Unsupervised Sentiment Analysis of Social Media Text: An Emotion Approach

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Abstract

In this study, we aim to address the challenge of conducting sentiment analysis on text found on social media, considering both explicit emotions and the usage of emoticons. Our approach is unsupervised, meaning that we will not train any models but instead rely solely on emotions and emoticons to determine the sentiment of the text in an unsupervised manner. Furthermore, we will compare our approach with other unsupervised models, such as "Vader" and "TextBlob", to evaluate their effectiveness compared to our unsupervised solution.

1 Introduction

Natural language processing (NLP) is a subfield of artificial intelligence that deals with the interaction between computers and humans using natural language. It involves the development of algorithms and models that can understand, interpret, and generate human language. NLP has numerous applications in fields such as information retrieval, machine translation, and text classification. Sentiment analysis is a crucial task in natural language processing (NLP) that aims to extract subjective information from text and understand the overall opinion, emotion, or attitude of the writer. In this paper, we propose a novel approach for sentiment analysis based on emotions and emoticons. We first extract emoticons from the text, and then use them to identify the underlying emotions.
In this study, two models were developed: SEU and SEU_2, with slightly different approaches. In the following chapters, everything will be explained in detail.

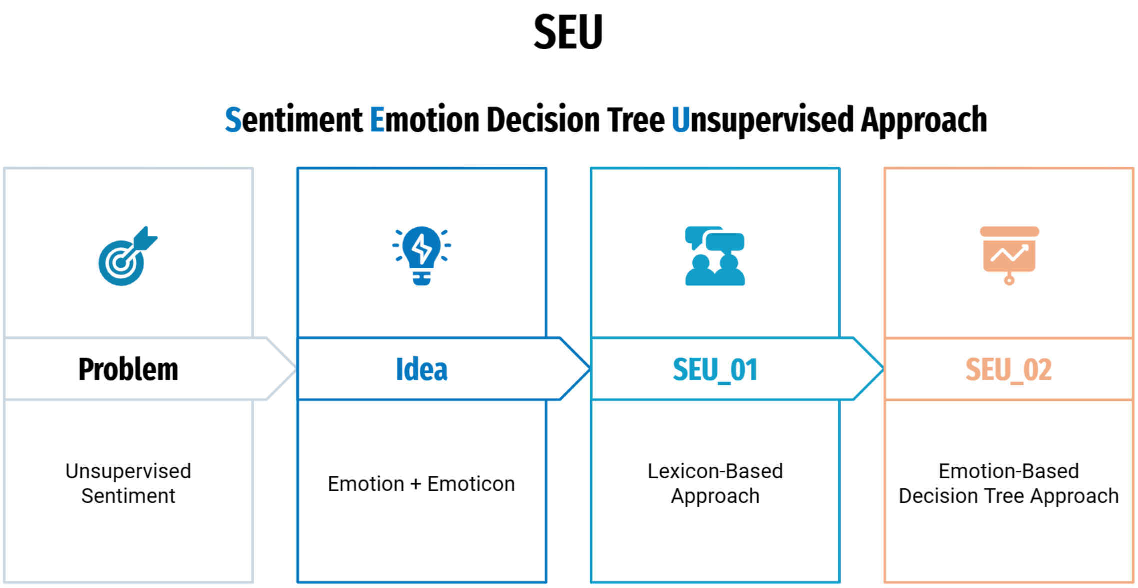


Figure 1: SEU

2 Dataset

In this research, we used two different datasets from Twitter to increase the probability of emojis in the text. In the following sections, we will describe the details of the two datasets used and how they were utilized in our analysis.

2.1 Twitter US Airline Sentiment

The Twitter US Airline Sentiment dataset is a collection of tweets related to sentiment towards six major US airlines. The dataset contains over 14,000 tweets, gathered from February 2015 to April 2015 and include information such as the text of the tweet, the sentiment expressed in the tweet (positive, negative, or neutral), the airline mentioned in the tweet, and the username of the person who posted the tweet. The dataset was created for the purpose of sentiment analysis and natural language processing research, and it is commonly used as a benchmark dataset for evaluating the performance of various sentiment analysis models.

2.2 T4SA

"Twitter for Sentiment Analysis" dataset developed by the Italian Natural Language Processing Lab. The dataset consists of a collection of tweets and their associated images, gathered from July to December 2016. The tweets were obtained via Twitter's Sample API and were pre-processed to exclude tweets that did not contain static images, were not written in English, had a text length less than 5 words, or were retweets. The dataset includes approximately 3.4 million tweets and 4 million images, each labeled according to the sentiment of the text as predicted by a classifier (positive, negative, or neutral). We utilized this dataset as source of data for our sentiment analysis study. Each tweet and image was labeled according to the polarity of the sentiment of the text (negative = 0, neutral = 1, positive = 2) using an LSTM-SVM architecture.

3 Models - Vader and TextBlob

In this study, we investigate the effectiveness of two popular sentiment analysis libraries, NLTK's VADER and TextBlob, in determining the sentiment expressed by emoticons. VADER, or the Valence Aware Dictionary and sEntiment Reasoner, is a lexicon-based model that utilizes a combination of lexical heuristics and pre-trained models to determine the sentiment of a given text. One of its key strengths is its ability to handle the use of emoticons in text, as it has a specific lexicon of emoticons that have been labeled with sentiment scores. On the other hand, TextBlob is a simple natural language processing library that utilizes a pre-trained model to classify the sentiment of a given text. It also has a built-in sentiment analysis feature which can classify the sentiment of text, including emoticons.

