Mobile and Ubiquitous Computing on Smartphones
Lecture 8b: Smartphone Sensing

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Recall: Smartphone Sensors

- Smartphone have many sensors
  - **Examples:** accelerometer, compass, GPS, microphone, camera, proximity
- Can use machine learning to analyze sensor data, predict user’s activity, behaviors, etc.

Recall: What Can We Detect/Infer using Smartphone Sensors

24/7 detection, in natural settings

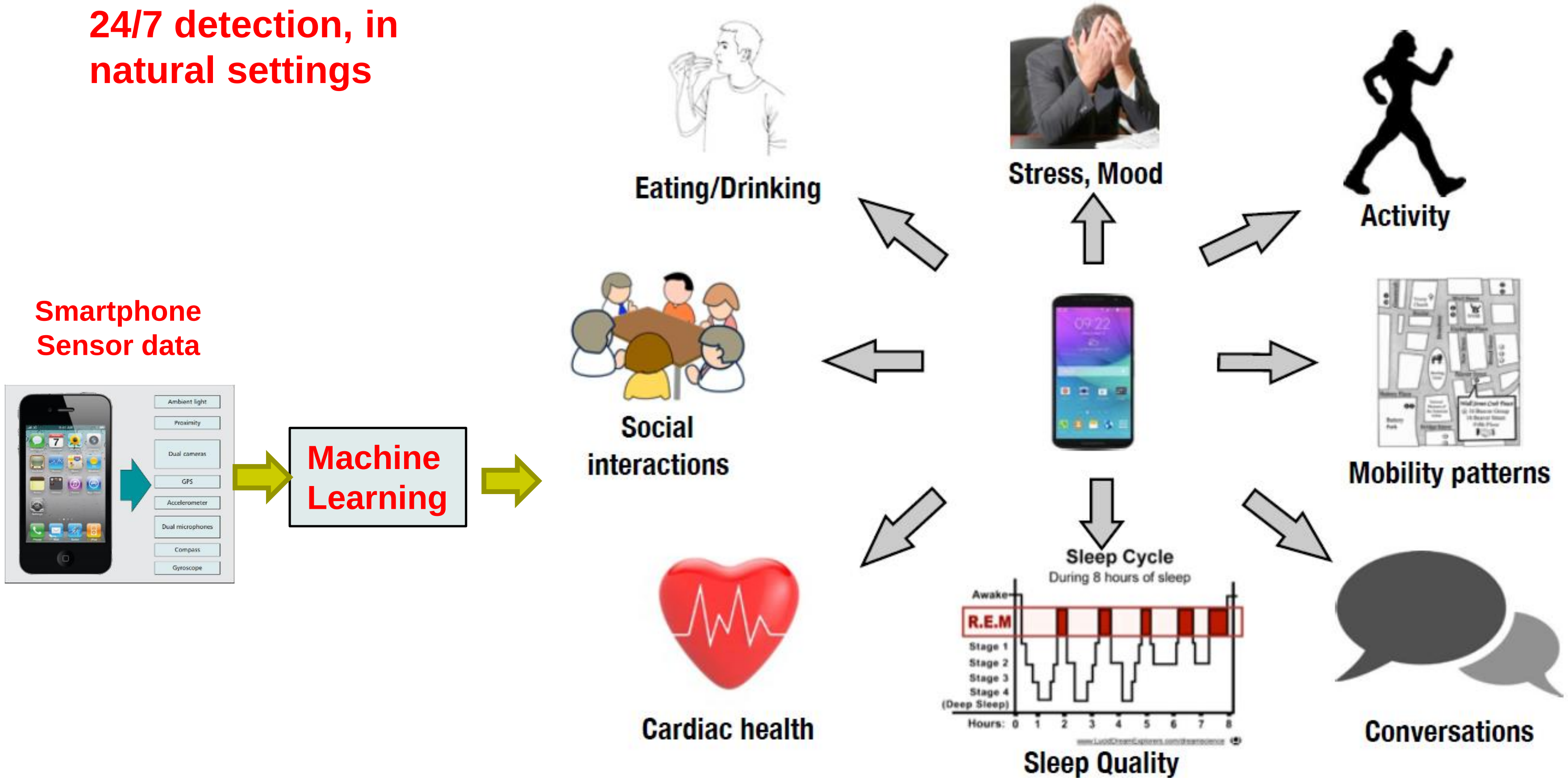
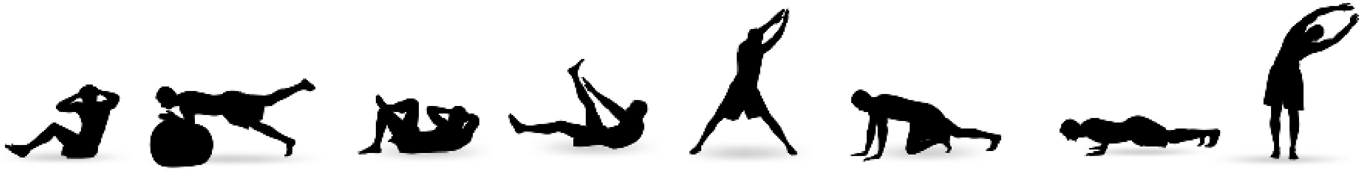


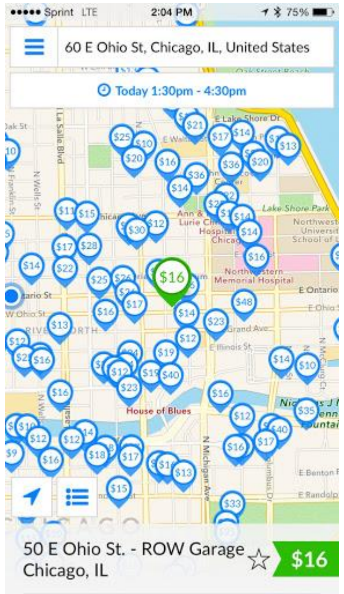
Image Credit: Deepak Ganesan, UMass

Sense What?

