New Opportunities for Measuring Physical Activity and the Resulting Research Needs

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Caveats

- Engineer's perspective
- Engineer's optimism
- Bias toward long-term measurement
- Anticipating industry developments on the horizon

Behavior measurement

Today (e.g., PA/SB)

- Surveys
- Proprietary objective sensors
- Limited information about context
- 1-7 days of data
- Costly compensation
- Expert-assisted recall for detailed timeline
- Limited location info
- Limited info on decision-making

Soon

- Open source phone apps (with optional add-on sensors)
- Months of continuous data
- Citizen scientists donating info
- Computer-assisted recall (using passive data collection)
- Full location information
- Context/purpose info...

Behavior measurement

Today (e.g., PA/SB)

- Hypothesis driven investigations to understand correlations

Soon

- Data driven, incremental and interactive discovery for intervention theory development

Thinking long term

- Two motivations for measurement
  - Scientific inquiry (Better tools for scientists)
  - Building effective (and hopefully cost-effective)...
    - Devices to measure changes in behavior/state
    - Devices to use measurement to intervene with health/wellness that are tailored based on behavior/state

This requires longer-term, less invasive measurement than scientific inquiry might

Measurement fidelity: "why"

Think like a designer

What happened last week?

Why is this person walking now?

Does this person normally walk in this situation?

What happened last year?

What immediate opportunities does the environment create?

What is the relationship & conversation between these two?

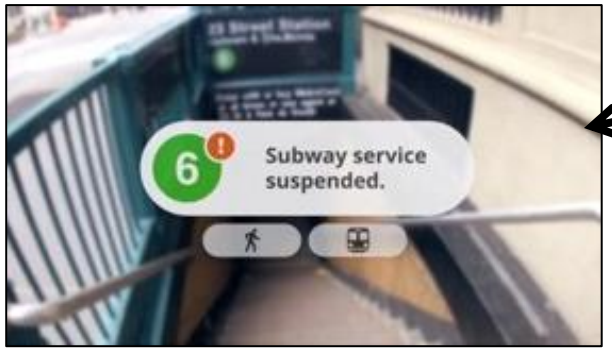
Who is this other person?

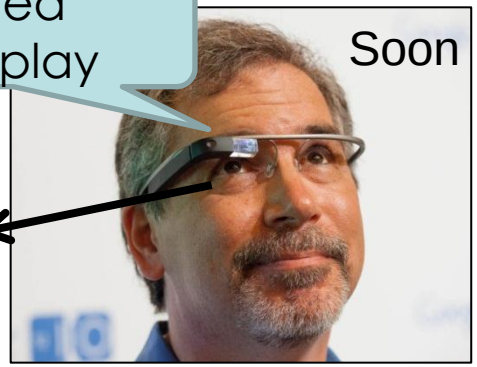
What are the characteristics of this environment?

What is this person most likely to do next?

What will this other person likely do next?

Interventions: How to touch?





Augmented reality display

Computers at home

Computer in car

Computers at work

Phone

Friend's phone

Nearby stranger's phone

Displays in environment

Messages from friends in social networks

Passive sensing assumption

Implied ideal model is one where subjects put on sensors, and wear with no training or interaction required

There is only so far that this will go...

Passive sensing insufficient

- "Fuzzy" behavior
- Noisy sensors
- Missing sensors
- Interventions require interaction
  - End-users must guide (with training data)
  - End-users must fix

Some self-report will be required ...

Context-sensitive EMA

- Triggering questions (on phone) based on automatic, passive or active sensing of person's context
- Minimize participant burden by targeting requests for context information
- Gather information about the "why" of behavior

CS-EMA

- Pros:
  - Less annoyance to EMA participant for acquisition of same info
  - Increasingly viable at low cost with sensing and processing power of mobile phones
  - Closer to just-in-time interventions
- Cons:
  - Noise in context detection
  - Statistical tradeoffs

CS-EMA & ubiquitous sensing

- CS-EMA might use a variety of passive sensors (think of "sensor" broadly)
  - In phone
  - Communicating with phone
  - In environment
- Passive sensor processing triggers active self-report to fill in gaps

Activity/context detection

Roughly two categories of motion...

"Moving light displays"
(Limb motion (2+) sensing best)

- Postures
- Ambulation
- Structured exercises
- Some sports
- ...

