

Using Mobile Phones for Measurement of Physical Activity and Health Behaviors

Stephen Intille, Ph.D.

Associate Professor

College of Computer and Information Science &

Bouvé College of Health Sciences

Northeastern University (450 WVH)

s.intille@neu.edu

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Take away #1

- Mobile phones are increasingly capable of sophisticated, real-time information processing using internal and wirelessly-connected sensors
- Most people will have this technology and carry it with them nearly everywhere

(See Pew Internet & American Life (<http://www.pewinternet.org/>))

Take away #2

- 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 #3

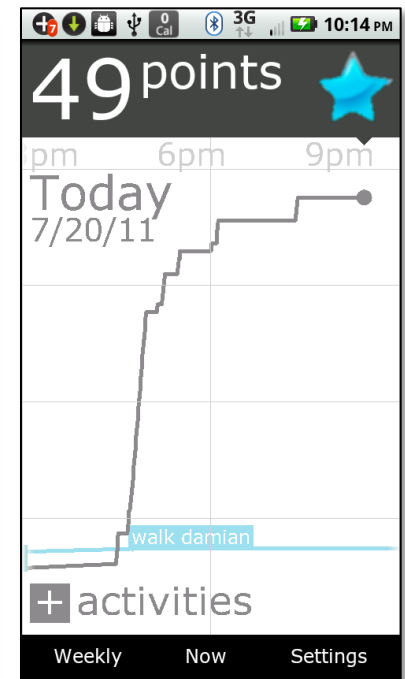
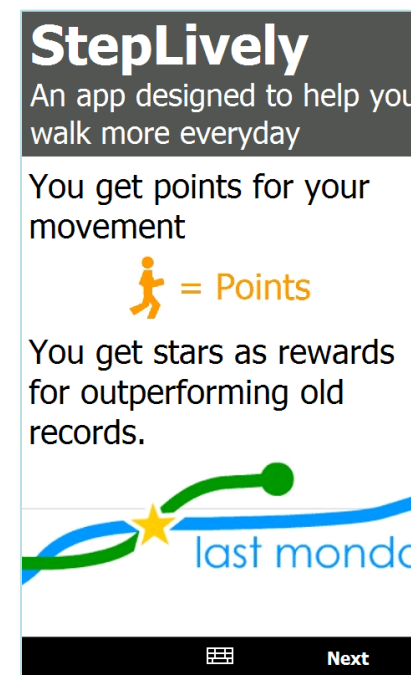
- Work in progress: There are some design and technical challenges, but they can be overcome with more research

Just-in-time intervention

Goals

- Continuous behavior measurement on consumer tech (especially phones) using sensors
- Instant, carefully-timed, tailored feedback for new interventions

... but will change measurement too ...



Just-in-time self report

Context-sensitive ecological momentary assessment (CS-EMA)

Prompted just after
inhaler used:



Teen asthma
measurement
with Genevieve
Dunton at USC

A screenshot of a mobile application interface. The status bar at the top shows the time as 08:55 and various icons. The main screen has a blue header with the text "Just before you used your inhaler, have you experienced COUGHING?". Below the header is a white list box containing four items, each with a yellow checkbox: "Not at all", "A little", "Quite a bit", and "Very much so". At the bottom of the screen are two buttons: a blue "Back" button and a gold "Next" button.

Prompted after 60
min of no phone
motion:

A screenshot of a mobile application interface. The status bar at the top shows the time as 08:59 and various icons. The main screen has a blue header with the text "What have you been DOING for the past hour? (Choose all that apply)". Below the header is a white list box containing six items, each with a yellow checkbox: "Reading or doing homework", "Using technology (TV, phone)", "Eating/Drinking", "Sports/Exercising", "Going somewhere", and "Other". The "Using technology" and "Eating/Drinking" checkboxes are checked. At the bottom of the screen is a single gold "Next" button.

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 and context

Why CS-EMA?

- Minimize participant burden by targeting requests for context information
- “Fix” problems with imperfect passive sensing (or fill in gaps)
- Get at the “why” of behavior for intervention development

Behavior measurement

Today

- 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

- Hypothesis driven investigations to understand correlations

Soon

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

Want to measure behavior?

- With a rich understanding of behavior + context
- In the field
- Long-term (weeks or months+)
- At reasonable cost
- With real-time feedback

Activity monitors abound



Prototype: Wockets system

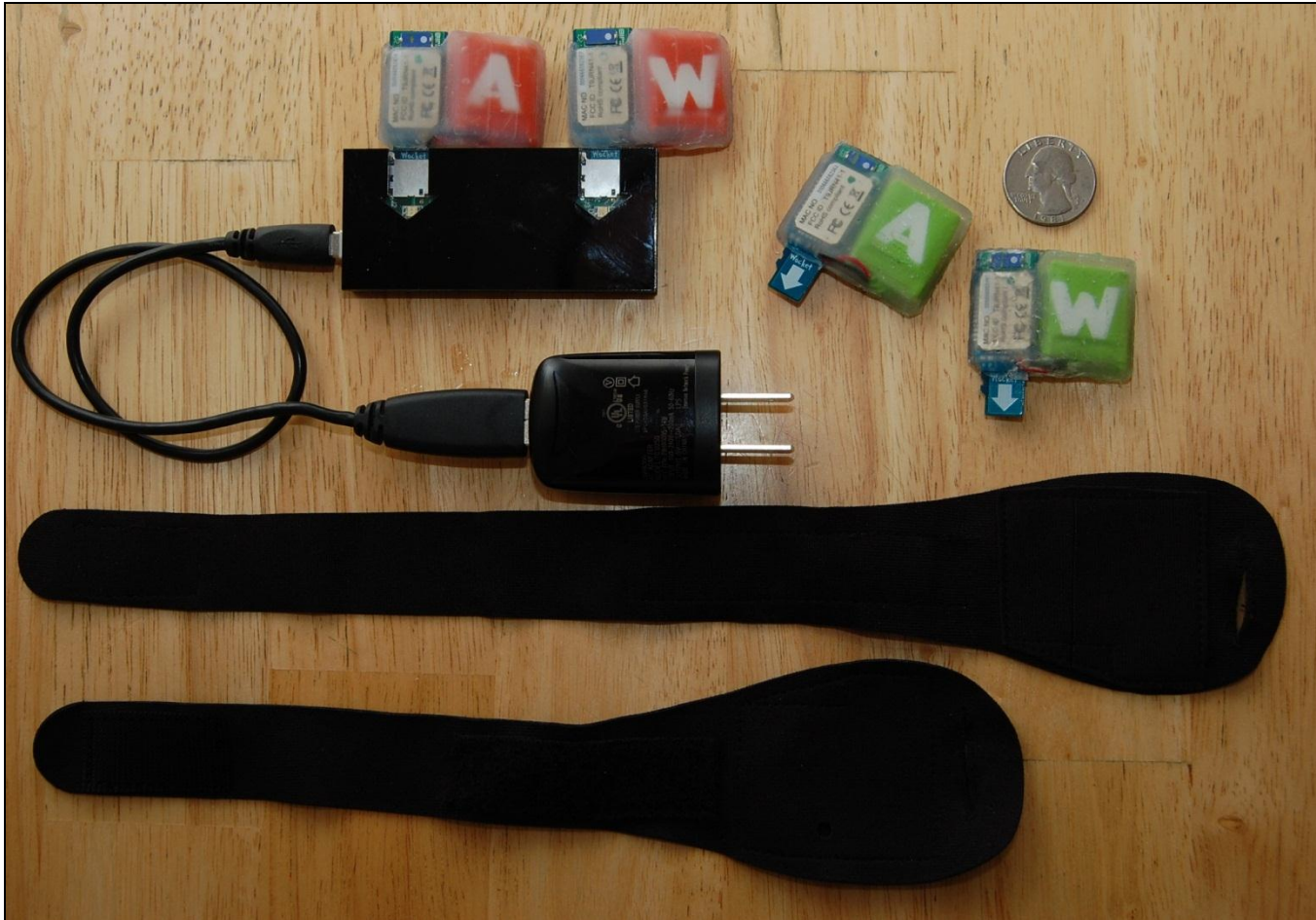
- Goal
 - 24/7 measurement of physical activity of
 - Type
 - Intensity
 - Duration
 - Location
 - For months+ (with compliance feedback)
 - Cost suitable for cohort studies
 - Exploit consumer phone technologies
 - All open source

