

CitiSense and MetaSense: Challenges & Technologies for Mobile Participatory Sensing for Air Quality

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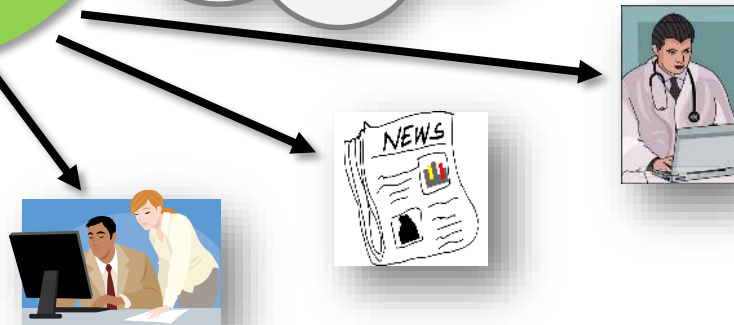
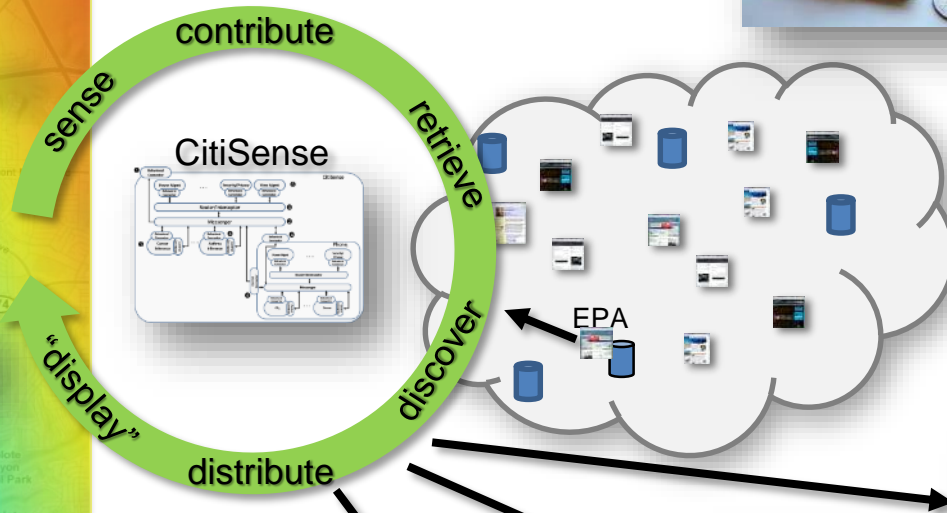
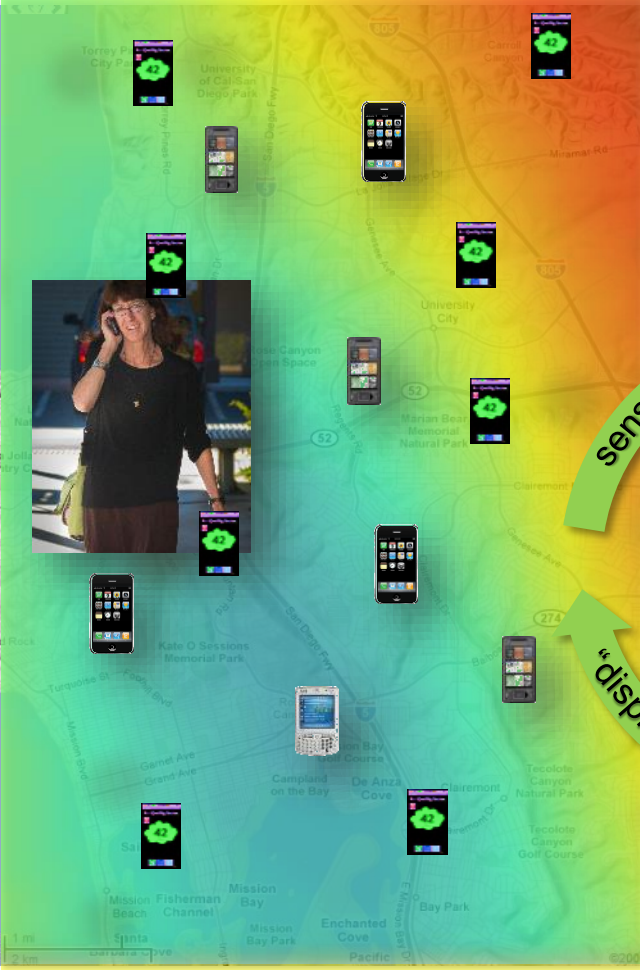
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Engineering

