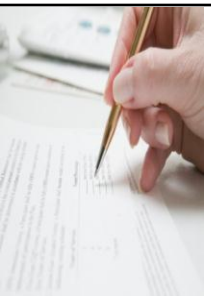

Measurement of Physical Activity Behavior

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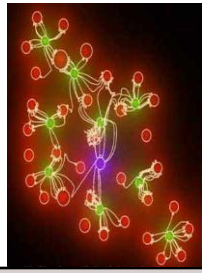
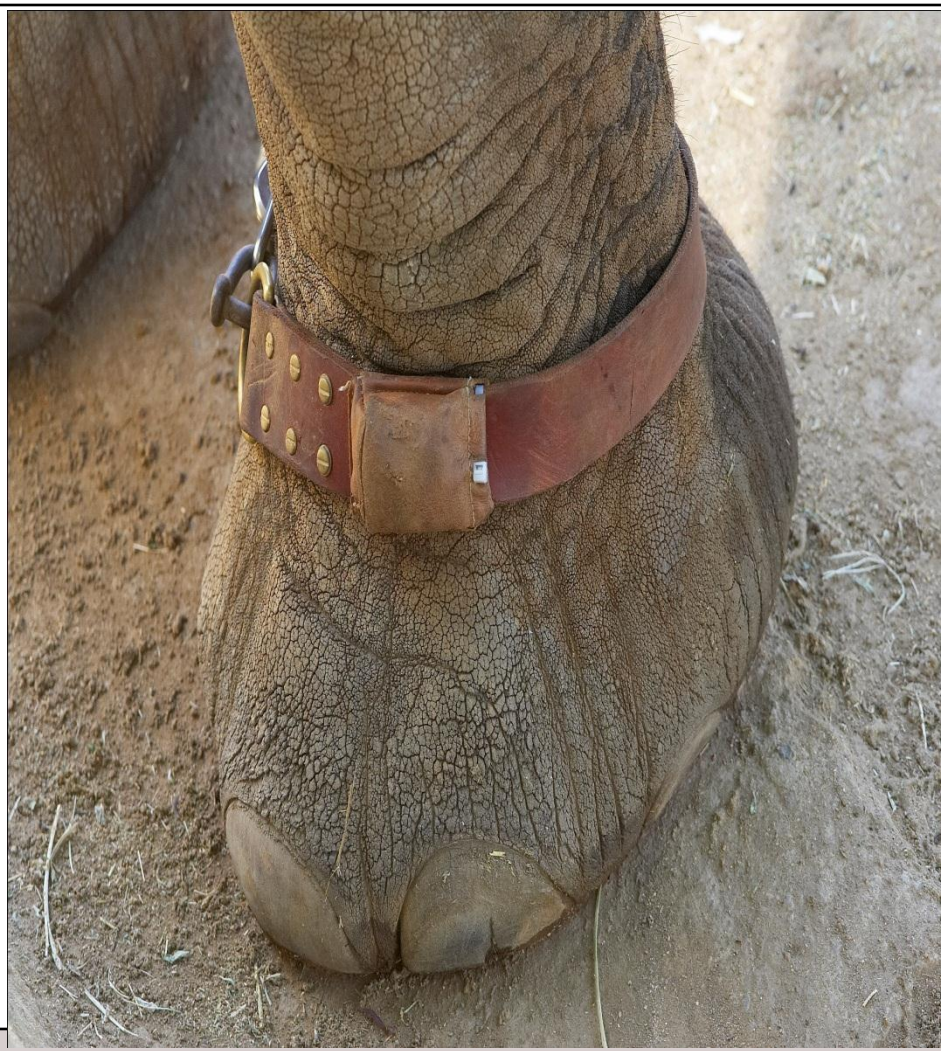
University of Massachusetts Amherst
School of Public Health and Health Sciences
Department of Kinesiology

Physical Activity and Disease Prevention: Identifying Research Priorities
Dec 13-14, 2012





Outline

- Current methods to assess physical activity and sedentary behavior
  - Self-report
  - Wearable sensors
- Calibration and validation of methods
  - Laboratory
  - Natural settings
- GIS/GPS
- Consumer devices
- Future research needs

Self- report

- Many different self report tools
- How tool is to be used should determine choice of self report

Strengths

- Low cost
- 'Easy to administer'
- Can assess context
- Can assess history
- Low burden to participant
- Most practical for surveillance research

Weaknesses

- Measurement error/recall bias
- May not assess one or more dimensions of behavior
- May also miss certain activities
- Lack of validation for assessment of change in behavior following interventions
- Many types of self report – lack of standards to match need with appropriate tool

Types of self-report tools

Table 1 Traditional Categorization of Approaches to Self-Reported Physical Activity

Category	Level of detail	Time frame	Common uses
Diaries	High: recording of duration of all activities, sedentary behaviors, and sleep throughout a 24-hour period	Real time, often maintained for several days or a week	Validation of less burdensome measurement approaches
Logs	High: recording of requested details of specific activities of interest	Real time, past day, may be maintained for many weeks	Adherence to interventions
Recalls	Medium: recall of varying levels of detail (duration, frequency, intensity) of specific activities or categories of activities	Past 24 hours, past 7 days	Effects of interventions, assessment of current activity
Quantitative questionnaires	Medium: estimate varying levels of detail (duration, frequency, intensity) of specific activities or categories of activities	Usual week, past month, past year, lifetime	Assessment of longer-term activity, usual activity
Global surveys	Low: general categorization of activity level	Current, not specified	Ranking of usual activity

Sternfeld and Goldman-Rosas, *JPAH*, 2012 (suppl.)

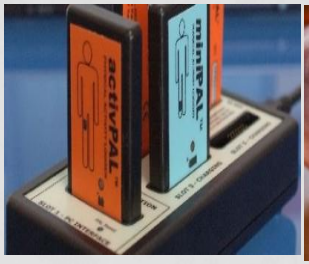
Primary concerns

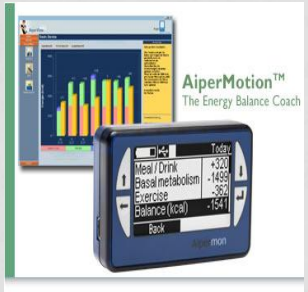
- Not matching aims of study with appropriate self report instrument
- Lack of broad acceptance of use of measurement error models to 'correct' activity misclassification from self report tools
- Uncertainty about validity of self report tools to assess behavior change
- Missing certain behaviors for certain populations

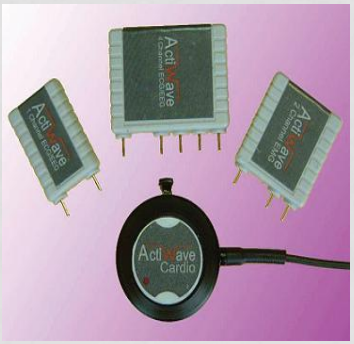
Finally, there is no need to be apologetic about assessing PA or SB with self-report. The self-reported methods are not "second choice" methods when so-called objective methods cannot be used. Rather, they are valid methods in their own right and the optimal choice in certain circumstances.

