Cost-Efficient Worker Trajectory Planning Optimization in Spatial Crowdsourcing Platforms

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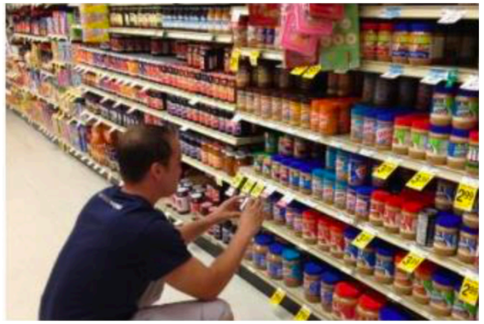
Research Background

- Crowdsourcing and Spatial Crowdsourcing
  - Crowdsourcing: organizing the crowd (workers) to do tasks which are hard for machines but easy for human.
  - Spatial crowdsourcing: Organizing the crowd (mobile workers) to do spatial tasks by physically moving to other locations

Research Background

- Tasks
  - General Spatial Task
    - Inventory identification
    - Placement checking
    - Data collection
    - …
  - Specific spatial task
    - Taxi calling service
    - Food delivery service
    - …



"Spatial Crowdsourcing: Challenges, Techniques, and Applications", in *Proceedings of the 43rd International Conference on Very Large Databases* (VLDB 2017), Munich, Germany

Research Background

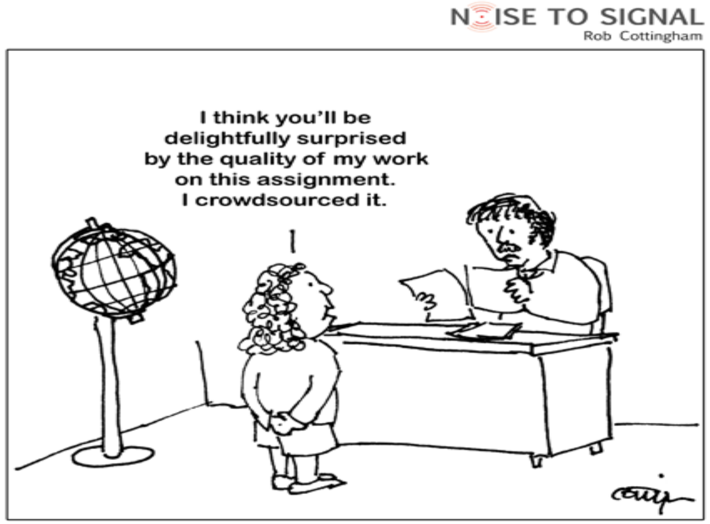
- Management Mode
  - Worker Selected Tasks (WST)
    - workers actively select tasks
  - **Server Assigned Tasks (SAT)**
    - workers passively wait for the platform to assign tasks

Worker Selected Tasks

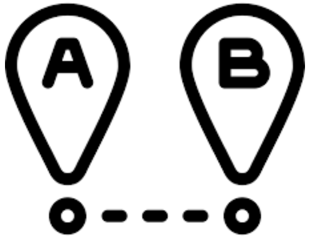
Server Assigned Tasks

Task Assignment: Challenges

- Quality-control
  - Different sensors (sampling frequency, reading-accuracy)
  - Different behaviors (e.g., following the instruction strictly or careless)

