Reconstructing social sensitivity from evolution of content volume in Twitter

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KEYWORDS

Public interest; media coverage; opinion dynamics.

EXTENDED ABSTRACT

In this work, we set up a simple mathematical model for the dynamics of public interest in terms of media coverage and social interactions. We test the model on a series of events related to violence in the US during 2020, using the volume of tweets and retweets as a proxy of public interest, and the volume of news as a proxy of media coverage. The model succesfully fits the data and allows inferring a measure of social sensibility that correlates with human mobility data. These findings suggest the basic ingredients and mechanisms that regulate social responses capable of ignite social mobilizations.

Our approach is grounded in the Granovetter model [1], originally proposed to explain the emergence of riots. In this model, agents adopt a binary state s which we interpret as interested ($s = 1$) or non-interested ($s = 0$) in the event. The dynamics of the system is described in terms of the *public interest*, the fraction $p = \sum_i^N s_i/N$, where N is the size of the system. Each agent is characterized by a threshold τ_i, which is the fraction of interested agents needed to induce interest on the agent. Thresholds are random variables whose cumulative distribution $S(p) = P(\tau < p)$ is interpreted here as *social engagement*, given that it represents the fraction of agents that become active due to their threshold lies below p. Assuming that thresholds are normally distributed $\tau \sim N(\mu, \sigma)$, we have:

$$S(p|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{p} e^{-\frac{(\tau-\mu)^2}{2\sigma^2}} d\tau. \qquad (1)$$

When μ is low, small groups can trigger the interest to the rest of the system. On the contrary, high values of μ would require a bigger fraction of interested people to induce interest to rest of the population. We therefore identify the quantity $1 - \mu$ as the *social sensitivity* of the population. In his original model, Granovetter described the dynamics of the public interest p regardless of the influence of the media. To include this, we propose a modified model that analytically reads:

$$\frac{1}{\gamma}\frac{dp}{dt} = -p + e\,C(t) + (1-e)\,S(p|\mu(t),\sigma). \qquad (2)$$

Equation 2 allows us to reconstruct the social variables from data. By integration this equation using the volume of twitted news as a proxy for the coverage $C(t)$, we seek for the functions $S(t)$ that minimize the difference between the resulting public interest and the volume of tweets and retweets. In panel (A) of figure 1 shows two of the analyzed cases: one related to the murder of George Floyd in May 2020 and, the other, the attack against Jacob Blake in August 2020 (other events was analyzed in [2]). Panel (B) of figure 1 shows the best fitting curves for the public interest and the reconstructed social engagement and social sensitivity for both cases. As can be seen in this figure, the two social variables are of a different nature. In fact, while the engagement $S(t)$ is a threshold-based variable whose dynamics can be expected to be fast, $1 - \mu(t)$ represents the slower, more gradual build-up of social sensitivity across the whole population. Accordingly, we find that this variable changes appreciably over periods of ~ 15 days which is, as expected, longer than the typical time scales of the media coverage and public interest.

Panel (B) of figure 1 also shows periods of time of increasing social sensitivity, which leads to a sudden increase of the social engagement, when a macroscopic fraction of agents becomes interested in the events. We expect that this increament impacts beyond the digital environment. Therefore, we investigate the emergence of measurable collective activity associated to an increase in social sensitivity by collecting mobility measures across the US territory. In panel (C) of figure 1 we show attendance to recreation places, groceries, pharmacies and public transport stations in the period of time when the events took place (Minneapolis, Minnesota for the case of George Floyd, and Kenosha, Wisconsin for Jacob Blake). We find different degrees of correlation between the social sensitivity and mobility patterns for the most populous events using a lag of 3 days.

