Social Data Science 2021

Emotions in climate change: a sentiment and impact analysis on climate related tweets using VADER

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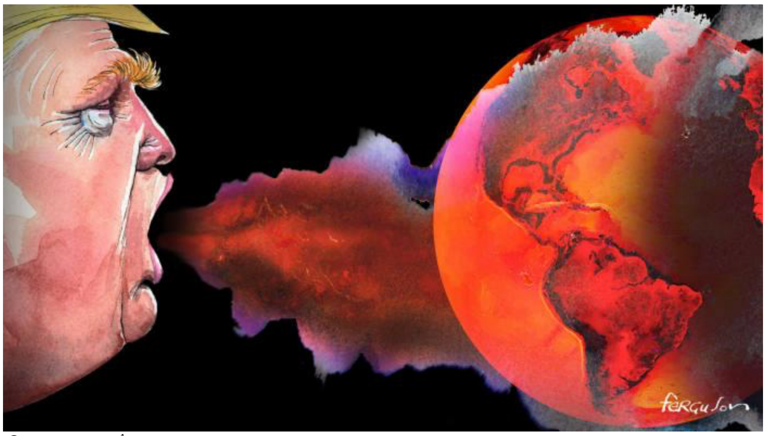

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[1] https://www.ft.com/content/27c9a6e8-ffb7-11e9-b7bc-f3fa4e77dd47

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1. Motivation

The 13th goal of the 2030 Agenda of Sustainable Development "Climate action" is a pressing issue in today's world (United Nations, 2015). Sustainable development issues can often be categorized as wicked problems - complex interconnected problems with no clear solution which leads to conflicting interests and differing perspectives (Kreuter, De Rosa, Howze, & Baldwin, 2004). Transparent communication between stakeholders and the public as well as among stakeholders themselves is important in the process of finding a solution. Hence, it is meaningful to explore how people react to information from different stakeholders such as governmental agencies or NGOs when it is formulated in a rather positive or in contrast a rather negative way.

As one of the most popular social media, Twitter serves as an important source of information, which can be used to observe how information is spread in a community. In combination with the above introduced topic of communication with regards to climate change, it is therefore of interest how the sentiment of a climate change related tweet influences the user's reaction. For example, would tweets stating the urgency of climate change impress users more than positive news about a new carbon sequestration project?

Considering this, the aim is to answer the question, whether different reaction patterns (measured by retweets) can be observed from Twitter users to either a hopeful (positive) tweet or one that focuses on the destructive (negative) impacts of climate change. Ultimately, the following research hypothesis is formulated:

The number of retweets, and thereby the impact of the original tweets is higher for negative tweets.

By confirming or rejecting this hypothesis, it is possible to shed light on a more effective way to communicate to the wide public about climate change and mobilize the population for behavioural change.

2. Project Plan

The project will be executed according to the following project plan:

1. Make a list of climate activists / organizations / etc. that mainly Twitter about climate related topics
2. Collection of the last 200 Tweets of these accounts and then excluding all tweets made within the last seven days
3. Pick randomly 200 tweets, label them regarding their relevance to climate change and evaluate the cleanliness of the dataset. Tweets will be labeled by two of the authors, in the latter called labelers, to get an estimate for the error of labeling.

(3.b) In case the cleanliness is not sufficient, searching tweets by keyword is considered as an alternative.

4. Analyse whether the tweets belong to the "positive" or "negative" group. Use an unsupervised sentiment analysis technique, such as VADER or the "nrc" library. (Depending on the quality of the results supervised models will be taken into account and train them using hand-labeled data)

5. Account for the popularity of the accounts by using a regression model (inspired by exercise 3 from the course). Explore the relationship of retweet number and followers, and consider a normalization of the retweet numbers with the follower number.
6. Final analysis of the results.

3. Data Retrieval

To retrieve tweets about climate change, a list of Twitter users targeting mainly this topic was created manually. To avoid getting a bias from observing only one specific kind of account, a broad range of account hosts was chosen, which is shown in detail in annex 1. Figure 1 shows the overall distribution of the 80 accounts over the following six categories: *activist* (a person active on social media to activate and inform people about the consequences of climate change), *government* (the official Twitter account of a governmental institution), *NGO* (the Twitter account of a climate or environment-oriented non-governmental institution), *mitigator* (the Twitter account of a company engaging in finding solutions to mitigate the effects of climate change), *media* (environment-oriented media accounts) and *polluter* (companies having a rather destructive image with regards to climate).

