The Effect of Message Sentiment on the Virality of Twitter Messages

Nathalie Maria Kirch (475068)

Supervisor: Rolf Zwaan, Arnout Boot

Erasmus University Rotterdam

Abstract

While the greater representation of negative information has been shown in a variety of domains, evidence concerning the existence of a *Negativity Bias* on the influential microblogging platform *Twitter* remains ambiguous. This observational study investigated the effect of message sentiment on the virality of Twitter messages by performing a lexical-based sentiment analysis of a random sample of tweets. Results indicate that negative tweets are more likely to be marked as favourite, but that there is no difference between the retweet count of positive versus negative tweets. These findings indicate that the concept of Negativity bias is not easily extended to the Twitter platform. Possible explanations are the greater effect of emotional divergence as opposed to polarity (i.e., positive or negative), heterogenous social functions of retweeting and liking – behaviour, as well as idiosyncratic characteristics of the platform. Moreover, the relationship between sentiment and virality might be nonlinear. For sharing information on Twitter, the present study advocates an overall rather negative tone to increase the number of likes. To maximize retweets, an overall emotional tone may be helpful.

Keywords: Twitter, Virality, Viral, Sentiment analysis, Negativity bias

The Effect of Message Sentiment on the Virality of Twitter Messages

Negativity Bias refers to the tendency of negative information to have a greater effect on cognitive processes and psychological states than positive information (Baumeister, Bratvansky, Finkenhauer & Vohs, 2001). This tendency is evident in a variety of domains, for instance, negative life- events are remembered in greater detail and have longer-lasting effects (Baumeister et al., 2001). Moreover, a negativity bias can already be detected in young infants (Kiley Hamlin, Wynn & Bloom, 2010). Baumeister et al. (2001) postulated that there are a few exceptions from Negativity Bias, where positive information has a greater impact than negative information. As we will see later, social media might be such an exception.

The present paper will examine the effect of message sentiment on the virality of Twitter messages. It will be inspected whether a negativity bias is also present on social media. The link between sentiment and virality is of significant practical and theoretical importance for viral marketing, spreading information, as well as for analysing and influencing public (political) opinion (Kim, 2018; Kumar & Sebastian, 2012a; Stiegliz & Dang-Xuan, 2012; Tsugawa & Ohsaki, 2015). Knowing whether such a bias exists, could be helpful for predicting the effect that different kinds of content have on sharing-patterns and hence audience selection.

The scope of the present paper is limited to the virality of messages on the microblogging platform *Twitter*. 330 million monthly active users and about 5 million daily tweets make Twitter a popular social media platform (Clement, 2019; Smith, 2020). Compared to other social media platforms, Twitter relies less heavily on pre-existing social relations, meaning that retweeting often occurs among strangers (Kwak, Lee, Park & Moon, 2010). This makes the platform more similar to traditional news media than other social media platforms and results more generalizable to other contexts. Twitter has also become an influential source of sociological and psychological research in the past years (Kumar & Sebastian, 2012b; Zhang, Wei & Boncella, 2019), which makes it important to identify trends and biases, characteristic to the platform.

There is some evidence suggesting that social media might be one of the few contexts where a bias towards *positive* instead of negative information is present. This especially seems to be the case for marketing- contexts and commercial e-mails (Dafonte-Gomez & Miguez-Gonzales, 2018; Kim, 2015; Nikolinakou & Whitehil King, 2018; Sharma & Kaur, 2020; Tellis, Maclinnis, Tirunillai & Zhang, 2019). This might be the case because *sharing* is a form of social behaviour, and people who retweet might be trying to evoke positive emotions in recipients (Kim, 2015). However, the evidence is far from being unanimous. Some sources suggest that the relationship between positive sentiment and virality is non-linear, but rather takes the shape of an inverted U (Berger & Milkman, 2012; Heinbach & Hinz, 2015). The expression of moderately positive emotions should thus lead to increased virality, while expression of extremely positive emotions should reduce the virality.

Other studies suggest that that emotional content, in general, is likely to go viral. This might be due to its tendency of capturing attention since it might be perceived as persuasive and important (Brady, Wills, Jost, Tucker & van Bravel, 2017; Brady, Van Bravel, & Gantman, 2020; Heimbach & Hinz, 2016; Valenzuela, Piña & Ramírez, 2017). Some studies even suggest that it is not message sentiment (i.e., positive or negative), but rather emotional intensity or emotional divergence which influences virality (Pfitzner, Garas, & Schweitzer, 2012). That means that *polarity* (i.e., positive or negative) does not have an effect on virality. In that case, there should be no overall difference in the effect of positive and negative sentiment on virality.

