Coverage and Workload Cost Balancing in Spatial Crowdsourcing

Ning Wang, Jie Wu and Pouya Ostovari
Temple University

Outline

- Introduction
- Model and problem
- Solution in 1-D scenario
- Solution in 2-D scenario
- Experiments
- Conclusion and future work

Background

From crowdsourcing to Spatial Crowdsourcing

- Crowdsourcing
  - Outsourcing at set of task to a set of workers
    - ❖ Human Intelligence Tasks (hard for computer, easy for human)

amazon mechanical turk™
Artificial Artificial Intelligence

- Spatial Crowdsourcing
  - Crowdsourcing a set of spatial task to a set of workers
    - ❖ Traffic monitoring
    - ❖ climate measurement
    - ❖ Interesting point review

Background

Real applications:

- Spatial Crowdsourcing Service
  - ❖ TaskRabbit (Home repair and refresh)
  - ❖ Uber (Passenger/food delivery)
  - ❖ WeGoLook (Inspection)
  - ❖ FiELD Agent/ Gigwalk

- Information sharing*
  - ❖ Waze/Trapster (Traffic update)
  - ❖ WeatherSignal/OpenSignal
  - ❖ Local review (Google Local guide)

Related Works

Related works

- Worker trajectory planning
  - Plan worker's trajectory in crowdsourcing service
    - ❖ Maximize number of a worker's task
    - ❖ Maximize multiple workers' tasks (competition)
    - ❖ Crowdsourcing task can be time conflicted

- Worker recruitment problem*
  - Ensure crowdsourcing quality with worker's trajectory
    - ❖ Maximize the coverage area
    - ❖ Minimize the overall recruitment cost

Network Model

Our model

- Information sharing*
- Worker recruitment problem*

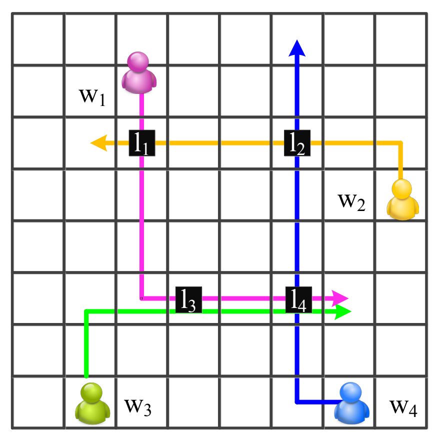
Sharing economy!

- You will not be bothered by the crowdsourcing platform, but you and others can benefit from this.

Network Model

Network Model

- Multiple Workers, $\{w_1, w_2, \dots w_n\}$
  - known trajectory, t_i, and recruiting cost, c_i, for visiting a crowdsourcing location.
- Many crowdsourcing locations, $\{l_1, l_2, \dots l_m\}$
  - Pay worker c_i when w_i passes this location
- Grid network
  - Fit real road networks



Problem Formulation

Coverage and Balanced Crowdsourcing Recruiting (CBCR) problem

- Coverage requirement
  - All the crowdsourcing locations should be covered/visited
- Balancing crowdsourcing location cost
  - The maximum cost of crowdsourcing location should be minimized

$$\min \quad \max_i \sum_{l_i \in t_j} c_j x_j$$

$$\text{s.t.} \quad \sum_{l_i \in t_j} x_j \geq 1, \quad \forall l_i \quad x_j \in \{0, 1\},$$

