TEMPLE UNIVERSITY

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# Combinatorial Multi-Armed Bandit Based Unknown Worker Recruitment in Heterogeneous Crowdsensing

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# Road Map

- Background & Motivation
- Model & Problem
- Solution
- Extension
- Simulation
- Conclusion

# Background

- Mobile Crowdsensing
  - Crowd workers are coordinated to perform some sensing tasks over urban environments through their smartphones.

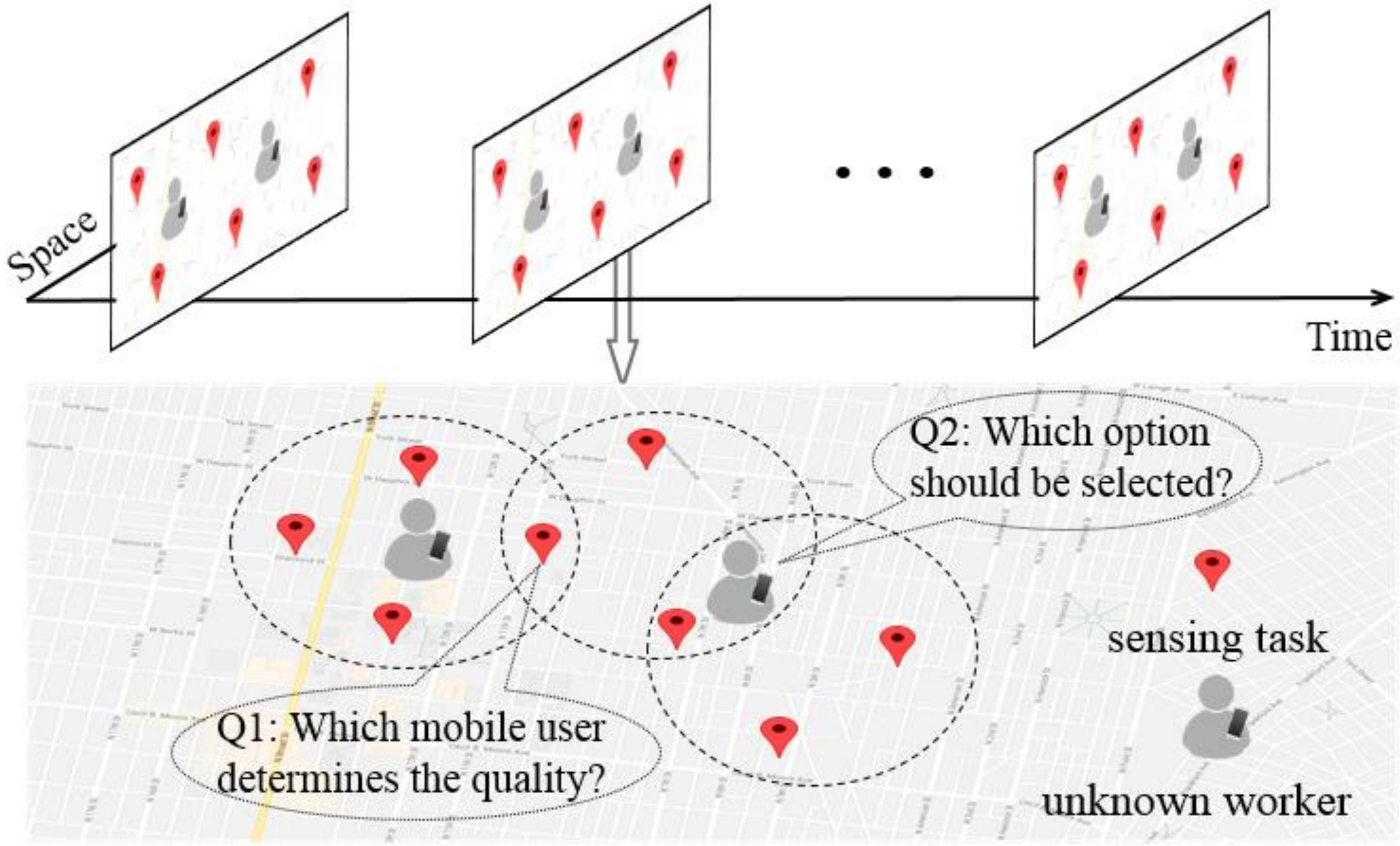
- Typical Applications
  - Collecting traffic information
  - Monitoring noise level
  - Measuring climate, etc

# Motivation

- Task Assignment
  - Objectives: maximizing coverage, maximizing qualities, etc.
  - Constraints: fairness, deadline, acceptance ratio, budget, etc.
  - Models: offline/online, competition-based, probabilistic, etc.
- Worker Recruitment (our focus)
  - Deterministic: users' qualities are known in advance.
  - Non-deterministic: unknown qualities in prior (learning)
- Data Aggregation
  - Incentive mechanism, privacy-aware, etc.

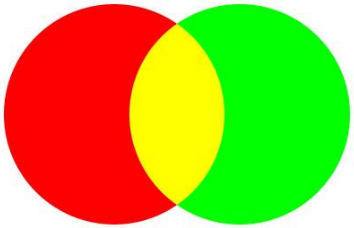
# Motivation

Unknown worker recruitment in heterogeneous crowdsensing

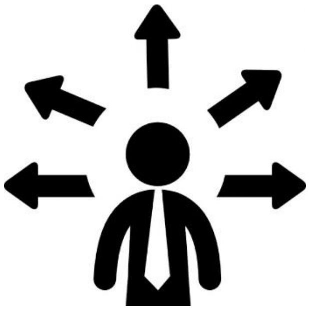


# Motivation

Unknown workers (sensing quality)



