Combinatorial Multi-Armed Bandit Based User Recruitment in Mobile Crowdsensing

Hengzhi Wang, Yongjian Yang, En Wang*, Wenbin Liu, Yuanbo Xu, Jie Wu

Outline

一、MCS Scenario

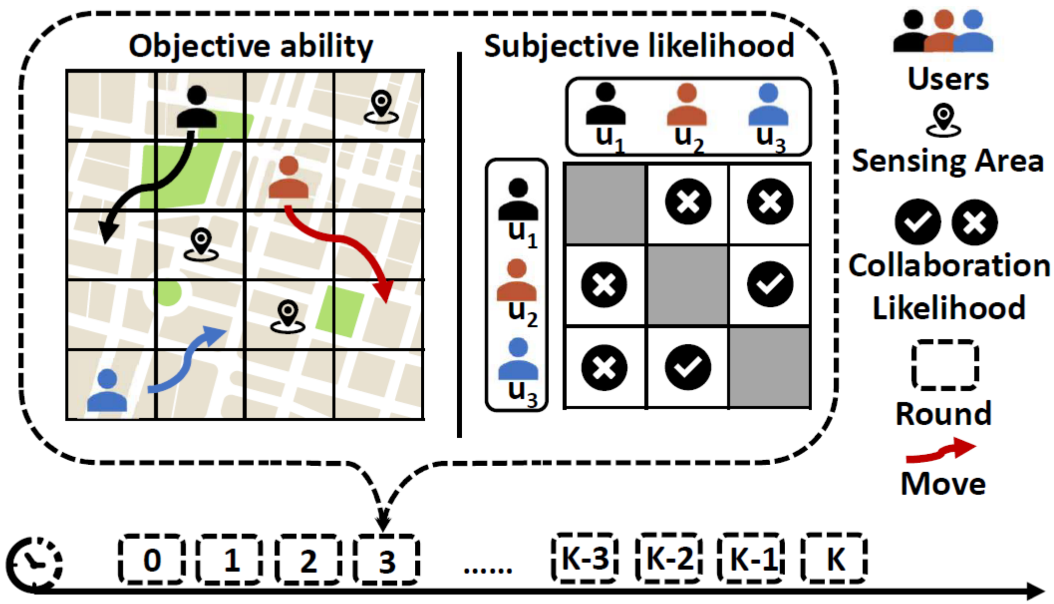
二、Problem Formulation

三、Strategy

四、Simulation

Recently, a popular sensing paradigm, mobile crowdsensing (MCS) has attracted much attention of researchers. MCS recruits mobile users to coordinately perform a complex sensing task based on their equipped devices.

User recruitment is an important researching part of Crowdsensing.



Scenario. I

Objective ability

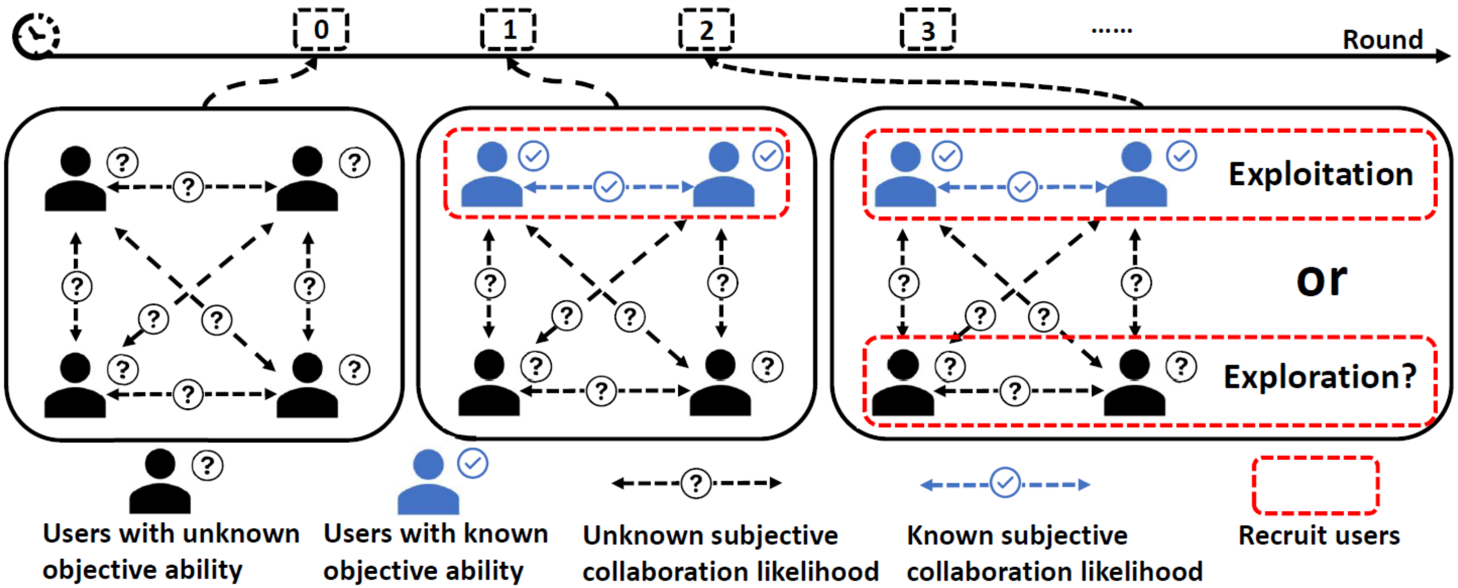
✓ The user's probability or frequency of covering the task locations

