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Mobile Crowd Sensing via Online Communities: Incentive Mechanisms for Multiple Cooperative Tasks

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Mobile crowd sensing

Accelerometer

light sensor

Digital Compass

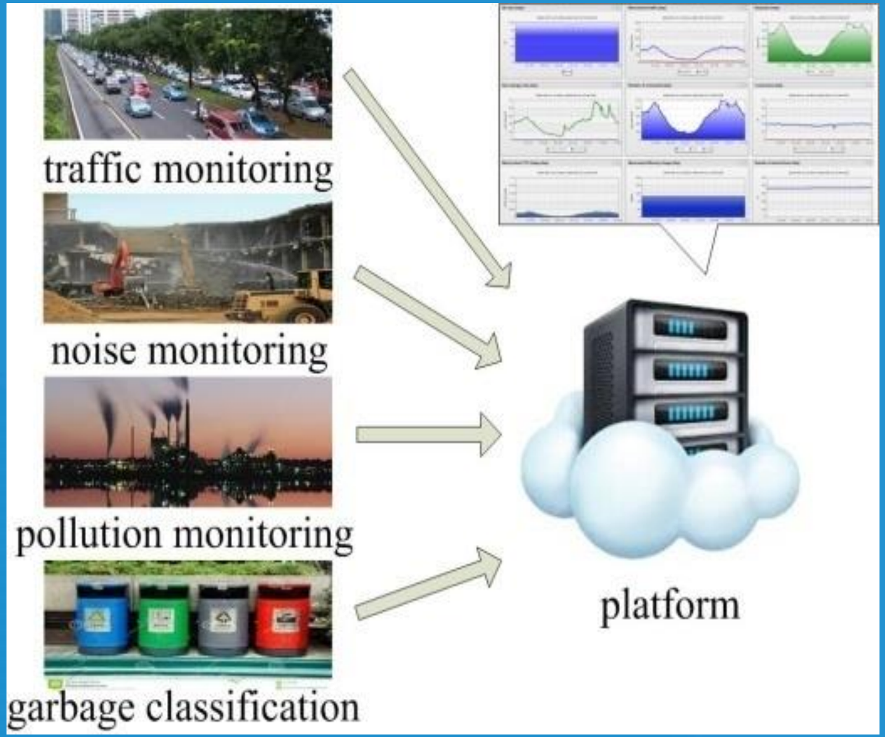
Microphone

Camera

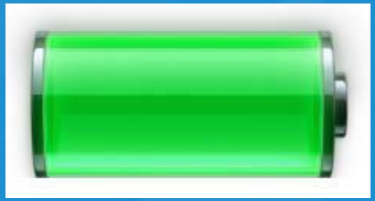
GPS

proximity sensor

Gyroscope



Incentive mechanisms for mobile crowd sensing



Power

Memory

Computing ability

TIME

Privacy

compensate users' cost

help to achieve good service quality

Existing work

Multiple tasks without cooperation of users

Yang[MobiCom'12], Koutsopoulos [Infocom'13], Feng[Infocom'14], Zhao[Infocom '14], Zhang[Infocom'15]

Single cooperative task

Xu[TWC2015], Xu [Wireless Networks2017], Xu[JCST2017]

Multiple cooperative tasks without compatibility

Luo[ICC'16], Luo[Mobile Networks and Applications2016]