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

Actigraph



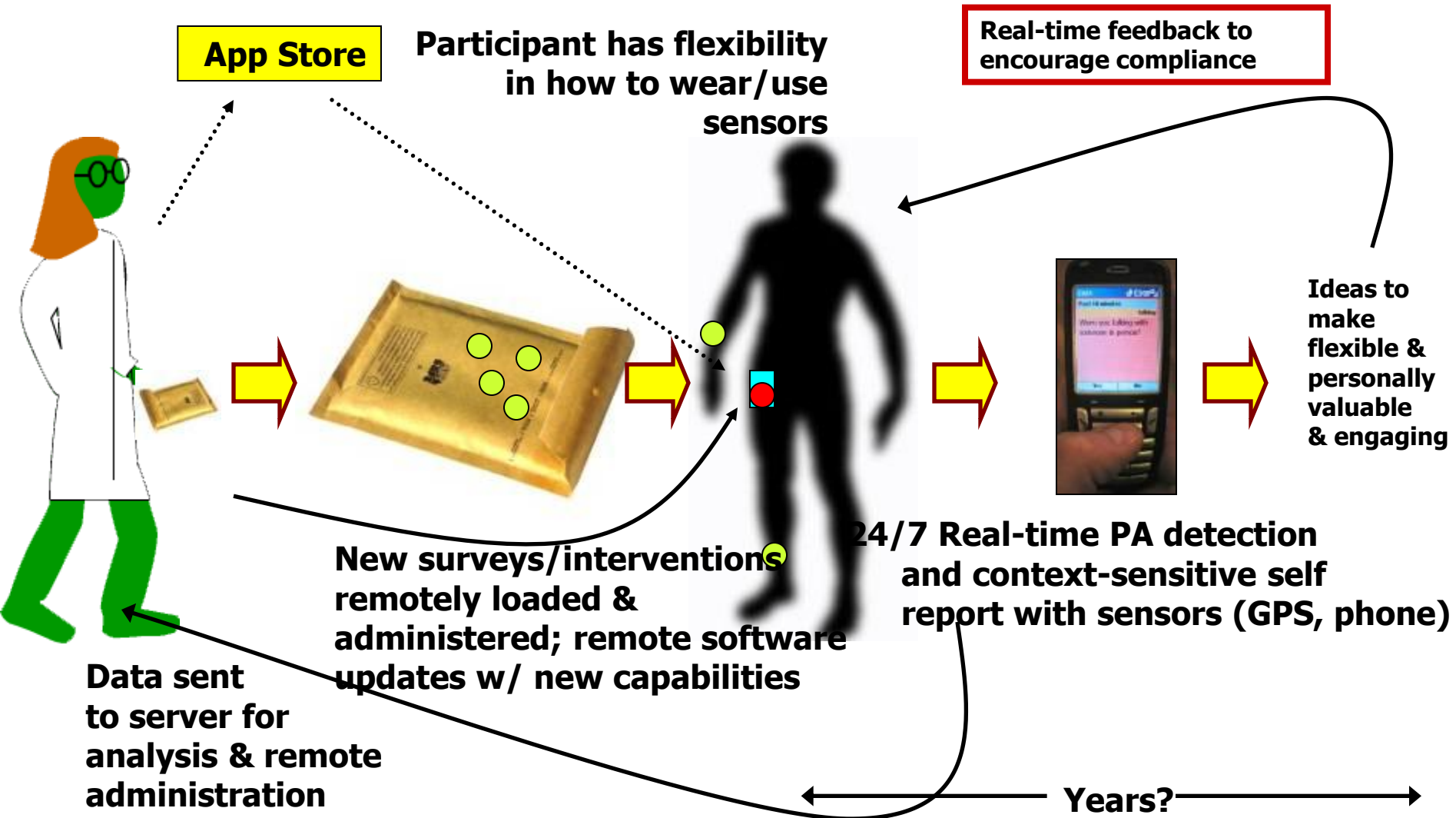
Wocket



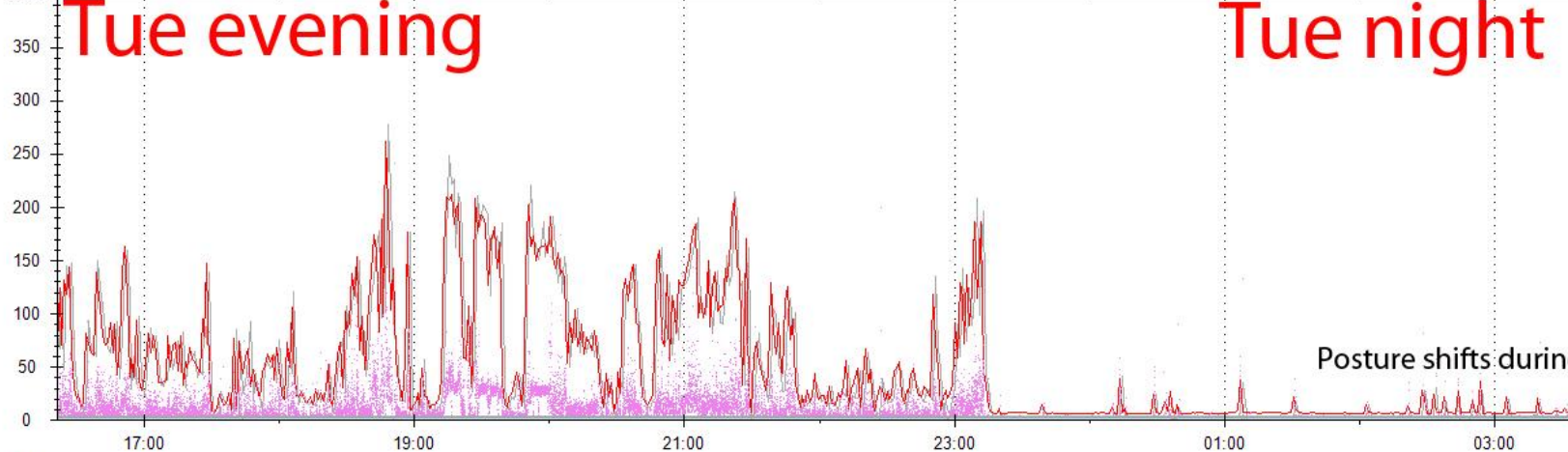
A day in the life of a participant

- In the morning, swap & select locations
 - Usually one upper body, one lower body
 - Internal phone sensors
- During the day – use phone normally
- At night, plug in phone next to bed
- Data transmitted to lab for remote monitoring and incremental analysis

