MODELLING ONLINE COMMUNITY MEMBERS' MOTIVATION: A COMPUTATIONAL MODEL BASED ON SOCIAL EXCHANGE THEORY

Research in Progress

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Abstract

Recent studies show a significant effect of online communication on campaign donations. Social exchange theory has been used in the literature to explain fundraisers motivatio. A limitation, however, is that motivation and the relation between online and offline actions are often derived from questionnaires that may suffer from selection and self-report biases, are often cross-sectional, do not scale-up and are often too costly to conduct. In an attempt to decrease such limitation, our study models the motivation of participants in an online campaign with social media analysis. We present a preliminary Satiation-Deprivation model, based on social exchange theory, that estimates fundraisers' motivation levels over time based on a Twitter mention network and a donation dataset obtained from the Movember 2014 campaign. Despite our limited sample size, we find that motivation levels may serve as predictors for likelihood of donations and may improve baseline predictors such as co-occurrences of mentions and donations. After further validation, our preliminary model may inform strategic mentioning policies by campaign organizers, in order to maintain high motivation levels in their on-line community. Our findings suggest that a quantitative approach may serve as an accessible and valuable tool for predicting effectiveness of donation campaigns in the future.

Keywords: Online communities, prosocial behaviour, social media, motivation, social exchange theory, computational methods

1 Introduction

Online communities gather geographically dispersed, like-minded people, often in order to form a networked organization that aims at collective action. Such collective action may range from knowledge exchange (Chen & Hung, 2010) and protest behaviour (Van den Broek, Langley, & Hornig, 2017) to online fundraising (Saxton & Wang, 2014). Social media are increasingly employed by NGOs to motivate fundraisers to collect donations, e.g., acquiring funding for health research (Chou, Prestin, Lyons, & Wen, 2013). However, there is limited attention in the literature to the motivation of fundraisers in online communities over time and how to use social media data to measure their motivation over time (Saxton & Wang, 2014). Similarly, a question among information systems (IS) scholars remains why community members, such as fundraisers, voluntarily engage in collective action and how their interaction with other community members is related. Hence, previous researchers have investigated the motivational antecedents of collective action in online communities (Chen & Hung, 2010; Wasko & Faraj, 2005).

Social exchange theory (SET) has been one of the major theoretical perspectives in the field of social psychology to explain motivation (Emerson, 1976). SET has been widely applied to explain social concepts, mechanisms and processes, such as social status, influence, social networks, fairness, coalition formation, solidarity, trust, affect and emotion (Cropanzano & Mitchell, 2005). Consequently, IS scholars use SET to explain motivation in online communities (Yan, Wang, Chen, & Zhang, 2016; Lin & Huang, 2010; Tsai & Cheng, 2012; Wasko & Faraj, 2005). A limitation of those studies, however, is that motivation and the relation between online and offline actions are often measured with questionnaires that may result in selection and self-report biases, are often cross-sectional, do not scale-up to large sample sizes and are often too costly to conduct. Additionally, automatic text classifiers based on self-reported motivation statements perform weakly (Nguyen et al., 2015). Social network analysis may offer an unobtrusive observational alternative to study the underlying networks of fundraisers and their efforts to collect donations (González-Bailón & Wang, 2016).

Following up on these gaps, our research question is: "How can social exchange theory model fundraisers' motivation to collect donations based on campaign-related mentions received on Twitter?" We develop a preliminary Satiation-Deprivation model of fundraisers in the Movember campaign based on how often they are mentioned by others and their fundraising performance. Additionally, this model takes also the influence (operationalized as number of Twitter followers) of the fundraisers into account. To do so, we introduce the notion of motivation level as a mathematical construction: the social exchange between fundraisers, operationalized in being mentioned by fellow fundraisers, and the effort by the fundraiser to collect donations. After the construction of a motivation level, we shall use it as an intermediary construct to model the relationship between the observable mentions and donations. Results suggest that there exists a positive relationship between height of motivation level and donation occurrence.