Cooperate with trustworthy friends

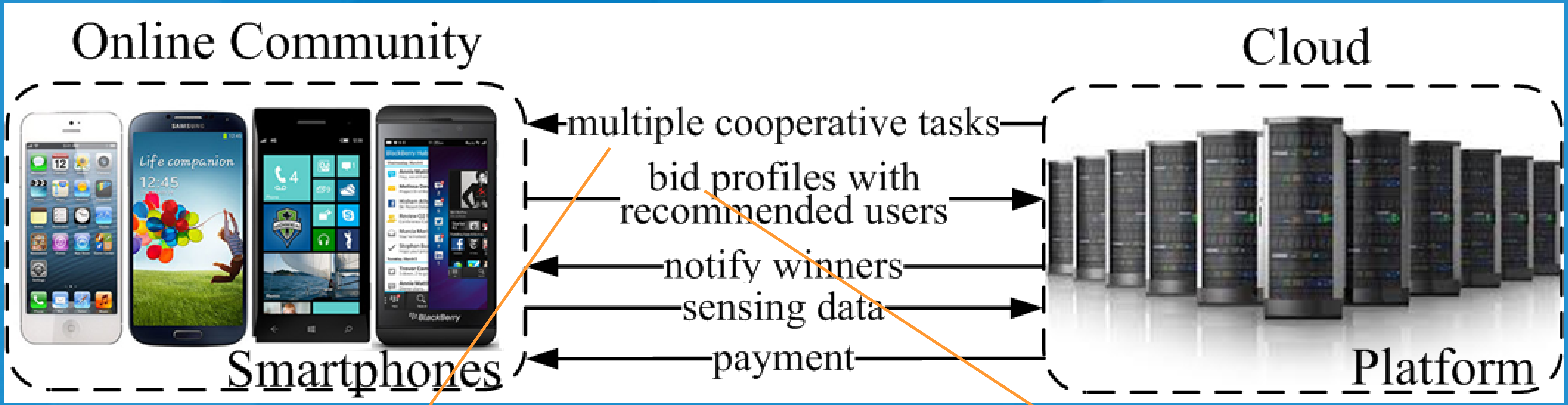
I prefer to cooperate with my friends

I'm willing to share my privacy with my friends

I can exchange tasks with my friends even the crowdsensing has already started

improve the participation willingness, quality and the success rate of mobile crowd sensing service!

Crowdsensing Process



each task is associated with a cooperative index: the least number of compatible users to perform the task

each consists of a task-bid pair and a compatible user set

compatible user set: a set of recommended users

Objective & Challenges

designing truthful incentive mechanisms to minimize the social cost such that each cooperative task can be completed by a group of compatible users

- measure the different compatibility levels
- optimize the social cost with compatibility constraints
- strategic behavior by submitting dishonest recommended users or bid price

SOCUS problem in the multi-bid model

Multi-bid model: Each user *i* submits a 2-tuple $B_i = (\beta_i, \zeta_i)$ where $\beta_i = \{\beta_i^1, \beta_i^2, \dots, \beta_i^{k_i}\}$ is a set of task-bid pairs, $\beta_i^j = \left(t_i^j, b_i^j\right)$, $t_i^j \in T$

Objective Function:

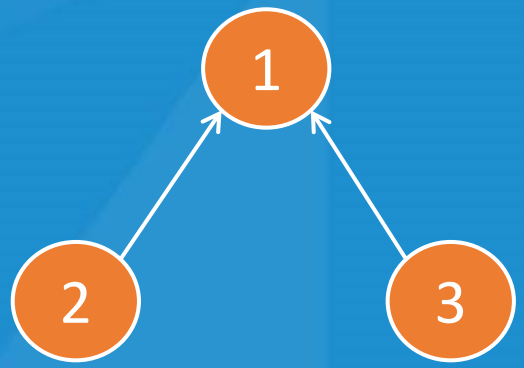
$$\min \sum_{\beta_i^j \in \beta_i \cap \beta_S} c_i^j$$

Constraint:

$$\sum_{\beta_i^j \in \beta_i \cap \beta_S, t_j = t_i^j} \left|\beta_i^j\right| \geq r_j, \forall t_j \in T$$

Compatibility Models

Weak Compatibility Model: depict the one-way preferences



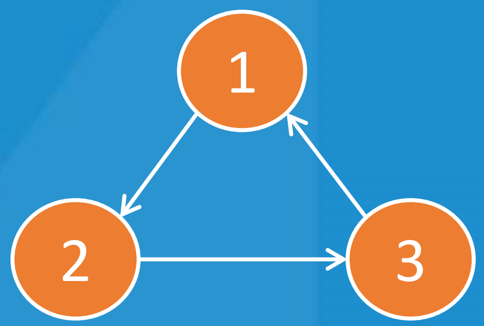
construct a directed graph based on the claimed *compatible user set*.

Remove the directions of all edges

compute the connected components of the undirected graph

Compatibility Models

Medium Compatibility Model:
depict the transitive two-way preferences

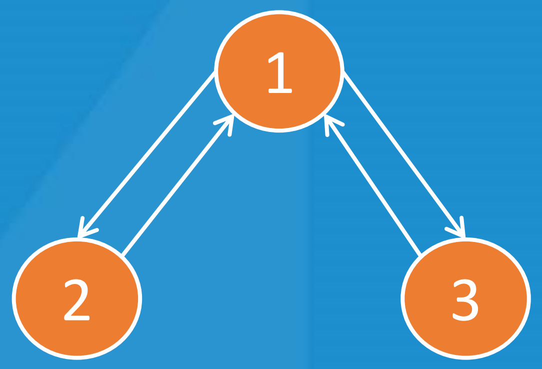


construct a directed graph based on the claimed *compatible user set*.

compute the strongly connected components of the directed graph

Compatibility Models

Strong Compatibility Model: depict the two-way preferences



construct an undirected graph by adding the edge only if the two users are both in the claimed *compatible user set* of each other

compute the connected components of the undirected graph

MCT-M

A two-step incentive mechanism for Multiple Cooperative Tasks in the Multi-bid model

Step1: compatible user grouping

divides the users into compatible user groups, in which each user is compatible with others

