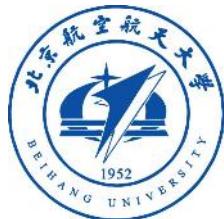




Spatial Crowdsourcing: Challenges, Techniques, and Applications

Yongxin Tong

Beihang
University



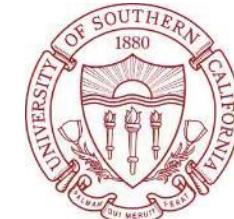
Lei Chen

Hong Kong University of
Science and Technology



Cyrus Shahabi

University of
Southern California



We get some pictures and materials from the Internet for this tutorial

Outline

- **Overview of Spatial Crowdsourcing (20min)**
 - Motivation
 - Workflow
 - Core Issues
 - Difference from Related Tutorials
- **Fundamental Techniques (50min)**
 - Task Assignment
 - Quality Control
 - Incentive Mechanism
 - Privacy Protection
- **Spatial Crowdsourced Applications (15min)**
 - Spatial Crowdsourcing Intrinsic Applications
 - Crowd-powered Spatial Applications
- **Open Questions (5 min)**

Crowdsourcing: Concept

□ **Crowdsourcing**

- ❑ Organizing the crowd (**Internet workers**) to do micro-tasks in order to solve human-intrinsic problems



Crowdsourcing: Applications

- Wikipedia
 - Collaborative knowledge

- reCAPTCHA
 - Digitalizing newspapers

- Yahoo Answer
 - Question & Answer

- ImageNet
 - Image labelling

- Amazon Mechanical Turk (AMT)
 - General purpose crowdsourcing



Crowdsourcing: An Example of AMT



Requesters



AMT

amazon mechanical turk
Amazon Mechanical Turk

Your Account | Help | Qualification | 280,000 HITs available | 0 HITs assigned to You | Log Out | Account Settings | Help for AMT

Log In | Create New Account | Help | Log Out | Account Settings | Help for AMT

AM HITs

1 of 1000 Results

Sort by: Relevance | Date | Rating | Price

Filter by: All Workers | All HITs

View: 1 HIT per page | View: 10 HITs per page

Search: Enter search terms here

Search icon

1 HIT

Sort by: Relevance | Date | Rating | Price

Requirer: [Mturk_1c](#) HIT Expiration Date: Sep 25, 2012 (2 weeks) Reward: \$0.00 Time allotted: 20 minutes HITs Available: 1000

Sort by: Relevance | Date | Rating | Price

Requirer: [Mturk_1c](#) HIT Expiration Date: Sep 25, 2012 (2 weeks) Reward: \$0.00 Time allotted: 20 minutes HITs Available: 264

Sort by: Relevance | Date | Rating | Price

Requirer: [Mturk_1c](#) HIT Expiration Date: Sep 25, 2012 (3 hrs) Reward: \$0.00 Time allotted: 20 minutes HITs Available: 252

Sort by: Relevance | Date | Rating | Price

Requirer: [Mturk_1c](#) HIT Expiration Date: Aug 25, 2012 (1 week) Reward: \$0.00 Time allotted: 20 minutes HITs Available: 1657



MTurk workers
(Photo By Andrian Chen)

Crowdsourcing in the Internet era connects
requesters and workers **on the Internet**

Spatial Crowdsourcing: Concept

□ Crowdourcing

- Organizing the crowd (**Internet** workers) to do micro-tasks in order to solve human-intrinsic problems

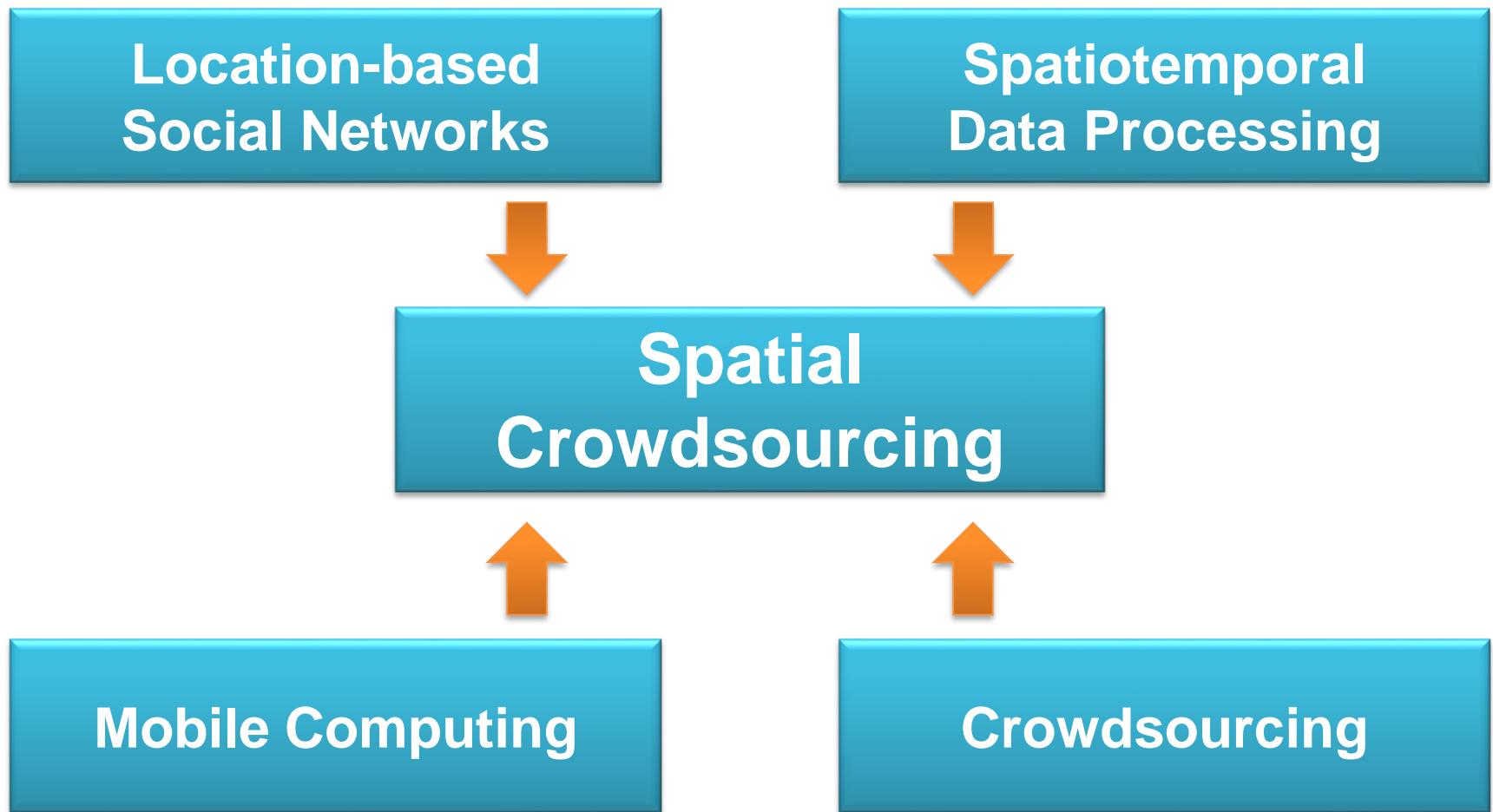


□ Spatial Crowdsourcing

- Organizing the crowd (**Mobile** Internet workers) to do **spatial tasks** by **physically moving to other locations**



Spatial Crowdsourcing: Concept



a.k.a. mobile crowdsourcing, mobile crowdsensing,
participatory sensing, location-based crowdsourcing

Spatial Crowdsourcing: Applications

- Open Street Map
 - Collaborative map



- Waze
 - Live traffic



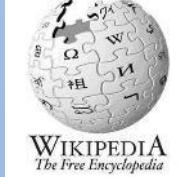
- Facebook
 - Check-in
- Uber
 - Smart transportation



- Gigwalk
 - General purpose spatial crowdsourcing



Application Comparison

	(Internet) Crowdsourcing	Spatial Crowdsourcing
Information Collection		
Passive Participation		
Question & Answer		
Specialized Platforms		
General Platforms		

Spatial Crowdsourcing: Other Apps



Local Search-and-discovery Service



Mobile Market Research & Audits



Repair & Refresh Your Home



Intelligent Transportation



Food Delivery



Location-based Game

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Spatial Crowdsourcing: Workflow

- ❑ Requesters

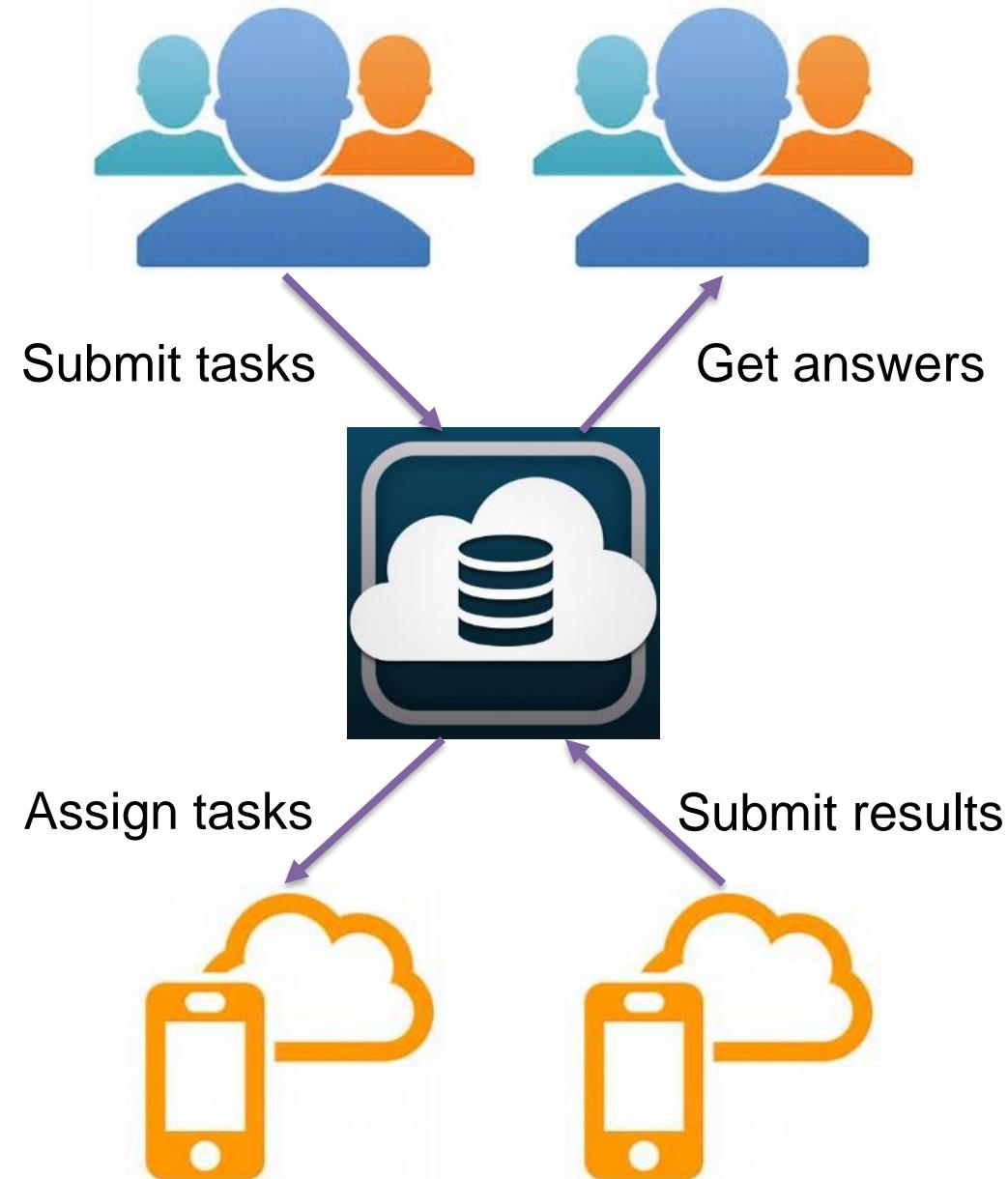
- ❑ Submit tasks

- ❑ Platforms

- ❑ Task management

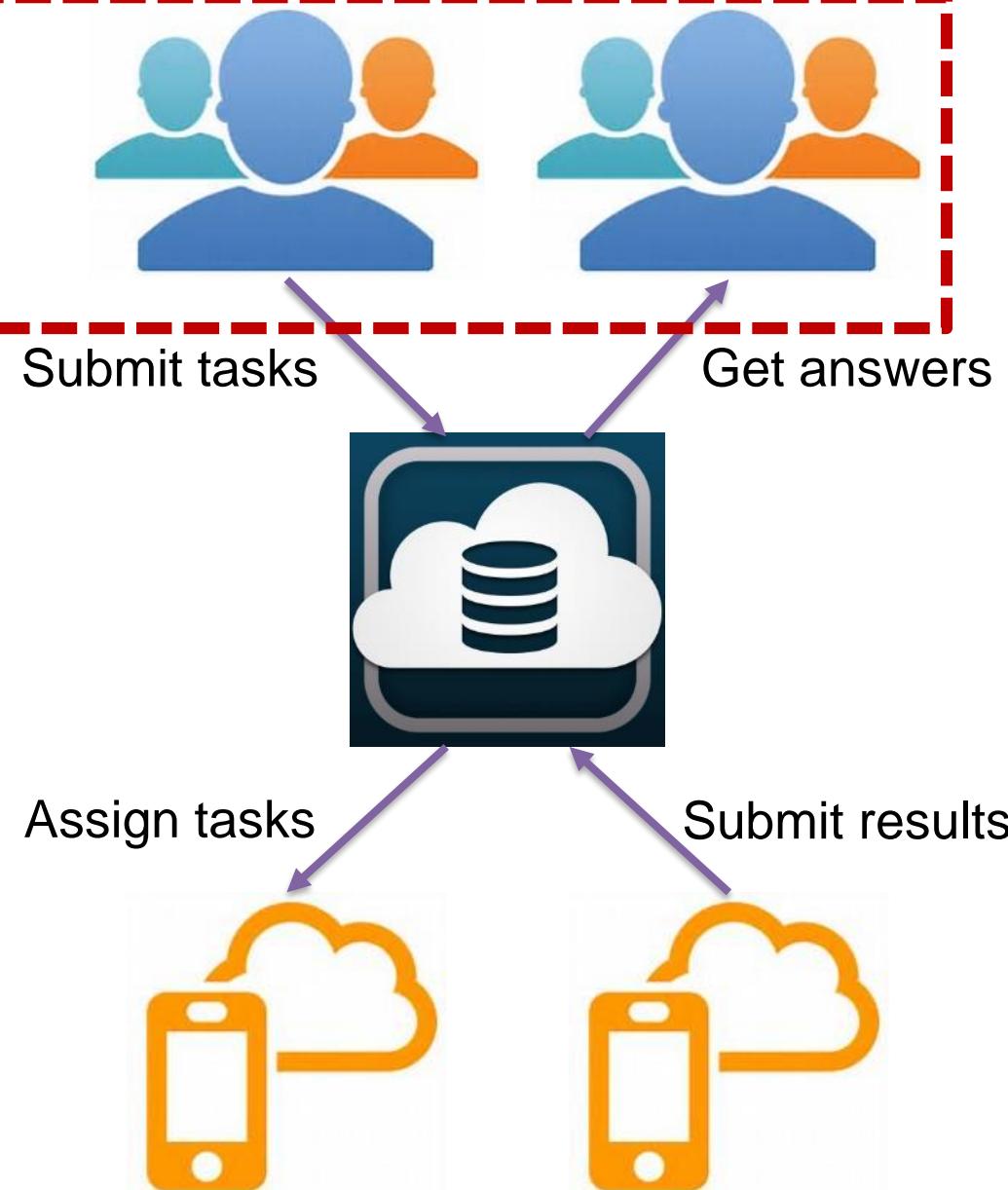
- ❑ Workers

- ❑ Perform tasks



Spatial Crowdsourcing: Workflow

- Requesters
 - Submit tasks



- Platforms
 - Task management
- Workers
 - Perform tasks

Spatial Crowdsourcing: Task

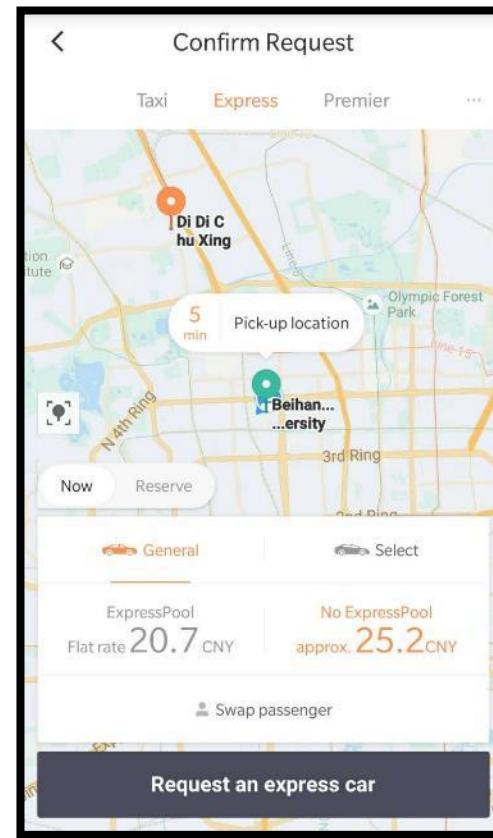
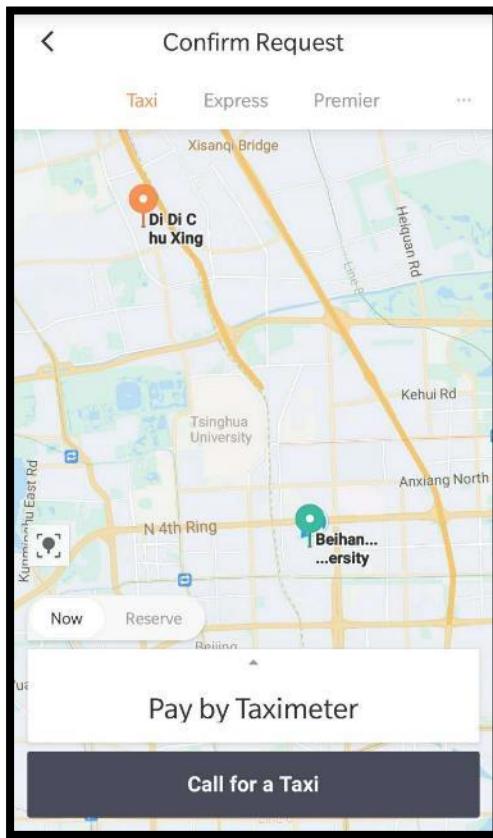
- General spatial tasks
 - Inventory identification
 - Placement checking
 - Data collection
 - Service evaluation

Gigwalk



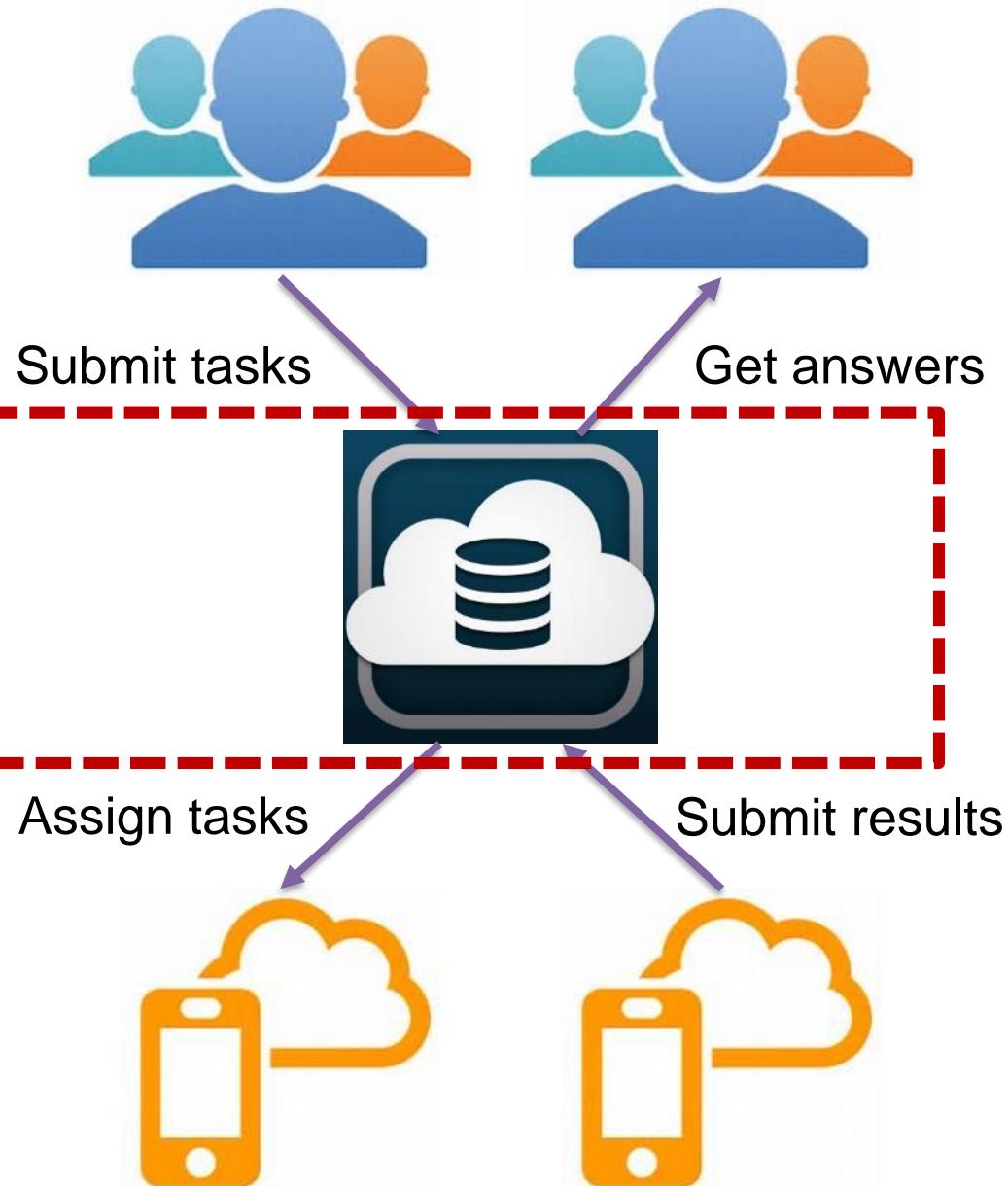
Spatial Crowdsourcing: Task

- Specific spatial tasks
 - Taxi calling service
 - Ridesharing service



Spatial Crowdsourcing: Workflow

- Requesters
 - Submit tasks



- Platforms
 - Task management

- Workers
 - Perform tasks

Spatial Crowdsourcing: Platform

□ Management Modes

- Worker Selected Tasks (WST)
 - Workers **actively** select tasks



TaskRabbit

Gigwalk

□ Server Assigned Tasks (SAT)

- Workers **passively** wait for the platform to assign tasks

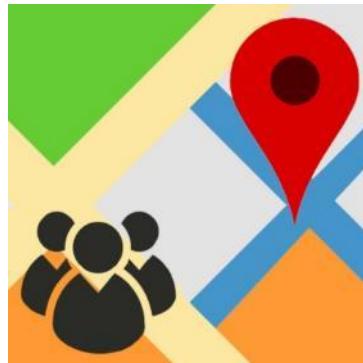
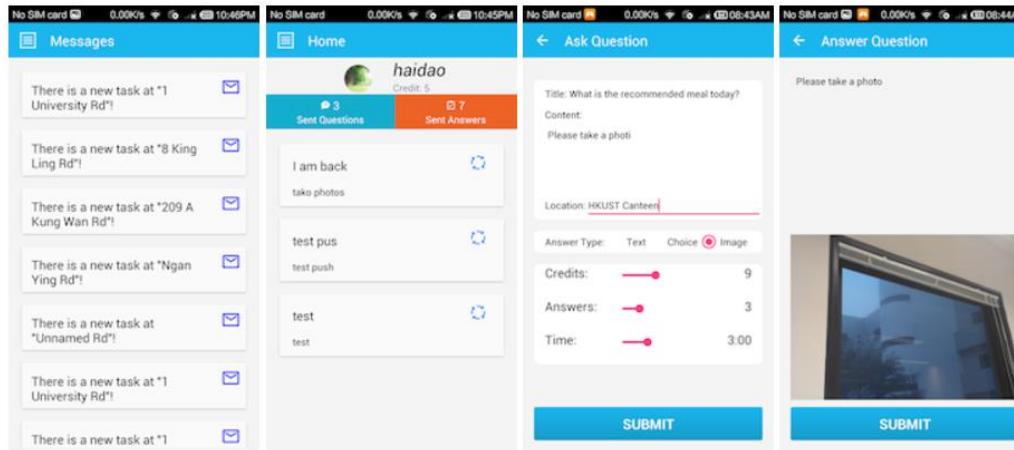


Most studies focus on SAT mode because more optimization techniques can be designed by platforms

Other Platforms

□ gMission

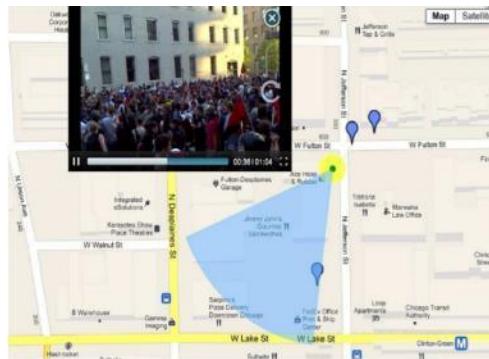
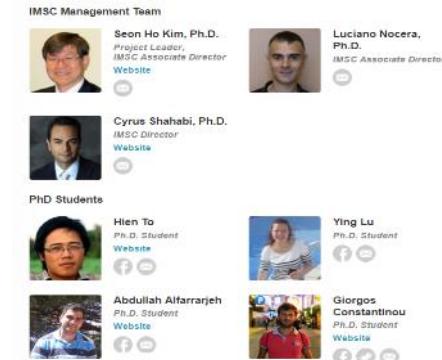
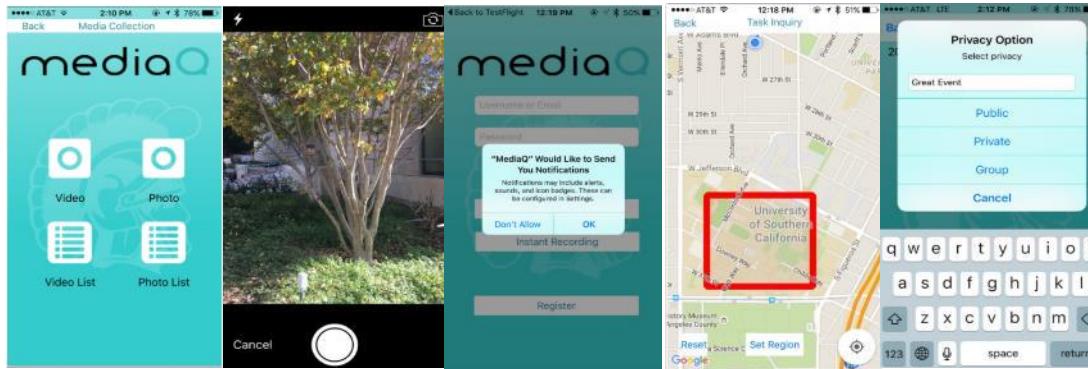
- An open sourced spatial crowdsourcing platform
- <http://gmission.github.io>



Other Platforms

□ MediaQ

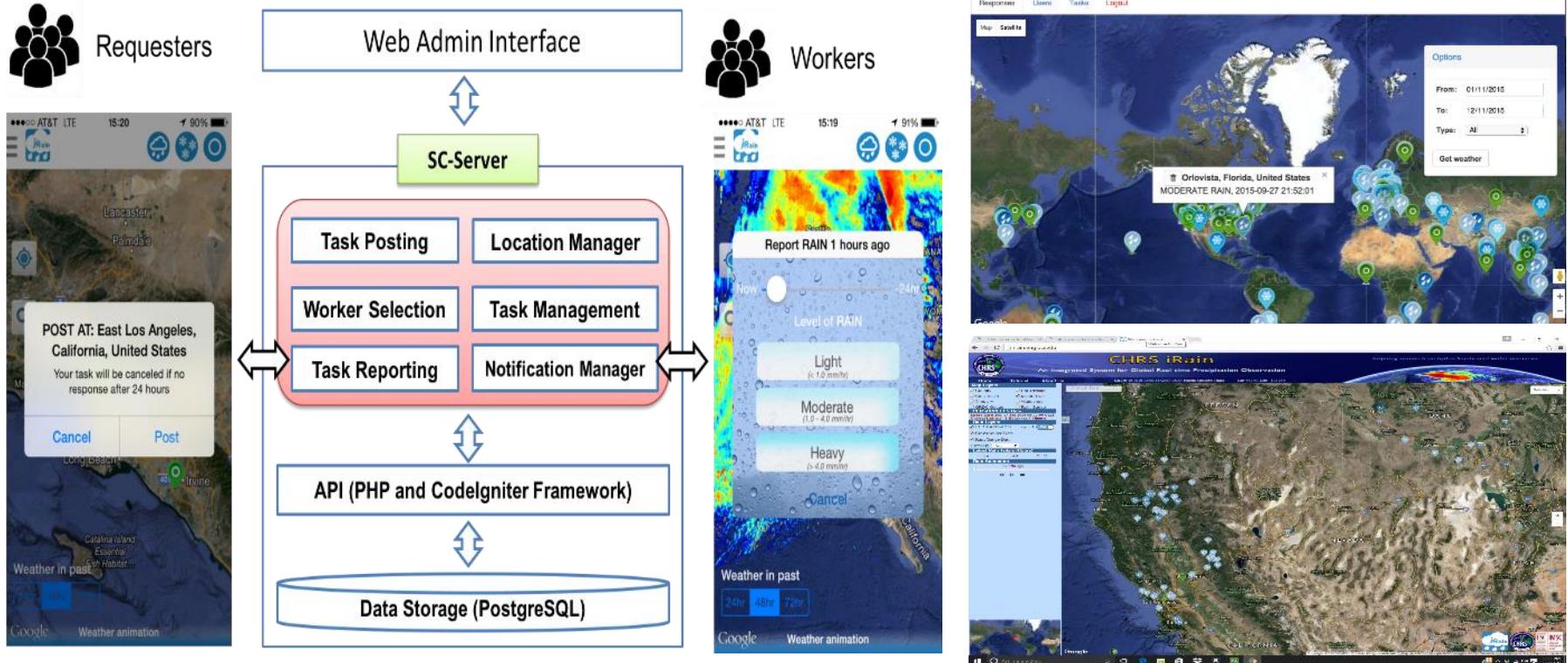
- An online spatial-crowdsourcing-based media management system
- <http://mediaq.usc.edu/>



Other Platforms

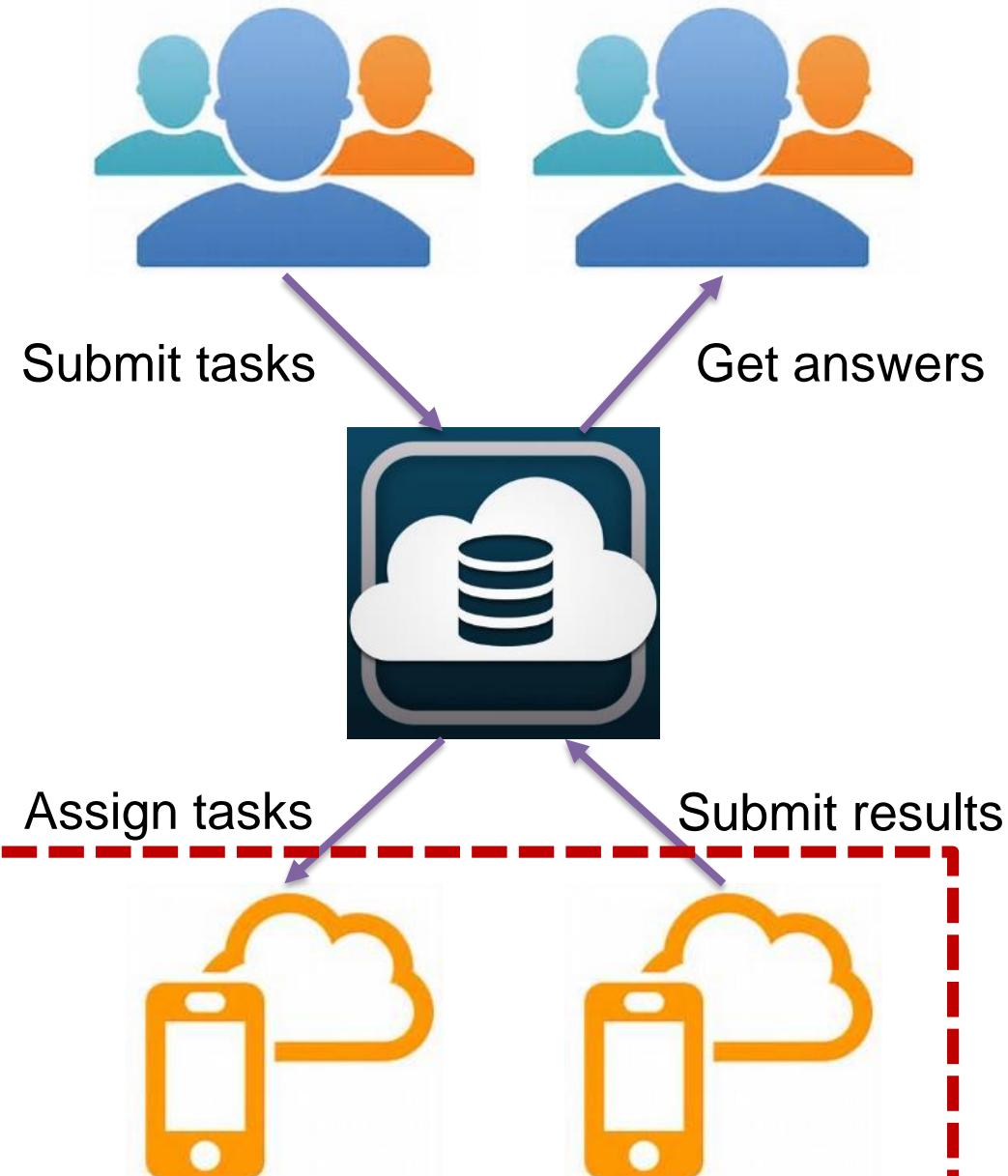
□ iRain

- A Spatial Crowdsourcing System for Real-time Rainfall Observation
- <http://irain.eng.uci.edu/>