3.0.1 Preprocessing Dataset

The T4SA dataset was analyzed, which contains information on tweets. The dataset already provided scores for positivity (POS), negativity (NEG), and neutrality (NEU) for each element, which were calculated by the authors using a NLP model. A "compound" value was calculated using the following formula: **(POS - NEG) / (POS + NEG + NEU)**.

The compound value enabled the determination of the general sentiment expressed in the dataset elements. To convert the compound value into a precise sentiment (negative, neutral, or positive), the following ranges were utilized:

- Values less than -0.05 were classified as negative;
- Values between -0.05 and 0.05 were classified as neutral;
- Values greater than 0.05 were classified as positive.

These ranges were chosen as they allowed for accurate discrimination between sentiments based on the calculated compound values. In particular, a lower threshold value was chosen for negative sentiments in order to avoid assigning a neutral sentiment to dataset elements with a compound score close to zero but with a slight predominance of negative scores. Lastly, a new column was added to the dataset, named "Sentiment", which contains the calculated sentiment for each element based on the compound value and the utilized thresholds. This column provided a comprehensive view of the sentiment expressed in the tweets present in the dataset.

The T4SA dataset was preprocessed by removing useless text such as links, tags, and hashtags. The dataset was then tokenized and stop words were removed. Additionally, two new columns were added to the dataset, 'Vader-Compound' and 'textblob-Compound', which calculated the compound sentiment using the Vader library from NLTK and TextBlob from NLTK.

In the US Airline Sentiment dataset, preprocessing was performed by eliminating unnecessary content such as links, tags, and hashtags. The dataset underwent tokenization and removal of stop words, but stemming was not implemented due to its impact on reducing prediction accuracy. As a result, an un-stemmed text was favored for analysis. Furthermore, the dataset was enriched with 'Vader-Compound' and 'textblob-Compound' columns, calculated using the Vader and TextBlob libraries from the NLTK library respectively, to determine the overall sentiment score of each observation. It is worth mentioning that emoticons were retained, but testing showed that even the most common emoticons such as hearts and smiling or frowning faces were not taken into account.

Both datasets were preprocessed following these steps:

- Remove useless text such as links, tags, and hashtags;
- Tokenization;
- Remove stop words;
- Add columns 'Vader-Compound' and 'textblob-Compound' which calculated the compound sentiment using the Vader library from NLTK and TextBlob from NLTK

3.1 Test Vader and TextBlob

In the following sections, we will present classification reports that showcase the performance metrics of precision, accuracy, recall, and f1 score, obtained through the analysis of text using the "Vader" and "TextBlob" models. A classification report provides information on precision, recall, f1-score, and support for each class.

- Precision measures the proportion of true positives to true positives plus false positives
- Recall measures the proportion of true positives to true positives plus false negatives
- Support is the number of examples for each class.

Macro avg and weighted avg are two types of averages that can be used to calculate the average of values in a classification report.

- Macro avg takes the average of precision, recall, and f1-score for each class and then calculates the average of these values, the unweighted average.
- Weighted avg takes into account the relative support for each class, the number of observations in each class.

3.1.1 Test Vader with Airline dataset

	precision	recall	f1-score	support
negative	0.89	0.44	0.59	9178
neutral	0.36	0.44	0.39	3099
positive	0.32	0.86	0.47	2364
accuracy			0.51	14641
macro avg	0.52	0.58	0.48	14641
weighted avg	0.69	0.51	0.53	14641

Figure 2: Test Vader with Airline dataset

As we can see from the figure, we have an average accuracy of 0.51 with a strong precision (0.89) in the Negative classes and a mean F1 Score of 0.48 and a weighted mean F1 Score of 0.53.

3.1.2 Test TextBlob with Airline dataset

	precision	recall	f1-score	support
0	0.89	0.30	0.44	9178
1	0.29	0.62	0.40	3099
2	0.34	0.72	0.46	2364
accuracy			0.43	14641
macro avg	0.51	0.54	0.43	14641
weighted avg	0.67	0.43	0.44	14641

Figure 3: Test TextBlob with Airline dataset

As we can see from the figure, we have an average accuracy of 0.43, worse than Vader's with a strong precision (0.89) in the Negative classes and a mean F1 Score of 0.43 and a weighted mean F1 Score of 0.44.
From this first analysis, we can conclude that at least for this dataset, the sentiment expressed by Vader is more truthful.

4 Introduction to SEU

SEU (Sentiment Emotion Unsupervised), which is an unsupervised classification model that uses emoticons as indicators of the sentiment of text written on social media such as Twitter, Reddit, or Facebook. This approach is supported by studies that have shown the impact of emoticons on the sentiment of text.[2][3] Thus, a dataset was obtained from Kaggle that gathered the instances of emojis from multiple datasets and evaluated them using a compound score that considers both positive and negative occurrences in which the particular emoji appears. [4]
Moreover, besides emojis, another element that could influence the sentiment of a text are emotions. To provide an interpretation of the sentiments in a text, a dataset from saifmohammad.com was used. The NRC Emotion Lexicon is a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). The annotations were manually done by crowdsourcing. The emotions present in the dataset refer to verbs or adjectives in different forms, so their interpretation was studied considering the different forms, for example the word "Hate." In its form "Hate," it expresses feelings of (Anger, disgust, fear, negativity, sadness). On the other hand, in its form "Hating," it expresses feelings of (Anger, negativity), with other variations also present in the forms "Hateful," "hating," and "hatred." A table serves as an example.