Theoretically, we aim to contribute to the literature on social exchange theory and motivations by extending previous findings on online activity, e.g. knowledge sharing (Yan, Wang, Chen, & Zhang, 2016; Lin & Huang, 2010; Tsai & Cheng, 2012), to offline behavioural outcomes such as donations collected. Specifically, we add to Yan, Wang, Chen, & Zhang (2016)'s finding that peer support (in our case mentioning by fellow fundraisers) and reputation increase motivation for offline collective action. We develop and test the model with a dataset that includes both Twitter messages from fundraisers and their collected donations of the Movember 2014 campaign. Our model potentially helps social scientists to build unobtrusive research methods to study the motivation for collective action in online communities. In the future, a further developed version of the model may provide practitioners insights in how leaders of online communities may motivate members to contribute to collective action.

2 Data and context

The Movember foundation campaigns for four of the most urgent worldwide issues concerning men's health: prostate cancer, testicular cancer, poor mental health, and physical inactivity. Movember aims to create awareness and to fund research worldwide. Movember is named for its well-known activity in the month of November, when men around the globe grow their moustaches to raise awareness and collect donations for the Movember foundation. These fundraisers can use any kind of social media in relation with the Movember campaign. We focus on the micro-blogging service Twitter in this research. We combine two datasets. The first consists of day-by-day country-classified networks of Twitter mentions, where a pair of users is included if one of them mentions the other in relation with the Movember campaign on that specific day. We limited our analysis to the Netherlands and Sweden. For each day we aggregated all Tweets and drew a directed graph where *arc (u, v)* was present if user *u* mentioned user *v* on this day.

The second dataset are individual donations that fundraisers of the Movember campaign collected over time during the campaign period (from 15th of October to the 15th of December 2014) in Sweden and The Netherlands.

We matched Twitter users to their donations, so that the Satiation-Deprivation model and the donation potential model can be empirically tested. To do so, the Movember Foundation provided us with the Movember IDs, names, team names and profile pictures (if present) from users in The Netherlands and Sweden. We were able to reliably match 191 fundraisers from the Netherlands and 56 fundraisers from Sweden.

3 Model development

The mechanisms of satiation and deprivation origins from social exchange theory (SET). Blau (1964) defines social exchange as "voluntary actions of individuals that are motivated by the returns they are expected to bring and typically do in fact bring from others". SET provides an utilitarian view of the human being, modeling motivation as an exchange of both tangible and intangible activities based on reciprocal costs and rewards from and towards the individual when interacting with at least one other person. One of the key propositions of social exchange theory is satiation-deprivation (Cook, Cheshire, Rice, & Nakagawa, 2013). This principle assumes a diminishing marginal utility in social exchange between persons: the more often a person has recently received a particular reward for an action, the less valuable is an additional unit of that reward.

Our Satiation-Deprivation (SD) model describes a dynamic motivation process of an online fundraiser that is boosted by Twitter mentions and that drops in the absence of Twitter mentions, also known as motivational decay. It is the analytical tractability of the SD Model and its ability to keep motivation levels contained in a range between 0 and 1 that makes it attractive as a numerical model for motivation First, we formulate model requirements. Second, we motivate the theoretical assumptions and choices behind the model and mathematically construct the SD model. Third, when we specify the model for the fundraisers' motivational level, we relate the SD model to a donation potential. Donation potential is the probability that a fundraiser will collect a donation, given his motivation level.

3.1 Model requirements

The model consists of a function that transfers mentions, located on a time axis, to a motivation level of each participant, that develops through time. Our model should satisfy the following criteria:

1. Motivation levels should always lie between 0 and 1, as a normalized motivation score.
2. Larger number of mentions from the campaign network in the recent past imply a higher motivation level.
3. Mentions from the campaign network that lie further in the past should contribute less to the current motivation level.

4. If there are more mentions in the recent past, a new mention from the campaign network relatively affects the motivation level less. This is in agreement with the satiation proposition in social exchange theory (Emerson, 1976).
5. Following social exchange theory, we argue that if there are less mentions in the recent past, a new mention relatively affects the motivation level more.
6. A mention from an influential mentioner in the campaign network should induce a higher motivation level than a mention from a less influential mentioner.

The motivation level is comprised of mentions in the recent and distant past, where those in the recent past weigh heavier than those in the far past. Thus, a high motivation level implies a few recent mentions or many of them in the past, and therefore implies a high level of satiation as well. In other words, the higher an individual is motivated, the more difficult it becomes to increase his motivation further. New mentions do not mean much to whom is already motivated.

