The Impact of Foursquare Checkins on Users' Emotions on Twitter

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Abstract. Performing observational studies based on social network content has recently gained attraction where the impact of various types of interruptions has been studied on users' behavior. There has been recent work that have focused on how online social network behavior and activity can impact users' offline behavior. In this paper, we study the inverse where we focus on whether users' offline behavior captured through their check-ins at different venues on Foursquare can impact users' online emotion expression as depicted in their tweets. We show that users' offline activity can impact users' online emotions; however, the type of activity determines the extent to which a user's emotions will be impacted.

Keywords: Observational studies · Causal effect · Behavioral patterns · Twitter · Foursquare

1 Introduction

The recent decade has witnessed the expansion of the availability of social network platforms where users have had a growing opportunity to share abundant content of various types including, but not limited to, textual data, social interaction behavior including follower-followee relationships, and geographical information. These behaviors retain patterned features with a potential to be mined. Furthermore, they result in unconscious and conscious involvement of users in the process of mutual influence. The promise of social networks and generated content thereby have turned them into a large-scale sensor that can provide insights into people's activities, behaviors, thoughts, emotions and health [5]. As a result, the study of human behavioral patterns leveraging those online sources of information has been a dominant topic in numerous recent studies whose results have found application in such fields such as healthcare [12], advertising [15], and customer care [21], to name but a few.

Specifically, there is a growing attention to find the relation between linguistic analysis of users' activity on social media and their behavior, e.g., text analysis has been used to find the transition from mental illness to suicide ideation [9]. Variety of measures such as language, emotion, and user engagement has been

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derived from Twitter to characterize depressive behavior and consequently predict likelihood of depression of individuals in future [6]. Similarly, in [4,18,19], linguistic analysis has been used to identify psychological disorders such as anxiety and depression. Additionally, some studies are trying to understand how users involve in their community by analyzing their social media activities. Authors in [3] define activity in social media as action in response to societal needs. Based on [1] social media can be considered as an arena for closing the information divide between countries.

Observational studies provide a relaxed way of experimentation in order to extract the causal effect where the assignment of users to treated and control groups is not random and investigators do not have control over the assignment. Relying on the power of observational studies and equipped with the potentially viable sources of information from social networks, numerous studies have been performed addressing a variety of issues. Studies have been done on observational studies over social media and social networks through the linguistic analysis of the users' textual content to discover causal knowledge from observational data [17] in the context of health [9] in a range of issues including mental health [8], nutrition [10], weight loss issues [7], to name but a few. The aforementioned works provide some great examples of the promise of social media application and particularly Twitter for the purpose of observational studies. There have been studies focused on assessing user personality aspects by examining their online behavior . Most of these works use supervised methods and are based on the big five personality traits including openness, conscientiousness, extraversion, agreeableness and neuroticism. Researchers have shown that these big five dimensions can be extracted through linguistic analysis of the users' generated textual content [22]. There are works which exploit the findings in a variety of fields including improvement of recommendations [13,20] and rating systems [14], location recommendation [23], improving rating prediction systems [16], just to name a few.

User behavioral traces are embodied in either *offline activities* which refer to activities users do in their real life, or *online activities* which refer to the actions users do on the Internet, such as expressing their ideas on social networks. Different patterns of offline activities and online actions could impact user's behavior differently. Recently, authors in [2] studied the influence of online social networks on users' online and offline behavior. Our work is the dual to the same problem; we attempt to study the effect of offline activities on users' online actions. To that aim, we design an observational study framework making use of two famous social networks, namely Twitter and Foursquare. In our framework, Foursquare check-ins are used to track users' offline activities, whereas Twitter posts represent users' online actions. More specifically, our research problem is to investigate how engaging in different offline activities, such as exercising and/or visiting a bar, impact users' emotions over time. The locations users visit and post on Foursquare enable us to track their offline activities. In order to track users' emotions, we define a metric called *Emotion Conformity*, whereby we measure users' emotional attitude towards active topics on Twitter compared to the broader community emotions towards the same topics.

2 Proposed Approach

2.1 Problem Definition

The objective of our work is to answer the question of whether engaging in an offline activity can impact user's online behavior and also the way different offline activities impact her behavior. More specifically, we aim at estimating how users' emotion conformity evolves as caused by engagement in an offline activity. To this end, we perform a cross-social network observational study in which user's posts on Twitter are considered as representative of users' online behavior and check-ins on Foursquare represent their offline activities. We extract a given user's interests through modelling her interest in active Twitter topics and denote it as the *User Interest Profile*. Also, we extract user's emotions towards the topics she contributes to and is interested in denoted as *User Emotion Profile*, which is a representation of user online behavior and is core to our framework.

