rijksuniversiteit
groningen

"Well, luckily Climate Change is only a hoax, eh?"

THE EFFECT OF DUTCH SARCASM USE WHEN PERFORMING SENTIMENT ANALYSIS ON CLIMATE COMMUNICATION ON TWITTER

Kas Jansma

8-3-2021

1 Abstract

In a world where social media usage is ubiquitous, computer-assisted sentiment analysis of online communication can be a valuable asset in assessing public opinions on certain topics, such as climate change. However, there is little information in how sentiment analysis can be performed accurately in languages other than English, such as Dutch. One problem in determining accuracy and validity is the occurrence of sarcasm and other forms of figurative language where the intended sentiment is different than the literal meaning of the words, because of the lack of non-verbal cues in online communication. In this research, it is explored to what extent the use of sarcasm is used in Dutch on the popular microblogging website Twitter. A dataset of 4000 tweets was coded for sentiment both manually and with an automated tool, while sarcasm and personal position towards climate change were also coded manually, to establish more information on the occurrence of sarcasm and its effect on sentiment analysis. Manual sentiment analysis turned out to be difficult and automatic sentiment analysis inaccurate, but it is clear that sarcasm is something to be considered when performing large-scale sentiment analysis. More research is needed to establish how sarcasm can be detected accurately and whether the topic of climate change is more prone to its use than other, similarly politicized topics.

2 Introduction

2.1 Background

In recent years, global social media usage has grown enormously, to a point where it can be considered ubiquitous in daily life. *Datareportal* reports that in 2020 up until October, 53% of the total world's population uses social media at least once a month, which is a 12.3% increase since 2019. The average user aged 16 to 64 spends 2 hours and 29 minutes per day on social networks and messaging apps (Kemp, 2020). In this time, users express opinions and communicate with each other at large in a way that is unmatched by platforms outside the internet. This research project focuses on communications via Twitter, a microblogging platform.

Twitter is a platform where the topic of climate change is discussed more than in traditional media (Boykoff, 2011). This gives rise to opportunity for Twitter to facilitate improved exposure on climate change and by that, contributing to the establishment of climate change as a public issue that needs to be addressed (Boykoff, 2011; Cody et al., 2015).

Literature suggests that the structure of these social networks has significant impact on opinions and behaviours related to climate change. Network analysis has shown that both online and offline social networks influence opinions and behaviours on other topics, such as obesity (Christakis & Fowler, 2007) and politics (Bond et al., 2012). It is also believed that the attitudes of peers in social networks towards climate change have strong influence on individual opinion on climate change (Kahan et al., 2012). Because of this, Williams et al. (2015) argue that Twitter has significant impact on the public opinion of climate change.

2.2 Sentiment analysis

To get a better understanding of the public opinion on climate change on Twitter, sentiment analysis can be performed. According to Pozzi et al. (2014, Chapter 11), sentiment analysis, also called opinion mining, is defined as the interpretation and classification of emotions within text data, such as tweets. For example, the sentiment of a tweet related to a certain event about climate change, such as an extreme weather event, can give some idea of the opinion of the user towards the subject. If the user tweets negatively about the disaster and also using the words climate change, one can assume that the user is a climate activist rather than a climate change sceptic. In this way, sentiment of a text can give some idea of the opinion of the writer of the text on the subject (Liu, 2018, p. 35).

Sentiment analysis is already used in some literature on climate communication on social media (Anderson et al., 2014; Anderson & Huntington, 2017; Cody et al., 2015) and some researchers even proclaim social media to be a 'proxy for wider public discourse' (Pearce et al., 2019).

Sentiment analysis can be done both manually and automated (i.e. done by a computer based on a script/program). Both methods have disadvantages; manual sentiment analysis can be cumbersome and difficult to do reliably, since coders have to be instructed and the codebook has to be concise and clear. Even so, even after extensive training sessions, high levels of reliability are difficult to achieve (van Atteveldt et al., 2021). Automated sentiment analysis is usually preferred because it allows for larger amounts of text to be analysed in a shorter period of time, but there are also drawbacks. For one, researchers outside of the field of computational linguistics are dependent on developed tools for their purpose, since validity of automated sentiment analysis programs is highly dependent on which subject they are used, but also the language and type of text (van Atteveldt et al., 2021). Since this is a relatively new field, not a lot of these tools are available. Automated sentiment analysis is also limited to less comprehensive coding than manual analysis; tools are often only able to score for subjectivity (the question whether a piece of text contains an opinion about something) and polarity (whether the text is negative or positive towards the subject), while in some cases, it might be useful to categorize sentiment more detailed, such as with more specific emotional attributes (e.g. joy, sadness, fear, ridicule).

2.3 Sarcasm in sentiment analysis

Another issue in sentiment analysis, especially within social networks, is the use of language where the meaning is different than the literal meaning of the words, such as sarcasm. Automated sentiment analysis tools are often not able to detect sarcasm accurately in text, which leads to inaccurate sentiment data (Liebrecht et al., 2013). This implies that manual coding might still be more accurate than automated sarcasm detection, at least when sarcasm is a topic of interest.

2.3.1 Sarcasm in climate change tweets

Some researchers have found that sarcasm use in tweets about climate change is lower than in other topics (Anderson & Huntington, 2017), while others have noted that the usage of sarcasm seems to have increased in recent times (Maynard & Greenwood, 2014). Climate change is a topic which is prone to polarization and incivility, because of the politicized nature around the subject (Anderson & Huntington, 2017). Online discussion on climate change has been denoted ‘polarized and sometimes ideologically driven’ (Holliman, 2011) and ‘strident and unproductive’ (Malone & Klein, 2007). Overall, online discussion and the dynamics of any social media interaction concerning the subject of climate change is poorly researched. In the field of climate communication, it might be interesting to get a better understanding of the use of sarcasm and other forms of incivility in online discussion.

Many researchers denote that automatic sarcasm detection is very much in its infancy and more knowledge on sarcasm detection and its effect on sentiment analysis is needed (Anderson & Huntington, 2017; Liebrecht et al., 2013; Liu, 2018; Maynard & Greenwood, 2014; Pozzi et al., 2014).

