Ubiquitous and Mobile Computing
CS 528: *Social Sensing for Epidemiological Behavior Change*

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Outline

- Introduction
- Related Work
- Methodology
- Evaluation/Results
- References

Social Sensing for Epidemiological 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 physical symptoms, behavior and mental health.

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INTRODUCTION
Face-to-face interactions are the primary mechanism for propagation of airborne contagious disease [28]. An important question in behavioral epidemiology and public health is to

[11]. Such research requires continious, long-term data about symptom reports, mobility patterns and social interactions amongst individuals. 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 for several reasons.

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 spatio-temporal data [15]. On the other hand, current research efforts in theoretical epidemiology model the rate of infection in a population whose behavior is stationary over time and do not account for individual changes [26]. 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, compartmental epidemiological models (e.g., the Susceptible, Infectious, Recovered or SIR model) commonly assume that movement and interaction patterns for individuals are stationary during infection, i.e., that individuals will continue their typical behavioral patterns when sick. More recent epidemiological models accommodate reduced mobility variations to to fit epidemic curves, but in a heuristic way due to lack of data at the individual level [4, 9, 14], which possibly limited their prediction accuracy during the 2009 H1N1 influenza epidemic [22]. To our knowl-

Introduction

Epidemiology: The study of how infectious disease spreads in a population

- Face-to-face contact is primary means of transmission
- Understanding behavior is key to modeling, prediction, policy

The Problem

- Models exist, but lack real data on behavior changes due to infection:
  - large numbers of people, many interactions
  - symptom reports
  - behavior, mobility patterns, social interactions
- Clinical symptoms/effects are understood, but...
  - Identification requires in-person physician or self-diagnosis
  - Real-time automatic data collection not possible

Questions Being Answered

- How do physical and mental health symptoms manifest themselves as behavioral patterns?
- Can cellphone be used as sensor to detect these behavior changes?
- Can behavioral pattern changes be used to identify underlying symptoms/syndrome?

Related Work

Social Sensing:

“Reality Mining” (Bluetooth proximity, call records, cell tower) --> social network structure ,patterns of activity

Human location trace: call records --> temporal and spatial regularity in mobility patterns

Electronic sensor badges (Sociometric badge) --> human activity patterns and conversational prosody features.

CENS and mHealth projects --> mobile phone to map human interaction networks

Computational Social Science:

Google Flue Trends --> search queries used to predict flu activity

Physical Symptoms / Behavioral Changes (Medical Literature)

stress --> illness behavior

stress --> infectious pathology

medical conditions --> depression symptoms

Methodology

- 70 residents of a dorm in North America
- Windows-Mobile device
- Daily Survey (symptom data)
- Sensor-based Social Interaction Data
- 10 weeks

Methodology (Symptom Data)

- Daily survey launcher
- 6AM - respond to symptom questions

Table 1. Symptom Survey Questionnaire. All questions were Yes/No responses

Survey Question (as shown on mobile phone)
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?

Methodology (Social Interaction Data)

Raw Data Captured:

- Bluetooth (scan every 6 minutes)
- WLAN: (scan every 6 minutes)
- SMS and Call records (log every 20 minutes)
- Late night / early morning
- On campus / off campus
- Absolute counts, Entropy

Provides evidence of

- Proximity to other devices (face-to-face)
- Approximate location
- Intensity of ties, size and dynamics of social network
- Consistency of behavior

Methodology (Data / Relationships)

Syndrome [Influenza, Cold/Allergies]

Symptoms [
Sore throat/cough,
Runny Nose/Conjestion/Sneezing,
Fever,
Vomiting/Nausea,
Sad/Lonely/Depressed
Stressed]

Behavioral [
Total Communication,
Late Night Communication,
Communication Diversity,
Bluetooth Proximity Entropy
WLAN Entropy]

Results:

Behavioral Effects of Runny Nose, Congestion, Sneezing

- Total communication increases ($p<.001$)
- Late-night communication increases ($p<.01$)
- Total WLAN AP increases ($p<.01$)
- Bluetooth entropy decreases ($p<.05$)

Behavioral Effects of Sore Throat, Cough

- Bluetooth entropy increases ($p<.001$)
- Total WLAN entropy (univ) decreases ($p<.05$)
- Total WLAN entropy (external) decreases ($p<.01$)

Behavioral Effects of Fever

- Early/Late Calls/SMS decreases ($p<.01$)
- Early/Late Bluetooth decreases ($p<.05$)
- WLAN entropy (university) decreases ($p<.001$)
- WLAN entropy (external) decreases ($p<.001$)

Results: Behavioral Effects of...

