Mobilizing Health

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Enabled by $>5 \times 10^9$ mobile phone users, increasingly with: GPS, imagers, touch screens, Internet, app stores

Motivated by $6 \times 10^9$ people on planet earth, their health needs, and economic realities
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*

**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*

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

*mHealth-enabled n-of-1 studies: systematic, individualized studies of treatment alternatives*

*mHealth evidence-base: which mHealth techniques are effective, and for whom*
rephrasing 'does it work?'

(Complexes of) Exposures
sertraline

strength of association?
individual

Outcome
depression

population
rephrasing ‘does it work?’

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population

‘does it work on average?’ (RCT)

Depression (PHQ-9)

- sertraline
  - 50

- venlafaxine
  - 50

50

population

100

Sim, Kravitz
rephrasing ‘does it work?’

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

Effexor

PHQ-9

Zoloft

Effexor

PHQ-9

Zoloft

individual


Sim, Kravitz

Wednesday, May 23, 12
Many features apply across mHealth 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 activities
  - Exercises/tools
  - Interventions
  - Games
  - Assessments

Ramanathan, Selsky, et al
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
Need to make raw data ‘actionable’ for self- and clinical-care

...move from traces to ‘bio markers’
Transform continuous passive traces into bio/outcome markers

Low-level state classification:
create time series of states after data cleaning
• sedentary/ambulatory
• at home/work
• interacting with app, people...
• ‘standard’ ML techniques

Estimate personally- and clinically-useful information:
• modular layered processing
• ranging from simple functions to machine learning classifiers

w/ Ramanathan, Longstaff, Alquaddoomi, et al
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Mid-level semantic features:
calculate domain-specific features
- daily minutes ambulatory, sedentary durations, walking speed
- sleep times, social interactions
- time spent before leaving house, “diameter of day”...

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“diameter of day”...

Higher level individual markers:
fuse features, metrics into ‘marker’
assessing persons state, variations
• fatigue, pain, depression,
insomnia, cognitive function...
• in-person variance, patterns,
correlations

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from phones to fitbits...
from chronic pain to depression...
from mobility to text...

w/ Ramanathan, Longstaff, Alquaddoomi, et al