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OpenSense 2 RTD 2013

FNSNF

Adaptive Sampling for Characterizing Sensor Accuracy and Sensor Selection

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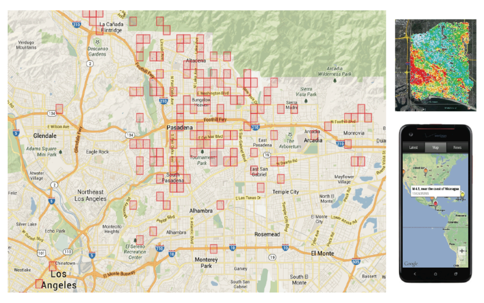
Community Sensing

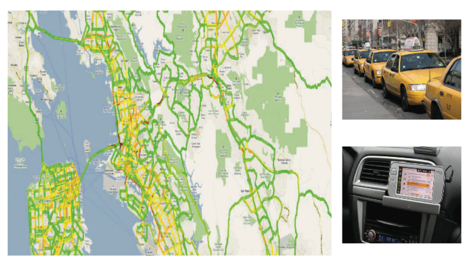
Estimate spatial phenomenon

- Community owned devices
- Low-cost sensors
- Dense sensing network

OpenSense 2:
Air quality monitoring
Lausanne/Zurich



Community Seismic Network (CSN)
Earthquake monitoring
Pasadena, California

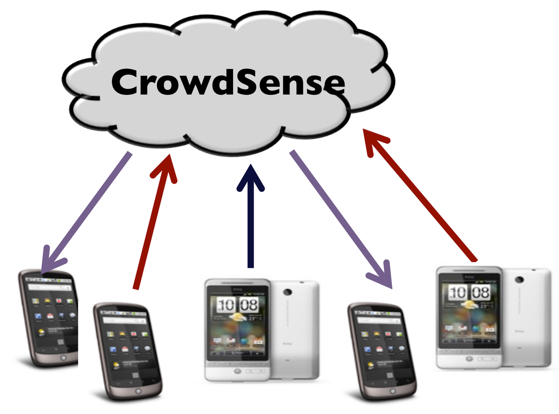


Mobile Millenium:
Traffic monitoring
Berkeley, California

Sensor Selection Problem

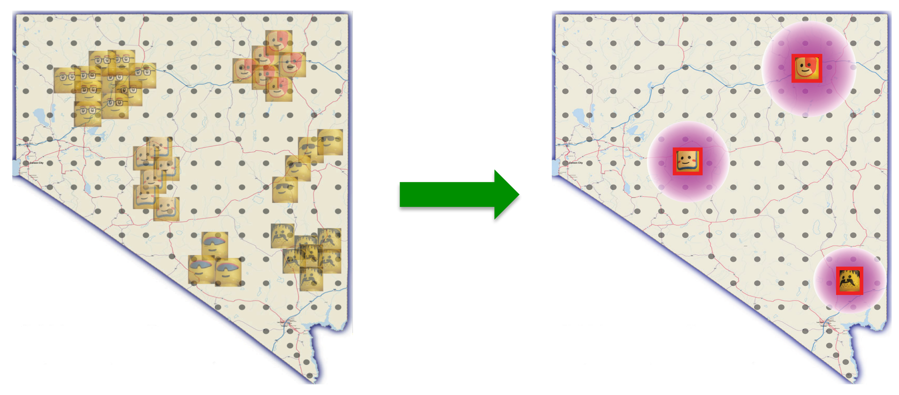
Challenges

- Typical sensors for crowdsensing **can't be continuously monitored**
- Concerns about privacy, bandwidth, energy, etc.
- Heterogeneity and unknown sensors' accuracies



Goal

- Optimally select
  - which sensors to query
  - which data to retrieve
- Balancing utility and sensing cost