Sternfeld and Goldman-Rosas, *JPAH*, 2012 (suppl.)

Wearable Sensors







PHYSICAL ACTIVITY AND HEALTH LAB

Strengths

- Objective measure
- Assess behavior continuously over extended periods of time
- Obtain estimates of multiple measures (e.g. kcals, minutes, MET hrs, breaks from sitting, bouts of activity or inactivity)
- Provide real-time feed-back to users or researchers
- Adaptable to mobile technology

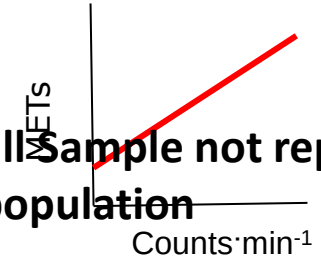
Weaknesses

- Lack of standards of practice
  - Placement of sensors
  - Sampling frequency
  - Defining wear time
  - Defining 'valid day'
- Different devices
- Different algorithms for translating output
- Compliance by user
- Data management/processing
  - Validity in natural settings

Early results of wearable monitor calibration/validation

- **Freedson et al. 1998**

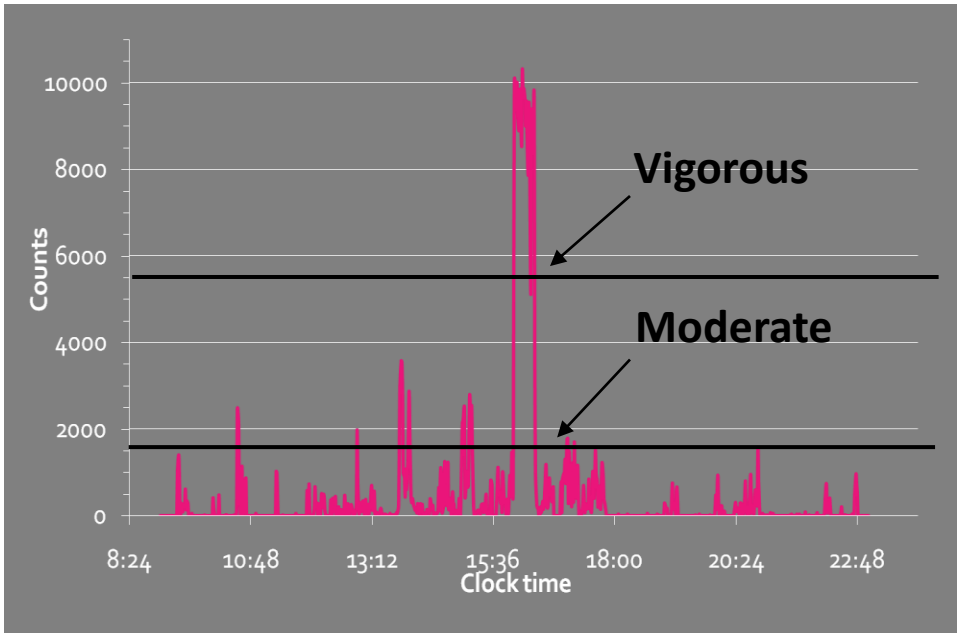
$y = m(\text{counts}\cdot\text{min}^{-1}) + b$



- Small Sample not representative of the population
- Only 3 treadmill activities

1. Point Estimates of Energy Expenditure (EE)
2. Cut-Point Method
   - Determine time spent in light, moderate or vigorous intensity activity

Cut-Point Method



Over 30 Prediction Models

Puyau et al. 2004

RT3 Proprietary

Heil et al. 2006

Hendelman et al. 2000

Brooks et al. 2005

RT3 Proprietary

Chen et al. 1996

Klippel et al. 2003

Crouter et al 2007

Treuth et al. 2001

Freedson et al. 2005

hols et al. 2000

Leenders et al. 2003

Eston et al.