Emotion Table “HATE”

Emotion

Word	Anger	Anticipation	Positive	Joy	Surprise	Trust	Negative	Sadness	Disgust	Fear
Hate	●						●	●	●	●
Hating	●						●			
Hatred	●						●	●	●	●

Figure 4: Emotion Hate

This also on positive words such as ”Happy.”

Emotion Table “Happy”

Emotion

Word	Anger	Anticipation	Positive	Joy	Surprise	Trust	Negative	Sadness	Disgust	Fear
Happily			●	●						
Happiness		●	●	●						
Happy		●	●	●		●				

Figure 5: Emotion Hate

Given this, it was considered advisable to refrain from implementing any form of text stemming in order to prevent the loss of valuable information.[5][6]

4.1 SEU - Models

Therefore, a model was created that takes a raw text and first performs preprocessing by following these steps:

- Remove Text Useless: Removing from the text (links, hashtags, mentions, and any other form of special characters through regular expressions);
- Tokenization;
- Remove stop word.

With reference to the aforementioned datasets, two compounds were derived: the Emoji Compound and the Emotion Compound. In regards to the emojis, the sum of all emoji compounds present in the text was calculated, then divided by the number of occurrences, producing an arithmetic average. Concerning emotions, polarities were determined based on a given schema:

- Anger: -1
- Anticipation: 1
- Positive: 2
- Negative: -2
- Disgust: -1
- Fear: -1
- Joy: 1
- Sadness: -1
- Surprise: 1
- Trust: 1

As demonstrated, the decision was made to assign robust polarities of +2 and -2 to words labeled "Positive" and "Negative", respectively. Moreover, a new emotion named "Contrast" has been introduced, which emerges when a text showcases conflicting emotions, such as Fear and Joy, Positive and Disgust, and so on. The inclusion of this emotion will facilitate future enhancements to the model. Afterward, the emoji and emotion compounds are calculated by summing them up and dividing the result by the number of occurrences, producing an arithmetic average. It was deemed appropriate to assign equivalent weighting to both compounds. It is noteworthy that the model is also capable of generating sentiment predictions for Italian phrases. This is because the NRC dataset associates the corresponding word in various languages, including Italian, with its English counterpart. Although this relationship is primarily based on literary translation, and thus the model's accuracy may decrease, it is still valuable to examine the model's output for sentiment prediction and the corresponding emotions expressed as a percentage, for both English and Italian phrases.

4.1.1 Positive phrase

Italian: La gioia che provo quando vedo i miei cari felici mi riempie il cuore di calore e di amore, rendendo la mia vita più luminosa e più bella. (0.8888888888888888, ['33.33% joy', '33.33% positive', '16.67% anticipation', '16.67% trust'])
English: The joy I feel when I see my loved ones happy fills my heart with warmth and love, making my life brighter and more beautiful. (0.9333333333333333, ['40.00% joy', '40.00% positive', '10.00% anticipation', '10.00% trust'])

4.1.2 Negative phrase

Italian: La tristezza che provo quando non riesco a raggiungere i miei obiettivi mi fa sentire debole e inadeguato, minando la mia autostima. (0.25, ['13.33% negative', '13.33% sadness', '20.00% trust', '13.33% Contrast', '13.33% anticipation', '13.33% joy', '13.33% positive'])
English: The sadness I feel when I fail to reach my goals makes me feel weak and inadequate, undermining my self-esteem. (-0.5555555555555556, ['33.33% negative', '33.33% sadness', '16.67% trust', '16.67% Contrast'])

4.1.3 Neutral phrase

Italian: La neve che cade dal cielo imbianca il paesaggio. (0.6666666666666666, ['100.00% positive'])
English: The snow falling from the sky whitens the landscape. (-0.14285714285714285, ['25.00% negative', '25.00% sadness', '25.00% positive', '25.00% Contrast'])

4.1.4 Contrast phrase

Italian: La gratitudine che provo per le opportunità che ho avuto nella vita si mischia con la tristezza per le occasioni perdute e le scelte sbagliate.
(0.13333333333333333, ['10.00% joy', '20.00% positive', '10.00% surprise', '20.00% negative', '20.00% Contrast', '10.00% sadness', '10.00% trust'])
English: The gratitude I feel for the opportunities I have had in life mixes with the sadness for missed opportunities and wrong choices. (-0.08333333333333333, ['12.50% joy', '12.50% positive', '25.00% negative', '25.00% Contrast', '12.50% sadness', '12.50% trust'])

4.1.5 Contrast phrase + Emoticon

The gratitude I feel for the opportunities I have had in life mixes with the sadness for missed opportunities and wrong choices (heart) .
(0.3313768115942029, ['12.50% joy', '12.50% positive', '25.00% negative', '25.00% Contrast', '12.50% sadness', '12.50% trust'])
The gratitude I feel for the opportunities I have had in life mixes with the sadness for missed opportunities and wrong choices (Cry).
(-0.08835504885993481, ['12.50% joy', '12.50% positive', '25.00% negative', '25.00% Contrast', '12.50% sadness', '12.50% trust'])

4.2 SEU - Results

4.2.1 Test SEU_01 with Airline dataset

	precision	recall	f1-score	support
0	0.83	0.36	0.50	9178
1	0.31	0.43	0.36	3099
2	0.21	0.56	0.30	2364
accuracy			0.41	14641
macro avg	0.45	0.45	0.39	14641
weighted avg	0.62	0.41	0.44	14641

Figure 6: Test SEU_01 with Airline dataset

4.2.2 Test SEU_01 with T4SA dataset

	precision	recall	f1-score	support
0	0.48	0.53	0.50	178583
1	0.20	0.31	0.24	211438
2	0.78	0.64	0.70	789936
accuracy			0.56	1179957
macro avg	0.48	0.49	0.48	1179957
weighted avg	0.63	0.56	0.59	1179957

