Dynamic User Recruitment with Truthful Pricing for Mobile CrowdSensing

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Outline

I. Background
II. Motivation and Challenges
III. Problem Formulation
IV. User Recruitment
V. Truthful Pricing
VI. Performance Evaluation
VII. Conclusion

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I. **Background**

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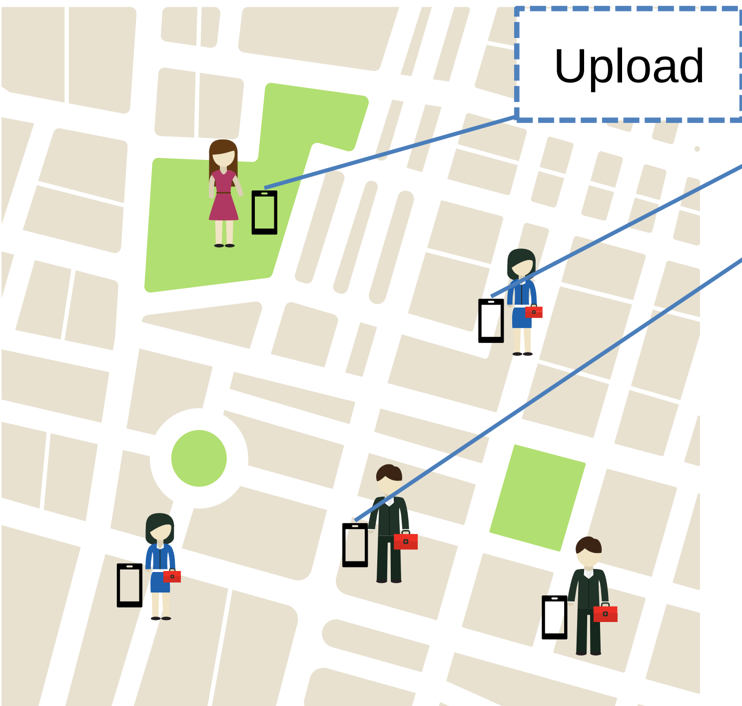
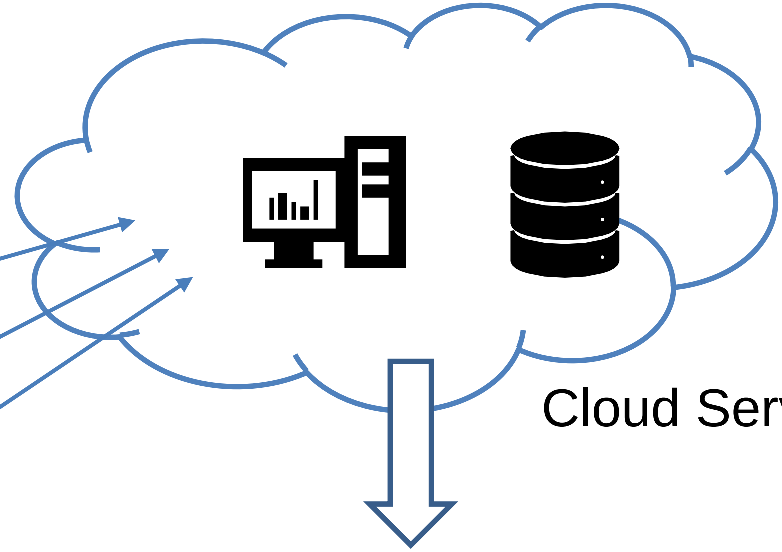
Mobile CrowdSensing (MCS)