Crouter et al 2005

Heil et al 2003

Puyau et al. 2004

Klippel et al. 2003

Trost et al. 2006

Yngve et al. 2003

Evenson et al. 2008

Yngve et al. 2003

Brooks et al. 2005

Brooks et al. 2005

Hendelman et al. 2000

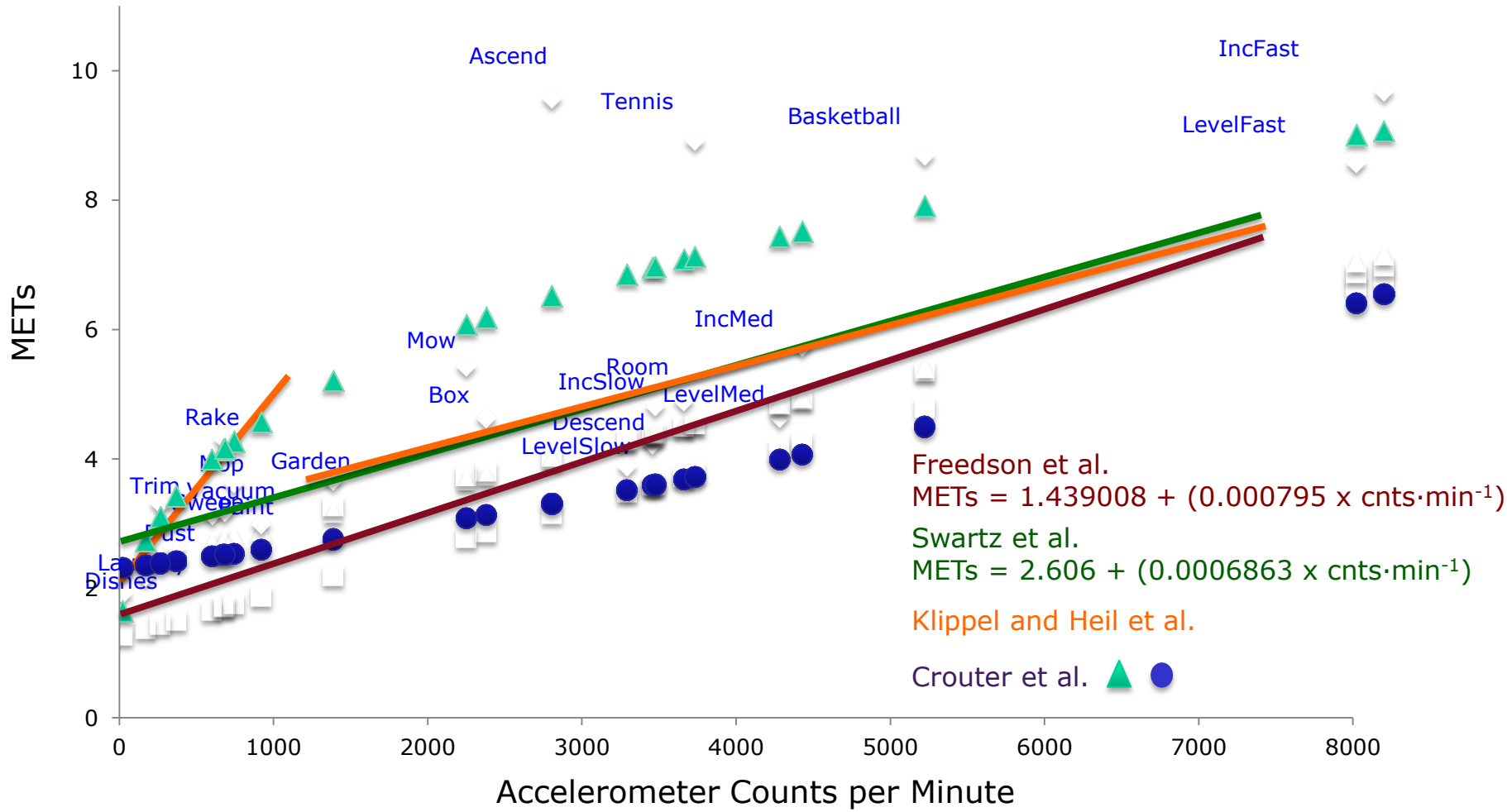
Swartz et al. 2000

AW-2, AW-Spectrum, AW-Score

Heil et al. 2006

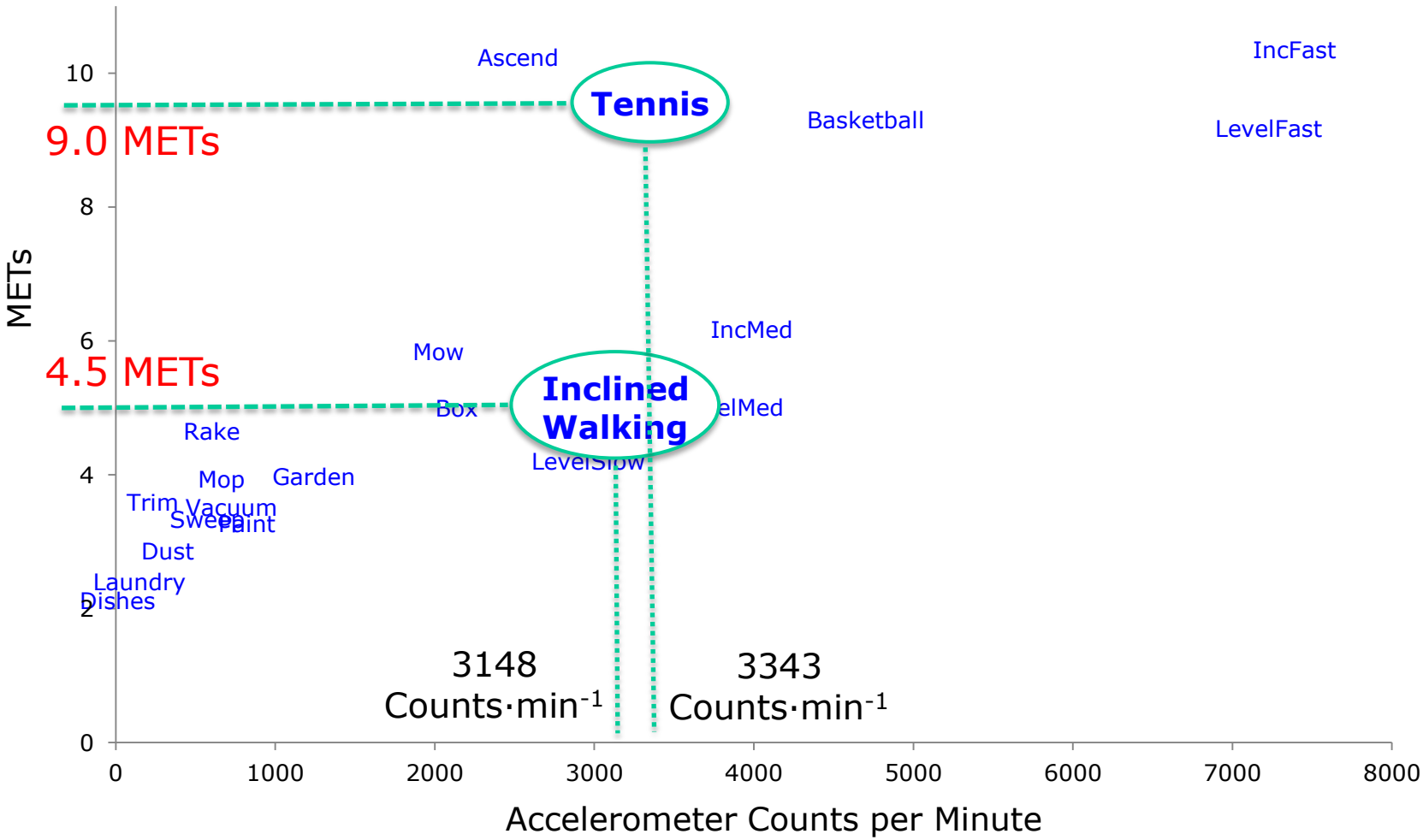
Heil et al. 2006

Simple, rigid relationship between counts and EE



Kozey et al. *J Phys Act Health*, 2010

Using counts.min^{-1} as the regression input ignores valuable information from the acceleration signal