A topic s is assumed to be active if it is subject to extensive attention from users. We do not make any specific assumption on topic representations and thus a topic can be represented as a multinomial distribution over the vocabulary of unique terms mentioned in the collection of tweets, as follows:

Definition 1 (Active Topic). *Let C be the collection of tweets that is broadcast in time interval T and $\mathbb{V}$ be the set of all unique terms mentioned in C. We build a vector of N weights for each topic s, i.e., $w^s(v_1), ..., w^s(v_N)$, where $w^s(v_N)$ denotes the contribution importance of the word $v_N \in \mathbb{V}$ to topic s.*

As mentioned later in the experiments, the set of active topics can be extracted using existing LDA-based topic modeling techniques. In a specific time interval t with M active topics $S = \{s_1, s_2, ..., s_M\}$, we define interest profile for each user $u \in \mathbb{U}$ denoted by $UIP^t(u)$, as follows:

Definition 2 (User Interest Profile). *The user interest profile of user $u \in \mathbb{U}$ denoted by $UIP^t(u)$ is modeled by forming a vector of weights for each of M active topics, i.e., $(f_u^t(s_1), ..., f_u^t(s_M))$, where $f_u^t(s_M))$ indicates u's interest in topic $s_M \in S$. A user interest profile is normalized so that the sum of all weights in a profile equals to 1.*

We also extract user's emotions. A tweet's emotion is calculated as the difference between positive emotion and negative emotion. Thus, besides the active topics which every tweet belongs to, we calculate the emotion of every tweet as well. In a specific time interval t with M active topics $S = \{s_1, s_2, ..., s_M\}$, we define emotion profile for each user $u \in \mathbb{U}$ denoted by $UEP^t(u)$, as follows:

Definition 3 (User Emotion Profile). *The user emotion profile of user $u \in \mathbb{U}$ in time interval t, denoted by $UEP^t(u)$ is modeled by forming a vector of weights for each of M active topics, i.e., $(g_u^t(s_1), ..., g_u^t(s_M))$, where $g_u^t(s_M))$*

denotes the average emotion of user u with respect to topic $s_M \in S$. A user emotion profile is normalized so that $0 < h(s_M) \leqslant 1$.

In order to measure emotion conformity, we need to be measure users' emotions within the context of the larger community. To this end, we extend Definitions 2 and 3 as follows:

Definition 4 (Community Interest Profile)). *Let U denote the set of users. The community Interest Profile, denoted by CIP^t , is represented by a vector of weights over the M topics, i.e., $(h^t(s_1), ..., h^t(s_M))$ as such CIP^t represents the normalized topic distribution for all tweets published in time t.*

Moreover, we define a community emotion profile to show the emotion of the general population towards each topic.

Definition 5 (Community Emotion Profile)). *The community emotion profile in time interval t, denoted as CEP^t, is represented by a vector of weights over the M topics, i.e., $(k^t(s_1), ..., k^t(s_M))$ where $k^t(s_i)$ denotes the average Emotion of users with respect to topic $s_m \in S$ and is normalized such that $0 < k^t(s_i) \leqslant 1$.*

2.2 Metric Definition

By contrasting user-level measures from Definitions 2 and 3 with community-level measures of Definitions 4 and 5, we can now define the dependent variables corresponding how degrees of conformity change during time.

The user behavioral pattern that we are interested to study is user's conformity with general population's emotions. In our model, we define conformity as the degree to which a user aligns with and shares tweets bearing similar emotions towards the interests of the community. We measure emotional conformity as the degree to which the user exhibits the same emotions towards topics as does the general population. For example, a user who shows positive polarity towards the release of a new iPhone given the dominant emotion towards this topic is positive in the whole social network, has a high degree of emotion conformity (EF). On this basis, we calculate emotion conformity as follows:

$$EF^t(u) = UEP^t(u) - CEP^t. \tag{1}$$

2.3 Methodology

Here, we describe the approach taken to distinguish potential users to be selected as treated group and control group participants for our experiments. To this end, users who change their offline activities by 'starting' to visit a specific venue are nominated to form the treated group. We also draw upon the method used to distinguish the matched users for treated group members, i.e., control group participants.

Detecting Potential Users. We identify two different groups of users, who are active both on Twitter and Foursquare. In this analysis, users are separated into 2 groups; the treated group and the control group. The treated group U_T consists of users who start to visit a specific location which is hypothesized to have effect on the user u, and the control group U_C includes users who are different from the treated group in terms of the place they start to visit. The condition, also referred to as 'the interruption', for users in both groups is a point in time where a user begins to visit a specific venue (e.g., gym or bar) which she would not visit prior to that time. The reason to use the condition based model is to:

1. Eliminate the effect of external parameters which can cause uncertainty in concluding whether visiting a specific venue has an effect on the user's online behavior; and,
2. To filter out the users and make the database more admissible and relevant.

The parameter of significance is the difference between the effect on the user in the treated group with a user in the control group. This parameter gives important information about the effect of visiting different specific locations and is denoted by T_u. The effect can easily be calculated using the equation: $T_u = CIE_{u,T} - CIE_{u,C}$ where $CIE_{u,C}$ and $CIE_{u,T}$ are the mean results of the two groups [11].

