Mobile sensing systems: from ecosystems to human systems

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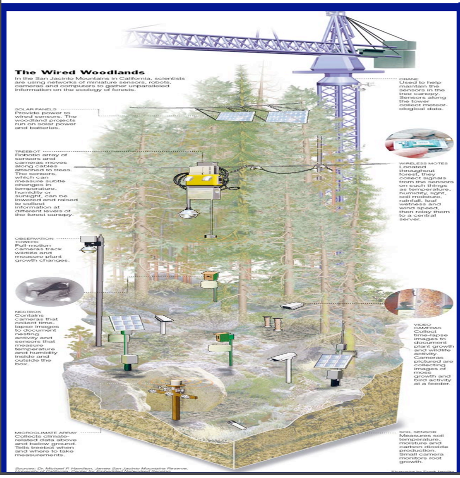
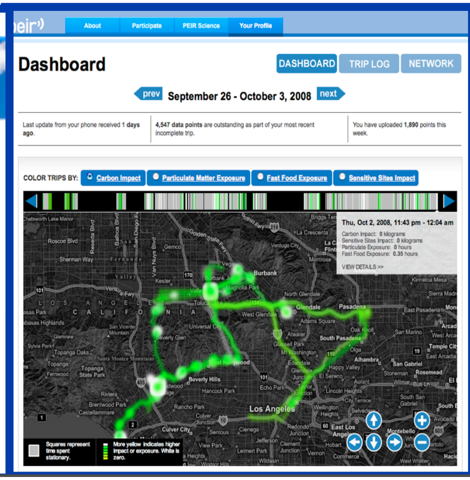




YouTube Video on PEIR

Many critical issues facing science, government, and the public call for high fidelity and real time observations of the physical world

Embedded sensing systems:

reveal the previously unobservable

help us understand and manage interactions with physical world, scarce resources, and one another

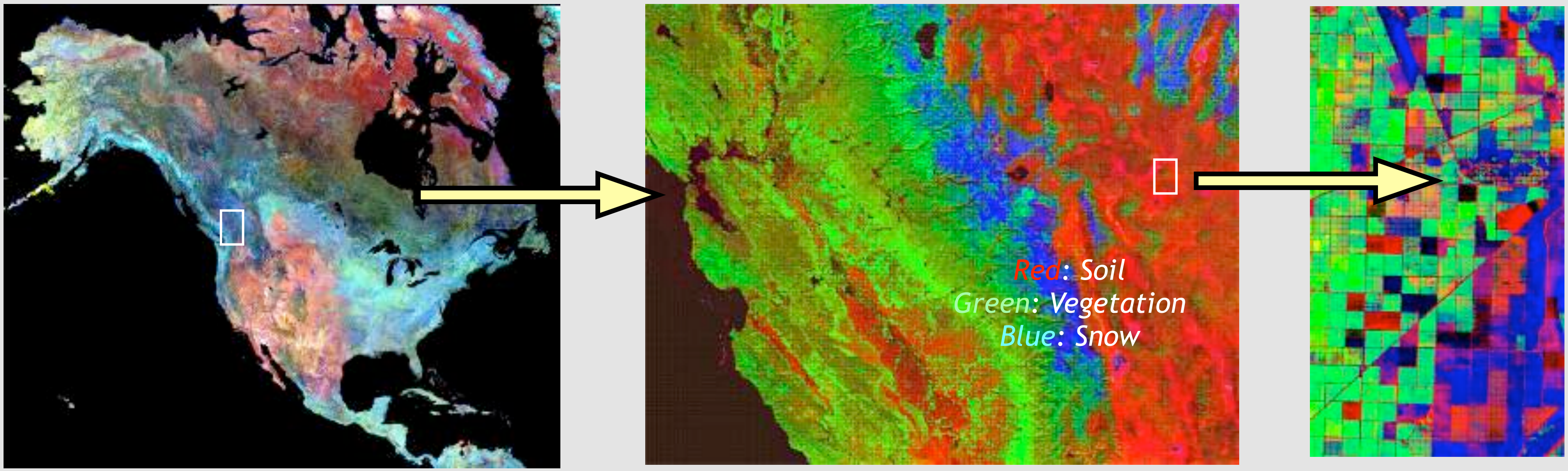
Why *embedded* sensing?

- Remote sensing transformed observations of large scale phenomena
- Embedded (in situ) sensing transforms observations of spatially rich processes

Embedded in the physical environment

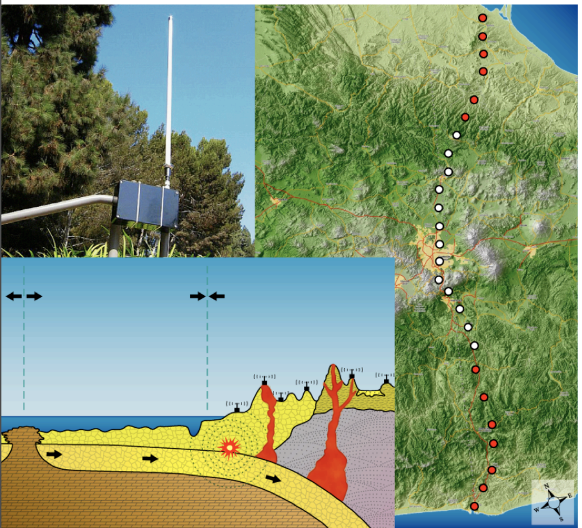
Networked to share information/adapt function

Sensing physical world phenomena



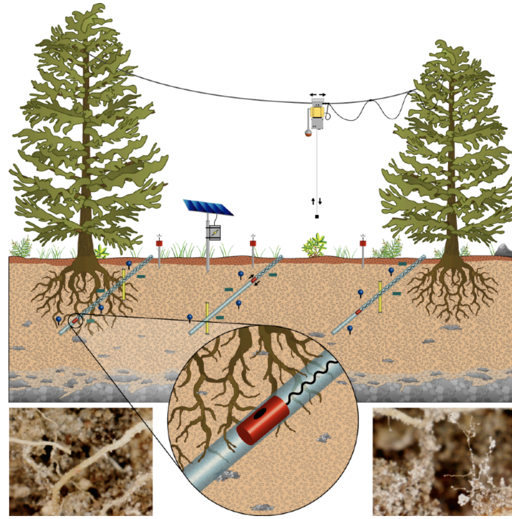
San Joaquin River Basin
Susan Ustin-Center for Spatial Technologies and Remote Sensing

Center-wide focus: embedded networked sensing *to reveal the previously unobservable*



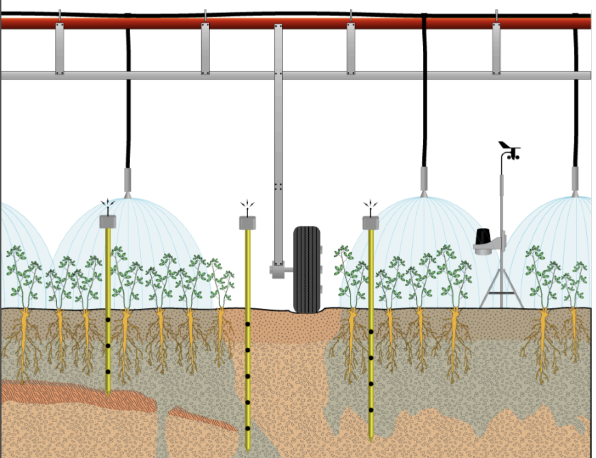
create programmable, distributed, multi-modal, multi-scale, multi-use observatories to address compelling science and engineering issues

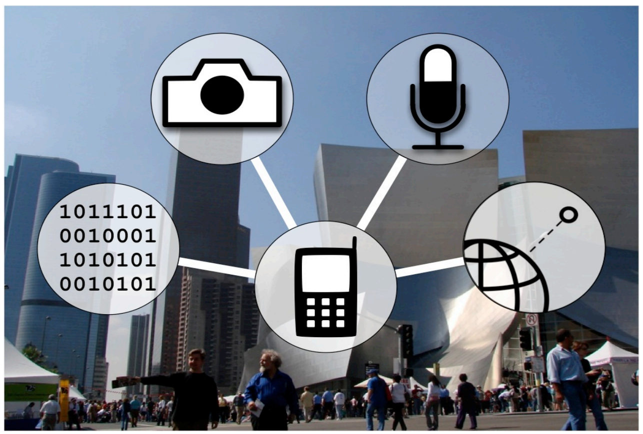
...and reveal the previously unobservable.

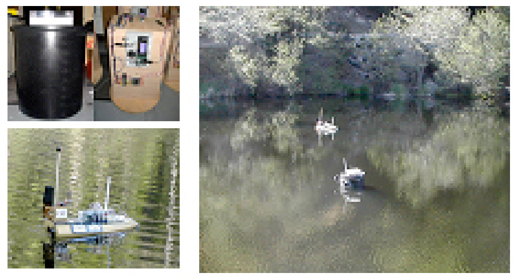


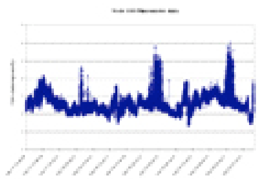
From the natural to the built environment...

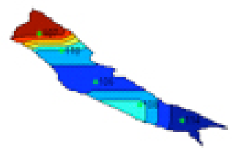
From ecosystems to human systems...











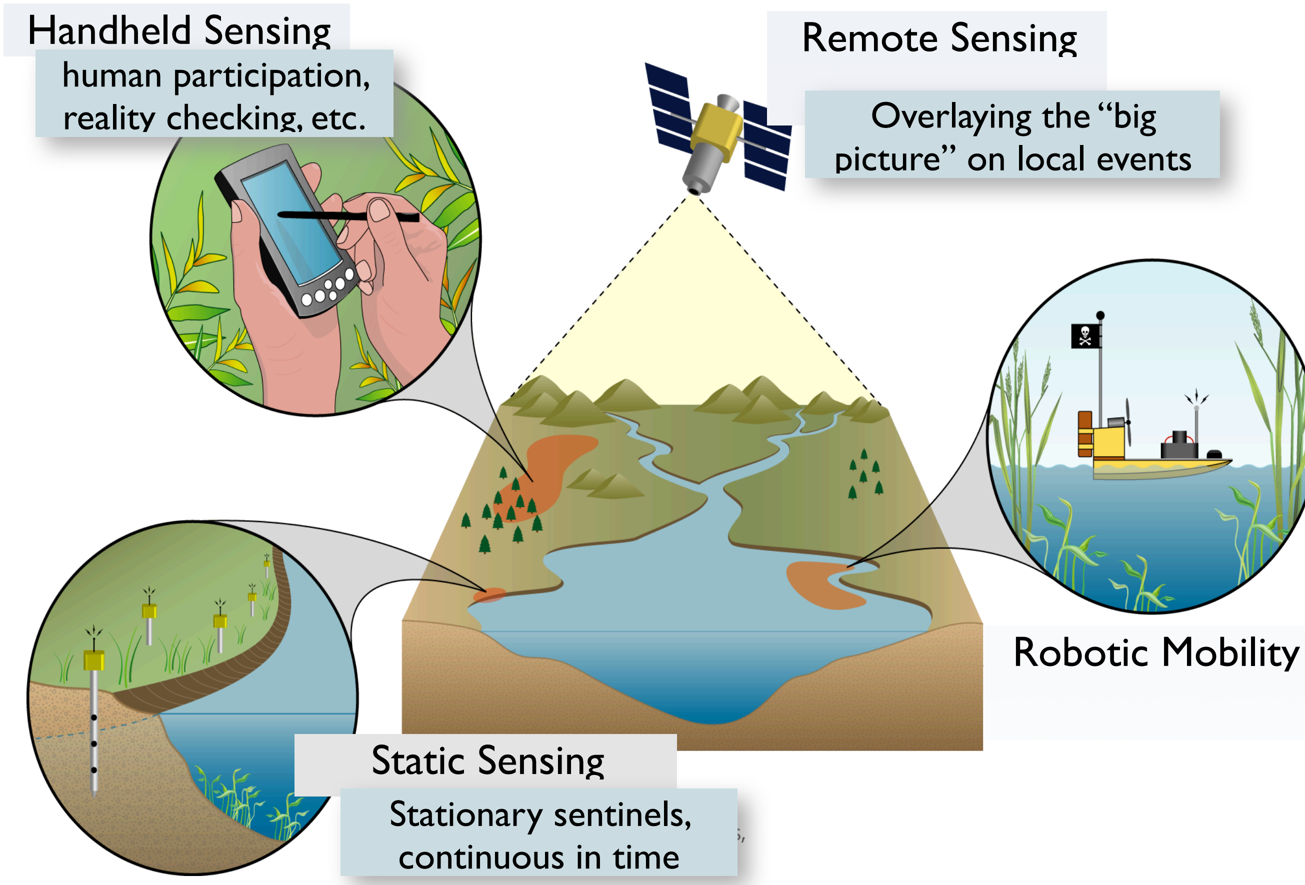
Lessons from the field lead to new approaches

Early Themes

- Thousands of small devices
- Fully autonomous systems

Current Themes

- Mobility
- Server-side models, data, analysis
- Coupled human-observation systems



If you can't go to the field with the sensor you want, go with the sensor you have

present → *future*

abiotic ↓ *biotic*

Physical Sensors: microclimate, location, acceleration

Chemical Sensors: gross concentrations

Chemical Sensors: trace concentrations

Acoustic and Image data samples

Acoustic, Image sensors with on board analysis

DNA analysis onboard embedded device

Personal medical devices

Sensor triggered sample collection

- System designs need to compensate for lack of sensor specificity, sensitivity, availability...particularly wrt biological response variables
- Leverage proxy sensors and model based interpretation/inference

Mobile Personal Sensing

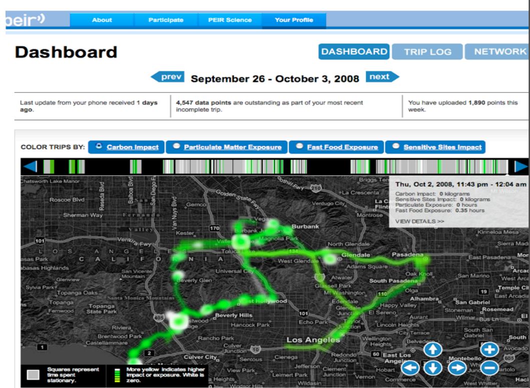
http://urban.cens.ucla.edu

Enabled by >3 x 10^9 mobile phone users, increasingly with...