"Invisible man movies"
(Sensing of object use/movement best)

- Making bed
- Cooking
- Socializing
- Some sports
- ...

Doing this well will require long-term, dense data on individuals to build models... "big, n=1 data"

Activity/context detection

Different problems ... requiring different models

"What's happening now?"

"What's going to happen next"

"What's influencing decisions?"

"What will influence decisions relative to what is happening now?"

Doing this well will require long-term, dense data on individuals to build models... "big, n=1 data"

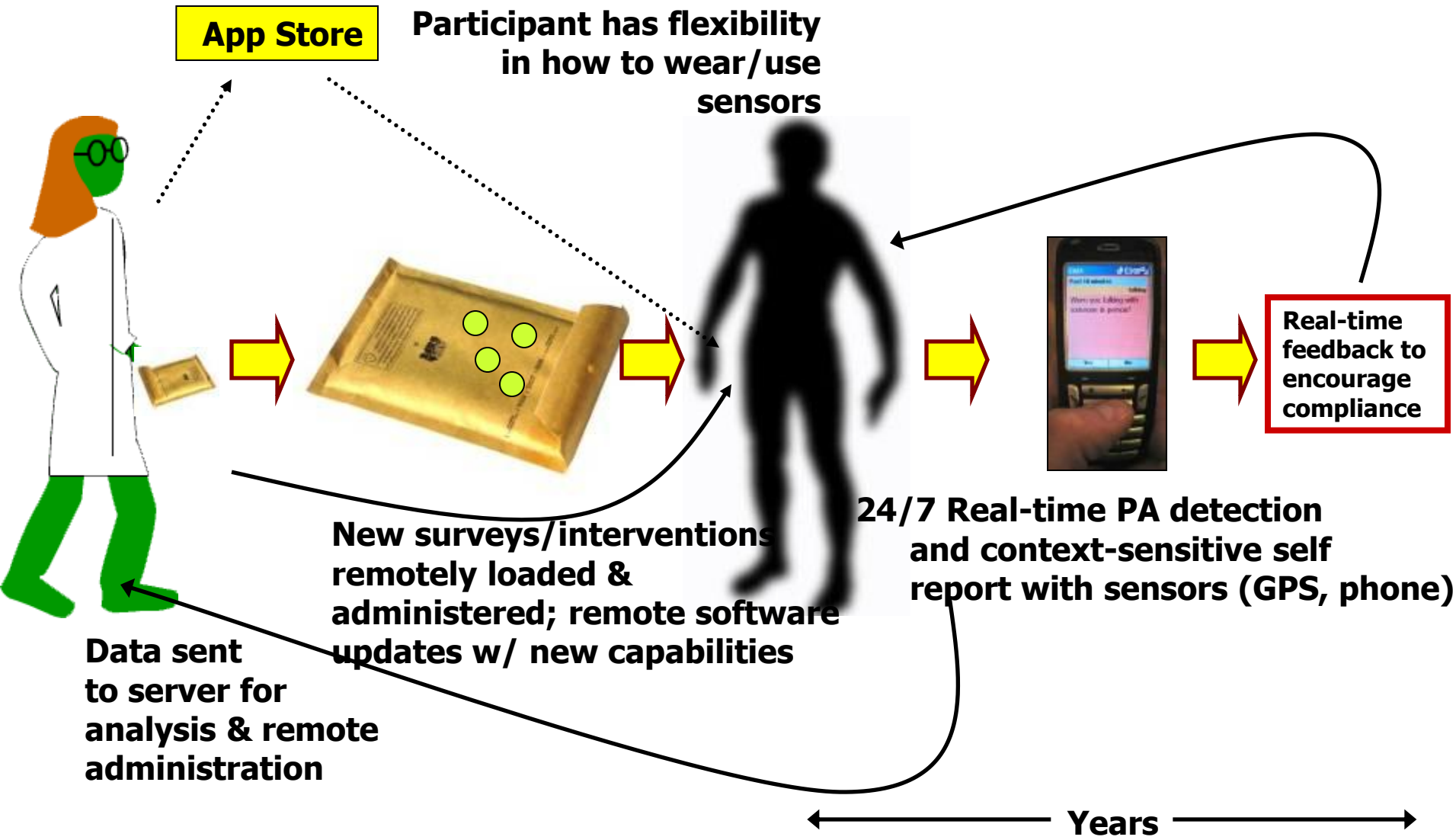
Long-term behavior data

"Primitive" example from Wockets system

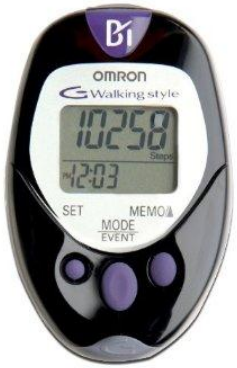
Prototype: Wockets system

- Goal
  - 24/7 measurement of physical activity of
    - Type
    - Intensity
    - Duration
    - Location
  - For months+ (with compliance feedback)
  - Cost suitable for cohort studies
    - Exploit consumer phone technologies
    - All open source

