Social sensing for epidemiological behavior change

Social Sensing for Epidimiological Behavior Change

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ABSTRACT
An important question in behavioral epidemiology and public health is to understand how individual behavior is affected by illness and stress. Although changes in individual behavior are intertwined with contagion, epidemiologists today do not have sensing or modeling tools to quantitatively measure its effects in real-world conditions.

In this paper, we propose a novel application of ubiquitous computing. We use mobile phone based co-location and communication sensing to measure characteristic behavior changes in symptomatic individuals, reflected in their total communication, interactions with respect to time of day (e.g. late night, early morning), diversity and entropy of face-to-face interactions and movement. Using these extracted mobile features, it is possible to predict the health status of an individual, without having actual health measurements from the subject. Finally, we estimate the temporal information flux and implied causality between symptoms, behavior and mental health.

Author Keywords
Socially aware mobile phones, epidemiology, reality mining.

General Terms
Algorithms, Design, Documentation, Experimentation, Measurement.

INTRODUCTION
Face-to-face interactions are the primary medium for propagation of airborne contagious disease [5]. An important question in behavioral epidemiology and public health is to understand how individual behavior patterns are affected by physical and mental health symptoms. Epidemiologists currently do not have access to sensing and modeling capabilities to quantitatively measure behavioral changes experienced by symptomatic individuals in real-world scenarios [10]. Such research requires simultaneously capturing symptom reports, mobility patterns and social interactions amongst individuals continuously over long-term duration. In this paper, we propose a novel application of ubiquitous computing, to better understand the link between physical respiratory symptoms, influenza, stress, mild depression and automatically captured behavioral features. This is an important problem in several different ways.

Quantitatively understanding how people behave when they are infected would be a fundamental contribution to epidemiology and public health, and can inform treatment and intervention strategies, as well as influence public policy decisions. On one hand, clinical epidemiology has accurate information on the evolution of the health of individuals over time but lacks realistic social interaction as well as spatiotemporal data [6]. On the other hand, current trends in theoretical epidemiology model the rate of infection in a population whose behavior is stationary over time and do not account for individual changes [9]. For instance, if a person infected with influenza continues his habitual lifestyle instead of isolating himself, he could pose a bigger risk to others in proximity. Based on our analysis and results, policymakers can recommend social interventions that minimize such risk.

On the modeling front, epidemiological models like SIS or SIR commonly assume that movement and interaction patterns for individuals are unchanged when they are infected, primarily due to absence of empirical evidence. However, our results show that this is not a correct assumption, as there are evident variations in behavior of symptomatic individuals that can be measured using mobile sensing. Accounting for these dynamics of behavior can be used to create realistic models of disease propagation in spatial epidemiology. From the individuals perspective, predicting likelihood of symptoms from behavior could lead to a possible early-warning system and intervention by medical experts.

In this paper, we describe experimental work that illustrates the use of co-location and communication sensors in mobile phones to characterize the change in face-to-face interactions and individual trajectories in the contagion process. The experimental context consists of residents of an undergraduate dormitory for two months, from February to April 2009. Individuals were surveyed on a day-to-day basis for symptoms of contagious diseases like common colds, influenza and gastroenteritis. We find that there are characteristic changes in behavior when individuals are sick, reflected in automatically captured features like their total communication, communication patterns with respect to time of day (e.g. late night, early morning), diversity of their network

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and entropy of movement within and outside the university. Due the pervasiveness of the mobile phones, this approach can be scaled to large-scale models of epidemiological contagion in the future.

Finally, we use a recently developed signal processing approach [11] to shed light on the information flux between physical symptoms, behavior changes and stress based on temporal information flux gathered by our mobile sensors. This is, to our knowledge, the first comprehensive empirical study in this direction.

RELATED WORK

Mobile Phones as Social Sensors

The four billion mobile phones worldwide are ubiquitous social sensors of location, proximity and communication. Eagle and Pentland [4] 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 [7] 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 [12] have been used to identify human activity patterns and analyze conversational prosody features.