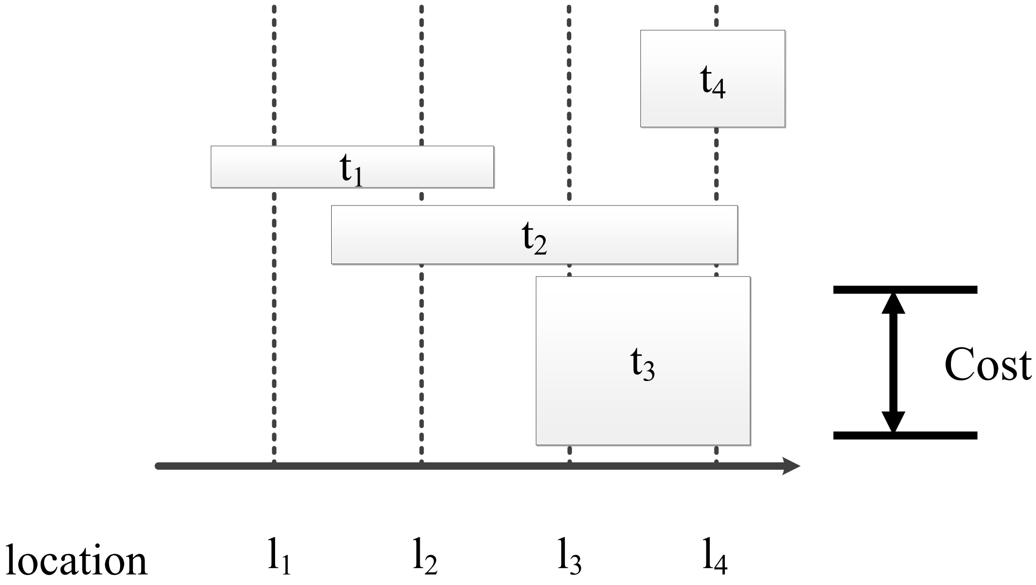
- NP-hard in general scenario

1-D scenario

Application scenario

People/vehicles in highway, main street

- illustration



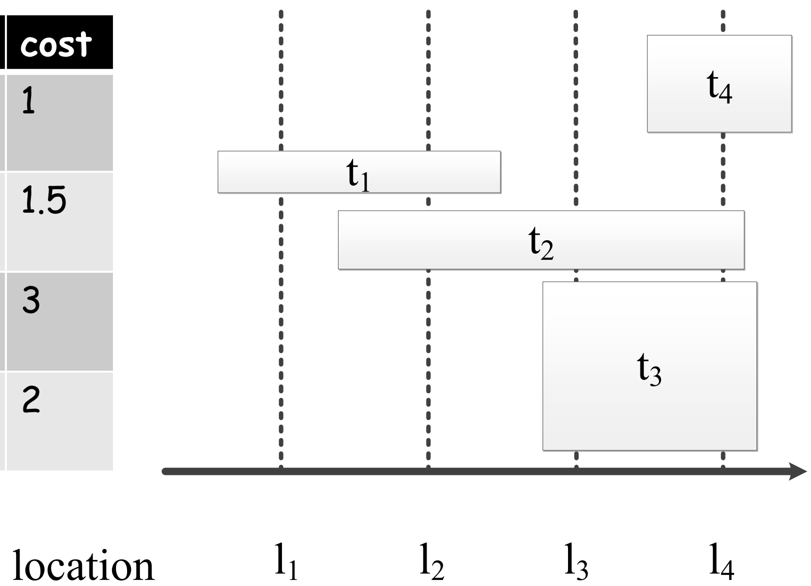
worker	Covered locations	cost
w1	l1, l2	1
w2	l2, l3, l4	1.5
w3	l3, l4	3
w4	l4	2

1-D scenario

- Min-max Greedy algorithm (MG)

  - While the network is not covered, we select the worker who can minimize the maximum cost among all the crowdsourcing locations in the network.

