

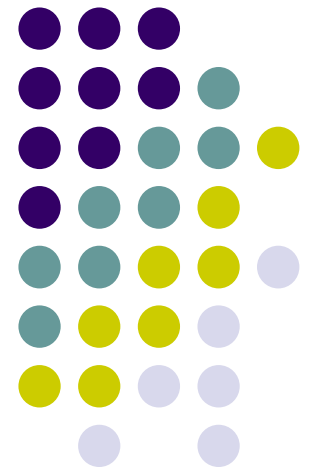
# Ubiquitous and Mobile Computing

## CS 528: *Automatically Characterizing Places with Opportunistic CrowdSensing using Smartphones*

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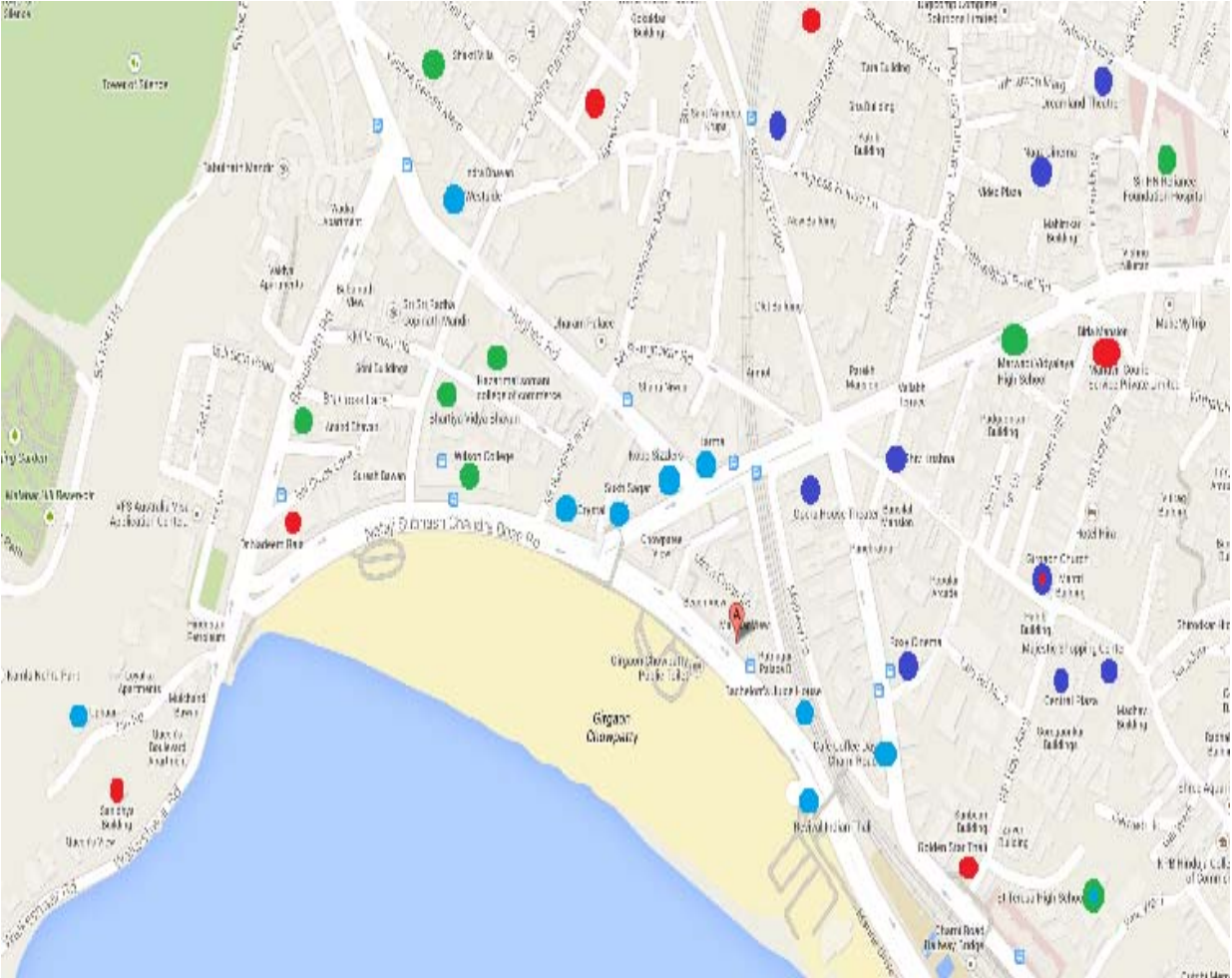
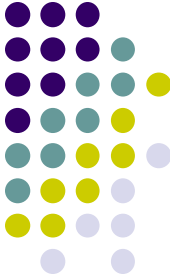


