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Incentive Mechanisms for Spatio-temporal Tasks in Mobile Crowdsensing

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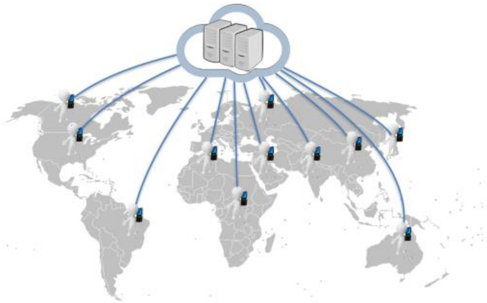
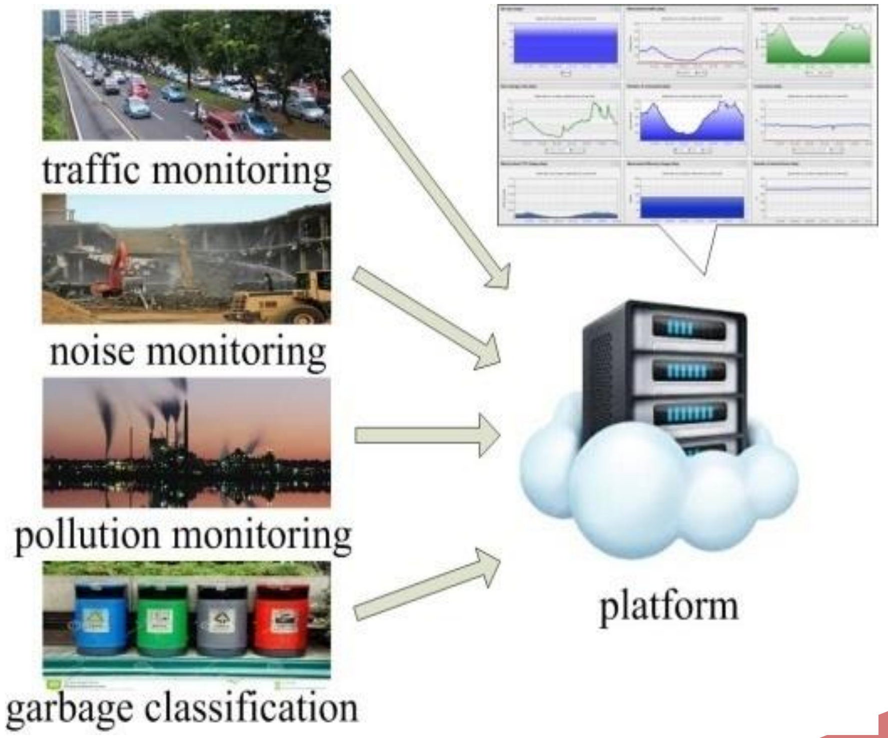
Mobile Crowd Sensing