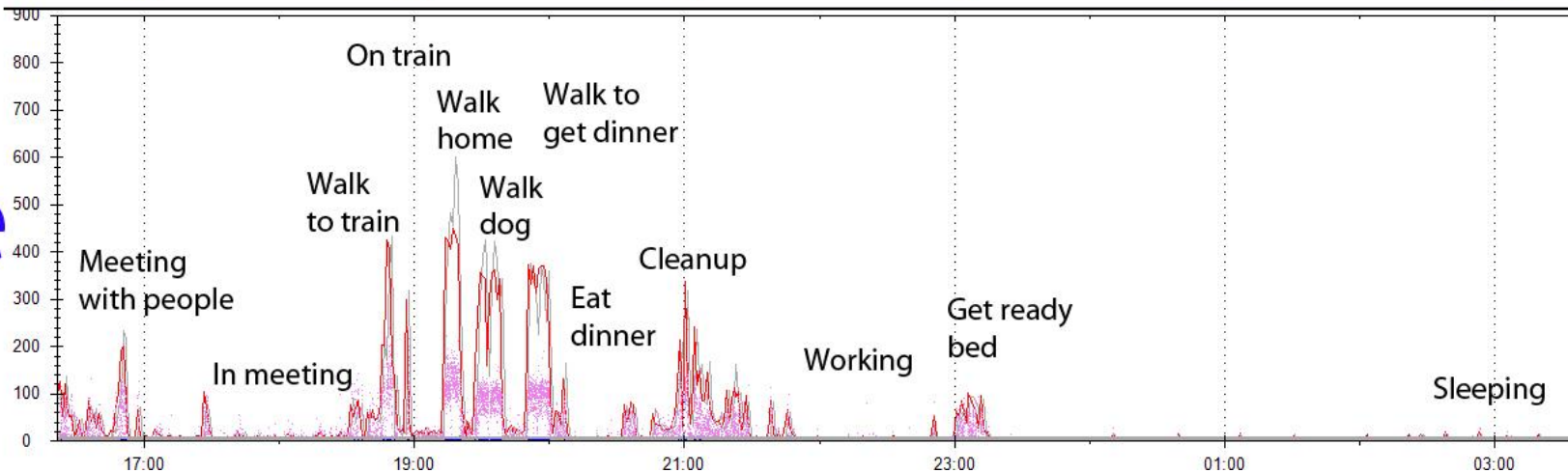
Vision: population-scale



Wrist



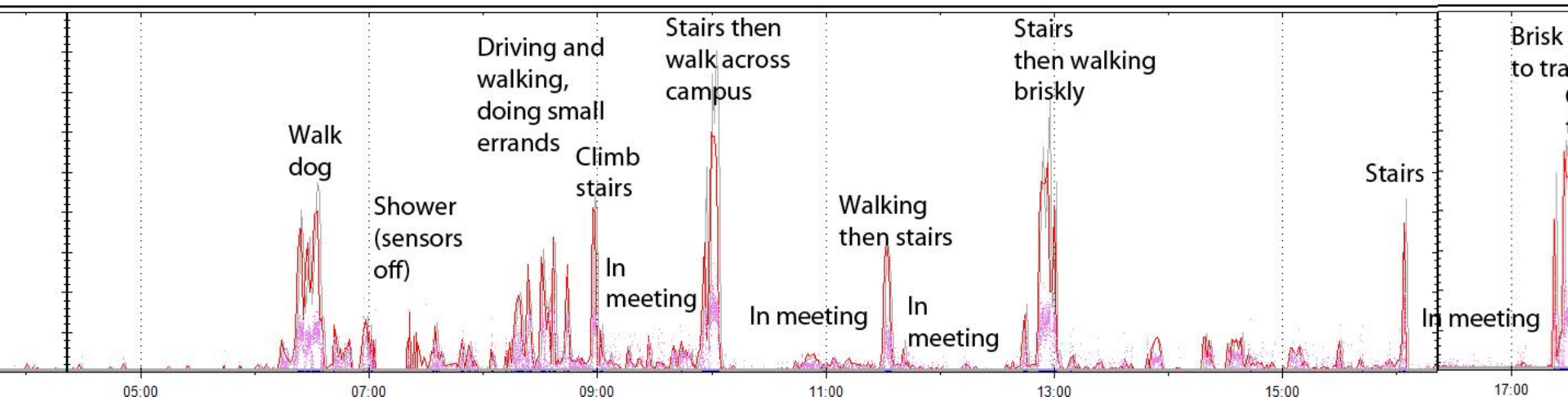
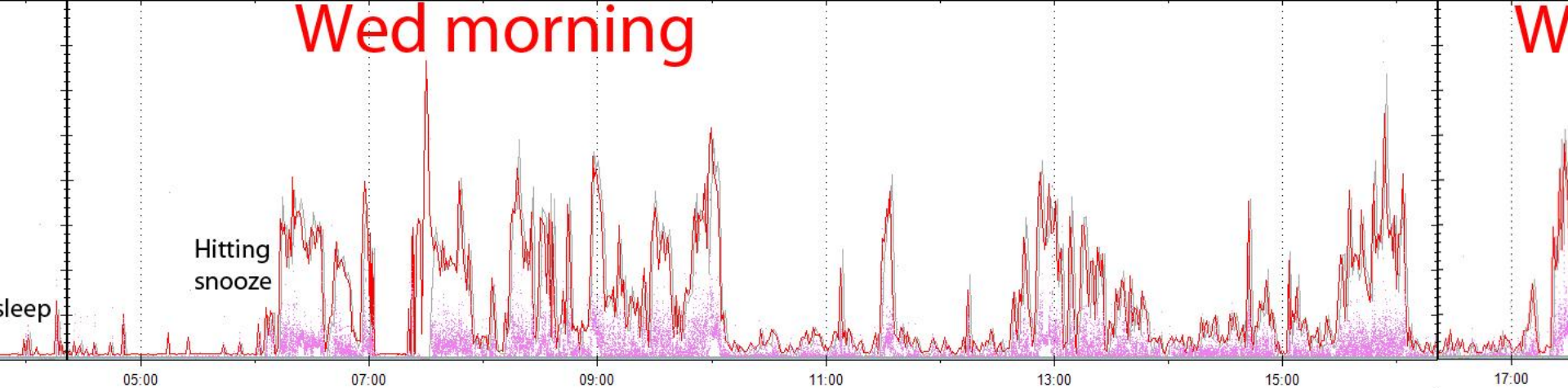
Ankle



Note: Activities manually labeled ...

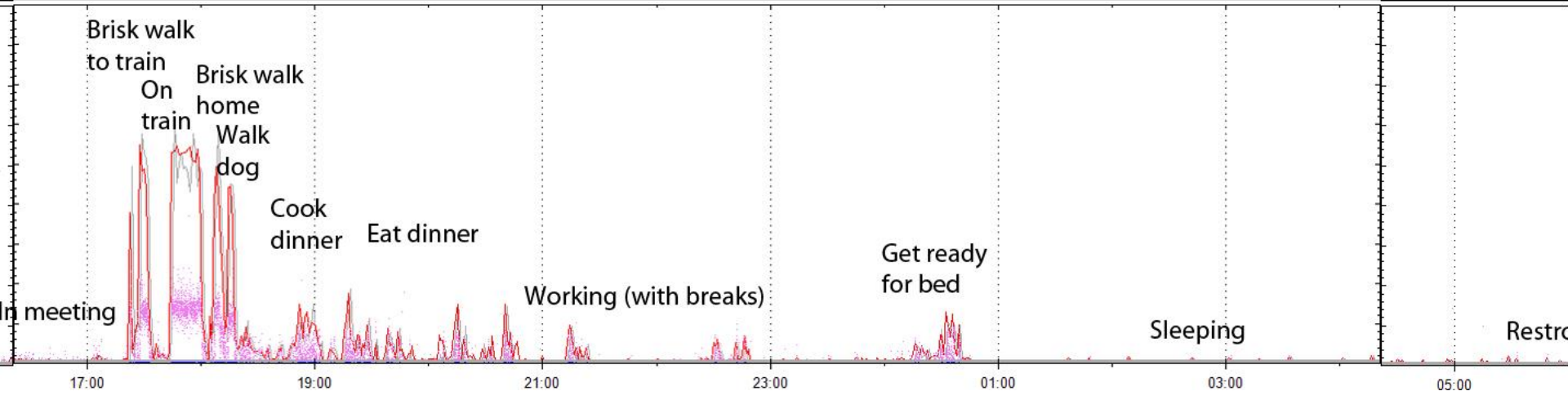
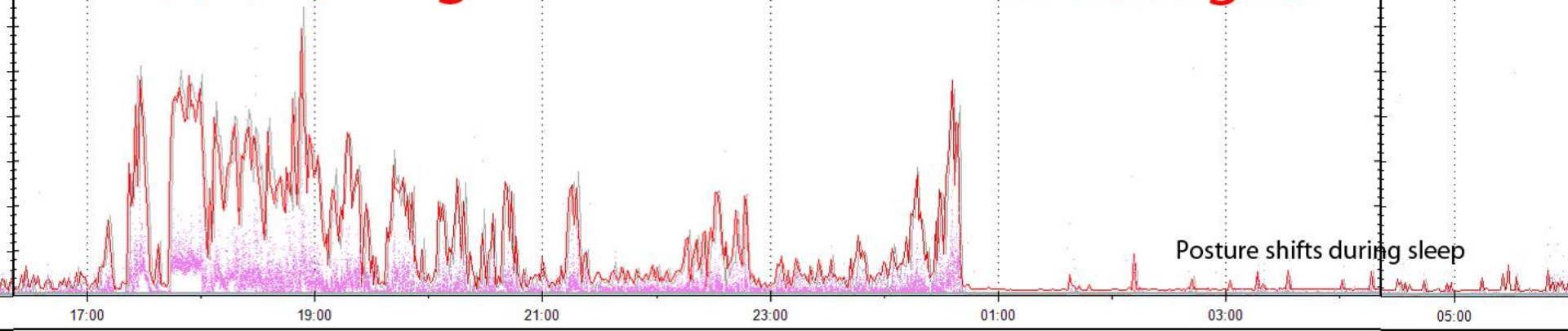
Working on real-time detection of some activity types and context (posture, ambulation, structure exercise, etc.)

Wed morning



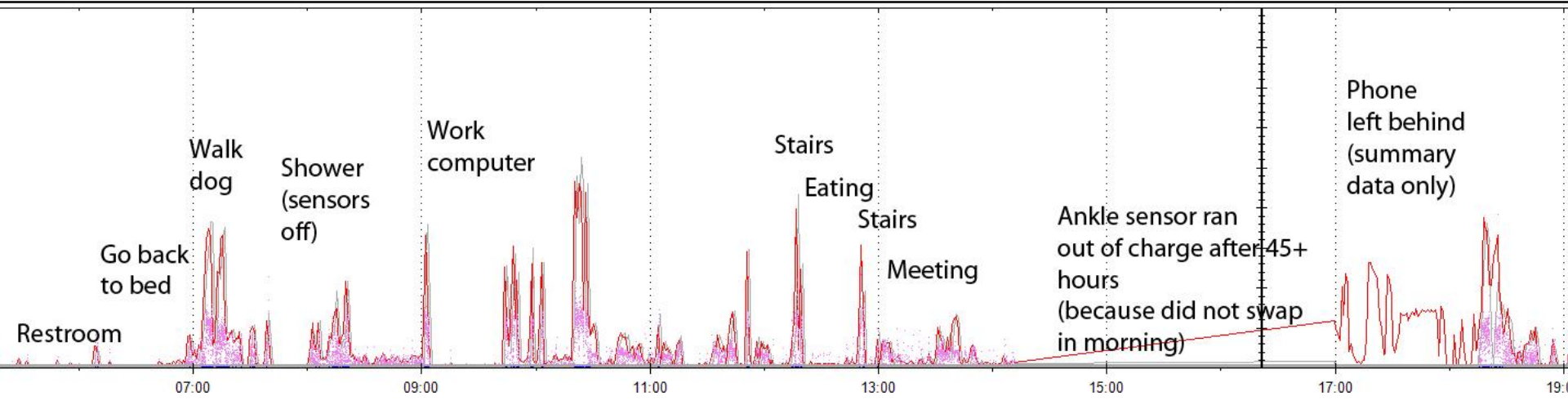
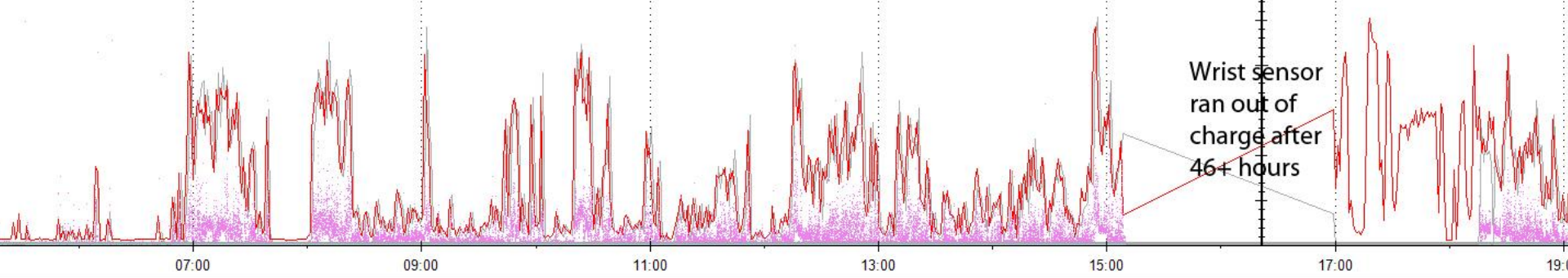
Wed evening