# Automatically Characterizing Places with Opportunistic CrowdSensing using Smartphones



- UbiComp'12, Pittsburgh, USA
  - Best Paper Award
- Authors:
  - Yohan Chon
  - Nicholas D. Lane
  - Fan Li
  - Hojung Cha
  - Feng Zhao

# Characterizing Places



Marine Drive,  
Mumbai, India

## Legend:

- Educational Institutions
- Restaurants
- Hospitals
- Shopping

# Design Approach



Low Level Sensor Data -  
Location

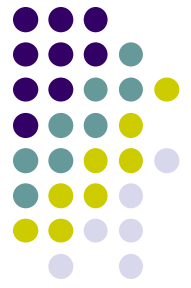


High Level  
Meaningful Data -  
Place

# CrowdSense@Place (CSP)



- Categorizes places
- Logical location meaningful to user
- Links places with
  - Place categories
    - Grocery store, restaurant, hospital, university
  - Activity
    - Shopping, eating, working



Bloomingdale, USA



Coffee Bean, India

The



# Collecting Data: How?



- Location and user trajectories using Wi-Fi/GPS
- Samples data from sensors
  - Microphone
  - Camera
- Crowdsourcing
  - Collect large volumes of data





# Collecting Data: What?

- Audio and visual place hints mined from opportunistic sensor data
  - Spoken words
    - “Can I have a Cappuccino please?”
  - Physical objects
    - Cups, shoes, clothes
  - Written texts
    - Menu, posters, hoardings





