Opportunistic CrowdSensing

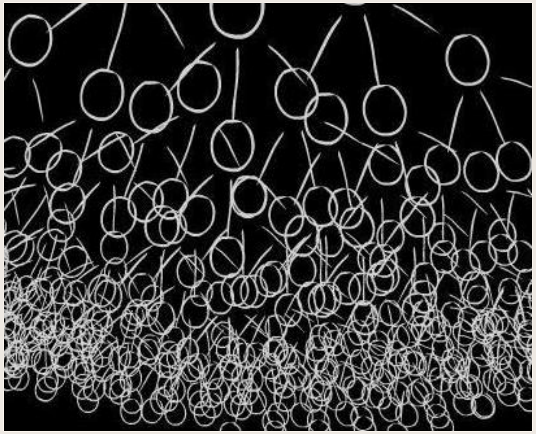
Nic Lane
Mobile and Sensing Systems Group (MASS)
Microsoft Research Asia (MSRA)

Microsoft Research

On-going Large-scale Opportunistic CrowdSensing Investigations in MASS

Lowering Energy Consumed by Participation

Incentivizing Users to Particip



collaboration with **Thomas Moscibroda**

Understanding Users and Communities

Characterizing Places (POI

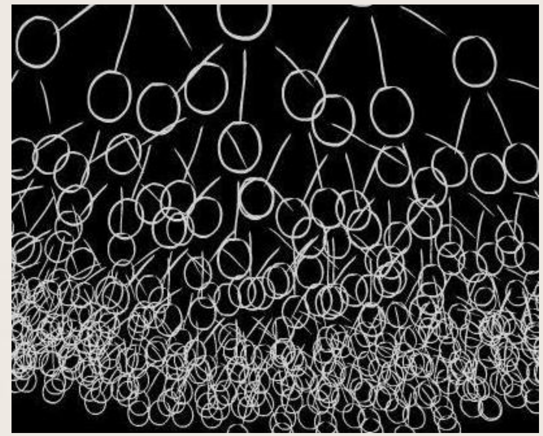
Ubicomp '12
Best Paper

Microsoft Research

On-going Large-scale Opportunistic CrowdSensing Investigations in MASS

Lowering Energy Consumed by Participation

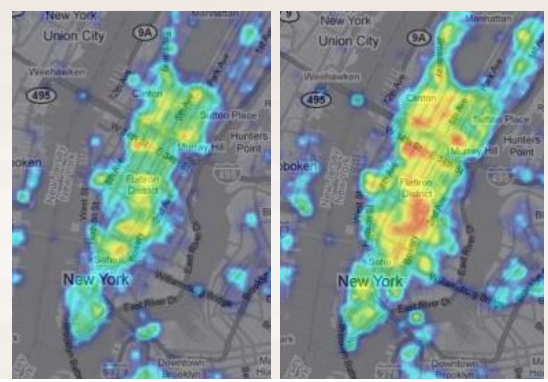
Incentivizing Users to Particip



collaboration with **Thomas Moscibroda**

Understanding Users and Communities

Characterizing Places (POI



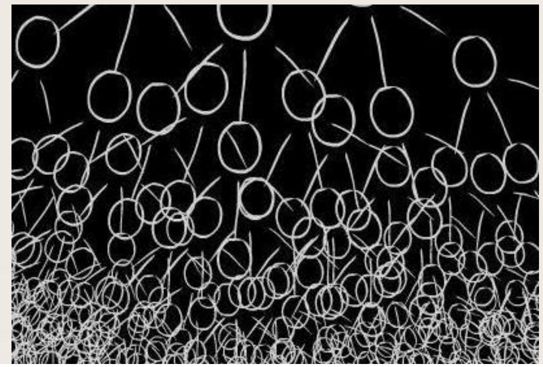
Ubicomp '12 Best Paper

Novel Uses of Large-scale Crowdsourced Sensor Data

On-going Large-scale Opportunistic CrowdSensing Investigations in MASS

Lowering Energy Consumed by Participation

Incentivizing Users to Particip



collaboration with **Thomas Moscibroda**

Eliminating Bottlenecks to Collecting Large Amounts of Data

Understanding Users and Communities

Characterizing Places (POI

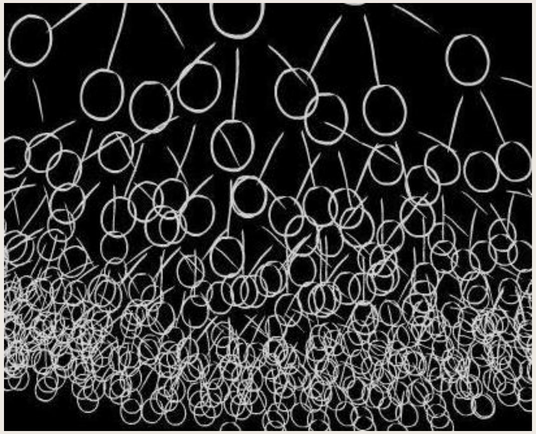
Ubicomp '12 Best Paper

Microsoft Research

On-going Large-scale Opportunistic CrowdSensing Investigations in MASS

Lowering Energy Consumed by Participation

Incentivizing Users to Particip



collaboratio
n
with
Thomas Moscibroda

Understanding Users and Communities

Characterizing Places (POI

UBI COMP 2012

Ubicomp '12
Best Paper

Microsoft Research

Low-Energy Opportunistic CrowdSensing

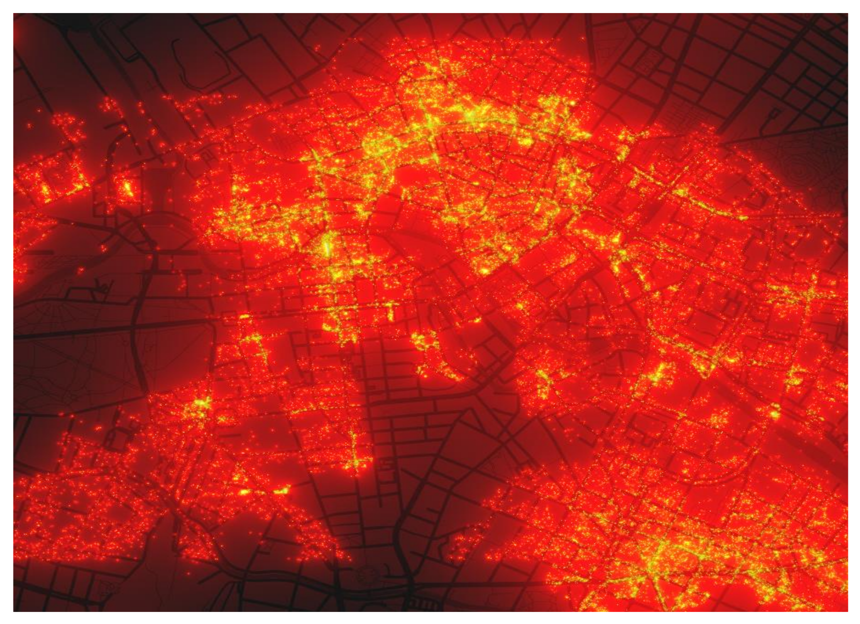
Nicholas D. Lane, Yohan Chon, Lin Zhao
Yongzhe Zhang, Guandong Ding, Fan Li, Feng Zhao

Under Submission

Participation in existing Crowdsourcing Mobile Sensor System drains Smartphone Batteries

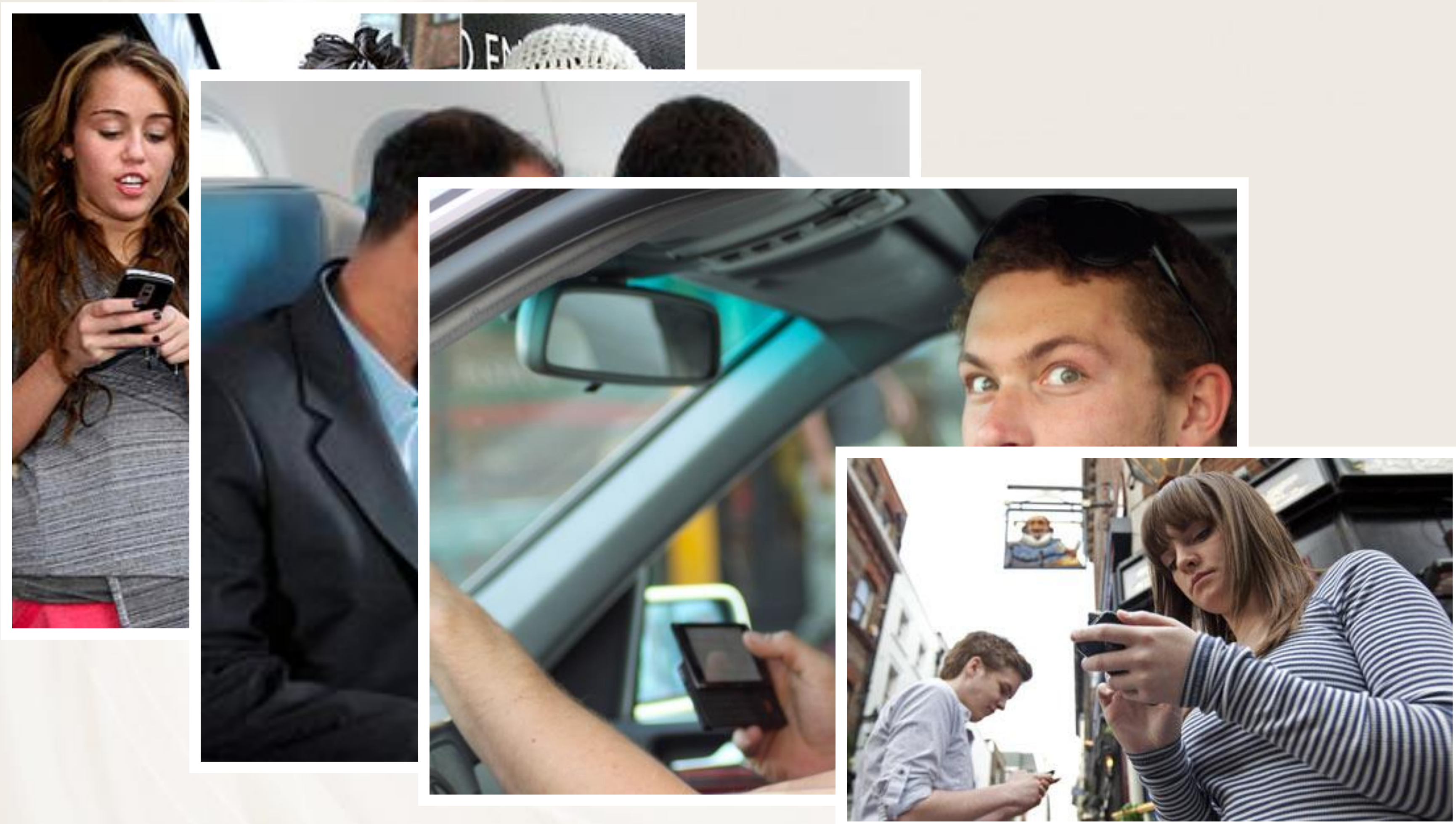
Collect GPS Traces from Traffic

Build WiFi Localization Maps



Even an hour or two of participation can reduce battery life by 10+ stand-by hours or more

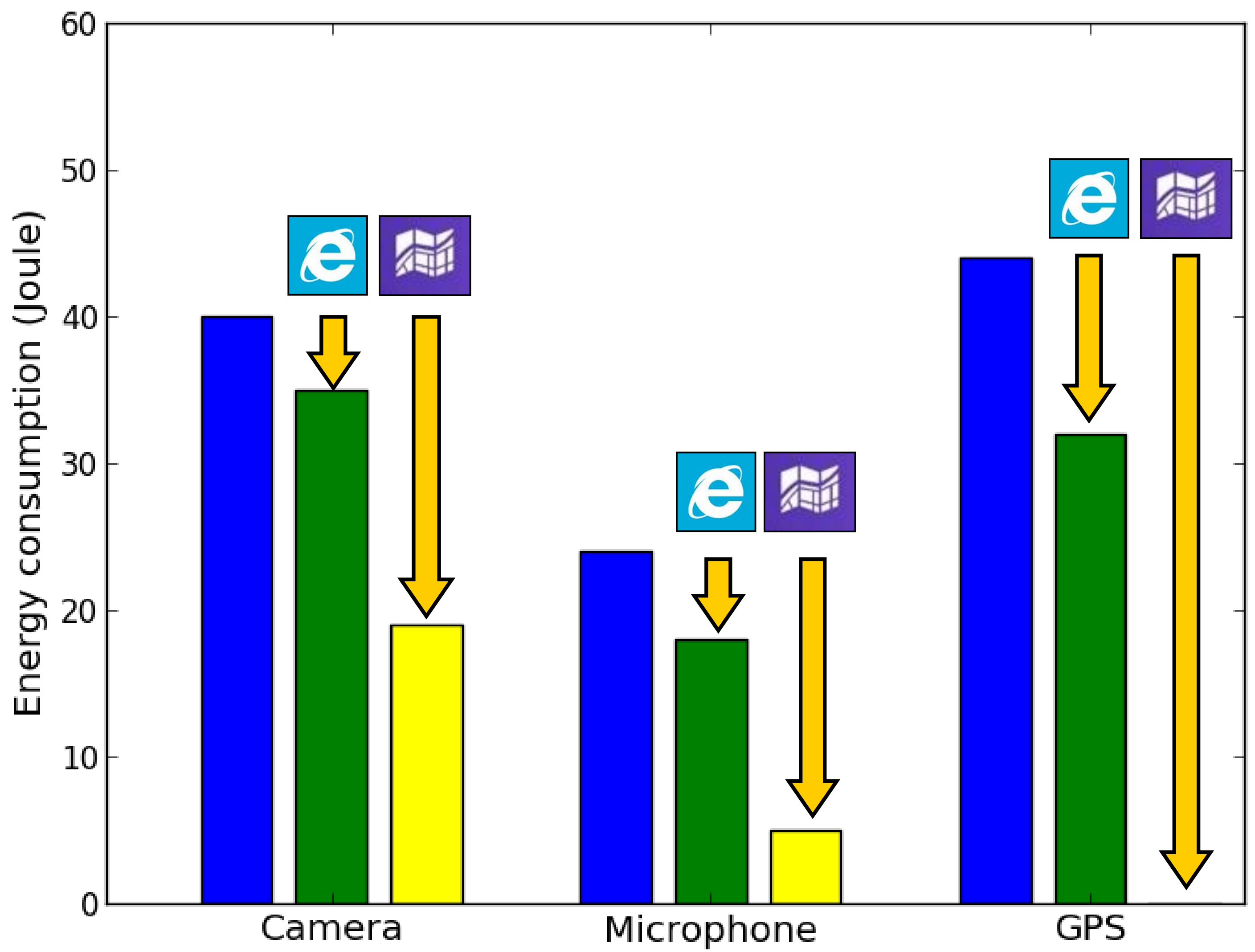
Opportunistic CrowdSensing (OCS)