Spatial Crowdsourcing: Workflow

- Requesters
 - Submit tasks

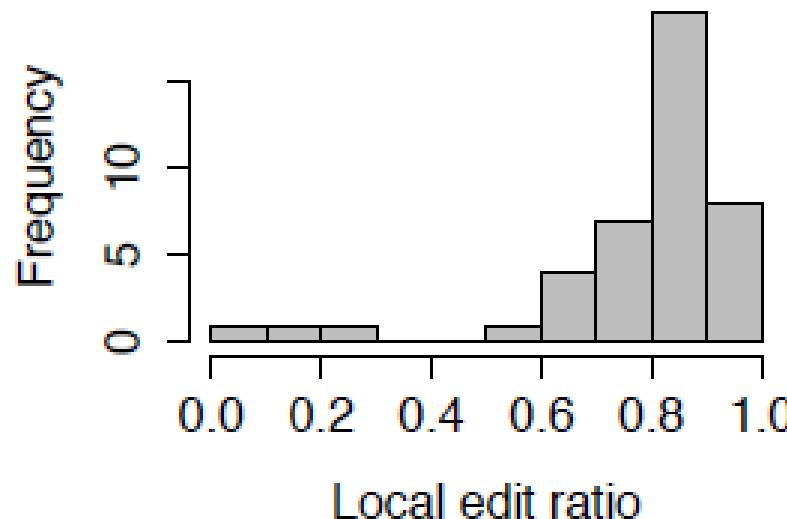


- Platforms
 - Task management

- Workers
 - Perform tasks

Spatial Crowdsourcing: Worker

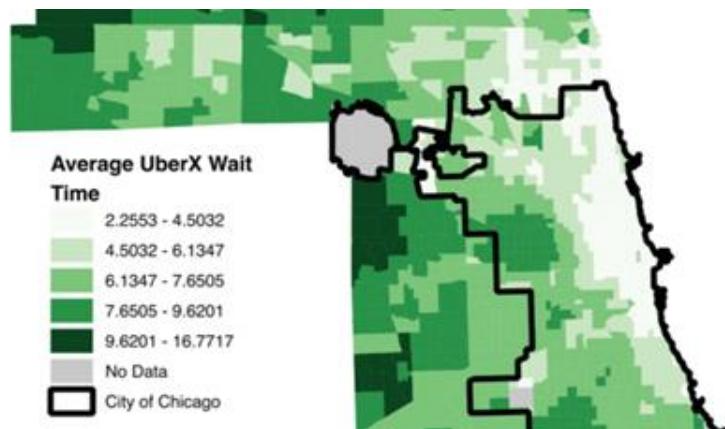
- Influential factor
 - Distance
 - Socioeconomic status



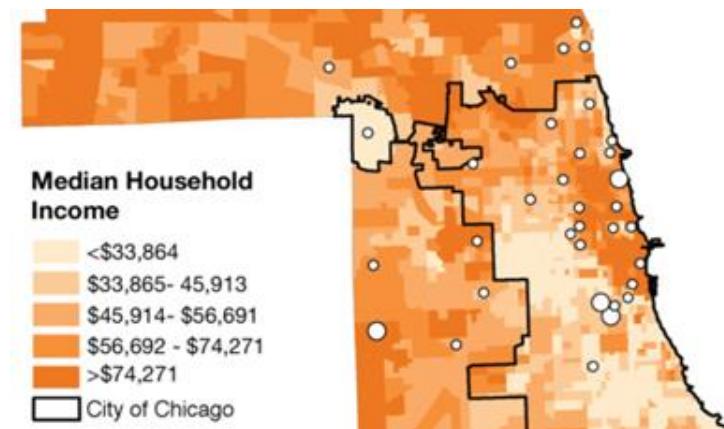
Workers tend to perform nearby tasks

Spatial Crowdsourcing: Worker

- Influential factor
 - Distance
 - Socioeconomic status



Average UberX Wait Time in Chicago



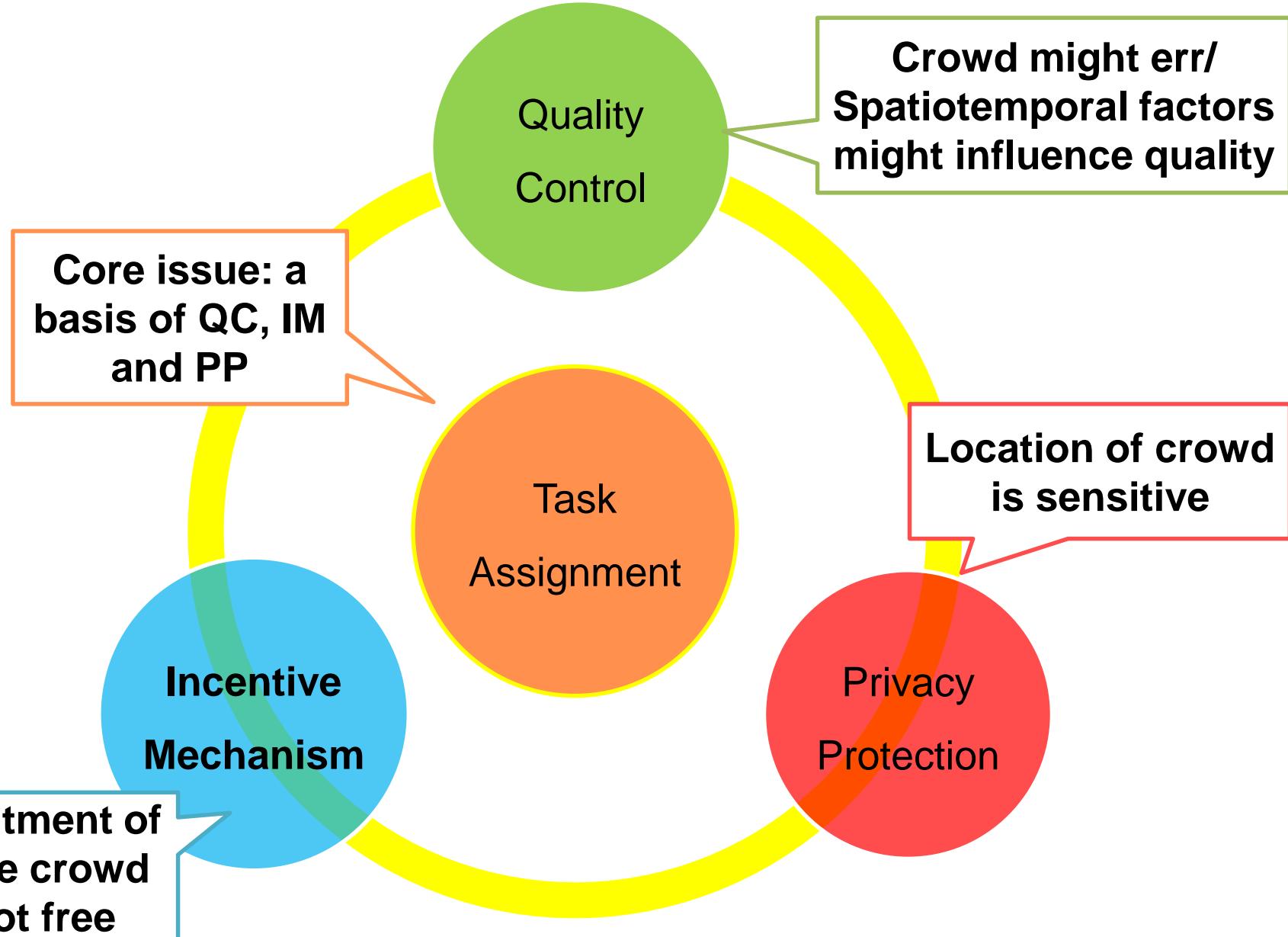
Average Median Household Income in Chicago

Workers tend to perform tasks in high income regions

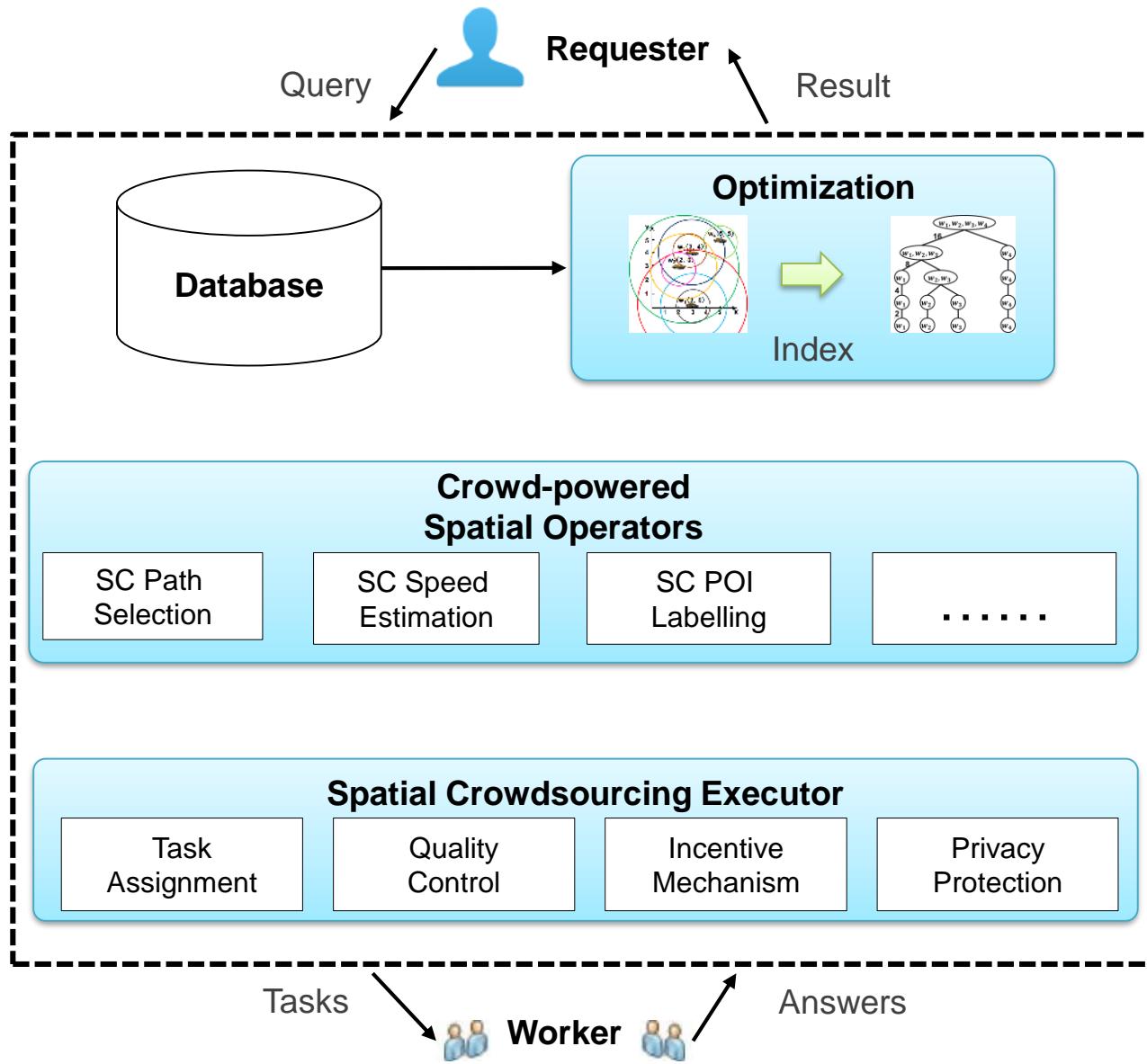
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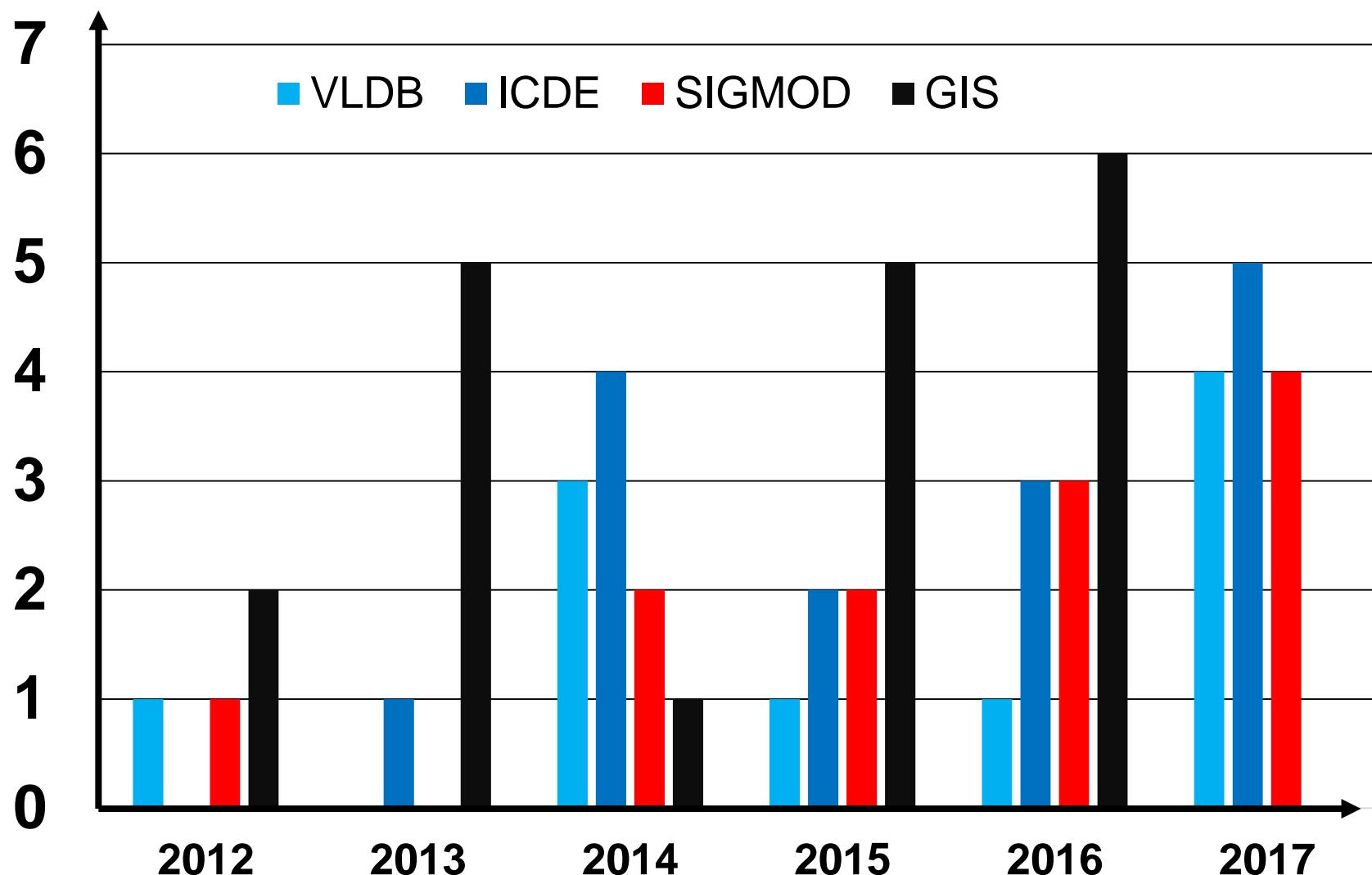
Core Issues in Spatial Crowdsourcing



A Spatial Crowdsourcing System



Existing Works



Outline

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Difference from Related Tutorials

- VLDB 2012
 - Crowdsourced platforms and principles
- CIKM 2014
 - Traditional crowdsourced knowledge management
- ICDE 2015
 - Traditional crowdsourced queries, mining and applications
- VLDB 2016
 - Human factors involved in task assignment
- SIGMOD 2017
 - Traditional crowdsourced data management
- Our Tutorial
 - **Spatial** crowdsourced data management
 - **Theories** and **applications** in spatial crowdsourcing

Reference: Overview

1. L. Chen, C. Shahabi. Spatial crowdsourcing: challenges and opportunities. *IEEE Data Engineering Bulletin*, 39(4):14-25, 2016.
2. G. Li, J. Wang, Y. Zheng, J. Franklin. Crowdsourced data management: a survey. *TKDE*, 28(9): 2296-2319, 2016.
3. H. Garcia-Molina, M. Joglekar, A. Marcus,A. Parameswaran,V. Verroios. Challenges in Data Crowdsourcing. *TKDE*, 28(4):901-911, 2016.
4. A. Chittilappilly, L. Chen, S. Amer-Yahia. A Survey of General-Purpose Crowdsourcing Techniques. *TKDE*, 28(9):2246-2266, 2016.
5. G. Chatzimilioudis, A. Konstantinidis, C. Laoudias, D. Zeinalipour-Yazti: Crowdsourcing with Smartphones. *IC*,16(5): 36-44, 2012.
6. R. K.Ganti, F. Ye,H. Lei, Mobile crowdsensing: current state and future challenges. *IEEE Commun. Mag.* , 49(11), 32-39 ,2011.
7. J. Thebault-Spieker, L. G.Terveen, B. J.Hecht. Toward a geographic understanding of the sharing economy: systemic biases in uberX and taskrabbit. *TOCHI*, 24(3): 21:1-21:40, 2017.
8. Z. Chen, R. Fu, Z. Zhao, Z. Liu, L. Xia, L. Chen, P. Cheng, C. Cao, Y. Tong, C. Zhang. gMission: a general spatial crowdsourcing platform. *PVLDB*, 7(13): 1629-1632, 2014.
9. Kim, S. Ho, Y. Lu, G. Constantinou, C. Shahabi, G. Wang, R. Zimmermann. Mediaq: mobile multimedia management system. In *MMSys*, pages 224-235, 2014.
10. F. Alt, A. Sahami Shirazi, A. Schmidt, U. Kramer, Z. Nawaz. Location-based crowdsourcing: extending crowdsourcing to the real world. In *NordiCHI*, pages 13–22, Iorian 2010.

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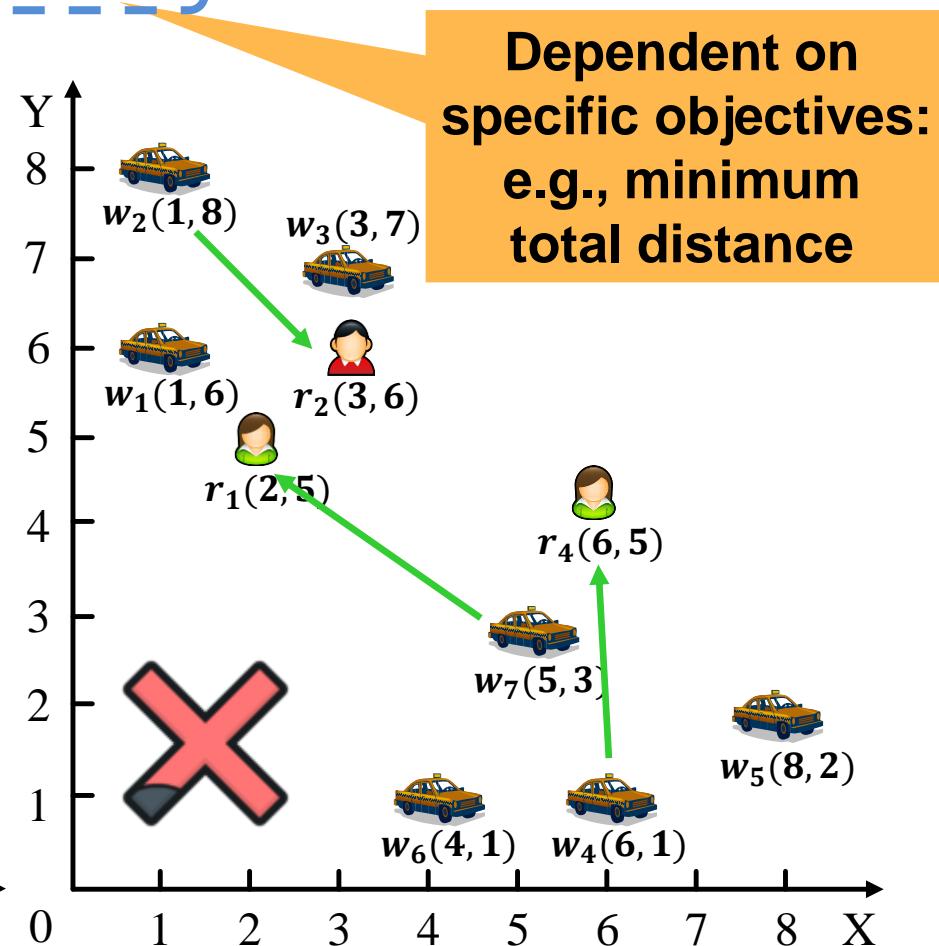
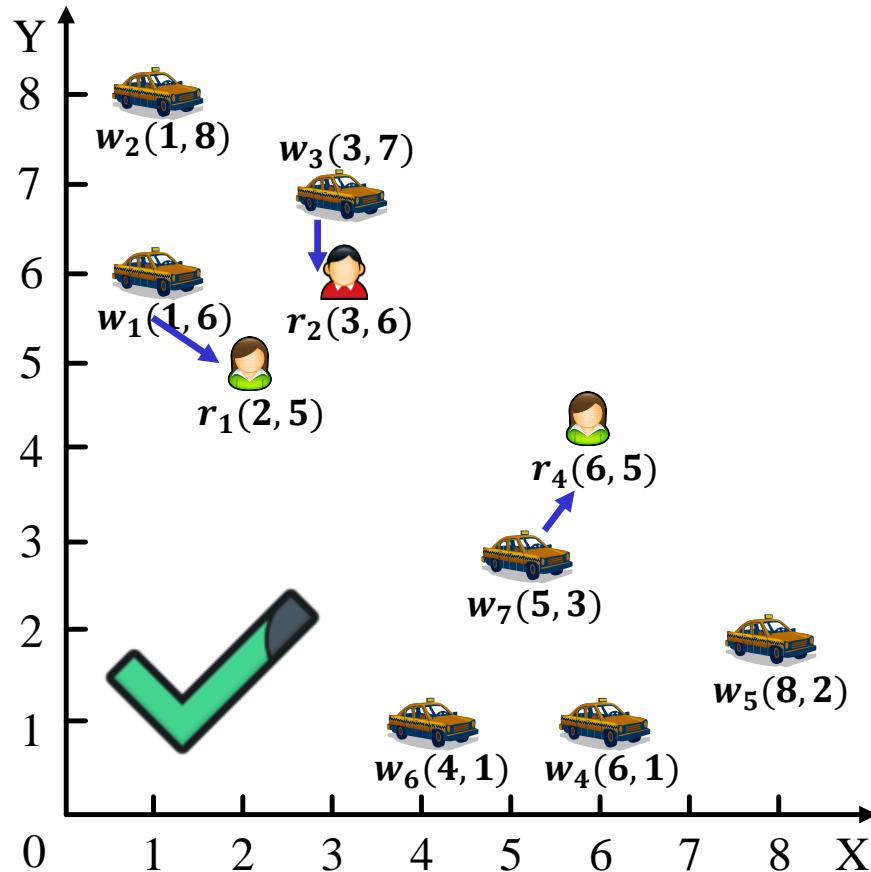
Why Task Assignment?

- ❑ Almost all other core issues in spatial crowdsourcing depend on task assignment
- ❑ The core operation connects tasks, workers and the platform



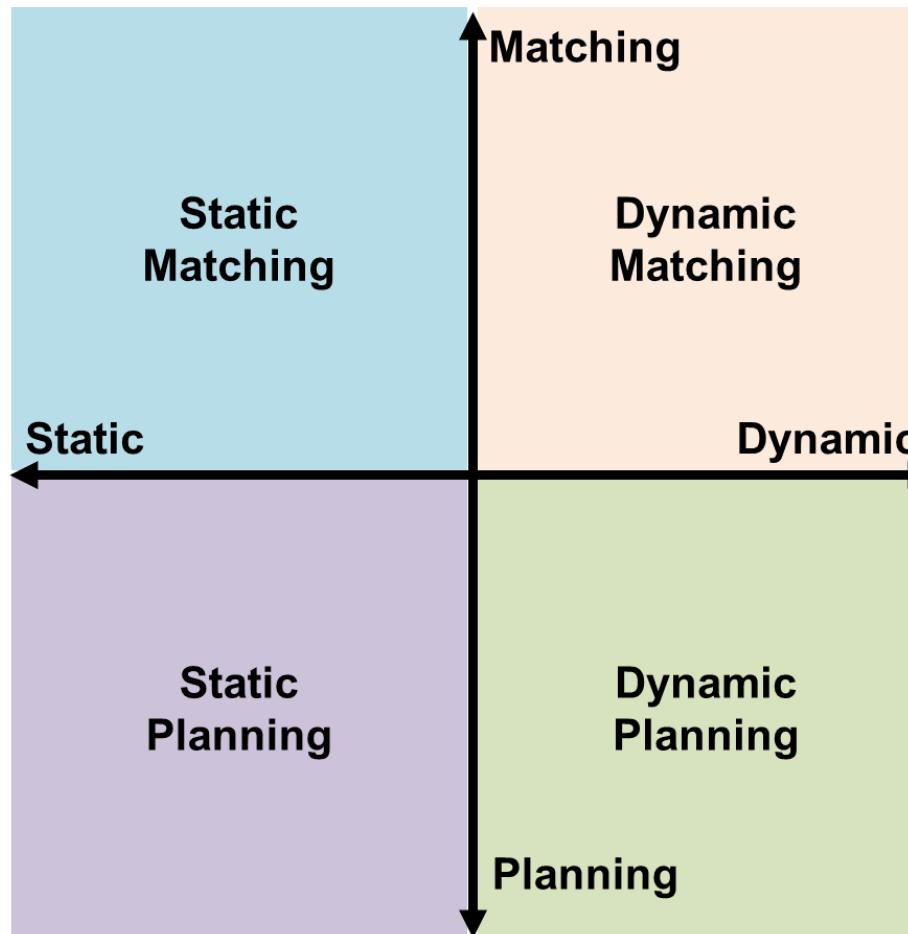
Problem Definition

- Given a set of workers and a set of tasks distributed in the physical space, the objective is to assign tasks to proper workers



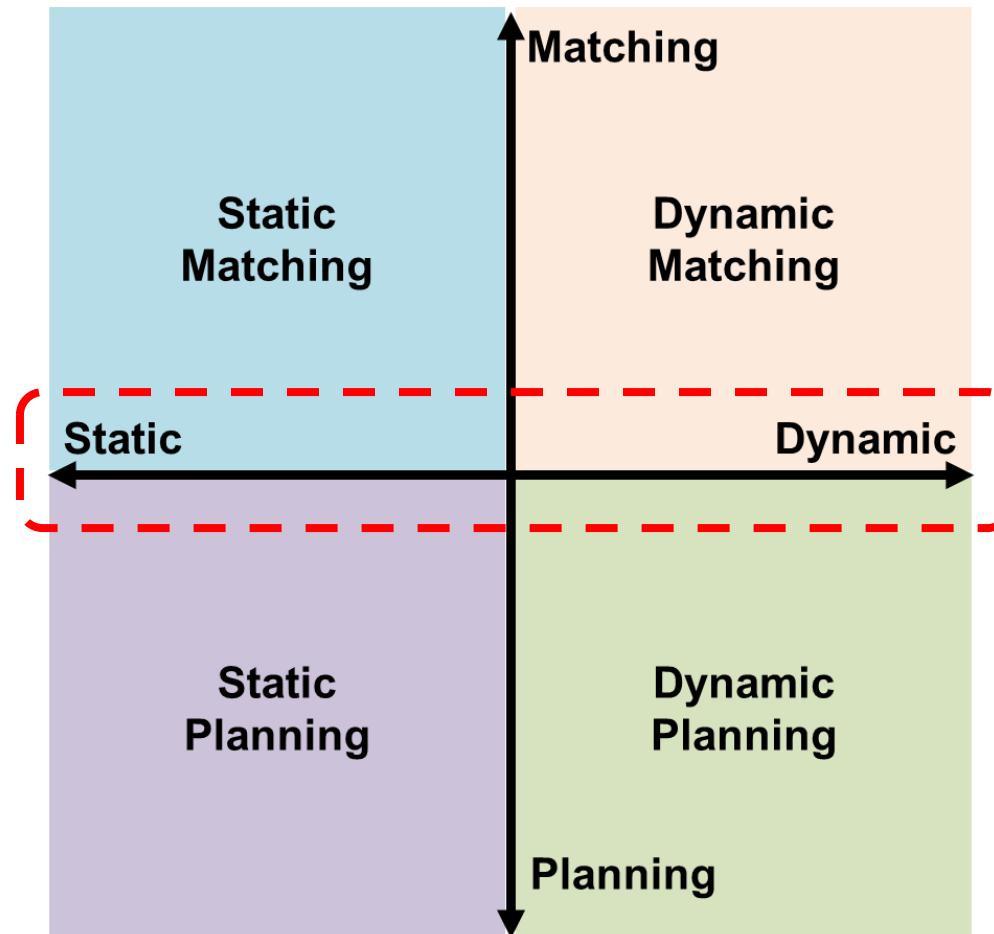
Categories of Existing Research

- Arrival Scenarios: Static vs. Dynamic
- Algorithmic Models: Matching vs. Planning



Categories of Existing Research

- **Arrival Scenarios: Static vs. Dynamic**
- **Algorithmic Models: Matching vs. Planning**



Static Scenario vs. Dynamic Scenario

□ Static Scenario

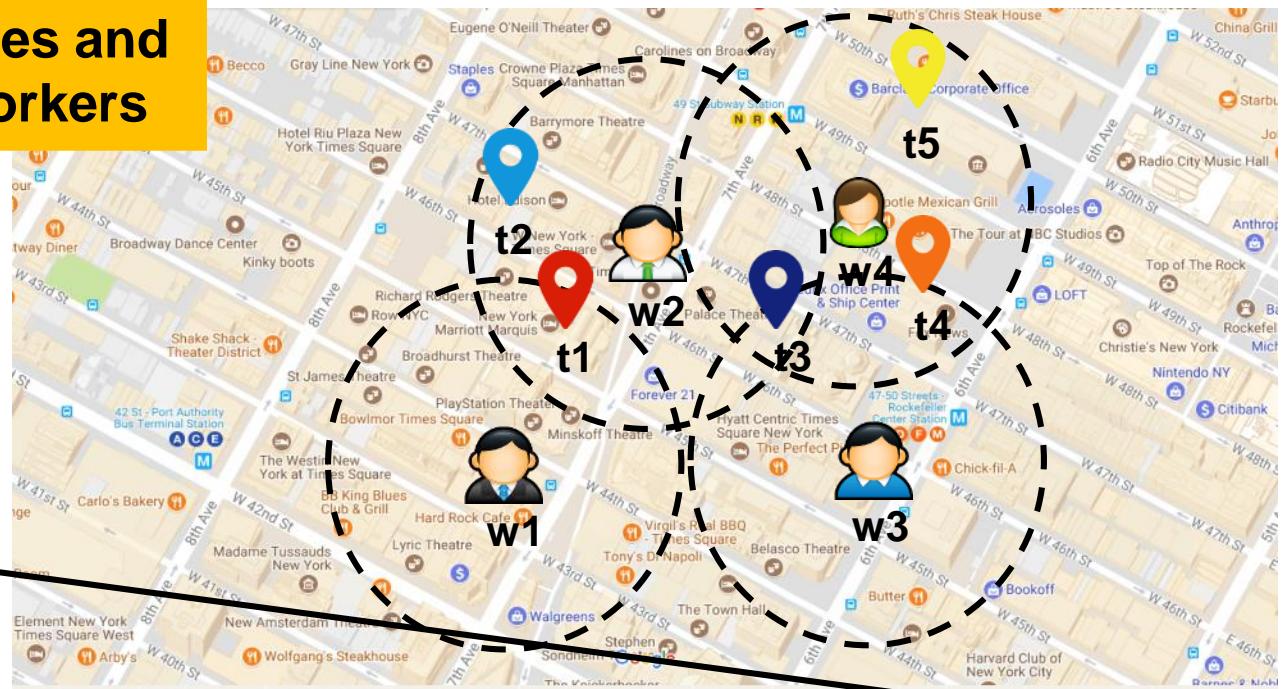
- The platform is assumed to **know all spatiotemporal information of tasks and workers at the beginning**

Refer to all arrival times and locations of tasks/workers

Platform



The platform knows all information when assigning tasks.



Arrival Time	8:00	8:01	8:02	8:07	8:08	8:09	8:09	8:15	8:18
	t_1	w_1	t_2	t_3	w_2	t_4	w_3	w_4	t_5

Static Scenario vs. Dynamic Scenario

□ Dynamic Scenario

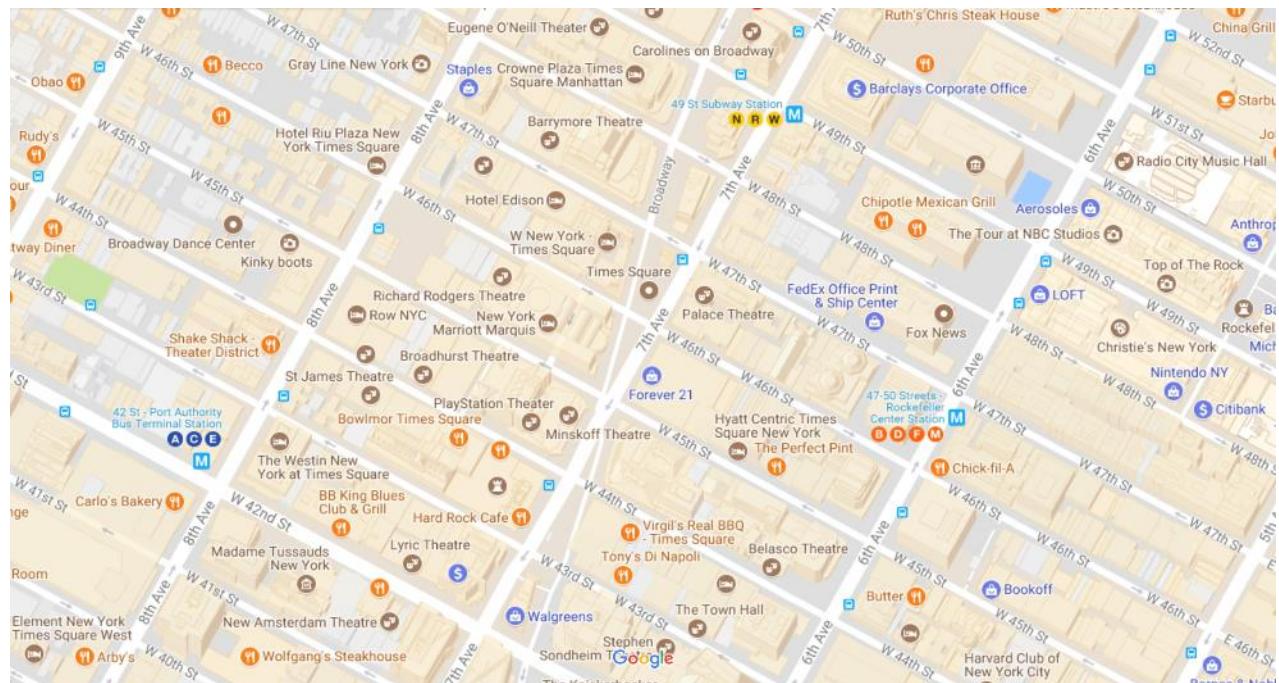
- Tasks/workers usually **dynamically appear**
- They usually need to be assigned **immediately** based on **real-time partial information**
 - Fast Food Delivery Service
 - Real-Time Taxi-Calling Service



Static Scenario vs. Dynamic Scenario

- **Dynamic Scenario: An Example**
 - New tasks and workers dynamically arrive at the platform during task assignment

Platform



Static Scenario vs. Dynamic Scenario

- Dynamic Scenario: An Example
 - New tasks and workers dynamically arrive at the platform during task assignment

Platform



Platform gradually knows information as time goes on.

