# Intelligent System Assignment: Sentiment Detection over labeled tweets

Delivery Date: 30 January of 2022
Student: Pablo Cabargas
Github link to code: https://github.com/pablocabargas/IntelligentSystemAssignment.git
Data used: https://www.kaggle.com/c/tweet-sentiment-extraction/data

## 1. Introduction

The following document exposes 2 different approaches to vectorize text snippets that are tweets which have been labeled with a positive, negative or neutral sentiment label. The dataset used consists of 31014 tweets with 9685 positive, 8782 negative and 12548 neutral tweets. For each vectorizacion used, a set of classification algorithms has been used and their performances have been compared, identifying the vectorization that provides the best performance in terms of accuracy.

## 2. Methodology

The procedure has been the following

a) Vectorization of Bag of Words: The tweets data set has been vectorized using the method CountVectorizer from the library sklearn.feature_extraction.text. This method uses the bag of words algorithm to vectorize.
b) Vectorizacion of Term frequency-inverse document frequency (TF-IDF): This vectorization method relies on the term frequency which is the frequency of the word in a text and the document frequency which is the number of different texts that contain a specific word, on this case the method TfidfVectorizer from the library sklearn.feature_extraction.text.

Once the vectorization has been made the following classification methods have been used

1. Multilayer perceptron: MultinomialNB from library sklearn.naive_bayes has been used
2. Logistic Regression: LogisticRegression from sklearn.linear_model
3. Multinomial Naive Bayes:  MultinomialNB from sklearn.naive_bayes

Finally these methods are compared to analyse which one has performed better in terms of accuracy.

# 3.Results

## 3.1)Bag of Words Vectorization:

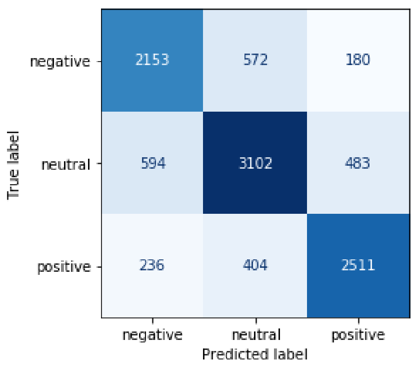
a) Top 10 common words without removing stop words and keeping them:

| Most Common words **without removing** stop words | Most Common words **removing** stop words |
|---|---|
| to 4315 | good 1023 |
| the 3904 | just 956 |
| it 2439 | day 915 |
| you 2410 | love 725 |
| my 2369 | happy 662 |
| and 2028 | like 612 |
| is 1764 | work 503 |
| in 1647 | today 482 |
| for 1568 | going 469 |
| of 1366 | lol 458 |

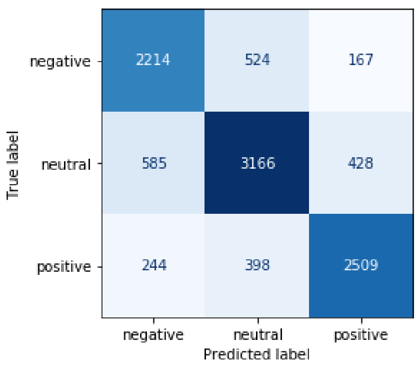
b) Classification performance

| | Logistic Regression | Multinomial Naive Bayes | MLP |
|---|---|---|---|
| Without removing stopwords | 78.9 | 75.7 | 78.36 |
| Removing Stopwords | 77.07 | 75.03 | 75.87 |

