Mobile Sensing to Model the Evolution of Political Opinions

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ABSTRACT

Exposure and adoption of opinions in social networks are important questions in education, business, and government. We describe a novel application of ubiquitous computing based on using mobile phone sensors to measure and model the face-to-face interactions and subsequent opinion changes of undergraduates during the US presidential election campaign. We find that self-reported political discussants have characteristic interaction patterns and can be predicted from sensor data. Mobile features can be used to estimate unique individual exposure to different opinions, and help discover surprising patterns of dynamic homophily related to external political events, such as election debates and election day (4th Nov 2008). To our knowledge, this is the first time such dynamic homophily effects have been measured.

Using sensor features and estimated exposure and past opinions, it is possible to predict future opinions for individuals (R^2 ˜0.8, p ˜0.001), and measured exposure increases explained variance by up to 30% over that of survey responses of past opinions alone.

Author Keywords

Mobile sensing, social evolution, political opinions, exposure and diffusion

General Terms

Algorithms, Design, Documentation, Experimentation, Measurement.

INTRODUCTION

A central question for social science, as well as for the practical arts of education, sales, and politics, is the mechanism whereby ideas, opinions, innovations and recommendations spread through society. Diffusion is the phenomena of propagation within a social network. The proliferation of social web applications on the Internet has generated copious amounts of data about how people behave and interact with each other in online communities – and these data, in turn, are being extensively used to model the role of social interactions in online diffusion. However, many characteristics of our lives are expressed only in real-world, face-to-face interactions. To model the adoption of these behaviors, we need fine-grained data about face-to-face interactions between people, i.e. who talks to whom, when, where, and how often. A complete picture of the social interactions between people, along with exogenous variables that affect the adoption process is required. This is a promising new application area for ubiquitous computing.

Social scientists have relied on self-report data to study social networks, but such approaches are not scalable. It is impossible to use these methods with fine resolution, over long timescales (e.g. months or years), or for a large number of people, (e.g. hundreds or thousands). Further, while people may be reasonably accurate in their reports of long term social interaction patterns, it is clear that memory regarding particular relational episodes is quite poor In a survey of informant accuracy literature, Bernard, Killingworth and colleagues have shown that recall of social interactions in surveys used by social scientists is typically 30-50 percent inaccurate [2]

A key question is how mobile sensing techniques and machine perception methods can help better model these social diffusion phenomena. This paper describes the use of mobile phone sensors at an undergraduate community to measure face-to-face interactions, phone communication, movement patterns and self-reported political opinions. We find that mobile sensing and modeling approaches can provide surprising new insight into the inner workings of these important social phenomena.

In the next section, we describe related work in modeling face-to-face interactions using mobile phones and electronic badges. We then describe our data collection methodology and the dataset collected during the McCain-Obama election campaign. We show that automatically captured interactions can be used to model individual exposure, patterns of dynamic homophily and estimate the likelihood of opinion change for individuals. The primary contribution of this paper is a novel approach that automatically captures effects of social ties on the evolution of opinions through face-to-face interactions.

RELATED WORK

UbiComp '10, Sep 26-Sep 29, 2010, Copenhagen, Denmark.

Mobile Phones as Social Sensors

The four billion mobile phones worldwide are ubiquitous social sensors of location, proximity and communication. Eagle and Pentland [3] coined the term Reality Mining, and used mobile phone Bluetooth proximity, call data records and cellular-tower identifiers to detect the social network structure and recognize regular patterns in daily user activity. For human location traces, Gonzalez et. al [6] showed that call detail records could be used to characterize human mobility patterns and test the proposed models better than random walk or Levy flight models. Similarly, electronic sensor badges like the Sociometric badge [10] have been used to identify human activity patterns and analyze conversational prosody features.

Face-to-Face Interactions and Opinion Change

What kind of mobile interaction features do we need to capture using mobile phone sensors to predict the diffusion of political opinions? Social scientists discuss that two types of ties are reflected in our daily lives: strong ties and long-distance weak ties. Friedkin [5] proposes that strong, cohesive ties between people lead to high interpersonal influence and faster diffusion. Such ties are likely to be easily detected in co-location and communication patterns of users.

In network theory, weak ties play a bridging role in the diffusion of information, by allowing for short-path lengths while maintaining high clustering between the nodes [12]. However, due to less-frequent real-world interaction, weak ties are not likely to be frequently expressed in location and communication data, and hence are harder to detect automatically from mobile phone features.

