Crowd and Mobile Sensing 2

Using Mobile Phones as Sensors

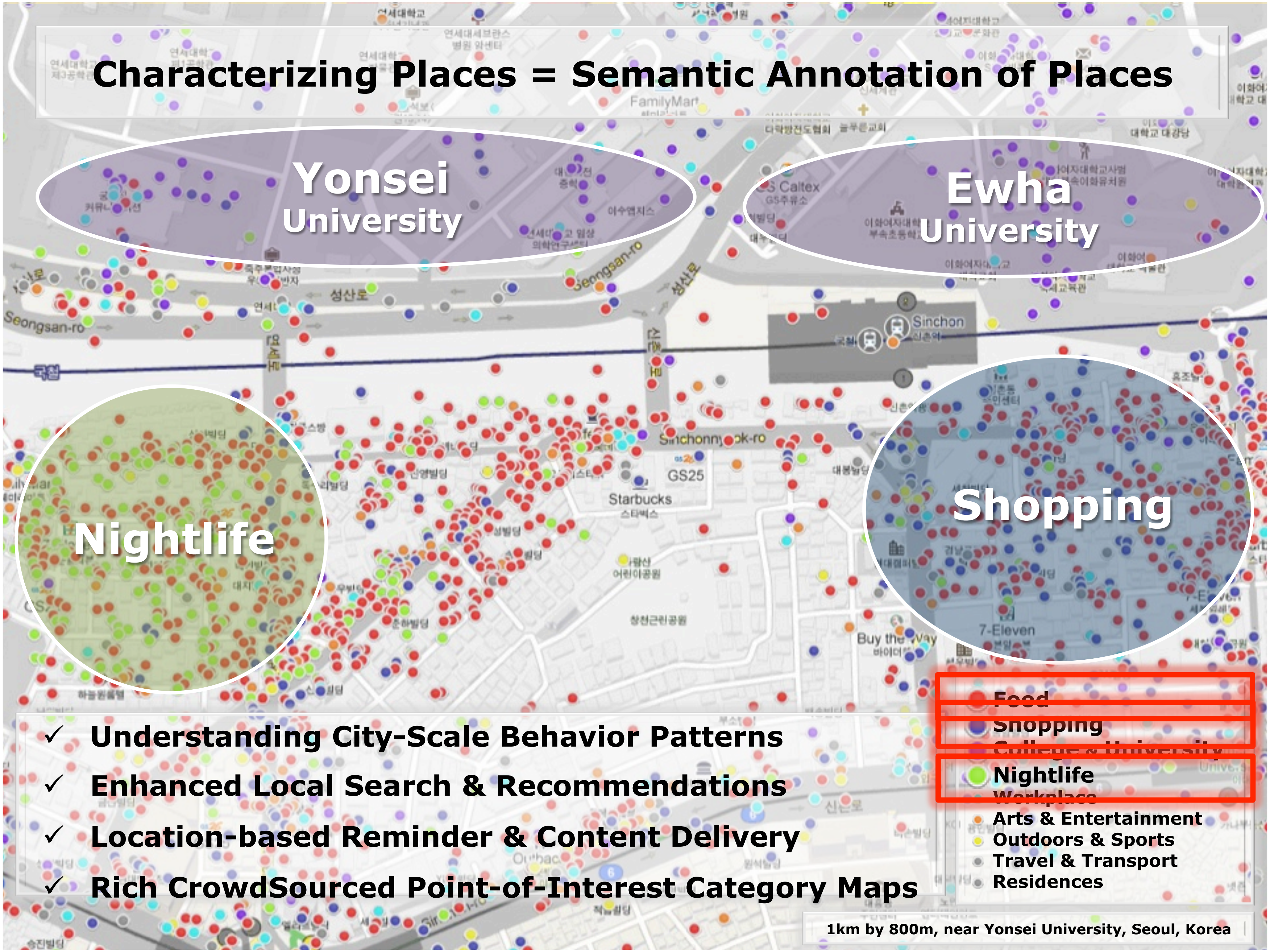
CSE 40437/60437-Spring 2015

Prof. Dong Wang

Papers

Paper 3: Automatically Characterizing Places with Opportunistic CrowdSensing using Smartphones. Chon, Yohan, et al. Proceedings of the 2012 ACM Conference on Ubiquitous Computing (Ubicom 12). ACM, 2012. (Best Paper Award)

Characterizing Places = Semantic Annotation of Places



- ✓ Understanding City-Scale Behavior Patterns
- ✓ Enhanced Local Search & Recommendations
- ✓ Location-based Reminder & Content Delivery
- ✓ Rich CrowdSourced Point-of-Interest Category Maps

1km by 800m, near Yonsei University, Seoul, Korea

Share your thoughts

Q: How would you design an app that can automatically characterize places using smartphone sensing data?

Q: What are the possible challenges of your design?

Location (low level sensor data) **-->**
Place (high level logical concepts)

Existing Approaches

✓ ... gitude)

... e

Te ... la ... de

an ... de.

Show ... paper.

Te ... vis ... e.

How about something else

Engineering approach

✓ Location-...

- Wide

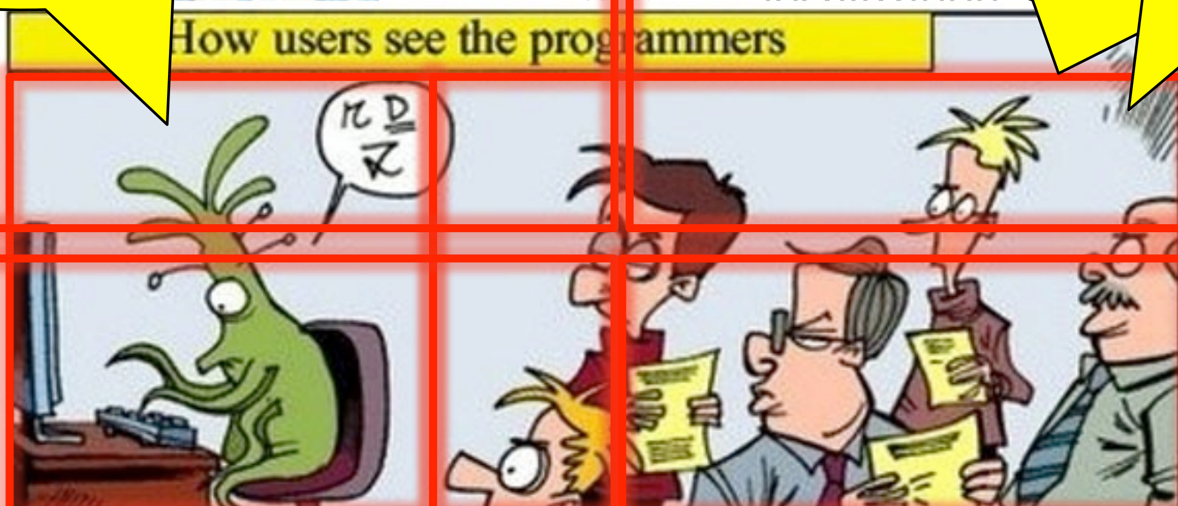
- Yelp,

- Subjec

localization

ca

We will guess!

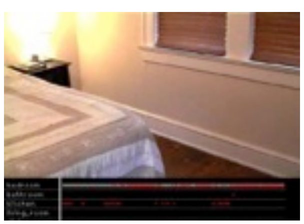


✓ Image-ba

- Category kitchen, l

- Object co

- Patterns at walls

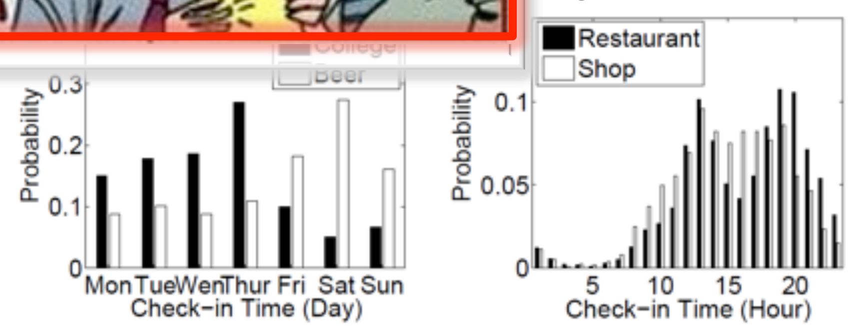


J. Wu et al., IRS'09, P. Viswanathan et al., CRV'11

alysis

ping, nightlife

me



M. Ye et al., KDD'11

CrowdSense@place (CSP)

Smartphone App

Images

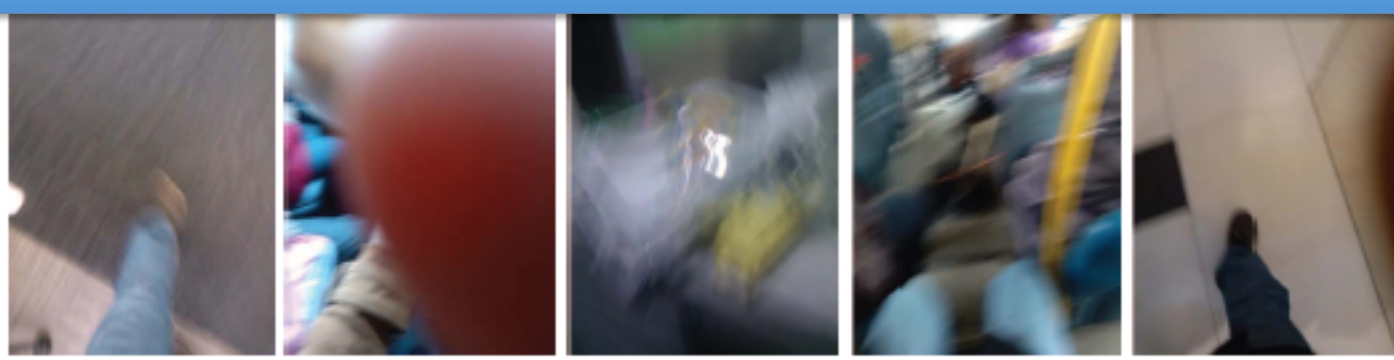
Audio Clips

Places

Examples of captured images

Hints

CrowdSense@Place: it *depends on crowdsensing to collect enough clean data.*



Noise

Main Idea

CSP exploits sensor-based hints to recognize place categories.

The category of this place is $\boxed{}$.

① Theater

② Shoe Store

✓ **Hints**

- **Shoes**
- **Converse**

Main Idea

CSP exploits sensor-based hints to recognize place categories.

The category of this place is $\boxed{}$ **.**

① Museum

② Supermarket

✓ **Hints**

- **Display stands**
- **Ice cream**
- **Snacks**
- **Desserts**
- **Everyday low prices**

Main Idea

CSP exploits sensor-based hints to recognize place categories.

The category of this place is ☐.

① Apple Store

② Fast Food Restaurant

✓ Hints

- **Super hot spicy cheese burger**
- **Here to go**

Conceptual Scenario

CSP considers a place as a document and build a document with sensor-based hints.

Image

Audio

ID: WiFi Fingerprint
order(.78) **here**(.78)
cup(.62) **discount**(.38)
coffee(.38)
one waffle(.43)
and(.43) **two**(.43)
Americanos(.43)
please(.43)
bottle(.53) **cash**(.75)
almond(.17) **bee**(.74)
chocolate(.53) **lotte**(.7)
Americano(.83)
dessert(.44)

Caveat: CSP assumes users will leave the WiFi and GPS sensors on (they are power hungry!)

CrowdSense@Place (CSP)

Framework

Conceptual Scenario

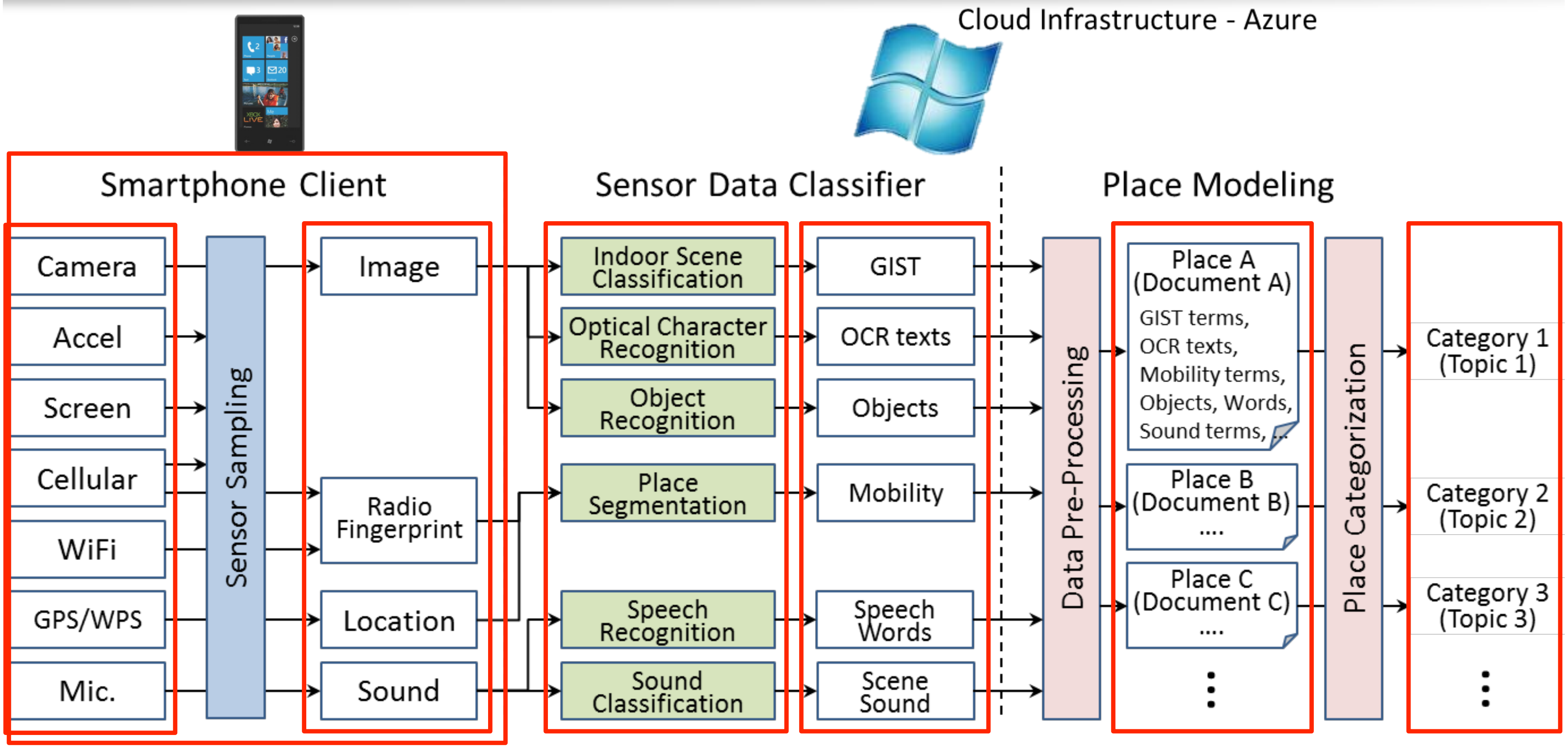
Documents are built by extracting place hints from data collected by CrowdSensing.

Trained place models are used to infer the category of other places.

A few places are labeled with a category by users.

Caveat: CSP assumes all ***place categories*** have been labeled in the training phase before any inference happens.

CrowdSense@Place Framework



Opportunistic Sensing from Smartphone

Multi-Modal Classifiers for Extracting Sensor Place Hints

Topic Modeling for Place Categorization

When to collect data?

Q: When do you think the sensors should start sensing?

When people use the phones

Q: How to ensure user's privacy (image and audio clips can be sensitive)?

