EXPERIENCE SAMPLING TWITTER USERS’ MOTIVES

Internship Report

Master Cognitive Neuroscience Berlin (MCNB)

Department of Education and Psychology
Freie Universität Berlin

by

Ekin Derdiyok

Berlin, 15.05.2023

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Abstract

Twitter hosts the online public discourse and has potential in studying psychological constructs and information dissemination dynamics online. 181 Twitter users participated in the online study and have reported their motives for their tweets every time they post. Tweets from preceding and following months to the study belonging to the participants were also collected. Participants rated their motives more clearly in original tweets and were more undecided in terms of the motives of their retweet. Negativity bias was present in the retweet count but not in the engagement rate or favorite count. No meaningful clusters of users were identified. Limitations of the current methods and implications of significant results are discussed.

Acknowledgement and Authors Contributions

Data were already acquired as part of an ongoing project by Dr. Philipp Lorenz-Spreen at Center for Adaptive Rationality at Max Planck Institute for Human Development when I started this project. Research questions and hypotheses were either formed by me or codeveloped during our one-on-one meetings with Dr. Philipp Lorenz-Spreen. Analysis scripts and the report are written by me. Dr. Philipp Lorenz-Spreen provided feedback on the first draft and helped formulating the methods section since I was not part of the project during the data collection.

1. Introduction

Twitter has become a central hub for public discourse, shaping opinions globally. It has emerged as a tool for studying opinion dynamics in various domains, such as politics, economics, and social issues (Conover et al., 2011) almost in real-time (Bollen et al., 2011). Techniques such as social network analysis and agent-based modeling can be employed to study psychological constructs, social influence, and information cascades (Weng et al., 2012). Negativity bias, the tendency for individuals to give more weight to negative information than positive information (Baumeister et al., 2001; Rozin & Royzman, 2001), has been studied extensively in offline settings. While there is evidence to suggest the existence of a negativity bias in online social networking, the results are sometimes consistent. While some studies have found that negative content tends to spread more widely and quickly than positive content on platforms like Twitter (de León & Trilling, 2021), other studies have found mixed results (Stieglitz & Dang-Xuan, 2013) or even the opposite effect (Ferrara & Yang, 2015), with positive content sometimes performing better than negative content. Going beyond positive and negative sentiments, anger is found to be more influential than joy (Fan et al., 2014). In a similar line of research, hostility towards members of different groups fuels interaction on social media platforms (Rathje et al., 2021). Just as with sentiments, users have different motives for using social networking sites. Even within a single platform, users may have different motives for using different platform features, e.g., retweets vs. replies may serve different purposes (Smock et al., 2011). There is limited literature specifically focused on asking Twitter users about their motives for tweeting. Other psychological constructs that can be studied on Twitter include personality traits (Golbeck et al., 2011), and collective attention (Lorenz-Spreen et al., 2019), and emotional contagion (Fan et al., 2020).

The study addresses three primary research questions: (1) Can we replicate negativity bias? (2) How do distributions of motive ratings differ between tweet types? (3) Is it possible to meaningfully cluster participants based on the available features, and subsequently utilize these cluster labels in future analyses, such as user profiling?

2. Methods

The study was approved by the IRB committee of the Max Planck Institute for Human Development. All experiments followed the IRB guidelines, ensuring that all research procedures were aligned with the Declaration of Helsinki. Necessary steps were taken in compliance with data privacy regulations: Participants provided informed consent prior to participation and were informed about the data handling. Data were anonymized and securely stored, while participants being represented with random IDs.

2.1 Participants

Participants (*N* = 181) were recruited through Twitter Ads (ads.twitter.com). The ads were targeted at English-speaking USA residents across different genders and age groups, with no specific keywords. Participants received a reimbursement of $20. Details about the recruitment can be found in the Appendix B (Lorenz-Spreen et al., 2023).

2.2 Materials

Twitter API (Twitter Developer Platform, n.d.) was used for collecting tweets. formr was used as an online survey tool due to its composability with Twitter (Arslan, 2018; Arslan et al., 2020). Finally, Syuzhet package was used for determining the sentiment scores for each tweet (Jockers, 2020). Details about the sentiment analysis and the survey can be found in the Appendix A section due to space constraints (Lorenz-Spreen et al., 2023).