Recruit users with mobile devices to perform various sensing tasks





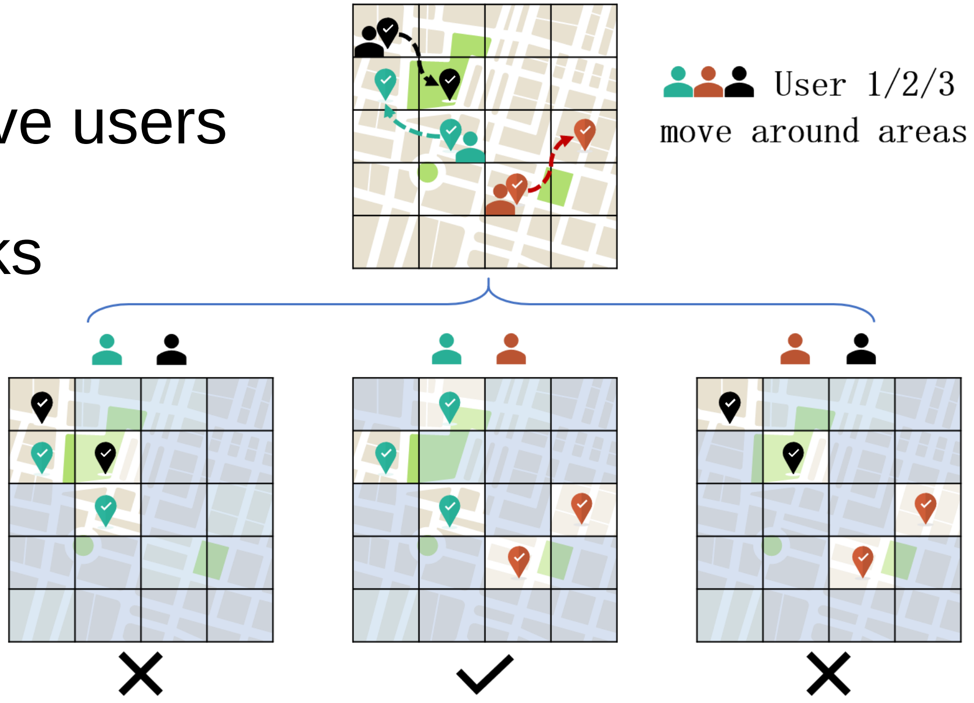
Air Quality Sensing

Traffic Monitoring

… …

User Recruitment in MCS

- User Recruitment is a fundamental problem in MCS
- Typical problem:
  - ✓ Budget constraint
  - ✓ Select some effective users
    - ➢ Cover more tasks