Link Between Physical Symptoms, Behavior Changes and Stress

In medical literature, substantial evidence has been found for an association between stress and increased illness behavior, and less convincing but provocative evidence was found for a similar association between stress and infectious pathology: Introverts, isolates, and persons lacking social skills may also be at increased risk for both illness behaviors and pathology [1]. Various medical conditions that involve activation of the immune system are associated with psychological and neuroendocrine changes that resemble the characteristics of depression. Recent studies have presented empirical evidence on the relationship between the behavioral effects of immune activation and depressive symptomatology, characterized by reduced locomotor, exploratory, and social behavior [15].

The association between psychosocial stress and susceptibility to upper respiratory tract infection has also been investigated in people with a history of recurrent common colds and flu. Several dimensions of psychosocial stress, including exposure to stressful experiences, stress-prone personality traits, and signs of emotional disturbance have been investigated in people with a history of recurrent common colds and flu. Experts conjecture that stress depletes local immune protection, increasing susceptibility to colds and flu. Alternatively, psychological disturbances could develop in response to frequent illness [3]

METHODOLOGY

Several projects have used existing call data records and mobile operator 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 a longitudinal study with seventy residents of an undergraduate dormitory. These residents represent eighty-percent of the total population, and most of the remaining twenty-percent are spatially isolated. The dormitory is known within the university for its pro-technology orientation and the decision of students to reside within the dorm is determined by self-selection by both students and the 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 mobile platform, dataset and analysis related to measuring the spread of influenza, common colds and stress in this community over a period of two months.

MOBILE SENSING PLATFORM

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

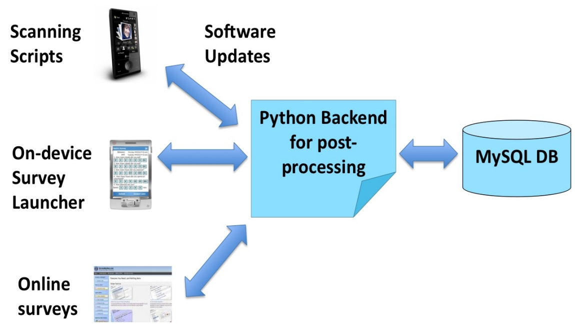
Device Selection

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 Figure 1.

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 real-world indoor sensing range of approximately 125 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



(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

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

Daily Survey Launcher

For collection of self-report data, the sensing platform includes a daily survey launcher. The application launches a foreground survey dialog at 6am everyday that asks the user to respond to six survey questions. After three reminders, the device was unusable until the user completed the survey. In the experiment deployment, users were paid $1 USD for every completed daily survey as participation incentive. The survey launcher invoked the following daily questions:

- Do you have a sore throat or cough?
- Do you have a runny nose, congestion or sneezing?
- Do you have a fever?
- Have you had any vomiting, nausea or diarrhea?
- Have you been feeling sad, lonely or depressed lately?
- Have you been feeling stressed out lately?

The design of the survey questionnaire and subsequent labeling of self-report responses was supervised by a trained epidemiologist.

Battery Impact

In past studies, mobile phones have been used as long-term behavior sensors with less than 20% impact on battery life [4]. In this study, periodic scanning of Bluetooth and WLAN APs reduced operational battery life by approximately 10-15 percent. Depending on the device model 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 browsing by the user and network communication between the mobile application and remote server had significantly more impact on battery life than the background sensing scripts. Using wireless Internet on Windows Mobile devices for 4-5 hours continuously on some handset models can drain batteries completely. When available, users were provided with extended batteries for specifc handset models. While the platform supports over-the-air data uploads, this was disabled for most of the study duration 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[14].

DATASET CHARACTERISTICS

Date Range

The dataset described here corresponds to the date range from 1st February to 15th April 2009, the peak influenza months in the New England region.

Mobile Phone Sensor Data

The phone sensor data during this period consists of 1,424,000 bluetooth samples, 201,000 WLAN AP samples, 15,700 call data records, 11,269 SMS records. The hourly Bluetooth, SMS and call counts from Jan-March are plotted in Figure 2.

Pre-Experiment Surveys (Baseline Labels)

In order to perform meaningful analysis, it is important to separate the effects due to immunization prior to the experiment. In a pre-study baseline survey completed few days before start of the study, 20 participants reported received influenza immunization via a flu-shot or flu-mist spray. These participants are not considered in the analysis in the next section.