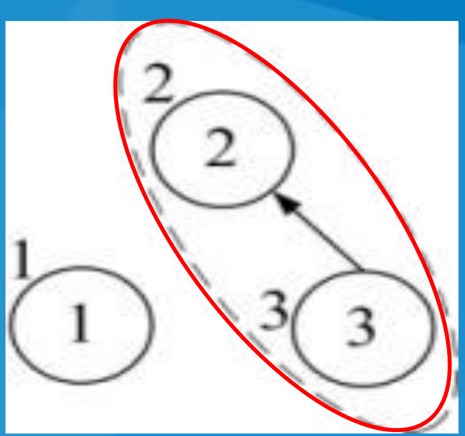
Step2: reverse auction

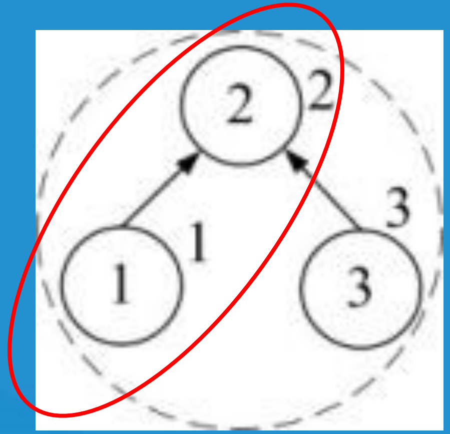
select the winning task-bid pairs and determine the payment for each user

Check the truthfulness of compatibility

A straightforward method:

Grouping based on the compatible user sets



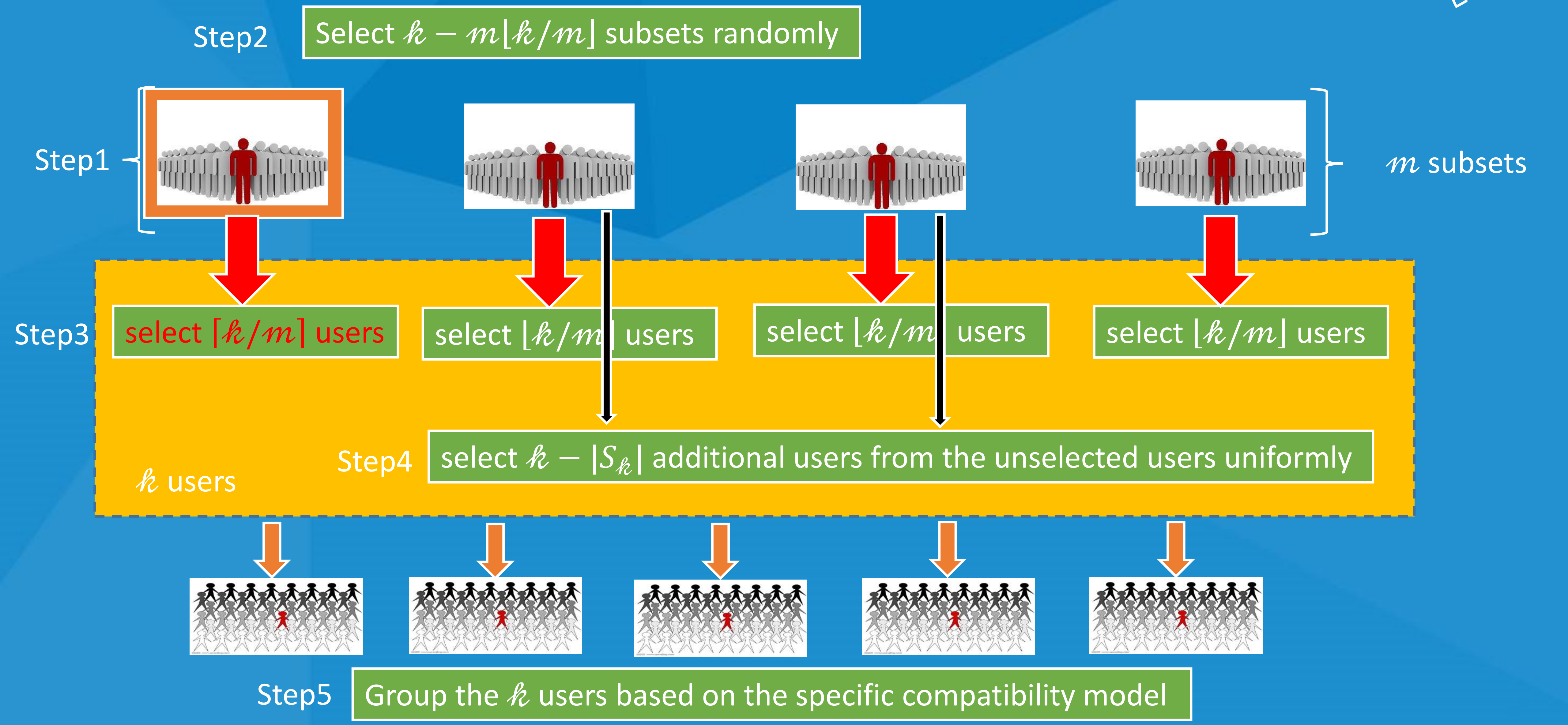


All users submit real compatible user sets

User 1 lies by submitting $\zeta_1 = \{2\}$

This method leads untruthfulness of compatibility!