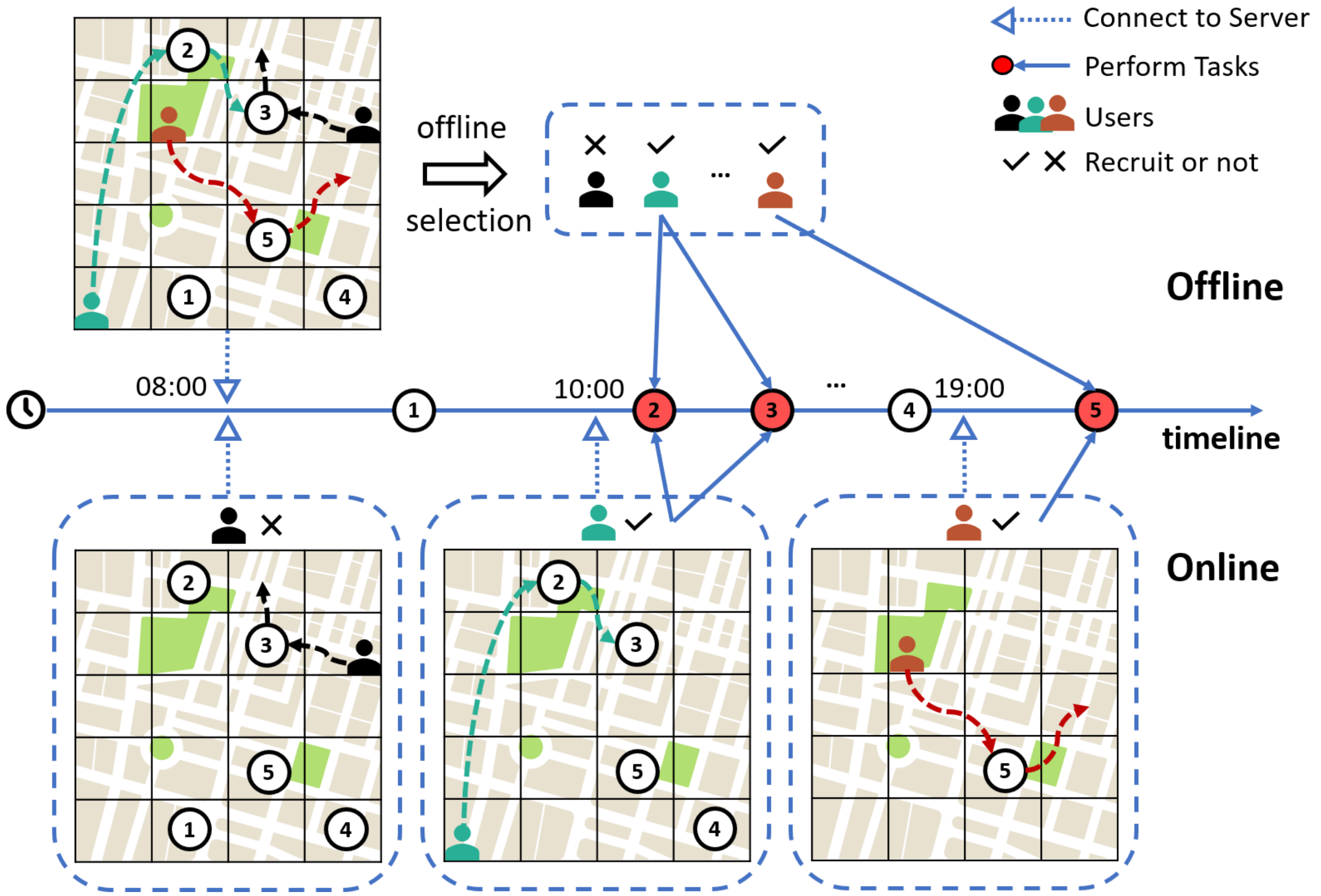


Offline vs. online

- Offline User Recruitment
  - Pre-determined user pool
  - At the beginning of the MCS campaign
- Online User Recruitment
  - Unknown users
  - Dynamically participate in MCS
    - ✓ More realistic scenarios

Offline vs. online

- Example:



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Online User Recruitment

- Existing Online User Recruitment
  - Optimal stopping problem
    - Decide whether to recruit the current user under the budget constraint
      - Dynamic programming
      - Secretary problem
      - Online auction model
  - Ignore the influence of the remaining time

Budget and time constraints

- Two constraints seem to be independent, but jointly affect the online user recruitment
  - Little time left → recruit all to use up the budget
  - Less budget but plenty of time → recruit users with more patience
- First challenge:
  - How to address the budget and time constraints in online user recruitment?

Uncertain factors

- Dynamical participation introduces a lot of uncertainty
  - user's contribution (estimated by mobility)
  - user's cost
  - participating rate (periodical participation)
    - The estimated results are not always precise.
- Second challenge:
  - How to dynamically re-adjust the strategy along with the online recruiting process?

Pricing mechanism

- Encourage user participation and avoid being deceived
  - Determine the payment for each recruited user
  - Satisfy the budget and time constraints
    - ✓ A supplement to the dynamic user recruitment strategy
- Third challenge:
  - How to determine a truthful price for each recruited user in this online manner?

