Spatial Crowdsourcing: Task Assignment & Scheduling

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USC Viterbi School of Engineering

IMSC Integrated Media Systems Center

OUTLINE

- Motivation
- Task Assignment
- Task Scheduling
- Task Assignment & Scheduling
- Example Application

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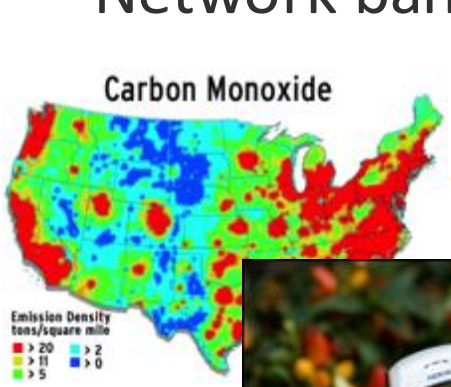
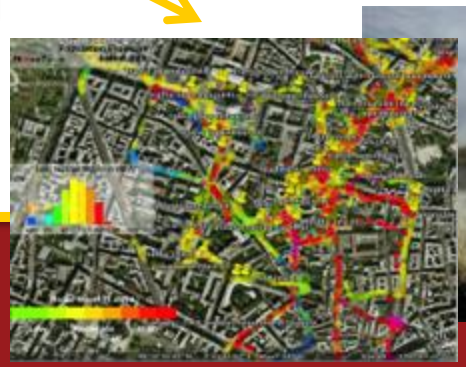
Motivation

- Ubiquity of mobile users
  - 6 billion mobile subscriptions by the end of 2011
    ≡ 87% of the world population[1]
- Technology advances on mobile phones (e.g., Cameras)
- Network bandwidth improvements





[1] http://mobithinking.com/mobile-marketing-tools/latest-mobile-stats

Spatial Crowdsourcing [ACMGIS'12]

Crowdsourcing: outsourcing a set of tasks to a set of workers. amazon mechanical turk™ Artificial Artificial Intelligence

Spatial crowdsourcing (SC)*:* requires workers to ***physically*** travel at the task's location in order to execute the task.

SC Applications

Ubiquity of mobile users — **6.5 billion** mobile subscriptions, 93.5% of the world population [1]

Technology advances on mobiles — Smartphone's **sensors**. e.g., video cameras

Network bandwidth improvements — From 2.5G (up to 384Kbps) to 3G (up to 14.7Mbps) and recently **4G** (up to 100 Mbps)

[1] http://www.itu.int/newsroom/id/2665715

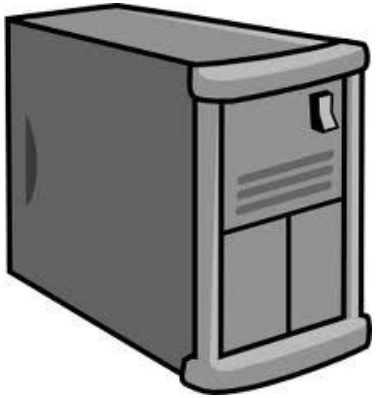
IMSC

GeoCrowd

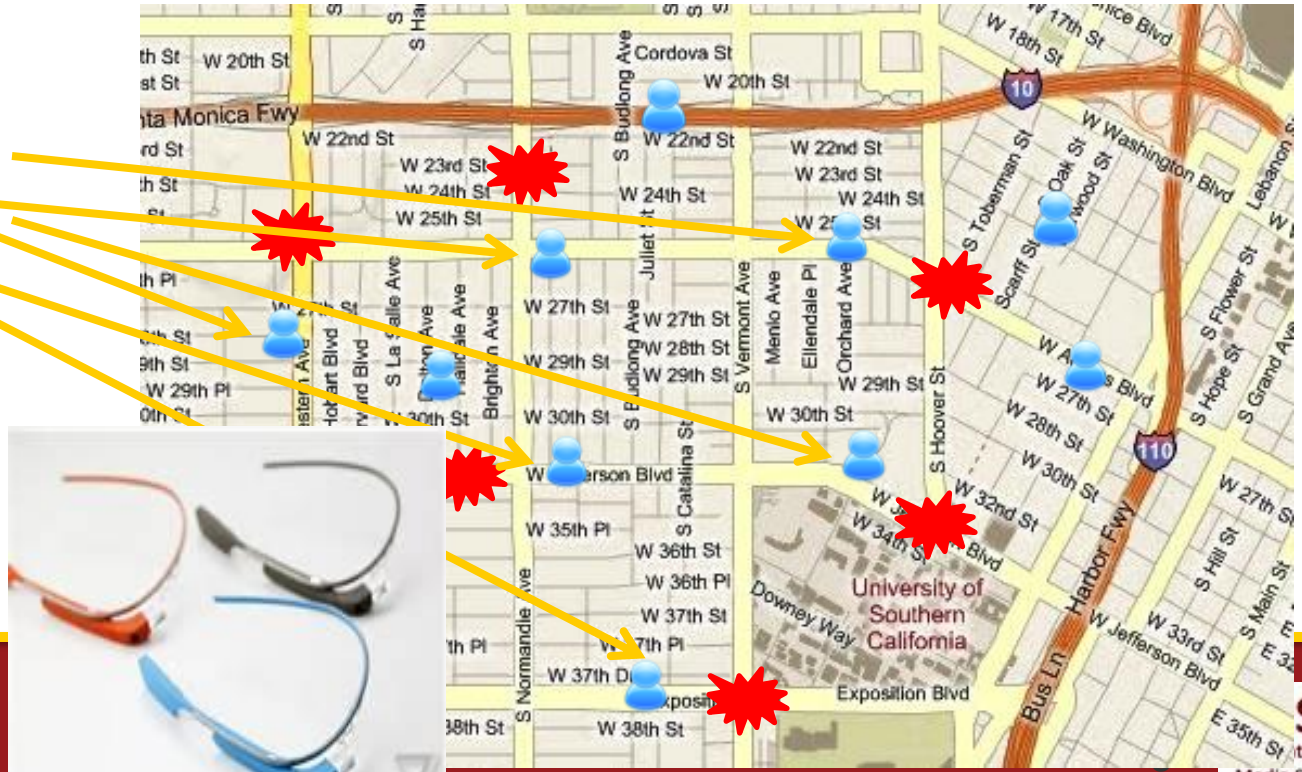
Worker

In Collaboration w Prof. Zimmermann, NUS

Requester



Spatial Crowdsourcing Server (SC-server)



NORTHROP GRUMMAN

Google

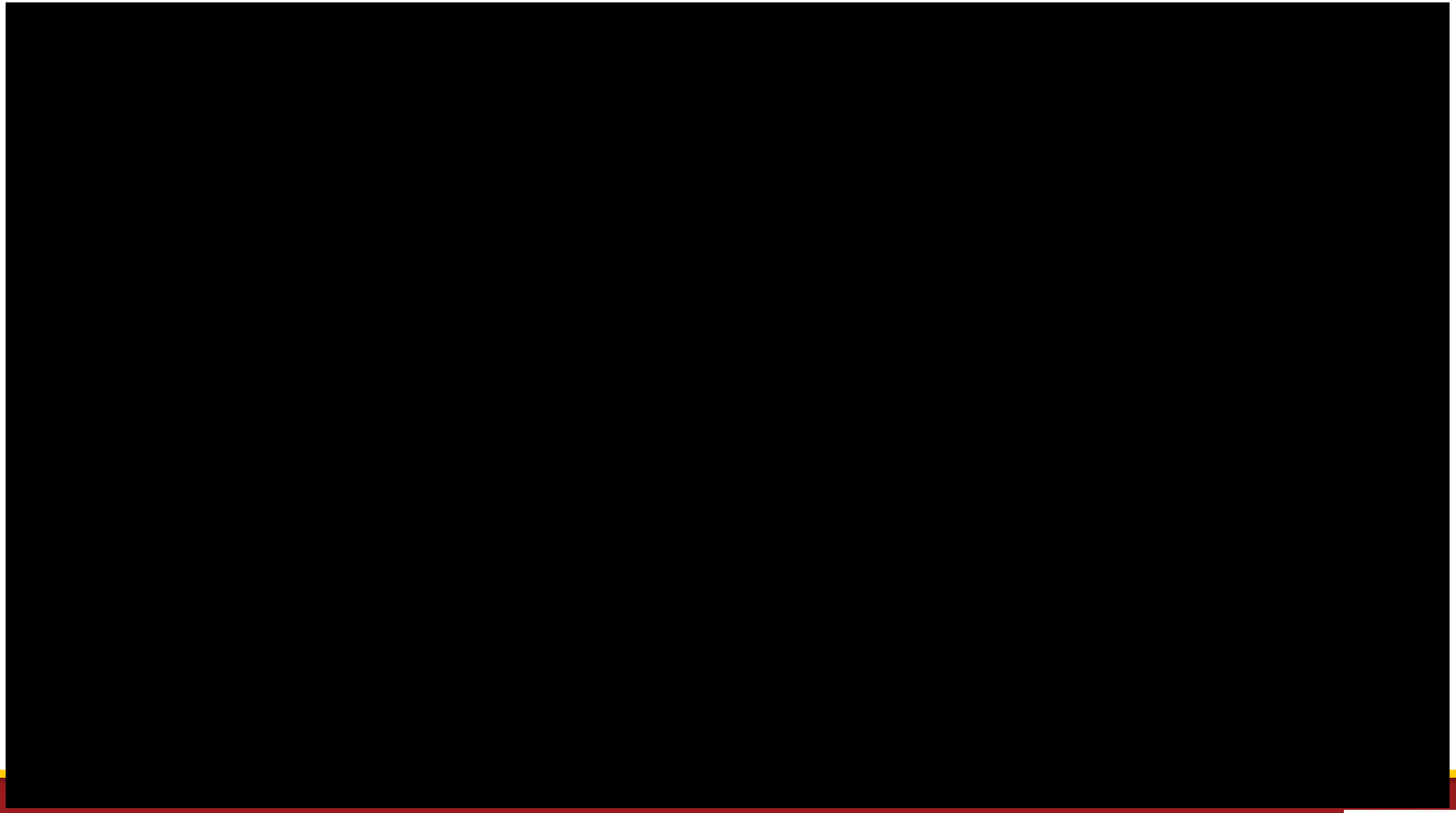
NSF

USC Viterbi School of Engineering

SC ted Media Systems Center

MediaQ Demo

http://mediaq.usc.edu/



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Problem Definition

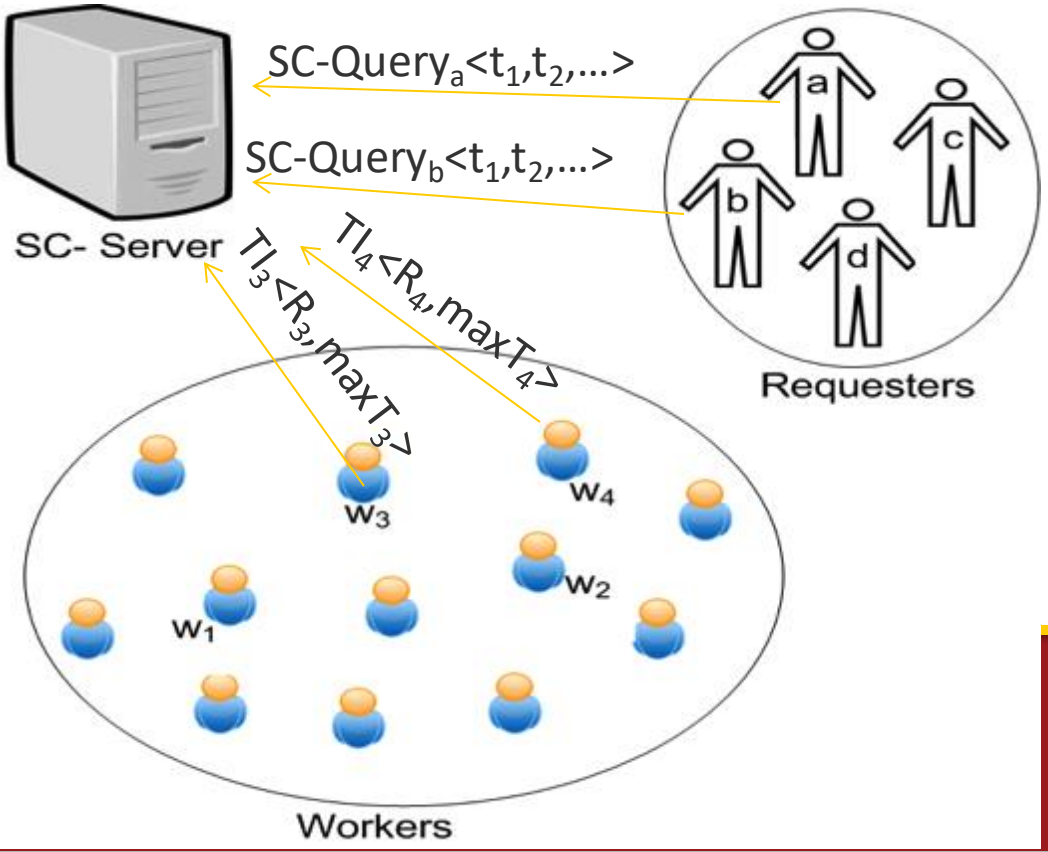
- Input: Given *m spatial task sets* and *k workers*
- Output: assign *spatial task sets* to *workers* and provide *schedules* of workers
- Objective: that minimize the *total cost* (or maximize the *number of assigned tasks*) under *time / order constraints*.
- Challenges: An OR problem with: scale (DB), online (Algo), dynamism (Control), spatial (Geo), etc.

Preliminaries

- *Spatial task t<d, l, s, δ>:* Task *t* with description *d* to be answered at location *l*, asked at time *s* and will be expired at time *s+δ*.

- *Spatial Crowdsourced Query (SC-Query) <t_1,t_2,..>:* A set of spatial tasks issued by a requester to the SC-server for crowdsourcing.