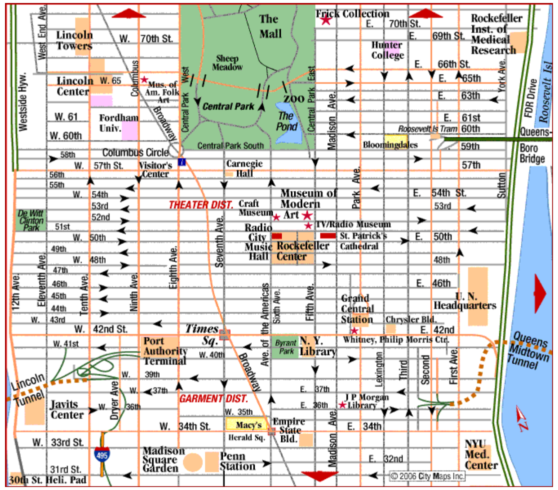


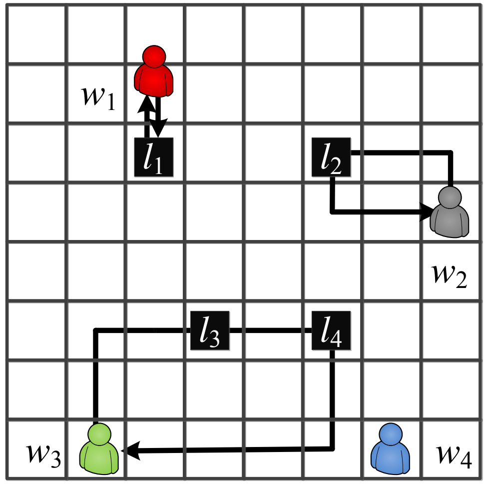
- Crowdsourcing Cost
  - Workers have to go the crowdsourcing locations from their current locations.
  - Different workers have different movement distances.



Network Model

- Multiple workers and crowdsourcing locations
  - Each worker has a certain quality for finishing crowdsourcing tasks.
  - The cost of a worker is proportional to the movement distance, e.g., ridesharing.
  - Each recruited worker generates a round crowdsourcing tour.





Cost-efficient Worker Recruitment Problem

- How to recruit a set of proper workers?
  - Maximize the worker recruitment efficiency
    - different crowdsourcing qualities for different workers
    - different crowdsourcing costs for different workers

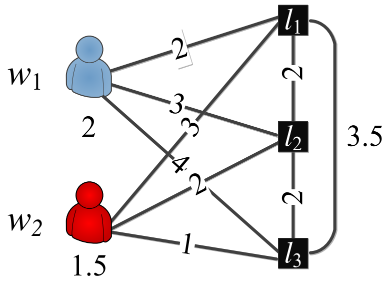
$$\textit{System efficiency} = \frac{\sum quality}{\sum cost}$$

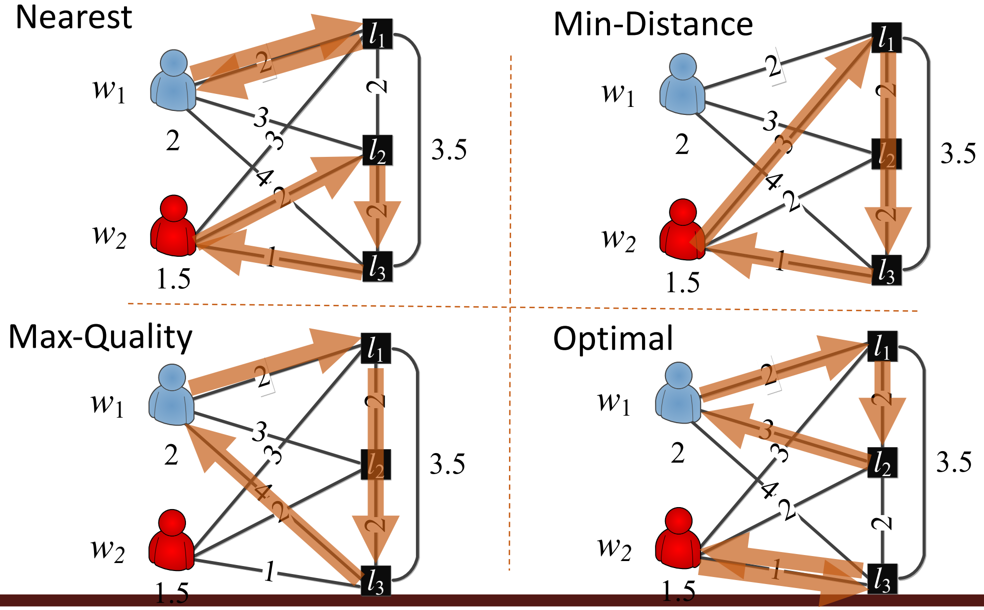
  - Coverage Constraint
    - All the crowdsourcing locations should be covered/reached, e.g., traffic/environment monitoring, route navigation, etc.