2.3.2 What is sarcasm?

It is very important to note that there is still confusion in literature as to how sarcasm can be defined. In the context of this research, it is defined as the use of figurative speech by a user to say the opposite of what he or she actually wants to say. In verbal communication, the use of sarcasm is often done with certain variations in word use and intonation, but for online text-based language, this is not applicable. This definition is important, as the idea of sarcasm can vary greatly between people because it has no clear-cut definition and also differs per language and culture. By using this definition, the term sarcasm or at least the effect that sarcasm has can be quantified by looking at its effect on sentiment. This means that some tweets that might be considered sarcastic by most people are not labelled as sarcastic in this analysis, because it does not cause sentiment to change. One example is the following (Gjvu, 2020):

Figure 1: example of a tweet that might be considered sarcastic but where the figurative speech does not impact sentiment. Translation: “Well #Tweets – The sun is going under. To save ‘the climate’, I’ve just changed the temperature of the jacuzzi outside. Higher”

In this tweet, the use of quotation marks around ‘het klimaat’ indicate that that part of the tweet can be interpreted as sarcastic, especially because the user proclaims to “save ‘the climate’”, while performing an action that might be considered a waste of energy (increasing the temperature of the outdoor jacuzzi) and thus is not climate friendly. While the intended meaning of that part of the tweet is indeed different than the meaning of the literal words, sentiment (when considered only positive, negative or neutral) is not affected.

Some literature makes a distinction between sarcasm and other forms of figurative speech such as irony, which is often defined as a form of sarcasm. There are multiple theories on the subtle differences between these forms of figurative language (Liu, 2018, p. 82; Pozzi et al., 2014, Chapter 7). However, there is no clear distinction between the use of sarcasm, irony, cynicism, etc., in English or in Dutch, but all forms can have the effect of changing the meaning of the literal words so that sentiment is affected (Maynard & Greenwood, 2014). The subtle differences between these forms are therefore not relevant to the use in this research, since all these forms of ironic language that have an immediate effect on sentiment is considered. In the rest of this report, all forms of figurative language that affect sentiment as to per the definition given above is considered 'sarcasm'.

Presence of figurative speech in tweets, regardless of the difference between sarcasm and irony, causes difficulties in automatic sentiment analysis; the use of figurative speech in a tweet that would be considered negative by an automatic language processer, could be intended positive or the other way around. Because of this, a sarcastic statement is defined in other research on this topic (Anderson et al., 2014; Anderson & Huntington, 2017; Liebrecht et al., 2013; Maynard & Greenwood, 2014) and also in this research, as a provocation or subtle attack where the opposite of the literal interpretation is intended as meaning.

An example tweet where sarcasm is used to mean the opposite of the literal interpretation is the following (monstersinalice, 2020) :

Figure 2: example of a sarcastic tweet about climate change. *Translation: "but hey, luckily climate change is just a hoax, eh?'*

In this example, the tweet could be interpreted as having positive sentiment, for example because of the word 'gelukkig'. In this case, it is clear because of the use of the hashtag #sarcasme that the opposite meaning is intended.

Motivation for the use of online sarcasm is not well understood, but Anderson and Huntington (2017) argue that it is often used as a passive-aggressive tool to engage in uncivil speech while maintaining the impression that one is not using incivility, or as a persuasive tool in discussions. Sarcasm can be categorized as online incivility, which has unwanted effects on perceptions towards emerging technologies and upcoming public issues, especially for science communicators for whom public acceptance of their information is important (Anderson et al., 2014).

2.4 Research questions

Current literature focuses on English language (Pearce et al., 2019; Schäfer, 2012), while there is little literature available about Twitter in Dutch-speaking countries. Liebrecht et al. (2013) used a computer algorithm to detect sarcasm in 77,948 Dutch tweets and compared with a manual analysis of 250 tweets that were labelled sarcastic by the algorithm. In this comparison, only 30% of those 250 tweets were labelled as sarcastic by the manual analysis.

While it is clear that automatic sentiment analysis is not yet capable of detecting sarcasm in Dutch tweets accurately, it remains to be seen whether this is a problem for the use of automatic sentiment analysis. If sarcasm is not used significantly in Dutch tweets, it might be of less relevance when performing sentiment analysis. However, because of the politicized nature of climate change discussion on Twitter and its proneness to the use of incivility such as sarcasm, it might be the case that sarcasm is something to take into account when performing sentiment analysis.

To determine whether sarcasm should be taken into account in sentiment analysis on Dutch tweets regarding climate change, it might be useful to know to what extent sarcasm is used. Therefore, the primary goal of this research was to determine how often sarcasm is used in Dutch tweets regarding climate change. The main research question is thus: **To what extent is sarcasm used in Dutch tweets regarding climate change?**

Furthermore, it might be interesting to know in what sentiment sarcasm is most often used, and what characteristics are of Dutch Twitter-users that are most prone to using sarcasm. To reach this goal, first it should be explored whether the use of sarcasm as well as its effect on sentiment can be detected accurately via manual coding. Also, it might be useful to compare manual sentiment analysis to automated analysis, to verify the hypothesis that the use of sarcasm is a problem for automated analysis.

Subquestions are formulated therefore as follows:

- Can the influence of sarcasm on sentiment readily be detected via manual coding of Dutch tweets regarding climate change?
- What sentiment is most often associated with sarcasm in Dutch sarcastic tweets regarding climate change?
- To what extent is sarcasm problematic for automatic sentiment analysis of Dutch tweets regarding climate change?

3 Method

3.1 Data collection

Twitter data was acquired via the official Twitter API by connecting the API to R via the 'rtweet'-package (Kearney, 2020). This package, together with a free Twitter developer account, was used to collect a set of 4000 tweets about climate change. The amount of tweets was chosen based on other similar research where manual coding was used (Anderson & Huntington, 2017; Dalrymple et al., 2016; Gastrow, 2015) and deemed the right balance between getting an accurate sample as well as manageable in terms of time required for coding.

The keywords used in the search query were "klimaat" and "opwarming" ("climate" and "warming" in Dutch), which means that the dataset contains all tweets where these words are used, as well as longer words containing the keywords (e.g. "klimaatverandering", "klimaathysterie", "klimaatbeleid").

The initial set of 4000 tweets was acquired with a date of tweeting starting from the 9th of November 2020. After a first glance through the dataset, it was deemed unusable because a large share of the tweets was either about or at least influenced by the U.S. Presidential Election, which was taking place at the time. A new set of tweets was acquired with a date of publishing up until the 1st of august 2020, which resulted in the final dataset of 4100 tweets, published by users between 28-7-2020 20:05 and 31-7-2020 23:58. The query and script used in R can be found in *Appendix A: R script*.

In the used dataset, quite a lot of instances (approx. 60%) were retweets, which are tweets that are originally posted by another user and then 'reposted' by the initial user. In accordance with similar research mentioned, these retweets were included in the analysis, as they still represent the sentiment of the reposting user, and also allow for the tweet to reach a greater audience.

