

Mobile Phone Sensing is the

Next Big Thing!

Andrew T. Campbell, Dartmouth College

ACM MobiOpp 2010 Keynote Address



Wireless sensor networks have driven many great innovations over the last decade - represents a very active area of on-going research



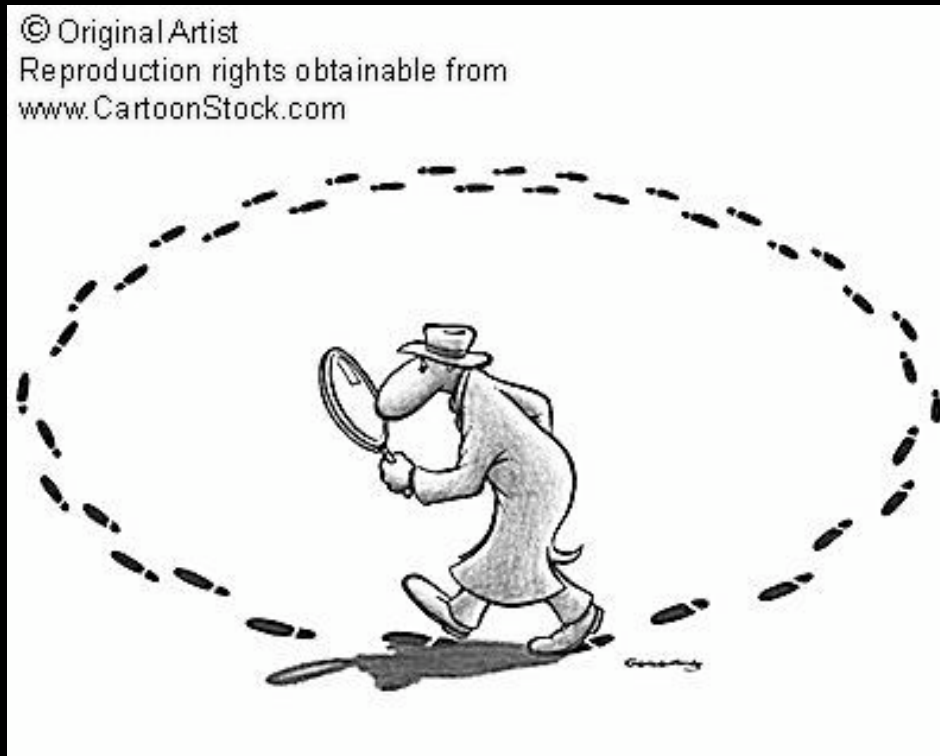
The mote have been a superb platform for research

But, challenges remain

- Not ubiquitous
- Energy problem
- Scaling (cost and performance) problem
- Event unpredictability
- Don't have economy of scale



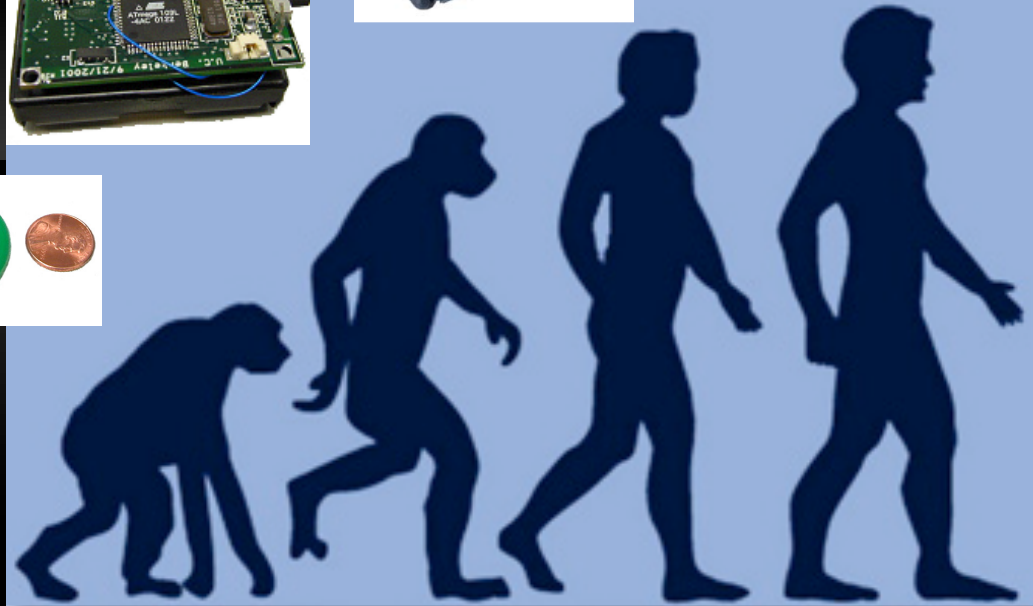
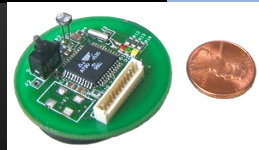
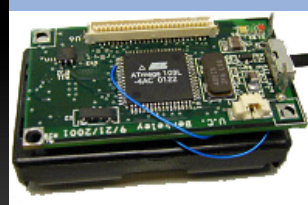
Importantly, sensor networks don't impact our everyday lives. Why?



People are out of the loop

But that's just changed

There's **revolution** going on ..



Meet the human “mote”



We're awash with sensor-enabled phones



Embedded sensors:

- 3-axis accelerometer
- Digital compass
- Proximity sensor
- Microphone
- Camera
- GPS

They're ubiquitous, sort of solve the energy problem, have economy of scale, and scale in performance.

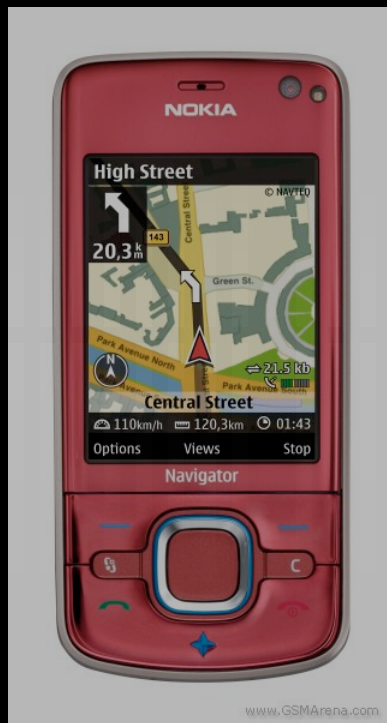
Google Nexus one



Embedded sensors:

- 3-axis accelerometer
- Digital compass
- Proximity sensor
- Microphone
- Camera
- GPS
- Bluetooth

Nokia 6210 Navigator



Embedded sensors:

- 3-axis accelerometer
- Digital compass
- Microphone
- Camera
- GPS
- Bluetooth

And, at some point in the future ..

My fantasy phone: the cool green “emotional” phone



Embedded sensors:

- 3-axis accelerometer
- Proximity sensor
- Digital compass
- Pollution/air quality sensor
- GSR “emotion sensor”
- RFID/NFC
- Microphone
- Camera
- GPS
- Bluetooth

Why is this moment great time for research?



- Availability of sensor-enabled phones
- “Openish” platforms (mostly Linux based) and good development tools
- App delivery system in place
- Large scale deployment and experimentation now possible
- Potential for huge rich data sets

Your research can have
significant impact.



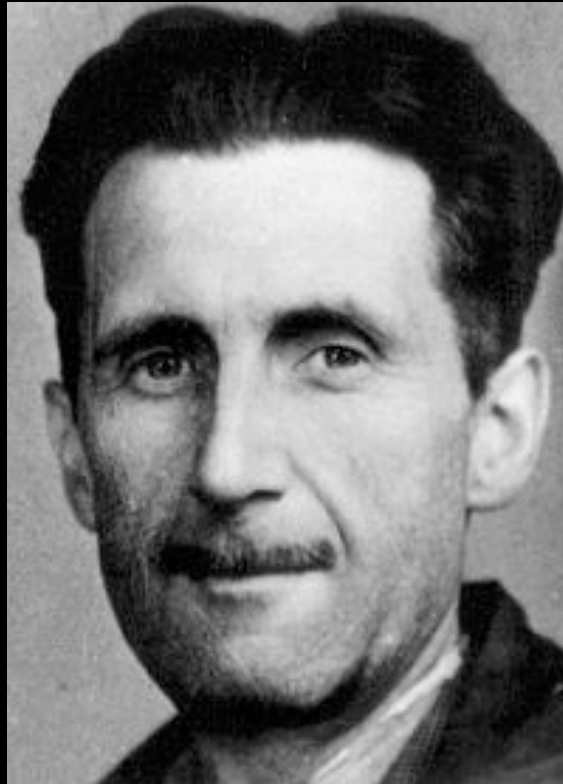
You don't need any infrastructure to do this –well, very little, mostly cloud stuff.



Your phone can learn your
behavior and about your life

I know what you are thinking

Sounds like an Orwellian nightmare!



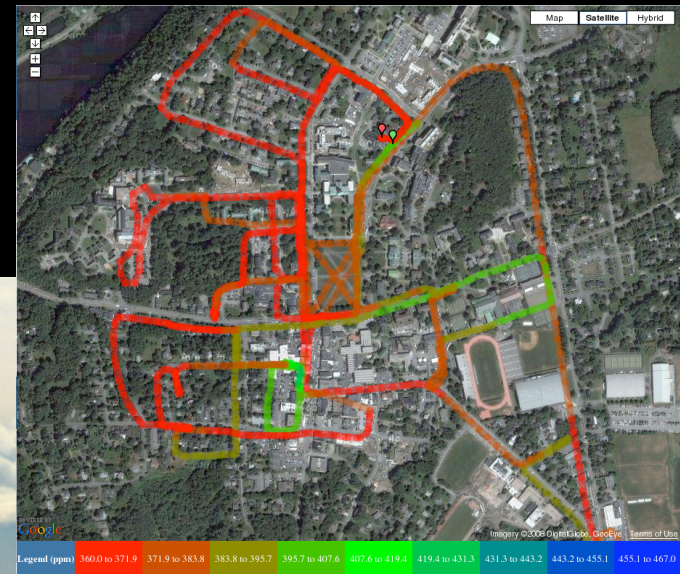
Critical challenges in trust, privacy, security
to be solved

Why do this, really?

You'll be able to answer lots of interesting questions and build new cool applications that could have significant societal impact

or, just have fun.

What is my personal air quality like today? Or, the air quality of my neighborhood, school, town, or city?



How stressed is the city this morning?