Vision: population-scale



Activity monitors abound

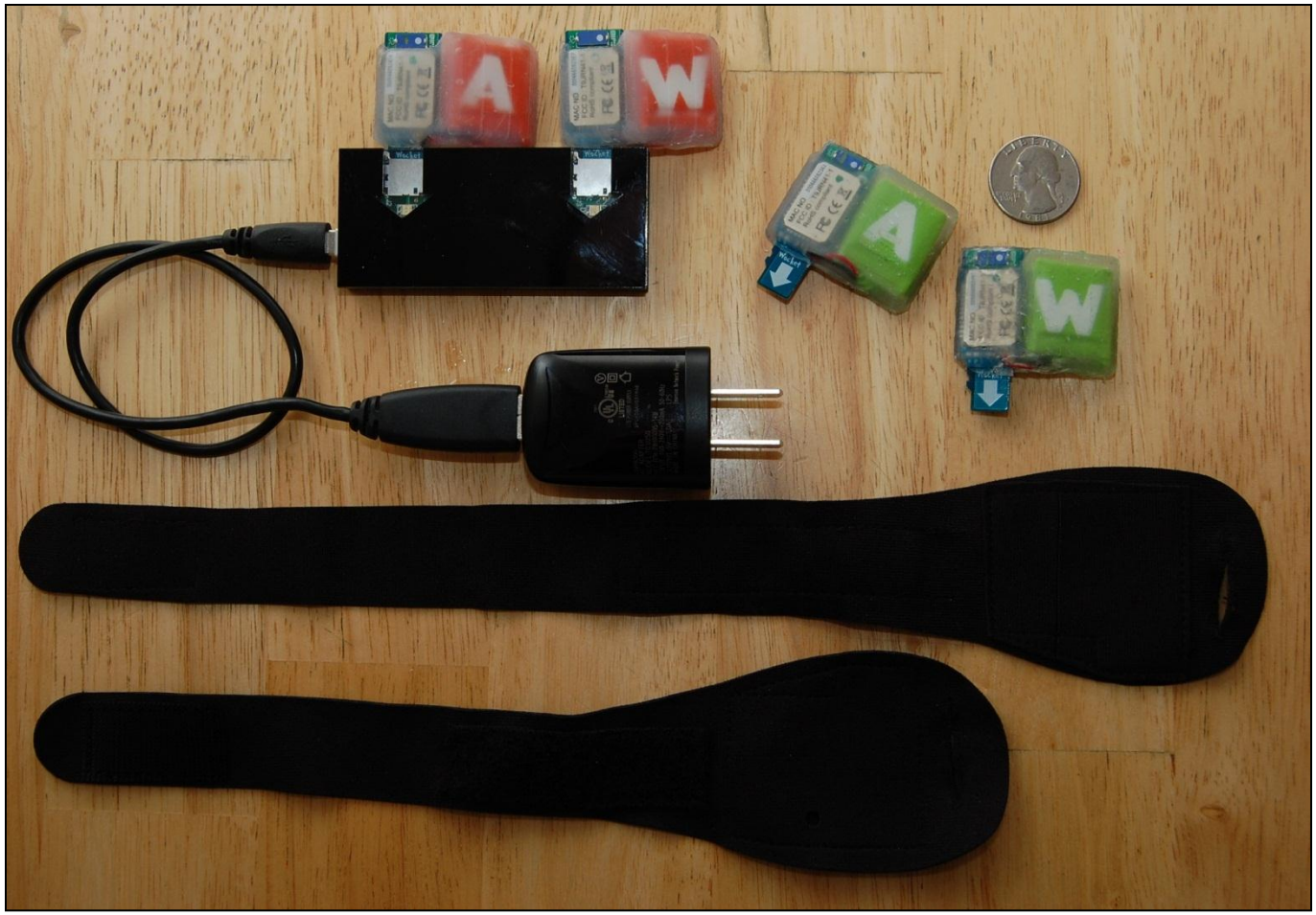


Wockets system fills a niche

- 24/7 remote data collection that may improve PA/SB research
  - Missing data
    - Real-time compliance feedback
    - Remote compliance monitoring
    - Less reliance on single body location
  - Sampling bias
  - Activity type info via pattern recognition with upper/lower body sensing
  - Combine passive monitor and trigger self-report to fill in context

Wocket “kit” (+ phone)

Charge 2



Wear 2 for 24h

Capture upper + lower body motion at 40Hz that can be processed for activity type and intensity detection

Thin for continuous wearability

A day in the life of a participant

- In the morning, swap & select locations
- Wear sensors under clothing
- Go about day; use phone normally
- Phone knows PA/SB level with 1 min latency; triggers questions
- At night, plug in phone next to bed
- Data transmitted to lab for remote monitoring
- Phone collects a variety of data types

Other data

- Phone location (indoor, outdoor)
- Phone motion and use
- Proximity friends/family
- Communication (e.g., calls, texts)
- Optional HR: (using modified Zephyr):

(Worn under shirt)

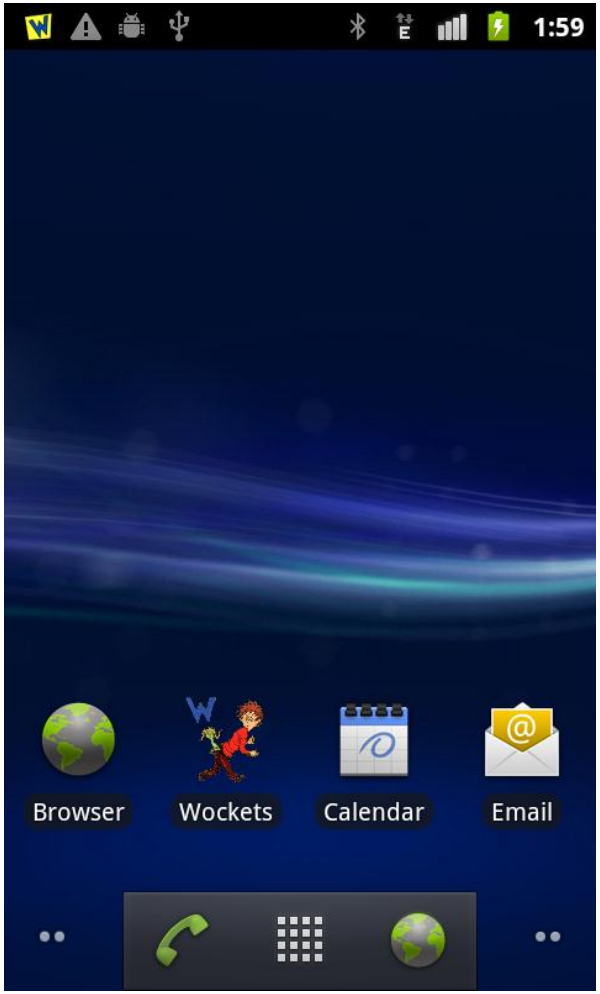
Working toward...