3.2 Codebook development

A codebook was initially developed based on the research questions. This initial codebook can be found in *Appendix D: Codebook*. The codebook was used via Google Forms via a set of questions, of which the answers were used to categorize the tweets.

3.2.1 Codebook reliability

To ensure proper reliability of the codebook, a practice session was held between six coders. First, 100 randomly selected tweets were coded by the author. Afterwards, the other coders coded a selected subset of 52 tweets from the 100 tweets that were already coded by the author. This subset contained 20 tweets that were coded as sarcastic by the author. After the practice session, a discussion was organized with the coders and the author to discuss some tweets that were coded differently. In this discussion, the coder was allowed to alter some answers after further clarification of the questions.

Krippendorff's Alpha was used to determine intercoder reliability (Krippendorff, 1980). This statistical metric compares answers from all coders and can be applied to data that contains missing values, on any number of coders and is also usable for small sample sizes, which makes it very useful for this research. Reliability per question is calculated by comparing the observed disagreement between coders with the disagreement that can be expected by chance. Alpha is displayed in a number $0 \leq \alpha \leq 1$, where an alpha of 1 indicates perfect reliability, 0 indicates complete absence of reliability.

Alpha values for all codebook questions where calculated using the 'irr'-package for R (Gamer & Lemon, 2019), the complete RScript can be found in *Appendix C: Krippendorff's Alpha*. The resulting Alpha-values can be found in Table 1.

Table 1: Krippendorff's Alpha values for initial codebook questions

Question	**Possible answers**	**α**
Is the word climate used in the context of atmospheric climate/average weather conditions?	• Yes • No • Unclear	0.8059126
What is the sentiment of the tweet?	• Positive • Negative • Neutral • Unclear	0.7761237
Do you think the user supports action against climate change?	• Yes • No • Unclear	0.7602804
What is the effect of the emojis on sentiment?	• To intensify the sentiment • To disambiguate the sentiment • To flip/negate the sentiment (sarcastic emoji)	0
Do you think (part of) the tweet is sarcastic?	• Yes • No • Unclear	0.8235294

3.2.1.1Emoji's

It is important to realise that there is a difference between how online content is perceived and what is intended by the user. When analysing opinions expressed online, this is more of a problem than in real life, because of the lack of facial expressions and other non-verbal cues. One way to take this difference into account is by analysing 'emojis', emoticons that are added to text in order to express or disambiguate the sentiment. Hogenboom et al. (2013) argue that analysing emoticons is an important addition to sentiment analysis in order to correctly account for the fact that online communication lacks non-verbal cues. They are categorized in the way they impact the sentiment, which can be one of the following three cases:

1. To intensify the sentiment
2. To disambiguate the sentiment
3. To flip/negate the sentiment (sarcastic emoji)

As can be seen in Table 1, this was a difficult question for most coders, where for most cases, at least two of the six coders denoted the effect to be unclear. One such example is this (Poessie78, 2020):

Figure 3: tweet where the effect of the emoji on sentiment might be unclear. Translation: "and they are talking about global warming. We have never had such a cold July as this year". Background: July 2020 was a relatively cold July in the Netherlands (KNMI, 2020)

In the tweet from Figure 3, two coders believed the emoji to intensify the sentiment, two coders believed the emoji to be sarcastic and flip the sentiment, while the remaining two coders found the effect to be unclear. From the sample, not a single tweet containing emojis was answered the same for all coders, resulting in a negative α. It is not clear what caused this value to be negative rather than zero. Because of the absence of reliability, the question was excluded from the final codebook. All other questions scored α-values of 0.76 or higher, which was deemed satisfactory for this research.

3.2.1.2 Markers

Other research has used different strategies in coding for sarcasm, for example by requiring two or more of the following markers to be present (Anderson & Huntington, 2017):

- Contradictory statements to suggest the user has opposing ideas to the remark
- Heavy punctuation or (more than one) quotation marks
- Excessive use of capital letters
- Laughter expression in the context of provocation
- Presence of extreme adjectives or adverbs together
- Exaggerated or melodramatic statements
- Subtle or covert attack
- Humor used within the context of a covert attack or contradictory statement

In the practice session, all coders also coded for these markers to see whether these can be reliably used to look for markers that might be more present in sarcastic tweets. Their reliability was also scored via Krippendorff's Alpha, the results of this can be found in Table 2.

Table 2: Reliability scores for linguistic markers of sarcasm

Marker	**α**
Excessive use of capital letters	1*
Laughter expression	0.595
Extreme adjectives	0.5496222
Exaggerated statements	0.1996333
Subtle attack	0.1891726
Humor in covert attack/contradictory statement	1*
Contradictory statements	0.2281173
Heavy punctuation or quotation marks	1*

*these markers only occurred once or did not occur at all in the sample, which results in an alpha of 1

All markers turned out to be difficult to code for with sufficient reliability. Because of this, they were excluded from the final codebook.

3.2.2 Final codebook

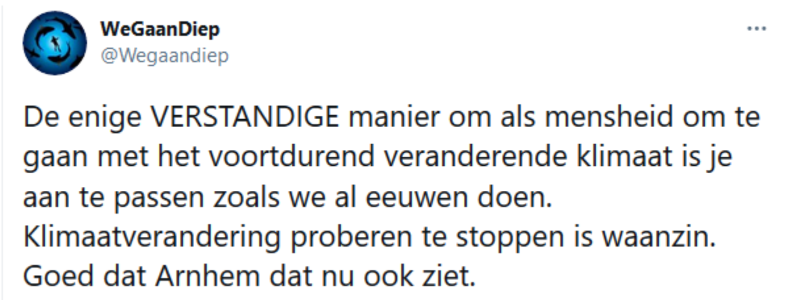
Following the reliability analysis, questions with low reliability (< 0.75) where removed, resulting in the following codebook and their possible answers:

1. The sentiment of the tweet
    a) Positive
    b) Negative
    c) Neutral
    d) Unclear
2. Whether the user supports action against climate change
    a) Yes
    b) No
    c) Unclear
3. The presence of sarcasm in the context of having effect on sentiment
    a) Yes
    b) No
    c) Unclear

Tweets that use climate or warming in a different context (e.g. work climate, economic climate, warming up in sports) are excluded before further analysis.

Tweets were categorized on their sentiment, either ‘Positive’, ‘Negative’, ‘Neutral’ or ‘Unclear’. Normally, sentiment can be categorized much more detailed than that, for example by labelling other emotional categories of tweets (e.g. joy, sadness, fear, ridicule) (Pozzi et al., 2017, Chapter 2), but automatic sentiment analysis is often limited to positive or negative and further categorization can be difficult to do by non-experts. No further criteria are given for the categorization for the questions.

