Embedding mobile computing and research in everyday life

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work done in collaborators with collaborators from UCLA, openmhealth.org, iSTC, ...

Enabled by >6 x 10⁹ mobile phone users, increasingly with: GPS, imagers, touch screens, Internet, app stores

Motivated by 6 x 10⁹ people on planet earth, their health needs, and economic realities
from embedded to mobile to participatory sensing

mhealth: ‘personal evidence’, n=me

whats next?
personal data APIs, mobile personal informatics, NEW YORK CITY!

an end-to-end argument for driving systems research with
data with authentic applications
Lessons from the field of embedded sensing 2002-2010

Early themes: many simple measurements
small platforms
autonomous operation
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Midterm themes: multi-modal measurements
varied platforms
human-assisted operation
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autonomous operation

Midterm themes: multi-modal measurements
varied platforms
human-assisted operation

Eventual themes: model-based measurement
mobile platforms
assistive systems, infovis
Participatory Sensing (starting ~2006)

individuals and communities using personal mobile devices and web services to systematically explore and document their lives
(builds on methodologies of experience sampling [Csik85] and photovoice [Wang95])

Real time
(always on)

Real place
(always carried)

Real context
(historical, environmental, spatial, social)

Real applications
(environment, education, community, health)

w/ Mark Hansen (Statistics/DMA), Jeff Burke (REMAP/TFT)
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Chose applications that scaled down... as well as up: i.e., utility at small n so real use can guide iterative cycles of innovation

w/ Mark Hansen (Statistics/DMA), Jeff Burke (REMAP/TFT)
Assessing environmental factors: Community data gathering (Boyle Heights, 2010)

Acker, Samanta, Belany et al
Snackboard dashboard to >3000 entries about snacking collected by high school students in 2012 (J. Ooms)

w/ Jeroen Ooms, Mark Hansen, Hongsuda T.
Telling traces: PEIR (2007-08)
model-based estimation using continuous location-activity-time series

Individual time-location traces used to automatically estimate daily personal carbon impact and air particulate exposure

http://peir.cens.ucla.edu
Wired NEXTFEST, Chicago 2008

w/ Mark Hansen (Statistics/DMA), Jeff Burke (REMAP/TFT); Funded by Nokia
Pivot to focus on mobile health (mhealth) ....and personal n=me evidence
The promise of mobile Health (mHealth)

transform previously unmeasured behaviors and practices into personalized, evidence-based, and evidence-producing care

- symptoms, side-effects, outcome measures, actions, activities, exposures...
- capture/record activity, mobility, self-reports, tool-use, “digital exhaust”
- visualize, summarize, highlight; inform, advise, persuade
- store, analyze, classify, fuse, mashup, filter, aggregate data

Photo: Marshall Astor, WWW
Why chronic disease management?

- 3 lifestyle behaviors (poor diet, lack of exercise, smoking) cause 1/3rd of US deaths; 50% Americans have 1 or more chronic diseases; age of onset getting younger.

- Over the next 20 years, Non Communicable Diseases will cost worldwide
  > $30 trillion; mental health > $16.1 trillion (WEF, 2011)

- Equip individuals, families w/tools for measurement, management, understanding outside clinical setting
mHealth derived data serves 3 essential workflows

**Participant self-care**
*How is this new medication working for me?*

*patient apps: personal-evidence and clinically-informed tools to engage and support healthy behaviors*

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**Clinical care**
*How is the patient responding to new care plan?*

*‘relevant-time’ clinical dashboards: summarizing and correlating symptoms, side effects, meds, and health behaviors*

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**Research evidence**
*What works best in different contexts?*

*mHealth evidence-base: which mHealth techniques are effective, and for whom*

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w/ Ida Sim, Open mHealth
Transformative methodological tool: recasting ‘evidence’

(Complexes of)
Exposures
sertraline

strength of association?
individual

Outcome
depression

population
Transformative methodological tool: recasting ‘evidence’

(Complexes of)

Exposures

sertraline

strength of association?

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(Outcome)

depression

population

‘does it work on average?’ (RCT)

sertraline

100

50

venlafaxine

50

Depression (PHQ-9)

Depression (PHQ-9)

population

Sim, Kravitz

Friday, April 5, 13
Transformative methodological tool: recasting ‘evidence’

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Depression (PHQ-9)

venlafaxine

Depression (PHQ-9)

population

N-of-1 study design: ‘does it work for Mr. Jones?’

Effexor

Zoloft

PHQ-9

Effexor

Zoloft

PHQ-9

individual


Sim, Kravitz

Friday, April 5, 13
Open mHealth co-innovation use case: Diabetes
Not just a mobile app: data analysis, sensemaking, as critical and more challenging

Correlations in time and space

Actigraphy over space

Actigraphy over time

Ramanathan, Selsky, et al
Many features apply across applications

- Self Report (EMAs)
  - Multiple choice
  - Scale
  - Free text
  - Image capture
  - Personalization

- Phonetop Buttons

- Passive Monitoring
  - GPS, Wifi, Accel
  - sms, calls, calendar, social media
  - actigraphy, mobility, comm

- Phone-based apps
  - Exercises/tools
  - Interventions
  - Games
  - Assessments

