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

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Introduction

- How individual behavior affected by illness and stress.
- Epidemiologists currently do not have such sensing or modeling tools.
- Solution: Use mobile phone based co-location and communication sensing to predict the health status of an individual

Related Work

- Mobile Phones as Social Sensors
  - Bluetooth proximity, call data records, cellular identifiers…
  - Web based and survey based data source.

    https://www.google.org/flutrends/us/#US
- Link between physical Symptoms, behavior changes and stress
  - In medical literature, substantial evidence has been found for an association between stress and illness behavior.

Methodology

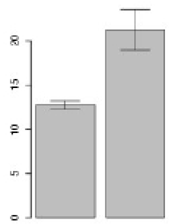
- Participants: 70 residents of an undergraduate residence hall.
- Time period: 2 months, from February to April.
- Devices: Windows Mobile 6.x devices
- Dataset source:
  - Social interaction data from mobile phones: call data, SMS logs, Bluetooth co-location sensing and WLAN-based location sensing.
  - Daily-self reported survey.

Methodology

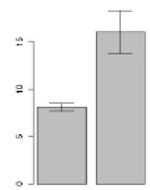
- User privacy consideration
- Proximity detection(Bluetooth)
- Approximate Location(802.11 WLAN)
- Communication(call and SMS records)
- Daily Survey launcher(Daily Symptom Survey)
- Battery Impact

Analysis

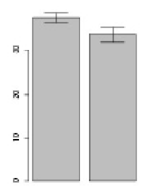
- Behavior effect with different intensity Symptoms.



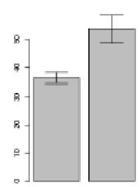
(a) Total communication increases ***



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

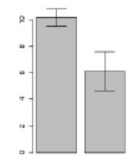


(c) Overall Bluetooth entropy decreases *

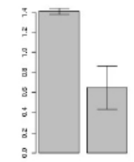


(d) Total WLAN APs detected increase **

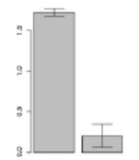
Figure 1. Behavior effects of runny nose, congestion, sneezing symptom, n=587/2283, *: $p < 0.05$ **: $p < 0.01$ ***: $p < 0.001$



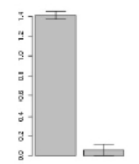
(a) Late night early morning calls and SMS decrease **



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



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

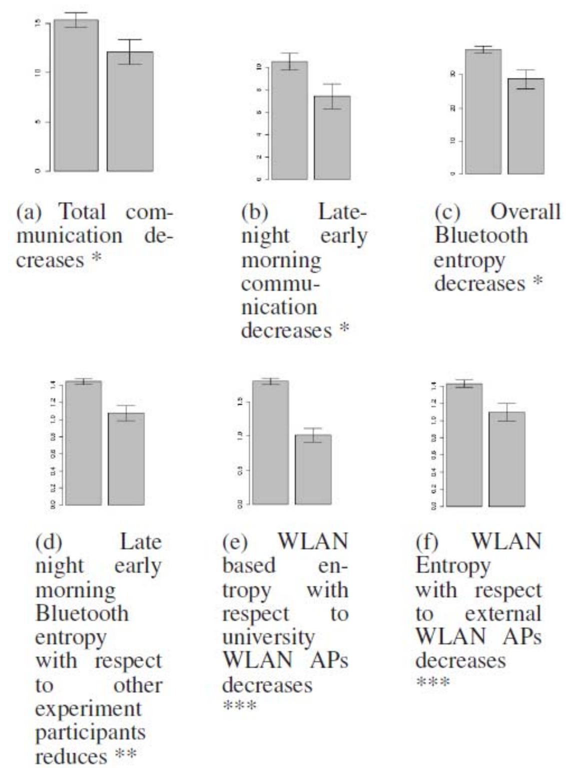


(d) WLAN Entropy with respect to external WLAN APs decreases ***

Figure 3. Behavior effects of fever, n=36/2283, *: $p < 0.05$ **: $p < 0.01$ ***: $p < 0.001$

Analysis (cont'd)