- Digital imagers, location, bluetooth-connected sensors
- Automatic-geocoding of data
- Programmed, user, and server-initiated capture
- Server-side/cloud processing/ archiving/ presentation of personal

Motivated by 6 x 10^9 people on planet earth and their concerns...

- Individual health and wellness
- Public health, urban planning, epidemiology
- Civic concerns (transportation, safety, culture...)
- Resource management



Participatory Sensing: Campaign Model
leveraging real-time, geo-coded, images

Distributed data gathering challenges as "Campaigns" -

Spatially and temporally constrained systematic data collection operations.

Exploring a single hypothesis, phenomena or theme.

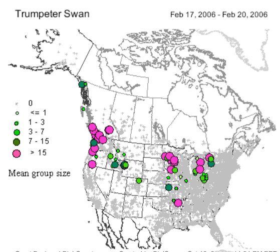
Using human-in-the loop sensing to gather data.

With automatic and manual classification, auditing, and analysis.

Precedent - Community-Based Participatory Research

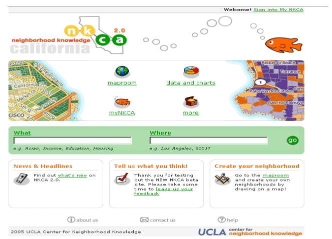
PhotoVoice
Caroline Wang, 1996

Citizen Science
World Water Quality Day



Citizen Science
Cornell e-Bird

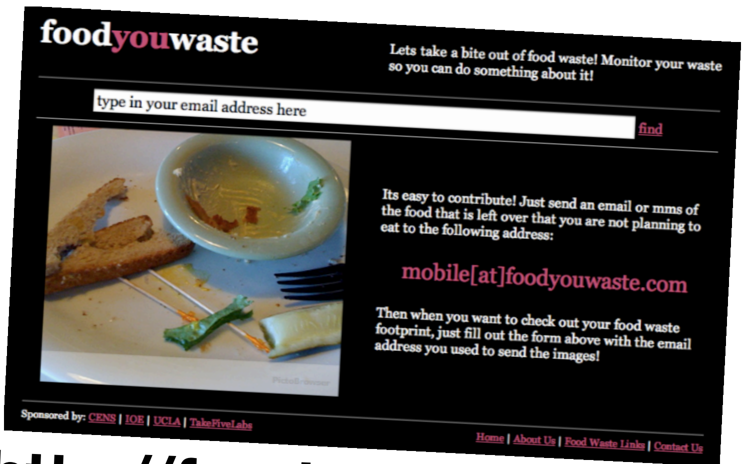
Civic Participation
Video the Vote



Participatory GIS
Ctr for Neighborhood Knowledge

Campus Sustainability Initiatives

http://garbagewatch.com



http://foodyouwaste.com

[challenge: automated campaign management, data integrity feedback]

CycleSense

Help bikers plan safe routes & collect data to improve routes.

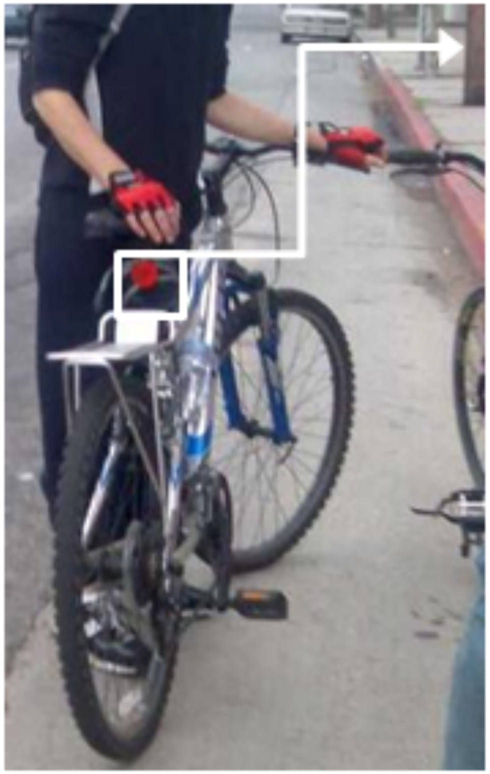
Capture/process/ share route data and features

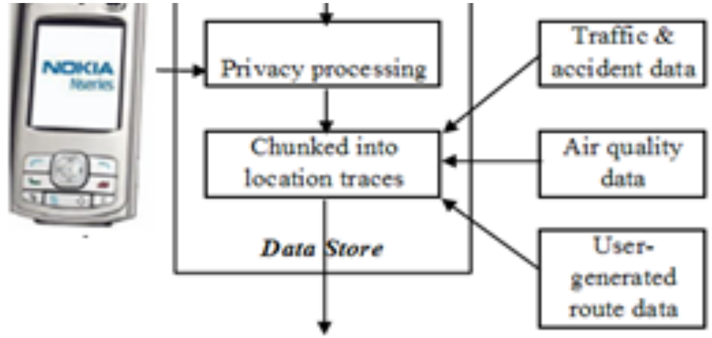
location, duration, stops/starts, roughness, sound samples, images of route features

Web interface compares routes' qualities

Mash up routes with air quality, traffic conditions & accidents

Community site for sharing information with LA bike community





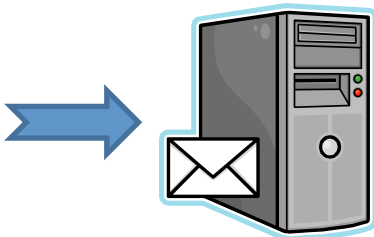
[challenge: activity classification, usability]

"...the total costs associated with HABs over past decades have been conservatively estimated at over $1 billion." - NOAA[1]

Mobile MERHAB

SMS / MMS

High spatial/temporal density data capture



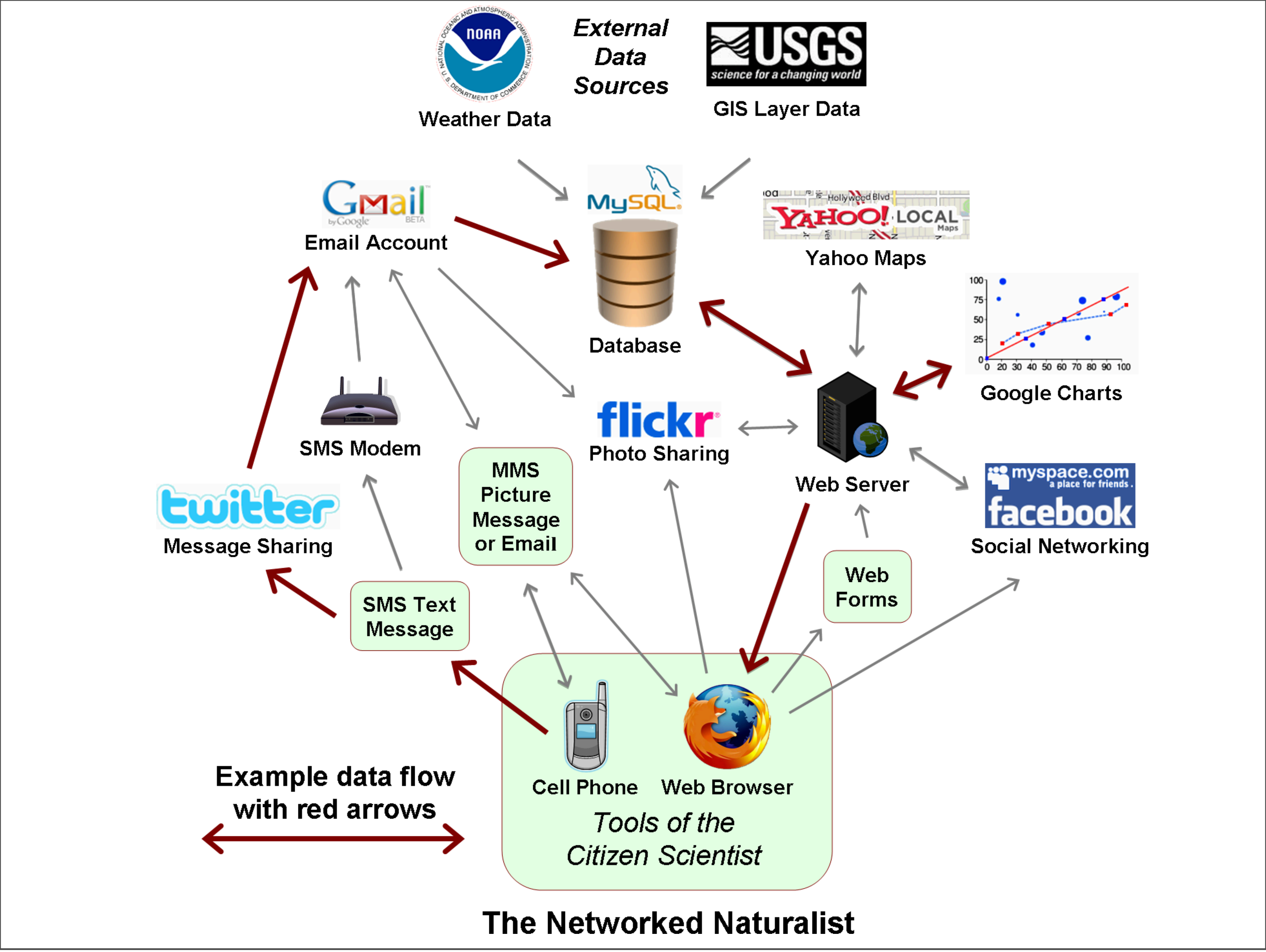
Networked Naturalist

SmartPhones

"... by monitoring changes in phenological events such as first bud, budburst, and flowering, scientists can detect climate change."- Project BudBurst

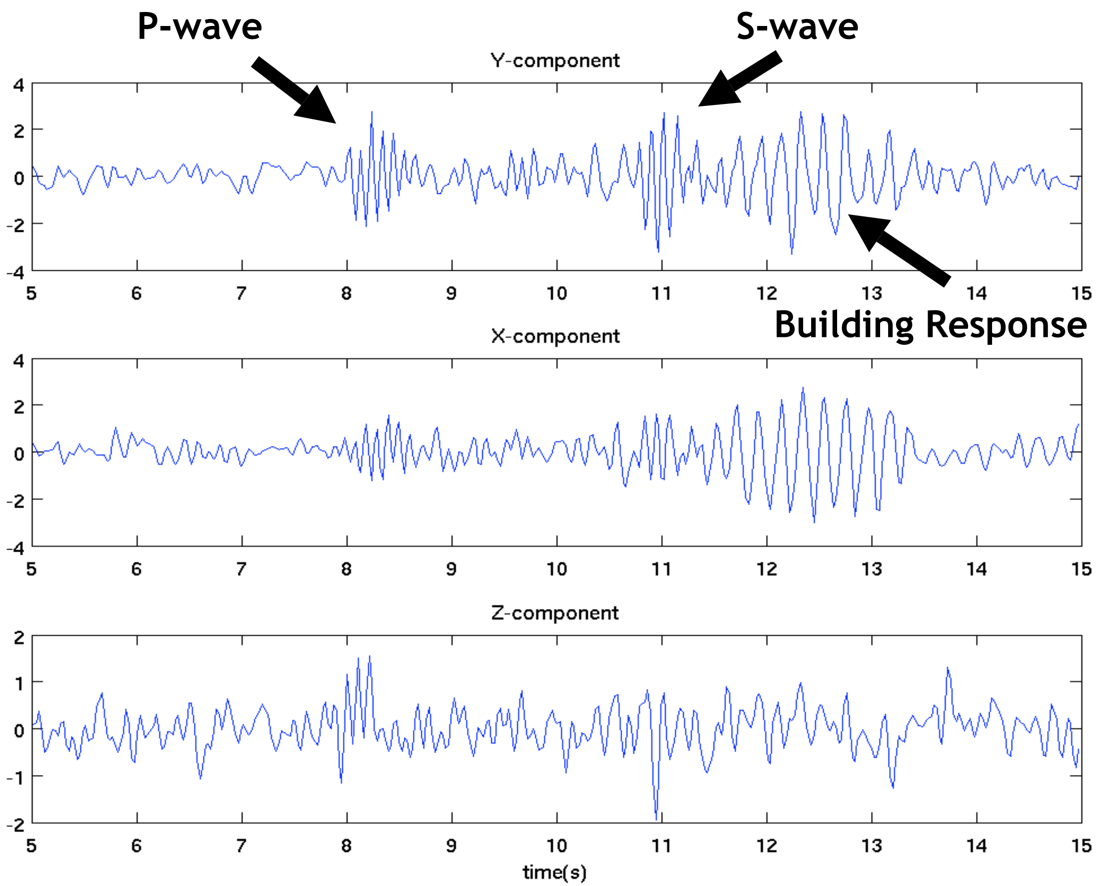
[challenge: automated data integrity checks, usability]

Moldovan, Ramanathan, Graham, Estrin et al


External Data Sources
Weather Data
GIS Layer Data
Email Account
Database
Yahoo Maps
Google Charts
SMS Modem
Photo Sharing
Web Server
Message Sharing
MMS Picture Message or Email
Social Networking
SMS Text Message
Web Forms
Cell Phone
Web Browser
Tools of the Citizen Scientist
Example data flow with red arrows
The Networked Naturalist

Geocoded person-scale samples (accelerometer) for seismic

- First (we think) capture of magnitude 3.4 earthquake on Nokia n95 cell phone (8-bit ~ 40Hz 2G accelerometer) 5 miles away from epicenter *(has been done on laptops--UCR)*
- 1/23/09: Santa Monica, California. Magnitude 3.4. (ID ci10373093)
- P and S waves observed at ~ 8 and ~11 seconds, respectively.
- Ringing after 11 seconds typical of response of buildings to seismic waves--not in records from nearby (buried) seismic station.



Detrended and low-pass filtered (10Hz)

Traditional measures: http://quake.wr.usgs.gov/recenteqs/Quakes/ci10373093.html

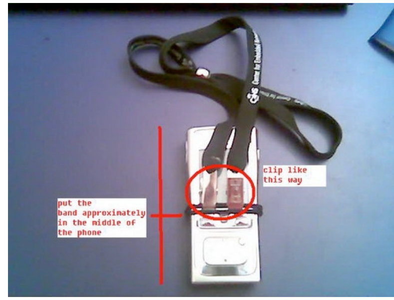
[challenge: calibration, what does it mean?]