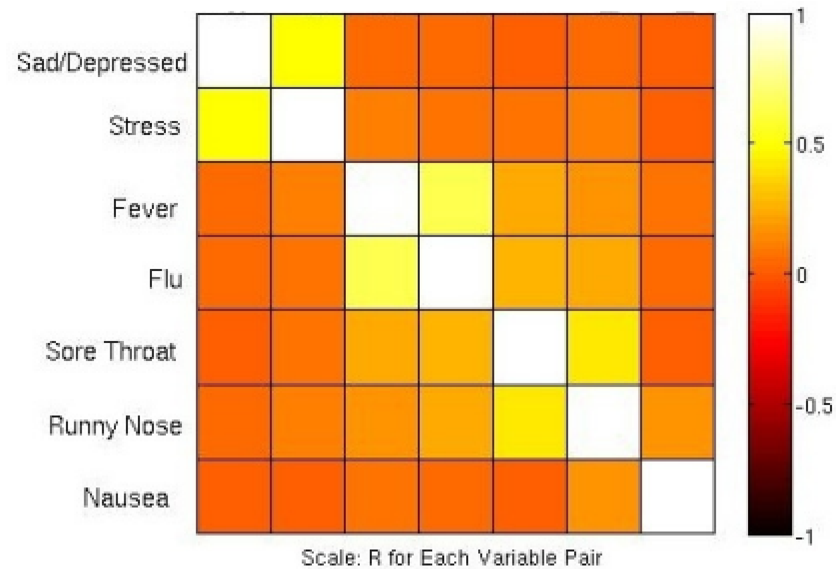
- "Sad/Lonely/Depressed"
  - 6 factors with $p<.05$
- "Stressed"
  - 5 factors with $p<.05$

Conclusion: *Behavioral changes are identified as having statistically significant association with reported symptoms.*

Goal 2: Symptom Classification based on Behavioral Features

- Detect variations in behavior -> identify likelihood of symptom and take action

- Need to consider correlation between symptoms
- K-nearest neighbor clustering (4 main clusters identified)



(a) KNN reordered correlations between dependent symptom variables

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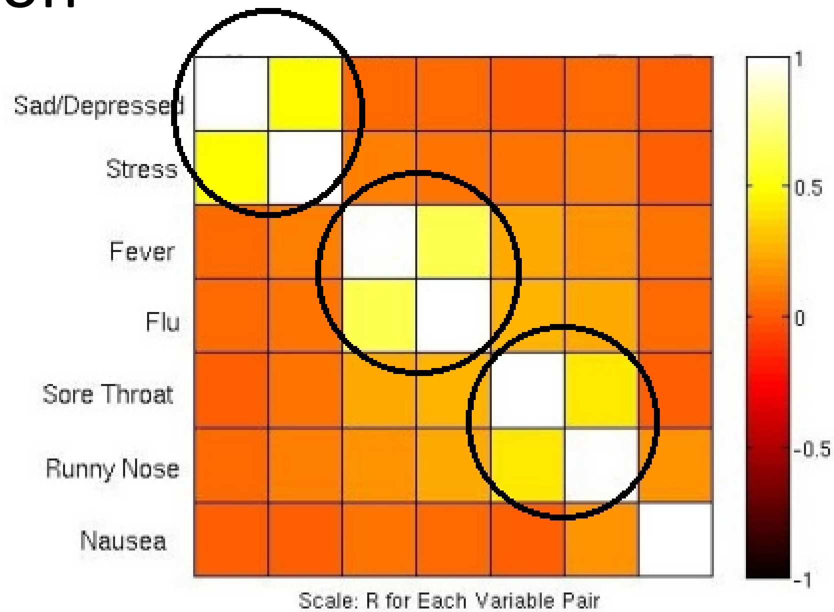

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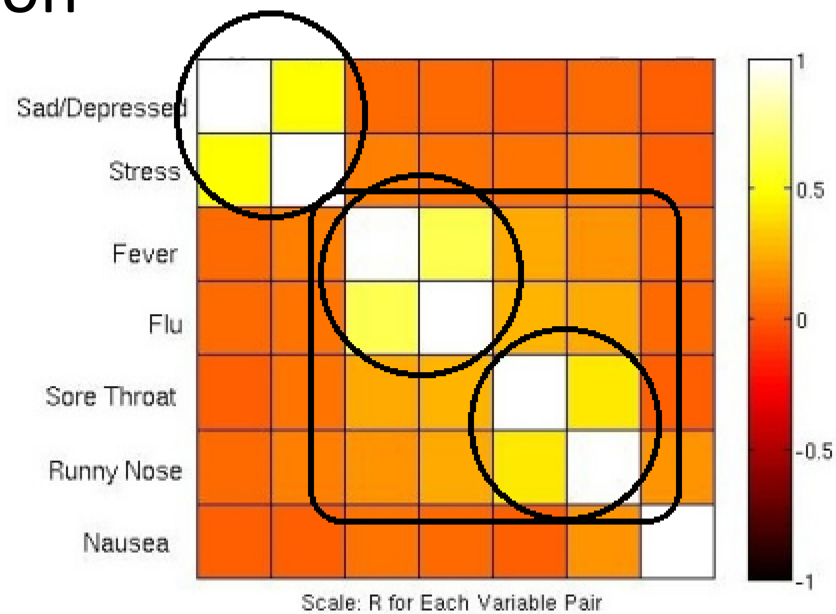