Outline

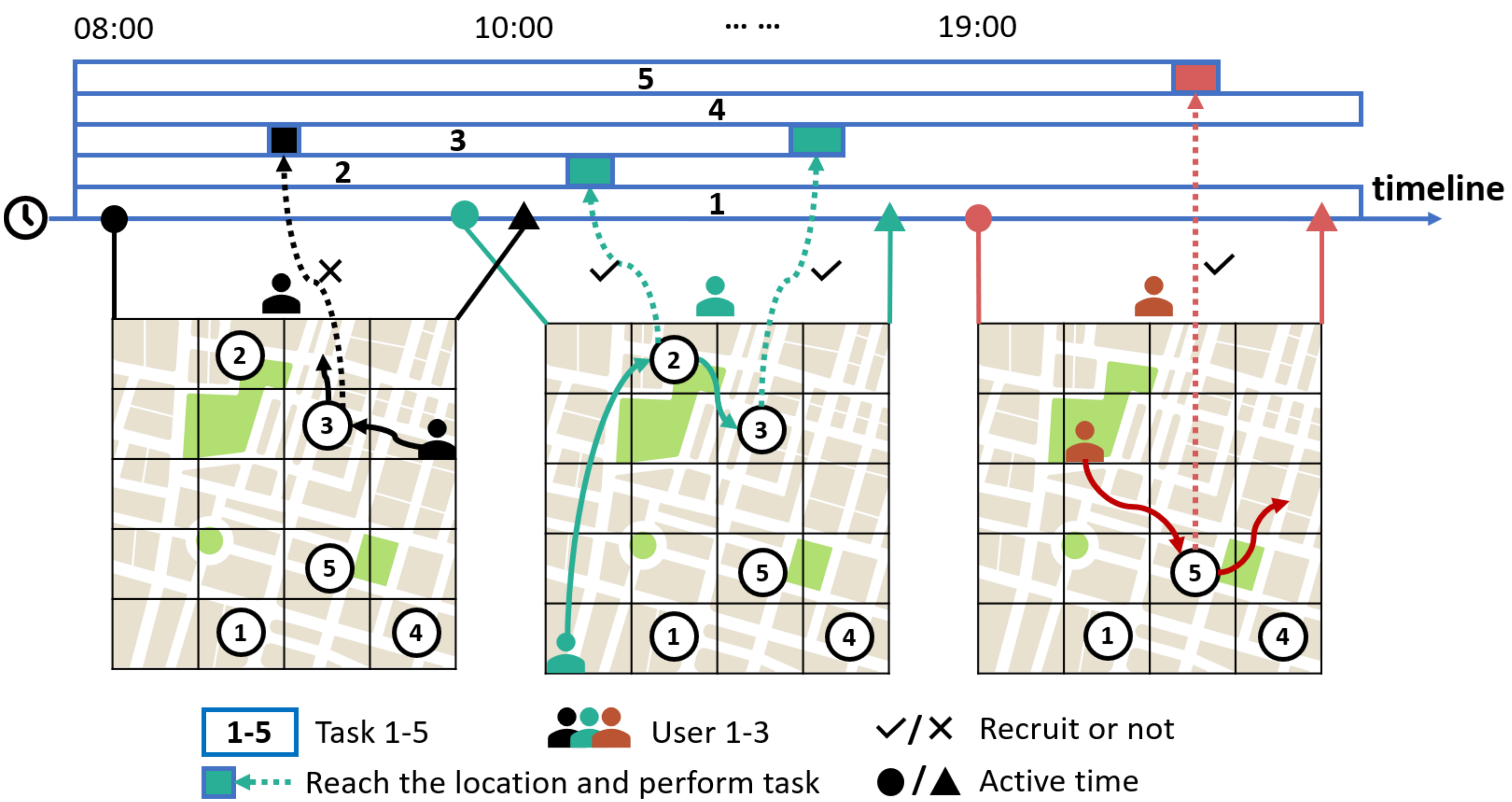
Problem Formulation

- **Problem** [Online User Recruitment under the Budget and Time Constraints]:
- Given a set of tasks S, with a limited budget B and the duration time of the MCS campaign T, we recruit a set of sequential participating μ
- Goal: maximizing the number of completed tasks $E(s, \mu)$

$$\text{maximize} \quad \Sigma_{s_j \in S} E(s_j, \mu)$$
$$\text{subject to} \quad \mu \subseteq U,\ \Sigma_{u_i \in \mu} p_i \leq B,\ T^b \leq t \leq T^e$$

Running example

- An example of online user recruitment in MCS.

