Unknown Worker Recruitment with Budget and Covering Constraints for Mobile Crowdsensing

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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

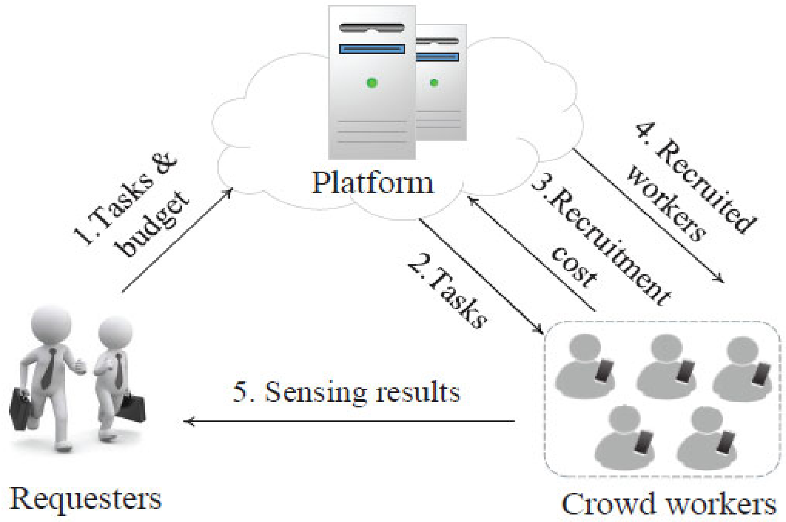
Related Work

- 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)
    - Limited budget
    - Covering constraint
- Data Aggregation
  - Incentive mechanism, privacy-aware, etc.

Crowdsensing Model

- N crowd workers: {1,…,i,…,N}
- M sensing tasks: {1,…,j,…,M}
- Sensing cost: $c_{i,j}$ & budget: B
- Sensing qualities $x_{i,j,t}$:

  an unknown independent and identically distribution with an unknown expectation $q_{i,j}$



- $x_{i,j,t} = 0$ means worker i does not perform task j in round t
- $x_{i,j,t}$ is revealed only after i completed task j in round t
- One worker only can perform one task in each round

Optimization Problem

- Objective: maximize the total expected qualities under the budget and covering (i.e., all tasks must be covered in each round) constraints by adopting reinforcement learning

- Formalization:

$$Maximize: \quad \mathbb{E}\Big[\sum_{t=1}^{T}\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}}\pi_{i,j,t}\cdot x_{i,j,t}\Big]$$

$$Subject\ to: \quad \sum_{t=1}^{T} C_t = \sum_{t=1}^{T}\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}}\pi_{i,j,t}\cdot c_{i,j} \leq B$$ budget constraint

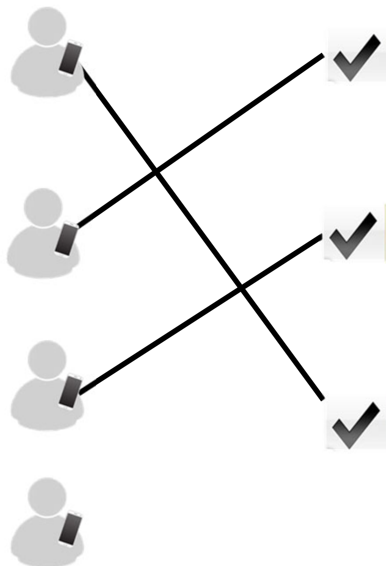
$$\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}}\pi_{i,j,t} = M \quad \text{for } \forall t \geq 1$$ covering constraint

$$\sum_{i\in\mathcal{N}}\pi_{i,j,t} = 1, \quad \sum_{j\in\mathcal{M}}\pi_{i,j,t} \leq 1 \text{ for } \forall t \geq 1$$ one-to-one constraint

$$\pi_{i,j,t} \in \{0,1\} \quad \text{for } \forall i \in \mathcal{N},\ j \in \mathcal{M},\ t \geq 1$$