- **Environmental:** water levels in a creek, pollution
- **Transportation:** traffic conditions, road condition, available parking
- **City infrastructure:** malfunctioning hydrants, infrastructure
- **Social:** bike route quality, petrol prices
- **Health and well-being:**
  - Diseases: Covid-19, influenza, depression, mental health
  - Exercise (amount, frequency, schedule),
  - Eating, drinking



myFitnessPal

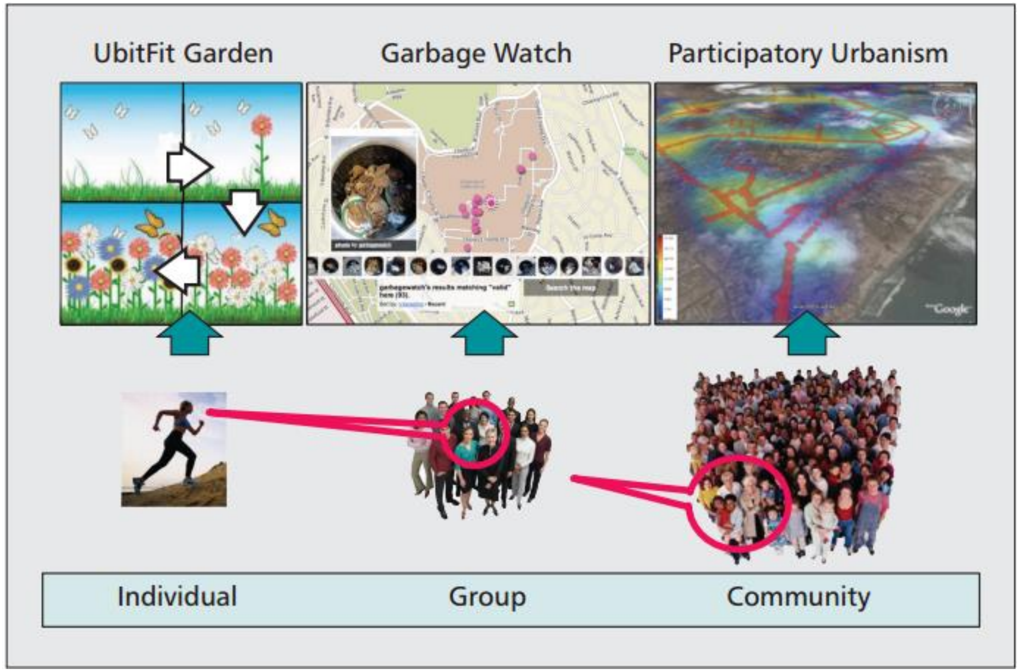


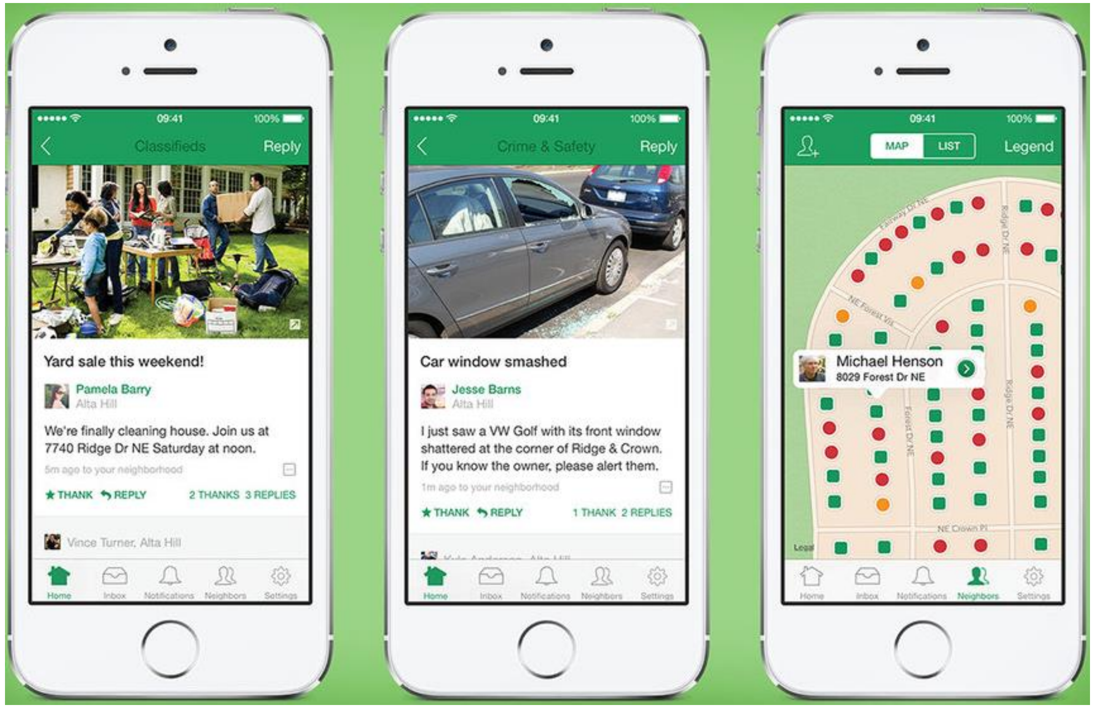
SpotHero Parking

AQI India

Mobile CrowdSensing Scale

- **Mobile CrowdSensing:** Sense collectively, various group sizes
- **Personal sensing:** for individual
  - E.g: activity recognition for individual's health monitoring
- **Group:** friends, co-workers, neighborhood
  - E.g. GarbageWatch, recycling reports, neighborhood surveillance