Mobile Phone Daily Surveys

A total of 3231 responses were generated using the on-device survey launcher described in the previous section within the relevant date range. In the following analysis, it is important to distinguish between symptoms that represent common colds and allergies versus CDC-defined influenza [8] which has a characteristic signature reflected in runny nose, sore throat and fever symptoms. Due to our limited expertise in this area, selected combinations of self-reported symptoms were labeled as CDC-defined influenza by a medically trained epidemiologist. In our dataset, twelve such cases of influenza, on average lasting 5-7 days and each affecting a distinct individual were observed.

The respiratory symptoms not identified as influenza cases by our expert, are considered common colds or seasonal allergies.

ANALYSIS

Mobile Behavioral Features

The following features were extracted from mobile phone sensor data over 2-day window sizes, with 50 percent overlapping windows. The 2-day window size was chosen for epidemiological reasons, as individuals take up to 24 hours to realize and self-report a symptom.

Total Communication

This is the total number of phone calls and SMS exchanged, both with other participants as well as third parties. This measure includes both incoming and outgoing communication.

Late night and Early Morning Communication

This is the Call and SMS communication between 10pm and 9am on weekdays, with both other participants as well as non-participants.

Communication Diversity

This is the number of unique individuals reflected in phone and SMS communication within the particular window.

Physical Proximity Entropy with Other Participants

This is the entropy of distribution of Bluetooth proximity with other participants

$$H_p = -\sum_{i=1}^{n} p(x_i) log_2 p(x_i)$$

where $p(x_i)$ is the probability of Bluetooth proximity with the remote device x_i belonging to another participant, within the particular time-window.

Physical Proximity Entropy with Other Participants Late Night and Early Morning

Similar to above, this is the entropy of the distribution of Bluetooth proximity with other participants in the study, but only during late-night and early morning periods.

Physical Proximity Entropy for Bluetooth Devices Excluding Experimental Participants

Similar to above, this is the entropy of distribution of Bluetooth proximity. However, all Bluetooth devices in discoverable mode scanned on the phone are considered in this case.

WLAN Entropy based on University WLAN APs

This is entropy for the distribution of WLAN access points scanned within the given period. Only WLAN APs belonging to the university are considered.

$$H_w = -\sum_{i=1}^{n} p(x_i) log_2 p(x_i)$$

where $p(x_i)$ is the probability of scanning a WLAN AP x_i within the particular time-window.

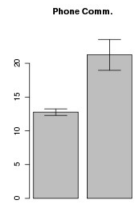
WLAN Entropy based on external WLAN APs

Similar to above, this is entropy for the distribution of WLAN access points scanned within the given period. Only WLAN APs external to the university are considered.

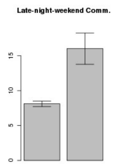
Behavioral Effects of Low Intensity Symptoms (Runny Nose, Sore Throat and Cough)

A sore throat or runny nose report may either be a symptom of CDC-defined influenza or simply an independent respiratory condition due to common colds or allergies.

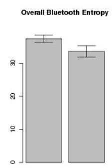
For the runny nose condition (n=587/2283), participants show increased total communication as well as increased



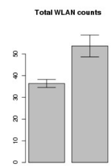
(a) Total communication increases ***



(b) Late-night early morning communication increases **

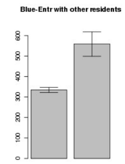


(c) Overall bluetooth entropy decreases *

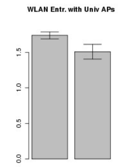


(d) Total WLAN APs detected increase **

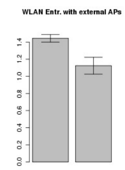
Figure 2. Behavior effects of runny nose, congestion, sneezing symptom, n=587/2283, *: p $<$ 0.05 **: p $<$ 0.01 ***: p $<$ 0.001



(a) Bluetooth entropy with respect to other dorm residents increases ***



(b) WLAN entropy with respect to university WLAN APs reduces *



(c) WLAN entropy with respect to external WLAN APs reduces **

Figure 3. Behavior effects of sore throat and cough symptom, n=393/2283, *: p $<$ 0.05 **: p $<$ 0.01 ***: p $<$ 0.001

late night early-morning communication. Additionally, total counts of Bluetooth proximity and measures of WLAN entropy increases, which is perhaps counter-intuitive. P-values are generated using unbalanced t-tests assuming unequal variance.