2.3 Procedure

Participants received a private direct message (DM) prompting them to fill out the survey every time two minutes after they send a post for a week. If they ignored the DM, they received up to three reminders that are 2 hours apart from each other, totaling a maximum of 6 hours of delay between the post and the last reminder received. An infographic on the procedure can be found in the appendix section. The questionnaire involved rating the degree of overlap between their motives while posting and the motives presented in the survey questions. Finally, to collect additional data for analysis, Twitter API and the rtweet package from R to gather all other tweets from the participants, spanning from January 1, 2022, to June 12, 2023 (Kearney, 2019).

3. Results

The Python analysis scripts used in this study are publicly available on GitHub; however, due to data sharing restrictions, the dataset itself is not accessible.

3.1 Negativity bias

To investigate the presence of negativity bias in the data, Mann-Whitney U Test was conducted to compare the retweet counts of positive and negative tweets, which accounts for the presence of outliers. Negative tweets (M = 2564.57, SD = 11607.29) received more retweets than positive tweets (M = 1937.29, SD = 11158.88, U = 3849744.0, p < .05) (Figure 1). Meaning that the negativity bias was present in the retweet count. Negativity bias was not found in the engagement ratio (i.e., the number of favorites and retweets a tweet received divided by the total number of followers of that account) or the favorite count (p > .05).

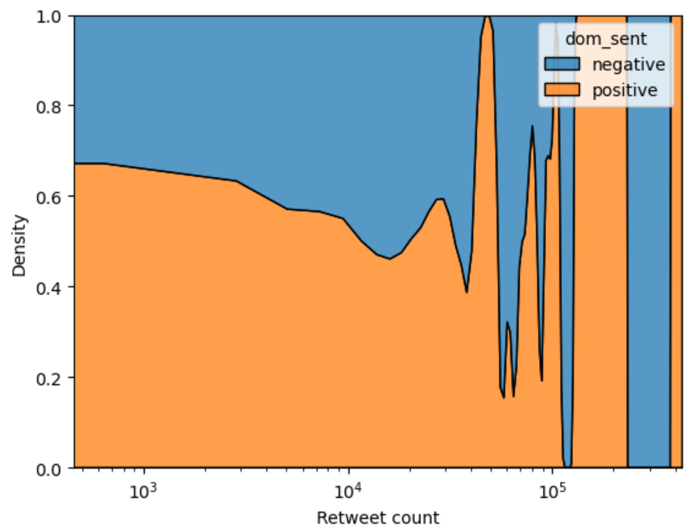

Figure 1: Kernel density estimate plot showing how retweet count differs for positive and negative sentiment tweets. As the retweet count increases, the proportion of tweets with negative sentiment increases. Graph gets noisier at higher retweet counts due to retweet count being right skewed.

3.2 Self-reported motives between tweet types

Bartlett's test for equality of variances revealed significant differences between variances of original tweets and retweets for most motive pairs (Figure 2). Put differently, original tweets were rated with more extreme values on the Likert scale (e.g., 1 and 6 instead of 3 and 4) than retweets.

motive	test statistics	p-values	Original post SD	Retweet SD	Percentage difference SD
Cause chaos	1408.07	< 0.0001	1.59	1.04	53.90
Show achievement	796.03	< 0.0001	1.76	1.26	38.99
Gain attention	217.60	< 0.0001	1.87	1.56	19.32
Surprise others	210.56	< 0.0001	1.83	1.54	18.99
Bring attention	102.63	< 0.0001	2.03	1.80	13.03
Show emotions	99.78	< 0.0001	2.06	1.83	12.84
Connect with others	94.51	< 0.0001	1.89	1.68	12.49
Show attitude	75.91	< 0.0001	2.05	1.85	11.15
Deceive others	60.00	< 0.0001	0.67	0.61	9.87
Influence	17.04	< 0.0001	1.96	2.06	-5.03
Prove point	16.86	< 0.0001	1.99	2.09	-5.00
Save content	15.20	< 0.0001	2.05	2.15	-4.75
Provoke	9.37	< 0.01	1.55	1.50	3.83
Inform others	7.36	< 0.01	2.06	1.99	3.39

Figure 2: Bartlett's test for equality of variance results. Most pair's self-report ratings for original posts had higher variance, most notable being the motives of causing chaos, showing achievement, gaining attention, and surprising others. SD stands for standard deviation.

