









## V. DISCUSSION & CONCLUSION

From a network perspective, a firestorm occurs when one user is being mentioned unusually high—focusing on a Twitter handle or a hashtag. The maximum in-degree in mention networks is significantly deviating from comparable time periods. By evaluating lexical cues from the Tweet comments, we evaluated collective behavior manifesting in individual choices of words.

During firestorms, users talk significantly less about themselves compared to non-firestorm periods. Simultaneously, the positivity in firestorms tweets vanishes and negativity rises. The extracted lexical features were applicable to streaming data. Using lexical features to monitor change in behavior has the advantage of constant memory requirements.

By applying a straightforward change point detection, we were able to detect the starting point of the firestorms closely and quickly. We further provide insight into which linguistic categories proved to be useful for monitoring change.

According to our posed questions, combining sentiment analysis and text statistics to explore firestorm data can reveal how people connect with each other to form an outrage. The usage of vocabulary changes at a certain point when every single user stops commenting with the I-perspective and starts commenting on others. As mentioned, pronouns refer to a referent. If the ‘I’ diminishes, the focus changes significantly. All of a sudden people stop talking collectively about themselves positively and collectively more negatively—against the others!

Our model picks up these features and is able to detect the starting point of outrages giving insights into collective changing behavior. Further research questions regarding spreading of rumours and moral outrages might be: What causes evolving collective emotionality? Why does a community or society may at times come together and simultaneously communicate the same thought and participate in the same action? A better knowledge of individual motivations and collective action can help to better understand and detect online firestorms.

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