Approach: Sense When Users Perform a Phone Task

Microsoft Research

Being Opportunistic Saves Energy



Sensing energy savings as much as 33%, 50%, 100%

ch

Opportunistic CrowdSensing

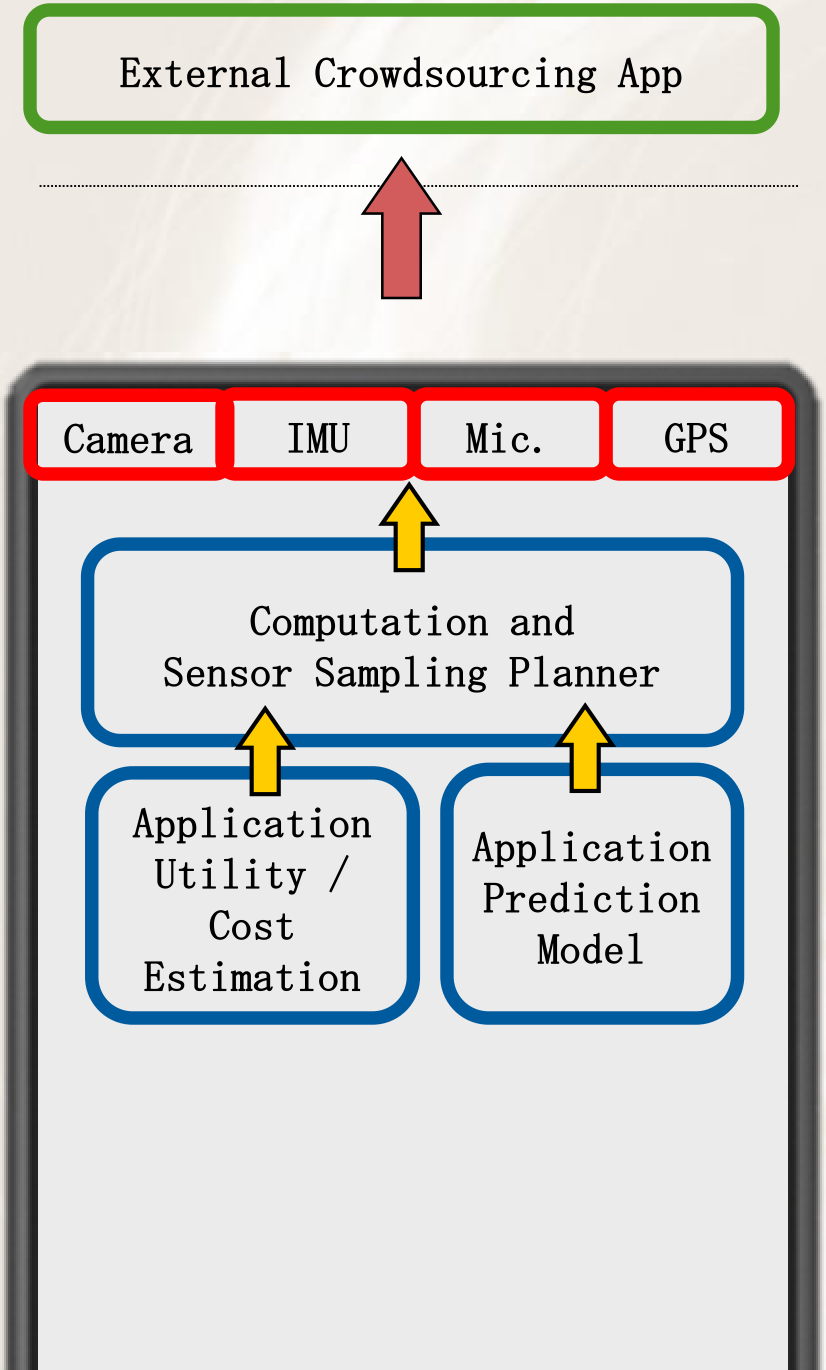
Framework

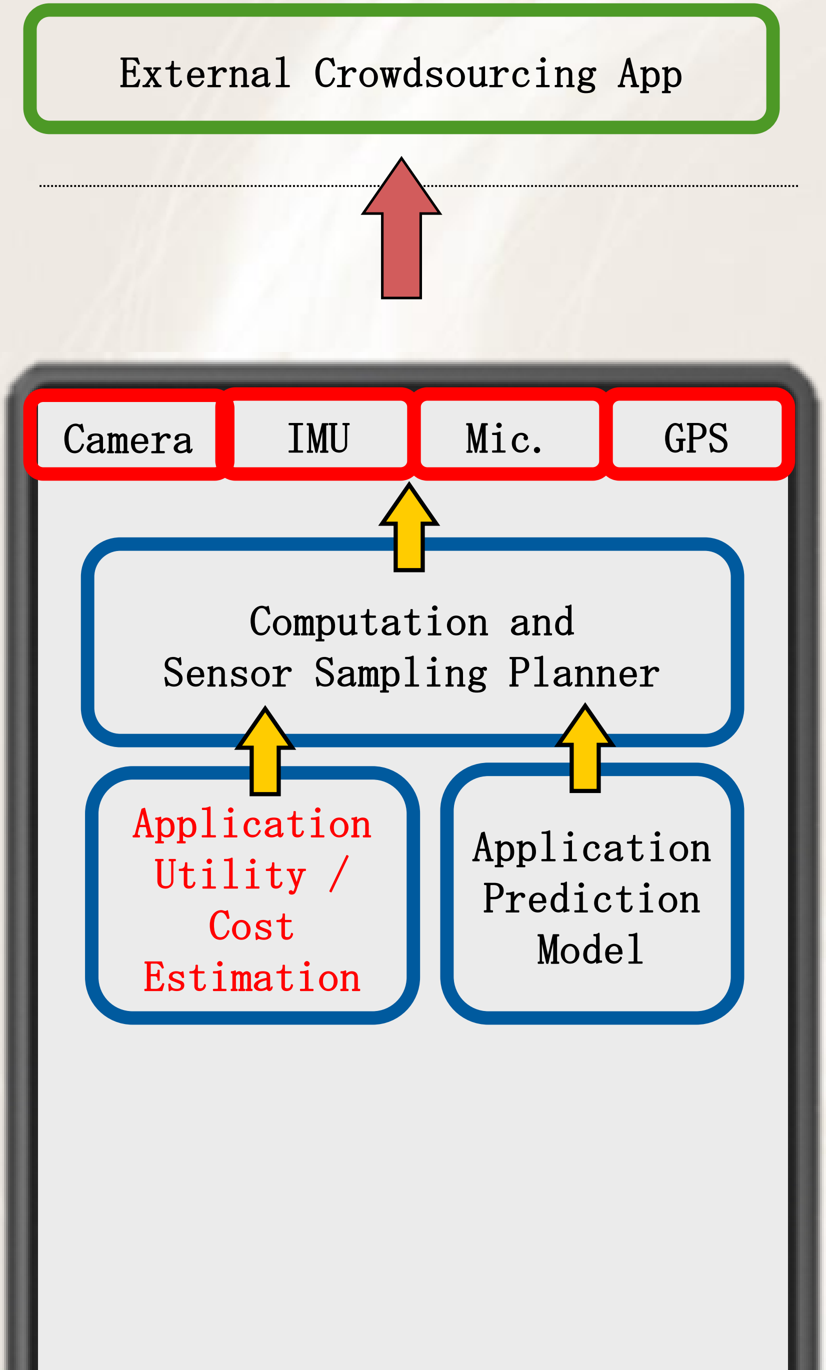
Microsoft Research

External Crowdsourcing App

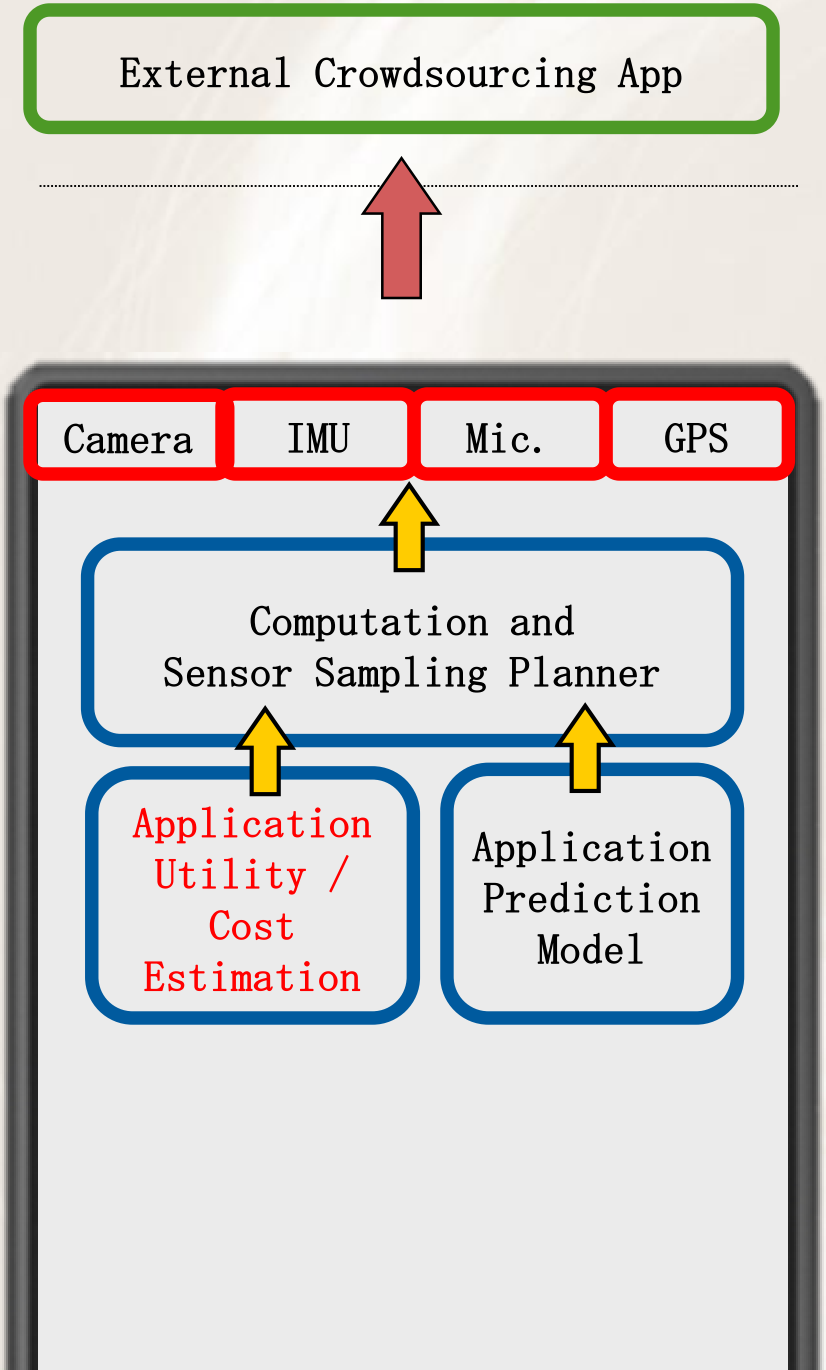
[sensor type, computation, sample rate, …]

Microsoft Research


External Crowdsourcing App
Camera
IMU
Mic.
GPS
Computation and
Sensor Sampling Planner
Application
Utility /
Cost
Estimation
Application
Prediction
Model