However, several studies demonstrate such a difference. Some sources report a negativity bias in shared information on Twitter and indicate that negative information is more likely to be shared than positive (Jenders et al., 2013; Meng et al., 2018; Tsugawa & Ohsaki, 2015; Tsugawa & Ohsaki, 2017; Zhang et al., 2019). Jenders et al. (2013) for instance, found a negativity bias in viral tweets by performing an exploratory analysis using the SentiStrength algorithm, a commonly used opinion mining program. Their findings contradicted an earlier analysis by Pfitzner, Garas and Schweitzer (2012), who found no overall effect of message sentiment or polarity (i.e., positive, neutral, or negative) on the probability to be retweeted. Because of this contradiction in the existing literature and because the data that were used in the analyses by Pfitzner et al. (2012) and Jenders et al. (2013) are all rather old (from 2012 and 2011), more research is warranted.

There are more studies which suggest that negative messages are more likely to go viral than positive information. However, many of them had limited generalizability because they only focused on sharing patterns on Twitter related to individual events (Hurricane) or (minority) cultures (Japanese) (Tsugawa & Ohsaki, 2015; Zhang et al., 2019). Moreover, in contrast to Jenders et al. (2013), Tsugawa and Ohsaki (2015) ignored the proportion of positive and negative tweets in the population. That is, their original sample of tweets consisted only of tweets that were retweeted multiple times. The problem with this approach is that if the number of negative tweets is higher, it is more likely to find a higher number of negative retweets. There are moreover slight deviations in the existing literature in the way positive and negative words are classified. For instance, Tsugawa and Ohsaki (2015) mixed objective and subjective classification methods to determine the emotional value (i.e., positive or negative) of words. Meng et al. (2018) on the other hand, classified the emotionality of tweets according to the feeling each message evoked in respondents of a survey. This is a different kind of classification in that it classifies tweets as positive or negative based on *evoked* emotion, rather than on the 'intrinsic' sentimental valence of the words. For instance, fear could be evoked through a positive statement.

There is also some evidence suggesting that the differential effect of sentiment on virality is mediated by the type of content (Guerini & Staiano, 2015; Hansen, Arviddson, Nielsen, Colleioni & Etter, 2011; Tellis, Maclinnis, Tirunillai & Zhang, 2019). Research suggests, that different kinds of content (e.g. sentimental vs. informational), have a different likeliness to go viral on different platforms. Most of the studies which report a positivity bias in shared content specifically refer to either a marketing context (advertisements, videos and commercial e-mails) or other 'narrowcasting'- contexts, where messages are shared with a limited number of people (Kim, 2015). This is not the case for studies which report a negativity bias on Twitter (Jenders et al., 2013; Meng et al., 2018; Tsugawa & Ohsaki, 2015; Tsugawa & Ohsaki, 2017; Zhang et al., 2019). As stated previously, tweets are usually shared with a broad audience (Kwak et al., 2010). Therefore, it might be the case that a positivity bias exists in content that is shared in a narrowcasting context, and a negativity bias exists in a broadcasting context, where information is shared with a larger audience.

Sentiment analyses have been demonstrated to be useful in predicting emotions (Agarwal, Xie, Voshval, Rambow & Passineau, 2011; Jenders et al., 2013; Pang & Lee, 2012; Philander & Zhong, 2016) and a lexical- based approach has been demonstrated to be a valid approach for sentiment classification (Hiu & Liu, 2004). For correct classification, it is important to combine a dictionary- based- method with a semantic method (Kumar & Sebastian, 2012b; Saif, He & Alani, 2012). That means that one relies on both a previously determined dictionary, in which numerous words are either assigned a sentiment score (e.g.: "-1") or put into a category (e.g.: "negative"), as well as on the semantic orientation of words within a sentence. For example, if there is a negation word placed in front of a positive word (e.g.: not happy), it should be classified as negative. The sentiment score of all relevant words in the tweets should then be combined with an overall sentiment score of the tweet. Hence, in order to investigate the link between message sentiment and virality on Twitter, a lexical- based sentiment analysis will be performed in the present study. A combination of a dictionary based- and semantic method will be used to classify words correctly.

To summarize, whereas research on the existence of negativity bias is rather unanimous, it is unclear whether it also exists on shared content in news- and social media. Different sources indicate both the existence of a positivity bias, as well as the existence of a negativity bias. This difference might be accounted for by type of content: While it seems that positive content is more likely to be shared with individual people, negative content might be more likely to be shared with a broader audience.