# Collecting Data: When?

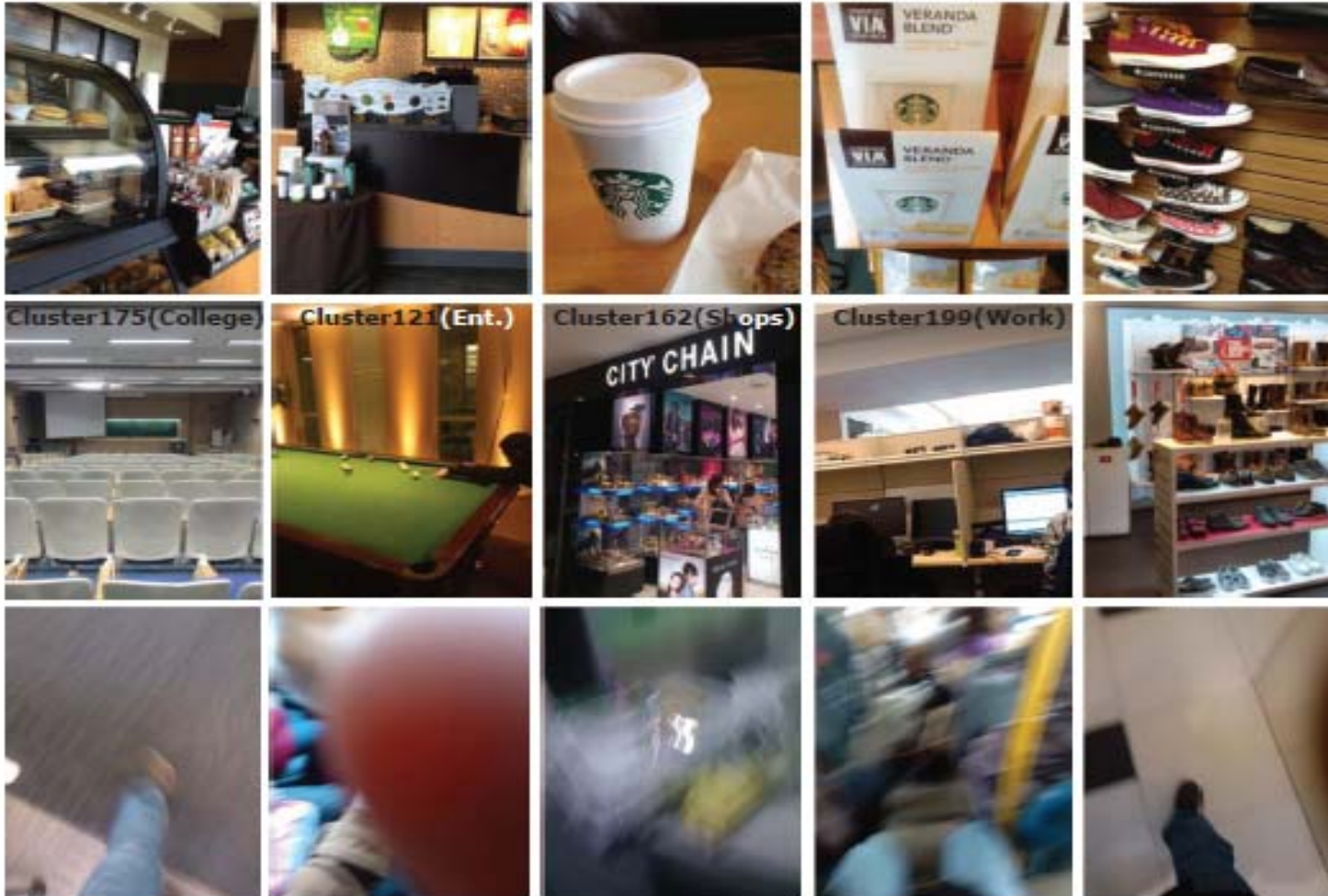


- User uses phone
  - Calls, emails, or browses
- Concern: Privacy
  - Full control of data collection
  - Buffered before transmission
  - Review collected data
  - Option to delete before upload



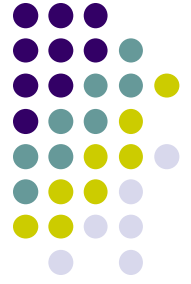


# Example of Captured Images



Hints

Noise



# Extracting Hints

- Image and audio classifiers
  - Scene classification
  - Object recognition
  - Optical character recognition
  - Speech recognition
  - Sound recognition
- Output merged with location based signals
  - Wi-Fi, GPS





# Let's Try To Pick Up Hints



- Bloomingdale's
- Outlet Store
- Mannequins
- Bag
- Skirt
- Trousers
- Jackets
- Belts

Bloomingdale, USA



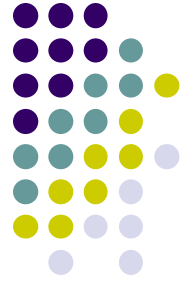
# Let's Try To Pick Up Hints



- The Coffee Bean
- Order Here
- Can I get a Latte to go please?

