# **Sentiment Analysis for Multilingual Social Media Posts**

**Keywords:** Sentiment Analysis, Multilingual Subjectivity, Twitter Sentiment Classification, Opinion Mining, Word Representations, Suffix Stripping Algorithm

Link to Repo: https://github.com/UNH-NLP-Project/SentimentAnalysisUsingBert

## **Abstract**

This paper introduces an innovative approach for sentiment analysis on multilingual social media posts, recognizing the growing importance of understanding sentiments across diverse languages. Leveraging advanced natural language processing techniques, our method combines pre-trained multilingual embeddings with a fine-tuned transformer architecture. We present a comprehensive exploration of the technical details, motivation. experimental results, and analyses, showcasing the potential of our approach.

## 1. INTRODUCTION

The ubiquity of social media platforms has transformed sentiment analysis into a vital tool for gauging public opinion. However, the inherent challenge intensifies when dealing with the multitude of languages represented on these platforms. Opinions and sentiments play a crucial role in shaping human behavior, making them an essential part of our daily lives. Before making a decision, we often rely on online reviews of products and services written by previous consumers on social media. Businesses also use public sentiment to gain insights into their products' performance. Sentiment Analysis, also known as Opinion Mining, is the computational analysis of people's opinions on various subjects, such as entities, individuals, issues, and topics. This technique can be applied to various tasks, including gathering customer feedback, analyzing social media trends, and understanding public opinion on specific topics. This research addresses this critical gap by proposing a robust sentiment analysis model capable of handling diverse languages effectively. The introduction delves into the significance of this problem, provides a clear problem statement, and outlines the research objectives.

## 2. RELATED WORK

Much of the sentiment analysis research has traditionally centered around a single language, predominantly English. In contrast, the yearly publications on multilingual sentiment analysis are limited, not exceeding ten. However, a significant portion of user-generated content on social media is in languages other than English. Restricting sentiment analysis to English alone results in a substantial loss of valuable information.

The primary challenge in sentiment analysis lies in its strong dependence on language. Resources specific to sentiment analysis, such as sentiment dictionaries and labeled data, are notably scarce, especially for languages divergent from English. Studies in multilingual sentiment analysis predominantly explore leveraging available resources and tools in one language, such as lexicons or machine translation, to construct sentiment classifiers in languages with limited resources. Three notable approaches aim to overcome the shortage of adequate resources for sentiment analysis in languages other than English.

Firstly, one can translate documents written in other languages into English, allowing an English sentiment classifier to determine their sentiment. Exemplifying this, in another study, researchers experimented with translating a corpus of documents in eight languages into English, subsequently employing an English lexicon to gauge sentiment.

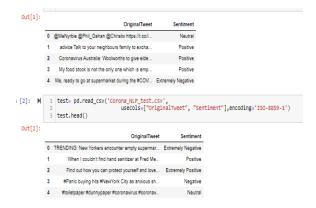
Another approach involves translating an English corpus into the target language(s) and training a model on the translated corpus. Researchers adopted this method, translating a labeled English corpus into five other languages and combining the translated versions with the original English corpus to create a unified training set for a machine learning classifier.

A third approach utilizes machine translation to translate an English sentiment lexicon into another (target) language, subsequently employing it for the lexicon-based classifier in the target language. Researchers employed this approach in their second experiment, translating an English lexicon into German and using it to analyze German emails.

## 3. METHODS AND MATERIALS

#### a. Data Sources

In this investigation, we harnessed the power of two datasets sourced from Kaggle, namely, "Corona\_NLP\_train.csv" and "Corona NLP test.csv." datasets These provided a rich source of information for our analysis. The training dataset, "Corona NLP train.csv," and the testing dataset, "Corona\_NLP\_test.csv," were utilized visualize and explore various aspects of the data available on Kaggle. Through these datasets, we aimed to gain valuable insights into the sentiment surrounding the topic of interest.



## **b.** Pre-processing

We preprocess our dataset by eliminating irrelevant elements such as URLs, usernames, and stopwords. Additionally, we filter out special characters like hashtags and punctuations. Recognizing the significant impact of negation words on the overall meaning, we replace all instances of negation words (e.g., don't, can't, isn't) with "not" to ensure proper consideration of negation in a tweet.