3.2 Satiation-Deprivation model development

The input for the model are daily Twitter mentions and user's centrality in Twitter. On the one hand, the motivation level of a mentionee will increase when a mention occurs, and mentions from more central users will have a larger positive effect. On the other hand, when no activity occurs, motivation level decreases in time. This is captured in our model, which we describe in this section step by step.

3.2.1 Centrality

We start with defining centrality scores. For each user we introduce centrality score φ_i, and we wish to define a suitable φ_i between 0 and 1. We do not base centrality scores on mentions as mentions will be used to define the motivation dynamics. Therefore, to avoid reinforcement effects of the same data, we need a different, preferably independent, input for centrality scores. We choose to base the definition of centrality on the number of followers of a given user in Twitter during the campaign period. Such data is readily available through Twitter's API and is a part of our dataset. Formally, we define centrality φ_i of user *i* through the empirical quantiles of the number of followers, as given below:

$$\varphi_i = \frac{1 + \{\text{\# users with less followers than } i\} + \frac{1}{2}\{\text{\# users with as many followers as } i\}}{\{\text{total \# users in the data set}\}} \tag{1}$$

This definition is a normalized rank of the users by their number of followers, from small to large, and the users with the same number of followers receive an average rank. In this setting, a more followed user has larger influence, however, the difference in the influence of, say, the most- and second-most followed user is not large, even though their numbers of followers can be very different. We argue that this captures the influence of popular users in reality.

3.2.2 Mentions matrix

We use mentions to represent interactions between users. We set $Q_{ij}(t) = 1$ if user *i* mentions user *j* on day *t*, and $Q_{ij}(t) = 0$ otherwise. In other words, *Q* is merely an adjacency matrix of the mentions graph on a particular day.

3.2.3 Satiation-depravation

We proceed with modelling the SD phenomenon for the motivation level. Let $L_i(t) \in [0; 1]$ be a motivation level of user *i* on day *t*. SD means that mentions have greater effect when $L_i(t)$ is small, far away from its upper limit, which in our case is 1. It is more convenient to work with the quantity $(1 - L_i(t))$. Taking into account centralities, we assume that when user *j* mentions user *i*, the motivation level of i increases by $\varphi_j\,(1 - L_i(t))$. The new motivation level is then $L^{new}_i = L_i(t) + \varphi_j\,(1 - L_i(t))$, and we obtain an easy expression:

$$1 - L_i^{new} = 1 - L_i - \varphi_j(1 - L_i) = (1 - L_i)(1 - \varphi_j)$$

Clearly, the calculations repeat themselves when other mentions occur. Now consider all users j that mention i on day t. Recall that for such users we have $Q_{ji}(t) = 1$ and we have $Q_{ji}(t) = 0$ for all other users. Then the motivation level of user i at the end of that day will satisfy:

$$1 - L_i^{end}(t) = (1 - L_i(t))\prod_j(1 - Q_{ji}(t)\,\varphi_j) \tag{2}$$

Two features of this formula are worth noticing. First, if no mentions of user i occur on day t then $Q_{ji(}$(t) = 0 for all users j, and we may obtain L^{end}_i (t) = L_i(t). Second, we see that the order of mentioning does not play any role. Now, , from (2) we obtain an increment in motivation during the day:

$$\Delta L_i(t) = L_i^{end}(t) - L_i(t) = (1 - L_i(t))\left(1 - \prod_j(1 - Q_{ji}(t)\varphi_j\right) \tag{3}$$

3.2.4 Discount factor

We further assume that the motivation level decays at rate α. Such exponential decay is a natural model for many processes. For example, Google PageRank uses the `damping factor', because of which, the contribution of node u to the PageRank of node v decreases exponentially with the graph distance from u to v (Brin & Page, 2012). Similarly, TCP-IP protocols reduce the packet size by a factor when an error occurs in the previous transmissions (Fall & Stevens, 2011).

3.2.5 Final recursion

Denote by $L_i(t + 1) \epsilon (0, 1)$ the motivation level of user i on day t. At day $t + 1$, the motivation level consists of two parts: the current level is discounted by factor α, plus the increment as in (3) will be obtained from the mentions. This is formalized in the following recursive equation:

$$L_i(t + 1) = \alpha L_i(t) + (1 - L_i(t))\left(1 - \prod_j(1 - Q_{ji}(t)\varphi_j\right) \tag{4}$$

The recursion initializes at $t = 1$, and one can choose appropriate initial motivation levels. With no information available, $L_i(1)$ can be set to zero, or we relate initial values to our preliminary knowledge, e.g. users' Movember profile. The model is robust to the choice of initial motivation levels because their contribution decreases exponentially in time due to the discount factor α. Table 1 summarizes the parameters of the model.