3.3 Clustering users

The elbow method was applied to determine the appropriate number of clusters for the k-means algorithm (Figure 3, left), which assesses the relationship between the number of clusters and the sum of squared errors within these clusters (Kodinariya & Makwana, 2013). Using followers count, account age, post count, percentage of non-retweet tweets, and popularity (i.e., mean number of engagements an account receives), our analysis did not yield any discernible cluster structure to determine the optimal number of clusters. t-SNE is a common dimensionality reduction technique. It converts high-dimensional data into a lower-dimensional representation (Maaten & Hinton, 2008). t-SNE preserves the structures between data points, making it easier to visualize and interpret complex datasets. In social networking sites, t-SNE has been applied to user stance detection on Twitter (Darwish et al., 2020). However, no discernible cluster structure was found despite exploring the same features and attempting to visualize the data using t-SNE.

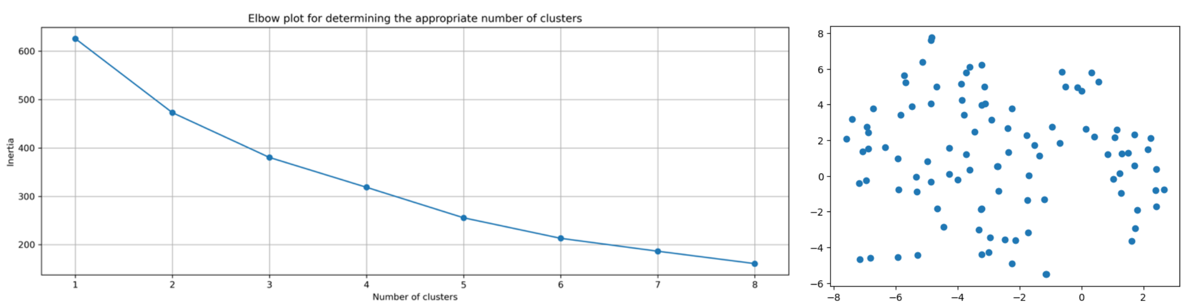

Figure 3: Elbow plot showing the decrease in inertia (a measure of how well the data is clustered) by increasing the number of clusters (left). An optimal number of clusters would have been visible in the graph by an elbow-like inflection point. t-SNE plot mapping the high dimensional data onto two-dimensional space (right)

4. Discussion

There were mixed results regarding negativity bias. Put clearly, negative tweets enjoyed a higher retweet count but a comparable favorite count to positive ones. The discrepancy can be attributed to the propensity to share negative tweets further but reluctance to endorse them with a favorite (designated by a heart icon).

Variances of original tweets were generally higher than retweets for self-reported motives, caused by more extreme ratings for original tweets. This can be interpreted as more apparent motives for writing original tweets than retweeting. The discrepancy may connect to the spread of information and news sharing on social networking sites since retweeting is much more easily done with little forethought.

Clustering users did not yield meaningful results. This outcome could be attributed to features needing to be more informative or the random nature of the dataset. Further research might be necessary to explore additional predictors or alternative analytical approaches better to understand the relationship between tweet characteristics and user motives.

Several limitations can be pointed out. First, self-reported data is susceptible to various response biases, such as social desirability bias. As a result, users may be reluctant to mark their motives as causing chaos or unaware of their motives altogether. Second, participants might struggle to recall their motives for past tweets accurately. Third, Twitter is a heterogeneous platform in terms of content and is used for a multitude of purposes, and some of them may be different. For example, the art community and political community may have little to no overlap, and some sentiments and motives for the Twitter art community may not be meaningful (for a discussion of limitations: Tufekci, 2014).

The literature on Twitter users' motives is limited. The primary strength of this study lies in its approach to understanding user motives by combining experience sampling methods with observational data. By directly asking participants about their motives for engaging on Twitter, the study benefits from users' perspectives. To my knowledge, this study is the first attempt to collect Twitter users' underlying motives using real-time experience sampling.

Several future directions can be pursued. First, incorporating machine learning techniques may provide a more sophisticated understanding of sentiment and contextual nuances in tweets, overcoming the limitations associated with dictionary-based methods (Kolchyna et al., 2015). Second, by focusing on subsets of users with well-defined interests, researchers can address the heterogeneity of the topics such as sports, arts, and politics.