For sentiment, the categorization is based on how the tweet is interpreted by the reader. A positive sentiment can be both for somebody who is happy that a certain action against climate change is taken, but also somebody who can be happy that some action supports his idea of not having to take action against climate change, such as the following tweet:


WeGaanDiep
@Wegaandiep

De enige VERSTANDIGE manier om als mensheid om te gaan met het voortdurend veranderende klimaat is je aan te passen zoals we al eeuwen doen. Klimaatverandering proberen te stoppen is waanzin. Goed dat Arnhem dat nu ook ziet.

Figure 4: example of a positive tweet where the user supports action against climate adaption but does not acknowledge the anthropogenic factor of climate change (https://twitter.com/Wegaandiep/status/1288402487410659329). Translation: “The only SENSIBLE way as humanity to deal with constantly changing climate is to adapt, like we have done for ages. Stopping climate change is madness. Good that Arnhem sees that now as well.”

In the example in Figure 4, difficulty also arises where it seems the user supports action against climate change, but the user only supports taking action to adapt to the changing climate, for example by protecting habitable lands from rising sea level; in contrast to actively stopping climate change, for example by lowering greenhouse gas emissions. These users often believe the fact that climate is indeed changing and global temperatures are rising, but they often also believe there is no anthropogenic factor involved, such as the example in Figure 5 (PeterKonings7, 2020).

Figure 5: example of a tweet where a user acknowledges the existence of climate change, but disagrees with the fact that there is an anthropogenic factor involved (https://twitter.com/PeterKonings7/status/1289017244635275267). Translation: It is a fact that climate changes, it has been doing that since it exists. That man contributes to this is plain nonsense and only meant to free up money for the climate lobby and the Green Deal.

These tweets are coded as the user **not** supporting action against climate change, as scientific consensus acknowledges that humanity is at least partly responsible for climate change and that action should be taken to mitigate climate change (IPCC, 2014).

3.3 Content analysis

3.3.1 Manual coding

After finalization of the codebook, the whole dataset was coded only by the author.

To ensure validity of coding, the same group coders that tested reliability of the codebook were asked to code all tweets from the dataset that were coded as sarcastic by the author. The coders coded these 156 tweets on sentiment (‘Positive’, ‘Negative’, ‘Neutral’ or ‘Unclear’) and sarcasm (yes/no).

3.3.2 Automated sentiment analysis

To answer the question whether sarcasm has significant effect on automated sentiment analysis, a computer-based form of sentiment analysis was also performed using the Pattern package for Python (De Smedt & Daelemans, 2012). This package is developed as a natural language processor to be utilized via Python and purposefully developed to accommodate research projects with a short development cycle, such as this one. Pattern is developed for many web mining services, one of which is quick and easy sentiment analysis of short texts in multiple languages, such as Dutch.

It is based on a lexicon approach, which means that it contains a database of adjectives with corresponding values between -1 and +1 for both polarity and subjectivity. The tool is tested on book reviews and an accuracy of 82% is reported by the developers. Since easy-to-use sentiment analysis tools for Dutch language are rare, it was chosen to use Pattern, with the comment that state-of-the-art machine-learning based tools might be more accurate and reliable for tweets. The python script used can be find in *Appendix B: Python script*.

4 Results

4.1 Face validity

Coding for sentiment turned out to be difficult for sarcastic tweets. Six coders analysed all tweets that were coded as sarcastic by the author (138 tweets), plus a small randomly selected sample of tweets that were coded as non-sarcastic by the author (18 tweets).
For this small subset of 156 tweets, the agreement level between the author and each individual coder was quite low. In the case of coding for sentiment, only 62.3% of the answers were the same on average for the whole subset (lowest agreement with a coder was 55.8%, highest was 69.6%), while the agreement for the 18 non-sarcastic tweets was 77.8% on average. One example where there was no agreement between coders is displayed in Figure 6 (Fmeeus1, 2020).

Figure 6: a tweet where agreement between coders for sentiment was low. Translation: "Climate good news: thanks to climate change, there are no natural disasters anymore.

In this tweet, all coders agreed that it was sarcastic. The tweet was coded by the author as having negative sentiment, while three coders denoted it as positive, and two thought it was unclear.

Sarcasm turned out to be accurately coded overall; 95% of the answers were the same on average between the author and individual coders.

4.2 Automatic vs. Manual coding

To get an idea of how lexicon-based automated sentiment analysis-algorithms handle Dutch tweets, the results of the sentiment analysis were compared between manual coding and automatic coding.

Table 3: comparison of automated vs. manual sentiment analysis

Automated sentiment analysis	**Manual sentiment analysis**	**Tweets** Amount (% of total)
Neutral	Negative	456 (12.6%)
Neutral	Positive	16 (0.4%)
Negative	Neutral	390 (10.2%)
Negative	Positive	25 (0.7%)
Positive	Negative	837 (21.8%)
Positive	Neutral	872 (22.8%)
Total tweets coded differently		*2596 (67.7%)*
Positive	Positive	216 (5.6%)
Negative	Negative	46 (12.1%)
Neutral	Neutral	538 (14.0%)
Total tweets coded the same		*1236 (32.3%)*

In total, 2596 tweets (67.7% of the total) were coded differently by manual sentiment analysis than by automated sentiment analysis. This is a very substantial amount, but the most obvious conclusion from this is that Pattern for Python is not really suitable for this type of sentiment analysis of tweets. This is not surprising, as validity of sentiment analysis is most of the time highly dependent on the domain and language with which it is used (van Atteveldt et al., 2021).

44.6% of the total tweets were labelled positive in automatic analysis while being labelled differently in manual coding. As displayed in Table 3, this represents the largest share of tweets where automatic sentiment analysis gives a different sentiment than in manual analysis. One such tweet is displayed in Figure 7 (Wisse_evert_jan, 2020)

Figure 7: example tweet where Pattern returns a positive sentiment, while manual analysis returns negative sentiment. Translation: '"Totally agree! What a super strong argument!" – no one #failed #vvd one of the key competences of politicians: being able to argue with facts #YouHadOneJob #stikstof #CO2 #klimaat

In this example, the first part is clearly labelled positive by Pattern, because of the words “Eens”, “super sterk”. The rest of the tweet makes it clear that the user in fact intended negative sentiment, as well as the use of parentheses to denote sarcasm. One interesting observation is that the user also used words in English that were more negative (“failed”), but this might be overlooked upon by Pattern, because it used only a Dutch lexicon.