Subjective collaboration likelihood

✓ The collaboration likelihood with others when performing a cooperative task

Problem. I

The single-round user recruitment problem



Scenario. II （Multi-round Scenario）

Exploitation

- ✓ Recruiting previously well-behaved user groups

Exploration

- ✓ Exploring other unknown user groups

Problem. II

EE dilemma & The multi-round user recruitment problem

Scenario. I

Objective ability & Subjective collaboration likelihood

$$Q^t(S^t) = \sum_{u_i \in S^t} \bar{\alpha}_i^t \cdot \rho_i^t$$

$$\bar{\alpha}_i^t = \sum\nolimits_{u_j \in S^t, j \neq i} \alpha_{ij}^t / (|S^t| - 1)$$

Problem. I

The single-round user recruitment problem

$$\begin{aligned} &\text{Maximize} \quad Q^t(S^t) \\ &\text{Subject to} \quad |S^t| = N. \end{aligned}$$

Scenario. II

Exploitation & Exploration

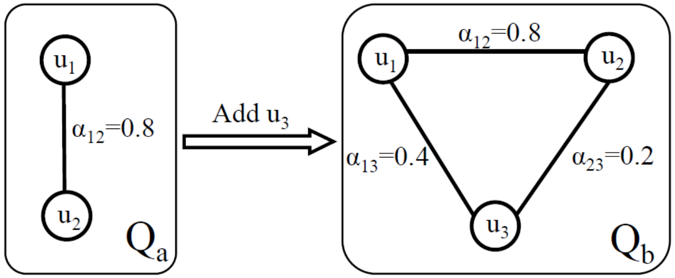
Problem. II

The multi-round user recruitment problem

$$\begin{aligned} &\text{Maximize} \quad \sum_{t \in T} Q^t(S^t) \\ &\text{Subject to} \quad |S^t| = N, \ \forall t \in T. \end{aligned}$$

Problem. I -> Strategy. I

The single-round user recruitment strategy

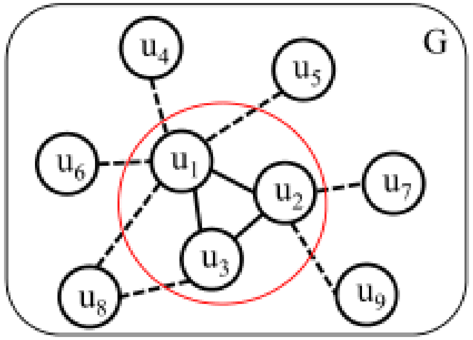


G=(V,E)