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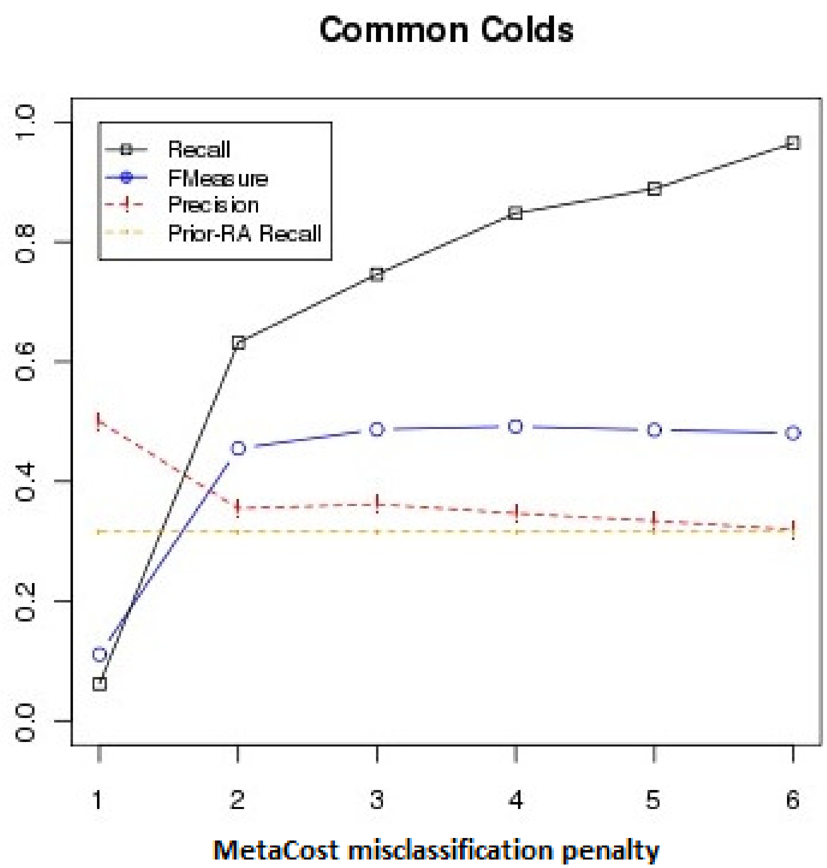
Symptom Classification using Behavioral Features

- Bayes Classifier w/MetaCost for misclassification penalty
  - 60% to 90% Recall for the 4 symptom classes



Conclusion

- Mobile phone successfully used as sensing device to capture behavior changes from cold, influenza, stress, depression
- Demonstrated the ability to predict health status from behavior, without direct health measurements
- Opens avenue for real-time automatic identification and improved modeling

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Anmol Madan, Manuel Cebrian, David Lazer, and Alex Pentland. 2010. Social sensing for epidemiological behavior change. In Proceedings of the 12th ACM international conference on Ubiquitous computing (UbiComp '10). ACM, New York, NY, USA, 291-300. DOI=http://dx.doi.org/10.1145/1864349.1864394

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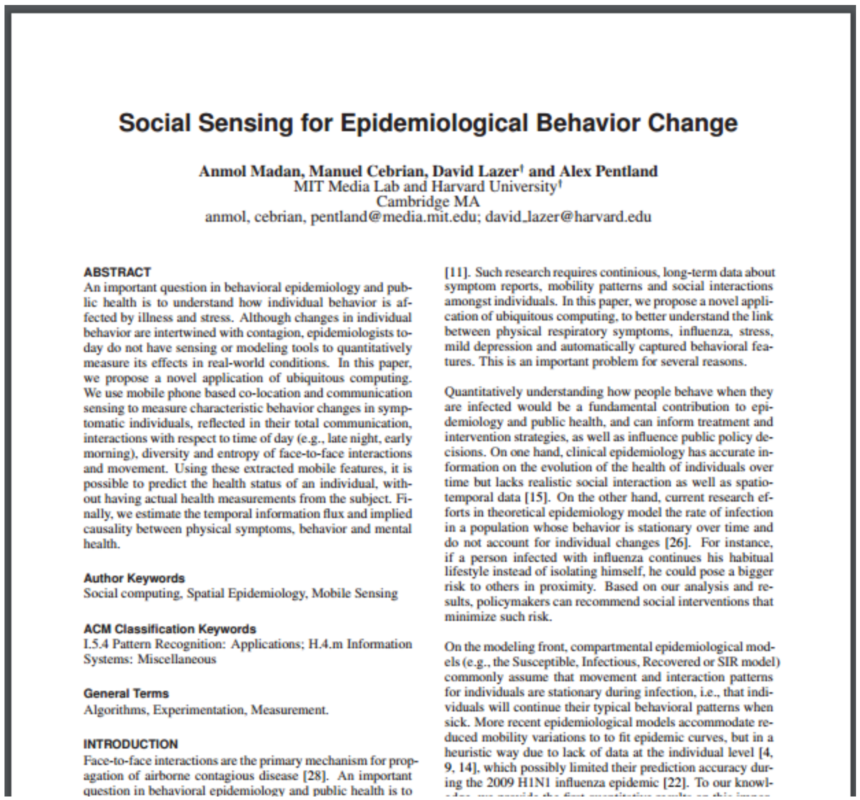
Thank You



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