  - *Task Inquiry TI<R,maxT>:* Request that a worker *w* sends to the SC-server when ready to work with constraints:
    - *R*: A spatial region (e.g., rectangle) in which *w* accepts tasks
    - *maxT*: Maximum number of tasks *w* can perform



Problem Definition

- *Task Assignment Instance Set I_i*
  - $W_i = \{w_1, w_2, \ldots\}$: Set of workers at time s_i
  - $T_i = \{t_1, t_2, \ldots\}$: Set of available tasks at time s_i
  - $I_i = \{<w,t> | w \in W_i, t \in T_i\}$: a spatial task *t* is assigned to a worker *w*, while satisfying the workers' constraints.
- *Maximum Task Assignment (MTA)*
  - $\phi = \{s_1, s_2, \ldots, s_n\}$ *:* A time interval
  - *MTA:* Maximizing the total number of assigned tasks during ϕ while satisfying the workers' constraints
    - Maximizing $\sum_{i=1}^{n} |I_i|$

Related Work

- Crowdsourcing
  - Services/Markets/App
    - Amazon's Mechanical Turk (MTurk)
    - CrowdFlower, oDesk, Waze
  - Research
    - Databases [MIT, Stanford, Berkeley]
    - Data Analytics [Liu et al. and Wang et al., PVLDB'12]
    - Image search [Yan et al., MobiSys'10]
    - Natural language annotations [Snow et al., EMNLP'08]
    - Social games [Guy et al., CHI'11]
    - Search [Alonso et al., SIGIR'11]

  Non-Spatial

- Spatial Crowdsourcing
  - [Alt et al., NordiCHI'10]
  - [Bulut et al., PerCom Workshops'11]

  → Worker Selected Spatial Crowdsourcing (application)

  → Non-spatial tasks

- Participatory Sensing: An instance of spatial crowdsourcing in which there is only one requester (i.e., campaign) and tasks are only sensing tasks
  - CENS
  - [Hull et al., SenSys'06]
  - [Mohan et al., SenSys'08]
  - [Cornelius et al., MobiSys'08]
  - [Shirani-mehr et al., GIS'09]

  ✓Not focused on task assignment

  ✓ Focus on single campaign
  ✓ Not a general framework

- Volunteered Geographic Information (VGI) : Create geographic information provided voluntarily by individuals
  - StreetMap
  - Google Map Maker
  - WikiMapia

  ✓ Users unsolicited participation by randomly contributing data

Related Work (Task Assignment)

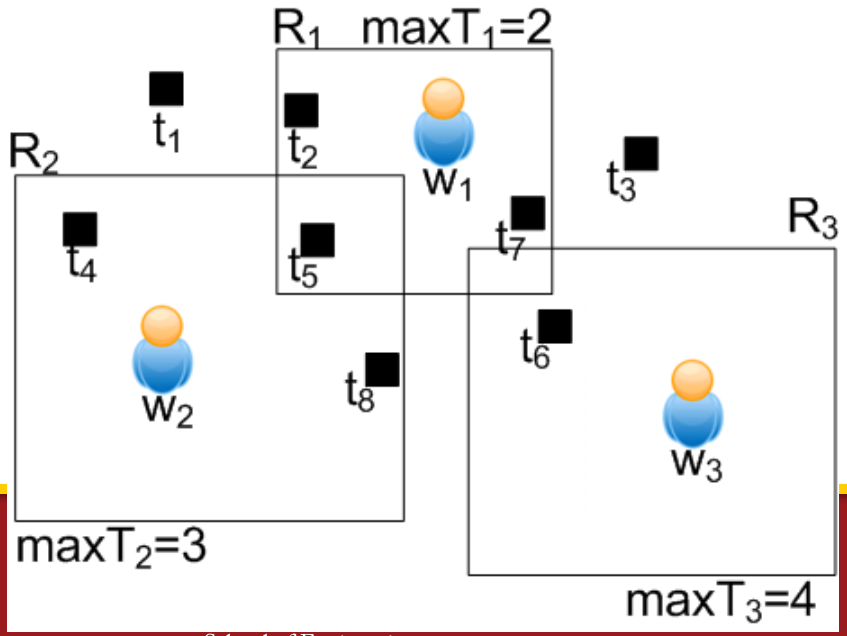
- Classic Matching problems – matching tasks w workers
- Real-time matching – [Kalyanasundaram and Pruhs, 1993 & 2000]
  - Spatial characteristic of tasks and workers
    - Adding spatial feature as a metrics increase complexity (not scalable)
- Spatial matching – [Wong, Tao, Fu and Xiao, 2007][U, Yiu, Mouratidis and Mamoulis, 2008]
  - Dynamism of tasks and workers (i.e., tasks and workers come and go without our knowledge),
    - The challenge is to perform the task assignment at a given instance of time with the goal of global optimization across all times
  - Workers need to travel to task locations causes the landscape of the problem to change constantly
    - This will add another layer of dynamism to spatial crowdsourcing that makes it a unique problem

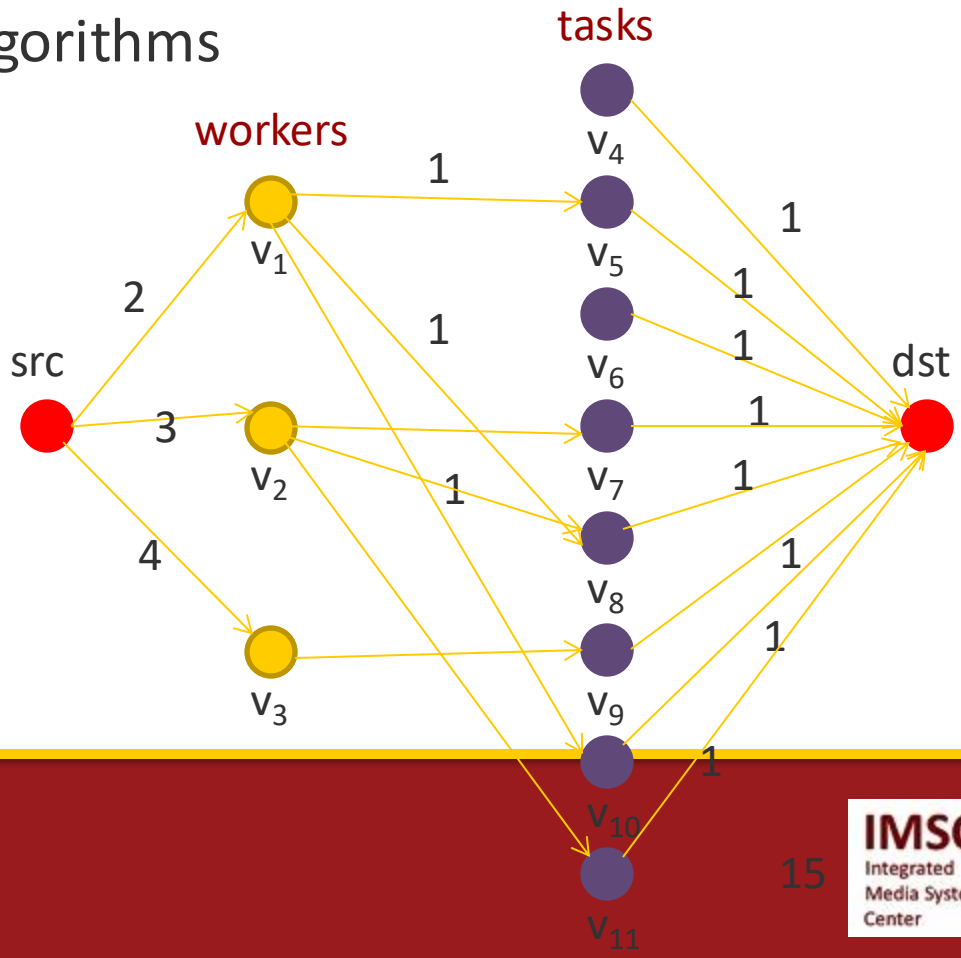
Assignment Protocol

- Future knowledge → Optimal assignment → Solving MTA
- Challenge
  - Current knowledge at every time instance → Local optimization
- Goal
  - Optimizing the task assignment locally by utilizing the spatial information that workers share during their task inquiries
- Approaches
  - Greedy (GR) Strategy
  - Least Location Entropy Priority (LLEP) Strategy
  - Nearest Neighbor Priority (NNP) Strategy

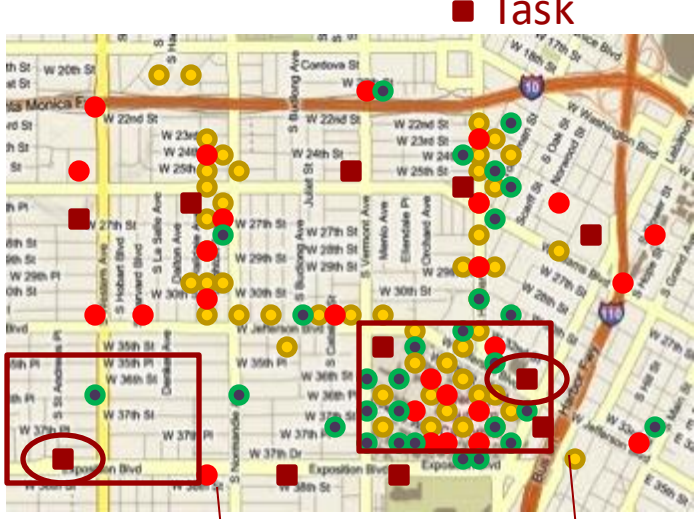
Greedy (GR) Strategy

- Goal → Maximizing the assignment at every instance of time s_i → solving Maximum Task Assignment Instance ($MTAI_i$)
- $MTAI_i$ is equivalent to max-flow problem
- Apply any of the max-flow algorithms
  - Ford-Fulkerson





Least Location Entropy Priority Strategy (LLEP)



- Goal
  - Exploiting the spatial characteristics of the environment to maximize the overall task assignment
- Intuition
  - A task is more likely to be completed when located in areas with higher worker densities
- Heuristic
  - Assigning higher priority to tasks which are located in worker-sparse areas
- Location Entropy: Measuring the total number of workers in a location as well as the relative proportion of their visits to that location
  - l : location
  - O_l : Set of visits to location l
  - W_l : Set of distinct workers that visited l
  - $O_{w,l}$: Set of visits that worker w has made to the location l
  - $P_l(w) = |O_{w,l}| / |O_l|$

$$Entropy(l) = -\sum_{w \in W_l} P_l(w) \times \log P_l(w)$$

Major Observations

- Experiments on both real and synthetic data demonstrated
  - The superiority of LLEP in comparison with GR in terms of the number of assigned tasks by up to 36%

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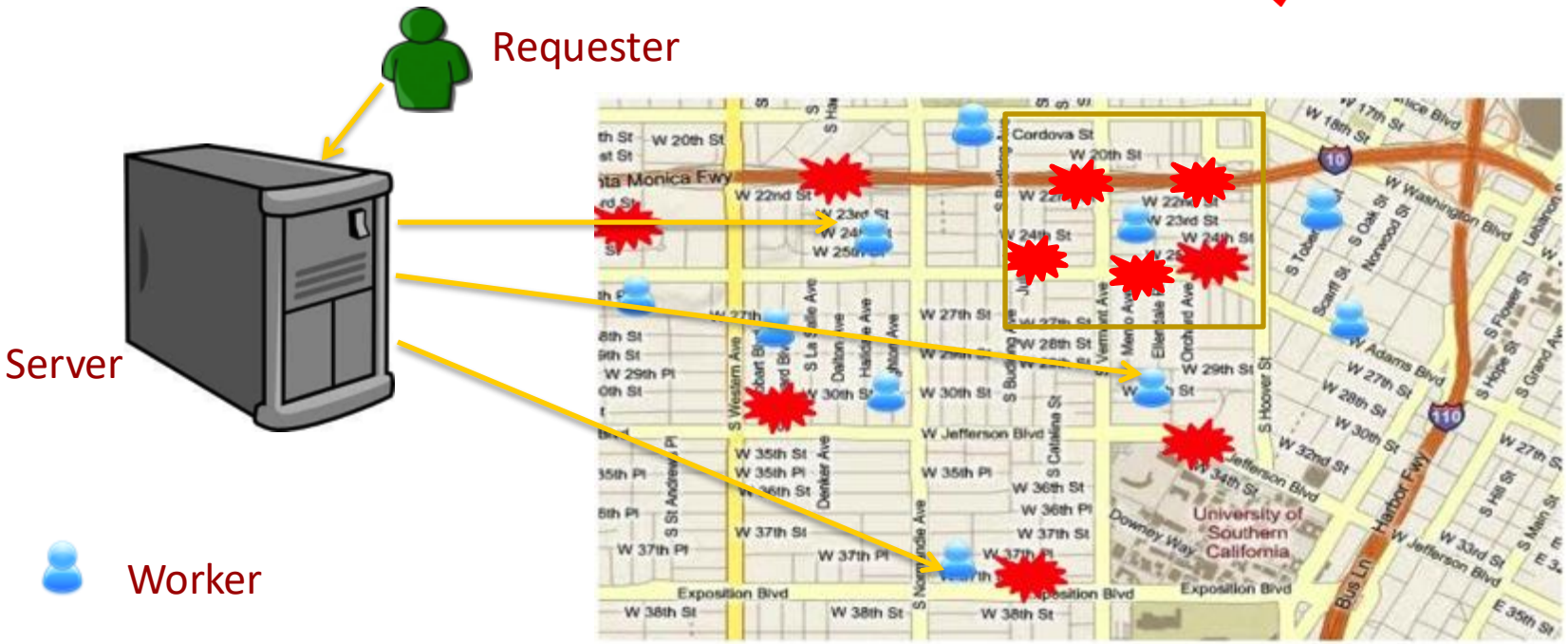
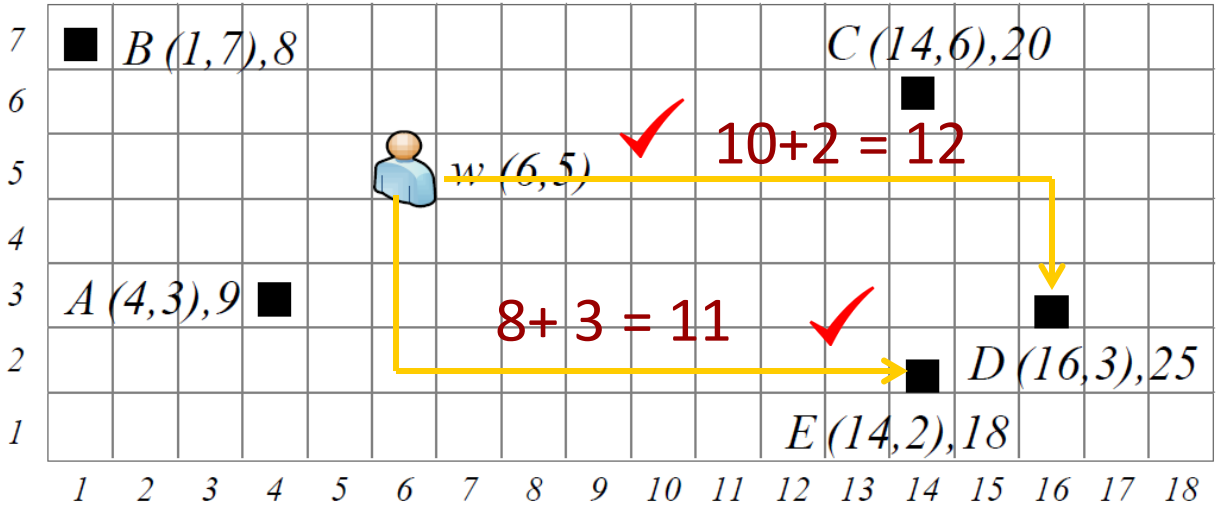
Spatial Crowdsourcing