- Behavior effects of stress and mental health Symptoms



(a) Total communication decreases *

(b) Late-night early morning communication decreases *

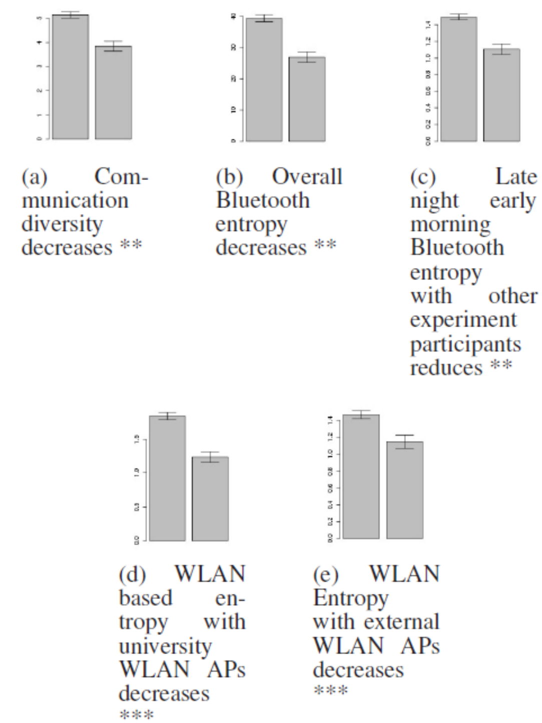
(c) Overall Bluetooth entropy decreases *

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



(a) Communication diversity decreases **

(b) Overall Bluetooth entropy decreases **

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

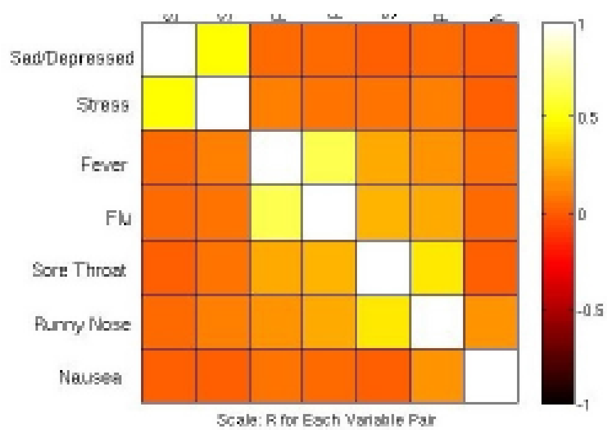
(d) WLAN based entropy with university WLAN APs decreases ***

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

Figure 6. Behavior Changes with self-reported often-stressed responses n=559/2283, *: $p < 0.05$ **: $p < 0.01$ ***: $p < 0.001$

Symptom Classification

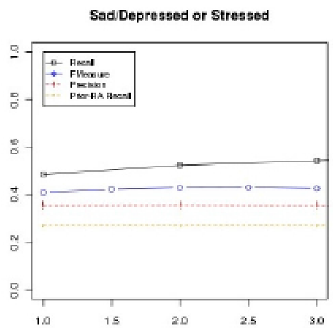
- Symptom Classification Using behavior feature
  - K-nearest-neighbor clustering



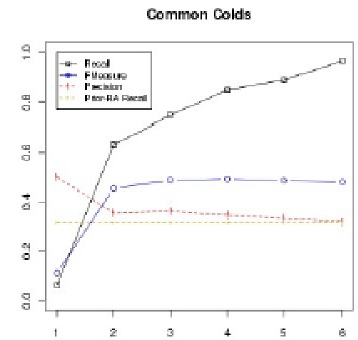
(a) KNN reordered correlations between dependent symptom variables

Symptom Classification (Cont'd)

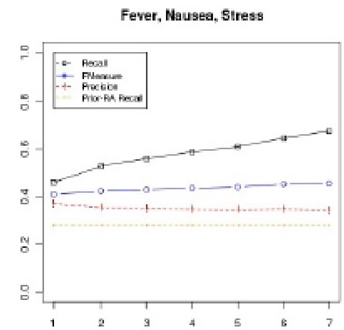
- Bayesian-network classifier



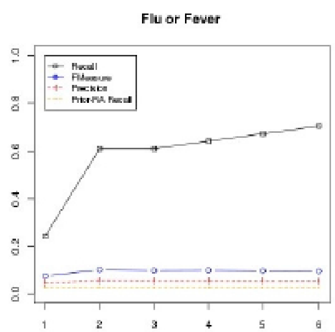
(b) Sad-Depressed-Stressed Symptoms



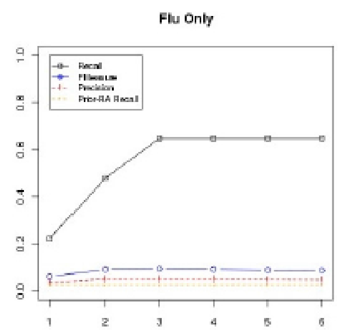
(c) Sore-Throat, Cough, Runny Nose, Congestion, Sneezing Symptoms



(d) Fever, Nausea, Stress Symptoms



(e) Flu and Fever Symptoms



(f) Flu only (as per CDC definition)

Temporal Flux

- Temporal Flux between Behavior, Stress and Physical Symptoms
  - The phase Slope Index method

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

C_{ij} is the complex coherency.

