

Supplementary Material for: The affiliative use of emoji and hashtags in Twitter discourse around the Black Lives Matter Movement

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Black Lives Matter and Protests

As of 2020, during the time where George Floyd was murdered, the Black Lives Matter movement—which was founded in response to the killing of Trayvon Martin by George Zimmerman (Lebron, 2017)—had been active for nearly eight years. This gave it more time to build capacity than many short-lived networked protests such as the Occupy Wall Street movement, the Gezi Park protests, and the Tahrir Square protests (Tufekci, 2017; Zeynep, 2019).

As mentioned in the main text, the prevalence of emoji and hashtags related to LGBTQ issues – the rainbow of hearts, the rainbow emoji (🌈), #black-translivesmatter and #pride2020 – speaks to the ‘intersectionality’ (Crenshaw, 1989) of the Black Lives Matter movement, which, unlike earlier generations of civil rights activism that at times tacitly reproduced patriarchal and heteronormative forms of oppression (Clark et al., 2018), deliberately draws attention to the experiences of historically-marginalized victims of racism, sexism, homophobia, and transphobia (Collins, 2017).

Emoji and BLM

From a technological standpoint, certain emoji are actually made up of multiple emoji characters at the programming level (e.g. 🖤 is composed of 🟡 + 🟤). Such *modified emoji* appear alongside *non-modified* emoji (continuing the example, just 🟡) appear in all three communities in our study, albeit to a lesser degree. How do we make sense of this?

One possible explanation for this is that navigating the tricky domain of skin tone modifiers might be challenging for white folks participating in the Black Lives Matter movement. While using lighter tones – especially for emoji like the raised fist (👊) – may come across as advocating white supremacy, using darker tones can be construed as a form of cultural appropriation or digital blackface (Princewill, 2017).

Faced with this dilemma, opting for the neutral tone may seem like a reasonable strategy to some users. Alternatively, using the light skin-tone *alongside* darker raised-fist skin-tones, akin to the automatically inserted Twitter ‘sticker’

36 appended to #BlackLivesMatter¹ may function as a show of solidarity and ally-
37 ship, without connotations of appropriation or blackface.

38 Methods

39 Social Network Construction Specifics

40 In constructing the network, we considered only blank retweets and not quote
41 tweets, on the grounds that blank retweets are more likely to indicate endorse-
42 ment of the original content. A Several caveats are worth noting.

43 First, the Twitter API does not indicate intermediate retweets: if y retweeted
44 x 's tweet and z retweets y 's retweet, our network would see this as an edge from
45 x to y and from x to z . Second, for all content-based analyses, if a user retweets
46 a quote tweet, our method treats both the author and the content retweeted as
47 that of the quote text, rather than that which is being commented upon by the
48 quote text.

49 Anecdotal evidence from the early 2010s, just before Twitter began to formal-
50 ize the concept of retweeting in its application interface, found that retweets
51 serve three purposes: "spreading tweets, to start a conversation, and to draw
52 attention to the originating user" (Cheong, 2013; Boyd et al., 2010). The first
53 and third cases lend evidence to our assumption on tweet propagation and en-
54 dorsement respectively; the second case fits the use case of a quote tweet which
55 we do not consider.

56 Finally, because we used the public Streaming API, there may be some gaps
57 in our dataset from the most active days immediately after George Floyd's
58 murder due to Twitter's rate-limits.

59 Classification Specifics

60 For each of the data types (emoji, hashtags, text, and some subsets of its combi-
61 nations) we randomly generated three equal-sized labeled classes corresponding
62 to the three largest communities. Second, given that labeled data, we did an
63 80/20 train/test split. Note that this requires two randomization steps, one in
64 generating the labeled data and another one in the train/test split.

65 For the classifiers, we used two different data representations, correspond-
66 ing to two different types of classifiers. For more classical machine learning
67 (Burkov, 2019) techniques (*Scikit-Learn* logistic regression, random forests, lin-
68 ear stochastic gradient descent) we used the bag of words representation or
69 embedding. Here, word (including emoji and hashtag) tokens are features and
70 each author's document gets a score corresponding to the occurrences of that
71 token in the document.