Advances in Sensing and Computing have Put Mobile Personal Air Monitoring within Reach



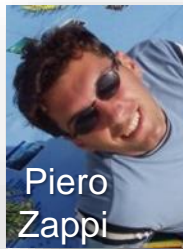
How can such sensing be designed to produce the most benefit at the least cost?

CitiSense – A Crowdsourcing Approach

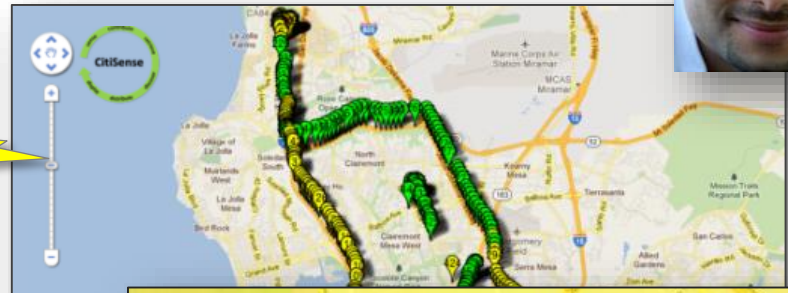
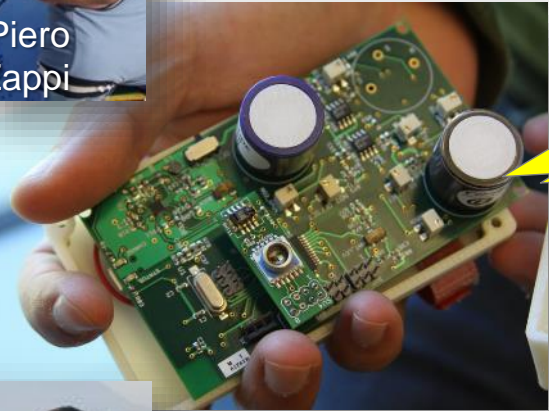


CitiSense Components

Celal Ziftci



Piero Zappi



Tajana Rosing



Nima Nikzad



Sanjoy Dasgupta



Nakul Verma

2012 UCSD Commuter Study



Nichole Quick (Public Health)



Liz
Bales



Kevin Patrick
(Public Health)

What would they *encounter*?

Affect Awareness?