Overlapping tasks between workers



Multiple options for each worker

Limited budget for the platform

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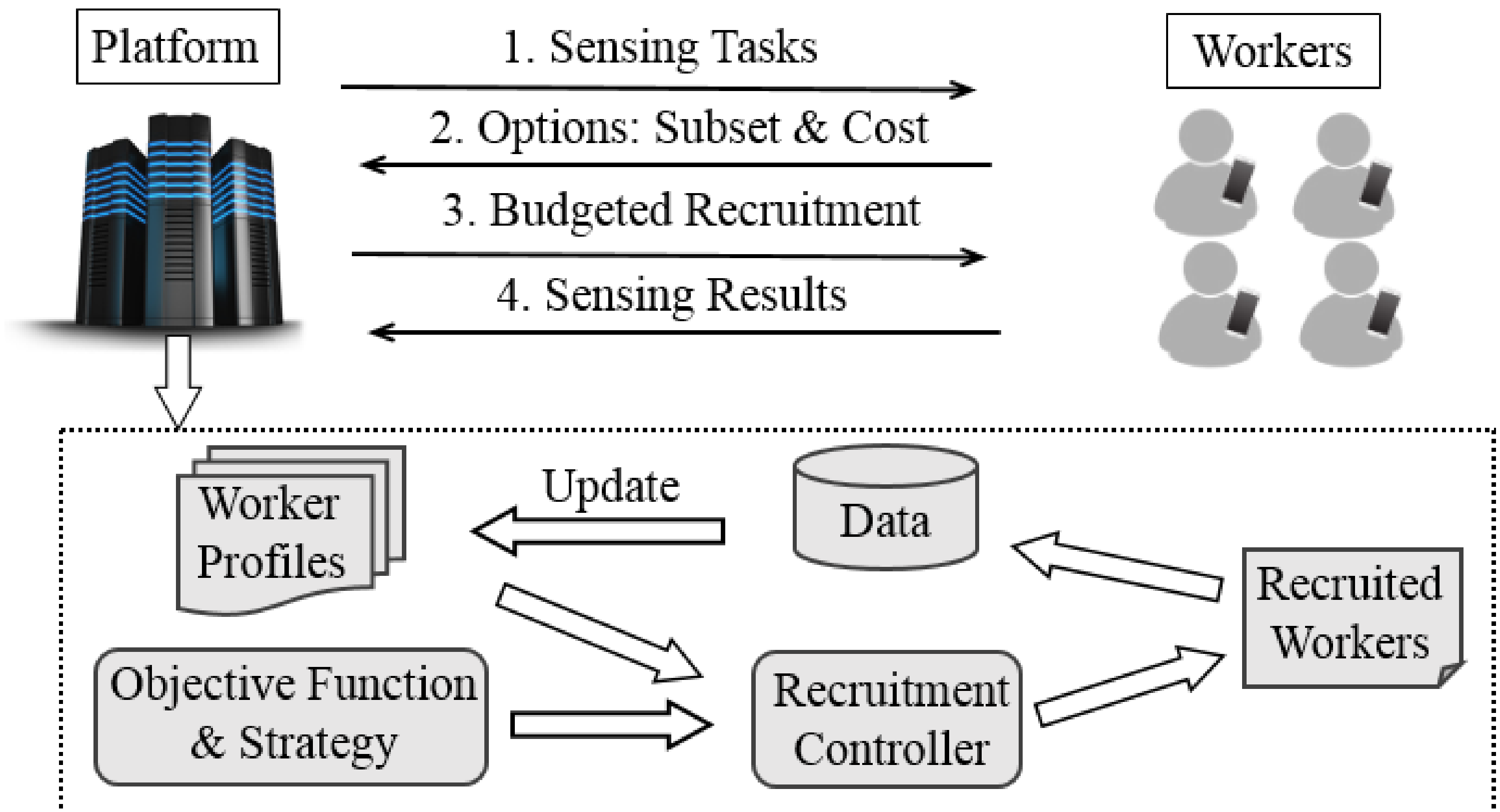
# Model

## main procedures in the mobile crowdsensing



# Model

the index of round: t

N crowd workers: $\{1, \ldots, i, \ldots, N\}$

M sensing tasks: $\{1, \ldots, j, \ldots, M\}$

$w_j$: the weight of the j-th task, $\sum_{j=1}^{M} w_j = 1$

limited budget: B

# Model

total L options for each worker:

$p_i^l = < M_i^l, c_i^l >$: the l-th ($1 \le l \le L$) option for worker i

$M_i^l \subseteq M$: the subset of tasks in the l-th option

$c_i^l$: the corresponding cost

$q_{i,j}^t$: the quality of worker i completing task j in round t

$q_i$: the expectation on the quality of worker i

# Problem

$P$: all options; $P^t \subset P$ : the selected options in the round t

When task j is covered by multiple workers, let the maximum quality value denote the completion quality in this round:

$$u^j(\mathcal{P}^t) = \begin{cases} 0; & j \notin (\cup_{p_i^l \in \mathcal{P}^t} \mathcal{M}_i^l), \\ \max\{q_{i,j}^t \mid p_i^l \in \mathcal{P}^t\}; & j \in (\cup_{p_i^l \in \mathcal{P}^t} \mathcal{M}_i^l). \end{cases}$$

The total weighted completion quality of all tasks in round t:

$$u(\mathcal{P}^t) = \sum_{j \in \mathcal{M}} (w_j \cdot u^j(\mathcal{P}^t)).$$

# Problem

Objective: determine $\{P^1, P^2, \ldots P^t, \ldots\}$ in each round, such that the total expected weighted completion quality of all tasks is maximized under the budget constraint

$$
\begin{aligned}
Maximize: \quad & \mathbb{E}\Big[\textstyle\sum_{t\geq 1} u(\mathcal{P}^t)\Big] \\
Subject\ to: \quad & \textstyle\sum_{t\geq 1}\sum_{p_i^l \in \mathcal{P}^t} c_i^l \leq B \\
& |\mathcal{P}^t| = K \ \text{ for } \ \forall t > 1 \\
& \textstyle\sum_{l=1}^{L} \mathbb{I}\{p_i^l \in \mathcal{P}^t\} \leq 1
\end{aligned}
$$