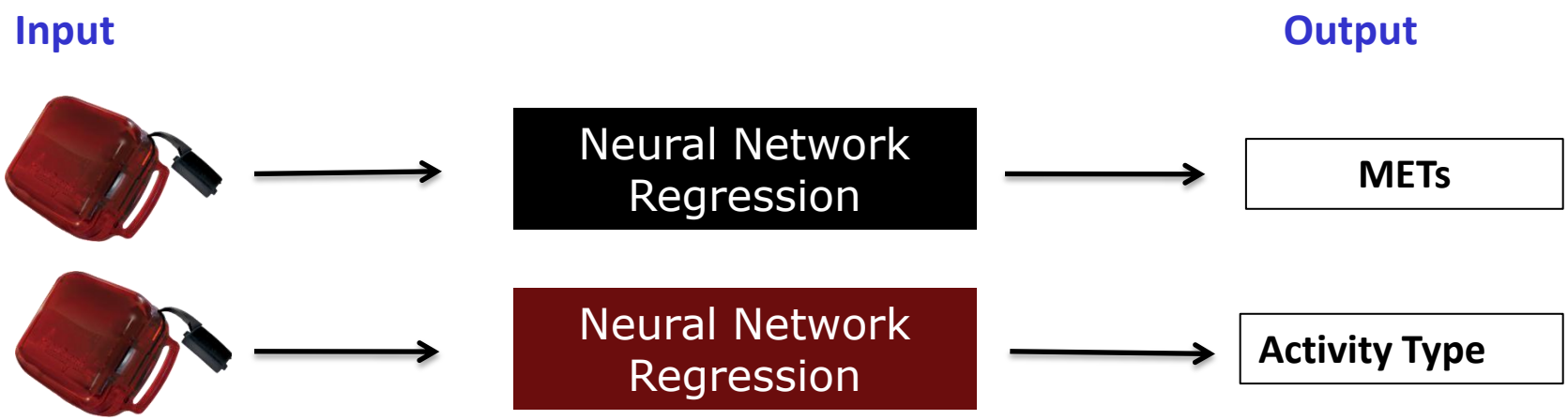


Artificial Neural Network

- **Artificial Neural Network (ANN) – Non-linear statistical modeling tools**
  - **Very sophisticated, adaptive modeling technique that can change its structure based on internal and external information**
  - **Two step process**
    1. **Using representative data, invokes training algorithms to learn structure of data**
    2. **After "training phase" ANN can be applied to independent data sets to predict the output from known inputs**
  - **Often used in prediction and classification models**
    - **Predict medical condition**
    - **Stock market prediction**

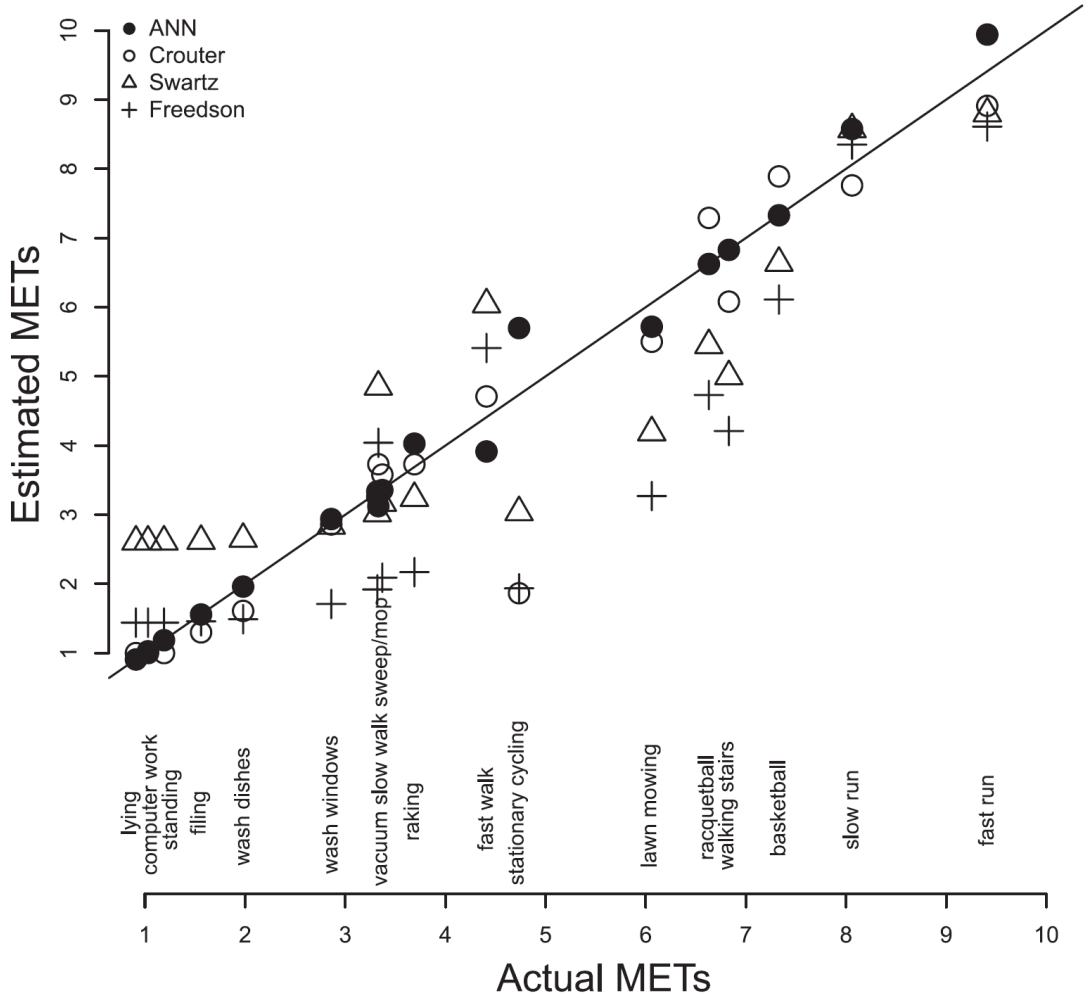
ANN Development

- Staudenmeyer et al. (2009)



- 48 subjects – variety of household and sporting activities
- Indirect calorimetry – measure energy expenditure for each person and activity
- Model Development – Leave 1 out cross validation
  - Never fit and evaluated on same subject's data