Table 1. Parameters of the recursive motivation model (4).

Parameter	Definition	Source
$Q_{ij}(t)$	1 if user i mentions user j on day t; 0 otherwise	Mentions data
$L_i(t)$	Motivation level of user i	Computed recursively by (4)
φ_j	Centrality of user j, given in (1)	Twitter follower graph
A	Discount factor	Chosen from the range (0, 1)

Figure 1 shows the dynamics of motivation levels for 6 users with the highest average motivation levels, where we took α = 0.9. The stochastic recursion of the type presented is well studied in probability theory. In particular, it follows from Theorem 1 of Brandt (1986) and its corollary that if the mentions follow a stationary process and we choose $0 < \alpha < 1$ then the motivation levels converge to a stationary distribution in the limit. Hence, for a typical and stable stochastic process of mentions, on a long run, we will get a typical stochastic distribution of the motivation levels. When α = 1, so there is no discount, the motivation levels can only increase and will converge to 1 in the infinite time limit. This is obviously not desirable and not realistic. On the other hand, when α = 0, the motivation levels will be equal exactly to the increment (3). This is also not realistic because, e.g. the motivation level of a very active user will be counted zero on the day when by chance this user did not receive any mention. Therefore, we suggest to use $0 < \alpha < 1$.

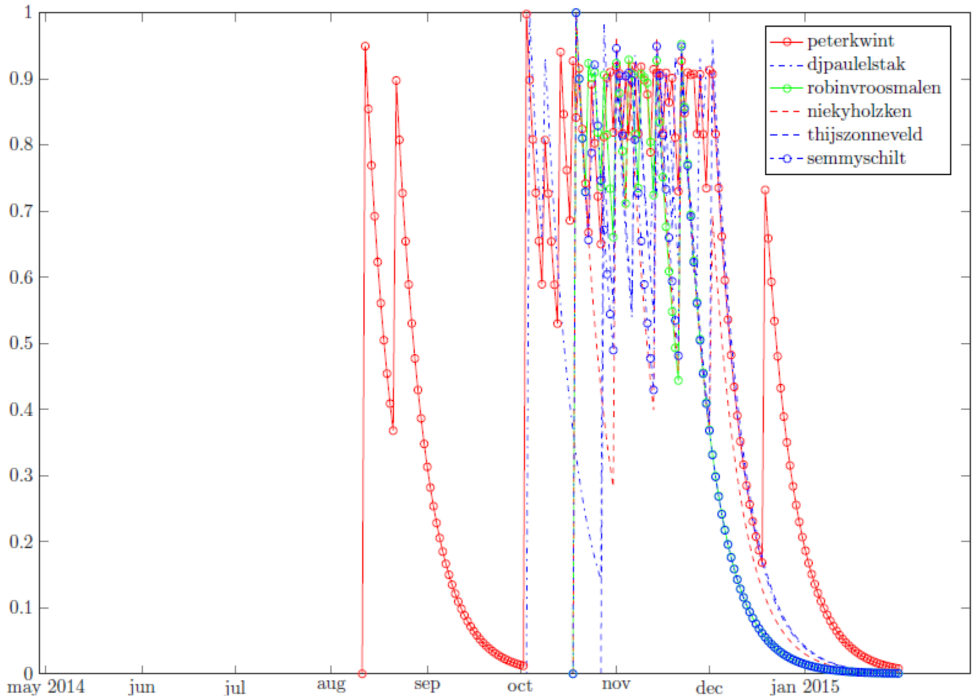

Figure 1. Satiation-Deprivation Model evolution for the top-6 matched users with highest average motivation levels in the Netherlands 2014 dataset, α = 0.9