Matching Through Propensity Score Matching. An observational study differs from RCT (randomized control trial) in that the subjects are not randomly assigned to treated and control groups. This experimental methodology relieves the effect of confounding parameters. In order to eliminate confounding effects, statistical matching is executed in order to reduce the effect of confounding variables. We use a standard approach of matching called *Propensity Score Matching* (PSM). In PSM method, users in the treated and control groups are matched across the groups based on their propensity scores. Propensity score is defined as the probability of assigning a particular treatment to a user given a set of observed confounding variables and is obtained using the logistic regression. The propensity score can be defined Prob(T = 1 — X = x) where T is a binary variable showing user is in the treatment group and X is the set of confounding variables. We employ number of tweets, number of twitter followers, number of Twitter friends, Gender and number of Foursquare checkins as the variables in PSM with a median absolute standard mean difference of 0.12. We exploited PSM in order to rule out any radical parameters that could possibly yield uncertain results. We match a given user from the treated group with one in control group with similar propensity scores.

3 Experiments

3.1 Dataset Description and Experimental Setup

We build our dataset with data collected from users who are active on both Twitter and Foursquare. These social networks provide us with complete and comprehensive information about user online and offline behavior, with Twitter representing the online actions of users and Foursquare providing the data about users' offline actions. Users active on both Twitter and Foursquare social networks are found through recognizing Twitter users who share their Foursquare check-ins using the Swarm application. Swarm is a mobile application provided by Foursquare that lets users share the places they visit by posting on user's Twitter timeline.

In our experiments, we extract recent tweets for 17,220 users who are active on both Twitter and Foursquare using Twitter API. In order to calculate Emotion Conformity values for each user we implement TwitterLDA to extract active topics and we use LIWC 2015 to extract user's emotions. After dividing users' tweets into monthly time intervals, we determine the Emotion Conformity for each user by calculating the differences of emotion distributions for user and community in the same time intervals. For the treated group, we distinguish users who do not check-in at any bar related venues for two months but start going to a bar related venue weekly after an interruption and continue this behavior for the next 8 months. For the control group, we find users who do not check-in at any gyms or fitness centres but start going to a gym related venue weekly for at least 8 months after the interruption. We match each user from the treated group with a user in the control group using propensity score matching.

3.2 Study Findings

Our findings are summarized in Fig. 1. As seen in the figure, the three groups of users, those in the control group as well as those in the treated groups of going to the bar and going to the gym where fully matched in the first two months of the study, meaning that the both the propensity scores for the users as well as their emotion conformity was the same. This indicates that the users in the these

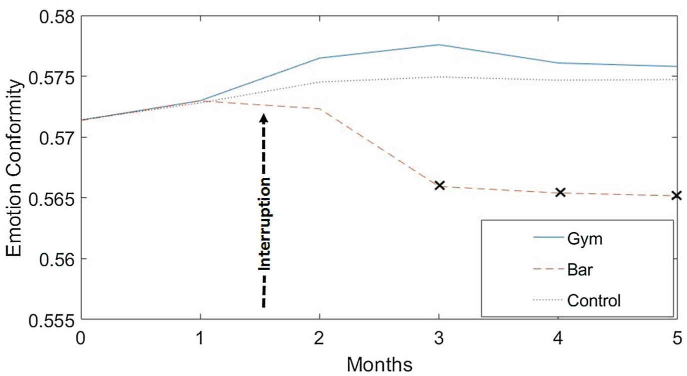

Fig. 1. The results of experiments for treated and control groups comparison in terms of Emotion Conformity.

three groups are comparable and any behavior change after the application of the treatment is attributable to the observed offline activity.

We find that the emotion conformity of the users in the control group does not change beyond the second month as the users in this group do not experience any new offline activity. On the other hand, those users who embark on going to the gym, have an increased emotion conformity. However, the increase is not statistically significant. In contrast, those users who start to go to a bar after the second month and consistently go to the bar, as mentioned earlier, at least once a week, experience a reduced emotion conformity. The observed changes in emotion conformity is also statistically significant over both the control group as well as the treated group who went to the gym. This means that the observed change in the behavior of those users who went to the bar consistently cannot be attributed to chance and can be attributed to their offline behavior. So our findings can be summarized as follows:

– Information collected from different social networks can be collected and aligned to extract insight about both users' online and offline activities;
– While it was shown in previous studies that online behavior can be have impact on users' offline activities, we have also shown preliminary results that indicate that users' offline activities can impact their online activities;
– We have demonstrated that some offline activities have a higher potential to more significantly disrupt the users' regular online behavior. For instance in our study, while going to the gym does insignificantly change a users emotion conformity, the impact is removed with time; on the other hand, the impact of going to the bar is significant and sustained over time.

As future work, we are interested in studying this phenomenon more extensively by covering a wider range of offline activities and a broader user set.

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