Coffee Bean, India

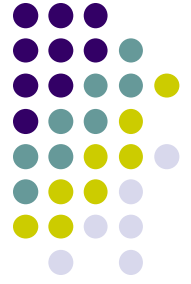
The



# Let's Try To Pick Up Hints



- Laptop
- Dell
- SSD
- Store



# CSP Working

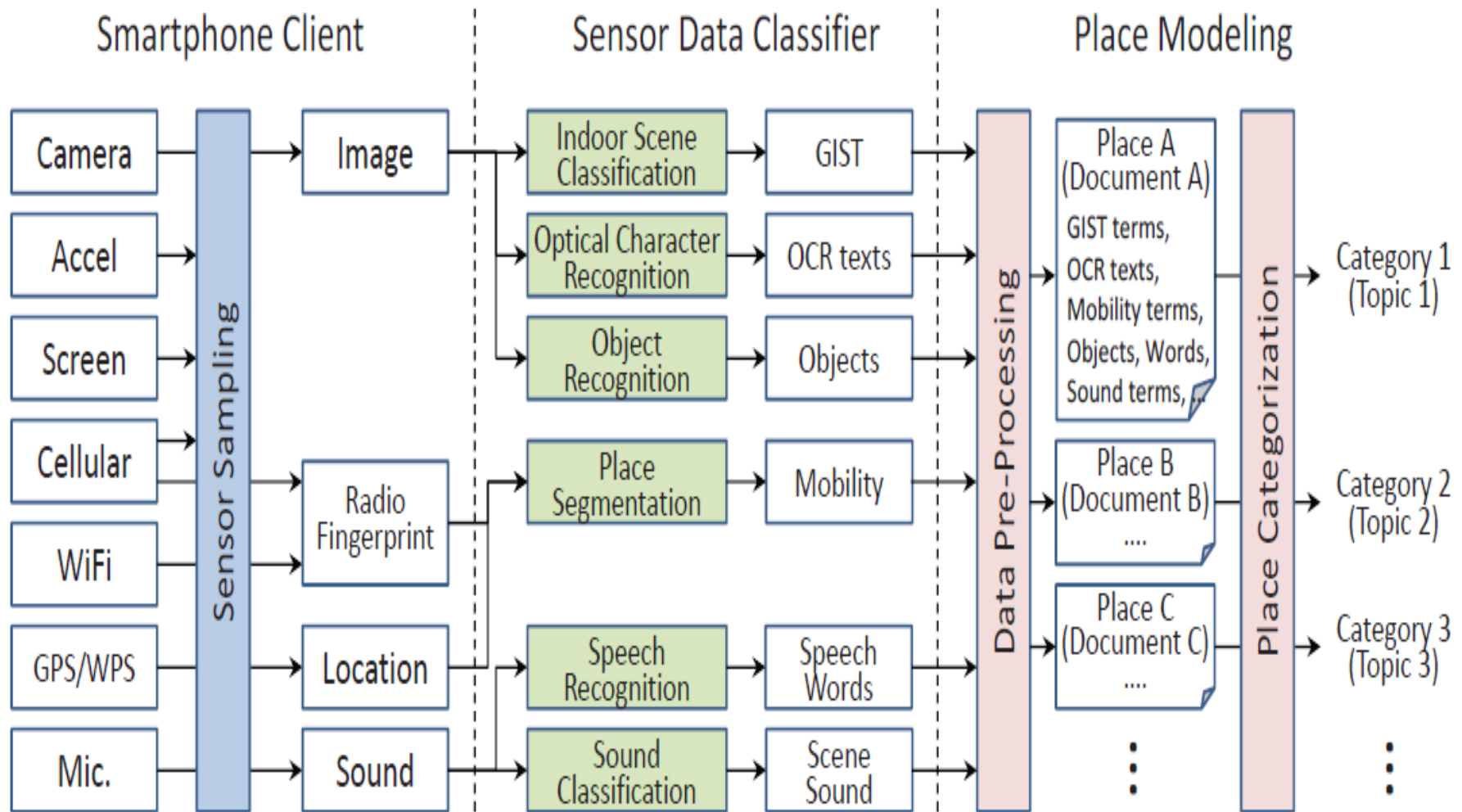
- Place as a document
- Builds the document with sensor based hints



**ID: WiFi Fingerprint**  
**Bloomingdale (0.75)**  
**mannequin (0.87)**  
**trouser (0.83)**  
**blouse (0.65)**  
**shirt (0.76)**  
**belt (0.4)**  
**bag (0.56)**  
**outlet (0.87)**  
**store (0.76)**  
**35-75% (0.23)**