8:00

t_1



Static Scenario vs. Dynamic Scenario

- Dynamic Scenario: An Example
 - New tasks and workers dynamically arrive at the platform during task assignment

Platform



Platform gradually knows information as time goes on.



Arrival Time	8:00	8:01
	t_1	w_1

Static Scenario vs. Dynamic Scenario

- Dynamic Scenario: An Example
 - New tasks and workers dynamically arrive at the platform during task assignment

Platform



Platform gradually knows information as time goes on.



Arrival Time	8:00	8:01	8:02
	t_1	w_1	t_2

Static Scenario vs. Dynamic Scenario

□ Dynamic Scenario: An Example

- New tasks and workers dynamically arrive at the platform during task assignment

Platform



Platform gradually knows information as time goes on.



Arrival Time	8:00	8:01	8:02	8:07
	t_1	w_1	t_2	t_3

Static Scenario vs. Dynamic Scenario

- Dynamic Scenario: An Example
 - New tasks and workers dynamically arrive at the platform during task assignment

Platform



Platform gradually knows information as time goes on.



Arrival Time	8:00	8:01	8:02	8:07	8:08
	t_1	w_1	t_2	t_3	w_2

Static Scenario vs. Dynamic Scenario

□ Dynamic Scenario: An Example

- New tasks and workers dynamically arrive at the platform during task assignment

Platform



Platform gradually knows information as time goes on.



Arrival Time	8:00	8:01	8:02	8:07	8:08	8:09
	t_1	w_1	t_2	t_3	w_2	t_4

Static Scenario vs. Dynamic Scenario

- Dynamic Scenario: An Example
 - New tasks and workers dynamically arrive at the platform during task assignment

Platform



Platform gradually knows information as time goes on.



Arrival Time	8:00	8:01	8:02	8:07	8:08	8:09	8:09
	t_1	w_1	t_2	t_3	w_2	t_4	w_3

Static Scenario vs. Dynamic Scenario

□ Dynamic Scenario: An Example

- New tasks and workers dynamically arrive at the platform during task assignment

Platform



Platform gradually knows information as time goes on.



Arrival Time	8:00	8:01	8:02	8:07	8:08	8:09	8:09	8:15
	t_1	w_1	t_2	t_3	w_2	t_4	w_3	w_4

Static Scenario vs. Dynamic Scenario

- Dynamic Scenario: An Example
 - New tasks and workers dynamically arrive at the platform during task assignment

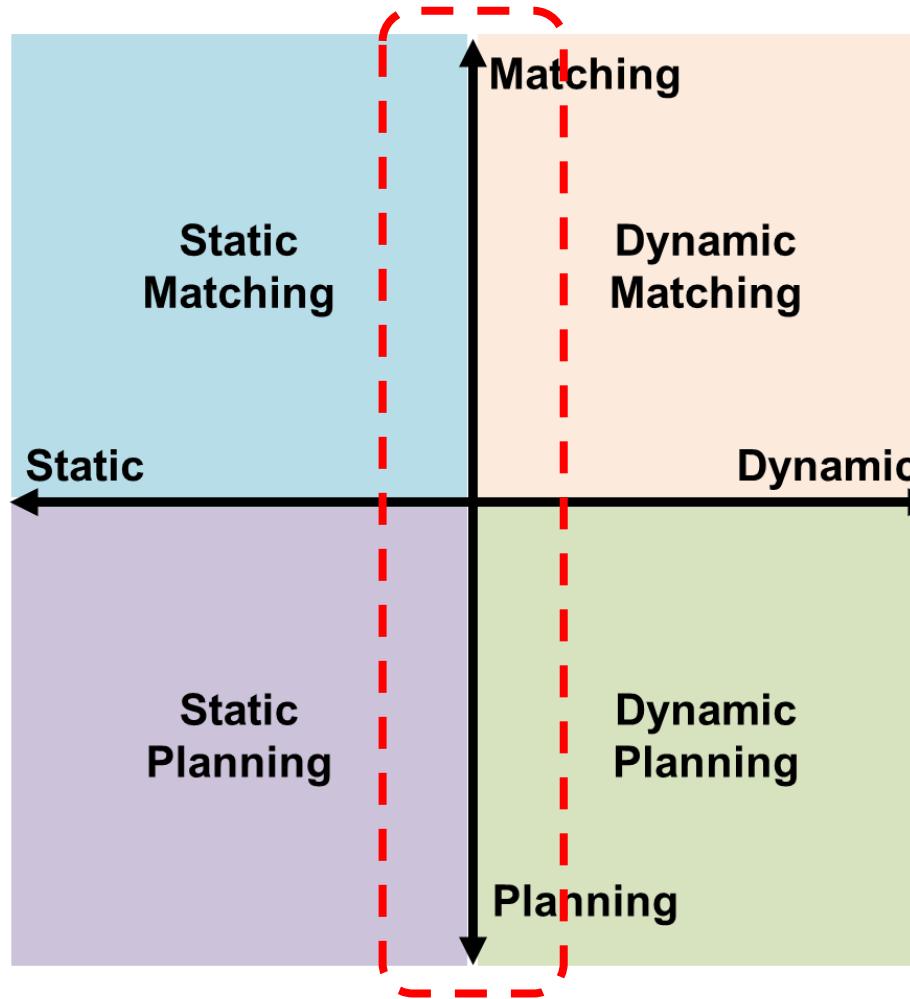


The platform does not know information of subsequent tasks/workers when it performs task assignment dynamically

Arrival Time	8:00	8:01	8:02	8:07	8:08	8:09	8:09	8:15	8:18
	t_1	w_1	t_2	t_3	w_2	t_4	w_3	w_4	t_5

Categories of Existing Research

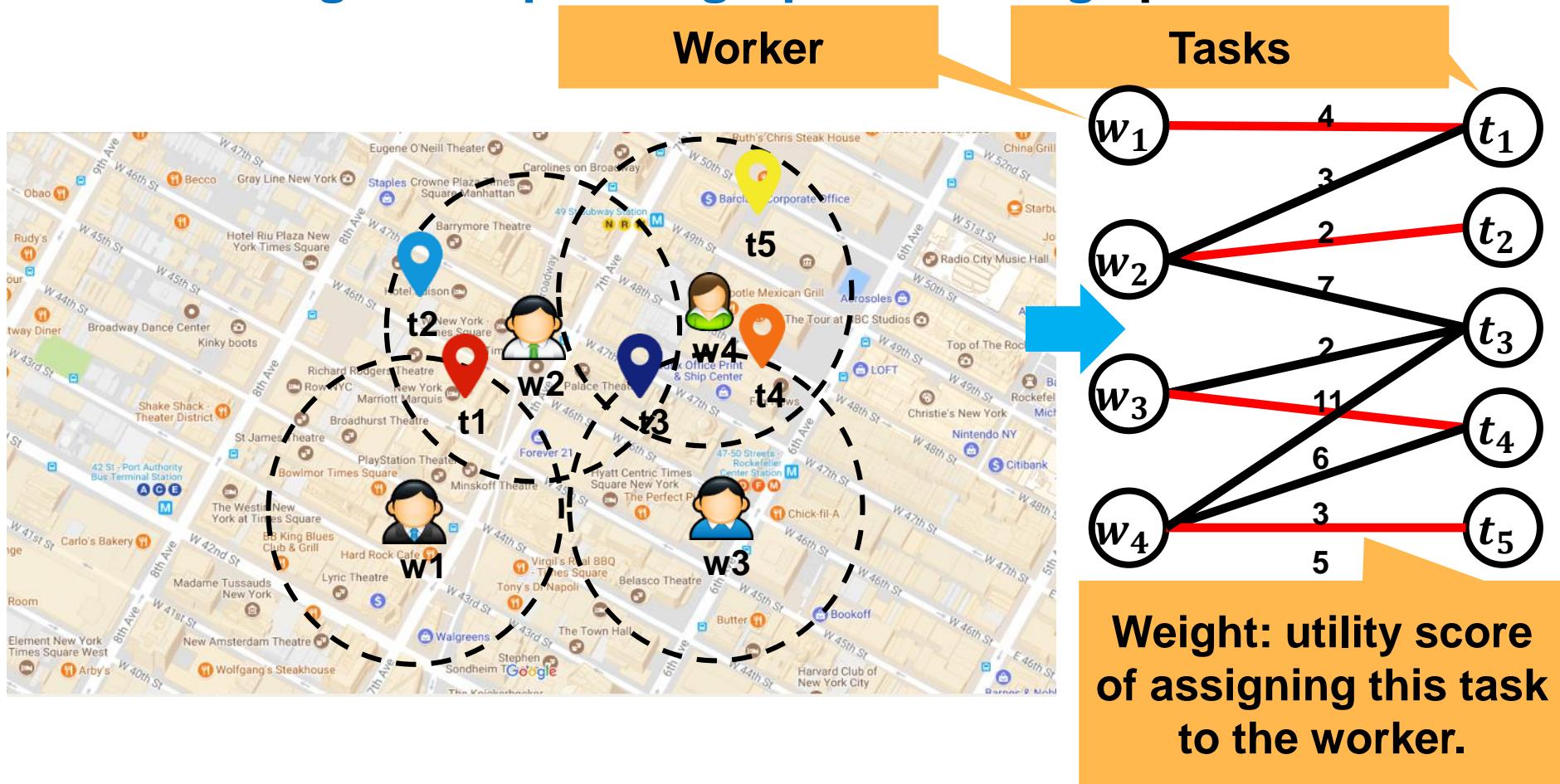
- Arrival Scenarios: Static vs. Dynamic
- Algorithmic Models: Matching vs. Planning



Matching vs. Planning

□ Matching Model

- Formulate task assignment problem as classic “**weighted bipartite graph matching**” problem



Matching vs. Planning

□ Planning Model

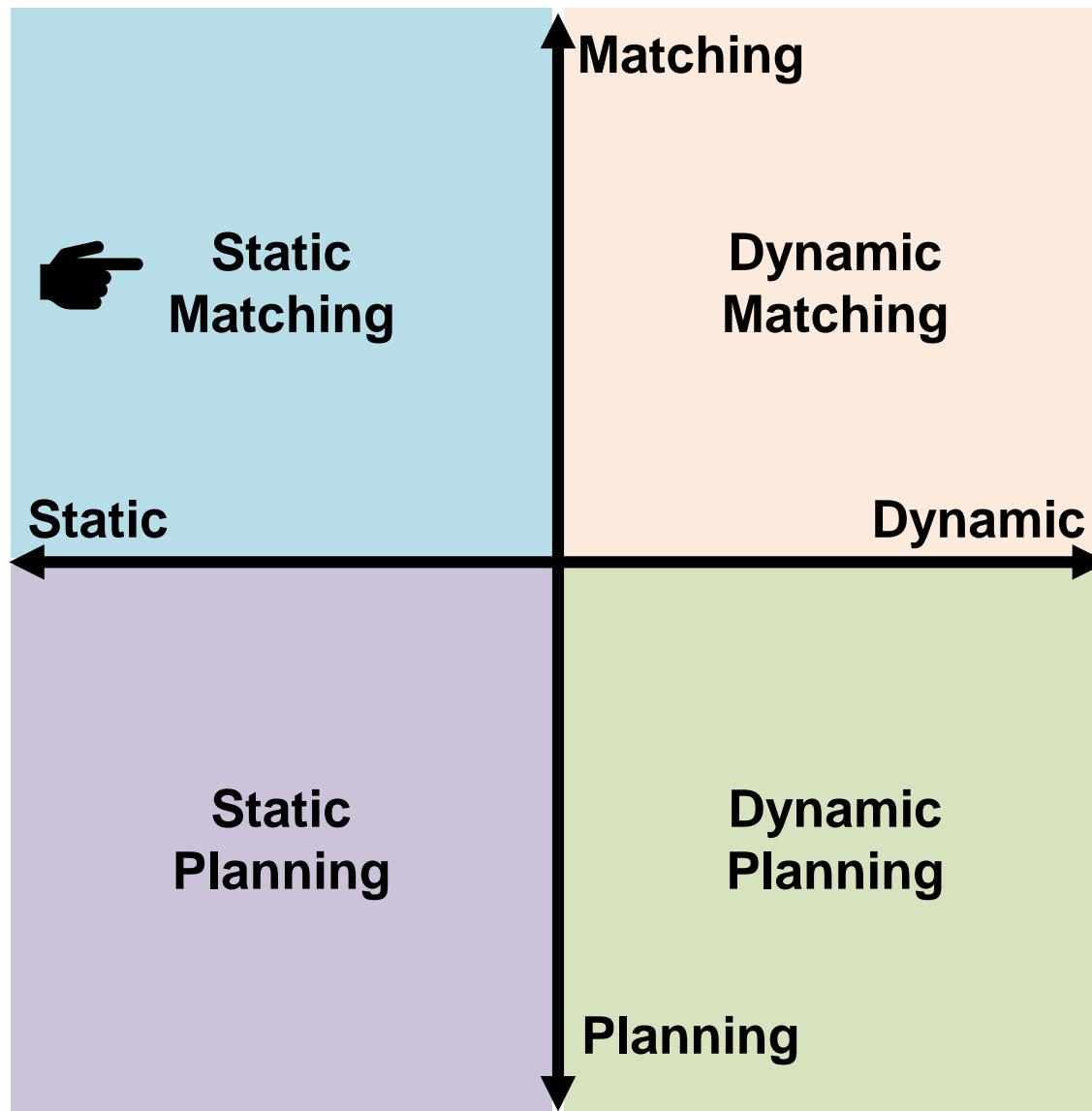
- Plan a route for a worker or workers to complete a number of tasks
- Each worker usually performs multiple tasks instead of performing a single task in the matching model



Plan 1: $t2 \rightarrow t3 \rightarrow t4 \rightarrow t1$

Plan 2: $t1 \rightarrow t3 \rightarrow t4 \rightarrow t2$

Static Matching



Static Matching

- **Problem Definition**

- **Existing Research**
 - **Objective 1: MaxSum Matching**

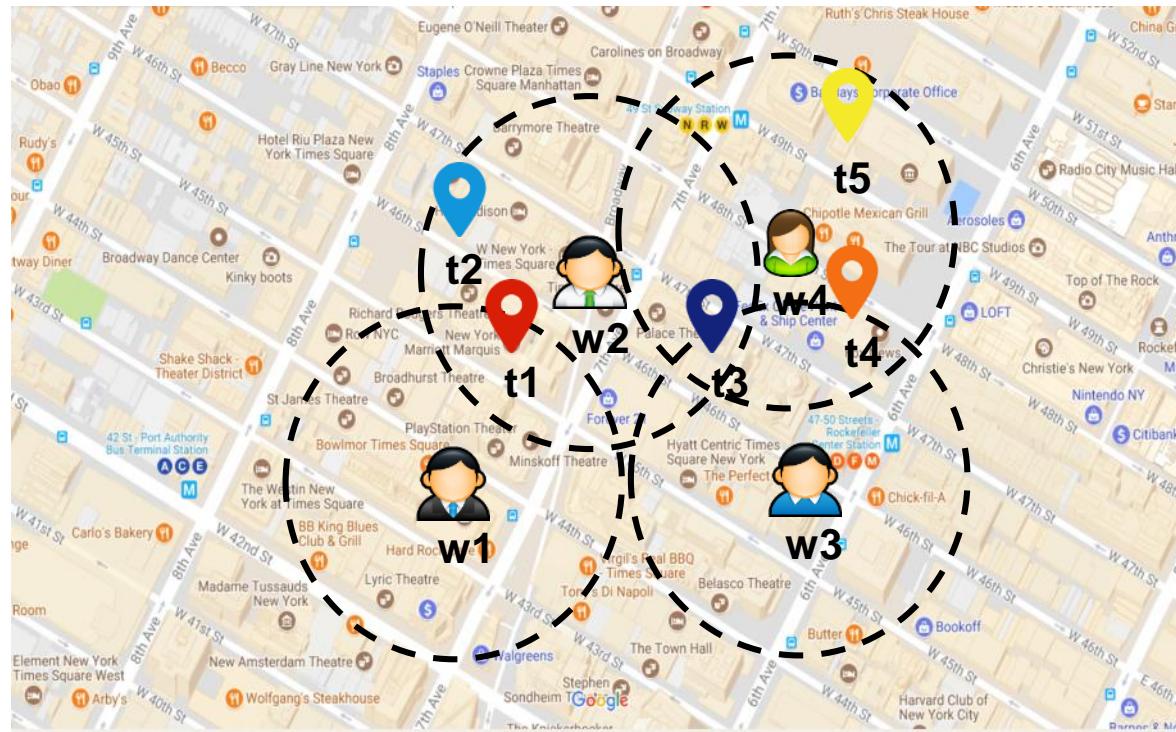
 - **Objective 2: MinSum Matching**

 - **Objective 3: Stable Marriage Matching**

Static Matching

□ Problem Definition

- Given all spatiotemporal information of a set of workers and tasks, the problem is to assign the tasks to the proper workers based on the specific objective function



Static Matching

□ Problem Definition

□ Existing Research

□ Objective 1: MaxSum Matching

□ Objective 2: MinSum Matching

□ Objective 3: Stable Marriage Matching

Spatial information acts
as constraints

Spatial information is the
optimization goal

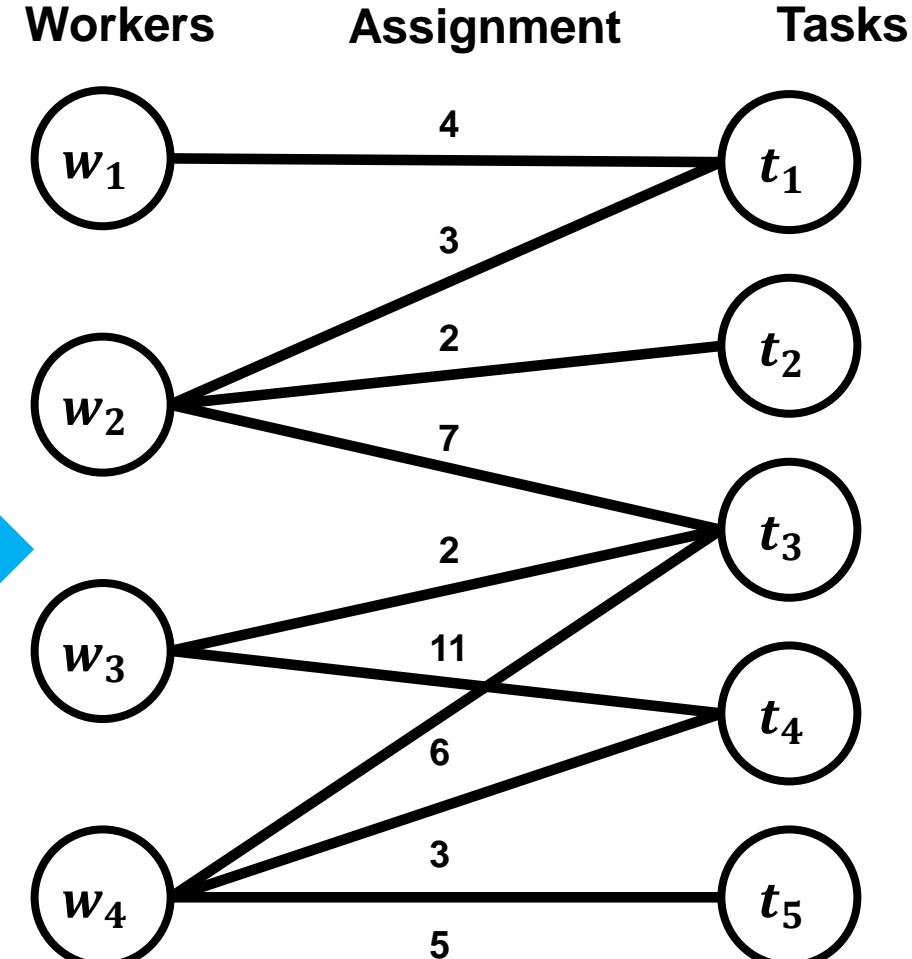
Static Matching

- Problem Definition
- Existing Research
 - Objective 1: MaxSum Matching
 - Objective 2: MinSum Matching
 - Objective 3: Stable Marriage Matching

MaxSum Matching

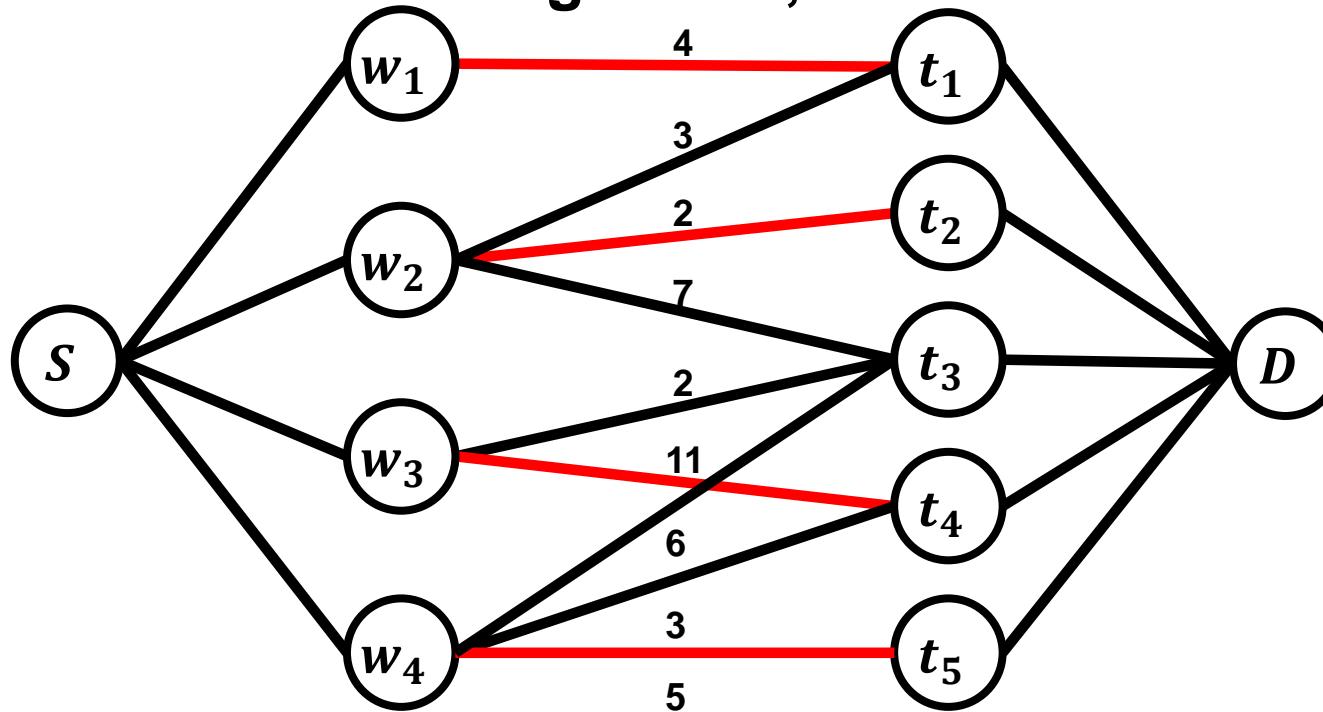
- Objective 1: Maximizing the total utility/number of the matching

The problem of static matching with Objective 1 equals to the **Maximum Weighted Bipartite Matching (MWBM)** problem.



MaxSum Matching

- The MWBM problem can be solved by various of classical **Max-Flow algorithms**
 - Ford-Fulkerson Algorithm, etc.



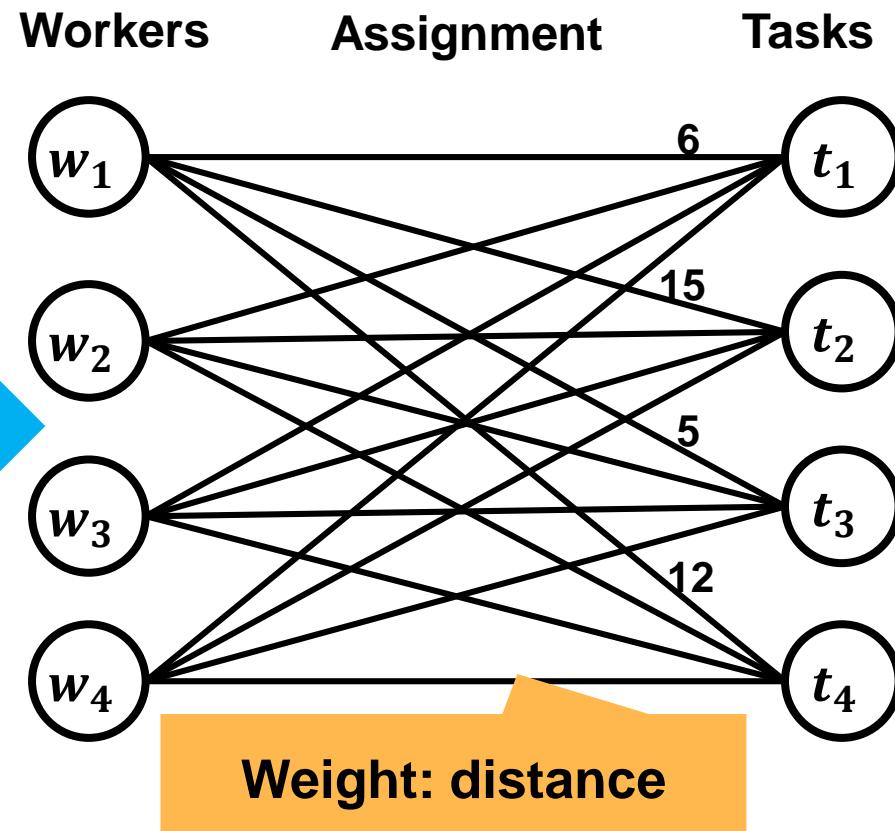
Static Matching

- Problem Definition
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 - Objective 2: MinSum Matching
 - Objective 3: Stable Marriage Matching

MinSum Matching

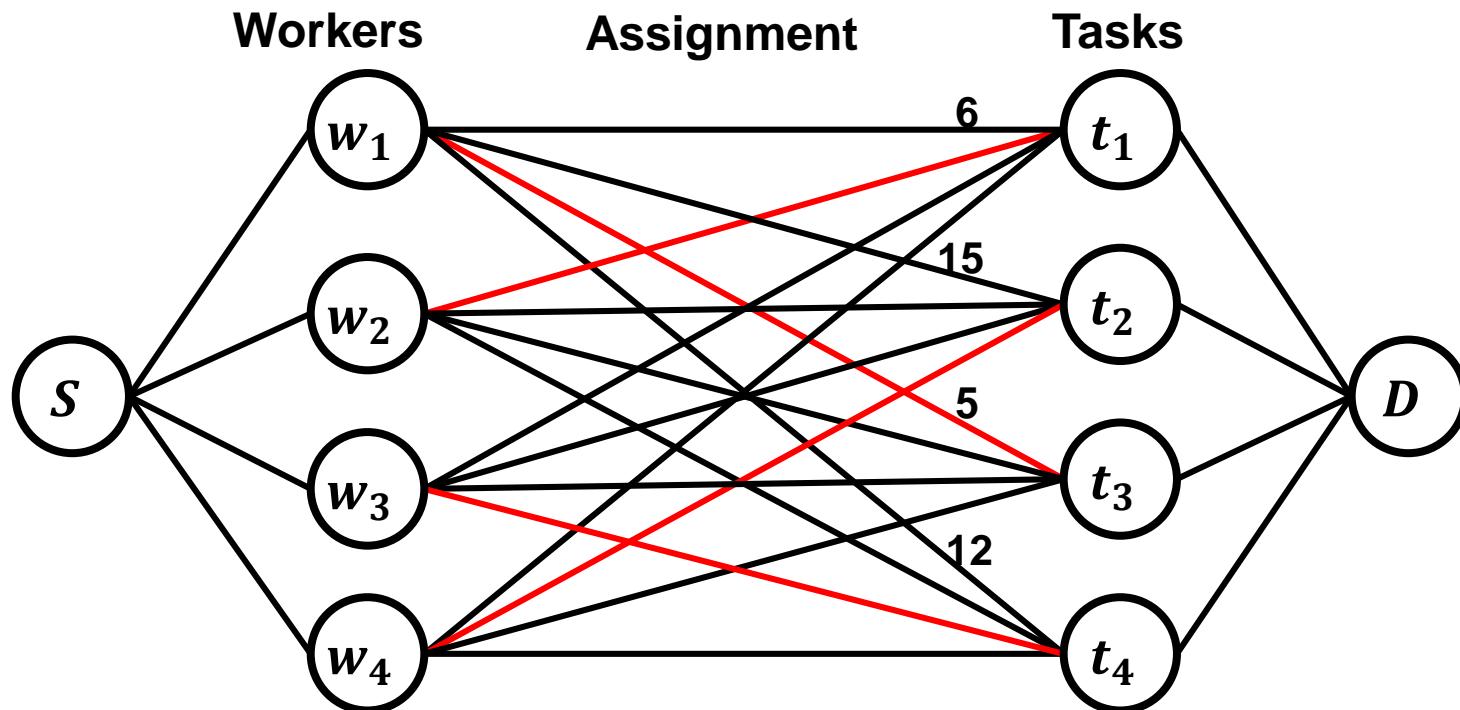
- Objective 2: Minimizing the total distance cost of the maximum-cardinality matching (perfect matching)

The problem of static matching with Objective 2 equals to the Maximum Flow with Minimum Cost problem.



MinSum Matching

- The MimSum problem can be solved by a serial of classical **assignment algorithms**
 - Successive Shortest Path Algorithm (SSPA)
 - Leverage index and I/O optimization techniques



Static Matching

- Problem Definition
- Existing Research
 - Objective 1: MaxSum Matching
 - Objective 2: MinSum Matching
 - **Objective 3: Stable Marriage Matching**

Stable Marriage Matching

- **Stable Marriage:** Given the preference lists of n women and n men, the problem is to find a perfect matching with no unstable pairs

- **Spatial Stable Marriage:** Given the preference lists of n tasks and n workers **based on the order of their distances**, the problem is to find a perfect matching with no unstable pairs

Stable Marriage Matching

- A worker-task pair (w, t) is an **unstable pair** if
 - $|w, t| <$ the distance between t and t 's partner in the given matching
 - $|w, t| <$ the distance between w and w 's partner in the given matching



The given matching

Stable Marriage Matching

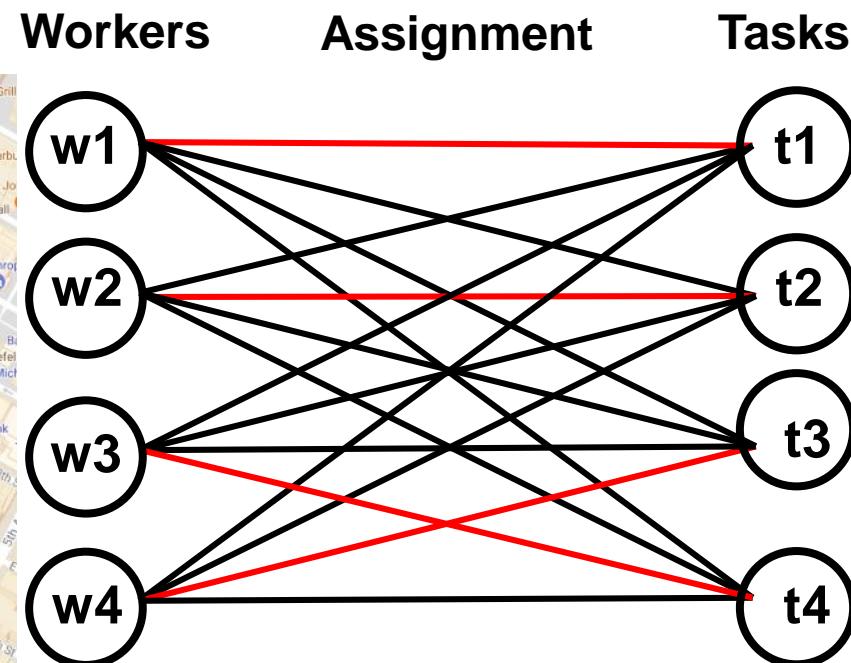
- A worker-task pair (w, t) is an **unstable pair** if
 - $|w, t| <$ the distance between t and t 's partner in the given matching
 - $|w, t| <$ the distance between w and w 's partner in the given matching



Stable Marriage Matching

- Classical Gale-Shapley algorithm is impractical for large-scale spatial data
- Design a Chain algorithm, which iteratively utilizes NN operation to enhance the efficiency

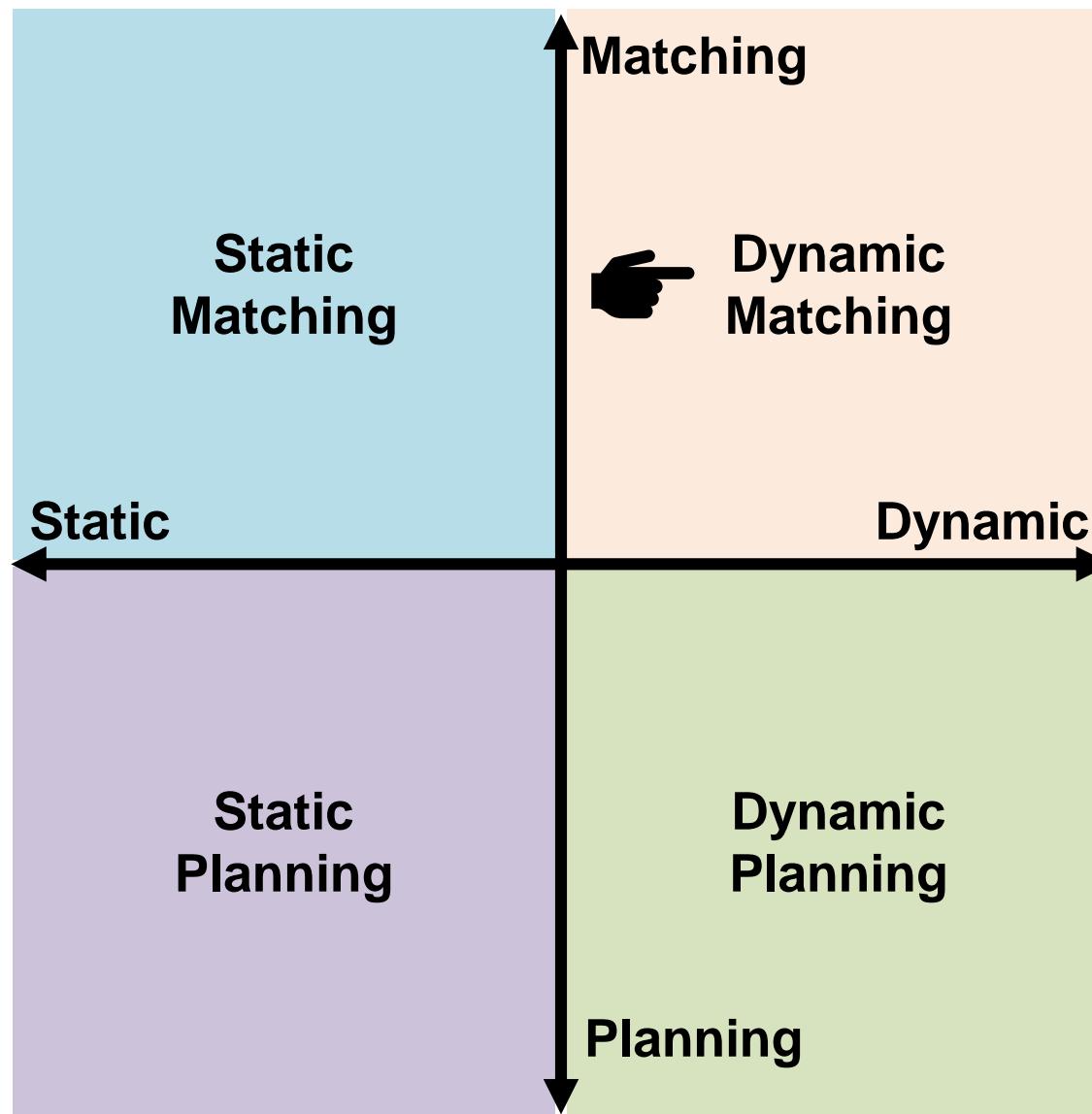
Iteratively find NN



Reference: Static Matching

1. R. Burkard, M. Dell'Amico, S. Martello. Assignment problems. Society for Industrial and Applied Mathematics, 2009.
2. L. Kazemi, C. Shahabi. Geocrowd: enabling query answering with spatial crowdsourcing. In SIGSPATIAL/GIS, pages 189-198, 2012.
3. H. To, C. Shahabi, L. Kazemi. A server-assigned spatial crowdsourcing framework. TSAS, 1(1):2, 2015.
4. L. U, M. Yiu, K. Mouratidis, N. Mamoulis. Capacity constrained assignment in spatial databases. In SIGMOD, pages 15-28, 2008.
5. L. U, K. Mouratidis, M. Yiu, N. Mamoulis. Optimal matching between spatial datasets under capacity constraints. TODS 35(2): 9:1-9:44, 2010.
6. L. U, N. Mamoulis, K. Mouratidis: A fair assignment algorithm for multiple reference queries. PVLDB, 2(1): 1054-1065, 2009.
7. R. C. Wong, Y. Tao, A. Fu, X. Xiao. On efficient spatial matching. In VLDB, pages 579-590, 2007.
8. G. Dan, and R. W. Irving. The stable marriage problem: structure and algorithms. MIT press, 1989.
9. C. Long, R. Wong, P. S. Yu, M. Jiang. On optimal worst-case matching. In SIGMOD, pages 845-856, 2013.

