The Capture of Kabul on August 15, 2021: Analyzing Public Opinion with Sentiment Analysis
Machine Learning for Natural Language Processing 2022

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Abstract

People are increasingly giving their opinions on social networks. This study aims to study the feelings of citizens from different countries following the capture of Kabul by the Taliban on August 15, 2021. The idea is to build a model to predict the sentiment of a tweets. An analysis of tweets allows the government to capture public opinion in real time following different shocks (here a geopolitical shock).

1 Problem Framing

The Doha agreement on 19/02/2020 was the starting point for a process of withdrawal of American troops from Afghanistan under the Trump administration. Following this agreement, the Taliban received much of what they wanted, and we entered a transition phase(Maley and Jamal, 2022) leading to the capture of Kabul by the Taliban on 15/08/2021 following Biden's announcement of the departure of American troops. In August 2021, the Taliban controlled 90% of the territory and American troops began to leave the country.(Lee et al., 2022). Following the capture, many voices were raised (including international and humanitarian organizations) and different opinions were posted on social networks, including twitter. Social networks have become an important channel of expression for citizens, and analyzing the tweets concerning the capture of Kabul allows to understand the public opinion of the moment(Kamyab et al., 2018). The goal of the project will be to do a sentiment analysis of tweets about Afghanistan following the capture of Kabul. To do so, we will also do data visualization in a first step before moving on to sentiment analysis.

2 Experiments Protocol

The purpose of sentiment analysis is to study opinions in a process of identification, classification and generation of results on individual opinions, and to see if the opinions are positive, negative or neutral(Kamyab et al., 2018). The data used in the project[1] are tweets from August 11, 2021, to August 19, 2021 with 359904 values. There are 7 different values in the data table: the location, the date, the text (i.e. the content of the tweet), whether the tweet is positive, negative or neutral -there are more negative tweets than neutral and positive[A-, the hashtag as well as the source of the tweets (computer, iphone ects). There are 46.3% of neutral tweets in our database, against 32.6% of negative and 21.1% of positive[A]. We notice that the number of tweets increases strongly following the capture of Kabul on August 15[B].However, there does not seem to be a clear trend between the pre- and post-Taliban takeover of Kabul in the distribution of negative and positive tweets[B].

The tweets we extracted contain words that are similar from day to day, such as the word Taliban or Afghanistan. We used words cloud to see the words that are the most present in the tweets in relation to the situation during the fall of Kabul. We removed the most common words in the representation, i.e. 'afghanistan', 'kabul', 'taliban'. We notice first of all that the tweets with a negative sentiment are more likely to talk about the airport (and therefore about people trying to flee the country) while the positive tweets put forward the concept of right [C] but also of "new afghan". We can therefore see at first glance that the words used in the positive and negative tweets are different. When we look at the word-clouds in time, we notice first of all that the word airport appears only on

[1] Lien vers les données

the 15th, and that the tweets talk about the cause of women from this date : *"afghan women"*[C].

3 Results

The goal of this project is to perform a sentiment analysis, i.e. to predict the sentiment of a tweet from its content. The first model we used is a sentiment classification model (count based model using logistic regression on extracted features) which will be used as a baseline in our project. The underlying idea is that if a word appears more frequently in a negative tweet, then if that word is present in a tweet, there is a higher probability that the tweet is negative.

	precision	recall	f1-score	support
Negative	0.33	0.59	0.43	16107
Neutral	0.67	0.32	0.43	37385
Positive	0.40	0.55	0.46	18814

We present the results of this model in the following confusion matrix:

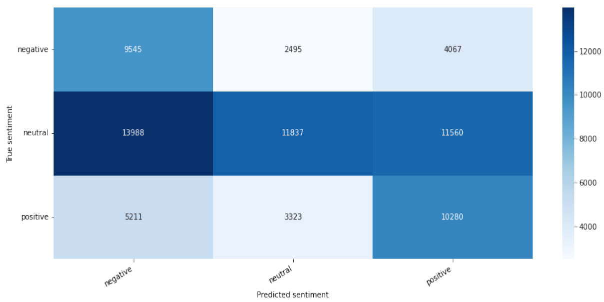

Figure 1: Confusion Matrix

We notice that the baseline model is not very efficient. Indeed, we notice that if a tweet is neutral, we predict more that it is a negative tweet than a neutral tweet. Thus, we decided to use another model to improve the sentiment analysis: a BERT model.

First of all, we had to do a first preprocessing phase and change our data into tokens, by removing punctuation for example, or "RT" which are very present in the tweets. We notice then that the number of tokens present in each tweet decreases strongly (the mean in the distribution is lower)[E]. Now that the preprocessing step is done, we can do the estimation using BERT.

We notice that the BERT results are much better than what we could find with the baseline model.