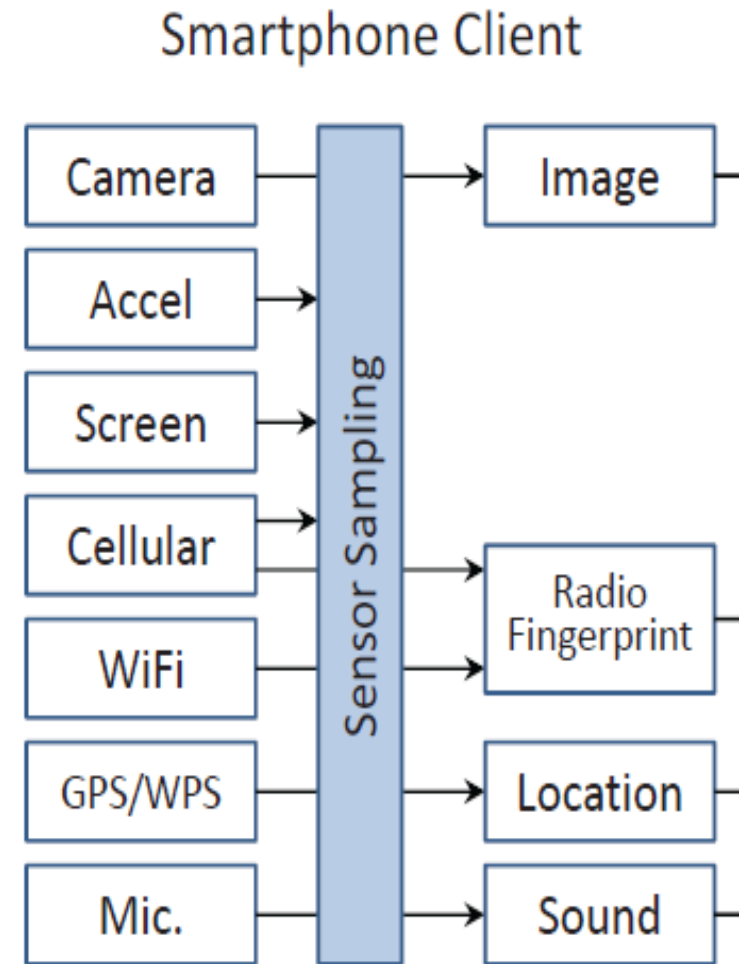
# CSP Framework



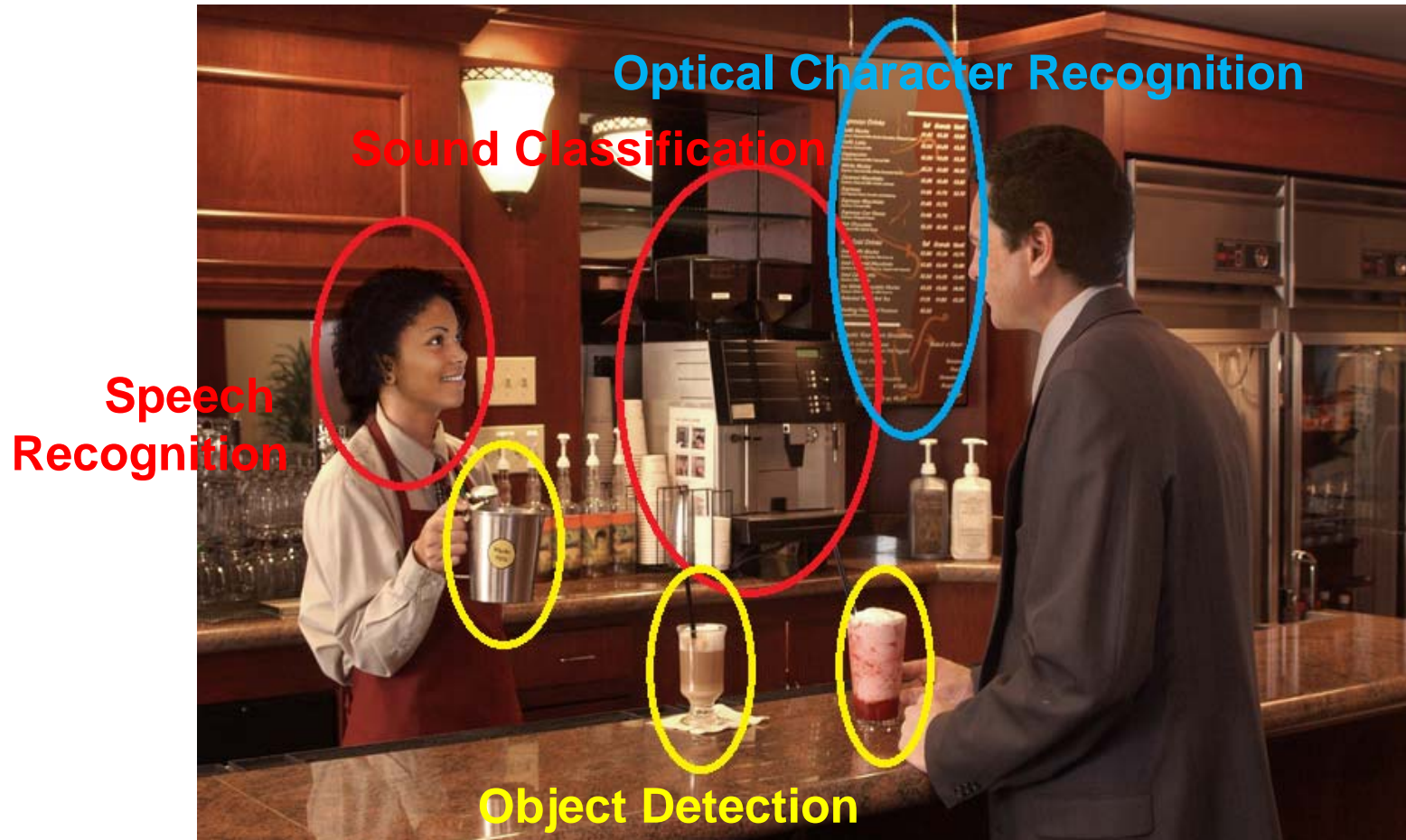


# Opportunistic Sensing of Data

- Smartphone
- Application usage
  - Phone calls, browsing
- Piggy-back on user actions
- Screen state and light sensor
- Accelerometer
  - Orientation, movement
- GPS & Wi-Fi
- Microphone
- Camera