- Challenges:
  - Task Assignment
- Approach
  - Server Assigned Tasks (SAT) V.S Worker Selected Tasks (WST)



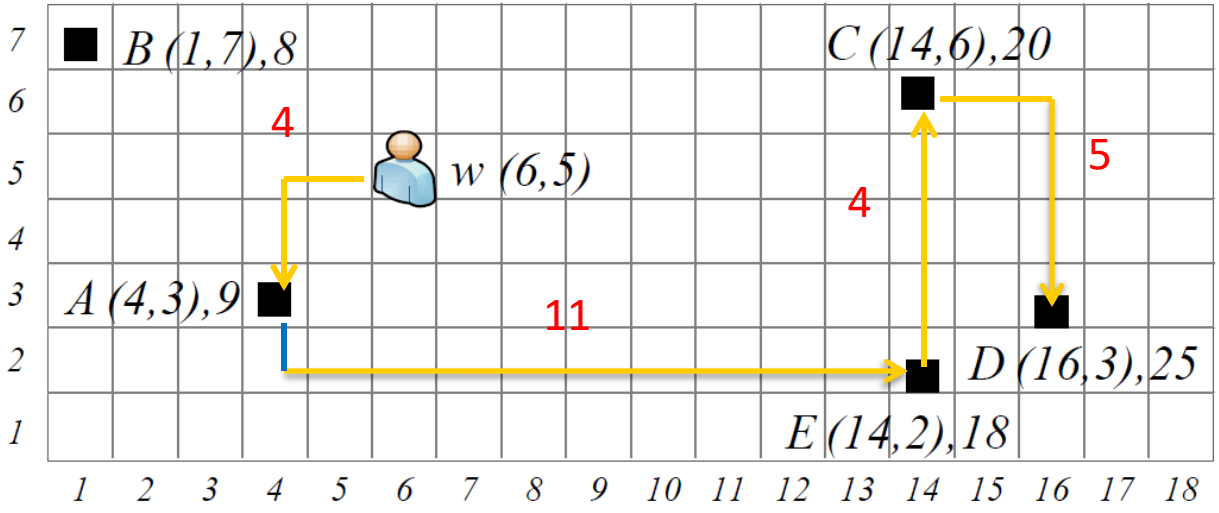
Example

- Tasks with location and deadlines
  - E.g. task D needs to be finished in 25 minutes
- Suppose travel time for one grid is one minute
  - Consider Manhattan distance
  - E.g., cost(w, D) = 10 + 2 = 12 minutes



Problem Definition

- Maximum Task Scheduling (MTS)
  - Given a worker *w* and a set of *n* tasks *T with locations and deadlines*
  - Find a maximal task sequence *R*



Maximal Task sequence: (A, E, C, D)

Problem Complexity

- The MTS problem is NP-hard by reduction from Traveling Salesman Problem (TSP)

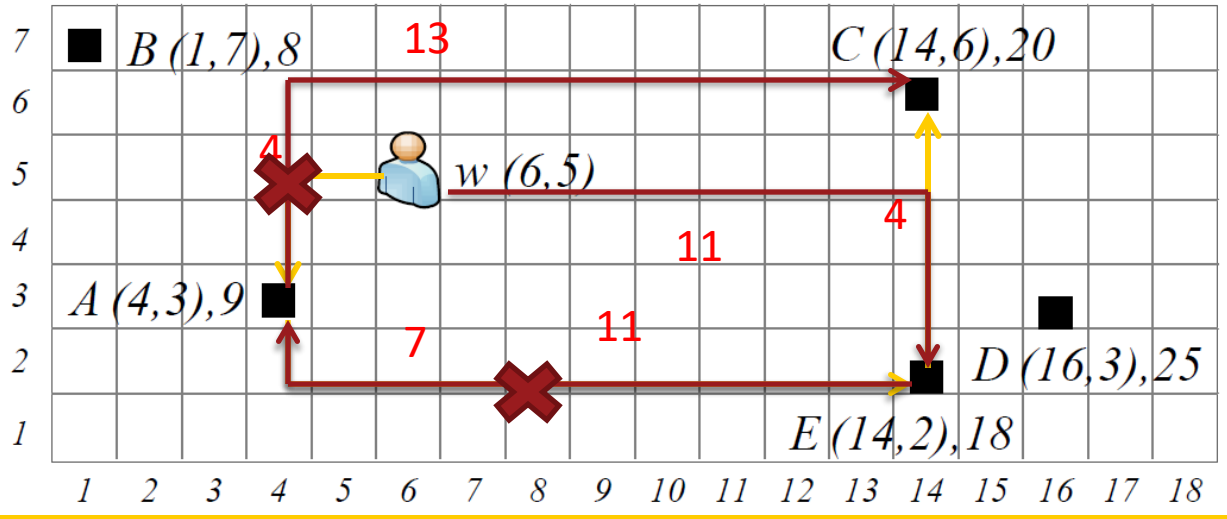
- Brute force takes O(n!) time

Outline

- Problem Definition
- **Exact Algorithms**
  - Dynamic Programming
  - Branch-and-Bound Algorithm
- Approximation Algorithms

Dynamic Programming

- Let's schedule task set *{A, C, E}* s.t. it ends w *C*
  - Schedule *{A, E}* ends with *E* → *3*
  - Or schedule *{A, E}* ends with *A* → *1*
  - *Choose the best among them*



Dynamic Programming

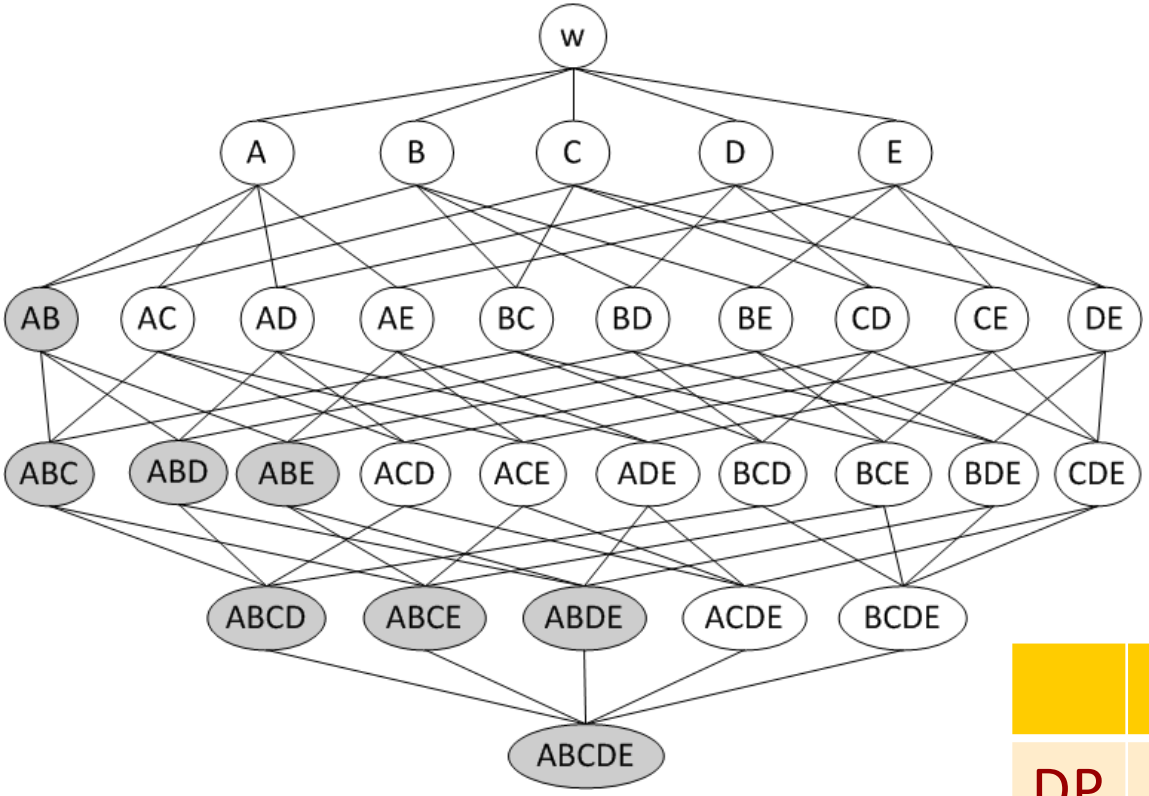
- Define *opt(S, j)* as the optimum number by scheduling all the jobs in S, ends with *j*
  - *Task i* is the *second-to-last* finished task before *j*

$$opt(S, j) = \max_{i \in S, i \neq j} (opt(S - \{j\}, i) + d_{ij})$$

$$d_{ij} = \begin{cases} 1 & \text{if job } j \text{ can be finished after job } i \\ 0 & \text{else} \end{cases}$$

Dynamic Programming

- Subsets needs to be explored



$$\binom{n}{1} + \binom{n}{2} + \ldots + \binom{n}{n} = 2^n$$

subsets in total

	Space Cost	Time Cost
DP	$O(n \cdot 2^n)$	$O(n^2 \cdot 2^n)$

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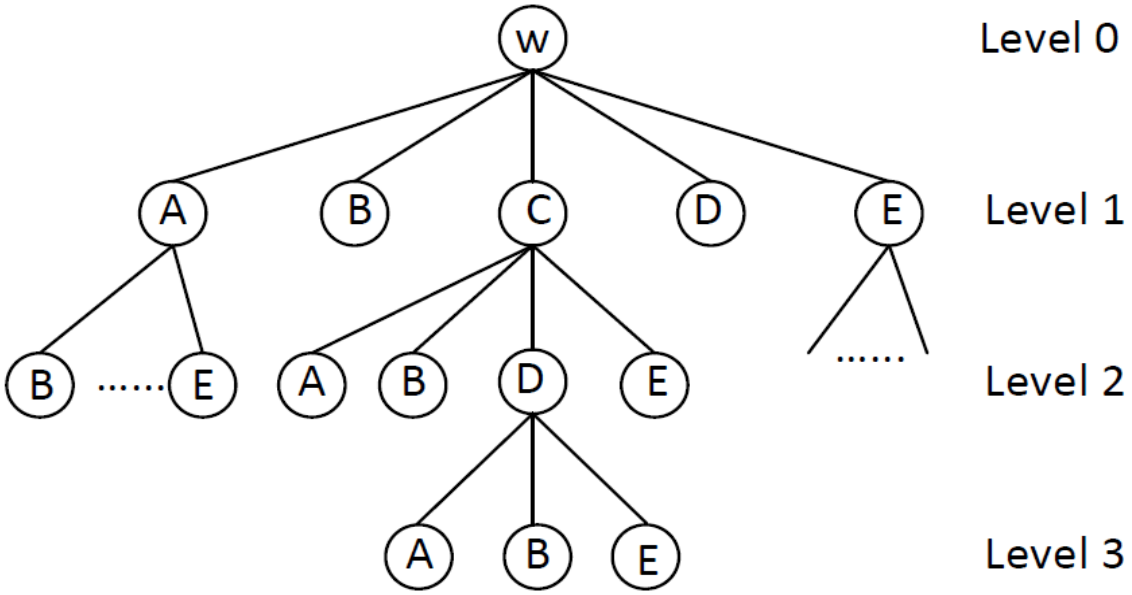
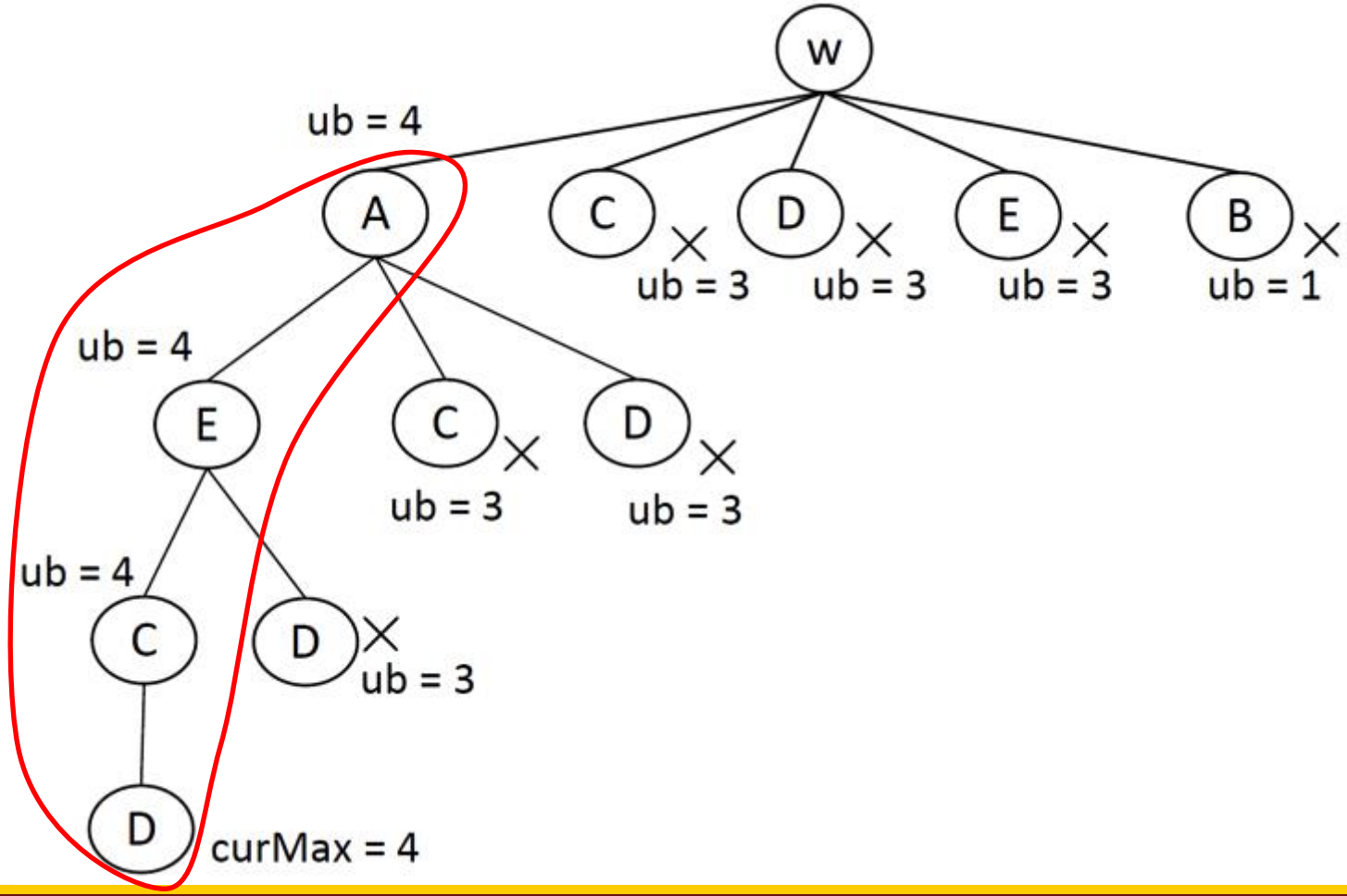
- Problem Definition
- **Exact Algorithms**
  - Dynamic Programming
  - **Branch-and-Bound Algorithm**
- Approximation Algorithms