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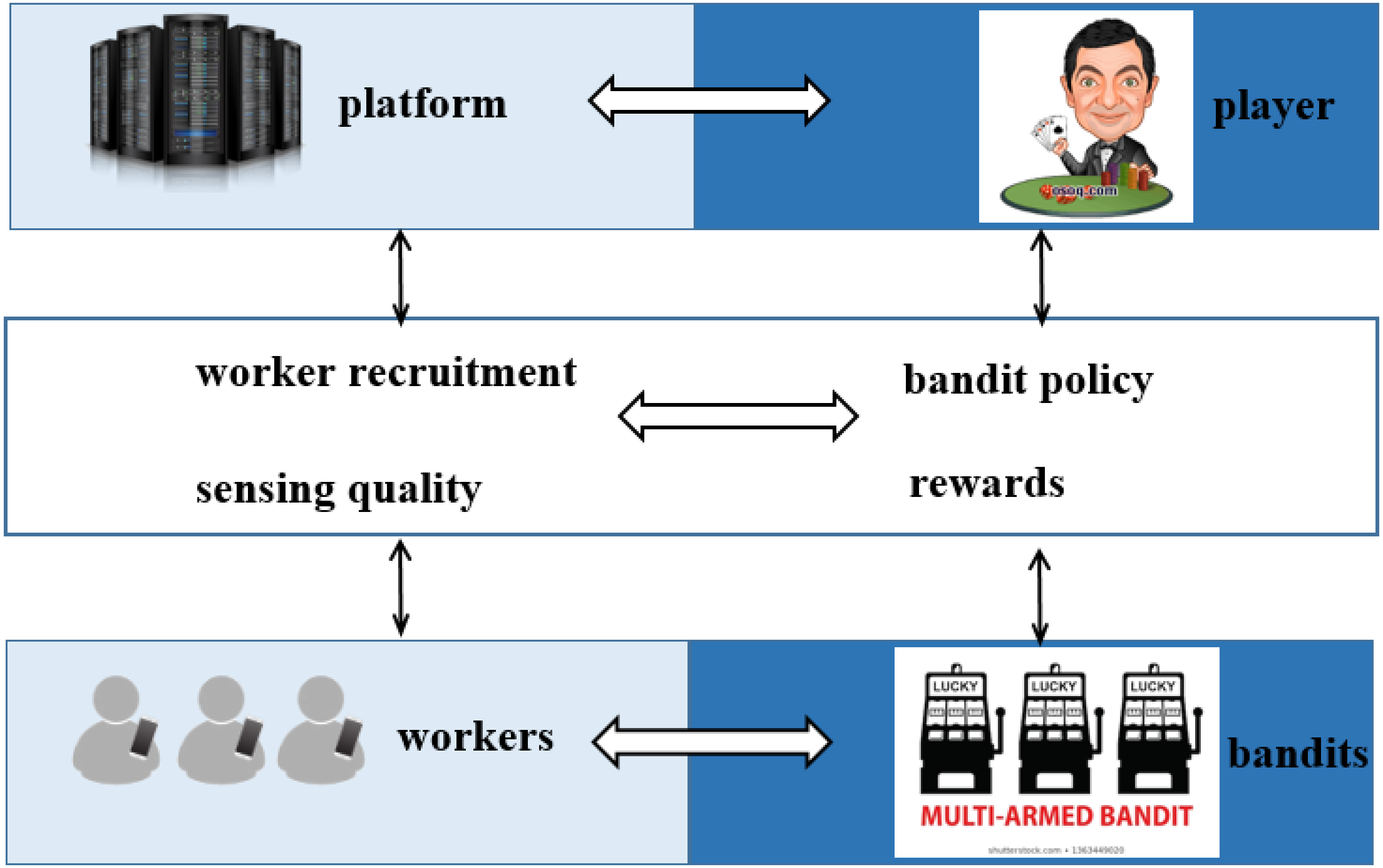
# Solution

Extended Multi-Armed Bandit (MAB) model:



# Solution

**platform** ⟺ **player**


maximize total weighted quality ↔ maximize total rewards

worker's quality is learned multiple times in each round ↔ reward is learned once

K workers are selected in a round ↔ one bandit in each round

# Solution

## Upper Confidence Bound (UCB):

optimism in the face of uncertainty

$$\overline{w_j}(n) + \sqrt{\frac{2ln(n)}{N_{j,n}}}$$

average reward

bonus

# Solution

1) extending UCB expression for each worker

$$\sqrt{\frac{(K+1)\ln(\sum_{i' \in \mathcal{N}} n_{i'}(t))}{n_i(t)}}.$$

extended bonus

2) UCB-based quality function at the beginning of round t

weighted quality

3) greedy strategy: the most cost-effective option

$$p_i^l = \operatorname*{argmax}_{p_{i'}^{l'} \in (\mathcal{P} \setminus \mathcal{P}^t)} \frac{u_{[\widehat{q}_i(t-1)]}(\mathcal{P}^t \cup \{p_{i'}^{l'}\}) - u_{[\widehat{q}_i(t-1)]}(\mathcal{P}^t)}{c_{i'}^{l'}}.$$

# Solution

Detailed algorithm

initialization period

recruitment period

cost ? remaining budget

update information

**Algorithm 1** The UWR Algorithm

**Require:** $\mathcal{N}, \mathcal{M}, \mathcal{P}=\{p_i^l | i \in \mathcal{N}, 1 \leq l \leq L\}, \{w_j | j \in \mathcal{M}\}, B, K$

**Ensure:** $\mathcal{P}^t \subseteq \mathcal{P}$ for $\forall t \geq 1$, $u_B$ and $\tau(B)$.

**Initialization**: $t=1$, recruit all workers, i.e., $\mathcal{P}^1=\{p_i^1 | i \in \mathcal{N}\}$, and obtain the quality $q_{i,j}^1$ for $p_i^1 \in \mathcal{P}^1$.