Basic Concepts

- Multi-armed bandits (reinforcement learning):
  - Exploitation (select the best arm so far)
  - Exploration (try others to discover the potentially best arm)
  - Upper confidence bound (UCB) strategy
- Bipartite matching:
  - Maximum weighted bipartite matching
  - Kuhn-Munkres algorithm (i.e., Hungary algorithm)



- * A combination of the multi-armed bandits and maximum weighted bipartite matching (Our method: UCB strategy + Hungary algorithm)

Homogeneous Cost

- Homogeneous cost: $c_{i,j} = c$ for $\forall i \in N$ and $\forall j \in M$.
- Overview:
  - The cost in each round is determined, i.e., $c \times M$
  - The stopping round is certain, i.e., $\lfloor B/(c \times M) \rfloor$
  - Initial phases: test the qualities of each worker-task pair
  - Later phases: how to select M worker-task pairs in each round ?
    - UCB-based index (quality) for each work-task pair
    - conducting maximum bipartite matching algorithm

Homogeneous Cost

- UCB-based index (quality) $\widehat{x}_{i,j}(t) = \overline{x}_{i,j}(t) + \sqrt{\frac{(M+1)\ln t}{n_{i,j}(t)}}.$
- $n_{i,j}(t)$: the number of worker i performs task j until round t
- $\overline{x}_{i,j}(t)$: the average sampling quality

$$\overline{x}_{i,j}(t) = \begin{cases} \frac{\overline{x}_{i,j}(t-1) \cdot n_{i,j}(t-1) + x_{i,j,t}}{n_{i,j}(t-1)+1}; & (i,j) \in \Phi_t, \\ \overline{x}_{i,j}(t-1); & (i,j) \notin \Phi_t. \end{cases}$$

- Maximum bipartite matching: $\widehat{x}_{i,j}(t)$ is the weights of edges
- Update the values of selected number and average quality.

Homogeneous Cost

- Detailed Algorithm:

Algorithm 1 Recruitment Algorithm with Homogeneous Cost

Require: $\mathcal{N}$, $\mathcal{M}$, B, and $c_{i,j}=c$ for $\forall i\in\mathcal{N}$, $\forall j\in\mathcal{M}$

Ensure: $\Phi_t=\{(i,j)|\pi_{i,j,t}=1,\forall i\in\mathcal{N},\forall j\in\mathcal{M}\}$ for $\forall t\geq 1$.

Initialization: $T=\lfloor\frac{B}{cM}\rfloor$, $t=0$, $Q(t)=0$, $n_{i,j}(t)=0$ and $\overline{x}_{i,j}(t)=0$ for $\forall i\in\mathcal{N}$ and $\forall j\in\mathcal{M}$;
Platform builds the bipartite graph $\mathcal{G}=\{\mathcal{N}\cup\mathcal{M},\mathcal{E},\widehat{\mathcal{X}}\}$, where $\widehat{x}_{i,j}(t)=\overline{x}_{i,j}+\sqrt{\frac{(M+1)\ln t}{n_{i,j}(t)}}\in\widehat{\mathcal{X}}$ is initialized to 0;
while $t\leq T$ **do**
  if $n_{i,j}(t)=0$ for $\forall(i,j)\in\mathcal{E}$ **then**
    // The platform explores the qualities of workers;
    $t\Leftarrow t+1$;
    Obtain the matching Φ_t including (i,j) based on $\mathcal{G}$ in terms of weight value $\widehat{x}_{i,j}(t)\in\widehat{\mathcal{X}}$;
    Output the qualities $x_{i,j,t}$ for $\forall(i,j)\in\Phi_t$;
    Update the two matrixes $(n_{i,j}(t))_{N\times M}=0$ and $(\overline{x}_{i,j}(t))_{N\times M}=0$ according to Eqs. (6) and (7);
    $Q(t)=Q(t-1)+\sum_{(i,j)\in\Phi_t}x_{i,j,t}$;
  end if
  $t\Leftarrow t+1$;
  Conduct the maximum weight matching algorithm [7, 9] in terms of the weight $\widehat{x}_{i,j}(t)$, and output Φ_t;
  Obtain the qualities $x_{i,j,t}$ for $\forall(i,j)\in\Phi_t$;
  Update the two matrixes $(n_{i,j}(t))_{N\times M}=0$ and $(\overline{x}_{i,j}(t))_{N\times M}=0$ according to Eqs. (6) and (7);
  $Q(t)=Q(t-1)+\sum_{(i,j)\in\Phi_t}x_{i,j,t}$;
end while
Output: Φ_t for $t\in[1,T]$, and $Q(T)$;