Moreover, we notice that the number of epochs used in the model strongly influences the accuracy of the algorithm. The accuracy increases with the

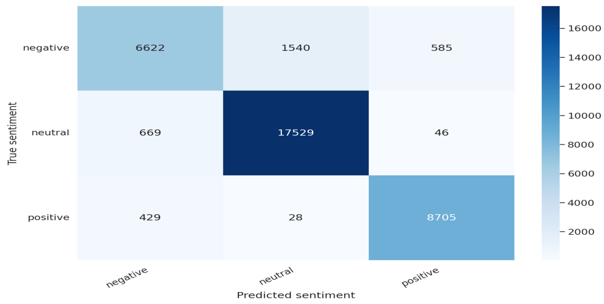

Figure 2: Confusion Matrix

	precision	recall	f1-score	support
Negative	0.86	0.76	0.80	8747
Neutral	0.92	0.96	0.94	18244
Positive	0.93	0.95	0.94	9162

number of epochs we put in the hyperparameters of the model, but takes a long time to run. We would have had even more accurate results if we could have increased the number of epochs in the model.

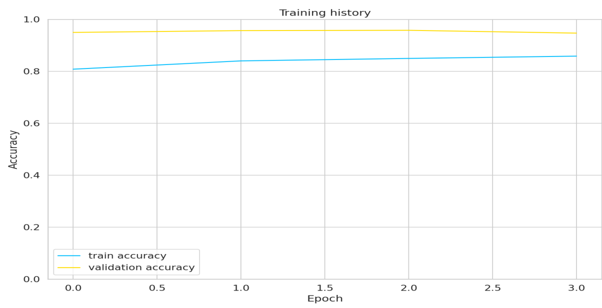

Figure 3: Training accuracy

4 Discussion/Conclusion

In a first descriptive analysis, we were able to understand which words stood out more in the negative and positive tweets. Then, we tried to understand how to predict the feelings of the tweets using two approaches: first a count based model and then a Bert model.

If the count based model is a limited approach (we do not take into account the context of the words for example) the BERT model seems to bring a more satisfactory and more precise approach even if it can be greatly improved (use of more epochs for example). It might now be interesting to use this sentiment analysis data to see if the seizure of Kabul might have had an impact on sentiment in tweets using an event studies model, in order to inform policy makers.

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References

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Appendix

A Distribution of tweets

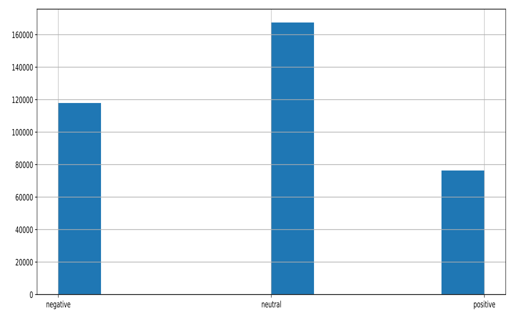

Figure 4: Distribution of positive, negative and neutral tweets

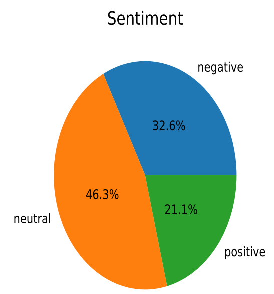

Figure 5: Distribution of positive, negative and neutral tweets.

B Distribution of the tweets in the time

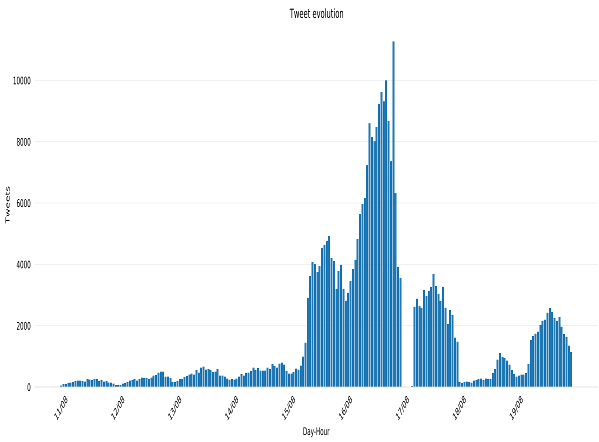

Figure 6: Distribution of tweets in the data by sentiment

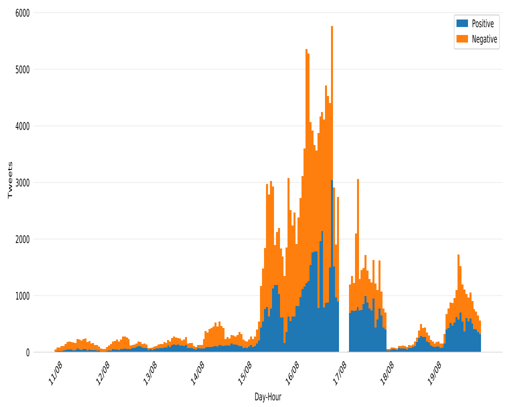

Figure 7: Distribution of tweets in the data by sentiment over time

Figure 8: Distribution of tweets in the data by sentiment

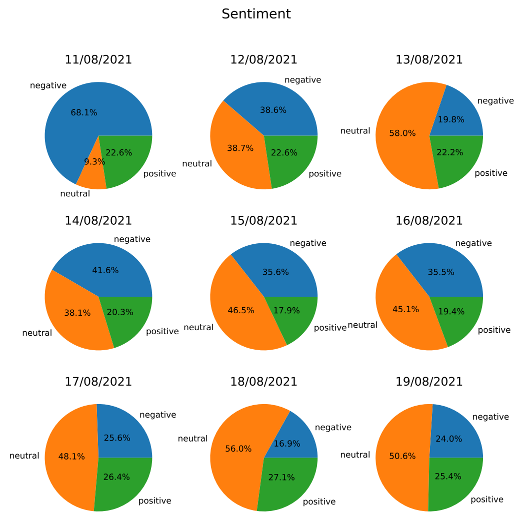

Figure 9: Comparing number of words and sentences in positive, negative and neutral tweets