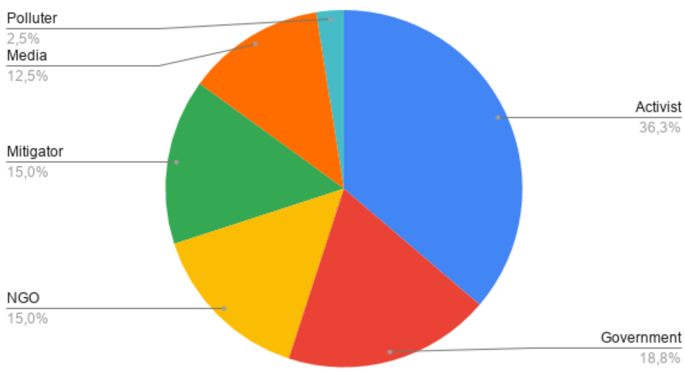

Figure 1: Distribution of Twitter users

Utilizing the *rtweet* package as an interface to the Twitter API, the latest 200 tweets of these users were extracted considering only tweets that were not retweets themselves. Subsequently, all tweets younger than 7 days were excluded to account for the time it takes for a tweet to get retweeted. The date of retrieval was the 9th of March 2021.

4. Data Processing

Prior to processing the data, the goal was to evaluate how many tweets were related to climate change. For this purpose, 200 tweets were randomly selected and labeled by two people according to their relevance to climate change (*Yes* or *No*) and their sentiment (*Negative*, *Neutral*, *Positive*). Within this sample, more than 70% of tweets were relevant while the degree of agreement between two labelers was at 95%. The "cleanliness" of 70% is seen as sufficient to continue with the data processing.
As a next step, the *VADER* package, which was specifically designed for social media content, was utilized for sentiment analysis of all extracted tweets. For each tweet, VADER outputs a compound valence score between -1 (very negative) and 1 (very positive). Using the threshold

less than or equal to -0.3 for negative tweets and greater than or equal to 0.8 for positive tweets and neutral for all tweets in between, the tweets were put into three discrete categories based on the valence score. These thresholds were selected to maximize the degree of correctly classified positive and negative tweets while retaining enough samples for both classes, based on the previous hand-labeled sample tweets. The classification results are displayed in the confusion matrices in Table 1 and Table 2.
The agreement of two labelers was above 80% when considering the relevance and the sentiment of a tweet. The lines between positive and neutral, as well as negative and neutral were somewhat blurry and led to most of the disagreements between the two labelers. This is also reflected in the confusion matrix, where it is clear to see that most wrongly classified positive tweets are truly neutral and vice versa for predicted negative tweets. True positive tweets are seldom labeled as negative ones and the same holds for true negative tweets, which are rarely confused with positive tweets. So even though the unsupervised method allows some tweets which are deemed neutral by the human brain to be classified as positive or negative, the positive subset chosen by VADER tends to reveal a true positive content, and the same holds for the negative subset. Therefore, the conclusion is made that the unsupervised classification method with the chosen thresholds is sufficiently accurate for further analysis.

Table 1 (left): labeler 1**; Table 2 (right):** labeler 2

		Reference			Reference		
		Negative	Neutral / Non Relevant	Positive	Negative	Neutral / Non Relevant	Positive
Prediction	Negative	11	8	1	11	9	0
	Neutral / Non Relevant	15	87	51	13	94	46
	Positive	2	10	15	1	11	15

To gain further insights and possibly identify some criteria to clean the dataset, the 100 most positive and most negative tweets (i.e. being closest to 1 or -1) according to the unsupervised classification were carefully examined. Although the regression fitted on these tweets did not show a clearer behavior regarding the research question (i.e. showing a bigger difference between the slopes), the analysis helped to gain a better understanding and to clear the dataset from certain unwanted patterns. Firstly it was found during the process of labeling that within the positive tweets, many tweets were congratulations or were welcoming the upcoming holidays. These are positive occasions and good reasons to be happy, however hardly relevant to climate change and therefore not interesting for the research question in place. As a result, these tweets were filtered out by scanning for keywords such as "*Happy Birthday*", "*New Years*", "*Holiday*" or "*merry*" (A detailed list of all filtered words can be found in annex 2). Moreover, there were some duplicate tweets in the data. Direct duplicates were filtered out by only allowing unique values for the text. Additionally, the user @ClimateDesk from was deleted from the user list because this account simply changed the URL contained within its tweets but posted the otherwise identical tweets several times. Ultimately the resulting data frame which contained 1074 negative tweets and 918 positive tweets, was used for the analysis.