Branch-and-Bound

- Search Tree
  - Depth-first or best-first search

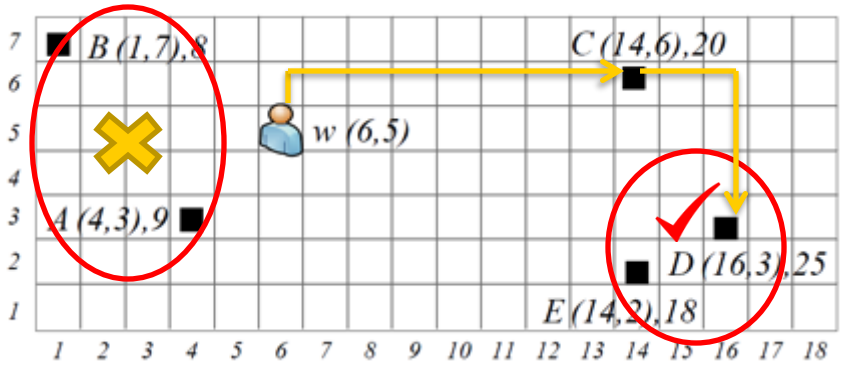


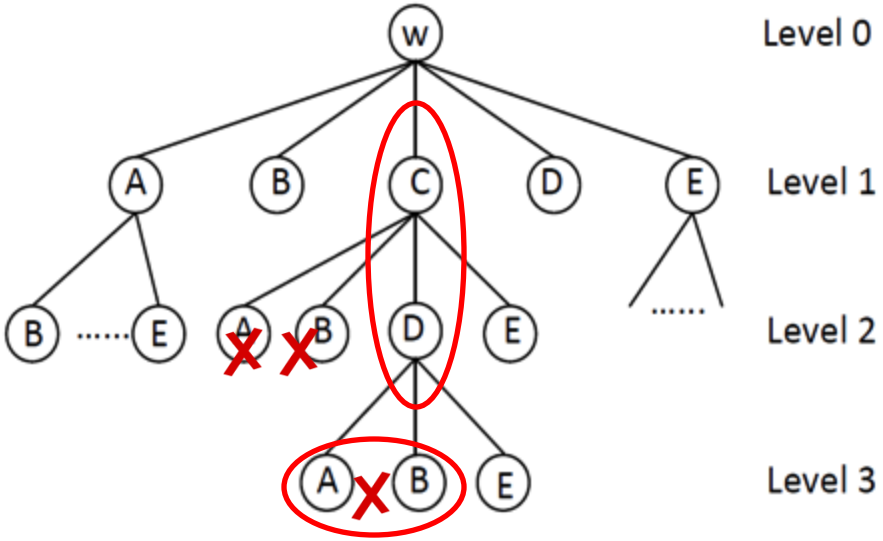
Example of B&B



Candidate Task Set

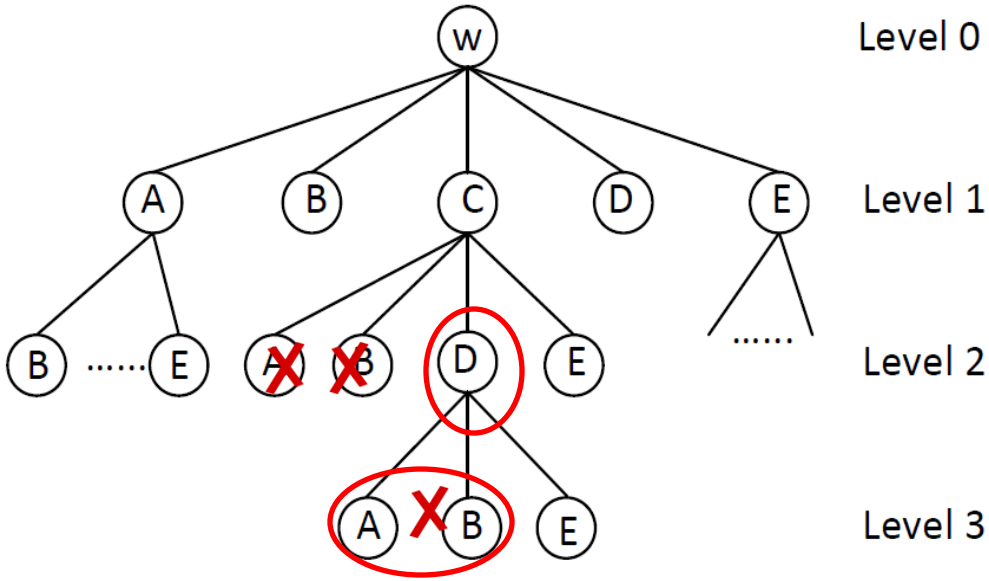
- Suppose we are at (C, D), do we still need to try A, B at level *3*?





Candidate Task Set (*cand*)

- A candidate task set maintains the promising tasks to be expanded at the next level:
  - e.g. *cand*(C) = {D,E} *cand*(C, D) = {E}



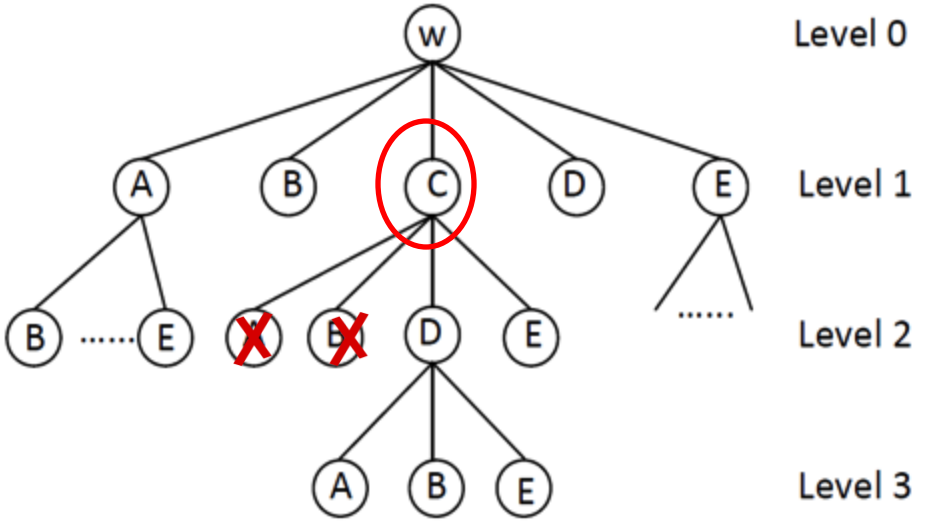
- **Property**: A node's candidate tasks set is the subset of its parent's candidate task set

Bound of Branch

- R is current path from w
- Upper-bound of R

maxi # of tasks that can be finished
by following the corresponding branch.

  - ub(R) = |R| + |cand_R|
  - E.g., ub(C) = 1 + 2 = 3



- Lower-bound of R
  - Minimum number of tasks that can be completed by following this branch

Branch-and-Bound

- Complexity

	Space Cost	Time Cost
DP	$O(n \cdot 2^n)$	$O(n^2 \cdot 2^n)$
B&B	$O(n^2)$	$O(n!)$

Worst case

- In reality, n is the number of tasks in the vicinity of the worker, it might be very large!

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- Problem Definition
- Exact Algorithms
  - Dynamic Programming
  - Branch-and-Bound Algorithm
- **Approximation Algorithms**

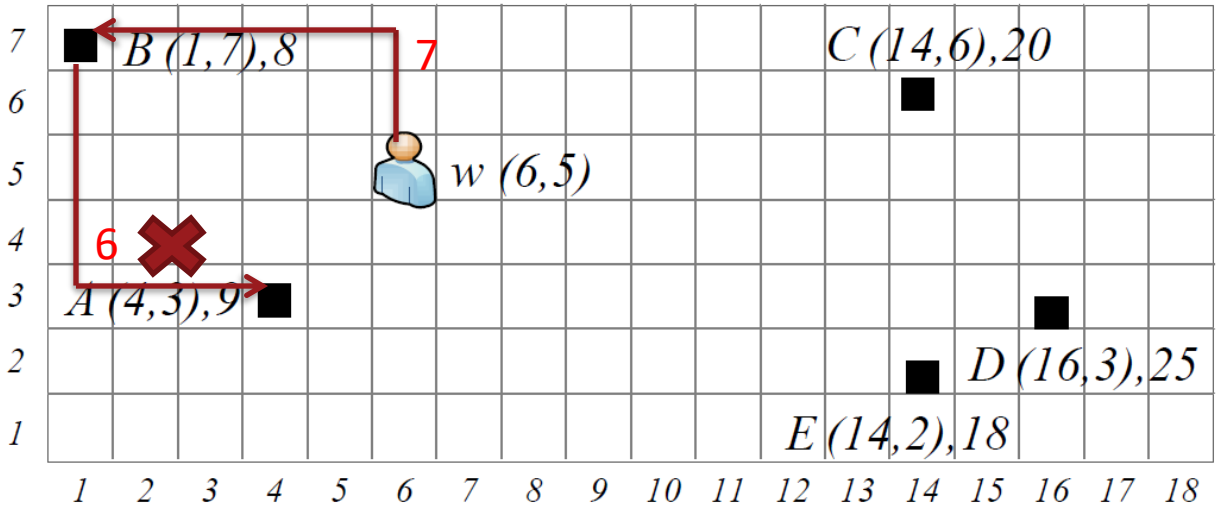
Limitation of Exact algorithms

- Restriction of Mobile platform
  - Limited CPU and memory resources
  - Interactive environment for the user
    - Response in milliseconds level

- Exact algorithms cannot scale
  - Exponential running time and/or huge memory consumption

Least Expiration Heuristics (LEH)

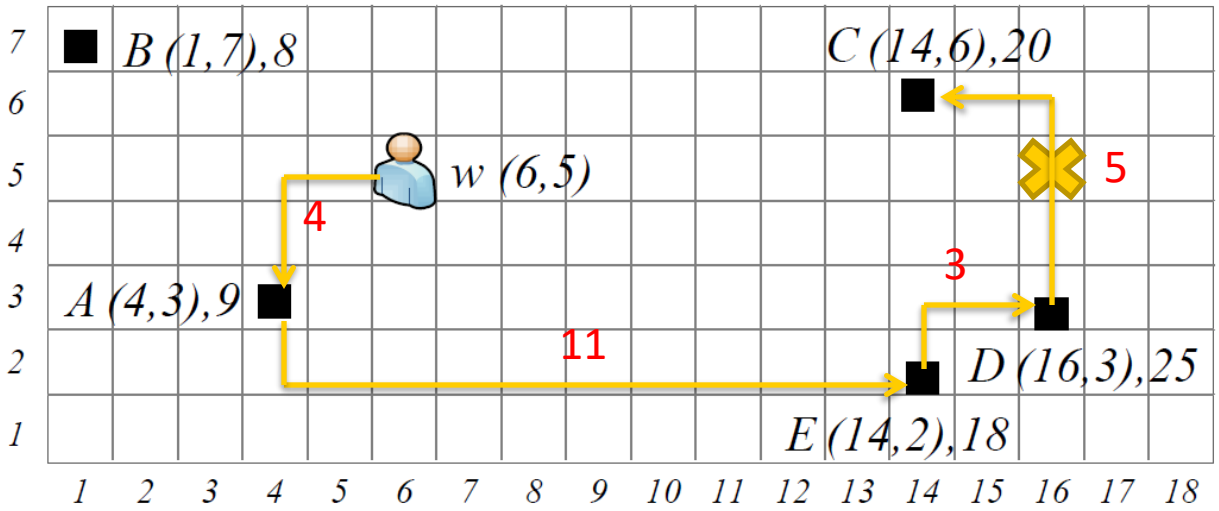
- Greedily choose the task with least expiration time



Task Sequence: <B>

Nearest Neighbor Heuristics (NNH)