worker	cost
w1	1
w2	1.5
w3	3
w4	2



round	Selected worker	cost
1	w1	1
2	w4	2
3	w2	3.5

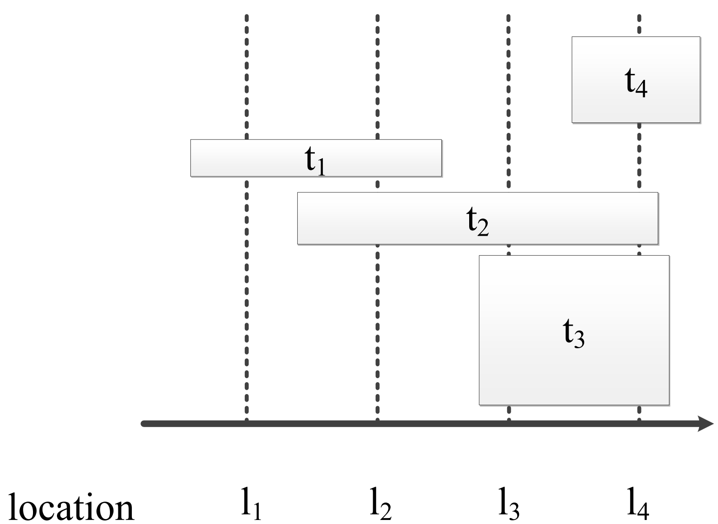
-Analysis: the error can be accumulated/ nonsubmoduar

1-D scenario

- Coverage-Only Greedy algorithm (CO)

  -While the network is not covered, we select the worker who can increase coverage most from one side to the other side (e.g., from left to right).

worker	cost
w1	1
w2	1.5
w3	3
w4	2



round	Selected worker	cost
1	w1	1
2	w3	3

Theorem: The CO algorithm has a $2\max|c_i/c_j|$, for all i,j, approximation ratio in the 1-D scenario.

1-D scenario

- PTAS in CO algorithm
  - Analysis: worker with high cost can be selected
  - Idea: Set work with high cost a low priority

  - Algorithm implementation
    - ❖Set a threshold, ϵ, separate workers into two sets in terms of cost
      - costly workers and cheap workers
    - ❖Apply CO algorithm in cheap workers
      - If it successes, reduce the threshold
      - If it fails, increase the threshold
    - ❖Binary search to find the smallest threshold

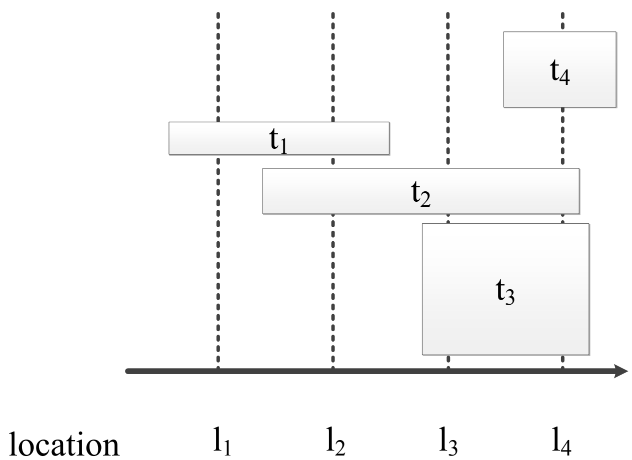
Theorem: The CO algorithm has a 2+ε approximation ratio in the 1-D scenario.

1-D scenario

- Dynamic programming (Optimal sub-structure)
  - -Sort all trajectories based on end points from left to right
  - -The optimal solution for crowdsourcing location i with worker w_j as the last worker.

$$d[i,j] = \begin{cases} 0 & \text{i = 0} \\ \underset{i'<i, j'\leq j}{min} \max\{d[i',j'], c_{j'} + c_j\} & \text{Otherwise} \end{cases}$$