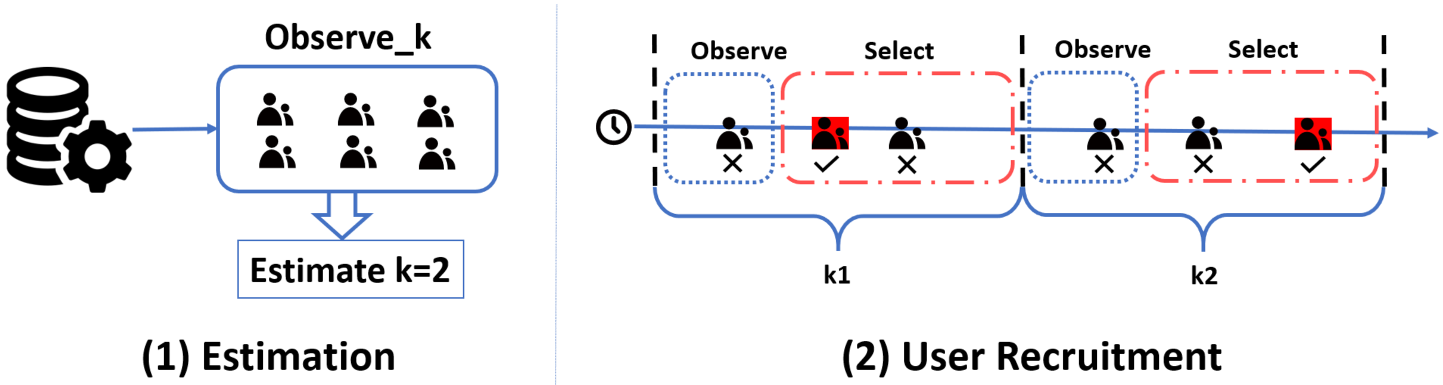


Outline

Segmented Strategy

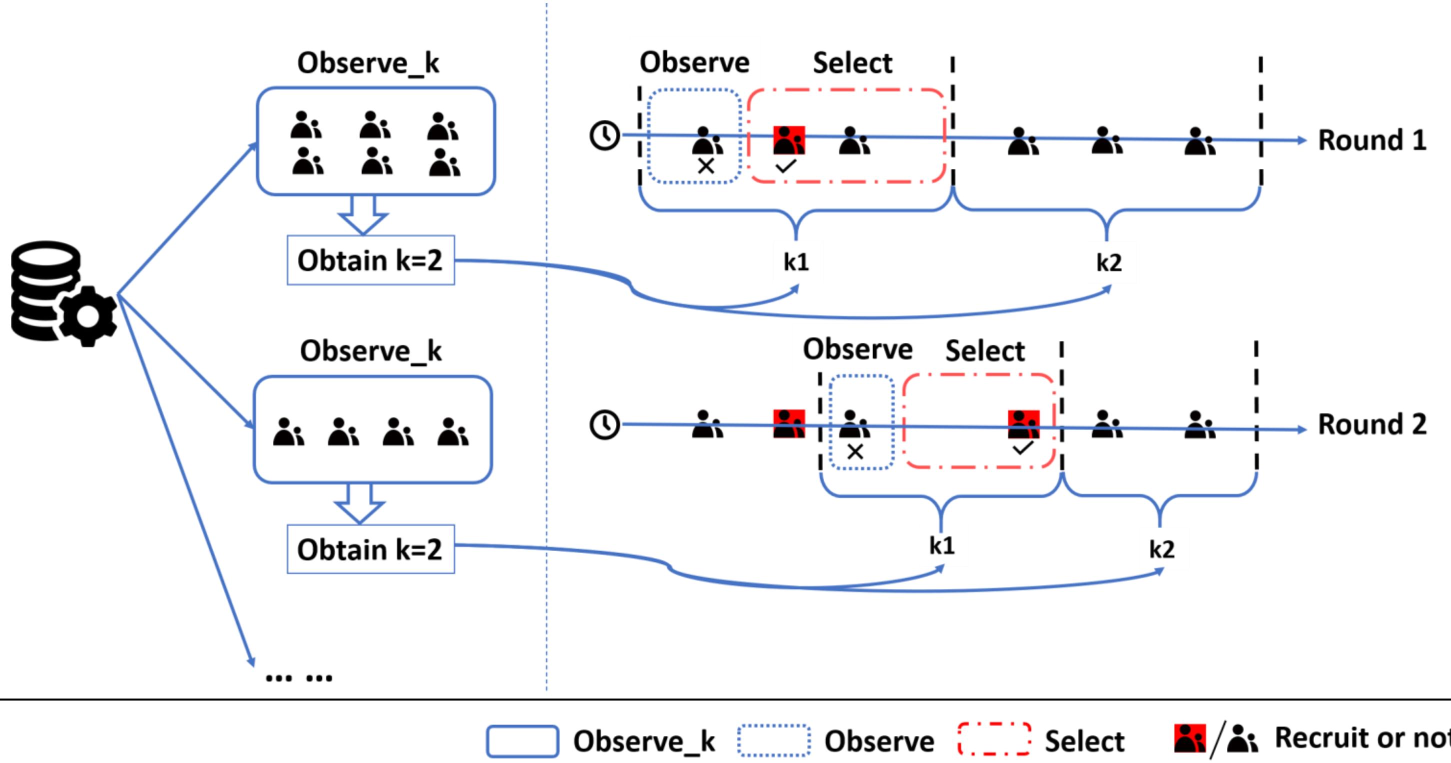
- A. Segmented Online User Recruitment Strategy