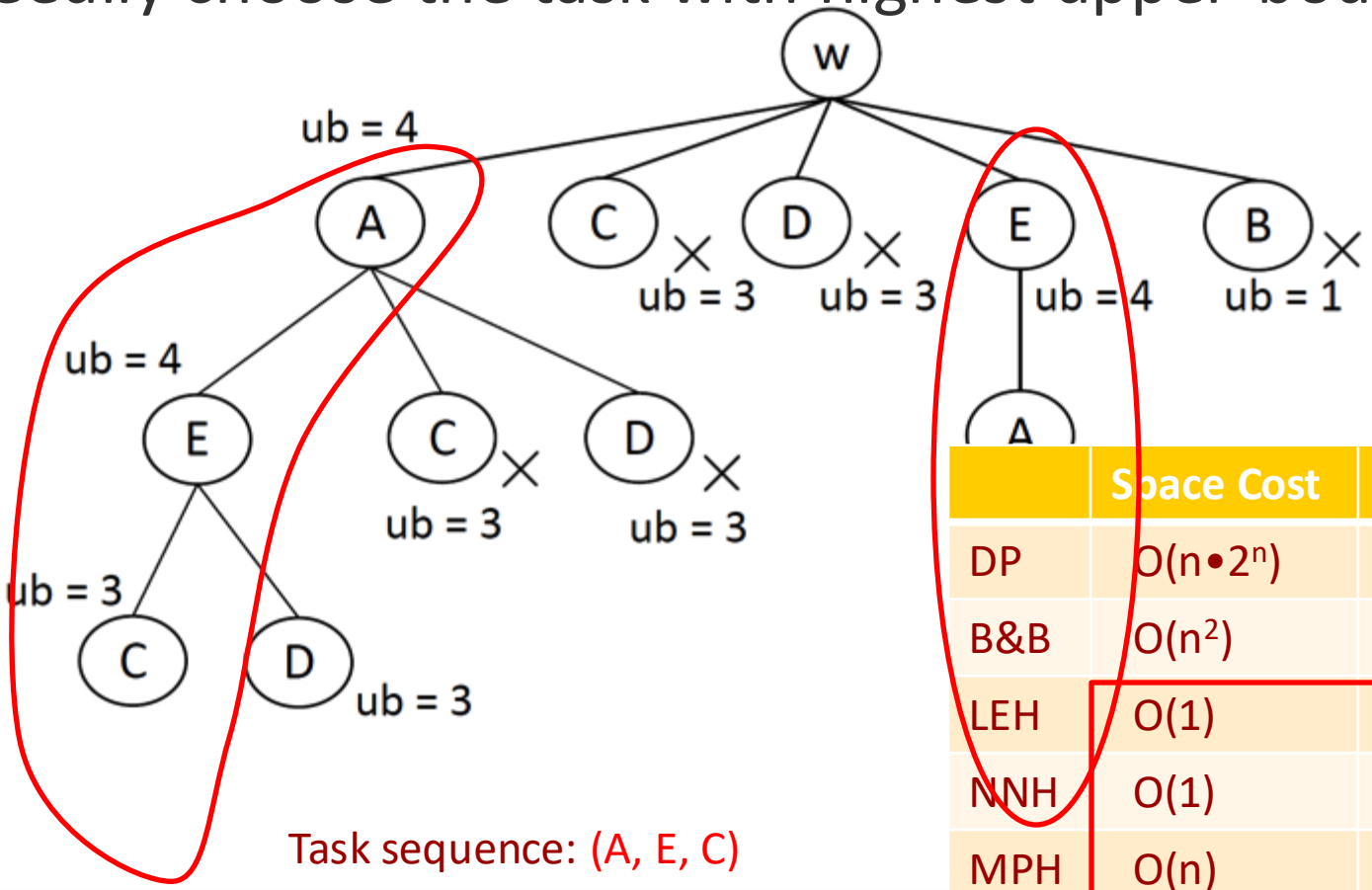
- Greedily choose the task nearest to the worker



Task sequence: (A, E, D)

Most Promising Heuristic (MPH)

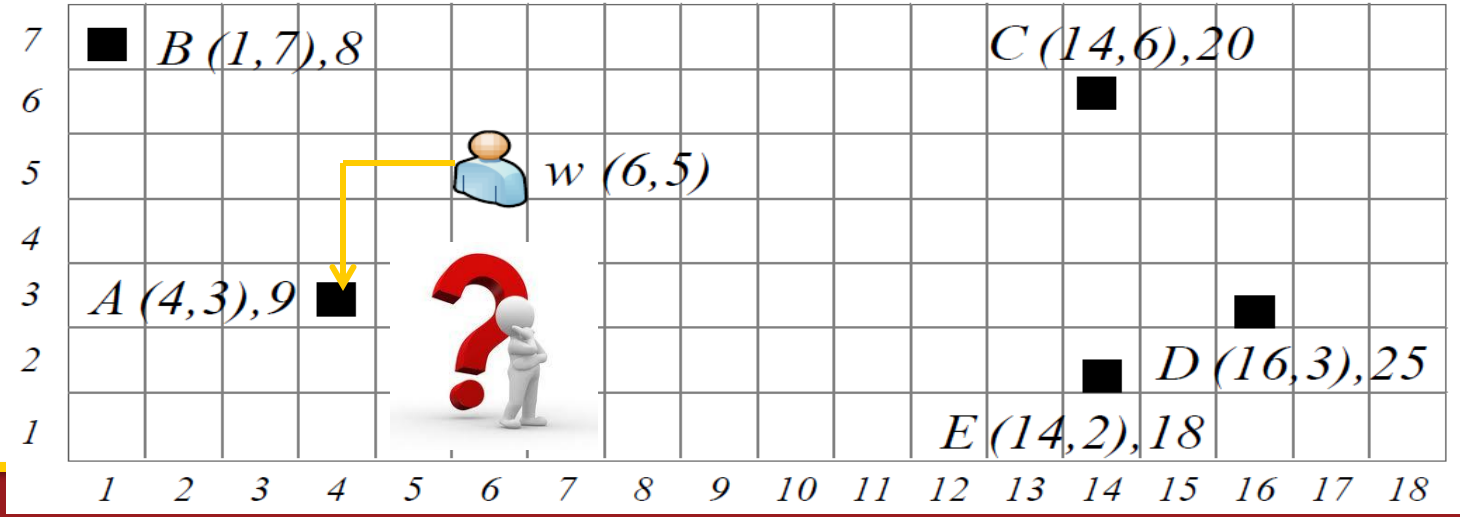
- Greedily choose the task with highest upper-bound



	Space Cost	Time Cost
DP	$O(n \cdot 2^n)$	$O(n^2 \cdot 2^n)$
B&B	$O(n^2)$	$O(n!)$
LEH	$O(1)$	$O(n \cdot \log(n))$
NNH	$O(1)$	$O(n^2)$
MPH	$O(n)$	$O(n^2)$

Progressive algorithms

- Approximation algorithm + Exact algorithm
  - NNH to choose the first task
  - Branch and Bound for the remaining *4* tasks



Progressive Algorithms

- Pros
  - Quick response time
  - Near-optimum results
- Cons
  - Preemption of other workers
  - Worker may prefer the whole plan

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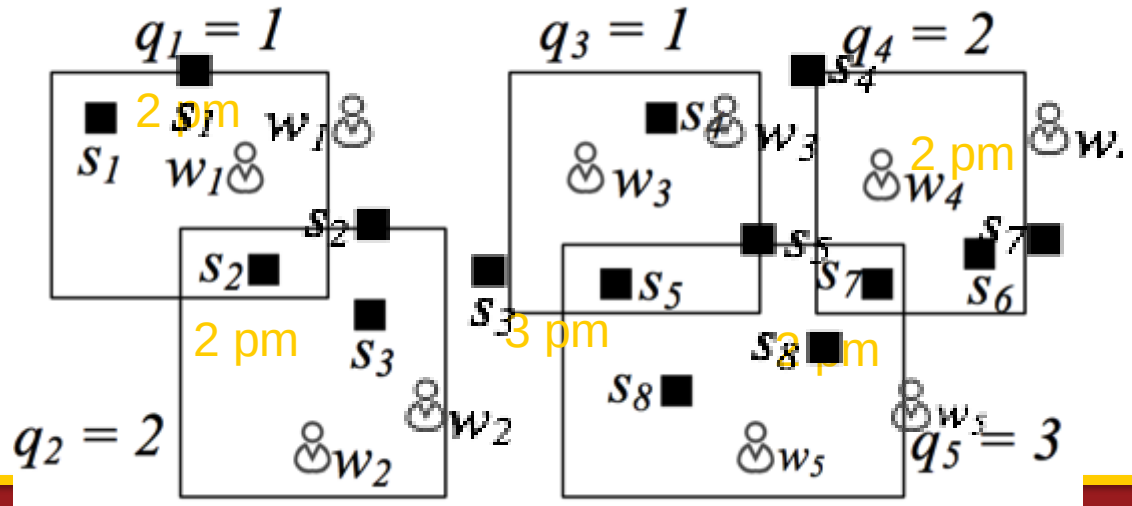
Problem definition

Input: Given a set of workers ***W*** and a set of tasks ***S***

- worker: **spatial and capacity constrain**
- task: **expiration time constraint**



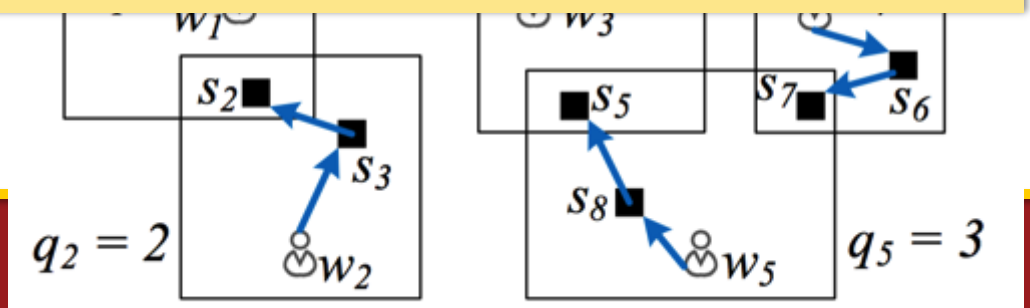
Problem definition

Input: Given a set of workers ***W*** and a set of tasks ***S***

Goal: find a scheduling plan for each worker:

1. Maximize the number of completed tasks (**primary goal**)
2. Minimize the average travel cost per task (**secondary goal**)

NP-hard Problem



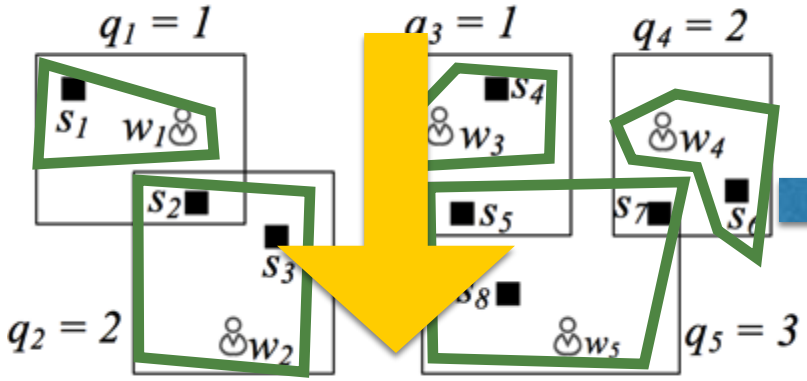
One potential plan

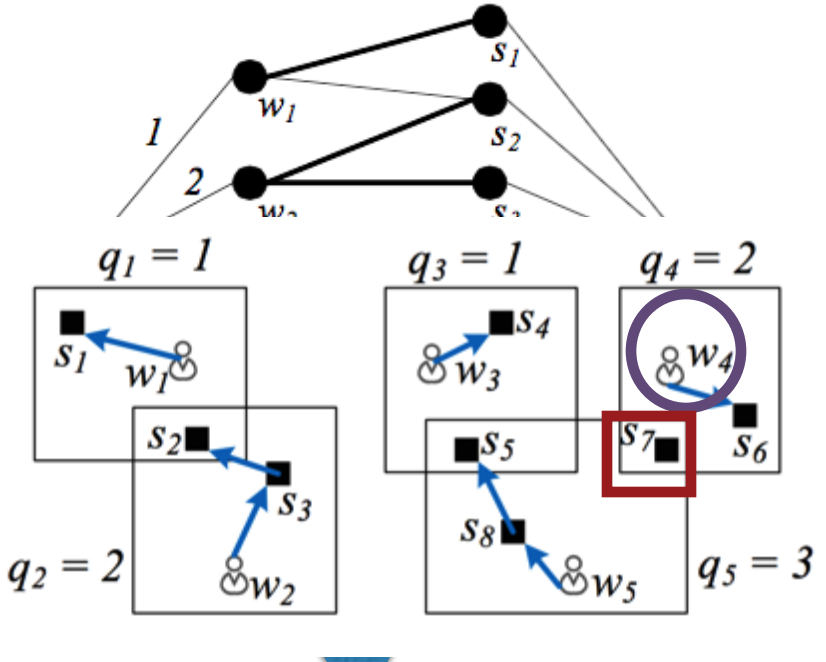
Outline

- **Global Assignment and Local Scheduling (GALS)**
- Local Assignment and Local Scheduling (LALS)
- Experiments

Baseline

1. Assignment via max-flow [Kazami'GIS12]





Initial Assignment:

w_1: s_1

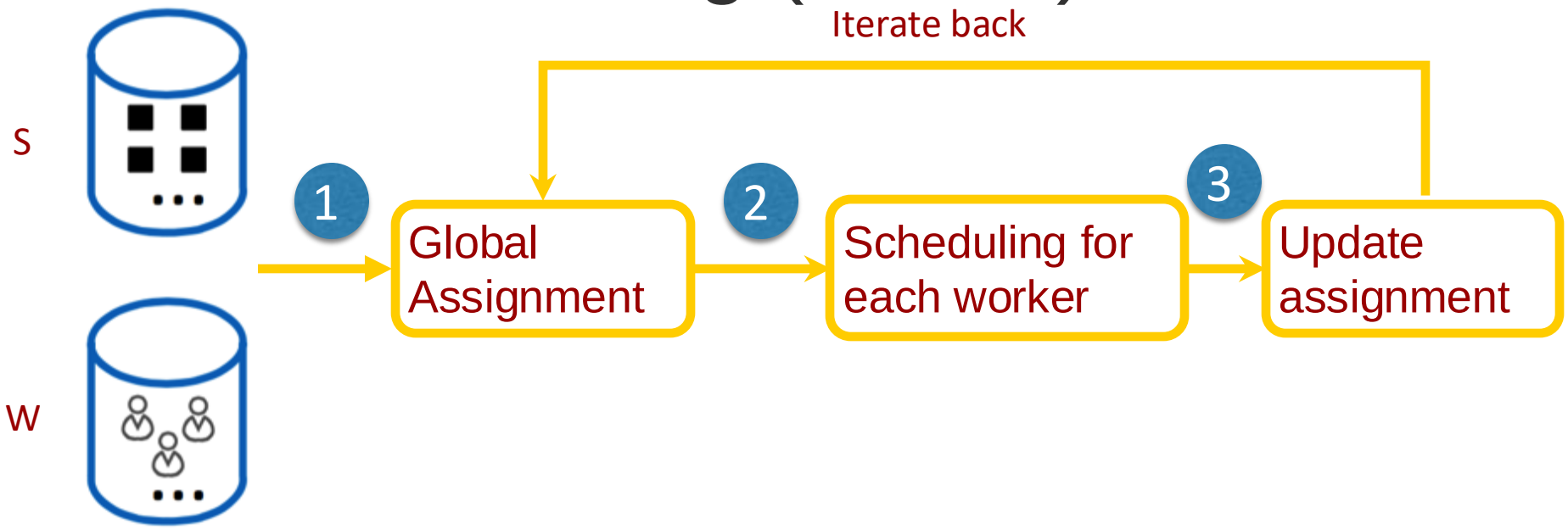
2. Schedule for each worker [Deng'GIS13]