- NP-complete in general scenario
  - Reduce to the TSP problem

Cost-efficient Worker Recruitment Problem

- A motivation example
  - Three algorithms:
    - Nearest: each location is assigned to the closest worker
    - Min-Distance: overall crowdsourcing distance is minimized
    - Max-Quality: each location is assigned to the worker with the highest quality



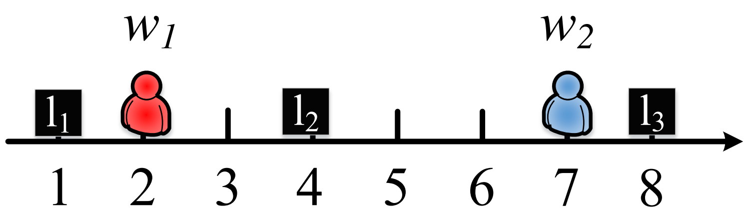


Schedule	w_1	w_2	Efficiency Ratio
Nearest	$\{l_1\}$	$\{l_2, l_3\}$	(3+2)/(5+4) = 0.56
Min dist.	{}	$\{l_1, l_2, l_3\}$	4.5/8 = 0.56
Max quality	$\{l_1, l_2, l_3\}$	{}	6/10 = 0.60
Optimal	$\{ l_1, l_2\}$	$\{l_3\}$	(1.5 + 4)/(2 +7) =0.61

Proposed Problem in 1-D Scenario

- All workers and tasks can be reached via a line, e.g., people/vehicles in highway or main street.

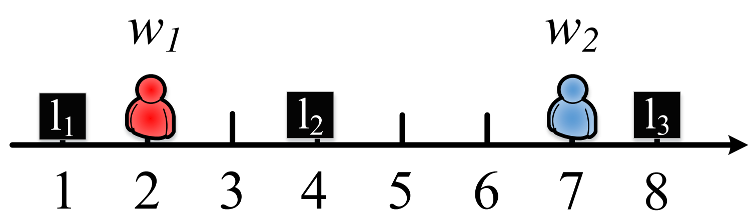
- An example
  - two workers and three crowdsourcing locations



Proposed Solution: Dynamic Programming

❖ Algorithm

- ❑ Sort the worker locations and crowdsourcing location separately from one side to another side, e.g., from left to right
- ❑ Define opt[i,j] as the maximum ratio between first i workers with first j crowdsourcing locations
  - ➢ The opt[i.j].c and opt[i,j].q are the corresponding total tour(s) length and the total quality.



Worker i is not recruited for first j tasks

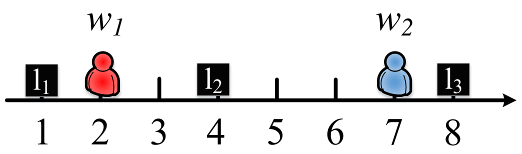
$$opt[i,j] = \max \begin{cases} opt[i-1,j], \\ \dfrac{opt[i',j'].q + q_i(j-j')}{opt[i',j'].c + 2(\max\{l_i,l_j\} - \min\{l_i,l_{j'}\})} \\ \forall i',j',i'<i,j'<j. \end{cases} \quad (3)$$

Worker i is recruited for crowdsourcing tasks between j' to j

Proposed Solution: Dynamic Programming

❖ A toy example

➢ Dynamic programming (An illustration example: $q_1 = 0.5$ and $q_2 = 1$)



opt[i,j].q	0	1	2	3
0	0	0	0	0
1	0	0.5	1	1.5
2	0	1	2	2.5

opt[i,j].c	0	1	2	3
0	0	∞	∞	∞
1	0	2	6	14
2	0	12	8	10

opt[i,j]	0	1	2	3
0	0	0	0	0
1	0	1/4	1/6	3/28
2	0	1/12	3/16	1/4

➢ Calculate opt[2,3]

$$\text{opt}[2,3] = \max\left\{\frac{\text{opt}[1,0].q+3*1}{\text{opt}[1,0].c+7*2}, \frac{\text{opt}[1,1].q+2*1}{\text{opt}[1,1].c+4*2}, \frac{\text{opt}[1,2].q+1*1}{\text{opt}[1,2].c+1*2}, \text{opt}[1,3]\right\}$$