References

Arslan, R. C. (2018). *Formr.org survey framework utility R package*. Zenodo. https://doi.org/10.5281/zenodo.1326523

Arslan, R. C., Walther, M. P., & Tata, C. S. (2020). formr: A study framework allowing for automated feedback generation and complex longitudinal experience-sampling studies using R. *Behavior Research Methods*, *52*(1), 376–387. https://doi.org/10.3758/s13428-019-01236-y

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

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8. https://doi.org/10.1016/j.jocs.2010.12.007

Conover, M. D., Goncalves, B., Ratkiewicz, J., Flammini, A., & Menczer, F. (2011). Predicting the Political Alignment of Twitter Users. *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing*, 192–199. https://doi.org/10.1109/PASSAT/SocialCom.2011.34

Darwish, K., Stefanov, P., Aupetit, M., & Nakov, P. (2020). Unsupervised User Stance Detection on Twitter. *Proceedings of the International AAAI Conference on Web and Social Media*, *14*, 141–152. https://doi.org/10.1609/icwsm.v14i1.7286

de León, E., & Trilling, D. (2021). A Sadness Bias in Political News Sharing? The Role of Discrete Emotions in the Engagement and Dissemination of Political News on Facebook. *Social Media + Society*, *7*(4), 20563051211059710. https://doi.org/10.1177/20563051211059710

Fan, R., Xu, K., & Zhao, J. (2020). *Weak ties strengthen anger contagion in social media* (arXiv:2005.01924). arXiv. https://doi.org/10.48550/arXiv.2005.01924

Fan, R., Zhao, J., Chen, Y., & Xu, K. (2014). Anger Is More Influential than Joy: Sentiment Correlation in Weibo. *PLOS ONE*, *9*(10), e110184. https://doi.org/10.1371/journal.pone.0110184

Ferrara, E., & Yang, Z. (2015). Measuring Emotional Contagion in Social Media. *PLOS ONE*, *10*(11), e0142390. https://doi.org/10.1371/journal.pone.0142390

Golbeck, J., Robles, C., Edmondson, M., & Turner, K. (2011). Predicting Personality from Twitter. *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing*, 149–156. https://doi.org/10.1109/PASSAT/SocialCom.2011.33

Jockers, M. (2020). *Introduction to the Syuzhet Package*. https://cran.r-project.org/web/packages/syuzhet/vignettes/syuzhet-vignette.html

Kearney, M. W. (2019). rtweet: Collecting and analyzing Twitter data. *Journal of Open Source Software*, *4*(42), 1829. https://doi.org/10.21105/joss.01829

Kodinariya, T., & Makwana, P. (2013). Review on Determining of Cluster in K-means Clustering. *International Journal of Advance Research in Computer Science and Management Studies*, *1*, 90–95.

Kolchyna, O., Souza, T. T. P., Treleaven, P., & Aste, T. (2015). *Twitter Sentiment Analysis: Lexicon Method, Machine Learning Method and Their Combination* (arXiv:1507.00955). arXiv. https://doi.org/10.48550/arXiv.1507.00955

Lorenz-Spreen, P., Kozyreva, A., Arslan, R. C., Swire-Thompson, B., Geers, M., Herzog, S. M., & Hertwig, R. (2023). *The various motives for sharing content on Twitter, a field study in real time.*

Lorenz-Spreen, P., Mønsted, B. M., Hövel, P., & Lehmann, S. (2019). Accelerating dynamics of collective attention. *Nature Communications*, *10*(1), Article 1. https://doi.org/10.1038/s41467-019-09311-w

Maaten, L. van der, & Hinton, G. (2008). Visualizing Data using t-SNE. *Journal of Machine Learning Research*, *9*(86), 2579–2605.

