Mobile and Ubiquitous Computing on Smartphones
Chapter 8b: Smartphone Sensing

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MIT Epidemiological Change
Introduction

Ref: A. Madan, Social sensing for epidemiological behavior change, in Proc Ubicomp 2010

**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
Research Questions

- Can smartphone reliably detect sick owner?
  - Based on sensible behavior changes (movement patterns, etc)

- **Q1:** How do physical and mental health symptoms manifest themselves as behavioral patterns?
  - E.g. worsening cold = reduced movement?

- **Q2:** Given sensed behavioral pattern (e.g. movement), can smartphone user’s symptom/ailment be reliably inferred?
Potential Uses of Smartphone Sickness Sensing

- **Early warning system (not diagnosis)**
  - Doesn’t have to be so accurate

- Just flag “potentially” ill student, nurse calls to check up

- Insurance companies can reduce untreated illnesses that result in huge expenses
General Approach

- Semester-long Study of 70 MIT Students
  - Continuously gather sensible signs (movement, social interactions, etc)
  - Administer sickness/symptom questionnaires periodically as pop-ups (EMA)

- Labeling: what movement pattern, social interaction level = what illness, symptom
Methodology

- 70 residents of an MIT dorm
- Windows-Mobile device
- Daily Survey (symptom data)
- Sensor-based Social Interaction Data
- 10 weeks
  - Date: 02/01/2009 - 04/15/2009
  - Peak influenza months in New England
Methodology (Symptom Data)

- Daily pop-up survey
- 6AM every day - respond to symptom questions
Methodology (Social Interaction Data)

- SMS and Call records (log every 20 minutes)
  - Communication patterns
  - Time of communication (e.g. Late night / early morning)
  - E.g. may talk more on the phone early or late night when in bed with cold

- Tracked number of calls/SMS, and with who (diversity)
  - E.g. sick people may communicate with/seeing same/usual people or new people (e.g. nurse, family?)
  - Intensity of ties, size and dynamics of social network
  - Consistency of behavior
Analyze Syndrome/Symptom/Behavioral 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
Data Analysis

- Behavior effects of CDC-defined influenza (Flu)
  - Flu is somewhat serious, communication, movement generally decreased
Data Analysis

- Behavior effects of runny nose, congestion, sneezing symptom (mild illness)
  - Cold is somewhat mild, communication, movement generally increased
Results: Conclusion

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

- Can we classify illness, likely symptoms based on observed behaviors?

- Why? Detect variations in behavior -> identify likelihood of symptom and take action
Symptom Classification using Behavioral Features

- Yes!!

- Bayes Classifier w/MetaCost for misclassification penalty

- 60% to 90% accuracy!!
**Conclusion**

- Mobile phone successfully used to sense 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

- Led to startup Ginger io (circa 2012)
  - Patients tracked, called by real physician when ill
  - funded > $25 million till date

- Now DARPA is funding us to do similar research for COVID, flu detection
WASH Project:
TBI, Infectious Disease Biomarkers
Smartphone BioMarkers to Improve Warfighter Health

PI: Agu, co-PI: Rundensteiner

- US military want early signs of warfighter ailment:
  - Traumatic Brain Injury (bomb blasts, explosions, fall, etc)
  - Infectious diseases (E.g. tuberculosis, pneumonia, measles, meningitis, malaria, Ebola, cholera and influenza)
- **WASH Concept**: Smartphone-sensible biomarkers may manifest first
  - E.g. reduced mobility, sedentary, sleep problems, stay close to home
- WPI received $2.8 from DARPA (military) to research smartphone biomarkers for TBI and infectious diseases
Examples of TBI, Infectious Disease Biomarkers Detectable by Smartphone

Sleep problems
Pupils dilated
Hands shaking

Slow phone interactions
Avoiding light
Slurred speech

Walking Problems
Coughing

Increased Bathroom usage
Sneezing

Traumatic Brain Injury (TBI)
Smartphone Biomarkers

Infectious Disease
Smartphone Biomarkers

Note: Specific tests (e.g. hands shaking) in specific situations (e.g. user holding phone)
Our Research Approach

- Working with doctors, we now have specific list of 30 contexts in which we will run 14 specific TBI/infectious disease tests

- **Research Question 1**: Can smartphone detect when a smartphone user is in one of our specific contexts?