Microsoft Research



Application Utility/Cost Estimation

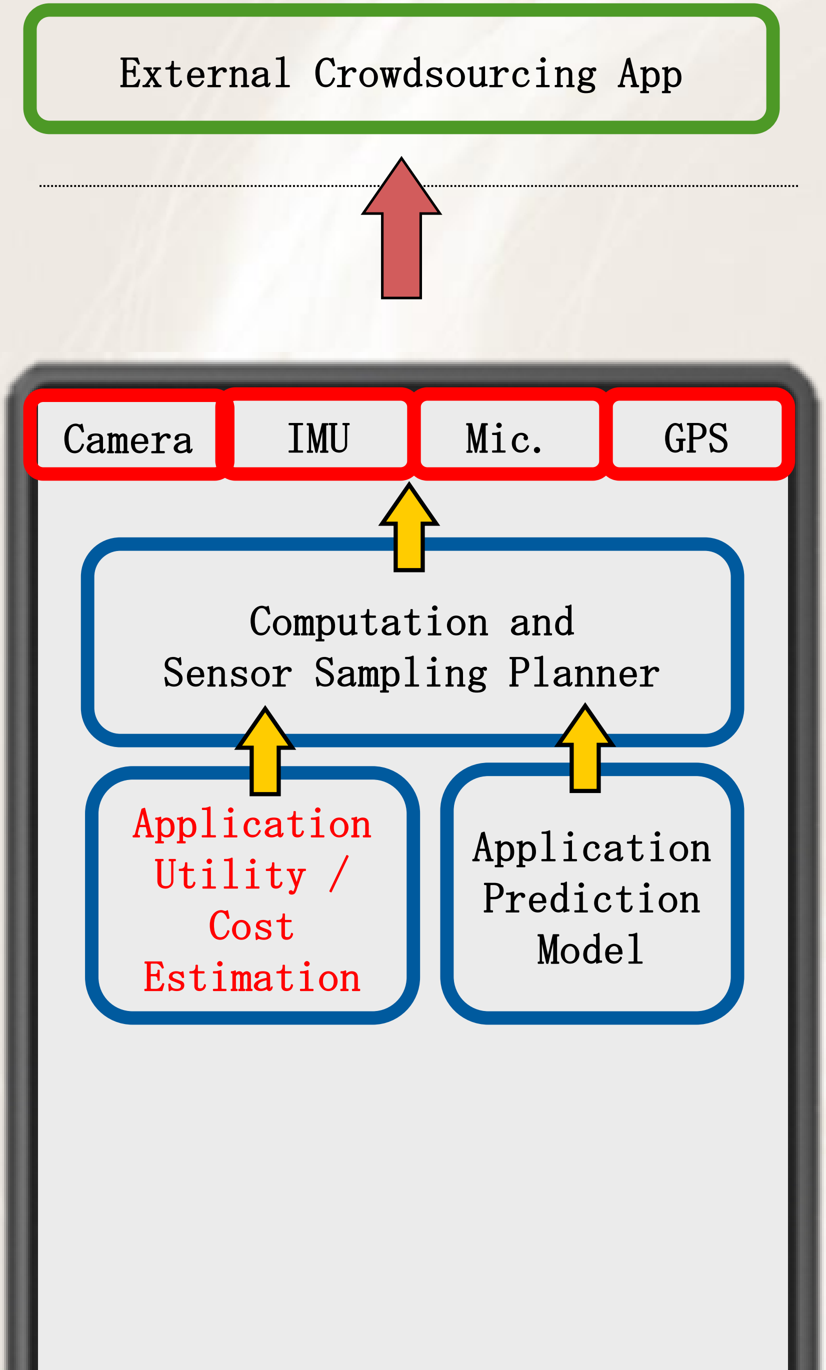
Utility ~ Sensor Quality

Application	Sensor Quality
	Accuracy Quantity etc.
	…

Cost ~ Energy Used

Application	Energy
	Joules
	…

Application Utility/Cost Estimation



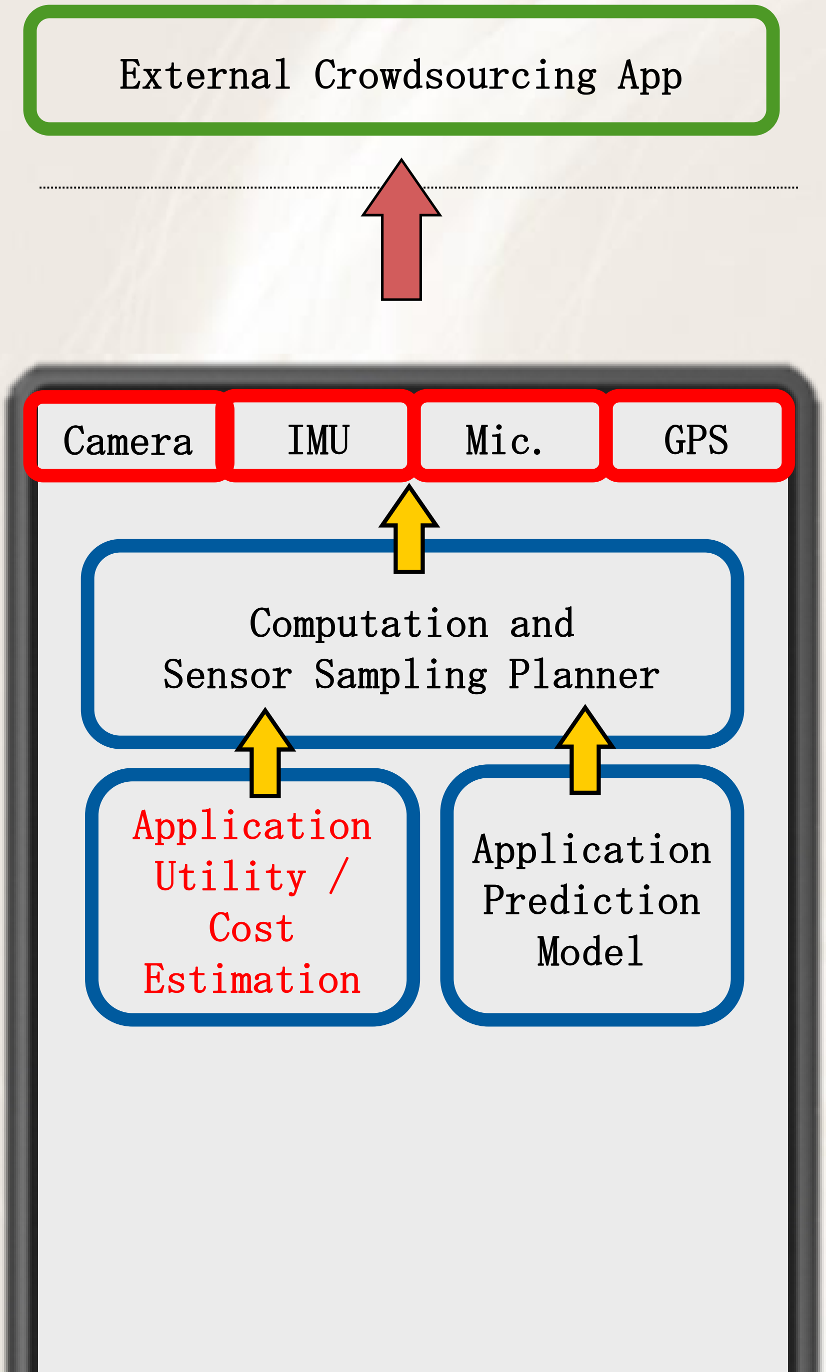
Utility ~ Sensor Quality

$$f\left(\begin{matrix}\text{App}\\ \text{Category}\end{matrix}, \begin{matrix}\text{Crowd}\\ \text{App}\end{matrix}\right) = \begin{matrix}\text{Sensor}\\ \text{Quality}\end{matrix}$$

Cost ~ Energy Used

$$f\left(\begin{matrix}\text{App}\\ \text{Category}\end{matrix}, \begin{matrix}\text{Crowd}\\ \text{App}\end{matrix}\right) = \text{Energy}$$

Microsoft Research



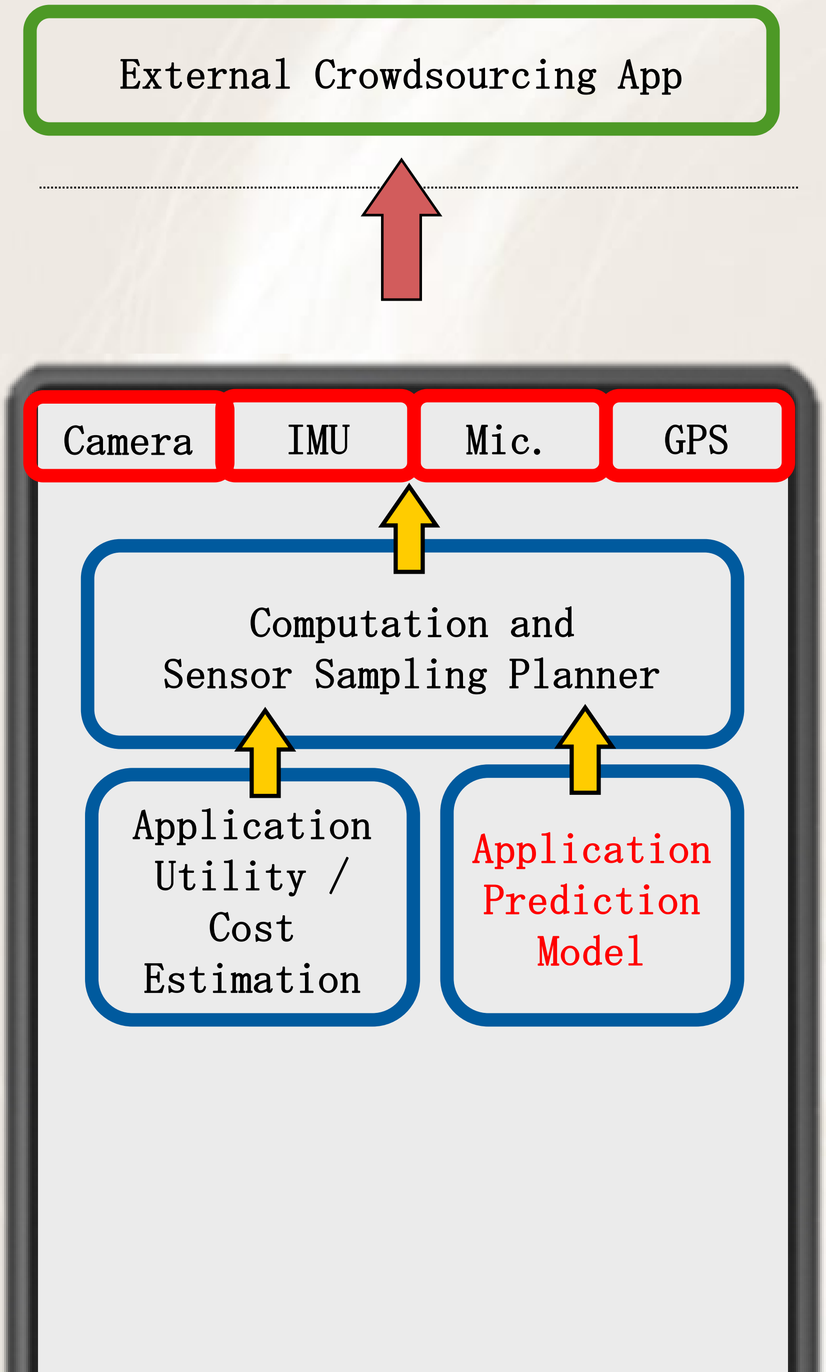
Application Utility/Cost Estimation

Utility ~ Sensor Quality

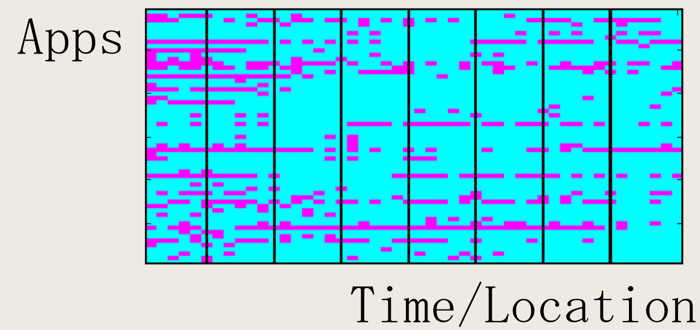
$$f(\text{App Category}, \text{Crowd App}) = \text{Sensor Quality}$$