Figure 7: Test SEU_01 with T4SA dataset

4.2.3 Confusion Matrix Airlines SEU_01

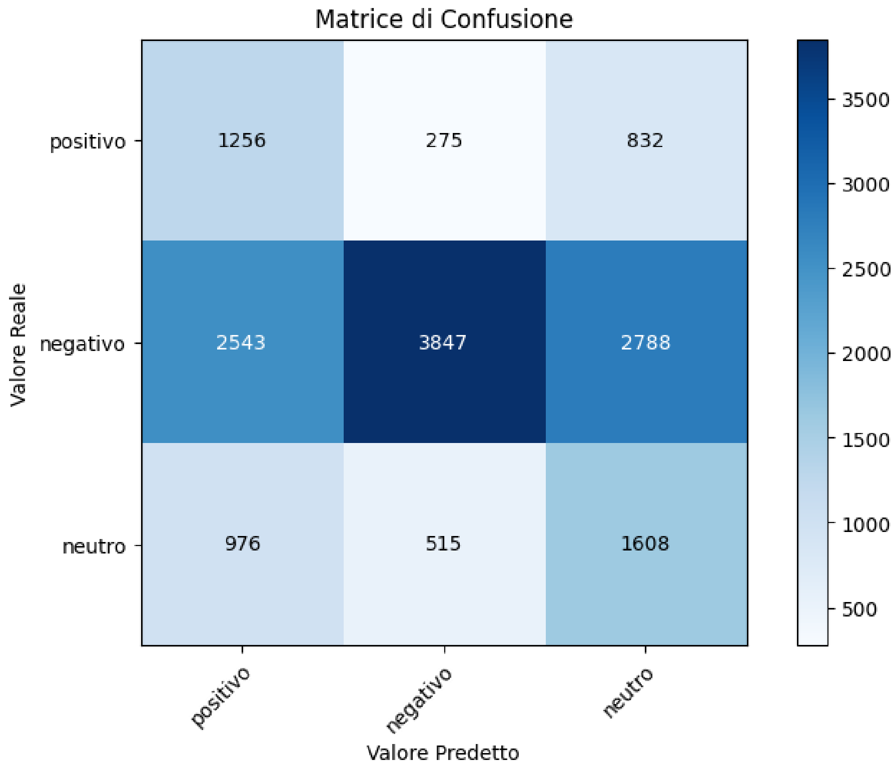


Figure 8: Confusion Matrix Airlines SEU_01

4.2.4 Confusion Matrix T4SA SEU_01

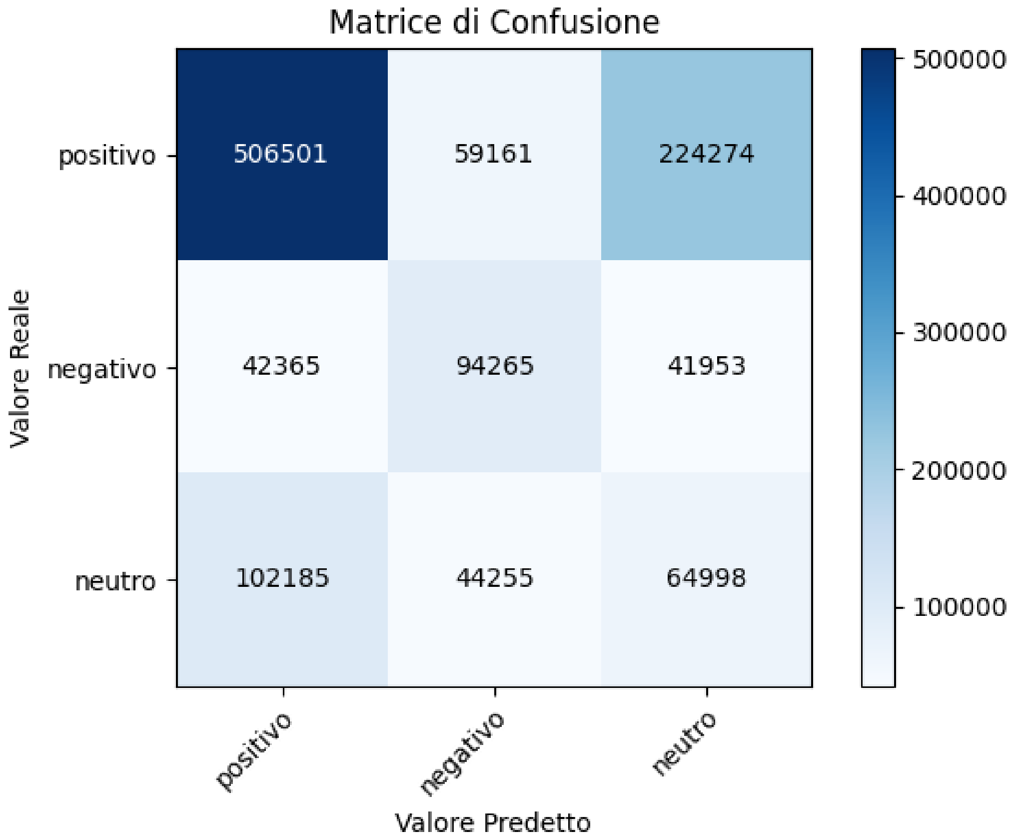


Figure 9: Confusion Matrix T4SA SEU_01

5 SEU_02 Emotion

The initial results of SEU_01 (as shown in Figures 5 and 6) had an accuracy range of 41% to 56%. Afterward, the low F1 score (0.24) for neutral emotions in the T4SA dataset and a slightly higher F1 score (0.30) for positive emotions in the Airline dataset were investigated. The analysis of mislabeled sentences revealed that the NRC Emotion Lexicon dataset did not include some words, such as "great," "thanks," "like," and "amazing," which, although not emotions themselves, had an impact on the mislabeling of certain sentences.