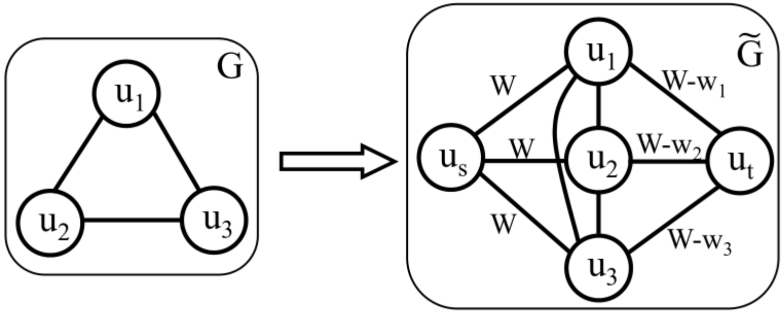
$$w_{ij} = \frac{(\rho_i + \rho_j) \cdot \alpha_{ij}}{N-1}, \forall u_i, u_j \in U, i \neq j.$$

The problem of finding the subgraph with maximum edge weight

$$\begin{aligned} \text{Maximize} \quad & \sum_{u_i, u_j \in V', i \neq j} w_{ij} \\ \text{Subject to} \quad & |V'| = N. \end{aligned}$$



$$
\begin{aligned}
\tilde{V} &= V \cup \{u_s, u_t\},\\
\tilde{E} &= \{(i,j) | (i,j) \in E\} \cup \{(u_s, u_i) | u_i \in V\} \cup \{(u_i, u_t) | u_i \in V\},\\
w_{si} &= W, \quad u_i \in V,\\
w_{it} &= W - w_i, \quad u_i \in V.
\end{aligned}
$$



The problem of finding the minimum cut of the graph

$$
\sum_{u_i, u_j \in V', i \neq j} w_{ij} = \frac{1}{2} \cdot \left(\sum_{u_i \in V'} w_i - w(c(V', V \setminus V')) \right)
$$

Algorithm 1: Minimum Cut

Input: Graph $G = (V, E)$
Output: cut $c(S', V \setminus S')$, S'

```
w_0 ← +∞ ;
for each u_i ∈ {u ∈ V | u ≠ u_s, u ≠ u_t} do
    S ← {u_i};
    while |S| ≠ N + 1 do
        Search the vertex a such that
          w(S, a) = max{w(S, b) | b ∈ V \ S, b ≠ u_t};
        S ← S ∪ {a};
    if w(c(S, V \ S)) ≤ w_0 then
        w_0 ← w(c(S, V \ S));
        S' ← S;
return cut c(S', V \ S'), S'
```

$$
\text{Maximize} \quad \frac{1}{2} \cdot \left(\sum_{u_i \in V'} w_i - w(c(V', V \setminus V')) \right)
$$

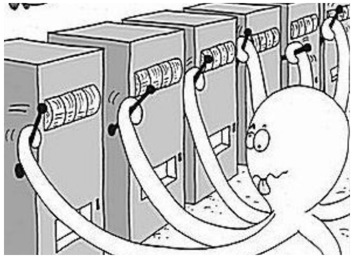
$$
\Leftrightarrow \text{Minimize} \quad w(c(V', V \setminus V')) - \sum_{u_i \in V'} w_i
$$