- **Methodology**:
  - Run a *scripted* user study
    - Recruit 100 subjects
    - Subjects using smartphone, enter each of 32 contexts
    - Gather smartphone data continuously in background
    - Later: analyze data (machine learning)
  
  - Run *Unscripted* user study
    - 100 subjects, 2 weeks, periodically prompted, label their context
    - Data is very real, very noisy
Context: Definition & Final List of Contexts

Context = ( User Activity, Phone Perception, App Category, Social)

- Sitting
- Standing
- Walking
- Lying down
- Sleeping
- Awake/not sleeping
- Interacting with phone
- Coughing
- Exercising
- Running
- Sneezing
- Sitting down
- Lying down
- Standing up
- Talking into phone

- Phone in Hand
- Phone facing down
- Phone on table
- Trouser pocket
- In bag
- Briefcase
- Jacket pocket

- Games
  - Video game
- Media & Video
  - Video Chat
  - Video streaming
- Communication
  - Messaging
- Social
  - Messaging
- Entertainment
  - Video streaming

- Alone
- 2 or more speakers
- More than 2 speakers
- Busy place
## 30 Contexts Needed for Our Tests

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;interacting with phone, phone in hand, *, *&gt;</td>
</tr>
<tr>
<td>2</td>
<td>&lt;*, phone in hand, *, *&gt;</td>
</tr>
<tr>
<td>3</td>
<td>&lt;lying down, *, *, *&gt;</td>
</tr>
<tr>
<td>4</td>
<td>&lt;sitting, *, *, *&gt;</td>
</tr>
<tr>
<td>5</td>
<td>&lt;standing, *, *, *&gt;</td>
</tr>
<tr>
<td>6</td>
<td>&lt;sleeping, *, *, *&gt;</td>
</tr>
<tr>
<td>7</td>
<td>&lt;awake, *, *, *&gt;</td>
</tr>
<tr>
<td>8</td>
<td>&lt;walking, in pocket, *, *&gt;</td>
</tr>
<tr>
<td>9</td>
<td>&lt;walking, in hand, *, *&gt;</td>
</tr>
<tr>
<td>10</td>
<td>&lt;walking, in bag, *, *&gt;</td>
</tr>
<tr>
<td>11</td>
<td>&lt;*, phone on table, *, *&gt;</td>
</tr>
<tr>
<td>12</td>
<td>&lt;*, phone facing down, *, *&gt;</td>
</tr>
<tr>
<td>13</td>
<td>&lt;talking into phone, *, *, *&gt;</td>
</tr>
<tr>
<td>14</td>
<td>&lt;*, *, *, more than 2 speakers&gt;</td>
</tr>
<tr>
<td>15</td>
<td>&lt;Coughing, *, *, *&gt;</td>
</tr>
<tr>
<td>16</td>
<td>&lt;Coughing, *, *, in busy place&gt;</td>
</tr>
<tr>
<td>17</td>
<td>&lt;Toilet, *, *, *&gt;</td>
</tr>
<tr>
<td>18</td>
<td>&lt;Toilet, Phone in pocket, *, *&gt;</td>
</tr>
<tr>
<td>19</td>
<td>&lt;sleeping, phone on table, *, 0&gt;</td>
</tr>
<tr>
<td>20</td>
<td>&lt;exercising, phone in hand, *, 0&gt;</td>
</tr>
<tr>
<td>21</td>
<td>&lt;exercising, phone on table, *, 0&gt;</td>
</tr>
<tr>
<td>22</td>
<td>&lt;exercising, *, *, more than 2 speakers&gt;</td>
</tr>
<tr>
<td>23</td>
<td>&lt;Sneezing, *, *, 2 or more speakers&gt;</td>
</tr>
<tr>
<td>24</td>
<td>In noisy/bust place</td>
</tr>
<tr>
<td>25</td>
<td>&lt;lying down, phone on table, *, *&gt;</td>
</tr>
<tr>
<td>26</td>
<td>&lt;Sneezing, *, *, alone&gt;</td>
</tr>
<tr>
<td>27</td>
<td>&lt;Sitting up, *, *, *&gt;</td>
</tr>
<tr>
<td>28</td>
<td>&lt;Standing up, *, *, *&gt;</td>
</tr>
<tr>
<td>29</td>
<td>&lt;Sitting down, *, *, *&gt;</td>
</tr>
<tr>
<td>30</td>
<td>&lt;Lying down, *, *, *&gt;</td>
</tr>
</tbody>
</table>
WASH Scripted Study
Context Collection Study: Overview