- "I like it"
- "Very great"
- "Thanks so much"
- "It's amazing, thanks"

5.1 Update SEU_02

The SEU system has been updated to version SEU_02 with the following changes:

1 The sentence structure was analyzed using Spacy and NLTK, and the dependency tree was extracted.

2 A custom "Compound" field with a polarized emotion value was added to each node in the dependency tree.

3 The polarity of certain sentiments, such as anticipation, surprise, and trust, was changed from positive to neutral. Positive and negative sentiments are now based on the following emotions: Positive_Emotion = ['positive', 'joy'] Negative_Emotion = ['negative', 'anger', 'disgust', 'fear', 'sadness'] Neutral_Emotion = [Anticipation, Surprise, Trust]

4 For each node in the tree, the "compound" field was filled with the sentiment polarity of that specific word. If the word was not present in the list of Emotions, it was passed to the sentiwordnet of nltk.corpus along with its grammatical identifier within the sentence.

5 A negation identification function was created: negation_words = ['not', 'n't', 'never', 'no', 'nothing', 'nowhere', 'noone', 'none'] along with a regular expression that identified their use within a word, invalidating the path in the tree and setting the compound to -1.

6 Starting from the root, a weighted sum of the "Compound" of the root's children is performed. If a negation is found in a particular child path, that path is set to (-1). Once the recursion returns to the root, each direct child node of the root in its "Compound" field has the weighted sum of its children and itself, or (-1) if one of its children is a negation. Subsequently, the sentiment is calculated by multiplying the "Compound" field of the root with all children that are equal to -1 and adding the results together with the sum of the other children, all of which is then divided by the number of direct children of the root that are not equal to 0.

5.2 Formalization

Let T be a dependency tree.
Let R be the root of the tree T, where $R.Compound$ is the sentiment of R.
Let V_i be the children of R where i ranges from 0 to n and V_i.Compound sentiment of V_i.
Let $list(Tv_i, ...Tv_n)$ list of direct children of Root : $\forall\ TV_i$

$$TV_i = Sum(TV_i) = \sum_{i=0}^{n} W_i \cdot S(T_i)$$

Where $S(T)$ is the function that calculates the weighted sum of the nodes in the tree V_i .

Let $Valid\_Children \in N$:

$$\sum_{i=0}^{n} [a_i \neq 0]$$

Then:

$$Sentiment(T) = \begin{cases} \text{Null} & \text{if } T = 0 \\ R.Compound & \text{if } T.Children = 0 \\ & or\ Valid\_Children = 0 \\ \dfrac{\left(\sum_{i=1}^{n} \text{list}(\text{Tv}_i, ...Tv_n) \setminus (\text{-1})\right) + \left(\text{R.Compound (-1) } \forall (-1) \in \text{list}(\text{Tv}_i, ...Tv_n)\right)}{Valid\_Children} & \text{if } (-1) \in \text{list}(\text{Tv}_i, ...Tv_n) \\ \dfrac{\sum_{i=1}^{n} \text{list}(\text{Tv}_i, ...Tv_n) + \text{R.Compound}}{Valid\_Children} & \text{else} \end{cases}$$

Figure 10: Formalization of SEU_02

5.3 Decision Tree SEU_02

Below are some examples of negative, positive, and neutral sentences analyzed with SEU_02