Give the users full control of data collection & the ability to delete data before upload

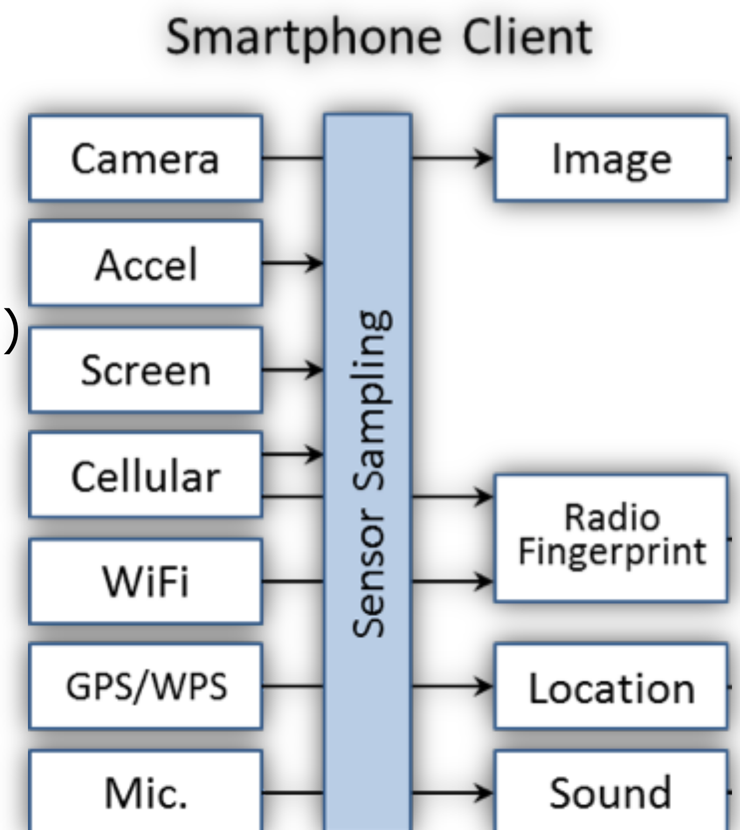
Opportunistic Sensing from Smartphone

Q. When should CSP turn on sensors for collecting high-quality data?

CSP opportunistically collects data based on user context.

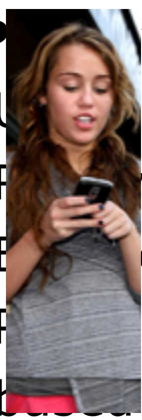
✓ **Opportunistic collection driven by context**

- Application usage
  e.g., phone calls, browsing, etc.,
- Screen state and light sensor
- Piggy-back on user actions
- Accelerometer (orientation,movement) to improve image quality

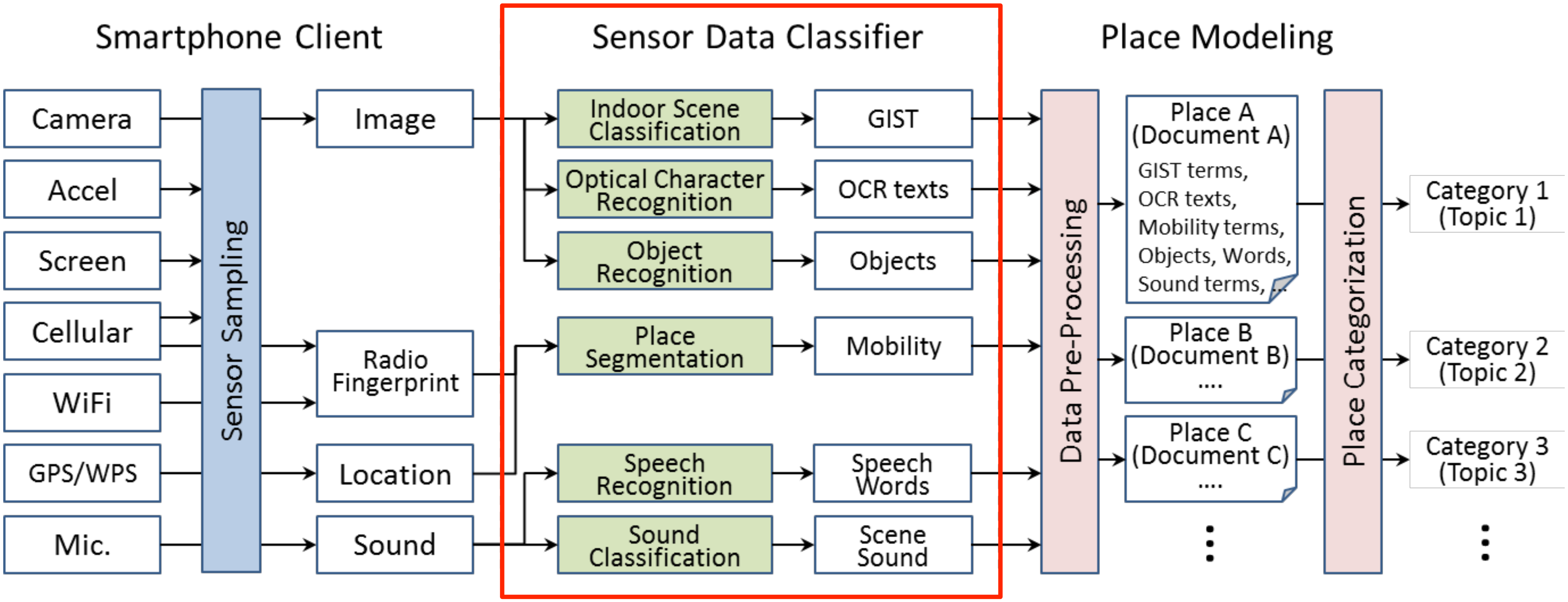


✓ **P y**

- U ont
- P w c d c
- E ed tr
- P dat si
  b on or location



CrowdSense@Place Framework



Opportunistic Sensing from Smartphone

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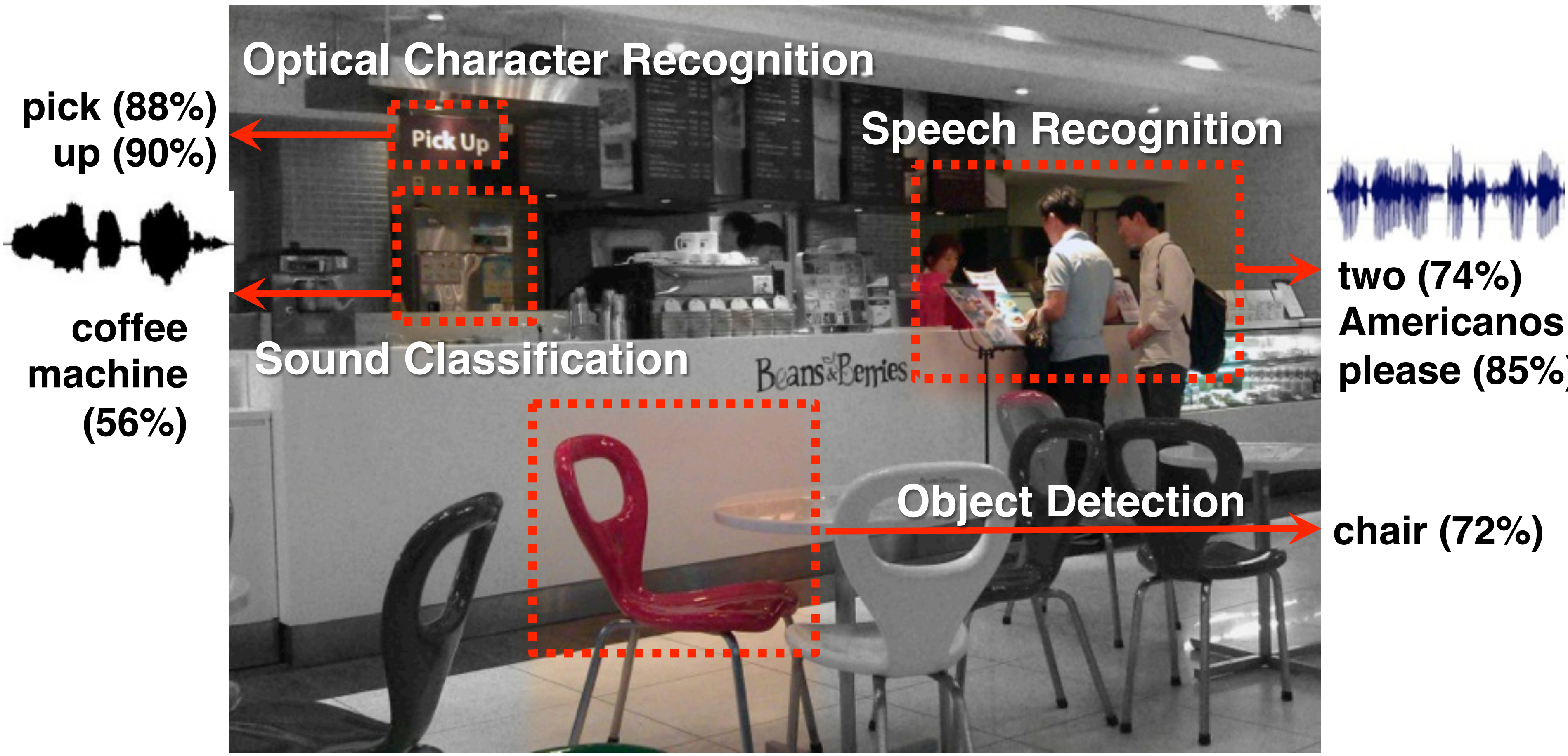
Topic Modeling for Place Categorization

Multi-Modal Classifiers

Q. How can we extract meaningful features?

CSP utilized a wide set of classifiers.



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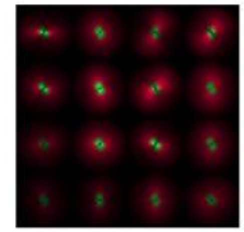
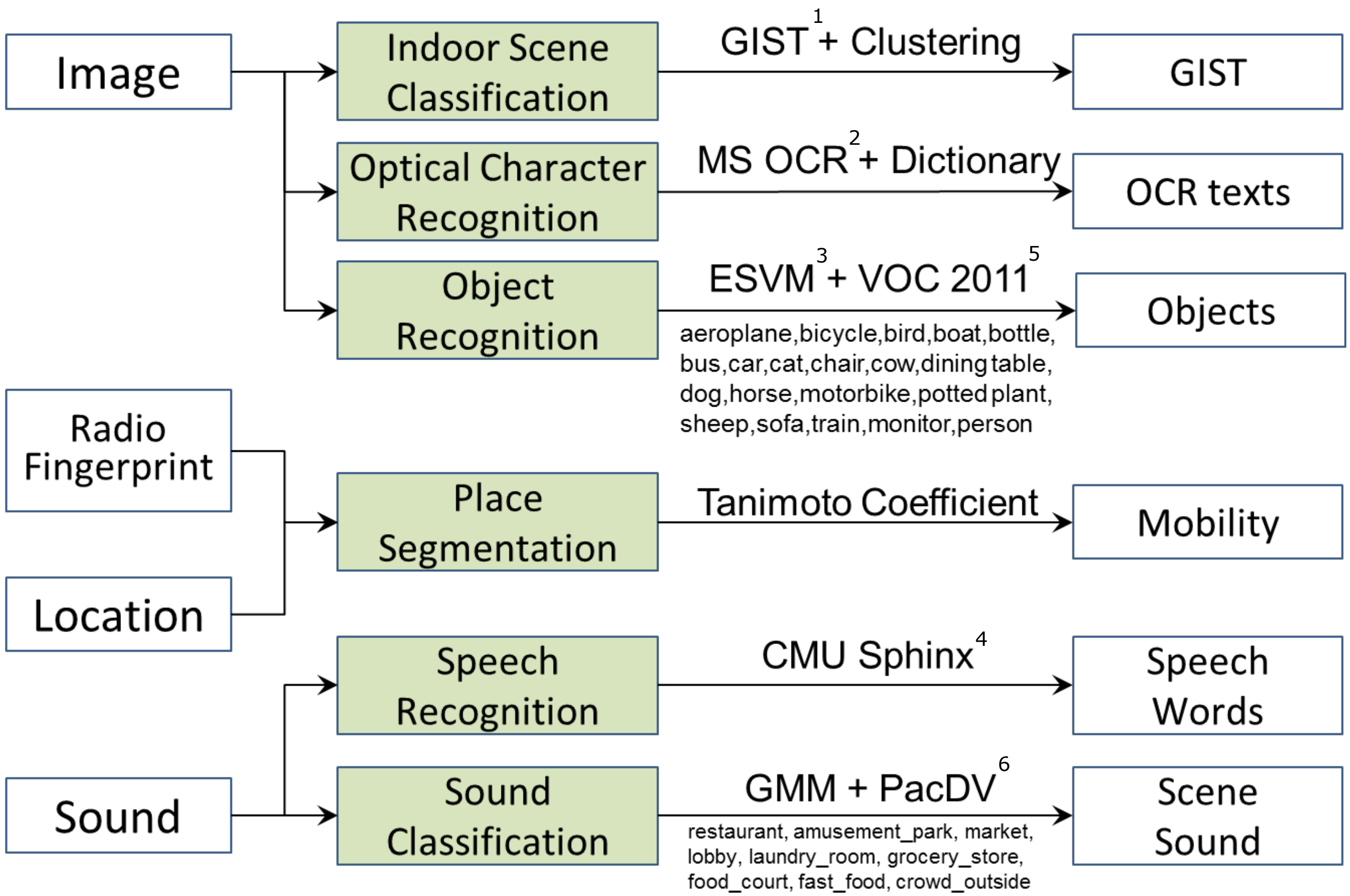




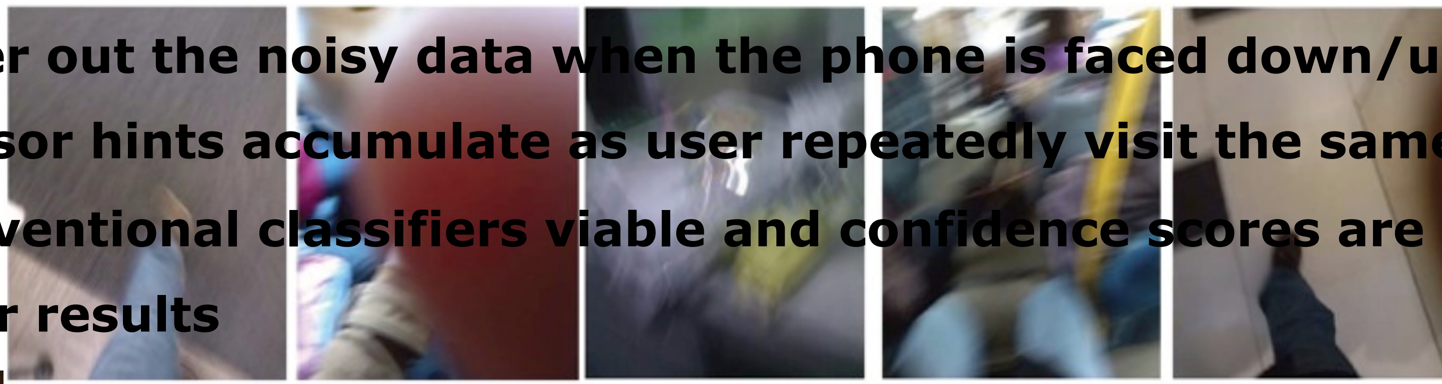
1. A Oliva, IJCV, 42(3), 2. J. Du, ICDAR'11, 3. T. Malisiewicz, ICCV'11, 4. cmusphinx.sourceforge.net, 5. M. Everingham, VOC'07, 6. pacdv.com