In the same trend, 34.4% of tweets were labeled as having negative sentiment in manual coding while being labeled either positive or neutral by Pattern. This is in line with the conclusion by Anderson & Huntington (2017) that figurative speech is most often intended to disguise incivility or negative sentiment via passive aggression.

4.3 Sarcasm

Table 4: coding results

Sarcastic?	Sentiment	Supports action against climate change	Result (% of total)
Yes			**7.91%**
Yes	Negative		*6.78%*
Yes	Negative	No	*4.72%*
Yes	Negative	Yes	*0.83%*
Yes	Negative	Unclear/Neutral	*1.23%*
Yes	Neutral		*0.68%*
Yes	Neutral	No	*0.08%*
Yes	Neutral	Yes	*0.18%*
Yes	Neutral	Unclear/Neutral	*0.42%*
Yes	Positive		*0.37%*
Yes	Positive	No	*0.05%*
Yes	Positive	Yes	*0.05%*
Yes	Positive	Unclear/Neutral	*0.26%*

No			***92.09%***

In total, 303 tweets were manually coded as sarcastic and having effect on sentiment. These represent 7.91% of the total amount of tweets considered. Interestingly, 86% of tweets coded as sarcastic contained negative sentiment, which corresponds to results from similar research on this topic (Maynard & Greenwood, 2014). This could mean that most of the time when sarcasm is used, the user wants to express a negative opinion, while the meaning of the literal words is positive.

264 of tweets coded differently between methods were coded as sarcastic in manual coding. This means that 87% of tweets that were coded manually as being sarcastic and having influence on sentiment were actually coded differently by automated analysis versus manual analysis.

4.4 Personals standpoint of users towards taking action on climate change

Table 5: results for tweets when looking at personal standpoints towards taking action on climate change

Supports action against climate change	**Sarcastic**	**Result (% of total)**
Yes		**57.42%**
Yes	Yes	*1.07%*
Yes	No	*56.35%*
No		***24.46%***
No	Yes	4.88%
No	No	*19.48%*
Unclear		***18.31%***

When looking at the personal standpoint of users towards climate change, some interesting patterns appear. Even though the majority of tweets regarding climate change are published by users who support action against climate change, more than four times as much sarcastic tweets (4.88% vs. 1.07%) are published by users who do not support action against climate change versus those who do. Note that this contains both people who do not believe that climate change exists and people who do believe it exists but are not in favour of taking (more) action against it, or do not acknowledge that climate change is human-caused. From the total dataset, 24.2% of users were coded as such; this means that the use of sarcasm is present more often in the group that is often denoted by other researchers as ‘climate change deniers’ (Anderson & Huntington, 2017; Maynard & Greenwood, 2014).

Apart from the use of sarcasm, the fact that 24.2% of tweets in the dataset belong to users who appear to disagree with the scientific consensus that climate change is an important topic on which action should be taken by the Dutch society, might be alarming.

5 Conclusions & Discussion

This research gives an insight into the current state of research into sarcasm use and sentiment analysis for Twitter, in particular in the Dutch language and on the topic of climate change. The goal of this research was not to perform sentiment analysis but to find out to what extent sarcasm is used in the debate of climate change in the Twitter sphere, and to verify whether the use of sarcasm in this debate has a significant effect on sentiment analysis. With ~ 8% of tweets being labelled as sarcastic (in the definition of this research), one could say that it is something that researchers should definitely take into account when performing sentiment analysis on twitter regarding climate change.

The abundance of sarcasm in tweets regarding this topic can be explained by the fact that climate change is a topic prone to incivility and polarization also in Dutch speaking countries, due to the politicized nature of the topic. The majority of the users tweeting on climate change are supporters of taking action against it and with that conform to the scientific consensus on the topic, while incivility in the form of sarcasm is more present among users who do not support action.

It seems from the data that sarcasm is most often used by users who want to express a negative sentiment but use words that would be interpreted as positive when looking at the literal meaning, but this conclusion cannot readily be made because of the limitations of manual sentiment analysis in this research.

Performing sentiment analysis on Twitter is still difficult with the limited resources that this research had available. While free options are present, the validity of automatic sentiment analysis using these options cannot be guaranteed, especially concerning sarcasm. Nevertheless, the large differences between manual and automatic analysis are a sign that sarcasm indeed influences sentiment analysis significantly, especially when automatic sentiment analysis is done via lexicon-based methods.

Even in manual analysis, sentiment analysis is difficult when using a small group of non-expert coders. Some questions were removed from the codebook because reliable coding could not be ensured, such as the question what effect the use of emojis have on sentiment of a tweet. This is in line with the difficulties of performing manual sentiment analysis, especially on sarcastic tweets. While sentiment analysis can be very useful to get an idea of public opinion on certain topics in online discourse, accurate analysis is dependent on the ability of researchers to detect forms of figurative language use that rely on non-verbal cues to deliver the intended message.
While coding for sentiment for the overall dataset was reliable, making conclusions on what sentiment is often used when using sarcasm is difficult. This is because it cannot be guaranteed that sarcastic tweets were coded accurately in terms of sentiment – this shows again that performing sentiment analysis as non-expert in linguistics is difficult and automatic sentiment analysis is more attractive for researchers outside of the field of linguistics.

Another goal of this research was to verify which type of markers were most used in sarcastic tweets, so as to gain information on how sarcasm can be more easily recognized by future automated sentiment analysis. Ensuring sufficient coding reliability for these markers turned out to be difficult, so it was decided that this analysis was not included. For further research, other types of coding are recommended, such as expert coding (using language experts to code and also let each tweet be coded by multiple experts) or crowd-based coding (coding by a much larger group of people, where each tweet can be coded by more than two people). With these methods of coding, higher reliability scores can be realized for difficult questions, such as which linguistic marker denotes the use of sarcasm.

When analysing twitter data, the generalizability of conclusions based on the dataset is dependent on the occurrence of news articles and other events that might urge someone to tweet about something. Of course, a completely 'eventless' period might be most suitable for this type of analysis, but these are hard to look for. In the first dataset, a large amount of tweets seemed influenced by the U.S. Presidential Election, which was dominating national news sources at the time. Because of that, a second dataset was acquired where there were no events happening that

dominated the dataset. One possibility is that the COVID-pandemic had some influence on the activity of users on Twitter, but no signs were found that it had significant impact.
There were some news publications that were represented in the tweets, such as the municipality of Arnhem publishing their plans to adapt the city to climate change (NOS, 2020). These smaller news publications were not deemed too influential to look for a new dataset. The used dataset is set in July, which was a relatively cold July (KNMI, 2020). This might effect the dataset, as colder temperatures might be an incentive for users to tweet about the ‘absence of global warming because it is colder’. On the other hand, the whole summer of 2020 was a hot and dry one, which might incentivize users to tweet about global warming being more present.