1. Estimation via Submodular Maximization with Knapsack Constraint (*budget and time constraints*)
2. User Recruitment via Submodular *k*-Secretaries Problem (*online recruiting process*)



Dynamic Strategy

- B. Dynamic Online User Recruitment Strategy
  - Basic idea is to conduct a re-estimation after recruiting a new user



Algorithm and Competitive Ratio

Algorithm 3 Dynamic Online User Recruitment

Input: S, B, $T = [t^s, t^e]$, $U\{u_1, u_2, ..., u_n\}$

```
μ = ∅, B_rest = B, S_rest = S, U_rest = U, T_rest = [t^s, t^e];
while B_rest > 0 and U ≠ ∅ do
    n', k ← Estimation(S_rest, B_rest, T_rest);
            ▷ If k = 0 or n > n', recruit users under B_rest
    μ ← Segmented(S_rest, B_rest, U_rest, n', k, μ);
              ▷ Break after a new user has been recruited
    Update S_rest, U_rest, B_rest, T_rest;
return μ
```

Greedy[1]: $1 - 1/e$

Online[2]: $(1 - 1/e)/7$

- Segmented (dynamic) online user recruitment strategy approximately achieves a competitive ratio of $\frac{(1-1/e)^2}{7}$

[1] M. Sviridenko, “A note on maximizing a submodular set function subject to a knapsack constraint,” Oper. Res. Lett., vol. 32, no. 1, pp. 41–43, Jan. 2004.

[2] M. Bateni, M. Hajiaghayi, and M. Zadimoghaddam, “Submodular secretary problem and extensions,” ACM Transactions on Algorithms (TALG), vol. 9, no. 4, p. 32, 2013.

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Dynamic Strategy

- Reverse auction-based pricing mechanism
  - Lightly build into online user recruitment strategy
  - Achieve truthfulness and individual rationality

Algorithm 4 Reverse Auction-based Pricing

Input: S, B, $U = \{u_1, u_2, ..., u_n\}$, n', k, $\mu = \emptyset$

In *Segmented()*, u_i *is coming*:

1: **if** $i > n'$ **and** $\sum_{u_j \in \mu} p_j + c_i \leq B$ **then**

2: Recruit u_i with pricing c_i;