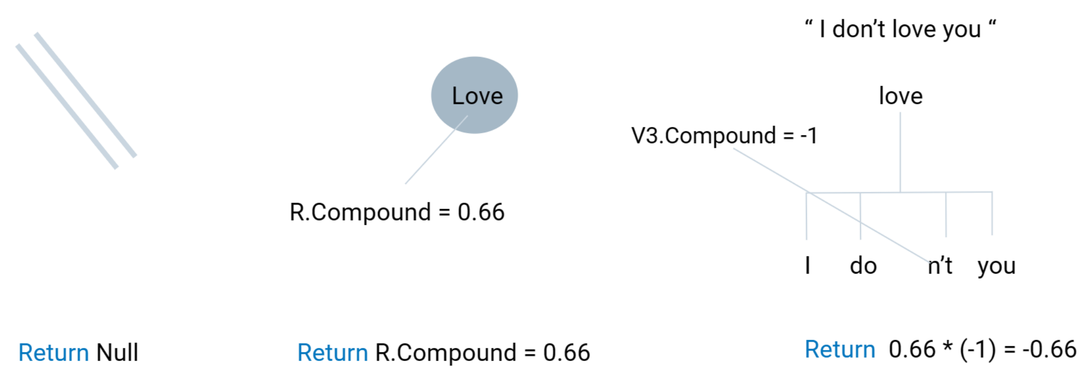


Figure 11: Negative

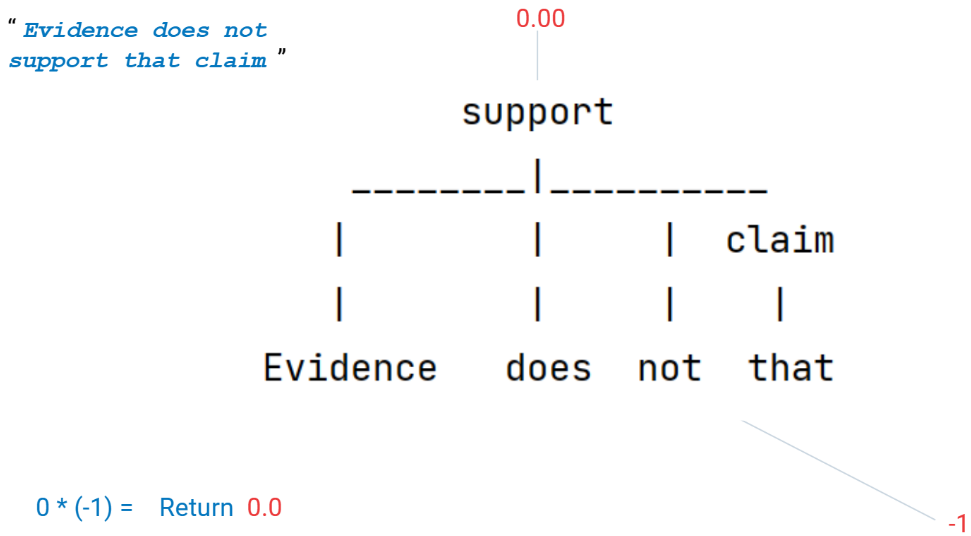


Figure 12: Neutral example

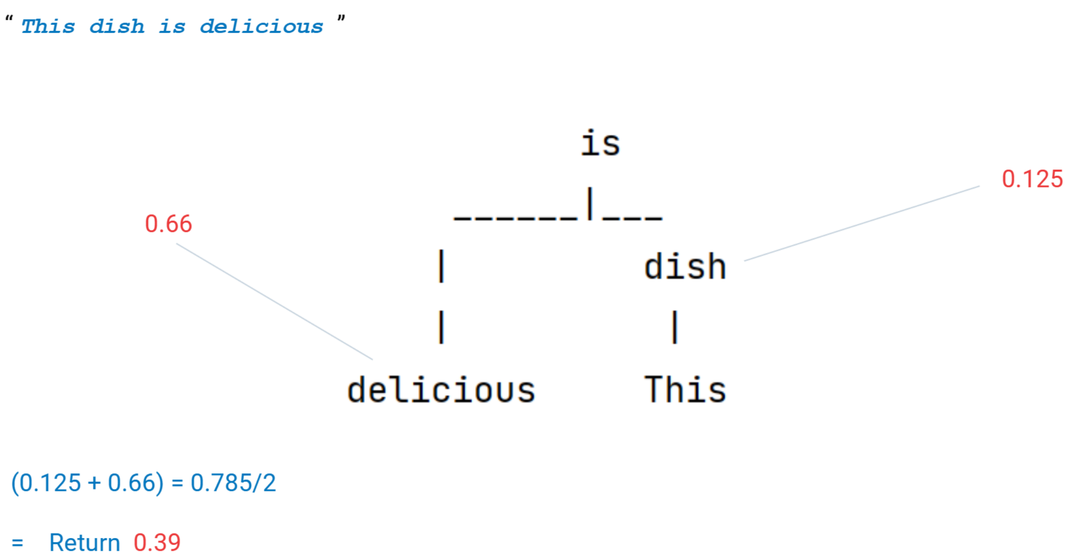


Figure 13: Positive

Below is an example of the SEU_02 model's output with the respective Compound values for the same sentence with or without an emoticon, and the sentiments found in that sentence. We can see how emoticons, with a total weight of 20% on the sentence, can change the result:

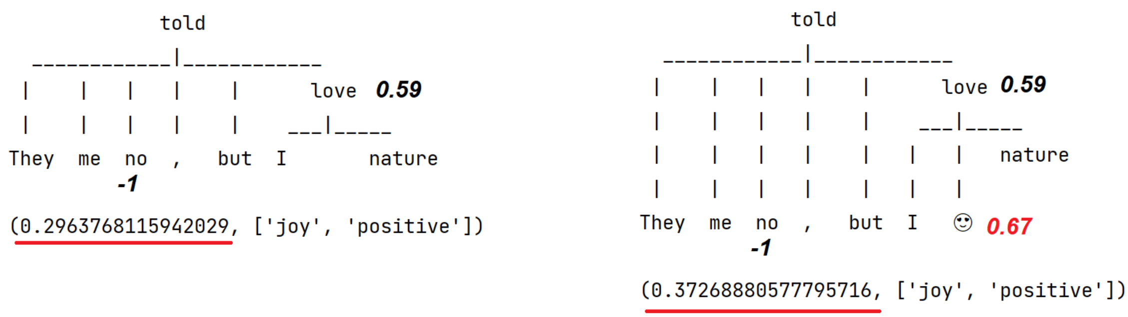


Figure 14: Positive

5.4 Result SEU_02

The following are the results of applying SEU_02 to the two datasets. It's worth noting that although precision did not improve, the new algorithm has brought some enhancements, as evidenced by the confusion matrix: we have been able to reduce both false negatives and false positives, which are phrases incorrectly labeled as positive but were actually negative, and vice versa. Currently, most of the errors consist of false neutrals, but there is still room for improvement by tweaking the hyperparameters of the algorithm.