# Sensor Data Classifier



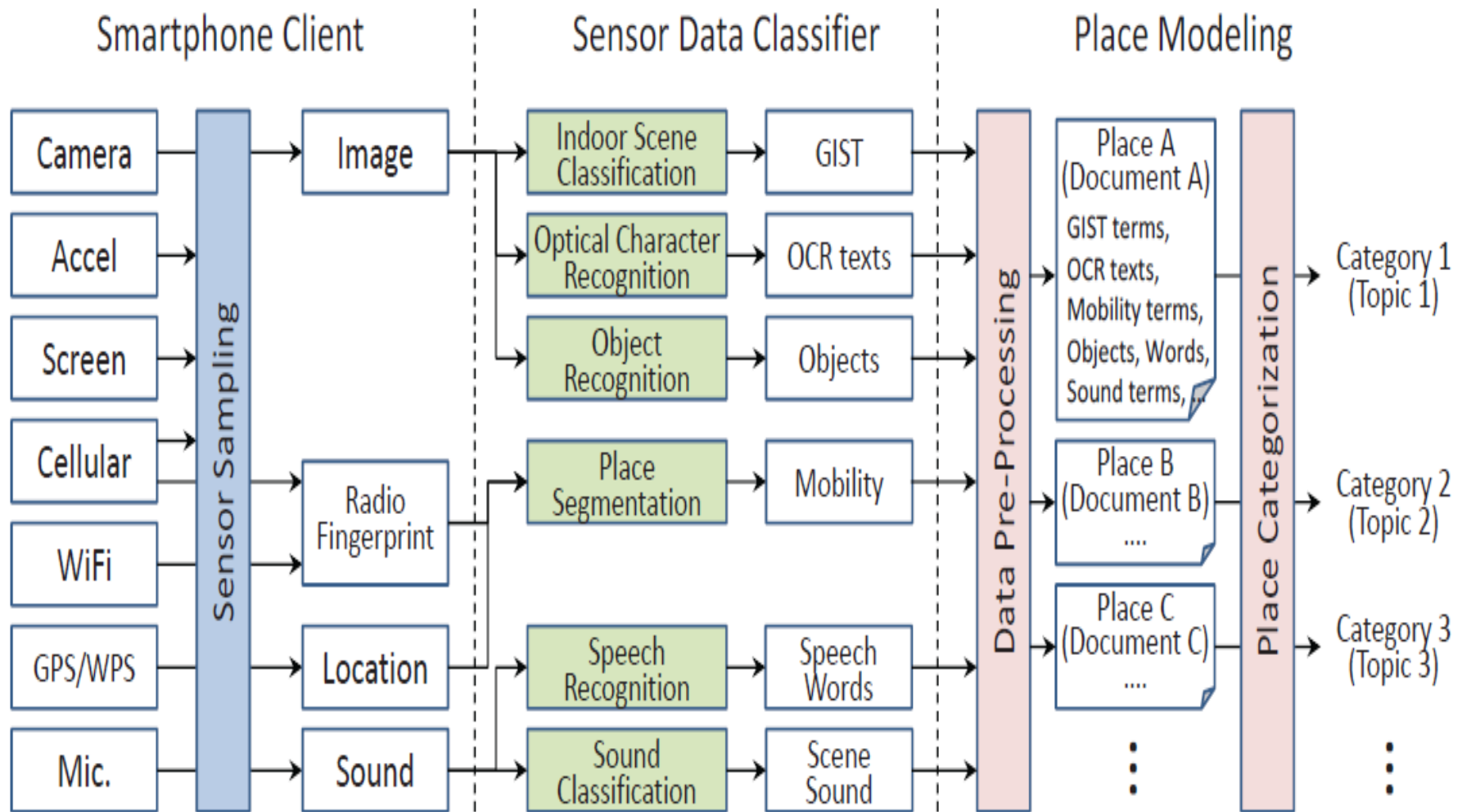


# Sensor Data Classifier

- Hints v/s Noise
  - Filter out the data
    - Phone is shaky or facing down
  - Crowdsourcing
  - Repeated visits to place



# CSP Framework





# Applications

- Location based reminders
- Content Delivery
- Activity recognition
- Understanding City-Scale Patterns
- Enhanced Local Search & Recommendations
  - Awareness of the types of places a user frequently visits leading to additional user profile attribute
- Rich CrowdSourced Point-of-Interest Category Maps
  - Maps that relate places to place categories
  - A targeted advertising app



# Limitations

## Limited Accuracy: 69%

Speech, object recognition contribute little

Future: Train the classifier using a small amount of specific place hints