You can learn quite a lot from the “continuous sensing” of a limited set of widely available sensors on the phone, e.g., accelerometer, microphone, GPS/WiFi/Bluetooth

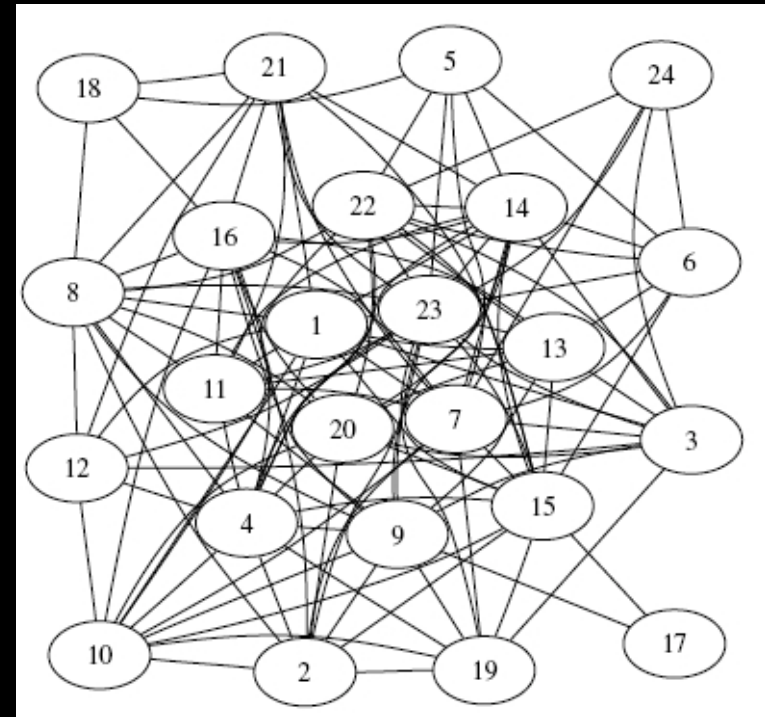
You can infer physical activity,
social interaction, context and
location.

In fact you should be able to infer
a lot more about:

social networks, co-location,
amount of time in conversation,
intonation, isolation, emotion,
loudness, modes of transportation,
types of restaurants visited,
cooking, eating, walking, cycling,
watching TV, listening to music, in
a meeting, jogging, using the ATM,
at the gym, playing squash,
depression, hypertension

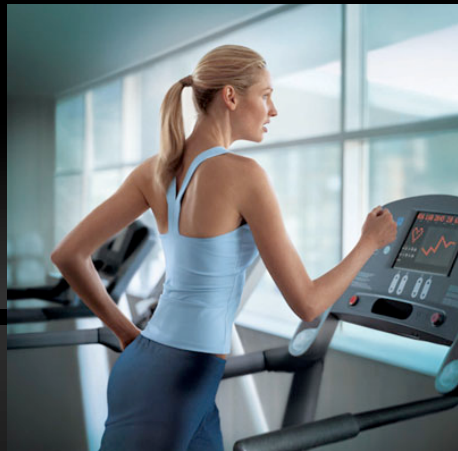
Many questions can be asked ...

How do social “conversation” networks evolve?



Work on audio networks by Tanzeem Choudhury (Dartmouth)

How is my physical, emotional and cognitive health?



Where are my friends and what are they doing **right now**?



Now imagine 1 billion “sensor enabled mobile phones” scattered across the planet



people are in the loop



This will lead to ...

Societal scale sensing

a global mobile sensor network



Likely to be cross-cutting research

- Social networks
- Population well-being
- Transportation
- Green applications
- Recreation sports
- Virtual worlds
- Others.

I know what you are thinking

You can't cover a volcano with mobile phones!



On second thoughts, phones are getting cheaper and we have a ready supply of adventurous grad students ;-)



At an exciting point in the
development of people-centric
sensing applications



We started the metrosense project
in 2006 to study people-centric
sensing

People-centric sensing application domains

Personal Sensing



Public Sensing



Social Sensing

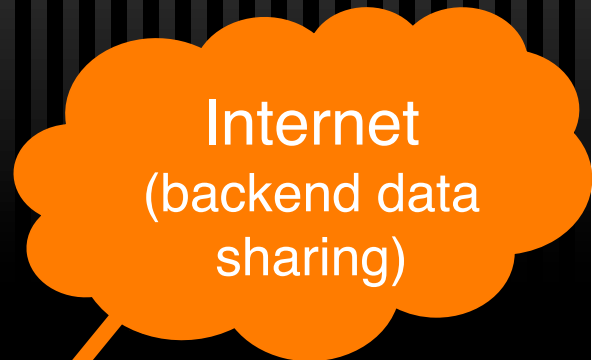


“The Rise of People-Centric Sensing”, IEEE Internet Computing, July/August 2008

Public sensing gains scalability and sensing coverage by using people opportunistically as mobile sensors



People-centric sensing is based on an “opportunistic sensing paradigm” and an “interaction model” that captures interaction between people, and, between people and their surroundings



GIS and crowd sourced data

Emerging sensing paradigms



Participatory
sensing (UCLA)

Hybrid
approaches

Opportunistic
sensing
(Dartmouth)

I'll give an overview of the apps/systems we built and learnt from

- BikeNet (personal/public sensing)
- CenceMe (social sensing app)
- SoundSense (personal sensing app)

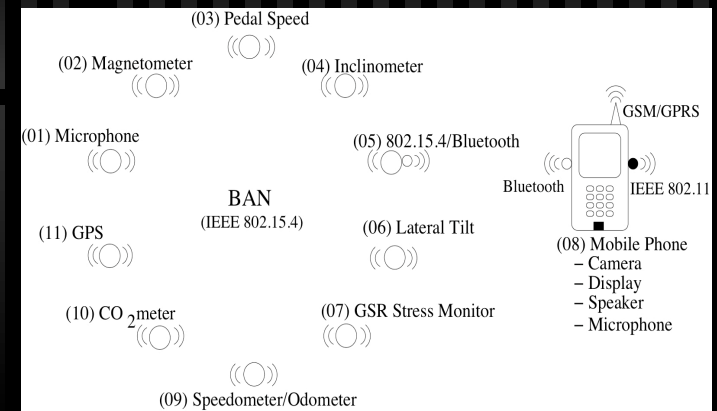
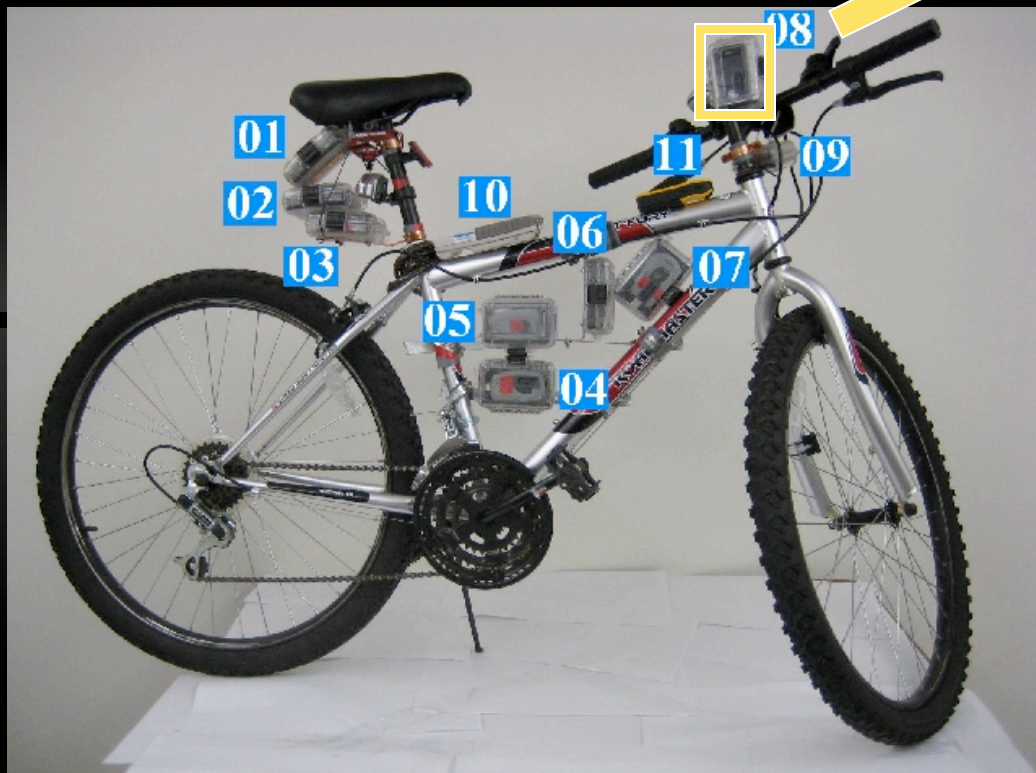
Then, I'll talk about the need for new research for mobile phone sensing:

- Sense-learn-persuasion model
- Software for the phone
- Killer app

BikeNet - sensor bikes



N80 phone



Phone controller for BAN

“The BikeNet mobile sensing system for cyclist experience mapping”, ACM SenSys '07

We can answer many questions from sensor data

- How fit are you?
- Many cars along the route?
- What was the air quality and noise like?
- Lots of trivia: slopes, coasting, braking, working hard
- Overall health and performance along the route
- How did you compare to your buddies, community?
- Share information with your social network


CO2 Map of Hanover

Bikenet Portal - Firefox

File Edit View Go Bookmarks Tools Help

http://bikenet.cs.dartmouth.edu/bikeView.php?data_type=11&

Latest Headlines

 Secret Squirrel bikeView

Total Rides: 7 Total Minutes: 320.0 mins Total Distance: 66.3 km [help]


Rides

Aug 14th 2007 14:35:38 (19.6 Km)
Aug 12th 2007 08:26:13 (18.1 Km)
Dec 20th 2006 14:03:39 (9.1 Km)
Dec 18th 2006 11:09:48 (4.8 Km)
Dec 16th 2006 15:02:39 (4.8 Km)
Dec 2nd 2006 13:47:04 (5.1 Km)
Nov 25th 2006 22:24:06 (4.8 Km)

Data Sharing / Live Query Submission


Control Panel

Click on Bike Sensor



joy performance

None



Map Satellite Hybrid

POWERED BY Google

Imagery ©2007 DigitalGlobe Terms of Use

Sensor Selected

CO2 reading

Selected Ride Statistics

Aug 14th 2007 14:35:38	
Distance	19.6 km
Duration	120.0 mins
Joy	N/A
Performance	N/A

Sensor Data

[zoom]



CO reading (PPM)

Distance (Kilometers)