Dynamic Matching



Dynamic Matching

- **Batch-based Matching**
 - Problem Definition
 - Existing Research
- **Online Matching**
 - Problem Definition
 - Existing Research
 - Objective 1: Online MaxSum Matching
 - Objective 2: Online MinSum Matching
- **Summary**

Batch-based Matching

- A set of workers and tasks **dynamically appear** in the physical space, this problem needs to perform a **series of static matching for new arrival workers/tasks per time slot** based on different objectives

Dynamic Matching

- **Batch-based Matching**
 - Problem Definition
 - Existing Research

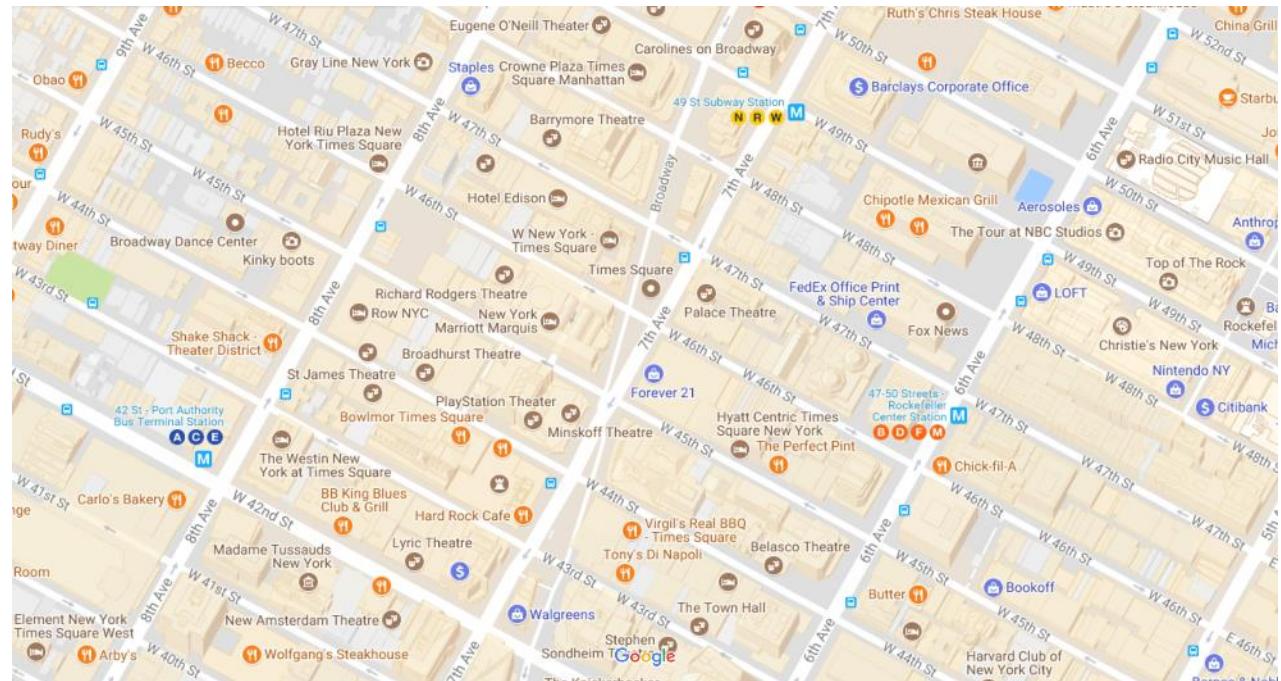
- **Online Matching**
 - Problem Definition
 - Existing Research
 - Objective 1: Online MaxSum Matching
 - Objective 2: Online MinSum Matching

- **Summary**

Batch-based Matching

- Objective: Maximizing the total utility/number of matching in all batches (batch size=4min)

Platform



Batch-based Matching

- Perform a MaxSum **static** matching for new arrival tasks/workers **per time slot** (e.g., 4min)

Platform



Platform gradually knows information (past and present) as time goes on

Arrival Time	8:00
--------------	------

t_1



Batch-based Matching

- Perform a MaxSum **static** matching for new arrival tasks/workers **per time slot** (e.g., 4min)

Platform



Platform gradually knows information (**past and present**) as time goes on



Arrival Time	8:00	8:01
	t_1	w_1

Batch-based Matching

- Perform a MaxSum **static** matching for new arrival tasks/workers **per time slot** (e.g., 4min)

Platform



Platform gradually knows information (**past and present**) as time goes on



Arrival Time	8:00	8:01	8:02
	t_1	w_1	t_2

Batch-based Matching

- Perform a MaxSum **static** matching for new arrival tasks/workers **per time slot** (e.g., 4min)

Platform



Platform gradually knows information (past and present) as time goes on



Arrival Time	8:00	8:01	8:02
--------------	------	------	------

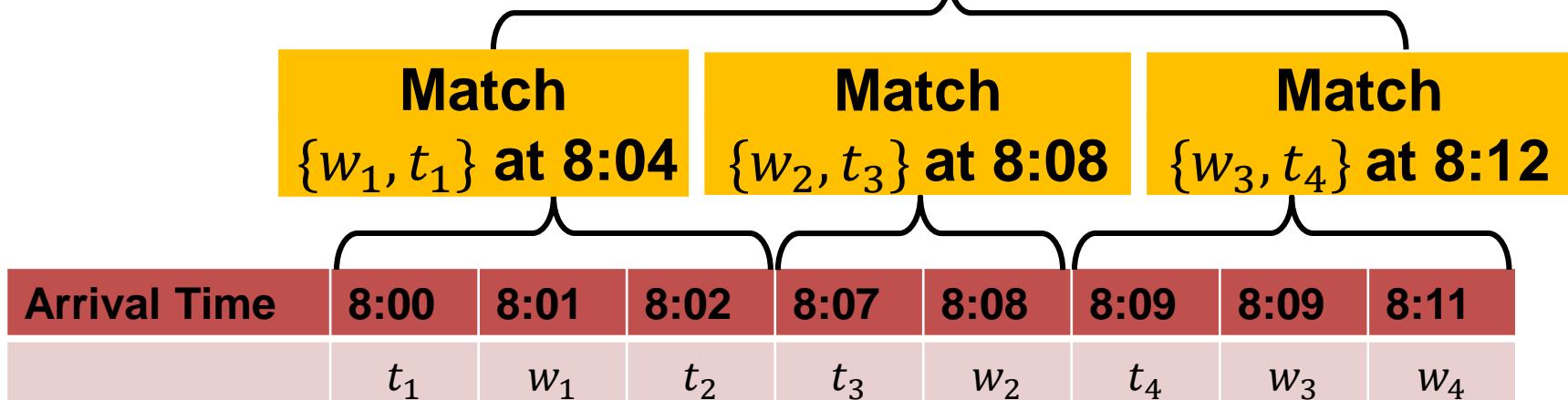
t_1 w_1 t_2

Perform an assignment at 8:04

Existing Research

- Perform a **local static assignment** in each time slot
 - Exact methods: Ford-Fulkerson algorithm
 - Approximation methods: Greedy algorithm
- Aggregate the total number of the assignments

The total number
of assignment is 3



Dynamic Matching

- **Batch-based Matching**
 - Problem Definition
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- **Online Matching**
 - Problem Definition
 - Existing Research
 - Objective 1: Online MaxSum Matching
 - Objective 2: Online MinSum Matching

- **Summary**

Online Matching

- A set of tasks/workers **dynamically appear one by one** in the physical space, the online matching based on a specific objective must be performed **immediately** and **irrevocably**, when a new task or worker arrives

Online Matching



Online Matching

- Evaluation of Online Matching Algorithms
 - Competitive Ratio (CR)

$$CR = \frac{\text{Value of an online algorithm}}{\text{Value of the corresponding offline algorithm}}$$

- Input Models

- Adversarial Model (Worst-Case Analysis)

$$CR_A = \min_{\forall G(T,W,U) \text{ and } \forall v \in V} \frac{\text{MaxFunc}(M)}{\text{MaxFunc(OPT)}}$$

$$CR_A = \max_{\forall G(T,W,U) \text{ and } \forall v \in V} \frac{\text{MinFunc}(M)}{\text{MaxFunc(OPT)}}$$

The worst input

The worst arrival order

- Random Order Model (Average-Case Analysis)

$$CR_{RO} = \min_{\forall G(T,W,U)} \frac{\mathbb{E}[\text{MaxFunc}(M)]}{\text{MaxSum(OPT)}}$$

$$CR_{RO} = \max_{\forall G(T,W,U)} \frac{\mathbb{E}[\text{MinFunc}(M)]}{\text{MinSum(OPT)}}$$

The worst input

The expectation of the total utility of all possible arrival orders

Dynamic Matching

- **Batch-based Matching**
 - Problem Definition
 - Existing Research

- **Online Matching**
 - Problem Definition
 - Existing Research
 - **Objective 1: Online MaxSum Matching**
 - **Objective 2: Online MinSum Matching**

- **Summary**

Online MaxSum Matching

- Objective 1: Assign tasks to workers **in the online scenario** to **maximize the total utility/number of the matching**

Online MaxSum Matching

- Baseline
 - Greedy
 - When a task/worker appears, the algorithm assigns it to a worker/task with the current maximum utility

Online MaxSum Matching

- Baseline

- Greedy

- When a task/worker appears, the algorithm assigns it to a worker/task with the current maximum utility

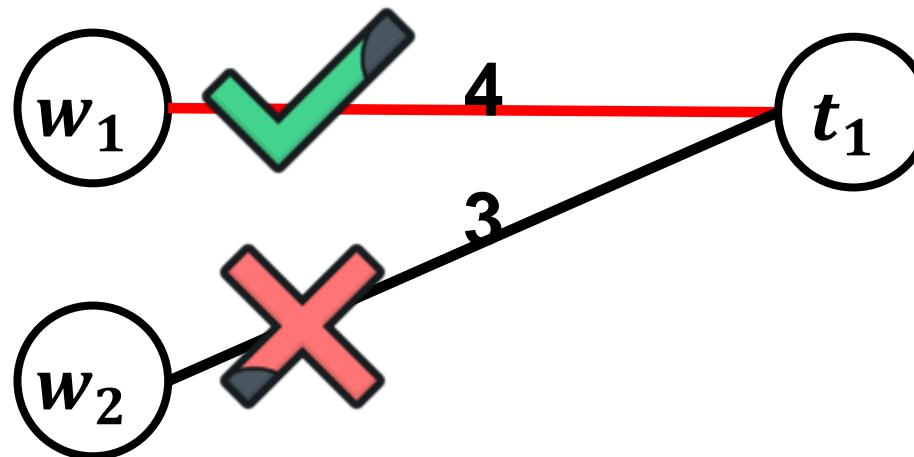


Online MaxSum Matching

- ❑ Baseline

- ❑ Greedy

- ❑ When a task/worker appears, the algorithm assigns it to a worker/task with the current maximum utility

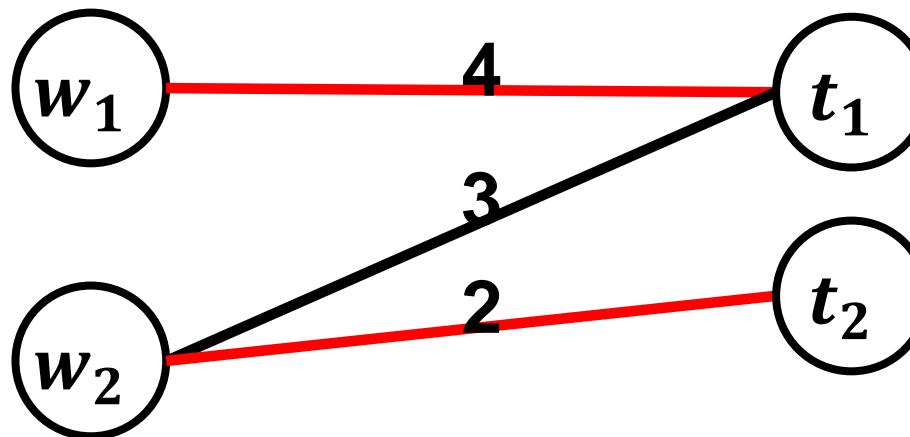


Online MaxSum Matching

- Baseline

- Greedy

- When a task/worker appears, the algorithm assigns it to a worker/task with the current maximum utility

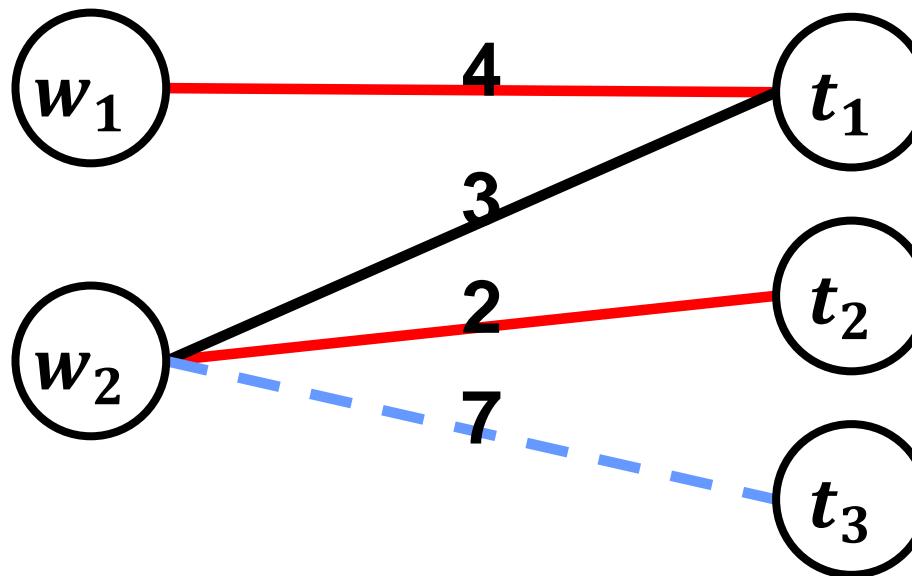


Online MaxSum Matching

- Baseline

- Greedy

- When a task/worker appears, the algorithm assigns it to a worker/task with the current maximum utility



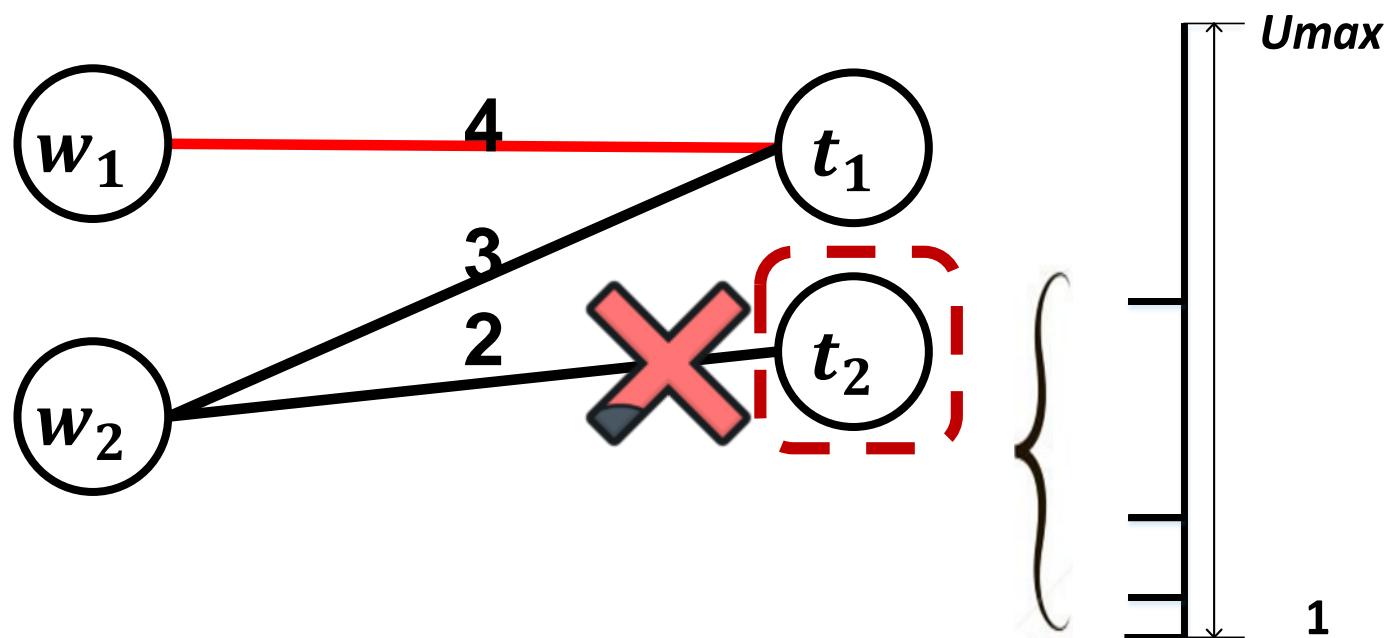
Online MaxSum Matching

❑ Improvements

❑ Extended Greedy

- ❑ Choose an integer k from 0 to $\lceil \ln(U_{max} + 1) \rceil$ randomly.
- ❑ Filter the edges with weights lower than the threshold e^k .
- ❑ Use a greedy strategy on the remaining edges.

Threshold is e



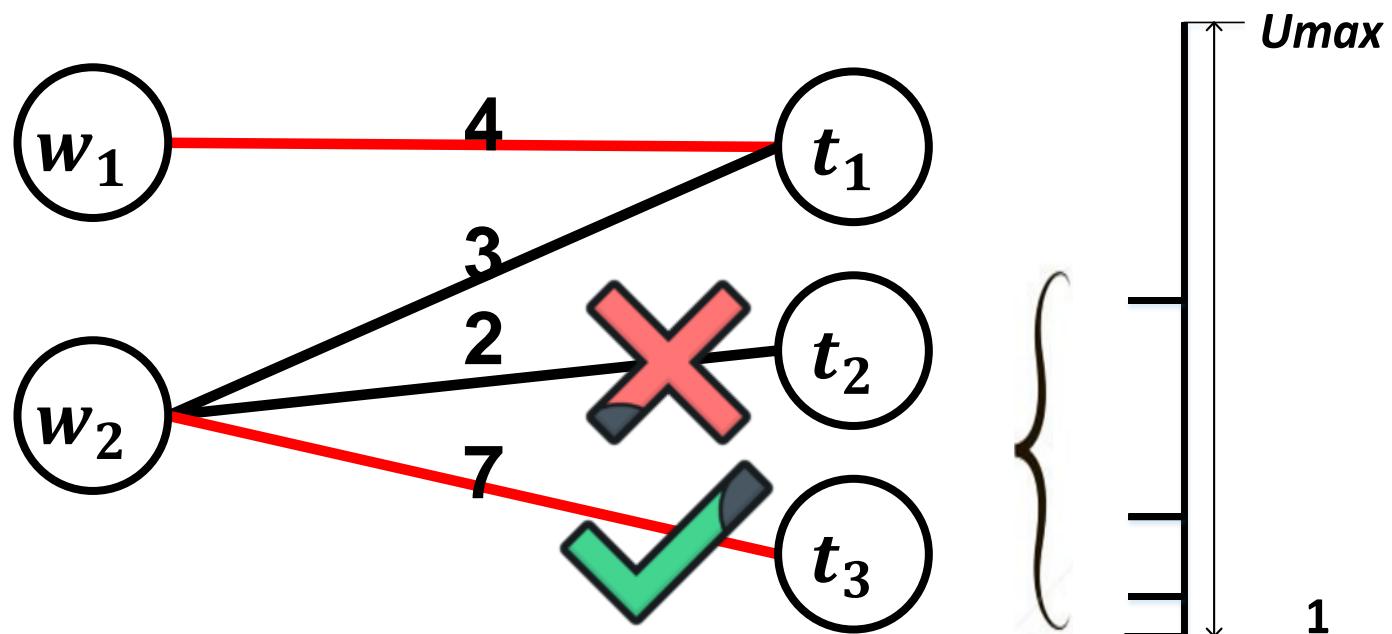
Online MaxSum Matching

❑ Improvements

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Dynamic Matching

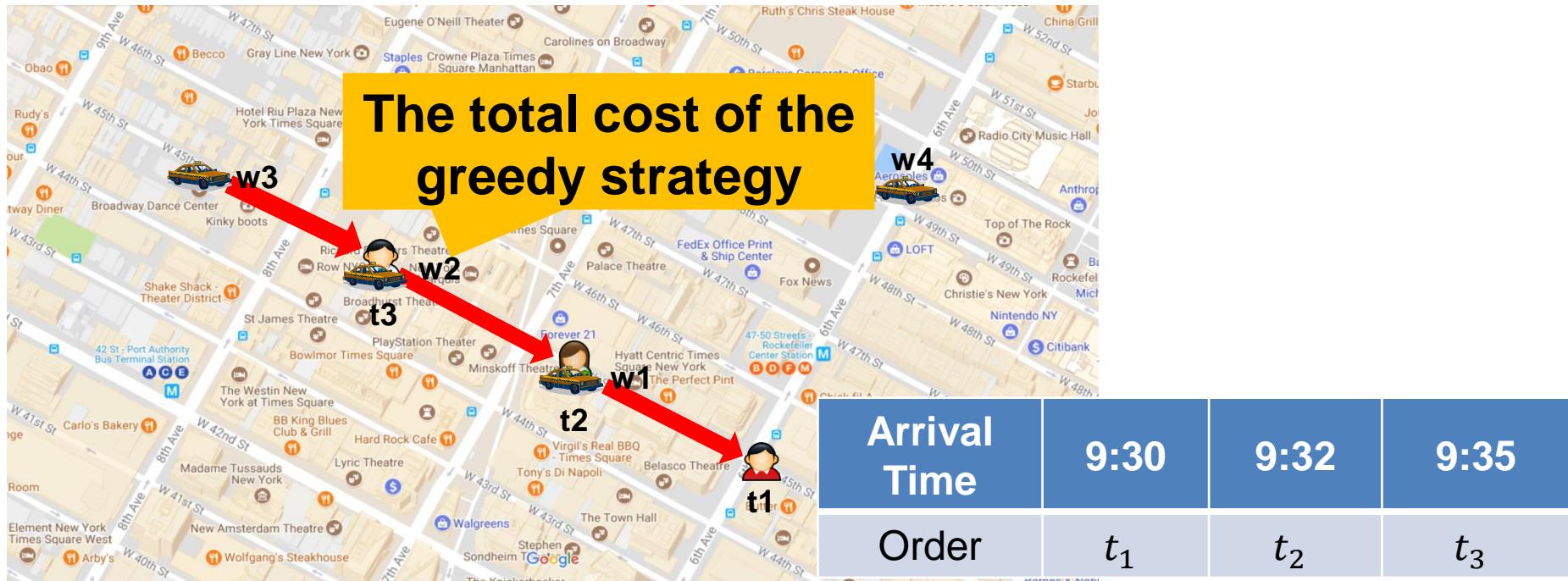
- **Batch-based Matching**
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- **Online Matching**
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- **Summary**

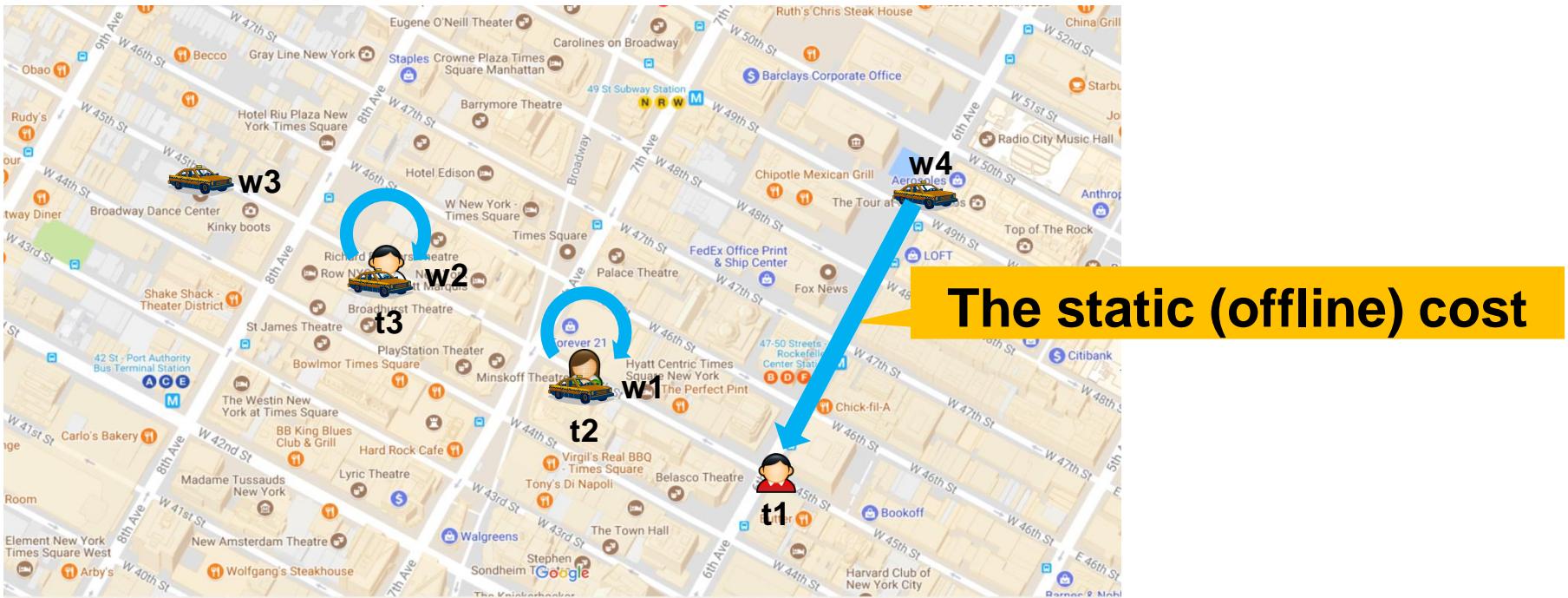
Online MinSum Matching

- Objective 2: Assign tasks to workers in the online scenario to minimize the total utility
 - A task/worker is assigned immediately on arrival based on partial information



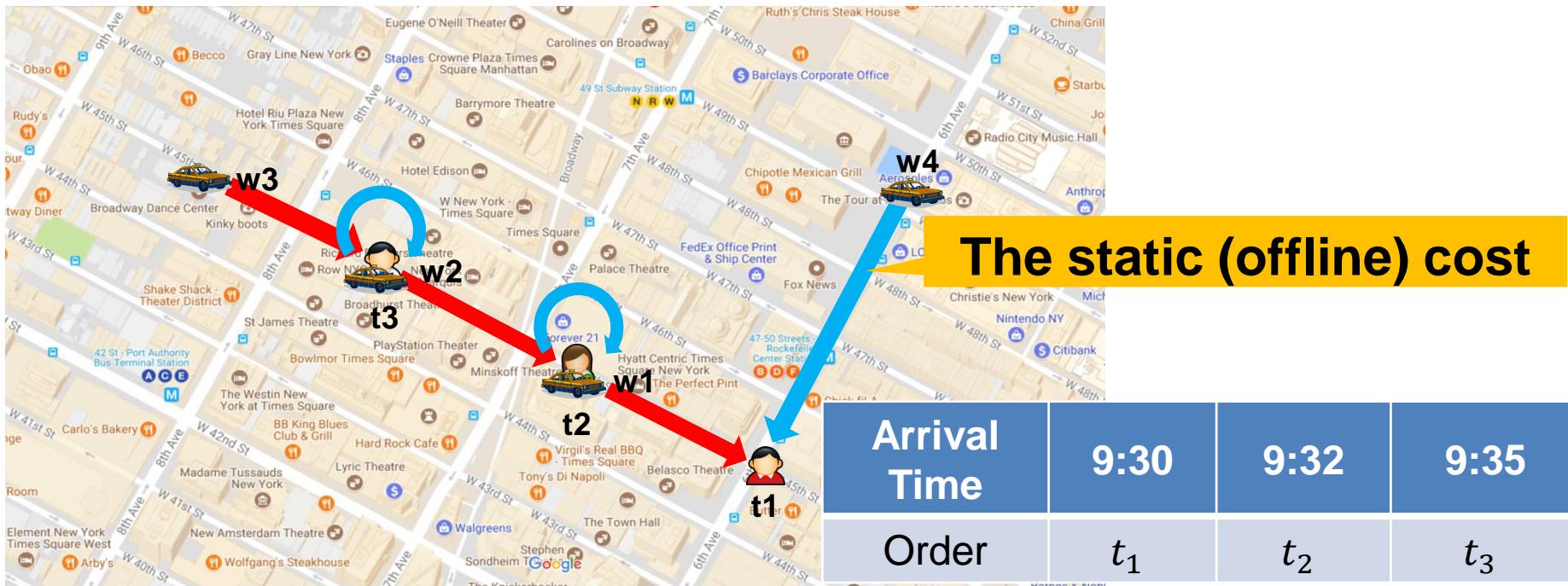
Review: Static MinSum Matching

- Objective: Minimize the total distance cost of maximum-cardinality matching
- Assume that all spatiotemporal information is known in advance (offline OPT)



Review: Static MinSum Matching

- Objective: Minimize the total distance cost of maximum-cardinality matching
- Assume that all spatiotemporal information is known in advance (offline OPT)



Online MinSum Matching

- Four representative algorithms

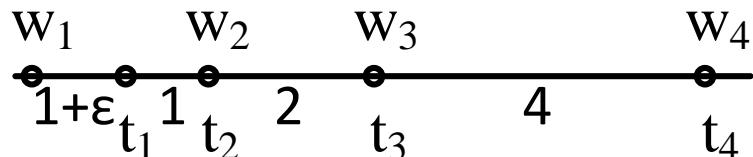
Algorithms	Time Complexity per Each Arrival Vertex	Randomization	Data Structure	Competitive Ratio (Worst-Case Analysis)
Greedy [SODA'1991]	$O(k)$	Deterministic	No	$O(2^k)$
Permutation [SODA'1991]	$O(k^3)$	Deterministic	No	$O(2k-1)$
HST-Greedy [SODA 2006]	$O(k)$	Randomized	HST	$O(\log^3 k)$
HST-Reassignment [ESA 2007]	$O(k^2)$	Randomized	HST	$O(\log^2 k)$

Hierarchically Separated Tree

Is the greedy algorithm really the worst?