Let $u_B = u(\mathcal{P}^1)$, $B_t = B - \sum_{p_i^1 \in \mathcal{P}^1} c_i^1$, $n_i(t) = |\mathcal{M}_i^1|$ and $\overline{q}_i(t) = (\sum_{j \in \mathcal{M}_i^1} q_{i,j}^t)/|\mathcal{M}_i^1|$ for $\forall i \in \mathcal{N}$;

**while** 1 **do**

  $t \Leftarrow t+1$, $\mathcal{P}^t = \phi$;

  **while** $|\mathcal{P}^t| < K$ **do**

    Let $\mathcal{P}^{t'} = \{p_i^{l'} \mid \text{for } \forall p_i^l \in \mathcal{P}^t\}$;

    Get $p_i^l = \underset{p_{i'}^{l'} \in (\mathcal{P} \setminus \mathcal{P}^{t'})}{\text{argmax}} \frac{u_{[\hat{q}_i(t-1)]}(\mathcal{P}^t \cup \{p_{i'}^{l'}\}) - u_{[\hat{q}_i(t-1)]}(\mathcal{P}^t)}{c_{i'}^{l'}}$;

    Add $p_i^l$ into $\mathcal{P}^t$, i.e., $\mathcal{P}^t = \mathcal{P}^t + \{p_i^l\}$;

  **if** $\sum_{p_i^l \in \mathcal{P}^t} c_i^l \geq B_{t-1}$ **then**

    **return** Terminate and output $u_B$ and $\tau(B) = t$;

  Obtain the qualities $q_{i,j}^t$ for $\forall p_i^l \in \mathcal{P}^t$;

  Update the worker profiles: $n_i^l(t)$, $n_i(t)$, $\overline{q}_i(t)$ and $\widehat{q}_i(t)$;

  $B_t = B_{t-1} - \sum_{p_i^l \in \mathcal{P}^t} c_i^l$, and $u_B = u_B + u(\mathcal{P}^t)$;

# Solution

hard to get optimal set of workers in polynomial time

regret bound ⟹ approximate regret bound

*Theorem 1*: The worst $\alpha$-approximate regret of Alg. 1, denoted by $R_{\alpha}^{A1}(B)$, is bounded as $O(NLK^3 \ln(B))$

N: number of workers L: number of options

K: number of selected workers in each round

B: total recruitment budget

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# Extension

## The extended problem:

the cost of each worker is also unknown, so the platform needs to learn workers' quality and cost, simultaneously.

## The extended solution:

1) UCB-based cost expression

2) greedy strategy: the most cost-effective option

# Extension

## Detailed algorithm

greedy strategy

learn workers' cost

update information

**Algorithm 2** The EUWR Algorithm

**Require:** $\mathcal{N}$, $\mathcal{M}$, $\mathcal{P}=\{p_i^l=\langle\mathcal{M}_i\rangle\}$, $\{w_j|j\in\mathcal{M}\}$, $B$, $K$, $f(\cdot)$

**Ensure:** $\mathcal{P}^t\subseteq\mathcal{P}$ for $\forall t\geq 1$, $u_B$ and $\tau(B)$.

1: **Initialization**: $t=1$, let $\mathcal{P}^1=\{p_i^1|i\in\mathcal{N}\}$ and obtain the quality $q_{i,j}^1$ and cost parameter $\varepsilon_i^1$ for $p_i^1\in\mathcal{P}^1$.

2: Let $u_B=u(\mathcal{P}^1)$, $B_t=B-\sum_{p_i^1\in\mathcal{P}^1}\varepsilon_i^1 f(|\mathcal{M}_i^1|)$, $n_i(t)=1$, $\overline{q}_i(t)=(\sum_{j\in\mathcal{M}_i^1} q_{i,j}^t)/|\mathcal{M}_i^1|$ and $\overline{\varepsilon}_i(t)=\varepsilon_i^1$ for $\forall i\in\mathcal{N}$;

3: **while** 1 **do**

4: $\quad t\Leftarrow t+1$, $\mathcal{P}^t=\phi$;

5: $\quad$ **while** $|\mathcal{P}^t|<K$ **do**

6: $\quad\quad$ Let $\mathcal{P}^{t'}=\{p_i^{l'}\,|$ for $\forall p_i^l\in\mathcal{P}^t\}$;

7: $\quad\quad$ $p_i^l=\underset{p_{i'}^{l'}\in(\mathcal{P}\setminus\mathcal{P}^{t'})}{\operatorname{argmax}}\; u_{[\widehat{r}_i^{\,l}(t-1)]}(\mathcal{P}^t\cup\{p_{i'}^{l'}\})-u_{[\widehat{r}_i^{\,l}(t-1)]}(\mathcal{P}^t)$;

8: $\quad\quad$ Add $p_i^l$ into $\mathcal{P}^t$, i.e., $\mathcal{P}^t=\mathcal{P}^t+\{p_i^l\}$;

9: $\quad$ Each recruited worker $i$ where $p_i^l\in\mathcal{P}^t$ obtains $\varepsilon_i^t$;

10: $\quad$ **if** $\sum_{p_i^l\in\mathcal{P}^t}\varepsilon_i^t f(|\mathcal{M}_i^l|)\geq B_{t-1}$ **then**

11: $\quad\quad$ **return** Terminate and output $u_B$ and $\tau(B)=t$;

12: $\quad$ Perform tasks and obtain the qualities $q_{i,j}^t$ for $\forall p_i^l\in\mathcal{P}^t$;

13: $\quad$ Update $n_i^l(t)$, $n_i(t)$, $m_i(t)$, $\overline{q}_i(t)$, $\overline{\varepsilon}_i(t)$, and $\widehat{r}_i^{\,l}(t)$;

14: $\quad$ $B_t=B_{t-1}-\sum_{p_i^l\in\mathcal{P}^t}\varepsilon_i^t f(|\mathcal{M}_i^l|)$, and $u_B=u_B+u(\mathcal{P}^t)$;

# Extension

***Theorem 2***: The worst $\alpha$-approximate regret of Alg. 2, denoted by $R_{\alpha}^{A2}(B)$, is bounded as $O(NLK^3 \ln(NMB))$

N: number of workers L: number of options

K: number of selected workers in each round

M: number of sensing tasks B: total budget

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# Simulation

**Trace:** Roma-taxi dataset

the GPS coordinates of approximately 320 taxi cabs collected over 30 days in Rome, Italy.