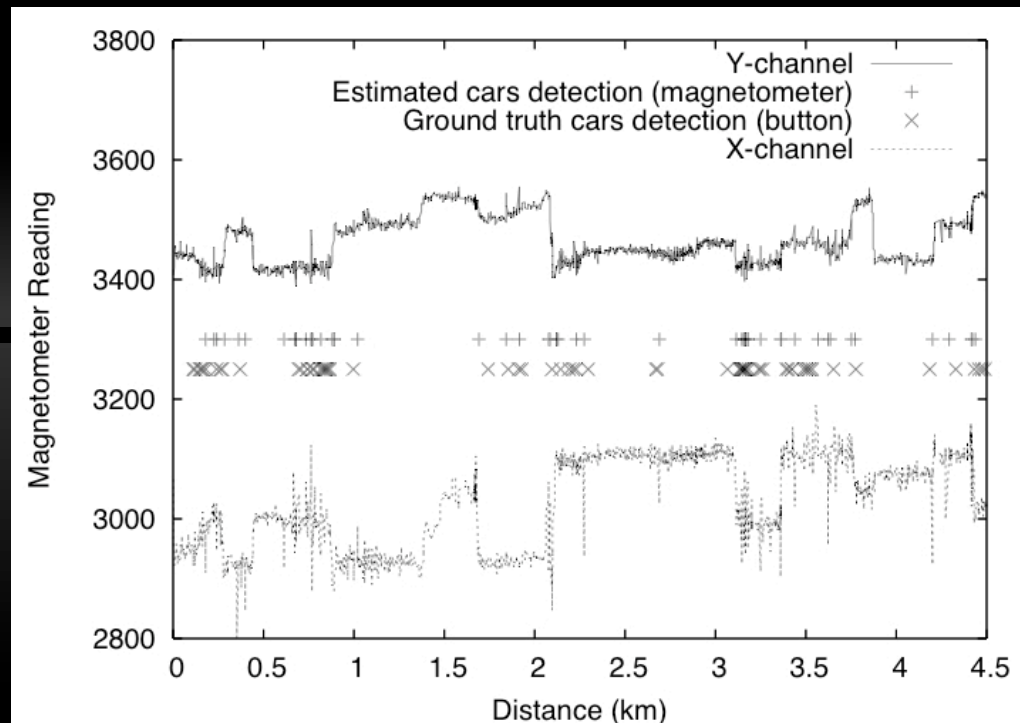
Legend (ppm)

360.0 to 371.9	371.9 to 383.8	383.8 to 395.7	395.7 to 407.6	407.6 to 419.4	419.4 to 431.3	431.3 to 443.2	443.2 to 455.1	455.1 to 467.0
----------------	----------------	----------------	----------------	----------------	----------------	----------------	----------------	----------------

Done Connected

http://bikenet.cs.dartmouth.edu

Lots of cars on that route?

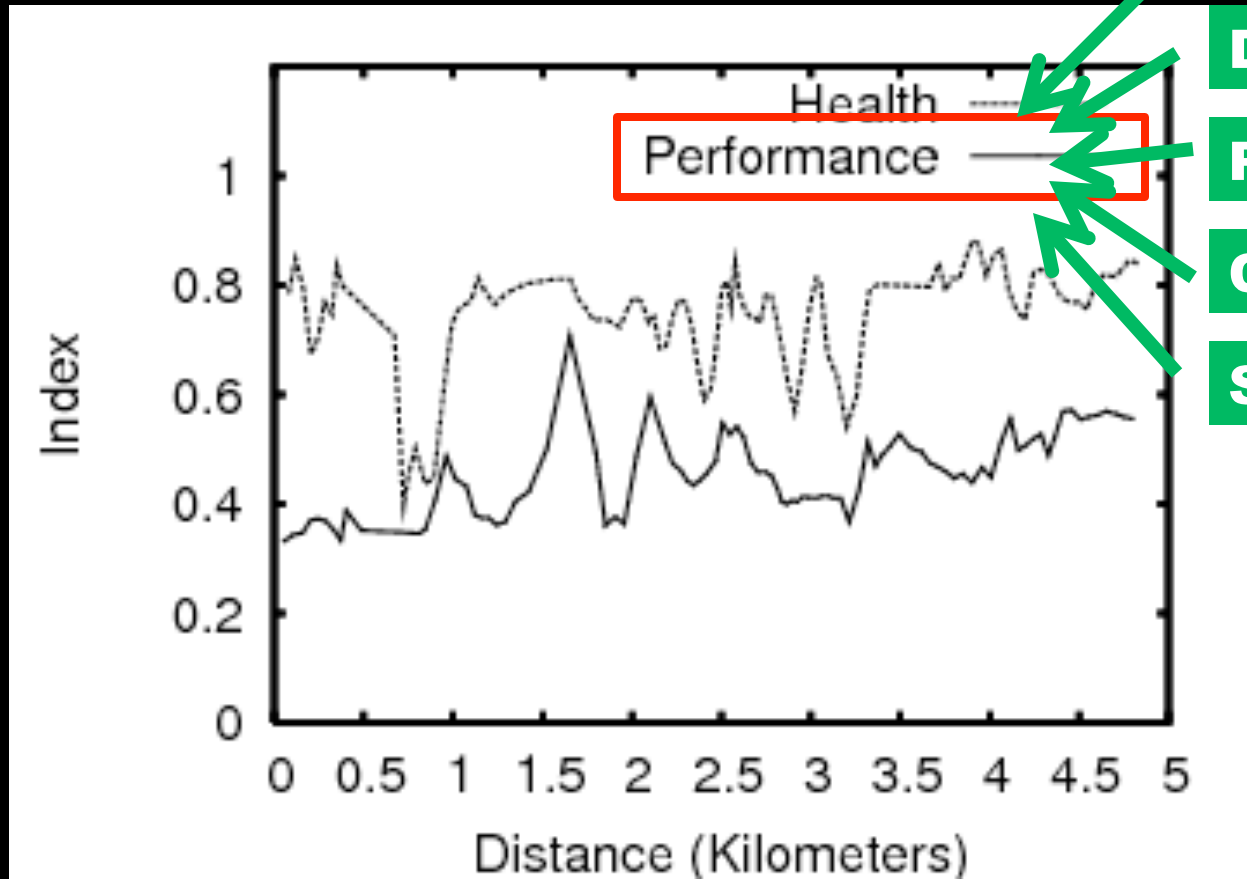


I know what you are thinking

How do you do ground truth?



Performance index



Distance

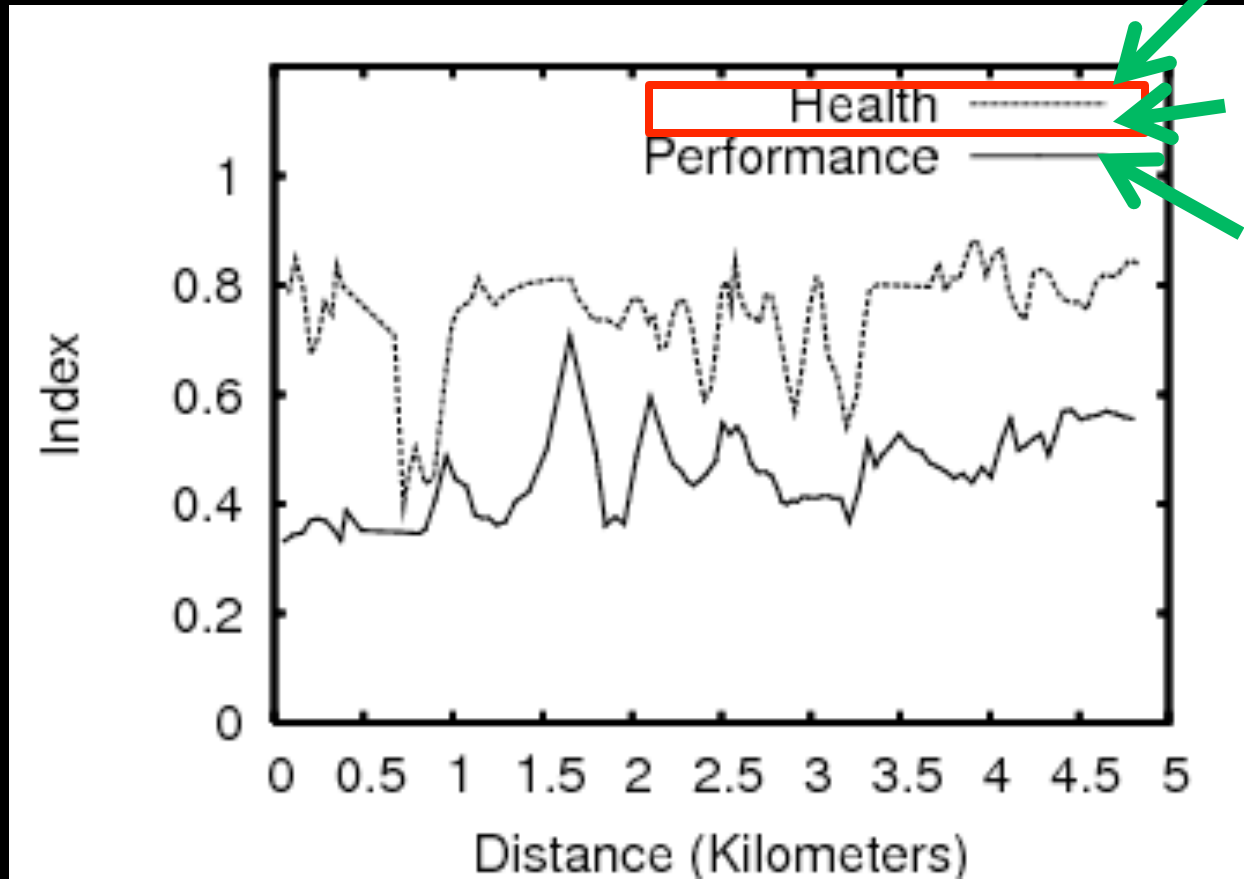
Duration

Path Slope

Coasting

Speed

Health index



Noise

Traffic
Density

CO₂ Level

Many lessons learnt



Debugging on the go is hard

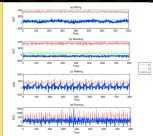


“Sensing Meets Mobile Social Networks: The Design, Implementation and Evaluation of the CenceMe Application”, ACM SenSys 2008

sensing with cenceme



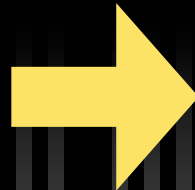
sensor data



inference



cencing with cenceme



sensor data

A line graph showing multiple data series over time, representing sensor data.

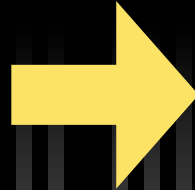
inference

A blue square icon with a white silhouette of a person sitting at a table with two other people, representing a meeting or inference process.