- Scripted, on-campus study to cover the majority of identified contexts
- Each subject completes a carefully planned circuit, timed
- Each subject given same Essential Android phones to ensure consistent data
- Mobile app automatically gathers sensor data, labels entered manually with timestamps
Context Data Study: Route @ WPI

1. Fuller Labs
   - Briefing

2. Recreation Center
   - Walking, running
   - Bathroom

3. Morgan Hall
   - Phone call
   - Water break
   - Being in a busy place

4. Fuller Labs
   - Lying down
   - Sitting down
   - Standing up
Context Collection Study: Sensors

Standard:
- Gyroscope
- Accelerometer
- Barometer
- Magnetometer
- Location Services
  - Speed
  - Distance traveled over a period of time

Experimental:
- Audio
  - Feature extraction on phone to mitigate privacy concerns
- Ambient light
- Proximity
- Discrete sensors
  - Is the phone charging?
  - Are they interacting with it?
WASH Unscripted Study
WASHSensory App to gather subjects data

- App continuously collected sensor data
- Subjects labeled 25 contexts
  - Laying Down, Phone on Table
  - Excising, Phone in Pocket
  - Toilet, Phone in Pocket
  - Walking, Phone in Bag
  - Walking, Phone in Hand
  - Walking, Phone in Pocket
  - Typing
  - Sleeping
  - Sitting
  - Running
  - Lying Down (state)
  - Jogging
  - Running
  - Standing
  - Talking On Phone
  - Bathroom
  - Phone in Pocket
  - Phone in Hand
  - Phone in Bag
  - Phone on Table, Facing Up
  - Phone on Table, Facing Down
  - Stairs - Going Up
  - Stairs - Going Down
  - Walking
Overview of our Classification Approach
175 features extracted from data gathered in our scripted user study

- Accelerometer, gyroscope, location, audio, phone state feature
- Also time features (time windows: 3am-9am, 6am-midday, 9am-3pm, etc)

- Classified features using XGBoost machine learning classifier
Classified WPI WASH Context Data using XGBoost Classifier

- **Main result:** Over 80% macro AUC-ROC for all 25 contexts, 14 contexts > 90%

- **Approach 1:** Classify individual binary labels, compute macro AUC-ROC
- **Approach 2:** Classify context tuple as target using XGBoost
  - Over 80% macro AUC-ROC for all 25 contexts
  - Over 80% AUC-ROC for 25 ensembled binary contexts

Met program objectives 25/25 contexts detected with > 80% accuracy
Affect Detection
MoodScope: Detecting Mood from Smartphone Usage Patterns (Likamwa et al)

- Define Mood based on Circumplex model in psychology
- Each mood defined on pleasure, activeness axes
  - **Pleasure**: how positive or negative one feels
  - **Activeness**: How likely one is to take action (e.g. active vs passive)

![Figure 1: The circumplex mood model](image)
**Classification**

- **Moodscope**: classifies user mood from smartphone usage patterns

<table>
<thead>
<tr>
<th>Data type</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Email contacts</td>
<td>#messages #characters</td>
</tr>
<tr>
<td>SMS contacts</td>
<td>#messages #characters</td>
</tr>
<tr>
<td>Phone call contacts</td>
<td>#calls call duration</td>
</tr>
<tr>
<td>Website domains</td>
<td>#visits</td>
</tr>
<tr>
<td>Location clusters</td>
<td>#visits</td>
</tr>
<tr>
<td>Apps</td>
<td>#app launches app duration</td>
</tr>
<tr>
<td>Categories of apps</td>
<td>#app launches app duration</td>
</tr>
</tbody>
</table>

![Smartphone usage features diagram](image-url)
MoodScope Study

- 32 Participants logged their moods periodically over 2 months
- Used mood journaling application
- Subjects: 25 in China, 7 in US, Ages 18-29

Figure 2: Mood journaling application view
MoodScope: Results

- Multi-linear regression
- 66% accuracy using general model (1 model for everyone)
- 93% accuracy, personalized model after 2 months of training
- Top features?