METHODOLOGY

Past projects have used mobile operator call data records and location information to model movement patterns, social ties and spatial epidemiology. Our approach is to build a mobile phone software platform for long-term personal use by participants.

The dataset described below was collected as part of longitudinal study with seventy residents of an undergraduate dormitory. These residents represent eighty-percent of the total population; most of the remaining twenty percent residents were located in a spatially isloated section of the building. The dormitory is known within the university for its pro-technology orientation and the decision of students to reside was based on self-selection by both incoming students as well as existing residents. The students were distributed roughly equally across all four academic years (freshmen, sophomores, juniors, seniors) and 60 percent of the students were male. The study participants also included four graduate resident tutors that supervised each floor.

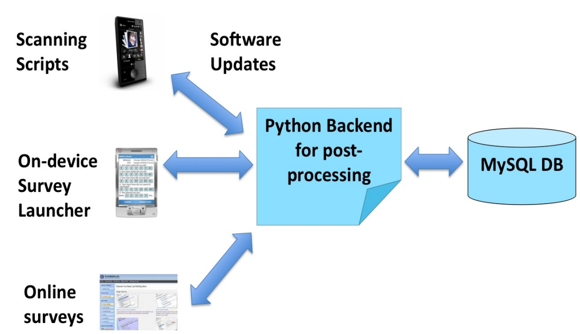
This overarching experiment was designed to study the adoption of political opinions, diet, exercise, obesity, eating habits, epidemiological contagion, depression and stress, dorm political issues, interpersonal relationships and privacy. A total of 320,000 hours of human behavior data was collected in this experiment. In this paper however, we only discuss the dataset and analysis related to measuring the spread of political opinions over three months of the Obama-McCain presidential campaign.

MOBILE SENSING PLATFORM

The mobile phone based platform for data-collection was designed with the following features and long-term sensing capabilities.

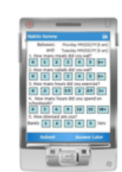
Device Selection

The platform is based on Windows Mobile 6.x devices, as they can be deployed with all four major American operators. Software was written using a combination of native-C and managed-C#. The software-sensing package was supported for six different handset models in the Windows Mobile product range. All supported devices featured WLAN, EDGE and SD Card storage, and most featured touch screens, flip-out keyboards. The HTC Tilt, a popular GSM phone in our experiment is shown in Fig 1.



(a) Platform Architecture and Data Sources

(b) HTC Tilt: the most popular WiMo device in our deployment



(c) On-device survey launcher screenshot

Figure 1. Data Collection Platform

Proximity Detection (Bluetooth)

The software scanned for Bluetooth wireless devices in proximity every 6 minutes. The Windows Mobile phones used in our experiment were equipped with class 2 Bluetooth radio transceivers, which have a realistic indoor sensing range of approximately 10 feet. Scan results for two devices in proximity have a high likelihood of being asymmetric, which is accounted for in our analysis. Due to API limitations with

Windows Mobile 6.x, signal strength was not available to the sensing application. Bluetooth logs were captured in the following format:

UTC timestamp   1-way hash of remote device MAC

Approximate Location (802.11 WLAN)

The software scanned for wireless WLAN 802.11 Access Point identifiers (hereafter referred to as WLAN APs) every 6 minutes. WLAN APs have an indoor range of xxx and the university campus has almost complete wireless coverage. Across various locations within the undergraduate residence, over 55 different WLAN APs with varying signal strengths can be detected. WLAN logs were captured in the following format:

UTC timestamp   1-way hash of AP MAC   AP ESSID   Signal Strength 0-100

Communication (Call and SMS Records)

The software logged Call and SMS details on the device every 20 minutes, based on recent events. These logs included information about missed calls and calls not completed. Calls were logged in the following format:

UTC start timestamp   UTC end timestamp   1-way hash of remote phone number   incoming vs. outgoing flag 0-1   missed call flag 0-1   user roaming flag 0-1

And for SMS messages:

UTC timestamp   1-way hash of remote phone number   incoming/outgoing flag 0-1

Battery Impact

In past studies where mobile phones have been used as long-term behavior sensors [3], batter impact has been minimal. In this study, periodic scanning of Bluetooth and WLAN APs reduced operational battery life by about 10-15 percent. Depending on the device models and individual usage patterns, the average usable battery life was between 14-24 hours. Windows Mobile 6.x phones have relatively poorer battery performance than their competitors in the smart-phone market.