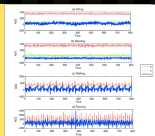
inference

Two blue square icons: the first shows a white silhouette of a person in a wheelchair, and the second shows two white silhouettes of heads with sound waves between them, representing communication or inference.

cencing with cenceme



sensor data



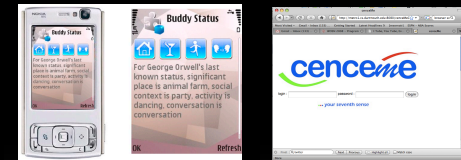
inference



inference



cencing with cenceme



sensor data

inference

application representation

inference

supported inferences: sensing presence

activity



supported inferences: sensing presence

activity



social context



supported inferences: sensing presence

activity



social context



significant places



supported inferences: sensing presence

activity



social context



significant places



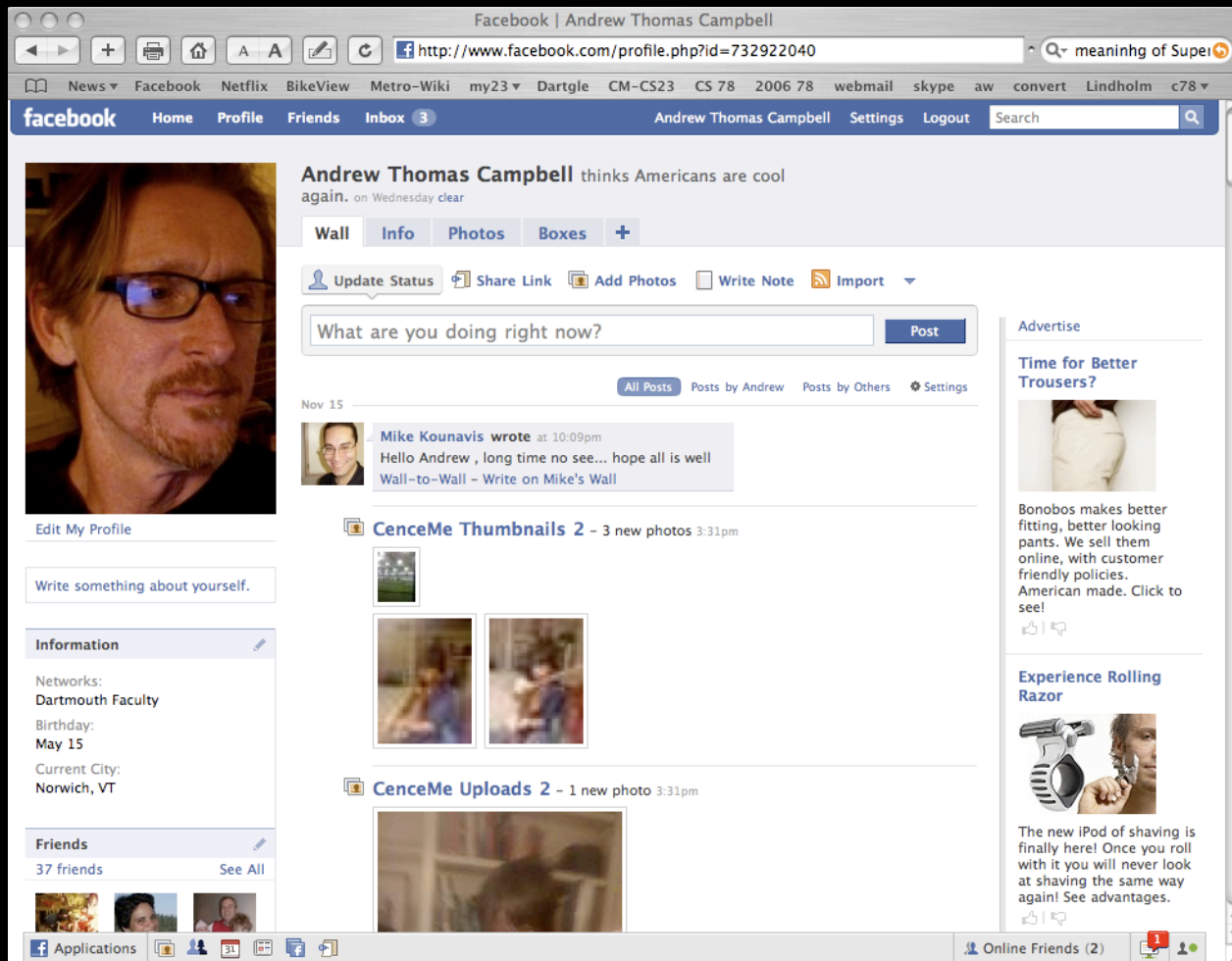
behaviour



CenceMe demo



Sensor presence is published on Facebook, myspace, twitter



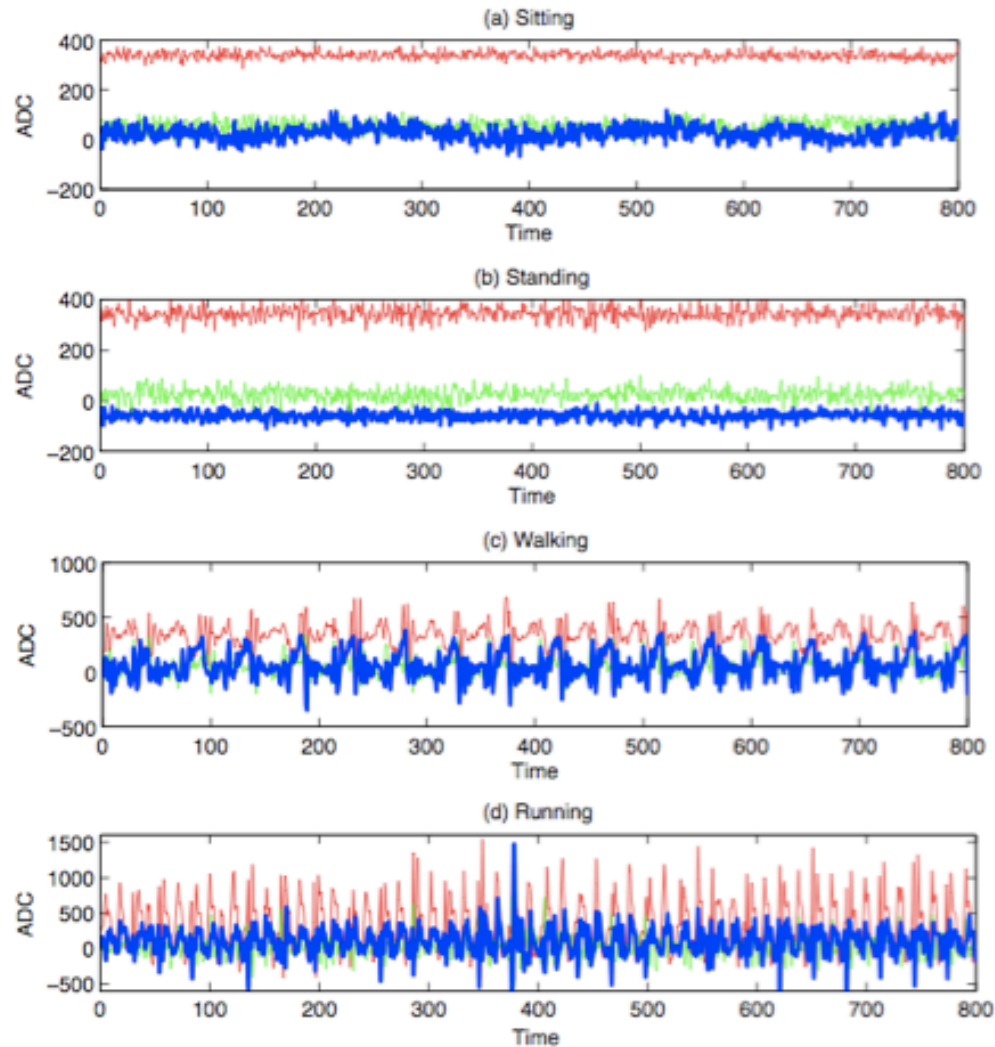
Classifying activity on the Nokia N95

sitting

standing

walking

running



Activity classifier confusion matrix on the Nokia N95

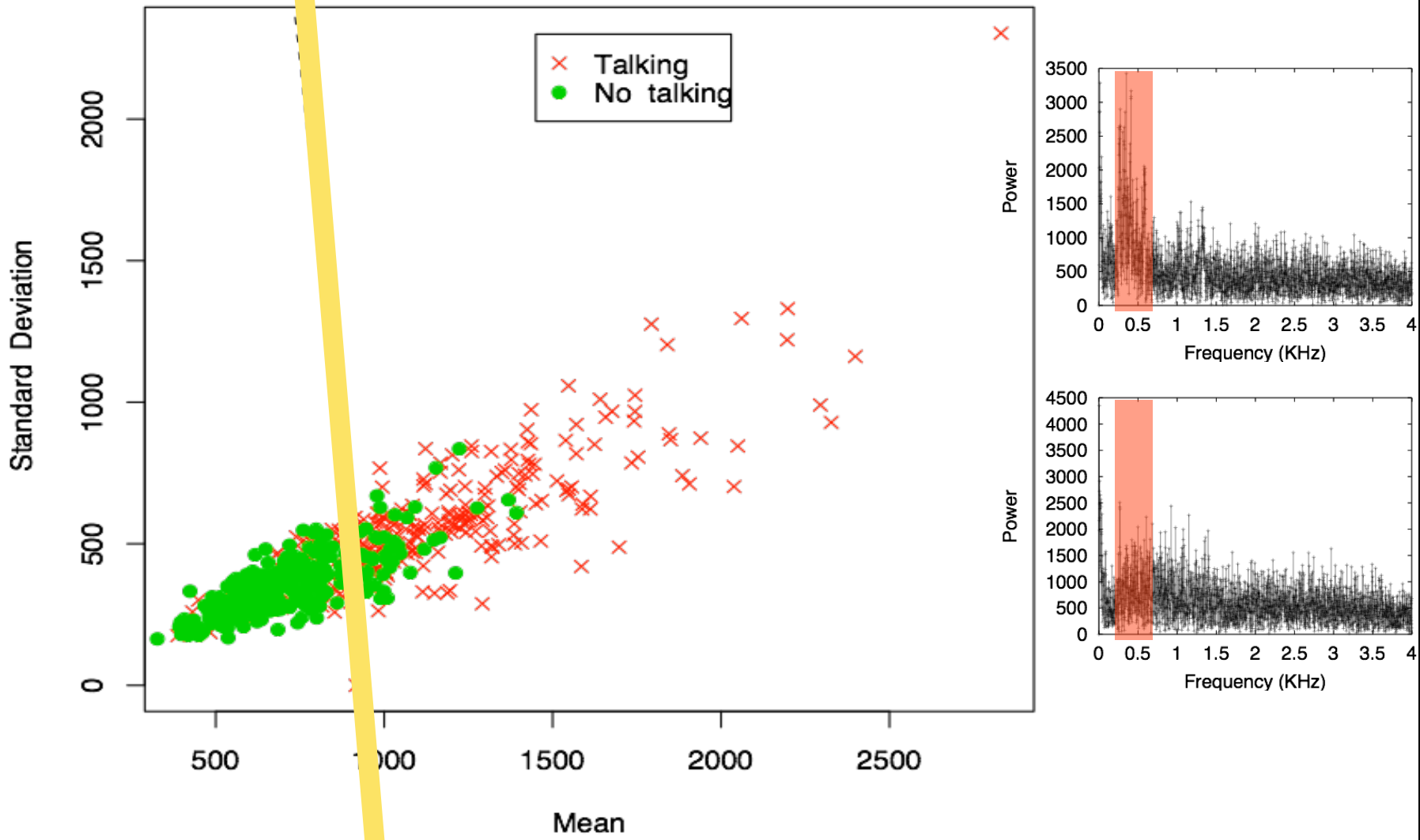
	Sitting	Standing	Walking	Running
Sitting	0.6818	0.2818	0.0364	0.0000
Standing	0.2096	0.7844	0.0060	0.0000
Walking	0.0025	0.0455	0.9444	0.0076
Running	0.0084	0.0700	0.1765	0.7451