worker	cost
w1	1
w2	1.5
w3	3
w4	2

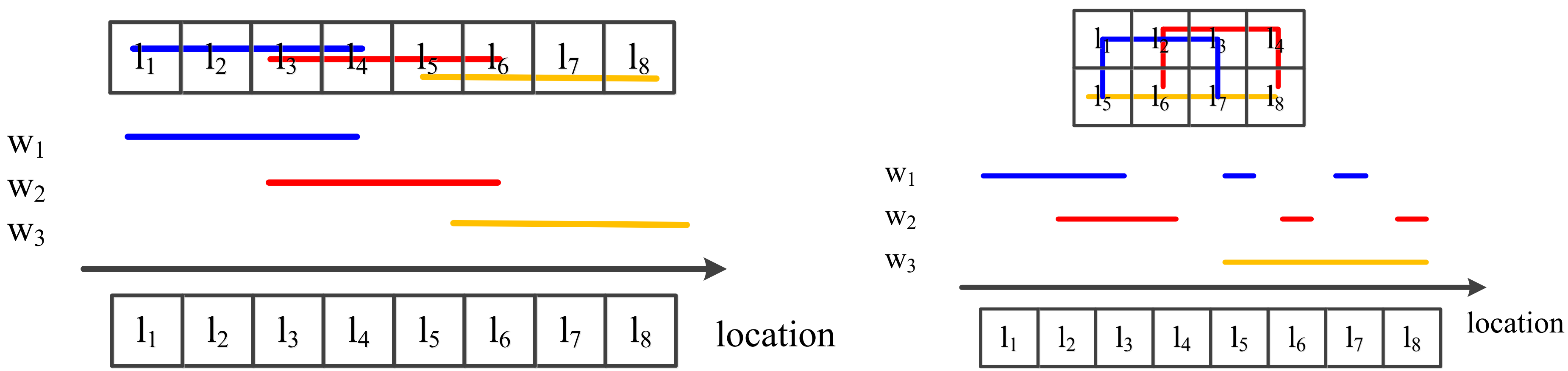


location \ worker	1	2	3	4
1	1			
2	1	2.5		
3		2.5	3	
4		2.5	3	3.5

2-D scenario

Challenge

- The overlapping relationship becomes complex
  - 1-D continuous overlap
  - 2-D discrete overlap



  - Optimal substructure does not exist and dynamic programming does not work

2-D scenario

Idea

- Extend the proposed algorithms in 1-D scenario
  - Min-max algorithm is still the same.
  - Coverage-only algorithm can be used line-by-line.

Randomized Rounding Algorithm

- Relax the original problem into the linear problem

$$\min \quad \theta$$
$$\text{s.t.} \quad \sum_{l_i \in t_j} c_j x_j \leq \theta, \qquad \sum_{l_i \in t_j} x_i \geq 1, \quad \forall i, j \qquad x_i \in [0, 1]$$

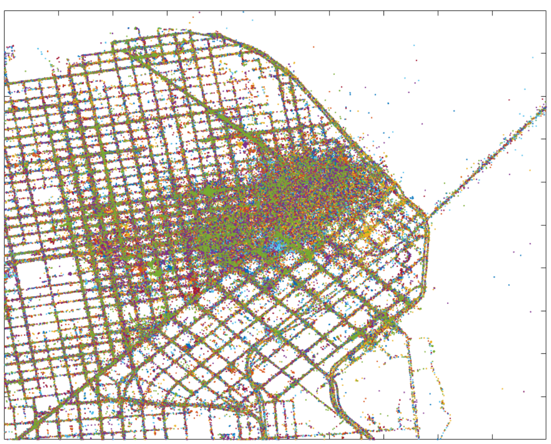
- Use the expected value as the selection probability and randomly select workers.

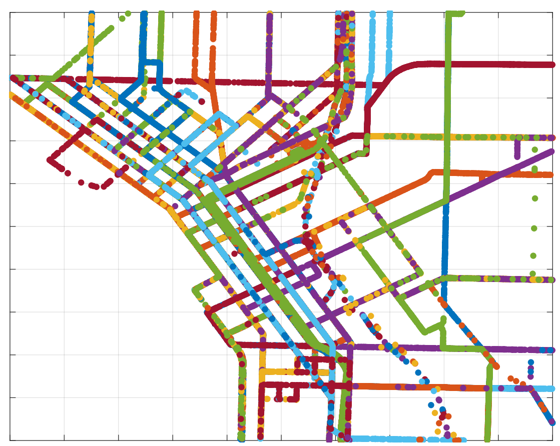
Theorem: The randomized rounding algorithm has a O(log(n)/loglog(n)) expected approximation ratio

Experiment Evaluation

Experiment Setting

- Trajectory Trace Information
  - EPFL: 500 taxies in San Francisco, USA
  - Seattle: 236 buses in Seattle, USA
- Trajectory Trace Information
  - Uniform/exponential distribution with 5 cost
- Experimental area: downtown