Reassignment and rescheduling?

w_4: s_6

w_5: s_5, s_7, s_8

Global assignment and local scheduling (**GALS**)



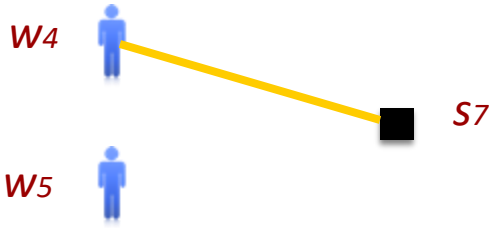
matching + scheduling **iteratively**

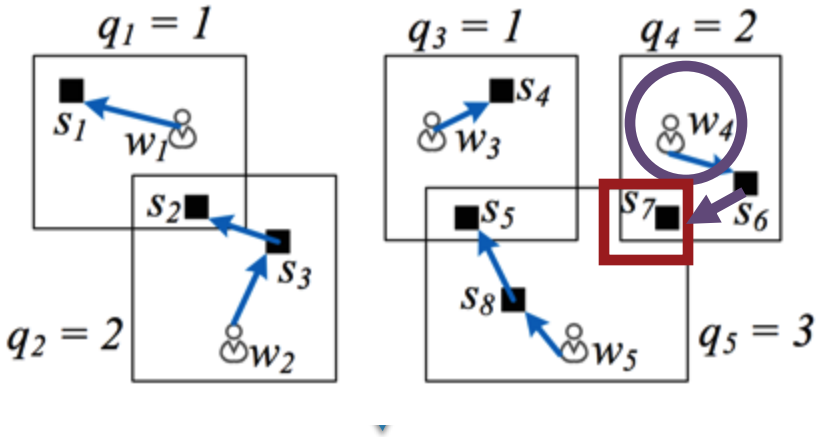
Example of GALS

1. Assignment via max-flow [Kazami'GIS12]

2. Schedule for each worker [Deng'GIS13]

3. Build remaining flow network and update scheduling





Insert s_7 into w_4's existing schedule

Property of GALS

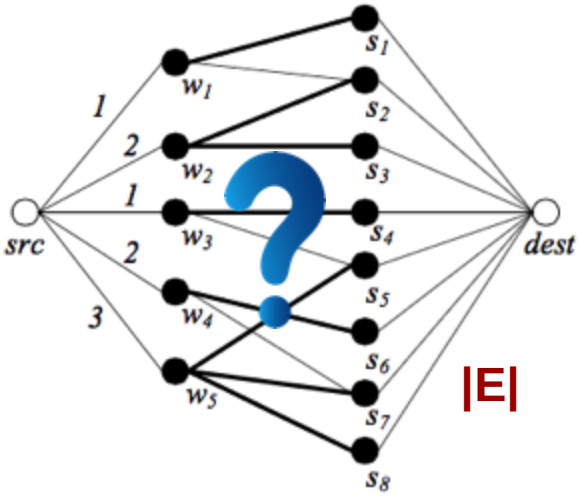
High quality

- Global assignment maintains the **connectivity** information

- The **iterative** refining process further improves the quality

Bottleneck of GALS

Not efficient



$$O(n^2|E|)$$

Suffers from the large number of edges in the flow network

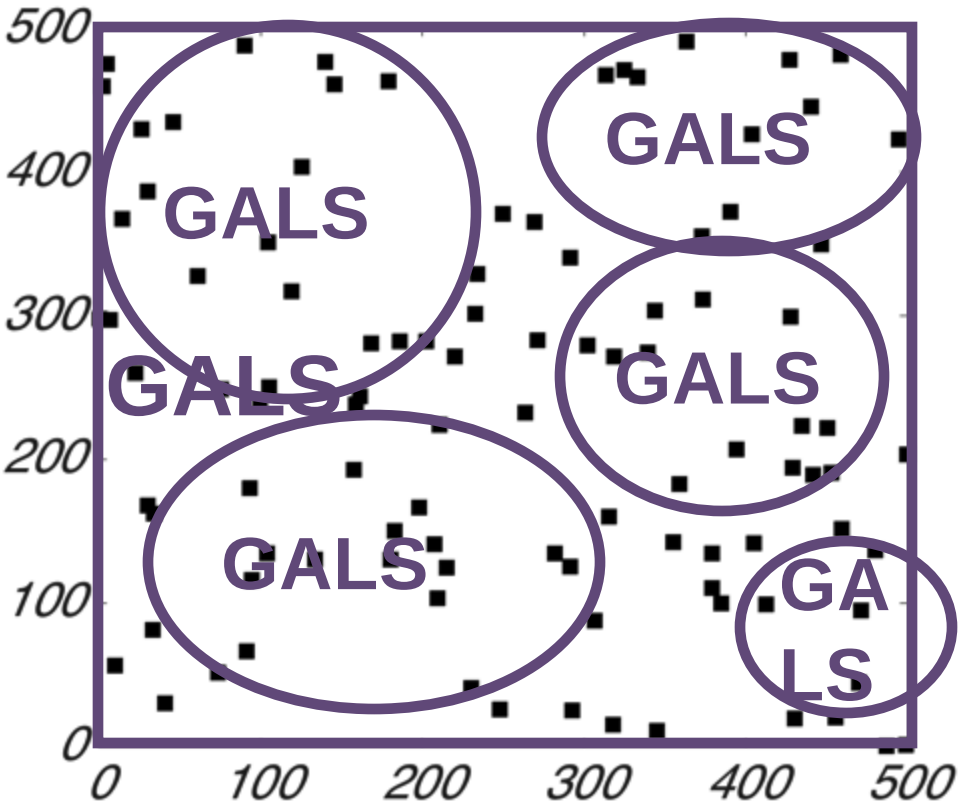
For an instance with 25k tasks and 500k edges

GALS takes more than **1000** seconds

Outline

- Global Assignment and Local Scheduling (GALS)
- **Local Assignment and Local Scheduling (LALS)**
  - **Naive LALS**
  - Bisection-based LALS
- Experiments

Naive LALS



1. Generate partitions

2. Schedule for each partition **GALS**

3. Combine the remaining workers and tasks

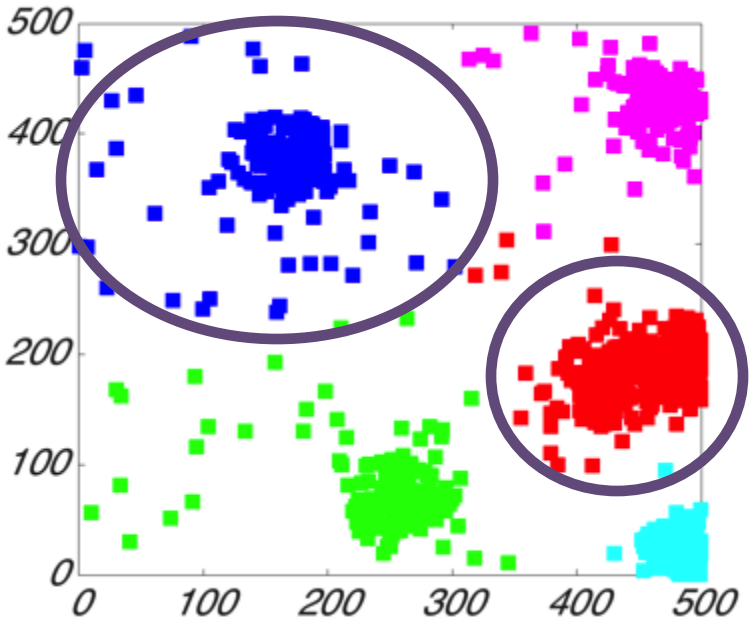
Break global assignment into a set of **local assignments and local scheduling** (LALS)

Naive LALS

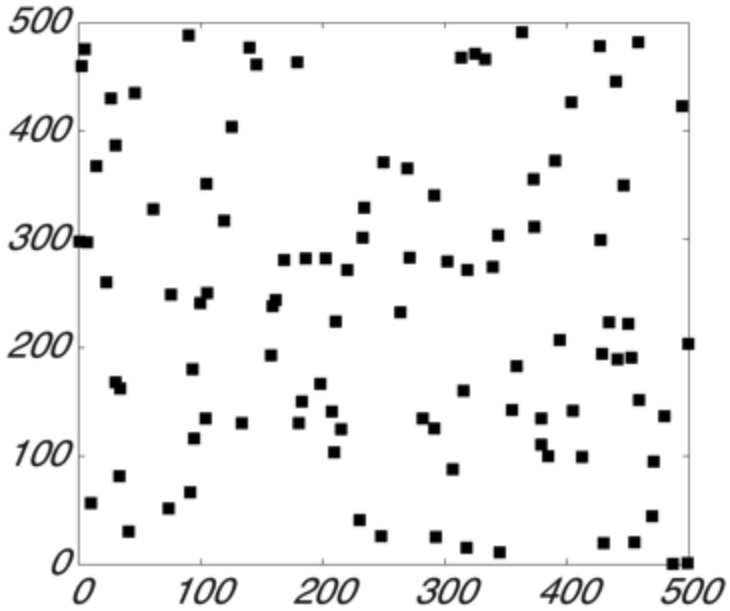
Sacrifice the solution quality

Problems

- Partitions with **large** number of edges



- **Large** remaining flow network



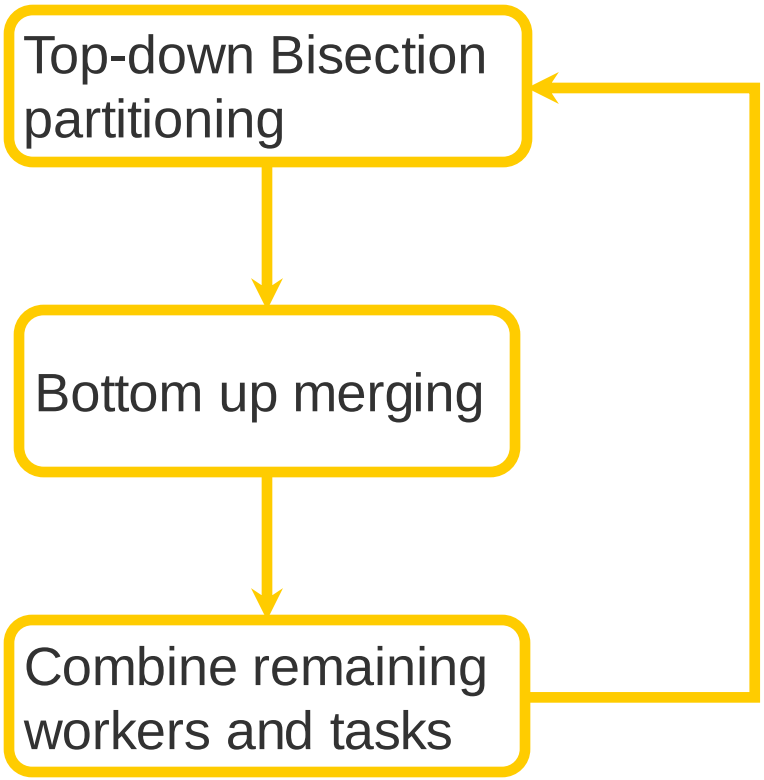
Balanced workload at each partition

Small remaining workloads

Outline

- Global Assignment and Local Scheduling (GALS)
- Local Assignment and Local Scheduling (LALS)
  - Naive LALS
  - **Bisection-based LALS**
- Experiments

Bisection-based LALS



Outline

- Global Assignment and Local Scheduling (GALS)
- Local Assignment and Local Scheduling (LALS)
  - Naive LALS
  - Bisection-based LALS
- **Experiments**

Experiment

- Dataset
  - Synthetic: **SYN-SKEW,** SYN-UNI from 500 * 500 grid
  - Real dataset from **Gowalla** and **Yelp**
- Algorithms
  - Baseline, **GALS**
  - Naive LALS (**NLALS)**, Bisection LALS(**BLALS)**