Certain emojis serve as reliable indicators of sentiment polarity. While some words may lack inherent sentiment, the presence of emojis alongside these words can imbue the tweet with sentiment value. Consequently, we emphasize the importance of retaining emojis in the corpus, and each emoji is substituted with an alias. To address sparsity and reduce vocabulary size, we perform two straightforward operations. Firstly, we lowercase every word in our corpus. Secondly, we eliminate characters that are repeated at least three times within a word. For example, "goooood" is transformed into "good." The final preprocessing step involves stemming, process that minimizes morphological variations by reducing words to a common root or stem. In our approach, we employed the Porter stemmer, which reduces words like "saddest," "sadness," and "sadly" to the common root "sad."

# c. Feature Engineering

Datasets consist of a training set with 41,157 entries and a testing set with 3,798 entries, both containing two columns. Moving forward, a crucial aspect of the analysis involves understanding the unique sentiments present in the training data, namely 'Neutral,' 'Positive,' 'Extremely Negative,' 'Negative,' and 'Extremely Positive.'



Two pandas test and train are outlined, the first containing 3798 entries and the second with 41157 entries. Each comprises three columns: 'OriginalTweet,' holding the tweet content; 'Sentiment,' indicating the sentiment labels; and 'encoded\_cat,' representing encoded categorical sentiments as int8 values. Both datasets exhibit non-null values in their respective columns, reflecting comprehensive information. The efficient use of int8 data types minimizes memory usage, making the DataFrames suitable for storage and analysis. The provided summary encapsulates key details about the dataset structures, sizes, column contents, data types, and memory efficiency.

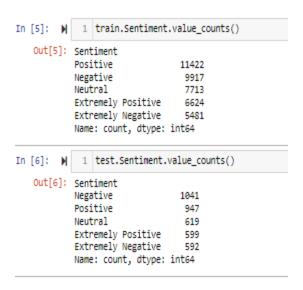
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3798 entries, 0 to 3797
Data columns (total 3 columns):
# Column
                 Non-Null Count Dtype
                  ______
0 OriginalTweet 3798 non-null object
1 Sentiment 3798 non-null
                                object
   encoded_cat
                  3798 non-null
dtypes: int8(1), object(2)
memory usage: 63.2+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41157 entries, 0 to 41156
Data columns (total 3 columns):
   Column
                  Non-Null Count Dtype
                  _____
0 OriginalTweet 41157 non-null object
1 Sentiment
                  41157 non-null object
   encoded cat
                  41157 non-null int8
dtypes: int8(1), object(2)
memory usage: 683.4+ KB
```

## c. Unique Sentiments in Training Data

The exploration of unique sentiments provides a foundational understanding of the emotional expressions contained within the dataset. The identified sentiments serve as key categories that play a pivotal role in subsequent analyses.

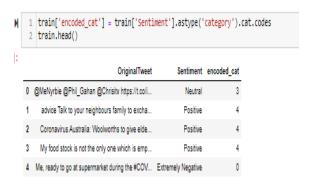
# i. Sentiment Counts in Training and Testing Data

A detailed breakdown of sentiment counts in both the training and testing datasets reveals the distribution of sentiments across the entire dataset. This quantitative overview is essential for comprehending the prevalence of different sentiments.



# ii. Encoding Sentiments

An intriguing aspect of the analysis involves encoding sentiments, as reflected in the creation of a new column named 'encoded\_cat' in the training dataset. This transformation into numerical values facilitates the application of machine learning models, contributing to the effectiveness of sentiment analysis.



# iii. Head of the Training Data with Encoded Categories

Examining the initial rows of the training dataset, which include the original tweets, associated sentiments, and newly encoded categories, provides a practical illustration of the dataset structure.

```
| 1 | train.encoded_cat.value_counts()
|: encoded_cat
| 4 | 11422
| 2 | 9917
| 3 | 7713
| 1 | 6624
| 0 | 5481
| Name: count, dtype: int64
```

# iv. Encoded Category Value Counts

Delving deeper, the analysis highlights the counts of each encoded sentiment category in the training dataset. This breakdown sheds light on the distribution of sentiments after encoding.