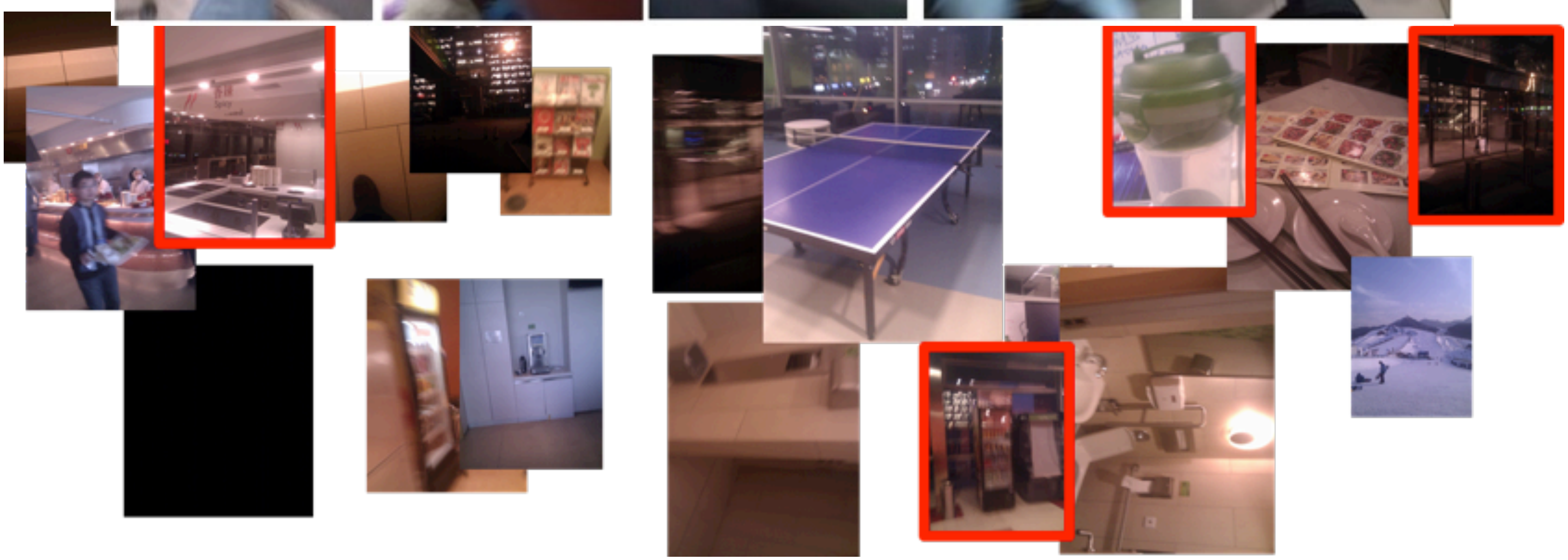
Multi-Modal Classifiers

Q. How can we extract meaningful features?

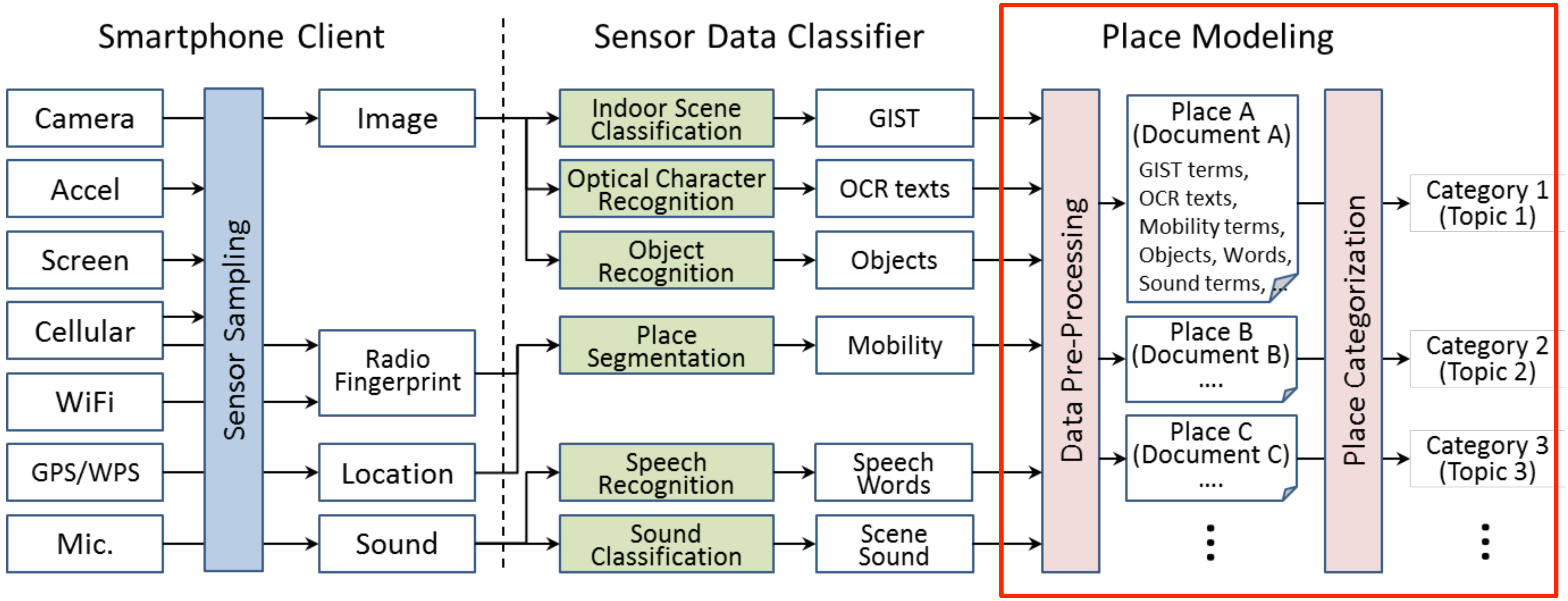
Challenge of Low Quality Sensor Data.

- **Overcome by quantity of samples from CrowdSensing**
- **Filter out the noisy data when the phone is faced down/up/shaky**
- **Sensor hints accumulate as user repeatedly visit the same place**
- **Conventional classifiers viable and confidence scores are used to filter results**





CrowdSense@Place Framework



Opportunistic Sensing from Smartphone

Multi-Modal Classifiers for Extracting Sensor Place Hints

Topic Modeling for Place Categorization

Topic modeling

A topic model: statistical model for discovering the abstract "topics" that occur in a collection of documents.

Example:

- "dog" and "bone" will appear more often in documents about dogs
- "cat" and "meow" will appear in documents about cats
- "the" and "is" will appear equally in both.

A topic model allows examining a set of documents and discovering, based on **the statistics of the words** in each, **what the topics might be** and what each document's balance of topics is.

Topic Modeling for Place Categorization

Q. How can we automatically categorize places?

A **place (document)** is comprised of **place hints (terms)** corresponds to multiple **place categories (topics).**

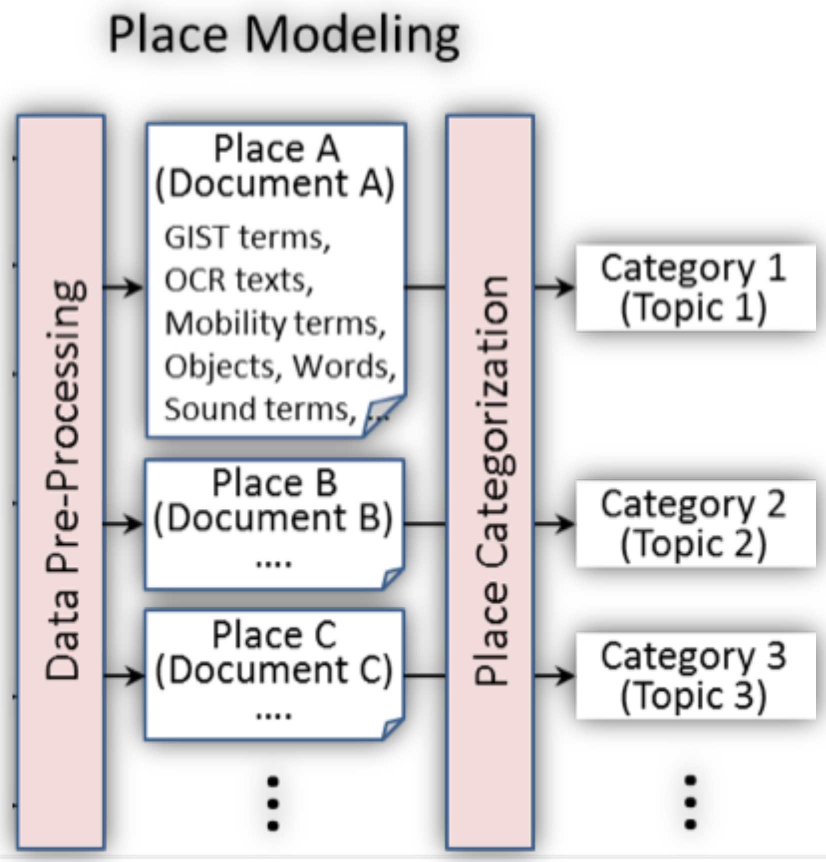
Place	**=**	**Document**
Place Hints	**=**	**Terms**
Categories	**=**	**Topics**

✓ **Pre-Processing**

- Confidence of features
- Term frequency-inverse document frequency (TF-IDF)[1]

✓ **Category assignment**

- Adopt supervised topic model (LDA) [2]



1. B.C. Salton, IPM 24(5), 2. D. Ramage, EMNLP'09

CrowdSense@Place (CSP)

Evaluation

Evaluation Setup

- ✓ **Experiment Questions**
  - How accuracy does CSP classify places?
  - Which features types are most discriminative for place categorization?
  - How well do certain feature types operate in noisy environments?
- ✓ **Metrics**
  - Accuracy of place categorization: # of correctly recognized places/# of places
- ✓

	Feature	Method	Cons.
GPS	Latitude Longitude	Closest place using Foursquare API	Noise in indoor Dense POIs in urban
Mobility	Stay duration Visit count & time	Place modeling using residence-time distribution	Confused by similar residence pattern

Evaluation – Category Definition

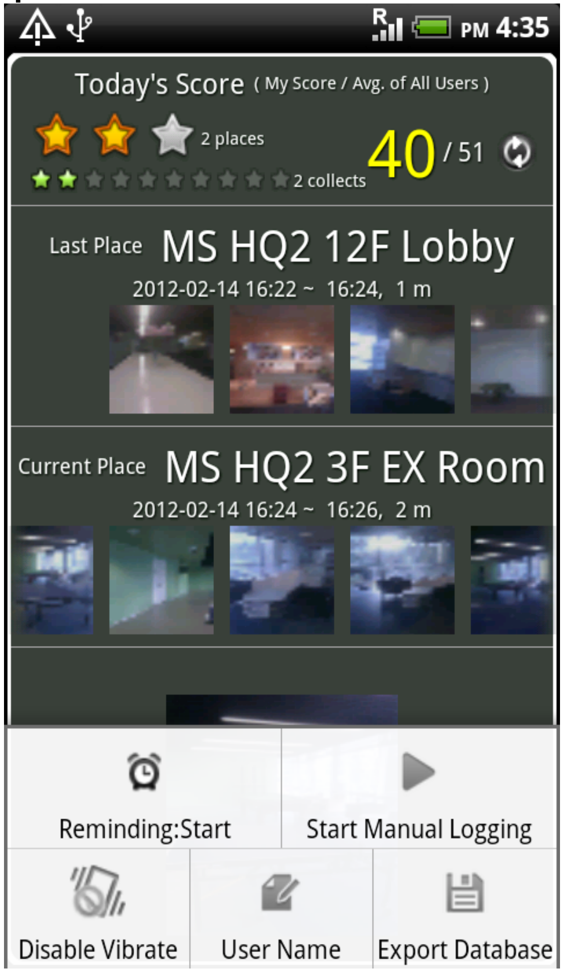
CSP follows category definition of Foursquare.

Category	Sub categories
College & Education	classroom, library, high school, educational institute
Arts & Entertainment	cinema, theater, museum, exhibit hall, gym, karaoke, gaming room, pool hall, stadium
Food & Restaurant	restaurant, fast food restaurant, cafe, dessert shops, ice cream shops, bakery
Home	home, friend/families' home, dormitory
Shops	bank, bookstore, clothing store, accessories store, shoe store, cosmetics shop, department store, convenience store, supermarket, salons, grocery store, jewelry store, high tech outlet
Workplace	workplace, office, meeting room, laboratory, conference room, seminar room, focus room
Others	transportation, church, temple, hospital, hotel, bars, pubs, clubs, street, unknown

Evaluation - Data Collection

- ✓ 36 participants in Korea, China, and USA
- ✓ Run collection app. in Android SDK 1.5 smartphone

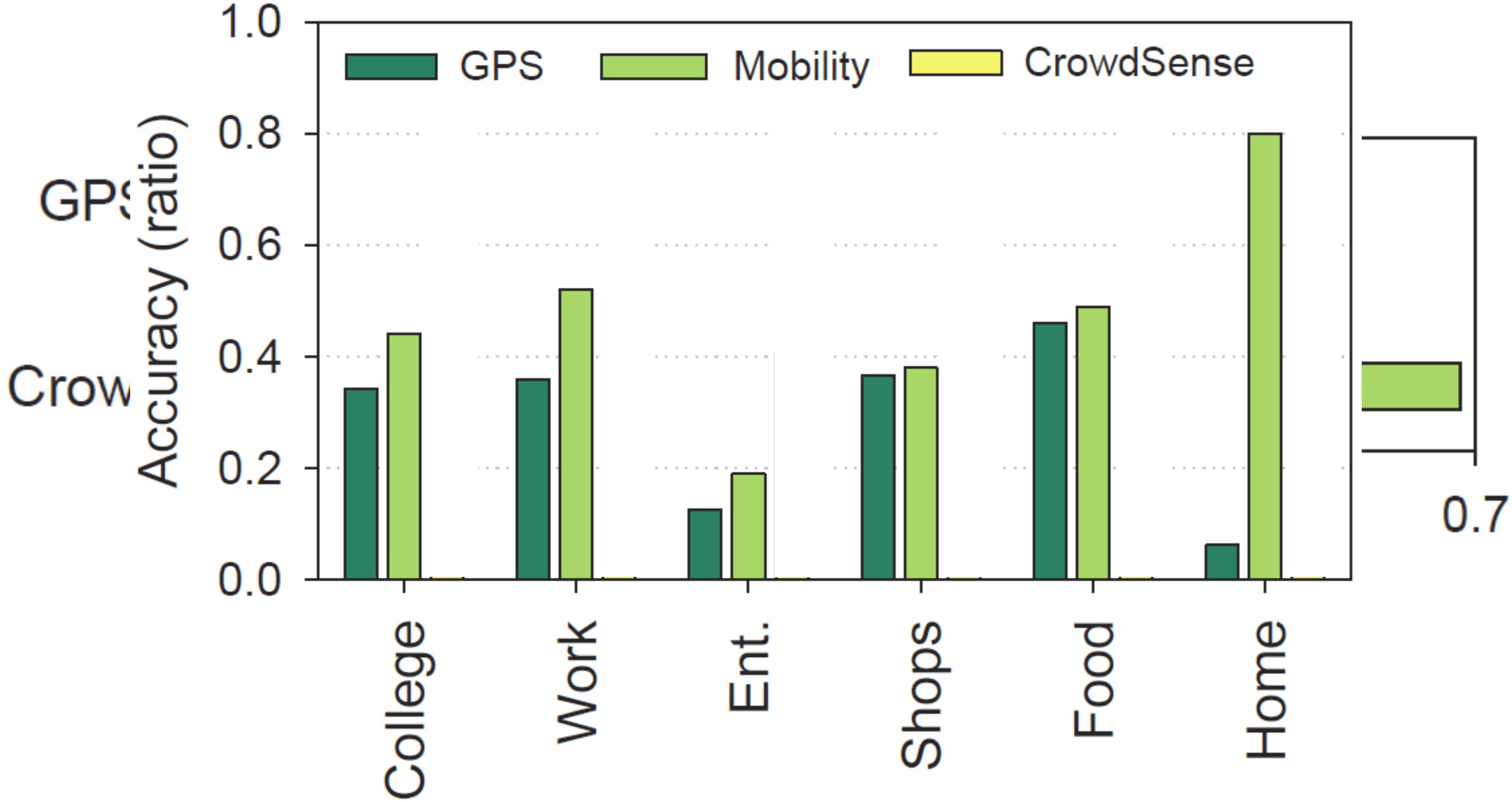
Category	# of place	# of visit	Stay duration (hour)	# of image	# of audio
College & Education	120	1,570	2,222	60	-
Arts & Entertainment	89	218	361	81	37
Food & Restaurant	578	1,426	926	534	236
Home	64	3,899	29,632	72	2208
Shops	112	255	175	1026	254
Workplace	116	4,882	12,306	386	1307
Others	162	656	491	156	121



- 1,300 places for 46,000 hours
- 2,300 images and 4,200 audios
- **22% of images are either blurred or completely black**