3: **else if** $i >$ *segmentID* $* l + l_{ob}$ **and** $\delta_{u_i} \geq \varepsilon$ **then**

4: $p_i = c_i \cdot \delta_{u_i} / \varepsilon$;

5: **if** $\sum_{u_j \in \mu} p_j + p_i \leq B$ **then**

6: Recruit u_i with pricing p_i;

Outline

Three real-world data sets

- Feeder[3], Shanghai, and GeoLife[4]
  - GPS records from taxies, trucks, and phones
  - Split the urban area into 15*10 grids

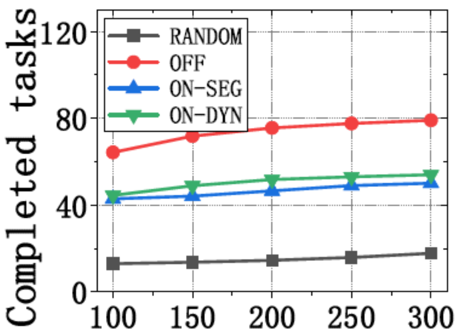
(a) *Feeder* (b) *Shanghai* (c) *GeoLife*

[3] D. Zhang, J. Zhao, F. Zhang, R. Jiang, and T. He, "Feeder: Supporting last-mile transit with extreme-scale urban infrastructure data," in Proceedings of the 14th International Conference on Information Processing in Sensor Networks, ser. IPSN '15. New York, NY, USA: ACM, 2015, pp. 226–237.

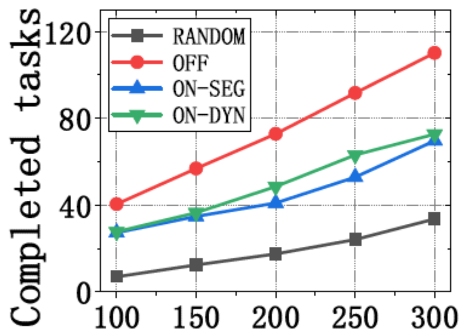
[4] Y. Zheng, Q. Li, Y. Chen, X. Xie, and W.-Y. Ma, "Understanding mobility based on gps data," in Proceedings of the 10th International Conference on Ubiquitous Computing, ser. UbiComp '08. New York, NY, USA: ACM, 2008, pp. 312–321.

Main results

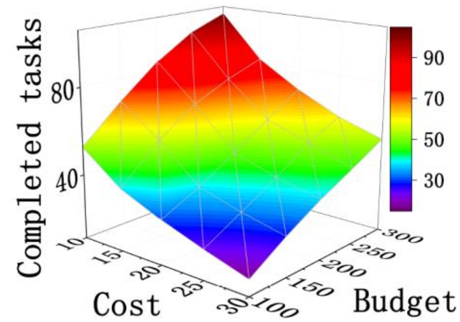
- Feeder: 1) Completed tasks; 2) Budget;