For sore-throat reports, Bluetooth-based entropy with respect to other residents in the study dormitory increases. This again, is slightly counter-intuitive, but may be explained if participants are spending more time indoors and hence have a higher likelihood of interacting with other participants, than they would if they were spending time in classes and activities. It is also found that WLAN based entropy measures, both with respect to university WLAN APs and external WLAN APs decrease with sore-throat reports, indicating more predictable movement patterns for the individual.

Behavior Effects of Higher-Intensity Symptoms (Fever and Influenza)

For more intense conditions like a fever or CDC-defined influenza, participants have lower activity and entropy levels, and this is captured using mobile sensors. Due to the severity of these symptoms, the number of reported cases in our dataset is lower than that of low intensity symptoms (runny nose, sore throat/cough). The number of rate of infection amongst participants and study cohort sizes, however, are comparable to Phase I clinical trials [13].

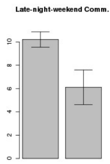
For fever, variations are observed in the late night early morning behavior. Phone communication, Bluetooth proximity counts, and Bluetooth entropy all show a decrease for the late night early morning window. WLAN-based entropy measures with respect to the university WLAN APs as well as external WLAN APs both reduce dramatically.

Similar effects are seen for days labeled as CDC-defined Influenza, as overall bluetooth entropy, bluetooth entropy with regard to other dorm residents and WLAN based entropy features decrease. This is also expected because fever is a known influenza symptom.

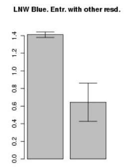
Behavioral Effects of Stress and Mental Health Symptoms

In addition to the physical symptoms described in the above section, the on-device mobile questionnaire also includes two daily questions related to stress levels and sadness, loneliness or depression. As discussed in the previous section, the link between behavior change, physical symptoms and stress is not very well understood. Measuring these self-report variables alongside symptom data allows modeling the covariance and potentially causation across the three sets of variables. With both often-stressed and sad-depressed-lonely responses in our dataset, participants show a consistent tendency to isolate themselves, reflected in various sensor modalities.

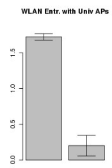
For the often-stressed response, participants communication diversity decreases, both overall Bluetooth based en-



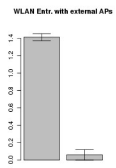
(a) Late night early morning calls and SMS decrease **



(b) Late night morning Bluetooth counts and entropy decrease*



(c) WLAN based entropy with respect to university WLAN APs decreases ***



(d) WLAN Entropy with respect to external WLAN APs decreases ***

Figure 4. Behavior effects of fever, n=36/2283, *: $p < 0.05$ **: $p < 0.01$ ***: $p < 0.001$

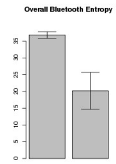
tropy and Bluetooth entropy with respect to other residents during late-night early morning hours decreases, and WLAN based entropy decreases both with respect to university WLAN APs and external WLAN APs.

For the sad-lonely-depressed responses, a similar tendency to isolate themselves is observed. Total communication decreases and communication during late-night early morning decrease, overall Bluetooth entropy and Bluetooth entropy with respect to other residents decreases.

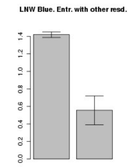
Symptom Classification using Behavioral Features

It is evident that there are characteristic behavioral changes associated with respiratory symptoms, fever, influenza, stress and depression. With this is in mind, is it useful to train a classification scheme that identifies when individuals are likely to be symptomatic from behavioral features alone. There are two key considerations with regard to designing such a classification scheme.

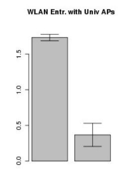
First, consider how such a classification system would be used in a scenario where the user has the mobile sensing application installed on their personal phone. When this application detects uncharacteristic variations in behavior, it could predict the likelihood that the user is infected with a known symptom and potentially inform a health-care professional. In this sense, the classification represents a behavior-based early warning system. With this goal



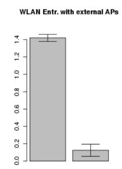
(a) Total Bluetooth interactions and entropy decrease **



(b) Late night early morning Bluetooth entropy with respect to other participants decreases **



(c) WLAN based entropy with respect to university WLAN APs decreases ***



(d) WLAN Entropy with respect to external WLAN APs decreases ***

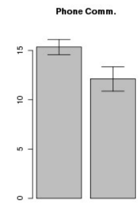
Figure 5. Behavior effects of CDC-defined influenza, n=54/2283, *: $p < 0.05$ **: $p < 0.01$ ***: $p < 0.001$

in mind, the classification model should have asymmetric misclassification penalties.