Wed night



Thu morning

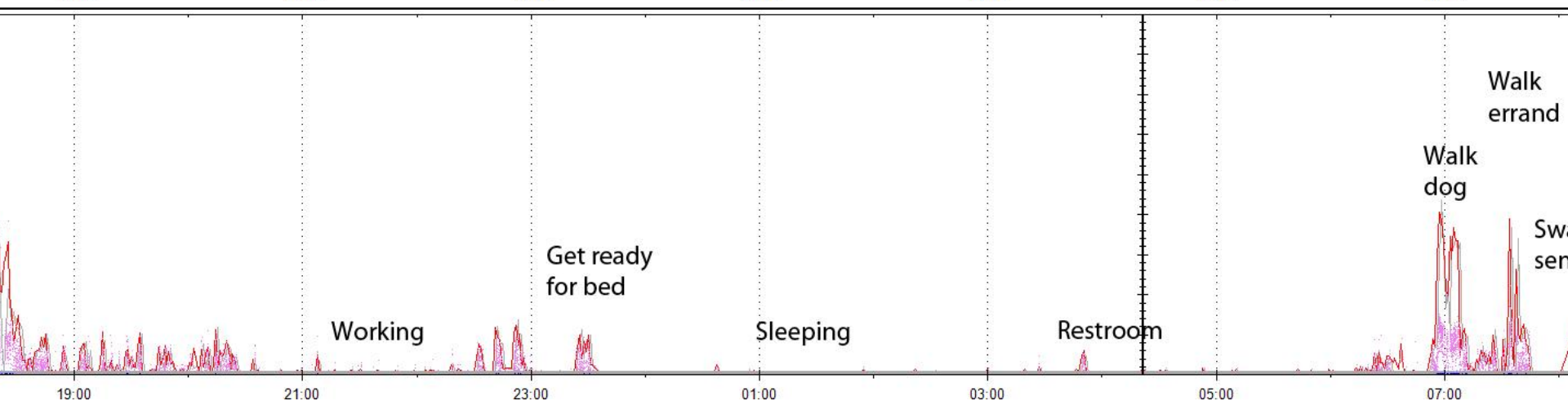
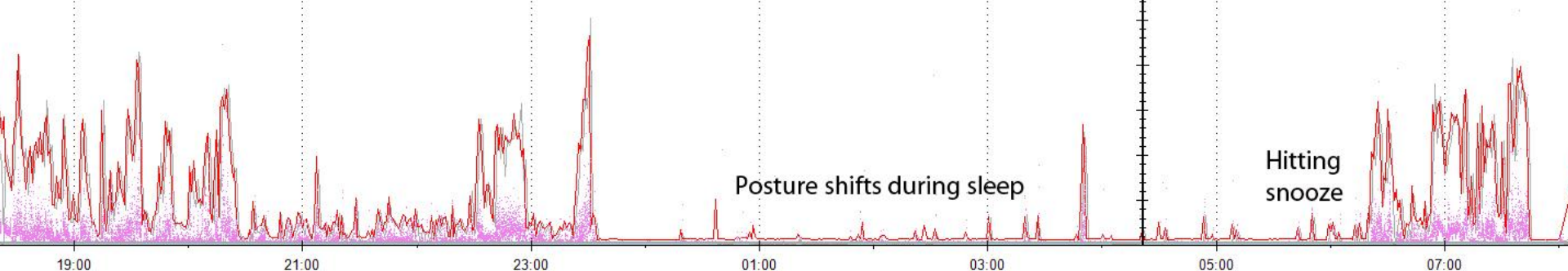
Thu eve



Evening

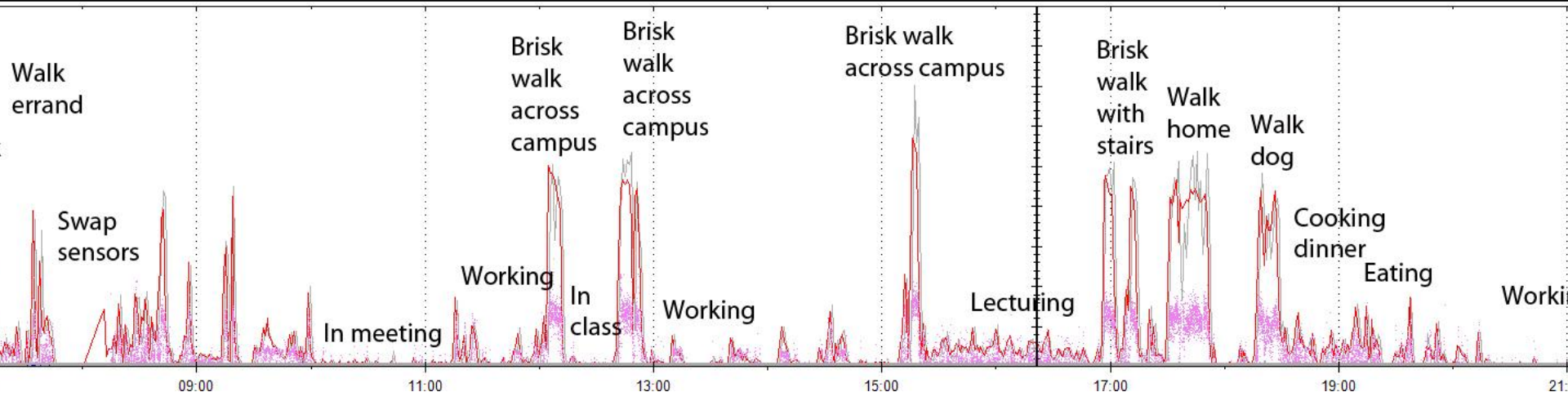
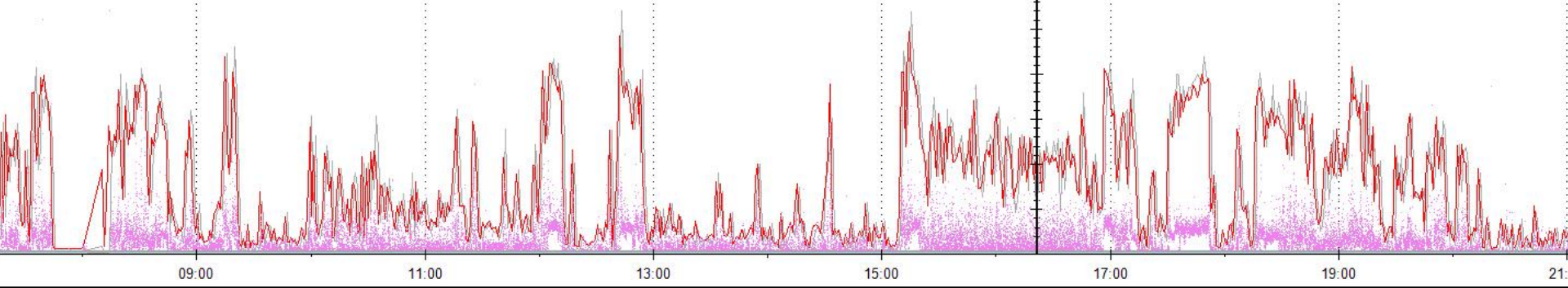
Thu night