WLAN usage for web browsing by the user and application-server network communication had significantly more impact on battery life than background sensing scripts. Using wireless Internet on Windows Mobile devices for 4-5 hours continuously on some handset models can drain batteries completely. Where available, we provided users with extended batteries for models where available. While our platform supports over-the-air data uploads, this was disabled for most of the experimental deployment due to WLAN battery considerations.

User Privacy Considerations

A key concern with long-term user data collection is securing privacy. This experiment was approved by the Institutional Review Board (IRB) and participants were financially compensated. The sensing scripts for our platform capture only hashed identifiers, and data is secured and anonymized before aggregate analysis.

Backend Post-Processing and SQL Database

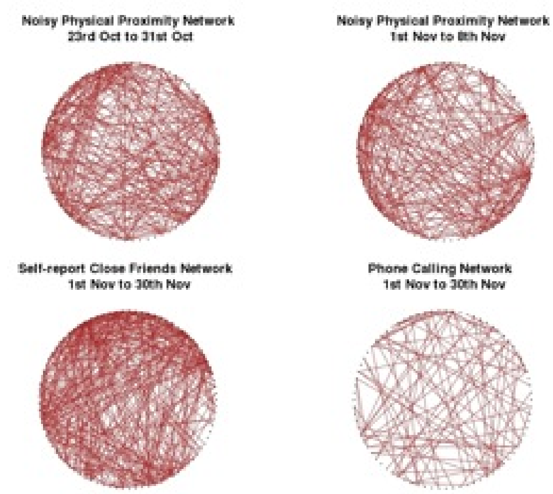
Daily captured mobile sensing data was stored on-device on read/write SD Card memory. On the server side, these logs files were merged, parsed and synced by an extensive Python post-processing infrastructure, and finally stored in various MySQL tables for analysis.

Open Source Availability

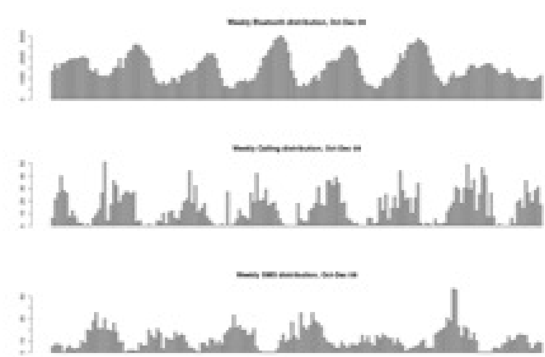
This sensing software platform for Windows Mobile 6.x has been released under the LGPLv3 open source license for public use, and is available for download here[11].

DATASET CHARACTERISTICS

The dataset described here corresponds to the date range from 10th September to 10th November 2008, the last few months of the Obama-McCain election campaigns.



(a) Different interaction networks for the participants



(b) 24x7 distribution of sample counts, aggregated across all weeks

Figure 2. Dataset Characteristics

Mobile Phone Sensor Data

The mobile phone interaction data during this period consists of approximately 450,000 bluetooth proximity scans, 1.2 million WLAN access-point scans, 16,900 phone call records and 17,800 SMS text message events. The average duration of phone calls is approximately 138 seconds, and 58% of measured interactions were during weekdays. About 8-10% of the expected samples are missing, due to phones not being charged and software errors. These mobile interaction features capture the temporal evolution of the social network in this community, as shown in Figure 2.

Training Labels (Survey responses)

The dependent political opinions were captured using three monthly web-based surveys, once each in September, October, and November 2008 (immediately following the presidential election). The survey was designed as a Likert scale and consisted of the following questions:

- Are you liberal or conservative?: 7-point scale, from extremely conservative to extremely liberal
- How interested are you in politics: 4-point scale, from not interested to very interested
- What is your political party preference?: 7-point scale, from strong Democrat to strong Republican
- Which candidate are you likely to vote for? (Sept) & Which candidate did you vote for? (Nov)
- Are you going to vote in the upcoming election? (Sept) & Did you vote in the election? (Nov)

  Political scientists [8] believe that changes in political opinions are gradual, and this is observed in our dependent variables. For the first three questions, approximately 30 percent of the participants changed their opinions in the entire period. The shifts are 1 or 2 levels on 4-point or 7-point Likert scales.