## Completely opportunistic

Accumulates high quality slowly

Learns slowly over long time period

## Energy Issues

Power consuming Wi-Fi & GPS

Clicking pictures, capturing videos drains battery

## Privacy

Users have choice to upload photos

Future: Local processing & Anonymous





# Evaluations

- Statics:
  - 36 users
  - 5 locations
  - 1241 places
  - 1,300 places
  - 46,000 hours
  - 2,300 images
  - 4,200 audios
  - 22% of images are either blurred or completely black
  - Accuracy: 69%

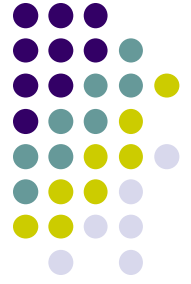
Excellent  
 Good  
 Satisfactory  
 Poor



# Evaluations



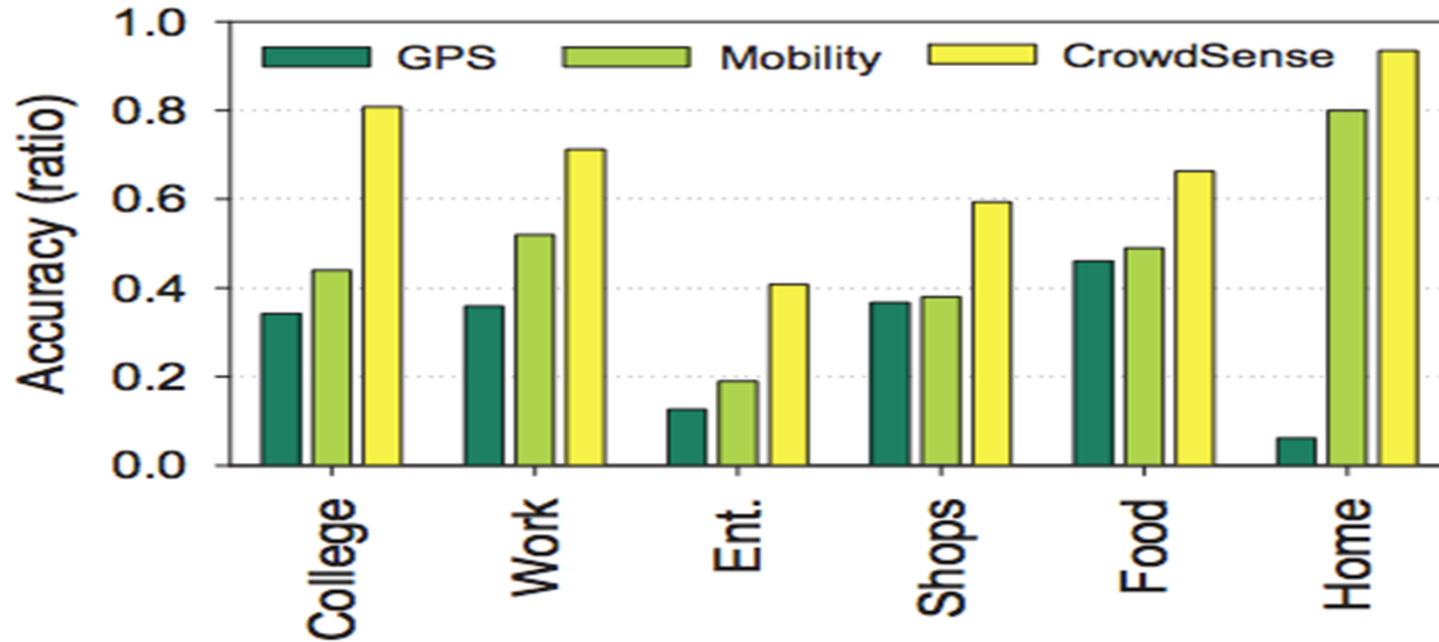
- Questions
  - How accurate?
  - Which features types are most discriminative?
  - How well do certain feature types operate in noisy environments?