Fri m



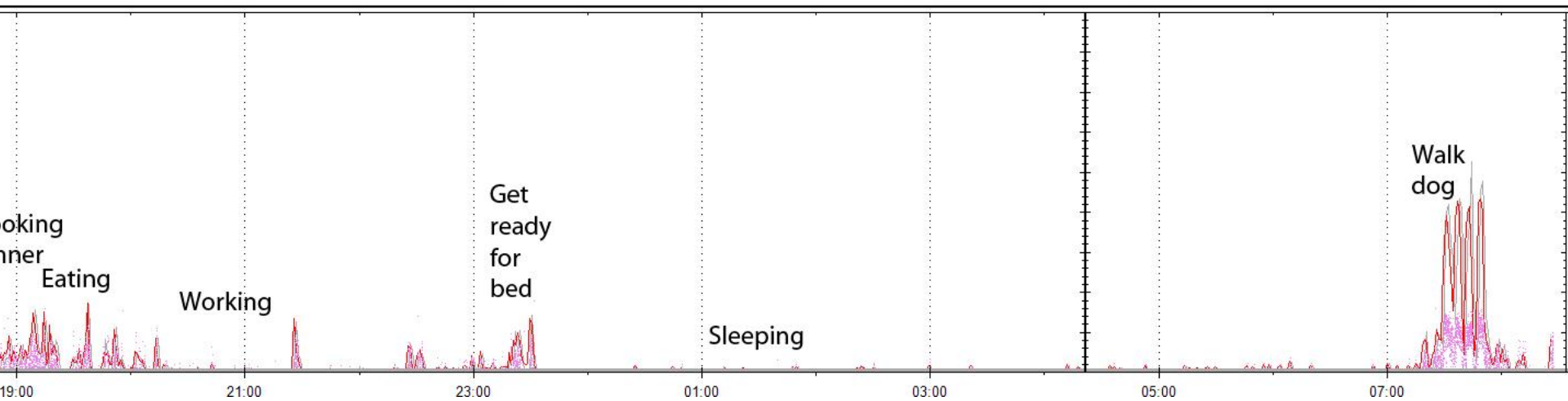
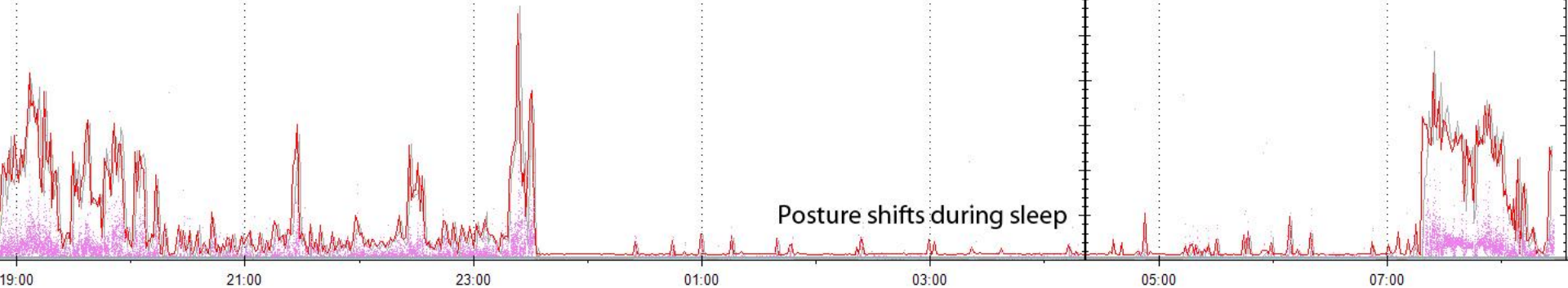
Fri morning

Fri evening

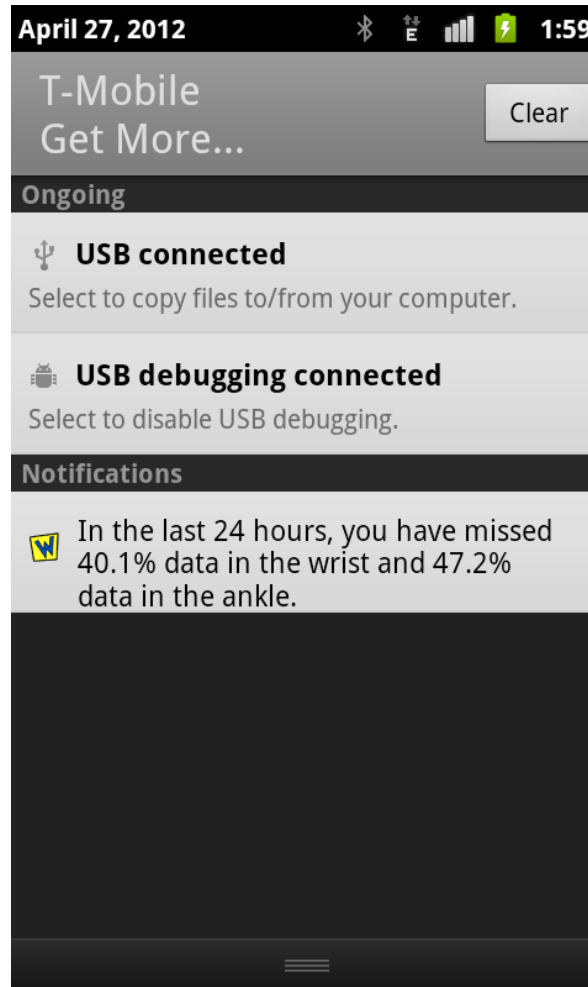
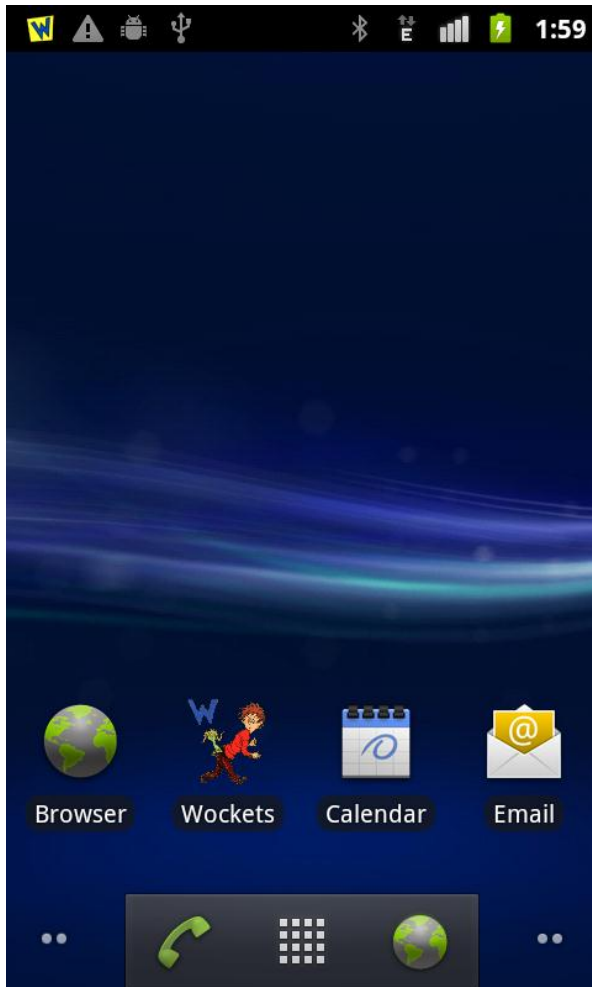


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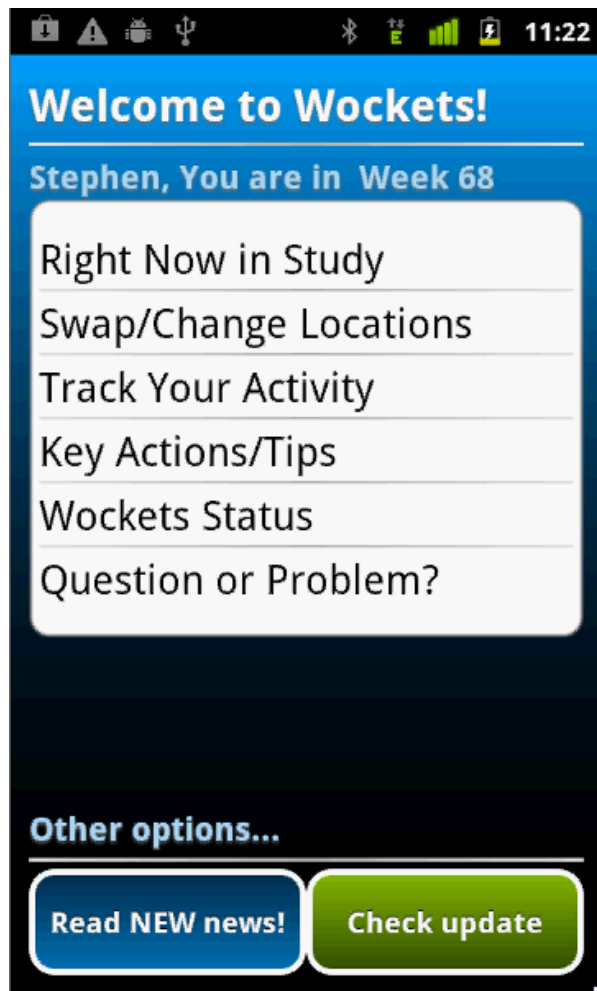
Fri night