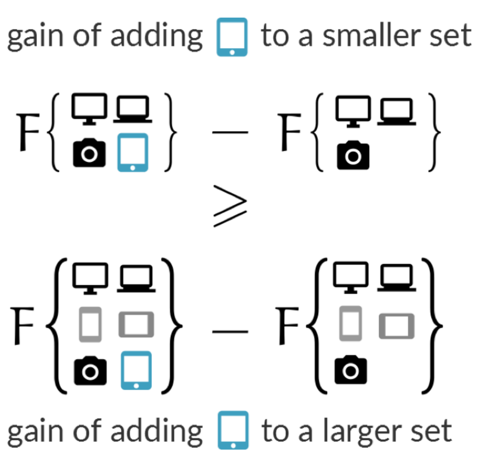


Exploration vs. exploitation tradeoff

Characterizing Sensor Accuracy

When accuracy is known

- Set of sensors V with known accuracy
- Utility of selected sensors $S \subseteq V$ is given by $f(S)$
- f is submodular set function
  - Notion of diminishing returns
  - Captures many complex utility functions
  [Krause and Guestrin'07; Nushi, Singla et al.'15]
- Marginal gain: $f(a|S) = f(S \cup \{a\}) - f(S)$



Realistic settings: Unknown accuracy

- Equivalent to unknown utility function f
- Estimate gain $f(a|S) = f(S \cup \{a\}) - f(S)$ via sampling
- Given noisy estimates, need to select sensors, i.e. compare

$$f(a|S) \text{ vs. } f(b|S)$$

Main research problem addressed

- Provably optimal adaptive sampling techniques for maximizing unknown submodular function [Singla et al. AAAI'16]

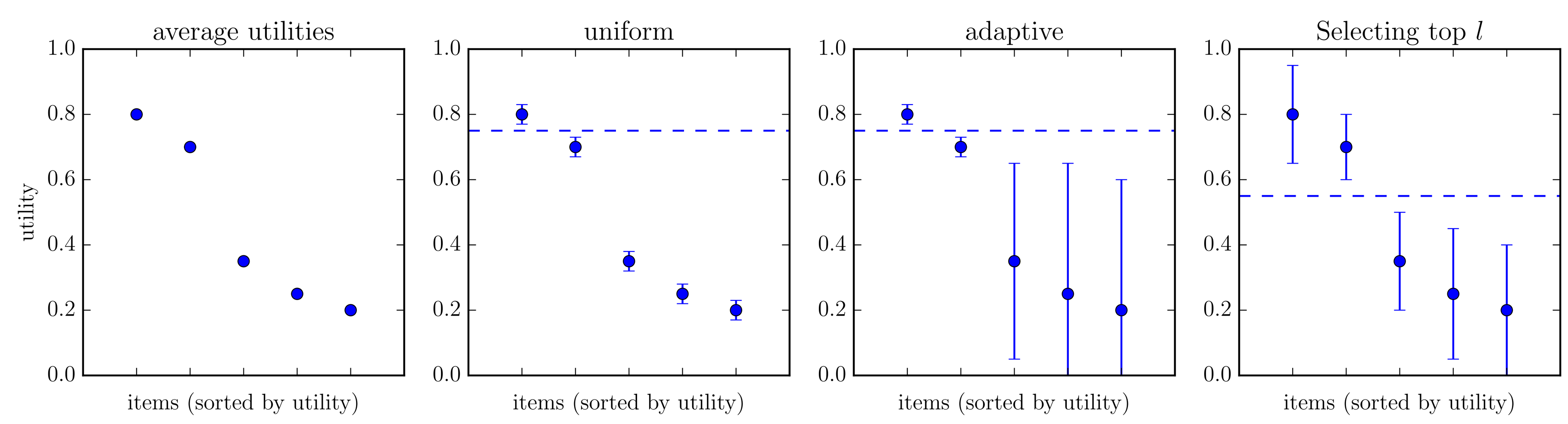
Key Ideas for Adaptive Sampling

Existing approach: Uniform sampling

- Sample all sensors uniformly and non-adaptively
- Estimate $f(a|S)$ up to desired confidence ϵ
- High sample complexity (i.e. the number of queries performed or samples acquired)

Key ideas to reduce sample complexity

- Estimate marginal gains only up to the confidence needed to select next best sensor
- Sufficient to select a sensor from a small subset of top-L best instead of the best sensor (where L is adaptively chosen)