$$
\text{Subject to} \quad |V'| = N.
$$

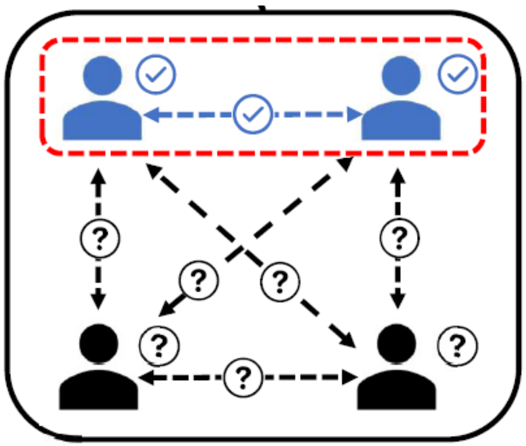
Problem. II -> Strategy. II

The user recruitment strategy in the multi-round scenario

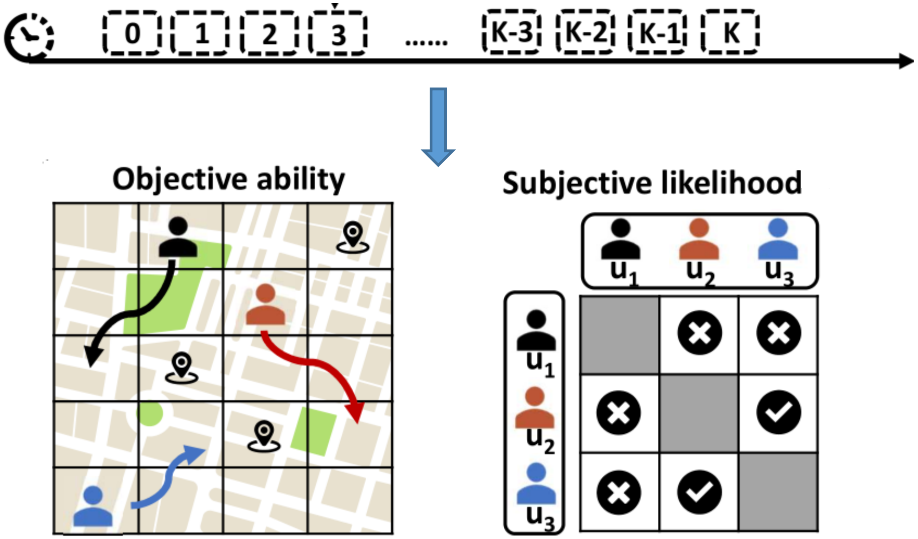
Combinatorial Multi-armed bandit problem (CMAB)



➢ The single-round user recruitment strategy



➢ Update Strategy

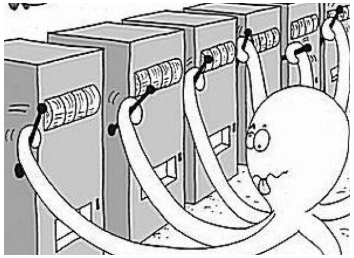


Update based on the feedback

Problem. II -> Strategy. II

The user recruitment strategy in the multi-round scenario

Combinatorial Multi-armed bandit problem (CMAB)



- Update Strategy

  Update on objective ability:

$$\rho_i^{t+1} = \frac{\sum_{r=1}^{k(t)} \rho_{i,r}}{k(t)},$$

- Update Strategy

  Update on collaboration likelihood:

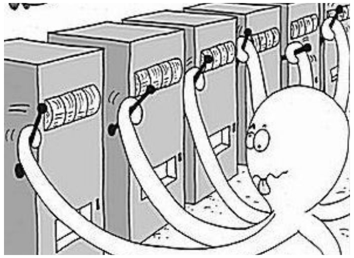
$$\hbar(\boldsymbol{\alpha}^t, \boldsymbol{\rho}^t) = Q^t(S^t) = \sum_{u_i \in S^t} \bar{\alpha}_i^t \cdot \rho_i^t,$$

$$J(\boldsymbol{\alpha}^m) = \frac{1}{2m} \sum_{t=0}^{m} (\hbar(\boldsymbol{\alpha}^m, \boldsymbol{\rho}_o^t) - Q_o^t)^2,$$

Problem. II -> Strategy. II

The user recruitment strategy in the multi-round scenario

Combinatorial Multi-armed bandit problem (CMAB)



Algorithm 1: Minimum Cut

Input: Graph $G = (V, E)$
Output: cut $c(S', V \setminus S')$, S'

$w_0 \leftarrow +\infty$;
for each $u_i \in \{u \in V | u \neq u_s, u \neq u_t\}$ **do**
  $S \leftarrow \{u_i\}$;
  while $|S| \neq N + 1$ **do**
    Search the vertex a such that $w(S, a) = \max\{w(S, b) | b \in V \setminus S, b \neq u_t\}$;
    $S \leftarrow S \cup \{a\}$;
  if $w(c(S, V \setminus S)) \leq w_0$ **then**
    $w_0 \leftarrow w(c(S, V \setminus S))$;
    $S' \leftarrow S$;
return cut $c(S', V \setminus S')$, S'

Algorithm 2: Update Among Rounds

Input: All the observed data $(\rho_o^t, Q_o^t), t \in [0, m]$
Output: Updated likelihood matrix α^{m+1}