Supervised learning approach

Differentiated between sitting and standing is hard

Custom sensing hardware (e.g., Intel's MSP)
can do better but these results are from the Nokia N95

Classifying talking/ non-talking on the Nokia N95



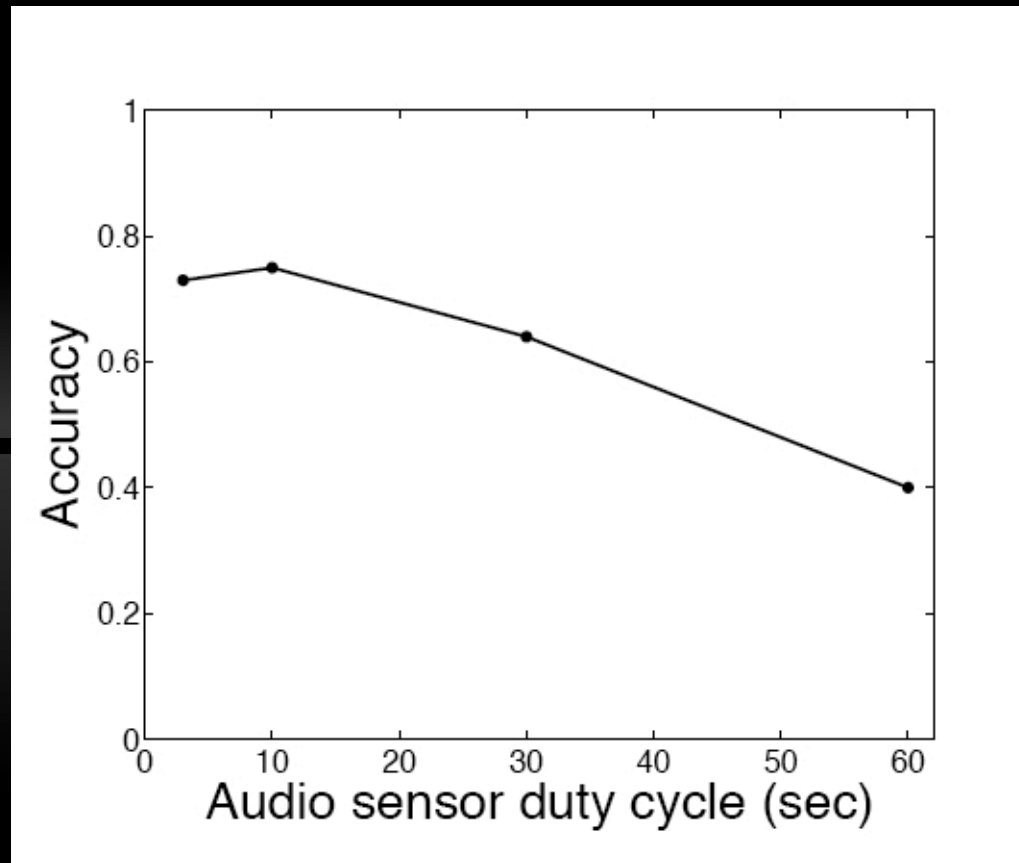
Conservation classifier confusion matrix on the Nokia N95

	Conversation	Non-Conversation
Conversation	0.8382	0.1618
Non-Conversation	0.3678	0.6322

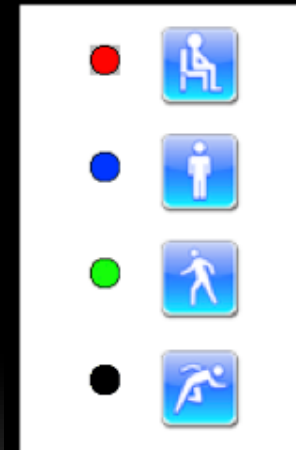
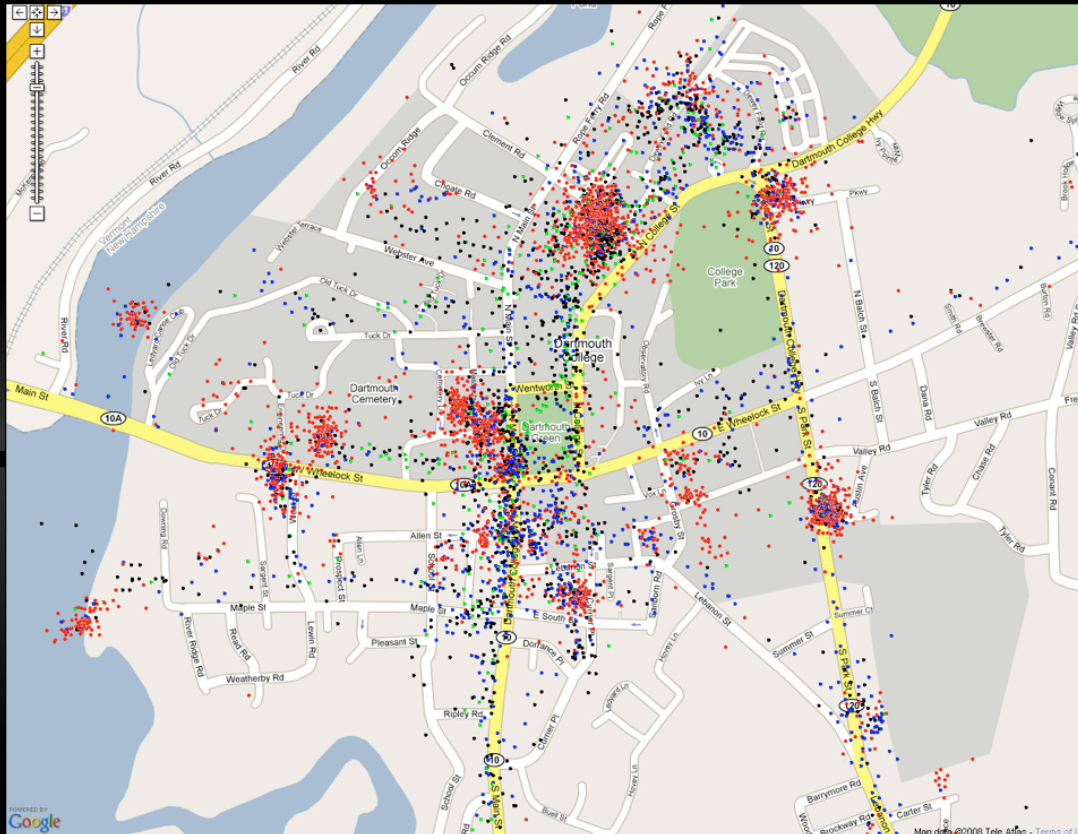
Design decision of 2/5 talk primitives to get into conversation and 4/5 to get out – more conservative

Poor performance for non conservation results because people aren't talking but others nearby are.

Duty-cycling on the phone for continuous sensing is critical

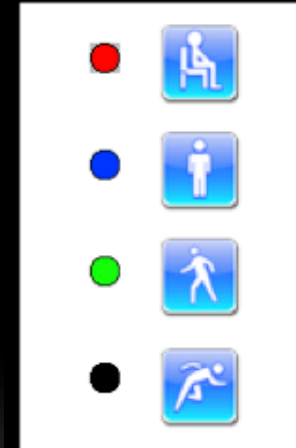
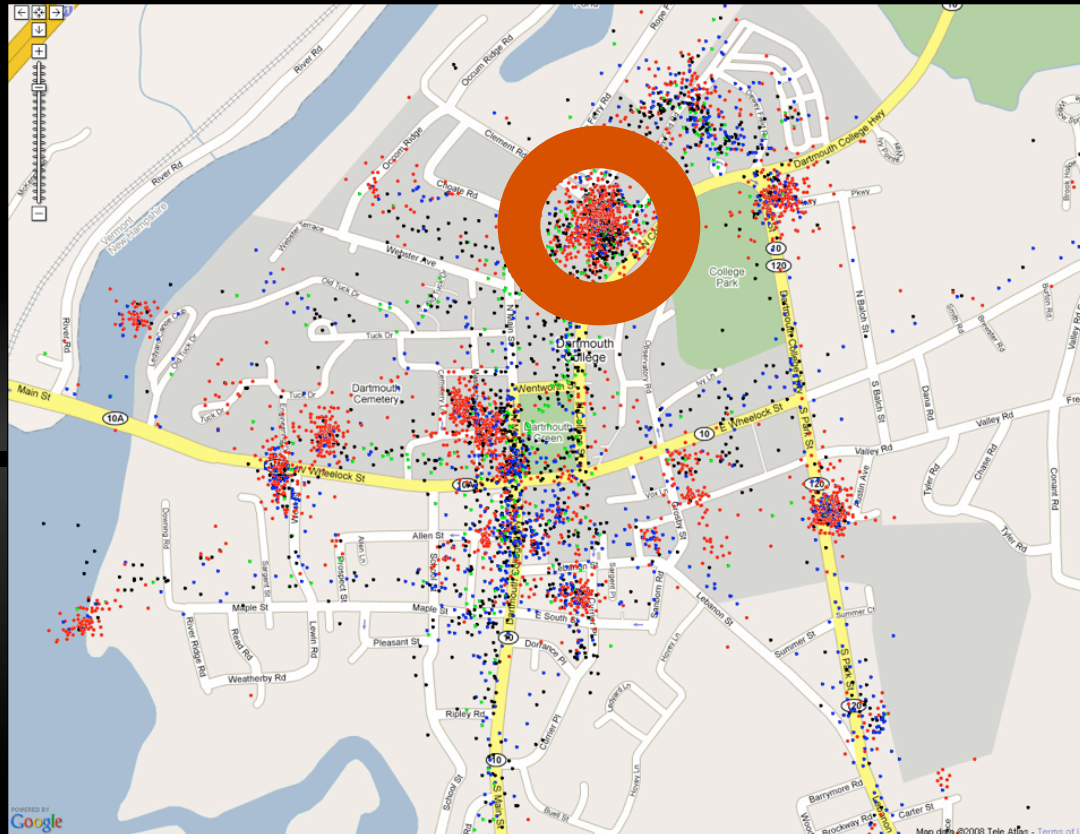