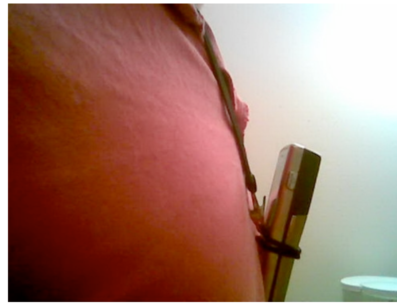
DietSense as alternative to self-reporting

leveraging real-time, automated, personal, images

mobile phones

worn on a lanyard around the neck that automatically collect geo-coded, time-stamped images of food choices or purchases.





participant data repository

receives annotated media collected by the devices, allows individuals private access to their own data before they are available to others, and supports filtering and alerting based on upload patterns and basic analysis of received data.

annotation, filtering, and analysis tools

provide efficient mechanisms to navigate, annotate, filter, and analyze collected data, including capability to export reports to common statistical software packages.

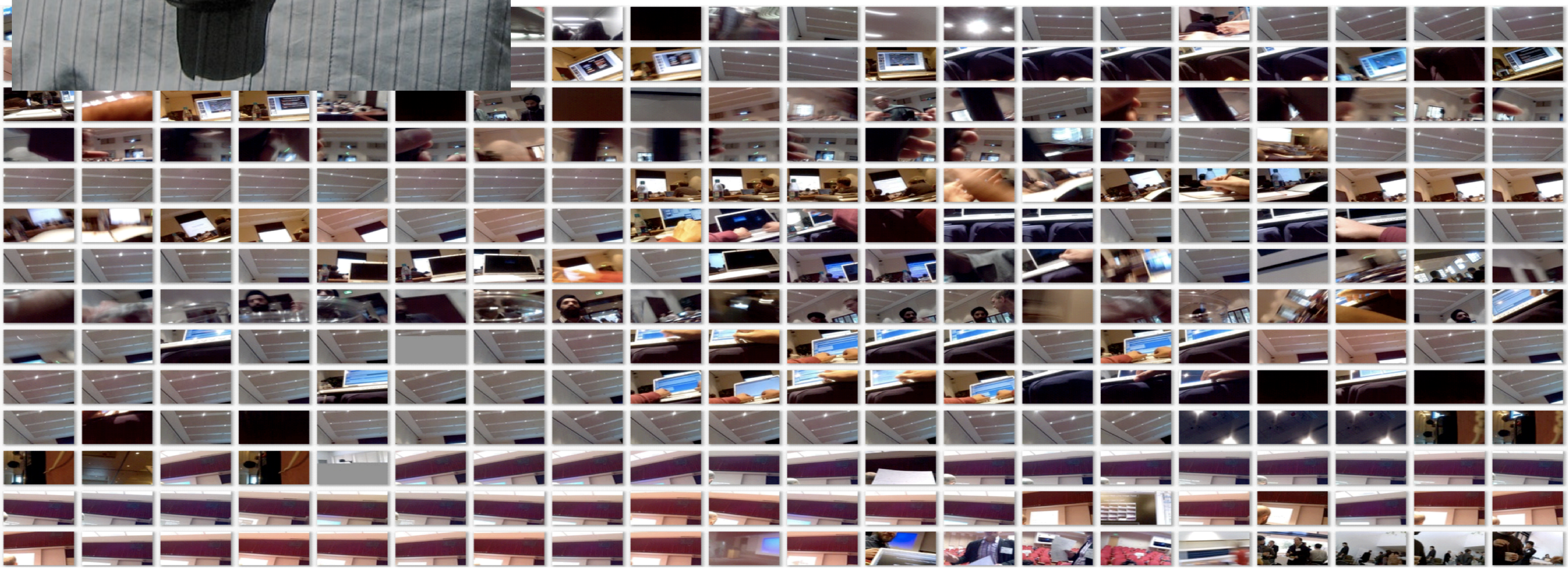
[challenge: computer vision category recognition, wearable cameras]

Kim, Kim, Petersen, Burke, Estrin, Arab...

Privacy concerns dominate system design

Automated pre-filtering, clustering, to reduce number of viewed images
[challenge: computer vision, category recognition]

Privacy concerns dictate image viewing/tagging by individual, not by third party
[challenge: privacy filtering]



Kim, Kim, Petersen, Arab, Burke, Estrin, ...

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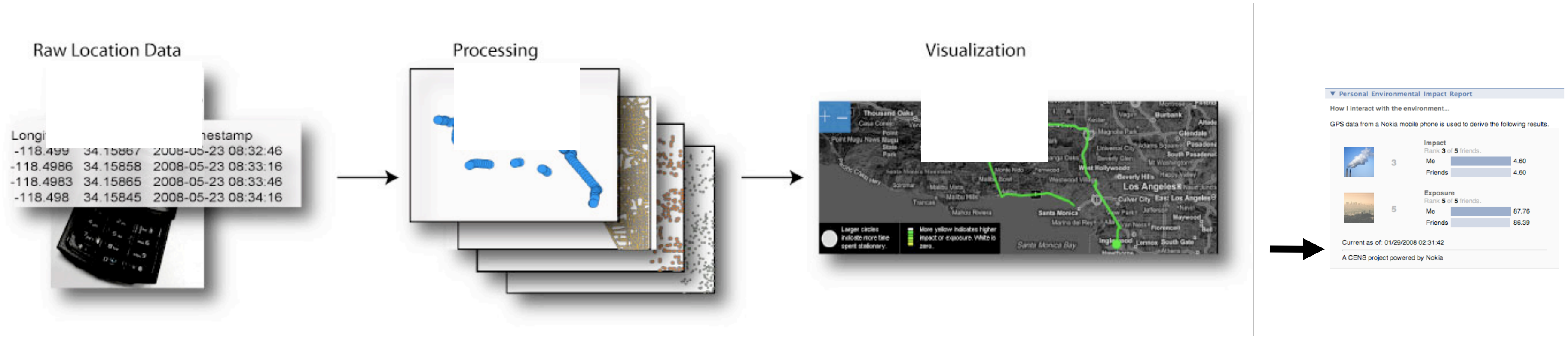
Geo-coding as primary (not just meta) data:
leveraging real-time location traces



Device data capture and interaction:
- software on mobile prompts/captures and uploads
- data types: location image, audio, text tagging, worn sensors
- UI on phone

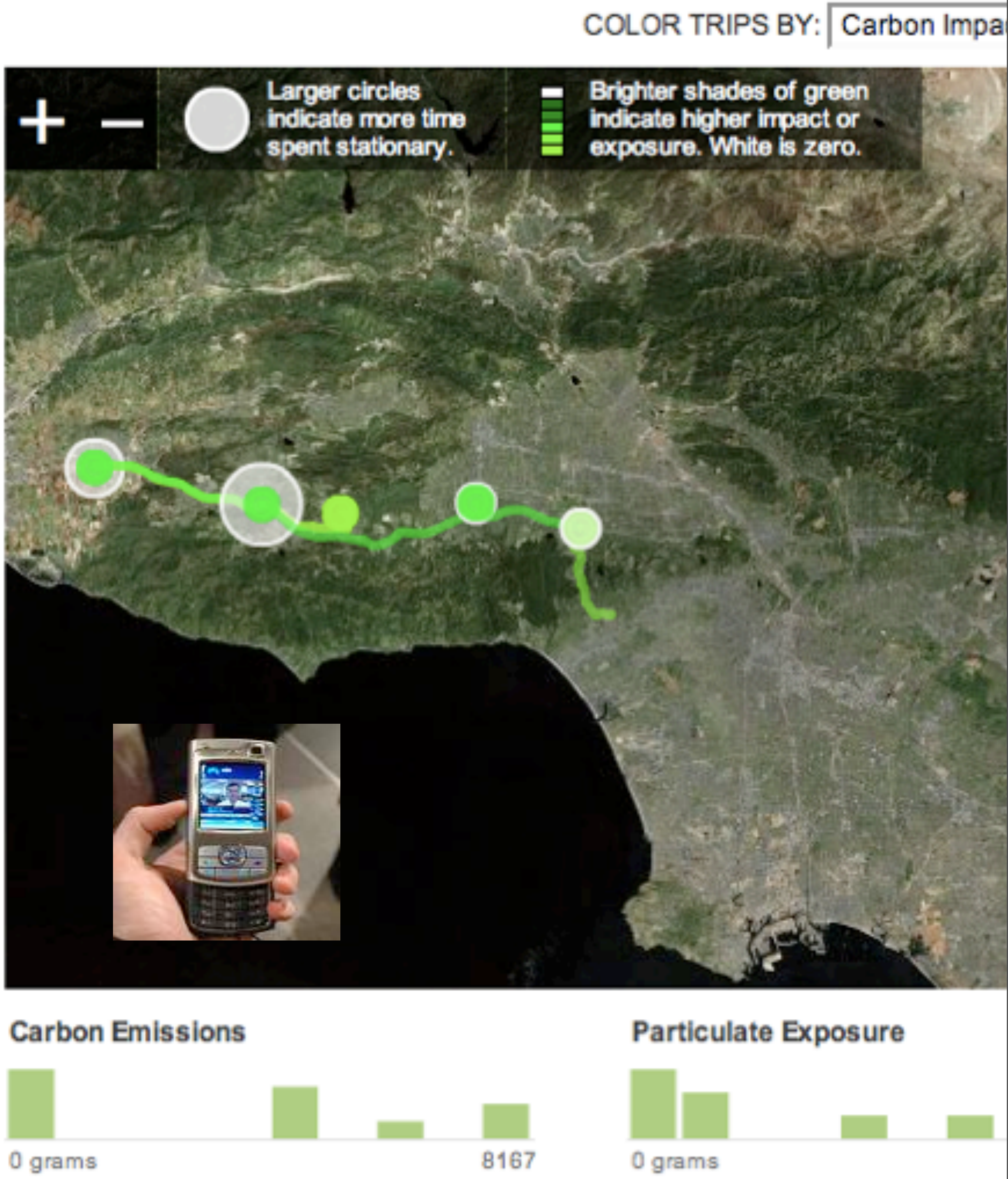
Processing
- activity classification
- mapping
- integrate with other GIS and realtime data about built and natural environment
- index into models
- privacy relevant filtering

Visualization
- for personal and professional insight
- legible, contextualized
- use/user configurable
- difficult to generalize
  - projects need support
  - platforms available for development

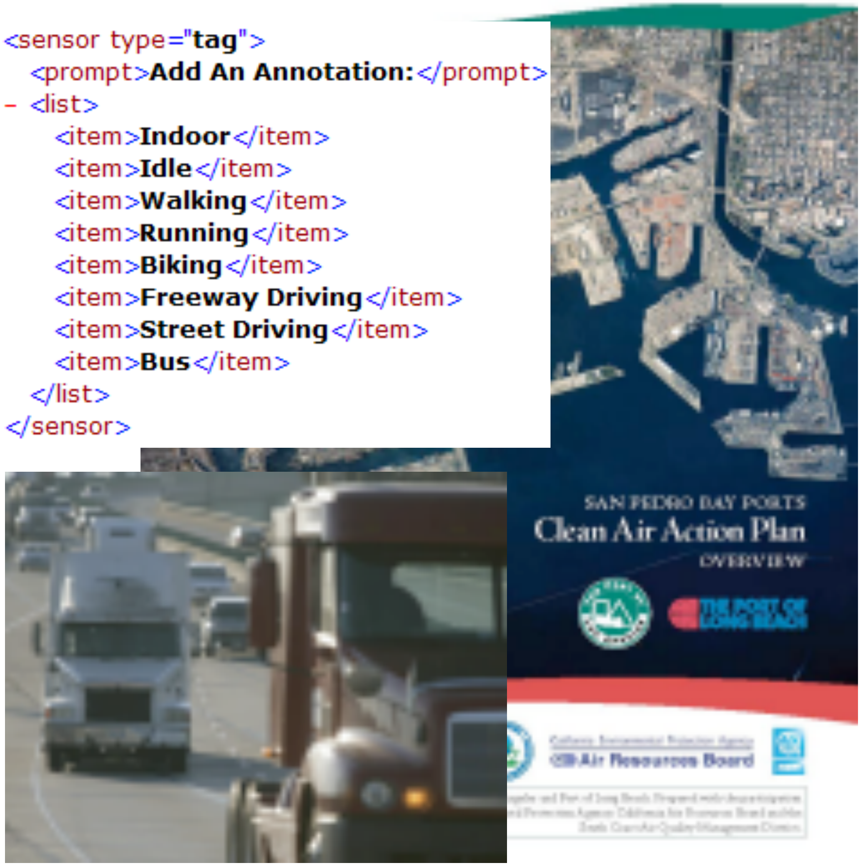
Sharing/Aggregating
- social networking
- web and device
- participatory privacy
- track data access for visibility/ transparency

Imagine if….

Our **everyday cell phones** could show us *how we impact the environment*, and *how it impacts us*, just as they now alert us to traffic jams on the highway.



```xml
- <sensor type="tag">
    <prompt>Add An Annotation:</prompt>
  - <list>
      <item>Indoor</item>
      <item>Idle</item>
      <item>Walking</item>
      <item>Running</item>
      <item>Biking</item>
      <item>Freeway Driving</item>
      <item>Street Driving</item>
      <item>Bus</item>
    </list>
  </sensor>
```



Exposure Assessment

Personal Environment Impact Report

▼ Personal Environmental Impact Report

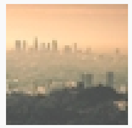
How I interact with the environment...

GPS data from a Nokia mobile phone is used to derive the following results.

3

Impact
Rank **3** of **5** friends.

Me		4.60
Friends		4.60



5

Exposure
Rank **5** of **5** friends.