3.2.6 Donation potential model

Using the Satiation-Deprivation model from the previous section, we can compute a motivation level, obtaining a number between 0 and 1 for each user on each day. We now want to investigate whether this gives us information on the likelihood of donation from the users on a given motivation level. To this end, we use a moving averages approach as follows. First, choose a small window size *w*. Then, for any point *l ϵ (l –w/2, 1 + w/2)* we evaluate the empirical probability of donation from the users, of whom the motivation level is in the interval *(l – w/2, l + w/2)*. Formally, let 1{·} be the indicator function, which is 1 if the event in brackets holds and zero otherwise. Then the donation potential at level *l*, denoted by *d(l)*, is defined as follows:

$$d(l) = \frac{\sum_t \sum_i 1\{L_i(t) \in [(l - \frac{w}{2}, l + \frac{w}{2}),\ \text{donation on day t}\}}{\sum_t \sum_i 1\{L_i(t) \in [l - \frac{w}{2}, l + \frac{w}{2}\}} \quad (5)$$

4 Results

4.1 Donation potential

We have ran the Satiation-Deprivation model for the 191 matched fundraisers in the Netherlands 2014 dataset. Figure 2 plots the data-induced donation potential in 2014 for the Netherlands and Sweden for the matched fundraisers (191 matches in the Netherland sand 56 matches in Sweden den) with α = 0.9. We see a distinct positive relation between motivation levels and donation potentials. Between motivation levels 0 and 1 there is about an 11% difference in donation potential in the Netherlands dataset and about 26% difference in the Sweden dataset.

4.2 Motivation levels on donations

In this section we analyse a random set of 40 matched fundraisers in the Netherlands 2014 dataset, as a first experiment to test the developed model. We want to verify whether the motivation levels on donation days have a different distribution from other days. Let n_D be the number of donation instances (a donation of one user on one day counted as an instance), and n_N the number of non-donation instances. Define as the test statistic:

$$D(n_D, n_N) = \sup |F_{n_D}(l) - G_{n_N}(l)|$$

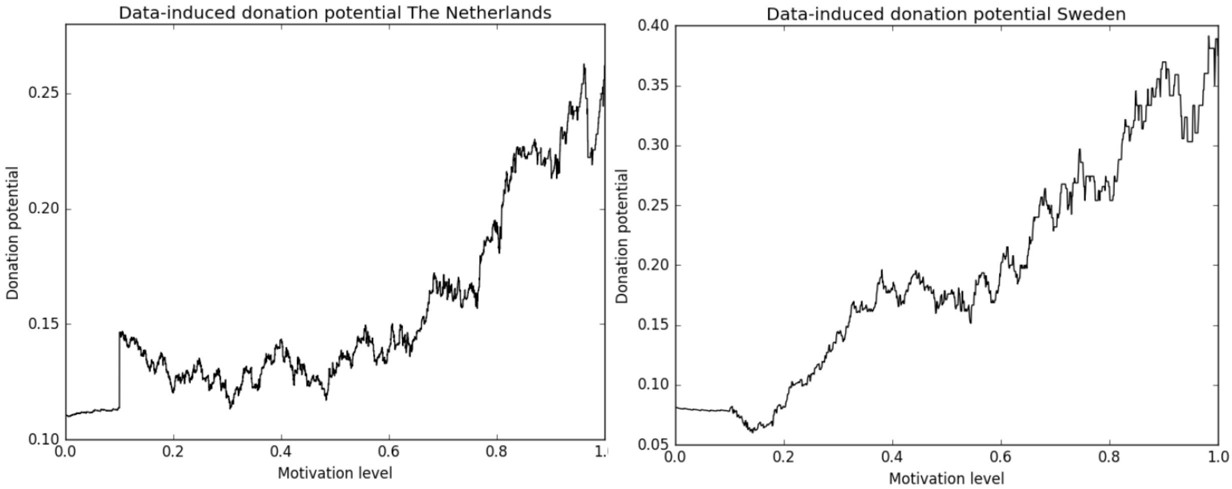

Figure 2. Data-induced donation potential in Netherlands (n=191) and Sweden (n=56) of each motivation level, using the moving average approach, see (5).

where F_{nD} is the empirical distribution function of motivation scores found at all donation instances, and G_{nN} is the empirical distribution function of motivation scores found at all non-donation instances. The null-hypothesis says that F_{nD} and $G_{n\mathrm{N}}$ are realizations of the same distribution. We find that the *p*-value is approximately 0.001. Thus, we reject the null-hypothesis. Hence, we conclude that motivation scores related to donation instances are distributed significantly different from the overall distribution.