Cost ~ Energy Used

$$f(\text{App Category}, \text{Crowd App}) = \text{Energy}$$



Application Prediction Model

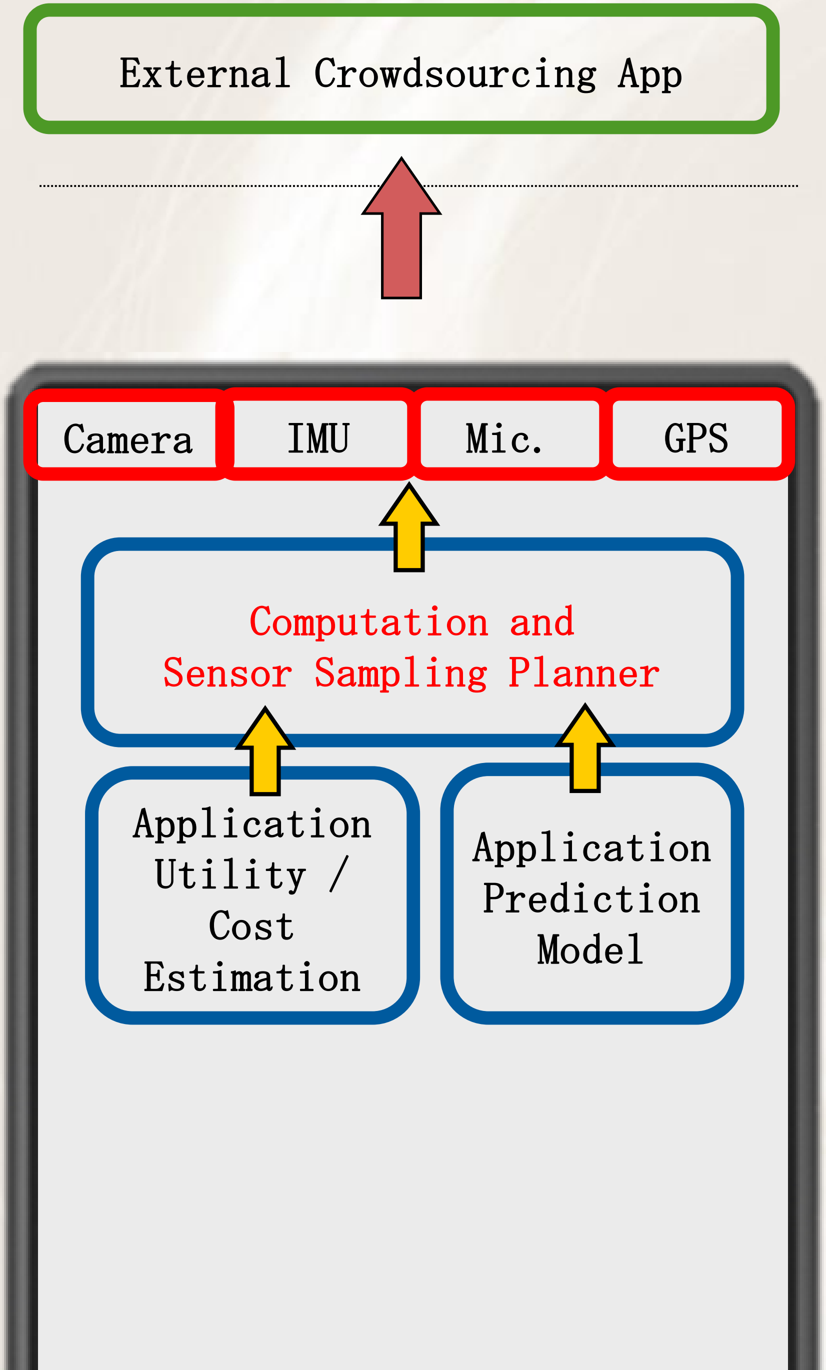


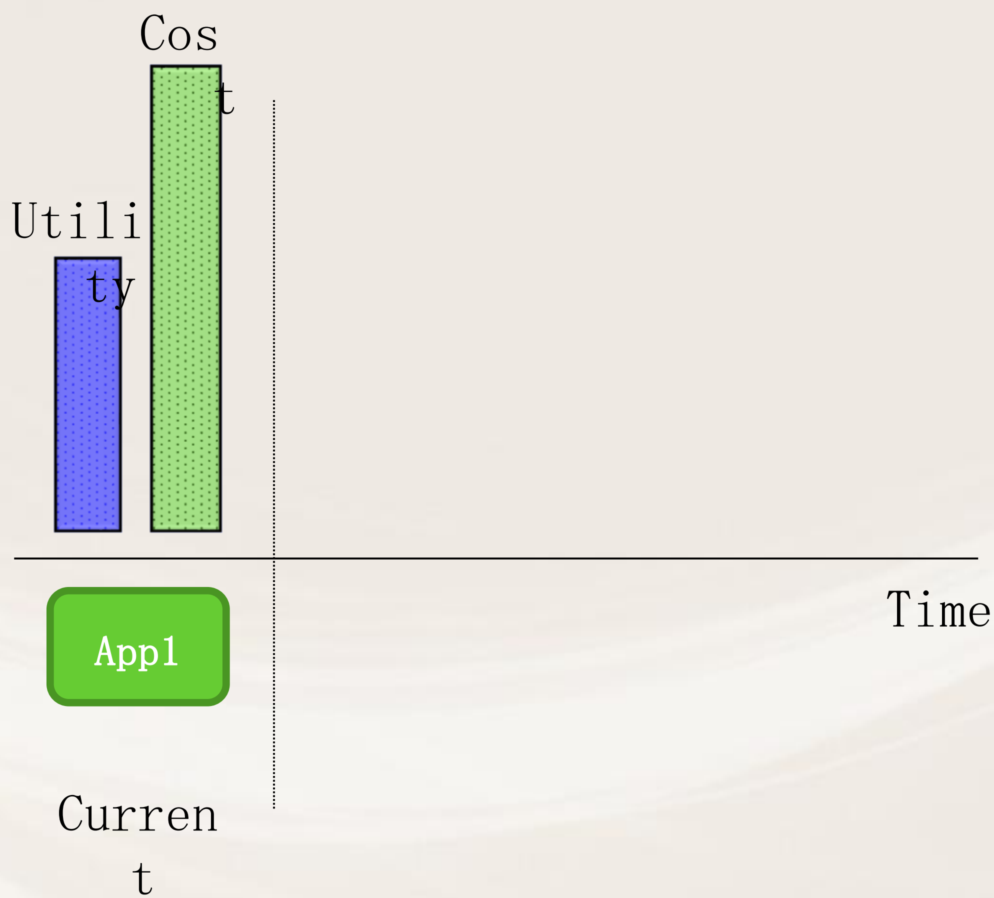
$$f\left(\begin{array}{c}\text{Time}\\ \text{Location}\\ \text{Context}\\ \text{Phone State}\end{array}\right) = \begin{array}{l}\text{Application}\\ \text{App Duration}\end{array}$$

- Online version of Naïve Bayes Model
- Incrementally learn per-user patterns
- Operating with low-cost features