Me		87.76
Friends		86.39

Current as of: 01/29/2008 02:31:42

A CENS project powered by Nokia

Exposure to Traffic-related Pollutants

Lifelong damage found in 13-year study of 3,600 Southland youngsters living within 500 yards of a highway.
The Los Angeles Times, 1/26/07

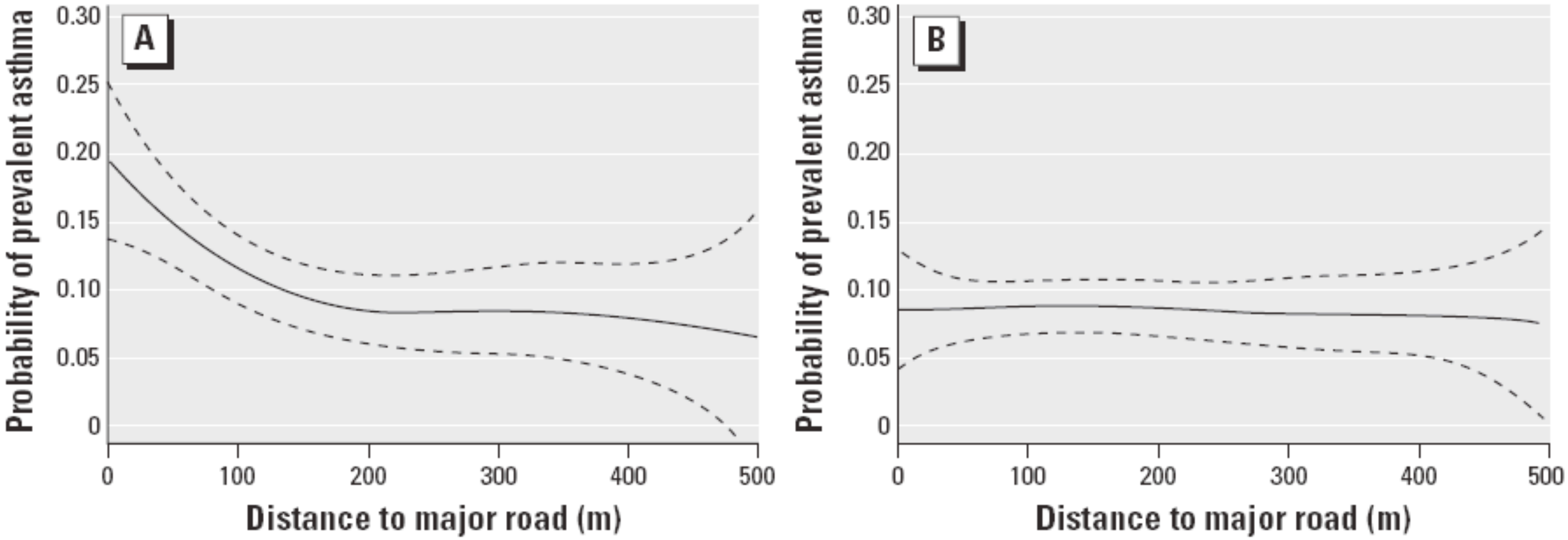


Figure 2. Prevalence of asthma by distance of residence to a major road within 500 m, among long-term (*A*) and short-term (*B*) residents with no family history of asthma. Dotted lines indicate 95% confidence interval.

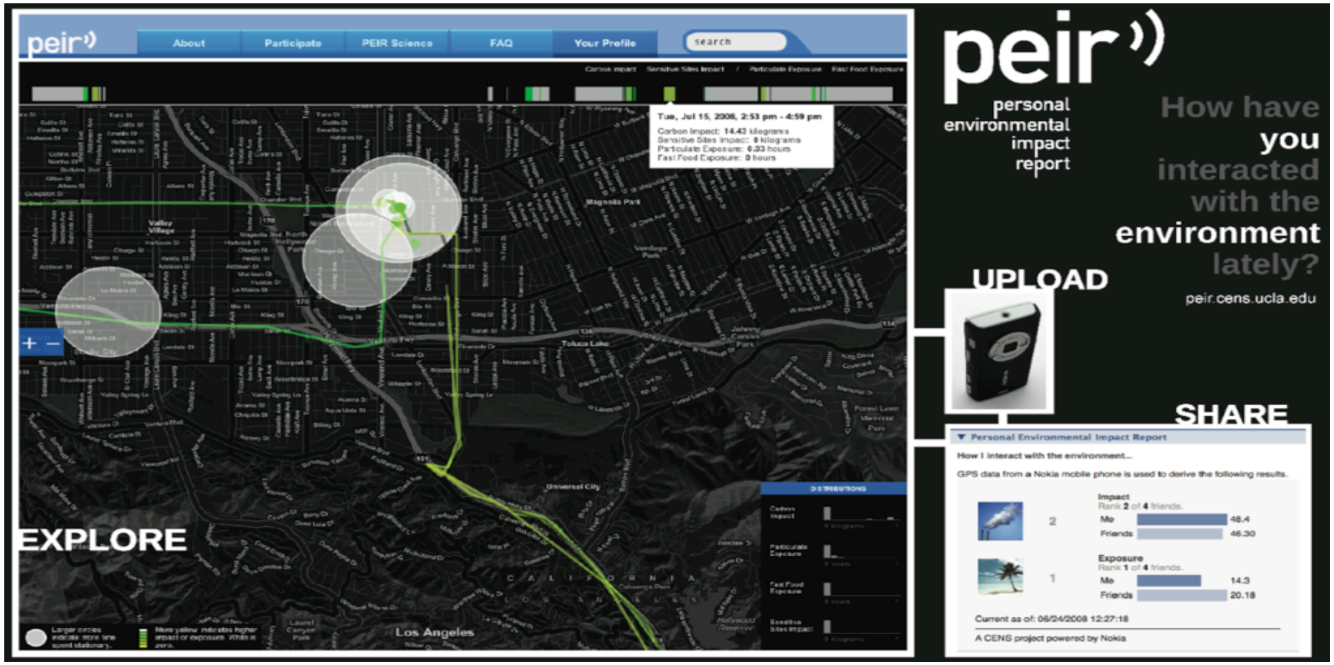
Source: McConnell et al. Traffic, Susceptibility, and Childhood Asthma. Environ Health Perspect 114:766–772 (2006)

PEIR: Personal Environmental Impact Report

Personal, real-time, location traces....combined with micro-environmental models ...to provide personal exposure and impact assessment

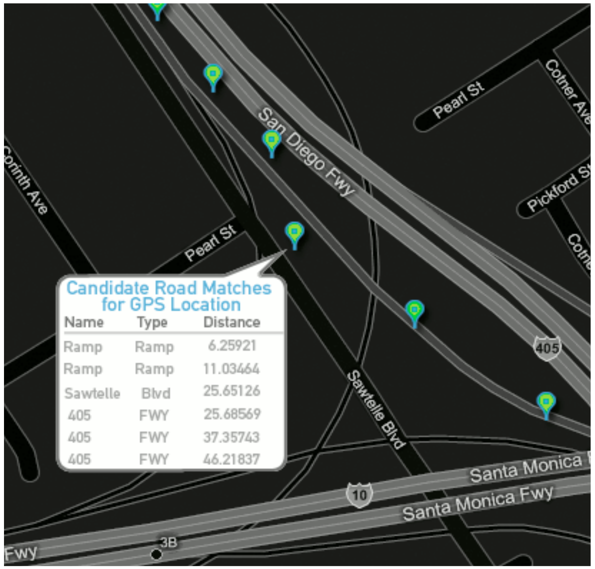
Invite investigation of individual habits overtime:
...in relationship to others and the environment
...as seen in data and inferred from models.

http://peir.cens.ucla.edu

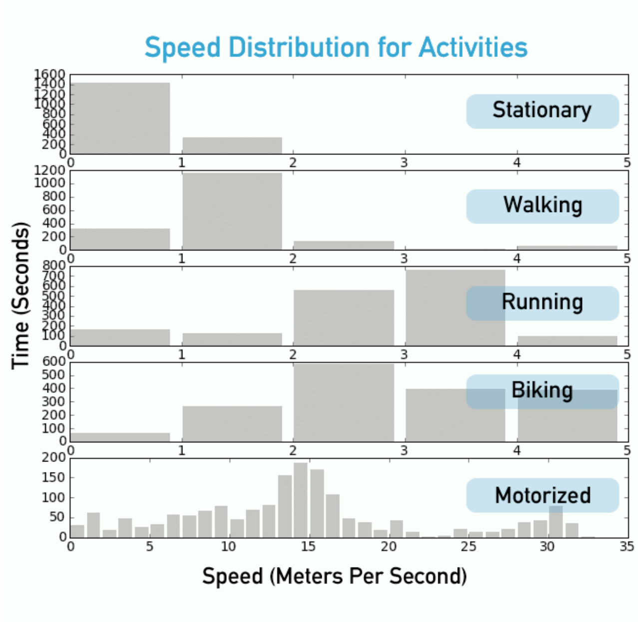


Mun, Yau, Burke, Estrin, Hansen, West, ...

Activity estimated from location trace on secure servers



Map Matching



Activity Classification

Automatically annotate GPS trace: **still, walking, driving**, cycling, bus, train

filter anomalous GPS points;
map match freeway;
GPS speed feature;
decision tree w/6 speed/freeway combinations;
HMM recognition;
trip chunking w/configurable dwell time (10 mins)

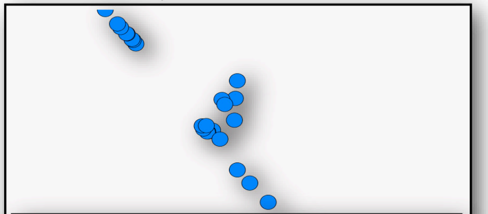
[challenge: robust and parsimonious activity classification]

Mun, Burke, Hansen, ...

Location-Activity Trace processed through scientific models

Location Trace Processing

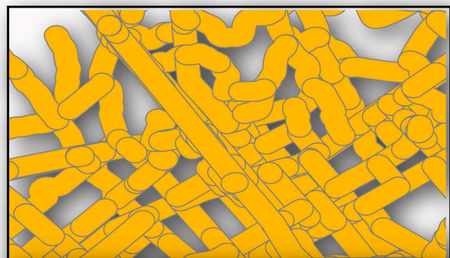
Location Trace + Weather
+ Activty Classification



Lat.	Lon.	Temp (K).	R.H.	Act. Class
34.048257	-118.447998	282.039	80%	Driving
34.045795	-118.445858	282.039	80%	Driving
34.02637	-118.429833	284.817	79%	Driving

+

Road Buffers

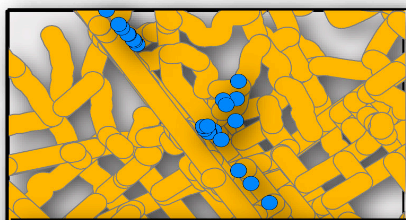


Name	Length (Mi)	A-B Car	A-B LDT	A-B HDT	A-B Speed
Westwood	0.38	2550	13	7	20
Westwood	0.36	3776	22	20	19
Wilshire	0.5	5095	36	25	23

+

EMFAC

Trip Aggregation

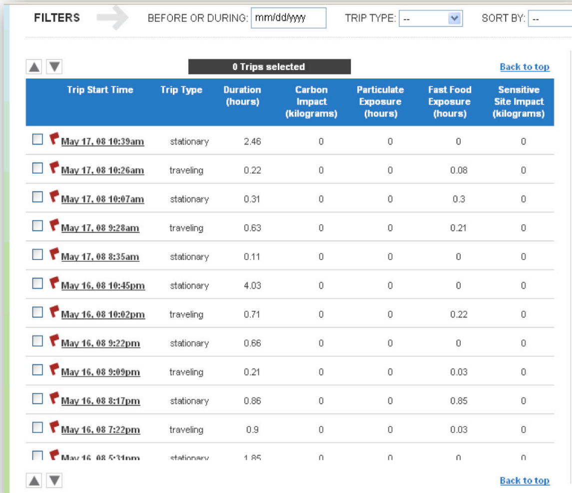


Lat.	Lon.	PM 2.5 (g/sec)	PM 2.5 (μg/m3/sec)
34.048257	-118.448	1.471601	0.443403
34.045795	-118.44586	2.533434	0.335633
34.02637	-118.42983	1.992753	0.360976

Trip Summary

Trip	Avg. PM 2.5 Exposure	time spent over 0.112716 (hours)
2432	0.470002	0.15
2423	0.235333	0.27
2410	0.210576	0.04

PEIR U.I.



FILTERS BEFORE OR DURING: mm/dd/yyyy TRIP TYPE: -- SORT BY: --

0 Trips selected

Back to top

Trip Start Time	Trip Type	Duration (hours)	Carbon Impact (kilograms)	Particulate Exposure (hours)	Fast Food Exposure (hours)	Sensitive Site Impact (kilograms)
May 17, 08 10:39am	stationary	2.46	0	0	0	0
May 17, 08 10:26am	traveling	0.22	0	0	0.08	0
May 17, 08 10:07am	stationary	0.31	0	0	0.3	0
May 17, 08 9:28am	traveling	0.63	0	0	0.21	0
May 17, 08 8:35am	stationary	0.11	0	0	0	0
May 16, 08 10:45pm	stationary	4.03	0	0	0	0
May 16, 08 10:02pm	traveling	0.71	0	0	0.22	0
May 16, 08 9:22pm	stationary	0.66	0	0	0	0
May 16, 08 9:09pm	traveling	0.21	0	0	0.03	0
May 16, 08 8:17pm	stationary	0.86	0	0	0.85	0
May 16, 08 7:22pm	traveling	0.9	0	0	0.03	0
May 16, 08 5:31pm	stationary	1.85	0	0	0	0

