

# Validating daily social media macroscopes of emotions

*Keywords: sentiment analysis, emotion detection, NLP, survey, validation*

Measuring sentiment in social media text has become an important practice in studying emotions at the macroscopic level. However, this approach can suffer from methodological issues like sampling biases and measurement errors. To date, it has not been validated if social media sentiment can actually measure the temporal dynamics of mood and emotions aggregated at the level of communities. We ran a large-scale survey at an online newspaper to gather daily mood self-reports from its users, and compare these with aggregated results of sentiment analysis of user discussions. We find strong correlations between text analysis results and levels of self-reported mood, as well as between inter-day changes of both measurements. We replicate these results using sentiment data from Twitter. We show that a combination of supervised text analysis methods based on novel deep learning architectures and unsupervised dictionary-based methods have high agreement with the time series of aggregated mood measured with self-reports. Our findings indicate that macro level dynamics of mood expressed on an online platform can be tracked with social media text, especially in situations of high mood variability.

Figure 1 shows the time series of the fraction of responses that report a positive mood and the text sentiment aggregate from the forum of the Austrian online newspaper page "Der Standard". The Pearson correlation coefficient between both measurements is 0.93 ([0.82, 0.97],  $p < 10^{-8}$ ), indicating a very strong positive correlation with daily resolution over a period of almost three weeks. The regression line in the scatter plot on Panel B in Figure 1 confirms the relationship. A linear model with Heteroskedasticity and Autocorrelation Consistent (HAC) estimates shows the same robust effect. The model has an adjusted R-squared of 0.852, with a coefficient  $\hat{\beta} = 0.597$  ([0.465, 0.728],  $p < 10^{-7}$ ) for the unscaled average of sentiment aggregates. The text sentiment aggregate can explain 85% of the variance in the daily proportion of positive mood.

We additionally tested if *changes* in the text sentiment aggregate can approximate daily changes in the proportion of positive mood in the survey compared to the previous day. A similar regression model as before yields a coefficient of  $\hat{\beta} = 0.533$  ([0.390, 0.675],  $p < 10^{-16}$ ) for changes in the text sentiment aggregate and an adjusted R-squared of 0.704 (Panel C of Figure 1). This model has a non-significant intercept of 0.002 ([-0.002, 0.005],  $p = 0.29$ ) showing that, in addition to explaining 70% of the variance in emotion changes at the macro level, the model's prediction of trend in mood changes is not significantly biased.

To test the robustness of our results as well as their generalizability to a different platform, we pre-registered a replication of our analysis using 515,187 tweets by Austrian Twitter users in the survey period instead of Der Standard forum posts (<https://aspredicted.org/blind.php?x=vb3gp2>) (see Methods for more details on sample size and selection criteria). The correlation coefficient between the survey and sentiment on Twitter is positive and significant (0.63 [0.26, 0.84],  $p < 0.003$ ), confirming our pre-registered hypothesis and the robustness and generalizability of the results. Although it is somewhat lower than the correlation of the survey with text sentiment from the Der Standard forum, a coefficient above 0.6 is still sizeable, especially given that the survey and the postings now come from different platforms. Following our pre-registration, we filtered out accounts tagged as "organisational" by the aggregation service Brandwatch