Microsoft Research

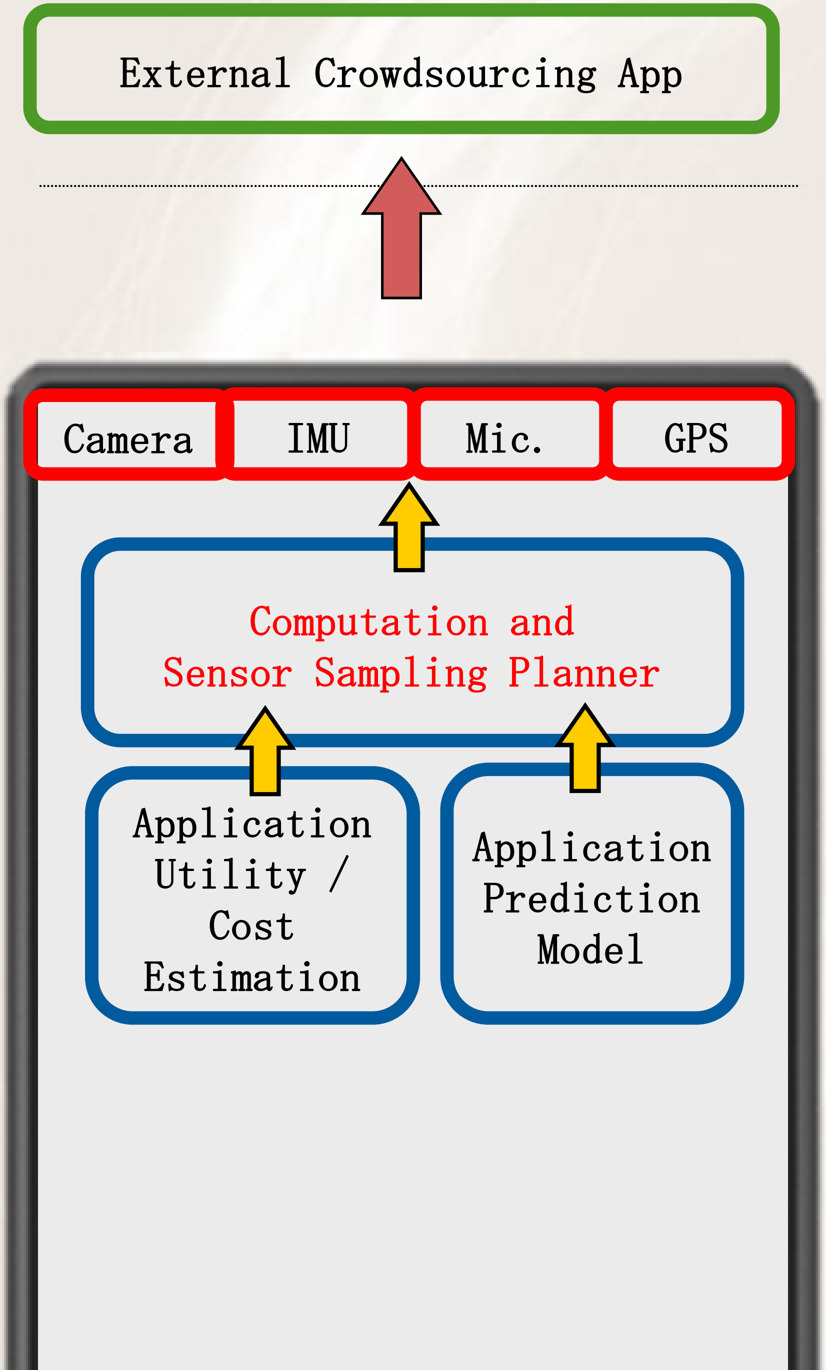
Computation and Sensor Sampling Planner

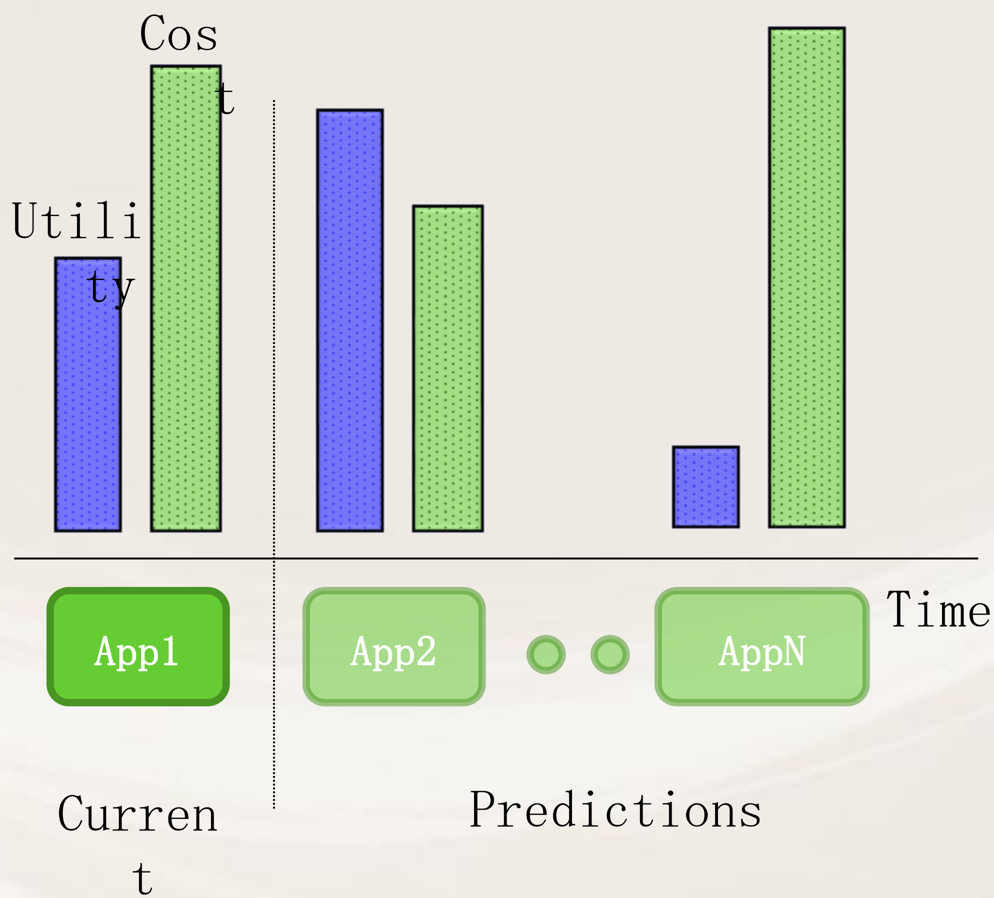




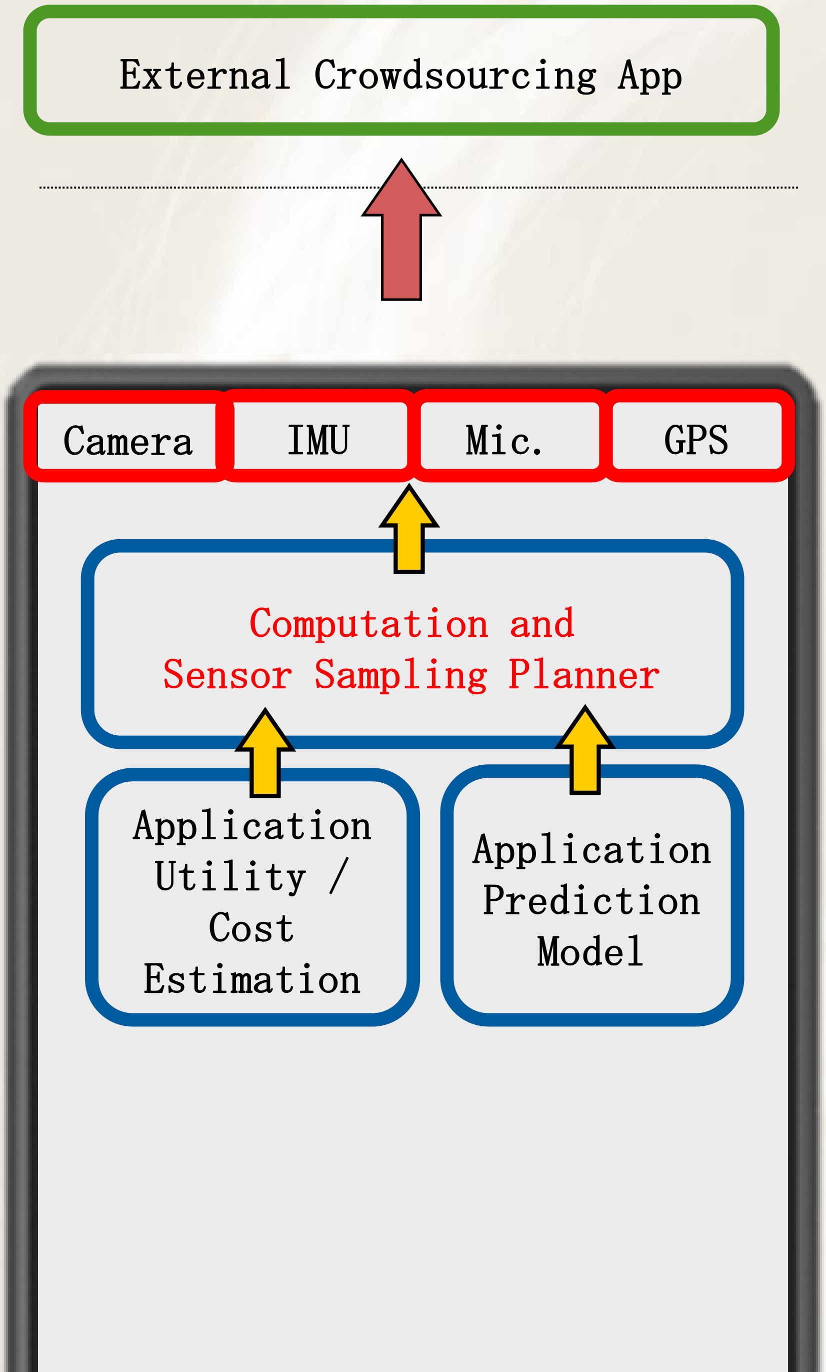
Microsoft Research

Computation and Sensor Sampling Planner

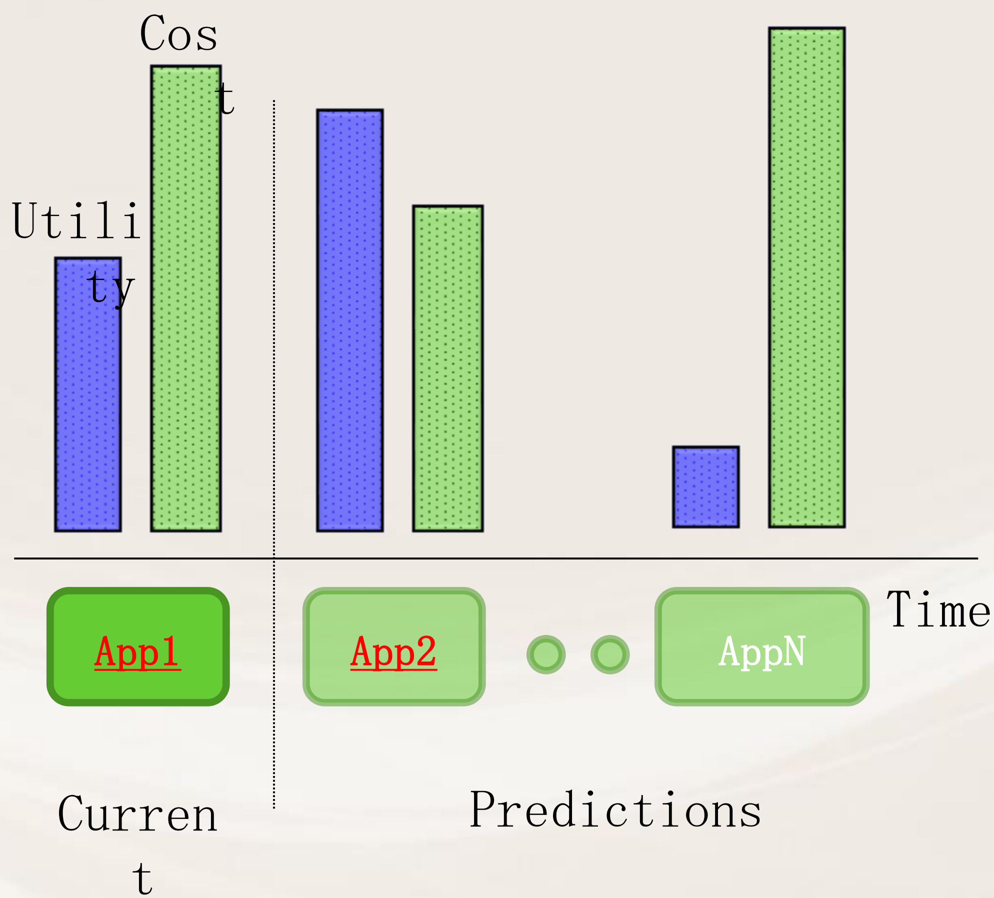




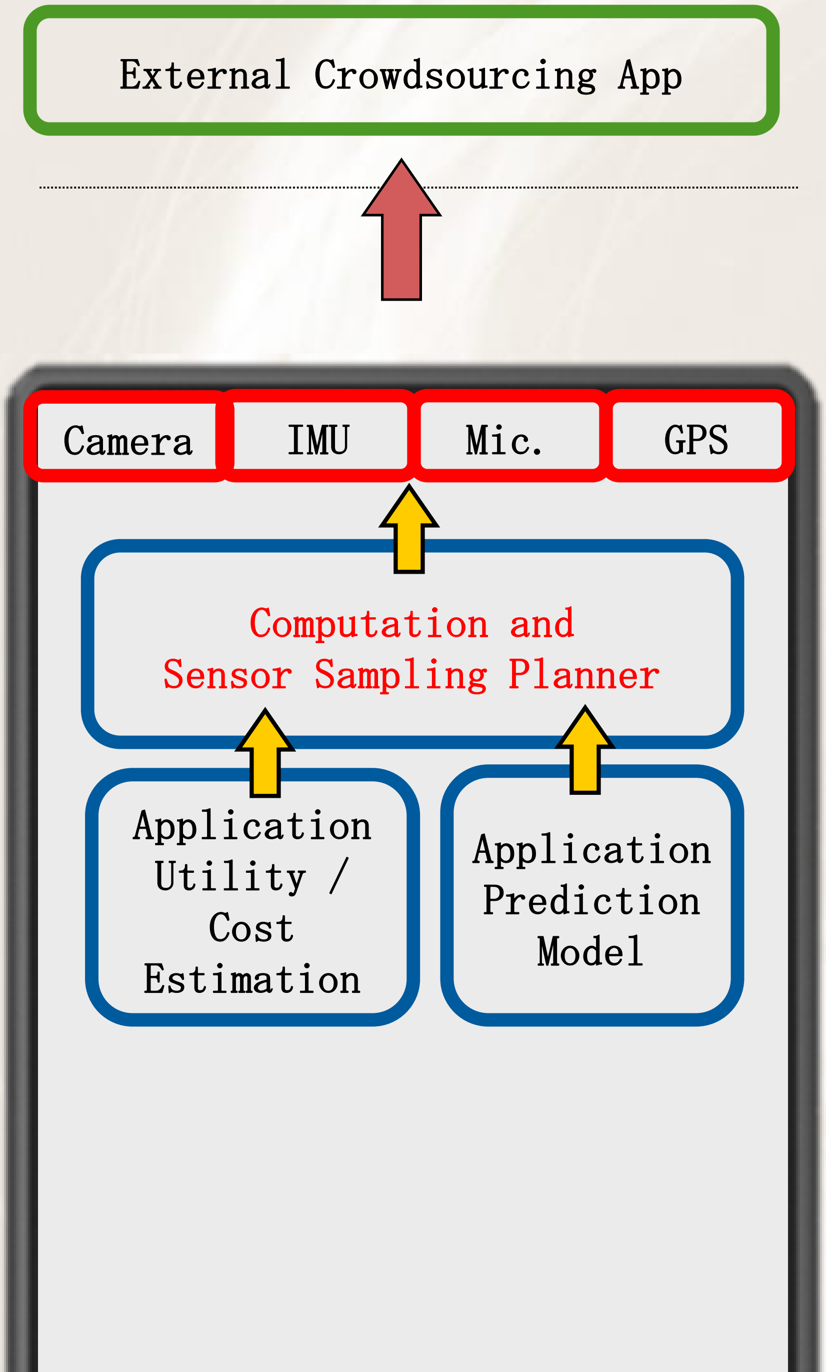
Computation and Sensor Sampling Planner

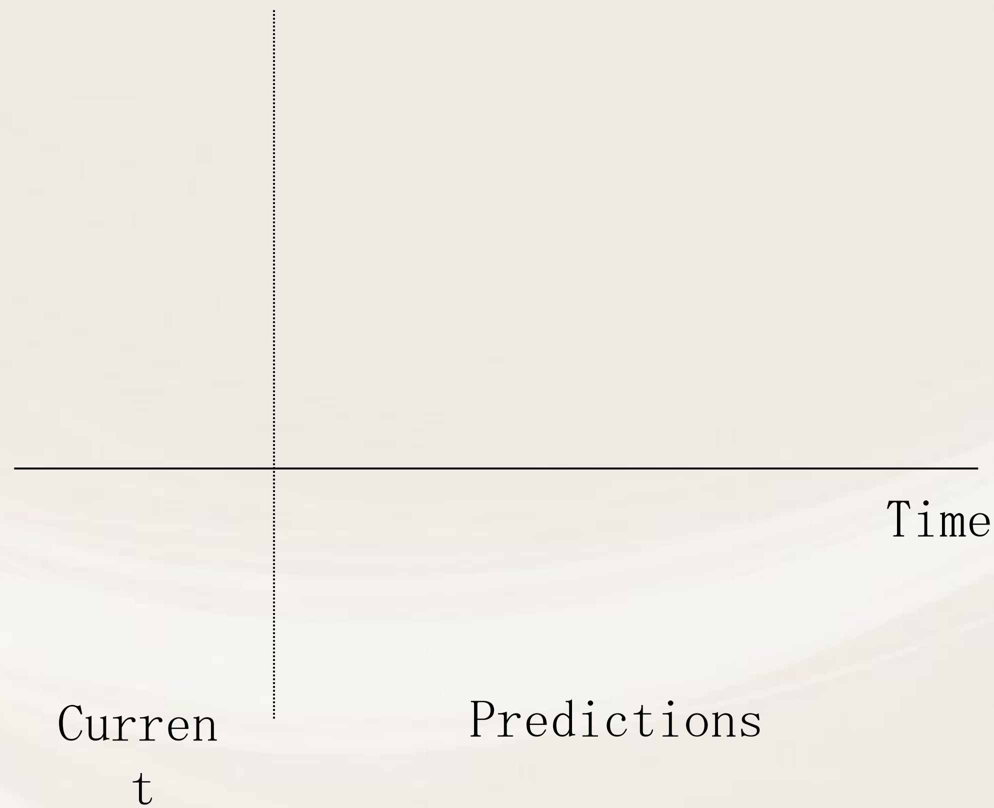


$$\max \sum r_i \, \mu_i \, \lambda_i \, x_i \; - \; d \cdot E[> b | x_i]$$
$$s.t. \; x_i \in \{0, 1\}$$