Unknown utilities | NON-ADAPTIVE (Uniform) | ADAPTIVE-BEST (Key Idea#1) | ADAPTIVE-TOP^L (Key Idea#2)

Theoretical Guarantees

Theorem 1 – Utility acquired

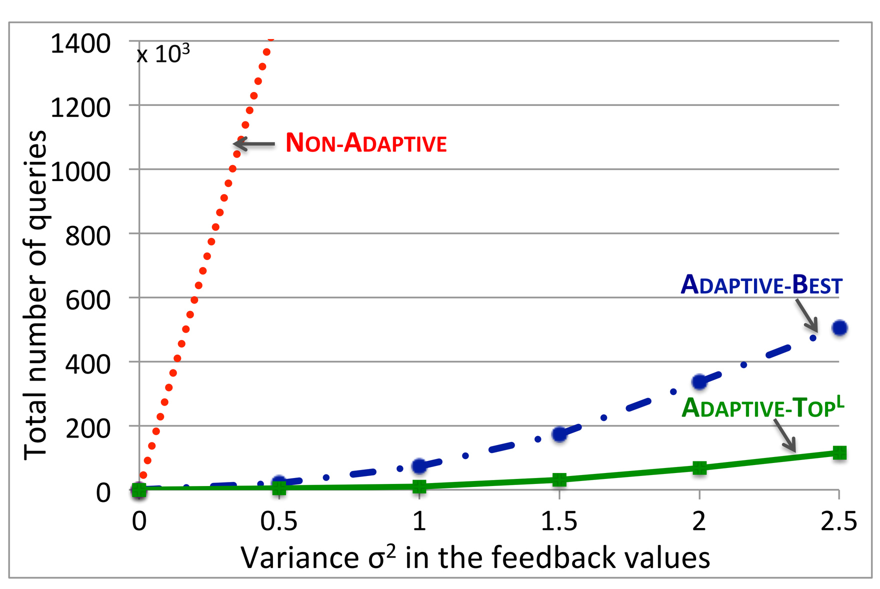
- Tight guarantees (lower bounds) on the utility acquired

Theorem 2 – Sample complexity

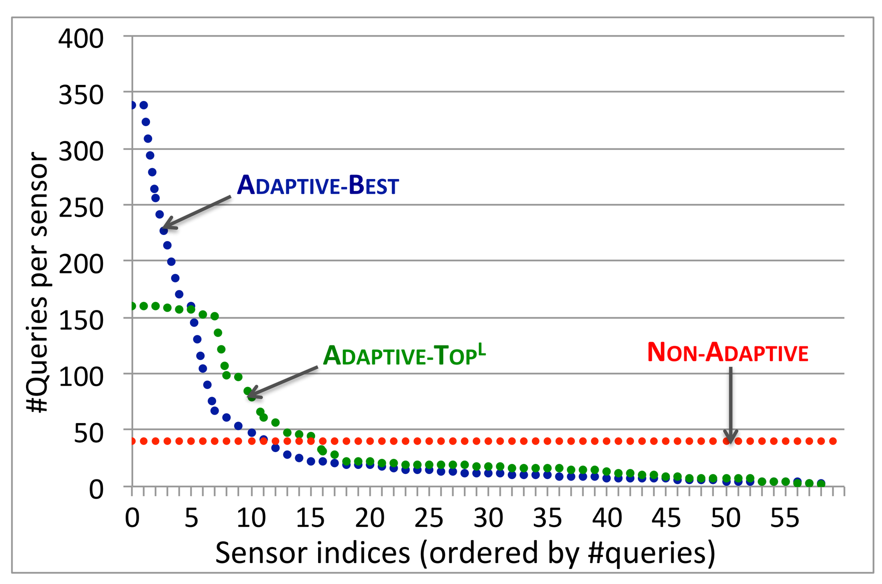
- Tight guarantees (upper bounds) on the sampling cost

Formal statements and technical details in *Singla et al. AAAI'16*

Experimental Results



Sample complexity
(Total number of queries)



Exploration across sensors
(Distribution of queries in one iteration)