ANN vs. Simple Regression

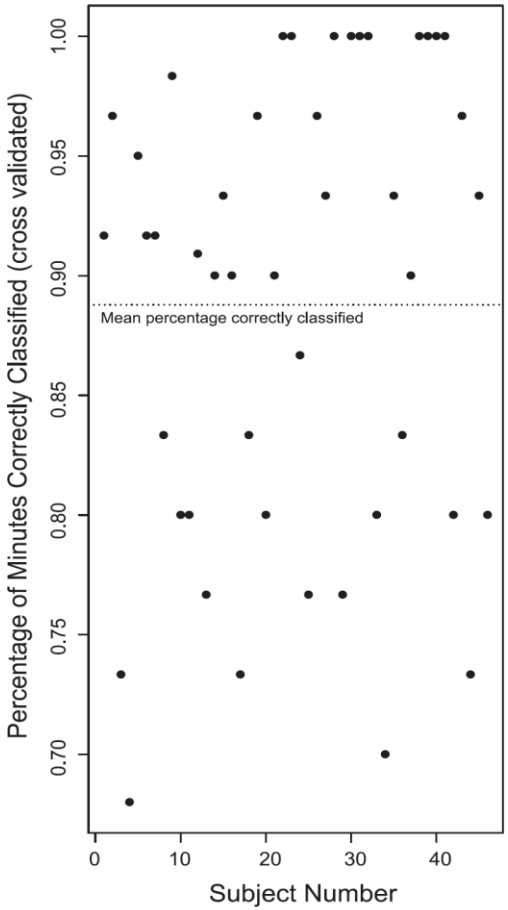


Model	rMSE (METs)
ANN ●	1.22
Crouter ○	1.61
Swartz △	1.77
Freedson +	2.09

Staudenmeyer et al. *J Appl Physiol*, 2009

Identification of Activity Type

- **Average time correctly identified; 88.8% (95% CI: 86.4-91.2%)**
  - **Sedentary, Locomotion, Lifestyle (ADL) or Vigorous Sport**
- **Several subjects with 100% correct classification**



Staudenmeyer et al. *J Appl Physiol*, 2009

How does the neural network perform on independent dataset with different activities?