C Word cloud

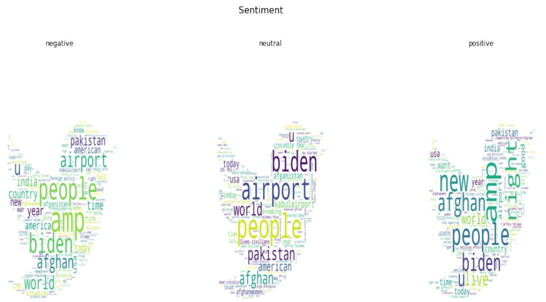

Figure 10: Word cloud of the collected dataset

Figure 11: Word cloud of the collected dataset

D Count based model

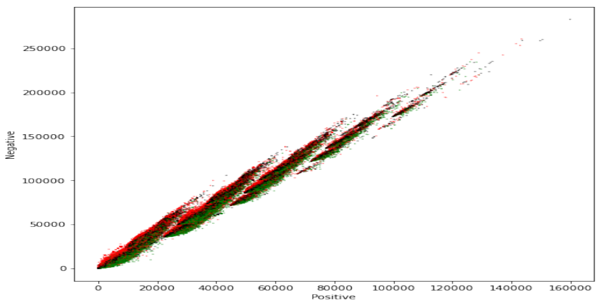

Figure 12: Negative and Positive tweets of the sample

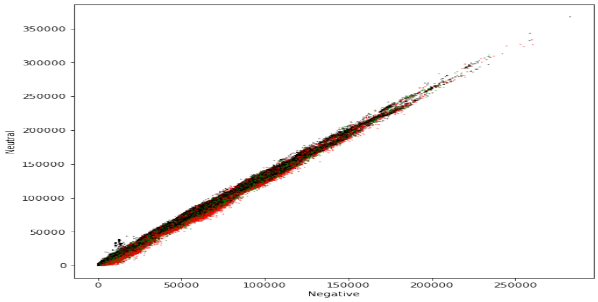

Figure 13: Negative and Neutral tweets of the sample

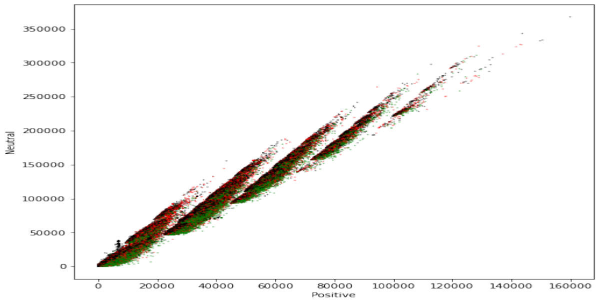

Figure 14: Neutral and Positive tweets of the sample

E Preprocessing

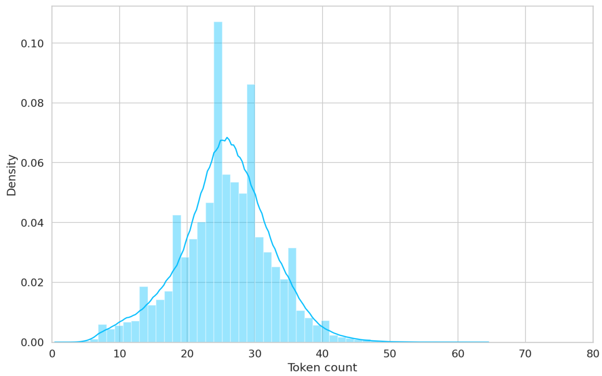

Figure 15: Density of tokens before cleaning

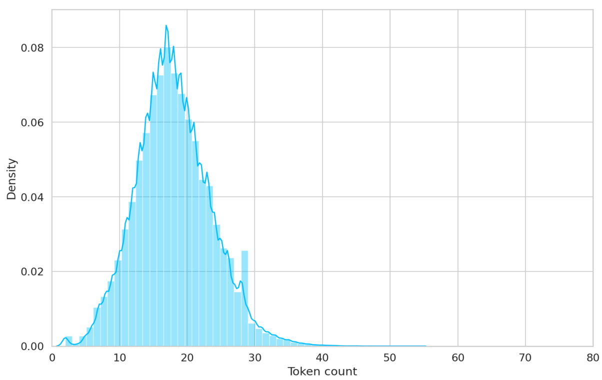

Figure 16: Density of tokens after cleaning