Online MinSum Matching

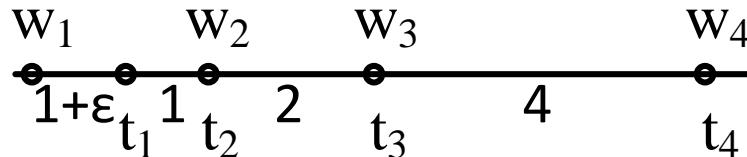
□ Greedy Revisited



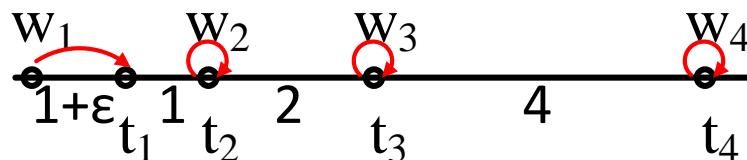
(a) Locations

Online MinSum Matching

□ Greedy Revisited



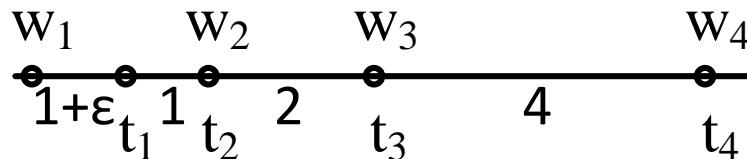
(a)Locations



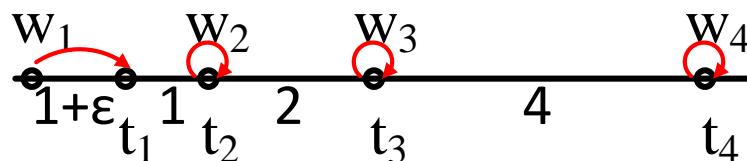
(b)Matching of Offline OPT

Online MinSum Matching

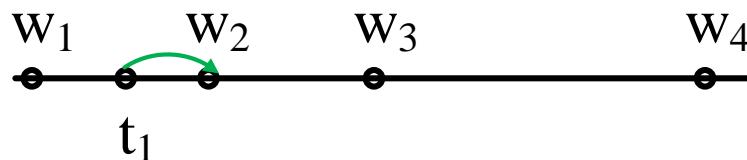
□ Greedy Revisited



(a)Locations



(b)Matching of Offline OPT

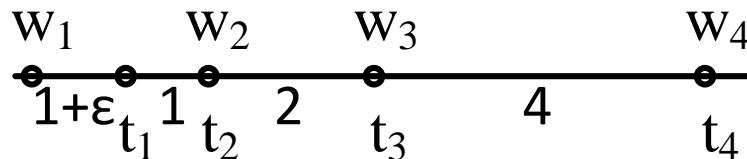


(c)Matching of Worst-Case Greedy

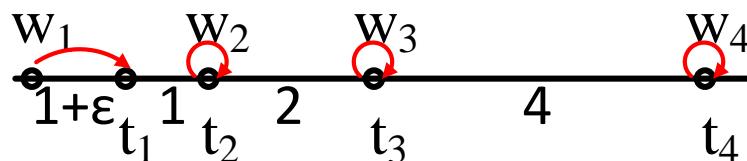
When t_1 appears, w_2 will be assigned to t_1 by Greedy

Online MinSum Matching

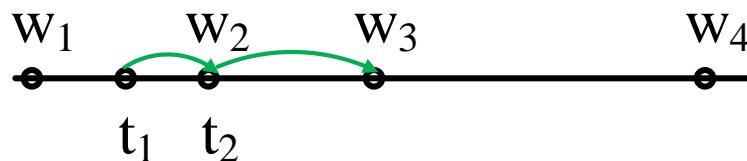
□ Greedy Revisited



(a)Locations



(b)Matching of Offline OPT

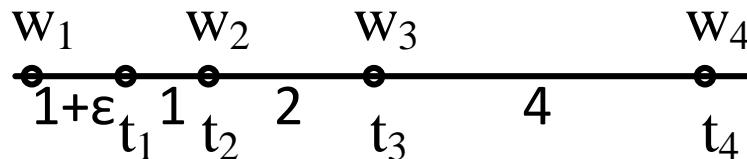


(c)Matching of Worst-Case Greedy

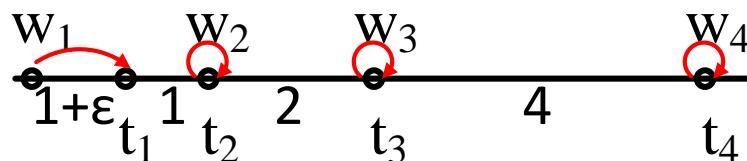
When t_2 appears, w_3 will be assigned to t_2 by Greedy

Online MinSum Matching

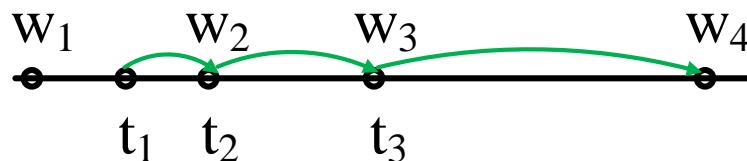
□ Greedy Revisited



(a)Locations



(b)Matching of Offline OPT

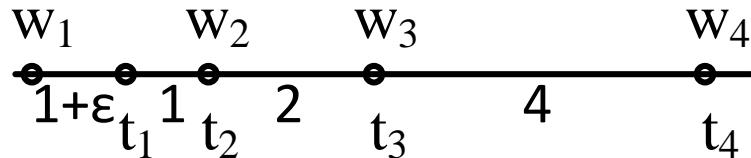


(c)Matching of Worst-Case Greedy

When t_3 appears, w_4 will be assigned to t_3 by Greedy

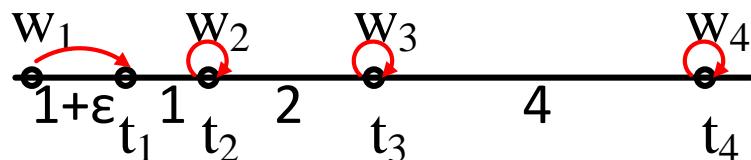
Online MinSum Matching

□ Greedy Revisited

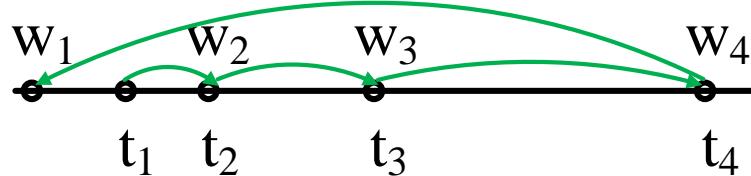


Competitive Ratio $CR_{RO}=3.195$

(a) Locations



(b) Matching of Offline OPT

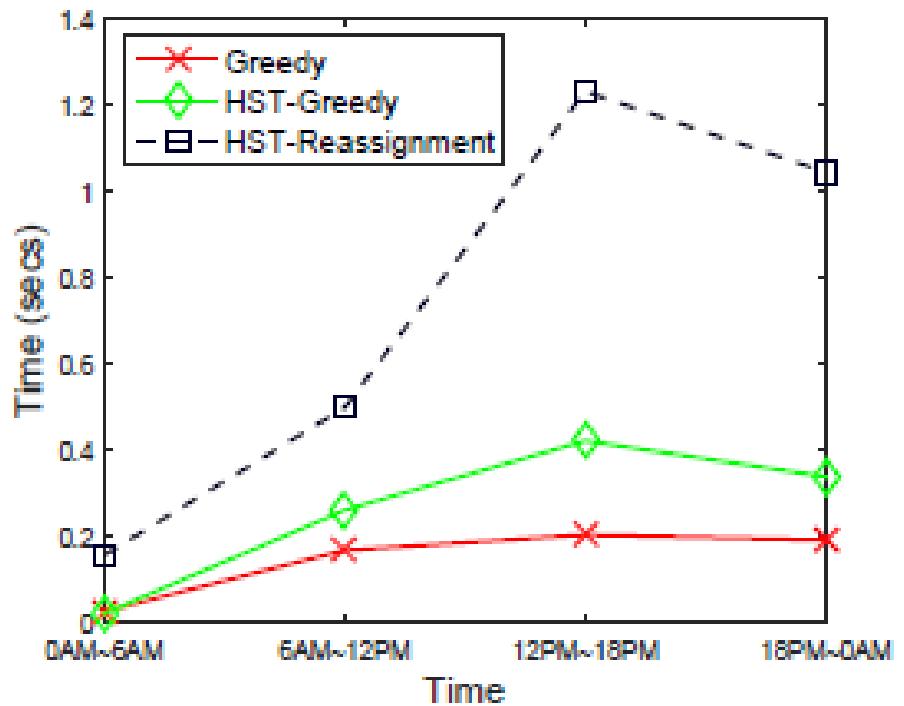
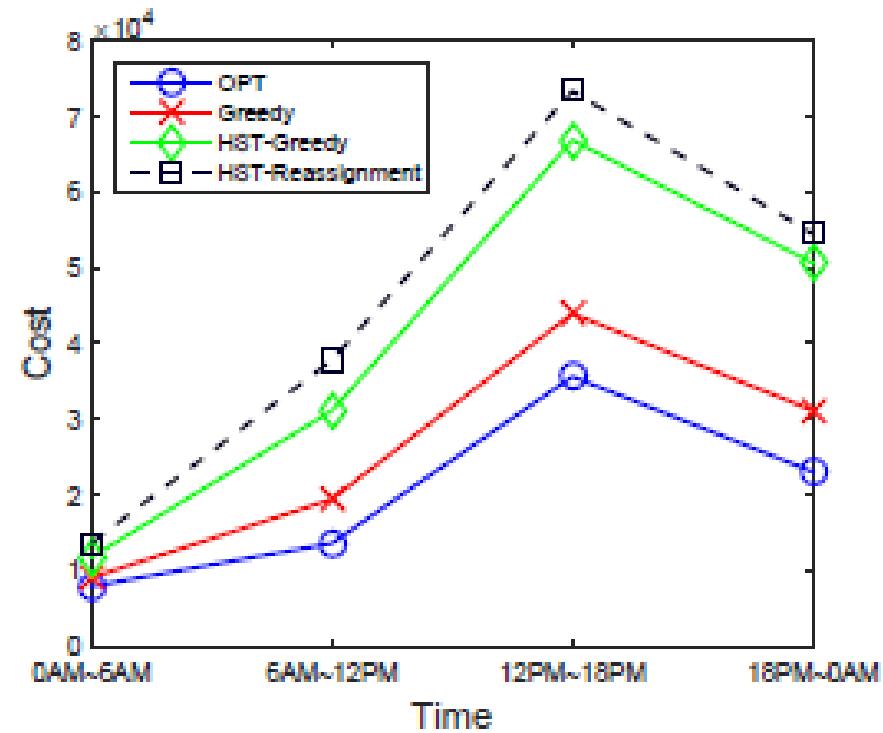


(c) Matching of Worst-Case Greedy

When t_4 appears, w_1 has to be assigned to t_4 by Greedy

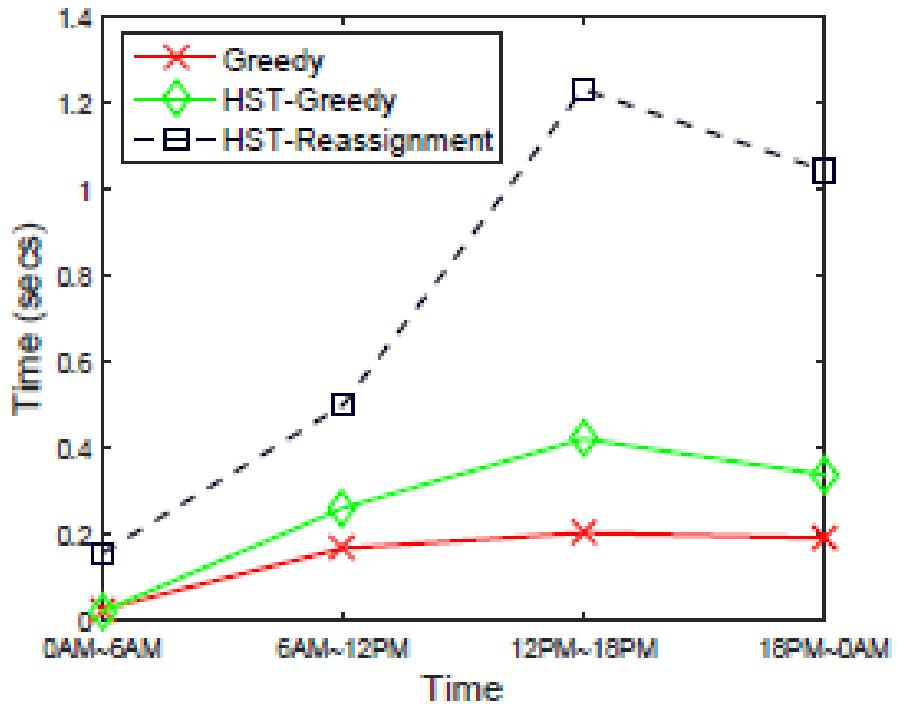
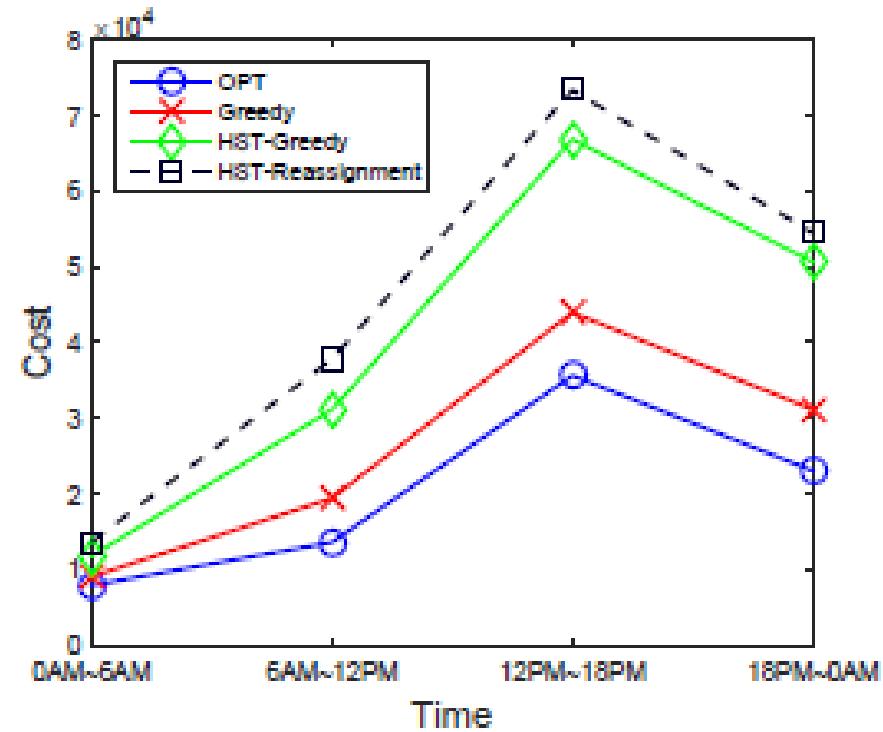
The probability that the worst-case happens is only 1 over the factorial of k , which is the number of workers (taxis)

Online MinSum Matching



Their extensive experiments on real datasets and synthetic datasets shows that the greedy algorithm is not bad and always outperforms other state-of-the-art online algorithms!

Online MinSum Matching



Open question: the average-case competitive ratio under the random order model of Greedy for the online MinSum matching problem should be constant or $O(k)$?

Dynamic Matching

- **Batch-based Matching**
 - Problem Definition
 - Existing Research

- **Online Matching**
 - Problem Definition
 - Existing Research
 - Objective 1: Online MaxSum Matching
 - Objective 2: Online MinSum Matching

- **Summary**

Summary of Matching Models

	Static/Dynamic Scenario	Effect of Spatial Factors	Optimization Target
U et al. SIGMOD08	Static	Target	MinSum Distance
Wong et al. VLDB07	Static	Target	Spatial Stable Marriage
Long et al. SIGMOD13	Static	Target	MinMax Distance
She et al. ICDE15	Static	Constraint	Conflict-based MaxSum Utility
Alfarrarjeh et al. MDM15	Static	Target	MinSum Distance in Distributed SC
Kazemi et al. GIS12	Batch-based	Constraint	MaxSum Number
To et al. TSAS15	Batch-based	Constraint	MaxSum Utility
Liu et al. ICDE16	Batch-based	Constraint	MaxSum Utility
Cheng et al. ICDE17	Batch-based	Constraint	Prediction-based MaxSum Utility

Summary of Matching Models

	Static/Dynamic Scenario	Effect of Spatial Factors	Optimization Target
Tong et al. ICDE16	Online	Constraint	MaxSum Utility
Tong et al. VLDB16	Online	Target	MinSum Distance
She et al. TKDE16	Online	Constraint	Conflict-based MaxSum Utility
Song et al. ICDE 17	Online	Constraint	Trichromatic MaxSum Utility
Tong et al. VLDB 17	Online	Constraint	Prediction-based MaxSum Number
Hassan et al. UIC14	Online	Constraint	MaxSum Utility
To el al. Percom 16	Static and Online	Constraint	MaxSum Utility

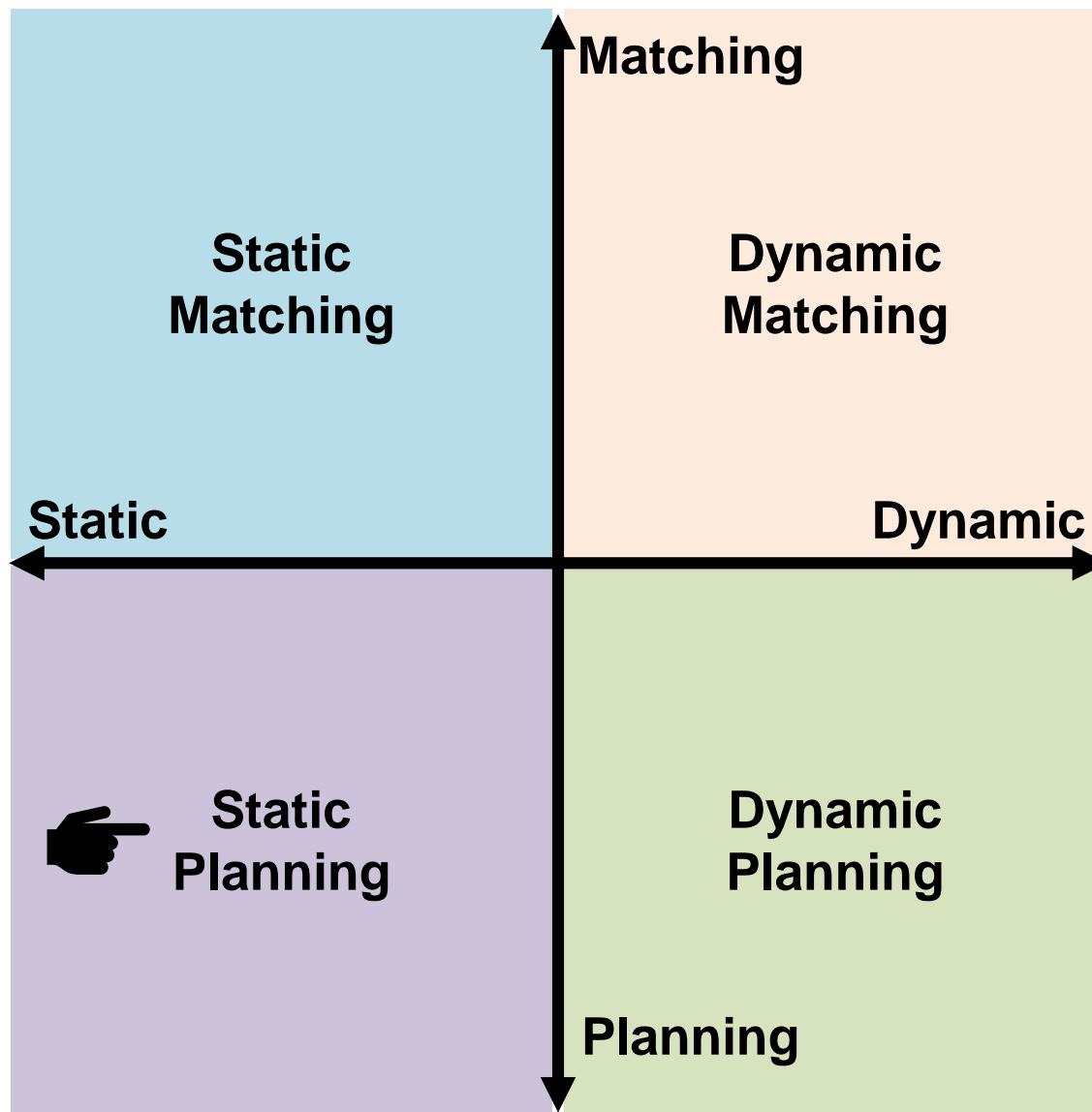
Reference: Dynamic Matching

1. L. Kazemi, C. Shahabi. Geocrowd: enabling query answering with spatial crowdsourcing. In GIS, pages 189-198, 2012.
2. H. To, C. Shahabi, L. Kazemi. A server-assigned spatial crowdsourcing framework. TSAS, 1(1):2, 2015.
3. Y. Tong, J. She, B. Ding, L. Wang, L. Chen. Online mobile micro-task allocation in spatial crowdsourcing. In ICDE, pages 49-60, 2016.
4. Y. Tong, J. She, B. Ding, L. Chen, T. Wo, K. Xu. Online minimum matching in real-time spatial data: Experiments and analysis. PVLDB 9(12): 1053-1064, 2016.
5. Y. Tong, L. Wang, Z. Zhou, B. Ding, L. Chen, J. Ye, K. Xu. Flexible online task assignment in real-time spatial data. PVLDB, 10(11): 1334-1345, 2017.
6. P. Cheng, X. Lian, L. Chen, C. Shahabi. Prediction-based task assignment in spatial crowdsourcing. In ICDE, pages 997-1008, 2017.
7. J. She, Y. Tong, L. Chen, C. Cao. Conflict-aware event-participant arrangement. In ICDE, pages 735-746, 2015.
8. J. She, Y. Tong, L. Chen, C. Cao. Conflict-aware event-participant arrangement and its variant for online setting. TKDE, 28(9): 2281-2295, 2016.
9. L. Zheng, L. Chen. Mutual benefit aware task assignment in a bipartite labor market. In ICDE, pages 73-84, 2016.

Reference: Dynamic Matching

10. T. Song, Y. Tong, L. Wang, J. She, B. Yao, L. Chen, K. Xu. Trichromatic Online Matching in Real-Time Spatial Crowdsourcing. In ICDE, pages 1009-1020, 2017.
11. H. To. Task assignment in spatial crowdsourcing: challenges and approaches. In SIGSPATIAL PhD Symposium, pages 1:1-4, 2016.
12. H. To, L. Fan, L. Tran, C. Shahabi. Real-time task assignment in hyperlocal spatial crowdsourcing under budget constraints. In PerCom, pages 1-8, 2016.
13. L. Tran, H. To, L. Fan, C. Shahabi. A real-time framework for task assignment in hyperlocal spatial crowdsourcing. TIST, 2017
14. A. Alfarrarjeh, T. Emrich, C. Shahabi. Scalable Spatial Crowdsourcing: A Study of Distributed Algorithms. In MDM, pages 134-144, 2015.
15. U. ul Hassan, E. Curry. A Multi-armed bandit approach to online spatial task assignment. In UIC, pages 212-219, 2014.
16. U. ul Hassan, E. Curry. Efficient task assignment for spatial crowdsourcing: A combinatorial fractional optimization approach with semi-bandit learning. ESA, 58: 36-56, 2016.

Static Planning



Static Planning

- Problem Definition
- Background
 - Orienteering Problem (OP)
- Existing Research
 - One-Worker-To-Many-Task Planning
 - Many-Worker-To-Many-Task Planning

Static Planning

□ Problem Definition

- Given a set of spatial tasks with some constraints (e.g., deadline), and the spatiotemporal information of tasks is known, the problem is to find a proper route of tasks for workers



Static Planning

- Problem Definition

- Background

- Orienteering Problem (OP)

- Existing Research

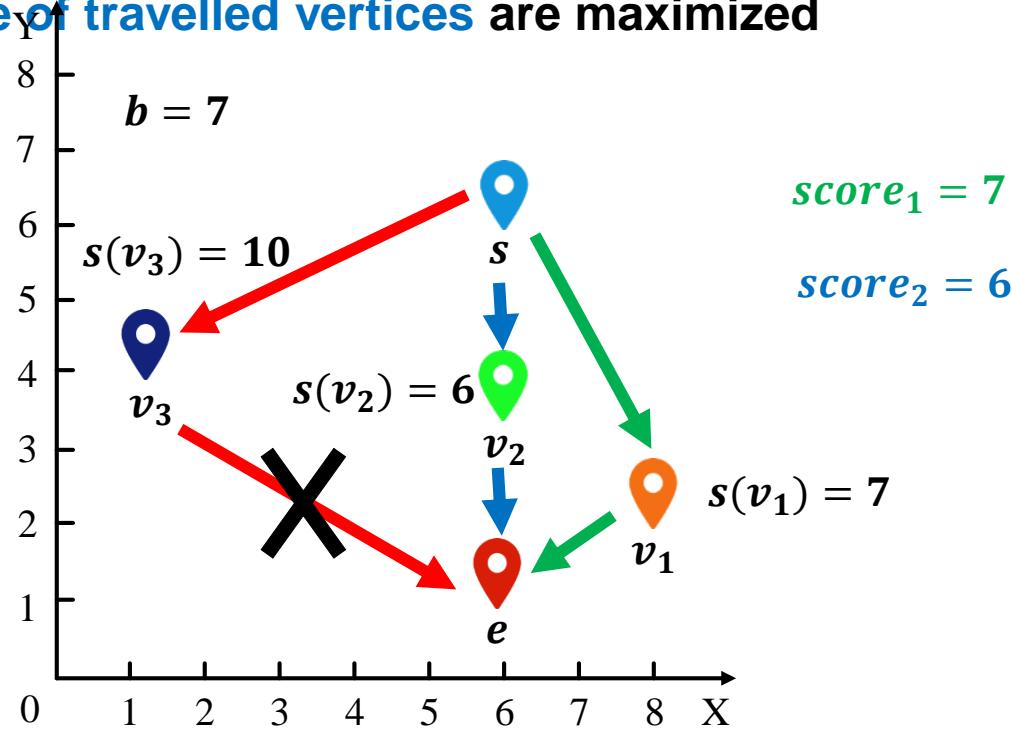
- One-Worker-To-Many-Tasks Planning
 - Many-Worker-To-Many-Tasks Planning

Static Planning

❑ Orienteering Problem (OP)

- ❑ Given a set of vertices, each associated with a score, a travel budget b , a start vertex s , an end vertex e , and the distance matrix among them, the problem is find a route from s to e such that:
 - ❑ The total travel distance is no more than the travel budget b
 - ❑ The total score of travelled vertices are maximized

A variant of the Traveling Salesman Problem (TSP)



Static Planning

- Problem Definition
- Background
 - Orienteering Problem (OP)
- Existing Research
 - One-Worker-To-Many-Task Planning
 - Many-Worker-To-Many-Task Planning

One-Worker-To-Many-Tasks Planning

- Objective: Find a route for one worker to maximize the number of the tasks satisfying travel/time budgets
- Difference from Orienteering Problem
 - The utility score of each task is zero or one
 - The end vertex of the path is not given



One-Worker-To-Many-Tasks Planning

□ Heuristic Methods

□ Nearest Neighbor first

□ Limitation first (e.g., time expiration)



One-Worker-To-Many-Tasks Planning

□ Heuristic Methods

- Nearest Neighbor first
- Limitation first (e.g., time expiration)



Static Planning

- Problem Definition
- Background
 - Orienteering Problem (OP)
- Existing Research
 - One-Worker-To-Many-Task Planning
 - Many-Worker-To-Many-Task Planning

Many-Worker-To-Many-Tasks Planning

- Objective: Find routes for all workers to maximize the total utility/number satisfying travel/time budgets



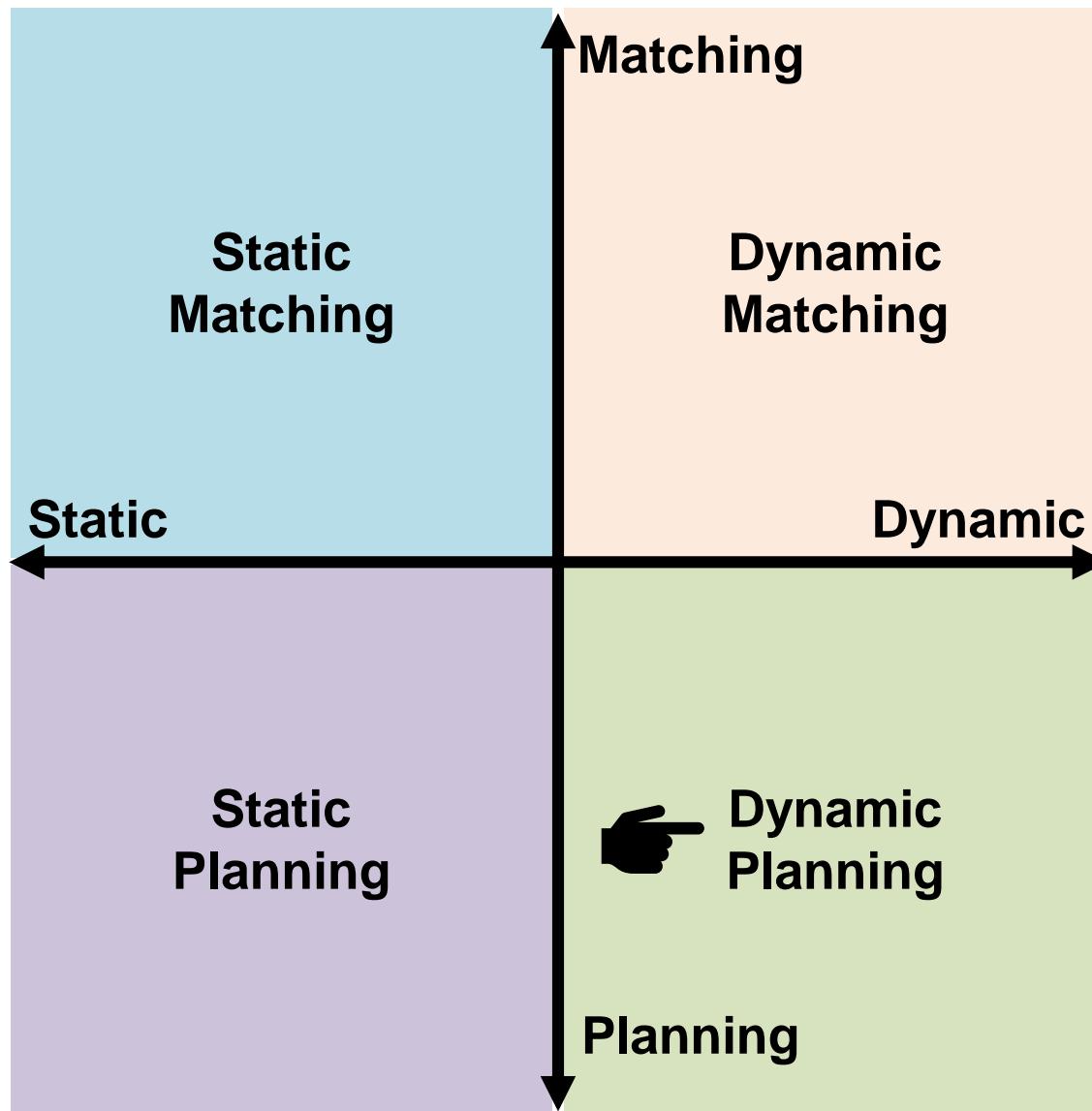
Many-Worker-To-Many-Tasks Planning

□ Greedy-based Algorithm

- Greedily choose the pair $\langle w, t \rangle$ with the maximum utility/travel cost ratio for each worker



Dynamic Planning



Dynamic Planning

- Problem Definition (One-worker-to-many-tasks)
 - Given one worker and a set of spatial tasks, which are dynamically released and have some constraints (e.g., deadline), the problem is find a route for the worker such that the number of the finished tasks is maximized
 - The route can only be updated when a task is released

Dynamic Planning

□ Task-layer Greedy

- Greedily choose the next nearest task after finishing the current task



Reference: Planning

1. C. H. Papadimitriou. The Euclidean travelling salesman problem is NP-complete. *TCS*, 4(3):237-244, 1977.
2. P. Vansteenwegen, W. Souffriau, D. V. Oudheusden. The orienteering problem: A survey. *EJOR*, 209(1): 1-10, 2011.
3. D. Deng, C. Shahabi, U. Demiryurek. Maximizing the number of worker's self-selected tasks in spatial crowdsourcing. In *GIS*, pages 314-323, 2013.
4. S. He, D. Shin, J. Zhang, J. Chen. Toward optimal allocation of location dependent tasks in crowdsensing. In *INFOCOM*, pages 745-753, 2014.
5. J. She, Y Tong, L. Chen. Utility-aware event-participant planning. In *SIGMOD*, pages 1629-1643, 2015
6. D. Deng, C. Shahabi, L. Zhu. Task matching and scheduling for multiple workers in spatial crowdsourcing. In *GIS*, pages 21:1-10, 2015.
7. D. Deng, C. Shahabi, U. Demiryurek, L. Zhu. Task selection in spatial crowdsourcing from worker's perspective. *GeoInformatica*, 20(3): 529-568, 2016.
8. Y. Li, ML. Yiu, W. Xu. Oriented online route recommendation for spatial crowdsourcing task workers. In *SSTD*, pages 137-156, 2015.
9. M. Asghari, D. Deng, C. Shahabi, U. Demiryurek, Y. Li. Price-aware real-time ride-sharing at scale: an auction-based approach. In *GIS*, pages 3:1-3:10, 2016.