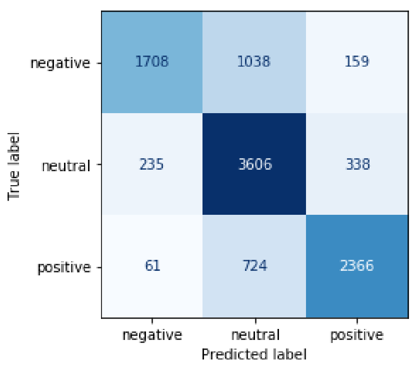
c) Confusion Matrix



MLP confusion matrix



Logistic Regression



Naive Bayes

## 3.2) Vectorizacion of Term frequency-inverse document frequency (TF-IDF)

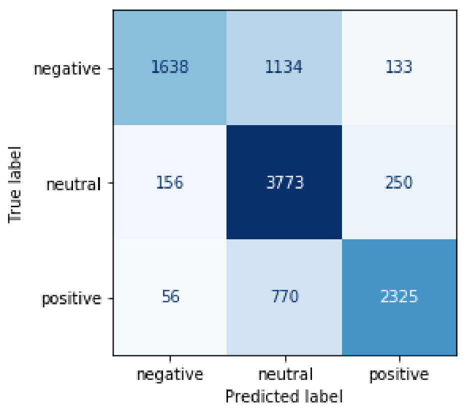
a) Top 10 highest score

| Most Common words **without removing** stop words | Most Common words **removing** stop words |
|---|---|
| to 571.526135 | good 507.248380 |
| the 500.226164 | love 390.717756 |
| good 462.322082 | happy 388.901422 |
| you 447.110865 | day 268.709957 |
| it 422.019709 | thanks 262.030469 |
| happy 370.596851 | miss 239.096681 |
| my 367.702183 | sad 219.677516 |
| love 357.259020 | just 213.615296 |
| is 316.406699 | great 210.886488 |
| and 291.280952 | fun 202.401850 |

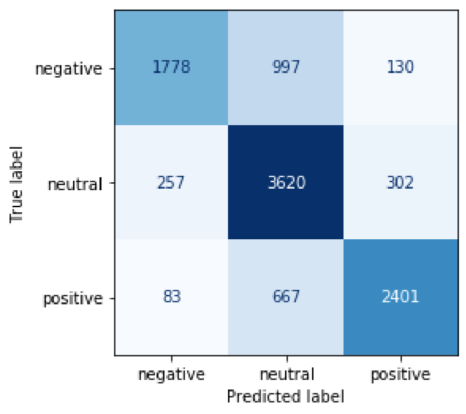
b) Classification Performance

| | Logistic Regression | Multinomial Naive Bayes | MLP |
|---|---|---|---|
| Without removing stopwords | 80 | 75.5 | 77.6 |
| Removing Stopwords | 76.2 | 75.5 | 77.6 |

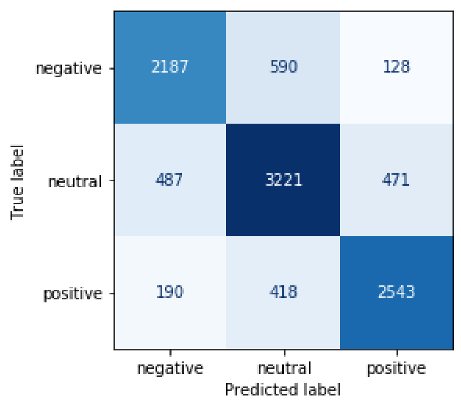
c) Confusion Matrix



Naive Bayes



Logistic Regression



## 4. Discussion

Regarding Bag of words vectorization , when we see the top 10 most common words on table 1, it is possible to see that when stop words are not considered, the most common words end up being the ones that most of the time do not provide much information at least semantically , with instances such as “to, the, it, is”. The situation changes dramatically when we see the results of the top 10 on table 3.1.a when stop words are considered, where we see examples such as “good, day,love , happy”, which indeed carry a more meaningful information semantically speaking.

Despite the previous, it is relevant to remind that when stop words are considered, that just impacts on the extension of the vocabulary and thus on the vector dimension that represents each of the tweets in this case. With that being said, the use of stop words generate almost the same results in terms of accuracy for each of the 3 models used as is possible to see on table 3.1.b, just logistic regression presents a small detriment but nevertheless , accuracies to identify whether a tweet is positive, negative or neutral are quite good reaching values in the range of 75.03-78.9 % depending on the model used.

Regarding TF -IDF vectorization, once again it’s possible to observe this situation ,on table 3.2.a,where not influential words in terms of semantics are included in the top 10 highest tf-idf score on the case when stop-words are not considered, and in the case when they are considered the highest ranked words are meaningful words such as ‘good, love, happy’. Just as the bag of words vectorization, the performance obtained over the 3 models in the scenario of considering and not considering stop words it’s almost the same, but there is a slight increase in terms of accuracy in comparison to bag of words, reaching at its highest point an accuracy of 80%.

## 5. Conclusion

In order to classify texts it is possible to turn them into a vector representation that suits as input of traditional classification methods, as it was possible to see , using the vectorization of bag of words and the tf-idf , each text (in this case tweets) were mapped to vectors of length of the vocabulary produced, one where stop-words were considered and one were not. When considering stop-words, it is possible to see that most repeated or highest ranked words are more meaningful in terms of semantics in comparison when not considering stop-words. Although the latter does not influence in this case that much on the performance of classification methods, this could be due to the fact that tweets use quite particular language distortions thus it would be considerably better to create a particular list of stop-words for tweets. As a next step, it would be interesting to try out vectorization methods that take into consideration stronger relations of the content of the tweets, using concurrent networks.