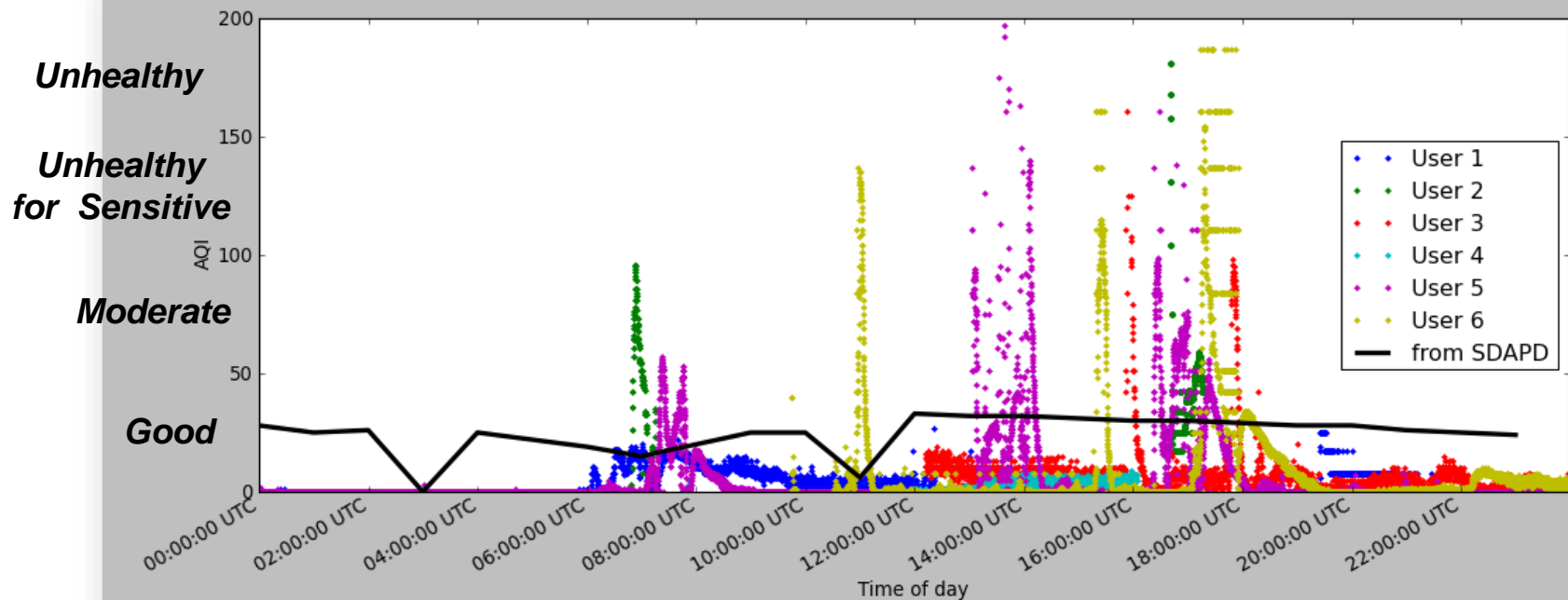
Behavior?



Pollution Levels Varied Widely by Locale



Individual exposures varied widely compared to reported EPA “AQI”



Affected User Awareness and Behavior

- **Awareness:** *“It never occurred to me how bad the air is, as cars drive by, while I'm waiting for the bus.”*
- **Attitudes:** *“It's made me aware that polluting our air is like fish pooping in their tank.”*
- **Behavior:** *“I'm more conscious of leaving my car idling and keeping the windows closed on the freeway.”*

MetaSense: Improving Accuracy

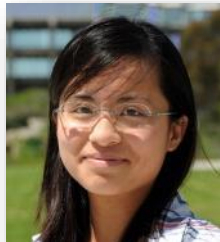
- Low-cost sensors have proven difficult to calibrate
 - Calibration parameters from manufacturer inadequate
 - Sensors seem affected by many factors besides pollutant
- Idea: field calibration
 - Co-locate mobile monitors at regulatory sites, gather data
 - Build machine learning models of sensor and environment
 - (Later will attempt inter-monitor calibration)



Mike Hannigan
(CU Boulder)



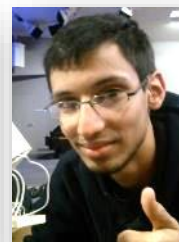
Ashley Collier
(CU Boulder)



Christine Chan



Max Menarini



Sharad Vikram



Michael Ostertag



New Modular, extensible platform

- Particle or Arduino processor
 - 16-bit ADC, I2C, UART, SPI headers
- NO₂, CO, O₃, (opt. CO₂, VOCs)
 - +temp, pressure, humidity
- BT 2.3/4.0, USB, Serial, WiFi, 3G
 - JSON or packed binary message
- Hierarchical processing: monitor, phone, AWS
- 8 days on 6.8 Wh battery (5s sample rate)