Algorithm comparison

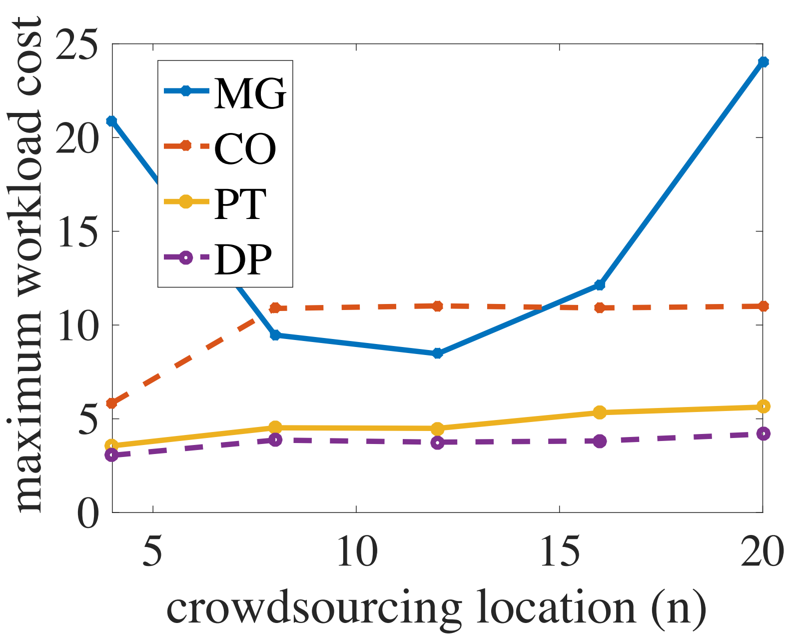
- Four algorithms in 1-D:
  - Min-Max greedy (MG)
  - Coverage-Only (CO)
  - PTAS (PT)
  - Dynamic programming (DP)

- Four algorithms in 2-D:
  - Min-Max greedy (MG): the same
  - Coverage-Only (CO): row-by-row /
  - PTAS (PT)
  - Dynamic programming (DP): do not apply
  - Randomized Rounding (RD)