$\rho_i^{t+1} \leftarrow \sum_{r=1}^{k(t)} \rho_{i,r} / k(t)$;
while $\eta \frac{\partial J(\alpha^m)}{\partial \alpha_{ij}^m} \leq \varepsilon, \forall \alpha_{ij}^m$ in α^m **do**
  for each α_{ij}^m in α^m **do**
    $\alpha_{ij}^m \leftarrow \alpha_{ij}^m - \eta \frac{\partial J(\alpha^m)}{\partial \alpha_{ij}^m}$;
$\alpha^{m+1} \leftarrow \alpha^m$;
return ρ^{m+1}, α^{m+1}

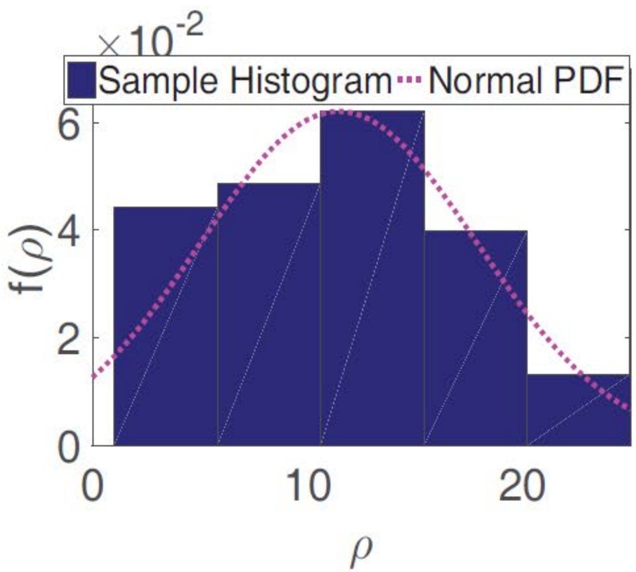
Algorithm 3: Multi-Round User Recruitment

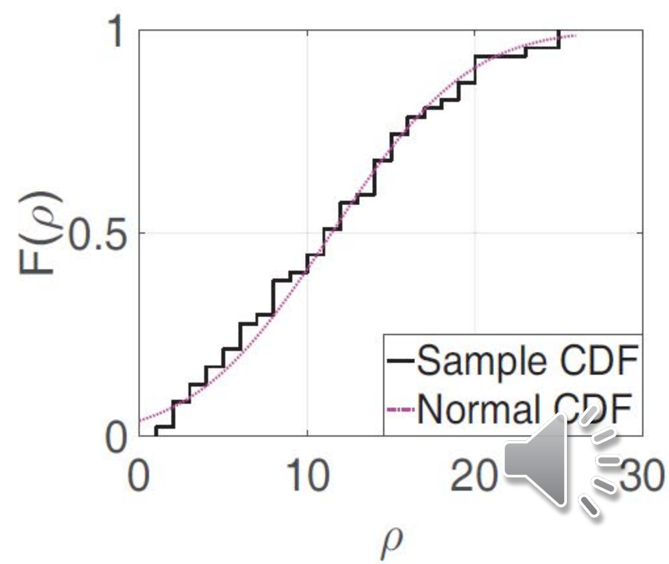
Input: User set U, user objective ability vector ρ, likelihood matrix α
Output: Total QoD Q after K rounds