5. Analysis

In the following, the findings from the data shown in chapter 4 are analyzed, starting with a general overview of the log-log plotted data, further observations in a bootstrapped sample, and a permutation test and finishing with a detailed look on one user, reflecting the overall characteristics of the observation.

5.1. Information from the log-log plot

From a linear plot, the observation was made that the data points are concentrated in the bottom-left corner of the graph. By using a log-log scale, a distribution of data points which allows for a reasonable linear regression is generated and displayed in Figure 2.

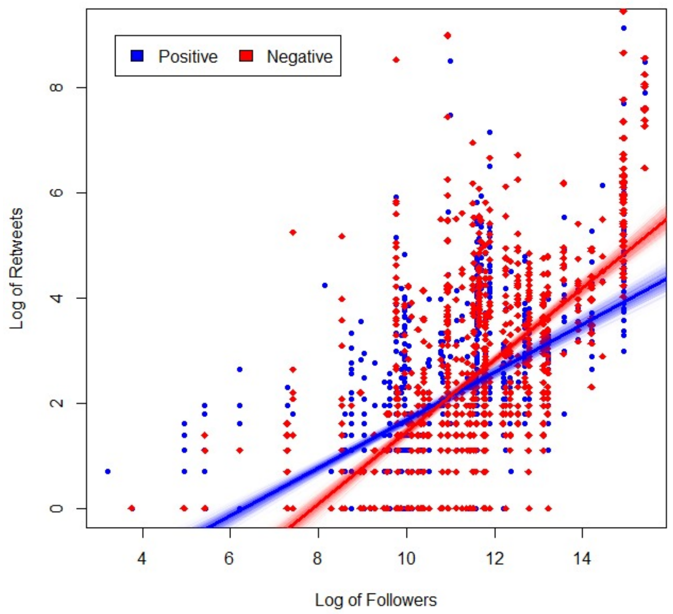

Figure 2: Plot of the data on log-log scale (incl. bootstrapped regressions)

Considering only the positive (blue) and negative (red) tweets, Figure 2 shows the linear regression results for the plotted data of the log of retweets and the log of followers (red and blue line). Due to the small number of accounts with little followers and the possible arbitrariness in their retweet number, the analysis focuses on the slope of the regression, leaving out the intercept with the y-axis.

Roughly speaking, the observed dataset displays a steeper slope in negative tweets than positive tweets, meaning negative tweets become more easily influential when the account has a larger audience. The regression line of negative tweets is not always above the positive one, indicating no overarching advantage of the influence of negative tweets compared to positive tweets.

5.2. Bootstrapping test

To explore whether there exists a stable pattern in negative and positive tweets, a bootstrapping test has been performed and the resulting lines are plotted as thinner blue or red lines in Figure 2. The bootstrapping provides an idea of whether the difference of the slopes would have been consistent when analyzing different samples generated based on the retrieved dataset. A histogram as shown in Figure 3 is drawn to show more clearly the bootstrapped slope distribution. For both the positive and the negative tweets, 10’000 bootstrapping samples were used.

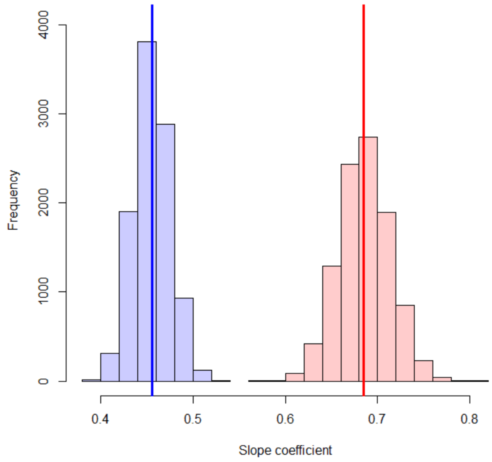

Figure 3: Bootstrapped slope distributions

The observed values stand clearly in the middle of the range of the bootstrapped lines, while both ranges are rather concentrated and do not overlap. This confirms that the patterns of influence, i.e. the relationship between retweets number and followers number, expressed by the slope of the regression are salient.