The present paper will investigate the effect of message sentiment (i.e., positive or negative) on the virality of Twitter messages. More specifically, we will examine the effect of message sentiment on how often a message has been shared by other users (i.e., number of retweets), as well as how many times a user has explained their explicit positive sentiment towards a post (i.e., number of likes). Not all words can be unambiguously classified as either positive or negative. Emotionally ambiguous words are more likely to be classified arbitrarily, which is why they were excluded from the present analysis. Since Twitter messages are normally determined for a broad audience, and the platform thus belongs to a broadcasting context, it is hypothesized that negative messages are more likely to go viral than positive messages.

Methods

Data Collection and Pre-processing

For all data processing, RStudio Version 1.2.5042 was used. Using the Twitter Application Programming Interface (API), a random sample of tweets posted from 23. 04. 2009 – 07 .05. 2020 was collected. The package "rtweet" was used for data collection. With the function "search_tweets", an initial random sample of *n* = 17,997 tweets was drawn. After removing bots and automated sources, *n* = 16,518 Twitter natural twitter IDs were extracted. With the function "get_timelines()", which allows for data collection of all tweets from specified targets, a sample of *n = 769*,729 Tweets was collected. From each user, 100 Tweets were extracted. Because the Twitter API has a rate limit of 90,000 tweets per call, the tweets were collected in 18 iterations, in which 100 Tweets of 900 users were extracted per iteration.

Data Cleaning and Sentiment Classification

For Data Cleaning and Sentiment classification the packages "tidytext", "tidyr", "dplyr", and "stringr" were used. To clean the data, contractions were expanded (e.g.: isn't to is not) and URLs, unwanted signs (i.e., ^a-zA-Z'"(@#_;:&\\-\\.,!\\?), non-words (unigrams with less than 2 or more than 25 characters), and screen names were deleted. For sentiment classification, the NRC (Saif, Kiritchenko & Zhu, 2013) and AFINN (Nielsen, 2011) lexicon were used. Sentiment words with a negating word standing in front of them were assigned to the opposite category (e.g.: not happy -> negative).

After calculating the overall sentiment score for each tweet, all tweets were assigned to either the 'negative' or 'positive' category. Then, non-English and neutral tweets (with a sentiment score of zero) were excluded, so that in total n = 392, 847 tweets were excluded, and the final sample consisted of N = 376,882 Tweets.

Data Analysis

A sentiment analysis was performed, in which tweets were classified as either positive or negative. The number of retweet counts (i.e., the number of times a tweet has been shared) and the number of favourite counts (i.e., the number of times a user has expressed their positive sentiment towards a tweet) was compared between the two sentiment classifications. The R package 'brms' was used to fit two Bayesian Poisson regression models for zero-inflated count data to estimate the effects of (1) tweet sentiment on retweet count and (2) tweets sentiment on favourite count (Bürkner, 2017). This kind of analysis was chosen because contrary to a parametric or non-parametric significance test, it is able to account for the non-normal distribution of the present dataset, as well as to give an accurate representation of important effects given the large sample size. That is, if the sample size is large, a p-value can be significant even if the detected differences are marginal and unimportant. Moreover, means and medians do not reflect the data accurately. The distribution is non-normal because many tweets that are published on twitter have a favourite- or retweet count of zero.

Results

The total time span of data collection ranged from 23.04. 2009 to 07. 05. 2020, which is 2032 days. The total number of tweets is 378, 882, which were collected on 1,771 unique days. 90% of tweets were collected within one month, from 06.04. 2020 to 07.05.2020. Figure 1 shows the distribution of the number of tweets collected per day.

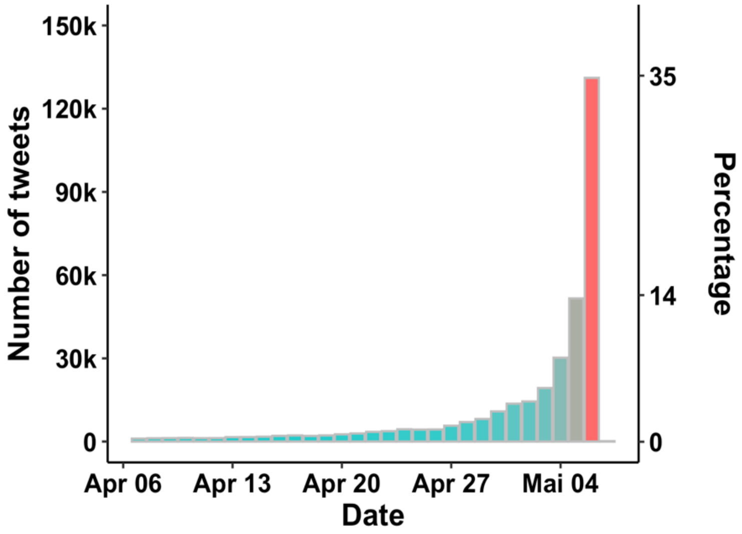

Figure 1. Number of tweets over time in the sample, displaying 90% of days. The total time span ranges from 23.04.2009 to 07.05. 2020, which is 4,032 days. The number of unique days is 1,771 and the total number of tweets is 378, 882.
Note. k = 000

The distribution of retweet counts, and favourite counts is displayed in Figure 2 and Figure 3, respectively. Both distributions are non-gaussian, with the majority of tweets having zero retweet counts and favourite counts.