Random m-Partition Mechanism (m-RP)



MCT-M

A two-step incentive mechanism for Multiple Cooperative Tasks in the Multi-bid model

Step1: compatible user grouping

divides the users into compatible user groups, in which each user is compatible with others

Step2: reverse auction

select the winning task-bid pairs and determine the payment for each user

Reverse Auction for Multi-bid Model

Winner Selection

Payment Determination

For each task, process each compatible user group iteratively

In each compatible user group, select the task-bid pairs as winning task-bid pairs with minimum cost until the number of users reaches to r_j

For each task, select the task-bid pairs with minimum cost among all compatible user groups

Reverse Auction for Multi-bid Model

Winner Selection

Payment Determination

VCG payment rule: the difference between other users' minimum social cost with and without it

```
foreach i∈U do p_i←0;
foreach β_i^j ∈ β_S do
    p_i^j ← cost(∪_{i∈U_G} β_i \ {β_i^j}) − (cost(∪_{i∈U_G} β_i) − b_i^j);
end
foreach i∈S do  p_i = Σ_{β_i^j ∈ β_i ∩ β_S} p_i^j;
```

$$p_i^j \leftarrow cost\left(\bigcup_{i\in U_{\mathcal{G}}} \beta_i \setminus \{\beta_i^j\}\right) - \left(cost\left(\bigcup_{i\in U_{\mathcal{G}}} \beta_i\right) - b_i^j\right);$$

$$p_i = \sum_{\beta_i^j \in \beta_i \cap \beta_S} p_i^j;$$

Generalize to the single-bid model

Single-bid model: Each user *i* submits a triple $B_i = (\beta_i, b_i, \zeta_i)$, where $\beta_i = \{t_i^1, t_i^2, \dots, t_i^{k_i}\}$ is a set of k_i tasks

Objective Function:

$$\min \sum_{i \in S} c_i^j$$

Constraints:

$$\sum_{i \in S, t_i^j \in \beta_i, t_j = t_i^j} \left| t_i^j \right| \geq r_j, \forall t_j \in T$$

MCT-S

The SOCUS problem in the Single-bid model is NP- hard since it is a generalization of the WSMC(Weighted Set Multiple Cover) problem

Step1: compatible user grouping

m-RP

Step2: reverse auction

use greedy method to select winners

Reverse Auction for single-bid Model

Winner Selection

Payment Determination

For each task, process each compatible user group iteratively

In each compatible user group, select additional users as winners with minimum cost until the number of users reaches to r_j

For each task, select the additional winner set with minimum cost among all compatible user groups