w_2: {l_1, l_2, l_3}

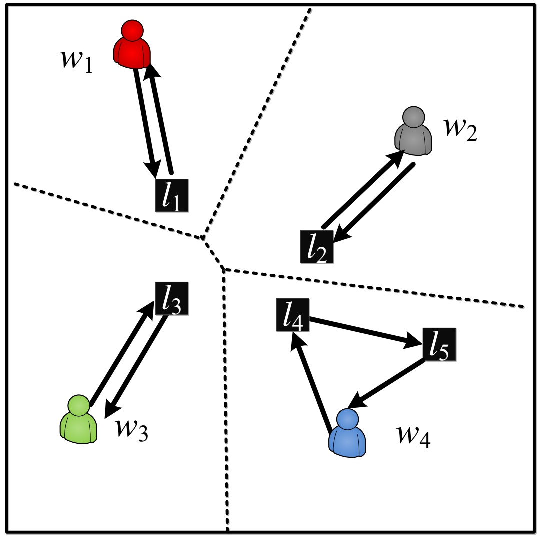
w_1: {l_1}
w_2:{l_2, l_3}

w_1: {l_1, l_2}
w_2:{l_3}

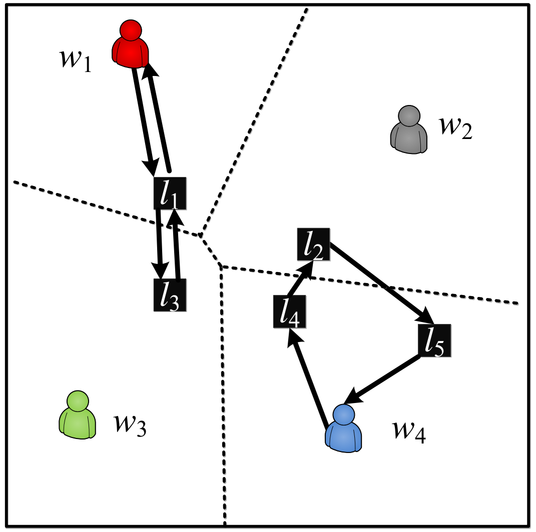
w_1 : {l_1, l_2, l_3}

Proposed Problem in 2-D Scenario

- Homogenous 2-D scenario (all workers have the same quality)
  - Objective: minimize the overall tour(s) length
- A simple nearest assignment solution
  - Voronoi graph partition



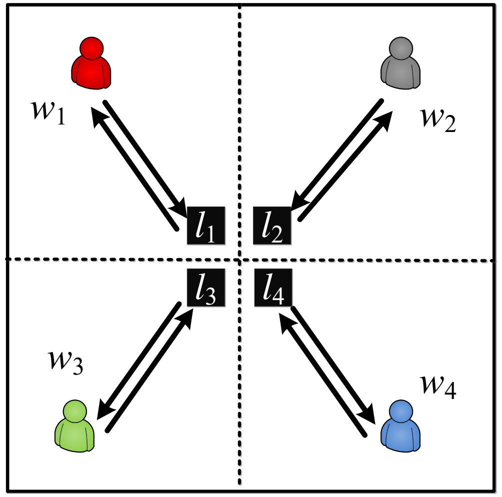
Nearest assignment



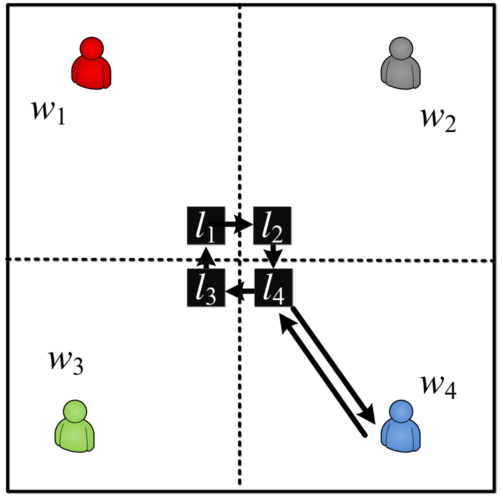
Optimal assignment

Proposed Problem in 2-D Scenario

- Homogenous 2-D scenario
  - Performance Analysis: to minimize the total tour length, the nearest assignment can be as bad as n times of the optimal solution, where n is the total number of workers in the network.
  - an extreme example