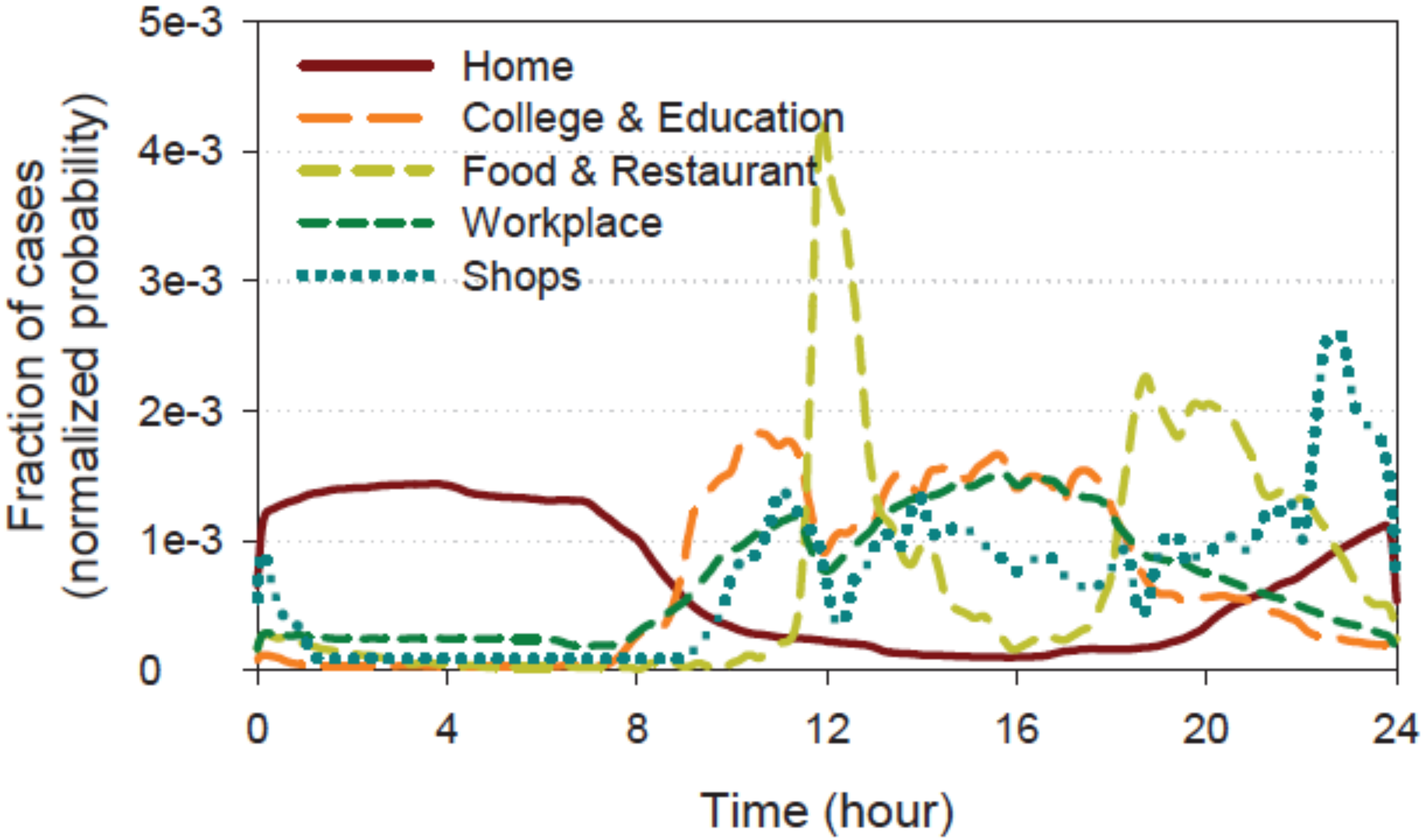
Evaluation - Overall

CrowdSense outperforms existing techniques with 69% overall accuracy.



Home, college, workplace shows relatively higher accuracy and entertainment shows worst accuracy.

Mobility Patterns



CSP vs Mobility: Confusion Matrix

Mobility-based Method

Label \ Result	Col.	Work	Ent.	Shops	Food	Home	Oth.
College	0.44	0.30	0.01	0.04	0.04	0.04	0.12
Work	0.33	0.52	0.01	0.03	0.07	0.01	0.03
Ent.	0.07	0.07	0.19	0.15	0.11	0.19	0.22
Shops	0.00	0.06	0.13	0.38	0.06	0.06	0.31
Food	0.10	0.04	0.02	0.08	0.49	0.05	0.20
Home	0.00	0.00	0.00	0.09	0.00	0.80	0.11
Others	0.06	0.14	0.17	0.14	0.04	0.16	0.30

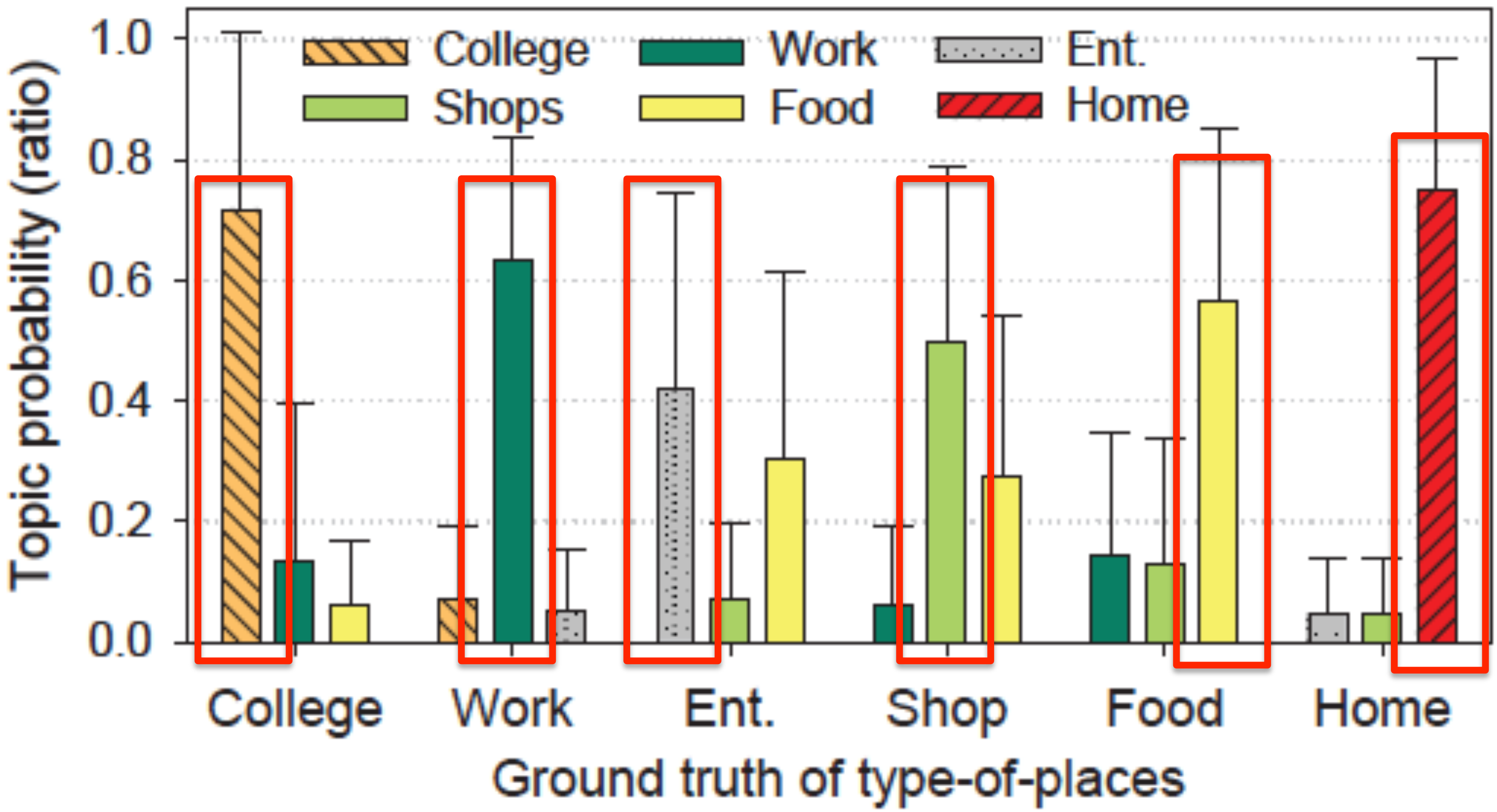
User Mobility Only

CrowdSense@Place

Label \ Result	Col.	Work	Ent.	Shops	Food	Home	Oth.
College	0.80	0.10	0.01	0.01	0.03	0.00	0.04
Work	0.05	0.71	0.03	0.01	0.02	0.01	0.03
Ent.	0.04	0.04	0.41	0.04	0.33	0.00	0.15
Shops	0.00	0.03	0.00	0.59	0.28	0.00	0.09
Food	0.02	0.11	0.05	0.09	0.66	0.00	0.06
Home	0.00	0.00	0.04	0.02	0.00	0.93	0.00
Others	0.05	0.09	0.09	0.20	0.12	0.10	0.36

User Mobility + Images + Audio

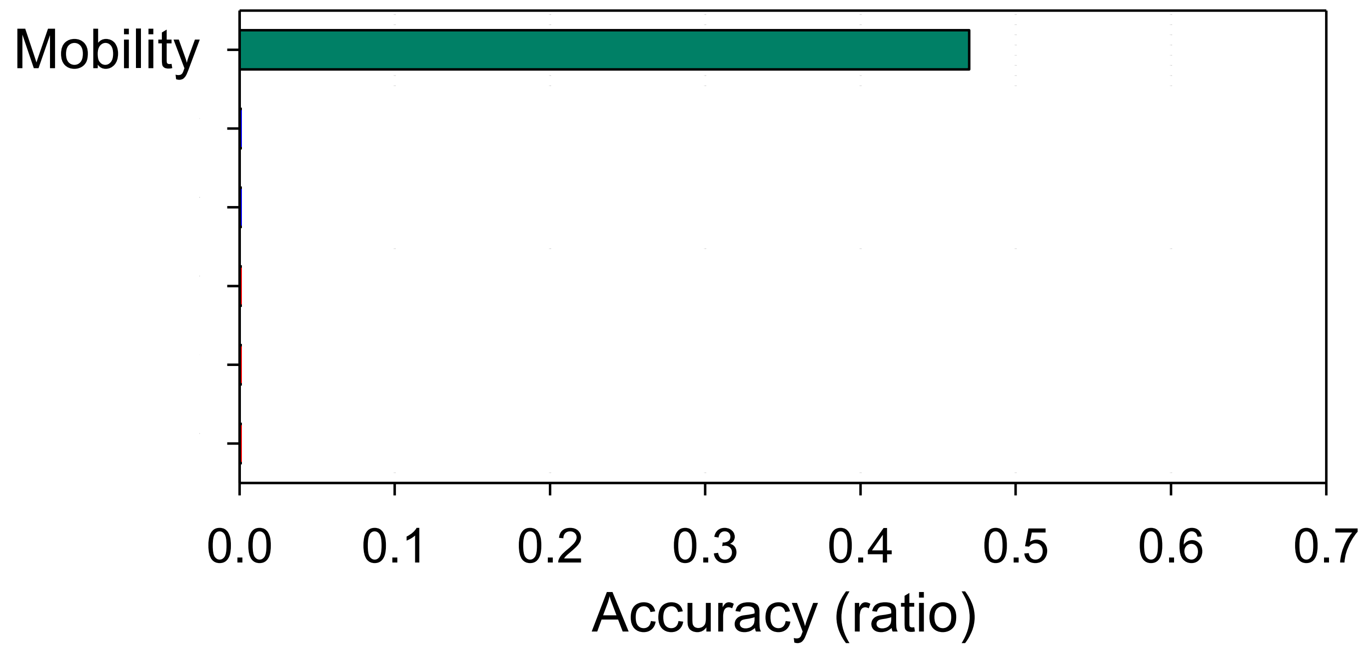
Some Places Belong to More Than One Category



Top-three highest-probability topics for each category

Evaluation - Classifiers

Mobility is the most powerful feature.