Performance Bound

Theorem: the regret $R(B)$ satisfies (φ_1, φ_2 are constants)

$$R(B) \leq \varphi_1 \ln(\frac{B}{cM}) + \varphi_2$$

- Definition of regret:

  the difference of total achieved qualities between the optimal matching and the matching of our algorithm in each round

- Applying Chernoff-Hoeffding bound theorem [1]

[1] P. Auer, N. Cesa-Bianchi, and P. Fischer. Finite-time analysis of the multiarmed bandit problem. Machine learning, 47(2-3):235–256, 2002.

Heterogeneous Cost

- Heterogeneous cost: the values of $c_{i,j}$ are different.
- The total cost in each round and stopping rounds are uncertain.
- Difference:
  - The edges in the bipartite graph contain not only the weight (i.e., the unknown quality) but also the cost
  - A modified UCB-based quality: $\widetilde{x}_{i,j}(t) = \overline{x}_{i,j}(t) + \sqrt{\frac{\alpha \ln t}{n_{i,j}(t)}}$
    - α is a constant (will be evaluated in the simulations)
  - The selection criterion changes from $\widehat{x}_{i,j}(t)$ (homogeneous case) to $\frac{\widetilde{x}_{i,j}(t)}{c_{i,j}}$ (heterogeneous case)

Heterogeneous Cost

- Detailed Algorithm:

  (similar to the procedures of the homogeneous case)

Algorithm 2 Recruitment Algorithm with Heterogeneous Cost

Require: $\mathcal{N}$, $\mathcal{M}$, B, α, and $c_{i,j}$ for $\forall i \in \mathcal{N}$, $\forall j \in \mathcal{M}$

Ensure: $\Phi_t = \{(i,j) | \pi_{i,j,t} = 1, \forall i \in \mathcal{N}, \forall j \in \mathcal{M}\}$ for $\forall t \geq 1$.

Initialization: $t = 0$, $B_t = B$, $Q(t) = 0$, $n_{i,j}(t) = 0$ and $\overline{x}_{i,j}(t) = 0$ for $\forall i \in \mathcal{N}$, $\forall j \in \mathcal{M}$;

Platform builds the bipartite graph $\mathcal{G} = \{\mathcal{N} \cup \mathcal{M}, \mathcal{E}, \widetilde{\mathcal{X}}, \mathcal{C}\}$, where $\widetilde{x}_{i,j}(t) = \overline{x}_{i,j}(t) + \sqrt{\frac{\alpha \ln t}{n_{i,j}(t)}} \in \widetilde{\mathcal{X}}$ is initialized to 0;

Platform obtains the matching with minimum cost (i.e., Φ_{min}), so that $C_{min} = \sum_{(i,j) \in \Phi_{min}} c_{i,j} \leq C_k$ for $\forall \Phi_k \in \Pi$;

while $B_t \geq C_{min}$ **do**

  if $n_{i,j}(t) = 0$ for $\forall (i,j) \in \mathcal{E}$ **then**

    $t \Leftarrow t + 1$;

    Obtain the matching (i.e., Φ_t) including (i,j) based on $\mathcal{G}$ in terms of the weight $\widetilde{x}_{i,j}(t) \in \widetilde{\mathcal{X}}$;

    Observe the qualities $x_{i,j,t}$ for $\forall (i,j) \in \Phi_t$;