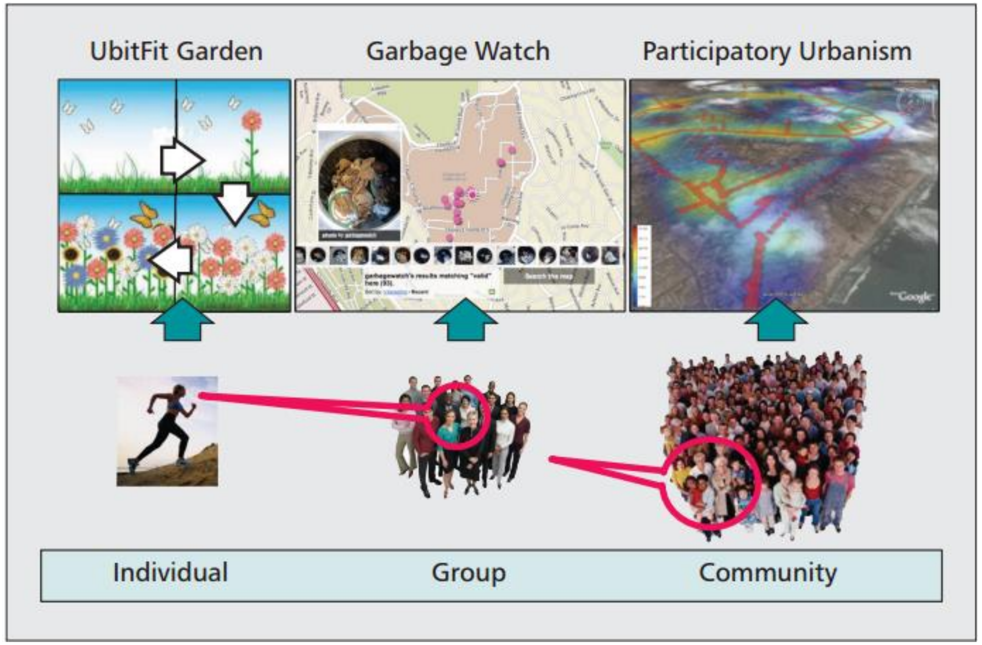


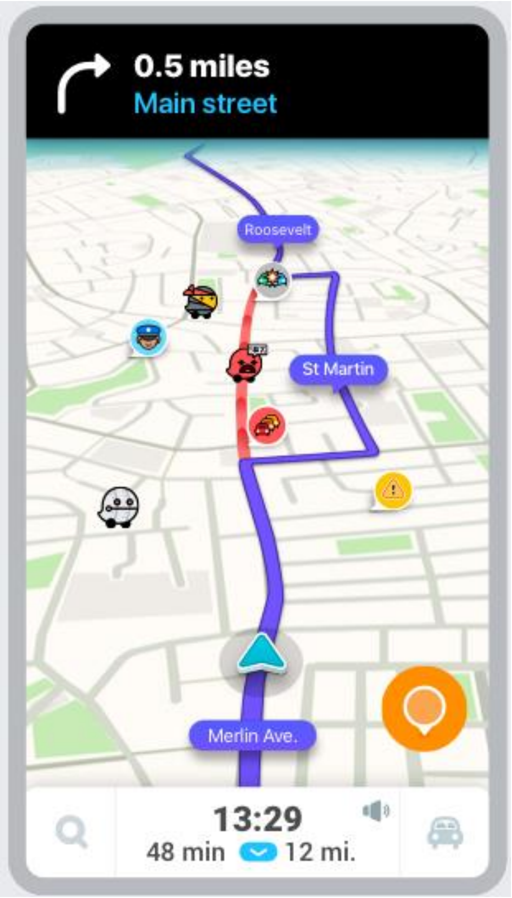


NextDoor Neighbourhood Surveillance App

Mobile CrowdSensing (Contd)

- **Community sensing:**
  - Large-scale phenomena monitoring
  - Many people contribute their individual readings
  - **Examples:** Traffic congestion, air pollution, spread of disease, migration pattern of birds, city noise maps



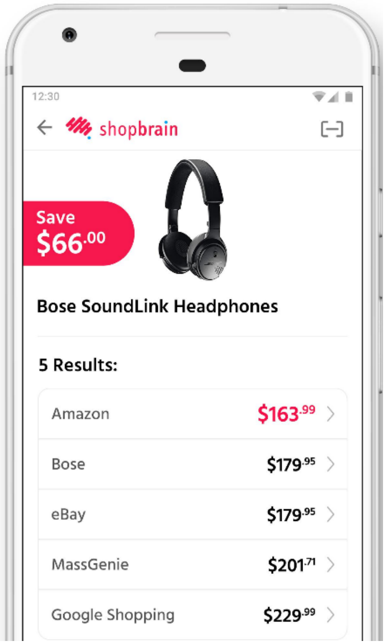


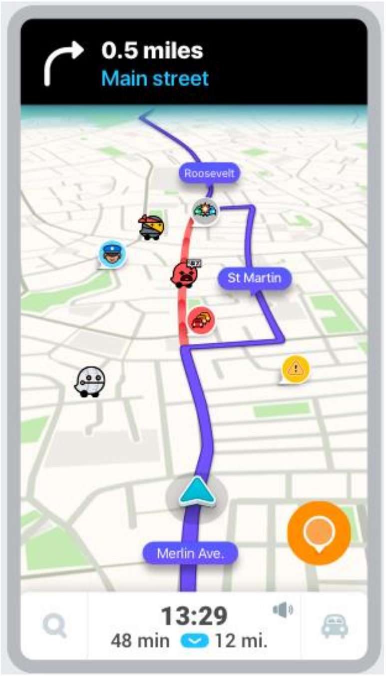
Waze Traffic app

Mobile CrowdSensing Types: User's involvement

- Many people cooperate, share sensed values
- User can be involved in types of ways:
  1. *Participatory Sensing:* User manually enters values (**active** involvement)
     - **E.g. Comparative shopping:** Compare price of toothpaste at CVS vs Walmart
  2. *Opportunistic Sensing:* Mobile device **automatically** senses data (**passive** involvement)
     - E.g. Waze crowdsourced traffic