Strong discriminative power

Texts by OCR

Scene features by GIST

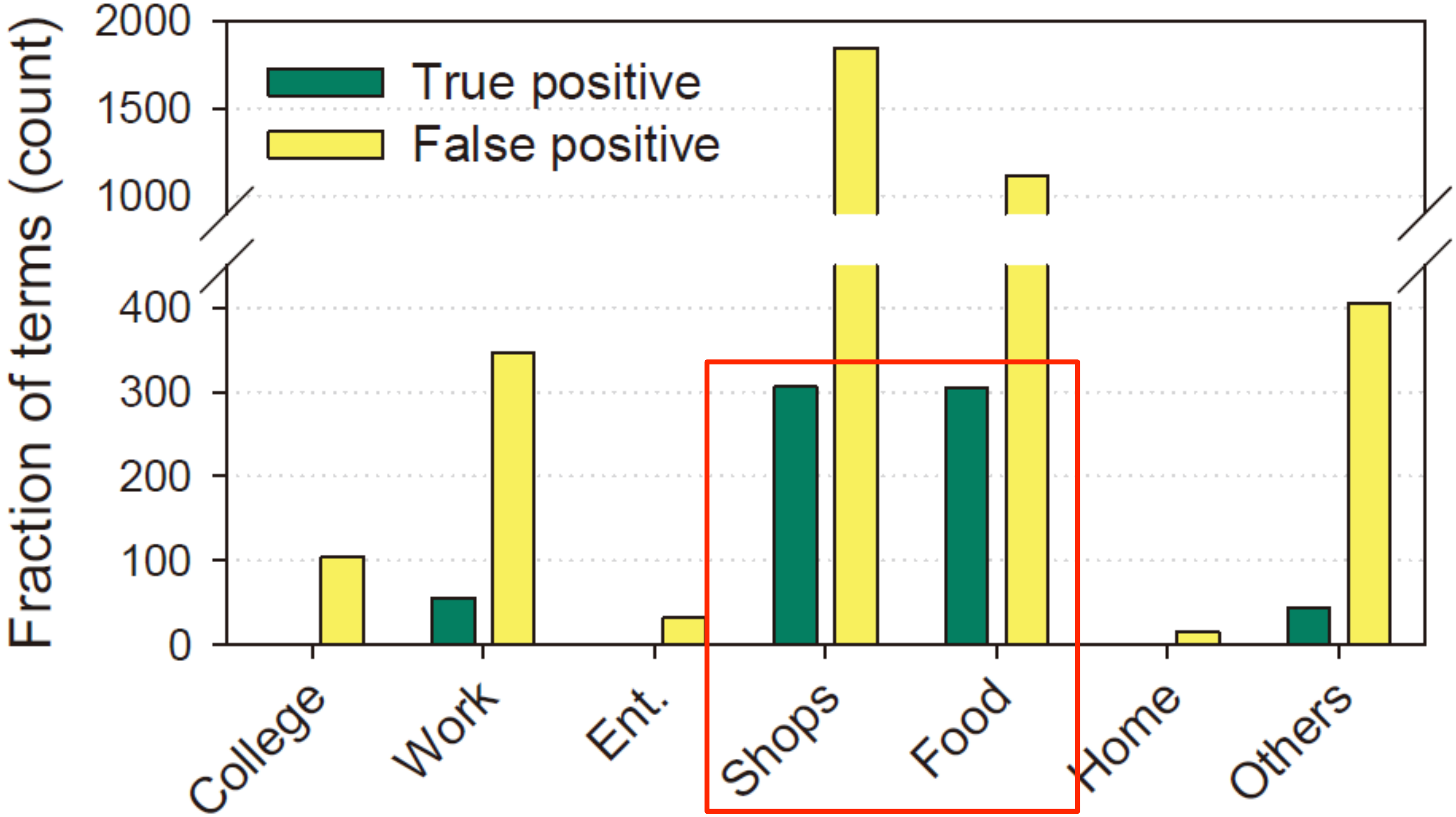
Weak discriminative power

Object detection in indoor

Speech words and sounds

Evaluation - Classifiers

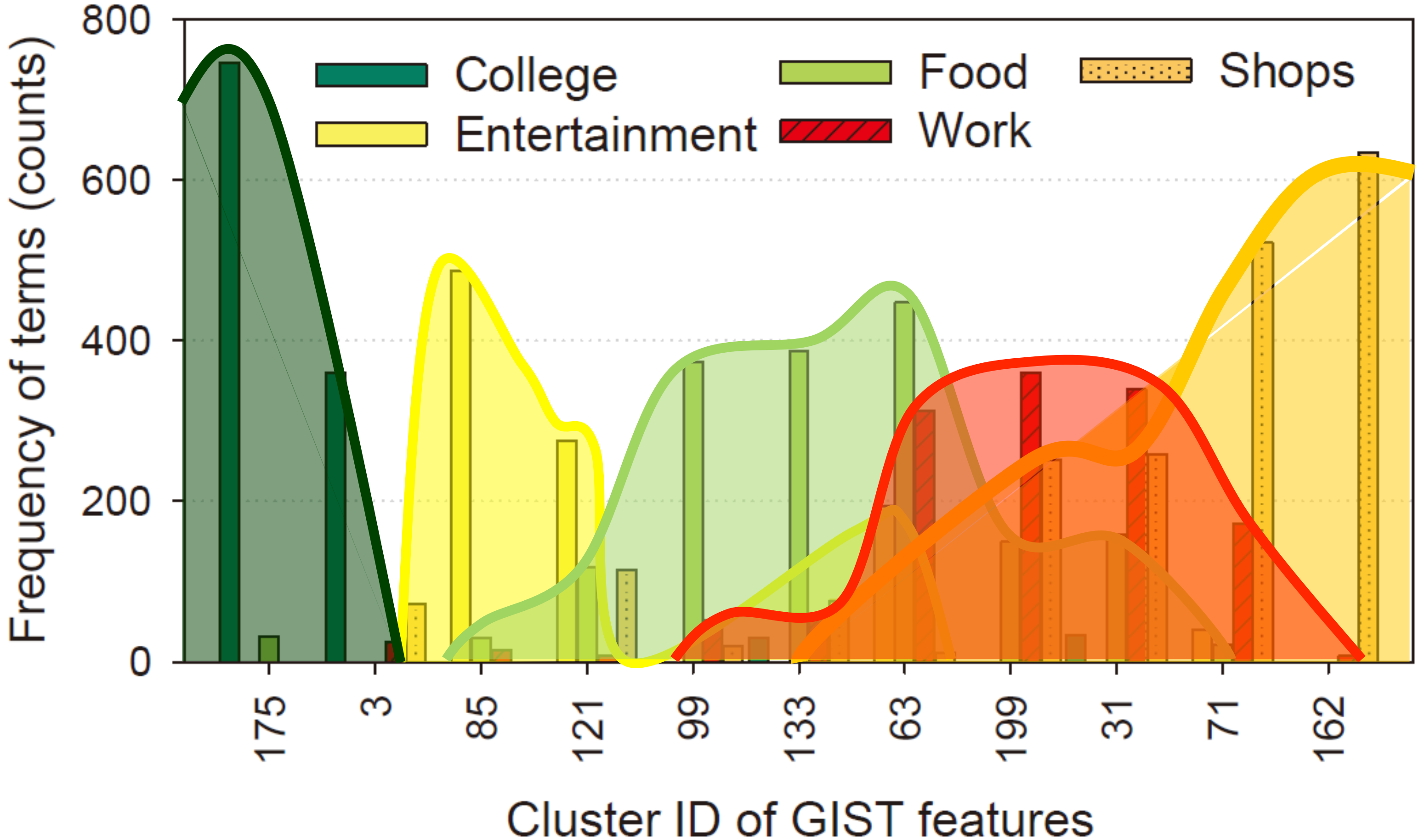
Texts are mainly observed in shopping and food-related places.



Frequency of recognized words from different place categories

Evaluation - Classifiers

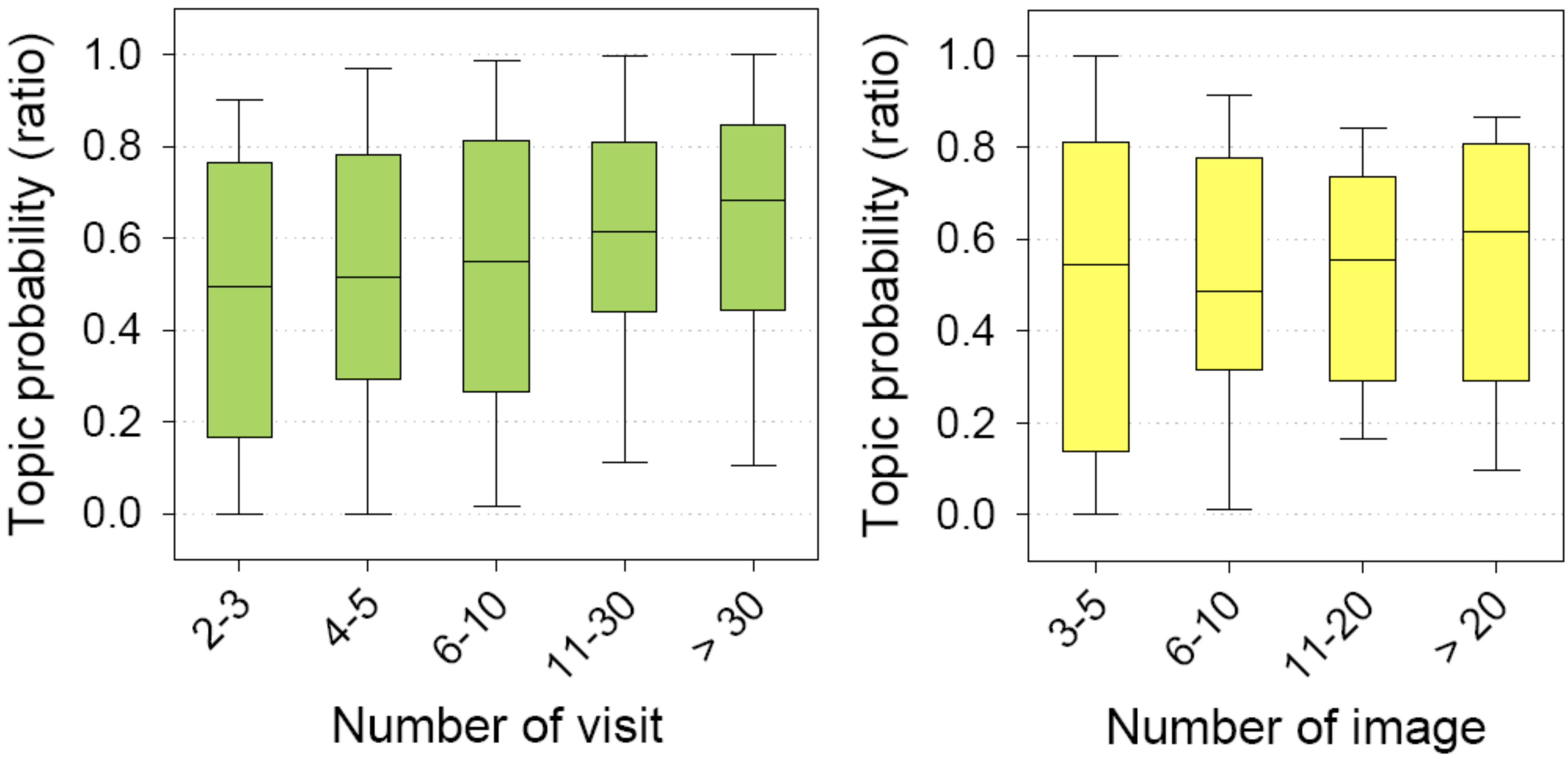
Scene features are distributed differently for different place categories.



Distribution of indoor scene features (GIST) at different place categories

Evaluation - Classifiers

CSP becomes more certain about place categories as users visit places multiple times.



Box plot of correctly allocated topic probability

Discussion (1)

Good Example of CrowdSensing Framework

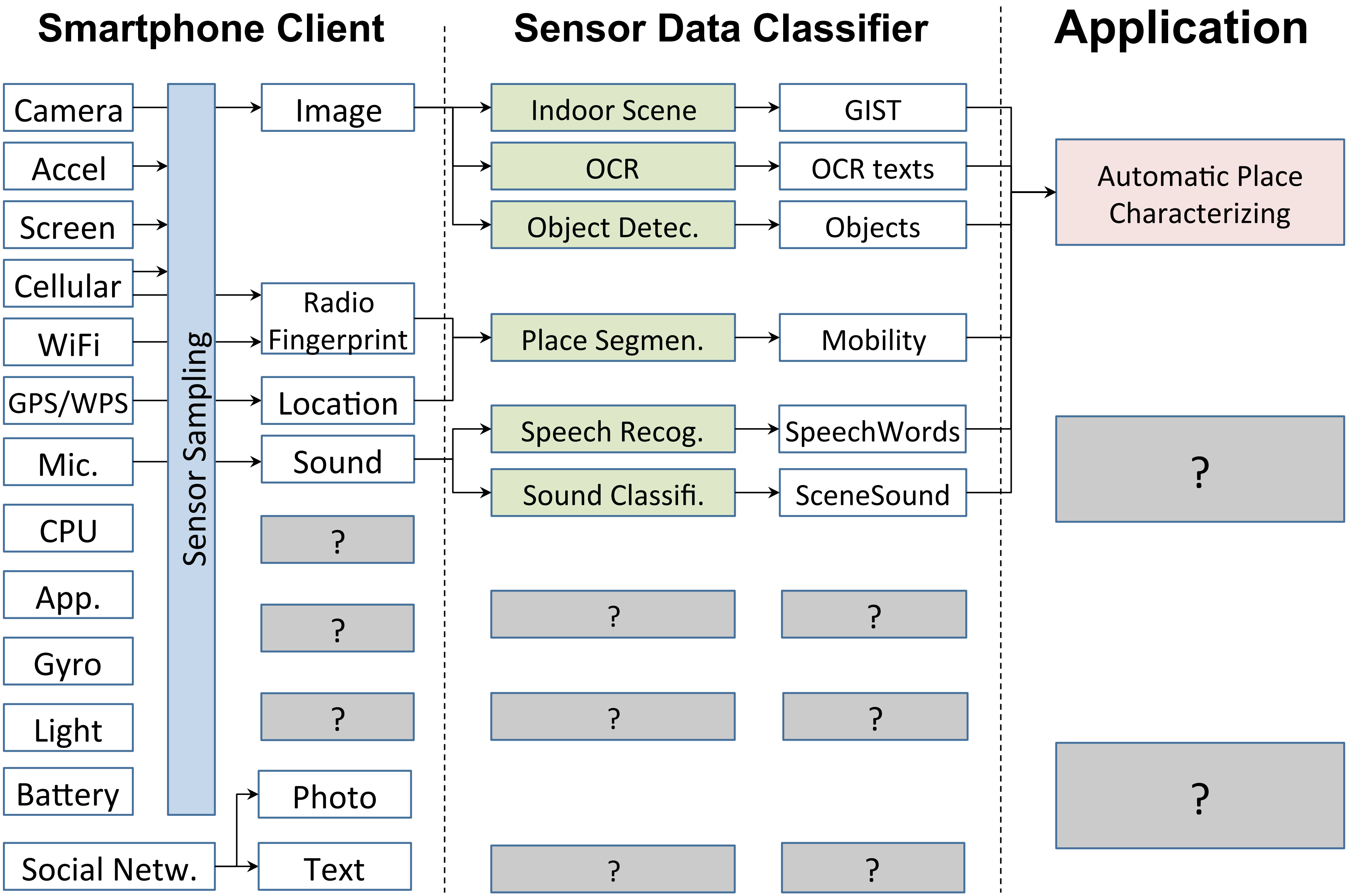
Privacy Concern
Local processing & Anonymization

Induce User Participation
Incentive for data collection

Accurate & Efficient Classifier
Extract high-level context from real data

Advanced Applications
Use crowd context

Discussion (2)



Application Scenarios

Enhanced Local Search and Recommendation

- It provides a richer awareness of the types of places a user frequently visits -> additional user profile attribute.
- Places can be compared using more refined place hints (e.g., lighting conditions and background music)

Rich Crowdsourced Point-of-Interests Category Map

- It can be used to build “maps” that relate places to place categories
- A targeted advertising app can determine the user’s current place category based on a WiFi scan performed by his or her smpartphone

Limitations of CSP

It has limited place categorization accuracy (< 70%)

- Some features (e.g., speech, object recognition) contribute little to the ability to classify places
- In future, they plan to train the classifier using a small amount of specific place hints (e.g., discriminative words)

Data collection is completely opportunistic

- High-quality hints accumulate slowly
- It is better suited to incrementally learning static information over long time scales

Limitations of CSP

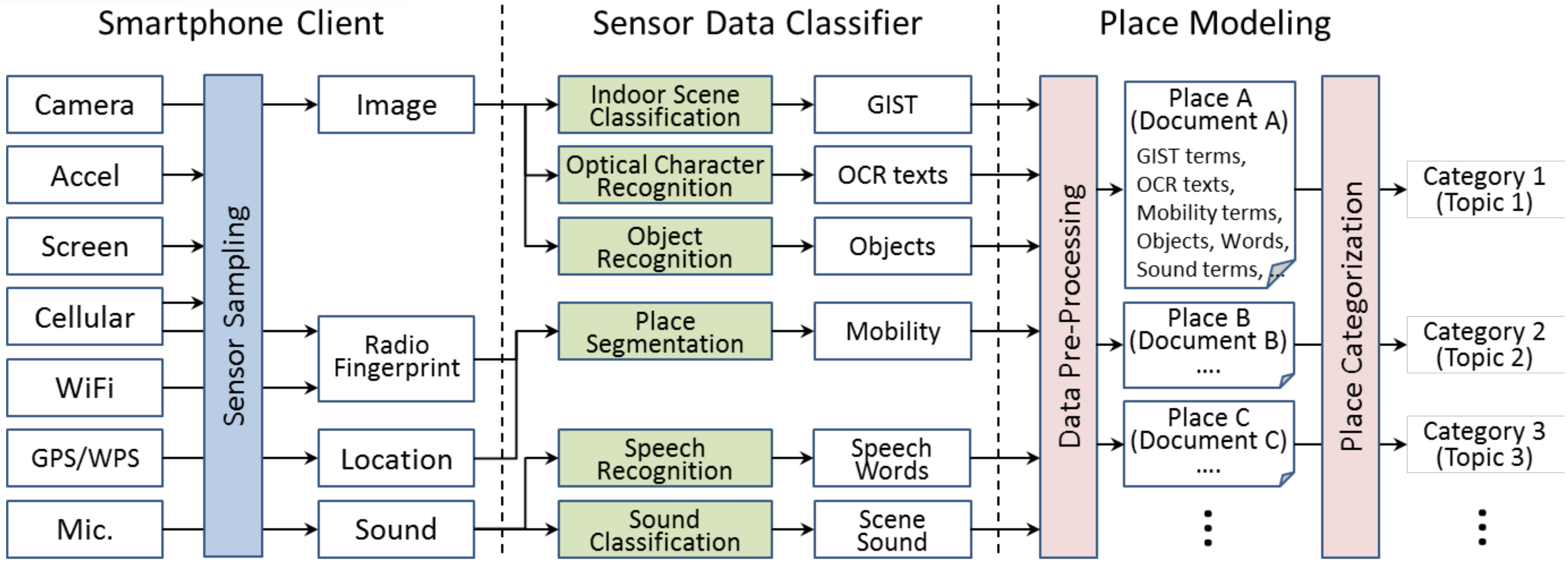
It did not consider energy issues in their solution

- WiFi and GPS are power hungry
- Taking many pictures and audio clips will certainly shorten phone's usage time

Privacy concern is still a BIG problem

- It relies on users to decide what images/audio clips to upload, which might not be reliable
- In future, it can choose to process sensor data on the phone and then upload features instead of raw data to the backend

Conclusion



Use Hints as Human Does

Recognize a diversity of categories

Integrate Topic Models

with Leveraging Conventional Classifiers

Large-Scale Evaluation

36 users visiting 1300 places in 5 cities

Providing Insights to CrowdSensing Systems

The Author's Follow up work

Crowdsensing data

GPS Coordinates
(with noises)

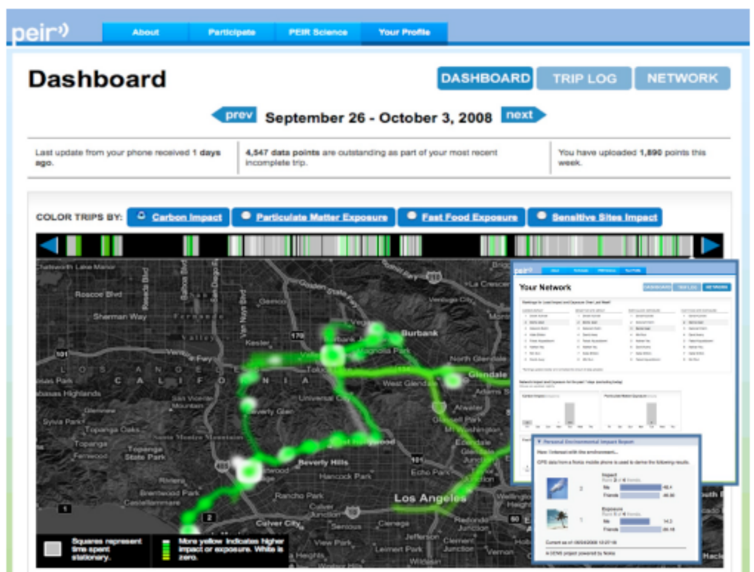
Actual Name of
the Place

Social Network Services

Chon, Yohan, et al. "Autonomous place naming system using opportunistic crowdsensing and knowledge from crowdsourcing." Information Processing in Sensor Networks (IPSN), 2013 ACM/IEEE International Conference on. IEEE, 2013.