Taken together, these results suggest that our low-dimensional approximation of the Granovetter model

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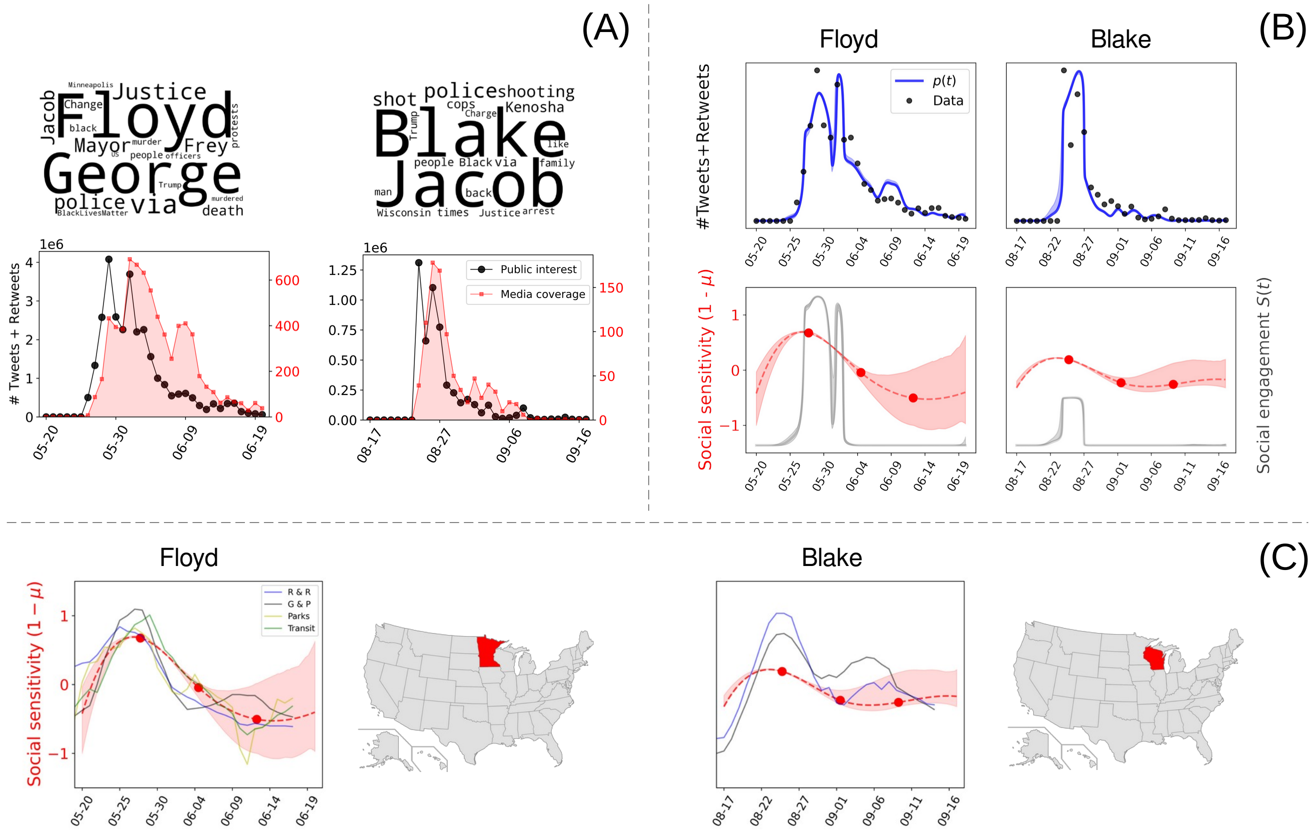

FIG. 1. **Panel(A)** Time traces of the volume of tweets and retweets (black circles, same data as panel (b)) and media accounts tweets (filled area). **Panel(B)** In the top panel points correspond to public interest (tweets and retweets) along with the best fitting curves $p(t)$ (blue) obtained with the model of equations 2 and 1; bottom panel shows in red lines social sensitivity $1 - \mu(t)$, while in grey lines the normalized social engagement $S(t) = S(p|\mu(t), \sigma)$. **Panel (C)** Social sensitivity (red) and standardized mobility observables of the corresponding county. R & R: retail and recreation; G & P: groceries and pharmacies; Parks: public parks; Transit: transit in public transport stations (Parks and Transit not shown for Blake due to lack of data). All mobility measures were shifted -3 days and inverted for visualization purposes.

captures the basic ingredients that regulate social responses of very different magnitudes, which are indeed capable of ignite social mobilizations. The model implements the hypothesis that agents become involved from media exposure and also from the presence of a critical mass of interested agents in the system, which leads to characterize the social sensitivity of the population. Further details and the analisis of other events can be found in [2].

[1] M. Granovetter, Threshold models of collective behavior, American journal of sociology **83**, 1420 (1978).

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