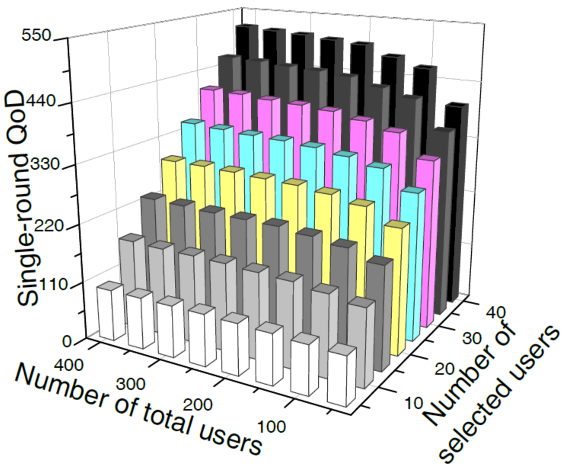
$Q \leftarrow 0$, $t \leftarrow 0$, $\rho^t \leftarrow \rho$, $\alpha^t \leftarrow \alpha$;
$r_i \leftarrow 1$ for each $u_i \in U$;
while $t \leq K$ **do**
  $t \leftarrow t + 1$;
  for each ρ_i^t *in* ρ^t **do**
    $\tilde{\rho}_i^t \leftarrow \rho_i^t + \sqrt{\frac{3 \ln t}{2 r_i}}$;
  Convert the user set U to graph G through Eq. 6 with $\tilde{\rho}^t$, α^t;
  Convert graph G to graph $\tilde{G}$ through Eqs. 13-16;
  $S' \leftarrow$ Minimum Cut $(\tilde{G})$;
  Select the users in $S' \setminus \{u_s\}$;
  for each $u_i \in S' \setminus \{u_s\}$ **do**
    $r_i \leftarrow r_i + 1$;
  Users perform the task and we observe the actual values of ρ_o^t and Q_o^t at the end of round t;
  $\rho^{t+1}, \alpha^{t+1} \leftarrow$ Update Among Rounds ();
  $Q \leftarrow Q + Q_o^t$;
return Q

(a) Brightkite (b) Gowalla (c) Foursquare

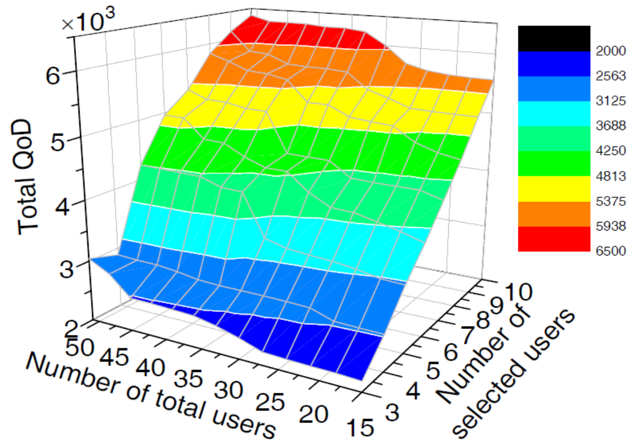
- These three datasets contain both the user’s location and social information
- Users’ objective abilities (frequencies of passing through the sensing



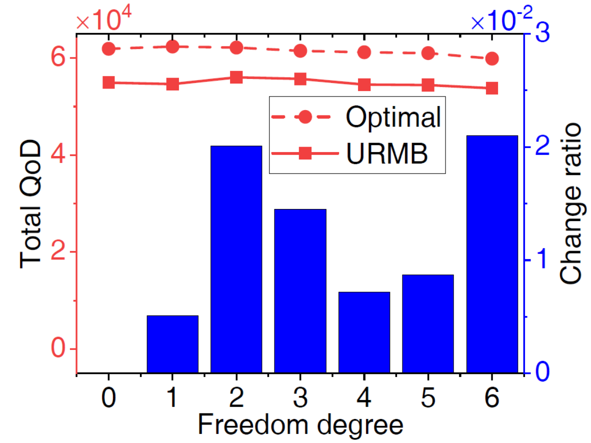




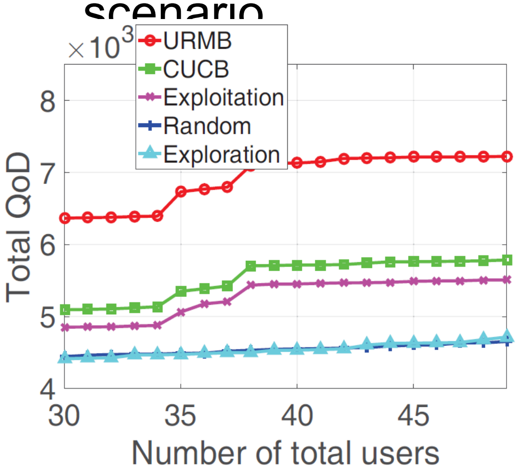
▲ QoD evaluation in the single-round scenario