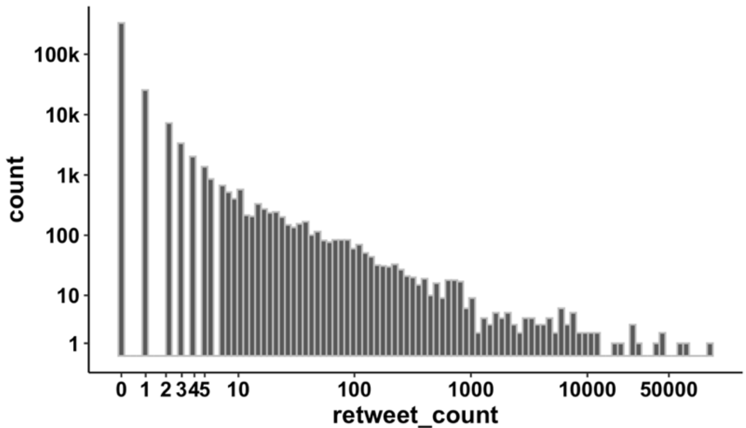

Figure 2. Distribution of retweet counts. Both axes are displayed on a logarithmic scale. Retweet count represents the number of times a tweet has been shared by other users.
Note. k = 000

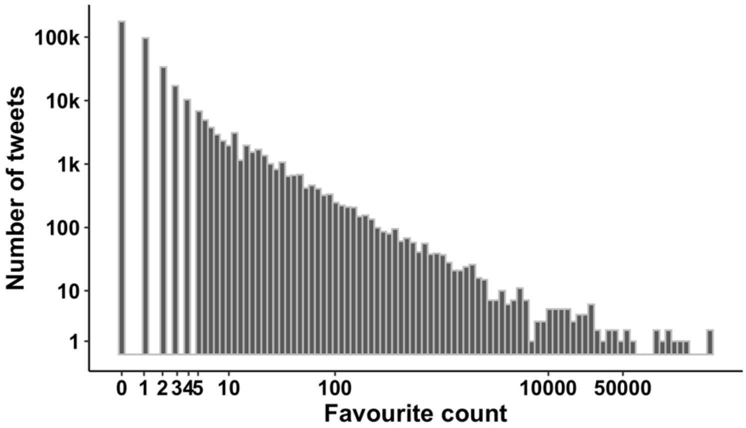

Figure 3. Distribution of favourite counts. Both axes are displayed on a logarithmic scale. The favourite count represents the number of times users have explicitly expressed their positive affect towards the tweet.

Note. k = 000

The number of negative tweets is 146,592 and the number positive tweets is 230,290. The distribution of tweets relative to their sentiment classification (i.e., positive or negative) and retweet or favourite count is displayed in Figure 4 and Figure 5, respectively.

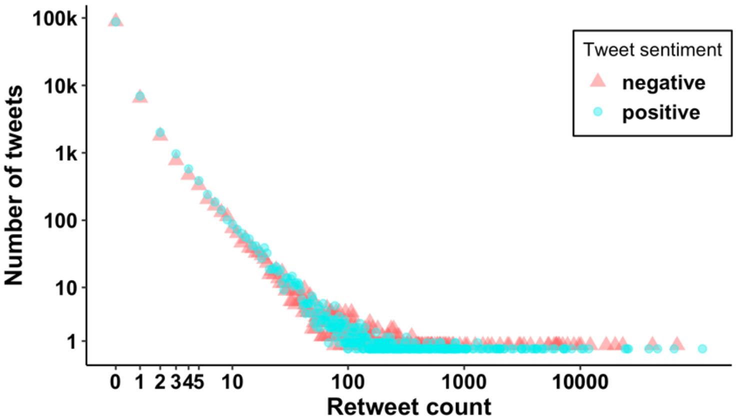

Figure 4. Scatterplot of the relative number of tweets per 100k. Both axes are displayed logarithmic scales. The retweet count represents the number of times a tweet has been shared by other users.