5.5 Comper SEU_01 and SEU_02

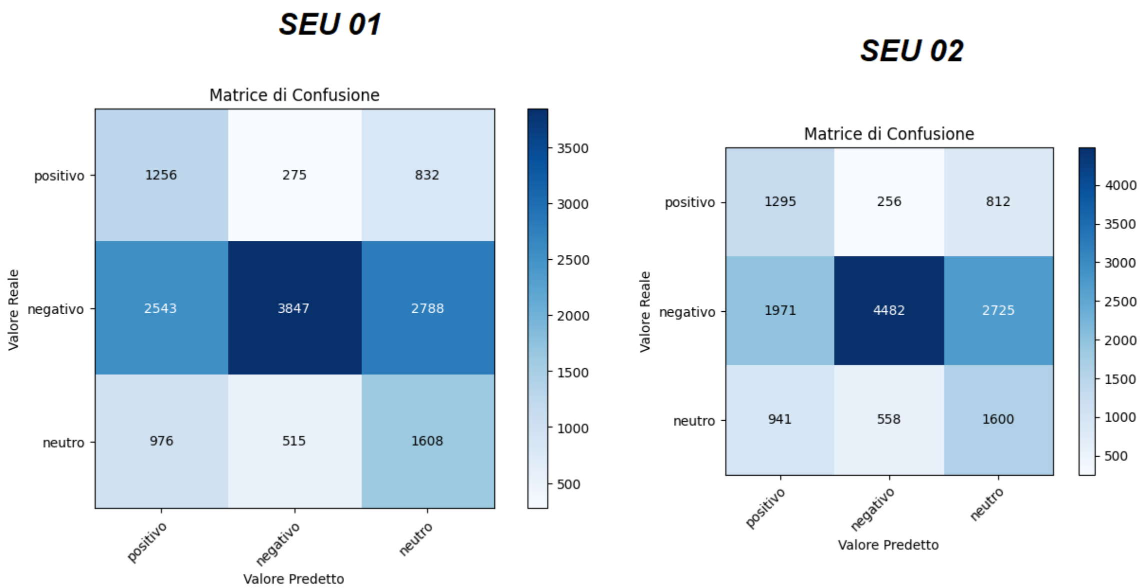


Figure 15: Comper SEU_01 and SEU_02 Matrix

We can observe that false positives have decreased, correct negative predictions have also increased, and the prediction of false neutrals has decreased, albeit slightly.
In the following graph, we notice an overall improvement in both Accuracy and f1 score for all labels. The new algorithm is definitely more effective in the Airlines dataset.

SEU 01

	precision	recall	f1-score	support
negative	0.83	0.36	0.50	9178
neutral	0.31	0.43	0.36	3099
positive	0.21	0.56	0.30	2364
accuracy			0.41	14641
macro avg	0.45	0.45	0.39	14641
weighted avg	0.62	0.41	0.44	14641

SEU 02

	precision	recall	f1-score	support
negative	0.85	0.49	0.62	9178
neutral	0.31	0.52	0.39	3099
positive	0.31	0.55	0.39	2363
accuracy			0.50	14640
macro avg	0.49	0.52	0.47	14640
weighted avg	0.65	0.50	0.53	14640

Figure 16: Comper SEU_01 and SEU_02 Classification Report

5.6 Comper on Airline dataset

SEU 02

	precision	recall	f1-score	support
negative	0.85	0.49	0.62	9178
neutral	0.31	0.52	0.39	3099
positive	0.31	0.55	0.39	2363
accuracy			0.50	14640
macro avg	0.49	0.52	0.47	14640
weighted avg	0.65	0.50	0.53	14640

TextBlob

	precision	recall	f1-score	support
negative	0.89	0.30	0.44	9178
neutral	0.29	0.62	0.40	3099
positive	0.34	0.72	0.46	2364
accuracy			0.43	14641
macro avg	0.51	0.54	0.43	14641
weighted avg	0.67	0.43	0.44	14641

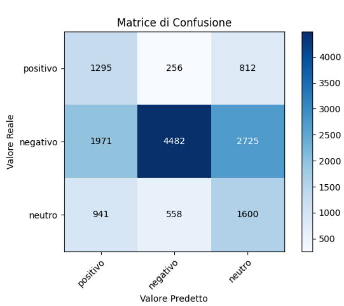
SEU 02

	precision	recall	f1-score	support
negative	0.85	0.49	0.62	9178
neutral	0.31	0.52	0.39	3099
positive	0.31	0.55	0.39	2363
accuracy			0.50	14640
macro avg	0.49	0.52	0.47	14640
weighted avg	0.65	0.50	0.53	14640

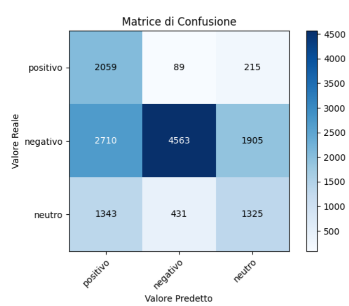
Vader

	precision	recall	f1-score	support
negative	0.89	0.44	0.59	9178
neutral	0.36	0.44	0.39	3099
positive	0.32	0.86	0.47	2364
accuracy			0.51	14641
macro avg	0.52	0.58	0.48	14641
weighted avg	0.69	0.51	0.53	14641

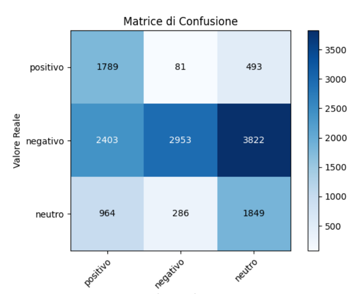
SEU 02



Vader



TextBlob



5.7 Comper on T4SA dataset

SEU 02

	precision	recall	f1-score	support
negative	0.59	0.54	0.56	5000
neutral	0.37	0.44	0.40	5000
positive	0.48	0.43	0.46	5000
accuracy			0.47	15000
macro avg	0.48	0.47	0.47	15000
weighted avg	0.48	0.47	0.47	15000