Participatory sensing example:
Comparative Shopping



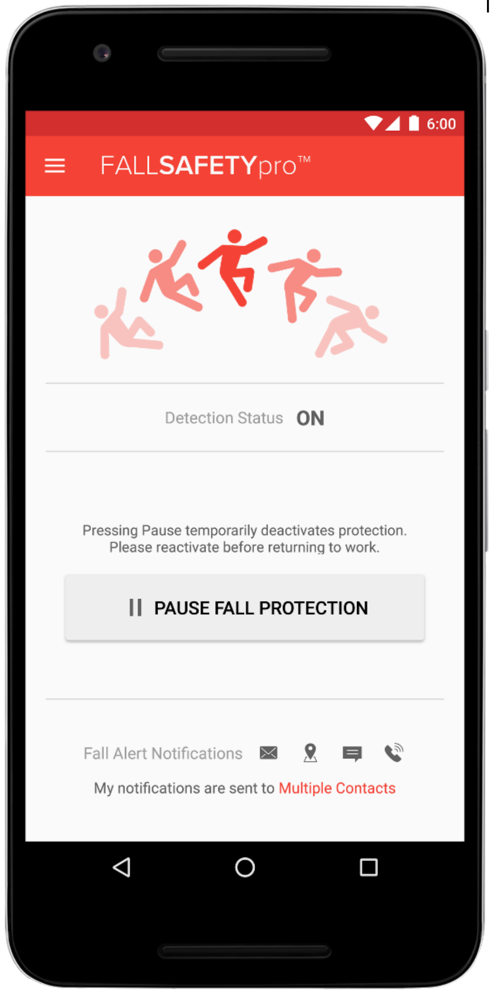


Opportunistic sensing example:
Traffic congestion app

More examples:
Smartphone Sensing

Personal Opportunistic Sensing

- Fall detection app
- Uses phone sensor to detect user's fall
  - Automatically sends alert for help
- Target users:
  - Extreme work environments (e.g. construction)
  - Seniors living alone



Public Opportunistic Sensing

- Crowd Counting: detect crowd size, density
  - E.g. Concerts, large malls, airports, public transport
- Why?
  - Monitor/manage crowds, avoid stampedes
  - Improve efficiency/staffing, congestion management

Airports

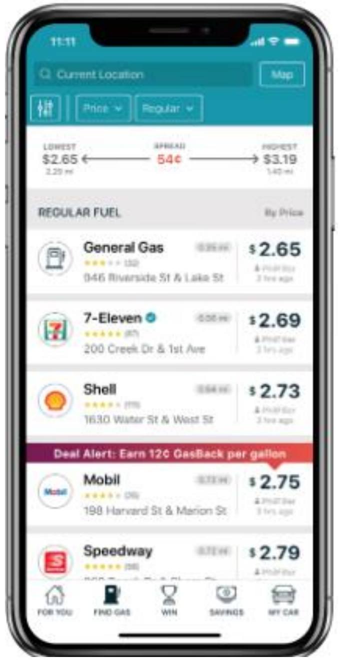
Concerts

Shopping malls

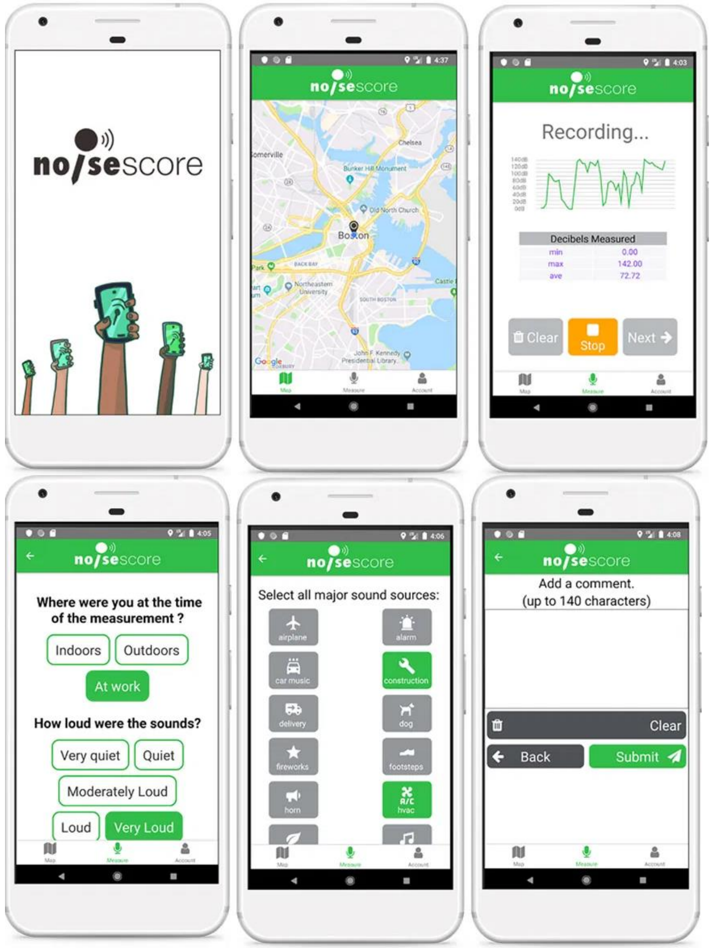
Public Transportation

Public Participatory Sensing Examples

- **NoiseScore:** Cooperate to monitor city noise levels, build noise map
- **GasBuddy:** Cooperate to find cheap gas
  - Each user shares gas prices at stations around them
  - Build database, compare gas prices
  - Query: GPS determines nearby gas stations