5.3. Permutation test

To further verify the slope difference between the two sentiments, a permutation test with 10.000 permutations is performed to see whether it is likely to reproduce the result as a coincidence. The null hypothesis is, that the two sentiment tweets do not have any difference in the retweet-follower relationship, namely zero slope difference. The alternative hypothesis is that a positive slope difference is observed, meaning that the negative slope is larger than the positive one.

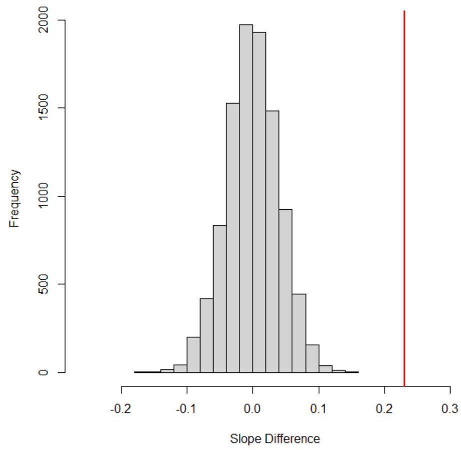

Figure 4: Permutated difference between slopes of positive and negative tweets in comparison to observed difference (red)

One parameter was chosen, namely the slope of negative tweets minus the slope of positive tweets, and the data shuffled to generate a stochastic slope difference distribution. As displayed in Figure 4 this distribution is a well-shaped normal distribution with the highest frequency at zero difference, while the observed value stands at the far positive end of the distribution. The calculated one-sided p-value is 0.0001, which is an order of magnitude lower than 0.001, reflecting a high level of statistical significance.
This confirms the initial hypothesis, that negative climate change related tweets are more easily retweeted compared to tweets with an underlying positive sentiment, especially for a higher number of followers.

5.4. User analysis

Taking out the followers dimension and zooming in to each user, paradigmatic users that confirm the initial hypothesis could be found. @algore (Albert Arnold Gore Jr., former US vice president and active environmentalist) was chosen as an example since this account has an even distribution of positive and negative tweets. Furthermore, all tweets display a certain number of retweets which enables an analysis of the difference of impact with regards to the sentiments of the tweet.

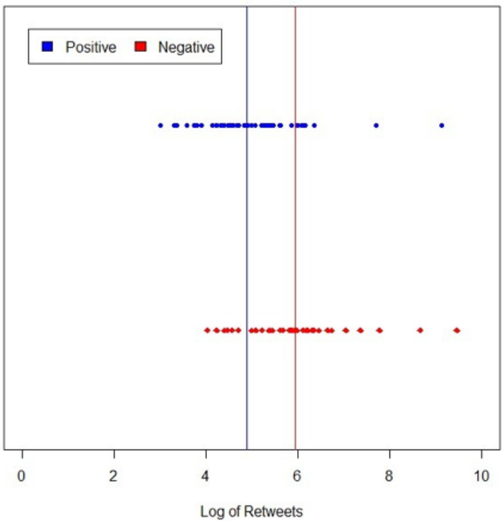

Figure 5: log of retweets of negative (red) and positive (blue) tweets of Twitter user @algore

As is shown in the graph of Figure 5, the negative tweets cluster is more shifted to the right compared to the positive tweets. The vertical lines represent the mean of the log of retweets. The negative line stands one order of magnitude higher than the positive one, which corresponds to the original hypothesis, that negative emotion tweets generate more retweets than positive ones.

6. Conclusion

In summary, the tweets with negative sentiment on climate change show for the chosen 80 (79) accounts a steeper slope of the regression than the tweets with an underlying positive sentiment. The bootstrapping confirms that the slopes would have been different for the range of samples drawn from the entire tweet set and the permutation test displayed shows that the result was not generated by coincidence. However, the effect of small accounts blurs the overall image because the intercept with the y-axis was lower for tweets with a negative sentiment. In chapter 7 this issue is outlined more in detail. In any case, it can be said that it is critical for the initially chosen research design, to have accounts with a certain number of followers and a certain average number of retweets. In a follow-up study, this question could be investigated more in detail.

Due to the above-described effect, the focus was put on the slope of the two regressions which overall confirms the initially stated hypothesis, that tweets with a negative sentiment have a stronger impact, i.e. are retweeted more often. This opens up the question of causation, which would require further intensive analysis to further examine possible causal relationships and their effect. In the following, a brief outline is provided, which direction these further investigations could take.