  In addition to opinions, users also reported their relationships with other experimental participants, i.e. whether they were close friends, political discussants, or did not know the person at all. These self-reports are used to predict political discussants.

ANALYSIS

Exposure to Diverse Opinions

What is the exposure to diverse ideas and opinions for a person? Threshold and cascade models of propagation of information or opinions [7, 9] assume that participants are equally at risk or that they have a uniform exposure to different opinions. In reality however, exposure to different opinions is dynamic and characteristic for every individual. Using mobile sensor data, dynamic exposure can be estimated for each participant, on a daily or hourly basis. Contact between two individuals is a function of different extracted features e.g. time spent together during the day or in classes, time spent socializing in the evenings or late at night, phone calls and SMSs exchanged, the sum of detected interactions or the total duration.

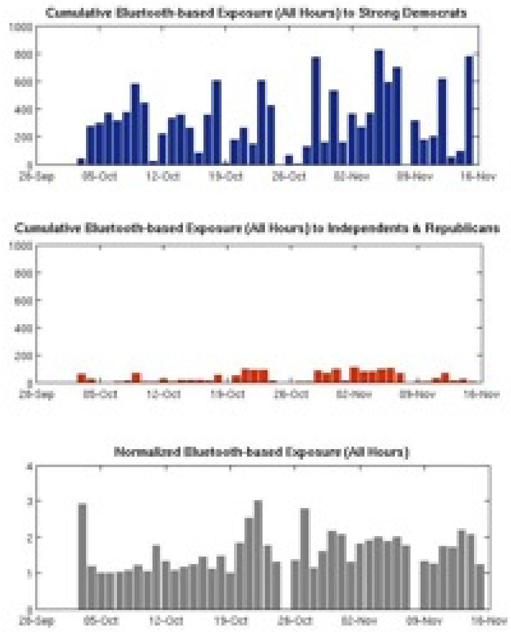


Figure 3. Characteristic daily normalized and cumulative exposure for one resident during the election period

Normalized exposure, N_i represents the average of all opinions a person is exposed to on a daily basis, weighted by the amount of exposure to different individuals and their self-reported opinions, where opi_j represents the opinion reponse for person j for a particular question, $contact_{ij}$ is strength of tie between i and j, and $Nbr(i)$ is the set of neighbors for i in the interaction network.

$$N_i(t) = \sum_{j \in Nbr(i)} contact_{ij} \cdot opi_j / \sum_j contact_{ij}$$

Cumulative exposure, C_i to a particular political opinion O, represents the magnitude of a particular opinion that a person is exposed to on a daily basis, and is a function of the amount of contact with different individuals and their self-reported opinion, where $contact_{ij}$ is strength of tie between i and j, and $Nbr(i)$ is the set of neighbors for i in the interaction network.

$$C_{iO}(t) = \delta_j \cdot \sum_{j \in Nbr(i)} contact_{ij}$$

where δ_j = 1 only if person j holds opinion O, and 0 otherwise. Figure 3 below shows cumulative and normalized exposure for one participant during the election campaign period.

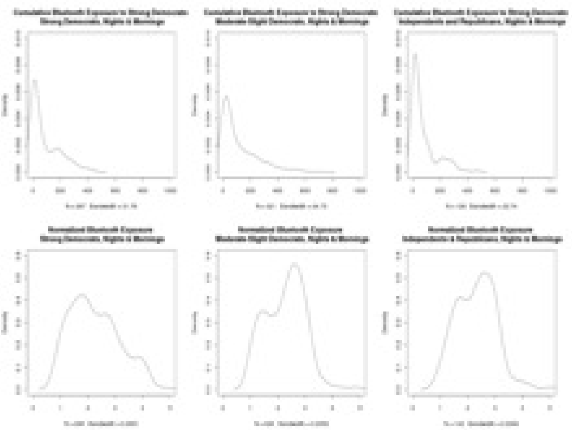


Figure 4. Distributions of cumulative and normalized exposure during late-nights and early-mornings for three different classes of participants. Cumulative exposure is calculated with respect to strong democrats.

The majority of the participants in this dataset are democrats. Figure 4 shows the distributions of cumulative and normalized exposure during late-nights and early-mornings to strong democrats for 3 types of participants, (a) strong democrats (b) moderate-slight democrats and (c) independents-republicans.