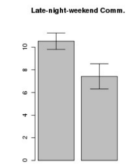
A second consideration is due to correlations amongst dependent symptoms. While behavior variations with respect to symptoms are reported individually in the previous section, in reality, self-reported symptoms are correlated. Fig 8(a) shows the correlations between these variables, reordered using K-nearest-neighbor clustering based on effect size. Four main clusters that emerge are: stress + depression; runny nose + sore throat; fever + influenza; and runny nose + sore throat + fever + influenza.

Given these considerations and unbalanced class sizes, classification is done using a Bayesian-network classifier with MetaCost, a mechanism for making classifiers costsenstive[2]. Structure learning for the network is performed using K2 hill climbing and the results are based on 4-fold cross-validation.

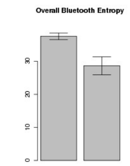
Recall, Precision and F-measure for the symptoms class as a function of increasing misclassification penalty for the symptoms class are plotted in Fig 8(b) - 8(f), for different symptom clusters. Recall from the trained classifier is also compared with random assignment of priors averaged over 1000 simulated runs, to illustrate improvement over chance. Overall prediction accuracy is not a useful



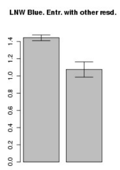
(a) Total communication decreases *



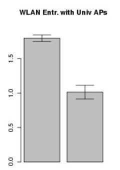
(b) Late-night early morning communication decreases *



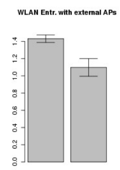
(c) Overall Bluetooth entropy decreases *



(d) Late night early morning Bluetooth entropy with respect to other experiment participants reduces **



(e) WLAN based entropy with respect to university WLAN APs decreases ***



(f) WLAN Entropy with respect to external WLAN APs decreases ***

Figure 6. Behavior Changes with self-reported sad-lonely-depressed responses n=282/2283, *: $p < 0.05$ **: $p < 0.01$ ***: $p < 0.001$

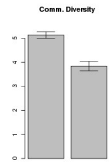
quality metric due to unbalanced classes, and ranges between 60-80 percent depending on the model and misclassification weights.

Temporal Flux Between Behavior, Stress and Physical Symptoms

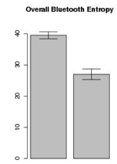
As discussed in the related work section, there is extensive medical and social health policy interest in understanding the causal implications between behavior change, stress and physical symptoms.

The Phase Slope Index (PSI) Method

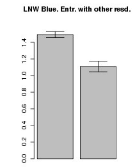
PSI [11] is a recently proposed spectral estimation method designed to measure temporal information flux between time-series signals. The method is based on the knowledge that the phase slope of the cross-spectrum of two signals can be used to estimate information flux between these signals in the time domain. Independent noise mixing does not affect the complex part of the coherency between multivariate spectra, and hence PSI is considered more noise immune than Granger analysis. PSI has been used to make causal inferences for brain cell activation



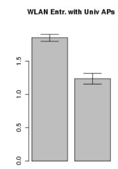
(a) Communication diversity decreases **



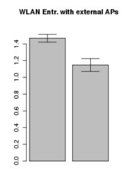
(b) Overall Bluetooth entropy decreases **



(c) Late night early morning Bluetooth entropy with other experiment participants reduces **



(d) WLAN based entropy with university WLAN APs decreases ***



(e) WLAN Entropy with external WLAN APs decreases ***

Figure 7. Behavior Changes with self-reported often-stressed responses n=559/2283, *: $p < 0.05$ **: $p < 0.01$ ***: $p < 0.001$

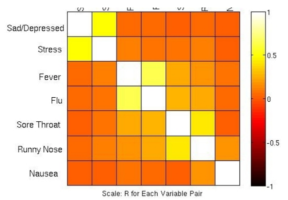
and other domains, and is calculated as,

$$\Psi_{ij} = \Upsilon\left(\sum_{f \in F} C^{*}_{ij}(f) C_{ij}(f + \delta f)\right)$$

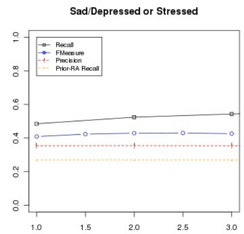
where C_{ij} is the complex coherency. When the input signals are distributed across multiple epochs, then this estimate is normalized by its standard deviation, calculated using the Jackknife method.