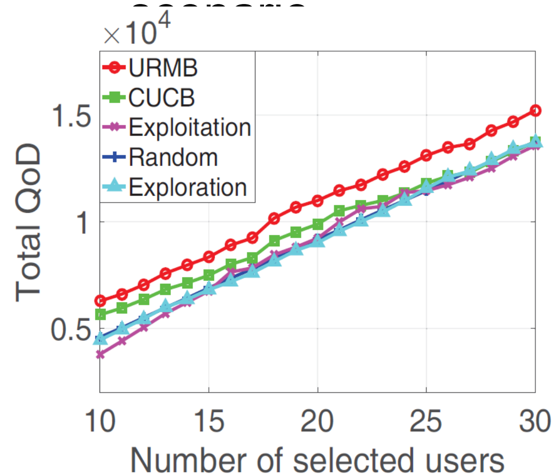


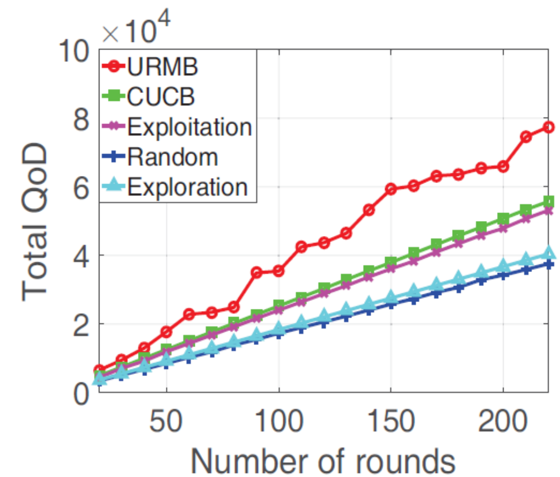
▲ QoD evaluation in the multi-round scenario



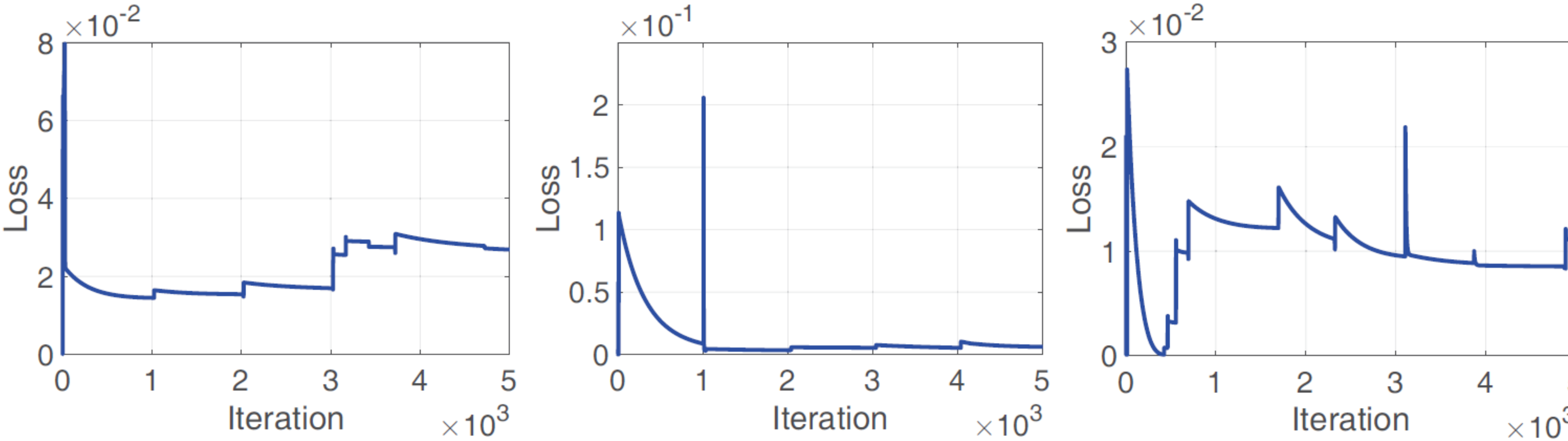
▲ QoD evaluation with the freedom degree







▲ QoD evaluation on different variables in the multi-round scenario



(a) Brightkite (b) Gowalla (c) Foursquare

▲ Loss evaluation in multiple rounds

Thanks for listening!