End-User Dashboards

Data collection

Internet
“Real Sensor” streams
http://ginger.io/the-platform/
http://ohmage.org
continuous activity, location traces and prompted self-report
Photographic Affect Meter: PAM (Pollak et al)
My comparisons feedback screen

Blood Glucose
- >= 150
  - Carb: 83g (pumpkin smash)
  - Fat: 0g
  - Protein: 10g
  - 12:15, 12:30, 12:45, 01 PM
- <= 120
  - Carb: 1g (smoothie)
  - Fullness: Just Right
  - Homemade Meal
  - 01:15, 01:30, 01:45, 02 PM

Mood
- tired, sleepy, gloomy

Blood Glucose
- Mood

Food
- Runkeeper

Glucose: 152
Event: After dinner

Mood
- Positive Emotions

Cycling
- Excited

Runkeeper
- Excited

09 AM 10 AM 11 AM
Next steps: transforming passive information into behavioral biomarkers for chronic diseases

Personalized, rapid, indicators of health improvement, relapse, side-effects, symptoms using: mobility logging and digital traces (vocabulary, games, spending)

Hours at home per day

Walking periods > 6 min per day

Friday, April 5, 13
Deriving behavioral biomarkers...from app and sensor streams

behavioral biomarker/indicator
- in-person variance/patterns of fatigue, pain, depression, insomnia, cognitive function...

summarization
- ambulatory/sedentary cumulative and durations, walking speed
- sleep times, social interactions
- time spent before leaving house, hours spent at home

state classification
- sedentary/ambulatory
- at home/work
- using apps
- communicating
# Lifestreams: Modular Data Analysis Software Stack

<table>
<thead>
<tr>
<th>Lifestreams Inference</th>
<th>Correlation Summary</th>
<th>Change Detection</th>
<th>Correlation Change Detection</th>
<th>Multi-dimensional Pattern Detection</th>
<th>Prediction</th>
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<tbody>
<tr>
<td>Feature Selection</td>
<td>Pairwise Correlation Analysis</td>
<td>Interactive UI for Manual Selection</td>
<td>Factor Analysis (PCA, MRMR)</td>
<td>Temporal Aggregation</td>
<td>Spatial Aggregation</td>
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<td>Feature Extraction</td>
<td>Self-report Features</td>
<td>Place Detection</td>
<td>Activity Features</td>
<td>Acoustic Features (Voice/Non-voice)</td>
<td>App Usage Features</td>
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<tr>
<td>ohmage Personal Data Streams</td>
<td>Self-report Data</td>
<td>Geolocation / WiFi Fingerprints / Accelerometry</td>
<td>Audio(MFCC)</td>
<td>Phone Usage Logs</td>
<td></td>
</tr>
</tbody>
</table>
Behavioral Biomarkers can drive tailored infographics, informational incentives, feedback, game mechanics

ubifit participants who...

had the garden       did NOT have the garden

ubifit (S. Consolvo et al, UW/Intel)

NIH funded new-moms study in progress (Ramanathan, Ketcham, Estrin...)

Mobile Ambient Wellbeing Display (T. Choudhury, Cornell)

ubifit
Data reduction, selective sharing, privacy

usability and privacy served by sharing only extracted data features

TMI (too much information) filter

New privacy models emerging for raw data

- http://www.weforum.org/issues/rethinking-personal-data
- http://personal.com
- http://wethedata.org

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Third IT pillar of personalized, precision, medicine

“Big data” (EHRs, Web mining) + Omics + “small data” (mHealth, digital traces)
Open architecture and community
so mHealth solutions can integrate best available apps and techniques
open architecture for mobile health

a small set of common principles/practices by which these modules are described and interface to one another

Open mHealth light-handed approach to semantics

Foster broad ecosystem of software components that can process or visualize a single payload ID

- competition, different algorithms, new approaches ...
- after all … this is all ‘new stuff’...processes and products will be iterating rapidly as we learn

Enable a data standard process that supports rapid evolution

- fits the desired and unavoidable dynamics of a learning healthcare ecosystem

Data payload defined by Schema ID, version, lightweight schema

- utilize payload IDs to represent existing standards as well
- accommodate both existing software and existing standards
Whats next …

mHealth Greenhouse

- collaborate with innovative clinicians to develop new ways to address patient care by leveraging mobile data: behavioral biomarkers
- tools to support patients’ disease-management
- support rapid, iterative prototyping and piloting

mpire: mobile personal informatics research and experimentation

- Open up programmatic access to individuals to obtain their personal digital traces from mobile, search, social, e-commerce, games, apps
- Personal Data APIs to foster personal services/apps
- Testbed in NYC with access to 1000’s of mobile subscribers for experiments with privacy and detailed analytics
End to end arguments in systems-research design: a case for including authentic applications in experimental systems research

Original argument [Saltzer, Reed, Clark, 1981]

• “...functions placed at low levels of a system may be redundant or of little value when compared with the cost of providing them at that low level.”

• “The argument appeals to application requirements, and provides a rationale for moving function upward in a layered system, closer the application that uses the function.”
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Implications for systems-research/innovation

• authentic applications needed as part of systems research exploration to keep functional and performance requirements on a purposeful track

• need to build...and use...
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More general lessons from systems

- architecture, modularity, well-defined interfaces, analytics are critical
- enable rapid, iterative, automated, learning and sharing across applications, institutions, markets
- importance of shared robust open infrastructure
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Collaborators

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