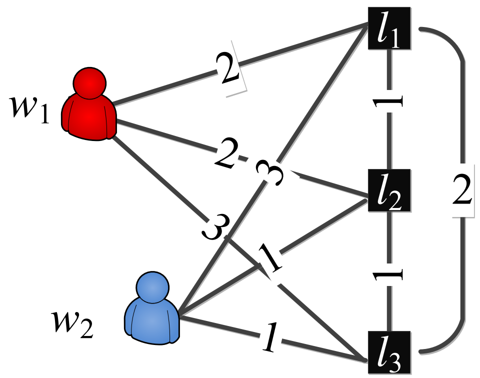
Nearest assignment



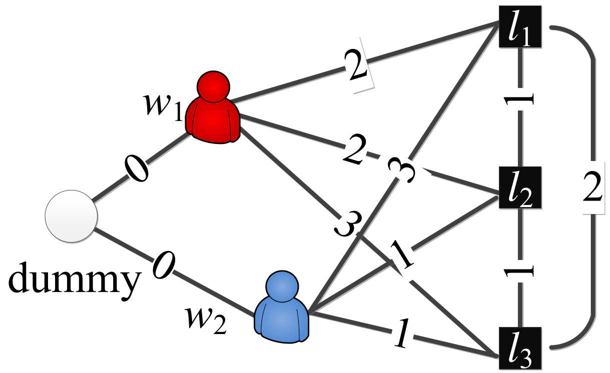
Optimal assignment

Proposed Solution in Homogenous 2-D scenario

- ❖ A Minimum-Spanning Tree (MST) based approach
  - ❑ Transfer the network into a graph where links are shortest distance between them.
  - ❑ Add a dummy node and it has links (zero-weight) with all workers



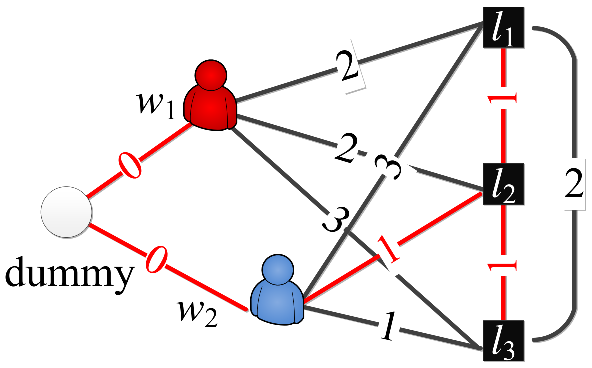
Step 1



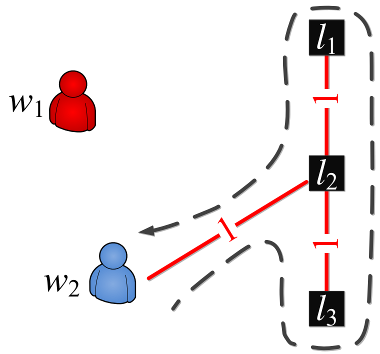
Step 2

Proposed Solution in Homogenous 2-D scenario

- A Minimum-Spanning Tree (MST) based approach
  - Find the MST in the new graph
  - Got a spanning forest by removing the dummy nodes and the corresponding link
  - Find the best visiting tour for each selected workers based on the generated spanning tree(s)