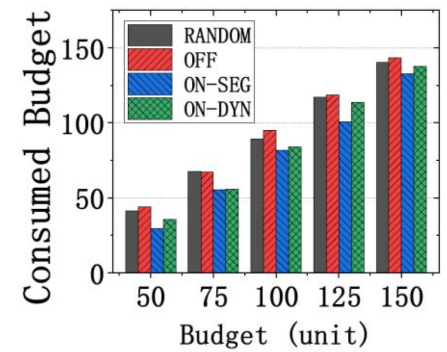
(a) Number of users



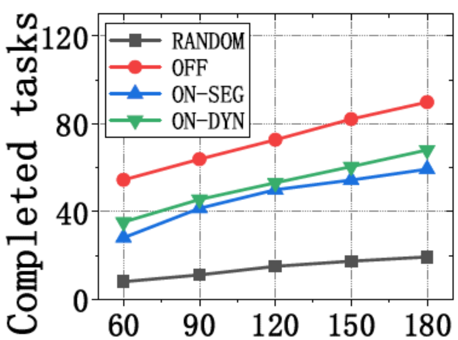
(b) Number of tasks



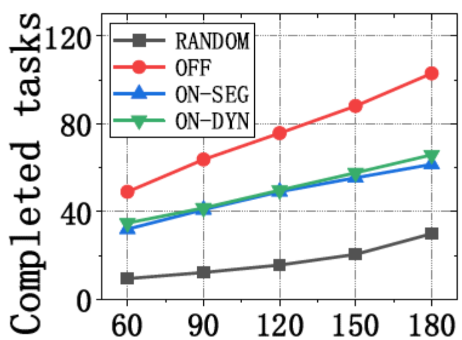
(a) *Feeder*



(a) *Feeder*



(c) Active time (min)



(d) Duration time (min)

	Feeder			
Budget	ON-SEG	ON-DYN	OPT	Ratio-DYN
100	22.9	30.5	71.3	0.4277
150	37.5	38.725	90.5	0.4279
200	46.4	48.75	115.3	0.4228
250	52.8	59.4	137	0.4335
300	67.5	69.6	160.5	0.4336

TABLE II: Completed tasks and competitive ratio.

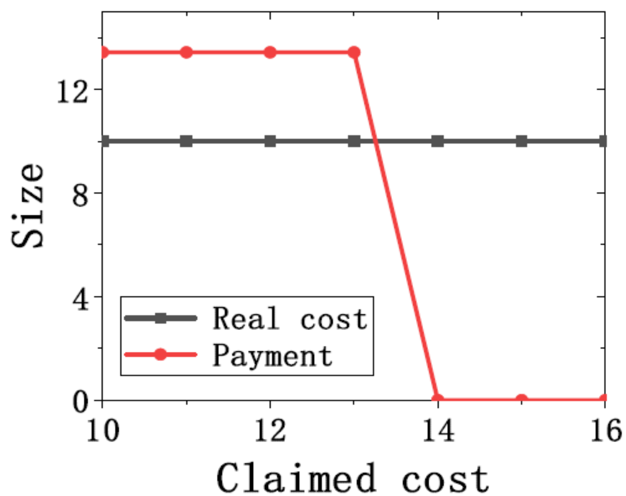
Pricing

- 3) pricing

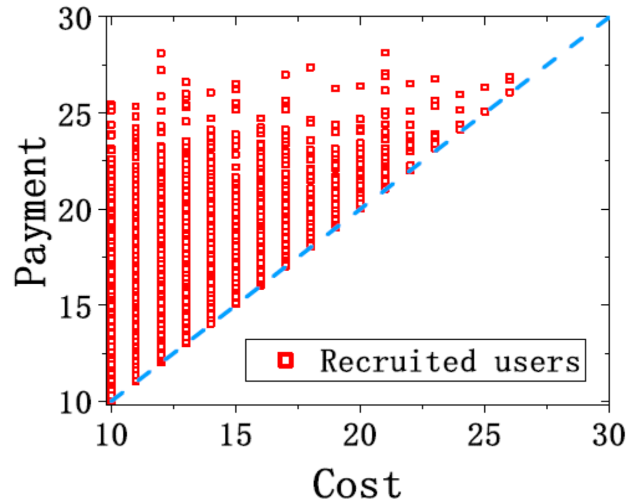
TABLE III: Overpayment ratio.

	Budget				
	100	150	200	250	300
Feeder	0.2201	0.3080	0.3863	0.3954	0.3966
Shanghai	0.2229	0.3045	0.3812	0.3945	0.3942
GeoLife	0.2195	0.3046	0.3801	0.3920	0.3972

- 4) Truthfulness and individual rationality



(a) Truthfulness



(b) Individual rationality

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Conclusion

- *Dynamic Online User Recruitment*:
  - The budget and time constraints
    - Segmented online user recruitment strategy
    - Dynamic re-estimation
- *Reverse Auction-based Online Pricing*:
  - Truthfulness and individual rationality
    - Build into strategy without much extra computation
- *Extensive Evaluation*
  - Three real-world data sets

Q&A

Thank you!

Q&A