Emotional Collocates of Lockdown Tweets

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The coronavirus has forced many countries across the world into lockdown. A novel and constricting situation such as this has elicited strong reactions from the world's population. In order to examine these reactions closer, this study evaluates emotional expression on twitter regarding the lockdown.

When comparing the emotions expressed during the two lockdown periods, we assume the following hypotheses:

1. The general tone of emotions expressed in tweets during the two lockdown periods have changed from the first lockdown to the second lockdown.
2. The emotions expressed during the 2nd lockdown were more negative than during the 1st lockdown.

Two data sets have been extracted from twitter according to following criteria: date between 20th of March to 10th of April 2020 or 15th to 22nd of December 2020, tweet includes the word *lockdown*, tweet is written in English. These two data sets of 2000 tweets each have been extracted through a twitter API. The data has been analyzed in two ways with different programs. The program LIWC2015 (Pennebaker et al., LIWC | Linguistic Inquiry and Word Count (wpengine.com)) has been used to assign a numerical value to emotions expressed in the data sets in order to compare the amount of occurrences of negatively or positively loaded tweets. The program AntConc was used to extract collocates to the search term *lockdown*, which were then looked up in the emotion lexicon from Mohammad & Turney 2013 (NRC Emotion Lexicon (saifmohammad.com)). AntConc is a freeware application and a corpus analysis toolkit designed by Anthony Lawrence (Laurence Anthony's AntConc). The results from both data sets were compared and assigned to either positive or negative emotional status according to the lexicon.

In the first run-through of the LIWC program a change between the data sets from the first to the second lockdown can be noticed. While in the first set (March-April) the percentual amount of positive emotions expressed in the tweets is 2.65%, the percentual amount of negative emotions in the tweets came up to 1.83%. The dataset from December reveals 1.54% of the words express positive emotions, while 2.12% express negative emotions, an increase in negative emotions expressed through the tweets is recognizable. This is furthermore remarkable, as the increase of negative emotions collided with an increase of the word count (about 3000 more words in December than in March-April), leading to the raw count of negative emotion words of 969,9 in March-April and 1187,2 in December.

The same results can be found in the program AntConc as well. The top 40 ranked collocates were picked in both sets and analysed whether they are positive or negative in the emotion lexicon. In the first set (March- April), the most prominent collocates of the word *lockdown*, are words like *paradise, delight, accepting, relax* and *patiently*, which according to the emotion lexicon are connected with positive emotions. While words like *restrictive*, *violators* and *sucks* are connected with negative emotions and they are less frequent. On the other hand, during the second lockdown (December), people expressed their feelings through a variety of words like *destructive*, *scary*, *protesting, protestors* and *stricter* which are related to negative emotions. Positive emotions were expressed through words like *recover* and *widespread*, but they were less frequent. This shows that there are clear differences between the first and the second lockdown with respect to the feelings people express in their tweets. In March the amount of positive emotional collocates are 5 out of 40, while in December there are only 2 out of 40 in total. On the contrary most negative emotional collocates appear in December, which are 5, while in March there are only 3 out of 40 in total again.

Our data shows that the tweets from the two lockdown periods display a shift in the expression of emotion, furthermore, a shift from positive to negative emotions can be seen from the collected data as well. As there had been made no distinction of tweets from different countries, it is impossible to say whether there had been any emotional changes restricted to a country and therefore to a certain government and their steps in the battle against Covid. In a further step this could be researched by concentrating on data from individual countries.

References: • Mohammad, Saif M. & Peter D. Turney. 2013. Crowdsourcing a word-emotion association lexicon. *Computational Intelligence* 29.3. 436-465. • Pennebaker, James W., Ryan L.Boyd, Kayla Jordan & Kate Blackburn. 2015. *The development and psychometric properties of LIWC2015*. Austin, TX: University of Texas at Austin. doi: 10.15781/T29G6Z. • Plutchik, Robert. 2001. The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American Scientist* 89.4. 344-350. • Tausczik, Yla. R. & James W. Pennebaker. 2010. The psychological meaning ofwords: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology 29*.1. 24-54. doi:10.1177/0261927x09351676.

Laurence Anthony's AntConc (https://www.laurenceanthony.net/software/antconc/)

LIWC | Linguistic Inquiry and Word Count (wpengine.com) (https://liwc.wpengine.com/)

NRC Emotion Lexicon (saifmohammad.com (https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm)