

Academia Sinica, Taipei, Taiwan

SNHCC: Mobile Social Networks

Socially Aware Computing: Concepts, Technologies, and Practices

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Ubiquitous Computing

- ❑ Research topic for more than 2 decades
 - Instead of desktop/laptop computing, **ubiquitous computing is made on any device, at any location, and in any form**
- ❑ A.k.a. pervasive computing
- ❑ Integrated (distributed) systems with capabilities of
 - Sensing
 - Computations
 - Communications
- ❑ **Affecting our daily life!**
 - ❑ **Targeted advertisements**



Example: Smart Home

The screenshot displays the Samsung Smart Home app interface. At the top, the Samsung logo and 'Samsung Smart Home' text are on the left, and a settings gear icon is on the right. Below this is a status bar with 'Smart Home Welcome to Samsung Smart Home' on the left, 'Just now' in the center, and 'No Registered Device' on the right. The main content area features five device cards: 1. Refrigerator: Shows 'Freezer -18°C' and 'Fridge -2°C'. 2. Air Conditioner: Shows 'Desires 26°C' and 'Current 32°C'. 3. Washer: Shows 'Wash' with a progress bar and 'Time left 01:30'. 4. Robot Cleaner: Shows '50' and 'Cleaning'. 5. AV: Shows 'ON'. At the bottom, a 'Master Key' section contains five scene cards: 'Good Morning' (5 devices selected, sun icon), 'Good Night' (6 devices selected, moon icon), 'Going Out' (3 devices selected, house icon), 'Movie Mode' (2 devices selected, film icon), and 'User Created' (5 devices selected, person icon).

Socially Aware Computing

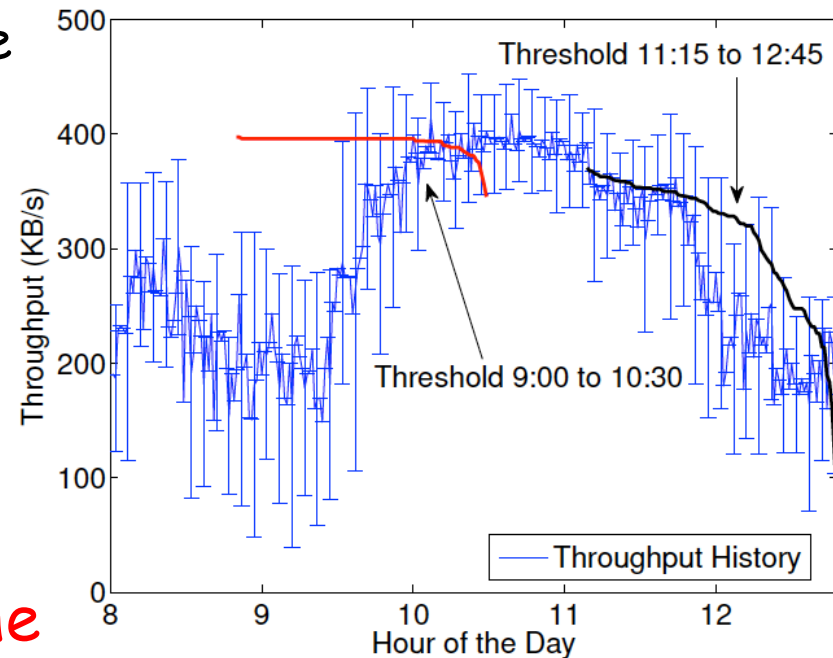
- To capture, quantify, and visualize social context to enhance **human social interaction** [Pentland 2005]
 - Tone
 - Gesture
 - posture
- Use **massive data** from the real world to understand [David Lazer et al. 2009]
 - Individuals
 - Organizations
 - Communities
 - Society

Problem with Traditional Way to Understand Humans

- ❑ Traditional way to understand the **behavior** and **interaction** of humans (in the physical world) is via self-reported questionnaires, but
 - Subjective and could be biased
 - Static, cannot reflect dynamics
 - Small scale, due to high cost
- ❑ With the introduction of the Internet and WWW, computers can be used to analyze human behavior and interaction in the **virtual world (cyberspace)**
- ❑ But the physical world analyses are still done using (online) questionnaires

Solution: Using Smartphones

- ❑ Use the smartphone sensors to sense the real world environment for sociological studies
 - No self-reported questionnaire
- ❑ **Digital footprints of users**
- ❑ This solves all 3 limitations
 - Objective outcomes
 - Spans over long time periods
 - Logs from many mobile users
- ❑ **Smartphones enable socially aware computing, which is the combination of ubiquitous computing and social networks**



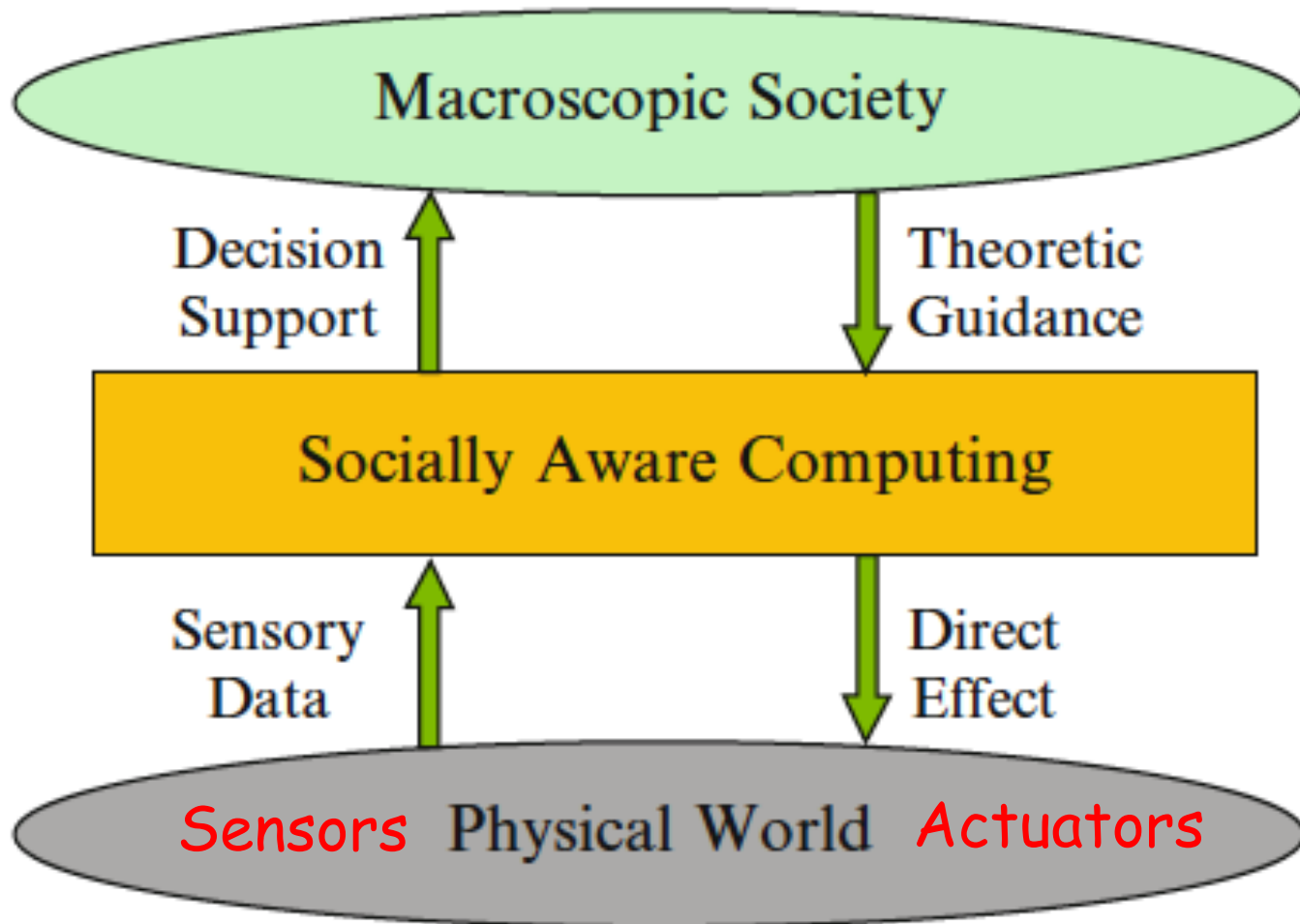
Socially Aware Computing

- Definition: Leverages large-scale, dynamic, continuous, and real-time sensory data to recognize individual behaviors, discover group interaction patterns, and support human communications and collaborations

- Sensors include
 - Ubiquitous (in-situ, infrastructure) sensors
 - Smartphone sensors
 - Internet data (emails, Web, call logs)

- Directly affect the physical world

High-Level Picture



Research Issues in Socially Aware Computing

This chapter covers the following 5 sample issues

1. Large-scale pervasive sensing
2. Activity and interaction inference
3. Social interaction support
4. Software framework and methodology
5. Applications

....Many more

Issue 1: Large-scale Pervasive Sensing

- ❑ Three sources of sensory data: **mobile sensors, social Web, and infrastructure sensors**
- ❑ Mobile sensors are attached to moving objects
 - Cars (GPS loggers and in-vehicle cameras) and human (smartphones, smart watches, and smart rings)
- ❑ Social Webs are online social networks
 - Twitter, Facebook, and others ← Web 2.0 users are considered as citizen sensors [Sheth 2009]
- ❑ Infrastructure sensors are fixed sensors
 - Surveillance cameras, environmental sensors, and positioning sensors

Issue 1: Large-scale Pervasive Sensing (cont.)

Challenge #1: Multimodal Data Processing

- ❑ Sensory data can be video, image, audio, text, and other continuous or discrete values
 - Continuous (analog) or discrete (digital) in various domains
- ❑ Different sensors achieve different **accuracy levels** and consume different **energy amount**
- ❑ How to extract the main **features** from the sensory data from each sensor?
- ❑ There may be some correlation among contexts
 - I am home => I'm not driving

Issue 1: Large-scale Pervasive Sensing (cont.)

Challenge #2: Semantic Representation

- ❑ The features (and maybe raw data) need to be represented in a unified way

Challenge #3: Large-Scale Sensing Data Fusion

- ❑ To infer different contexts, different sets of sensors can be used ← but for different accuracy/energy tradeoff

Challenge #4: Large-Scale Sensing Data Storage

- ❑ How to store, add, lookup multimodal data

Issue 2: Activity and Interaction Analysis

- ❑ Using sensory data, it is possible to recognize
 - Individual activity
 - Group interaction

- ❑ To infer individual activity, there are two approaches
 - Monitoring the human body using the sensors on the body
← such as walking, running, and exercising
 - Monitor how a human interacts with objects (sensors or tags are on objects) ← such as phoning, cooking, and washing hands

Issue 2: Activity and Interaction Analysis (cont.)

- The performance of individual activity depends on the learning model
 - Supervised learning ← classification problems ← static or temporal classifiers
 - Unsupervised learning ← clustering problems

- Analyzing individual activities is still hard
 - Multi-goal activities? ← I'm reading and eating at the same time
 - Multiple user perform a cooperative activity
 - Detecting abnormal activities ← unbalanced data problem
← we have little historical data on abnormal activities

Issue 2: Activity and Interaction Analysis (cont.)

- Various types of group interaction analysis
 - Group relationship reasoning ← e.g., friendship based on proximity (Bluetooth scans)
 - Interaction pattern discovery ← e.g., human interaction patterns on head gestures, attention, speech tone, and speak time
 - Community structure detection ← e.g., analyzing call records to implicitly build social networks
 - Evolution analysis ← e.g., dynamics of co-authorship

Many other possibilities given the tremendous amount of data from sensors!

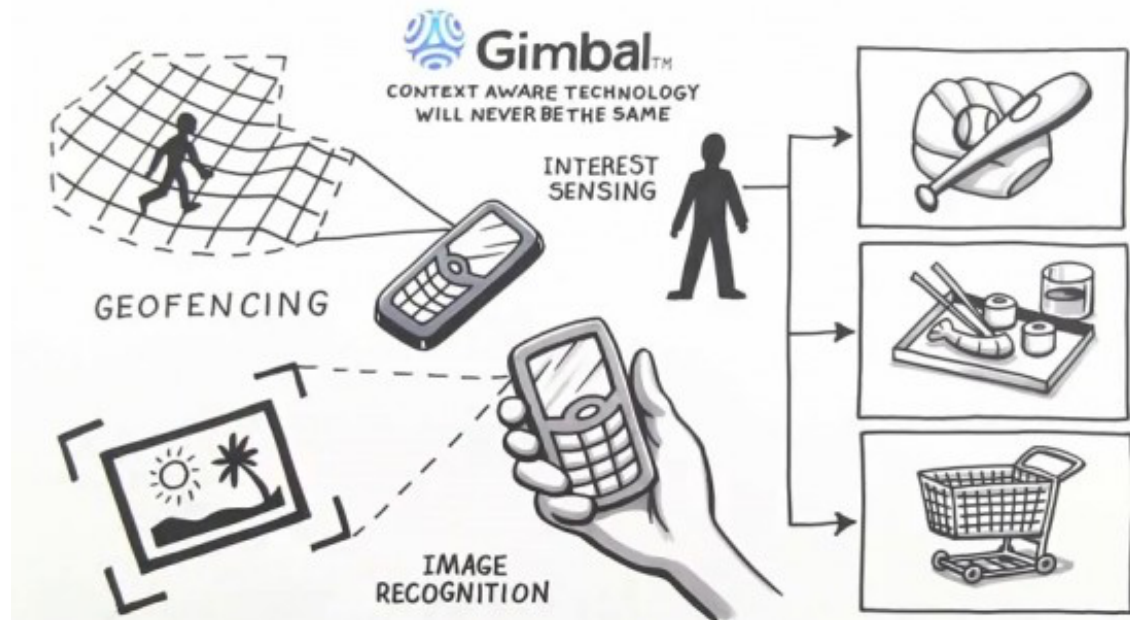
Issue 3: Social Interaction Support

- How analysis results affect how human beings interact with system?
 - Personalized recommendation ← e.g., sync up two users' smartphone contacts if they share at least one friend
 - Social status visualization ← e.g., help the meeting organizer to understand whether all participants reach a consensus
 - Group collaboration ← e.g., show the co-authorship on a big display at a conference to introduce participants to each other
 - Smart decision-making ← e.g., targeted advertisements, the Macdonald example

Issue 4: Software Framework and Methodology

- ❑ Several projects aim to develop a framework for socially aware computing
 - WearCom is a framework proposed for wearable devices [Kortuem and Segall 2003] ← much earlier than wearable devices become hot recently
 - Sharing real-time context information among users in the same group [Raento and Oulasvirta 2008] ← several design decisions are presented

- ❑ **There is a huge room for framework development**

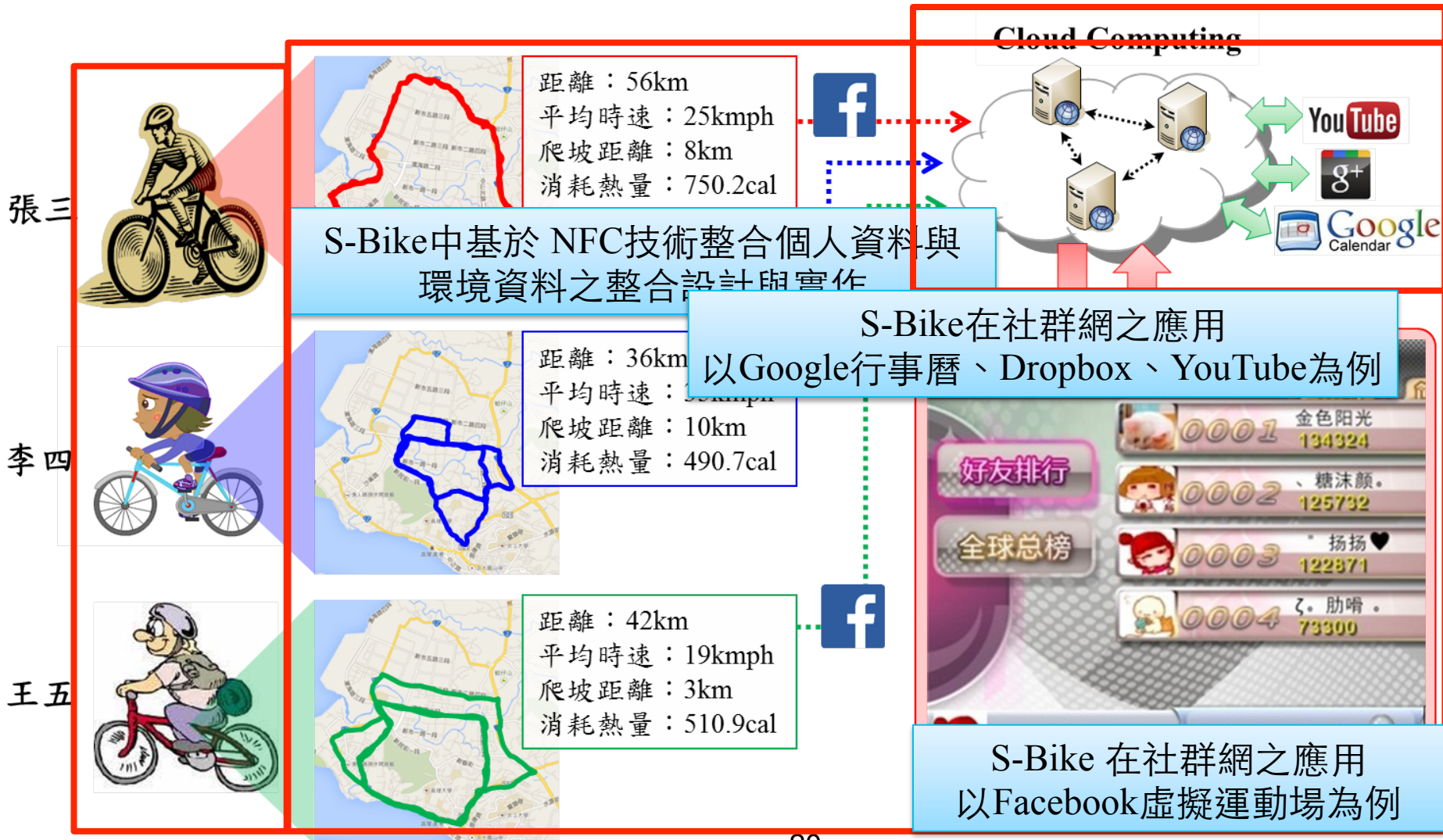


Issue 5: Applications

- Different socially aware computing applications have been proposed
 - **Public health** ← based on friendship relation, give people shots to control the outbreak
 - **Public safety** ← detecting the disasters, say warning system for earthquakes
 - **Urban planning (computing)** ← put sensors on public bikes, so that bikers can use their smartphone to find the shortest routes based on the road conditions and congestion levels

Issue 5: Applications (cont.)

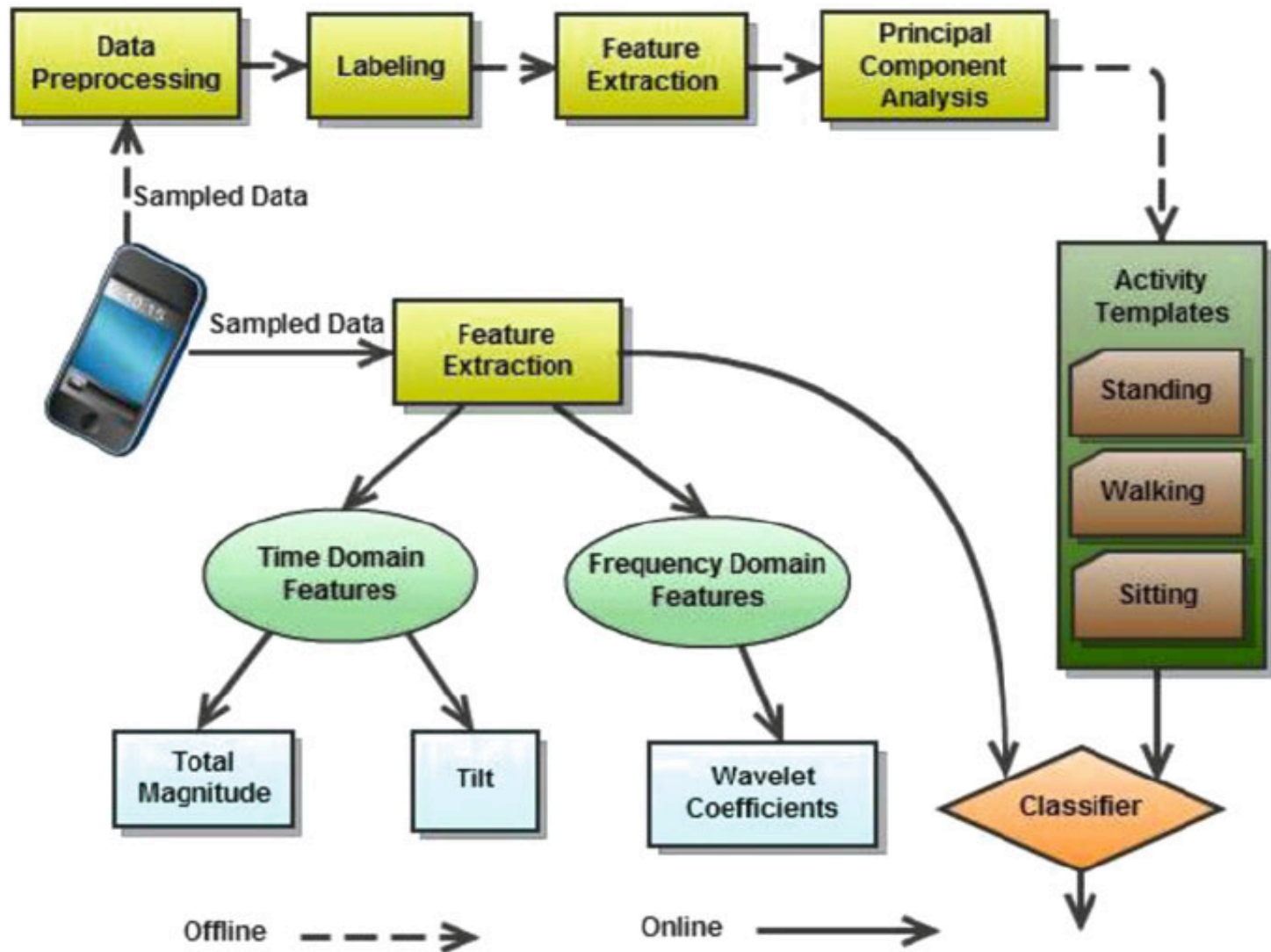
Virtual biking tournaments: An ongoing project at NTHU



Case Study #1: Activity Recognition

- ❑ Detecting activities using 3-axis accelerometers on smartphones
- ❑ Two types of activities
 - Static activities: such as standing, sitting, and driving
 - Repetitive activities: such as walking, running, cycling, and jumping
- ❑ Divided into two steps
 - Offline data training → activity templates
 - Online classification → feature extraction and classifier

Case Study #1: Activity Recognition (cont.)



Case Study #1: Activity Recognition (cont.)

□ Two takeaways

- Good overall recognition rate
- Static activities only need time-domain feature ← lightweight

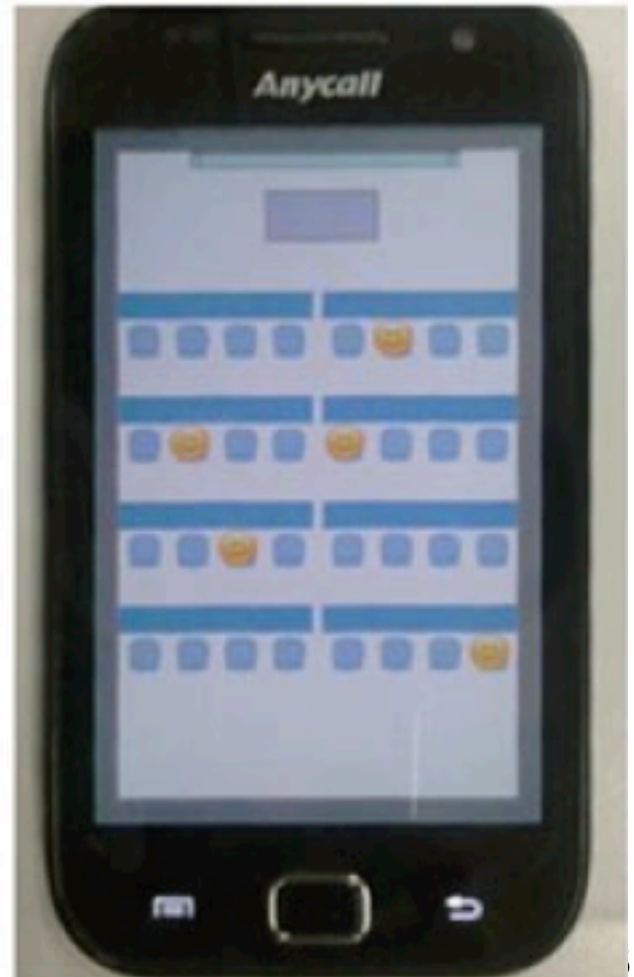
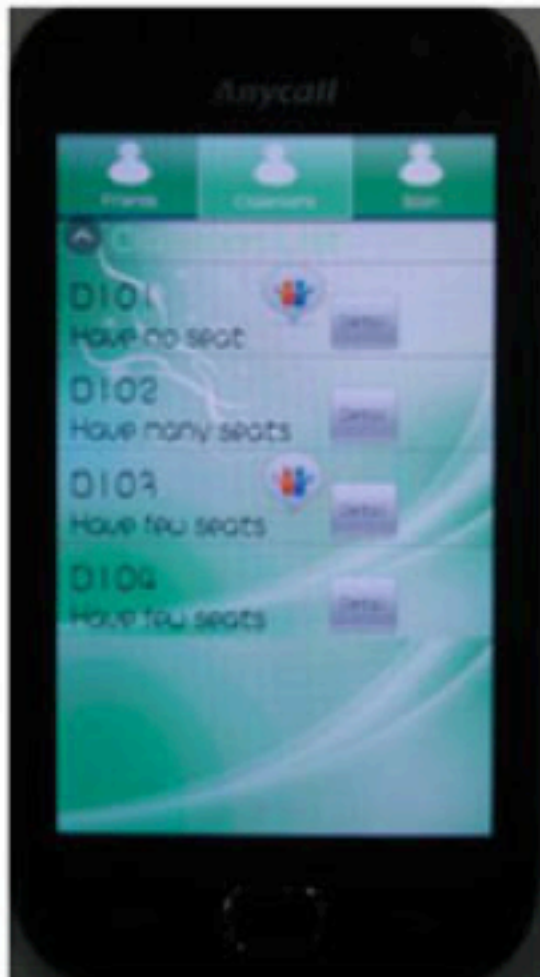
Activity	Percentage of records correctly recognized		
	Time-domain features (%)	Frequency-domain features (%)	Recognition rate (%)
Standing	98.98	1.02	98
Sitting	100	0	100
Lying (prone)	100	0	100
Lying (supine)	99.28	0.72	100
Driving	37.69	62.31	80
Walking	0	100	80
Running	56.76	43.24	86
Ascending	0	100	88
Descending	0	100	82
Cycling	97.50	2.50	84
Jumping	0	100	82
Average	53.66	46.34	89.1

Case Study #2: Enhancing Social Interaction

- ❑ A complete platform to enhance campus life, answering questions like:
 - Is the study lounge available?
 - What classrooms are my friends in?
 - Is the tennis court crowded?
- ❑ Three apps:
 - Where2study ← find the room and location to study
 - I-sensing ← campus information-sharing system, asking others to sense for us ← we have a similar project called SAIS ← Will present later
 - BlueShare ← share multimedia content (videos) over short range Bluetooth ← we have a similar project called CCDN ← will present later

Case Study #2: Enhancing Social Interaction (cont.)

- ❑ Wheretostudy ← how to get the vacant seat???



Case Study #3: Mining Mobile Phone Data

- ❑ Dataset: from MIT Reality Mining project [Eagle et al. 2009]
- ❑ Features: **proximity, calls, and messages**
- ❑ First, use SVM to predict friendship
- ❑ Second, analyze the social relation evolution

- ❑ Not too much details, there might be some more recent details ← may present them in the class

Conclusion

- ❑ We define the present socially aware computing
- ❑ The research are **sensing-based, data-driven, and field-study-based**
- ❑ Many potential (cool) problems to solve
- ❑ Many open questions will be answered throughout this semester
- ❑ I will present two projects done at NTHU if time permits

Questions?



Contact me at chsu@cs.nthu.edu.tw anytime

SAIS: Smartphone
Augmented Infrastructure
Sensing for Public Safety
and Sustainability [EMASC'14]

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Aiman Erbad², Cheng-Hsin Hsu¹, and Nalini
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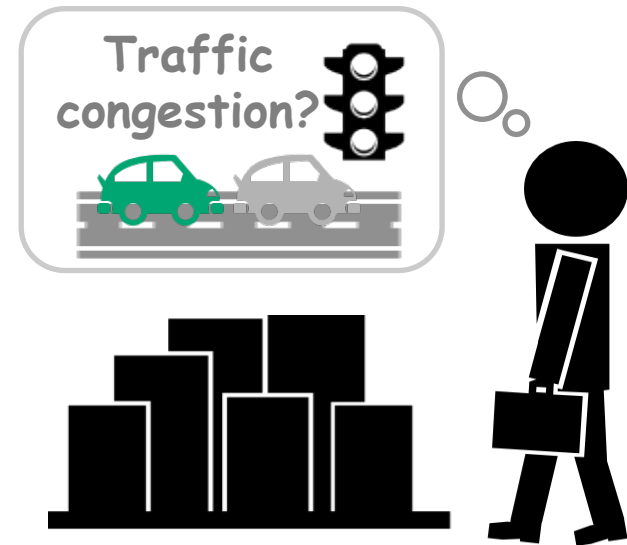
³Department of Computer Science, University of California Irvine, USA

Outline

- ❑ Overview
- ❑ Motivations
- ❑ Crowdsourcing System
- ❑ Task Assignment Problem
- ❑ Optimization Algorithm
- ❑ Efficient Task Assignment Algorithm
- ❑ Simulation Results
- ❑ Conclusion
- ❑ Future Work

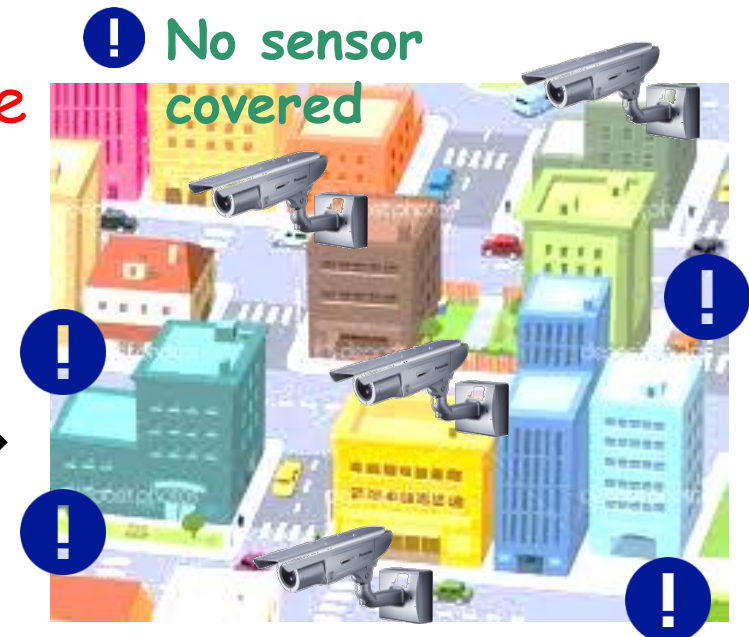
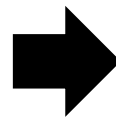
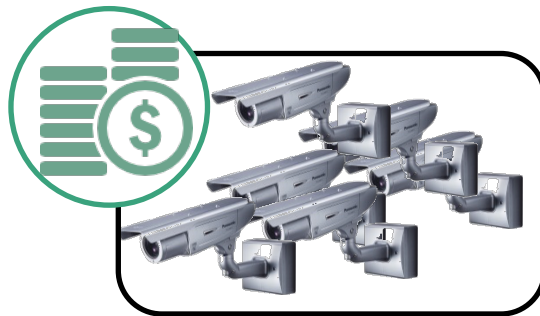
Sensing in Smart City

- ❑ Sensing platforms improve situation awareness by allowing individuals to query the environment for interested events
- ❑ For instance, we may want to know whether traffic jam occurs on the way we are going to take when we are in a hurry or whether shops are crowded



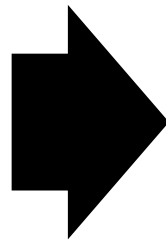
Infrastructure Sensing

- ❑ Infrastructure sensing helps for providing city information
- ❑ **But**, deploying, managing, and maintaining in-situ sensors is actually an expensive, labor intensive, and error-prone process
- ❑ We may suffer from incomplete or inaccurate sensory data due to limited resources
- ❑ **Our solution is to leverage the power of crowds**



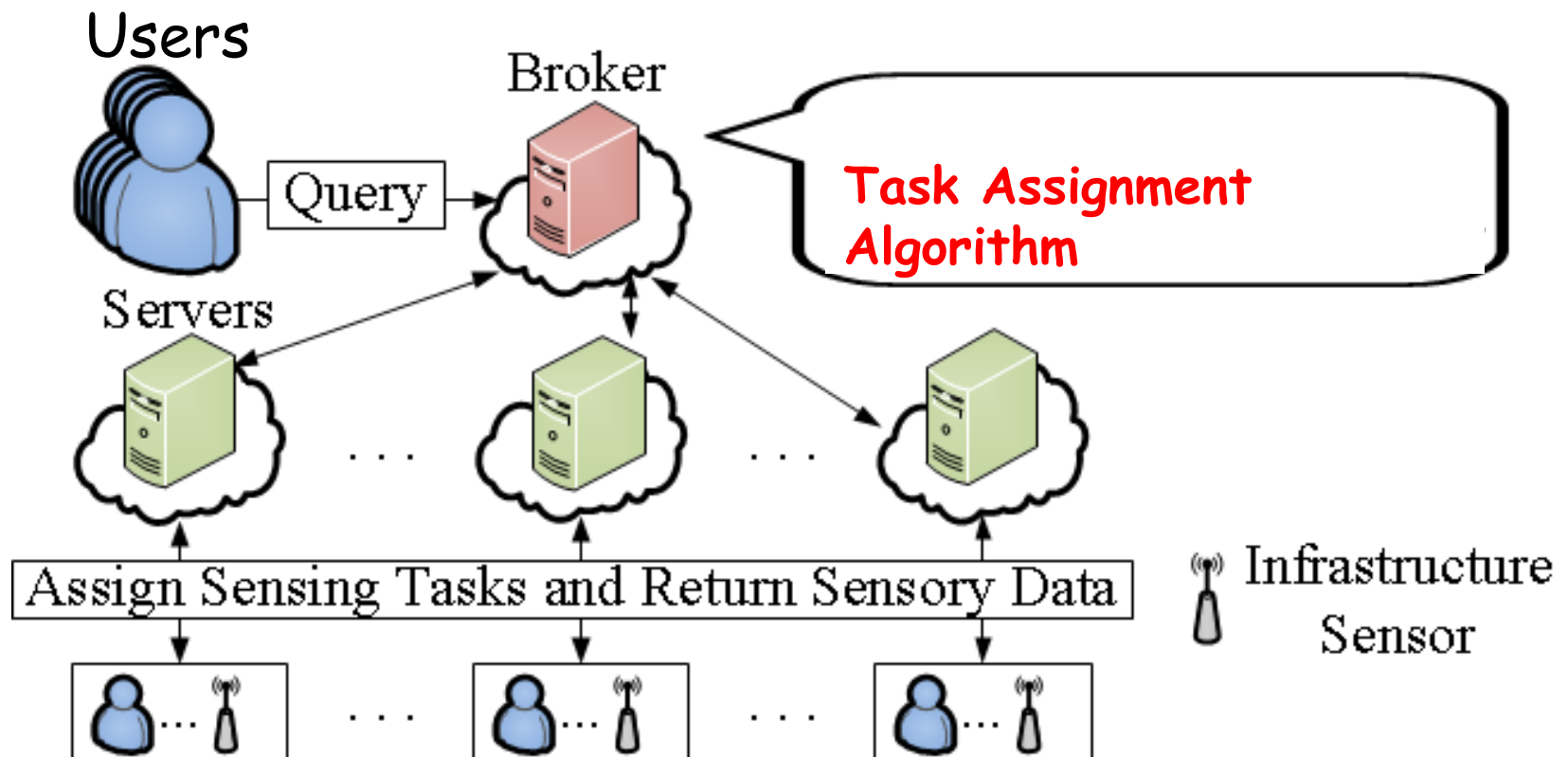
Smartphone-Augmented Sensing

- ❑ Smartphones are equipped with various kinds of sensors, such as GPS, gyroscopes, microphones, cameras, and etc.
- ❑ Using smartphones to augment infrastructure sensing by incorporating **crowdsensing for cost reduction**



Our Proposed SAIS Platform

- We develop a platform called Smartphone Augmented Infrastructure Sensing (SAIS)
- SAIS consists of *brokers, servers, and users*



How SAIS Works?

- ❑ **Users** submit queries to the **broker** for interested events, such as degree of crowdedness at a location
- ❑ Both smartphone users and in-situ sensors are workers that perform sensing tasks for each query
- ❑ The **broker** runs a **task assignment algorithm** that jointly determines: (i) the **assignment** of sensing tasks and (ii) the **dispatch** of smartphone users
- ❑ **Severs** collect sensory data, derive (compute) answers and return the answers to **users**

Prototype System Implementation

- ❑ We have implemented the proposed SAIS system on Linux (server) and Android (client)
- ❑ GUIs for: (a) submitting queries, (b) choosing a sensing task, and (c) performing the sensing task.



Fig (a)



Fig (b)

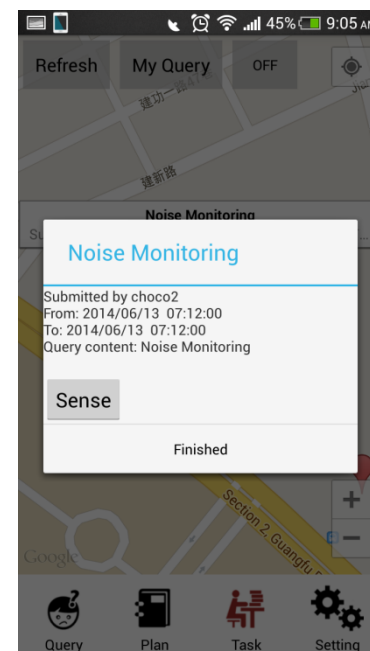
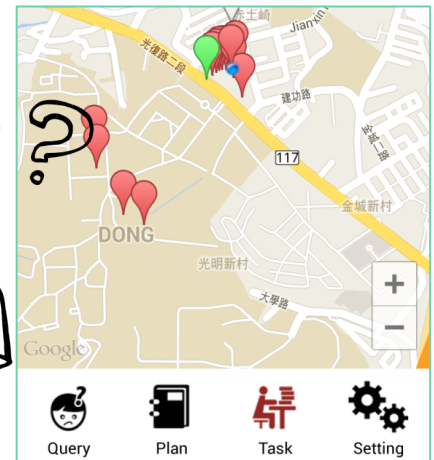


Fig (c)

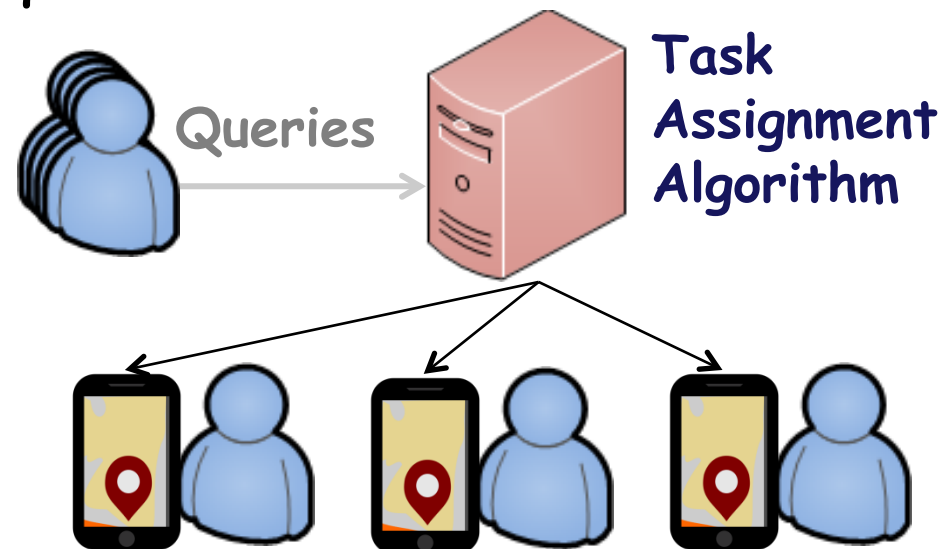
User Study

- ❑ 7 students for a 7-day experiment
- ❑ Most users thought the system helps their daily lives
- ❑ **However**, there are many sensing tasks submitted by users and all shown on the map
 - Users feel **confused** on which sensing tasks to choose and just randomly pick any of them
 - Tasks may be either performed too many times or left unanswered
- ❑ **Inefficient use of resources of crowds**



Task Assignment Problem

- ❑ An efficient task assignment algorithm is **needed** for our system that takes responsibility for the best leverage of resources from smartphone users
- ❑ The goal is to achieve sustainability of the system through energy-efficient design while satisfying requirements of each query



Problem Formulation

- We formulate the problem to minimize the overall energy consumption including both sensing and worker movement energy cost
- Our objective function

$$\min \left\{ \alpha \sum_{w \in W} \sum_{l \in L} \sum_{s \in S} e_{w,s} x_{w,l,s} + \beta \sum_{w \in W^*} \sum_{l \in L} \sum_{l' \in L} d_{l,l'} E_{l,l'}^w \right\}$$

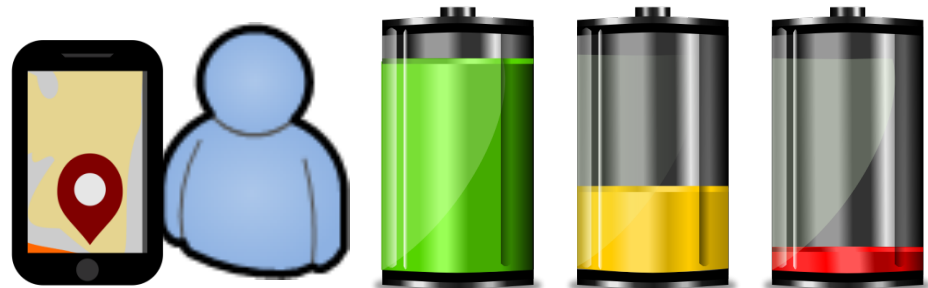
- Decision variables are defined to determine the assignment of sensing tasks to workers and the traveling routes of workers

Constraints

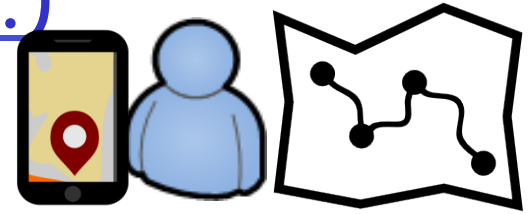
- Eq. (2): Query required accuracy levels are satisfied
- Eq. (3): Energy budget of each worker is not violated

$$Q_{r,s}(W'_{s,r_p}) \leq f_s, \forall r \in \mathbf{R}, \forall s \in \mathbf{r}_c; \quad (2)$$

$$F_w - \sum_{l \in \mathbf{L}} \sum_{s \in \mathbf{S}} e_{w,s} x_{w,l,s} \geq \theta_w, \forall w \in \mathbf{W}^*; \quad (3)$$



Constraints (cont.)



- Computing the paths for workers to travel along the query locations

$$\sum_{j \in \mathbf{L}} E_{j, A_w}^w = 0, \forall w \in \mathbf{W}^*; \quad (4)$$

$$\sum_{j \in \mathbf{L}} E_{A_w, j}^w = \left\lceil \frac{\sum_{j \in \mathbf{L} - A_w} \sum_{s \in \mathbf{S}} x_{w, j, s}}{|\mathbf{L}| |\mathbf{S}| + 1} \right\rceil, \forall w \in \mathbf{W}^*; \quad (5)$$

$$\sum_{j \in \mathbf{L}, j \neq i} E_{j, i}^w = \left\lceil \frac{\sum_{s \in \mathbf{S}} x_{w, i, s}}{|\mathbf{S}| + 1} \right\rceil, \forall i \in \mathbf{L} - A_w, \forall w \in \mathbf{W}^*; \quad (6)$$

$$\sum_{j \in \mathbf{L}, j \neq i} E_{i, j}^w \leq \left\lceil \frac{\sum_{s \in \mathbf{S}} x_{w, i, s}}{|\mathbf{S}| + 1} \right\rceil, \forall i \in \mathbf{L} - A_w, \forall w \in \mathbf{W}^*. \quad (7)$$

Optimization Algorithm

- ❑ The problem can be solved by generic optimization solvers, such as CPLEX and GLPK
 - We develop an optimal algorithm using CPLEX
- ❑ **However**, it leads to long running time even for small scale problems
- ❑ It may be **less practical** to employ the optimal algorithm in real deployment

Efficient Task Assignment Algorithm (ETA)

- We develop a greedy algorithm
- $T_{w,l}$ denotes the number of sensing tasks can be performed by worker w at location l
- $Y_{w,l}$ denotes the corresponding energy consumption
- The ratio between them is the utility!

$$T_{w,l} = \sum_{r \in \mathbf{R}} \sum_{s \in \mathbf{r}_c} z_{w,l,s} G_{s,l,r_p}^w w_{r,s}, \forall w \in \mathbf{W}, l \in \mathbf{L}. \quad (8)$$

$$Y_{w,l} = \alpha \sum_{s \in \mathbf{S}} e_{w,s} \left[\frac{\sum_{r \in \mathbf{R}} n_{r,s} z_{w,l,s} G_{s,l,r_p}^w w_{r,s}}{|\mathbf{R}|} \right] + \beta d_{A_w,l}, \forall w \in \mathbf{W}, l \in \mathbf{L}. \quad (9)$$

Simulation Setup

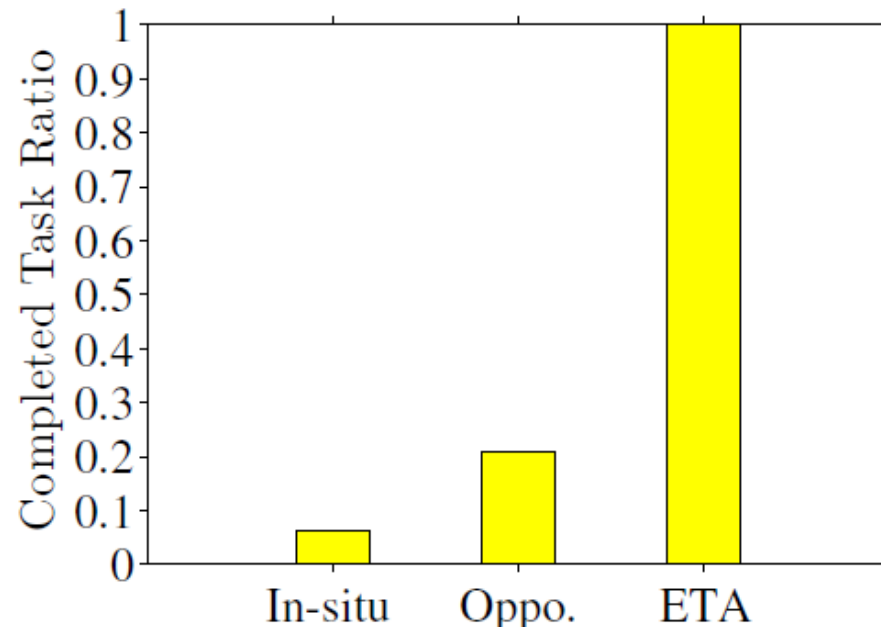
- ❑ We implement our and **3** baseline algorithms
 - Only *in-situ sensors* to provide sensory data
 - In-situ sensors with opportunistic sensing, where smartphone movement follows the random way point model
 - Optimal algorithm
- ❑ We use **trace data** collected from a popular Bulletin Board System (BBS) in Taiwan, PTT, to derive:
 - Poster locations (IPs)
 - Asked queries (keywords)
- ❑ In particular, 5700 posts in 10 days are collected and used to drive our simulator

Performance Metrics

- ❑ Several simulations are conducted to study the following performances
 - Completed task ratio
 - Energy consumption
 - Responding time, referred as the time difference between the broker receives the query and the query is answered
- ❑ Each simulation is repeated 5 times with mean, minimum, maximum results reported

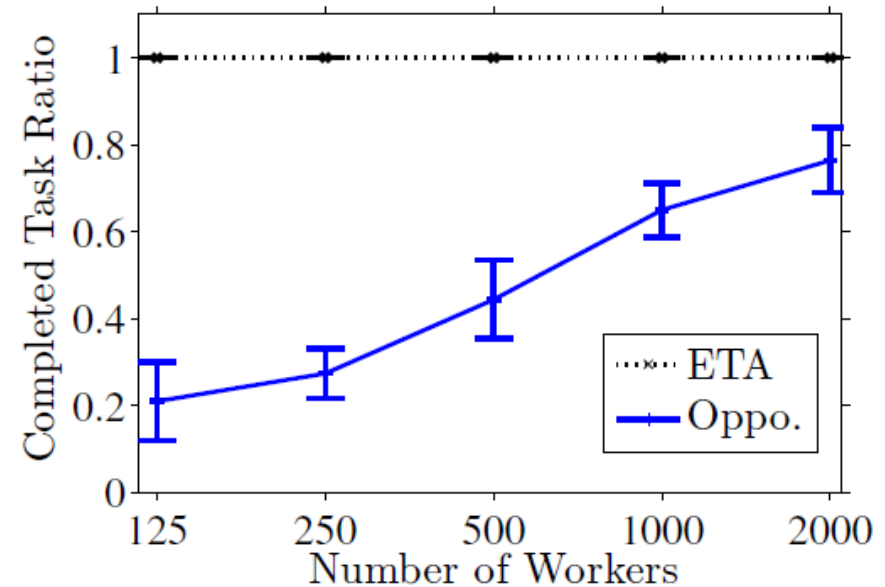
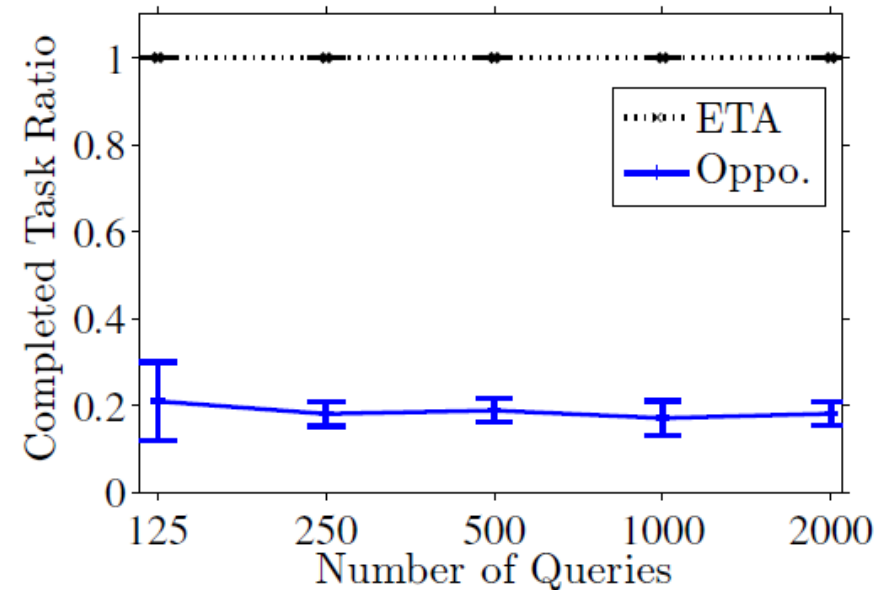
Overall Completed Task Ratio

- ❑ Lower ratios significantly degrade the user experience
- ❑ 90+% improvement compared to in-situ (only) sensing
- ❑ 80% improvement compared to (in-situ sensing with) opportunistic sensing



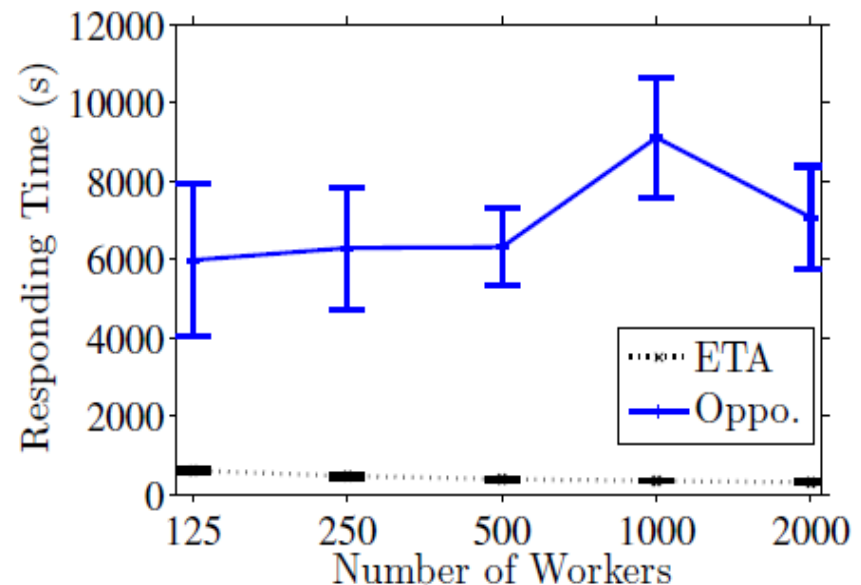
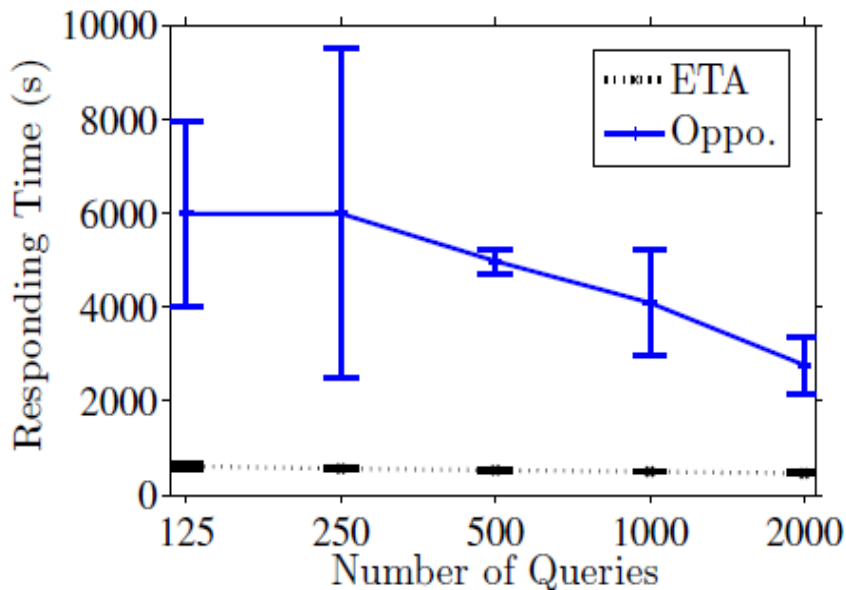
Impact of Number of Workers and Queries

- ETA achieves **high** completed ratio even with many queries ← Left figure
- In-situ sensors with opportunistic sensing requires large number (**two thousands, 16 times higher than ETA**) of workers to achieve high completed ratio ← Right figure



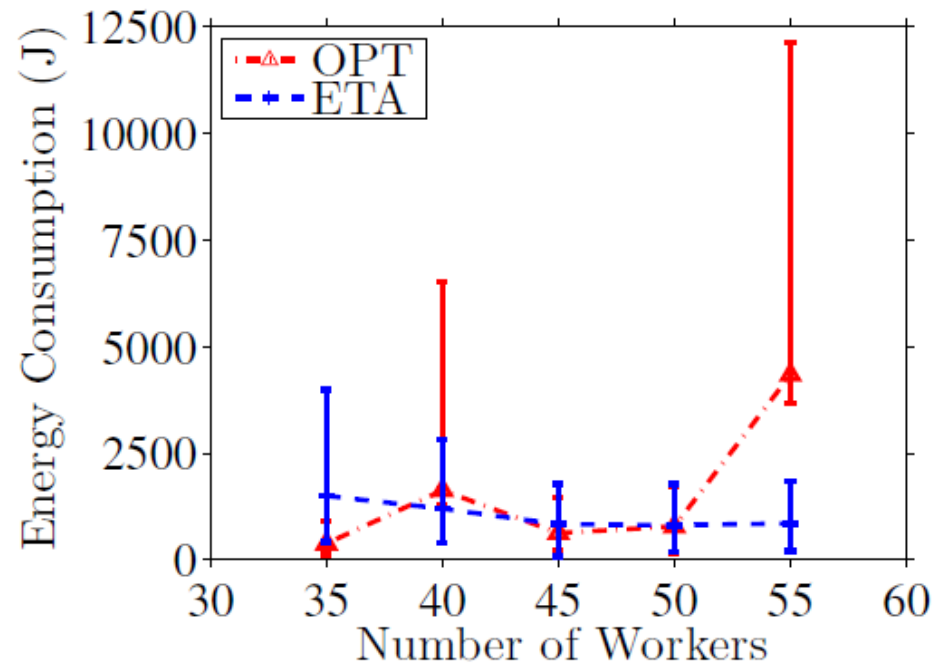
Impact of Number of Workers and Queries (cont.)

- The responding time of ETA is always less than 1000 seconds **because ETA instructs workers to the required locations**
- Opportunistic sensing cannot guide workers and thus suffer from up to **6 times** higher responding time



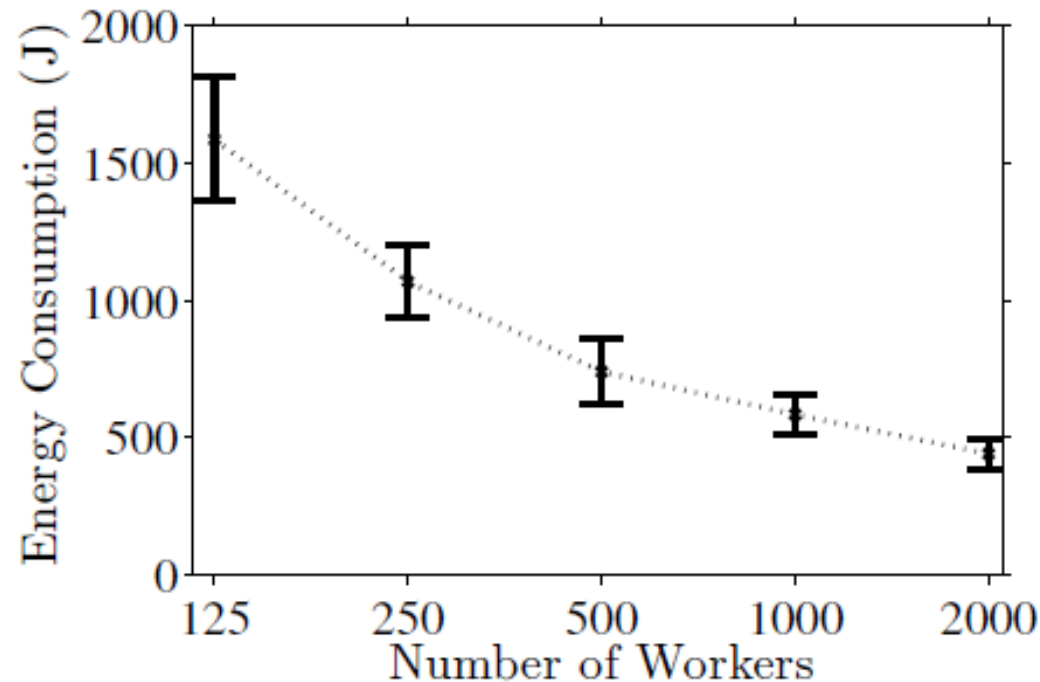
Optimality of ETA in Practical Settings

- ❑ The optimal algorithm is implemented in CPLEX with **1-min** running time limit (**realistic settings**)
- ❑ **ETA outperforms OPT once the number of workers exceeds 50**



Benefits of More Workers

- ❑ ETA leads to lower energy consumption with more workers participation
- ❑ **Because more workers allow ETA to choose better workers**

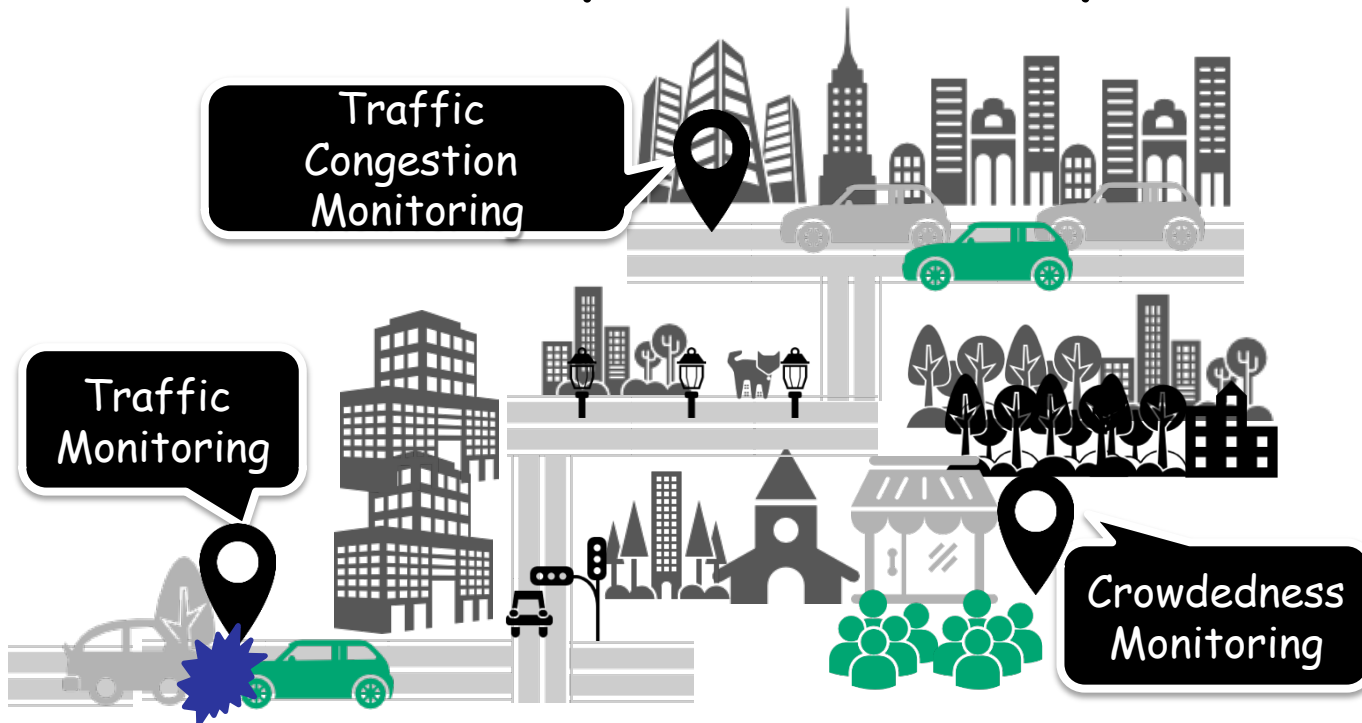


Conclusion and Future Work

- ❑ We present the **SAIS** platform of smartphone-augmented in-situ sensing
- ❑ We develop a **task assignment algorithm (ETA)** to leverage resources of smartphone users
- ❑ In our simulation results, we show
 - In-situ sensing achieves extremely low coverage
 - ETA completes 100% tasks with only 12.5% of workers compared to in-situ sensors with opportunistic sensing
 - ETA results in up to 6 times of responding time reduction
 - ETA performs better with more workers

Future Work

- ❑ A large-scale **(Urban Computing)** middleware design in order to ease the overhead of the deployment
- ❑ More research problems may surface



Questions?



Contact me at chsu@cs.nthu.edu.tw anytime

Distribution of Multimedia Content over Challenged Networks [Work-in-Progress]

Under **weak** network infrastructure, people cannot access any multimedia content.



In some **popular places**, they are still possible to have network access.

- We propose a system called CCDN to distribute multimedia content
- ✓ Deploy **local proxies (LP)** in the popular places to do distribution
 - ✓ Propose an efficient algorithm to decide that downloading which multimedia content from which LP (or user) can have **highest user quality experience**.

Usage Scenarios

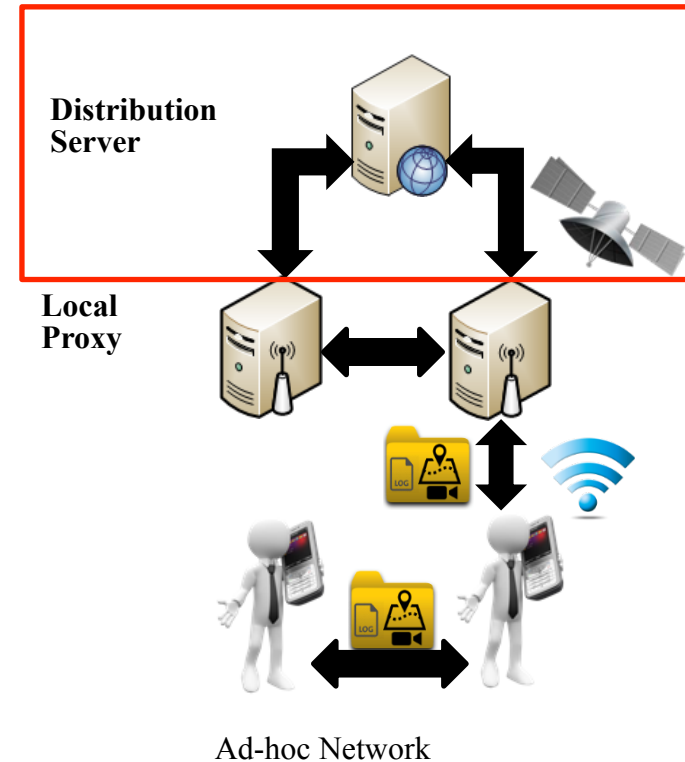
- ❑ Local Proxies are located in some popular places:
 - Bus stations
 - City halls
 - Stores ← Starbucks, MacDonal'd's, and so on
- ❑ Mobile Users utilizes their WiFi to download multimedia content whenever they run into local proxies



System Overview

□ Distribution server:

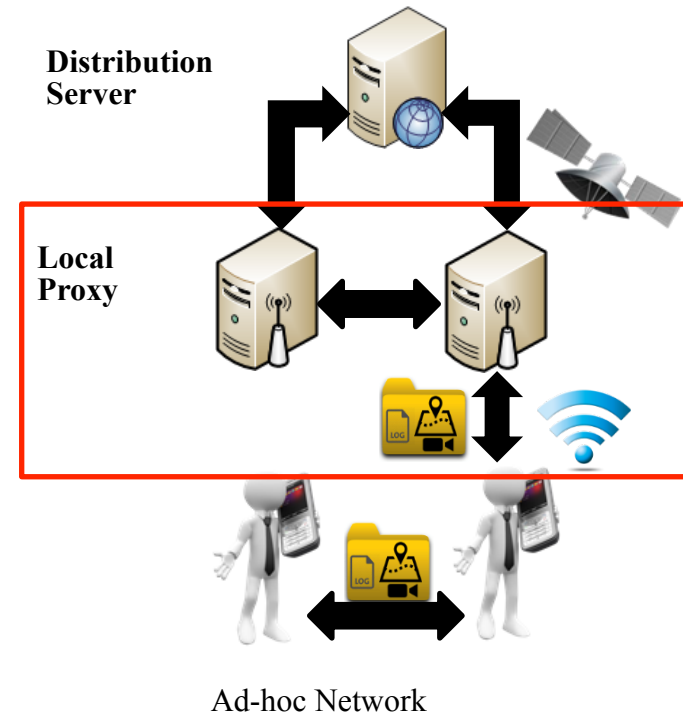
- Collect **social profiles of users** from local proxies ← What are social profiles?
- Create distribution plan
- Push multimedia content to local proxies



System Overview (cont.)

□ Local Proxy:

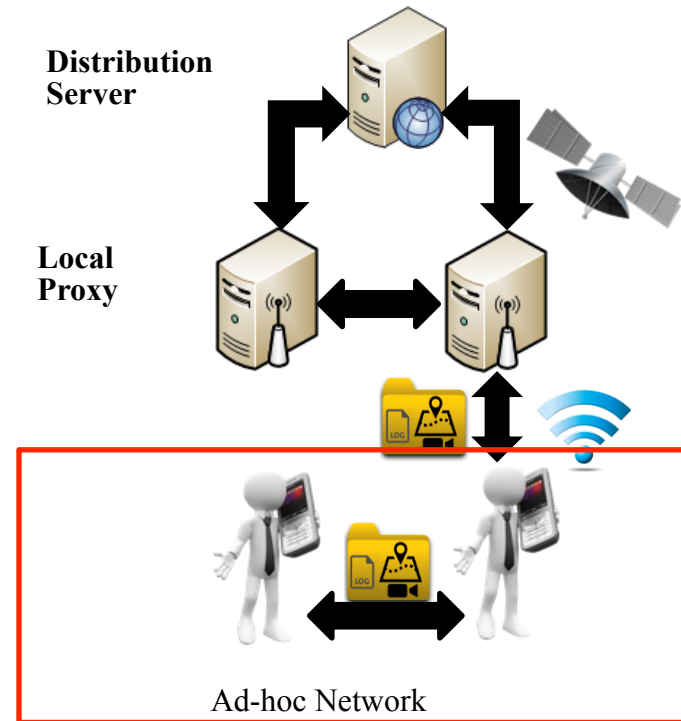
- Collect social profiles from users and push them to distribution server
- Forward the distribution plan to mobile users whenever there is a **contact**
- Deployed at popular places and cache the multimedia content for mobile users



System Overview (cont.)

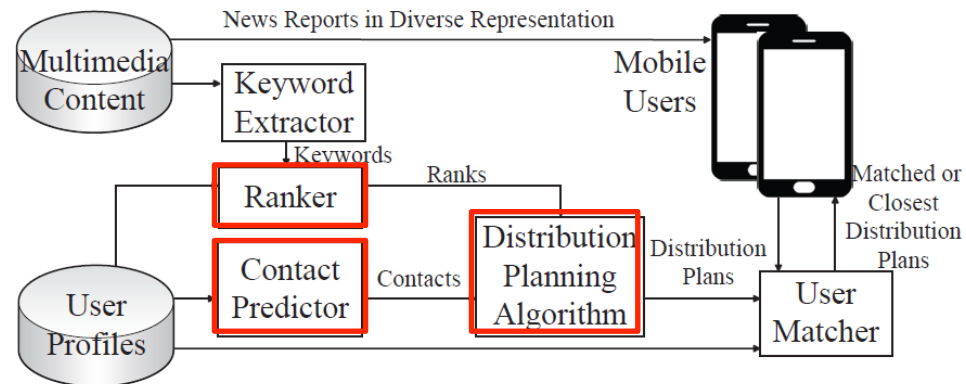
□ Mobile Users:

- Send their own social profiles, such as **encounters, watched multimedia content, contact duration, throughput**, etc to local proxies and then distribution server
- Follow the plan to download corresponding multimedia content **for later consumption**



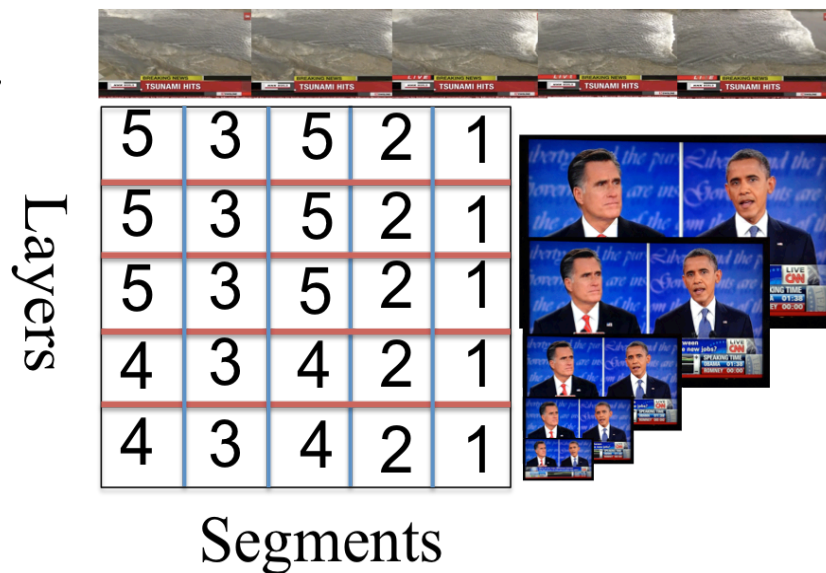
How to Create Distribution Plan?

- Ranker
 - Predict the viewing probability of each multimedia content based on historical social profiles.
- Contact Predictor
 - Predict the encounters of each user based on historical user trajectory
- **Distribution Planning Algorithm**
 - If we know the encounters, importance of multimedia content, and some information of multimedia content, we can design an algorithm to disseminate useful content to mobile users



Multi Layer Multimedia Content

- ❑ In our system, the contacts may too short to transfer the **whole** multimedia contents
- ❑ We can reduce the size of multimedia content
 - Temporal: segments
 - Special: transcoding
- ❑ We give different layer different user experience improvements



Problem Formulation - Objective

$$\max \sum_{u=1}^U \sum_{n=1}^N \sum_{l=1}^L \sum_{c=1}^C x_{u,n,l,c} \rho_{nL+l} \psi_{u,n} \quad (1a)$$

- The first step is to define the objective function
 - Maximize the total user experience improvement
- Decision variable
 - X is the 0-1 decision variable to decide which unit should be downloaded from which contact

Problem Formulation - Constraints

$$st : \psi_{p_{u',c',n'}} \geq \bar{\psi} x_{u',n',l',c'} \quad \forall 1 \leq u' \leq U, 1 \leq n' \leq N, 1 \leq l' \leq L,$$

$$1 \leq c' \leq C$$

(1b) Viewing Probability

$$\sum_{n=1}^N \sum_{l=1}^L b_{nL+l} x_{u',n,l,c'} \leq r_{u',c'} \kappa_{u',c'} \quad \forall 1 \leq c' \leq C, 1 \leq u' \leq U$$

(1c) Bandwidth Budget

$$\sum_{c=1}^C x_{u',n',l',c} \geq \sum_{c=1}^C x_{u',n',l'',c} \quad \forall 1 \leq u' \leq U, 1 \leq n' \leq N,$$

$$1 \leq l' < l'' \leq L$$

(1d) Layer Dependency

$$\sum_{n=1}^N \sum_{l=1}^L \sum_{c=1}^C b_{nL+l} x_{u',n,l,c} \leq d_{u'} \quad \forall 1 \leq u' \leq U$$

(1e) Disk Budget

$$\sum_{u=1}^U \sum_{n=1}^N \sum_{l=1}^L \sum_{c=1}^C \{1 - \min[1, \max(p_{u,c}, u') - \min(p_{u,c}, u')]\} b_{nL+l}$$

$$x_{u,n,l,c} \hat{e}_{u',c} + \sum_{n=1}^N \sum_{l=1}^L \sum_{c=1}^C b_{nL+l} x_{u',n,l,c} \check{e}_{u',c} \leq q_{u'} \quad \forall 1 \leq u' \leq U$$

(1f) Energy Budget

$$\sum_{c=1}^C x_{u',n',l',c} \leq 1 \quad \forall 1 \leq u' \leq U, 1 \leq n' \leq N, l \leq l' \leq L$$

(1g)

$$x_{u,n,l,c} \in \{0, 1\} \quad \forall u, n, l, c.$$

(1h)

Distribution Planing Problem

$$\max \sum_{u=1}^U \sum_{n=1}^N \sum_{l=1}^L \sum_{c=1}^C x_{u,n,l,c} \rho_{nL+l} \psi_{u,n}$$

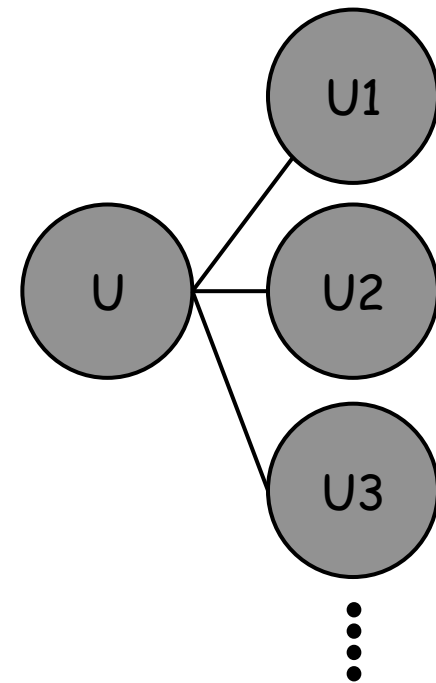
- Objective: maximize total user experience improvement
- Decision Variable: which layer of which news should we download from which contact
- Constraints:
 - Disk
 - Energy
 - Bandwidth
 - ...

Intuitions of Contact-Driven Round Robin (CDRR) Algorithm

- ❑ Get higher user experience improvement using less resources
- ❑ Allocate more resources to users who can make more contributions in the future
- ❑ Get news from the user who can make more limited contributions

Get Higher User Experience Using Less resources

- Unit = layers of news
- Each user will run into multiple users. We put the units that can be downloaded from those users in a queue $Q_u = \{\text{unit1}, \text{unit2}, \dots\}$
- We then sort Q_u by user experience improvement/size
 - resources = disk, energy, and bandwidth, all are proportional to the unit size
- Finally we know which news to get with the highest benefit/overhead ratio



Allocate More Resources to Users Who Can Make More Contributions

- When I get a unit, the energy of contacted user (sender) will be consumed.
- Hard decisions: If I get all units in a queue, it will consume too much energy of the sender and affect other users.
- Moreover, it may not be the best decision based on our first intuition.
- Therefore,
 - for fairness and get more user experience, we do **round robin** to make all the users (receivers) get a unit from Q_u (sender) until all resources are consumed or all units are distributed
 - for maximize total user-experience, we allow a user who has higher probability to distribute news later to get more unit at each round \leftarrow probability is proportional to **number of contact * contact duration**

Get News from the User Who Can Only Make More Limited Contributions

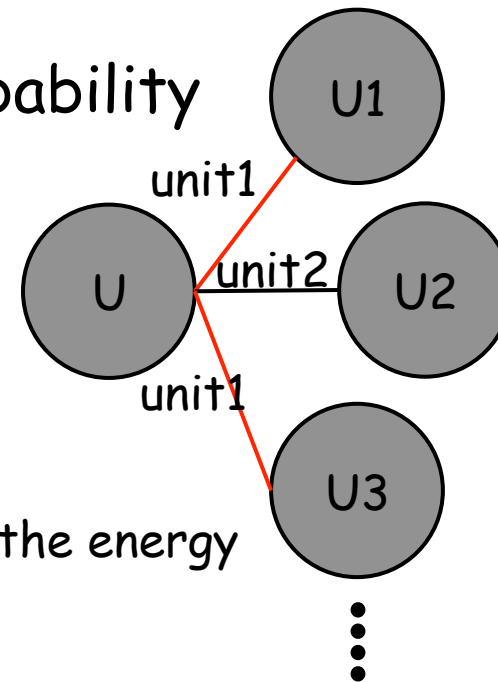
- Now, we know which units should we get and how many units should I get at each round
 - but we have not decided where (which contact) should I get the units

- Get a unit from the user who has lowest probability to distribute news in the future

- probability is proportional to **number of contact * contact duration**

- For example

- contact durations are the same
- number of contact of U1 = 1, U3 = 2
- answer: I will get the unit from U1 because consuming the energy of U1 does not affect other user



Existing Algorithms for Comparisons

- Epidemic Routing [1]
 - Flood the message
- CSI-Dissemination algorithm [2]
 - Relay the message to the contact users with dissimilar mobility
 - Reduce the overhead (transmission, storage...)

[1] A. Vahdat and D. Becker. "Epidemic routing for partially connected ad hoc networks." Technical Report CS-200006, Duke University, 2000.

[2] W. Hsu, D. Dutta, and A. Helmy. "CSI: A paradigm for behavior-oriented profile-cast services in mobile networks." Ad Hoc Networks, 2012.

Differences with Our Work

- **Prefetching**: we do not have specific receiver of each multimedia content
- **Resource constraints**: we consider resource limitations of mobile devices

Simulation Setup

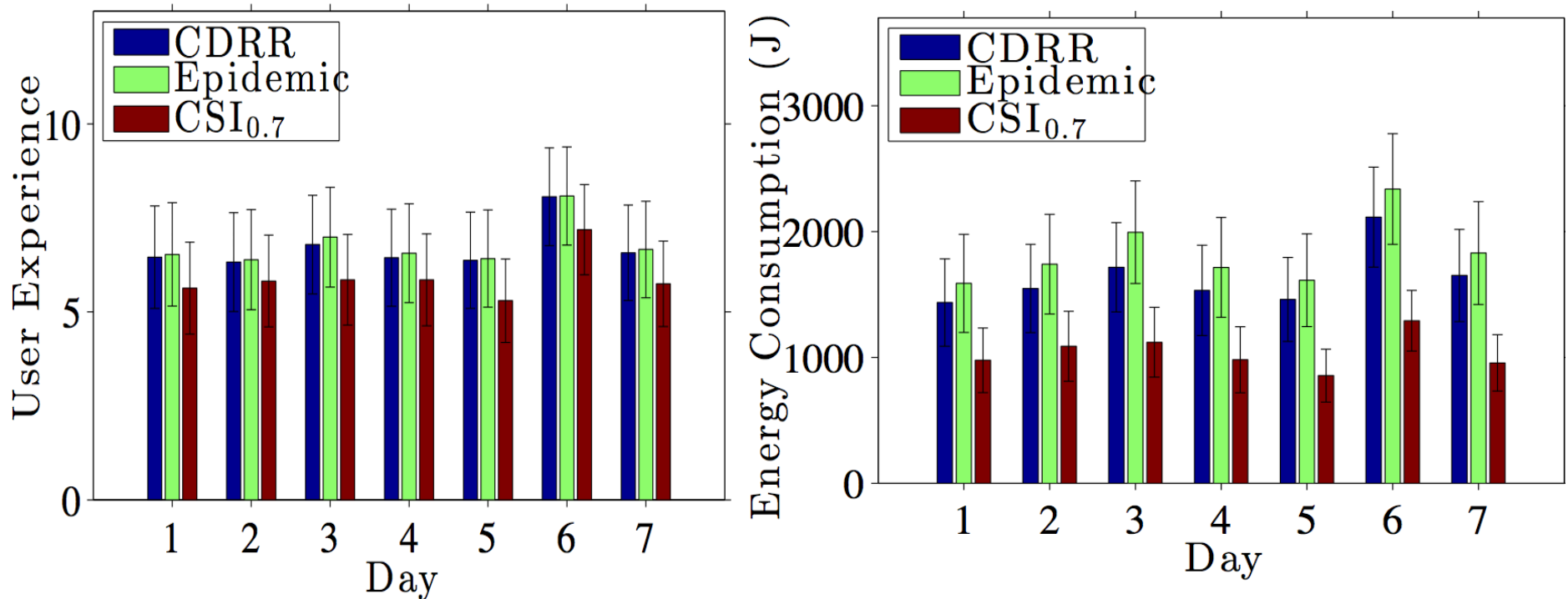
- ❑ We implement the two baseline algorithms and our algorithm in the simulator
 - Epidemic
 - CSI
 - CDRR
- ❑ We use a trace to simulate real scenarios
 - Collected in Beijing
 - 4-year traces
 - 178 users
 - GPS trajectory
- ❑ We preprocess the traces to drive our simulator

Performance metrics

- ❑ User experience: the average user experience of all the watched news reports
- ❑ Energy consumption: the average energy consumption of mobile devices
- ❑ Disk efficiency: the ratio of user experience and disk consumption
- ❑ Used disk space: the amount of used disk space
- ❑ Missed ratio: the fraction of unavailable news reports among all the user demanded ones
- ❑ Watched unit: the number of watched news reports among all the downloaded ones
- ❑ Received unit: the number of received news reports

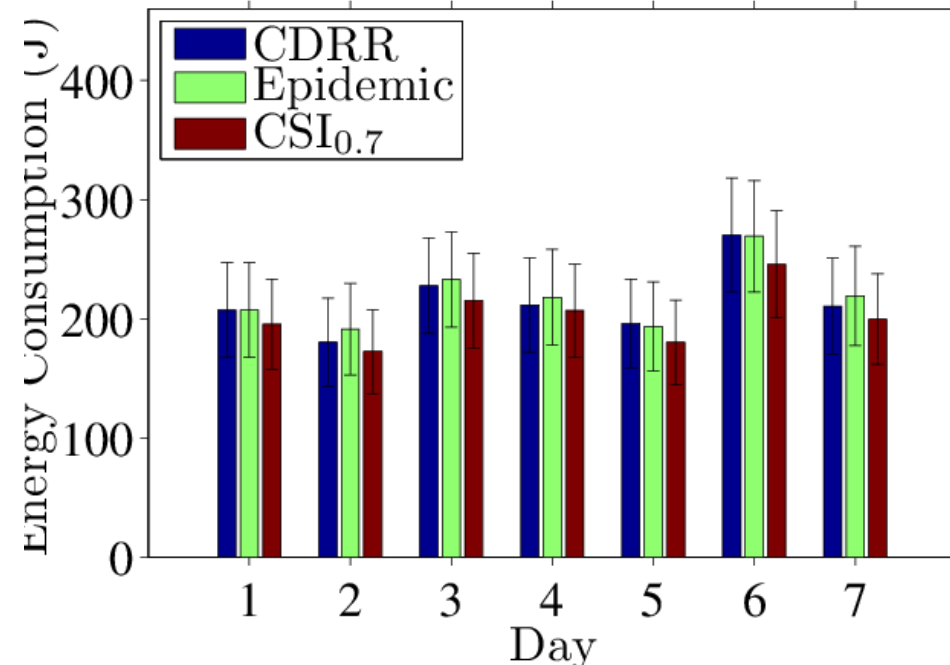
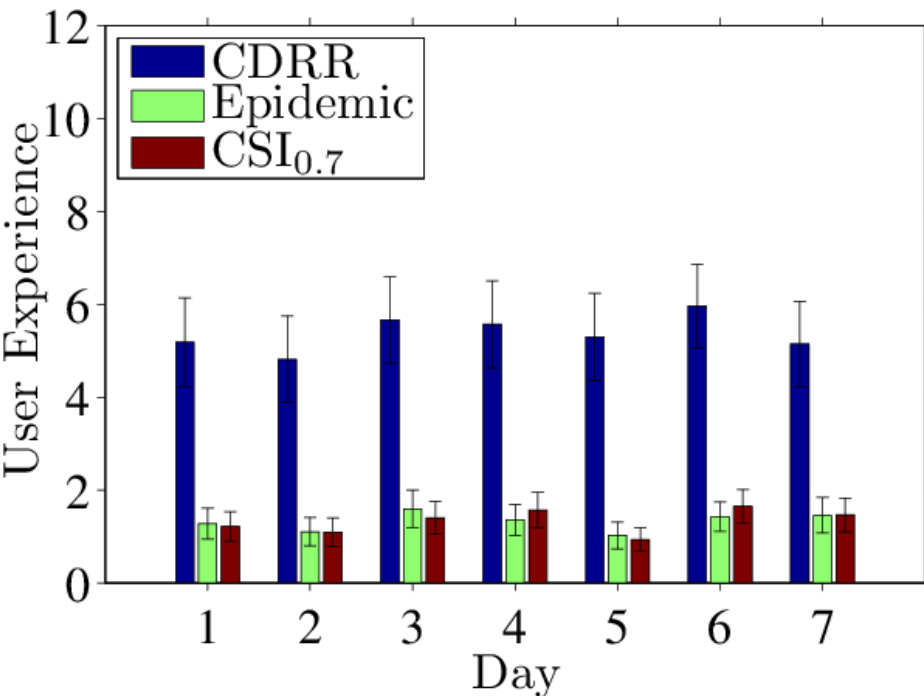
Simulation Results - Unlimited Resources

- Our CDRR algorithm can achieve 99% approximation factor, while epidemic giving highest user experience
- But unlimited resources are unrealistic!

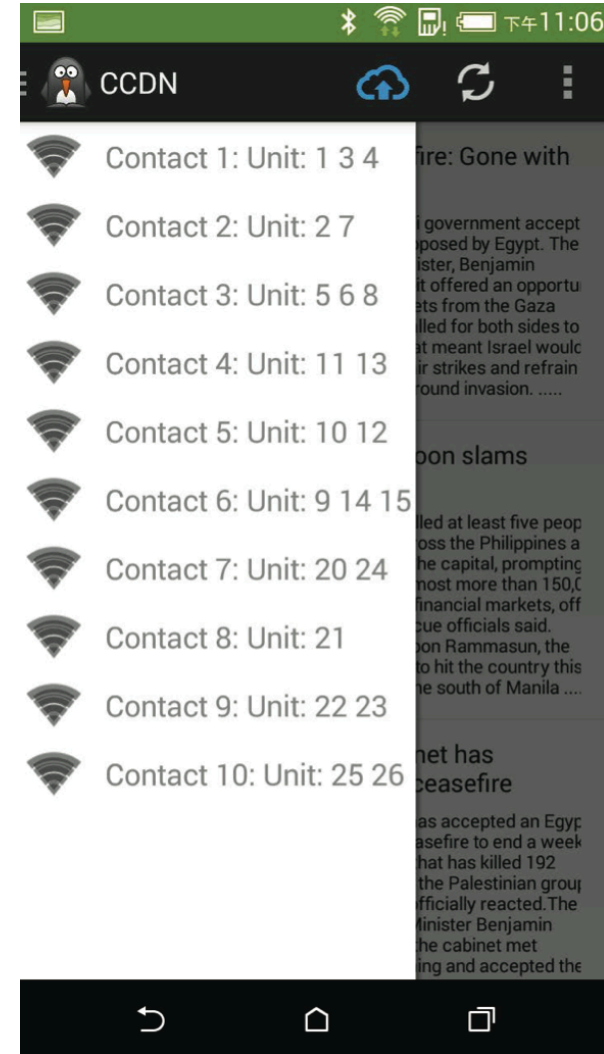
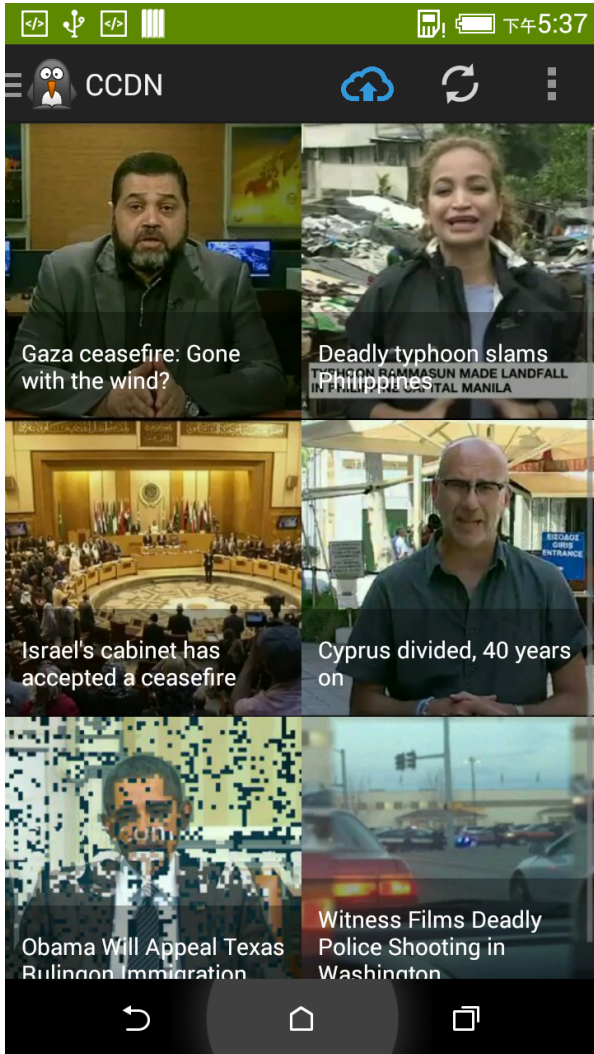


Simulation Results - Realistic Scenario

- ❑ Disk Budget = 250 MB
- ❑ Energy Budget = 2000J
- ❑ In realistic scenario, CDRR algorithm outperforms others by up to 4 times, while the energy consumption is only higher than others up to 15%

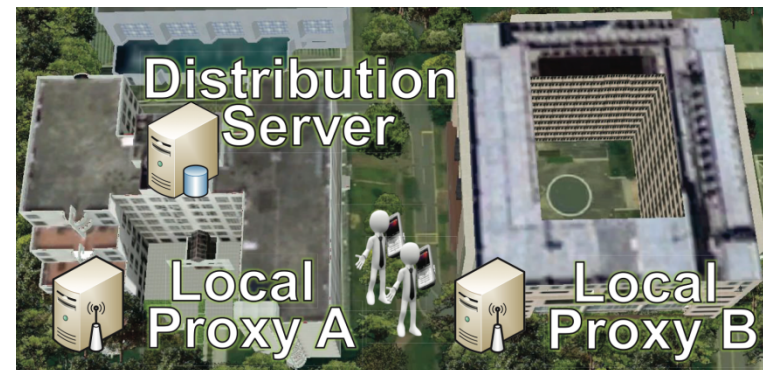
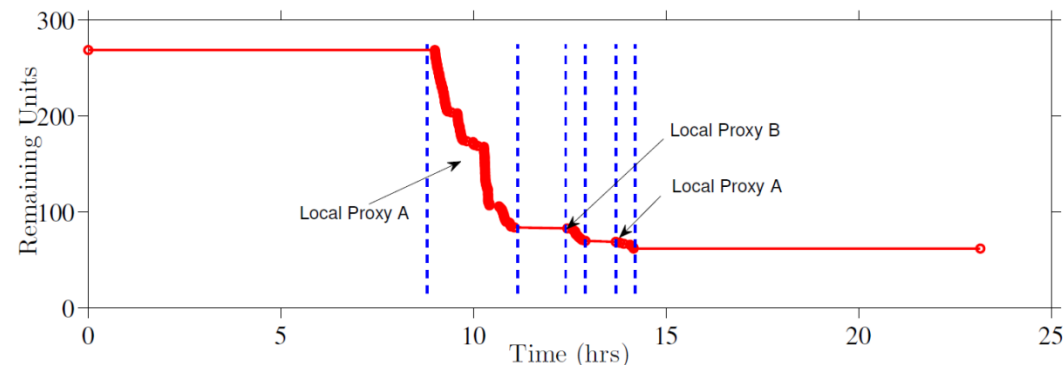


Prototype - Client



Preliminary Experiments

- ❑ Collect 3 days social profiles for creating the distribution plan of a user
- ❑ Running 24 hours experiments with
 - 2 local proxies, 1 distribution server and 54 news with 5 layers
- ❑ We clarify our prototype can follow the plan to download 77% of the multimedia content



Questions?



Contact me at chsu@cs.nthu.edu.tw anytime