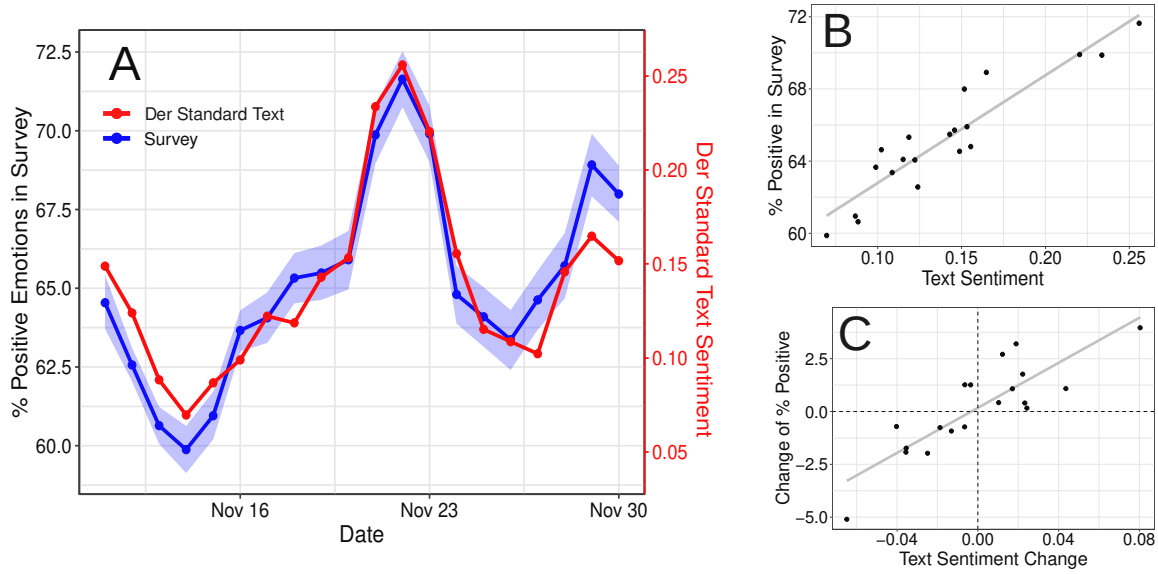


Figure 1: **Panel A:** Time series of the daily percentage of positive mood reported in the survey and the aggregated sentiment of user-generated text on derstandard.at. The shaded blue area corresponds to 95% bootstrapped confidence intervals. **Panel B:** Scatterplot of text sentiment and survey responses with regression line. **Panel C:** Scatterplot of the daily *changes* in both text sentiment and survey responses compared to the previous day, with regression line.

(formerly known as Crimson Hexagon) and accounts with less than 100 followers or more than 5000 followers. If we relax this criterion to include accounts with up to 100000 followers as in our previous study [1], the correlation increases to 0.71  $[0.39, 0.88]$ ,  $p < 0.0005$ . This suggests that influential accounts are also relevant to calculate sentiment aggregates, as central individuals in the Twitter social network might be serving as early sensors of sentiment shifts [2]–[4].

## References

- [1] H. Metzler, B. Rimé, M. Pellert, T. Niederkrotenthaler, A. D. Natale, and D. Garcia, “Collective Emotions during the COVID-19 Outbreak,” *PsyArXiv*, Tech. Rep., Jun. 2021, type: article. DOI: 10.31234/osf.io/qejxv. [Online]. Available: <https://psyarxiv.com/qejxv/> (visited on 06/08/2021).
- [2] M. Galesic, W. Bruine de Bruin, J. Dalege, S. L. Feld, F. Kreuter, H. Olsson, D. Prelec, D. L. Stein, and T. van der Does, “Human social sensing is an untapped resource for computational social science,” *en, Nature*, Jun. 2021, ISSN: 0028-0836, 1476-4687. DOI: 10.1038/s41586-021-03649-2. [Online]. Available: <http://www.nature.com/articles/s41586-021-03649-2> (visited on 07/01/2021).
- [3] M. Garcia-Herranz, E. Moro, M. Cebrian, N. A. Christakis, and J. H. Fowler, “Using Friends as Sensors to Detect Global-Scale Contagious Outbreaks,” *en, PLoS ONE*, vol. 9, no. 4, J. J. Ramasco, Ed., e92413, Apr. 2014, ISSN: 1932-6203. DOI: 10.1371/journal.pone.0092413. [Online]. Available: <https://dx.plos.org/10.1371/journal.pone.0092413> (visited on 07/26/2021).
- [4] D. Garcia, M. Pellert, J. Lasser, and H. Metzler, “Social media emotion macroscopes reflect emotional experiences in society at large,” *arXiv preprint arXiv:2107.13236*, 2021.