  - Communication
    - SMS
    - Email
    - Phone Calls

  - To whom?
    - # messages
    - Length/Duration

Consider “Top 10” Histograms

How many phone calls were made to #1? #2? ... #10?
How much time was spent on calls to #1? #2? ... #10?
Detecting Boredom from Mobile Phone Usage, Pielot et al, Ubicomp 2015
Introduction

- 43% of time, people seek self-stimulation
  - Watch YouTube videos, web browsing, social media

- **Boredom**: Periods of time when people have abundant time, seeking stimulation

- **Paper Goal**: Develop machine learning model to infer boredom based on features related to:
  - Recency of communication
  - Usage intensity
  - Time of day
  - Demographics
Motivation

If boredom can be detected, opportunity to:

- Recommend content, services, or activities that may help to overcome the boredom
  - E.g. play video, recommend an article
- Suggesting to turn their attention to more useful activities
  - Go over to-do lists, etc

“Feeling bored often goes along with an urge to escape such a state. This urge can be so severe that in one study … people preferred to self-administer electric shock rather than being left alone with their thoughts for a few minutes”

- Pielot et al, citing Wilson et al
Related Work

- Bored Detection
  - Expression recognition (Bixler and D’Mello)
  - Emotional state detection using physiological sensors (Picard et al)
  - Rhythm of attention in the workplace (Mark et al)

- Inferring Emotions
  - Moodscope: Detect mood from communications and phone usage (LiKamWa et al)
  - Infer happiness and stress phone usage, personality traits and weather data (Bogomolov et al)
Methodology

- 2 short Studies

  - Study 1
    - Does boredom measurably affect phone use?
    - What aspects of mobile phone usage are most indicative of boredom?

  - Study 2
    - Are people who are bored more likely to consume suggested content on their phones?
Methodology: Study 1

- Created data collection app *Borapp*
  - 54 participants for at least 14 days
    - Self-reported levels of boredom on a 5-point scale
      - Probes when phone in use + at least 60 mins after last probe
    - App collected sensor data, some sensor data at all times, others just when phone was unlocked
Study 1: Features Extracted

- **Assumption:** Short infrequent activity = less goal oriented

- Extracted 35 features, in 7 categories
  - **Context**
  - **Demographics**
  - **Time since last activity**
  - Intensity of usage
  - External Triggers
  - Idling

<table>
<thead>
<tr>
<th>Context</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>audio</td>
<td>Indicates whether the phone is connected to a headphone or a bluetooth speaker</td>
</tr>
<tr>
<td>charging</td>
<td>Whether the phone is connected to a charger or not</td>
</tr>
<tr>
<td>day_of_week</td>
<td>Day of the week (0-6)</td>
</tr>
<tr>
<td>hour_of_day</td>
<td>Hour of the day (0-23)</td>
</tr>
<tr>
<td>light</td>
<td>Light level in lux measured by the proximity sensor</td>
</tr>
<tr>
<td>proximity</td>
<td>Flag whether screen is covered or not</td>
</tr>
<tr>
<td>ringer_mode</td>
<td>Ringer mode (silent, vibrate, normal)</td>
</tr>
<tr>
<td>semantic_location</td>
<td>Home, work, other, or unknown</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>age</td>
<td>The participant's age in years</td>
</tr>
<tr>
<td>gender</td>
<td>The participant's gender</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Last Communication Activity</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>time_last_incoming_call</td>
<td>Time since last incoming phone call</td>
</tr>
<tr>
<td>time_last_notif</td>
<td>Time since last notification (excluding Borapp probe)</td>
</tr>
<tr>
<td>time_last_outgoing_call</td>
<td>Time since the user last made a phone call</td>
</tr>
<tr>
<td>time_last_SMS_read</td>
<td>Time since the last SMS was read</td>
</tr>
<tr>
<td>time_last_SMS_received</td>
<td>Time since the last SMS was received</td>
</tr>
<tr>
<td>time_last_SMS_sent</td>
<td>Time since the last SMS was sent</td>
</tr>
</tbody>
</table>

Table 3. List of features related to context, demographics, and time since last communication activity.
Study 1: Features Extracted (Contd)

- Extracted 35 features, in 7 categories
  - Context
  - Demographics
  - Time since last activity
  - Intensity of usage
  - External Triggers
  - Idling