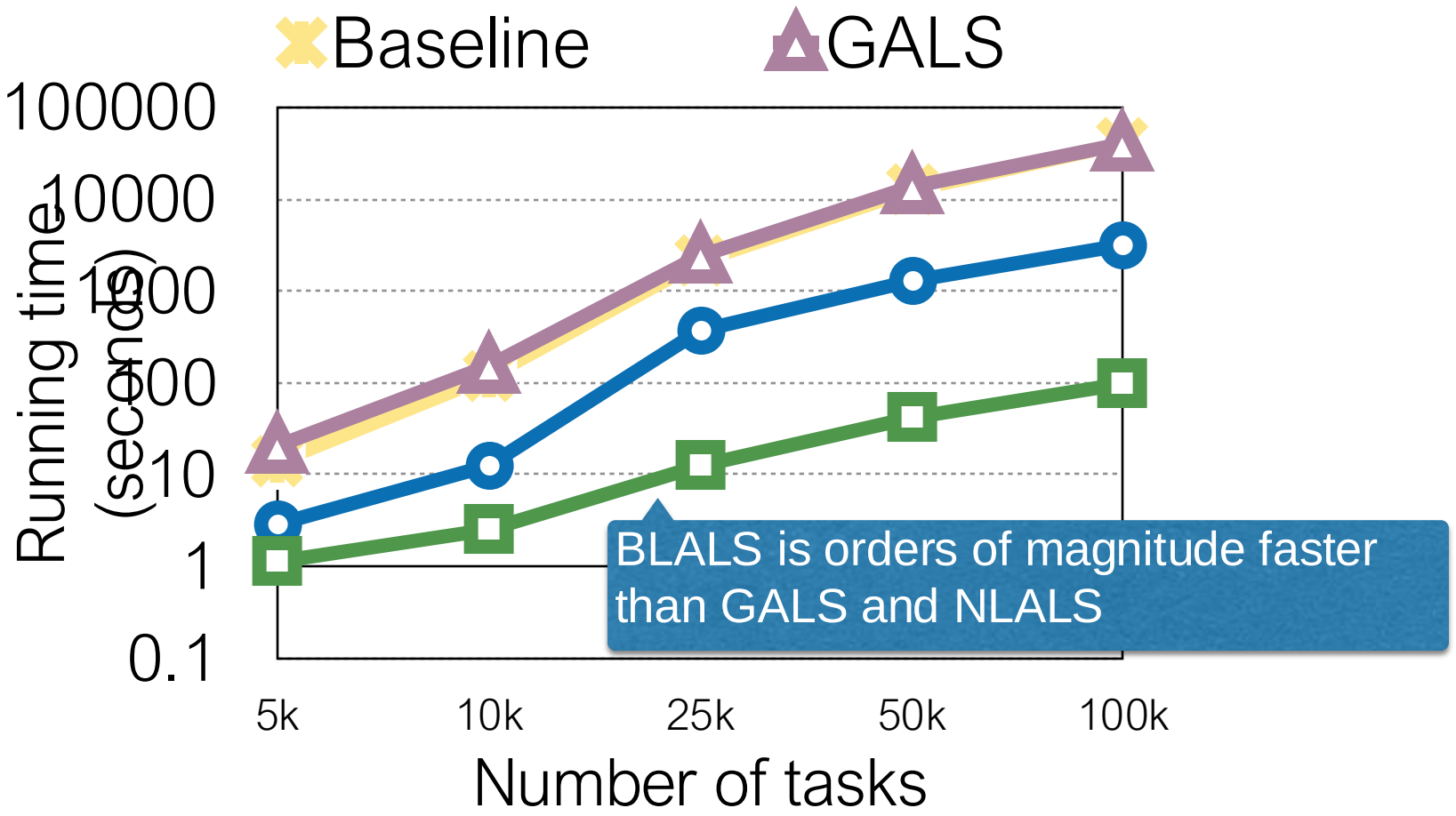
Varying |S| on SYN-SKEW

- No. of scheduled task

	baseline	GALS	NLALS	BLALS
5K	3379	**3986**	3911	3896
10K	7075	**8263**	8201	8093
25K	19049	**21849**	21717	21473
50K	35614	**43653**	43368	42095
100K	56511	**68505**	66275	63937

BLALS sacrifices only less than 5% of the schedule quality

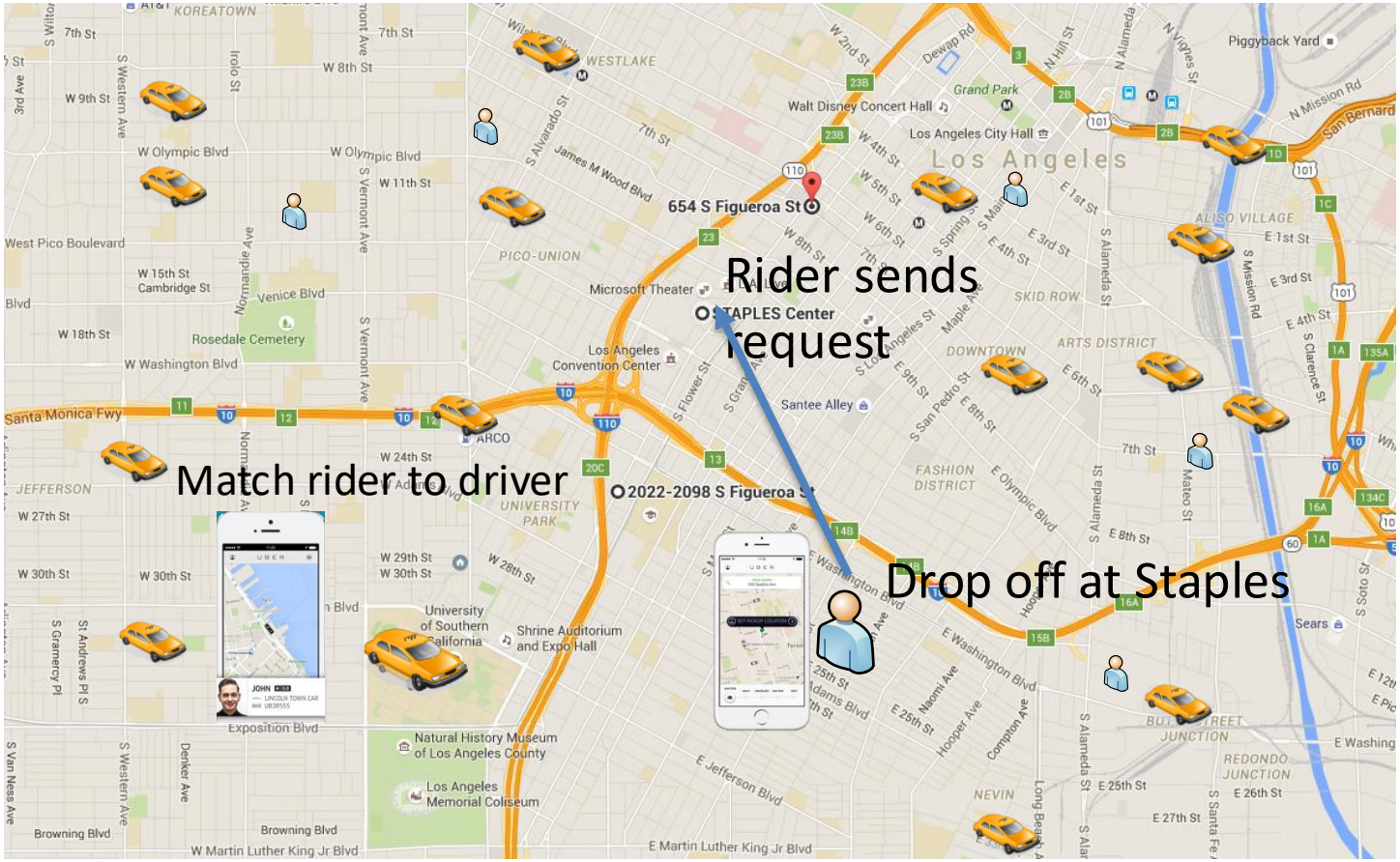
Running time on SYN-SKEW



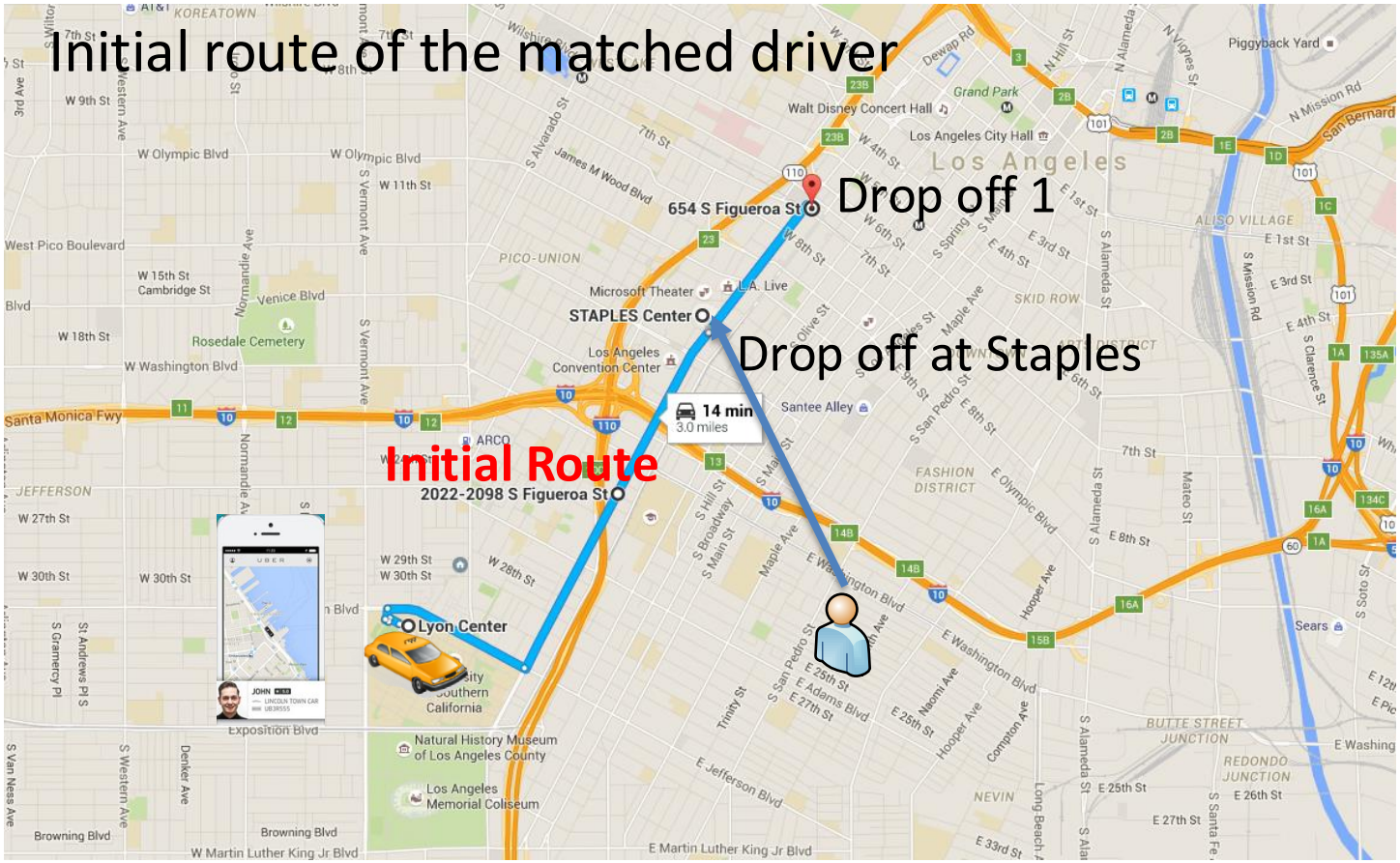
OUTLINE

- Motivation
- Task Assignment
- Task Scheduling
- Task Assignment & Scheduling
- Example Application

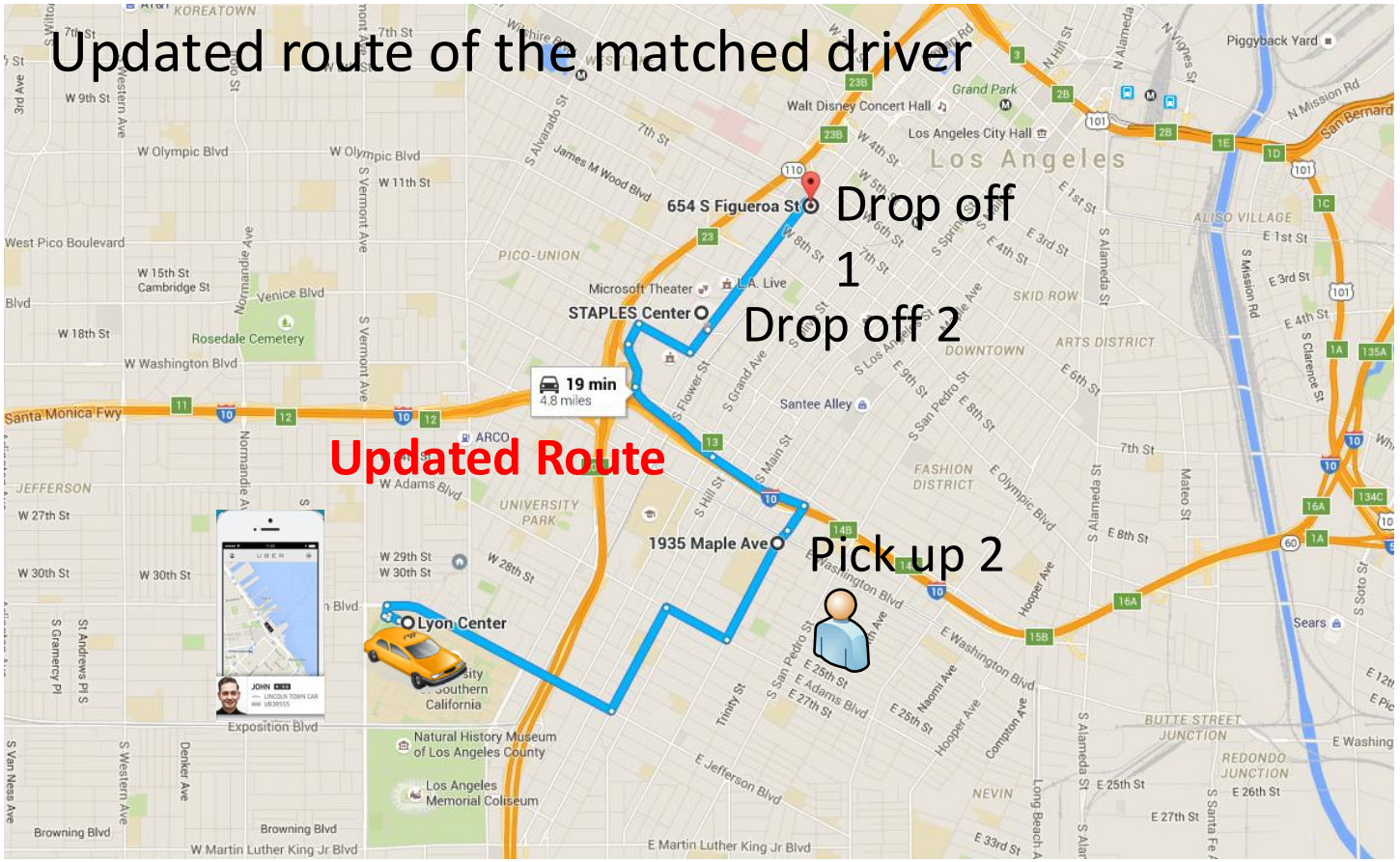
Ride Sharing



Ride Sharing



Ride Sharing



Background:
Dial-A-Ride Problem (OR)