Digital Compass
Camera
Accelerometer
light sensor





GPS

proximity sensor
Microphone
Gyroscope

Incentive mechanisms for mobile crowd sensing

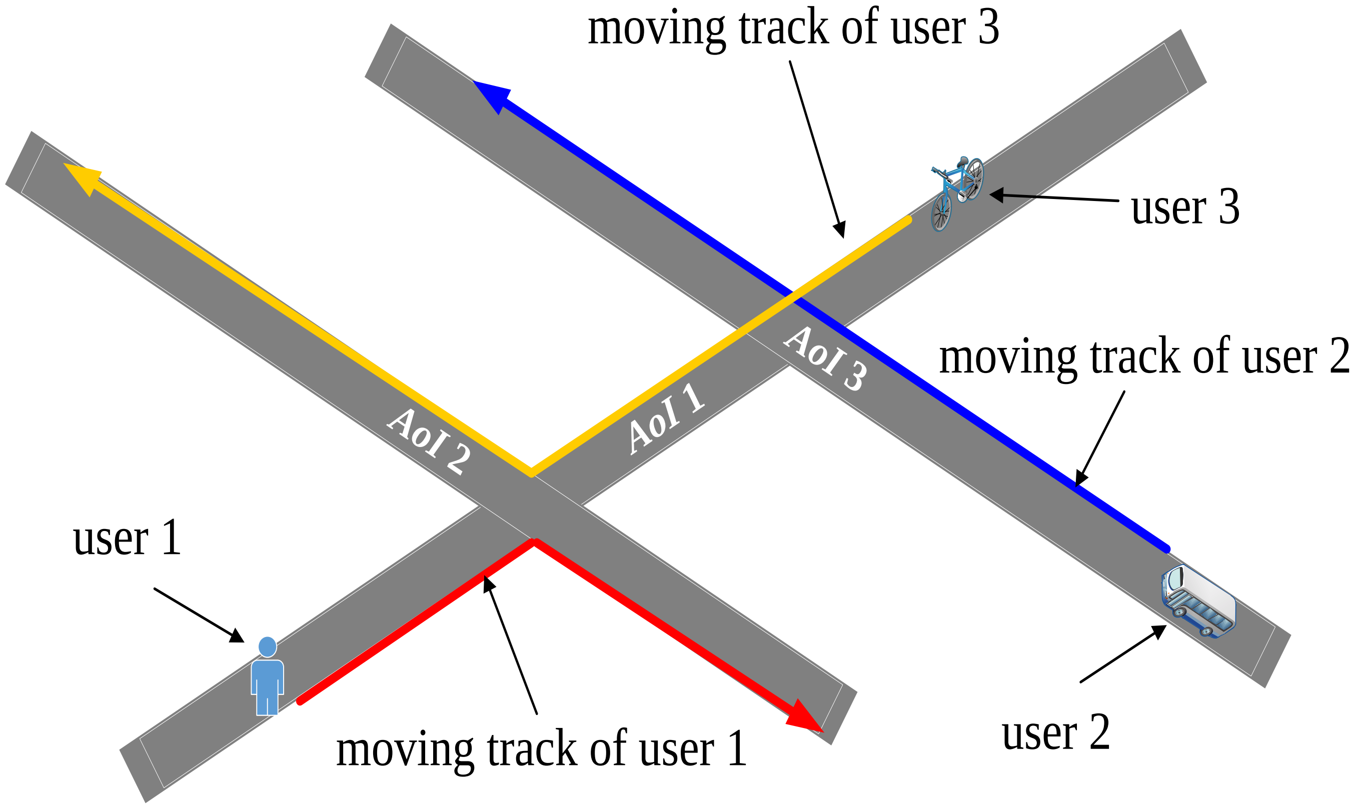
compensate users' cost

help to achieve good service quality

Related Work

- Location dependent task
  - Y. Chon, et al., UbiComp, 2013.
  - Y. Feng, et al., INFOCOM, 2014.
- Time dependent task
  - J. Xu, et al., IEEE Trans. on Wireless Communications, 2015.
  - K. Han, et al., IEEE Trans. on Computers, 2016.
  - J. Xu, et al., Wireless Networks, 2017.
- Spatio-temporal tasks without overlap
  - Q. Li, et al., PerCom, 2013.
  - Z. Wang, et al., Computer Networks, 2018.

A Motivating Example of Spatio-temporal Tasks



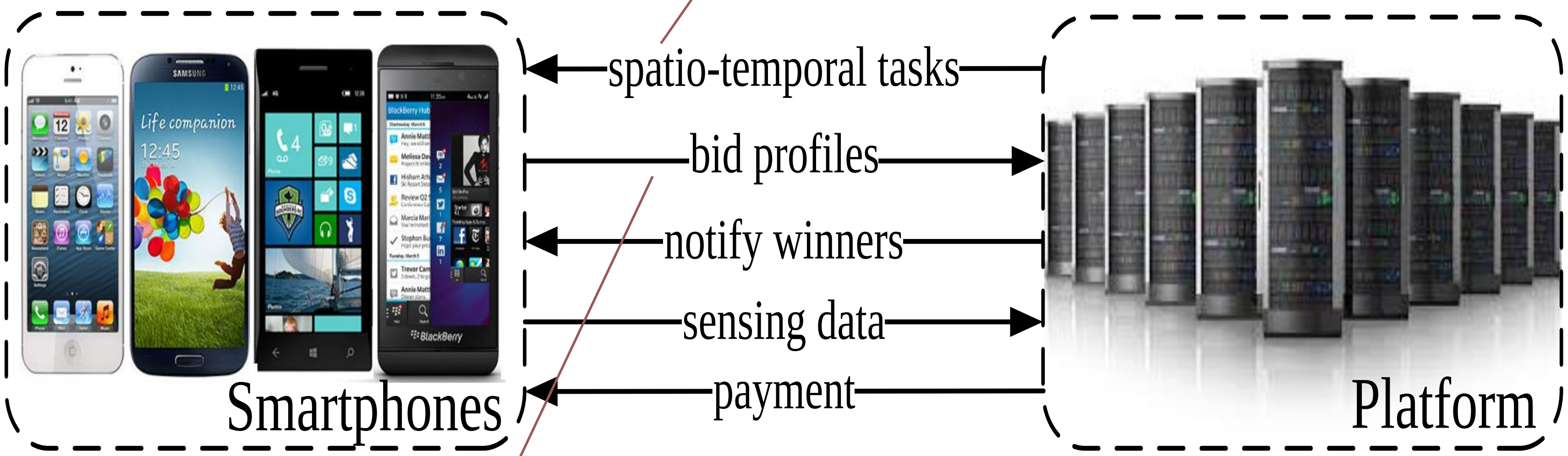
Spatio-temporal Tasks for Traffic Monitoring

Two Features:

- the sensing areas of tasks can have overlaps
- the collective sensing time for each task needs to meet the specified time duration

Reverse Auction Framework

(t^j, a^j)