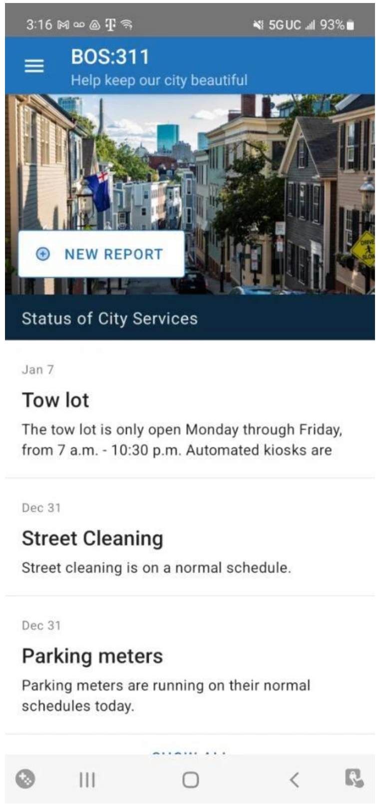
GasBuddy

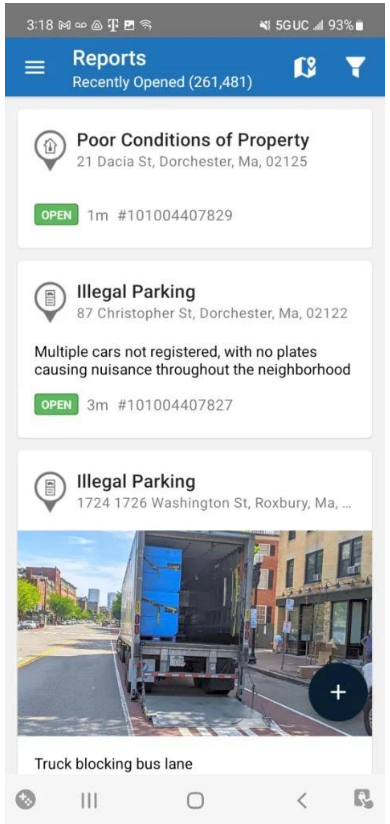


NoiseScore

Public Participatory Sensing

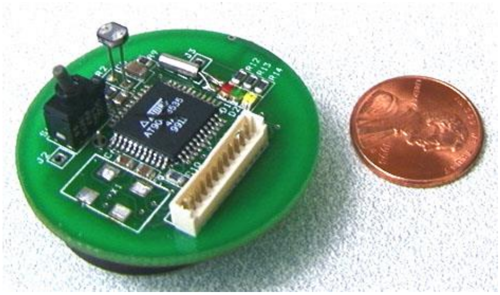
- **Pothole Monitor**
  - Combines GPS and accelerometer
  - Builds map of bad road spots that need fixing
- **Party Thermometer**
  - Detects parties from location (GPS) and sounds (microphone)
  - Asks user questions about parties
- **BOS:311 app**
  - City reports: potholes, trash collection, Covid-19: people not wearing masks