Results

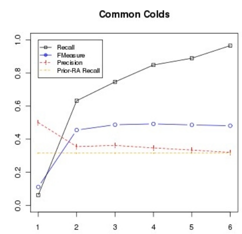
Our approach to using PSI for measuring information flux is based on validating causal links consistently across multiple participants in our dataset. To first ensure that this method can accurately recover at a per-user dataset scale simulated causal structure, we run PSI on two time series of varying length n, representing number of continuous samples available per user. The leader time series has x symptom days. The follower time series has y lagged symptom days and z days of additive uniform noise, where the lag can be 1 or multiple days. The scatter-plot in Figure 9 shows the ability of PSI to recover causal structure (normalized PSI coefficient > 0). The X and Y-axes represent n and x, and each point is averaged over 1000 runs with y=x/3 and z=x/3, values that would be intuitively expected for symptoms in our dataset. It is important to note that the method recovers the correct direction of informa-



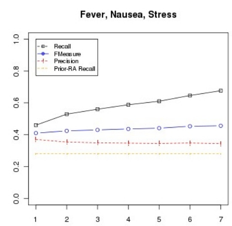
(a) KNN reordered correlations between dependent symptom variables



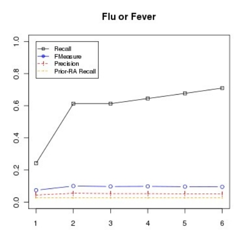
(b) Sad-Depressed-Stressed Symptoms



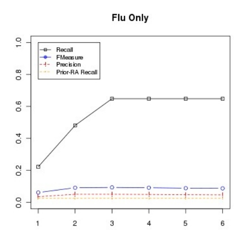
(c) Sore-Throat, Cough, Runny Nose, Congestion, Sneezing Symptoms



(d) Fever, Nausea, Stress Symptoms



(e) Flu and Fever Symptoms



(f) Flu only (as per CDC definition)

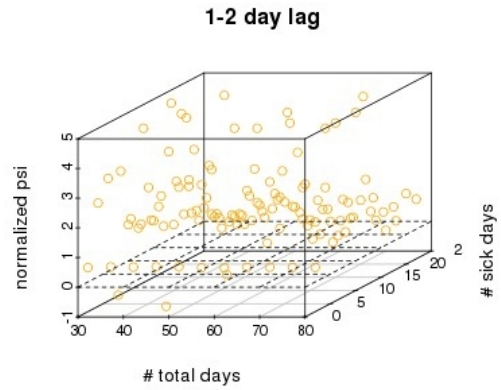
Figure 8. Classification results, recall for different symptoms ranges from 0.6 to 0.9 for the symptom class.

tion flux for 97.6% of the samples over the surface of the simulated signals.

In order to apply PSI to our dataset, the subset of participants that show both physical symptoms and stress and depression related responses are considered. There is however, a tradeoff to be made between using data from fewer participants with longer sequences and hence more reliable estimates, versus using data from more participants with shorter sequences, and better validation across participants. Hence, PSI was estimated using two scales:

Each approach generates slightly different directed links and normalized coefficients. The twelve largest PSI coefficients across both methods on the basis of a combined ranking score are listed below in descending order.