Neural Network: Laboratory Calibration and Validation

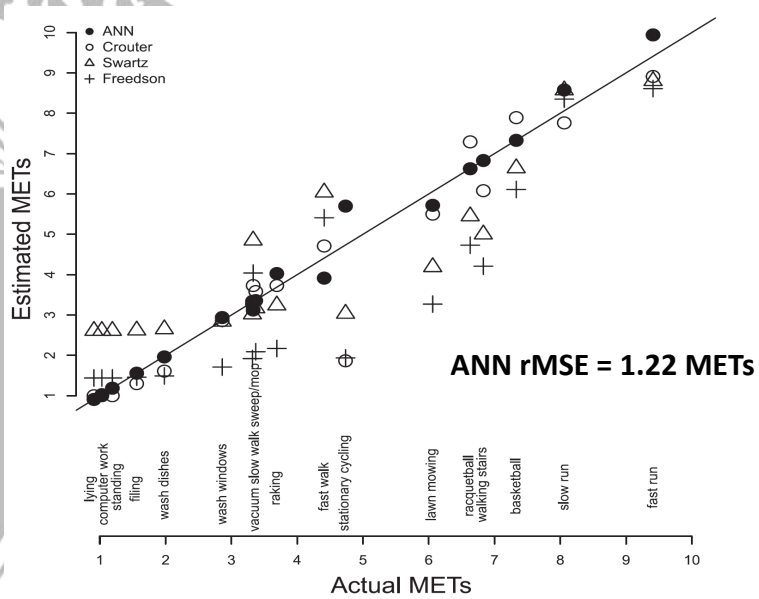
Input

1. **Temporal Dynamics**
2. **Distribution of Counts**

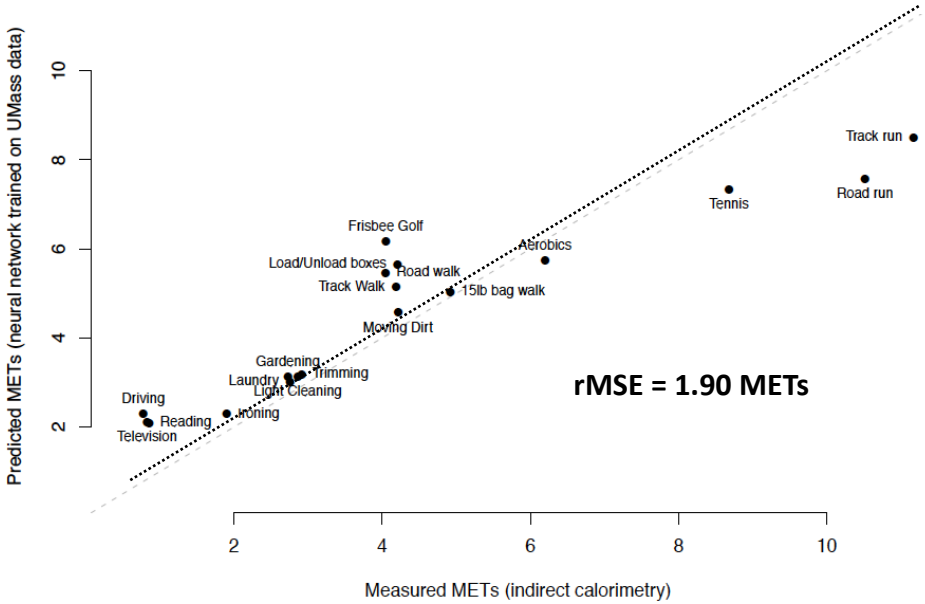
→ Lab-Nnet →

Output

METs



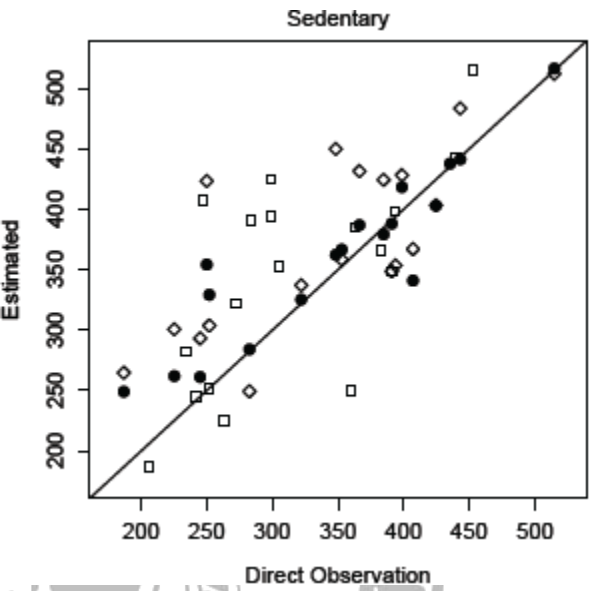
Staudenmayer et al. *JAP*, 2009

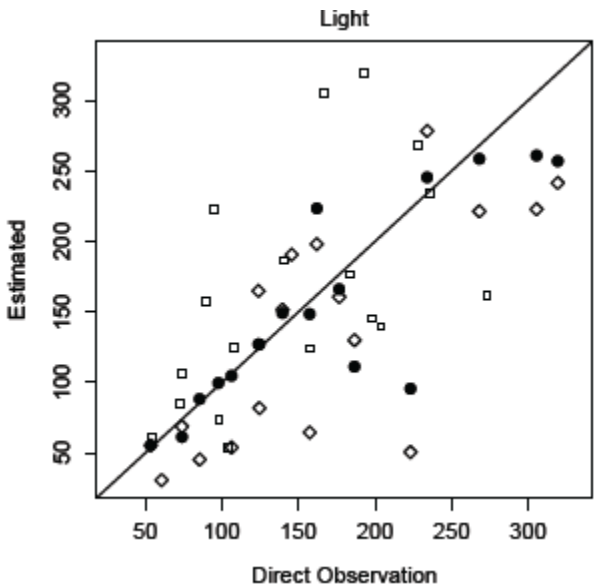


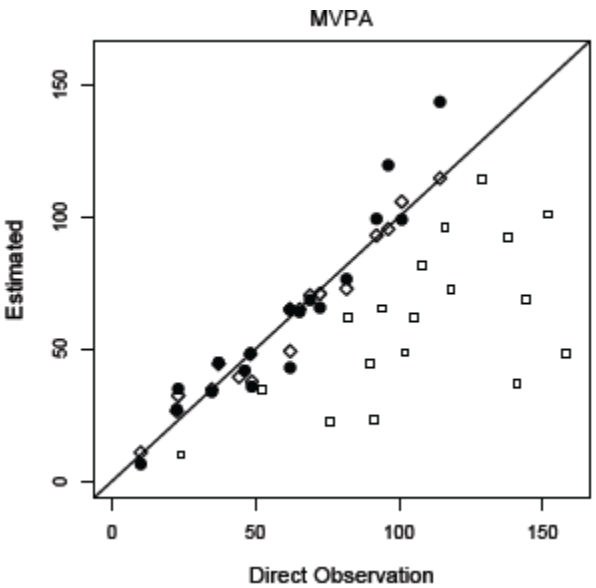
Freedson et al. *JAP*, 2011

Application of ANN in natural settings

- ANN developed and validated in lab did not work well in natural conditions
- Developed 'sojourn' method
  - Decision tree before applying ANN
    - One of 5 signal patterns
  - Then apply ANN
- N = 13
  - Trained on n = 6 (3, 10 hr observations)
  - Validated on 18, 10 hr observations