Note. k= 000

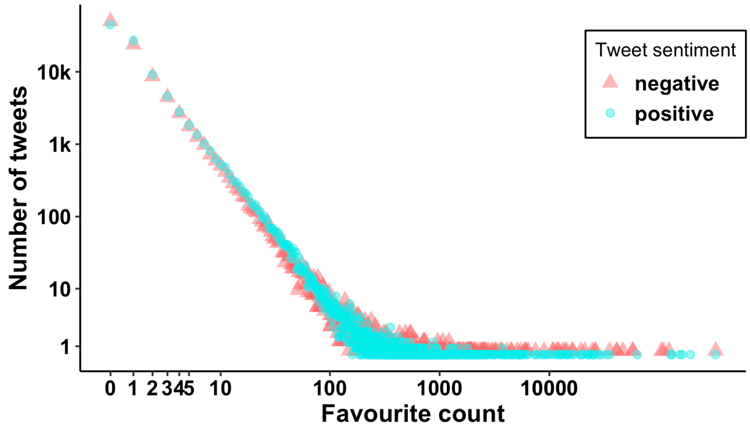

Figure 5. Scatterplot of the relative number of tweets per 100k. Both axes are displayed on logarithmic scales. The favourite count represents the number of users that have explicitly expressed their positive affect toward a tweet (i.e., likes).
Note. k= 000

The analysis with two Bayesian Poisson regression models for zero-inflated count data indicated that negative tweets are not more likely to be retweeted than negative tweets (95%CI [1, 0]) (Figure 6). Furthermore, negative tweets are 11% (95%CI [12, 11]) more likely to be marked as favourite (i.e., liked) than positive tweets (Figure 7).

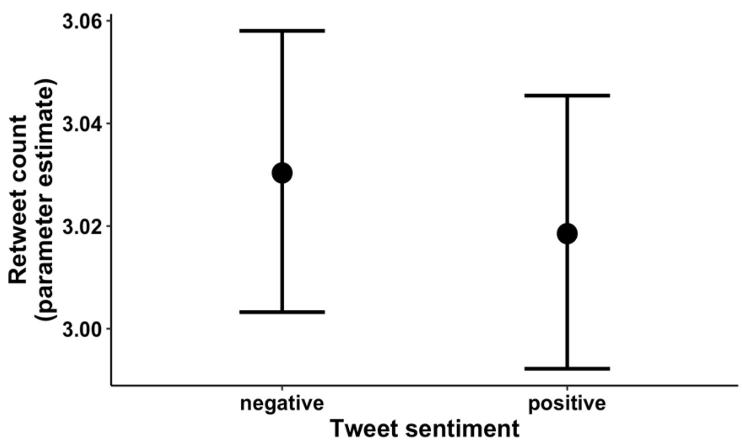

Figure 6. Comparison of the fitted parameter estimates of retweet count between negative and positive tweets using a Bayesian Poisson zero-inflated regression model.

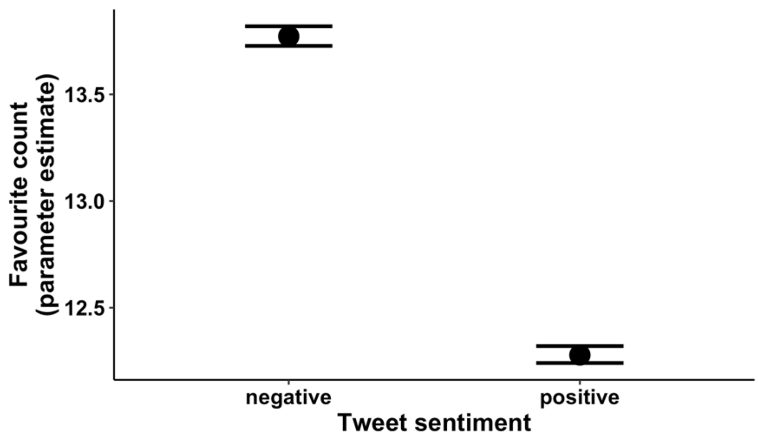

Figure 7. Comparison of the fitted parameter estimates of favourite count between negative and positive tweets, using a Bayesian Poisson zero-inflated regression model.

Discussion

The present paper investigated the effect of message sentiment on the virality of Twitter messages. Virality was defined as the number of retweets as well as the number of likes (i.e., how many users have expressed their explicit positive sentiment towards a tweet). Contrary to our expectations, the results indicate that negative tweets are not more likely to be retweeted than positive tweets. They are however more likely to be marked as favourite. This partially supports Baumeister's (2001), claim that negative information is usually stronger than positive information. Even though there might be a few exceptions to that rule, Twitter is no such one.