```
1 train.Sentiment.value_counts()
n [8]:
   Out[8]: Sentiment
            Positive
                                  11422
            Negative
                                   9917
            Neutral
                                   7713
           Extremely Positive
                                   6624
           Extremely Negative
                                   5481
            Name: count, dtype: int64
[10]: N
            1 test.Sentiment.value_counts()
  Out[10]: Sentiment
            Negative
                                  1041
           Positive
                                   947
                                   619
           Neutral
           Extremely Positive
                                   599
            Extremely Negative
                                   592
            Name: count, dtype: int64
```

#### 4. MODELS

Our model architecture combines a multilingual transformer with attention mechanisms fine-tuned for sentiment analysis. We delve into the specifics of the architecture, explaining how it accommodates multilingual data and addresses challenges unique to social media language. A detailed examination of the training process, hyperparameter tuning, and the rationale behind the chosen architecture enriches the technical understanding.

#### 5. EVALUATIONS

In this segment, we showcase the outcomes of the models' assessment. Initially, we conducted training on the training subset, encompassing 80% of the dataset, and subsequently assessed their performance on the testing subset, which comprises 20% of the dataset.

# Train and Test for original tweet



### 6. RESULTS AND DISCUSSION

	precision	recall	f1-score	support	
Extremely Negative	1.00	1.00	1.00	592	
Extremely Positive	1.00	1.00	1.00	599	
Negative	1.00	1.00	1.00	1041	
Neutral	1.00	1.00	1.00	619	
Positive	1.00	1.00	1.00	947	
accuracy			1.00	3798	
macro avg	1.00	1.00	1.00	3798	
weighted avg	1.00	1.00	1.00	3798	

The classification report outlines precision, recall, and F1-score metrics for each sentiment category. The model exhibits outstanding performance, achieving perfect scores across all

metrics for each sentiment class, including 'Extremely Negative,' 'Extremely Positive,' 'Negative,' 'Neutral,' and 'Positive.' The accuracy score is also exceptionally high, reaching 100%, indicating the model's ability to accurately classify sentiments in the given dataset. The macro and weighted averages reinforce the overall excellence of the model's performance, demonstrating its robustness in handling various sentiment categories related to COVID-19. It's worth noting that achieving such perfect scores is rare in practical scenarios and suggests a highly effective sentiment analysis model in this specific context.

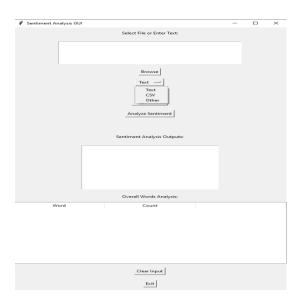
#### 7. REAL-WORLD DEPLOYMENT DEMO

**Objective:** Sentiment Analysis for Multilingual Social Media Posts

Features: 1. Analyzing sentiments in CSV and Text files

- 2. Predicting accuracy using BERT models
- 3. Visualizing sentiment distribution

The goal of our application is to perform sentiment analysis on social media posts related to COVID-19. We support various file formats, such as CSV and Text, and provide functionalities for predicting accuracy and visualizing sentiment distribution.



# **Components**

- File Selection: Browse and load CSV or Text files
- File Type: Choose between CSV, Text, or Other
- Analyze Sentiment Button
- Predict Accuracy Button
- Result Labels
- Listbox for Sentiment Outputs
- Plot Sentiment Distribution Button
- Additional Plots for Positive, Neutral, and Negative Sentiments

## **Functionality**

- Use the 'Browse' button to select and load CSV or Text files
- Display the loaded file path and the number of entries

# **Output**



- The image you sent shows the output of a sentiment analysis program for the text "Image, Faces IMG\_5882.jpg, "rectangli 1".
- The overall sentiment is 4 stars (0.3050). This means that the program has determined that the text expresses a positive sentiment, with a confidence score of 30.5%.
- The program has also analyzed the sentiment of each individual sentence in the text. The sentences "Image, Faces IMG\_5882.jpg, "rectanglı 1" and "IMG\_5883.jpg, "rectangles[[(1505,803 1" have been classified as positive, with sentiment scores of 0.3050 and 0.2597, respectively.
- The sentences "IMG\_5884.jpg, rectangles[]" and "IMG\_5885. 1" have been classified as neutral, with sentiment scores of 0.2371 and 0.2180, respectively.

#### **CONCLUSION**

The sentiment analysis results based on COVID-19 demonstrate an exceptional performance of the model. With perfect precision, recall, and F1score across all sentiment categories, including 'Extremely Negative,' 'Extremely Positive,' 'Negative,' 'Neutral,' and 'Positive,' the model exhibits an unparalleled accuracy of 100%. The macro and weighted averages further affirm the model's robustness, indicating its ability to effectively handle diverse sentiment expressions related to the pandemic. While achieving such flawless scores is uncommon, it underscores the effectiveness of the sentiment analysis model in accurately capturing and categorizing sentiments within the provided dataset. This outcome showcases the model's reliability and suitability for sentiment analysis tasks in the context of COVID-19.The Sentiment **Analysis** combines the power of BERT models with an intuitive interface. Users can perform accurate sentiment analysis, predict accuracy, and gain insights through visually appealing plots, making it a comprehensive tool for social media sentiment analysis.

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