Compliance feedback



Wockets self-report



You are viewing data for Thursday 21st of July 2011

Participants:

Intille, Stephen

July 2011							
wk	S	M	T	W	T	F	S
26	26	27	28	29	30	01	02
27	03	04	05	06	07	08	09
28	10	11	12	13	14	15	16
29	17	18	19	20	21	22	23
30	24	25	26	27	28	29	30
31	31	01	02	03	04	05	06

View By:

- Placement
- MAC Address

Show Options:

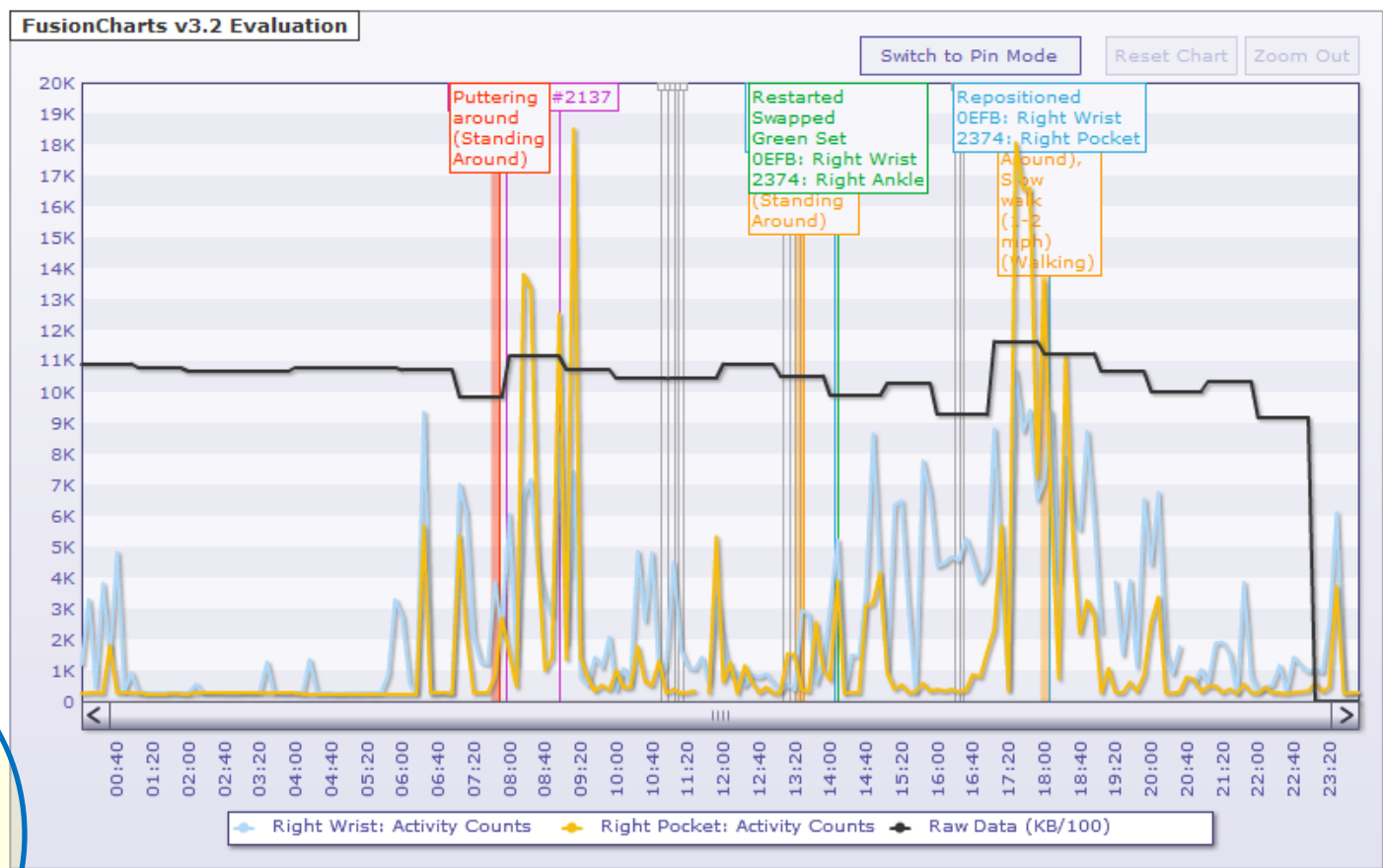
- Raw Data
- Bytes Sent
- Bytes Received
- Battery
- Phone Stats
- [Apply Settings](#)

SMS #2131

On Wednesday we recorded 99.7% of the data from your wrist sensor and 99.2% of the data from your ankle sensor.

SMS #2137

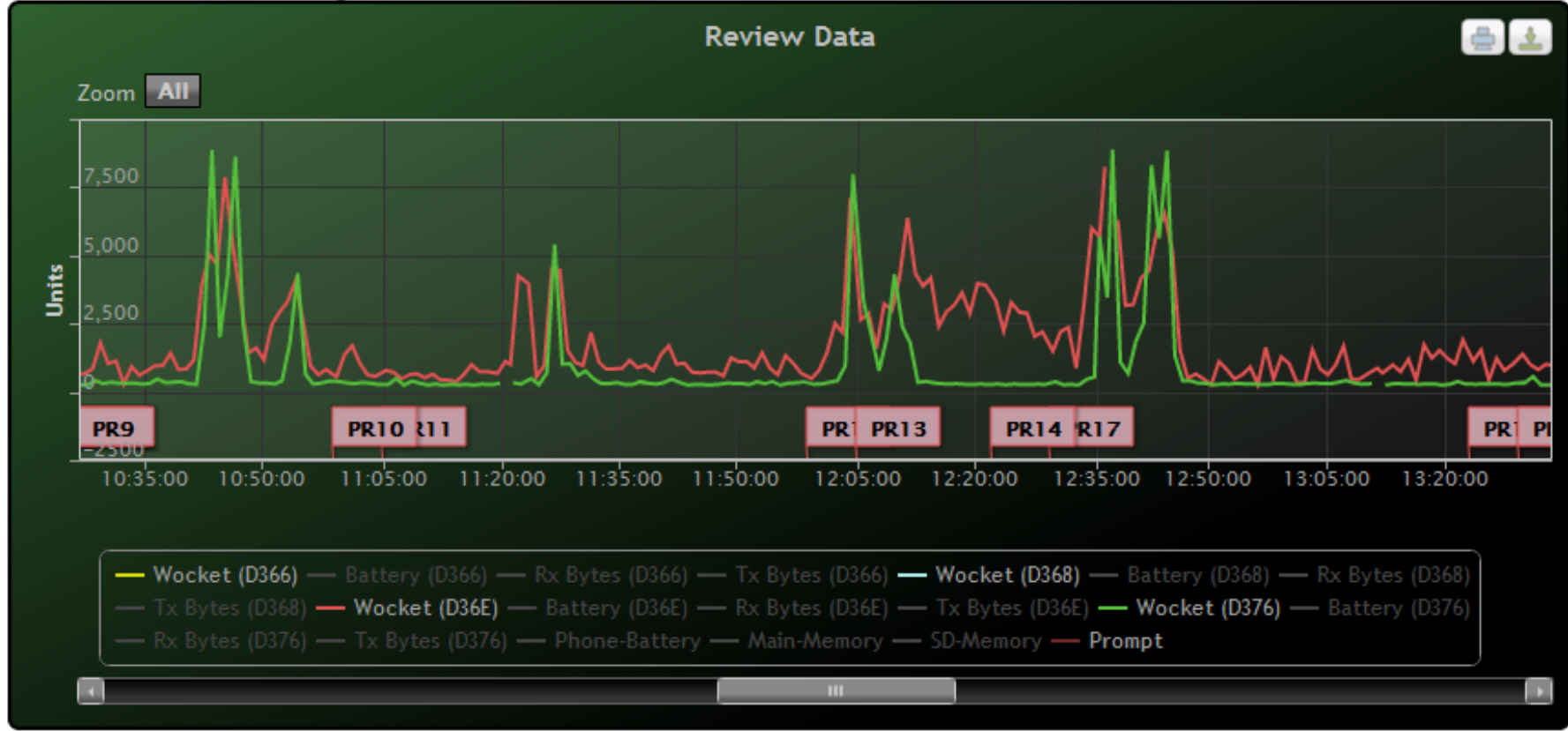
On Wednesday according to your ankle sensor: Sedentary 18 hours, Light activity 4 hours, Physically active 113 minutes.