Summary

		Matching Model	Planning Model
Computation Complexity	Static Scenario	Weighted Bipartite Matching [Polynomial Time Solvable Problem]	Traveling Salesman Problem (TSP) or Orienteering Problem (OP) [NP-hard Problem]
	Dynamic Scenario	Constant-competitive-ratio Online Algorithms	Non-constant-competitive-ratio Online Algorithms
Workload per Worker		One Task	Multiple Tasks
Representative Applications		Taxi Calling Service Bike Sharing	Food Delivery Service Ridesharing Service

Summary

		Matching Model	Planning Model
Computation Complexity	Static Scenario	Weighted Bipartite Matching [Polynomial Time Solvable Problem]	Traveling Salesman Problem (TSP) or Orienteering Problem (OP) [NP-hard Problem]
Workload per Worker	Dynamic Scenario	Constant-competitive-ratio Online Algorithms	Non-constant-competitive-ratio Online Algorithms
Representative Applications		One Task	Multiple Tasks
		Taxi Calling Service Bike Sharing	Food Delivery Service Ridesharing Service

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Outline

- Overview of Spatial Crowdsourcing (20min)
 - Motivation
 - Workflow
 - Core Issues
 - Difference from Related Tutorials
- Fundamental Techniques (40min)
 - Task Assignment
 - Quality Control
 - Incentive Mechanism
 - Privacy Protection
- Spatial Crowdsourced Applications (20min)
 - Spatial Crowdsourcing Intrinsic Applications
 - Crowd-powered Spatial Applications
- Open Questions (10min)

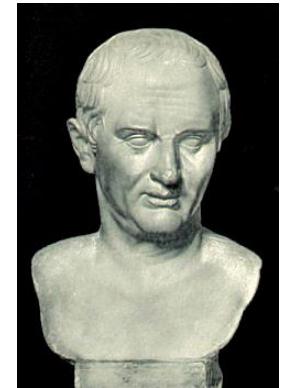
Quality Control

- **Why Quality Control**
- **Existing Research**
 - **Spatiotemporal-constraint-based Quality Control**
 - **Spatiotemporal-target-based Quality Control**
 - **Minimum Latency**
 - **Maximum Spatiotemporal Diversity**
- **Summary**

Why Quality Control

□ Traditional crowdsourcing

- Erroneous
 - “To err is human” by Marcus Tullius Cicero
- Existing research
 - Estimate the quality of workers
 - Infer the truth of tasks



□ Spatial crowdsourcing

- Spatiotemporal factors as constraints
 - Workers still err / truth of tasks still need to be inferred
 - Spatiotemporal factors are only used as constraints
- Spatiotemporal factors as goals
 - Quality of tasks is assessed by spatiotemporal factors

Quality Control

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Spatiotemporal-constraint-based QC

- Given a set of tasks and a set of workers with their **reputation**, the problem is to maximize the total number of assigned tasks such that
 - Quality requirement of each task is satisfied
 - **Spatiotemporal constraint:** tasks should locate in the service range of the assigned workers

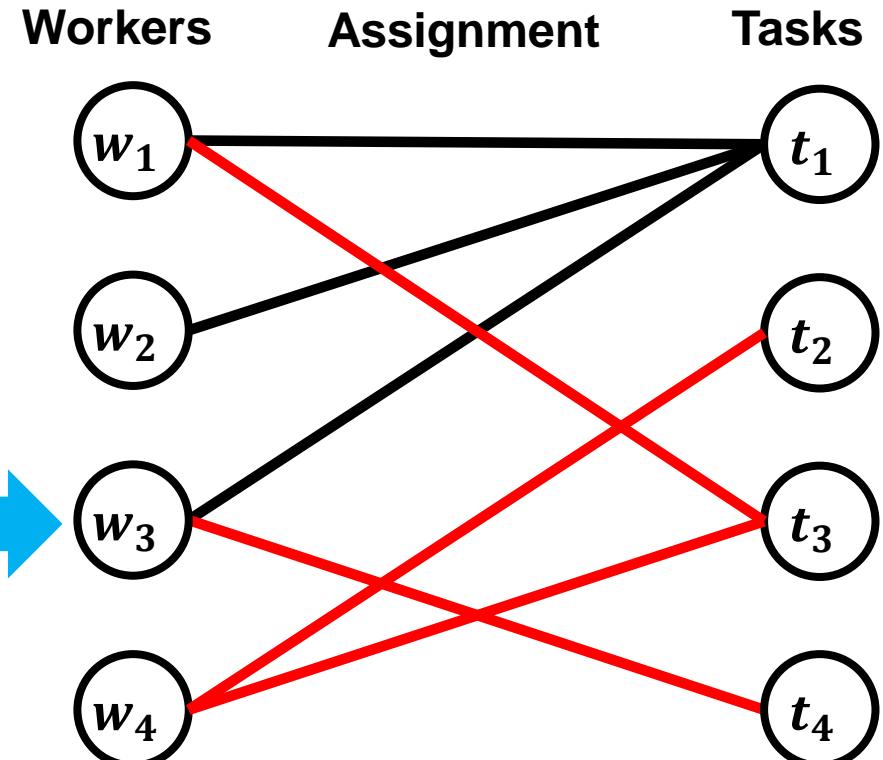
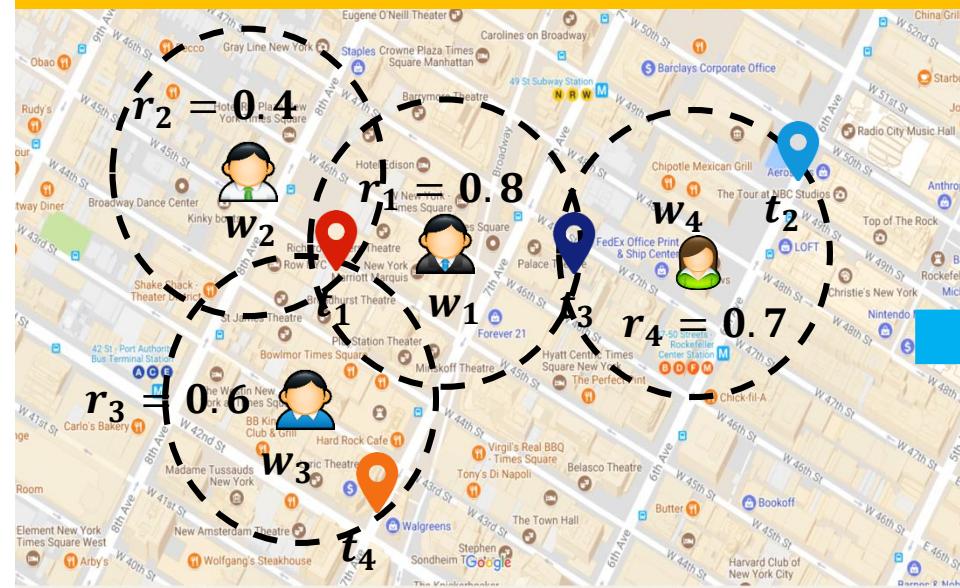


Spatial-constraint-based QC

- Quality requirement depends on quality control methods e.g. Majority Voting

Aggregate Reputation Score (ARS):

$$ARS(Q) = \sum_{k=\frac{|Q|}{2}+1}^{|Q|} \sum_{A \in F_k} \prod_{w_j \in A} r_j \prod_{w_j \notin A} (1 - r_j)$$



Quality Control

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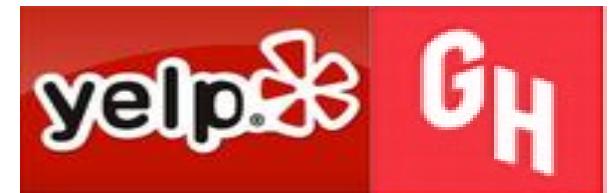
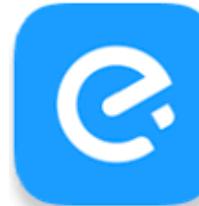
Minimum Latency

- ❑ Latency is a more important concern in spatial crowdsourcing than in traditional crowdsourcing



(Internet) Crowdsourcing

Latency: only care the **longest** completion time of the tasks



Spatial Crowdsourcing

Latency: also care the **total** completion time of **all the tasks**

Minimum Latency

- ❑ Latency is a more important concern in spatial crowdsourcing than in traditional crowdsourcing

- ❑ Solutions

- ❑ Modelled and solved by online matching or online planning



Online
Matching



Online
Planning

Quality Control

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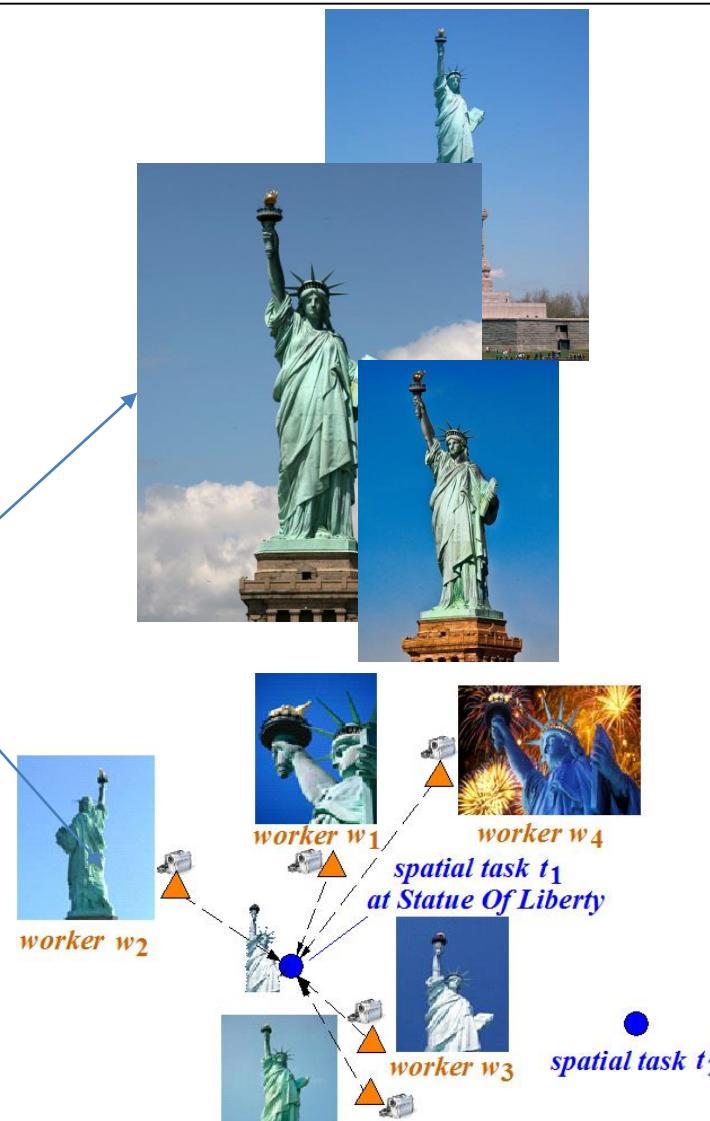
Maximum Spatiotemporal Diversity

□ Spatial Diversity

Take photos of a landmark

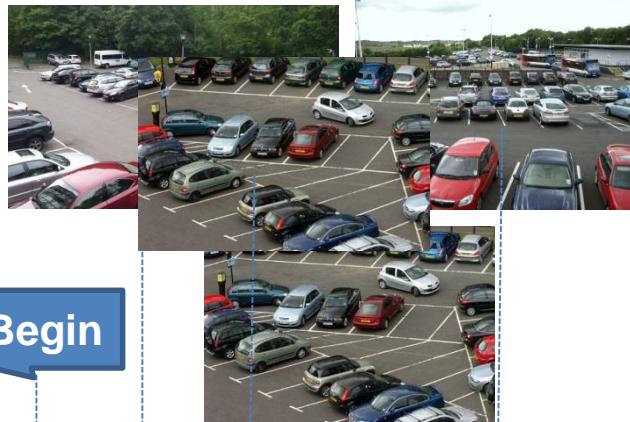


Post Task

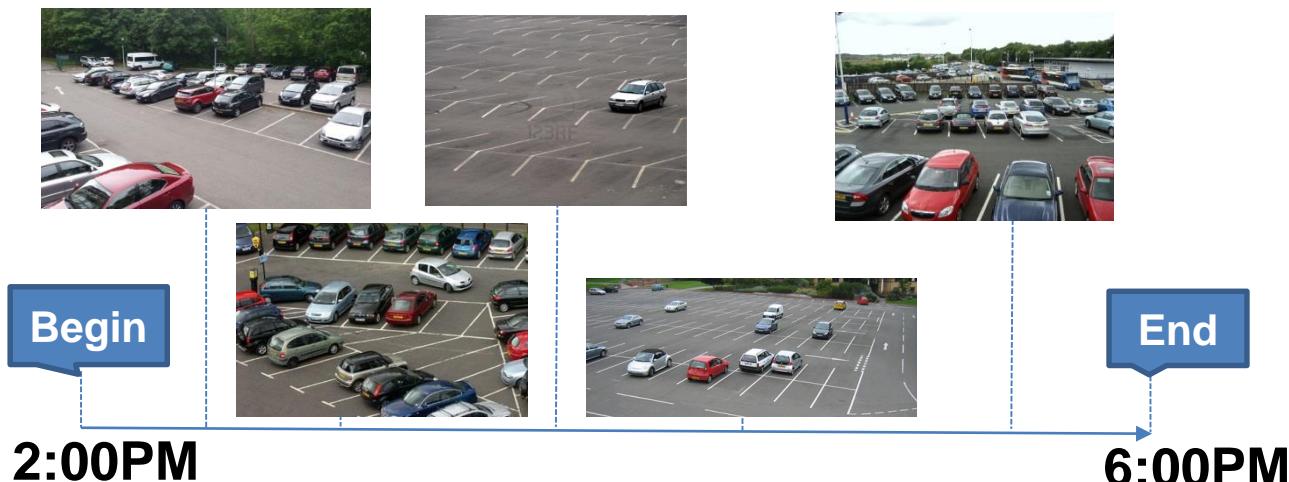
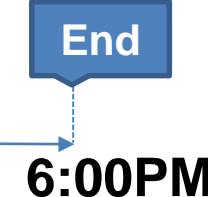


Maximum Spatiotemporal Diversity

□ Temporal Diversity



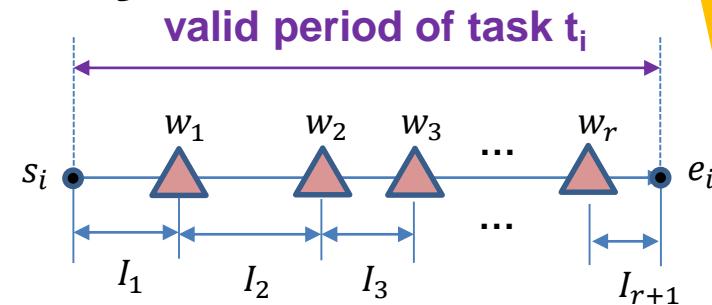
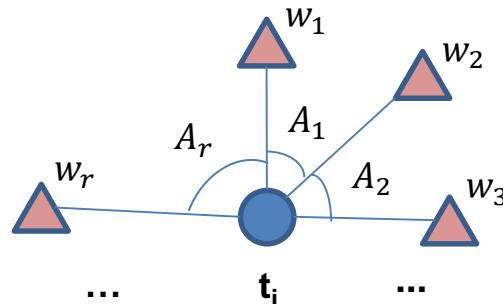
Monitor available parking spaces over a time period



Maximum Spatiotemporal Diversity

□ Spatiotemporal Diversity

Entropy of temporal diversity



Spatial Diversity is given as

$$SD(t_i) = - \sum_{j=1}^r \frac{A_j}{2\pi} \cdot \log \left(\frac{A_j}{2\pi} \right)$$

Entropy of spatial diversity

Temporal Diversity is given as

$$TD(t_i) = - \sum_{j=1}^{r+1} \frac{I_j}{e_i - s_i} \cdot \log \left(\frac{I_j}{e_i - s_i} \right)$$

Balance Spatial Diversity and Temporal Diversity:

$$STD(t_i, W_i) = \beta \cdot SD(t_i) + (1 - \beta) \cdot TD(t_i)$$

The goal is to maximize the spatiotemporal diversity of a given task

Quality Control

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Summary

- “To err is human”
- Spatiotemporal-constraint-based Quality Control
 - Tasks have quality requirement for truth of answers
 - Workers have spatiotemporal constraints
- Spatiotemporal-target-based Quality Control
 - Minimizing Latency
 - Maximizing Spatiotemporal Diversity

Reference: Quality Control

1. L. Kazemi, C. Shahabi, L. Chen. GeoTruCrowd: trustworthy query answering with spatial crowdsourcing. In GIS, pages 304-313, 2013.
2. B. Hecht, M. Stephens. A tale of cities: Urban biases in volunteered geographic information. In ICWSM, pages 197-205, 2014.
3. R. Teodoro, P. Öztürk, M. Naaman, W. Mason, J. Lindqvist. The motivations and experiences of the on-demand mobile workforce. In CSCW, pages 236-247, 2014.
4. P. Cheng, X. Lian, Z. Chen, R. Fu, L. Chen, J. Han, J. Zhao. Reliable diversity-based spatial crowdsourcing by moving workers. PVLDB, 8(10): 1022-1033, 2015.
5. J. Thebault-Spieker, L. Terveen, B. Hecht. Avoiding the south side and the suburbs: The geography of mobile crowdsourcing markets. In CSCW, pages 265-275, 2015.
6. T. Kandappu, N. Jaiman, R. Tandriansyah, A. Misra, S. Cheng, C. Chen, H. Lau, D. Chander, K. Dasgupta. TASKer: Behavioral insights via campus-based experimental mobile crowdsourcing. In UbiComp, pages 392-402, 2016.
7. C. Cai, S. Iqbal, J. Teevan. Chain reactions: The impact of order on microtask chains. In CHI, pages 3143-3154, 2016.
8. W. Ouyang, M. Srivastava, A. Toniolo, T. Norman. Truth discovery in crowdsourced detection of spatial events. TKDE, 28(4): 1047-1060, 2016.
9. P. Cheng, X. Lian, L. Chen, J. Han, J. Zhao. Task assignment on multi-skill oriented spatial crowdsourcing. TKDE, 28(8): 2201-2215, 2016.
10. D. Gao, Y. Tong, J. She, T. Song, L. Chen, K. Xu. Top-k team recommendation in spatial crowdsourcing. In WAIM, pages 191-204, 2016.

Reference: Quality Control

11. L. Zheng, L. Chen. Maximizing acceptance in rejection-aware spatial crowdsourcing. TKDE, 29(9): 1943-1956, 2017.
12. V. Sheng, F. Provost, P. Ipeirotis. Get another label? Improving data quality and data mining using multiple, noisy labelers. In KDD, pages 614-622, 2008.
13. P. Ipeirotis, F. Provost, J. Wang. Quality management on amazon mechanical turk. In KDD, pages 64-67, 2010.
14. X. Liu, M. Lu, B. Ooi , Y. Shen, S. Wu , M. Zhang. Cdas: A crowdsourcing data analytics system. PVLDB, 5(11): 1495-1506, 2012.
15. C. Cao, J. She, Y. Tong, L. Chen. Whom to ask? Jury selection for decision making tasks on micro-blog services. PVLDB, 5(11): 1495-1506, 2012.
16. V. Raykar, S. Yu. Eliminating spammers and ranking annotators for crowdsourced labeling tasks. JMLR, 13:491-518, 2012.
17. C. Cao, Y. Tong, L. Chen, H. Jagadish. Wisemarket: A new paradigm for managing wisdom of online social users. In KDD, pages 455-463, 2013.
18. N. Dalvi, A. Dasgupta, R. Kumar, V. Rastogi. Aggregating crowdsourced binary ratings. In WWW, pages 285-294, 2013.
19. M. Yin, Y. Chen. Predicting crowd work quality under monetary interventions. In AAAI, pages 259-268, 2017.

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Incentive Mechanism

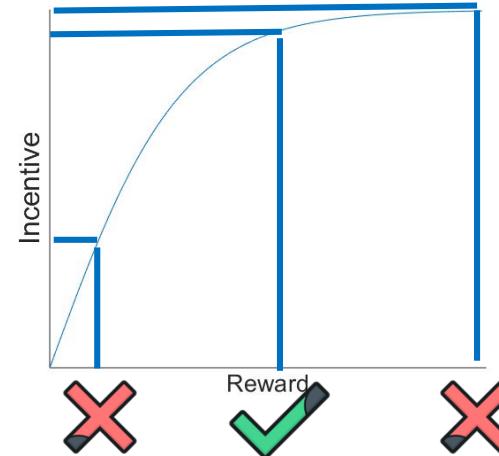
- Motivation
- Existing Research
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Incentive Mechanism

- Stimulate workers to complete tasks efficiently using proper reward
- A **tradeoff** between workers and tasks
 - Excessively low reward **discourages** the workers to finish the task
 - Excessively high reward **hurts** the benefit of the platform



Platform

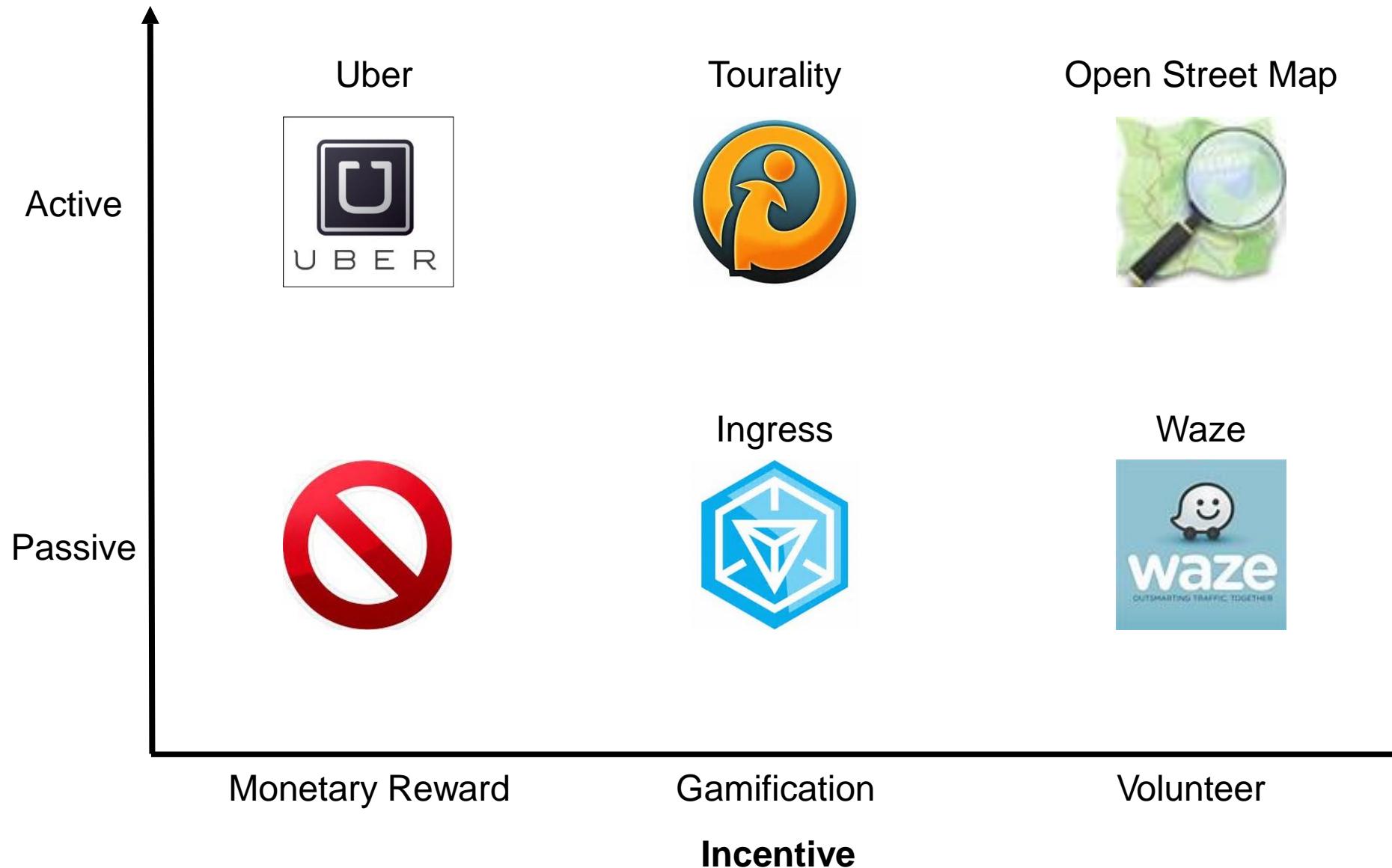


It hurts my benefit because
of the high reward

Too little reward that I
cannot work efficiently

Incentive Mechanism: Design Space

Task Execution Manner



Incentive Mechanism

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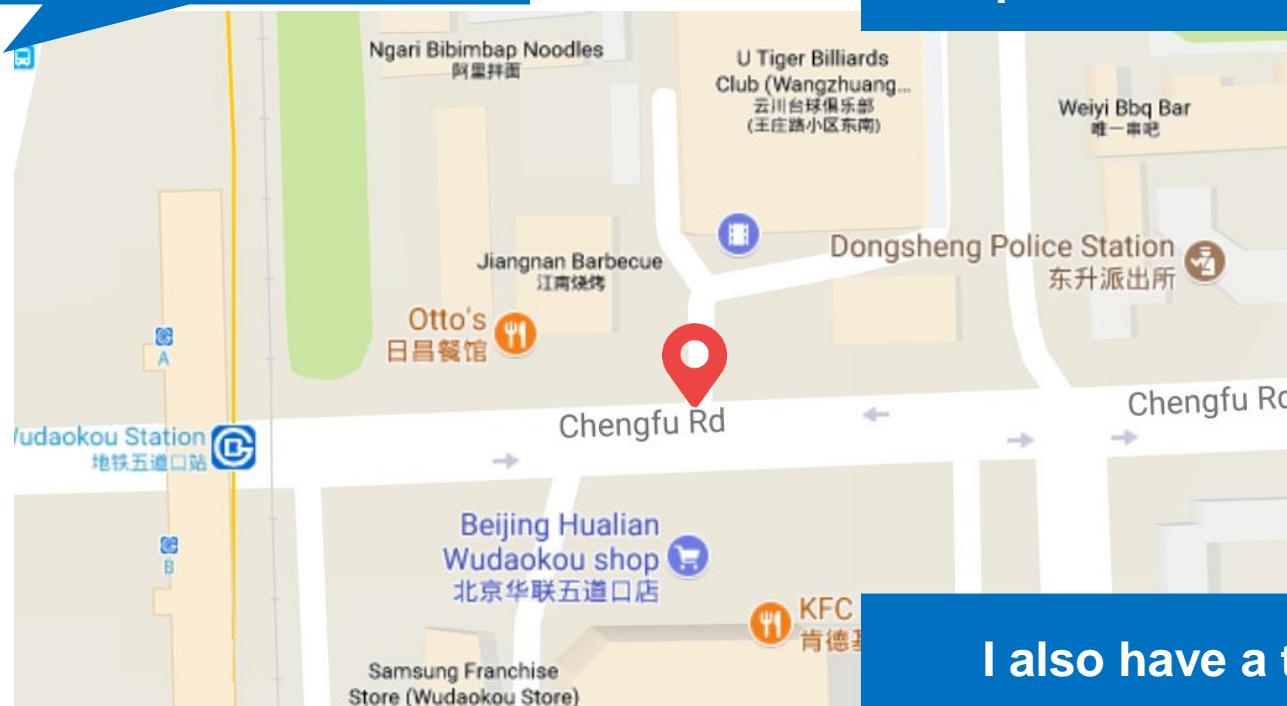
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Game Theory Based Mechanism

□ Platform-Centric Model

We need to compete for the total budget



I have a spatial task that needs to be completed collaboratively by multiple workers

Platform

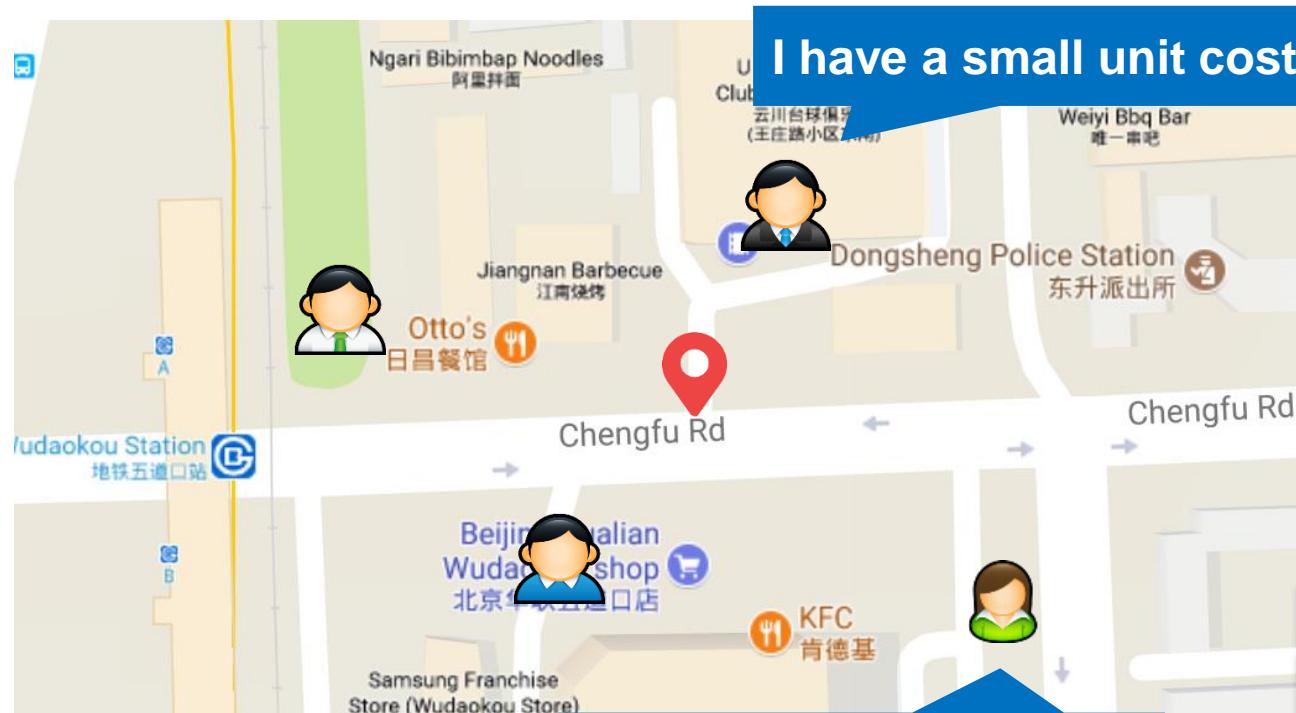


I also have a total budget

The total budget is allocated to the workers according to their contributions

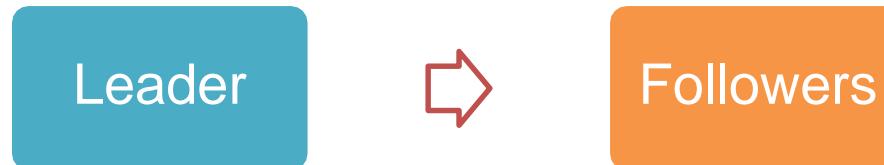
Game Theory Based Mechanism

□ Platform-Centric Model



Game Theory Based Mechanism

□ Stackelberg Game



□ Stackelberg Equilibrium

I know the leader's strategy, and want to maximize my utility

I have the knowledge of the followers' behavior, and want to maximize my utility



Game Theory Based Mechanism



Step 1: Estimate an optimal total budget and publish it



Step 2: Submit their actual plans of performing the tasks



Step 3: Allocate the budget to the workers according to their actual plans

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Background of Auction

□ Auction

- Buyers compete to obtain goods or services by offering increasingly higher prices



Background of Auction

❑ Auction

- ❑ Buyers compete to obtain goods or services by offering increasingly higher prices

❑ Reverse auction

- ❑ The sellers compete to obtain a business from the buyer and prices will typically decrease as the sellers underbid each other



Auction Based Mechanism

□ Objective

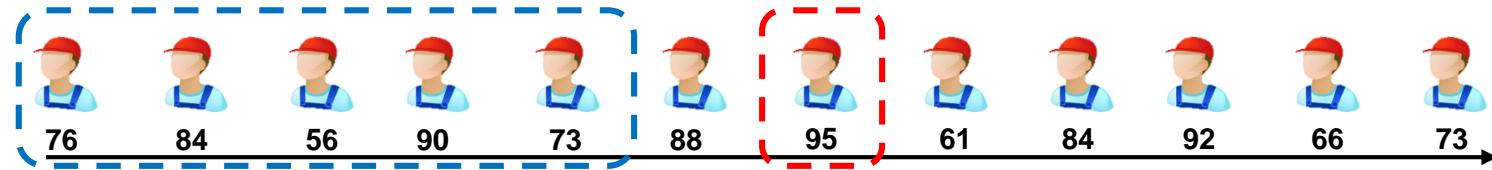
- Given a set of workers **dynamically coming**, each of which is associated with a **bidding price** and a **utility score**, the platform needs to hire m workers and irrevocably **decide the payment of accepted workers** to maximize the total utility.



Auction Based Mechanism

□ State-of-the-art

- Based on the secretary problem



□ Secretary Problem

- n applicants, which can be ranked in **strictly total order**, apply for a single position. The applicants are **interviewed sequentially** and immediately after an interview, the interviewed applicant is either **accepted** or **rejected irrevocably**. The objective is to have **the highest probability of selecting the best applicant** of the whole group

□ Solution of Secretary Problem

- Reject the first n/e applicants and hire the first applicant thereafter who has a higher score than all preceding applicants.
- With probability $1/e$ we can select the best applicant.

Auction Based Mechanism

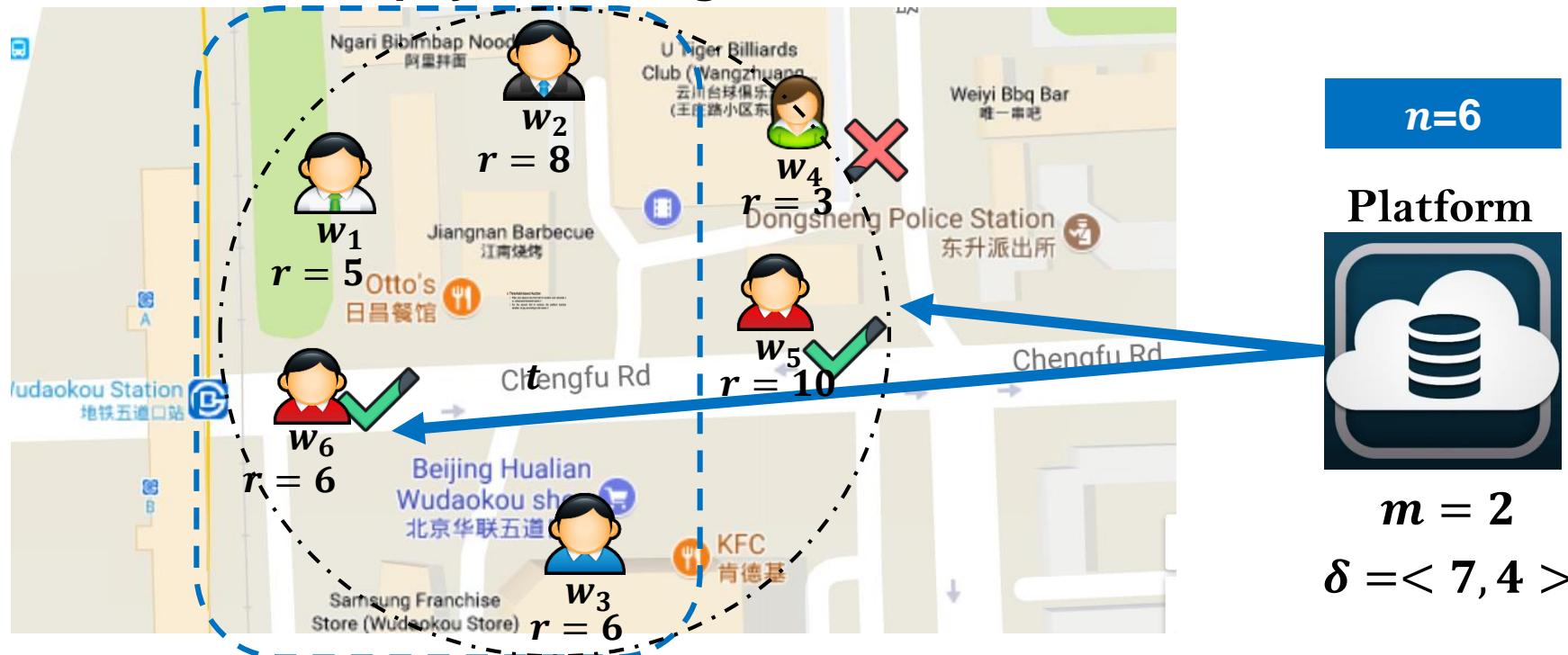
□ Threshold-based Auction

- Filter and observe the first half of workers and calculate a m -dimension threshold vector δ
- For the second half of workers, the framework decides whether the ratio of utility over bidding price by the new arrival worker is larger than the corresponding threshold in the vector δ
- If so, the platform hires the worker, otherwise rejects the worker.