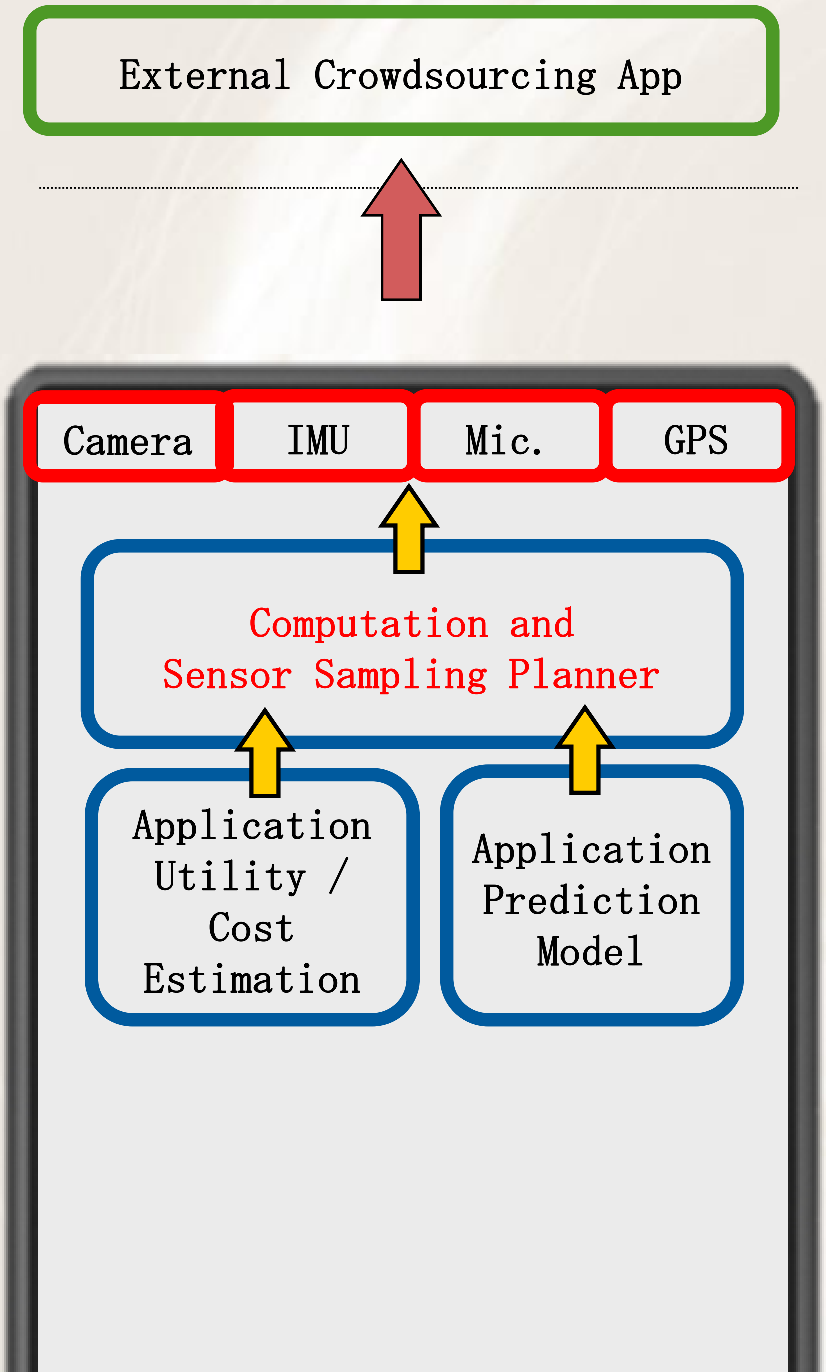


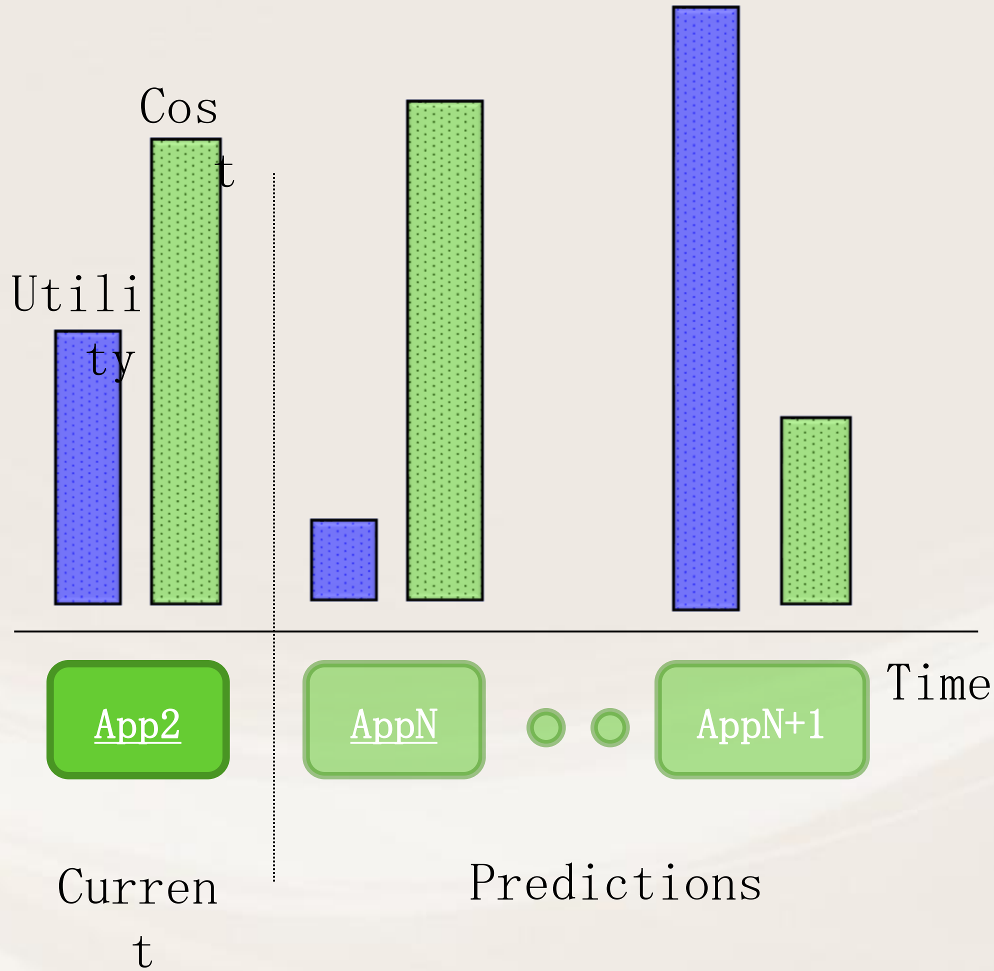
Computation and Sensor Sampling Planner



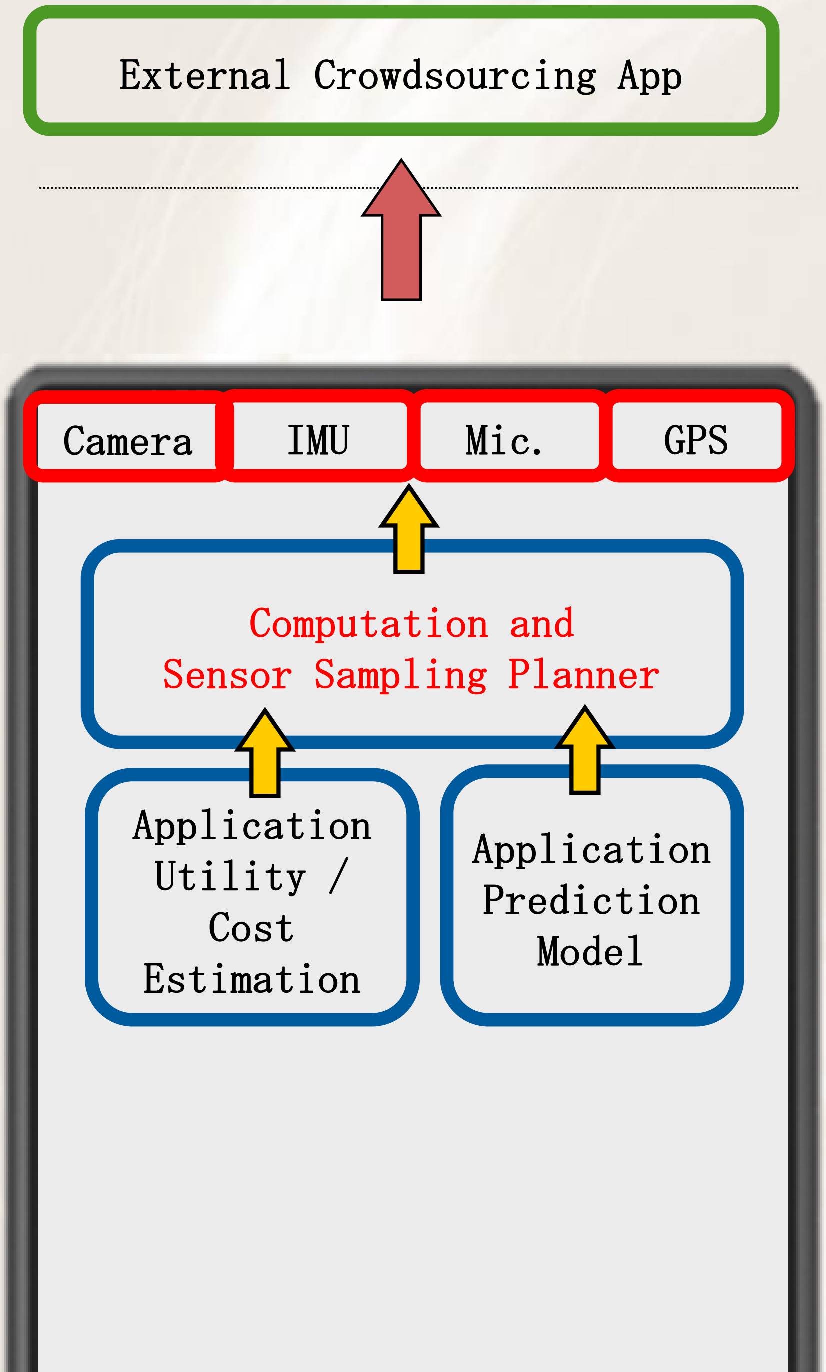


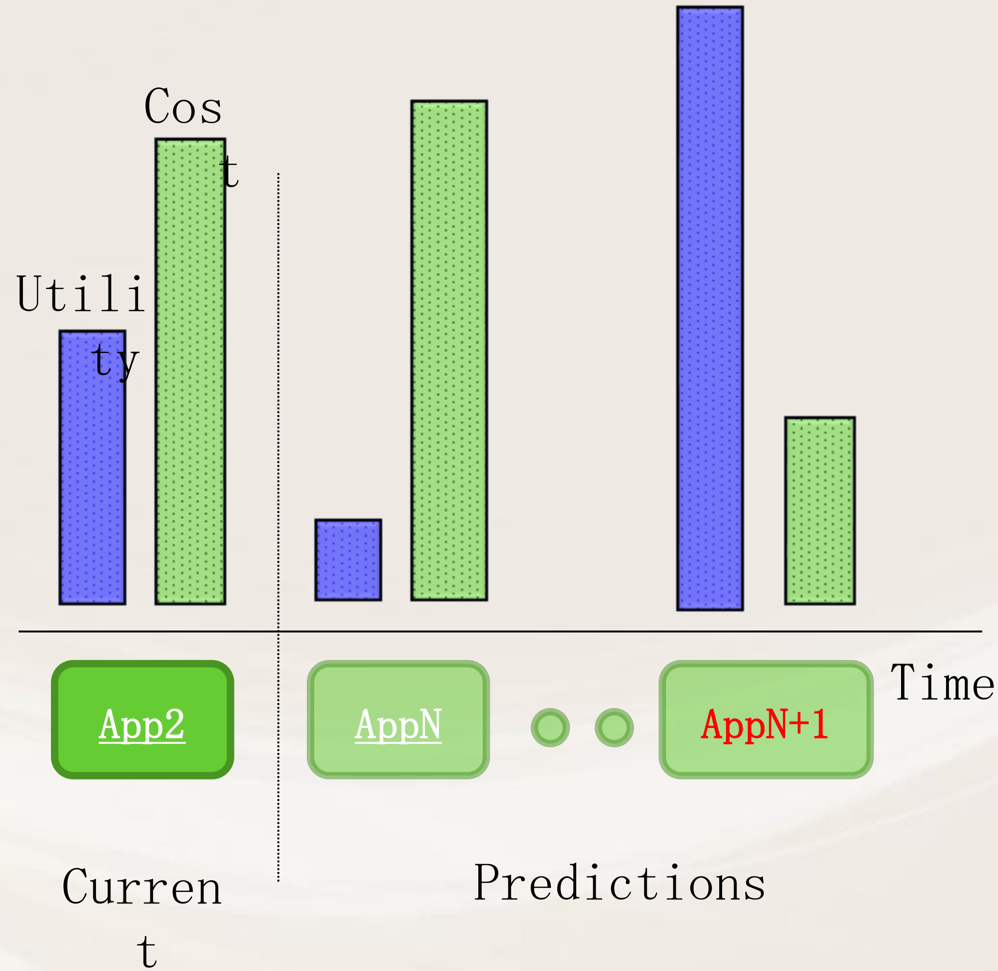
Computation and Sensor Sampling Planner





Computation and Sensor Sampling Planner





Evaluation

Evaluation Methodology

Questions Answered

1. How well can we predict application usage?
2. How much additional data can OCS collect?
    - Comparison to alternative approaches
3. If we embed OCS into an existing Crowdsourcing App – Indoor WiFi mapping – what is performance w.r.t :
    - Energy Saving
    - Impact on Accuracy