Papers

- Paper 4:"PEIR, the personal environmental impact report, as a platform for participatory sensing systems research." Mun, Min, et al. Proceedings of the 7th international conference on Mobile systems, applications, and services. ACM, 2009.



Participatory Sensing

Distributed data collection and analysis at the personal, urban, and global scale

Individuals and *communities* make decisions about when and how to

Capture -> Store -> Access -> Analyze -> Share

What, where and when to sense?

Participants use *mobile phones* to gather data and *web services* to aggregate and interpret the assembled information.

Health and Wellness : PM 2.5

" Los Angeles recently claimed the title of the metropolitan area most polluted by year-round particle pollution."
- America Lung Association

" We know that environmental pollutants have a very significant impact on children with asthma."
- Dr. Avril Beckford,
a pediatrician in Austell, Georgia

Health and Wellness : CO_2

" Transportation sector makes up 1/3 of CO_2 emissions."

" Increases in transportation and account for 41% of the growth of CO_2 emissions between 1990 and 2005."

Health and Wellness : Fast Food

" The risk of stroke in a neighborhood increased by 1% for every fast food restaurant"
- CNN

"Proximity to fast food correlates with increased obesity"
- National Bureau of Economic Research

Share your thoughts

- What are the environmental and health related application you could think of by using participatory sensing paradigm?

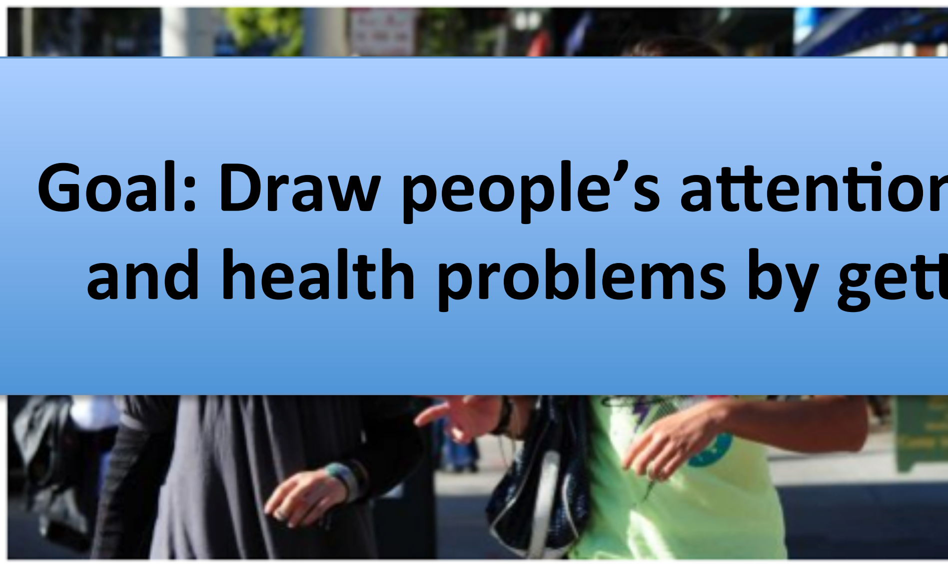
- What are the challenges to design and implement the system you proposed?

Personal Environmental Impact Report

- **Carbon Impact**: a measure of transportation-related carbon footprint (e.g., CO_2, etc.)
- **Sensitive Site Impact:** a user's transportation related airborne particulate matter emissions (e.g., PM 2.5) near sites with populations sensitive to it (e.g., hospitals and schools)
- **Smog Exposure:** a user's transportation-related exposure to particulate matter emissions (e.g., PM 2.5) from other vehicles
- **Fast Food Exposure:** the time integral of proximity to fast-food eating establishment

What We Expect from PEIR

Ultimately we want people to *take* ***notice of impact and exposure*** *and be able to start conversations*. The absolute numbers are not what’s key, but instead, **trends over time**. How can one reduce impact and minimize exposure?



Goal: Draw people’s attention to the environment and health problems by getting them involved!

PEIR is different from other existing carbon footprint calculators

Existing web-based and mobile carbon footprint calculators such as Ecorio, Carbon Hero, UbiGreen

> require users to **manually input** data *each time they travel*
> focus only on computing **carbon emission values**

PEIR senses pollution by using existing infrastructure **without much user intervention** and emphasizes how individual transportation choices simultaneously influence **both environmental impact and exposure**

PEIR as a Participatory Sensing System

"Sensing Pollution without Pollution-Sensors"

Existing Infrastructure	Annotation /Inferences	Scientific Models
GPS and Cellular Networks	Users Labe the Data to Train Activity Classifiers	Estimate the Environmental Impact and Exposure

Activity Classification

Determines whether a user is staying in one location, walking or driving.

What is the most important activity for PEIR:
Driving!

How to detect the driving behavior?
GPS readings are **noisy** to compute speed (especially for indoor scenarios)!

Uses **freeway annotation information** in addition to speed values in order to identify driving activities better.

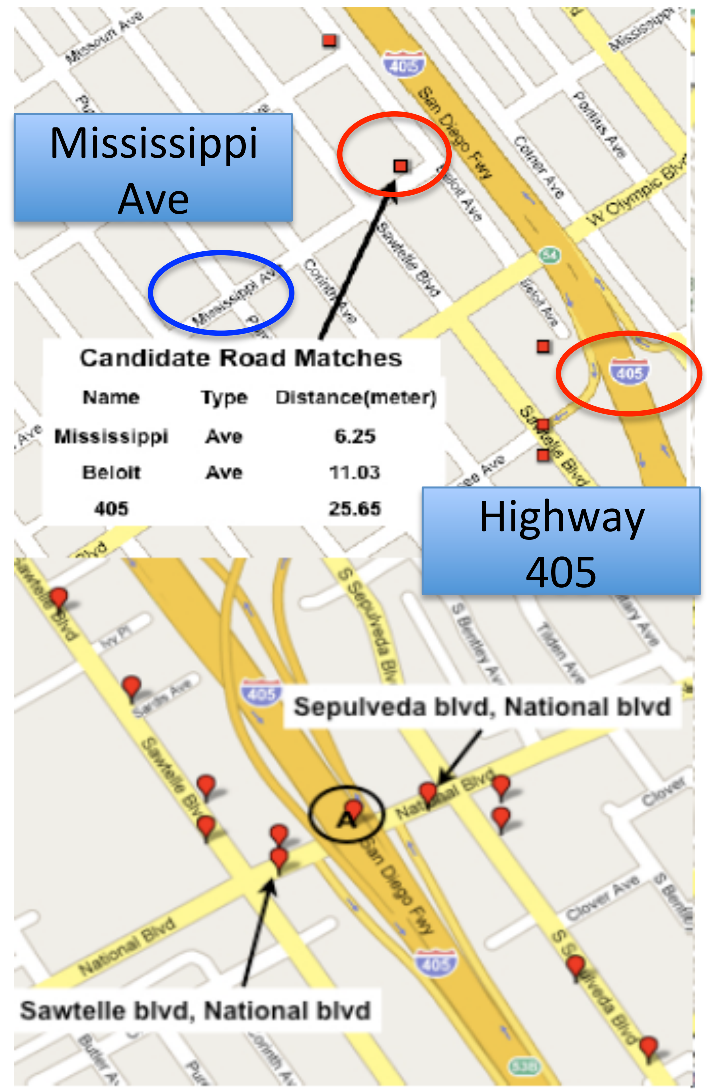
Activity Classification: Map Matching

Determines which road a user is on.

Naive approach: find the nearest road as a correct match

What is the problem of this approach?

Both GPS readings and map may not be accurate: nearest road may not be the correct road.



Activity Classification: Map Matching

Determines which road a user is on.

Naive approach: find the nearest road as a correct match
-> often fails in practice

Is there a way to get around this problem?

A better approach: Finds **pairs of intersection** roads that a user passes by and **extracts the common road** among subsequent intersections

Activity Classification: Map Matching

Problem 1: The captured GPS data points are not always near intersections

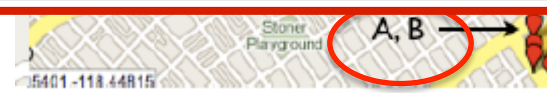
Problem 2: The erroneous identification of pre-intersections can lead to error propogation

Two enhancements:

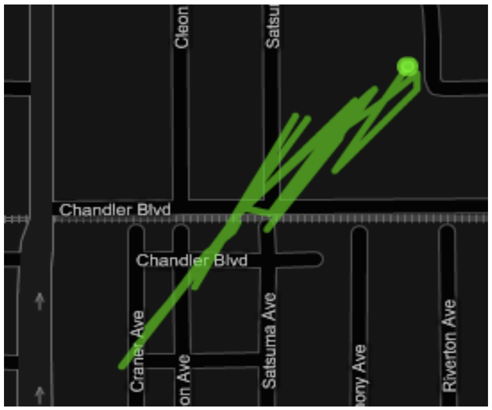
- A close enough road can be considered as a possible intersection point.

- It replaces both pre- and post-intersections when there is no common road among subsequent intersections

	Case 1	Case 2	Case 3	Case 4	Case 5	Average
Naive map-matching	76%	58%	93%	57%	56%	68%
Intersection-based	5%	83%	100%	77%	96%	72%
Intersection w/nearest road and substitution	89%	83%	100%	63%	96%	86%



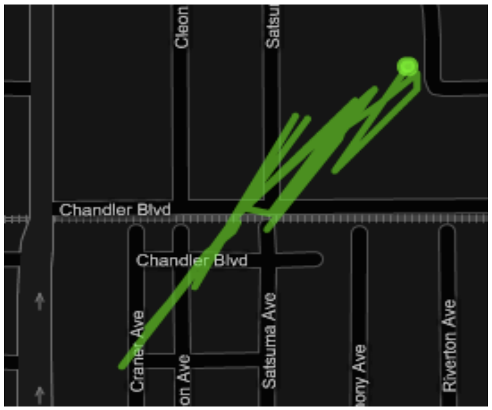
Activity Classification: Problems and Improvement by Leveraging GSM Data



Classification based on GPS data alone is difficult if GPS performance is compromised by **limited satellite visibility**. E.g. when users are indoors

Q: What can we do to mitigate this limitation without adding additional hardware/sensors?

Activity Classification: Problems and Improvement by Leveraging GSM Data



Classification based on GPS data alone is difficult if GPS performance is compromised by **limited satellite visibility**. E.g. when users are indoors

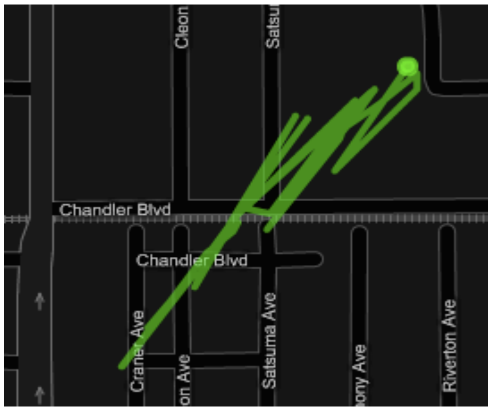
GSM (Global Systems for Mobile Communication), i.e., Cellular Network data is already available and can compensate for the speed values from GPS devices.

Unique cell ID: Country Code + Network Code + Area Code + Cell ID

↓

Rough indication of a user's location

Activity Classification: Problems and Improvement by Leveraging GSM Data



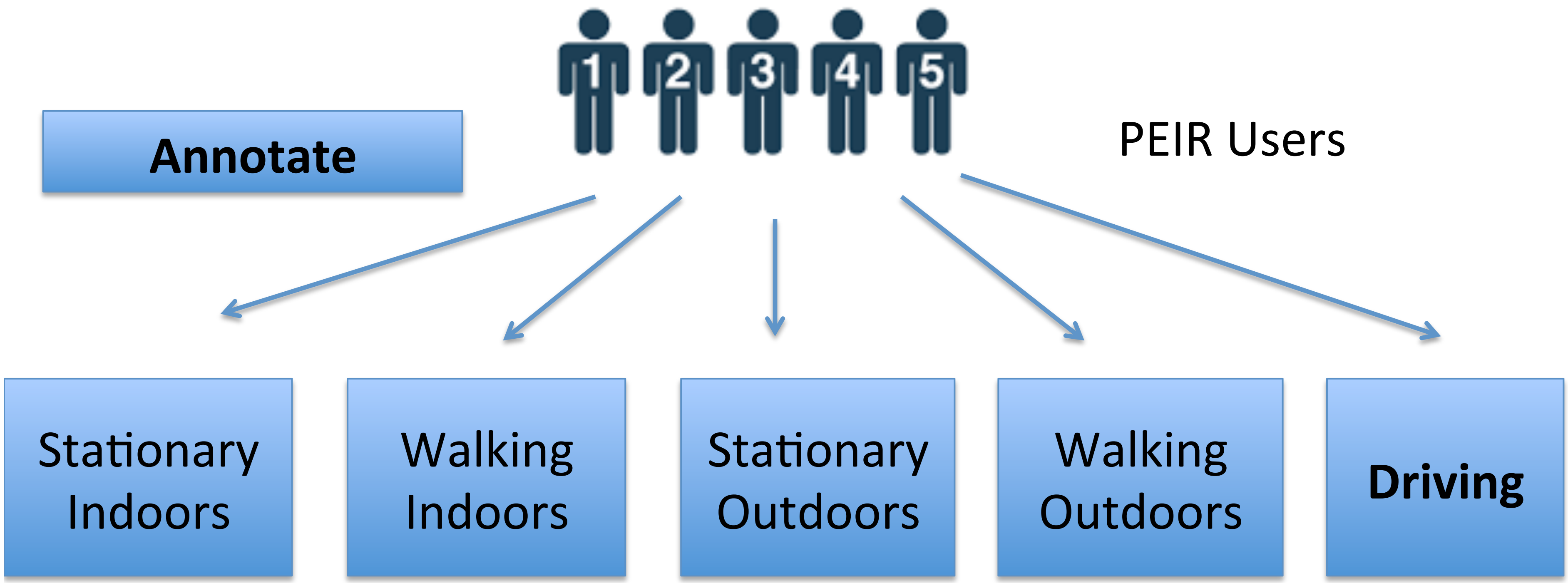
Classification based on GPS data alone is difficult if GPS performance is compromised by **limited satellite visibility**. E.g. when users are indoors

GSM (Global Systems for Mobile Communication), i.e., Cellular Network data is already available and can compensate for the speed values from GPS devices.