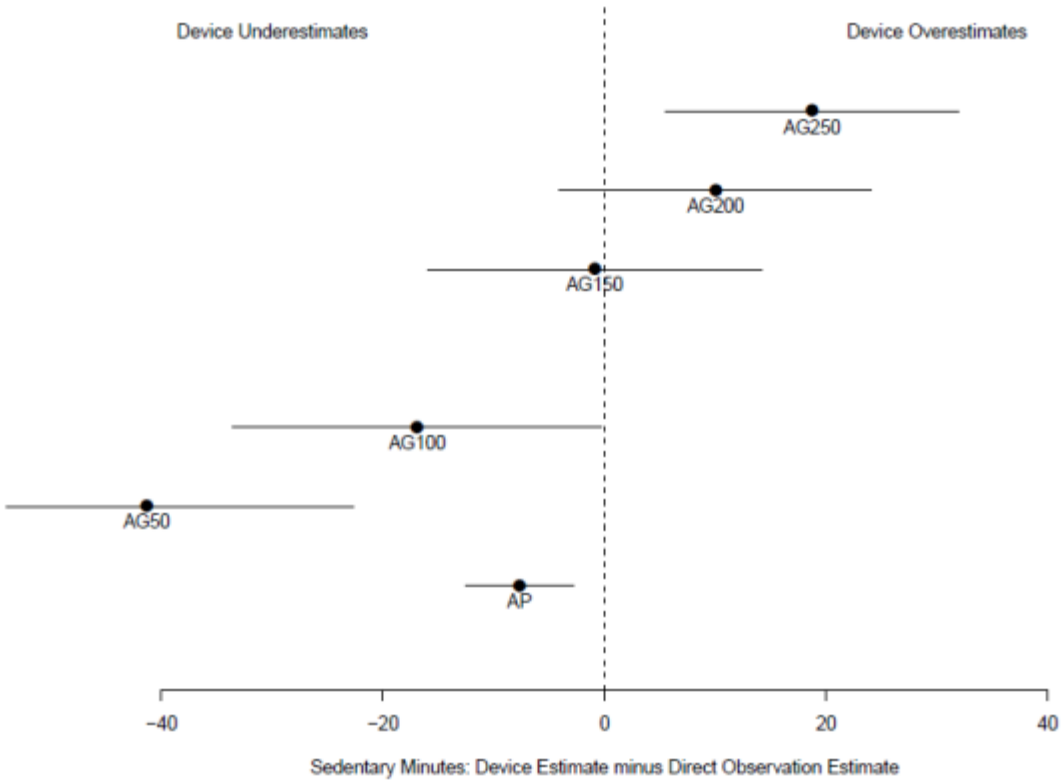


Lyden et al, unpublished data

Wearable Monitors to Assess Sedentary Behavior

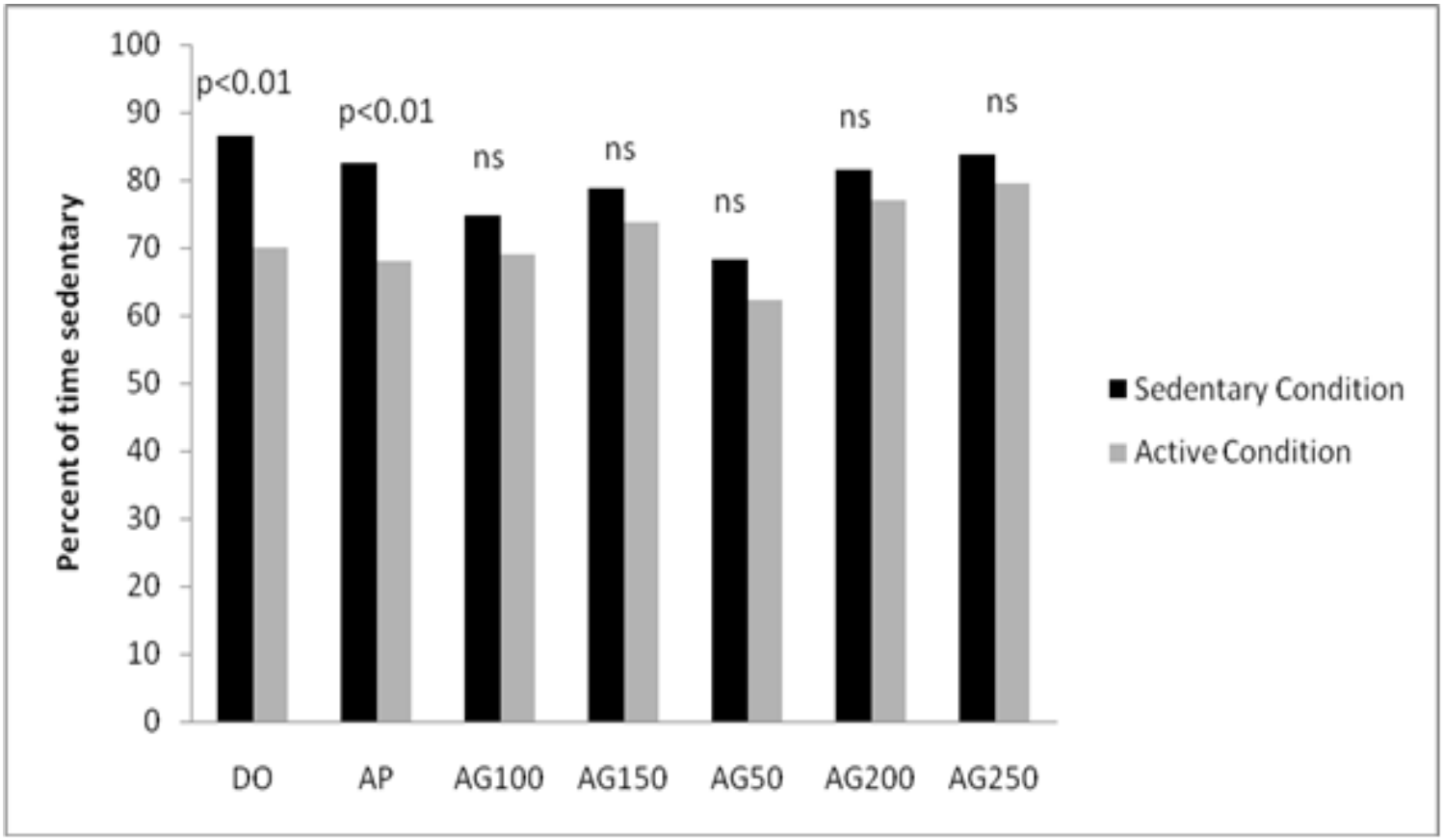
- Actigraph accelerometers secured to waist to assess physical activity
- Pedometer secured to waist to assess physical activity
- ActivPAL secured to thigh to assess sedentary behavior
- Natural setting
- Direct observation as criterion

Sedentary Minutes for ActivPAL and Actigraph in Comparison to Direct Observation



Kozey-Keadle et al., *MSSE*, 2011

Detection of change in percent time sedentary



Kozey-Keadle et al., *MSSE,* 2011

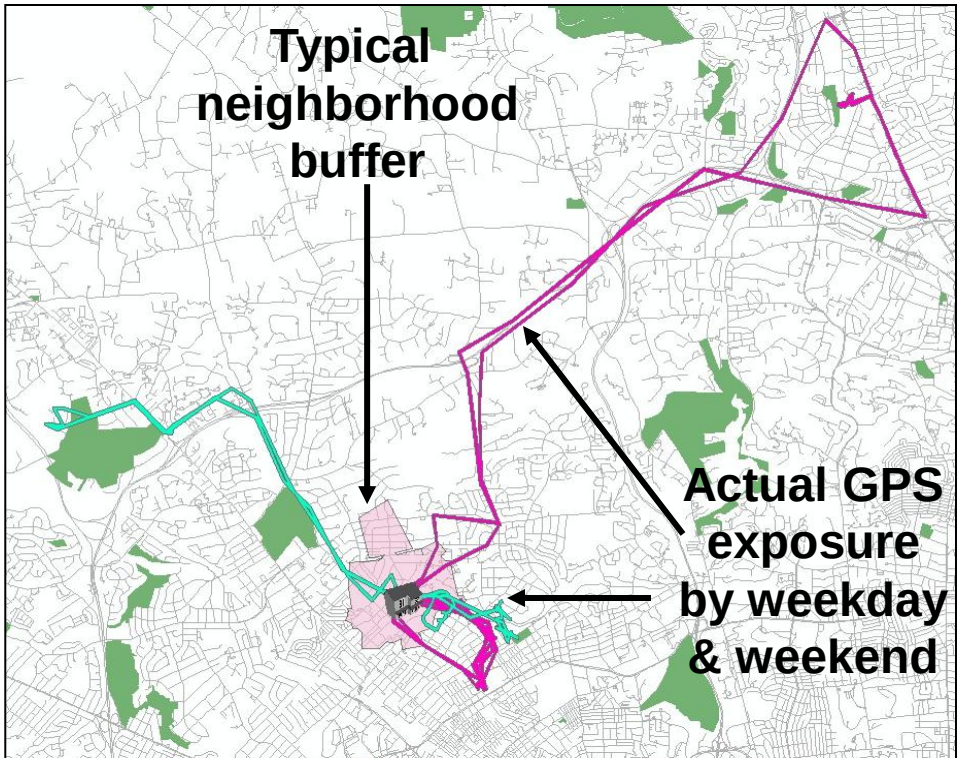
GIS/GPS Tools

Why measure **where** PA occurs?