However, no difference between positive and negative tweets could be observed for retweeting. This finding stands in contrast to a number of previous studies indicating that negative information is more likely to be shared on Twitter (Jenders et al., 2013; Meng et al., 2018; Tsugawa & Ohsaki, 2015; Tsugawa & Ohsaki, 2017; Zhang, Wei & Boncella, 2019) or that positive information is more likely to be shared (Dafonte-Gomez & Miguez-Gonzales, 2018; Kim, 2015; Nikolinakou & Whitehil King, 2018; Sharma & Kaur, 2020; Tellis et al.,). Together with previous research showing that extremely positive and extremely negative information is more likely to be retweeted than neutral information, these findings suggest that emotional divergence has a greater effect on retweeting behaviour than polarity (i.e., positive or negative) (Brady et al., 2017; Brady et al., 2020; Heimbach & Hinz, 2016; Wills et al., 2017; Valenzuela et al., 2017). The present study extends previous findings as it suggests that negative information is more likely to be marked as favourite, meaning that negative tweets are also more likely to elicit positive reactions in readers than positive tweets. However, future replications are needed to confirm this.

The present findings are important for the purposes of spreading information via Twitter and influencing public opinion. Accordingly, one does not have to rely on using a particularly negative tone in order to select a larger audience and spread information rapidly. However, using a generally emotional tone might help to increase the number of retweets and using a negative sentiment might lead to an increase in the number likes of a tweet. In contrast to some previous studies, the present one used a non- domain-specific analysis and a random sample of tweets that was not limited to a particular event or minority culture (Tsugawa & Ohsaki, 2015; Zhang et al., 2019). Furthermore, the original sample consisted of Tweets rather than retweets; The number of retweets was extracted out of the original sample of tweets. Consequently, results cannot be confounded by a greater number of positive or negative tweets in the original sample of tweets. Additionally, for studies using Twitter as a source to make inferences about a public reaction (Zhang et al., 2019), it should be kept in mind that a negativity bias for liking- behaviour and a bias for sentimental content for retweeting might be present. If analyses do not control for these biases, Twitter might not be a valid source to investigate the public opinion.

The lack of an effect of message sentiment on retweeting behaviour might be explained by idiosyncratic attributes of the Twitter platform. It can be classified as belonging to both social media as well as news media (Kwak et al., 2010), for example because sharing often occurs among strangers. That is why we classified the platform as belonging to a broadcasting context. However, the mismatch between typical attributes of broadcasting-media (i.e., negativity bias) and the here identified attributes of the Twitter platform suggest that Twitter can perhaps not be classified as belonging to either a broadcasting or a narrowcasting context. Rather, the platform might be inconsistently used for both purposes. If that is the case, a negativity bias might still be present in broadcasting contexts (i.e., News media), and a positivity bias might still be present for narrowcasting- (e.g.: forwarding e-mails or personal messages) or marketing contexts (Dafonte-Gomez & Miguez-Gonzales, 2018; Guerini & Staiano, 2015; Hansen et al., 2011; Kim, 2015; Nikolinakou & King, 2018; Sharma & Kaur, 2020; Tellis et al., 2019).

Different social functions of retweeting a post versus marking it as favourite shed more light on the present findings. Kim (2015) suggested that sharing- behaviour is less likely to reflect a negativity bias because it is a social behaviour. In contrast to retweeting a post, *liking* it is not a form of direct communication, which might explain the differential findings for the favourite count and retweet count of the present study. People do not share more negative content than positive content, because they do not want to reflect negatively on others. This is however not the case for expressing positive sentiment towards a message (i.e., marking it as favourite).

In the present study, neutral words were excluded, in order to avoid the influence of emotionally ambiguous, and possibly arbitrarily classified words. However, this approach of summarizing the tweets into a binary qualitative dataset is debatable. For example, it does not allow for a distinction between mild and intense emotions. Given the finding, that there was no influence of message sentiment on the number of retweets, it might be that emotional divergence or intensity has a larger effect on virality than polarity (i.e., positive or negative). Such an effect was previously suggested by Pfitzner et al., (2012). Another alternative explanation for the present findings might be that the emotions expressed in tweets were predominantly extremely positive, which, according to Heimbach & Hinz (2016), would make retweets less likely to be retweeted. Therefore, future research should investigate the effect of emotional divergence or intensity, and especially the effect of mildly positive versus extremely positive information.