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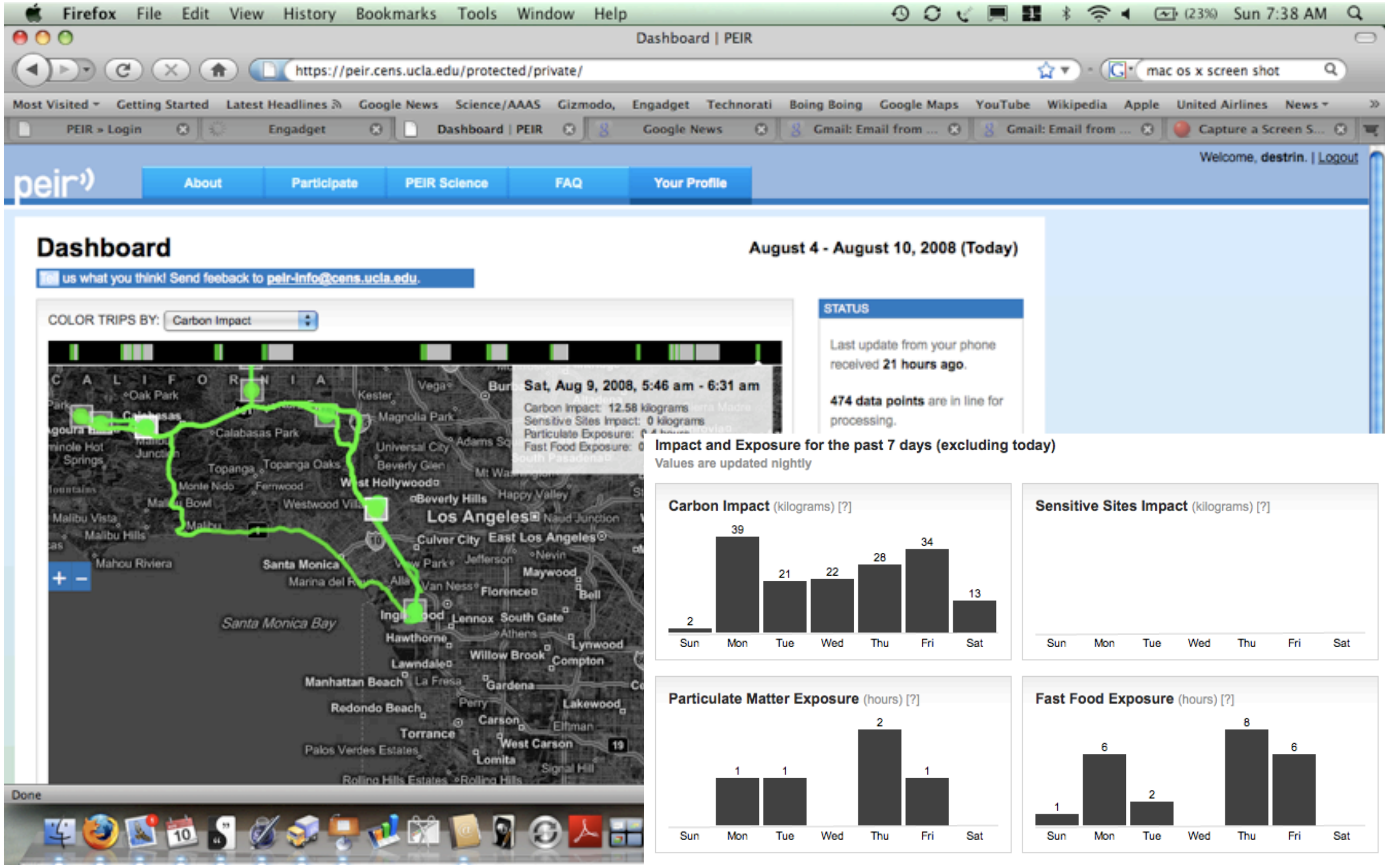
[challenge: tracking uncertainty/confidence, web services]

A week in PEIR



- User interface designed to promote data exploration and legibility
- User's data exploration begins with trip log
  - trip list sortable by model (e.g., most carbon impact/most particulate matter exposure)
  - calendar used to advance directly to specific points in time

[challenge: visualization]

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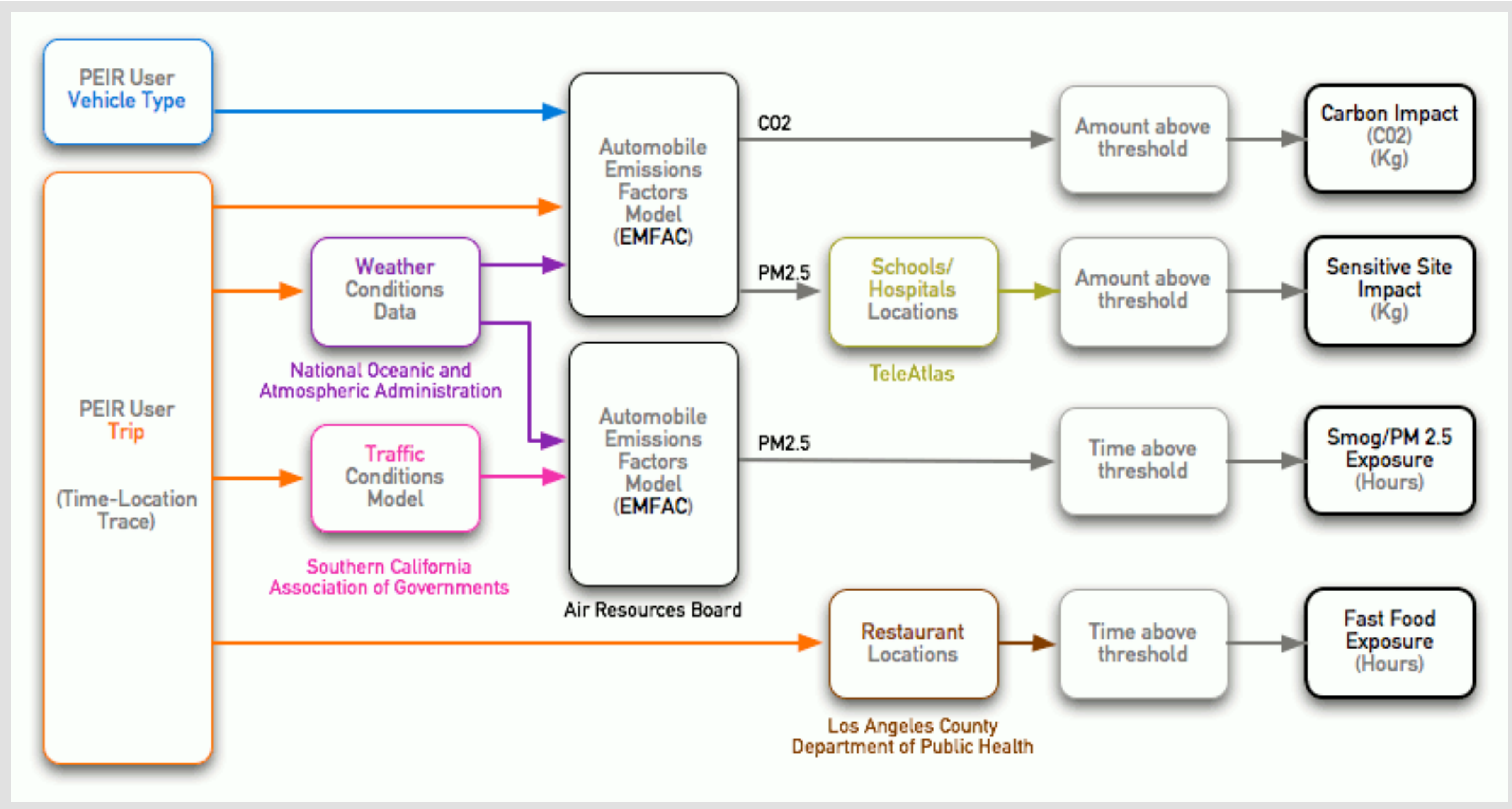
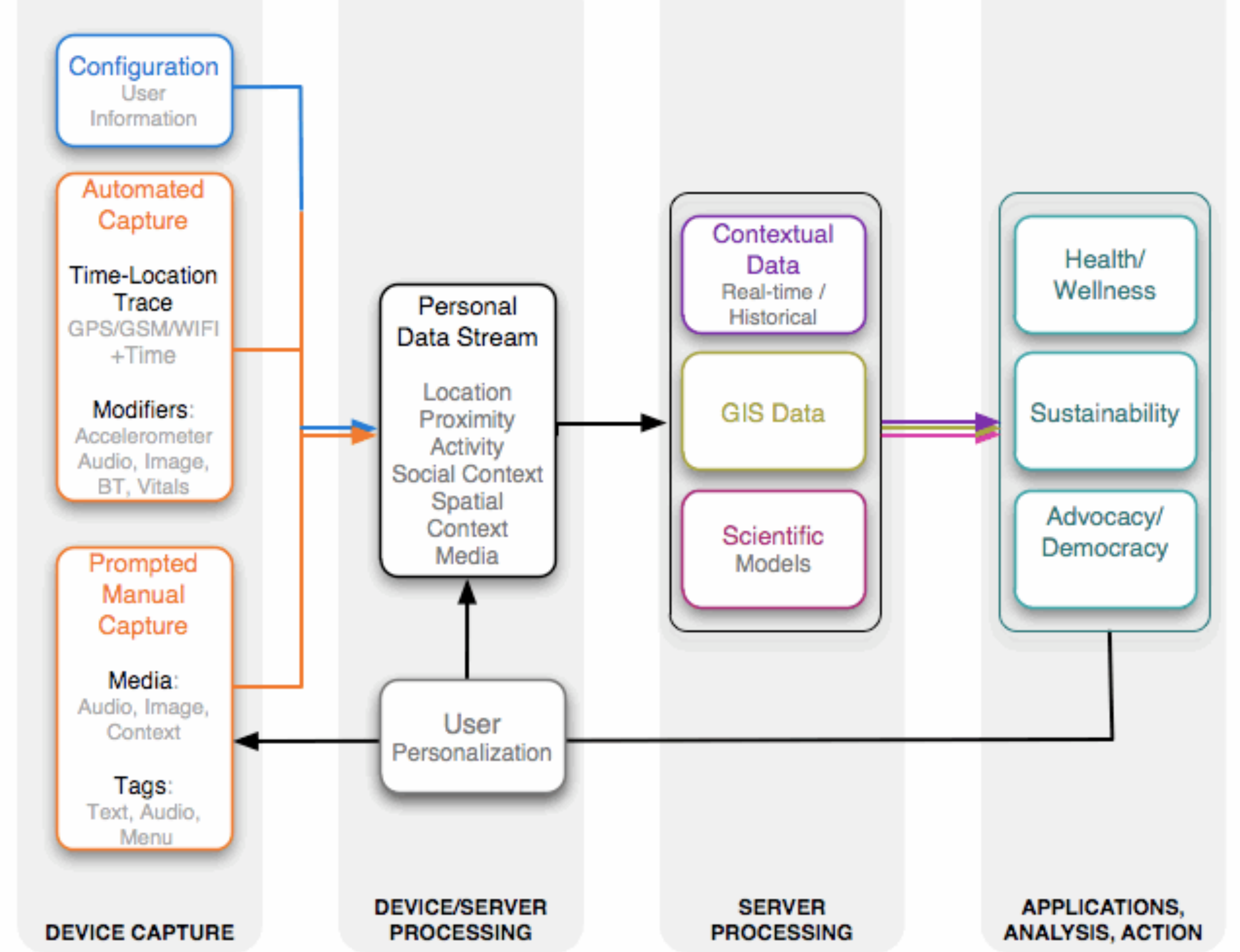
Yau, Hansen, Burke, West, Estrin, Naik, Chandler, Mun, ...

Non-trivial processing pipeline



[challenge: robust modular processing pipeline and scalable web services]

Emerging **mobile personal sensing** system architecture



Mobile personal sensing for health and wellness

INFERENCE
Multi-scale Measurement to Meaning

- **Epidemiology Cohort/Longitudinal**
- **Intervention & Treatment Outcomes**
- **Personalized Health Management Behavior Change**

Data Privacy / Visualization

PROCESSING
Device and Web Services

Location · Activity Type · Social Context · Spatial Context · Media

Annotation / Analysis

CAPTURE
Mobile Devices

Time-location trace: (GPS or GSM/Wifi + Time)
Modifiers: Motion, Audio, Image, Proximity, Biometrics

Automatic / Prompted-Manual

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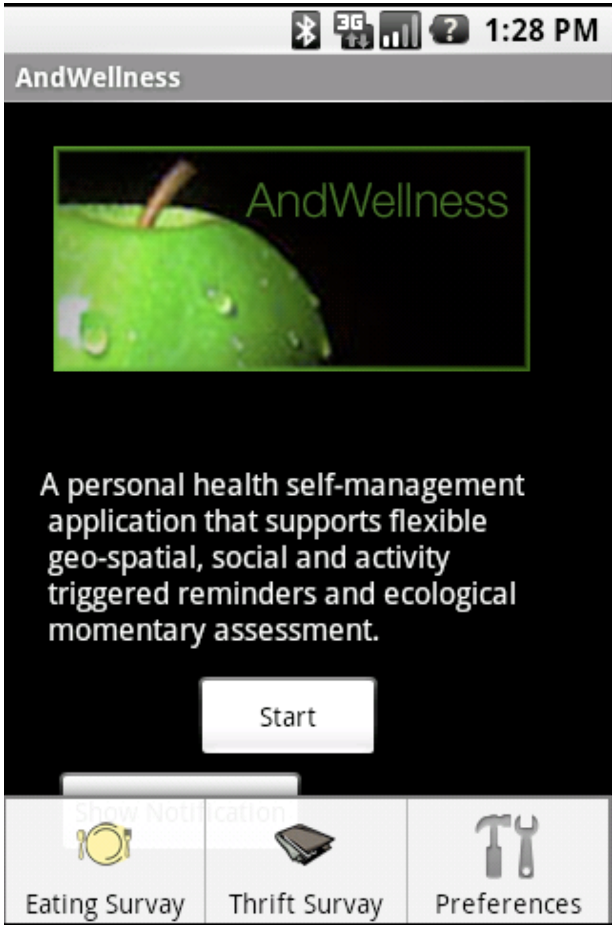
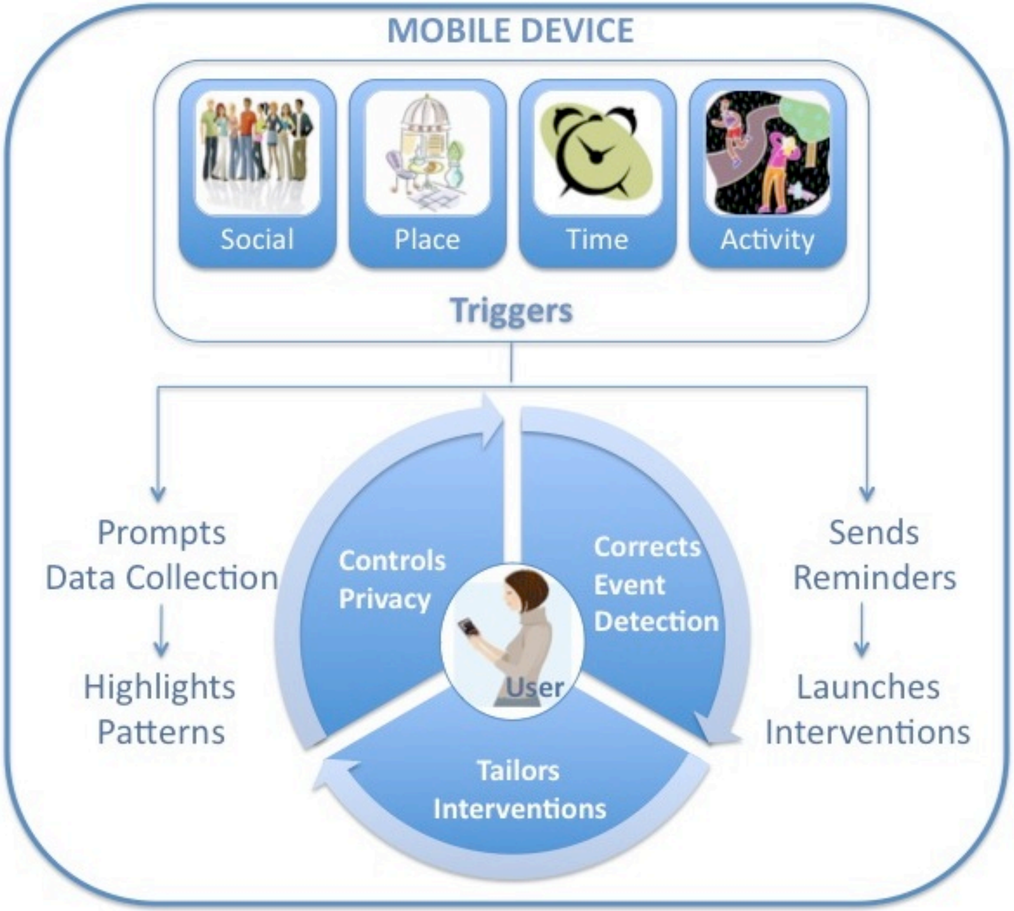
In collaboration with Mary Jane Rotheram et al at Global Center for Children and Families