Auction Based Mechanism

□ Threshold-based Auction

- Filter and observe the first half of workers and calculate a m -dimension threshold vector δ
- For the second half of workers, the platform decides whether to pay according to the vector δ



Incentive Mechanism

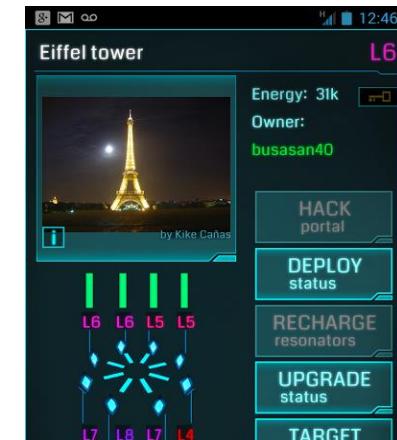
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Incentive Mechanism: Gamification

❑ Ingress (Niantic, Google)



- ❑ A location-based mobile game
- ❑ The gameplay consists of capturing "portals" at places of cultural significance such as public art
- ❑ Portals are set at specific positions to collect data during the capturing process using phones' camera



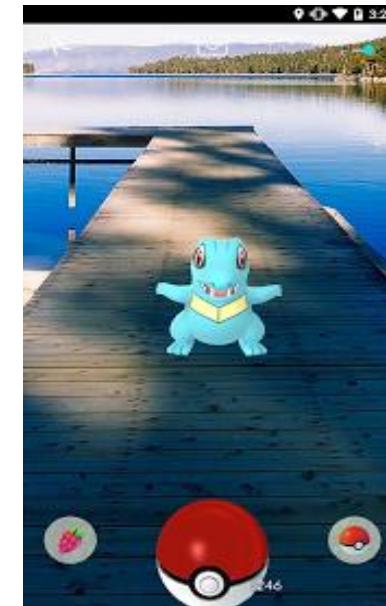
Data from Ingress was used to populate the locations for Pokéstops and gyms in Pokémon Go, released in July 2016

Incentive Mechanism: Gamification

❑ Pokémon Go (Niantic, Nintendo)



- ❑ A location-based, augmented-reality mobile game
- ❑ The game utilizes the player's mobile device to locate and capture virtual creatures called Pokémons
- ❑ Pokémons can be set at specific positions to collect data during the capturing process using phones' camera



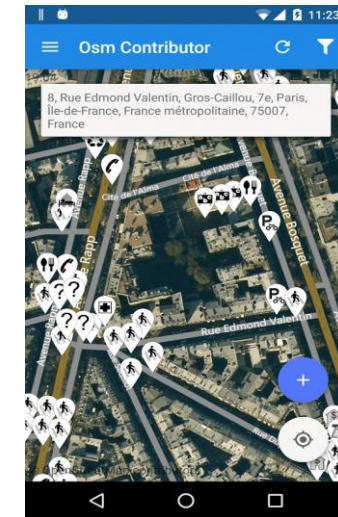
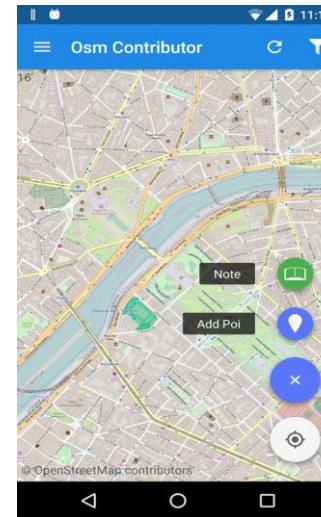
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Incentive Mechanism: Volunteer

□ Open Street Map

- A collaborative project to create a free editable map
- A prominent example of volunteered geographic information
- Map data is collected from scratch by volunteers using tools such as a mobile phone, handheld GPS unit, a notebook, digital camera, or a voice recorder



Incentive Mechanism

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Summary

- Workers always need to be motivated
- Tradeoff between workers and tasks
- State-of-the-art techniques
 - Monetary-Reward-based incentives
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1. M. Musthag, D. Ganesan. Labor dynamics in a mobile micro-task market. In CHI, pages 641-650, 2013.
2. G. Hui, C. Liu, W. Wang, J. Zhao, Z. Song, X. Su, J. Crowcroft, K. Leung. A survey of incentive mechanisms for participatory sensing. IEEE Communications Surveys and Tutorials 17(2): 918-943, 2015.
3. X. Zhang, Z. Yang, W. Sun, Y. Liu, S. Tang, K. Xing, X. Mao. Incentives for Mobile Crowd Sensing: A Survey. IEEE Communications Surveys and Tutorials, 18(1): 54-67, 2016.
4. B. Morschheuser, J. Hamari, J. Koivisto, A. Maedche. Gamified crowdsourcing: Conceptualization, literature review, and future agenda. IJHCS, 106: 26-43, 2017.
5. D. Yang, G. Xue, X. Fang, J. Tang. Crowdsourcing to smartphones: incentive mechanism design for mobile phone sensing. In MobiCom, pages 173-184, 2012.
6. I. Koutsopoulos. Optimal incentive-driven design of participatory sensing systems. In INFOCOM, pages 1402-1410, 2013.
7. A. Singla, A. Krause. Incentives for privacy tradeoff in community sensing. In HCOMP, pages 1-9, 2013.
8. D. Zhao, X. Li, H. Ma. How to crowdsource tasks truthfully without sacrificing utility: Online incentive mechanisms with budget constraint. In INFOCOM, pages 1213-1221, 2014.
9. X. Zhang, Z. Yang, Z. Zhou, H. Cai, L. Chen, X. Li. Free market of crowdsourcing: incentive mechanism design for mobile sensing. TPDS, 25(12): 3190-3200, 2014.

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10. W. A. Mason, . J. Watts. Financial incentives and the performance of crowds. SIGKDD Explorations, 11(2): 100-108, 2009.
11. J. Horton, L. Chilton. The labor economics of paid crowdsourcing. In EC, pages 209-218, 2010.
12. Y. Singer, M. Mittal. Pricing mechanisms for crowdsourcing markets. In WWW, pages 1157-1166, 2013.
13. A Singla, A Krause. Truthful incentives in crowdsourcing tasks using regret minimization mechanisms. In WWW, pages 1167-1178, 2013.
14. Gao Y, Parameswaran AG. Finish them!: pricing algorithms for human computation. PVLDB, 7(14):1965-1976, 2014.
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16. D. Difallah, M. Catasta, G. Demartini, P. Ipeirotis, P. Cudré-Mauroux. The dynamics of micro-task crowdsourcing: The case of Amazon MTurk. In WWW, pages 238-247, 2015.

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Privacy Protection

- Motivation & A Unified Framework
- Existing Research
 - Cloaked Locations-based Protection
 - Differential Privacy-based Protection
 - Encrypted Data-based Protection
- Summary

Motivation and Framework

□ Motivation

- Protect the privacy of workers' locations

□ A unified framework

- The locations of the workers are transformed by some techniques
- The platform performs task assignment based on the transformed locations of the tasks
- The workers confirm/refine the task assignment results based on their true locations

Task assignment results



Transformed
location data



Location data



workers

tasks

Motivation and Framework

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Task assignment results



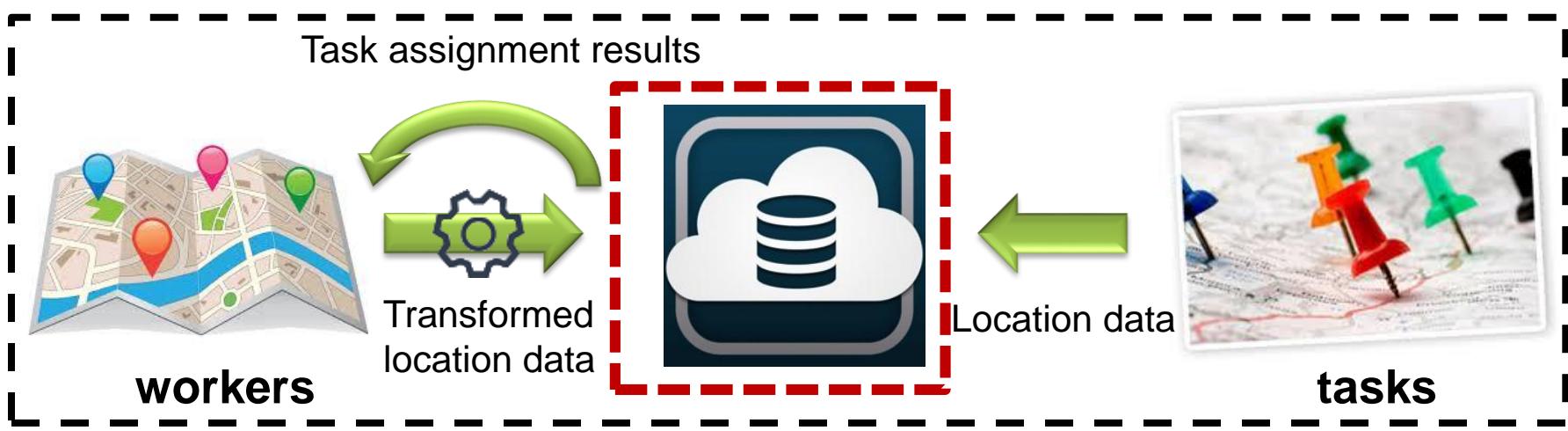
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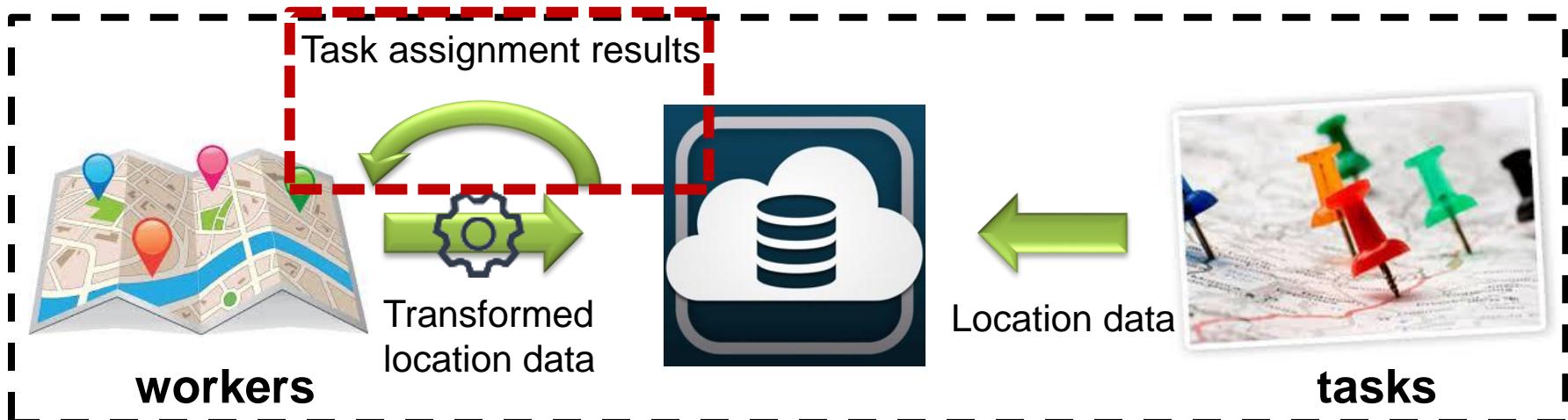
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- **The workers confirm/refine the task assignment results based on their true locations**

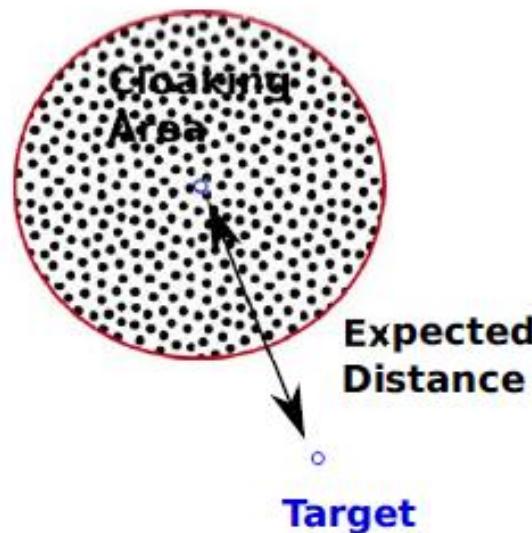


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Cloaked Area Based Protection

- The location of the worker is transformed as a **cloaked area**
 - A cloaked area is a pair $\langle \mathbf{a}, f \rangle$, where \mathbf{a} is a spatial range and f is the probability density function of the worker at each point in \mathbf{a}



- L. Pournajaf, L. Xiong, V. S. Sunderam, S. Goryczka. Spatial Task Assignment for Crowd Sensing with Cloaked Locations. MDM 2014.
- L. Pournajaf, L. Xiong, V. S. Sunderam, X. Xu. STAC: spatial task assignment for crowd sensing with cloaked participant locations. GIS 2015.

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 - Encrypted Data-based Protection
- Summary

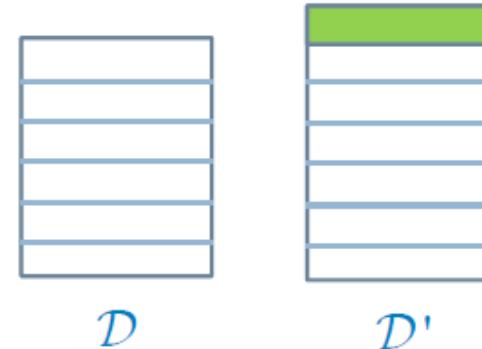
Differential Privacy based Protection

□ Differential Privacy (DP)

- Basic idea: limit the impact of any particular record on the output

□ Definition

- $\Pr[\mathcal{A}(\mathcal{D}) \in \mathcal{S}] \leq e^\epsilon \Pr[\mathcal{A}(\mathcal{D}') \in \mathcal{S}]$
- $\epsilon > 0$ controls the level of privacy

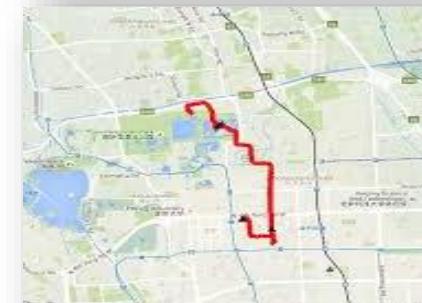


□ DP in spatial data

- Protect location information of points

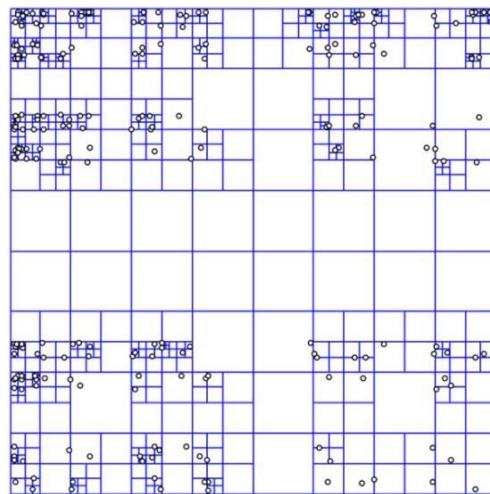


- Protect location information of trajectories

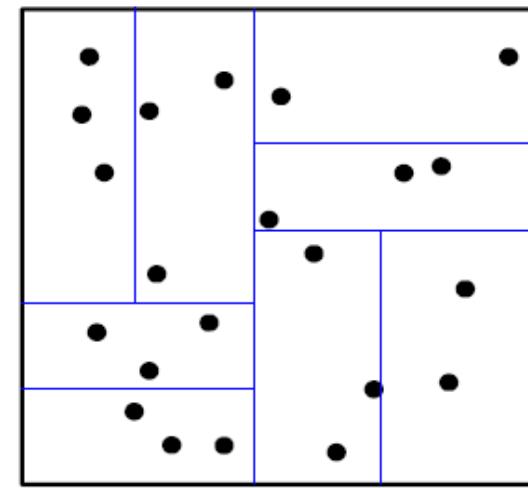


DP: Point Location Protection

- **Point** location protection
- Core Technique
 - Private spatial decompositions (PSD)
 - Decompose a geometric space, data points partitioned among the leaves

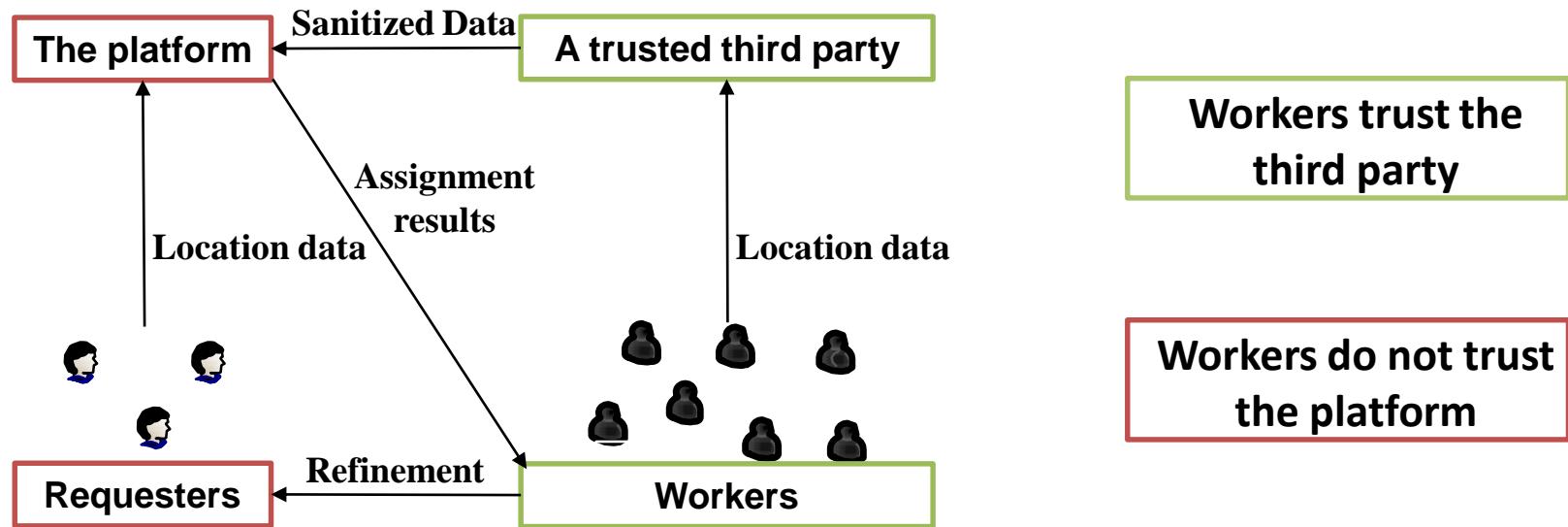


quadtree



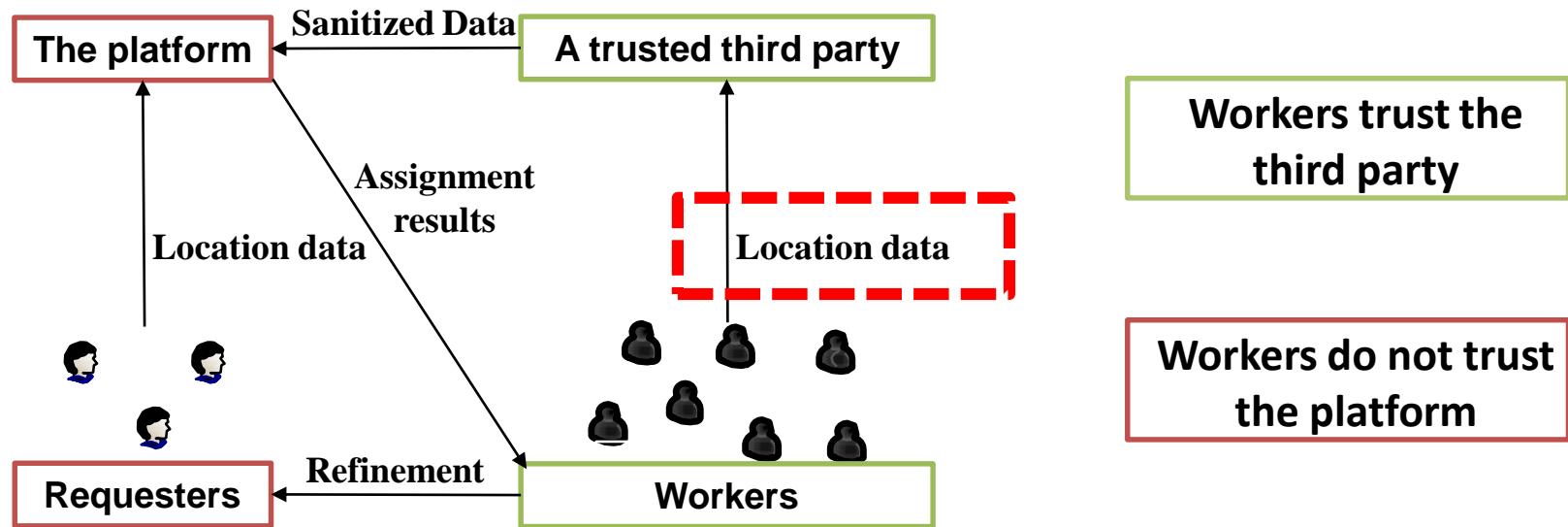
kd-tree

DP: Point Location Protection



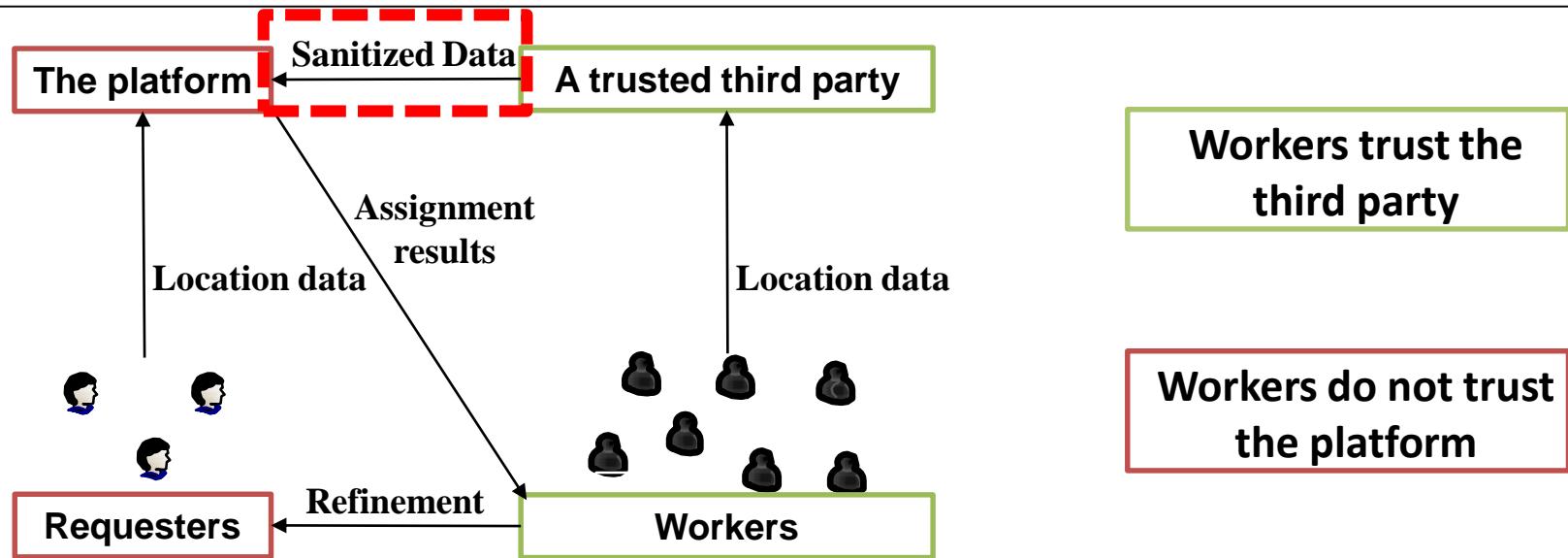
- **Workers send their locations to a trusted third party**
- **The third party sanitizes the location of workers according to differential privacy techniques and release it**
- **The platform performs task assignment according to PSD**
- **Workers refine the assignment using their exact locations**

DP: Point Location Protection



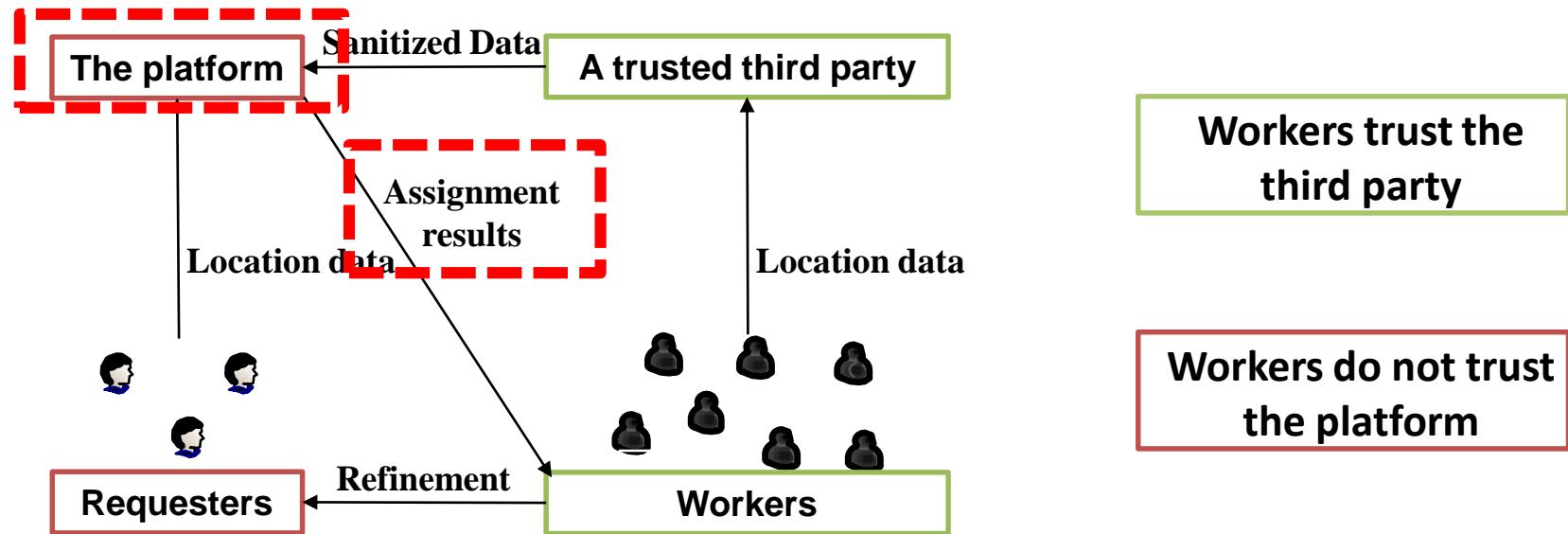
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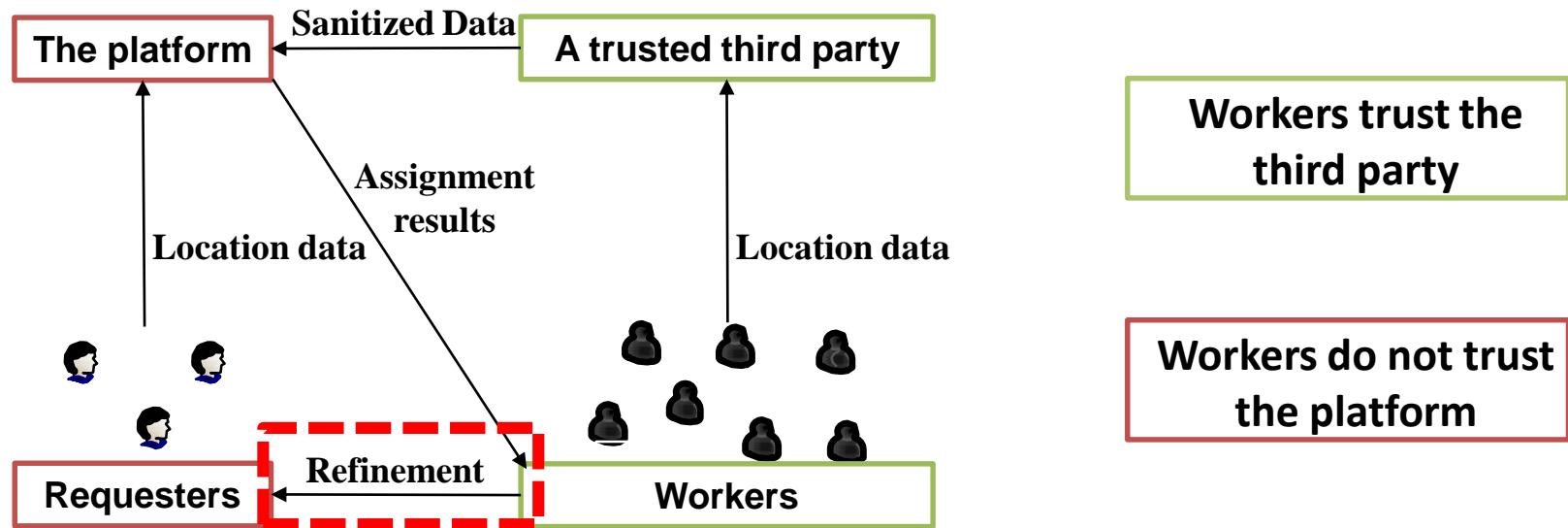
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DP: Point Location Protection



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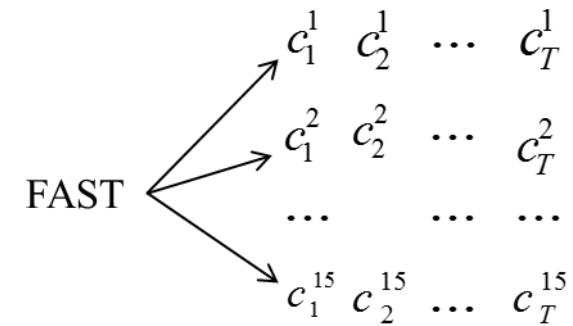
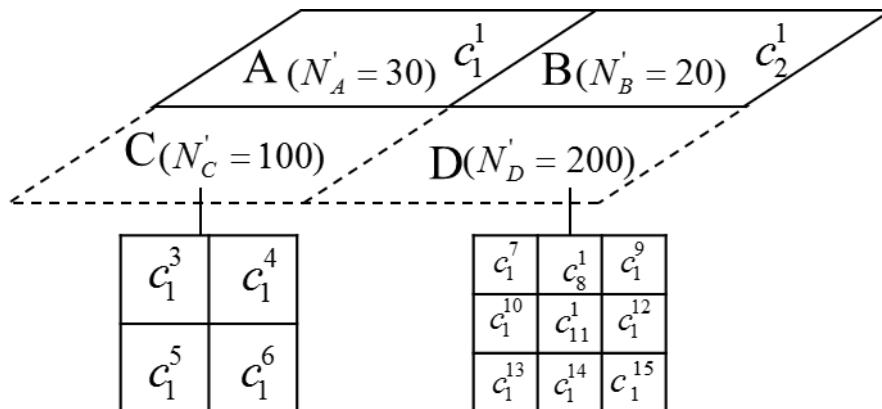


- **Workers send their locations to a trusted third party**
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DP: Trajectory Location Protection

□ Trajectory location protection

- Structure of PSD is computed at the first time instance and is reused for all remaining instances (use a fixed privacy budget)
- The remaining budget is used for each grid cell across multiple time instances using FAST – a time-series perturbation technique



- H. To, G. Ghinita, L. Fan, C. Shahabi. Differentially Private Location Protection for Worker Datasets in Spatial Crowdsourcing. TMC, 16(4): 934-949,2017.
- L. Fan, L. Xiong. An Adaptive Approach to Real-Time Aggregate Monitoring With Differential Privacy. TKDE, 26(9): 2094-2106, 2014.