Reverse Auction for single-bid Model

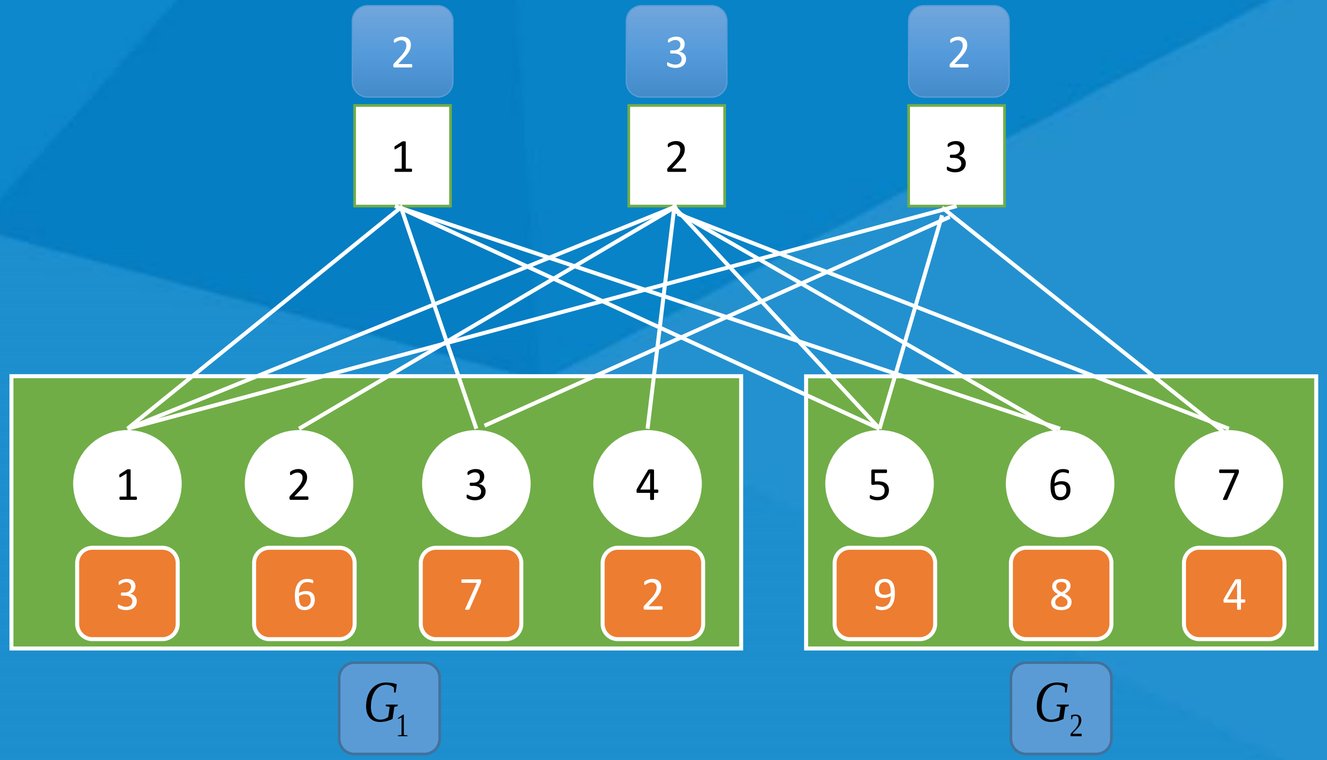
Winner Selection

Payment Determination

"critical payment" in Myerson's Theorem

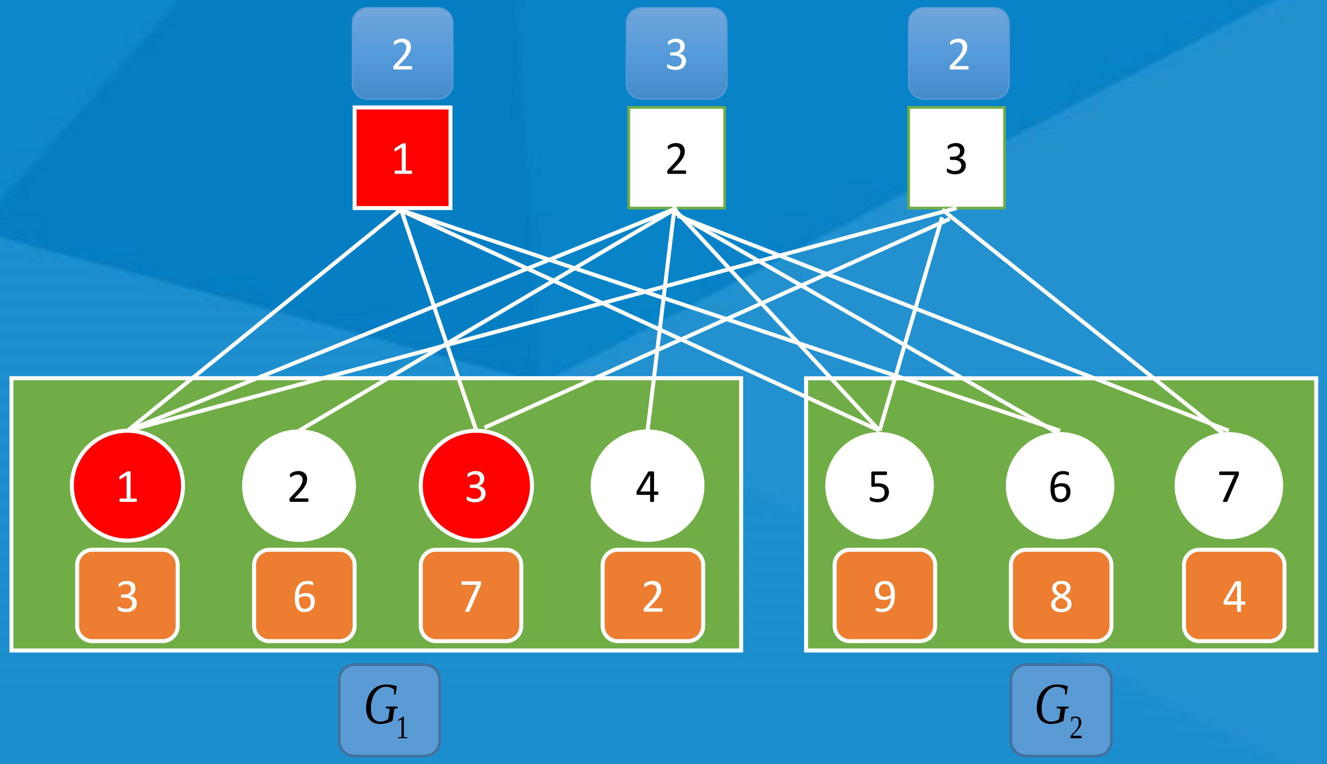
compute the maximum price of user *i* to make the group including *i* can be selected instead of another group without *i*.