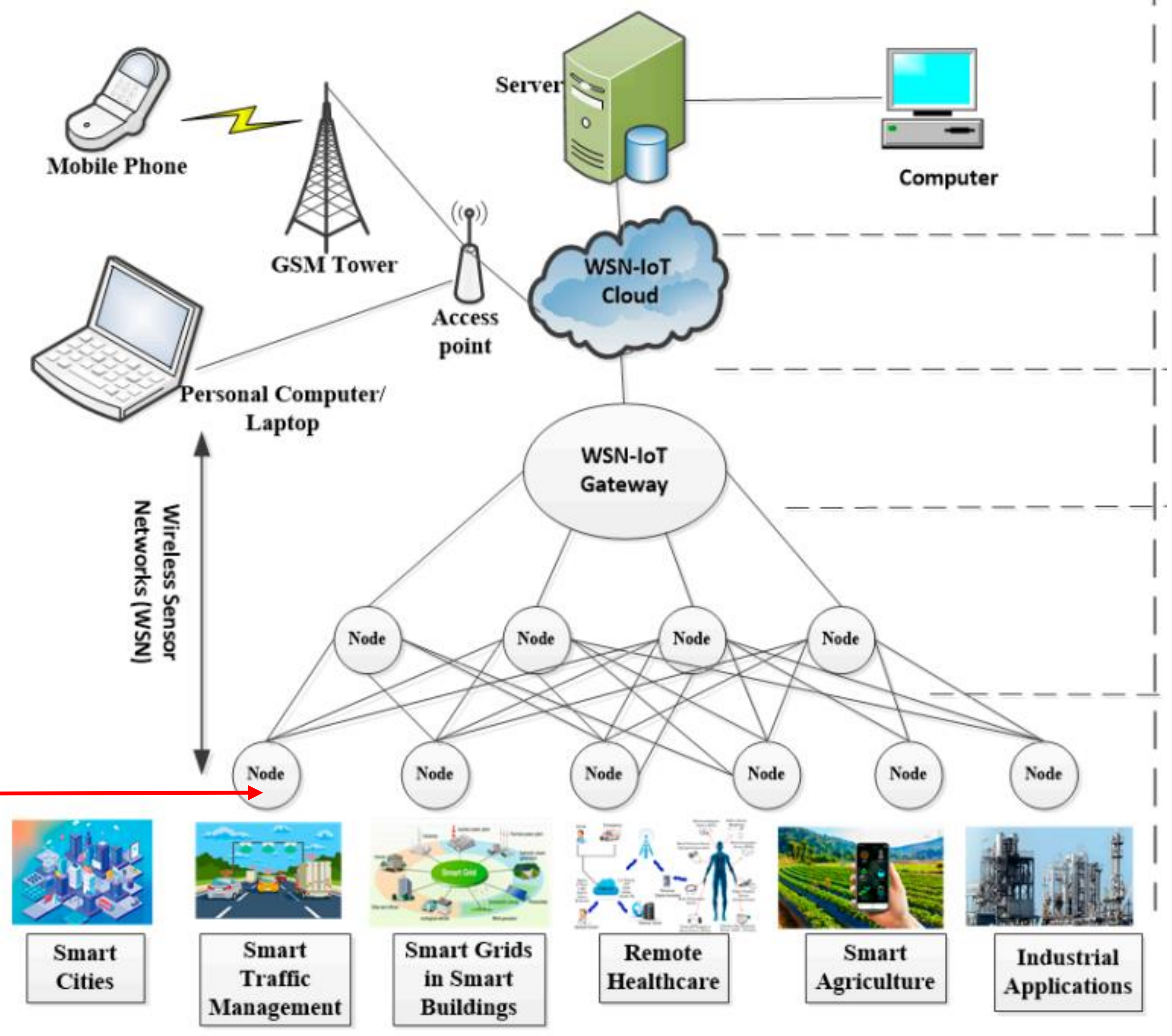
Smartphone Sensing vs Dedicated Sensors

VS



Background: Wireless Sensor Networks (WSNs)

- Sensors embedded in room/environment
- Monitors conditions (temperature, humidity, etc)
- Many sensors cooperate/communicate to perform task
- User can query sensor (What is temp at sensor location?)



Key point: sensor is specialized, measures specific phenomena. E.g. temperature

Sensing using Smartphones vs Dedicated Sensors

Smartphone sensing pros:

- **More resources:** Smartphones have much more processing and communication power

- **Easy deployment:** Millions of smartphones already owned by people
  - No installation required
    - Instead of installing sensors in road, detect traffic congestion using smartphones carried by drivers
  - Maintenance is easier. E.g. owner will charge their phone promptly

Smartphone cons:

- **Time-varying data:**
  - Changes in population of mobile devices (e.g. driving on a road), available sensor types on phone models
  - Accuracy changes due to user mobility and hardware/software differences between smartphones

Sensing with Smartphones vs Dedicated Sensors

Additional considerations

- **Smartphones re-use few general-purpose sensors:** While sensor networks use dedicated sensors, smartphones reuse relatively few (10-20) sensors for wide-range of applications
  - E.g. Accelerometers re-used to solve many different problems (transportation mode identification, pothole detection, human activity pattern recognition, etc.)

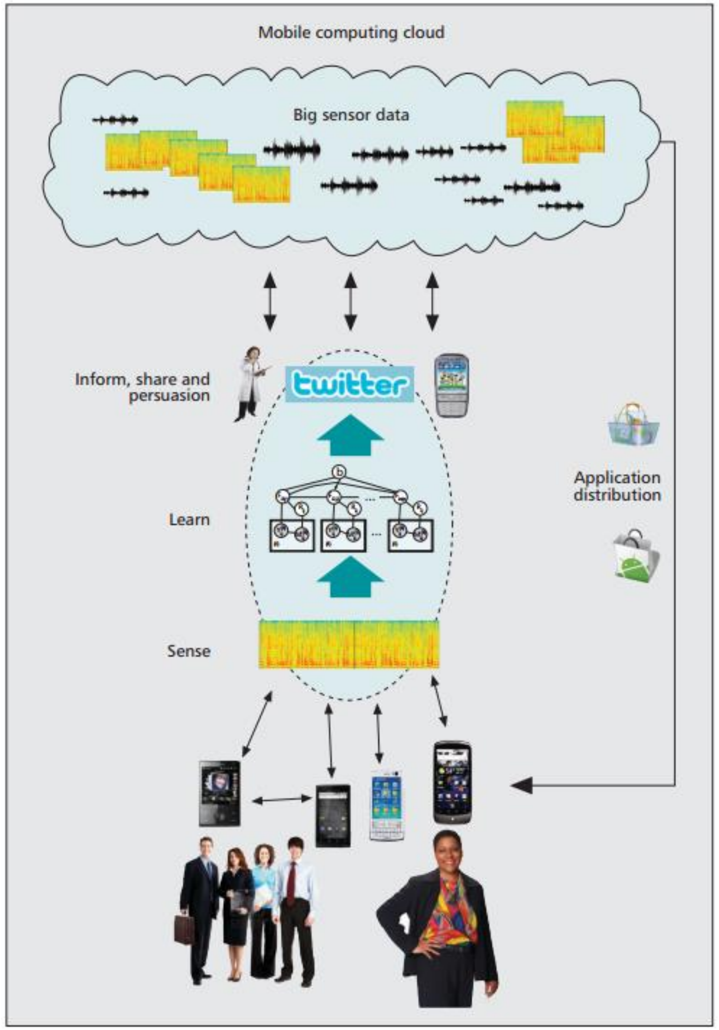
- **Human involvement:** humans who carry smartphones can be involved in data collection (e.g. taking pictures).
  - Participatory sensing
  - Human in the loop can collect complex data
  - However, human data collectors must be given incentives

Smartphone Sensing Architecture

Smartphone Sensing Architecture

Lane, N.D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T. and Campbell, A.T., 2010. A survey of mobile phone sensing. *IEEE Communications magazine*, *48*(9), pp.140-150.