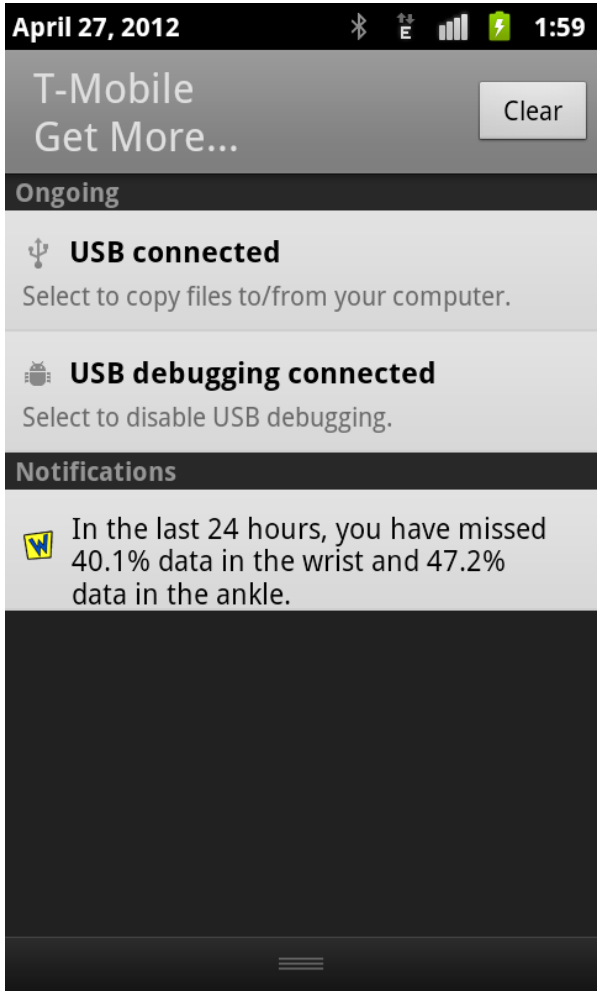
- 24/7 real-time knowledge of
  - Activity type
  - Duration
  - Intensity
  - Location
  - Other information gathered from phone
    - Communication
    - Social interaction