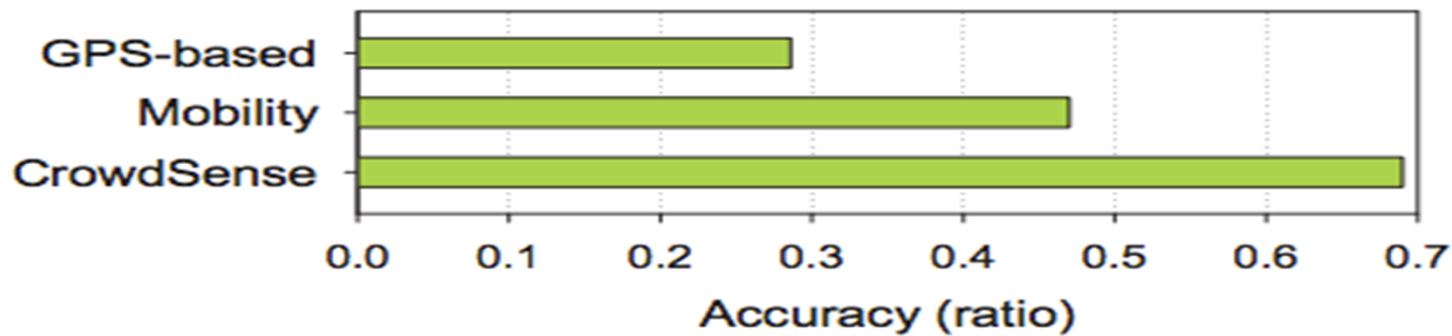
# Evaluations

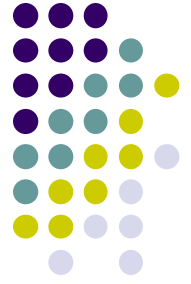
- Categories
  - College & Education, Arts & Entertainment, Food & Restaurant, Home, Shops, Workplace, Others
- Metrics
  - Accuracy of place categorization:
    - $(\text{No of correctly recognized places}) / (\text{No of places evaluated})$

# Evaluations



(a)





# Conclusion

- Efficient categorization of places
- Uses hints, like humans do
- Effective use of crowd sensing
- Accurate classifier
- Advanced applications
- Large scale evaluations
- Power consumption
- Privacy concern
- Future,
  - User participation
  - Social Networking Sites



## References

- [http://www.msr-waypoint.com/en-us/um/people/zhao/pubs/ubicomp12\\_cps.pdf](http://www.msr-waypoint.com/en-us/um/people/zhao/pubs/ubicomp12_cps.pdf)
- *D. Ashbrook and T. Starner. Using GPS to Learn Significant Locations and Predict Movement Across multiple users.*
- <http://foursquare.com>

# Questions