- Given m vehicles at the depot and n requests with pickup and delivery time window
- Find m routes which minimizes the total routing cost
- Assumptions
  - Vehicles and request are known a priori
  - Off-line scheduling

Real-Time Ride-Matching at Scale

New Businesses

Scale

Large nu
riders &
Large network

Dynamism

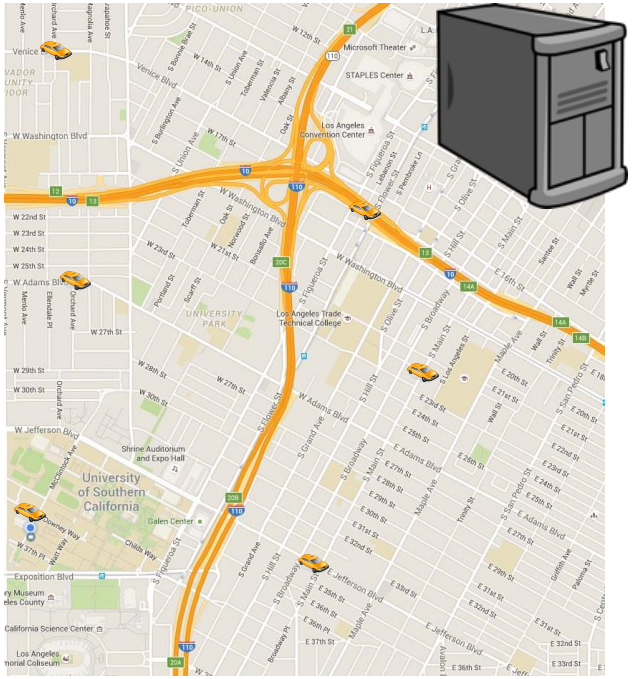
(time-dependent)

Response-Time

ne the
r and
update its route/schedule

Our Solution: Auction-based framework

Auction-Based Framework [SIGSPATIAL'16]



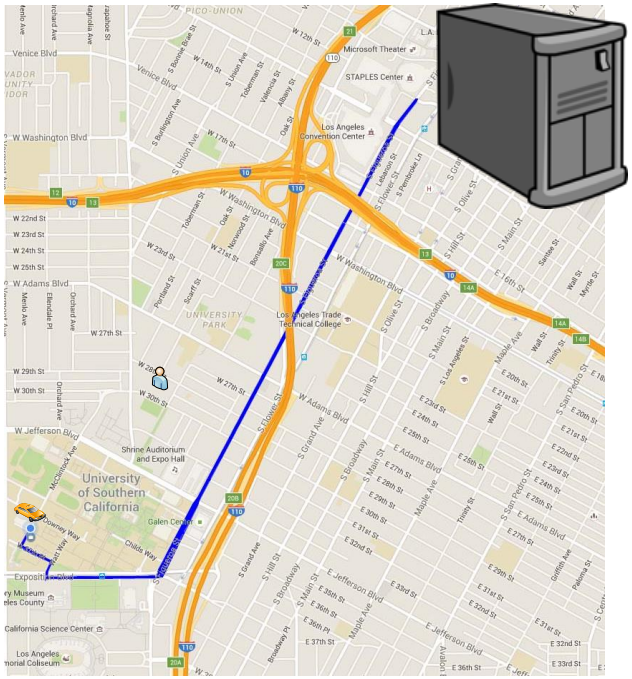
Auction-Based Framework

New ***request*** for LA Convention center

Auction-Based Framework

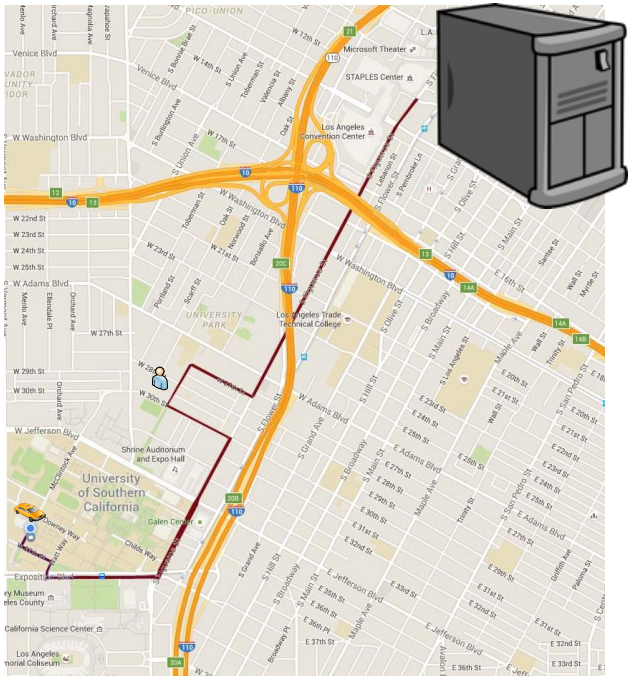
Send request to ***nearby*** drivers

Auction-Based Framework



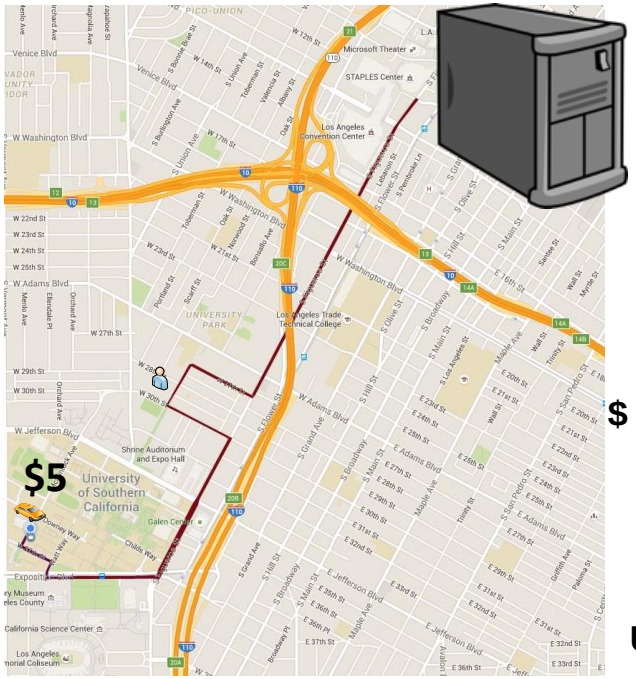
- Each driver has a ***current*** schedule

Auction-Based Framework

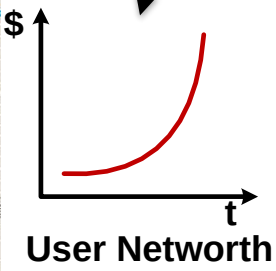


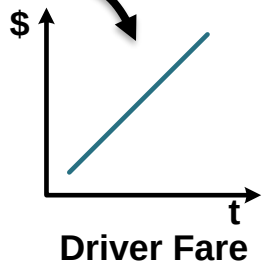
- Each driver has a ***current*** schedule
- Each driver computes a ***best potential*** schedule
- ***detour*** = *diff(**best potential**, **current**)*

Auction-Based Framework

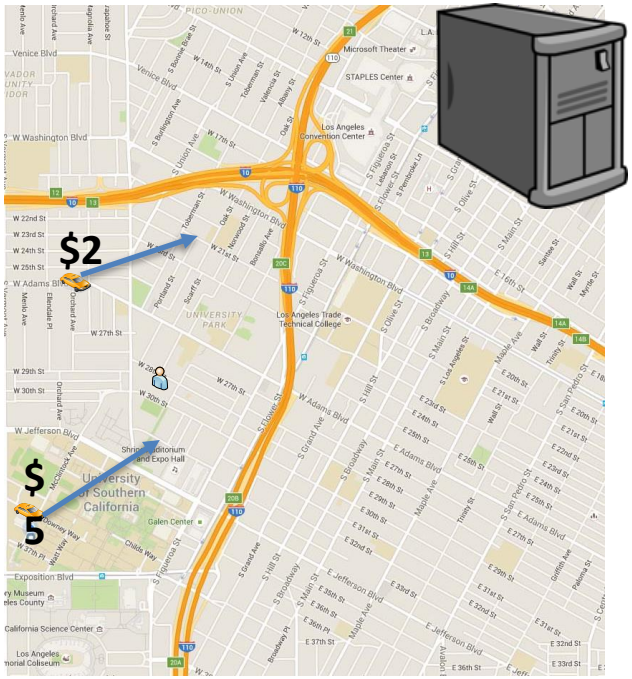


- Each driver has a ***current*** schedule
- Each driver computes a ***best potential*** schedule
- ***detour*** = *diff(**best potential**, **current**)*
- ***bid*** = *profit(**request, detour, user_networth, driver_fare**)*





Auction-Based Framework



A bid can be thought of as the “profit for Uber to add this ride”

Server receives bids from nearby drivers and assigns request to ***highest*** bidder.

Real-Time Ride-Matching at Scale

Our Solution: Auction-based framework

Scale

1. Local scheduling of a small number of riders per driver
2. Simple ranking across bids by the server

Dynamism

1. Bidding is triggered per rider's arrival
2. Local time-dependent routing per driver

Response-Time

In order of milliseconds (<300ms, interactive) per our preliminary experiments

Research Challenges in Spatial Crowdsourcing

Task assignment (or worker selection)

Process of identifying which tasks should be assigned to which workers

- **Asghari et al. SIGSPATIAL 2016**
- Bessai and Charoy ISCRAM ‘16
- Hassan and Curry ESA’16
- Zhang et al. TVT ’16
- Gao et al. WAIM ’16
- Cheng et al. TKDE ‘16
- Tong et al. VLDB ‘16
- Liu et al. DASFAA ‘16
- Hu et al. ICDE ’16
- Tong et al. ICDE’16
- Zhang et al. WCMC ‘16
- Liu et al. UbiComp ‘16
- Guo et al. THMS ’16
- **To et al. PerCom ’16**
- **To et al. TSAS ’15**
- **Alfarrarjeh et al. MDM ’15**
- Fonteles et al. MoMM ‘15
- Hassan and Curry. SIGSPATIAL ’15
- Xiao et al. INFOCOM ’15
- Xiong et al. PerCom ‘15
- Pournajaf et al. ICCS ‘14
- Hassan and Curry. UCI’14
- He et al. INFOCOM ’14
- Fonteles et al. SIGSPATIAL ‘14
- Zhang et al. UbiComp ’14
- **Dang et al. iiWAS ‘13**
- **Kazemi and Shahabi. SIGSPATIAL ‘12**

Research Challenges in Spatial Crowdsourcing

Privacy-preserving task assignment

- **To et al. TMC '16**
- Zhang et al. CN '16
- Zhang et al. ATIS '15
- Shen et al. GLOBECOM '15
- Gong et al. IoT'15
- Gong et al. TETC'15
- Hu et al. APWeb '15
- Pournajaf et al. MDM'14, SIGSPATIAL'15
- **To et al. VLDB '14, ICDE '15**
- Boutsis and Kalogeraki PerCom '13
- Vu et al. INFOCOM '12
- **Kazemi and Shahabi SIGKDD '11**

Task scheduling

Path planning for workers to perform tasks

- Wang et al. 2016
- Fonteles et al. JLBS '16
- **Deng et al. GeoInformatica '16**
- Mrazovic et al. ICDMW '15
- Chen et al. IJCAI '15
- Chen et al. AAMAS '15
- Hadano et al. HCOMP '15
- **Deng et al. SIGSPATIAL '15**
- Chen et al. HCOMP '14
- **Deng and Shahabi. SIGSPATIAL '13**

Research Challenges in Spatial Crowdsourcing

Trust and Quality

Consider quality of the report data or trustworthiness of workers

- Liu et al. Sensor '16
- Zhang et al. TETC '16
- Miao et al. DSS '16
- Fan et al. SOSE '15
- Shah-Mansouri et al. ICC '15
- An et al. HPCC '15
- Kang et al. MASS '15
- Cheng et al. VLDB '15
- Zhao et al. MDM '15
- Wang et al. UbiComp '15
- Song et al. TVT '14
- Boutsis et al. ICDCS '14
- Feng et al. INFOCOM '14
- **Kazemi et al. SIGSPATIAL '13**

Incentive mechanism

Incentivize workers to perform spatial tasks

- Zhang et al. TVT '16
- Kandappu et al. CSCW '16
- Kandappu et al. UbiComp '16
- Micholia et al. IJHCS '16
- **To et al. GeoRich '16**
- Li and Cao TMC '16
- Thebault-Spieker et al. CSCW '15
- Jin et al. MobiHoc '15
- Teodoro et al. CSCW '14
- Rula et al. HotMobile '14
- Musthag et al. CHI '13
- Heimerl et al. CHI '12
- Jainmes et al. PerCom '12
- Yang et al. MobiCom '12
- Lee and Hoh PMC '10
- Alt et al. NordiCHI '10

Research Challenges in Spatial Crowdsourcing

Generic frameworks

Discuss components, architecture, programming framework of SC apps

- **To et al. CROWDBENCH '16**
- Fonteles et al. RCIS '16
- Peng et al. ASE '16
- Kucherbaev et al. SIGCHI '16
- Sakamoto et al. COMPSAC '16
- Fernando et al. MOBIQUITOUS '13
- Tamilin et al. UbiComp '12
- Ra et al. MobiSys '12
- Yan et al. SenSys '09

Related surveys

- Pournajaf et al. SIGMOD '15
- Guo et al. Comp Survey '15
- Zhao and Han 2016
- Christin JSS '15

Applications

- Konomi and Sasao Urb-IoT '16
- Jaiman et al. UbiComp/ISWC '16
- Fan and Tseng MOBIS '15
- Konomi and Sasao UbiComp/ISWC '15
- Harburg et al. CHI '15
- Chen et al. SenSys '15
- Kim CHI '15
- Aubry et al. CROWDSENSING '14
- Chen et al. VLDB '14
- **Kim et al. MMSys'14**
- Benouaret et al. IEEE IC '13
- Coric and Gruteser DCOSS '13
- Koukoumidis et al. MobiSys '11
- Goodchild and Glennon IJDE '10