    Update the two matrixes $(n_{i,j}(t))_{N \times M} = 0$ and $(\overline{x}_{i,j}(t))_{N \times M} = 0$ according to Eqs. (6) and (7);

    $Q(t) = Q(t-1) + \sum_{(i,j) \in \Phi_t} x_{i,j,t}$;

    $B_t = B_{t-1} - \sum_{(i,j) \in \Phi_t} c_{i,j}$;

  end if

  $t \Leftarrow t + 1$;

  Conduct the maximum weight matching algorithm [7, 9] in terms of the criterion $\frac{\widetilde{x}_{i,j}(t)}{c_{i,j}}$, and output Φ_t;

  Obtain the qualities $x_{i,j,t}$ for $\forall (i,j) \in \Phi_t$;

  Update the two matrixes $(n_{i,j}(t))_{N \times M} = 0$ and $(\overline{x}_{i,j}(t))_{N \times M} = 0$ according to Eqs. (6) and (7);

  $Q(t) = Q(t-1) + \sum_{(i,j) \in \Phi_t} x_{i,j,t}$;

  $B_t = B_{t-1} - \sum_{(i,j) \in \Phi_t} c_{i,j}$;

end while

Output: Φ_t for $t \geq 1$, and $Q(t)$;

Experiment

- Simulation settings
  - $x_{i,j,t}$ is randomly sampled from a Gaussian distribution
  - Gaussian distribution is truncated to the interval $(0,1]$
  - The mean $q_{i,j}$ and variance of Gaussian distribution:
    - uniform distribution $(0,1)$
  - Cost $c_{i,j}$:
    - $c_{i,j} = 1$ in the homogeneous case
    - uniform distribution $(0,5)$ in the heterogeneous case

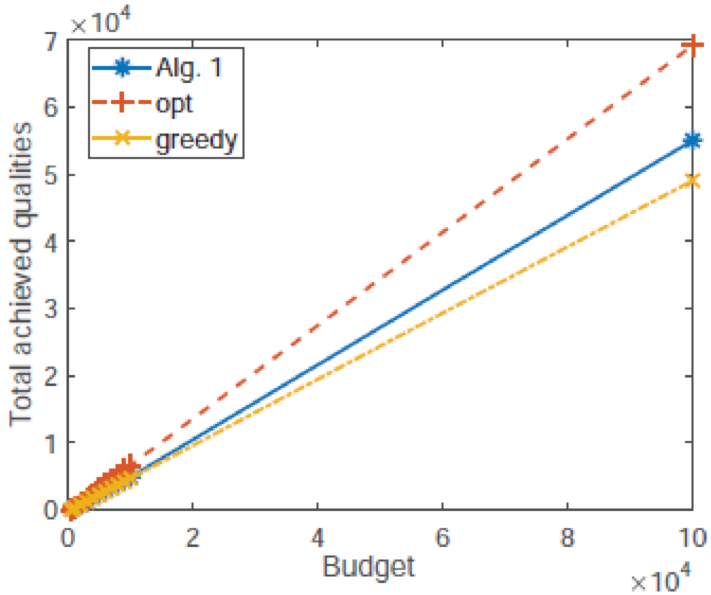
Parameter name	default	range
the number of tasks/workers, $N = M$	20	$10 - 50$
the budget, B	10000	$500 - 100000$
the recruitment cost, $c_{i,j}$	1	$0 - 5$
the parameter, α	1	$0.5 - 10$
the qualities of workers, $x_{i,j,t}$	Gaussian	$0 - 1$
the mean of Gaussian, $q_{i,j}$	uniform	$0 - 1$

