Estimating Community Feedback Effect on Topic Choice in Social Media

David I. Adelani, Ryota Kobayashi, Ingmar Weber and Przemyslaw A. Grabowicz

July 20, 2021

7 th International Conference on Computational Social Science IC^{2}S^2
July 27-31, 2021, ETH Zürich, Switzerland

Estimating Community Feedback Effect on Topic Choice in Social Media

David I. Adelani[1], Ryota Kobayashi[2], Ingmar Weber[3], Przemyslaw A. Grabowicz[4]

[1] Saarland University, Germany, [2] The University of Tokyo, Chiba, Japan, [3]QCRI, HBKU, Doha, Qatar, [4] University of Massachusetts Amherst, USA.

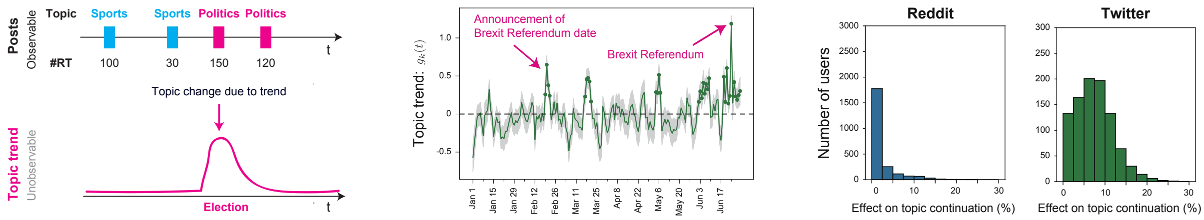
social influence, community feedback, treatment effect, topic continuation, social media

Social media users post content on various topics. A defining feature of social media is that other users can provide community feedback to their content in the form of retweets, likes, comments, up- and down-votes. Social impact theory suggests that a large amount of positive social feedback, such as support from friends, encourages individuals to continue the behavior that triggered the feedback [1]. We hypothesize that the amount of received feedback influences the choice of topics on which a social media user posts.

It is challenging to test this hypothesis due to user heterogeneity and external confounders. First, distinct kinds of users are likely to process community feedback in very different ways and not all will be influenced by it. The second difficulty lies in measuring and controlling for the external factors that can affect users. For example, users post burst of tweets due to events such as political elections. In this situation, topic changes might be incorrectly attributed to social feedback, rather than the external events that truly influenced users to switch their posts' topic (Figure 1a).

To address these challenges, we study two rich temporal datasets of the behaviors of nearly $14,000$ active users of Twitter and Reddit over a period of time, including millions of posts and the complete community feedback to these posts. We investigate the stated hypothesis with an interpretable semiparametric model of a user's decision to continue the topic of their previous post. In this model, we incorporate as a flexible time series an unobservable confounding factor — the global topic trend — that can potentially affect the estimate of the community feedback effect. To diminish the risk of model misspecification and examine how other factors affect topic choice, we test various structures of the model components representing community feedback and author properties, by optimizing model accuracy on a hold-out set of samples, drawing inspiration from philosophy of science [2] and score-based causal discovery [3].

Specifically, the probability that an author i continues a topic k at time t is described as $P[Y_i = 1|t,k,f] = S\left(g(k,t) + u_i(k) + \alpha_i f\right)$, where Y_i is a binary random variable representing whether the author continues the topic (1) or not (0), f is the community feedback that the user received to their previous post, and $S(x)$ is a logistic function. Causal effects are identifiable under this simple model, because its objective function is concave and model parameters are uniquely identified by its global minimum. The first component $g(k,t)$ is the effect of the topic trend defined as a flexible time series with fused ridge regularization, which we learn from the data (Figure 1b). The second component $u_i(k)$ represents the effect of author properties, including user's propensity to continue any topic and the effect of the topic preference on the probability of topic continuation. Finally, α_i represents author's susceptibility to the community feedback f. The feedback f is a function of the number of comments or up/down-votes



(a) Topic trend as a confounder (b) Learned topic trend (c) The effect of feedback

Figure 1: Various stages of the study: (a) an illustration of a challenging confounding effect, (b) the topic trend learned from users' likelihood to continue a topic, (c) the effect of changing feedback from a median value to the 99th percentile on the probability of topic continuation.

(Reddit), retweets or likes (Twitter) to author's previous post. We determine a specific form of both the user properties and the feedback function by optimizing the model predictive accuracy on a test set.

In this way, we identify two essential factors for topic change — author's topic preferences and global topic trends — and demonstrate that our model achieves high predictive accuracy (82%) for datasets from two social media platforms (Reddit and Twitter). We then use this predictive model to quantify how community feedback affects individual users.

Overall, we find that 33% and 14% of active users in Reddit and Twitter, respectively, are significantly influenced by community feedback — they tend to continue with the same topic if they receive a significant amount of feedback. The percentage of susceptible users is higher on Reddit than on Twitter, but the treatment effect (Figure 1c) and effect size (Cohen's d is 0.18 for Reddit and 0.29 for Twitter) are larger for the Twitter users than the Reddit users. Furthermore, the percentage of susceptible users decreases with user activity in Reddit, whereas it increases with user activity on Twitter. Note that active Twitter accounts often belong to celebrities or companies, who may be more motivated to maximise engagement than anonymous Reddit users. For the details, full discussion, and other results, see our full paper [4].

This research is the first work, to the best of our knowledge, to examine whether community feedback influences the topic choices of social media users. The impact of community feedback on user's choice of topic to post has practical implications for the design of social media systems. For instance, recommender systems optimize for community feedback and engagement. If the feedback affects topics posted by users, then such recommendation algorithms may inadvertently contribute to the growth of polarizing or biased topics that receive more attention than impartial topics [5].

References

[1] B. Latane. "The psychology of social impact". In: *Amer. Psych.* 36 (1981), pp. 343–356.

[2] M. Forster and E. Sober. "How to Tell when Simpler, More Unified, or Less Ad Hoc Theories will Provide More Accurate Predictions". In: *British J. of Phil. of Sci.* 45 (1994), pp. 1–35. ISSN: 0007-0882. DOI: 10.1093/bjps/45.1.1.

[3] C. Glymour, K. Zhang, and P. Spirtes. "Review of causal discovery methods based on graphical models". In: *Frontiers in genetics* 10 (2019), p. 524.

[4] D. I. Adelani et al. "Estimating community feedback effect on topic choice in social media with predictive modeling". In: *EPJ Data Science* 9 (2020), p. 25.

[5] M. B. Zafar, K. P. Gummadi, and C. Danescu-Niculescu-Mizil. "Message impartiality in social media discussions". In: *ICWSM*. 2016, pp. 466–475.