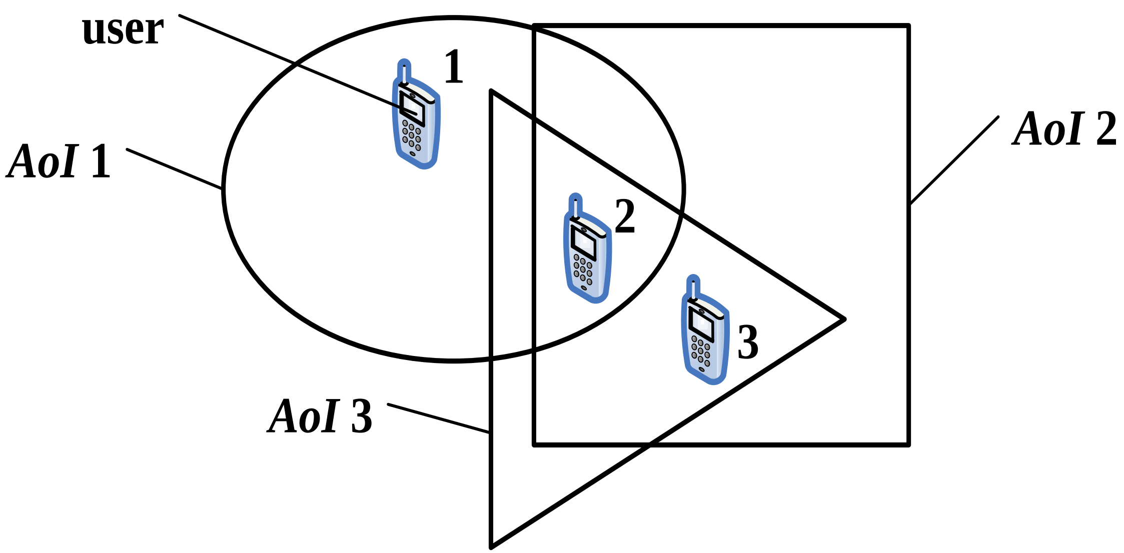
(t_i, l_i, b_i)

Challenges

- How to determine the value of sensing data provided by such users who can contribute for multiple tasks simultaneously?
- How to allocate the sensing time of the mobile users for their sensing areas?
- How to prevent the strategic behavior by submitting dishonest bidding price?

Location Sensitive Model

***Location Sensitive Social Optimization* (*LSSO*) problem**



Objective: $\min \sum_{i \in S} c_i$

Subject to: $\sum_{i \in U^j} t_i \geq t^j, \forall \tau_j \in \Gamma$

The *LSSO* problem is NP-hard since it is the Multi-set Multi-cover problem

Incentive Mechanism for Location Sensitive Model (MLS)

The effective average cost of user *i*

$$\frac{b_i}{\sum_{\tau_j \in \Gamma_i} \min\{t_i, t'^j\}}$$

Phase1: winner selection

while $\sum_{\tau_j \in \Gamma} t'^j \neq 0$ **do**

$\quad i \leftarrow \arg\min_{h \in U \setminus S} \frac{b_h}{\sum_{\tau_j \in \Gamma_h} \min\{t_h, t'^j\}}$;

$\quad S \leftarrow S \cup \{i\}$;

$\quad$ **foreach** $\tau_j \in \Gamma_i$ **do** $t'^j \leftarrow t'^j - \min\{t_i, t'^j\}$;

end

select the user with minimum effective average cost over the unselected user set as the winner until the winners' sensing time can meet the requirement of minimum sensing time of each task.

Incentive Mechanism for Location Sensitive Model (MLS)

Phase2: payment determination

execute the winner selection phase over $U\backslash\{i\}$, and the winner set is denoted by S'.

compute the maximum price that user can be selected instead of each user in S'.

foreach $i \in S$ **do**
$U' \leftarrow U\backslash\{i\}, S' \leftarrow \emptyset, t''^j \leftarrow t^j$;
while $\sum_{\tau_j \in \Gamma} t''^j \neq 0$ **do**
$i_h \leftarrow \arg\min_{h \in U' \backslash S'} \frac{b_h}{\sum_{\tau_j \in \Gamma_h} \min\{t_h, t''^j\}}$;
$S' \leftarrow S' \cup \{i_h\}$;
$p_i \leftarrow \max\{p_i, \frac{\sum_{\tau_j \in \Gamma_i} \min\{t_i, t''^j\}}{\sum_{\tau_j \in \Gamma_{i_h}} \min\{t_{i_h}, t''^j\}} b_{i_h}\}$;
foreach $\tau_j \in \Gamma_{i_h}$ **do** $t''^j \leftarrow t''^j - \min\{t_{i_h}, t''^j\}$;
end
end