+ Self-reported contextual information

Video

Compliance feedback





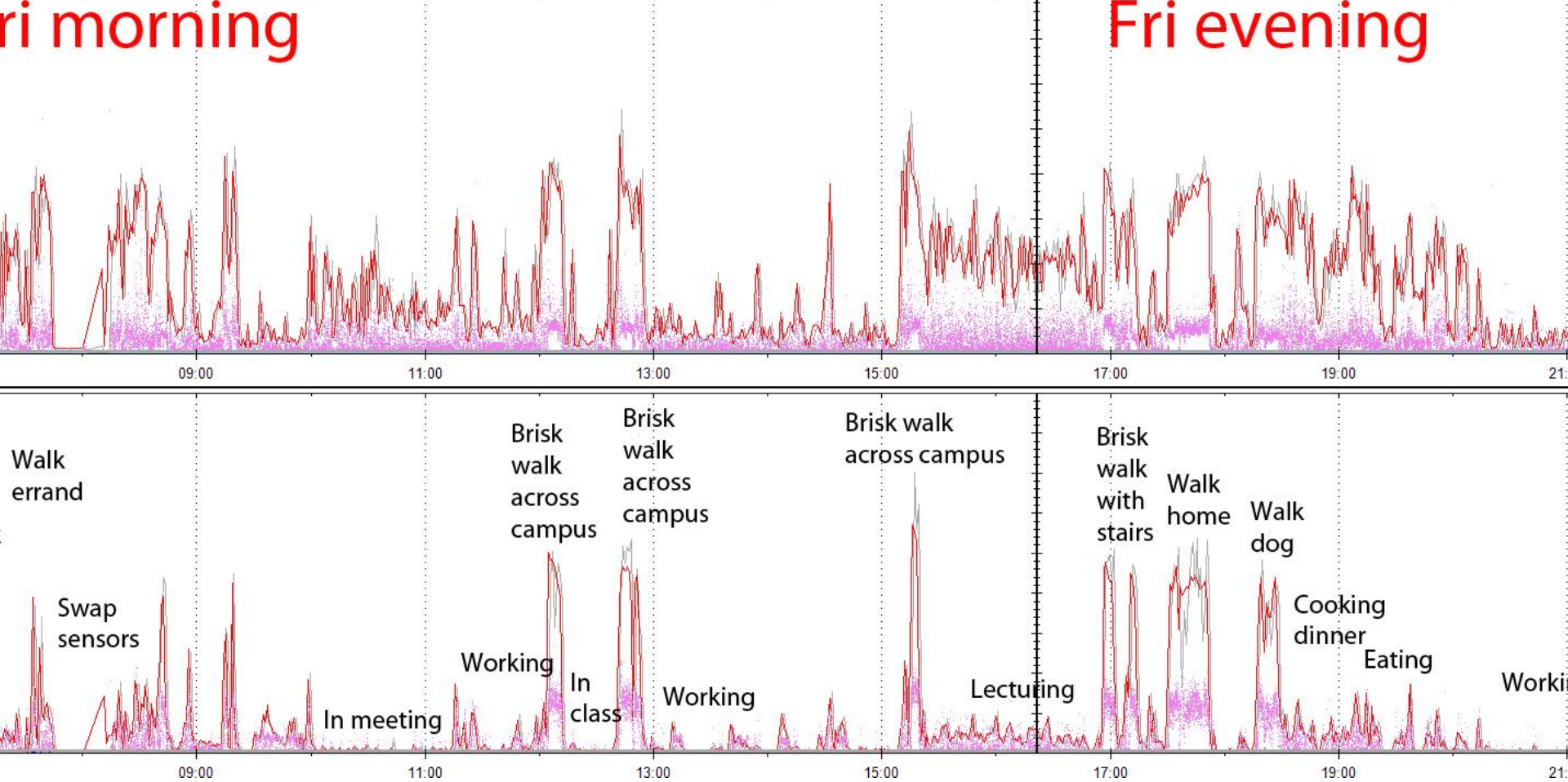
Video

Video

Lab performance: Activity rec

		Subject Dependent	Subject Independent
Activities to recognize	**Random Guess (%)**	**Total Accuracy (%)**	**Total Accuracy (%)**
All (51)	1.9%	87.9	50.6
All with no intensities (31)	3.2%	91.4	72.0
Postures, ambulation and two MET intensity categories (11)	9%	96.5	81.3
Postures and Ambulation with no intensity (8)	12.5%	98.4	92.9
Postures (4)	25%	99.3	98.0

Self-report can fill in gaps/fix errors



If you had this info, plus social interaction, location, and more ... for long time periods ... How might that change your research questions and the interventions you might build?

Opportunities to explore (or not ignore)

- Real-time feedback
  - Improve subject compliance
  - Drive novel "just-in-time" tailored interventions
- Remote subject data analysis &monitoring
  - Make longitudinal studies with high fidelity data possible
  - Lower the cost of running studies with very high numbers of subjects (thousands)

Opportunities to explore (or not ignore)

- Multi-sensor fusion
  - Improve type and energy expenditure estimation by capturing upper/lower body motion
  - Improve type detection using environmental sensors

- "Unusual" accelerometer locations
  - Test ankle, thigh, head (on HMD)
  - Let people swap locations around

Wrist vs. ankle

Unpublished data

Real-time walking/loc detection

- Video

Opportunities to explore (or not ignore)

- Subject-specific training data
  - Increase type detection accuracy
  - Learn how to build human-computer interactions systems that will be *necessary* for effective interventions

- Building large, annotated behavior datasets...

Datasets to drive innovation

- Data component properties:
  - Large numbers of participants
  - Sampled for several weeks+
  - While wearing a variety of sensors simultaneously
  - Where all activities are labeled in detail