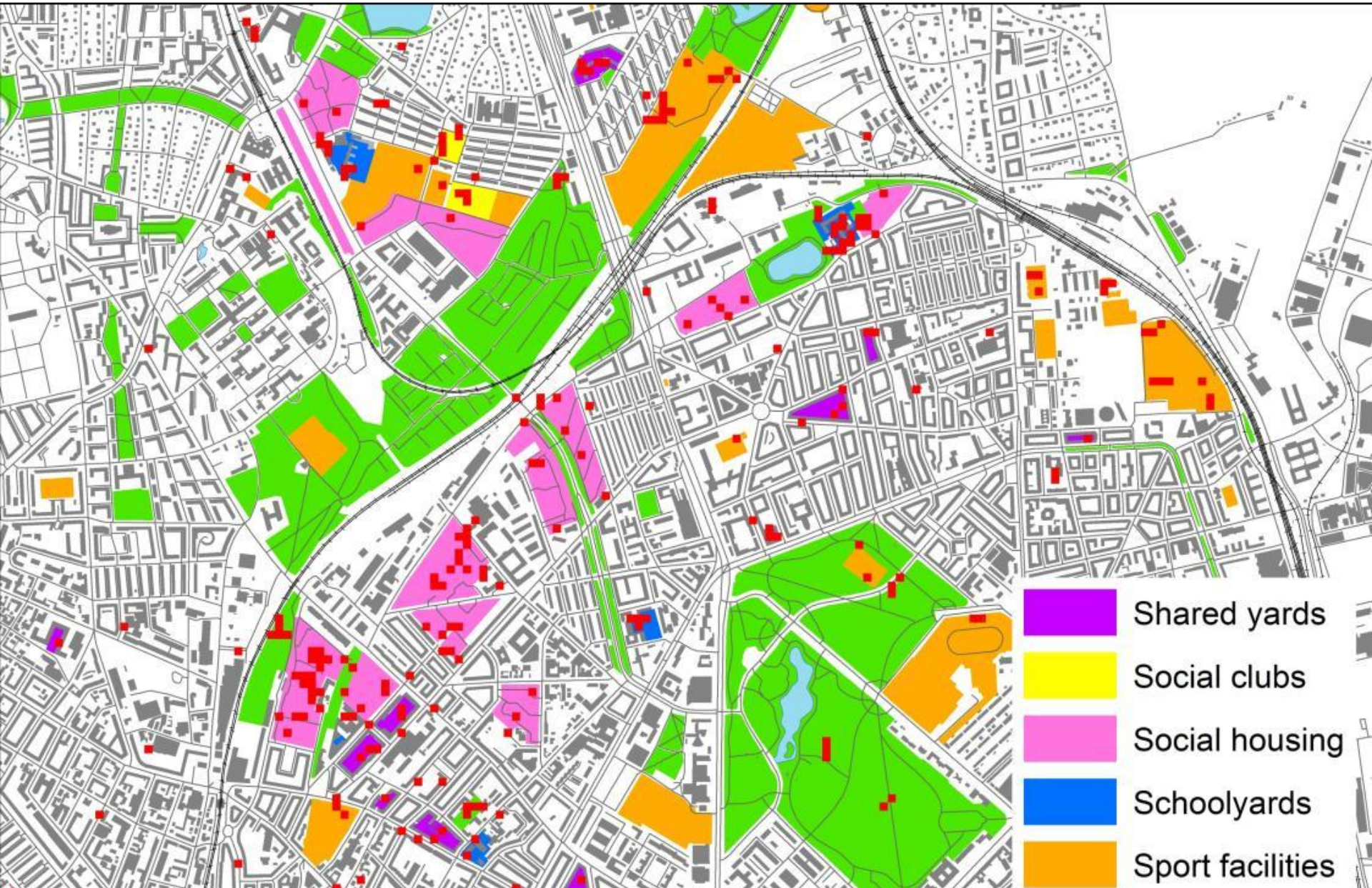
- Knowing where PA occurs is important to understand
  - What PA resources are being used?
  - What PA resources are needed where?
  - What disparities exist in use/need?
  - Does use of resources change with interventions?

How to measure **where** PA occurs?

- GPS devices matched with accelerometer data can indicate where PA occurs
  - Early studies have shown much PA occurs outside of our home neighborhood
- Programs like PALMS exist to help match GPS and accelerometer data
- Data are still messy & hard to aggregate into meaningful variables
- Need GIS expertise



A study in Denmark in teens demonstrated most PA occurs in shared yards



GPS can also improve PA measures

- If we invest in transportation infrastructure improvements e.g. bike lanes, sidewalks
  - We need to measure whether people use these new facilities
  - We need to better measure increases in biking, walking, and decreases in car driving due to these facilities
    - Laboratory studies don’t help us much with these free living behaviors
- Combining features of the GPS e.g. speed, satellite connectivity etc. can improve our assessment of biking, driving, walking.

UCSD TREC findings using Machine Learning, GPS, & accelerometer 92% accuracy in predicting transportation mode

		Predicted					
		Bike	**Bus**	**Car**	**Sit**	**Stand**	**Walk**
Known	**Bike**	**140**	0	0	1	4	0
	Bus	2	**86**	25	5	0	0
	Car	1	5	**364**	4	5	0
	Sit	0	0	5	**126**	17	0
	Stand	1	1	3	4	**243**	7
	Walk	3	1	1	0	15	**466**

SenseCam for more specificity?

- As GPS increases our accuracy in locating activities, we also see deficiencies in the GIS data available.
- SenseCam images

can provide more

detail of where specific

behaviors occur.

- Specificity will help

with intervention design

Summary

- GPS Pros
  - Accurate information on location (devices improving constantly)
  - GPS data can help predict key transportation behaviors
  - Knowledge in this area is growing & efforts at standardization being made (e.g. PALMS)
  - Participant compliance fairly high
- GPS Cons
  - Data requires smoothing
  - Algorithms to identify behaviors are complex & not available to everyone
  - GIS expertise required to map locations and match resources
    - GIS data may not match resolution of GPS data

Run to Golden Gate Bridge
started at 7:27 AM for 29 mins
25:20
0:40
3:39
7:27 AM
7:57 AM
471
calories
2.85
miles
10:23
min/mile
3,987
steps

TIME
CALS.
STEPS
FUEL

NEXT MILESTONE
34,345 / 50,000
TODAY
5,235
0 3 4 8
RAISE YOUR GOAL
SO SMOOTH

1094
4.54 KM
EXERCISE
1094
CALORIES BURNED

Future research needs

- Further development and validation of self-report tools and data processing methods for wearable devices
  - Establishment of evidence-based practices

    need to address relative vs absolute intensity

- Evaluation of performance of self report tools and wearable devices for detecting change in activity and sedentary behavior

- Evaluation of effectiveness of tools for real-time self-monitoring of behavior using wearable sensors and mobile phones

- Evaluation of consumer devices

- Integration of self-report and sensor measures of physical activity

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SAVE THE DATES FOR ICAMPAM 2013 AMHERST

Website: http://www.umass.edu/sphhs/icampam2013.html

Dates: June 17-19, 2013

Where: Amherst, Mass on the campus of the University of Massachusetts

Conference Themes: Physical Activity, Sedentary Behavior and Sleep Measurement

Topics
- Behavior and Health Outcomes
- Data Processing, Statistics, Computational Methods
- Validation and Calibration
- Engineering and Tool Development
- Clinical Applications

Session Format
- Keynote/Invited Lectures
- Symposia
- Oral Presentations
- Poster presentations

Key Dates
- Call for Abstracts/ Symposia Proposals: August 20, 2012
- Abstracts/Symposia Submission Deadline: November 19, 2012
- Registration Opens: December: December 2012
-

Mark your calendars!