Theoretical Analysis of MLS

Lemma 1. ***MLS is computationally efficient***

$O(n^3\varepsilon)$, ε is the maximum of overlaps of *AoIs*

Lemma 2. ***MLS is individually rational.***

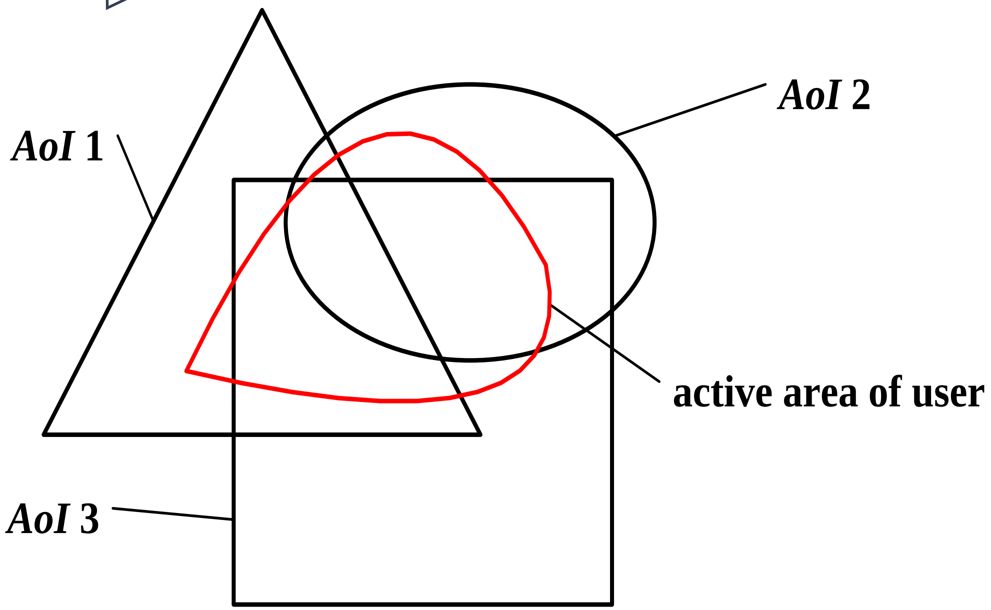
Each winner will have a nonnegative utility while bidding its true cost.

Lemma 3. ***MLS is truthful***

No user can improve its utility by submitting a false cost, no matter what others submit.

Lemma 4. ***MLS can approximate the optimal solution within a factor of*** H_K, ***where*** $K = \max_{i \in U} \sum_{\tau_j \in \Gamma_i} \min\{t_i, t^j\}$, $H_K = 1 + \frac{1}{2} + \cdots + \frac{1}{K}$.

Location Insensitive Model



Let $SA_i = \{sa_{i,1}, sa_{i,2}, \ldots, sa_{i,2^{|\Gamma_i|}-1}\}$ be the set of sensing areas of user *i*.

Let $tsa_{i,k}$ be the sensing time of user *i* allocated in sensing area $sa_{i,k}$

Location Insensitive Social Optimization **(*LISO*) problem**

Objective: $\min \sum_{i \in S} c_i$

Subject to: $\sum_{i \in U, sa_{i,k} \cap a^j \neq \emptyset} tsa_{i,k} \geq t^j, \forall \tau_j \in \Gamma$

The *LISO* problem is NP-hard since the *LISO* problem is a generalization of the *LSSO* problem.

Incentive Mechanism for Location Insensitive Model (MLI)

The effective average cost of user *i*

$$\frac{b_i}{\sum_{\tau_j \in \Gamma_i} \sum_{k: sa_{i,k} \cap a^j \neq \emptyset} (tsa_{i,k} \cdot |sa_{i,k}|)}$$

Phase1: winner selection

while $\sum_{\tau_j \in \Gamma} t'^j \neq 0$ **do**

$\quad$ **TSA** $\leftarrow$ **Allocation**$(\Gamma, U \backslash S, \mathbf{B}, \{t'^1, t'^2, \dots, t'^m\})$;

$\quad$ $i \leftarrow \arg\min_{h \in U \backslash S} \frac{b_h}{\sum_{\tau_j \in \Gamma_h} \sum_{k: sa_{h,k} \cap a^j \neq \emptyset} (tsa_{h,k} \cdot |(sa_{h,k}|)}$;

$\quad$ $S \leftarrow S \cup \{i\}$;

$\quad$ **foreach** $\tau_j \in \Gamma_i$ **do** $t'^j \leftarrow t'^j - \sum_{k: sa_{h,k} \cap a^j \neq \emptyset} tsa_{h,k}$;

end

calculate the sensing time for each area by calling function Allocation$(\cdot)$ for each user

Incentive Mechanism for Location Insensitive Model (MLI)

calculate the sensing time allocation matrix

select the sensing areas with most overlaps of AoIs

select the task with minimum residual sensing time of all tasks overlapping the selected sensing area

calculate the minimum value of this two time

foreach $i \in U''$ **do**

$\quad t'_i \leftarrow t_i;\ SA'_i \leftarrow SA_i;\ \{\overline{t'^1}, \overline{t'^2}, \ldots, \overline{t'^m}\} \leftarrow \mathcal{R};$