First, the link to climate change was not evaluated in this study. One could argue that the observations just confirm a general negativity bias in psychophysiological reactions to news (Soroka, Fournier, & Lilach, 2019).

Secondly a follow up study could show if the same observations hold true for a collection of accounts that fulfil the minimum requirements towards the numbers of followers and retweets.

Finally, under consideration of the outlined aspects and the critique in chapter 7, this report supports the thesis of a negativity bias in reactions to climate change related tweets.

7. Critique

7.1. Data retrieval

The first aspect to consider is the number of analyzed tweets. Starting with 80 accounts and 200 tweets per account, the number was reduced quite significantly throughout the filtering process. One way to make the result more reliable would be to increase the number of accounts and tweets per account.

In addition, assumptions were made that need to be closely examined. For the results to be generally applicable the choice of accounts should be representative of climate-related stakeholders. This was not fully taken into consideration when the 80 accounts were chosen. The first aspect to consider would be that small accounts, although they do have less reach, are more represented in society and should therefore be as well larger in number in such a research design. Since the Twitter accounts for this analysis were mainly picked based on matching algorithms of Twitter, the data set is over proportionally set up by accounts of a medium to large size. Thus, the possibility of a systematic error cannot be excluded. To closer examine this error other data retrieval methods would be needed.

Another aspect that was observed during the analysis is the blurriness of the result for small accounts with little followers and low retweet numbers. A possible explanation for this could be that small accounts might have more followers that are friends and family who react differently to positive or negative news than a greater public. For this reason, conclusions are hard to make for these accounts and further analysis would be needed. In addition, a limited number of small accounts has a very low number (close to 0) of retweets. The limited amount of data with a sufficient number of retweets makes it difficult to examine the influence of the sentiment on the retweets.

Furthermore, the labeling of the tweets with regards to relevance to climate change (see chapter 4) showed that 30% of the data was not relevant to climate change. Although the assumption was made that about 70% relevance is sufficient to reach conclusive results, the

relevance could be improved by filtering tweets for words that are likely relevant to climate change. However, this could lead to an exclusion of other tweets that are relevant and therefore requires a careful choice of keywords, which was out of the scope of this project. Although certain keywords were excluded (see annex 8.2), the possibility of false negatives and false positives remains. It would be interesting to analyze how these uncertainties propagate in further analysis.
Finally, the number of retweets is assumed as an appropriate measure for the influence of a tweet. While retweets are a significant type of influence on Twitter there are other types such as the adoption of hashtags and links, which were neglected in this study (Rosemann, 2012).

7.2. Data processing

In the analysis, there were further assumptions made. Even though a weighting system was not actively implemented, the accounts cannot be considered to have the same amount of influence. Each account should provide 200 tweets. The filtering of codewords used to improve the relevance of the tweets with regards to climate change and the exclusion of tweets of the last seven days is done after the retrieval of 200 tweets leaving some accounts with fewer data points. After filtering, all accounts were left with less than 200 tweets and therefore have less weight in the subsequent analysis. This was assumed to be negligible since the distribution of the 79 accounts with regards to their number of followers is anyways not representative and the choice of climate related accounts rather used as a method to get a set of climate change related tweets.
Furthermore, the threshold used for the determination of the sentiment was balanced between having a more balanced amount of tweets with positive/negative sentiments and having false positives in the results. Thus, the classification of positive and negative is based on an empirical analysis of this dataset and does not follow a generic decision rule. The low threshold for negative sentiments increases the risk of false positives for the negative sentiments further. The setting of the threshold also influences the weight of each account since only tweets with positive and negative sentiments were part of the actual analysis. The influence of the choice of the thresholds could be analyzed in a next step. Besides, there are general uncertainties regarding the sentiment. Irony could lead to a false positive, while neutral descriptions of nature or climate change might lead to a false negative classification.

7.3. Data analysis

Possible next steps could include a predictive analysis. This would potentially require opening up the initially stated research question and including other predictors.