Step 3



Step 4

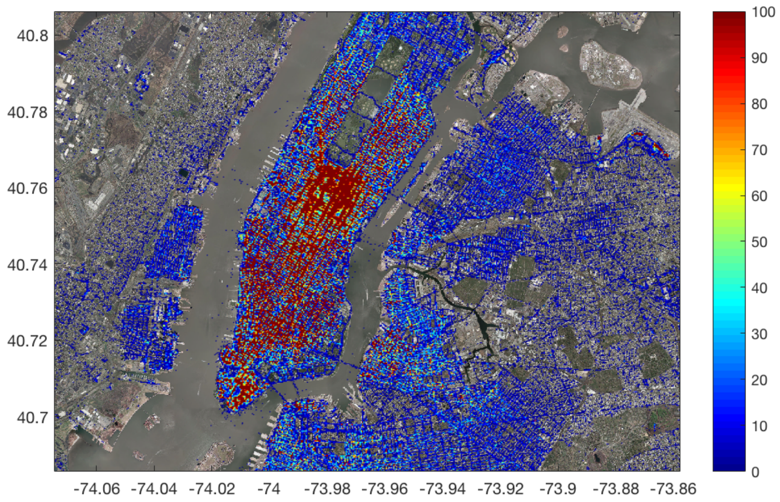
Proposed Solution: Analysis

- Homogenous 2-D scenario
  - MST can be calculated optimally based on the matroid theory.
  - The MST to the shortest tour transfer has an approximation ratio of 1.5 through greedy algorithm in the metric space.
  - The best shortest tour algorithm achieves an approximation of of $1 + \epsilon$ trough Fully Polynomial-time approximation scheme (FPTAS) in the Euclidean space.

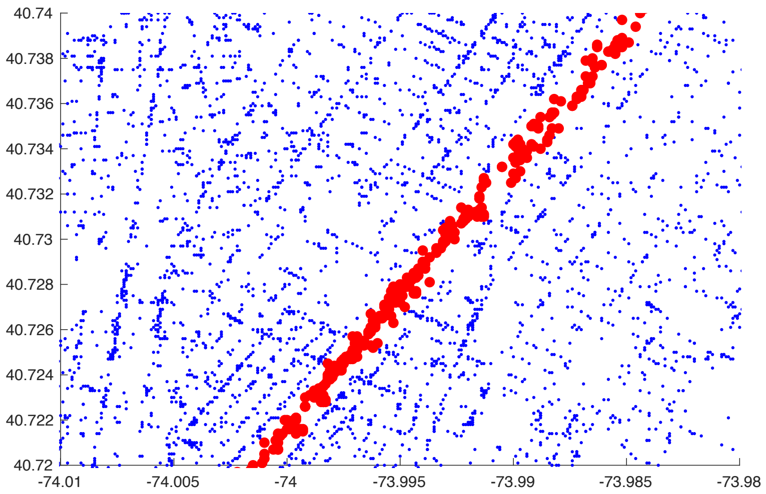
- Heterogeneous 2-D scenario
  - Apply the same solution, further bounded by the maximum quality ratio between workers in the network
    - further optimization is our future work

Performance Evaluation

- ❖ Uber pick-up trace from the NYC
  - ❑ April 2014, which has 564,516 records.
  - ❑ Worker and crowdsourcing locations are randomly generated.
  - ❑ 7 different worker qualities