Other possible limitations of the present study are the factors taken into account to predict virality as well as the type of sentiment analysis performed here. Jenders et al. (2013), suggest that a model that only takes isolated features into account is too simplified when predicting virality. Rather, researchers should include a combination of factors into their analysis, such as kind of content and message length. Because the present study only investigated the effect of message sentiment, the generalizability of the findings might be limited. In a similar vein, Zhang et al. (2019) suggest that sentiment analyses should be more fine-grained in order to account for subtle differences in users' emotional responses. Even though lexical- based approaches are a valid way to perform sentiment analyses, machine-learning models, such as tree kernels, have been reported to produce better results (Agarwal et al., 2011; Hiu & Liu, 2004).

That there was no effect of message sentiment on retweet count might be explained by the hypothesis that a negativity bias might lead to the *avoidance* of negative information. In a previous study Kiley Hamlin et al. (2010), observed a negativity bias in young infants in that they avoided looking at a negatively portrayed cartoon character. Such a hypothesis does not interfere with the hypothesis that negative information takes up more 'cognitive space' than positive information. It is, however, hard to test because it is unfalsifiable. The results of the present study would, for example, confirm this hypothesis, even though no difference was observed between the retweet count of positive and negative tweets. Moreover, since a difference *was* observed for the favourite count, the hypothesis that there is a Negativity Bias on social media leading to the avoidance of negative information can most likely be discarded.

In summary, there was no difference between the retweet count of positive and negative tweets. However, negative tweets were more likely to be marked as favourite. That means that the concept of a negativity bias cannot easily be extended to *Twitter*. Specific attributes of the platform might serve as an explanation for these findings. In contrast to other social media, the platform shares characteristics of both a News Media as well as a way to send information to a limited number of familiar people. In this context, retweeting a post is likely to serve a different function than liking it. In contrast to liking a post, *retweeting* is a more social behaviour and people might use it to maintain positive social contacts. Conversely, the findings might be explained by the differential effect of emotional divergence on the virality of positive or negative tweets. Previous research hints towards a difference between extremely emotional tweets and neutral tweets. Additionally, the relationship between sentiment and virality might be non-linear. For example, extremely positive emotions might have a detrimental effect on virality, while mildly positive emotions increase it. Future research is needed to replicate these findings using different ways of sentiment classification and -analysis.

Reference List

Baumeister, R., Bratslavsky, E., Finkenauer, C., & Vohs, K. (2001). Bad is Stronger than Good. *Review Of General Psychology*, *5*(4), 323-370. https://doi.org/10.1037/1089-2680.5.4.323

Berger, J., & Milkman, K. (2009). What Makes Online Content Viral?. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1528077

Brady, W., Gantman, A., & Van Bavel, J. (2020). Attentional capture helps explain why moral and emotional content go viral. *Journal Of Experimental Psychology: General*, *149*(4), 746-756. https://doi.org/10.1037/xge0000673

Brady, W., Wills, J., Jost, J., Tucker, J., & Van Bavel, J. (2017). Emotion shapes the diffusion of moralized content in social networks. *Proceedings Of The National Academy Of Sciences*, *114*(28), 7313-7318. https://doi.org/10.1073/pnas.1618923114

Bürkner, P. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal Of Statistical Software*, *80*(1). https://doi.org/10.18637/jss.v080.i01

Clement, J. (2020). *Twitter: number of active users 2010-2019 | Statista*. Statista. Retrieved 4 June 2020, from https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/#:~:text=How%20many%20people%20use%20Twitter,daily%20active%20users%20(mDAU).

Dafonte-Gómez, A., Míguez-González, M., & Corbacho-Valencia, J. (2020). Viral Dissemination of Content in Advertising: Emotional Factors to Reach Consumers. *Communication & Society*, *33*(1), 107-120. https://doi.org/10.15581/003.33.1.107-120

Guerini, M., & Staiano, J. (2015, May). Deep feelings: A massive cross-lingual study on the relation between emotions and virality. In *Proceedings of the 24th International Conference on World Wide Web* (pp. 299-305).

Hansen, L. K., Arvidsson, A., Nielsen, F. Å., Colleoni, E., & Etter, M. (2011). Good friends, bad news- affect and virality in twitter. In *Future information technology* (pp. 34-43). Springer, Berlin, Heidelberg.