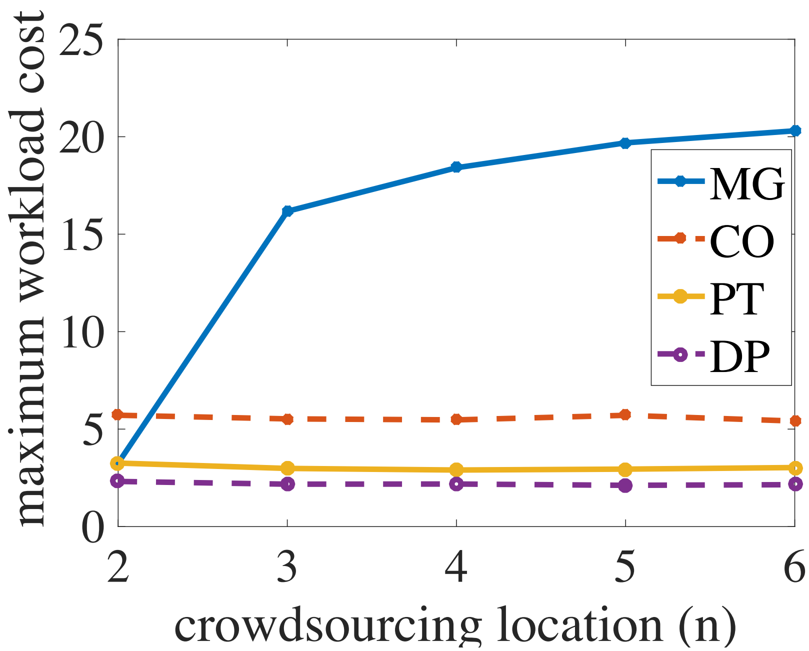
Performance Result

1D

- Different number of crowdsourcing locations



San Francisco

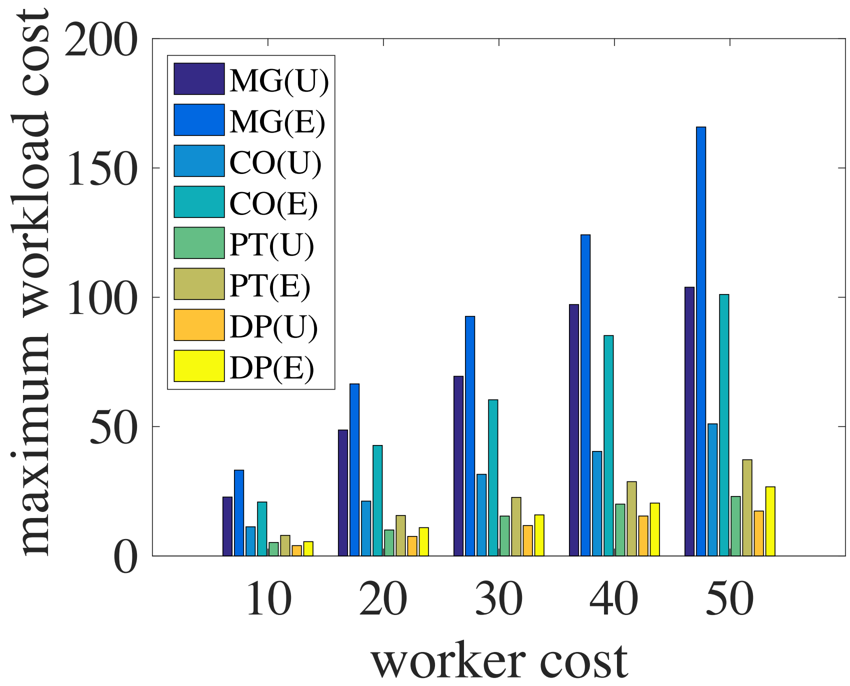


Seattle

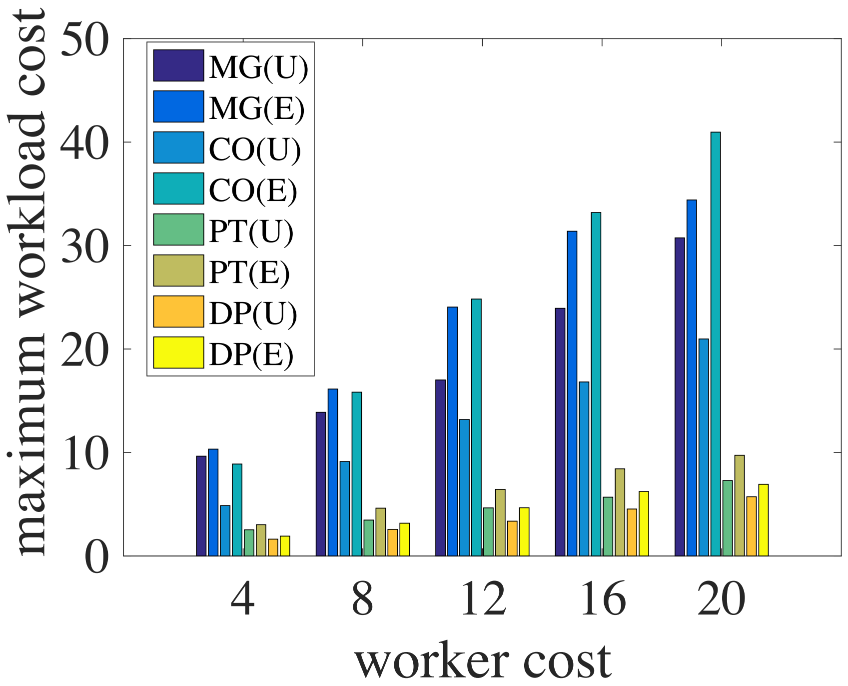
Performance Result

1D

- Different cost distribution
  - Uniform/Exponential



San Francisco

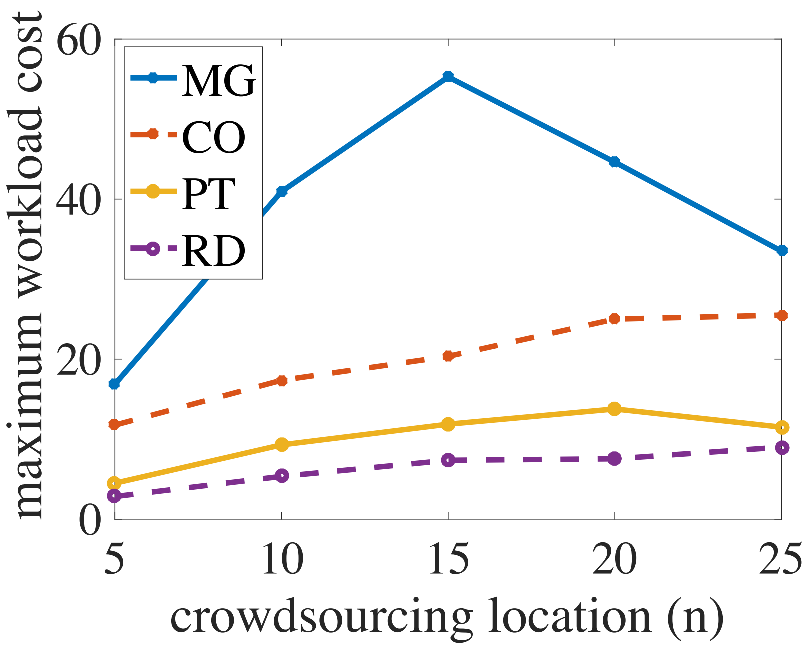


Seattle

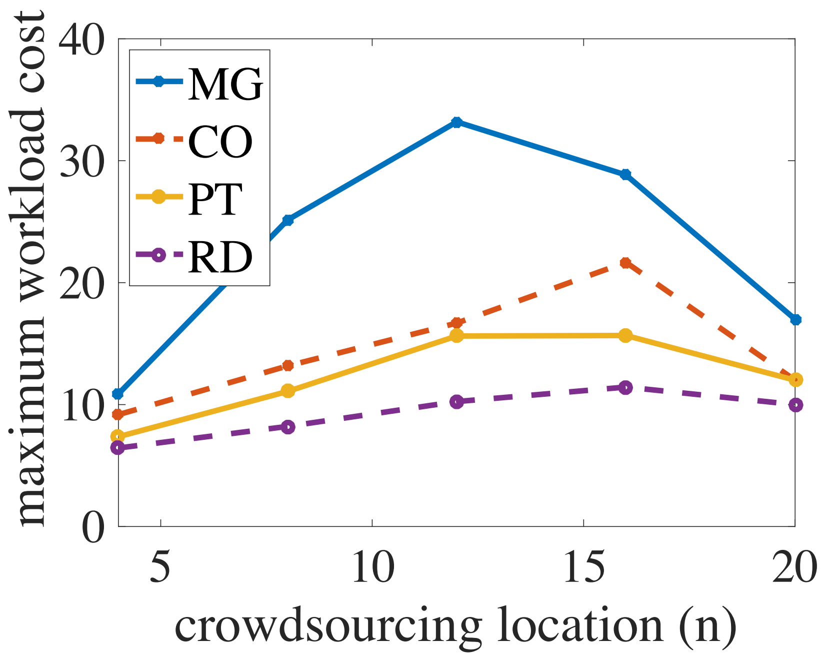
Performance Result

2D

- Different number of crowdsourcing locations



San Francisco



Seattle

Conclusions

- We investigate a worker recruitment problem in spatial crowdsourcing scenario, where coverage and balance location cost are jointly considered.
- A series of algorithm is proposed in 1-D scenario to trade-off the performance and computation complexity.
  - Coverage-Only algorithm
  - PTAS algorithm
  - Dynamic programming algorithm
- A randomized rounding scheme is proposed in a general scenario.

Future works

- Efficient deterministic algorithm in 2-D scenario
- Weighted coverage and heterogeneous cost
- Trade-off between detour and benefit
- System implementation (if possible)

Thank you and Question

Ning Wang

ning.wang@temple.edu