$\quad$ **while** $t'_i > 0$ **and** $SA'_i \neq \emptyset$ **do**

$\quad\quad k \leftarrow \arg\max_{k: sa_{i,k'} \in SA'_i} |sa_{i,k'}|;$

$\quad\quad j \leftarrow \arg\min_{j': a^{j'} \cap sa_{i,k} \neq \emptyset} \overline{t'^{j'}};$

$\quad\quad tsa_{i,k} \leftarrow \min\{\overline{t'^j},\ t'_i\};$

$\quad\quad t'_i \leftarrow t'_i - tsa_{i,k};$

$\quad\quad SA'_i \leftarrow SA'_i \backslash \{sa_{i,k}\};$

$\quad\quad$ **foreach** $\tau_j \in \Gamma_i$ s.t. $a^j \cap sa_{i,k} \neq \emptyset$ **do**

$\quad\quad\quad \overline{t'^j} \leftarrow \overline{t'^j} - tsa_{i,k};$

$\quad\quad$ **end**

$\quad$ **end**

end

Incentive Mechanism for Location Insensitive Model (MLI)

Phase2: payment determination

execute the winner selection phase over $U\backslash\{i\}$, and the winner set is denoted by S'.

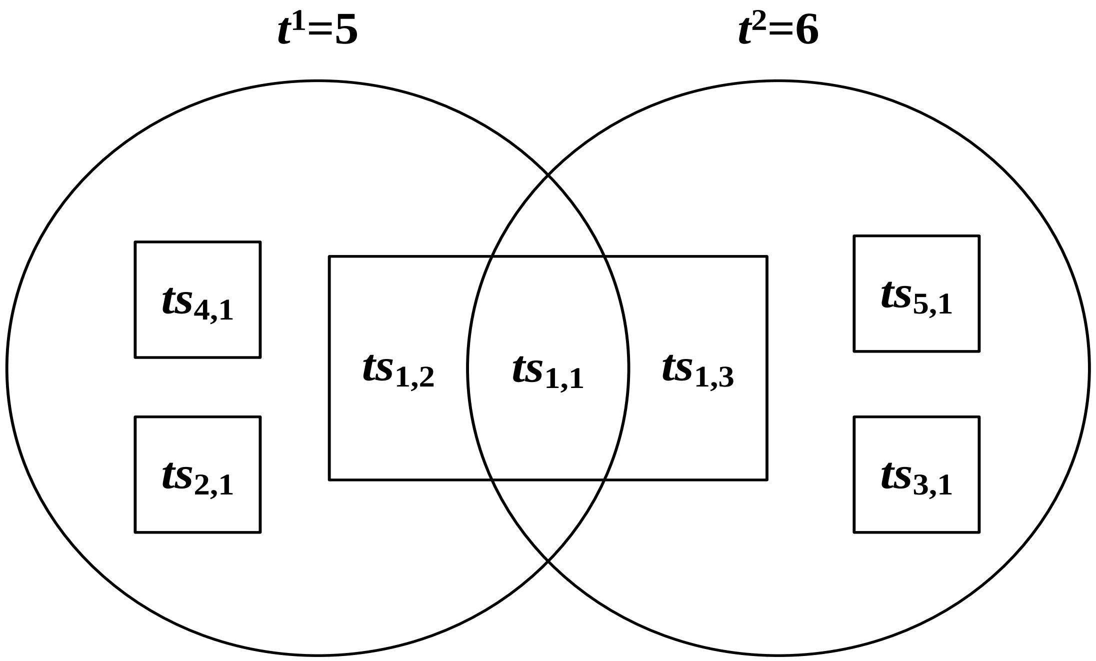
compute the maximum price that user can be selected instead of each user in S'.

foreach $i \in S$ **do**
  $U' \leftarrow U\backslash\{i\}, S' \leftarrow \emptyset, t''^j \leftarrow t^j$;
  while $\sum_{\tau_j \in \Gamma} t''^j \neq 0$ **do**
    $\mathbf{TSA}' \leftarrow \text{Allocation}(\Gamma, U'\backslash S', \mathbf{B}, \{t''^1, t''^2, \ldots, t''^m\})$;
    $i_h \leftarrow \arg\min_{h \in U'\backslash S'} \frac{b_h}{\sum_{\tau_j \in \Gamma_h} \sum_{k: sa_{h,k} \cap a^j \neq \emptyset} (tsa'_{h,k} \cdot |(sa_{h,k}|)}$;
    $S' \leftarrow S' \cup \{i_h\}$;
    $p_i \leftarrow \max\{p_i, \frac{\sum_{\tau_j \in \Gamma_i} \sum_{k: sa_{i,k} \cap a^j \neq \emptyset} tsa'_{i,k}}{\sum_{\tau_j \in \Gamma_{i_h}} \sum_{k: sa_{i_h,k} \cap a^j \neq \emptyset} tsa'_{i_h,k}} b_{i_h}\}$;
    foreach $\tau_j \in \Gamma_{i_h}$ **do**
      $t''^j \leftarrow t''^j - \sum_{k: sa_{i_h,k} \cap a^j \neq \emptyset} tsa'_{i_h,k}$;
    end
  end
end

Theoretical Analysis of MLI

MLI is computationally efficient, individually rational, truthful, and H_K ***approximate, where*** $K = \max_{i \in U} \sum_{\tau_j \in \Gamma_i} \sum_{k: sa_{i,k} \cap a^j \neq \emptyset} (tsa_{i,k} \cdot |(sa_{i,k}|)$.