Study Graph

Participant Id: 6810 Date: 2012-02-27

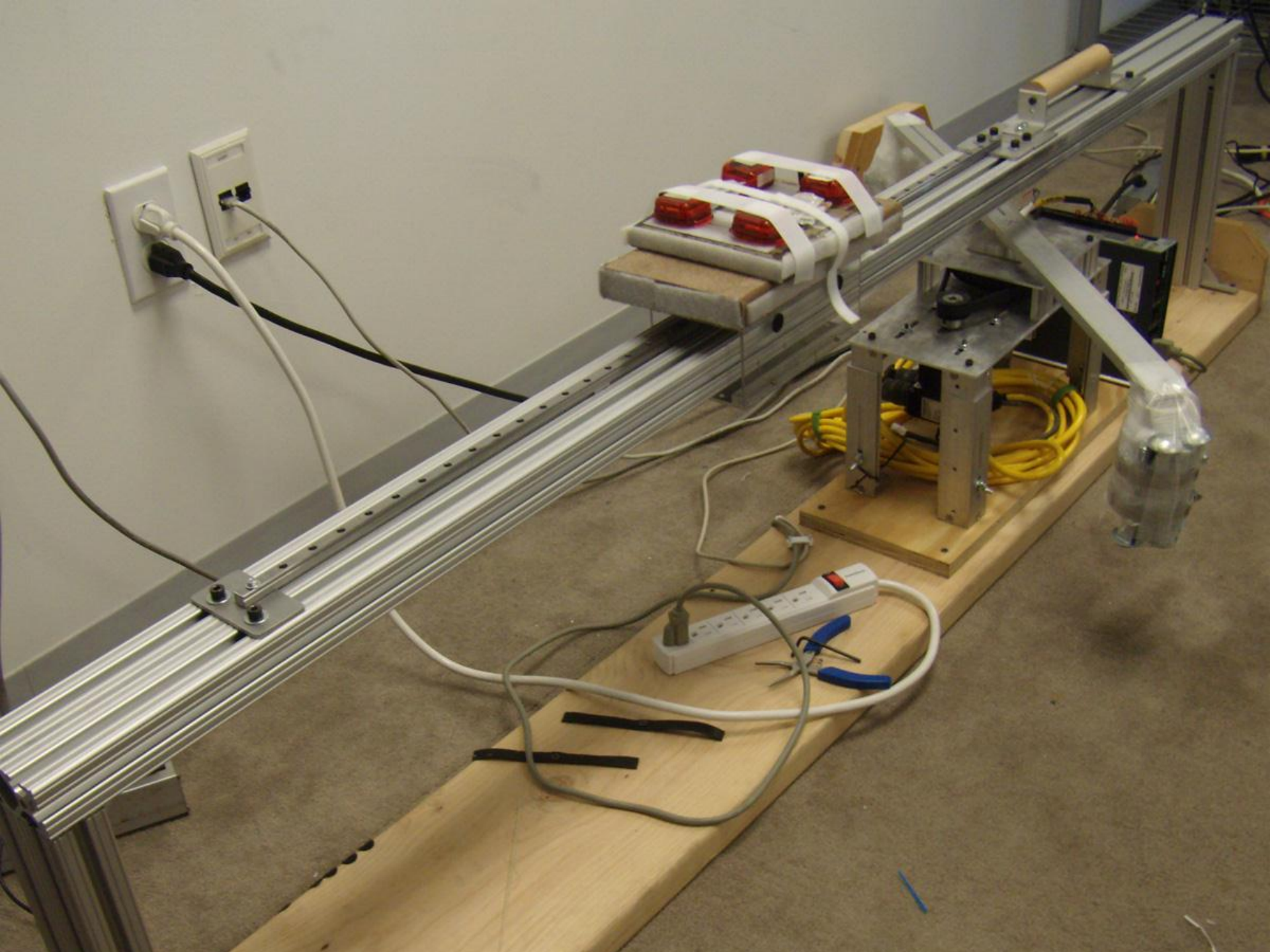
Enable Y-axis auto scaling



PR24
 Prompt-Type: Audible prompt (Ringer on vibrate - vibrate prompt)
 Prompt-Time: 2012-02-27 16:55:42.0
 Response-Time: null

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



Controlled data collection with Stanford collaborators



Oxycon mask

Oxycon harness

Polar strap

Zephyr bioharness

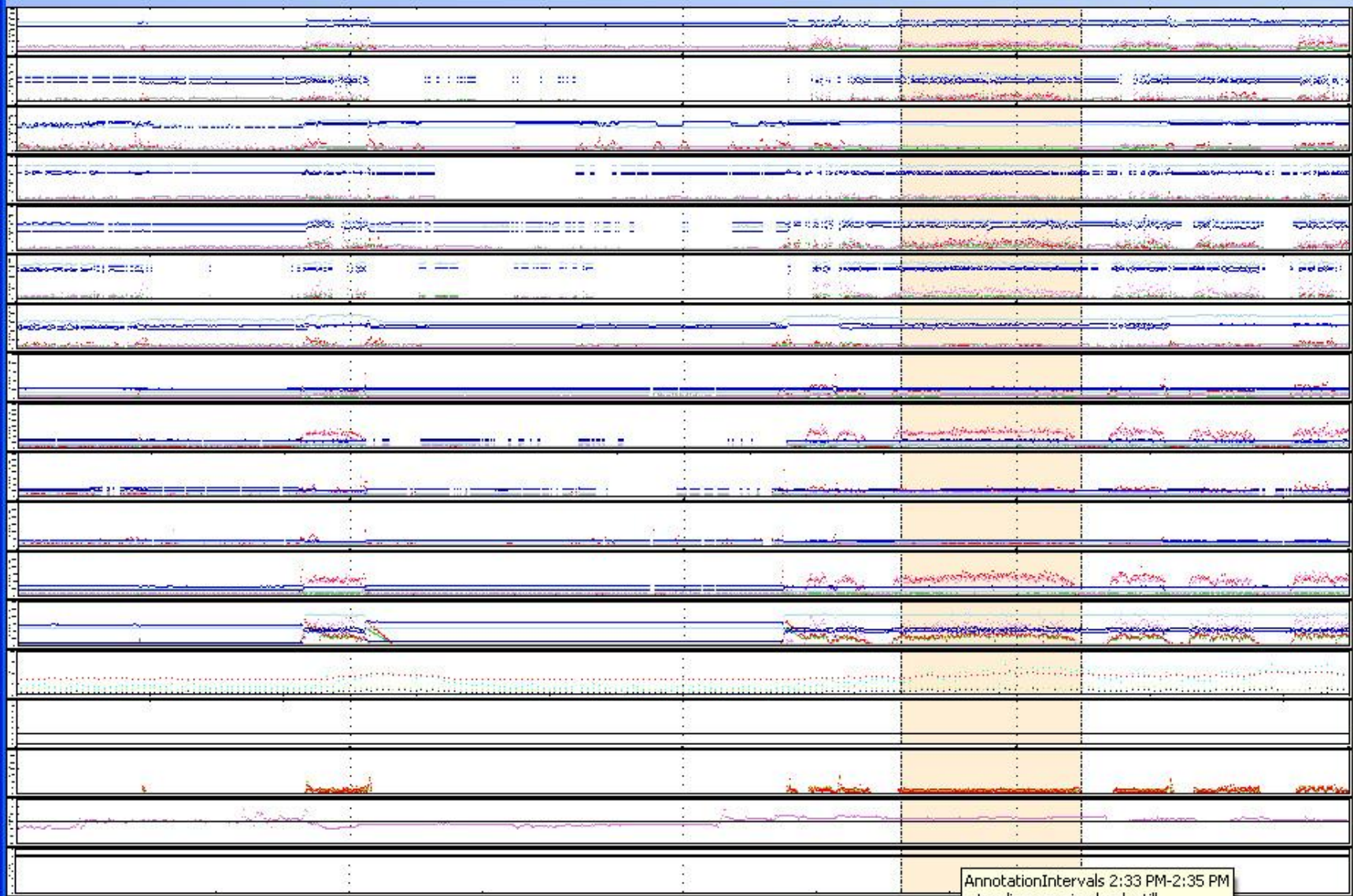
Actigraph

Multiple wireless accelerometers

Omron



File



- MITes 01
- MITes 04
- MITes 07
- MITes 08
- MITes 11
- MITes 14
- MITes 17
- Wocket 00
- Wocket 01
- Wocket 02
- Wocket 03
- Wocket 04
- Wocket 05
- Oxycon
- GPS
- Actigraphs
- Sensewear
- Heart Rate

2:20 PM-2:40 PM

AnnotationIntervals 2:33 PM-2:35 PM
 ,standing carrying load: still
 carrying load