A Walk-Through Example for MCT-S



For task 1, $S=\phi$, $S_1^{'}=\{1,3\}$, $\cos t_1^1=b_1+b_3=10$, $S_2^{'}=\{5,6\}$, $\cos t_2^1=b_5+b_6=17$

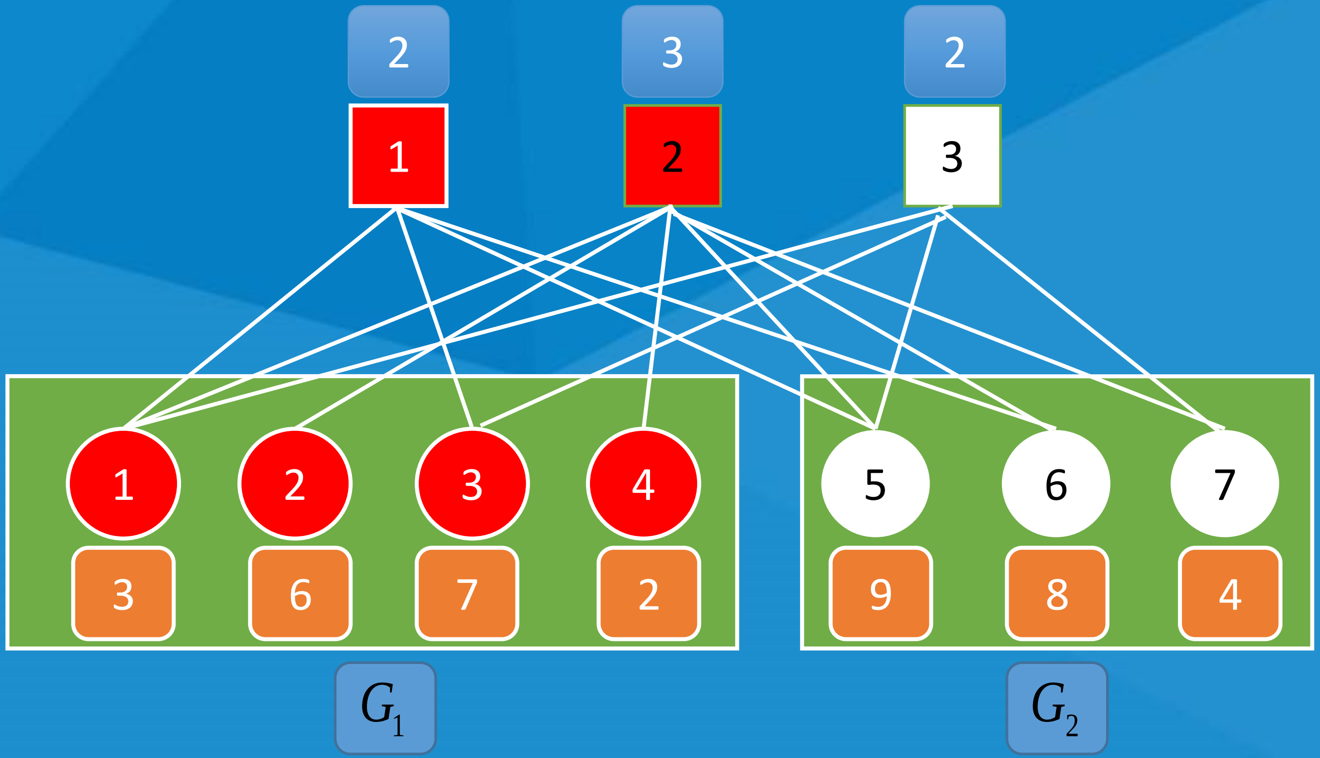
A Walk-Through Example for MCT-S



For task 2 , $S=\{1,3\}$, $S_1^{'}=\{2,4\}$, $\cos t_1^2 = b_2 + b_4 = 8$, $S_2^{'}=\{5,6,7\}$