*And*Wellness

Personal health self-monitoring and management: powered by automated location and activity detection, adaptive interface, integration with web assets

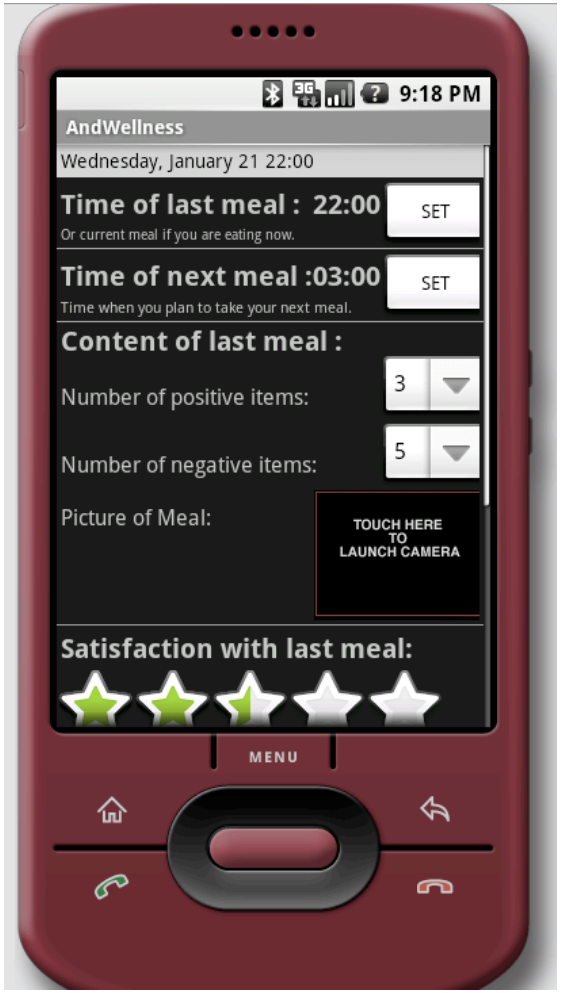




Adaptive event detection

- Automatically identify triggers to launch interventions or prompt user to record/journal.
  - Triggers based on the user's activity, place, temporal, or social context

- Incorporate user feedback to adapt to individuals and their environment.
  - Automatically groups similar events; only solicit feedback from users to label a group of unknown events, or to correct erroneous labels
  - Use lightweight clustering algorithms that are easy to modify

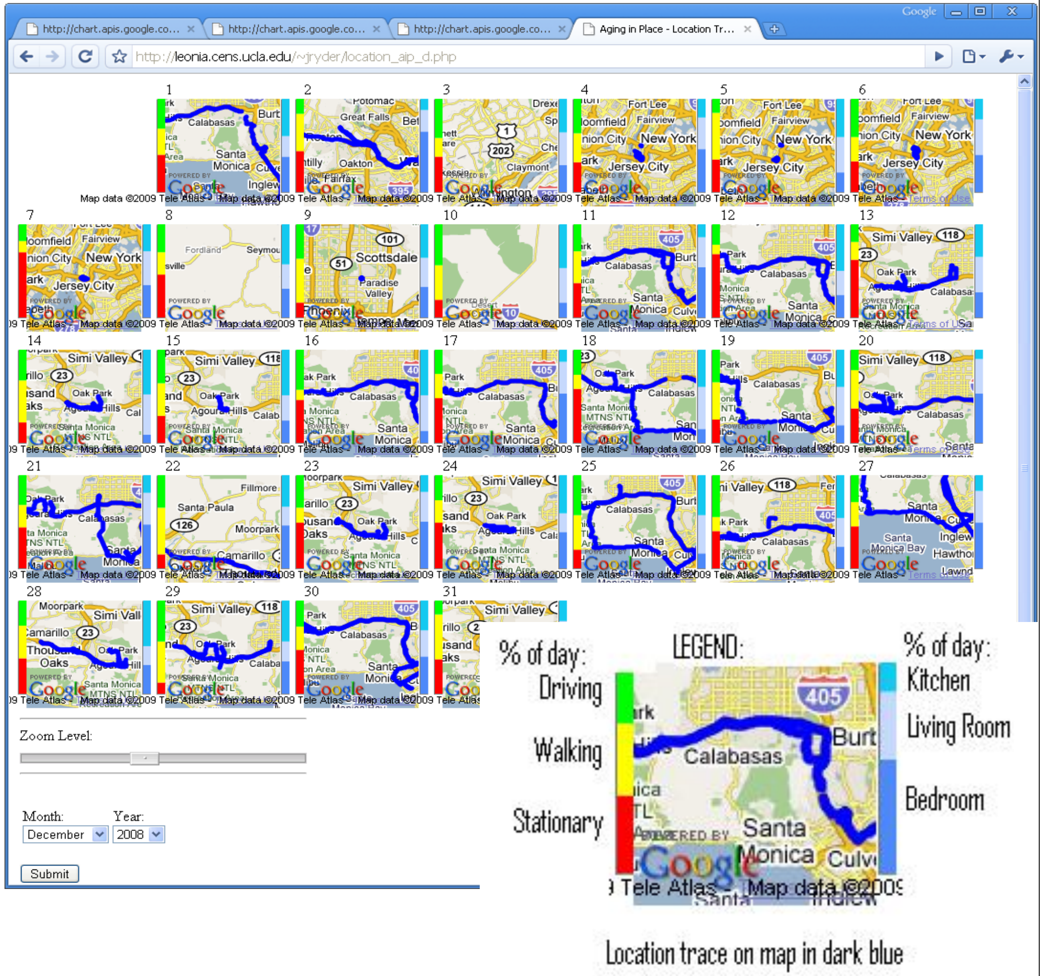


Partially automate services and incorporate limited user feedback to **shift the locus of control to the user while remaining non-invasive**

[challenge: adaptivity, learning, usability]

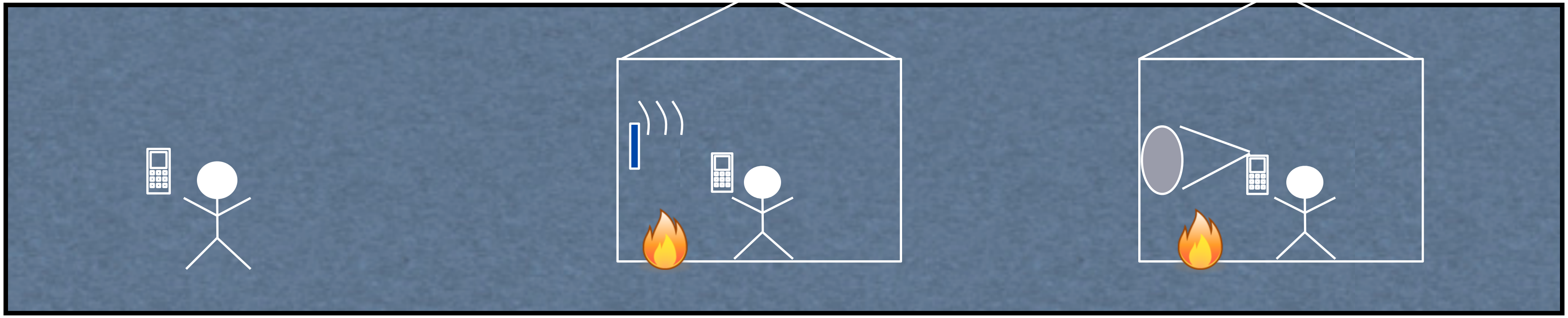
Related applications: activity and mobility profiles for those aging in place, or those managing chronic disease/conditions

- Observe patterns and trends in indicative activities of aging participants:
  - timing and frequency of trips to store, social activities, exercise routines
  - daily patterns of time spent in kitchen, dining area, TV room, bath/bedroom...
- Outdoor: time series of GPS and cell tower data points, combined with map matching
- Indoors: accelerometers and bluetooth stumbling



Community health application: monitor villagers' pollution exposure before and after introduction of clean cook stoves

profile participants' daily activities and exposure to indoor air pollution in unprecedented detail using mobile phone based location and proximity traces



Outdoor Activities are inferred from GPS and accelerometer data

Duration of exposure to cooking fires inferred when a user is in range of a Bluetooth temperature sensor in the kitchen.

Pollution Levels inferred from images of a special filter installed in the house

Epidemiologists at Sri Ramachandra University will deploy the cell-phone tool along with surveys and professional observation to evaluate Project Surya's impacts on the health of villagers.

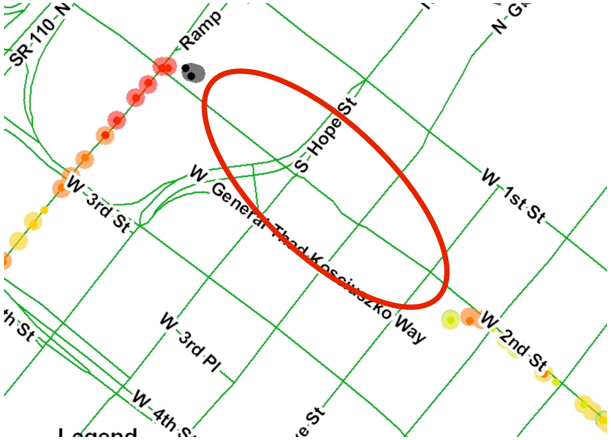
Key building block: activity classification

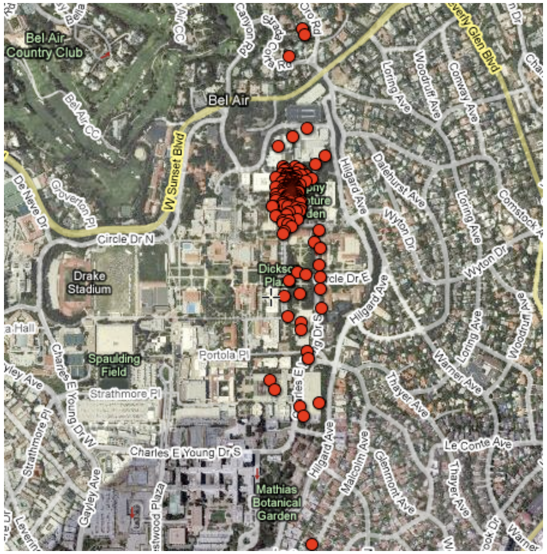
Mobile phones as a tool for introspection into the habits and situations of individuals and communities -- requires contextual information such as transportation mode

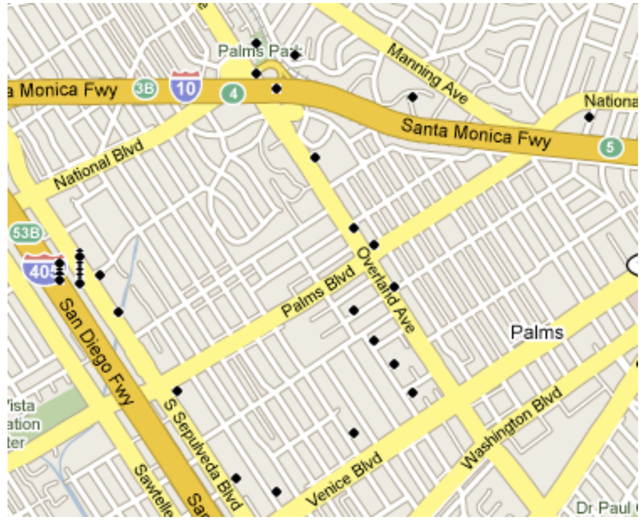
Extensive prior art

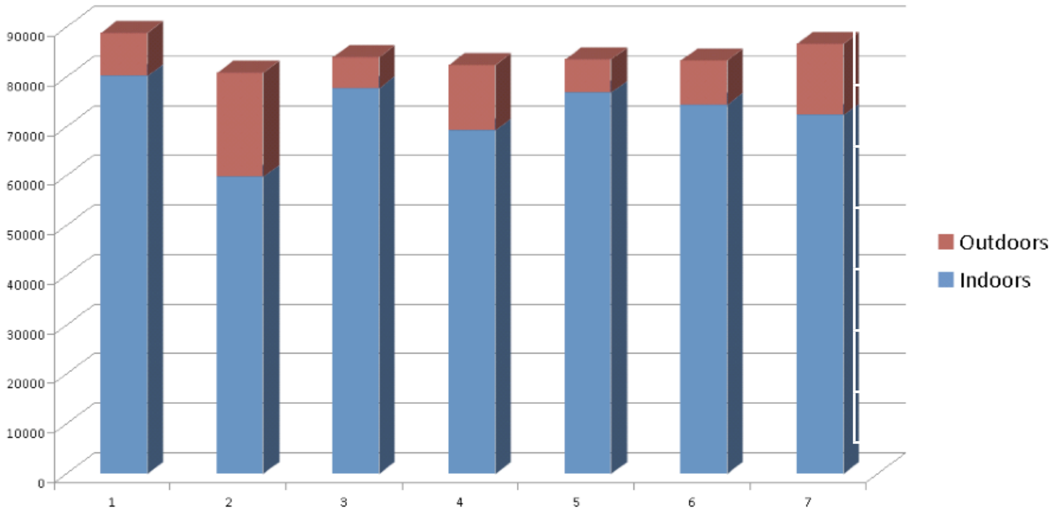
GPS, Contextual Models	Patterson 03 Liao 04,05,07 Zheng 08	- Models are too complicated to perform other tasks - GIS data is not always readily available
GSM	Anderson 06 Sohn 06	- A large portion of standard mobile phones does not release the information of multiple cell towers in range - They did not attempt to leverage smaller cell-size data such as Wi-Fi
Bluetooth	Tapia 04	- Bluetooth data is inappropriate to infer mobility states with different speed values because it is not practical to have static Bluetooth sensors distributed ubiquitously in outdoor settings. Also, it is difficult to distinguish whether an individual is moving or if the environment around him or her is changing
Wi-Fi	Bahl 00(RADAR) Ladd 02 Krumm 04(LOCADIO) Griswold 02 Muthukrishnan 06	- Wi-Fi data targets indoor environments with known access points and tower locations for localization.