## Simulation settings

| Parameters | Ranges | Default values |
|---|---|---|
| Number of tasks, M | [100,600] | 300 |
| Number of workers, N | [50,100] | 50 |
| Number of selected workers, K | [1/6*N,3/5*N] | N/3 |
| Budget | [500,10^4] | 1000 |

# Simulation

**Compared algorithms :**

our algorithms (Alg. 1 & Alg. 2)

$\alpha$-optimal algorithm: quality/cost is known

$\varepsilon$-first algorithm: $\varepsilon \cdot$B: randomness & (1-$\varepsilon$)B: best performance

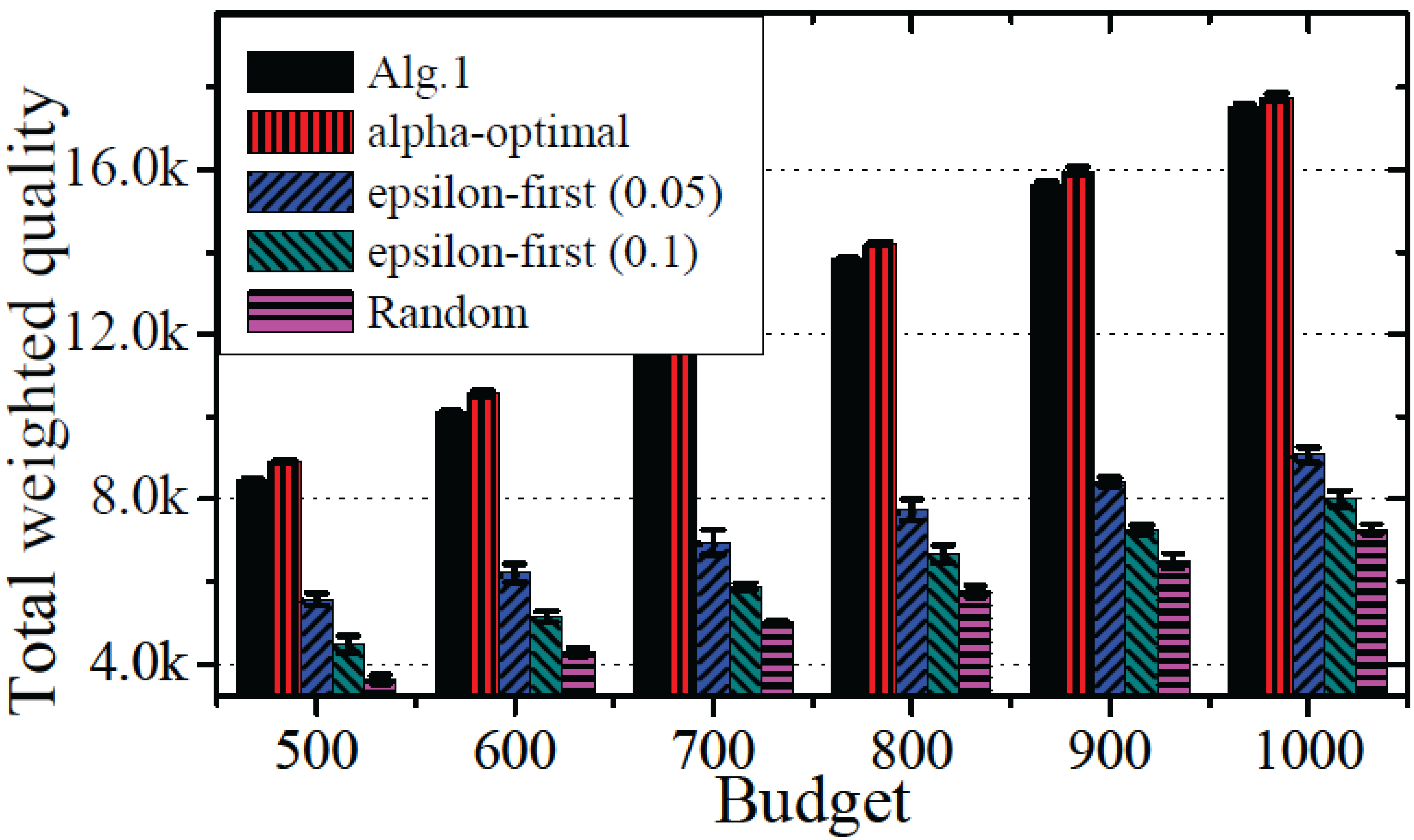
random algorithm: randomly selecting K workers in a round