Results: Location and activity



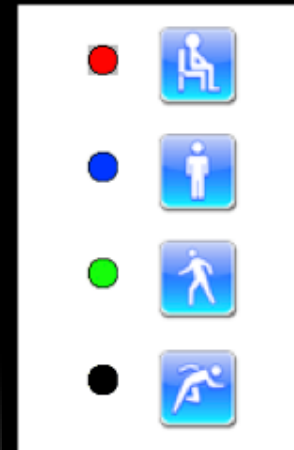
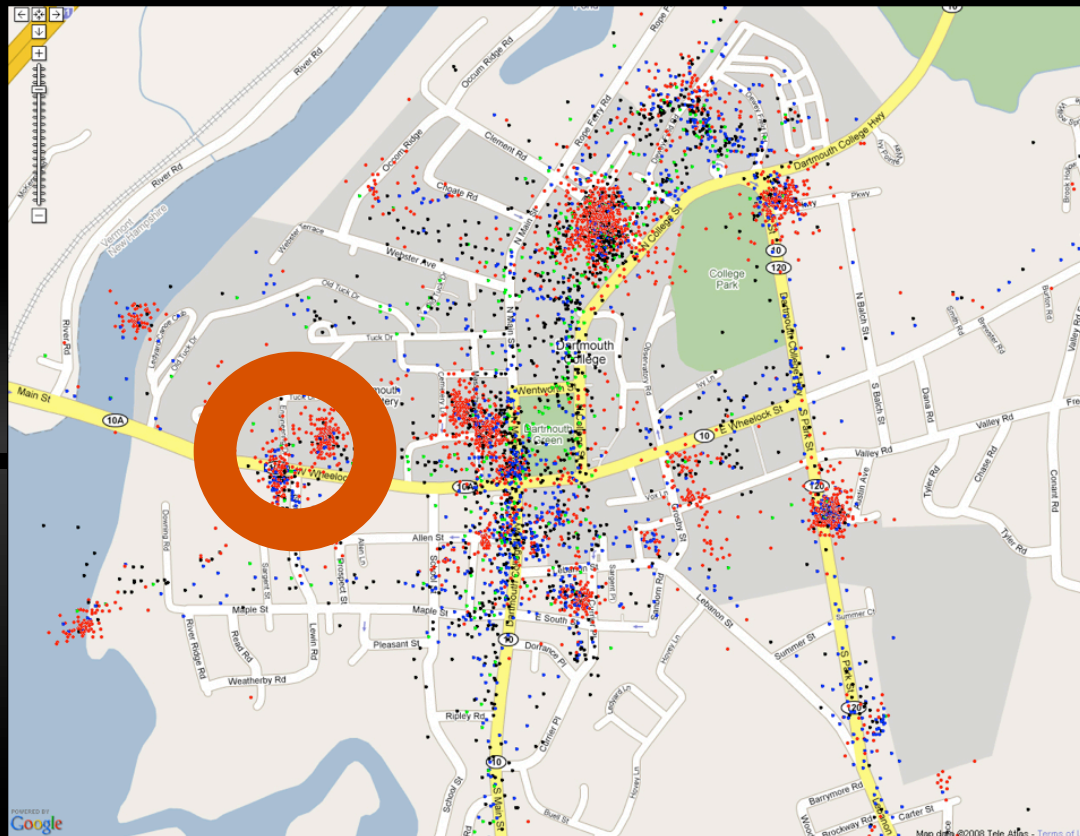
*“Supporting energy-efficient uploading for continuous sensing us mobile phones”,
Pervasive 2010*

Results: Location and activity



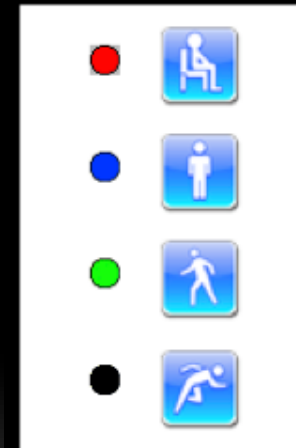
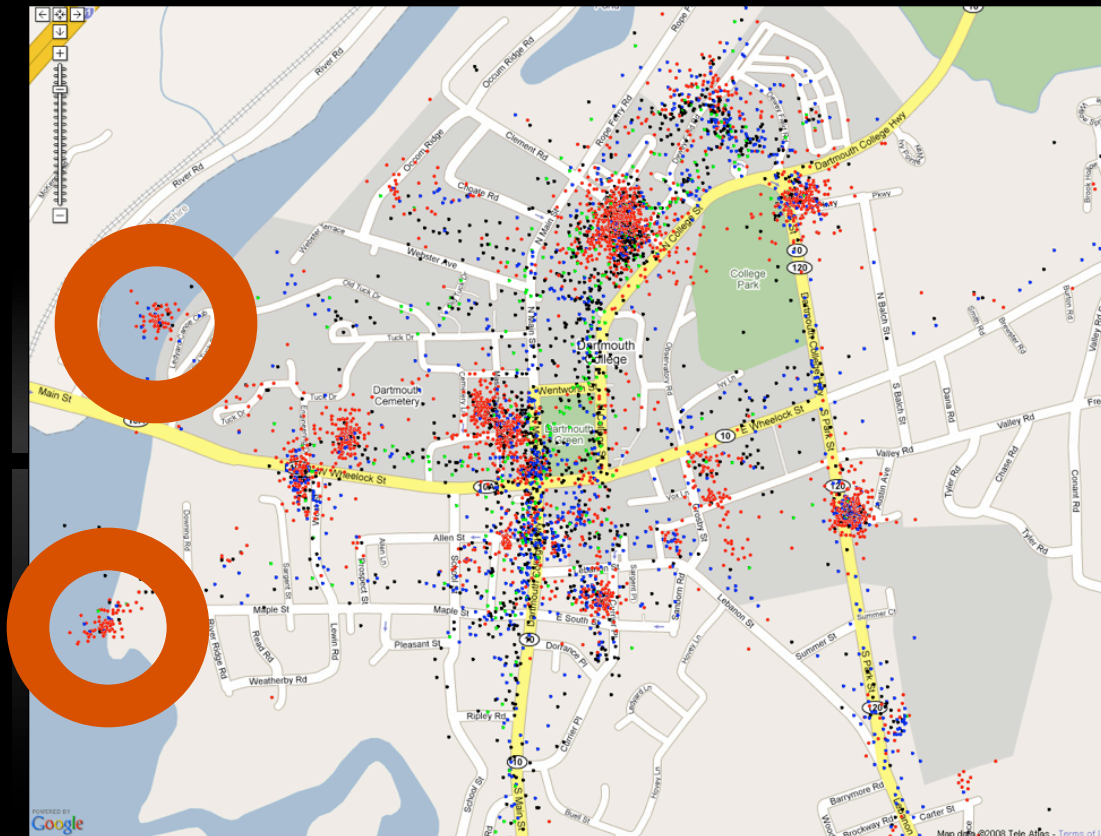
*“Supporting energy-efficient uploading for continuous sensing us mobile phones”,
Pervasive 2010*

Results: Location and activity



*“Supporting energy-efficient uploading for continuous sensing us mobile phones”,
Pervasive 2010*

Results: Location and activity

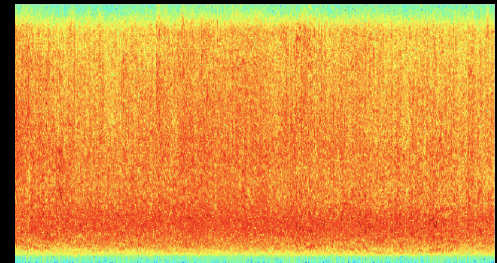
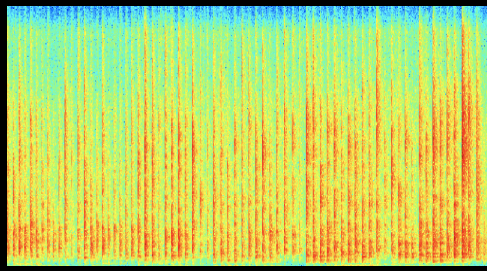
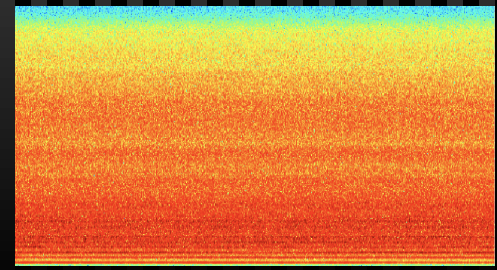
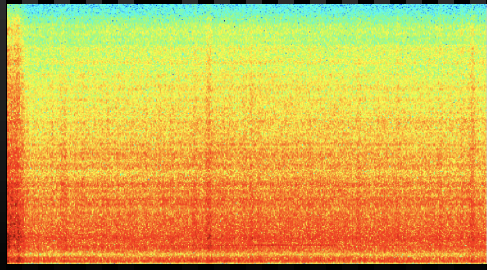
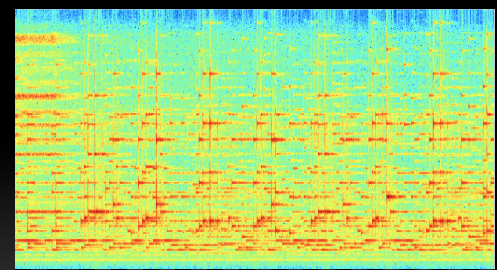
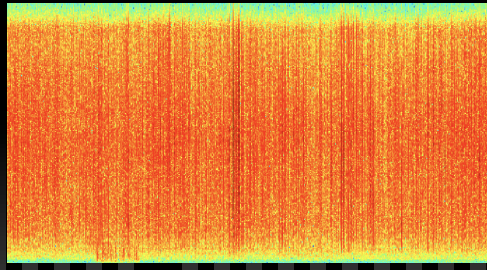
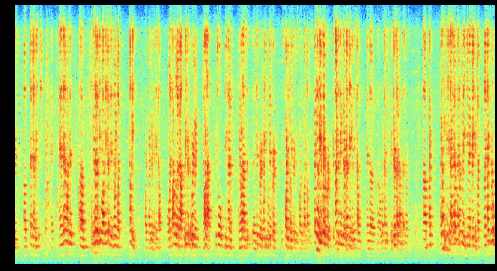