Experiment Data

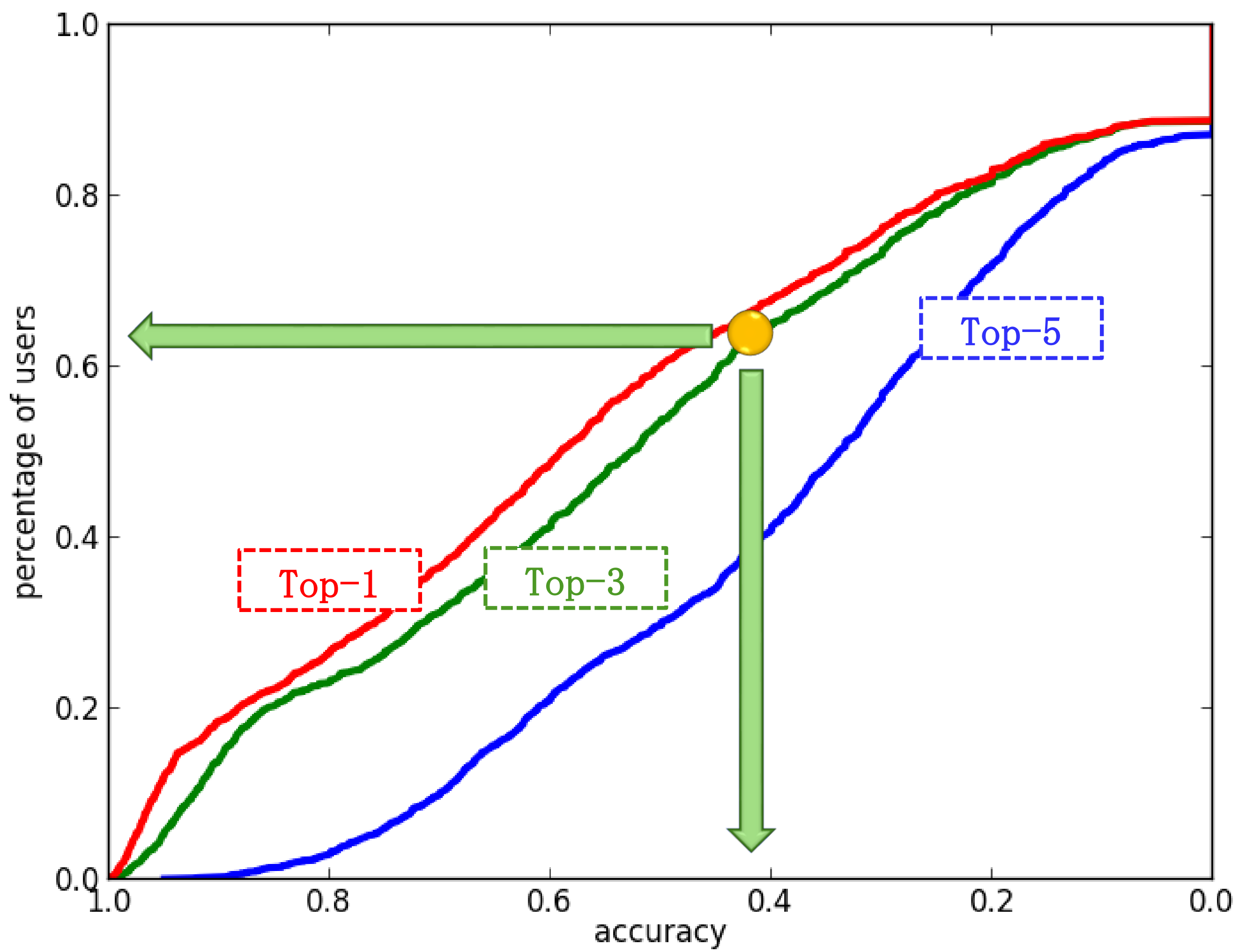
Simulation (questions 1 & 2)

- App Trace of Smartphone Usage – 1320 Users Worldwide [AppJoy Project]
- Fine-grain measurements of App and Sensor energy costs

Case Study (question 3)

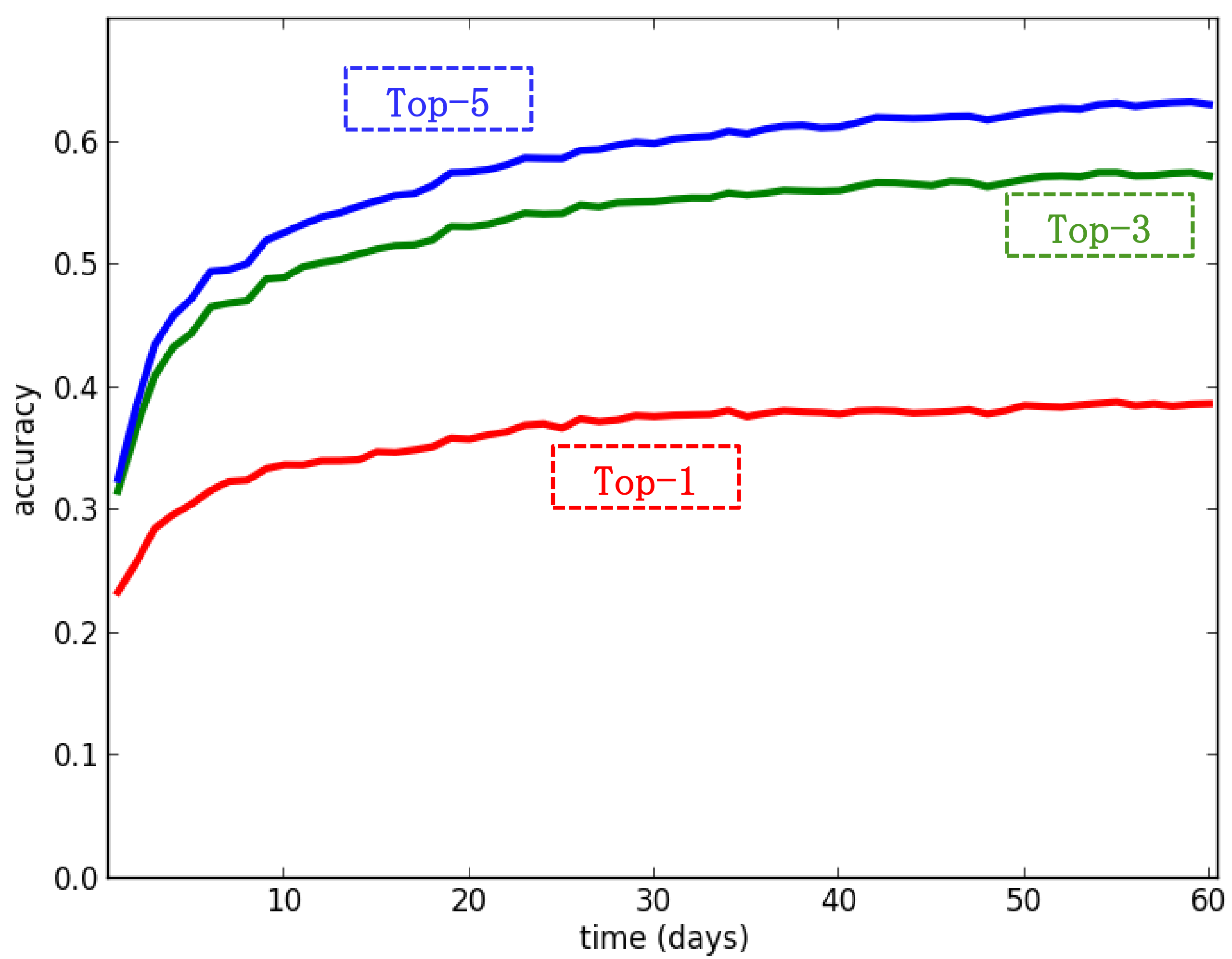
- 20 users – 3 weeks – MSRA building.

Low-cost Online Per-User Prediction of Application Usage



Microsoft Research

Application Prediction Accuracy Improves over Time



Microsoft Research

OCS collects more data across various crowdsourcing scenarios

Energy Budget (% of phone battery)	Periodic 1%	2%
Microphone / Speech Recognition	319%	270%

OCS collects more data across various crowdsourcing scenarios

	Periodic	
Energy Budget *(% of phone battery)*	1%	2%
Microphone / Speech Recognition	319%	270%

Experiment Parameters

- Assumed Fixed Energy Budget (approx. 1 - 2 % of daily battery life)
- Ignores Uploading Cost (assumed to occur overnight during recharge)

OCS collects more data across various crowdsourcing scenarios

Periodic		
Energy Budget *(% of phone battery)*	**1%**	**2%**
Microphone / Speech Recognition	319%	270%
Camera / No computation	145%	167%
GPS / No computation	293%	252%

Experiment Parameters

- Assumed Fixed Energy Budget (approx. 1 - 2 % of daily battery life)
- Ignores Uploading Cost (assumed to occur overnight during recharge)

Microsoft Research

OCS collects more data across various crowdsourcing scenarios

	Periodic		App-Driven	
Energy Budget *(% of phone battery)*	1%	2%	1%	2%
Microphone / Speech Recognition	319%	270%	168%	139%
Camera / No computation	145%	167%	81%	68%
GPS / No computation	293%	252%	53%	43%

Experiment Parameters

- Assumed Fixed Energy Budget (approx. 1 - 2 % of daily battery life)
- Ignores Uploading Cost (assumed to occur overnight during recharge)

Microsoft Research

OCS collects more data across various crowdsourcing scenarios

	Periodic		App-Driven		Context-Driven	
Energy Budget *(% of phone battery)*	1%	2%	1%	2%	1%	2%
Microphone / Speech Recognition	319%	270%	168%	139%	142%	110%
Camera / No computation	145%	167%	81%	68%	73%	68%
GPS / No computation	293%	252%	53%	43%	103%	94%

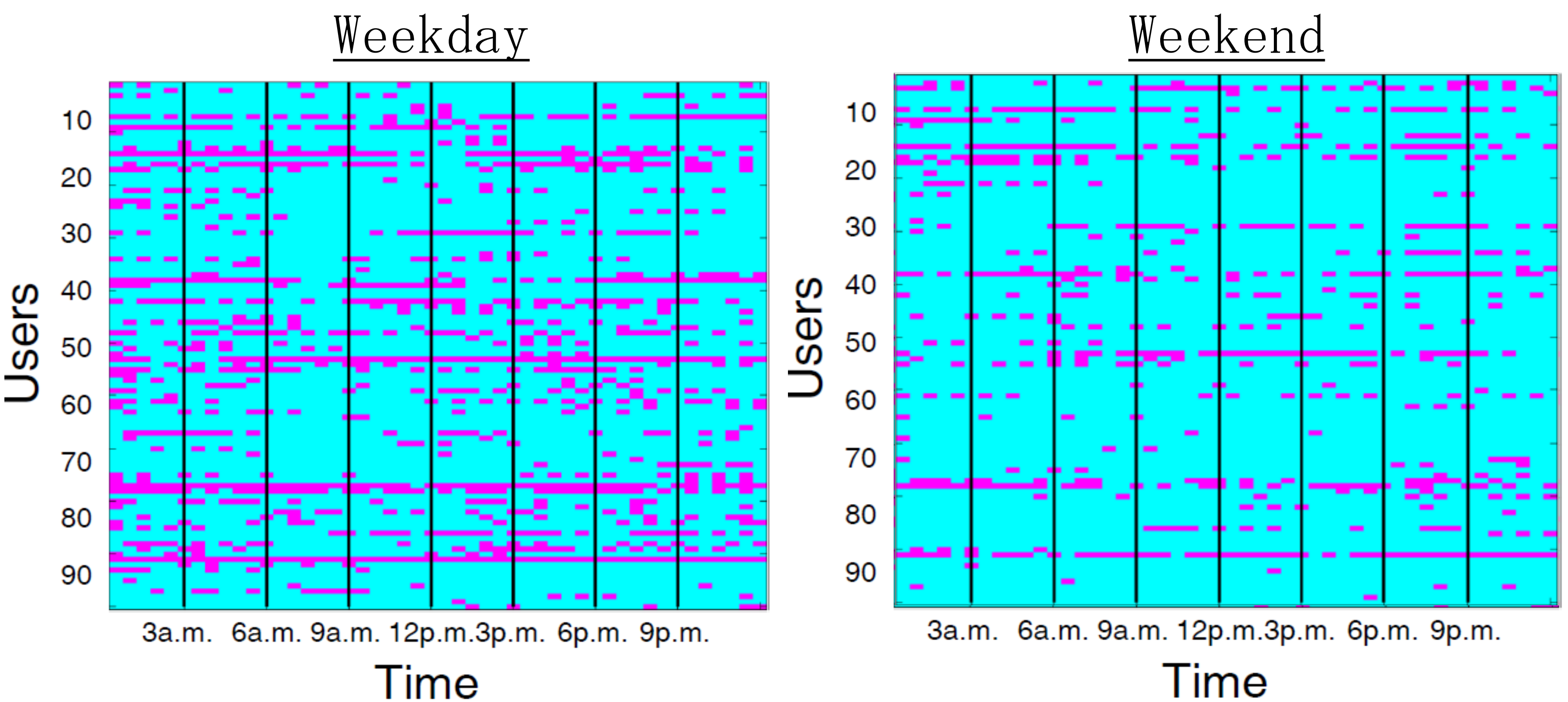
Experiment Parameters

- Assumed Fixed Energy Budget (approx. 1 – 2 % of daily battery life)
- Ignores Uploading Cost (assumed to occur overnight during

On average OCS collects 48% more data across all tested scenarios assuming the same energy budget

Microsoft Research

OCS results in *personalized* Sensing Schedules



OCS maximizes the unique app-usage based opportunities to sense w.r.t to crowdsourcing needs