- Paradigm proposed by Lane *et al*
- **Sense:** Phones collect sensor data (e.g. accelerometer)
- **Learn:** Information is extracted from sensor data by applying **machine learning and data mining** techniques (E.g. user's activity, step count)
- **Inform, share and persuasion:**
  - **Inform:** app users of information learned (e.g. accidents in Waze)
  - **Share:** with group/community/friends (e.g. fitness accomplishments on MyFitnessPal)
  - **Persuasion:** users to change behavior (e.g. avoid lazy lifestyle, or speed traps in Waze)



BES Sleep Duration Sensing

Unobtrusive Sleep Monitoring

Unobtrusive Sleep Monitoring using Smartphones, Zhenyu Chen, Mu Lin, Fanglin Chen, Nicholas D. Lane, Giuseppe Cardone, Rui Wang, Tianxing Li, Yiqiang Chen, Tanzeem Choudhury, Andrew T. Campbell, in Proc Pervasive Health 2013

- Sleep impacts stress levels, blood pressure, diabetes, functioning

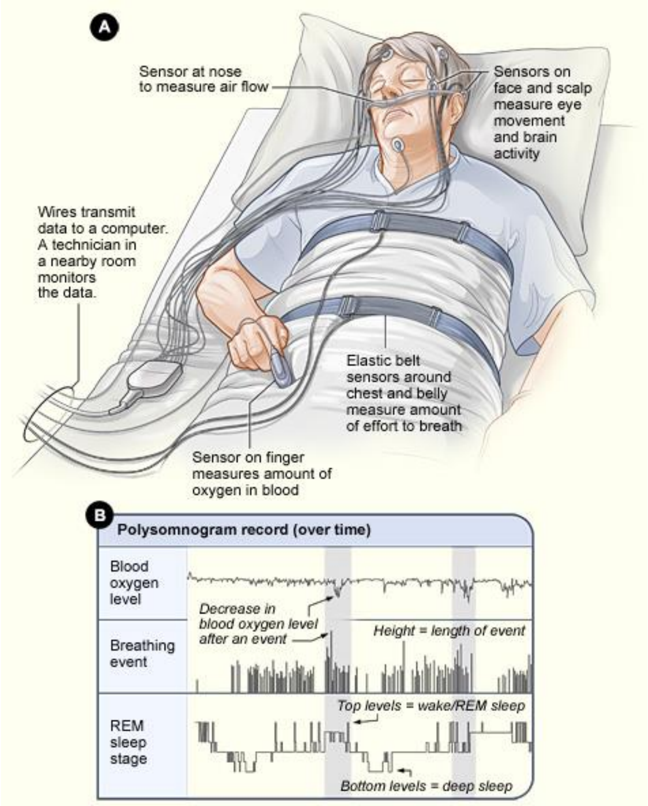
- Many medical treatments require patient records sleep duration
- Manually recording sleep/wake times is tedious

Unobtrusive Sleep Monitoring

- **Paper goal:** Automatically detect sleep (start, end times, duration) using smartphone, log it
- **Benefit:** No interaction, additional equipment worn
  - Practical for large scale sleep monitoring
- Even a slightly wrong estimate is still very useful

Sleep Monitoring at Clinics

- Polysomnogram monitors (gold standard)
  - Patient spends night in clinic
- Lots of wires to monitor:
  - **Brain waves** using electroencephalography (EEG),
  - **Eye movements** using electrooculography,
  - **Muscle contractions** using electrocardiography,
  - **Blood oxygen levels** using pulse oximetry,
  - **Snoring** using a microphone, and
  - **Restlessness** using a camera
- Complex, often impractical, expensive!



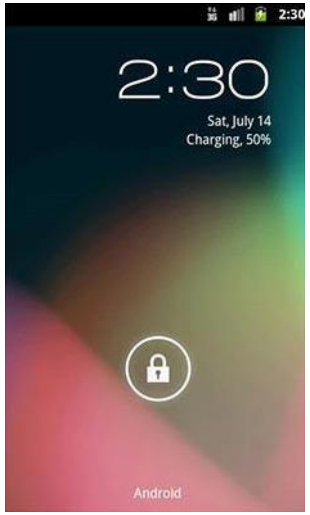
Commercial Wearable Sleep Devices

- Fewer wires
- Still intrusive, cumbersome
- Might forget to wear or start it

Can we monitor sleep with smartphone, no wires?

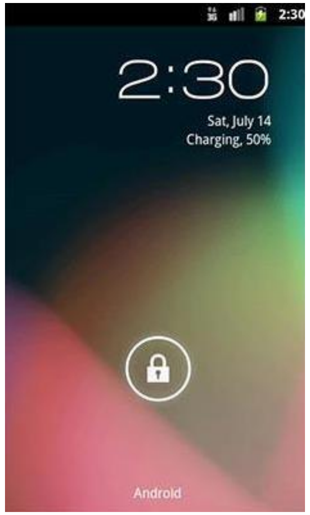
Observations: "Typical" sleep conditions

- Typically when people are sleeping
  - **Room is Dark**
  - **Room is Quiet**
  - **Phone is stationary (e.g. on table)**
  - **Phone Screen is locked**
  - **Phone plugged in charging, off**



Sense typical sleep conditions

- Use Android sensors to sense typical sleep conditions
  - **Dark:** light sensor
  - **Quiet:** microphone
  - **Phone is stationary (e.g. on table):** Accelerometer
  - **Screen locked:** Android system calls
  - **Phone plugged in charging, off:** Android system calls



Best Effort Sleep (BES) Model

- BES model Features used in paper:
- Phone Usage features.