Vader

	precision	recall	f1-score	support
negative	0.79	0.75	0.77	5000
neutral	0.55	0.62	0.58	5000
positive	0.59	0.54	0.57	5000
accuracy			0.64	15000
macro avg	0.64	0.64	0.64	15000
weighted avg	0.64	0.64	0.64	15000

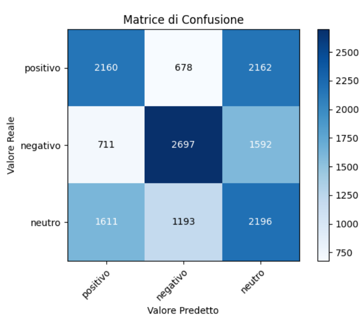
SEU 02

	precision	recall	f1-score	support
negative	0.59	0.54	0.56	5000
neutral	0.37	0.44	0.40	5000
positive	0.48	0.43	0.46	5000
accuracy			0.47	15000
macro avg	0.48	0.47	0.47	15000
weighted avg	0.48	0.47	0.47	15000

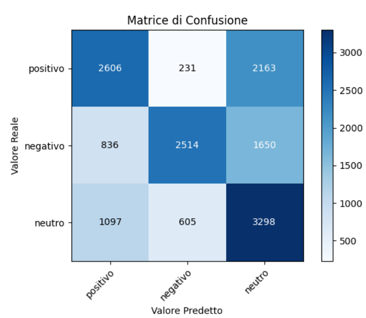
TextBlob

	precision	recall	f1-score	support
negative	0.75	0.50	0.60	5000
neutral	0.46	0.66	0.54	5000
positive	0.57	0.52	0.55	5000
accuracy			0.56	15000
macro avg	0.60	0.56	0.56	15000
weighted avg	0.60	0.56	0.56	15000

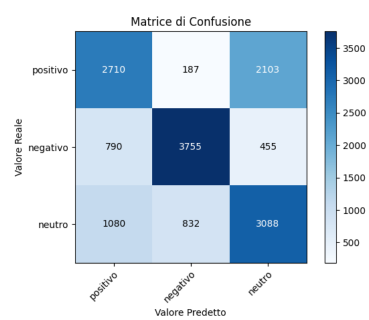
SEU 02



TextBlob



Vader



5.8 Comper on Airline only Emoticon

SEU 02

	precision	recall	f1-score	support
negative	0.78	0.37	0.50	174
neutral	0.33	0.22	0.27	129
positive	0.53	0.90	0.67	190
accuracy			0.54	493
macro avg	0.55	0.50	0.48	493
weighted avg	0.57	0.54	0.50	493

Vader

	precision	recall	f1-score	support
negative	0.75	0.44	0.56	174
neutral	0.47	0.50	0.48	129
positive	0.59	0.79	0.67	190
accuracy			0.59	493
macro avg	0.60	0.58	0.57	493
weighted avg	0.62	0.59	0.58	493

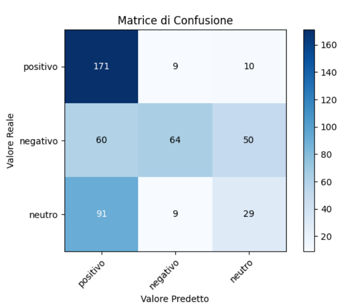
SEU 02

	precision	recall	f1-score	support
negative	0.78	0.37	0.50	174
neutral	0.33	0.22	0.27	129
positive	0.53	0.90	0.67	190
accuracy			0.54	493
macro avg	0.55	0.50	0.48	493
weighted avg	0.57	0.54	0.50	493

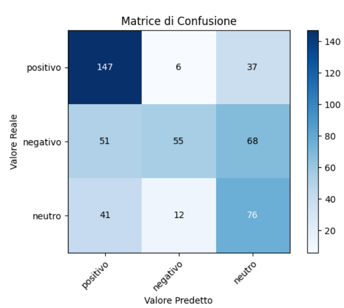
TextBlob

	precision	recall	f1-score	support
negative	0.75	0.32	0.45	174
neutral	0.42	0.59	0.49	129
positive	0.62	0.77	0.69	190
accuracy			0.56	493
macro avg	0.60	0.56	0.54	493
weighted avg	0.61	0.56	0.55	493

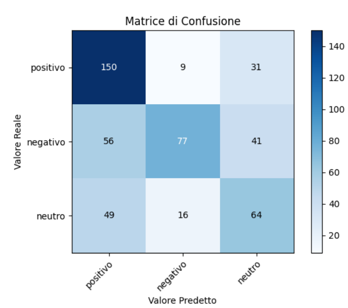
SEU 02



TextBlob



Vader



5.9 Conclusion

To delve deeper into the topic, one could investigate the different associations between emotions. For instance, joy and trust are typically considered positive emotions, and when they occur together, they can generate a strong positive polarity, along with surprise and anticipation.
Given SEU's highly algorithmic formalization, it would be useful to weigh all of its hyperparameters with specific algorithms. However, much of the Compound returned by SEU is often close to 0, necessitating the avoidance or manipulation of neutral sentences. Additionally, comparing the results of SEU with those of other sentiment analysis algorithms would be intriguing for evaluating its effectiveness and potential limitations.

Moreover, emotions could be clustered, and this approach could be used to extract the emotions contained in a new sentence and project them onto a space to determine which centroid they refer to. By doing so, a graphical representation of the emotions conveyed in the sentence could be created, which could aid in better comprehending the overall sentiment expressed.

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