  - Start with convenience samples
- Algorithm component properties
  - Open algorithms
  - Easy to use

Data: Think broadly

- Datasets should include (or at least not exclude)
  - Multiple accelerometers
    - Upper and lower body
  - Phones (used normally) and data they gather
  - Location (despite deidentification challenges)
  - New sensor types
    - Wearable cameras
    - Physiological sensors
    - Electronic use of devices
    - In home "object use" sensors

Transdisciplinary collaboration

- Big, easy-to-use datasets will
  - Lure engineers interested in machine learning, gait analysis, and human-computer interaction to this domain
  - Drive the community to common evaluation standards, permitting cross-study comparison
  - Encourage innovation
  - Lead to engineering competitions for novel solutions

Take away #1

- Mobile phones will become the hub device for PA data collection because they will...
  - Have a "backup" internal sensor
  - Facilitate long-term compliance monitoring
  - Permit gathering rich information about context from multiple types of sensors, including self-report
  - Be used for novel "just-in-time" interventions

Take away #2 and #3

- Phones + sensors can detect enough information about behavior to create new methods to facilitate context-sensitive self report (CS-EMA)

- No sensor is perfect: multi-sensor behavior recognition in combination with real-time or interactive time self-report is the path forward

Take away #4 and #5

- Large, open, extensible datasets are key to avoiding confusion in the field as more sophisticated data processing methods are introduced

- Think broadly about "sensors" and multi-sensor fusion and opportunity for data driven discovery with convenience samples

For more information

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- http://mhealth.ccs.neu.edu
- Ask me about Northeastern's transdisciplinary Ph.D. in Personal Health Informatics http://phi.neu.edu