*“Supporting energy-efficient uploading for continuous sensing us mobile phones”,
Pervasive 2010*

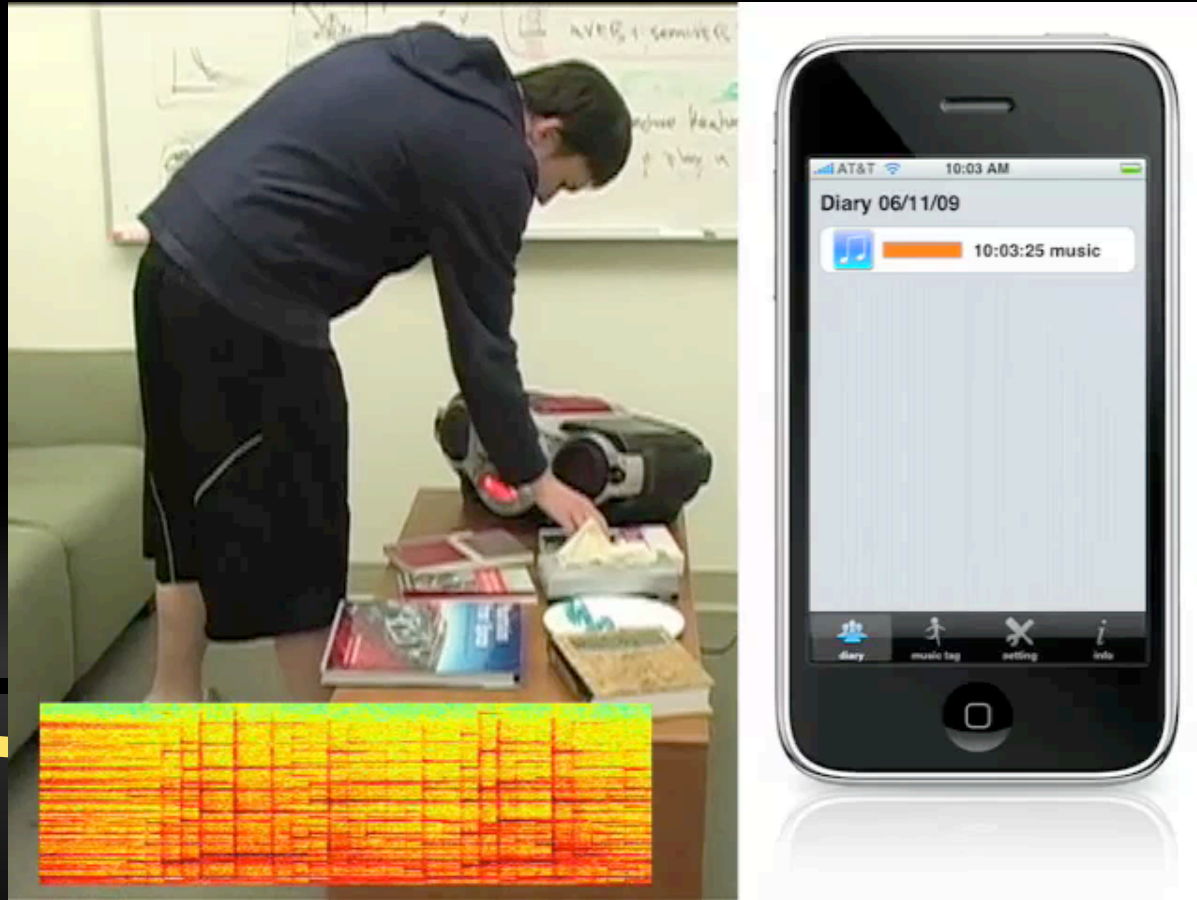
SoundSense



*“SoundSense: Scalable Sound Sensing for People-Centric Applications on Mobile Phones”, ACM MobiSys 2009
(with Tanzeem Choudhury)*



SoundSense: Learn on the go



Detect

Rank

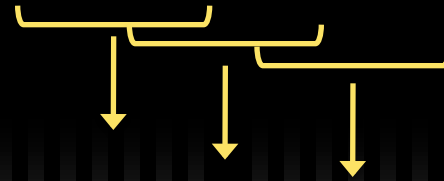
Learn

SoundSense system

Waveform



Windowing



Feature Extraction

Admission Control

[Acoustic Features]

Decision Tree Classifier

Category Classification

Markov Model Recognizer

voice

music

ambient sound (others)

Intra-Category Classification

Voice Analysis

Music Analysis

New Sound Classifier

Classification confusion matrix for iPhone

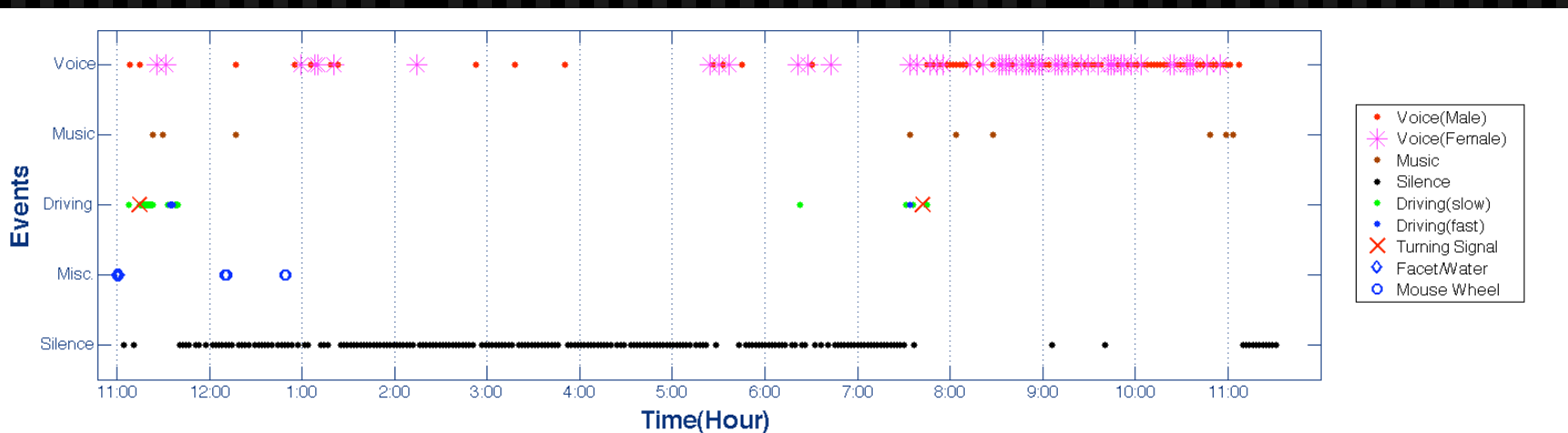
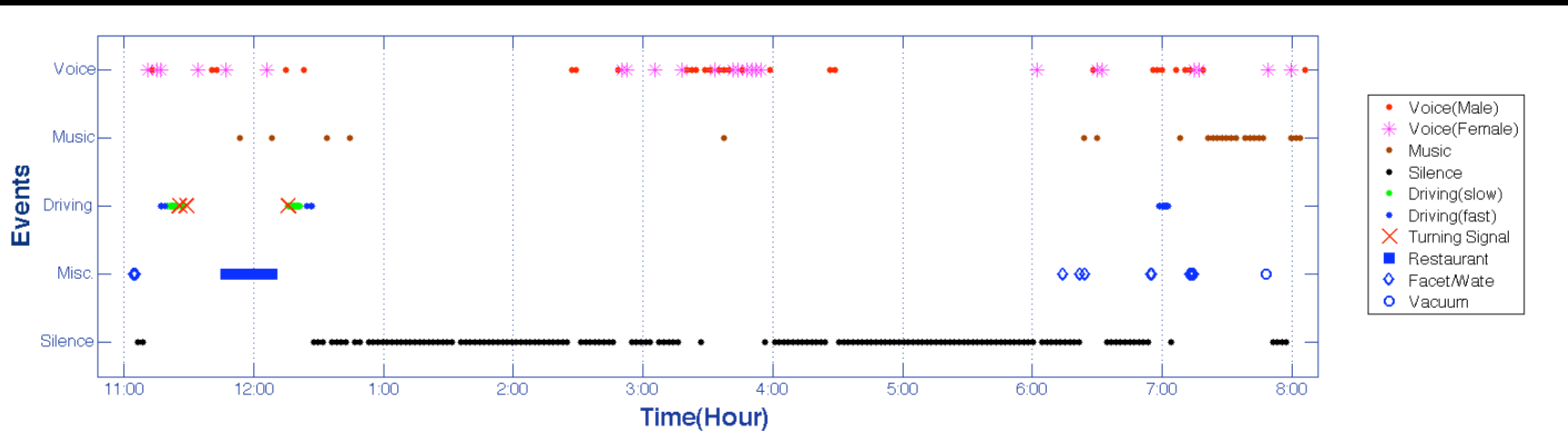
	Ambient Noise	Music	Speech
Ambient Noise	0.9159	0.0634	0.0207
Music	0.1359	0.8116	0.0525
Speech	0.0671	0.1444	0.7885

Accuracy of the decision tree classifier

	Ambient Noise	Music	Speech
Ambient noise	0.9494	0.0402	0.0104
Music	0.0379	0.9178	0.0444
Speech	0.0310	0.0657	0.9033

Accuracy of the markov model recognizer output

Daily diary app



New research needed in mobile
phone sensing to push the vision
forward

How much intelligence can we
push to the phone?