Privacy Protection

- Motivation & A Unified Framework
- Existing Research
 - Cloaked Locations-based Protection
 - Differential Privacy-based Protection
 - Encrypted Data-based Protection
- Summary

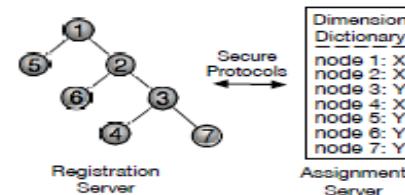
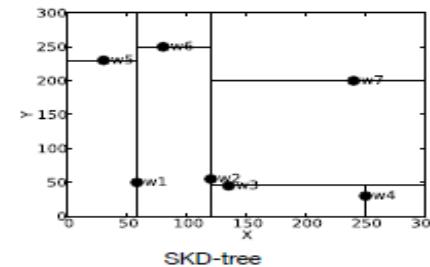
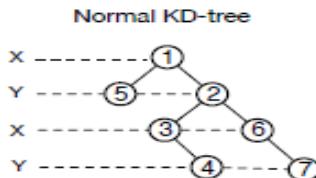
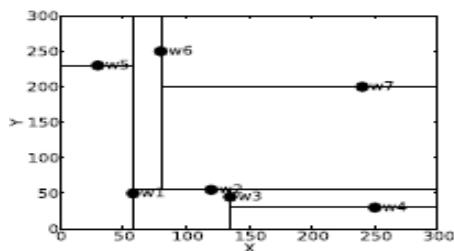
Encryption Based Protection

□ Homomorphic Encryption

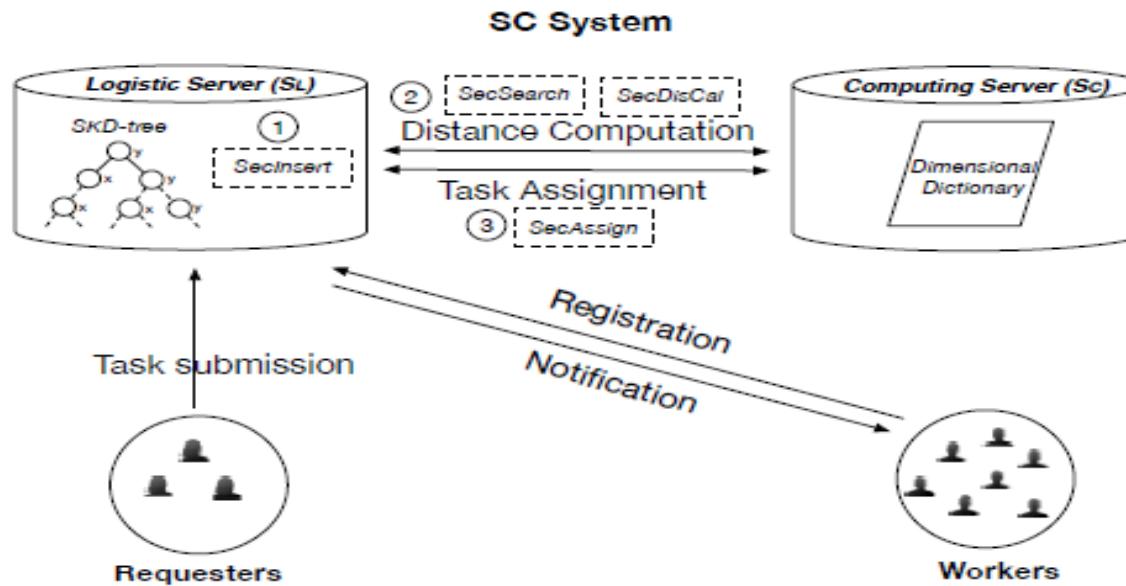
- The **exact** distances between tasks and workers can be computed based on their encrypted locations

□ Secure Indexing

- A secure indexing technique which combines homomorphic encryption with KD-tree

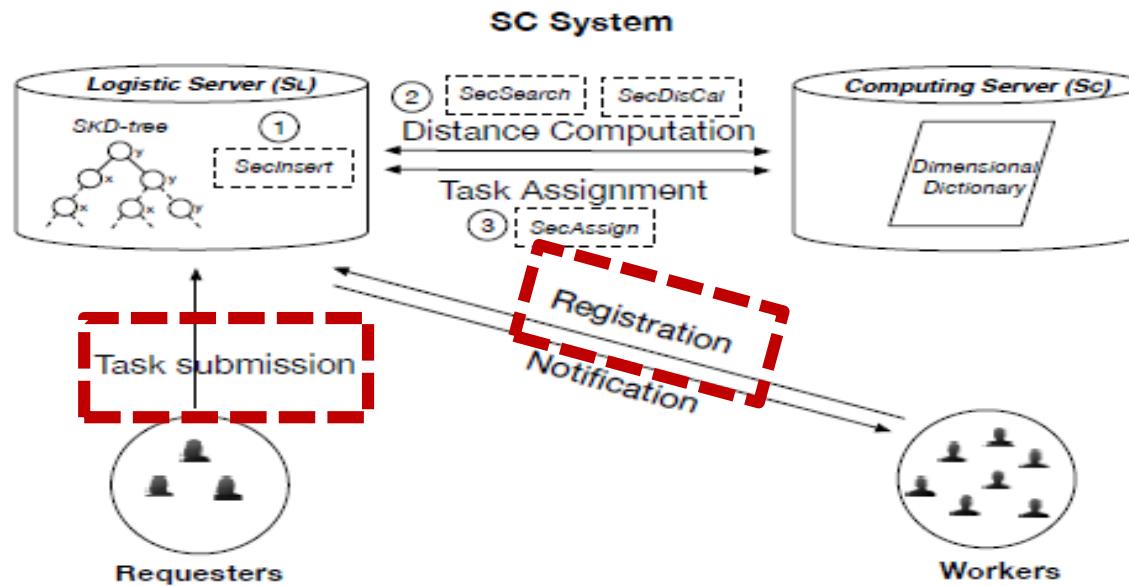


Encryption Based Protection



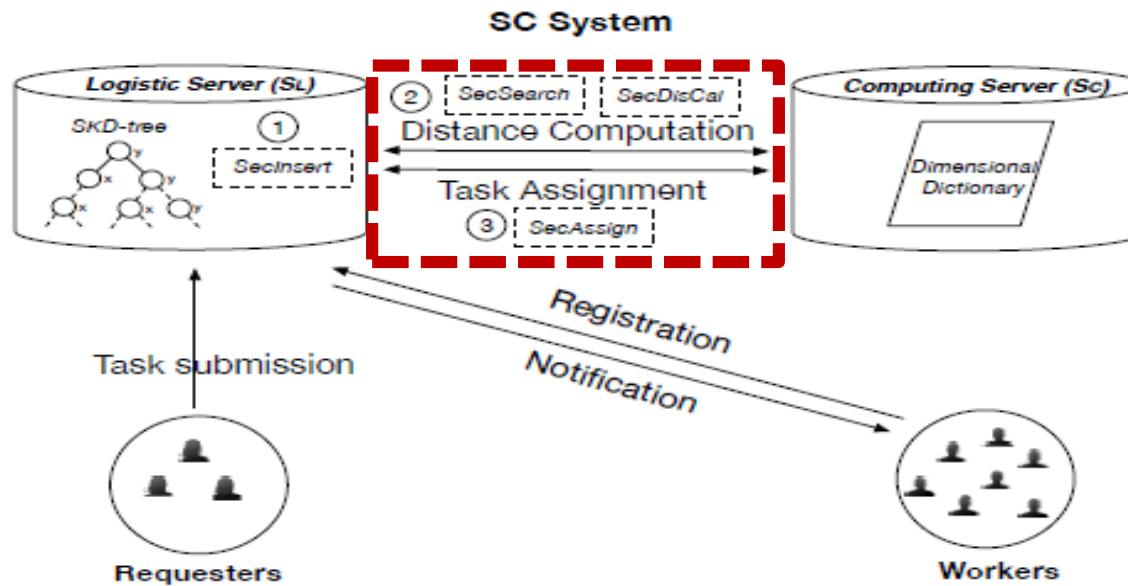
- ❑ The locations of tasks and workers are encrypted by homomorphic encryption
- ❑ The platform performs task assignment based on the distances computed by the encrypted data
- ❑ The workers receive the encrypted location of the task assigned by the platform, and decrypts it to get the location

Encryption Based Protection



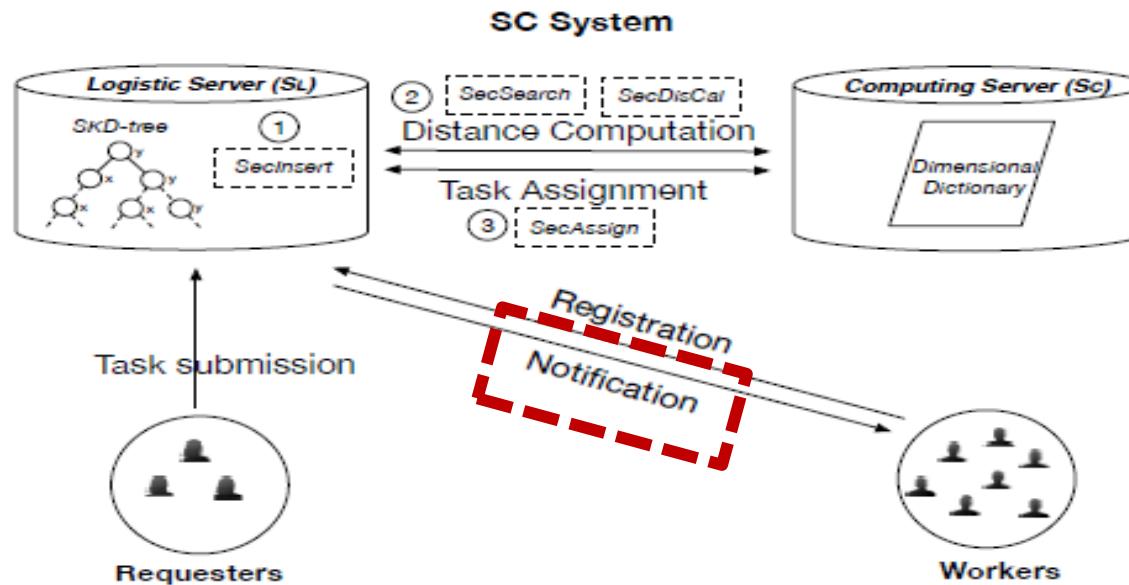
- The locations of tasks and workers are encrypted by homomorphic encryption
- The platform performs distance computation based on the distances computed by the workers. Locations of both the workers and the tasks are protected
- The workers receive the encrypted location of the task assigned by the platform, and decrypts it to get the location

Encryption Based Protection



- The locations of tasks and workers are encrypted by homomorphic encryption
- The platform performs task assignment based on the distances computed by the encrypted data
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Encryption Based Protection



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Privacy Protection

- Motivation & A Unified Framework
- Existing Research
 - Cloaked Locations-based Protection
 - Differential Privacy-based Protection
 - Encrypted Data-based Protection
- Summary

Summary

- **Challenge**
 - Location Security vs. Distance Accuracy
- **Framework**
 - Transform the locations of the workers
 - The platform performs task assignment based on the transformed locations of the workers
 - The workers confirm/refine the task assignment results based on their true locations
- **State-of-the-art techniques**
 - Cloaked Locations-based protection
 - Differential Privacy-based protection
 - Encrypted Data-based protection

Reference: Privacy Protection

1. L. Pournajaf, L. Xiong, V. S. Sunderam, S. Goryczka. Spatial task assignment for crowd sensing with cloaked locations. In MDM, pages 73-82, 2014.
2. L. Pournajaf, L. Xiong, V. S. Sunderam, X. Xu. STAC: spatial task assignment for crowd sensing with cloaked participant locations. In GIS, pages 90:1-90:4, 2015.
3. G. Cormode, C. M. Procopiuc, D. Srivastava, E. Shen, T. Yu. Differentially private spatial decompositions. In ICDE, pages 20-31, 2012.
4. H. To, G. Ghinita, C. Shahabi. A framework for protecting worker location privacy in spatial crowdsourcing. PVLDB, 7(10):919-930, 2014.
5. H. To, G. Ghinita, L. Fan, C. Shahabi. Differentially private location protection for worker datasets in spatial crowdsourcing. TMC, 16(4):934-949, 2017.
6. L. Fan, L. Xiong. An Adaptive Approach to Real-Time Aggregate Monitoring With Differential Privacy. TKDE, 26(9): 2094-2106, 2014.
7. L. Pournajaf, D. A. Garcia-Ulloa, L. Xiong, V. S. Sunderam. Participant privacy in mobile crowd sensing task management: A survey of methods and challenges. SIGMOD Record, 44(4):23-34, 2015.
8. H. To, G. Ghinita, C. Shahabi. PrivGeoCrowd: A toolbox for studying private spatial crowdsourcing. In ICDE, pages 1404-1407, 2015.
9. Y. Xiao, L. Xiong. Protecting locations with differential privacy under temporal correlations. In CCS, pages 1298-1309, 2015.

Reference: Privacy Protection

10. X. Jin, R. Zhang, Y. Chen, T. Li, Y. Zhang. DPSense: differentially private crowdsourced spectrum sensing. In CCS, pages 296-307, 2016.
11. B. Liu, L. Chen, X. Zhu, Y. Zhang, C. Zhang, W. Qiu. Protecting location privacy in spatial crowdsourcing using encrypted data. In EDBT, pages 478-481, 2017.
12. L. Wang, D. Zhang, D. Yang, B. Y. Lim, X. Ma. Differential location privacy for sparse mobile crowdsensing. In ICDM, pages 1257-1262, 2016.
13. X. Jin, Y. Zhang. Privacy-preserving crowdsourced spectrum sensing. In INFOCOM, pages 1-9, 2016.
14. L. Wang, D. Yang, X. Han, T. Wang, D. Zhang, X. Ma. Location privacy-preserving task allocation for mobile crowdsensing with differential geo-obfuscation. In WWW, pages 627-636, 2017.
15. H. To, C. Shahabi. Location Privacy in Spatial Crowdsourcing. arXiv preprint arXiv:1704.06860, 2017

Outline

- Overview of Spatial Crowdsourcing (20min)
 - Motivation
 - Workflow
 - Core Issues
 - Difference from Related Tutorials
- Fundamental Techniques (50min)
 - Task Assignment
 - Quality Control
 - Incentive Mechanism
 - Privacy Protection
- Spatial Crowdsourced Applications (15min)
 - Spatial Crowdsourcing Intrinsic Applications
 - Crowd-powered Spatial Applications
- Open Questions (5min)

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Intrinsic Applications

□ What are the Intrinsic Applications

- Naturally modelled by spatial crowdsourcing
- Share the same core issues with spatial crowdsourcing

□ Two kinds of representative applications

- Real-time taxi calling service



- Food delivery service



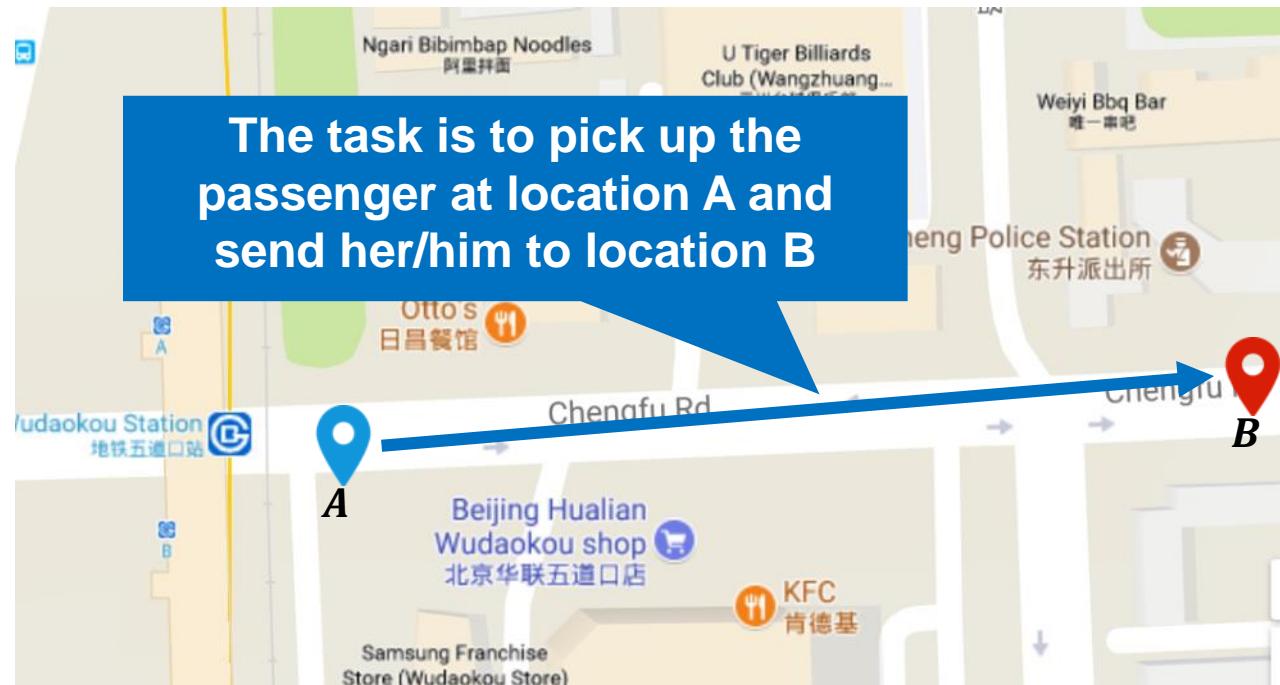
Intrinsic Applications

□ Real-time taxi calling service

Passenger is the task requester



The task is to pick up the passenger at location A and send her/him to location B



Intrinsic Applications

□ Real-time taxi calling service

A typical **dynamic matching** problem

Passengers and available taxis dynamically appear on the platform



Platform



Uber is the platform, and its core concern is how to assign taxis to pick up different passengers efficiently

Intrinsic Applications

□ Real-time taxi calling service

Task
Assignment



Platform



Incentive
Mechanism

Quality
Control

Privacy
Protection

Intrinsic Applications

□ Food delivery service

User is the task requester



The task is to pick up the food and send the food to the user



Intrinsic Applications

□ Food delivery service

A typical dynamic planning problem

Orders and available deliverers dynamically appear on the platform



Grubhub is the platform, and its core concern is how to design effective plans for the deliverers

Intrinsic Applications

□ Food delivery service

Task Assignment



Platform

Orders and available deliverers dynamically appear on the platform



Incentive Mechanism

Quality Control

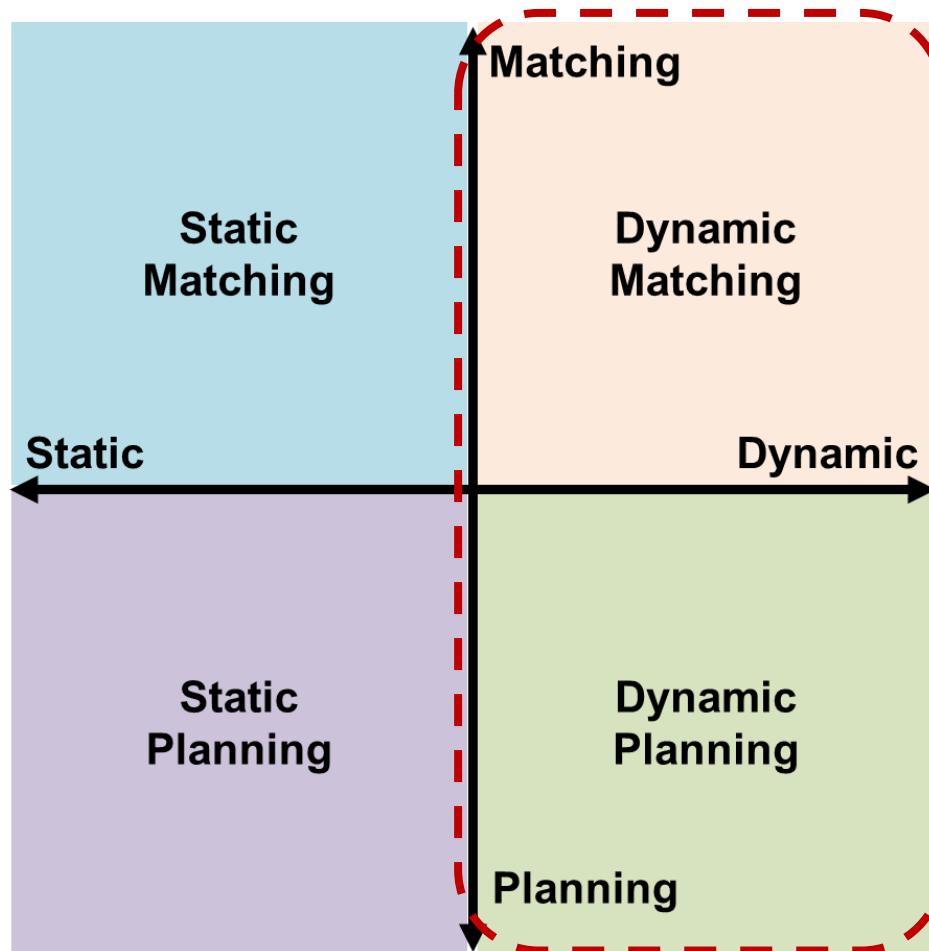
Privacy Protection

Intrinsic Applications

□ Ridesharing Service



Intrinsic Applications



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Outline

- Crowd-powered Spatial Applications
 - Crowdsourced Path Selection
 - Crowdsourced Speed Estimation
 - Crowdsourced POI Labelling

Path Selection

□ Motivation

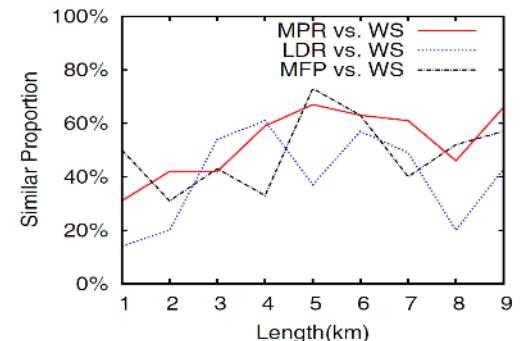
- Route recommendation service is indispensable in daily life

□ Solutions without crowdsourcing

- Using popular routes mined from historical trajectories as recommended routes
 - Most Popular Route
 - Local Driver Route
 - Most Frequent Path

□ Drawbacks

- **Sparsity:** insufficient historical trajectories for inference
- **Diversity:** different algorithms, different routes



Path Selection

- **Solutions using spatial crowdsourcing**
 - Leverage **crowds' knowledge** to improve the recommendation quality
- **Main Idea**
 - Consolidate candidate routes from different sources (e.g., map service providers, popular routes)
 - Request experienced drivers to select amongst them



Outline

- Crowd-powered Spatial Applications
 - Crowdsourced Path Selection
 - Crowdsourced Speed Estimation
 - Crowdsourced POI Labelling

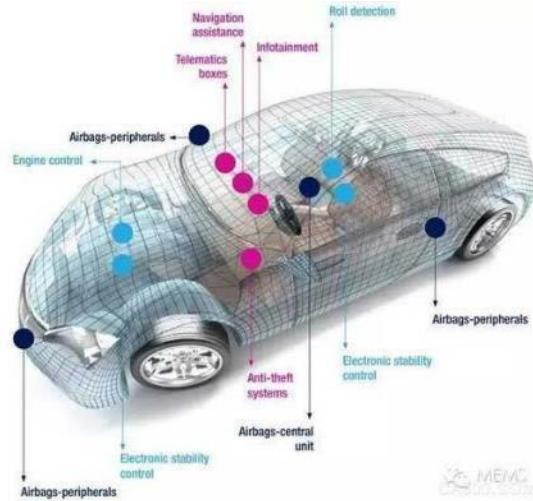
Traffic Speed Estimation

□ Motivation

- Real-time traffic speed represents the congestion of road and is one of the most important aspects for traffic monitoring

□ Speed Estimation without Crowdsourcing

- Use **sensor** or **trajectory data** for speed estimation
- It is hard to infer the speed of **remote roads**



Traffic Speed Estimation

- **Solutions using Spatial Crowdsourcing**
 - Assign crowd workers to physically check traffic speed of some ambiguous roads or remote roads
- **Key Idea**
 - A two-layer framework for speed estimation
 - Assign k roads (called seed road) to crowd workers to generate their real speeds
 - Infer speeds of other roads according to seed roads and historical speed information



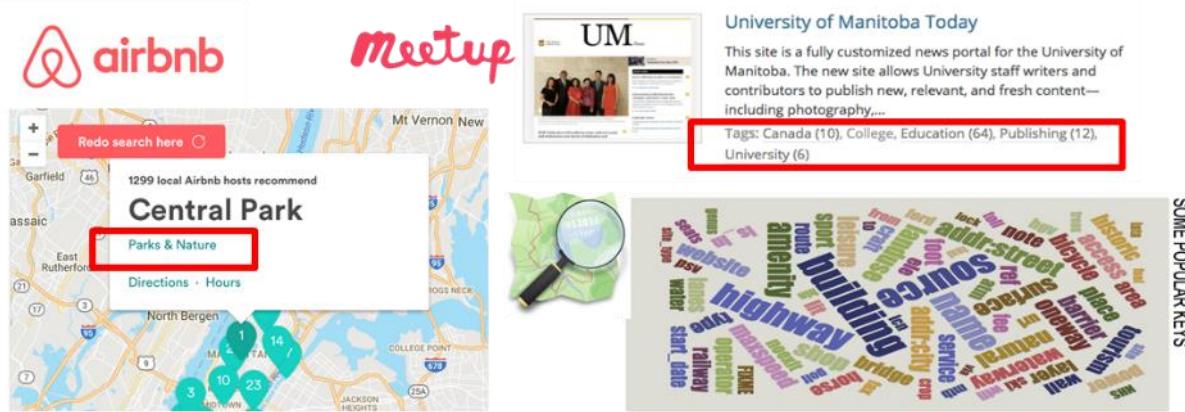
Outline

- Crowd-powered Spatial Applications
 - Crowdsourced Path Selection
 - Crowdsourced Speed Estimation
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POI Labelling

□ Motivation

- POI (Point of Interest) is one of the most useful and fundamental spatial data



❑ Incorrect labels exist

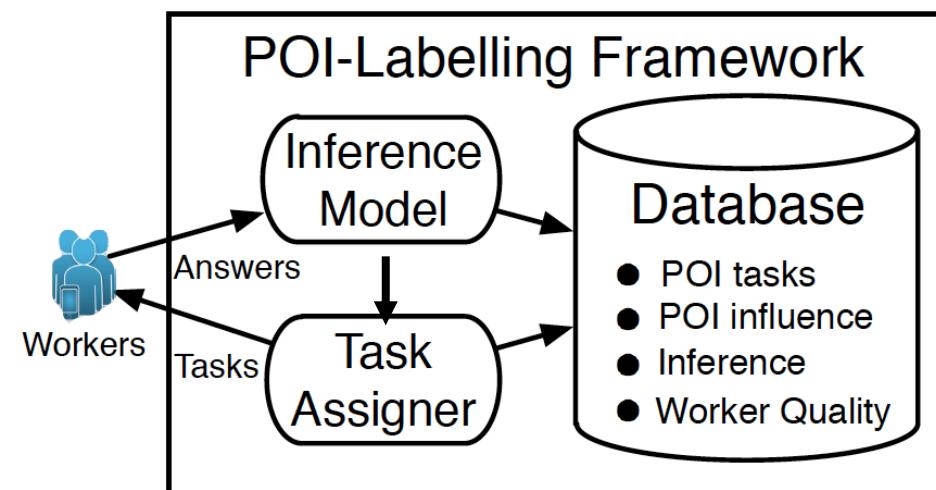
- ❑ Low quality POI labels from volunteers
 - ❑ Limited accuracies of AI algorithms

POI Labelling

□ Solutions using Spatial Crowdsourcing

□ An iterative framework

- Assign tasks to workers
- Collect the results and infer the truth of POIs
- Repeat until the budget is exhaustive



Framework

A photograph of a park with green trees and a paved path. To the right of the photo is a red text instruction: "Please select relevant labels for 'Beijing Olympic Forest Park'". Below the instruction is a list of 10 items, each preceded by a checkbox. Items 1, 3, 5, 6, 8, and 10 have a checked checkbox.

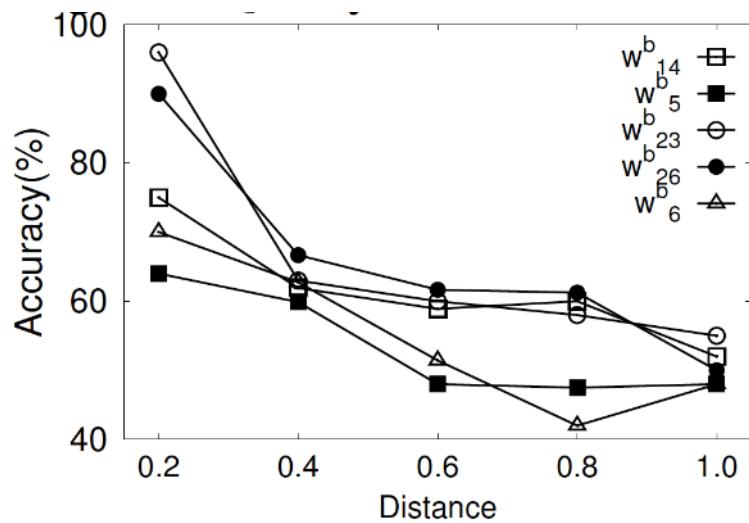
<input checked="" type="checkbox"/> 1. Park	<input checked="" type="checkbox"/> 2. Olympics
<input checked="" type="checkbox"/> 3. Sports	<input type="checkbox"/> 4. Fragrant hill
<input type="checkbox"/> 5. Places	<input checked="" type="checkbox"/> 6. Stadium
<input type="checkbox"/> 7. Business	<input checked="" type="checkbox"/> 8. Relax zone
<input type="checkbox"/> 9. Flag-rising	<input checked="" type="checkbox"/> 10. Take a walk

An Example

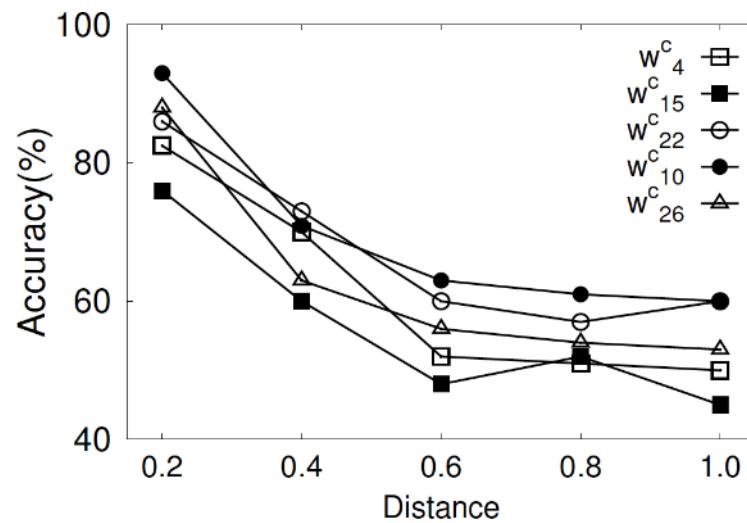
POI Labelling

□ Experimental Findings

- The distance between POIs and workers has a huge impact on POI labelling



(a) Beijing



(b) China

The longer distance, the lower accuracy

Summary

	Spatial crowdsourced intrinsic applications			Crowd-powered spatial applications		
	Taxi Calling	Ride Sharing	Food Delivery	SC Path Selection	SC Speed Estimation	SC POI Labelling
Task Assignment	✓	✓	✓	✓	✓	✓
Quality Control	✓	✓	✓	✓	✓	✓
Incentive Mechanism	✓	✓	✓	✓	✗	✓
Privacy Protection	✓	✓	✓	✗	✗	✗

Spatial crowdsourced intrinsic applications: Pure human effort
 Crowd-powered spatial applications: Hybrid human-machine effort

Reference: Applications

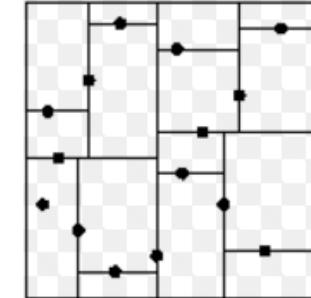
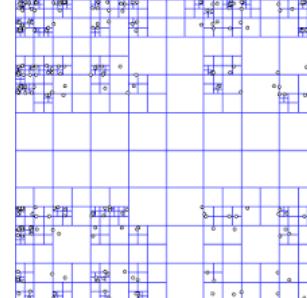
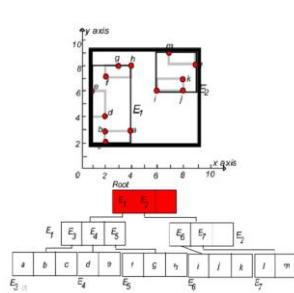
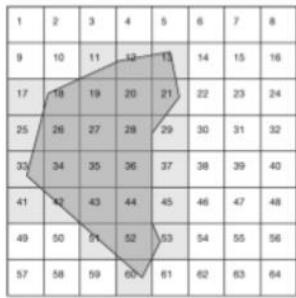
1. H. Su, K. Zheng, J. Huang, H. Jeung, L. Chen, X. Zhou. CrowdPlanner: A crowd-based route recommendation system. In ICDE, pages 1144-1155, 2014.
2. C. Zhang, Y. Tong, L. Chen. Where To: Crowd-Aided Path Selection. PVLDB, 7(14):2005-2016, 2014.
3. A. Artikis, M. Weidlich, F. Schnitzler, I. Boutsis, T. Liebig, N. Piatkowski, C. Bockermann, K. Morik ,V. Kalogeraki, J. Marecek, A. Gal, S. Mannor, D. Gunopulos, D. Kinane. Heterogeneous stream processing and crowdsourcing for urban traffic management. In EDBT, pages 712-723, 2014
4. H. Hu, G. Li, Z. Bao, Y. Cui, J. Feng. Crowdsourcing-based real-time urban traffic speed estimation: From trends to speeds. In ICDE, pages 883-894, 2016.
5. H. Hu, Y. Zheng, Z. Bao, G. Li, J. Feng, R. Cheng. Crowdsourced POI labelling: location-aware result inference and task assignment. In ICDE ,pages 61-72, 2014.
6. W. Ouyang, M. Srivastava, A. Toniolo, T. Norman. Truth discovery in crowdsourced detection of spatial events. TKDE, 28(4): 1047-1060, 2016.
7. D. A. Garcia-Ulloa, L. Xiong, V. S. Sunderam. Truth discovery for spatiotemporal events from crowdsourced data. PVLDB 10(11): 1562-1573, 2017.
8. Y. Huang, F. Bastani, R. Jin, X. Wang: Large scale real-time ridesharing with service guarantee on road networks. PVLDB 7(14): 2017-2028, 2014.
9. S. Ma, Y. Zheng, O. Wolfson. Real-time city-scale taxi ridesharing. TKDE, 27(7): 1782-1795, 2015
10. M. Asghari, D. Deng, C. Shahabi, U. Demiryurek, Y. Li. Price-aware real-time ride-sharing at scale: an auction-based approach. In GIS, pages 3:1-3:10, 2016.

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- **Open Questions (5min)**

Question 1: Index

- ❑ Abundant indexes in spatial data management
- ❑ Grid, R-tree, Quadtree, kd-tree, etc



- ❑ How to leverage existing indexes or design new indexes to optimize the efficiency of fundamental issues in spatial crowdsourcing?

Question 2: Dynamic Scenarios

- Although some recent research has focused on dynamic task assignment, there are several big gaps between theory and practice
 - E.g., good performance in practice versus bad theoretical results of the simple greedy algorithm for the online minimum matching problem



Question 2: Dynamic Scenarios

- The research of other core issues of spatial crowdsourcing in dynamic scenario is limited
 - How to design adaptive incentive mechanisms which can handle the dynamic supply and demand between tasks and workers?
 - How to protect the location privacy of the dynamic arrival tasks and workers



Question 3: Benchmark

- Abundant benchmarks for many classical spatial data management
 - E.g., DIMACS for shortest path

- Although there are a few synthetic data generators for spatial crowdsourcing, public real datasets are still inadequate
 - Platforms owning abundant real data are usually commercial, and would not like to open their data
 - Open sourced platforms do not have enough money recruitment enough workers

DIMACS

Salamat!

dank u
ju faleminderit
Tack
Asante 谢谢 Tak mulțumesc
kiitos
Gracias
Terima kasih Aliquam
Merci Dankie Obriqado
ありがとう köszönöm grazie
Aliquam Go raibh maith agat
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