8. Annex

8.1. Twitter user

Name	Account	Role
UN Environment Programme	@UNEP	Government
UN Environment Programme Europe	@UNEP_Europe	Government
Intergovernmental Panel on Climate Change	@IPCC_CH	Government
Green Climate Fund	@theGCF	Government
UN Climate Change	@UNFCCC	Government
Climate Adaption	@ClimateAdapt	Government
Planetary Security	@Planetary_Sec	Government
COP26	@COP26	Government
Climate Change Committee	@theCCCuk	Government
Climate Assembly UK	@NetZeroUk	Government
UNDP Climate	@UNDPClimate	Government
International Energy Agency	@IEA	Government
German Environment Agency	@GermanEnvAgency	Government
EU EnvironmentAgency	@EUEnvironment	Government
Fondazione Cmcc	@CmccClimate	Government
Greta Thunberg	@GretaThunberg	Activist
Xiye Bastida	@xiyebastida	Activist
Scarlett Westbrook	@ScarlettOWest	Activist
Svein T veitdal	@tveitdal	Activist
Erik Solheim	@ErikSolheim	Activist
Joyce Msuya	@JoyceMsuya	Activist
Dr. RIchard Munang	@RichardMunang	Activist
Terje Osmundsen	@OsmundsenTerje	Activist
Patricia Espinosa C.	@PEspinosaC	Activist
Al Gore	@algore	Activist
Special Presidential Envoy John Kerry	@ClimateEnvoy	Activist
Ben See	@ClimateBen	Activist
GO GREEN	@ECOWARRIORSS	Activist
Chris Stark	@ChiefExecCCC	Activist
Farah MK	@Farah_mkma	Activist
Anna Kernahan	@AnnaKernahan	Activist
Vanessa Nakate	@vanessa_vash	Activist
Alexandria Villaseñor	@AlexandriaV2005	Activist
Kate Aronoff	@KateAronoff	Activist
Treehugger.com	@Treehugger	Activist
Johanna Nilsson	@voice4theplanet	Activist
Carbon Brief	@CarbonBrief	Media

Name	Account	Role
Inside Climate News	@insideclimate	Media
Guardian Environment	@guardianeco	Media
NYT Climate	@nytclimate	Media
Yale Environment 360	@YaleE360	Media
Yale Program on Climate Change Communication	@YaleClimateComm	Media
Climate Desk (excluded)	@ClimateDesk	Media
Climate Central	@ClimateCentral	Media
Climate Change US	@ClimateChangeUS	Media
CBI climate change	@CBI_CC	Media
Empower New Energy	@EmpowerNEnergy	Mitigator
FootPrint Coalition	@fp_coalition	Mitigator
Aldersgate Group	@AldersgateGrp	Mitigator
Ørsted UK	@OrstedUK	Mitigator
First Solar	@FirstSolar	Mitigator
Canadian Solar	@Canadian_Solar	Mitigator
MIRRECO	@Mirrecogroup	Mitigator
SeeO2 Energy	@Seeo2E	Mitigator
Deep Branch	@DeepBranchBio	Mitigator
Ocean-Based Climate Solutions	@based_ocean	Mitigator
Carbon Engineering Ltd.	@CarbonEngineer	Mitigator
Climeworks	@Climeworks	Mitigator
Fridays For Future	@Fridays4Future	NGO
Extinction Rebellion	@ExtinctionR	NGO
Sunrise Movement	@sunrisemvmt	NGO
C40 Cities	@c40cities	NGO
We Don't Have Time	@WeDontHaveTime	NGO
Climate Power	@ClimatePower	NGO
Parents For Future	@parents4future	NGO
350 dot org	@350	NGO
Greenpeace	@Greenpeace	NGO
Earthwatch	@earthwatch_org	NGO
WILD Foundation	@WILDfoundation	NGO
European Environmental Bureau	@Green_Europe	NGO
Green Aliance	@GreenAlianceUK	NGO
Climate Home News	@ClimateHome	NGO
Climate Reality	@ClimateReality	NGO
Greenpeace USA	@greenpeaceusa	NGO
WRI Climate	@WRIClimate	NGO
Climate Nexus	@ClimateNexus	NGO
Climate Action Network - International (CAN)	@CANIntl	NGO

Name	Account	Role
World Wildlife Fund	@World_Wildlife	NGO
Shell	@Shell	Polluter
ExxonMobil	@exxonmobil	Polluter

8.2. List of words used as indicator to exclude tweets

#	Excluded words
1	merry
2	Merry
3	happy birthday
4	Happy Birthday
5	happy Birthday
6	Holiday
7	New Year

9. Bibliography

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