More research could have been done to determine the generalizability of this dataset, by comparing it with other similar sets, but this was not done because of limitations in the use of the free Twitter API.

There are similarities between results of this research and other literature, such as the fact that sarcasm was more often used by users who are opposed to taking action on climate change. Methods used by these researchers were not available for this research, due to the difference in language (Dutch vs. English). The indicators for sarcasm that are used in these papers turned out not to be applicable to Dutch language, so more research should be done on how sarcasm can be recognized more easily in Dutch tweets.

This research gives a first look into what extent sarcasm plays a role in online discussion on climate change in Dutch language. Researchers, policy makers and other people utilizing sentiment analysis should take into account the presence of sarcasm in politicized topics such as climate change, when mining for opinions. Twitter is a very useful source of large volumes of data that can be analyzed to get an idea of public discourse on certain topics, but there are still quite a lot of difficulties in making use of this data. When sentiment analysis can be performed more accurately, dynamics of online forums such as Twitter can be better understood and even utilized by policy makers and the like, to establish topics that need to be addressed and to get a feeling of public opinion on topics such as climate change.

6 Bibliography

Anderson, A. A., Brossard, D., Scheufele, D. A., Xenos, M. A., & Ladwig, P. (2014). The "nasty effect:" online incivility and risk perceptions of emerging technologies. *Journal of Computer-Mediated Communication*, *19*(3), 373–387. https://doi.org/10.1111/jcc4.12009

Anderson, A. A., & Huntington, H. E. (2017). Social Media, Science, and Attack Discourse: How Twitter Discussions of Climate Change Use Sarcasm and Incivility. *Science Communication*, *39*(5), 598–620. https://doi.org/10.1177/1075547017735113

Bond, R. M., Fariss, C. J., Jones, J. J., Kramer, A. D. I., Marlow, C., Settle, J. E., & Fowler, J. H. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature*, *489*(7415), 295–298. https://doi.org/10.1038/nature11421

Boykoff, M. T. (2011). *Who Speaks for the Climate? Making Sense of Media Reporting on Climate Change* (Vol. 3, Issue 3). Cambridge University Press. https://doi.org/10.1177/2043820613512233

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, *357*(4), 370–379. https://doi.org/10.1056/NEJMsa066082

Cody, E. M., Reagan, A. J., Mitchell, L., Dodds, P. S., & Danforth, C. M. (2015). Climate change sentiment on Twitter: An unsolicited public opinion poll. *PLoS ONE*, *10*(8), 1–19. https://doi.org/10.1371/journal.pone.0136092

Dalrymple, K. E., Young, R., & Tully, M. (2016). "Facts, Not Fear": Negotiating Uncertainty on Social Media During the 2014 Ebola Crisis. *Science Communication*, *38*(4), 442–467. https://doi.org/10.1177/1075547016655546

De Smedt, T., & Daelemans, W. (2012). Pattern for Python. *Journal of Machine Learning Research*, *13*, 2063–2067.

Fmeeus1. (2020). *Klimaat goed nieuws : dankzij klimaatverandering zijn er geen natuurrampen meer. ?[Tweet].* https://twitter.com/fmeeus1/status/1288745436451205120

Gamer, M., & Lemon, J. (2019). *irr: Various Coefficients of Interrater Reliability and Agreement*. https://cran.r-project.org/package=irr

Gastrow, M. (2015). Science and the Social Media in an African Context: The Case of the Square Kilometre Array Telescope. *Science Communication*, *37*(6), 703–722. https://doi.org/10.1177/1075547015608637

Gjvu. (2020). *Wel #Tweeps - de zon duikt. Om 'het klimaat' te redden, heb ik de buiten jacuzzi net eempies een tikkie gegeven. Omhoog ? [Tweet].* https://twitter.com/gjvu/status/1288907999059283970

Hogenboom, A., Bal, D., Frasincar, F., Bal, M., De Jong, F., & Kaymak, U. (2013). Exploiting emoticons in sentiment analysis. *Proceedings of the ACM Symposium on Applied Computing*, 703–710. https://doi.org/10.1145/2480362.2480498

Holliman, R. (2011). Advocacy in the tail: Exploring the implications of "climategate" for science journalism and public debate in the digital age. *Journalism*, *12*(7), 832–846. https://doi.org/10.1177/1464884911412707

IPCC. (2014). Climate Change 2014. In *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.

Kahan, D. M., Peters, E., Wittlin, M., Slovic, P., Ouellette, L. L., Braman, D., & Mandel, G. (2012). The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nature Climate Change*, *2*(10), 732–735. https://doi.org/10.1038/nclimate1547

Kearney, M. W. (2020). *Rtweet package*. https://cran.r-project.org/web/packages/rtweet/index.html

Kemp, S. (2020). *Digital 2020: October Global Statshot*. Datareportal. https://datareportal.com/reports/digital-2020-october-global-statshot

KNMI. (2020). *Zomer 2020: (juni, juli, augustus). Zeer warm en zeer zonnig, normale hoeveelheid neerslag*. https://www.knmi.nl/nederland-nu/klimatologie/maand-en-seizoensoverzichten/2020/zomer

Krippendorff, K. (1980). Content Analysis: An Introduction to its Methodology. In *Journal of the American Statistical Association*. https://doi.org/10.2307/2288384

Liebrecht, C., Kunneman, F., & Bosch, A. Van den. (2013). The perfect solution for detecting sarcasm in tweets #not. *Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, *June*, 29–37. http://www.aclweb.org/anthology/W13-1605

Liu, B. (2018). Sentiment analysis. In *International Journal of Advanced Computer Science and Applications* (Vol. 9, Issue 9). Cambridge University Press. https://doi.org/10.14569/ijacsa.2018.090981

Malone, T. W., & Klein, M. (2007). Harnessing Collective Intelligence to Address Global Climate Change. *Innovations: Technology, Governance, Globalization*, *2*, 15–26. https://doi.org/10.1162/itgg.2007.2.3.15

Maynard, D., & Greenwood, M. A. (2014). Who cares about sarcastic tweets? Investigating the impact of sarcasm on sentiment analysis. *Proceedings of the 9th International Conference on Language Resources and Evaluation, LREC 2014*, 4238–4243.

monstersinalice. (2020). *Maar hey, gelukkig is klimaat verandering maar een hoax hè #sarcasme [Tweet]*. https://twitter.com/monstersinalice/status/1213773355305840645