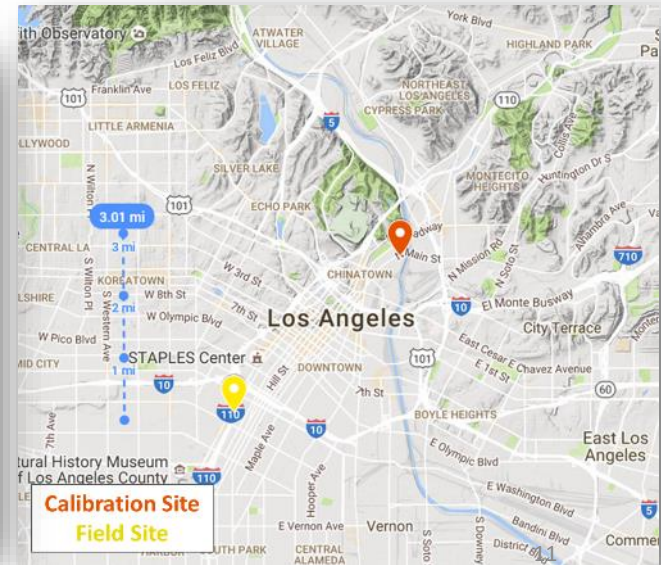
Pilot Deployment in LA (summer 2016)

Overview:

- Monitors with Alphasense A4 CO, NO₂, & O₃ sensors
- SCAQMD monitoring site & nearby community

Key Objectives:

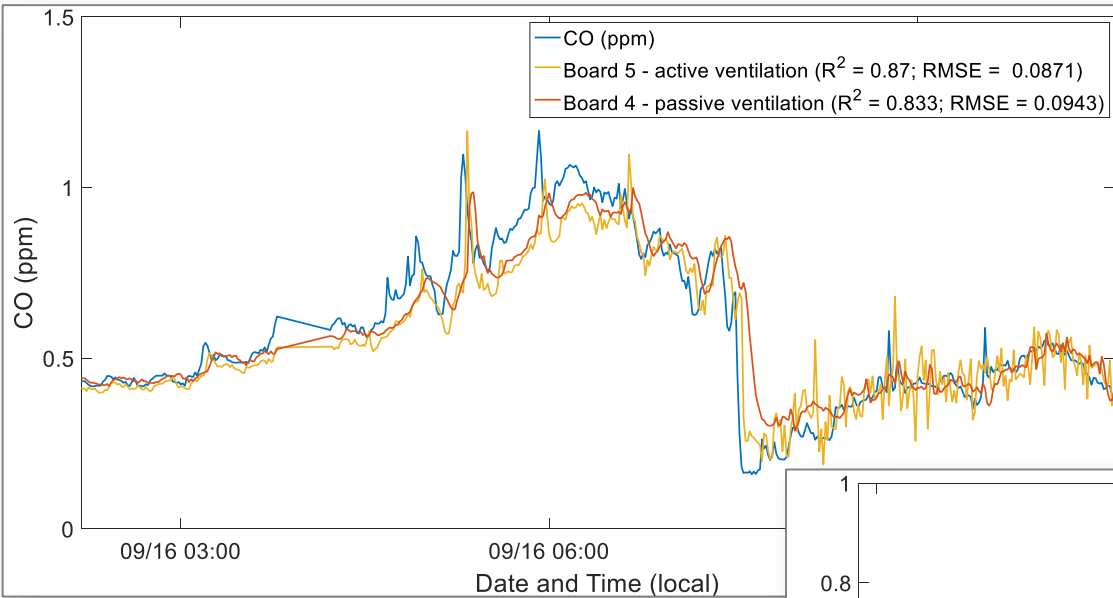
- Field-calibrate sensors by co-locating with regulatory monitors
- Effects of active vs. passive ventilation (fans are big, heavy, and suck power)



Importance of Active Ventilation?