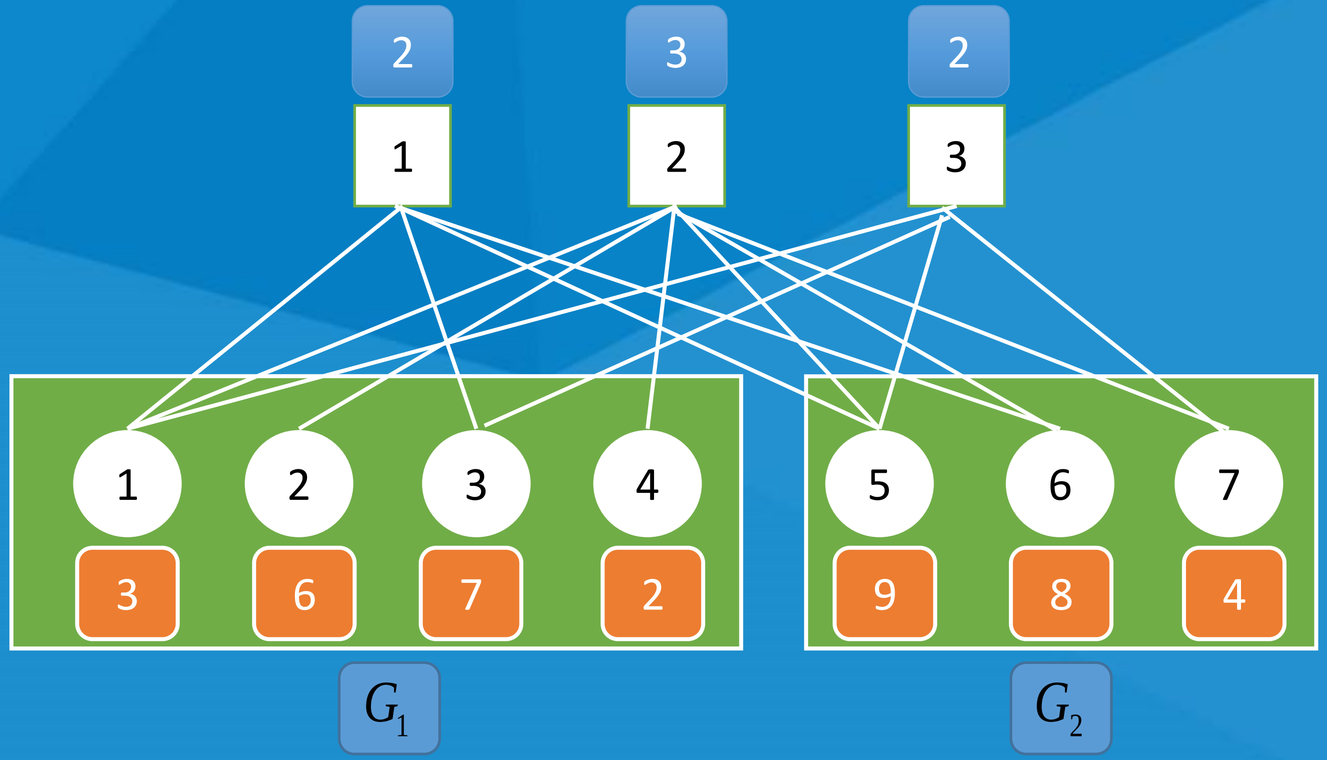
$\cos t_2^2 = b_5 + b_6 + b_7 = 21$

A Walk-Through Example for MCT-S



For task 3, $S=\{1,2,3,4\}$ **,** $S_1^{'}=\phi$**,** $\cos t_1^3=0$ **,** $S_2^{'}=\{5,7\}$ **,** $\cos t_2^3=b_5+b_7=13$

A Walk-Through Example for MCT-S



p_1:For task 1, additional winners are $\{5,6\}$, $p_1 = cost(\{5,6\})^1 - \left(cost(\{1,3\})^1 - b_1\right) = 10.$

For task 2, additional winners are $\{7\}$, $cost(\{1,2,4\})^2 > cost(\{7\})^2$

For task 3, additional winners are $\emptyset$， $cost(\{1,3\})^3 > cost(\emptyset)^3$

Thus, $p_1 = 10$

Summary of Theoretical Analysis

Theorem 1. ***MCT-M is computationally efficient, individually rational, truthful and an optimal algorithm of SOCUS problem in the multi-bid model***

Theorem 2. ***MCT-S is computationally efficient, individually rational and truthful in the single-bid model.***