NOS. (2020). *Arnhem komt met groen plan om gevolgen klimaatverandering op te vangen*. https://nos.nl/artikel/2342174-arnhem-komt-met-groen-plan-om-gevolgen-klimaatverandering-op-te-vangen.html

Pearce, W., Niederer, S., Özkula, S. M., & Sánchez Querubín, N. (2019). The social media life of climate change: Platforms, publics, and future imaginaries. *Wiley Interdisciplinary Reviews: Climate Change*, *10*(2), 1–13. https://doi.org/10.1002/wcc.569

PeterKonings7. (2020). *No TiDat klimaat verandert is een gegeven, dat doet het al sinds er sprake is van klimaat. Dat de mens hieraan bijdraagt is aperte nonsens en enkel bedoeld om geld vrij te maken voor de klimaatlobby en de Greendeal [Tweet]*. https://twitter.com/PeterKonings7/status/1289017244635275267

Poessie78. (2020). *En dan hebben ze het over de opwarming van de aarde. We hebben nog nooit zo'n koude maand juli gehad als dit jaar ? [Tweet]*. https://twitter.com/Poessie78/status/1288423527620775940

Pozzi, F. A., Baracho, R., Bax, M., Ferreira, L., & Silva, G. (2014). *Sentiment analysis in social networks* (E. Fersini, E. Messina, & B. Liu (eds.)). Morgan Kaufmann. https://doi.org/10.1016/b978-0-12-804412-4.00006-1

Pozzi, F. A., Fersini, E., Messina, E., & Liu, B. (2017). *Chapter 1 - Challenges of Sentiment Analysis in Social Networks: An Overview* (F. A. Pozzi, E. Fersini, E. Messina, & B. B. T.-S. A. in S. N. Liu (eds.); pp. 1–11). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-12-804412-4.00001-2

Schäfer, M. S. (2012). Online communication on climate change and climate politics: A literature review. *Wiley Interdisciplinary Reviews: Climate Change*, *3*(6), 527–543. https://doi.org/10.1002/wcc.191

van Atteveldt, W., van der Velden, M. A. C. G., & Boukes, M. (2021). The Validity of Sentiment Analysis:Comparing Manual Annotation, Crowd-Coding, Dictionary Approaches, and Machine Learning Algorithms. *Communication Methods and Measures*, *15*(01), 1–20. https://doi.org/10.1080/19312458.2020.1869198

Williams, H. T. P., McMurray, J. R., Kurz, T., & Hugo Lambert, F. (2015). Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Global Environmental Change*, *32*, 126–138. https://doi.org/10.1016/j.gloenvcha.2015.03.006

Wisse_evert_jan. (2020). *"Helemaal eens! Wat een super sterk argument!" -no one #failed #vvd een van de keyncompetenties van politici: kunnen beargumenteren met feiten #YouHadOneJob #stikstof #CO2 #klimaat [Tweet]*. https://twitter.com/wisse_evert_jan/status/1288215736461205510

7 Appendix A: R script data collection

```
install.packages("rtweet")
install.packages("writexl")
install.packages("rtools")
library(rtweet)
library(tidyverse)

## The actual key, secret and token are removed for privacy purposes
consumer_key <- "XXX"
consumer_secret <-"XXX"
access_token <- "XXX"
access_secret <- "XXX"
mytoken<- create_token(
  app="Klimaattweets",
  consumer_key,
  consumer_secret,
  access_token,
  access_secret)
get_token()
tweets <- search_fullarchive(q=("klimaat OR klimaatverandering OR
opwarming"),n=4000,env_name="Klimaat",toDate = "202008010000",token=mytoken)
tweets_extra <- search_fullarchive(q=("klimaat OR klimaatverandering OR
opwarming"),n=1011,env_name="Klimaat",toDate = "202007291400",token=mytoken)
tweets_final <- rbind(tweets,tweets_extra)
tweets_final_nort <- data.frame(tweets_final) %>%
  filter(is_retweet == FALSE)
tweets2 <- data.frame(tweets_final) %>%
  select(3,4,5,7,11,12,13,14,15,16,72) %>% ## select columns possibly of interest
  arrange(created_at) ## sort by date
write.table(tweets2,file="tweets_final.csv",sep=";",col.names=NA)
```

8 Appendix B: Python script

```
import importlib.util
import sys
import pandas as pd

## create dataset
df=pd.read_excel('20210104tweets_final_clean.xlsx')
df=df[['Unnamed: 0','text']]
df_columns=['tweet_id','text']
#print(df.head(3))

## check if pattern is installed
#name='pattern'
#if name in sys.modules:
    #print(f"{name!r} already in sys.modules")
#elif (spec := importlib.util.find_spec(name)) is not None:
   # module = importlib.util.module_from_spec(spec)
   # sys.modules[name] = module
   # spec.loader.exec_module(module)
   # print(f"{name!r} has been imported")
#else:
#    print(f"can't find the {name!r} module")

#import subprocess
#reqs = subprocess.check_output([sys.executable, '-m', 'pip', 'freeze'])
#installed_packages = [r.decode().split('==')[0] for r in reqs.split()]

#print(installed_packages)

from pattern.nl import singularize, pluralize, sentiment

pol=[]
subj=[]
for x in df["text"]:
    pol.append(sentiment(x)[0])
    subj.append(sentiment(x)[1])
df["Polarity"]=pol
df["Subjectivity"]=subj


writer = pd.ExcelWriter('tweets_final_met_sentiment.xlsx')
df.to_excel(writer)
writer.save()
print('DataFrame is written to excel')
```