Sensor Data and Dynamic Homophily

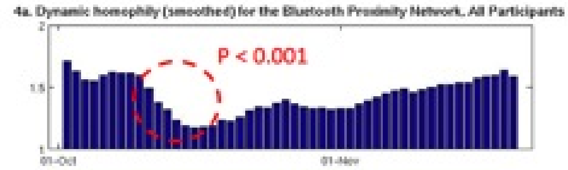
Homophily is a widely studied phenomenon in social science [8], which suggests that individuals have ties with others who have similar opinions or beliefs as themselves. Political science theories consider homophily a long-term phenomena, along the timescale of months or years. Measurements supporting homophily in political science are typically taken using self-reported surveys.

Unlike survey responses, mobile interaction features can be used to model homophily patterns based on much shorter timescales, e.g. days. A measure of dynamic homophily based on mobile phone interaction features and normalized exposure can be calculated as,

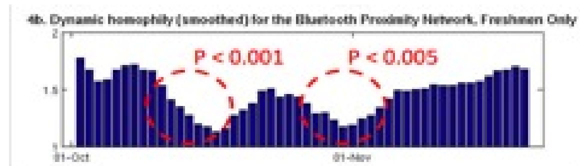
$$\Delta_i(t) = \left| O_i - \sum_{j \in Nbr(i)} contact_{ij} / \sum_j contact_{ij} \right|$$

$$H(t) = \sum_i \Delta_i(t)/n$$

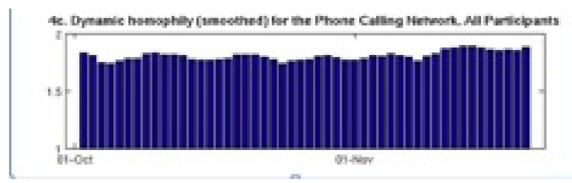
where $\Delta_i(t)$ is the difference between a persons opinions and exposure to others opinions, $H(t)$ is a daily measure of dynamic homophily for the entire community, and O_i are an individuals political opinion responses, on a 4 or 7-point scale, Survey-based opinions only change at monthly timescales, hence daily variations in H(t) are due to changes in mobile phone interaction features and a negative slope in H(t) implies that residents are spending



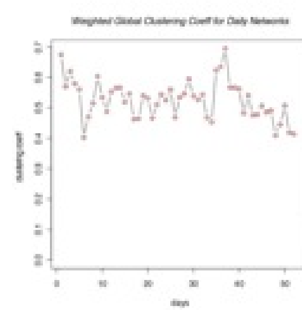
(a) Dynamic homophily based on Bluetooth proximity for all participants. Notice the decline, i.e. convergence of opinions, lasting for a few days, around Oct 15th, which was the last presidential debate ($p < 0.001$)



(b) Dynamic homophily based on Bluetooth proximity for freshmen only. There are two periods of decline, each lasting for a few days. The first is around Oct 15th, last presidential debate ($p < 0.001$), and the second is around 4th Nov, Election Day ($p < 0.005$).



(c) Dynamic homophily based on the daily phone-calling network shows no variation related to election events



(d) Weighted clustering coefficient (Y-axis) for daily Bluetooth interaction networks during the same period. X-axis represents days.

Figure 5. Dynamic homophily variations on the timescale of 2-3 days

more time with individuals who have opinions similar to theirs.

This measure reveals surprising behavior patterns during the election campaign period. Figure 4a shows $H(t)$ plotted on a daily basis, where selection of proximate neighbors for each individual is based on physical proximity counts measured based on Bluetooth proximity. The dip in this graph corresponds to the date of an election debate during the campaign, 14th Oct 2008. Fig 4b shows H(t) calculated only for freshmen (again, proximate neighbors for each node are chosen from all dorm residents based on Bluetooth scans). The dynamic homophily effects for freshmen, who only had a month to form ties in this community at this point, are even more pronounced, and a second drop is seen representing the tendency of indivduals to interact with like-minded others, is seen around 4th of November, which was Election day. In both figures 4a and 4b, the convergence of opinions effect is an effect that only lasts for a few days. This dynamic homophily effect is only observed in Bluetooth co-location networks, and not in calling or SMS networks, as shown in Figure 4c. This suggests that exposure to different opinions based on physical proximity is more relevant than exposure to opinions via other types of interaction modalities. The p-values provided were calculated using repeated-measure ANOVA. This measure captures dynamic patterns of homophily related to global political events from mobile phone sensor data. To our knowledge, this is the first time such an effect has been quantitatively measured.