**Metrics:**

total weighted quality; & total recruitment rounds

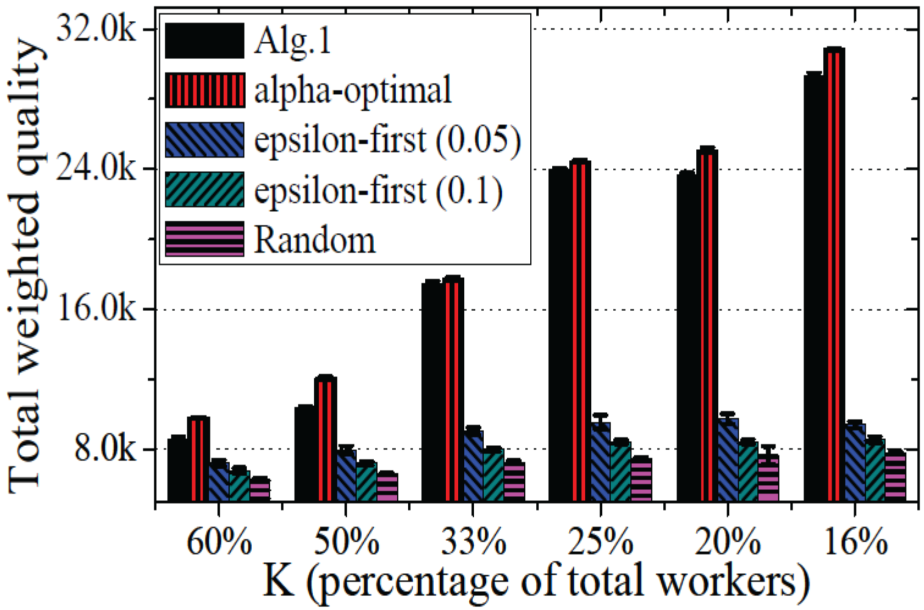
# Simulation

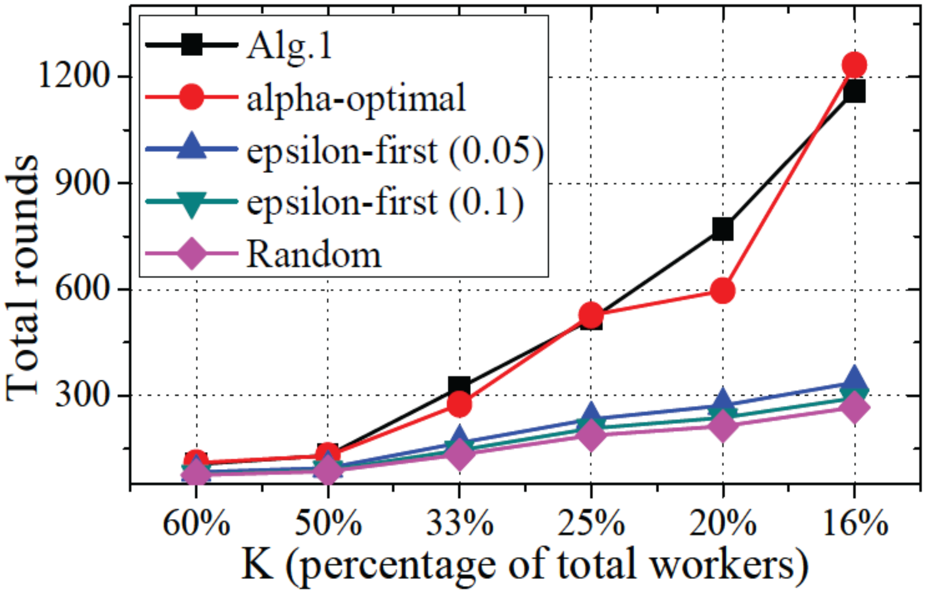
Results for Alg. 1: total weighted quality vs. budget



# Simulation

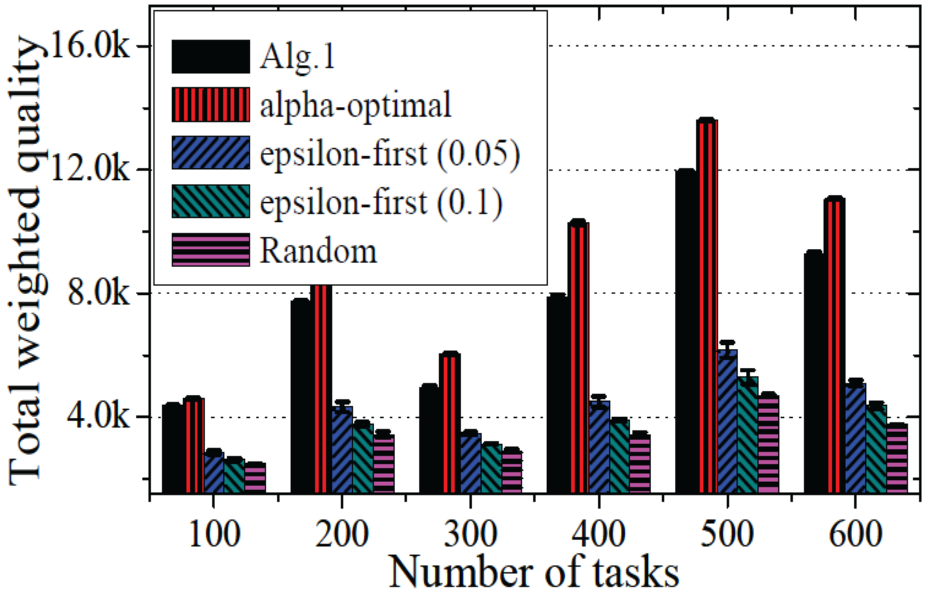
Results for Alg. 1: total weighted quality/rounds vs. K