A Toy Example for Winner Selection of MLI



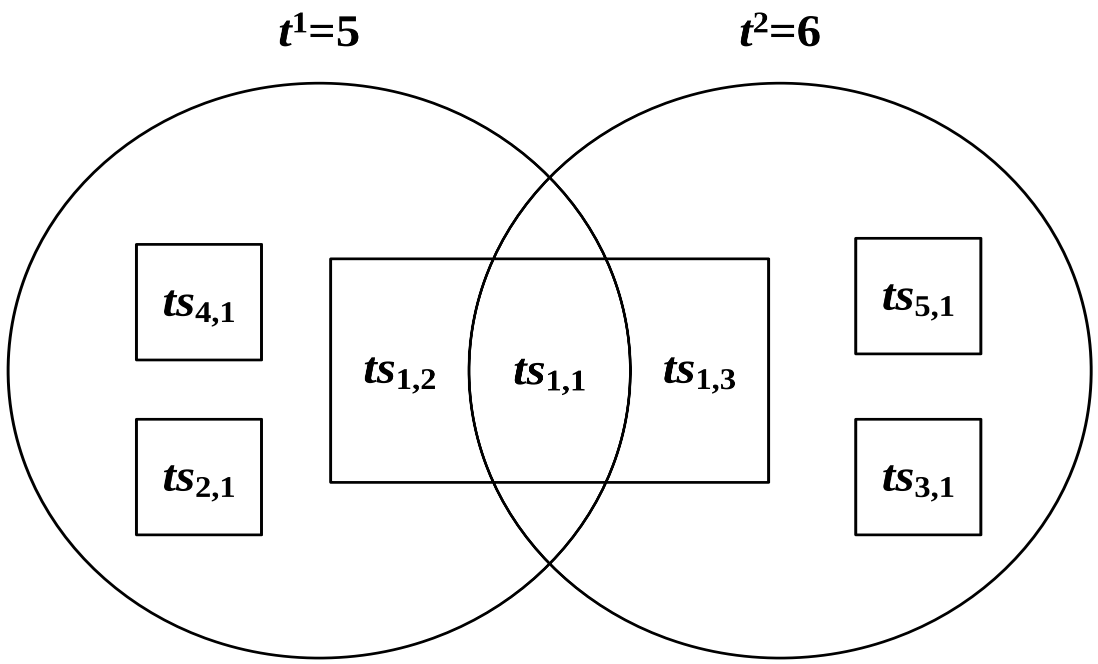
	User1			User2	User3	User4	User5
t_i	4			1	2	4	4
b_i	5			2	3	7	9
	$tsa_{1,1}$	$tsa_{1,2}$	$tsa_{1,3}$	$tsa_{2,1}$	$tsa_{3,1}$	$tsa_{4,1}$	$tsa_{5,1}$
Round 1	4	0	0	1	2	4	4
Winner							
Round 2				1	2	1	2
Winner							
Round 3				1		1	0
Winner							

Round 1: $t'^1 = 5, t'^2 = 6, S = \emptyset$

$\frac{b_1}{2tsa_{1,1}} = \frac{5}{8}, \frac{b_2}{tsa_{2,1}} = 1,\ \frac{b_3}{tsa_{3,1}} = \frac{3}{2},\ \frac{b_4}{tsa_{4,1}} = \frac{7}{4},\ \frac{b_5}{tsa_{5,1}} = \frac{9}{4}.$