We use a bootstrap method to identify the relation between mentions, motivation levels, and donations. To this end, we run multiple simulations of the null-model. Our null-model represents the motivation dynamics, when each fundraiser is mentioned exactly the same number of times and by exactly the same users as in the data, but the mentions are randomly distributed over time. In order to compute *p*-value, we compare the measurement on the real data to the empirical distribution of the null-model.

As a baseline, we first investigate whether mentions and donations often occur on the same day. In the data we find that the realized number of co-occurrences is 27. By running the probabilistic null model 1,000,000 times we find a *p*-value of 0.164, that is, in 16.4% of the runs with purely random realization of the mentions, the number of co-occurrences of mentions and donations is 27 or higher. We conclude that co-occurrence data does not give sufficient statistical evidence of the positive relation between mentions and donations.

Finally, we use the bootstrap approach to infer relation between a motivation level and the event of a donation. It is important to note that we disregard mentions made outside of the Movember period, even though these mentions can contribute to the motivation level of a user. This is because mentions in November are much more frequent than in any other month. For each donation instance, we record a motivation level of the user who made a donation, and we obtain the median of all motivation levels of all users at their donation instances. Then, we run the null-model 10,000 times and compute the p-value, which is the fraction of realizations of the null-model, where the median of the motivation levels at donation instances was equal to or higher than the one in the data. The results are given in Table 2.

Table 2. The median and the p-value of the motivation levels at donation instances in November 2014 for 40 fundraisers in the Netherlands.

Discount rate α	**Median(data)**	***p*-value**
1	1.8697830E-01	0.0057
0.99	1.7172259E-01	0.016
0.95	1.0888907E-01	0.0171
0.9	5.2330491E-02	0.0323
0.85	2.0857169E-02	0.0402
0.8	6.3944156E-03	0.0563
0.7	6.3141639E-04	0.0547
0.6	4.9710874E-05	0.0533
0.5	1.8838363E-06	0.0535
0.4	3.5723341E-08	0.0574
0.3	2.2902083E-10	0.0559
0.2	2.0371127E-13	0.0554
0.1	1.4225652E-18	0.0497

The fluctuations of the p-value for different values of $\alpha \epsilon [0.1, 0.8]$ can be related to the random nature of the data. For high α the motivation levels in the data are significantly higher compared to the null-model. Therefore we conclude that there is a positive relation between motivation levels and donation events. Still, the smallest *p*-value is achieved when $\alpha = 1$. We address this in the discussion below.

5 Discussion

This paper presents ongoing research on the development of a Satiation-Deprivation model of fundraisers' motivation to collect donations over time. This preliminary model, based on Social Exchange theory, estimates motivation levels over time based on a Twitter mention network and a donation dataset obtained from the Movember 2014 campaign in the Netherlands and Sweden.

5.1 Theoretical contributions towards Social Exchange Theory

We aim to contribute to literature on social exchange theory and motivation in online communities by extending previous findings on online contributions, e.g. knowledge sharing (Yan, Wang, Chen, & Zhang, 2016; Lin & Huang, 2010; Tsai & Cheng, 2012), to offline behavioural outcomes such as fundraising. Specifically, we add to Yan, Wang, Chen, & Zhang (2016)'s finding that peer support and reputation increase motivation for fundraising. Methodologically, we formalize social exchange theory in a model that may unobtrusively measure the motivational strength in large online communities.

5.2 Managerial contributions

In the future, a validated version of our model may help campaign organizations, such as Movember, to develop and implement mentioning strategies (Miller & Tucker, 2013) to motivate fundraisers to keep contributing to their online community. We may test our findings on more recent data to account for changes in Twitter's services (e.g. API, length of tweets and

5.3 Limitations & future scope of research

Our model has several limitations. First, the smallest *p*-value among the tested discount rates is found for $\alpha = 1$. This is not realistic as it means that a model without motivational decay performs best. A reason may be a focus on data from November during which the motivation remains high. Second, our sample to test the model's goodness of fit is limited. For now, we have only run the test for 40 random Dutch users and only for the month November. In future research, we plan to scale up the sample to all matched Movember participants and broaden the time window. Last, we recognize that online interactions on Twitter represent only a small part of the explained variance of fundraising. Hence, we plan to combine Twitter data with data of offline interaction, such as data on organizing offline fundraising events, to improve our model.

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