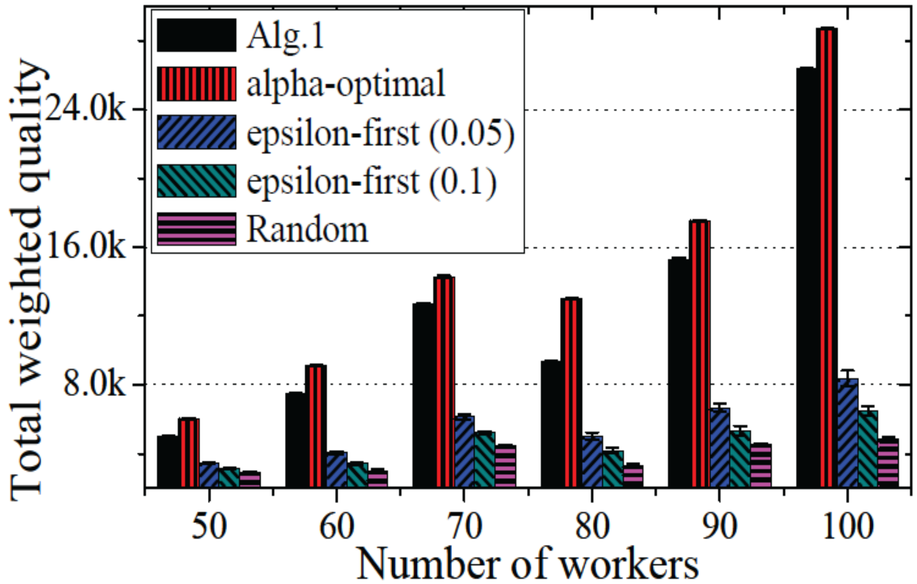


# Simulation

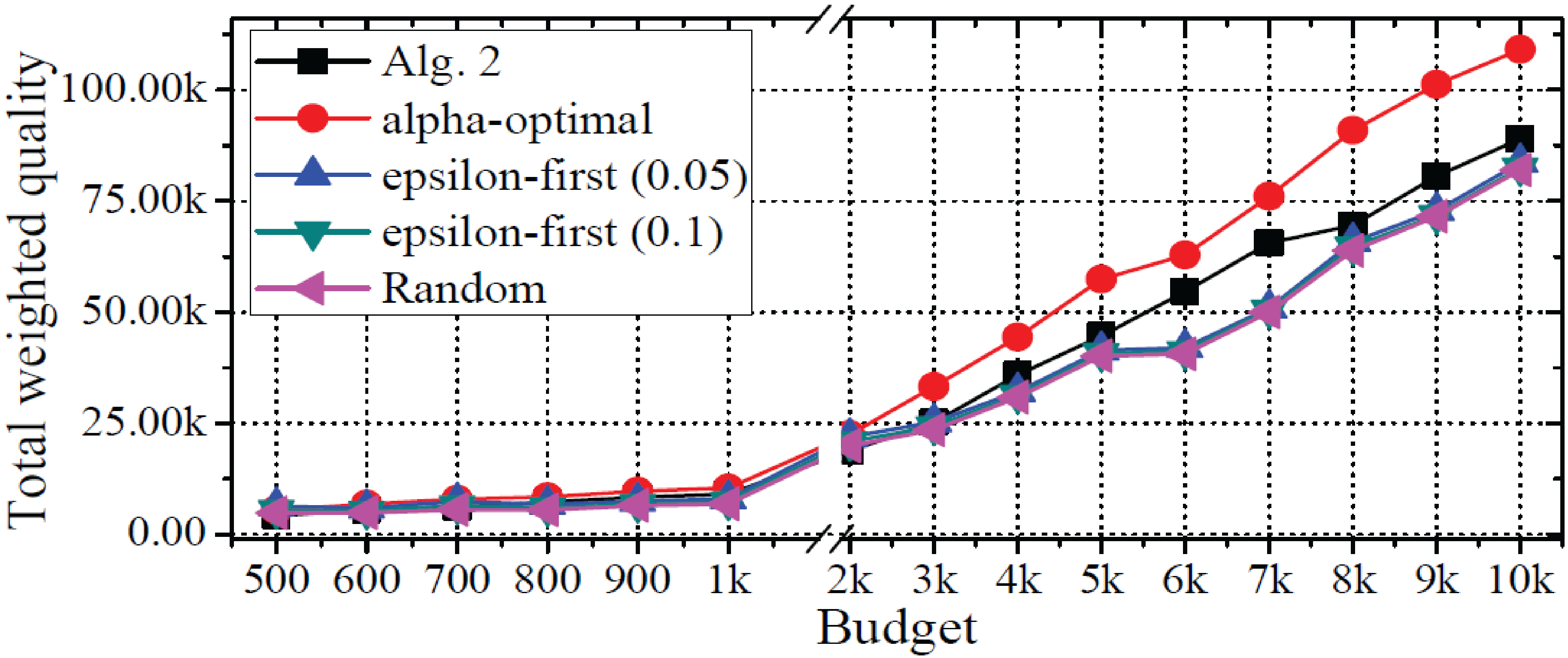
Results for Alg. 1: total weighted quality vs. N/M