user 1 wins

A Toy Example for Winner Selection of MLI



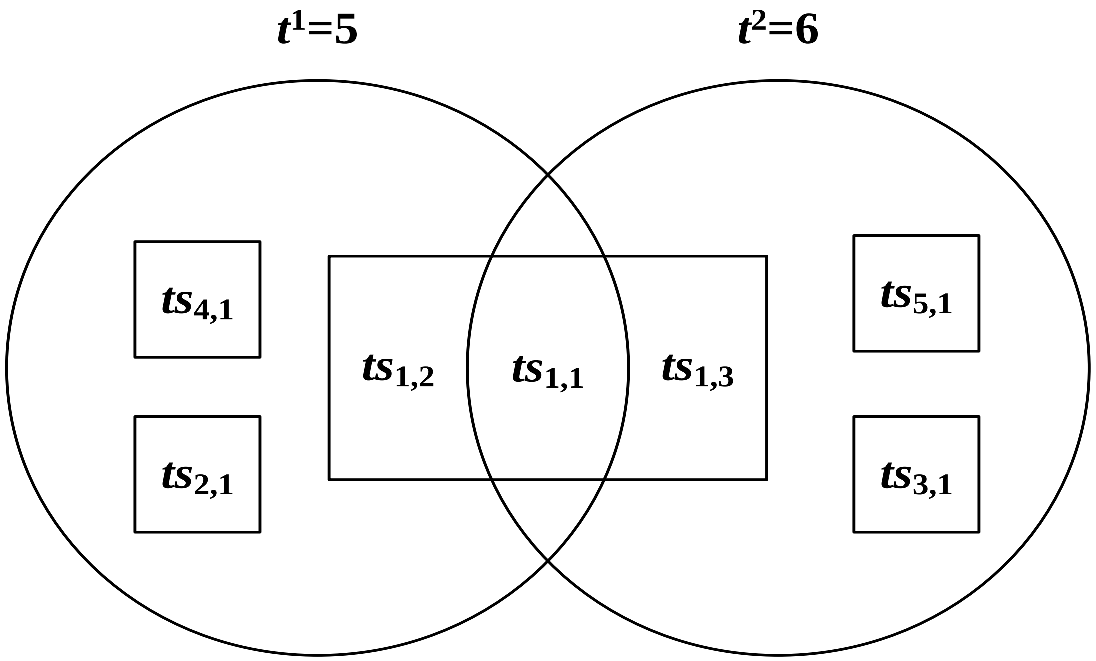
	User1			User2	User3	User4	User5
t_i	4			1	2	4	4
b_i	5			2	3	7	9
	$tsa_{1,1}$	$tsa_{1,2}$	$tsa_{1,3}$	$tsa_{2,1}$	$tsa_{3,1}$	$tsa_{4,1}$	$tsa_{5,1}$
Round 1	4	0	0	1	2	4	4
Winner							
Round 2				1	2	1	2
Winner							
Round 3				1		1	0
Winner							

Round 2: $t'^1 = 5 - 4 = 1, t'^2 = 6 - 4 = 2, S = \{1\}$

$\frac{b_2}{tsa_{2,1}} = 2, \quad \frac{b_3}{tsa_{3,1}} = \frac{3}{2}, \quad \frac{b_4}{tsa_{4,1}} = 7, \quad \frac{b_5}{tsa_{5,1}} = \frac{9}{2}.$

user 3 wins.

A Toy Example for Winner Selection of MLI



	User1			User2	User3	User4	User5
t_i	4			1	2	4	4
b_i	5			2	3	7	9
	$tsa_{1,1}$	$tsa_{1,2}$	$tsa_{1,3}$	$tsa_{2,1}$	$tsa_{3,1}$	$tsa_{4,1}$	$tsa_{5,1}$
Round 1	4	0	0	1	2	4	4
Winner							
Round 2				1	2	1	2
Winner							
Round 3				1		1	0
Winner							

Round 3: $t'^1 = 1, t'^2 = 2 - 2 = 0, S = \{1,3\}$

$\frac{b_2}{tsa_{2,1}} = 2,\ \frac{b_4}{tsa_{4,1}} = 7.$ user 2 wins.

Thus $S = \{1,3,2\}$.

Performance Evaluation

Bench Mark Algorithms

- ***MLS-GB :***greedily select the user with minimum bidding price as the winner in the location sensitive model
- ***MLS-GC:*** greedily select the user with maximal effective coverage as the winner in the location insensitive model
- ***MLI-GB :*** greedily select the user with minimum bidding price as the winner in the location sensitive model
- ***MLI-GC:*** greedily select the user with maximal effective coverage as the winner in the location insensitive model
- ***ApproxMCS:*** untruthful approximation algorithm [1] for maximizing the revenue of owner in mobile crowdsensing

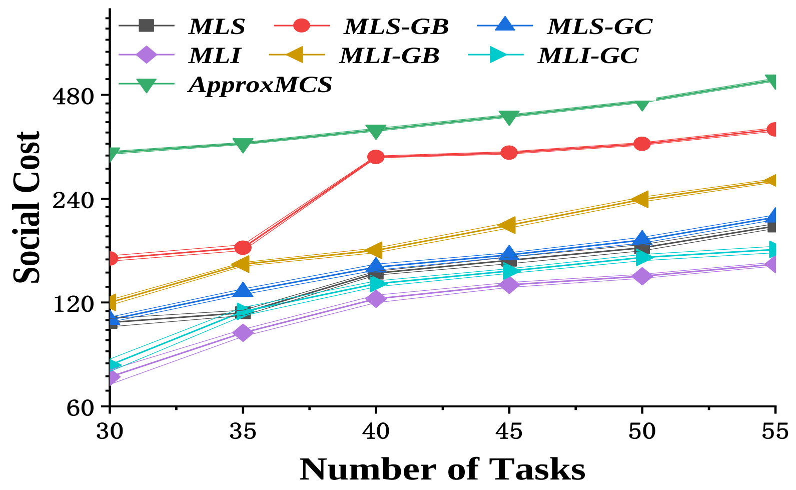
[1]K. Han, C. Zhang, J. Luo, M. Hu, and B. Veeravalli, “Truthful Scheduling Mechanisms for Powering Mobile Crowdsensing,” *IEEE Trans. on Computers*, vol.65, no.1, pp. 294-307, 2016.