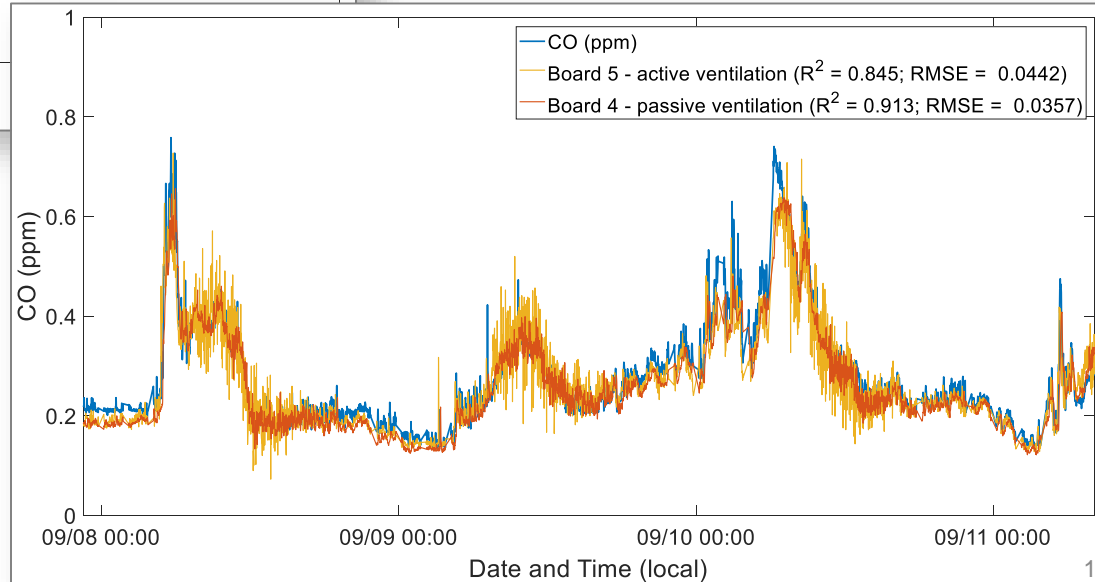
Passive ventilation better for longer time scales (days)

- Less noisy, captures trends well
- higher R^2 and lower RMSE



Active ventilation better for smaller time scales (hours)

- better captures trends/peaks
- higher R^2 and lower RMSE



Field “Calibration” via Machine Learning

- Machine learning is a way of fitting a model to your data, e.g., finding $v' = f(v, t, p, h)$
 - Simplest ex. is linear regression (least squares fit)
- Note: temperature (e.g.) affects both sensor behavior *and* atmospheric chemistry, etc.
 - Can't separate affects on sensor and on air
 - So can't truly *calibrate* the sensor, e.g., “correct” its reported voltage; *we're doing pollutant estimation*

Machine Learning Improves Estimation

- Environmental variables substantially reduce regression error (RMSE) for NO₂ and O₃
 - Non-linear models work better than linear ones
 - ML improves CO estimation, too; but fine without
- Benchmarked several non-linear ML techniques
 - Decision trees, random forests, gradient boosting, neural nets
 - **Deep neural nets best → high non-linearity in data**
 - More work required, e.g., test for overfitting

Current Deployment

- Need more data to untangle key factors
- Rotating monitors through 3 ref. sites

Sensors in each set:

- CO, NO₂, O₃ (electrochemical)
- O₃ (metal oxide)
- VOC (PID)
- VOC (metal oxide, 2 types)
- CO₂ (NDIR)

Reference Instruments:

- **Donovan** – NO₂, O₃
- **El Cajon** – NO₂, O₃, CO
- **Shafter DMV** – O₃, TNMHC, CO₂ (CO₂ – via Licor Analyzer maintained by CU, Boulder)



A map of California shows the deployment locations for the sensors. A red pin marks Shafter, a yellow pin marks El Cajon, and a blue pin marks San Diego. A red arrow points from the Shafter location to an inset photo of a monitoring station with a tall antenna. A yellow arrow points from the El Cajon location to an inset photo of a yellow sensor unit on a wooden deck. A blue arrow points from the San Diego location to an inset photo of a monitoring station with a tall antenna. Other inset photos show a yellow sensor unit in a field, a yellow sensor unit on a wooden deck, and a monitoring station with a tall antenna. The map also shows major cities like Los Angeles, San Diego, and Tijuana, and national parks like Sequoia National Forest and Joshua Tree National Park.

Parting Thoughts on Mobility & Machine Learning

- Mobile sensing + machine learning enables crowdsourcing exposure maps
- ML can also improve accuracy
- Goes anywhere, addressing challenges beyond government's reach
- Saw novel behaviors in users
- Potential to create new opportunities in environmental sensing