View All

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

Lab validation experiments



- Lab
- Lab + some everyday activities
- “Obstacle course” datasets

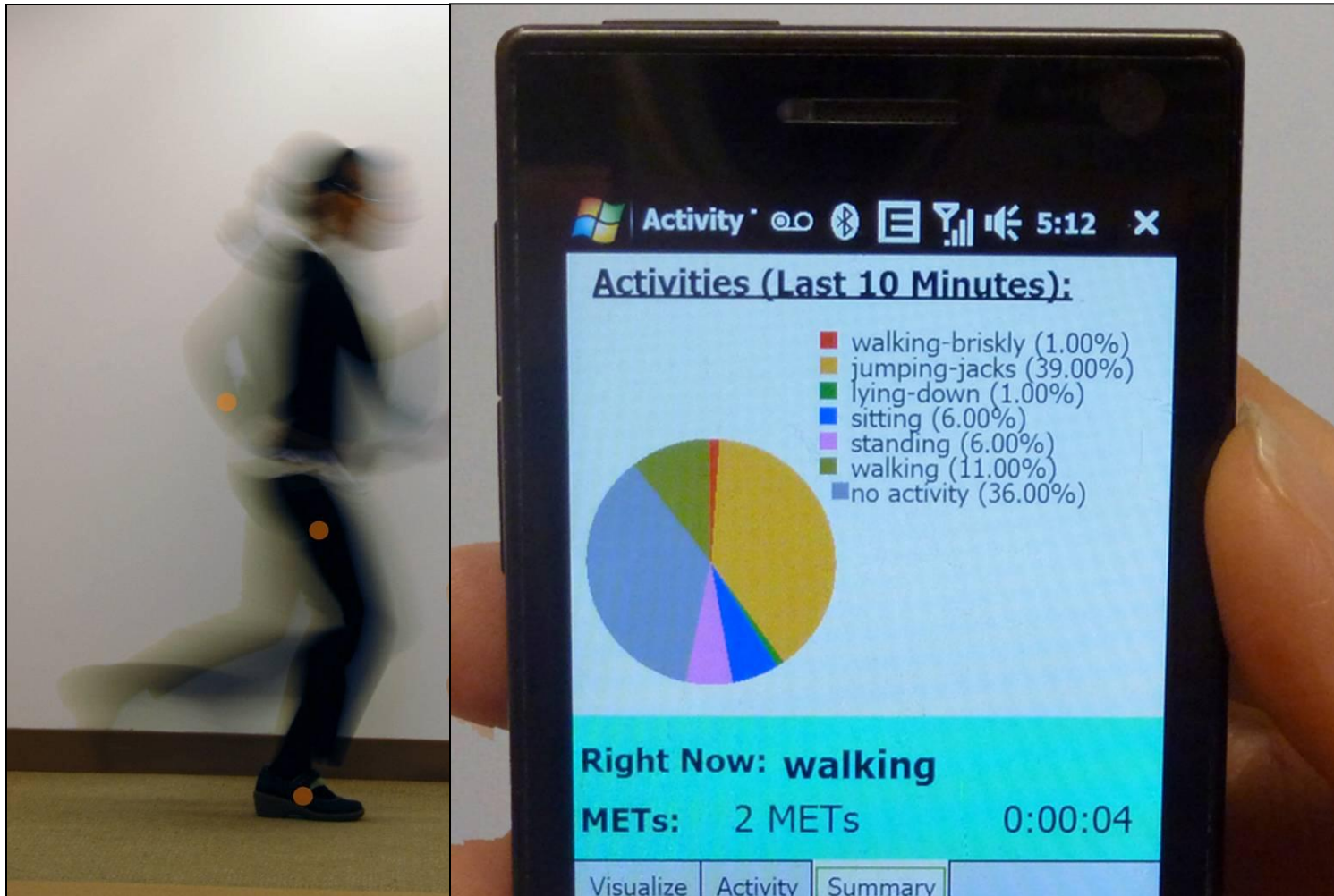
NHANES: hip to wrist and then ?

33 adults: Test wrist vs. ankle ambulation detection

	Wrist			Ankle		
	12.8 s	4 s	2 s	12.8 s	4 s	2 s
Overall accuracy (%)	84.7	84.2	82.8	95.0	94.6	93.8
Accuracy (ambulation)	87.2	87.4	87.1	99.5	99.1	98.8
Accuracy (cycling)	62.9	65.2	65.4	93.9	94.2	93.7
Accuracy (others)	81.6	77.0	72.6	81.6	78.7	76.7
Accuracy (sedentary)	91.2	90.6	88.9	96.0	96.1	95.3
F1-score (ambulation)	0.90	0.90	0.89	0.99	0.99	0.99
F1-score (cycling)	0.66	0.68	0.66	0.95	0.95	0.95
F1-score (others)	0.82	0.78	0.74	0.84	0.81	0.79
F1-score (sedentary)	0.88	0.87	0.86	0.95	0.95	0.94

Now: real-time implementation

Detect activity type in real-time



Open source/standards

- Open source
 - Access to hardware has been a barrier
 - Working to solve this
- Open standards
 - Collect/save raw data
 - Open algorithms
 - No proprietary “counts” to slow field

Wockets: last cost estimate

- In quantities of 100 (researchers build)
 - Wocket: \$63
 - Band: \$4.50
 - Charger: \$28
- System (without phone):
4 Wockets, 4 bands, charger: ≈\$298

(Single Actigraph GT3X: \$300+)

Are you scratching your head?

“Just a Bluetooth accelerometer”

“Why didn't you add a [pick a sensor]”

- Yes, but...
 - While each part is simple, the system is not; all design decisions are inter-related
 - Lab prototype is the easy part; robust deployment is the hard part!
 - Cost and field validation are key

Challenges we've had

- Bluetooth limitations on phones
- Avoiding feature/cost creep
- Thin+waterproof+inexpensive+low volume
- Battery life (on phones)
- Minimizing participant burden
- Remote data validation tools
- Robustness in all conditions

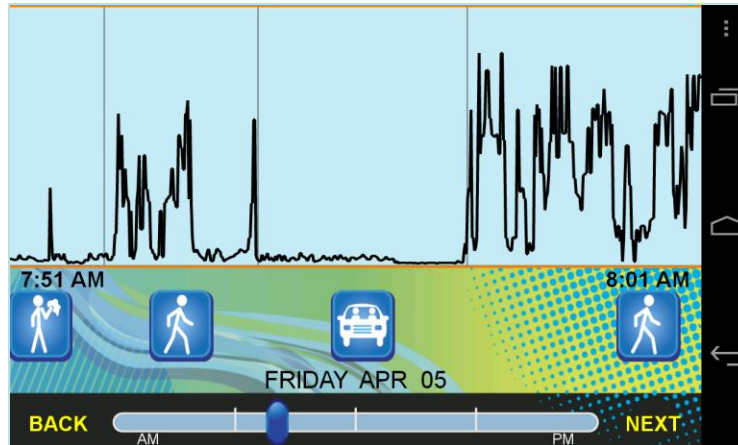
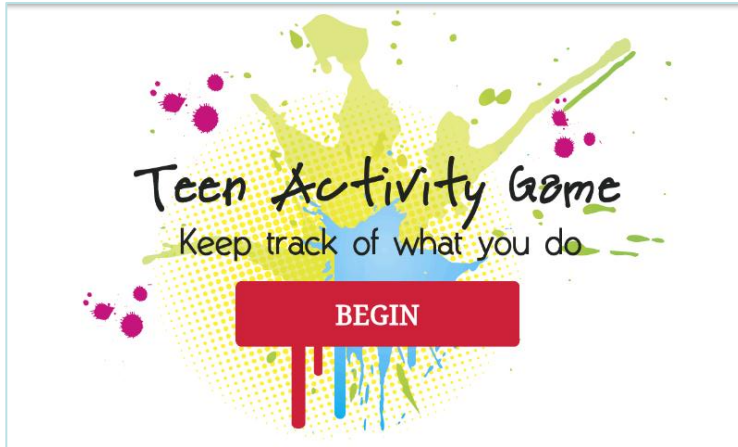
What health researchers say

- **Like** lower price than gold standard
- **Unsure** about new capabilities
 - Intrigued about improving what they measure
 - Uncertain about data-driven discovery and new information (“fishing expeditions”)
- **Dislike** higher risk
 - Require validation studies
 - Want comparison with common measures

Planned validation study

- 40 subjects (considered small)
- Wear Wockets system daily for 4 months
 - Use remote compliance monitoring tools
 - Gold standard comparison tricky
- Continue wearing Wockets (up to 4 mo)
 - No prompting from staff
 - Phone encourages compliance

Remember: need self-report!



- Use Wockets and/or phone's internal motion sensor to "chunk" day
- Data provide memory cues
- Easy to fill in gaps with precise timing

Teen activity measurement
with Genevieve Dunton at USC

So what's coming?

- Using a variety of “sensors” ...
 - Phone
 - Wearable
 - In-home
 - Data from environmental computers/systems
 - Sustainable, well-timed self-report questions
- Computer will incrementally build a rich, real-time model of behavior that enables better science and new interventions

Take away

- Mobile devices with real-time feedback create novel (and engaging?) behavioral **measurement** and **intervention** options that *can't be achieved without the technology*
- ***Just-in-time* delivery of tailored questions (CS-EMA)** may be important for behavior measurement/understanding
- New opportunities for how we do research being created

More info

- <http://mhealth.ccs.neu.edu>
- s.intille@neu.edu

Check out Northeastern's new
transdisciplinary Ph.D. in Personal Health
Informatics! (recruiting students/faculty)

<http://phi.neu.edu>