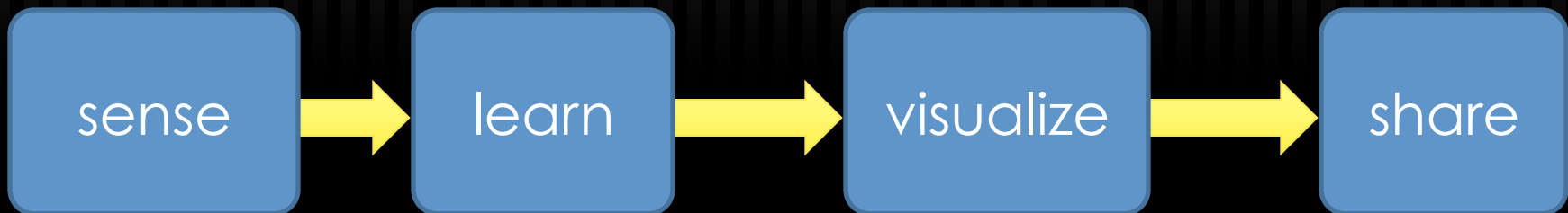
Human behavior/context modeling

Label \rightarrow Feature \rightarrow Learn \rightarrow Classify

User in the loop

Train supervised learner → Classify

Current people-centric sensing model

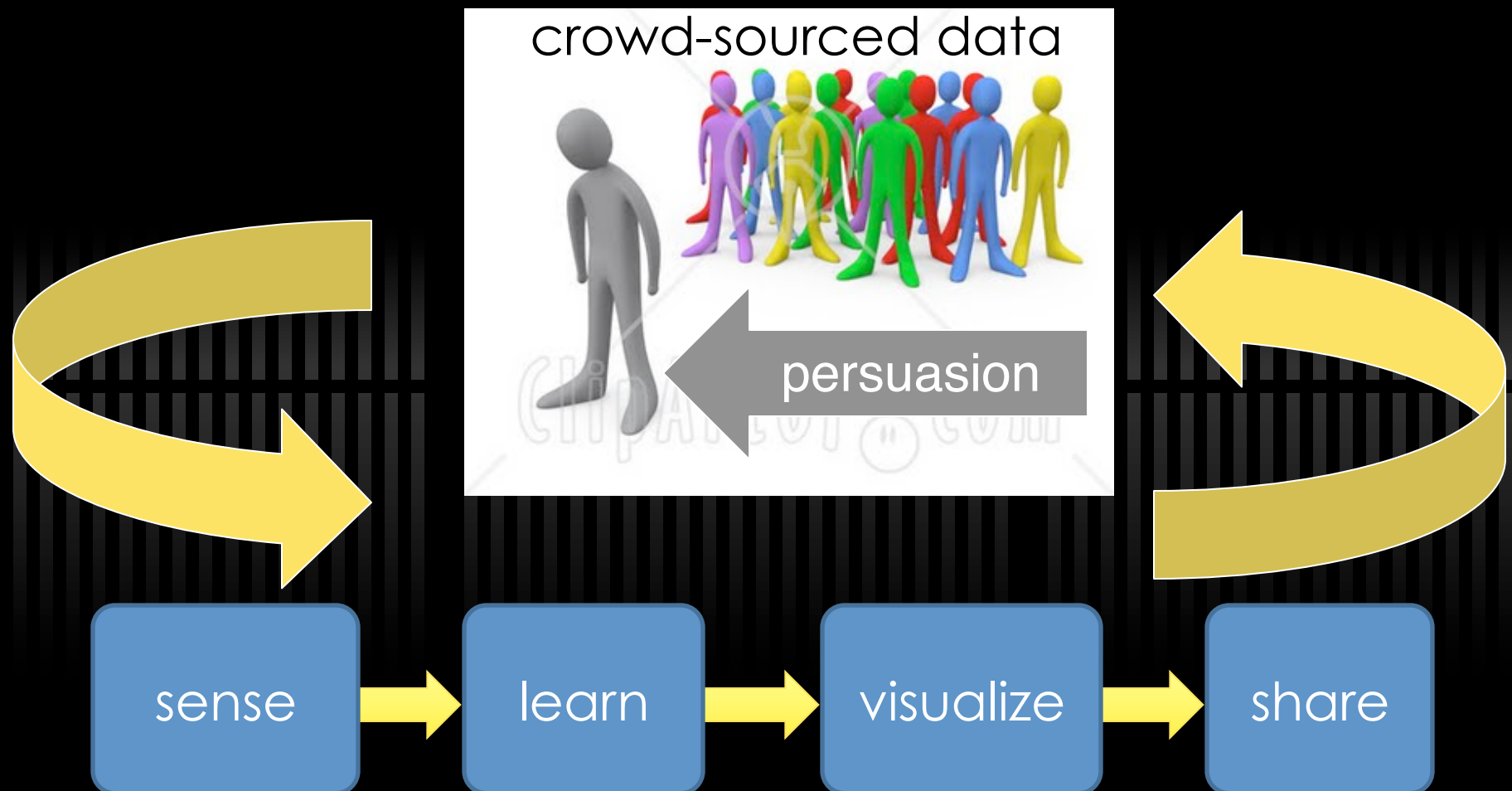


What else can we do with all that
sensor data?

We can close the loop.

Be persuasive!

Persuasion model



population
guided
persuasion



sense

learn

visualize

share

population
guided
persuasion



sense

learn

visualize

share

Sense-Learn-Persuasion Model

Killer app for Sense-Learn- Persuasion Model

A microscope for personal, community and population-scale well-being

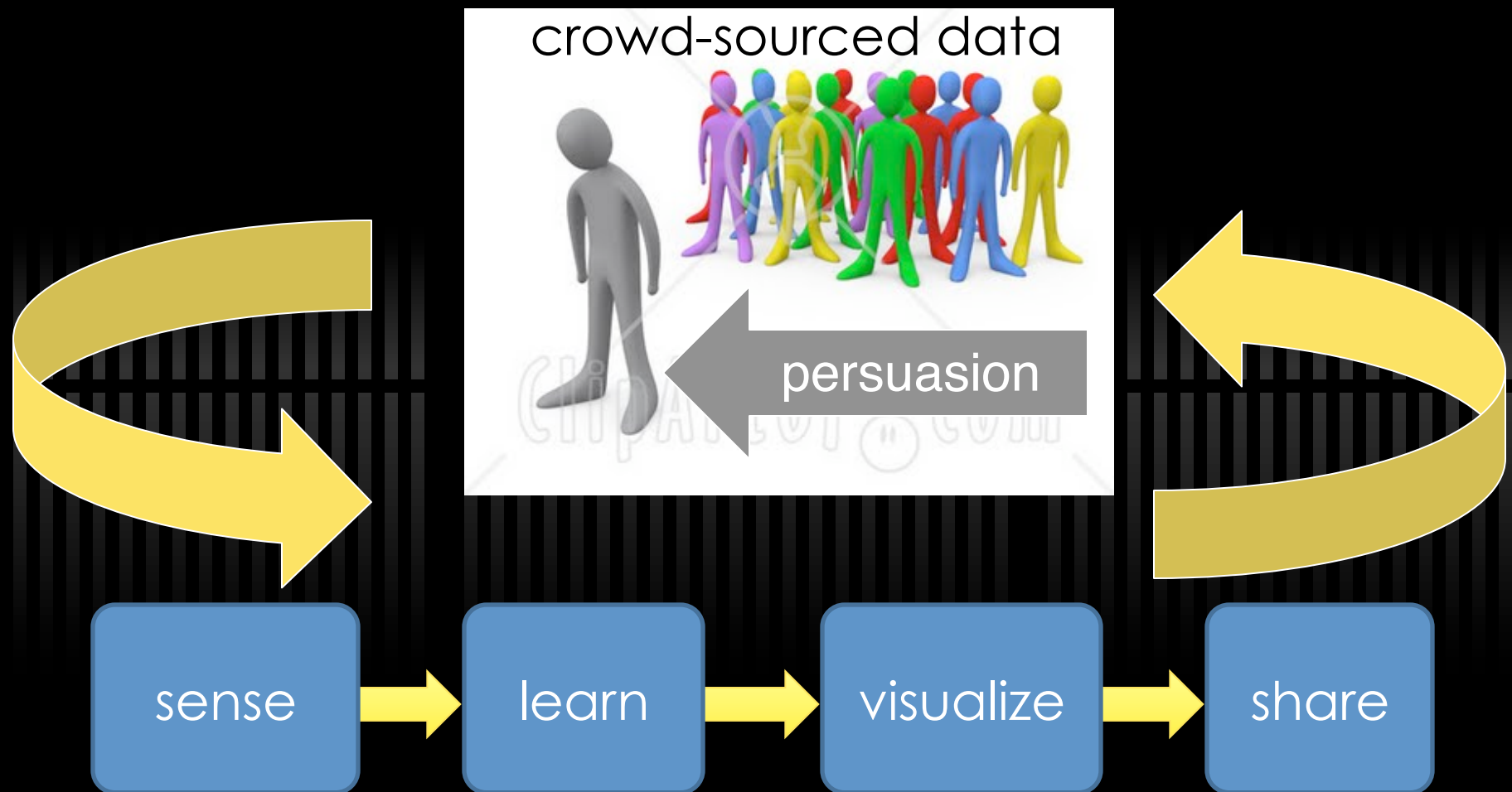


Well-being in health encompasses an overall state of wellness, not just the absence of disease.

Possible health related outcomes

Obesity, anxiety, depression,
dementia, aging in place,
metabolic syndrome (diabetes,
elevated lipids, blood pressure),
disease prevention (activity, food
choices)

Well-being networks: the killer app?

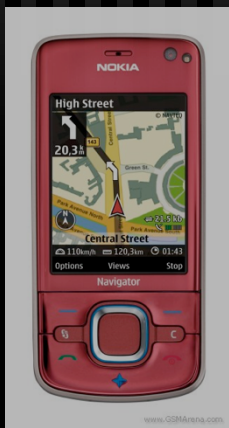


With Ethen Berke, John Canny, Tanzeem Chodury,
James Landay

Need for enabling software
technology for mobile phone
sensing

Phone SensorWare

Supporting continuous sensing significant challenge
Many open challenges



Priv.-aware sub/pub	
Inferencing	Context
Sensor sharing	
Duty cycling	
Calibration	
RF	Sensing
Andriod, iPhoneOS, Nokia	

Phone Machine Learning Toolkit

Sensing data collection and labeling tool

dataset



Offline training

Training Tool



models

Sensing data collection and feature extraction



Real time inference Engine

Phone Runtime

Many open technical challenges,
such as:

continuous sensing, duty cycling,
comms, privacy, robust features,
scaling, exploiting crowd-sourced
data, light-weight classifiers,
sharing, etc.

In summary,

Growing interest in sensing on mobile phones

Applications

WatchMe, iCAMS, PEIR, Nericell

Sensing with mobile phones

UCLA, UIUC, Intel, Nokia, Microsoft, Motorola, UW, Duke, start ups: e.g., Sense Networks

Human activity inferencing

MIT, Intel, UW

Workshops

UrbanSense 08, MODUS 08

The mobile phone will serve as the main platform for sensing innovation over the next decade.

Your mobile phone will sense your surroundings, learn your behavior (what you do, where you go and how you interact with people and your environment), and help you navigate your day and improve quality of life.

Collectively, mobile phones will form societal scale sensor networks in support of community, urban, and global sensing applications and problem solving.

Thanks for listening!

- Project page, papers, etc:

<http://metrosense.cs.dartmouth.edu>

- Thanks to many people's contributions

<http://metrosense.cs.dartmouth.edu/metro-people.html>

- Sponsors