Drawbacks of Using only GPS Data: coverage indoors/built areas, power draw









Activity	Power(Watts)
Phone Idle	0.054
GSM Sampling	0.056
GSM, WiFi Sampling	0.23
GPS Outdoor Sampling	0.407
Accelerometer Sampling	0.111

System Challenges: Phone Battery Life

Problem:

background applications should not jeopardize primary applications working for full charge cycle....

continuous gps sampling and uploading can reduce phone battery life to less than 12 hours

Approach:

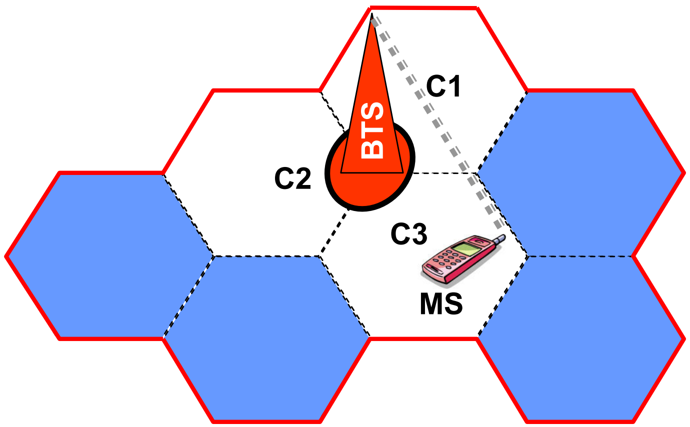
adapt operation rate or fidelity based on user preferences or current battery level

Need models of:

battery life, user's charging behavior, energy consumed by "legacy applications"

energy-performance trade-off of adaptive applications

Consider GSM and Wi-Fi



Cell tower locations can be used to **roughly indicate a user's location**.

Cell sizes in urban areas are **small/medium;** and density of BSs is **high** [*cell-ID location technique,limits and benefits: an experimental study, WMCSA 04*].

Features to leverage

- Number of Unique Cell IDs (C unique,w)
- Number of Cell ID Changes (C changes,w)
- Residence Time in a Cell Footprint (C residence)
- Duration of dominant wifi AP visibility
- Proportion of duration of dominant wifi
- Signal strength variance

- We do not try to find a user's exact location using location of WiFi access points. So neither a priori knowledge nor estimated location of access points are required.

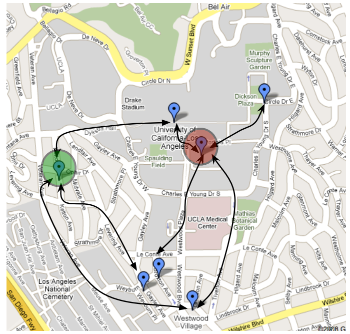
Comparing Mobility Profile for Similarity

- Build a base mobility profile from context information (location/activity).
- This profile can be represented as an "association matrix" that captures the amount of time spent in a particular context during a time period.
- Compare periods of mobility information by calculating the similarity of eigenbehaviors for different time periods.

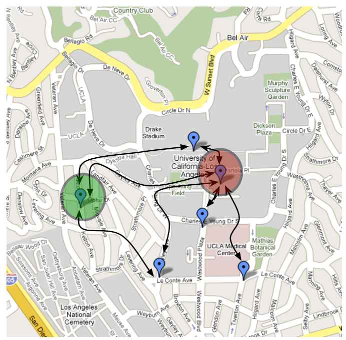
Amount of time spent at work.

	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.
8 a.m.	0.1	0.0	0.1	0.2	0.1	0.0	0.0
9 a.m.	0.1	0.0	0.1	0.3	0.1	0.0	0.0
10 a.m.	0.1	0.0	0.1	0.4	0.1	0.0	0.0
11 a.m.	0.1	0.0	0.1	0.1	0.1	0.0	0.0
12 p.m.	0.1	0.0	0.1	0.0	0.1	0.0	0.0

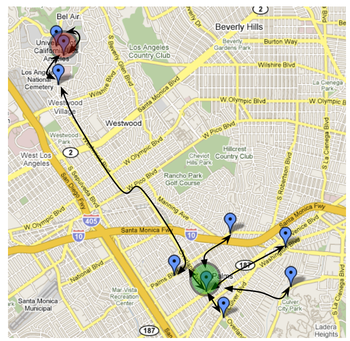
Base Profile



Natural Variations
(Participant at Different Restaurants/Stores)



Re-learning Needed
(Participant Moved)



Leveraging Accelerometer Data for Fine Grained Classification

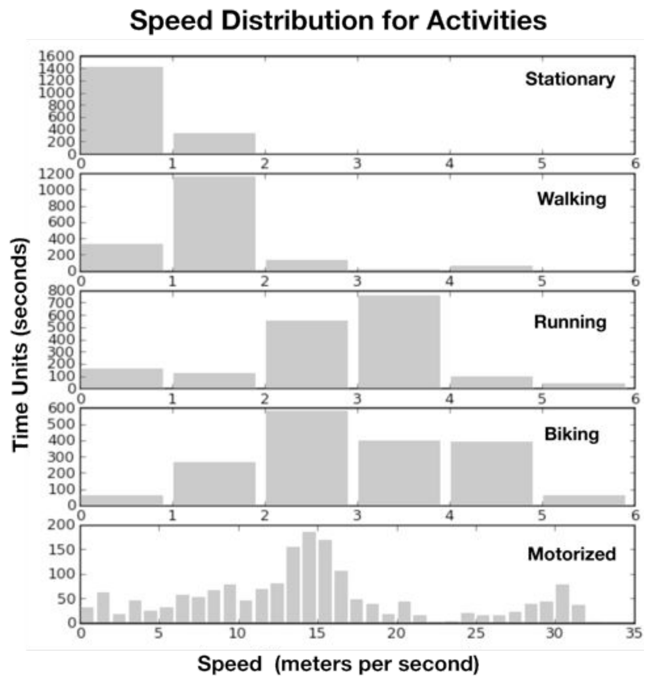
Transportation mode classifier
- decision tree followed by discrete HMM
- distinguishes among stationary, walking, running, biking, motorized transport

GPS receiver and 3-axis accelerometer as sensors

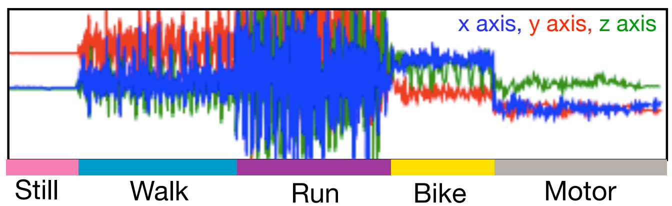
System does not have strict position/ orientation requirements--worn outside or inside of clothes

General classifier performance on par with user-specific and location-specific instances.

High accuracy levels in general
- greater than 93% - with user experiment witg 16 individuals



Accelerometer Data of User Carrying Cell Phone in their Pocket



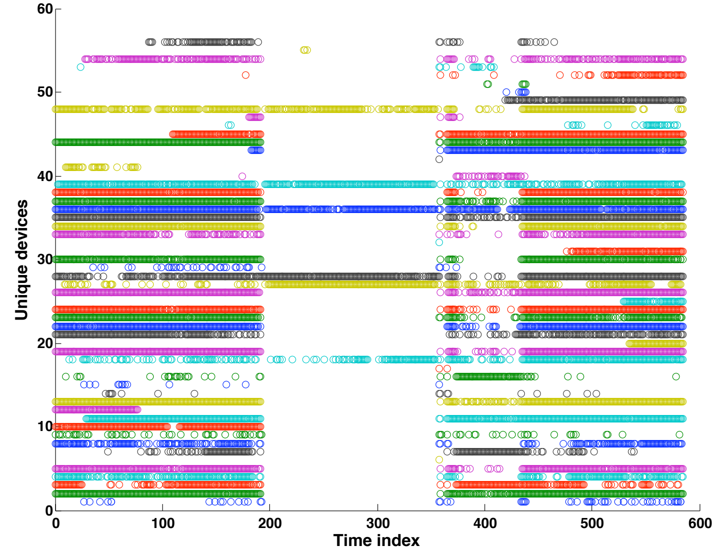
Mun, Reddy, et al

CENS
CENTER FOR EMBEDDED NETWORKED SENSING

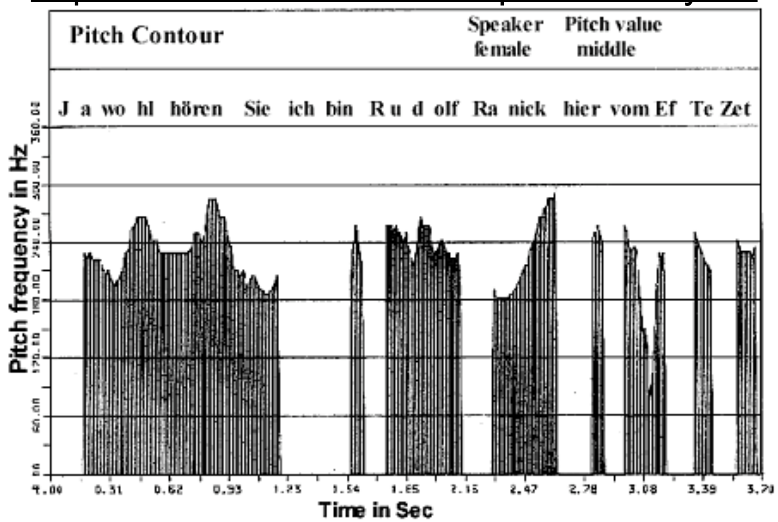
Social activity: an interesting indicator at all stages of life

- **Co-location** interaction patterns give insights for families
- Near term: use bluetooth proximity
- Mid term: Estimate frequency, duration, trends in human communication using audio samples
  - Programed automatic capture of short audio snippets (avoid content)
  - Processed locally/on-server to detect patterns of interactive communication (distinguish from TV, Radio; phone, in person)

- Observe aggregate data/trends to identify sudden or significant changes in social contact and interaction



http://www.kt.tu-cottbus.de/speech-analysis/



[challenge: robust speech feature extraction, training]

Activity classification future work

Adaptive mobility classification system

- different types of sensor data in various situations: e.g. when Wi-Fi APs are too sparse, only use GSM data; accelerometer when GPS speed and map matching makes inference ambiguous

- activate location and activity monitoring to capture outside events: avoid power draw of uniformly sampling when GPS has fix; trigger based on detected GSM-changes.

Opportunities to tune classification method.

-User input or monitoring usage improve accuracy

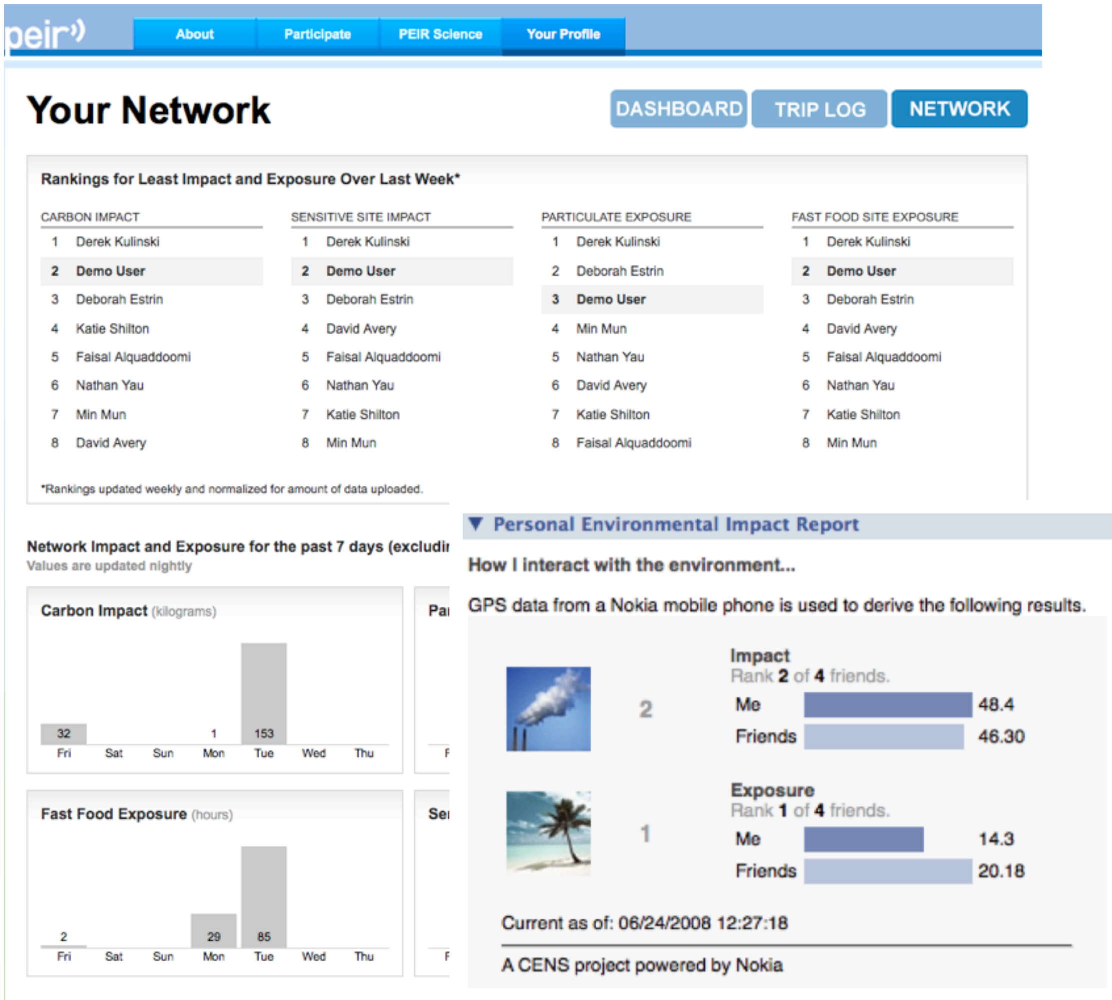
-Handle cases where features are not available

-Incorporate cost of capturing/processing features

-Use different device models

-Post-process to filter out unlikely series of activities

Key building block: privacy mechanisms and selective sharing



Share derived statistics instead of raw traces

- detailed data only accessible to individual

Simple example: peir Facebook app/widget

Research challenges

- selective sharing and retention
- model-equivalent substitute data
- system transparency and audit-trail wrt data use and provenance

Personal Data Stream Control

Individual control of time/space accountability

Location traces quantify habits, routines, associations & are easy to mine

Why control?