<table>
<thead>
<tr>
<th>Usage (related to usage intensity)</th>
<th>Usage description</th>
</tr>
</thead>
<tbody>
<tr>
<td>battery_drain</td>
<td>Average battery drain in time window</td>
</tr>
<tr>
<td>battery_level</td>
<td>Battery change during the last session</td>
</tr>
<tr>
<td>bytes_received</td>
<td>Number of bytes received during time window</td>
</tr>
<tr>
<td>bytes_transmitted</td>
<td>Number of bytes transmitted during time window</td>
</tr>
<tr>
<td>time_in_comm_apps</td>
<td>Time spent in communication apps, categorized to none, micro session, and full session</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Usage (related to whether it was triggered externally)</th>
<th>Usage description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_notifs</td>
<td>Number of notifications received in time window</td>
</tr>
<tr>
<td>last_notif</td>
<td>Name of the app that created the last notification</td>
</tr>
<tr>
<td>last_notif_category</td>
<td>Category of the app that created the last notification</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Usage (related to the user being idling)</th>
<th>Usage description</th>
</tr>
</thead>
<tbody>
<tr>
<td>apps_per_min</td>
<td>Number of apps used in time-window divided by time the screen was on</td>
</tr>
<tr>
<td>num_apps</td>
<td>Number of apps launched in time window before probe</td>
</tr>
<tr>
<td>num_unlock</td>
<td>Number of phone unlocks in time window prior to probe</td>
</tr>
<tr>
<td>time_last_notif_access</td>
<td>Time since the user last opened the notification center</td>
</tr>
<tr>
<td>time_last_unlock</td>
<td>Time since the user last unlocked the phone</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Usage (related to the type of usage)</th>
<th>Usage description</th>
</tr>
</thead>
<tbody>
<tr>
<td>screen_orient_changes</td>
<td>Flag whether there have been screen orientation changes in the time window</td>
</tr>
<tr>
<td>app_category_in_focus</td>
<td>Category of the app in focus prior to the probe</td>
</tr>
<tr>
<td>app_in_focus</td>
<td>App that was in focus prior to the probe</td>
</tr>
<tr>
<td>comm_notifs_in_tw</td>
<td>received in the time window prior to the probe</td>
</tr>
<tr>
<td>most_used_app</td>
<td>Name of the app used most in the time window</td>
</tr>
<tr>
<td>most_used_app_category</td>
<td>Category of the app used most in the time window</td>
</tr>
<tr>
<td>prev_app_in_focus</td>
<td>App in focus prior to app_in_focus</td>
</tr>
</tbody>
</table>

Table 4. List of features related to usage intensity, external trigger, idling and type.
Results: Study 1

- Machine-learning to analyze sensor and self-reported data and create a classification model
  - Compared 3 classifier types
    1. Logistic Regression
    2. SVM with radial basis kernel
    3. Random Forests
  - Random Forests performed the best (82% accuracy) and was used

- Feature Analysis
  - Ranked feature importance
  - Selected top 20 most important features of 35

- Personalized model: 1 classification model for each person
Results: Study 1, Most Important Features

- **Recency of communication activity**: last SMS, call, notification time

- **Intensity of recent usage**: volume of Internet traffic, number of phonelocks, interaction level in last 5 mins

- **General usage intensity**: battery drain, state of proximity sensor, last time phone in use

- **Context/time of day**: time of day, light sensor

- **Demographics**: participant age, gender
Results: Study 1

- Could predict boredom ~82% of the time
- Found correlation between boredom and phone use
- Found features that indicate boredom
Motivation: Study 2

Now that we can predict when people are bored.

- Are bored people more likely to consume suggested content?
Methodology: Study 2

- Created app *Borapp2*
- 16 new participants took part in a quasi-experiment
  - When participant was bored, app suggested newest Buzzfeed article
- Buzzfeed has articles on various topics including politics, DIY, recipes, animals and business
Methodology: Study 2 Measures

- **Click-ratio**: how often user opened Buzzfeed article / total number of notifications
- **Engagement-ratio**: How often user opened Buzzfeed article for at least 30 seconds / total number of notifications

**Preliminary findings**: Bored Users were more likely to click on, and engage with suggested content
References

1. **A Survey of Mobile Phone Sensing.** Nicholas D. Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, Andrew T. Campbell, In IEEE Communications Magazine, September 2010