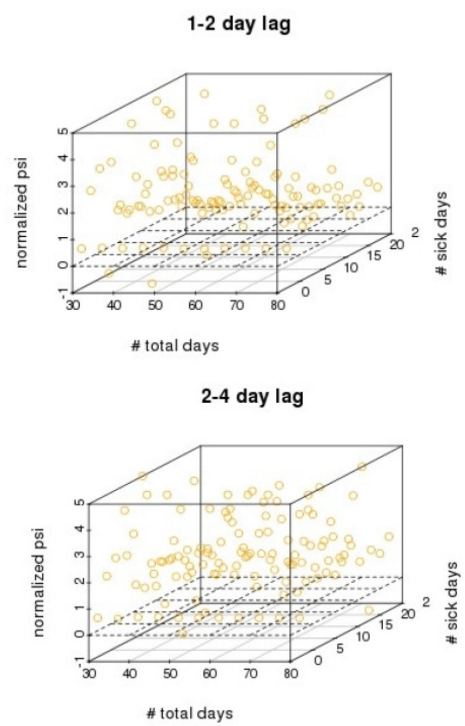


Figure 8. PSI evaluation on simulated data. Z-axis is the estimated PSI value, across a wide range of total days (n) and sick days(x), with additive noise. Points above the Z=0 plane (97.6%) represent correctly estimated direction of information flux.

Temporal Flux (Cont'd)

- The 12 largest PSI coeffients across both methods on the basis of a combined ranking scores.

Table 2. PSI Results ordered by combined scores

Source	Follower
Runny nose	WLAN entropy with external APs
Sad-depressed-lonely	Sore throat-cough
Often stressed	Total Bluetooth proximity counts
Communication diversity	Late-night early morning Bluetooth proximity counts
Often stressed	Communication diversity
Often stressed	Late-night early morning Bluetooth proximity counts
Bluetooth entropy with other residents	External WLAN entropy
Runny nose	Total WLAN counts
Often stressed	WLAN entropy with university APs
Bluetooth proximity counts with other residents	External WLAN entropy
Late-night early morning communication	Overall Bluetooth entropy
Sad depressed lonely	Bluetooth entropy

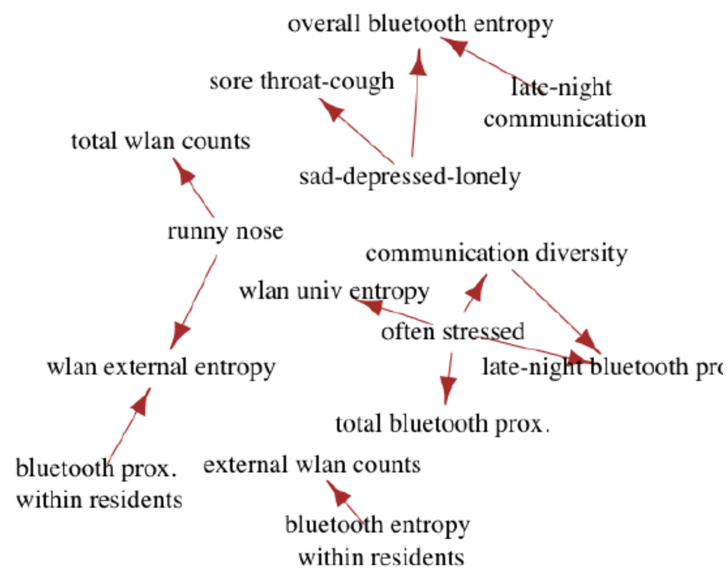


Figure 10. Highest-ranked PSI relationships across both data subsets. Directed ties represent temporal flux.

Conclusion

- The study shows that it is possible to determine the health status of individual using information gathered by mobile phones alone, without having actual health measurements.

https://ginger.io/for-individuals/

Future work

- Repeated-measures approach
- Take external events into consideration, e.g final exams
- Battery consumption.

References

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Q&A