72 For newer (Zhang et al., 2017; Ray Chowdhury et al., 2020) deep learning
73 techniques (Tensorflow DNNs, GRUs, LSTMs) we used a sequential represen-
74 tation, since some of those techniques can detect sequential patterns. In short,
75 we encode each document as a sequence, where each word token is encoded as
76 a number. Later, in the learning process, those numbers are embedded into a
77 vector, so that each document is effectively a matrix.

¹See <https://emojigraph.org/theme/black-lives-matter/>.

For evaluation, we chose accuracy as our metric. Given that the classes are of equal size, the expected accuracy of random classification is ~ 0.3333 .

Important to add here as well is that even if these classifiers are capable of determining community membership on the basis of emoji and hashtag usage, they do not tell us *which* specific emoji and hashtags each community uses.

Finally, to get to a better sense of each community’s unique emoji and hashtag use, a conditional probability analysis (see main text) – that determines distinctiveness – will complement our data science workflow.

Usage Statistics

Figure 1 shows the mean number of retweets as a function of number of emoji and number of hashtags in the tweet. To remove outliers for the emoji calculation, means were determined after removing the top tweet at each level. An additional outlier point with an SEM > 40 was manually removed. No outliers were removed for the hashtag group. Both correlations significant at $p < 10^{-7}$. Note that because hashtags must take more space than emoji, the x scales differ.

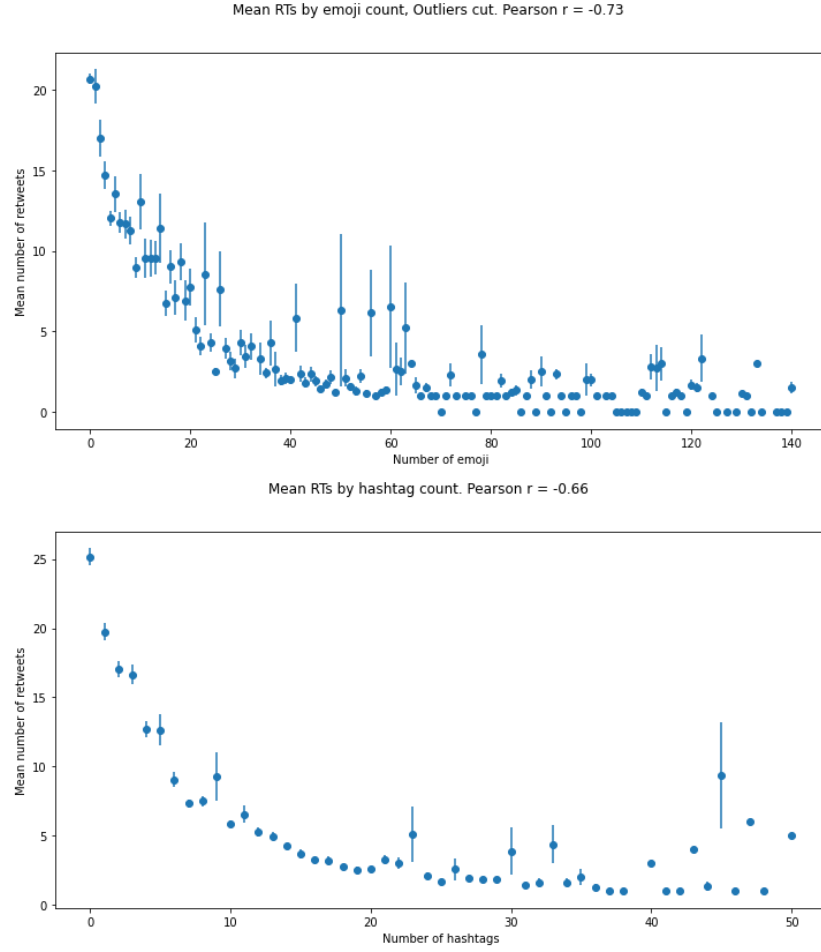


Figure 1: Mean number of Retweets as a function of number of emoji and hashtags. Bars represent standard error of the mean.

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