  --phone-lock (F2)

  --phone-off (F4)

  --phone charging (F3)

  -- Light feature (FI).

  -- Phone in darkness

  --Phone in a stationary state (F5)

  --Phone in a silent environment (F6)

- Individually, each feature = weak indicator of sleep, errors!
- Combined, co-occur (together) = stronger indicator
- Combine these into Best Effort Sleep (BES) Model

BES Sleep Model

- Assume sleep duration is a weighted linear combination of 6 features

$$Sl = \sum_{i=1}^{6} \alpha_i \cdot F_i,\ \alpha_i \geq 0$$

- Gather data (sleep duration + data, extract 6 features) from 8 subjects
- Train BES regression model

$$\min_{\alpha_i} \sum_{j=1}^{4} (Sl^j - \sum_{i=1}^{6} \alpha_i \cdot F_i^j)^2$$

Sleep duration

Weight for each feature

Feature

Results

Feature	Coefficient
Light (F_1)	0.0415
Phone-lock (F_2)	0.0512
Phone-off (F_3)	0.0000
Phone-charging (F_4)	0.0469
Stationary (F_5)	0.5445
Silence (F_6)	0.3484

TABLE I: Weight coefficients for each feature in BES

Most predictive features

1. Phone stationary (e.g. on table)
2. silence,
3. …etc

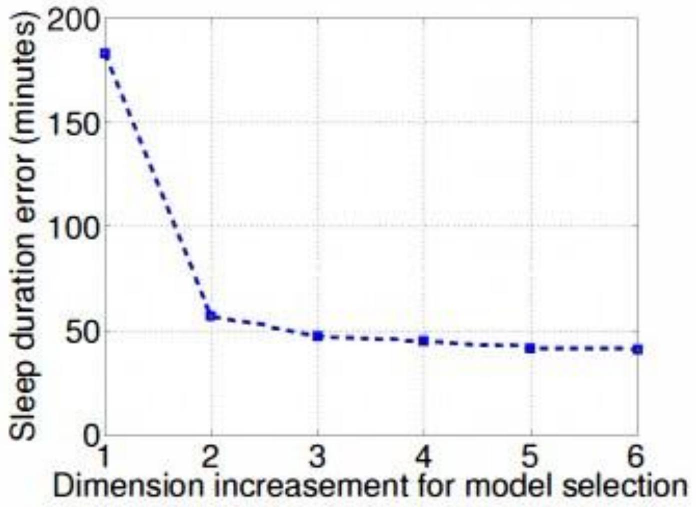


Fig. 2: The reduction in sleep duration error for BES by incrementally adding stationary, silence, phone-lock, phone-charging, light and phone-off features, respectively.

Results

Compared to best wearable sleep monitors available then (SWP, Jawbone, Zeo, etc.)

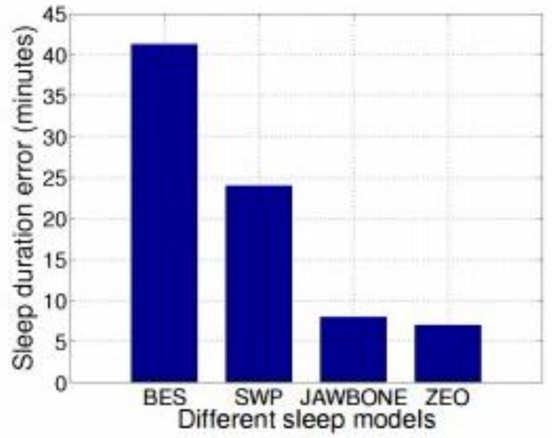


Fig. 3: Overall sleep duration error for BES compared to the three alternative sleep monitoring systems (SWP, Jawbone, Zeo).

1 subject, 6 days

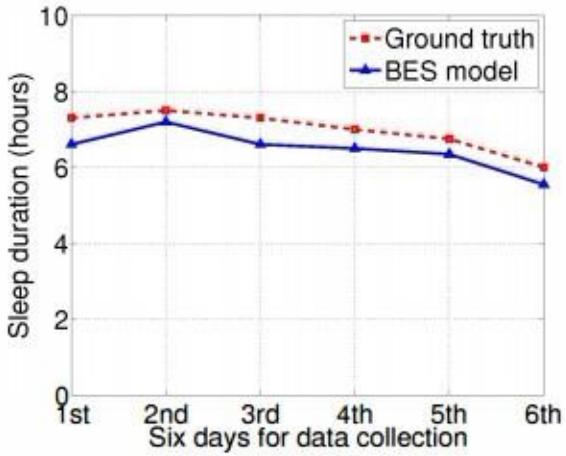


Fig. 5: Comparison of estimated and actual sleep duration under BES for one representative study subject.

My actual Experience

- I worked with WPI undergrad student to implement BES sleep model
- **Results:** About ± 20 minute error for 8-hour sleep
- Errors/thrown off by:
  - Loud environmental noise. E.g. garbage truck outside
  - Misc. ambient light. E.g. Roommates playing video games

References

1. ***A Survey of Mobile Phone Sensing.*** Nicholas D. Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, Andrew T. Campbell, In IEEE Communications Magazine, September 2010
2. ***Mobile Phone Sensing Systems: A Survey,*** Khan, W.; Xiang, Y.; Aalsalem, M.; Arshad, Q.; , Communications Surveys & Tutorials, IEEE , vol.PP, no.99, pp.1-26