Experiment

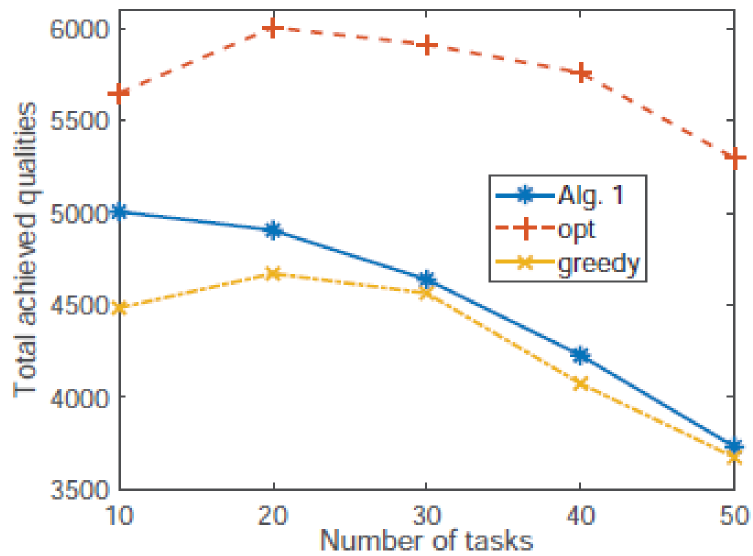
- Compared algorithms:
  - The optimal algorithm (just for homogeneous case):
    - the expected mean $q_{i,j}$ is assumed to be known in advance
    - always output the maximum matching based on $q_{i,j}$
  - The greedy algorithm (applied for both cases):
    - select the worker-task pairs locally based on $\widehat{x}_{i,j}(t)$
- Metrics:
  - The accumulative qualities
  - The average regret (the total regret divided by $\log(B)$)
  - The consumed time

Experiment Results

- Homogeneous case



Total quality vs. Budget

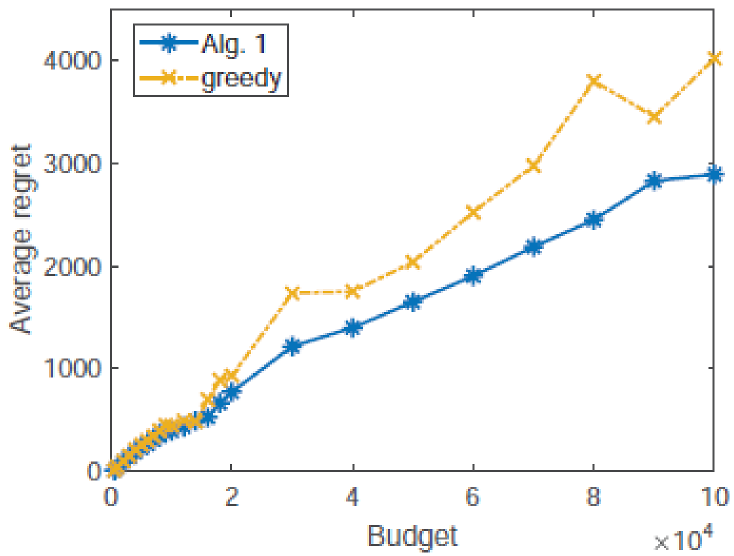


Total quality vs. Num. of Tasks

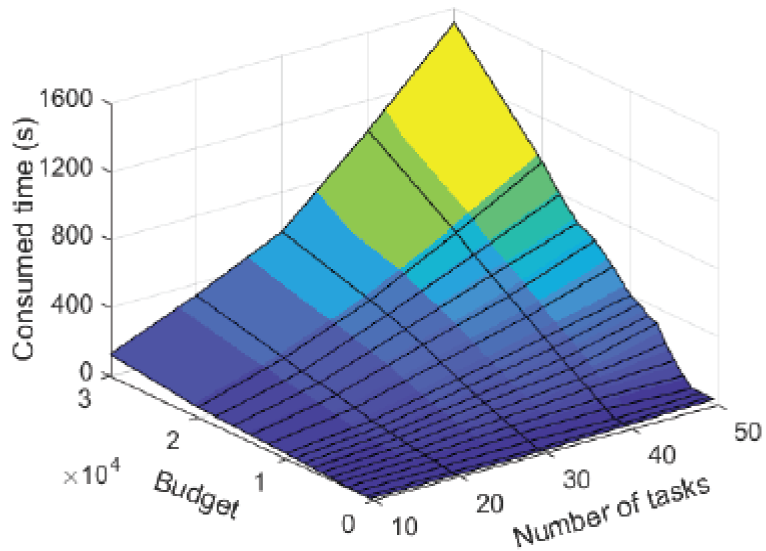
- Our algorithm outperforms the greedy algorithm;
- The total achieved qualities are proportional to the budget;