9 Appendix C: Krippendorff's Alpha

```
library(tidyverse)
library(googlesheets4)
library(irr)
gs4_auth_configure(api_key = "AIzaSyDnr3ApbkVXK6UovJiZW9BiyMBCy7xVQSo")
gs4_deauth()

# vraag1: Is klimaat het belangrijkste onderwerp van de tweet?

vraag1<-
data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Belangrijkste
onderwerp")) %>%
  select(2,3,4,5,6,7)
vraag1[vraag1 == "Ja"] = 1
vraag1[vraag1 == "Nee"] = 2
a1=kripp.alpha(t(vraag1),method=c("nominal"))

# vraag2: Wat is het sentiment van de tweet?
vraag2<-
data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Sentiment")) %>%
  select(2,3,4,5,6,7)
vraag2[vraag2 == "Positief"] = 1
vraag2[vraag2 == "Negatief"] = 2
vraag2[vraag2 == "Neutraal"] = 3
vraag2[vraag2 == "Onduidelijk"] = 4
a2=kripp.alpha(t(vraag2),method=c("nominal"))

# vraag3: Denk je dat de tweeter voor of tegen actie tegen klimaatverandering
is?
vraag3<-
data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Voor of tegen CC"))
%>%
  select(2,3,4,5,6,7)
vraag3[vraag3 == "Voor"] = 1
vraag3[vraag3 == "Tegen"] = 2
vraag3[vraag3 == "Onduidelijk/Neutraal"] = 3
a3=kripp.alpha(t(vraag3),method=c("nominal"))

# vraag4: Wat is het effect van de emoji op het sentiment?
vraag4<-
data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Effect Emoji")) %>%
  select(2,3,4,5,6,7)
vraag4[vraag4 == "Versterkt"] = 1
vraag4[vraag4 == "Onduidelijk/eutraal"] = 2
vraag4[vraag4 == "Draait het sentiment om (sarcastische emoji)"] = 3
a4=kripp.alpha(t(vraag4),method=c("nominal"))
```

```
# vraag5: Vind je (een gedeelte van) de tweet sarcastisch?
vraag5<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Sarcasme")) %>%
  select(2,3,4,5,6,7)
vraag5[vraag5 == "Ja"] = 1
vraag5[vraag5 == "Nee"] = 2
a5=kripp.alpha(t(vraag5),method=c("nominal"))

# vraag6: Zorgt het sarcasme ervoor dat het sentiment wordt omgedraaid?
vraag6<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Sentiment Sarcasme")) %>%
  select(2,3,4,5,6,7)
vraag6[vraag6 == "Ja"] = 1
vraag6[vraag6 == "Nee"] = 2
#vraag6 <- vraag6[rowSums(is.na(vraag6))<=1,]
a6=kripp.alpha(t(vraag6),method=c("nominal"))


# Hoofdletters
vraag7<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Hoofdletters")) %>%
  select(2,3,4,5,6,7)
vraag7[vraag7 == "Ja"] = 1
vraag7[vraag7 == "nee"] = 2
a7=kripp.alpha(t(vraag7),method=c("nominal"))
# Uitlachen
vraag8<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Uitlachen")) %>%
  select(2,3,4,5,6,7)
vraag8[vraag8 == "Ja"] = 1
vraag8[vraag8 == "Nee"] = 2
a8=kripp.alpha(t(vraag8),method=c("nominal"))
# Positieve uitingen
vraag9<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Positieve")) %>%
  select(2,3,4,5,6,7)
vraag9[vraag9 == "Ja"] = 1
vraag9[vraag9 == "Nee"] = 2
a9=kripp.alpha(t(vraag9),method=c("nominal"))
# Negatieve uitingen
vraag10<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-
Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Negatieve")) %>%
  select(2,3,4,5,6,7)
vraag10[vraag10 == "Ja"] = 1
vraag10[vraag10 == "Nee"] = 2
a10=kripp.alpha(t(vraag10),method=c("nominal"))
```

```
# Subtiele aanval
vraag11<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Subtiel")) %>%
  select(2,3,4,5,6,7)
vraag11[vraag11 == "Ja"] = 1
vraag11[vraag11 == "Nee"] = 2
a11=kripp.alpha(t(vraag11),method=c("nominal"))
# Hashtag
vraag12<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Hashtag")) %>%
  select(2,3,4,5,6,7)
vraag12[vraag12 == "Ja"] = 1
vraag12[vraag12 == "Nee"] = 2
a12=kripp.alpha(t(vraag12),method=c("nominal"))
# Retorisch
vraag13<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Retorisch")) %>%
  select(2,3,4,5,6,7)
vraag13[vraag13 == "Ja"] = 1
vraag13[vraag13 == "Nee"] = 2
a13=kripp.alpha(t(vraag13),method=c("nominal"))
# Anekdote
vraag14<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Anekdote")) %>%
  select(2,3,4,5,6,7)
vraag14[vraag14 == "Ja"] = 1
vraag14[vraag14 == "Nee"] = 2
a14=kripp.alpha(t(vraag14),method=c("nominal"))
# Ander stukje tekst
vraag15<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Ander stukje tekst")) %>%
  select(2,3,4,5,6,7)
vraag15[vraag15 == "Ja"] = 1
vraag15[vraag15 == "Nee"] = 2
a15=kripp.alpha(t(vraag15),method=c("nominal"))
# Interpunctie
vraag16<-data.frame(read_sheet("https://docs.google.com/spreadsheets/d/15mlksefuT-Y-Gb_eTcYuY5KK193L9I4XpJRVcIQhM4o/edit?usp=sharing",range="Interpunctie")) %>%
  select(2,3,4,5,6,7)
vraag16[vraag16 == "Ja"] = 1
vraag16[vraag16 == "Nee"] = 2
a16=kripp.alpha(t(vraag16),method=c("nominal"))

###

column_names=c("a1","a2","a3","a4","a5","a6","a7","a8","a9","a10","a11","a12","a13","a14","a15","a16")
alpha=c(a1[5],a2[5],a3[5],a4[5],a5[5],a6[5],a7[5],a8[5],a9[5],a10[5],a11[5],a12[5],a13[5],a14[5],a15[5],a16[5])
result=data.frame(column_names,alpha)
```

10 Appendix D: Codebook

10.1 Initial codebook

1. Is the word climate used in the context of atmospheric climate/average weather conditions?
    a. Yes
    b. No
2. What is the sentiment of the tweet?
    a. Positive
    b. Negative
    c. Neutral
    d. Unclear
3. Do you think the user supports action against climate change?
    a. Yes
    b. No
    c. Neutral/Unclear
4. What is the effect of the emojis on sentiment?
    a. It intensifies the sentiment
    b. Without the emoji, the sentiment would have been unclear
    c. The emoji negates the sentiment (sarcastic emoji)
    d. Neutral/unclear
5. Do you think (part of) the tweet is sarcastic?
    a. Yes
    b. No
    c. Unclear
6. Which of the following markers does this tweet contain?
    a. Heavy punctuation
    b. Quotation marks
    c. Excessive use of capital letters
    d. Laughter expression in the context of provocation
    e. Exaggerated positive statements
    f. Exaggerated negative statements
    g. Subtle or covert attack
    h. Use of certain hashtags
    i. Rhetorical question
    j. Illustrating an anecdote
    k. Contradictory statements to suggest the user has opposing ideas to the remark

10.2 Final codebook

1. What is the sentiment of the tweet
    a) Positive
    b) Negative
    c) Neutral
    d) Unclear
2. Do you think the user supports action against climate change?
    a) Yes
    b) No
    c) Neutral/Unclear
3. Do you think (part of) the tweet is sarcastic in the context of having effect on sentiment?
    a) Yes
    b) No
    c) Unclear