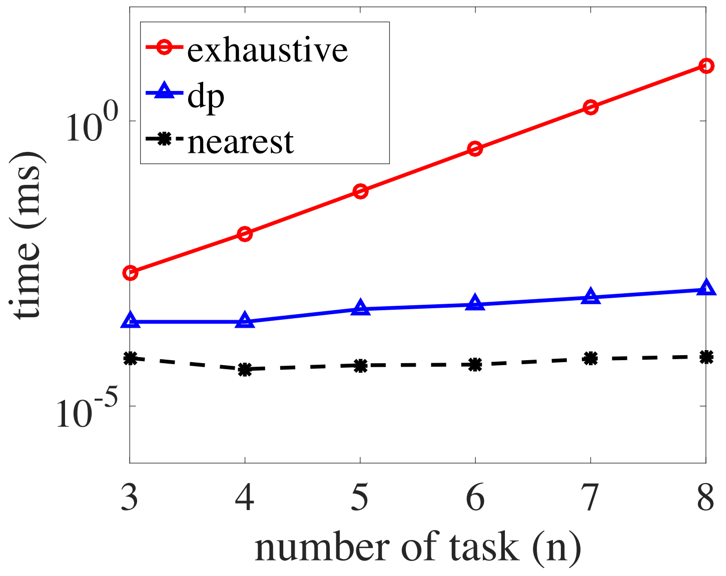
Trace visualization

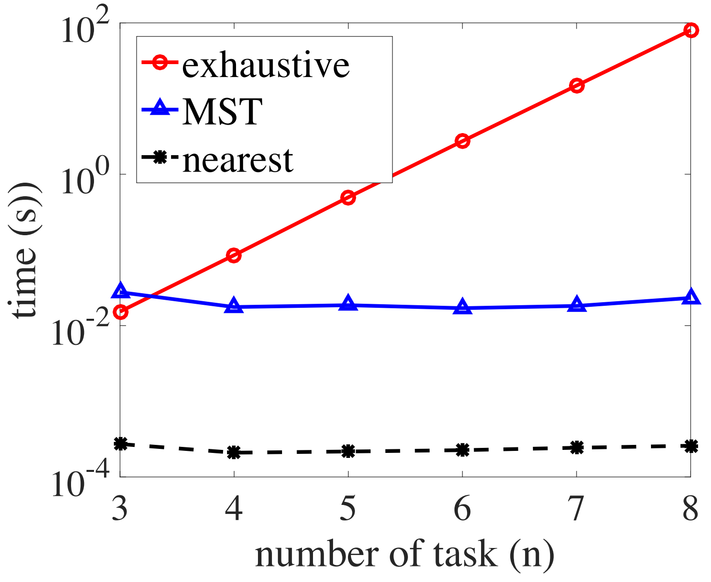


Broadway, Manhattan.

Performance Evaluation

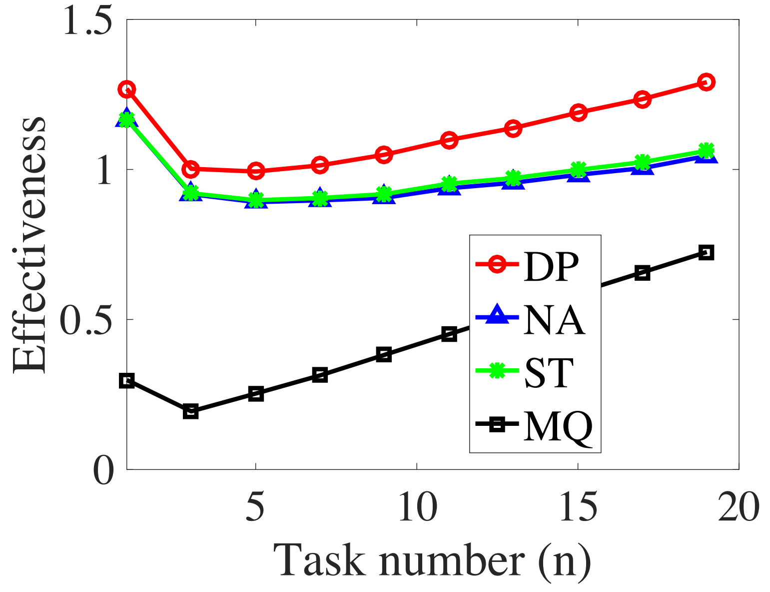
- Time complexity (logarithmic axis)
  - The proposed approaches have similar running-time in different scales