Experiment Results

- Homogeneous case



Average regret vs. Budget

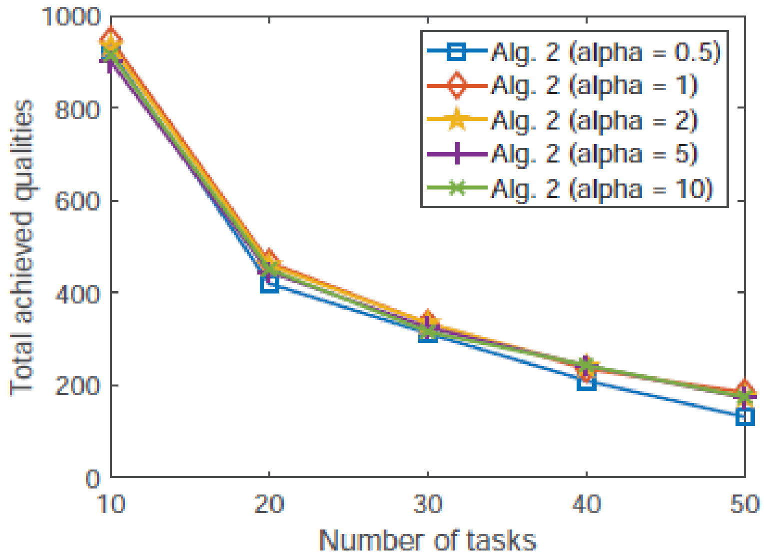


Consumed time

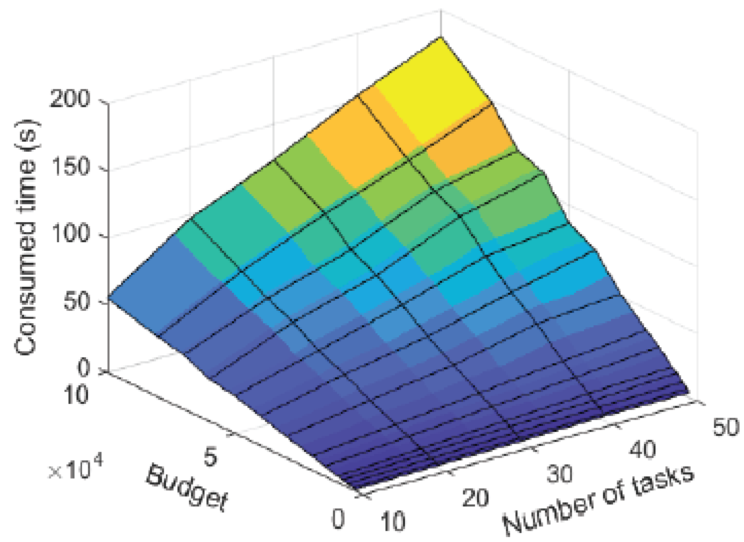
- The average regret will increase with the increase in budget;
- The matching algorithm included in our algorithm leads to the relatively high computation overhead.

Experiment Results

- Heterogeneous case



Total quality vs. Num. of Tasks



Consumed time

  - The total achieved qualities are inversely proportional to the number of tasks;
  - The consumed time is proportional to the budget and the number of tasks;

Summary

- Unknown worker recruitment problem is more practical
  - especially with budget and covering constraints
- The combination of learning and matching is difficult
  - extending the upper confidence bound in multi-armed bandits
  - applying the maximum weighted bipartite matching
- Experiments
  - homogeneous performance with budget and the number of tasks
  - heterogeneous performance with the values of budget, the number of tasks, and the parameter α

Thank you

Q & A