Indicate the user's travel mode

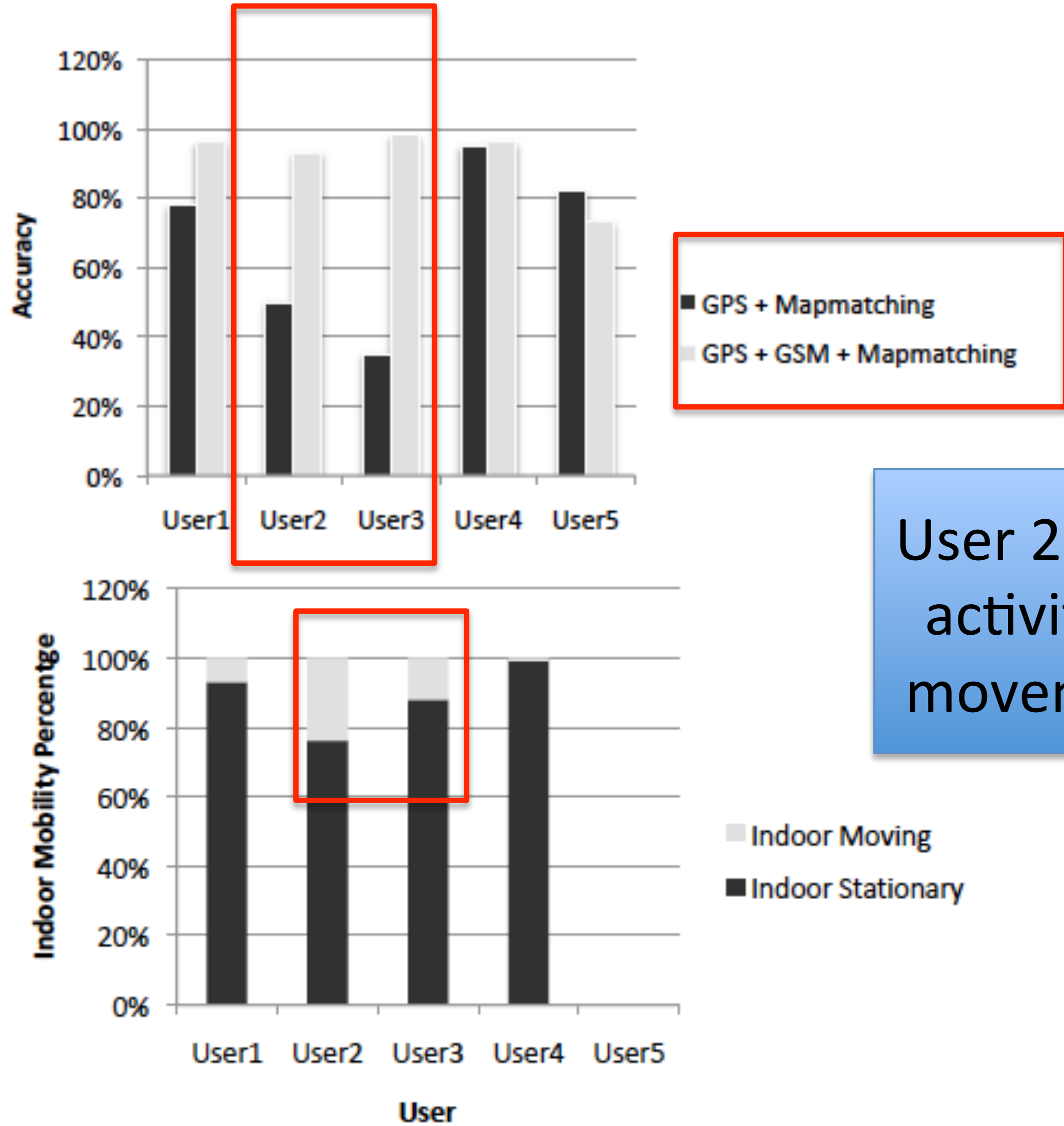
Features	Window Size(Seconds)
Total Traveling Distance	60
Average Speed Differences	120
Average Speed	180
Average Traveling Distance	240
Number of Unique Cell IDs	150,300
Number of Cell ID Changes	240
Freeway Annotation	1

Activity Classification: Problems and Improvement by Leveraging GSM Data



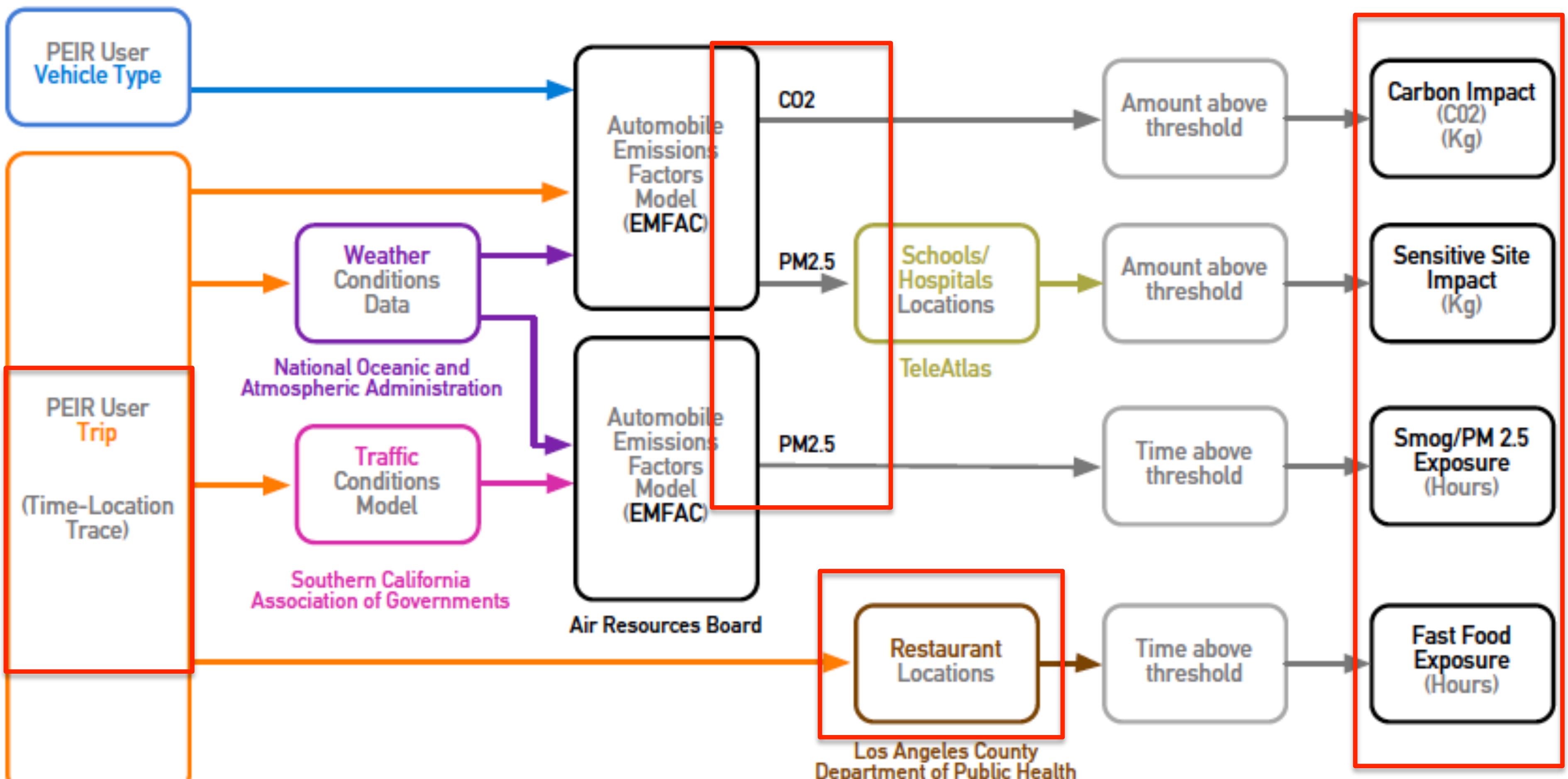
Accuracy: percentage of the number of the correctly predicted data points

Activity Classification: Problems and Improvement by Leveraging GSM Data



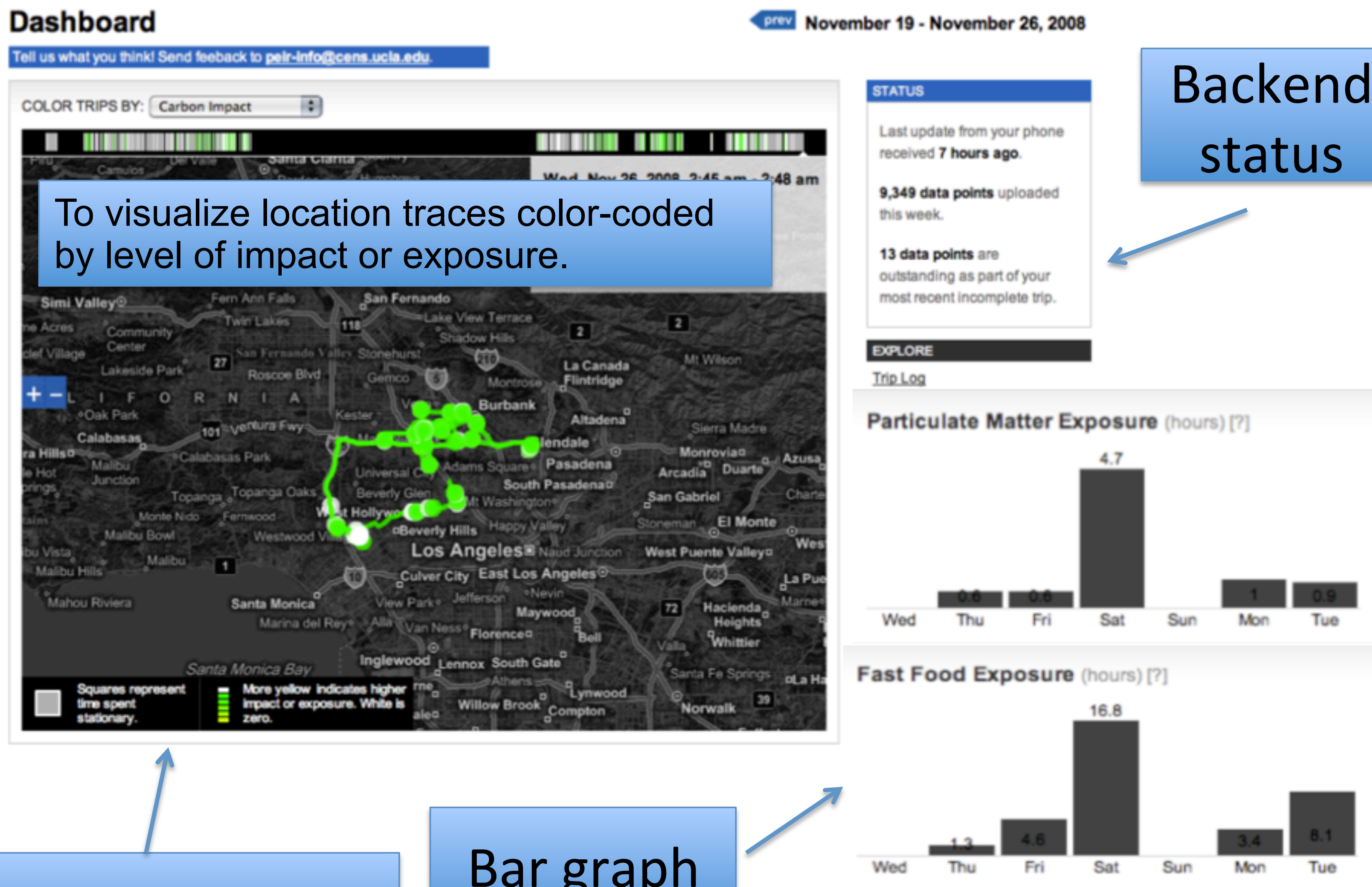
User 2 and 3: Staying-in-place activities involve a lot more movements than other users

Modeling of Impact and Exposure



Dataflow Diagram

Shall We Explore PEIR



To visualize location traces color-coded by level of impact or exposure.