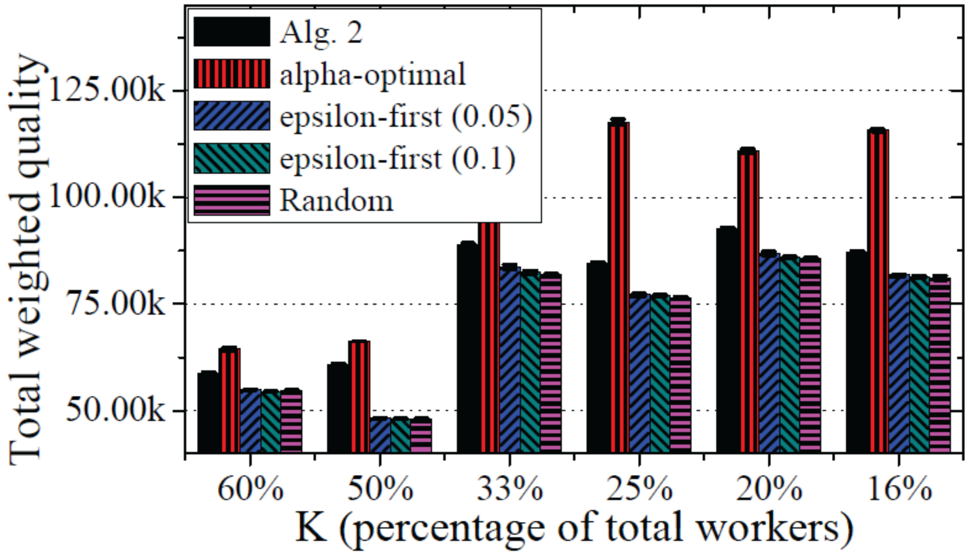
# Simulation

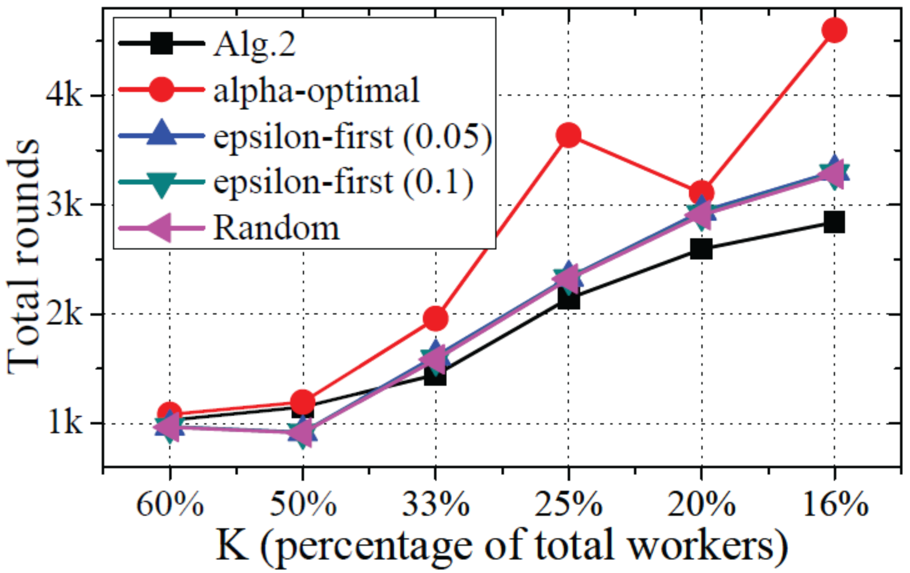
Results for Alg. 2: total weighted quality vs. budget



# Simulation

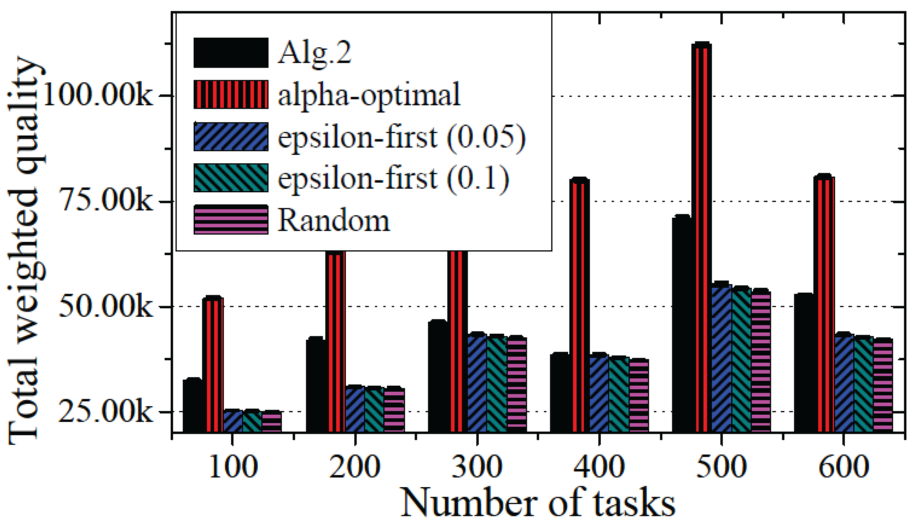
## Results for Alg. 2: total weighted quality/rounds vs. K

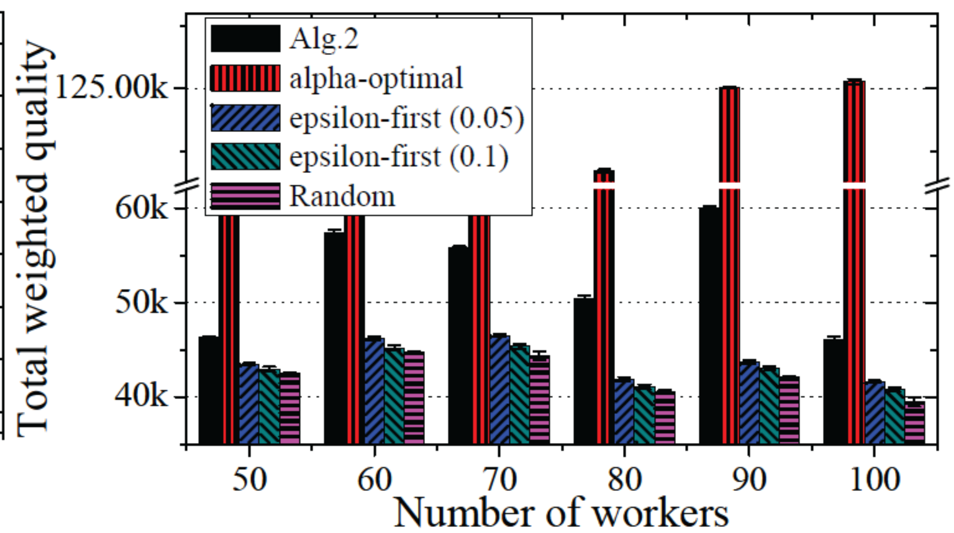


# Simulation

## Results for Alg. 2: total weighted quality vs. N/M



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# Conclusion

1) Alg. 1 almost catches up with the $\alpha$-optimal algorithm, and outperforms other compared algorithms, in any case.

2) The total weighted quality achieved by Alg. 2 is larger than that of other compared algorithms in any case.

3) Due to two unknown parameters existing in the extended problem, the advantage of Alg. 2 over the compared algorithms is not as overwhelming as that of Alg. 1.

# @Contact me

# Thank you !

# Q & A

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