Research

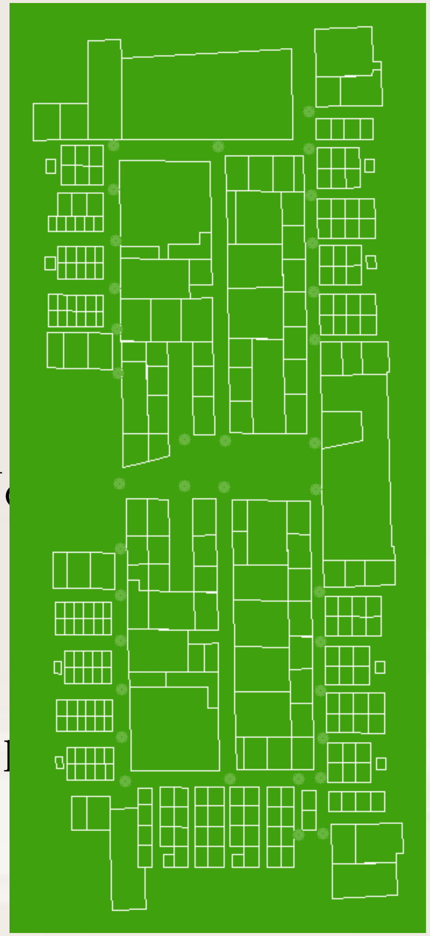
Case Study

Low Energy WiFi Maps for Indoor Localization

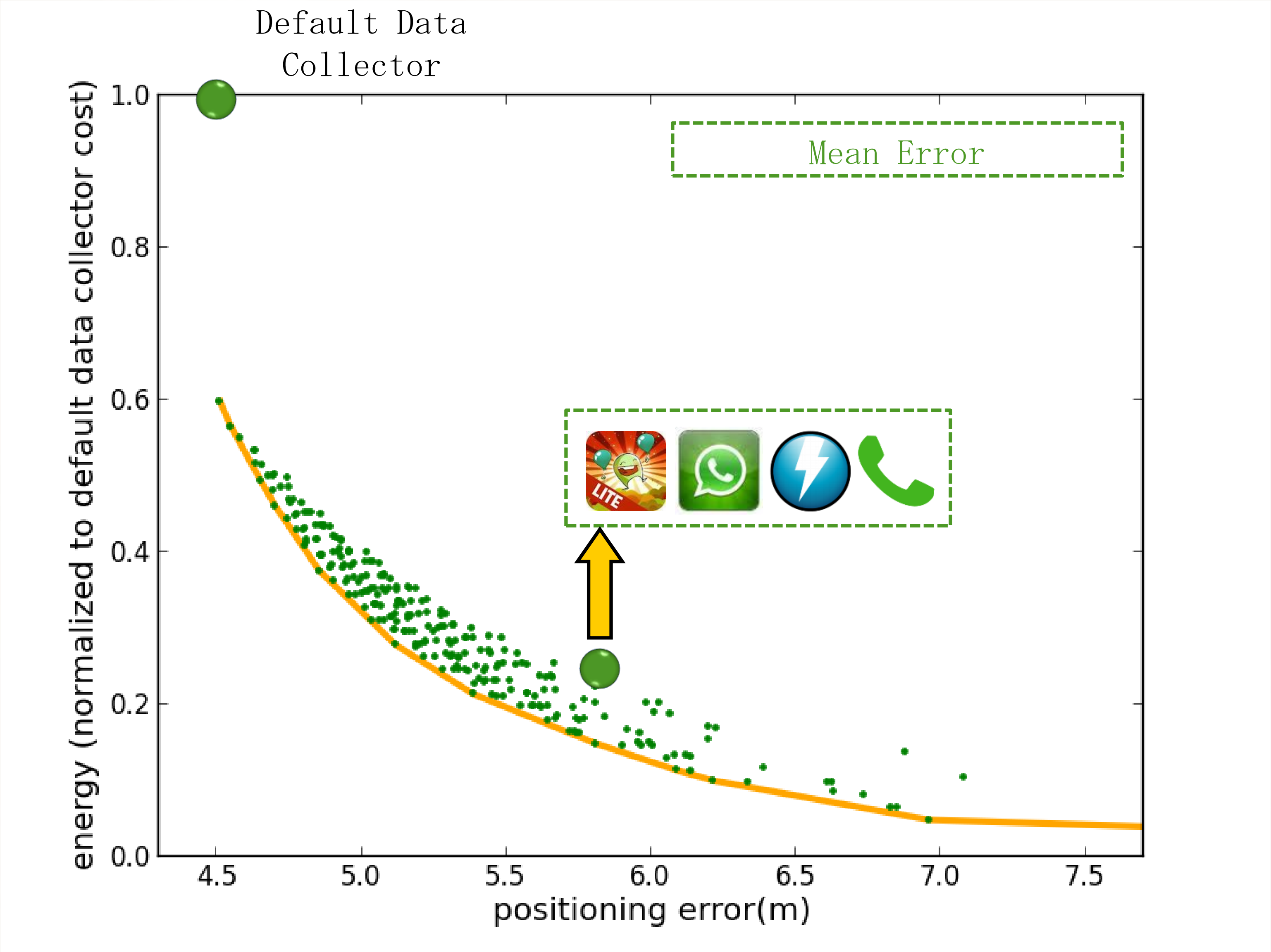
collaboration with Chunshui Zhao and Jacky Shen

Methodology

- 13th floor of MSRA building
- Intern data collection, replicate typical mobility patterns
- Measure sensor quality and cost w.r.t the location accuracy and the default data collection application
- Prediction model trained from large-scale AppJ dataset
- Simplified version of indoor navigation code
  - For example: No personalization
- Ground-truth: Basic corner-detection + IMU ste detection during map construction

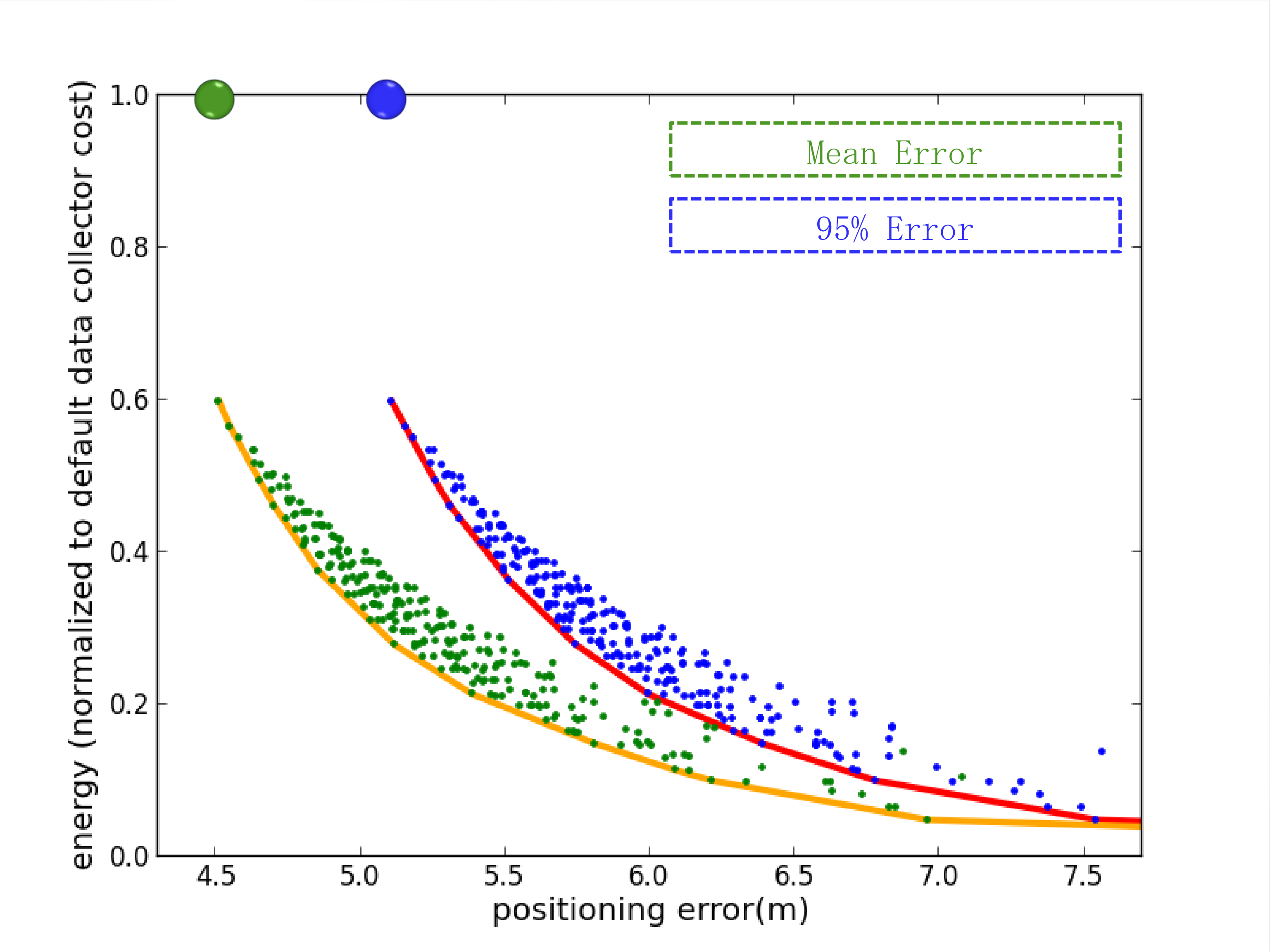


Significant energy savings with acceptable accuracy reductions



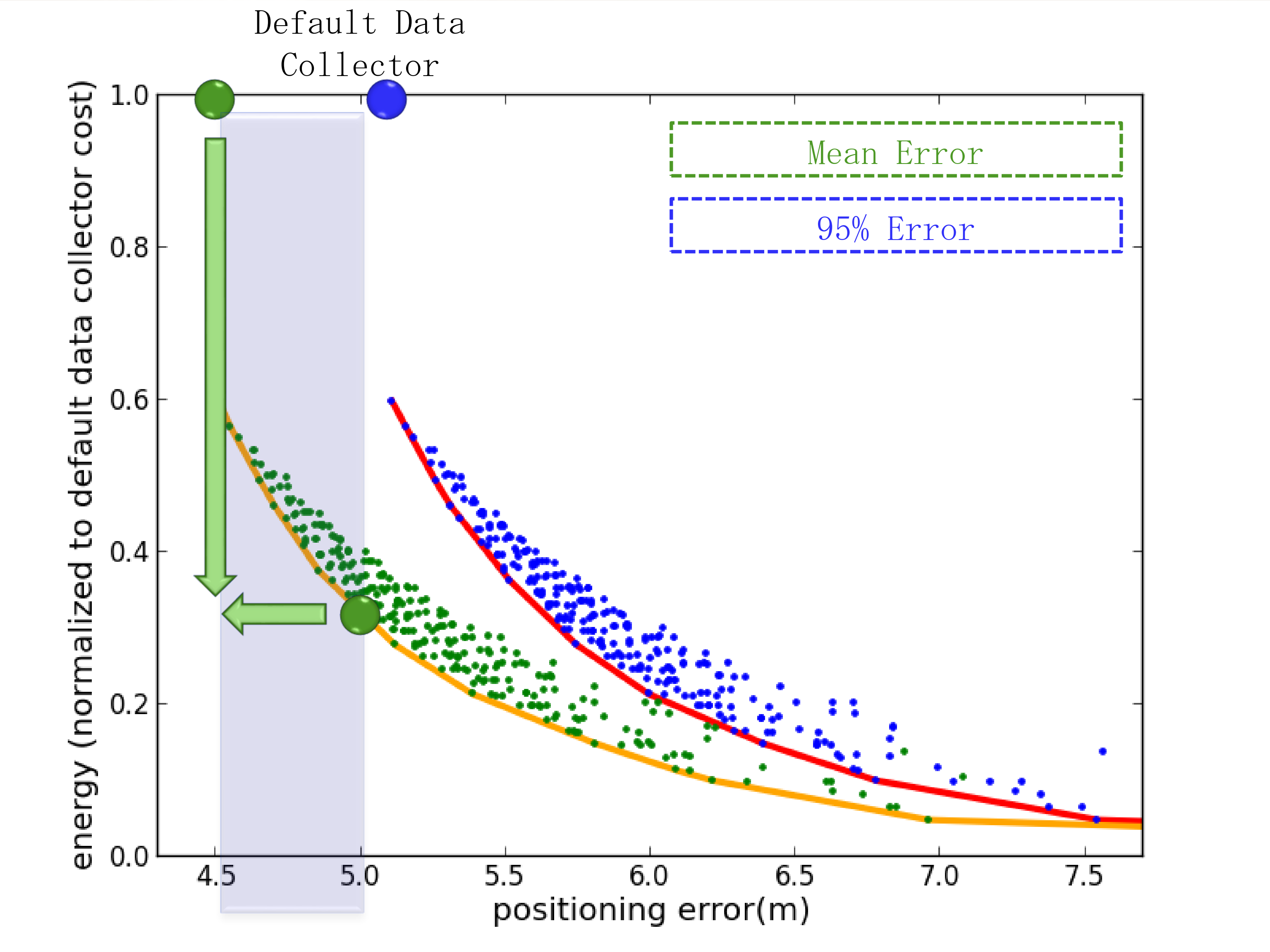
Microsoft Research

Significant energy savings with acceptable accuracy reductions



Microsoft Research

Significant energy savings with acceptable accuracy reductions



Microsoft Research

Conclusion

Low-Energy Opportunistic CrowdSensing

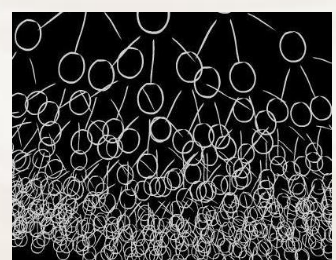
- *Insight:* Low-energy sensing opportunities presented by app usage
- OCS framework provides a sensing decision engine that makes the most of limited app opportunities.
- Systematic evaluation and case study (WiFi localization)

On-going Agenda examining Opportunistic Crowdsensing

Lowering Energy Consumed by Participation

Characterizing Places (F

Understanding Users and Communities



Incentivizing Users to Participate

Microsoft Research