Rathje, S., Van Bavel, J. J., & van der Linden, S. (2021). Out-group animosity drives engagement on social media. *Proceedings of the National Academy of Sciences*, *118*(26), e2024292118. https://doi.org/10.1073/pnas.2024292118

Rozin, P., & Royzman, E. B. (2001). Negativity Bias, Negativity Dominance, and Contagion. *Personality and Social Psychology Review*, *5*(4), 296–320. https://doi.org/10.1207/S15327957PSPR0504_2

Smock, A. D., Ellison, N. B., Lampe, C., & Wohn, D. Y. (2011). Facebook as a toolkit: A uses and gratification approach to unbundling feature use. *Computers in Human Behavior*, *27*(6), 2322–2329. https://doi.org/10.1016/j.chb.2011.07.011

Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior. *Journal of Management Information Systems*, *29*(4), 217–248. https://doi.org/10.2753/MIS0742-1222290408

Twitter Developer Platform. (n.d.). *Twitter API for Academic Research | Products*. Retrieved April 18, 2023, from https://developer.twitter.com/en/products/twitter-api/academic-research

Weng, L., Flammini, A., Vespignani, A., & Menczer, F. (2012). Competition among memes in a world with limited attention. *Scientific Reports*, *2*(1), Article 1. https://doi.org/10.1038/srep00335

Appendix A

How motives and sentiments were measured

Motives

The survey consists of 14 questions, each offering seven response options ranging from "strongly disagree" to "strongly agree." Participants are asked to evaluate the extent to which their tweet aligns with given motives, providing a quantitative measure of the relationship between the tweet and the user's intention. The motives measured in the survey where the following: provoke, save content, show emotion, connect with others, show achievement, show attitude, deceive others, gain attention, prove point, cause chaos, bring attention, influence, surprise others, inform others.

Sentiments

Sentiment scores were determined using a dictionary method as part of the Syuzhet package (Jockers, 2020). The dictionary counts the number of occurrences of pre-determined words in each tweet. Data were collected for the following sentiments: anger, disgust, fear, anticipation, joy, sadness, surprise, trust, positive, negative. The scores ranged between 0 (no occurrence of a word related to that word) to 10 (an arbitrary number that turned out the be the maximum times words within a tweet were marked with given sentiment)

Appendix B

What the experimental procedure looked like

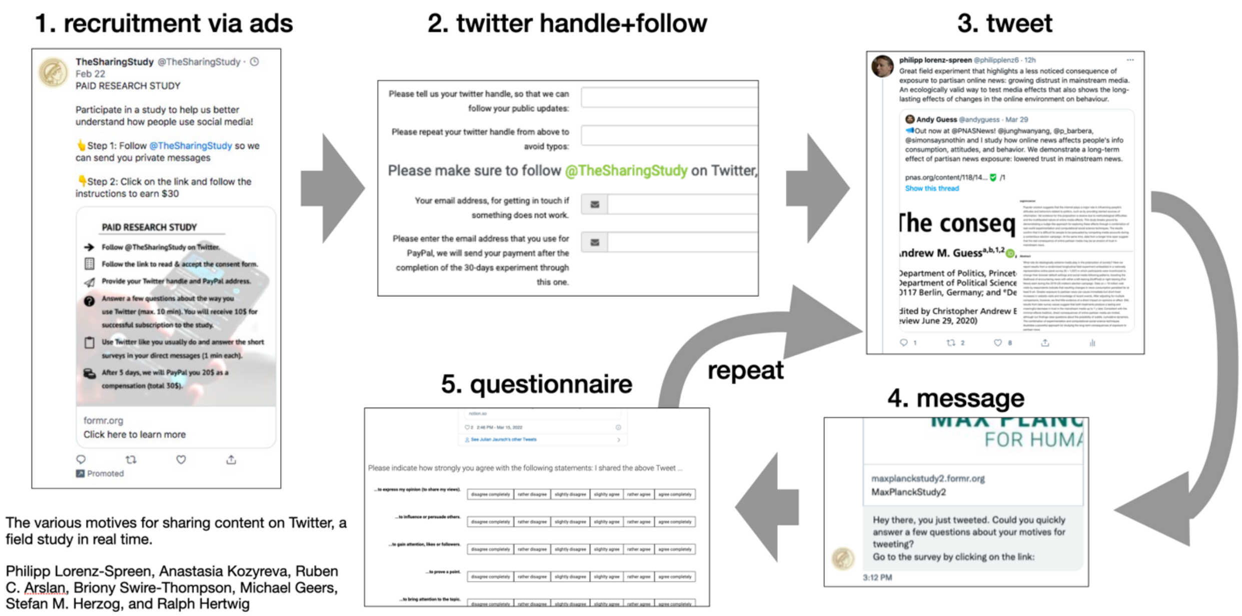

Figure B1: Study flowchart starting with recruitment to experimental procedure (Lorenz-Spreen et al., 2023).