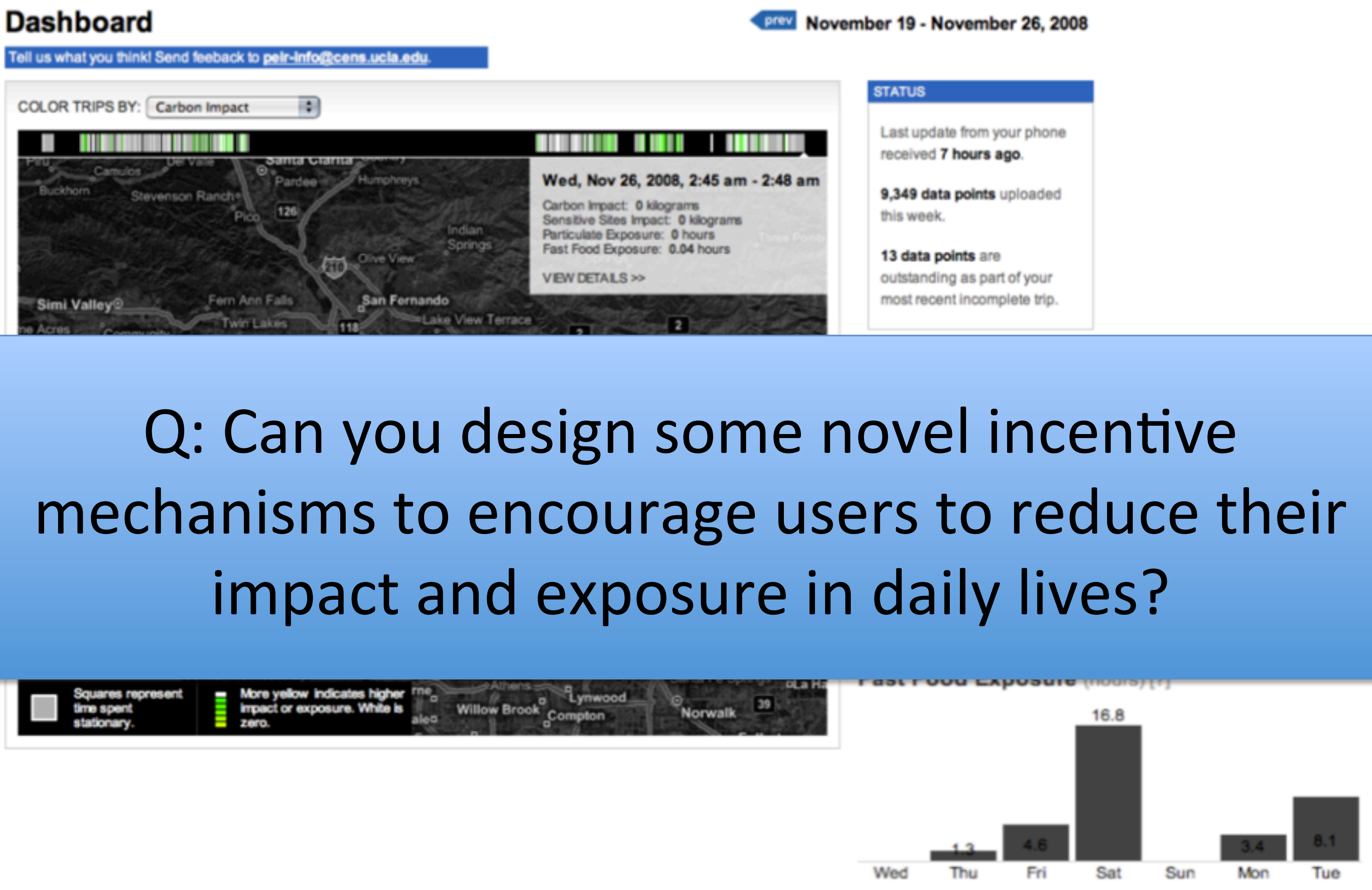
Backend status

Interactive Map

Bar graph

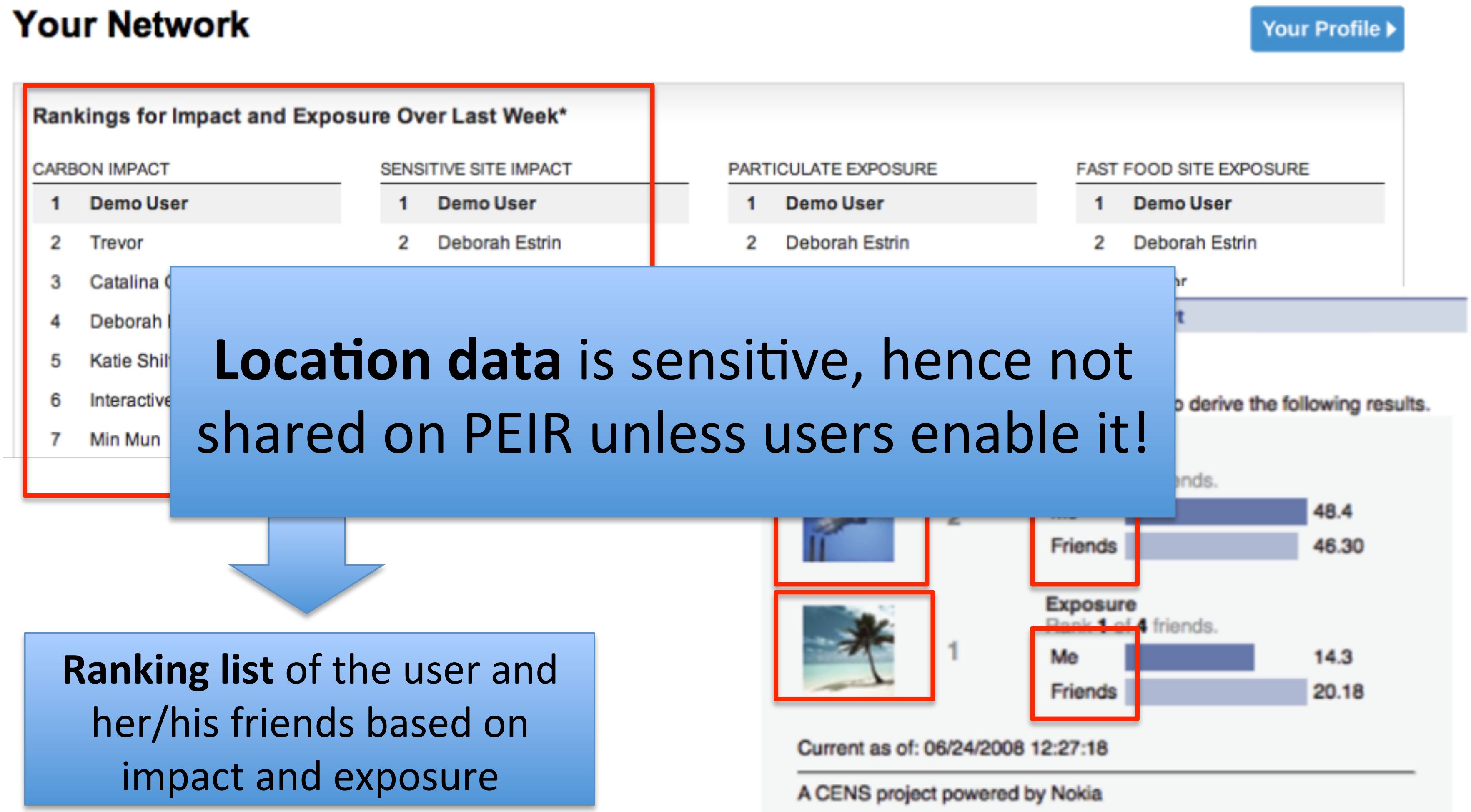
Impact and exposure in a day-by-day break down

Shall We Explore PEIR



Q: Can you design some novel incentive mechanisms to encourage users to reduce their impact and exposure in daily lives?

Share and Compare: Peer Pressure -> Incentive to Reduce Impact and Exposure



Location data is sensitive, hence not shared on PEIR unless users enable it!

Ranking list of the user and her/his friends based on impact and exposure

Facebook App: Compare the impact/exposure of the user with the average of friends

Deployment

The PEIR system has been running since June 8, 2008

As of November 28, 2008, over **four million** individual GPS points grouped into over **20,000** separate trips.

50-60 high school students have been using PEIR in the Northern California area as part of a sustainability challenges.

go green foundation

Lessons

User's feedback:

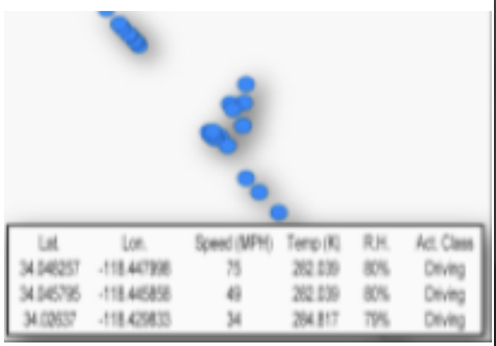
"It's hard to step away from the car. But even though it takes an extra step to walk or bike, we see it can make a difference."

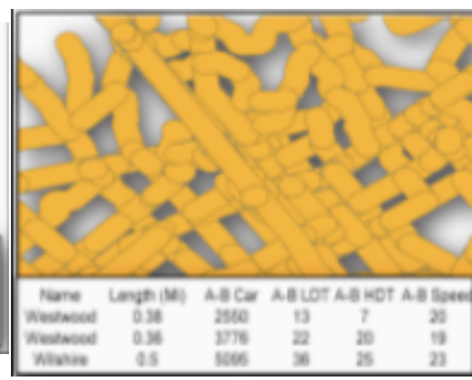
"Instead of driving, I'm biking more because I'm subconsciously connecting this phone in my pocket with how much energy I'm using,"

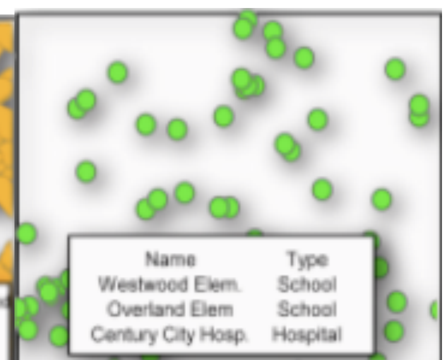
Lessons

More choices about the types of transportation

The point-based computations or annotations of location traces and GIS data are expensive.







PEIR produces all the valuable information for individuals while individuals **give up their privacy** (since they upload their **time-location trace** to the system).

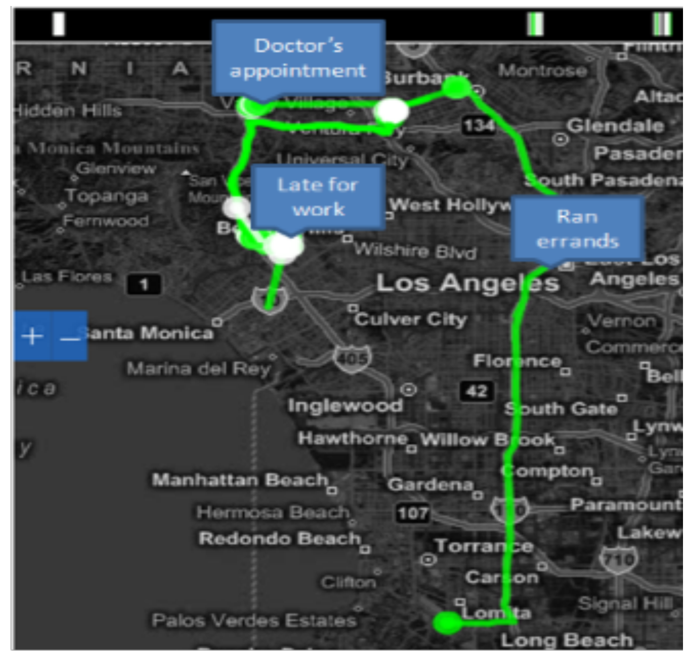
Participatory Privacy Regulation

Location traces quantify habits, routines, associations

Individual control of time/space accountability

Potential consequences:

Location-based discrimination
Safety & security threats
Inference of personal activities

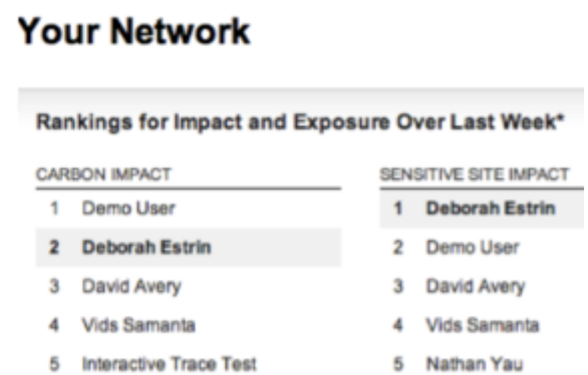


Legibility of PEIR Data and Selective Sharing

PEIR allows users to break down the trip and select **what** and **with whom** they feel comfortable to share

By default, they system will delete all location information after **six months** unless users specify otherwise.

Trip Breakdown



Selective Sharing

Selective Hiding

People want to hide a trip to a particular significant destination (e.g., hospital, a certain store, or a particular restaurant, etc.)

However**, simply removing the trip is suspicious:** the lack of data may raise attention to the space/time to be protected.

Q: What is your solution to address the above problem (i.e., hide a trip to a particular destination without introducing extra suspicion?)

Selective Hiding

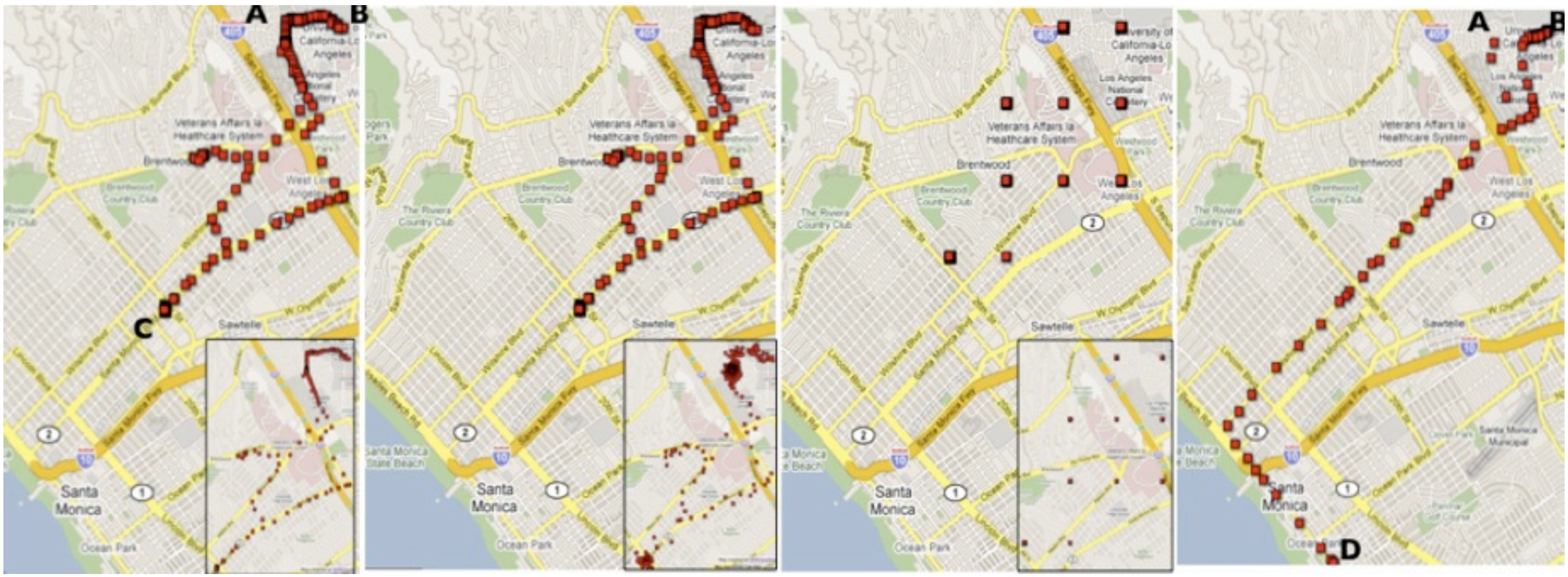
Proposed solution: **replace a particular route with a trace which satisfying the following:**

(a) Privacy enhancement:
Increase the user's sense of privacy when sharing a substituted-trace.

(b) Application output equivalency:
The substitute trace results in minimal changes to the PEIR metrics.

(c) Believability:
The substitute trace should be credible to the people with whom the user shares his/her data.

Selective Hiding: Hide Location C



The Original Trace | Adding Noise | Spatial Rounding | Selective Hiding

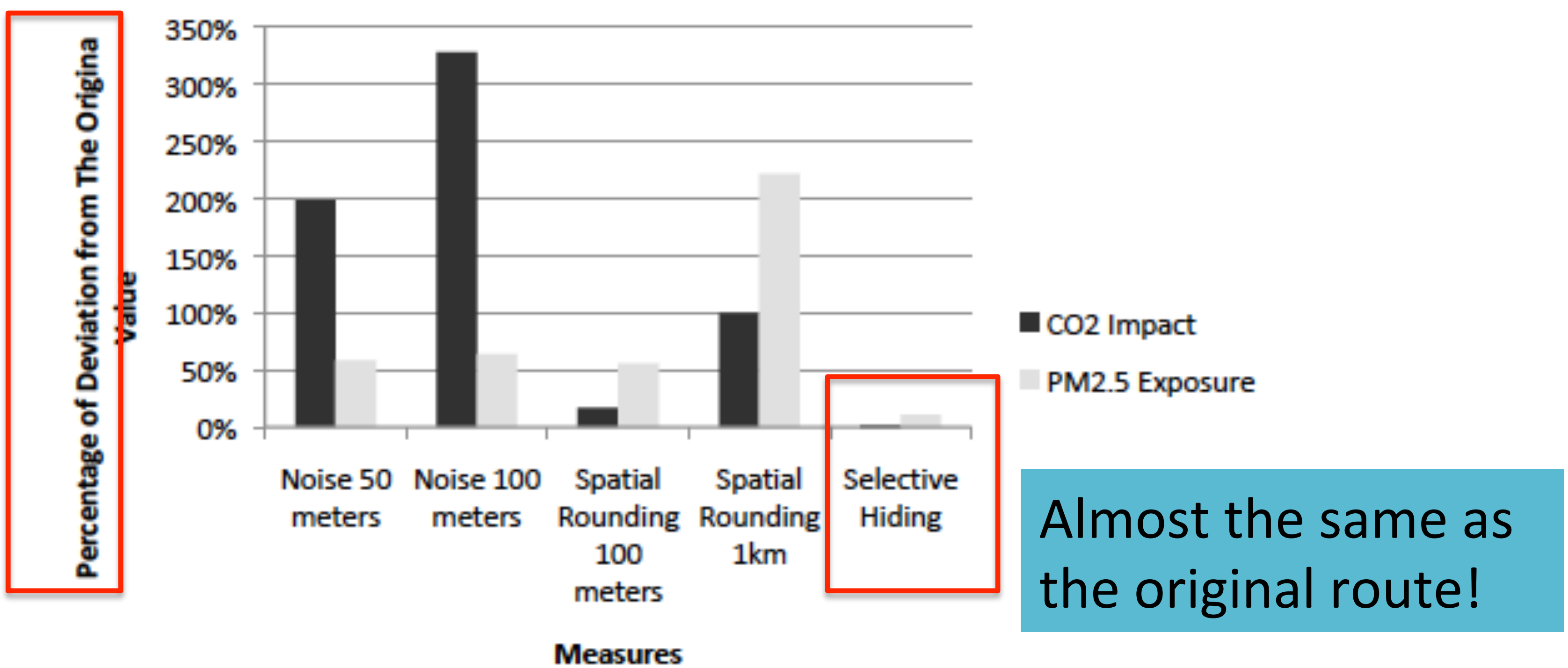
Original Route:
A->B->A->C->A

Selective Hiding:
A->B->D->A

Selective Hiding

The high degree of data corruption is required to preserve privacy using prior art counter measures

Selective hiding with substitute path segments produces **nearly the same** PEIR model output met



Conclusion and Future Directions

Exemplified an emerging class of adaptive, human in-the-loop sensing systems

Detailed PEIR’s architecture, implementation and enhancements are presented

Where do we go from here?

Focus on scalability, stability, performance and usability

Extend activity classification to accommodate other modalities such as cycling, bus, train, and subway

Enhance sustained usability of the system through the introduction of goal setting and feedback