The weighted clustering co-efficient [1] and average path length, calculated for daily Bluetooth interaction networks during the same period do not show equivalent significant variations around these periods of interest. The tendency to associate with like-minded residents during the election period is not evident in measures of centrality and clustering used to model network interactions.

Inferring Political Discussants

What are the behavioral patterns of political discussants? In monthly self-reported survey responses, about 30-50 percent of political discussants are also close friends. Similarly, sharing similar political opinions does not increase the likelihood that two individuals will be political discussants in this dataset.

Classification results based on mobile phone interaction features – total communication; weekend/late-night communication; total proximity; and late-night/weekend proximity, that characterize a political discussant are shown in Table 1. Two different approaches are compared, an AdaboostM1 based classifier [4] and a Bayesian network classifier[] where each input sample represents a possible tie, and show similar results. As the classes are severely unbalanced, cost-sensitive approaches are used in both case. Political discussants are considered unidirectional ties for this analysis, and precision and recall numbers are similar if stated relationships are converted to bi-directional ties.

	Precision	**Recall**	**F-Measure**
Meta-cost AdaboostM1 (individual classifiers are decision stumps), 5-fold cross validation			
Class 0	0.87	0.62	0.72
Class 1	0.35	0.67	0.46
Cost-sensitive Bayesian Network classifier, 5 fold cross-validation K2 hill-climbing structure learning			
Class 0	0.87	0.61	0.72
Class 1	0.35	0.70	0.46

Table 1. Identifying political discussants from social interaction features. Class 1 = self-reported political discussants

Linear Predictor of Opinion Change

Exposure based features described in the previous section can be used as a feature to train a linear predictor of future opinions. Specifically, the model shown above incorporates the persons past opinion (September), normalized exposure during the period and a constant that represents a linearly increasing amount of media influence during this period. For the various political opinion questions, regression values are in the r=0.8 range, with p ¡ 0.0001. Thus, using exposure based features explains an additional 15% - 30% variance across different political opinion questions. The effects for freshmen are approximately twice as strong as compared to the entire population. In the context of social science literature, this is considered a strong effect. Also, since the evolution of political opinions is quite gradual, this approach would be expected to explain more variance for opinions and habits which evolve faster, e.g. purchasing preferences or food eating habits.

CONCLUSION

In this paper we describe a novel application of mobile phone location and proximity sensors in modeling the spread of opinions based on real-world face-to-face interactions. Based on automatically captured mobile phone data, we can estimate exposure to different opinions for individuals on a daily basis. Around notable political events in this dataset, individuals show a tendency to spend more time with peers who share similar opinions; however, this effect only lasts only for a few days. To our knowledge, this is the first time such a dynamic homophily effect has been discovered in empirical data.

Based on automatically estimated exposure to different opinions, we can build a predictive model of future opinions for an individual, with normalized proximity accounting for up to 30 percent of the variance. The predictive ability however does not explain the underlying causal mechanism.

It is presently unclear whether the explain variance is a limit of the predictive ability of mobile features, or a limitation imposed by the linearity of our simple model. We are currently exploring dynamic stochastic models to es-

Political Opinion	SR Political Discussants	SR Close Friends	Norm. Exposure	Past Opi. + Norm. Exposure
Preferred Party	not sig.	not sig.	0.21^{**}	0.78^{***}
Liberal Conservative	not sig.	not sig.	0.16^{*}	0.81^{***}
Interest in Politics	not sig.	$0.07*$	0.24^{**}	0.74^{***}
Pref. Party (freshmen)	not sig.	not sig.	0.46^{*}	0.83^{*}
Interest in Politics (freshmen)	not sig.	not sig.	0.21^{**}	0.78^{***}

Table 2. Correlations between self-reported political opinions, self-reported relationships and mobile phone based features. As seen, automatically captured mobile phone features substantially outperform self-reported close friends or political discussants. All values are R^2, *: p $<$ 0.05 **: p $<$ 0.01 ***: p $<$ 0.001

timate the same opinion change, and expect to have additional results to report by the time of the conference.

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