Source $\longrightarrow$ Follower
Runny nose $\longrightarrow$ *WLAN entropy with external APs*
Sad-depressed-lonely $\longrightarrow$ *Sore throat-cough*
Often stressed $\longrightarrow$ *Total Bluetooth proximity counts*



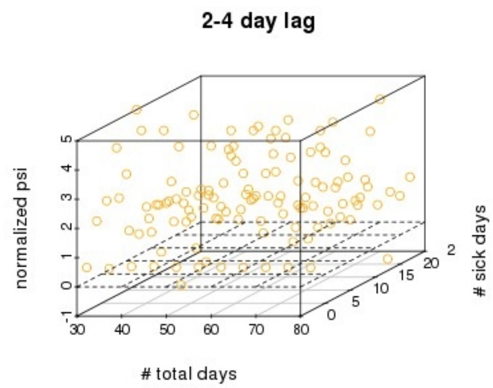
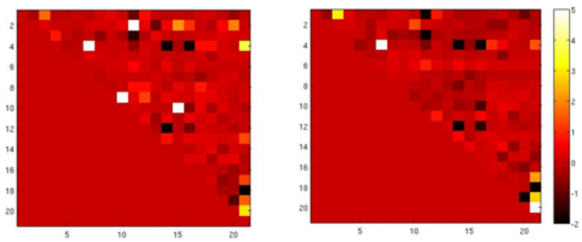


Figure 9. PSI evaluation on simulated data

Communication diversity $\longrightarrow$ *Late-night early morning Bluetooth proximity counts*
Often stressed $\longrightarrow$ *Communication diversity*
Often stressed $\longrightarrow$ *Late-night early morning Bluetooth proximity counts*
Bluetooth entropy with other residents $\longrightarrow$ *External WLAN entropy*
Runny nose $\longrightarrow$ *Total WLAN counts*
Often stressed $\longrightarrow$ *WLAN entropy with university APs*
Bluetooth proximity counts with other residents $\longrightarrow$ *External WLAN entropy*
Late-night early morning communication $\longrightarrow$ *Overall Bluetooth entropy*
Sad depressed lonely $\longrightarrow$ *Bluetooth entropy*

CONCLUSION

In this paper, we describe a novel application of ubiquitous computing. We use mobile phones as an active sensing and prediction platform to identify behavior changes reflected in mobile phone sensors, when individuals suffer from common colds, influenza, fever, stress and mild depression. We show that it possible to determine the health status of individuals using information gathered by mobile phones alone, without having actual health measurements about the subject. Given the pervasiveness of the mobile phone, this opens the door for the modeling of epidemiological contagion in social networks without the need for



(a) Min Length 40 (b) Min Length 60

Figure 10. PSI co-efficients for two sets of sequences based on participant data. List of features: 1=sad-depressed-lonely 2=often-stressed 3=sore-throat 4=runny-nose 5=fever 6=nausea 7= influenza 8=total communication 9=latenight/early morn comm. 10= communication diversity 11=total Bluetooth proximity 12=overall Bluetooth entropy 13=Bluetooth proximity with other residents 14=Bluetooth entropy with other residents 15=late-night/early morn Bluetooth proximity with other residents 16=late-night/early morn Bluetooth entropy with other residents 17=WLAN counts 18=external WLAN counts 19=overall WLAN entropy 20=WLAN entropy with university APs 21=WLAN entropy with external APs

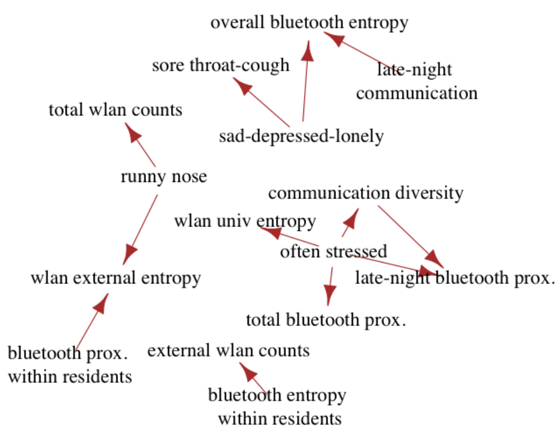


Figure 11. Highest-ranked PSI relationships across both data subsets. Directed ties represent temporal flux.

medical intervention.

There are several extensions of the analysis that we intend to pursue in the future. The analysis in this paper does account for confounding behavior changes due to various external events, e.g. exams. The current prediction model does not include stochastic information about symptoms or behaviors from previous days. For the distributions of behavior change, we need to further explore inter-individual differences.

We believe this work opens an interesting new area for the ubiquitous computing community. Aside from the mobile sensing and modeling aspect discussed in this paper, we hope our findings can impact spatial and behavioral epidemiology as well.

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