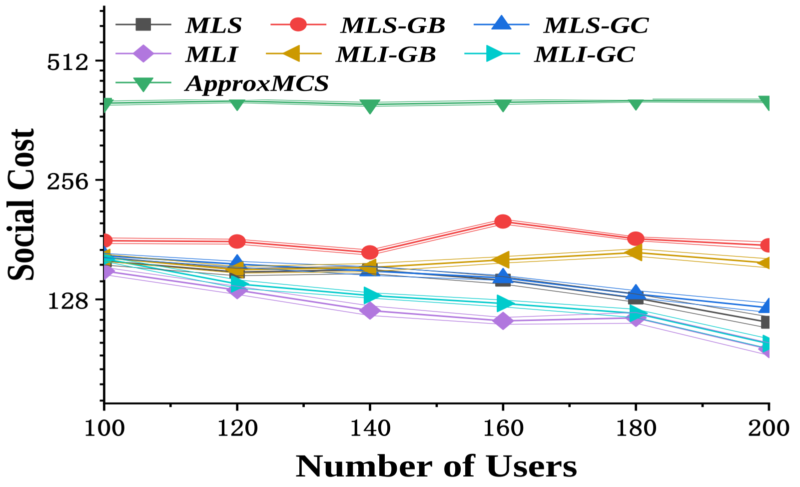
Performance Evaluation

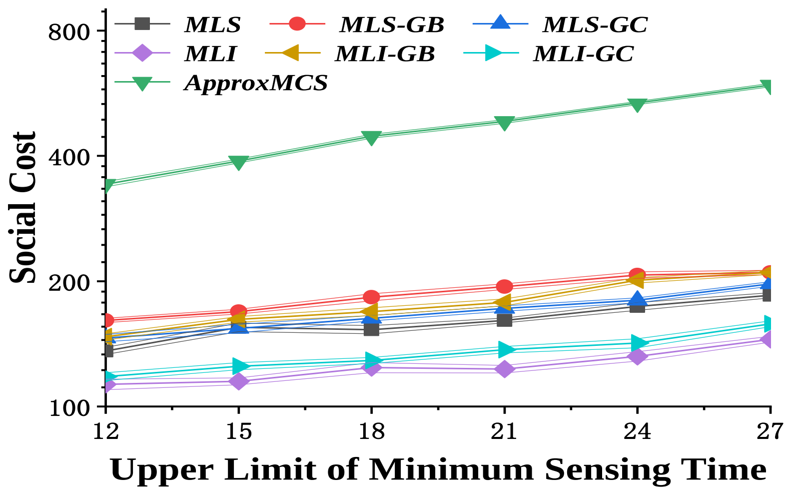
Datasets

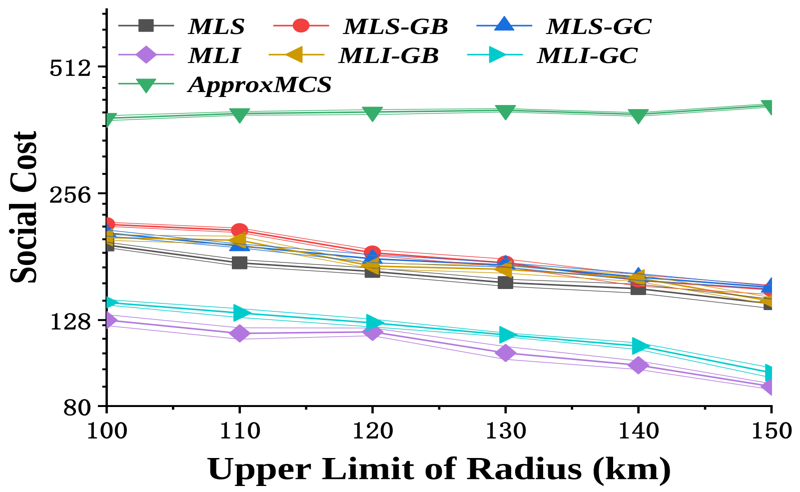
- air pollution data [2] from the sites in Beijing
- T-Drive trajectory data [3] in Beijing
- contains trajectories of 10,357 taxis in Beijing
- regard the taxi trajectory between 14:30:29 and 15:00:29 as the active areas of the user

[2]http://beijingair.sinaapp.com/
[3]https://www.microsoft.com/en-us/research/publication/t-drive-trajectory-data-sample/









MLS outputs 22.3% and 5.3% less social cost than *MLS-GB* and *MLS-GC* on average, respectively. *MLI* outputs 33.6% and 7.8% less social cost than *MLI-GB* and *MLI-GC* on average, respectively.

Thank you!

Q & A

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