Heimbach, I., & Hinz, O. (2016). The impact of content sentiment and emotionality on content virality. *International Journal Of Research In Marketing*, *33*(3), 695-701. https://doi.org/10.1016/j.ijresmar.2016.02.004

Kim, H. (2015). Attracting Views and Going Viral: How Message Features and News-Sharing Channels Affect Health News Diffusion. *Journal Of Communication*, *65*(3), 512-534. https://doi.org/10.1111/jcom.12160

Kim, J. (2018). Rumor has it: The effects of virality metrics on rumor believability and transmission on Twitter. New Media & Society, 20(12), 4807-4825. https://doi.org/10.1177/1461444818784945

Kiley Hamlin, J., Wynn, K., & Bloom, P. (2010). Three-month-olds show a negativity bias in their social evaluations. *Developmental Science*, *13*(6), 923-929. https://doi.org/10.1111/j.1467-7687.2010.00951.x

Kumar, A., & Sebastian, T. (2012a). Sentiment Analysis: A Perspective on its Past, Present and Future. *International Journal Of Intelligent Systems And Applications*, *4*(10), 1-14. https://doi.org/10.5815/ijisa.2012.10.01

Kumar, A., & Sebastian, T. M., (2012b). Sentiment analysis on twitter. *International Journal of Computer Science Issues (IJCSI)*, *9*(4), 372.

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media?. *Proceedings Of The 19Th International Conference On World Wide Web – WWW '10*. https://doi.org/10.1145/1772690.1772751

Nielsen, F. Å. (2011). A new ANEW: Evaluation of a word list for sentiment analysis in microblogs. *arXiv preprint arXiv:1103.2903*.

Meng, J., Peng, W., Tan, P., Liu, W., Cheng, Y., & Bae, A. (2018). Diffusion size and structural virality: The effects of message and network features on spreading health information on twitter. *Computers In Human Behavior*, *89*, 111-120. https://doi.org/10.1016/j.chb.2018.07.039

Mohammad, S., Zhu, X., Kiritchenko, S., & Martin, J. (2015). Sentiment, emotion, purpose, and style in electoral tweets. *Information Processing & Management*, *51*(4), 480-499. https://doi.org/10.1016/j.ipm.2014.09.003

Nikolinakou, A., & King, K. (2018). Viral video ads: Emotional triggers and social media virality. *Psychology & Marketing*, *35*(10), 715-726. https://doi.org/10.1002/mar.21129

Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. *Foundations And Trends® In Information Retrieval*, *2*(1–2), 1-135. https://doi.org/10.1561/1500000011

Philander, K., & Zhong, Y. (2016). Twitter sentiment analysis: Capturing sentiment from integrated resort tweets. *International Journal Of Hospitality Management*, *55*, 16-24. https://doi.org/10.1016/j.ijhm.2016.02.001

Pfitzner, R., Garas, A., & Schweitzer, F. (2012, May). Emotional divergence influences information spreading in twitter. In *Sixth international AAAI conference on weblogs social media*.

Saif, H., He, Y., & Alani, H. (2012, November). Semantic sentiment analysis of twitter. In *International semantic web conference* (pp. 508-524). Springer, Berlin, Heidelberg.

Sharma, R., & Kaur, B. (2020). E-mail viral marketing: modeling the determinants of creation of "viral infection". *Management Decision*, *58*(1), 112-128. https://doi.org/10.1108/md-03-2017-0215

Smith, K. (2020). *60 Incredible and Interesting Twitter Stats and Statistics*. Brandwatch. Retrieved 4 June 2020, from https://www.brandwatch.com/blog/twitter-stats-and-statistics/#:~:text=There%20are%20500%20million%20tweets,That's%206%2C000%20tweets%20every%20second.

Stieglitz, S., & Dang-Xuan, L. (2012). Social media and political communication: a social media analytics framework. *Social Network Analysis And Mining*, *3*(4), 1277-1291. https://doi.org/10.1007/s13278-012-0079-3

Tellis, G., MacInnis, D., Tirunillai, S., & Zhang, Y. (2020). What Drives Virality (Sharing, Spread) of YouTube Video Ads: Emotion vs Brand Prominence and Information. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3583613

Tsugawa, S., & Ohsaki, H. (2015). Negative Messages Spread Rapidly and Widely on Social Media. *Proceedings Of The 2015 ACM On Conference On Online Social Networks - COSN '15*. https://doi.org/10.1145/2817946.2817962

Valenzuela, S., Piña, M., & Ramírez, J. (2017). Behavioral Effects of Framing on Social Media Users: How Conflict, Economic, Human Interest, and Morality Frames Drive News Sharing. *Journal Of Communication*, *67*(5), 803-826. https://doi.org/10.1111/jcom.12325

Yuan, B., Liu, Y., & Li, H. (2013). Sentiment classification in Chinese microblogs: lexicon-based and learning-based approaches. *International Proceedings of Economics Development and Research*, *68*, 1.

Zhang, L., Wei, J., & Boncella, R. (2020). Emotional communication analysis of emergency microblog based on the evolution life cycle of public opinion. *Information Discovery And Delivery*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/idd-10-2019-0074