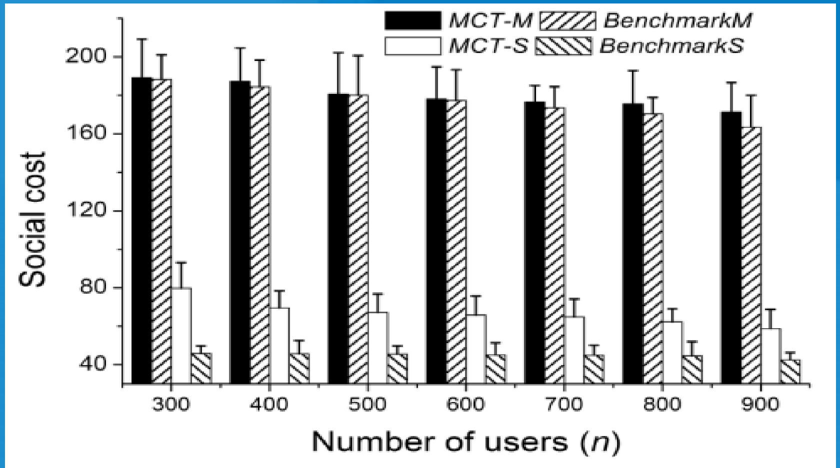
Performance Evaluation

benchmark algorithms: *Benchmark-M* & *Benchmark-S*

Data Set: Wikipedia voting data for adminship

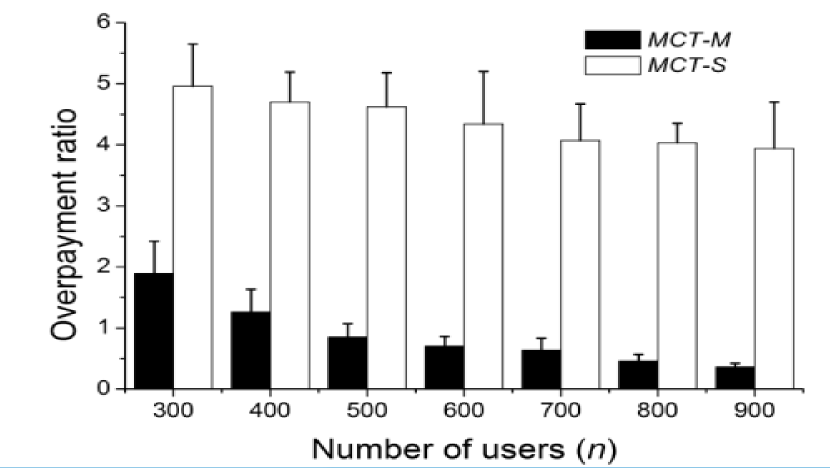
Performance Evaluation

A. Impact of the number of users



The social cost decreases with increasing user number since the platform can find more cheap users.

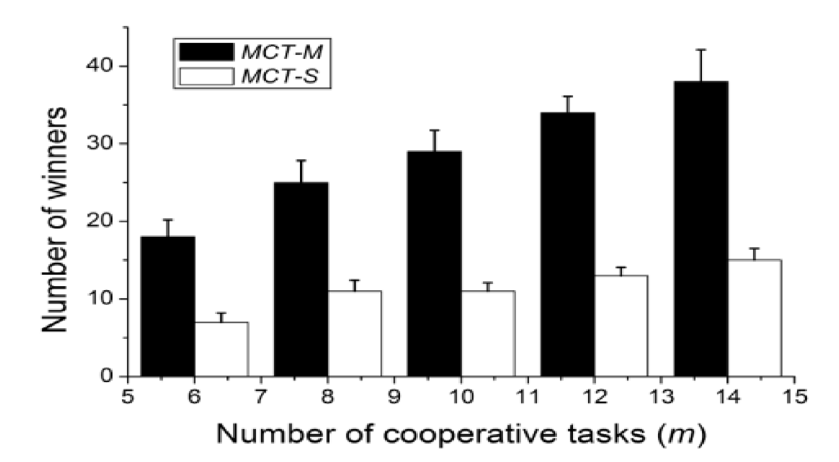
The social cost of *MCT-M* is very close to that of *BenchmarkM*. *MCT-S* outputs 48.9% more social cost than *BenchmarkS*.



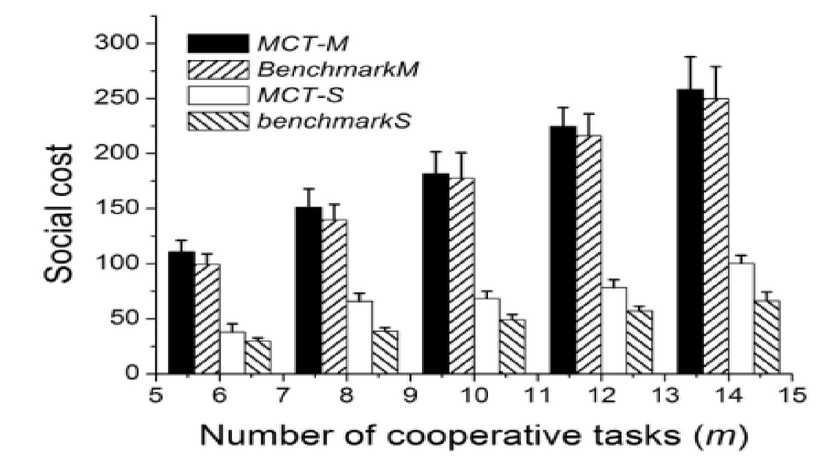
The overpayment ratio of MCT-M is much smaller than that of MCT-S because the competition of users in *MCT-M* is more than that of *MCT-S*

Performance Evaluation

B. Impact of the number of tasks



The winners of MCT-M are much more than that of MCT-S because in MCT-M, any user will be the winner if one of the task-bid pairs it submits is selected



Accordingly, the social cost of MCT-M is more than that of MCT-S

Conclusion

We have designed the incentive mechanisms for the mobile crowd sensing system with multiple cooperative tasks.

We have presented two bid models and three compatibility models for this new scenario, and designed two incentive mechanisms: MCT-M and MCT-S to solve the SOCUS problem for the two bid models, respectively.

Extensive results are presented to verify our theoretical analysis.

Thank You!

Q & A

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