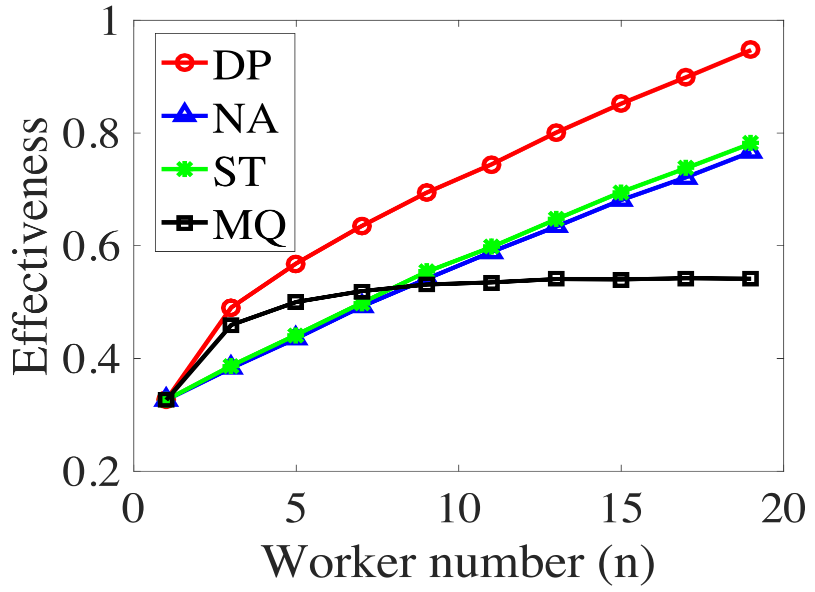




Performance Evaluation

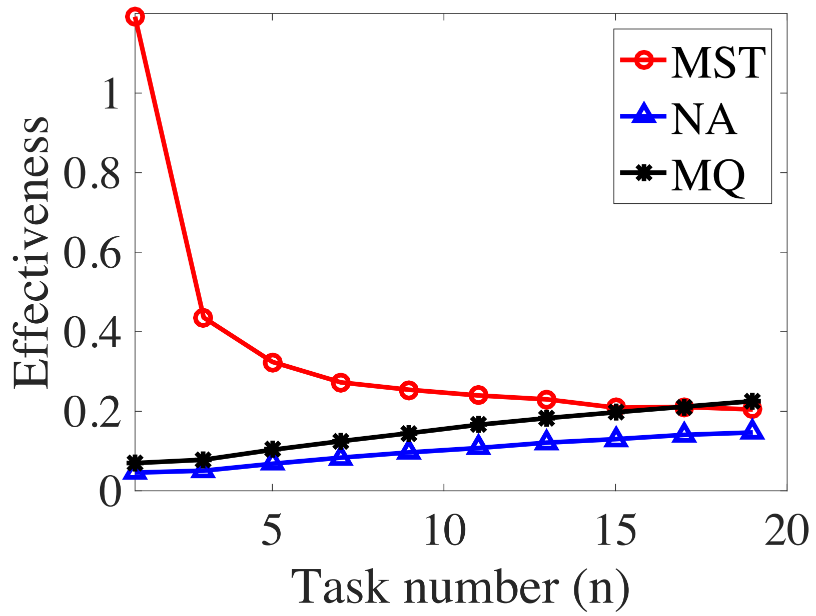
- Effectiveness (1-D scenario)
  - DP: Dynamic Programming, NA: Nearest Assignment, ST: Shortest Tour(s), and MQ: Max-Quality

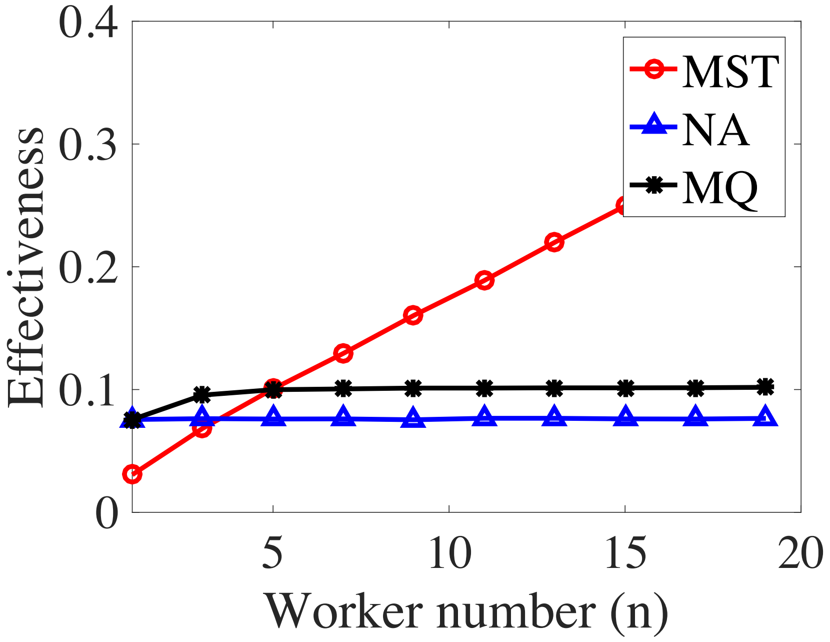




Performance Evaluation

- 2-D scenario
  - MST: proposed approach, NA: Nearest Assignment, and MQ: Max-Quality





Summary

- ❖ Work recruitment problem in spatial crowdsourcing is still not well-solved by considering heterogeneous worker qualities.

- ❖ We proposed the concept of the System efficiency and proposed solutions in 1-D and 2-D scenario.
  - ❑ Optimal solution in 1-D scenario
  - ❑ Approximation solution in 2-D scenario

- ❖ We demonstrated proposed approaches in Uber NYC traces.

Thanks!

- Contact
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