52 in the case of VADER and 68 for TextBlob). In contrast, BERT has a significantly higher recall for positive statements (94 %). Although it does not do this perfectly (it still makes errors), it correctly classifies more negative instances (29), which results in its stronger overall performance.

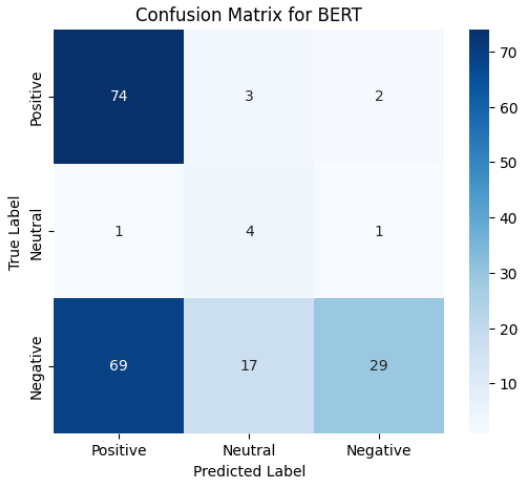


Fig. 2. Example of sentiment polarity distribution.

Table 3: Overall Classification Performance Metrics

Model	Accuracy	F1-weighted
VADER	0.350	0.303
TextBlob	0.335	0.310
BERT	0.535	0.497

6.2 The Impact of the Sarcastic Punctuation: A Detailed Analysis

This is how the main research finding manifests itself as we compare the performance of this model on regular sentences and sarcastic ones. The results outlined in Table 3 and 4 provide good reasons why the nuances related to punctuation marks are a major shortcoming of sentiment models.

Table 4: F1-Scores on Standard vs. Sarcastic Subsets

Model	F1 (Standard)	F1 (Sarcasm/Irony)
VADER	0.597	0.114
TextBlob	0.573	0.143
BERT	0.810	0.219

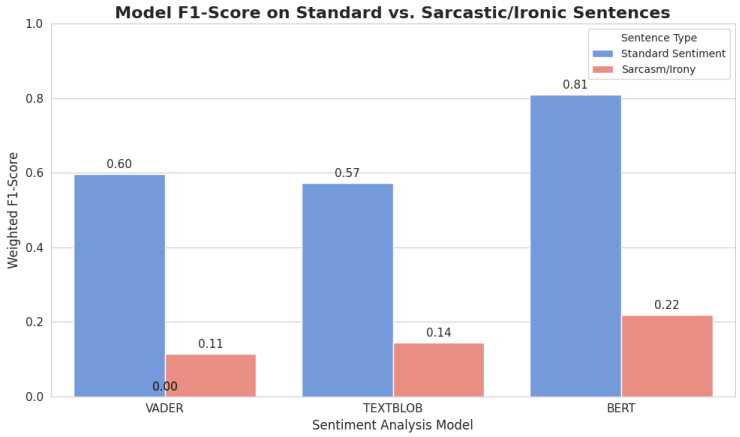


Fig. 3. Model F1-Scores on Standard vs. Sarcastic/Ironic Sentences, showing a significant performance drop for all models on sarcastic text.

Figure 3 powerfully illustrates two key conclusions:

1. **Rule-Based and Lexical Models Are Unreliable for Nuanced Text:**

   VADER and TextBlob do not work well in the case of sarcasm. The F1 score of VADER reduces to 0.114 on sarcastic sentences compared to 0.597 on regular sentences, a drop of 81 percent. TextBlob also experiences a 75 percent decline, that is, 0.573 to 0.143. It demonstrates that such models can be easily deceived by positive words (e.g great, fun) in the case when the punctuation marks show sarcasm.

2. **BERT Is Significantly More Robust:** Compared to other models, BERT is more stable.Its F1 score of 0.219 is close to half that of VADER, even though it performs poorly on sarcastic

texts. This is due to its structure that breaks down words in their context and punctuation. Through the enormous sizes of datasets BERT has been imprinted to pick out patterns in the form of a positive. phrase, followed by an ellipsis of negative feeling, this enables it to have a more in-depth semantic interpretation.

7 Conclusion

Our research focused on determining how punctuation symbols impact the performance of sentiment analyzers, which is a minor but meaningful linguistic construct that delivers a lot of emotional background. We created a set of base sentences randomly manipulated with punctuations and used sentiment analyzers: VADER, TextBlob, and the BERT-based model cardiffnlp/twitter-roberta-sentiment-lates. The effectiveness of these tools in capturing emotional changes brought about by punctuation was compared with human ratings.

The analysis has shown that VADER performs better than other models in continuous regression scores, but the negative R^2 among models shows that different models fail to represent the broad and complex range of human emotions. BERT, however, was very strong in the sentiment (positive, negative, neutral) classification with the highest accuracy compared to VADER and TextBlob. However, none of the models performed well, particularly with negative sentiments which were often misclassified as positive, especially when sarcasm is involved where positive words are used to express negative feelings with modified punctuation. This shows a common weakness in detecting subtle emotional clues expressed through punctuations.

In general, all these scores reveal the discrepancy between human perception of punctuation and the interpretation of punctuation by the current models. Even highly advanced algorithms such as BERT, which are robust in their ability to understand content, show weaknesses in consistently processing the affective aspects of punctuation, especially when working with sarcasm.

This reflects a bigger problem faced by older sentiment models, where the length of a word, the presence of emoticons, or its punctuation is ignored. In the future, research should develop models sensitive to punctuation, with larger word representations, features of the models' voice and intonation, or by training these models on datasets where punctuation is meaningful. Treating punctuation as if it were only for decoration is a failure. Punctuation should be treated as important and a carrier of an emotional message. This makes building sentiment analysis models complicated; it is the reason why it is so difficult for these models to exhibit an accurate sense of the structures of human communication. This is the main reason why developing systems that correctly represent the understanding of human language is difficult without cultivating such awareness. This sensitivity is no longer a luxury, but a necessary part of developing sentiment analysis models. It enables these models to go beyond literal meaning and understand the subtle aspects of human communication.

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