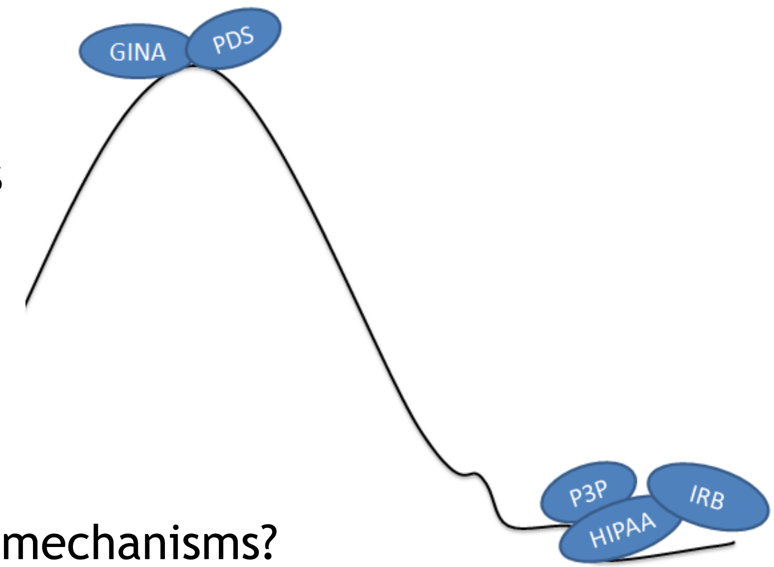
- Prevent discriminatory practices
- Maintain safety/security
- Respect social boundaries
- Protect stigmatized activities

Full disclosure not inevitable

- Selective sharing, hiding, archiving
- Information flow control in supporting systems

Abuse never preventable

- Need strong audit trails
- Legibility/transparency
- Laws concerning fair use



Can we design lightweight, scalable, but effective mechanisms?

- P3P, HIPAA, IRB are not embraced even if they are implemented
- Could become as important as genetic discrimination (GINA)

Personal Data Stream Control Architecture

CAPTURE
PERSONAL MOBILE DEVICES

Provide Expressive Default Policies
Enable Users to Configure Preferences

FILTER [Metadata]

filters define selective upload

ARCHIVE/DISPATCH
PRIVATE DATA VAULT

Decouple Conflicts of Interest
Foster Marketplace of 'Certified' Services

e.g., *personal container in web cloud*

FILTER [Metadata]

filters define selective sharing with various services

ACT
APPLICATIONS /SERVICES

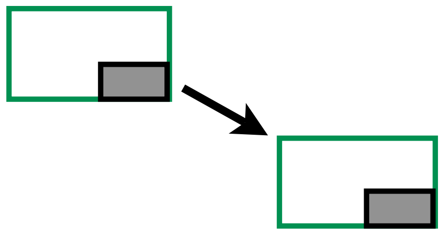
Provide Transparency of Data Access, Uses, Inferences and Manupulations
Enable Audits by Users/Agents

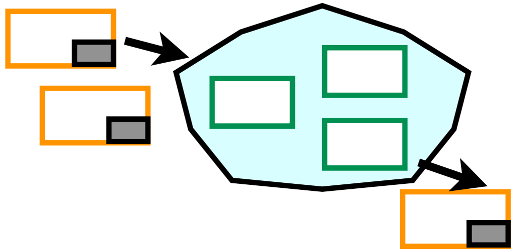
establish certified services

[challenge: scalable architecture, verifiable mechanisms]

'Private Data Vault' Functions

Technical precedents: Mail Servers/Webmail, Yahoo Fire Eagle, Cloud services





Alternatives--Limitations

- Physically private store--robustness
- Virtually-private store maintained by applications--conflict of interest

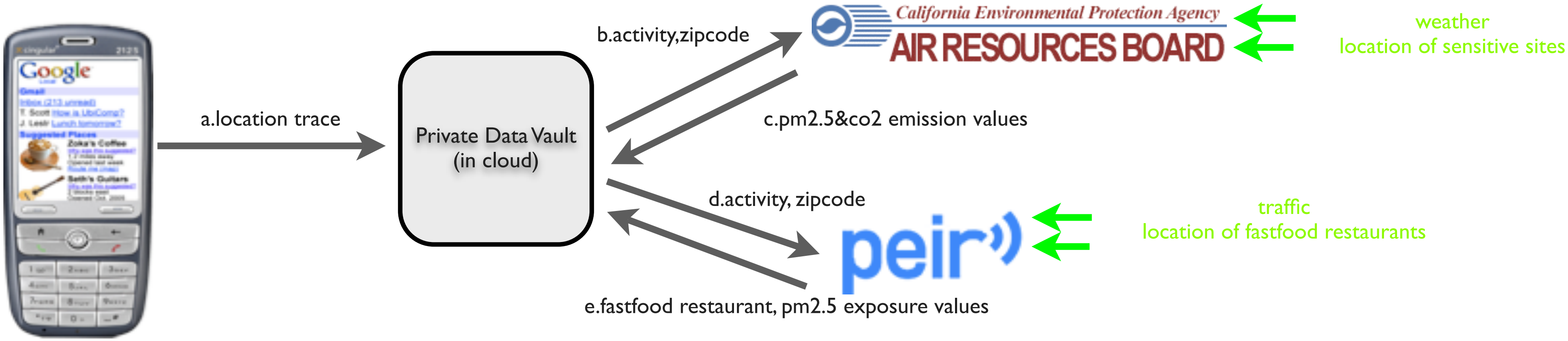
Private data vault model

- Guards against conflicts of interest
- Supports robust storage and archiving
- Enable a marketplace of 'certified' applications
- But need a vault mechanisms that can export filtered/processed data

[challenge: scalable architecture, verifiable mechanisms]

traceaudit

Enable records of access, use, inference, and manipulation of data at multiple points in the system.



traces

outside data sources

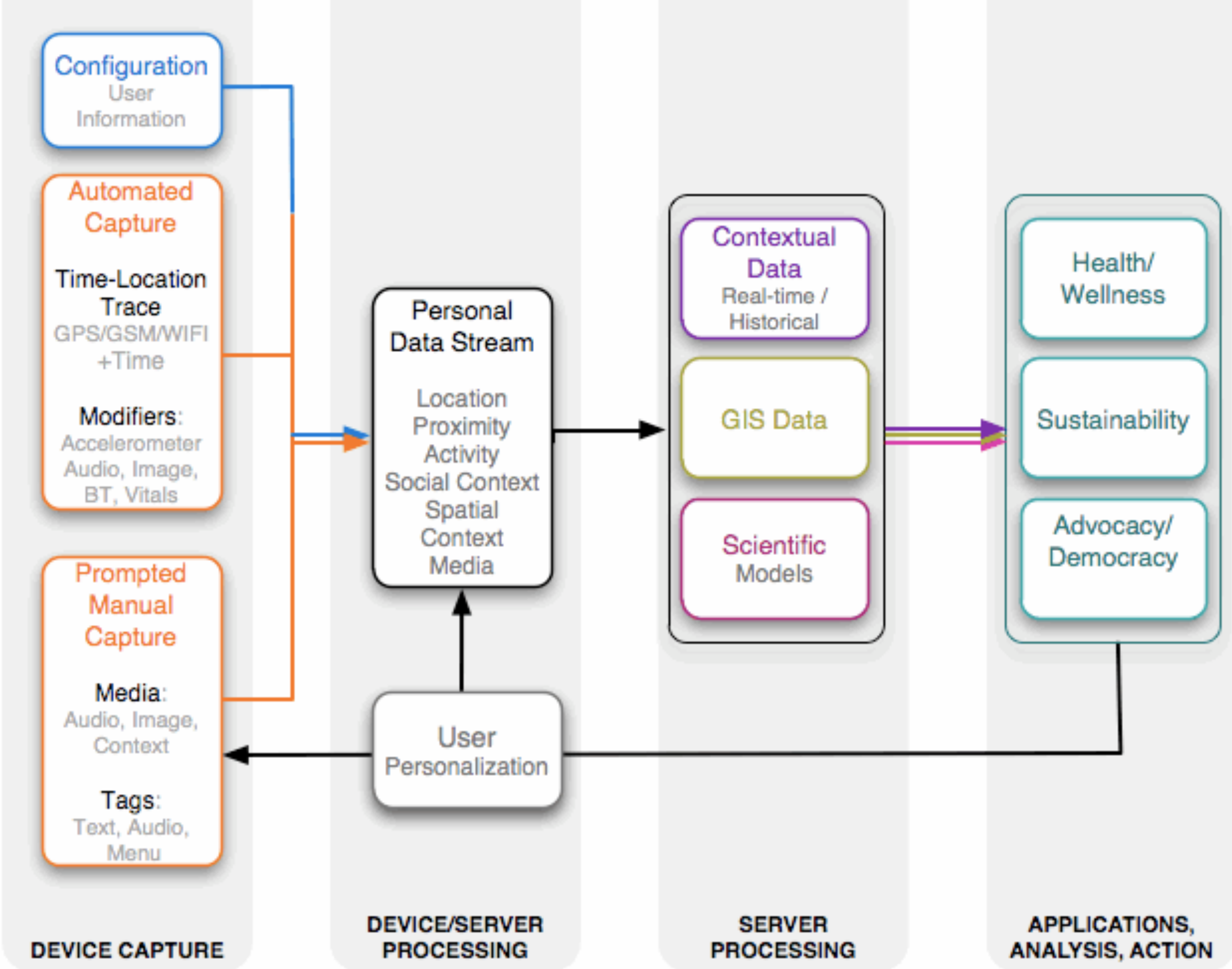
input data sources from users

inferred data

0	datavault 1	ARB 3	datavault	PEIR 5
1	locations of freeways	zipcode map		
2	location	activity	zipcode	
3	weather	locations of sensitive sites		
4	activity,zipcode	co2 emission	pm2.5 emission	
5	traffic	locations of fastfood restaurants		
6	activity,zipcode	pm2.5 exposure	fastfood exposure	

An example of metadata to support ***traceaudit*** and check mechanism services

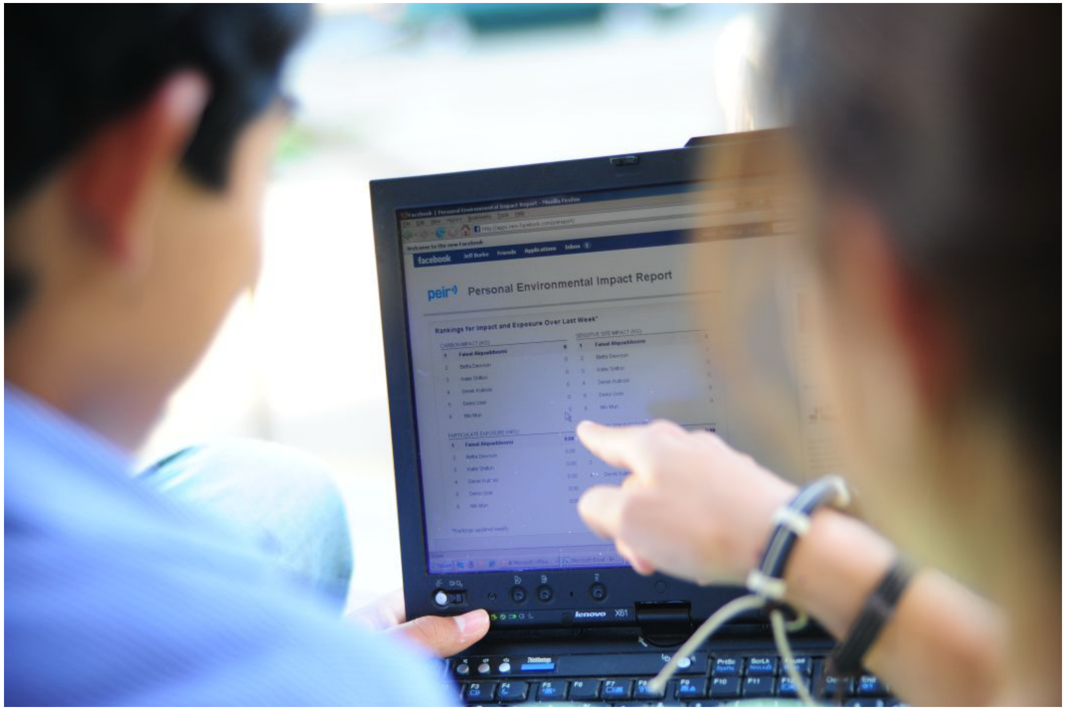
Emerging **mobile personal sensing** system architecture



Conclusion

If you can’t go to the field with the sensor you want...
go with the sensor you have! (Anon)

The power of the Internet, the reach of the phone (Voxiva)



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- NSF: OIA, NETS-FIND Program, CRI Program, CISE, Engineering, Bio
- Nokia, Cisco, Sun, Intel, Samsung, Google, MSR, Crossbow, Agilent
- UC Micro, Participating campuses (UCLA, UCR, UCM, USC, Caltech)
- Wilson Foundation, Conservation International

YouTube Video on PEIR