A Framework for Protecting Worker Location Privacy in Spatial Crowdsourcing

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Motivation

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://mobithinking.com/mobile-marketing-tools/latest-mobile-stats/

Spatial Crowdsourcing

- Crowdsourcing
  - Outsourcing a set of tasks to a set of workers

amazon mechanical turk™
Artificial Artificial Intelligence

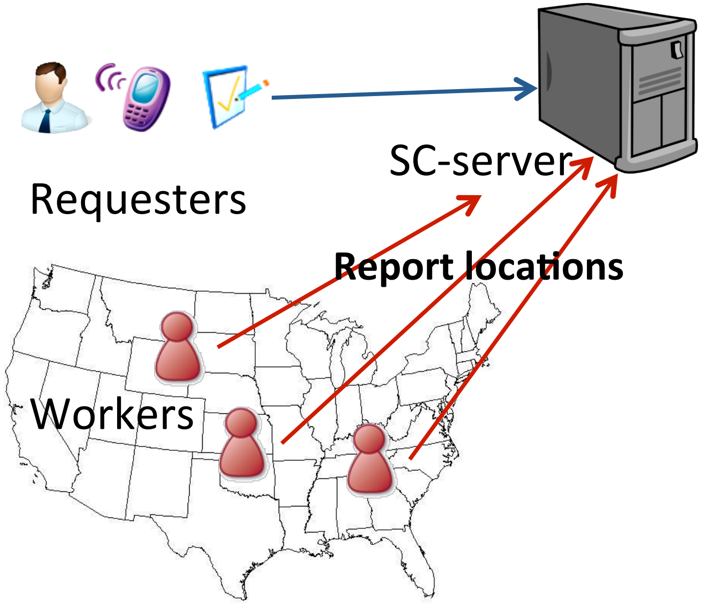
- Spatial Crowdsourcing
  - Crowdsourcing a set of *spatial* tasks to a set of workers.
  - *Spatial* task is related to a location .e.g., taking pictures

taskrabbit

Location privacy is one of the major impediments that may hinder workers from participation in SC

Problem Statement

Current solutions require the workers to disclose their locations to untrustworthy entities, i.e., SC-server.

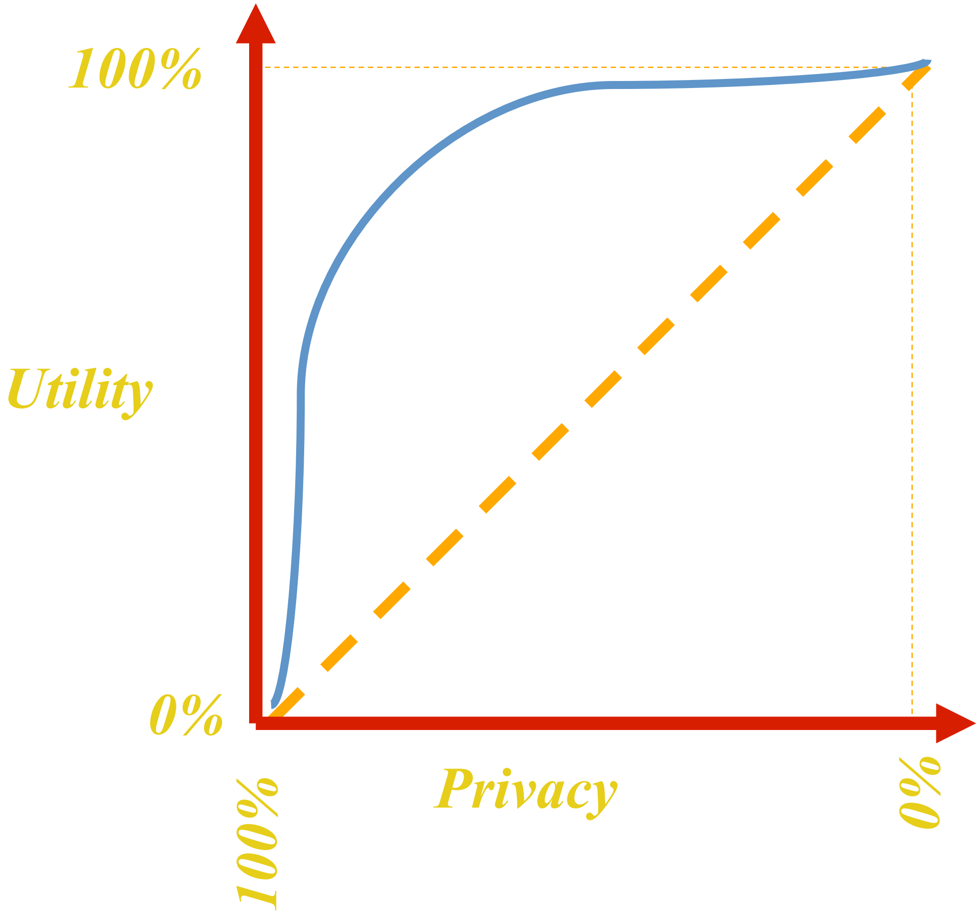


A framework for protecting privacy of worker locations, whereby the SC-server only has access to data sanitized according to *differential privacy.*

Outline

- **Background**
- Privacy Framework
- Worker PSD (Private Spatial Decomposition)
- Task Assignment
- Experiments

Utility-Privacy Trade-off



Related Work

- Pseudonymity (using fake identity)
  - e.g. fake identity + location == resident of the home
- K-anonymity model (not distinguish among other k records)

  identities are known

  the location k-anonymity fails to prevent the location of a subject being not identifiable

  all k users reside in the exact same location

  k-anonymity, do not provide rigorous privacy
- Cryptography

  such technique is *computational expensive*

=>not suitable for SC applications

Differential Privacy (DP)

DP ensures an adversary do not know from the sanitized data whether an individual is present or not in the original data

$\mathcal{E}$-***distinguishability*** *[Dwork'06]*

A database produces transcript *U* on a set of queries. Transcript *U* satisfies $\mathcal{E}$-distinguishability if for every pair of sibling datasets D_1 and D_2, $|D_1| = |D_2|$ and they differ in only one record, it holds that

ε : *privacy budget*

$$\ln \frac{\Pr[QS^{D_1} = U]}{\Pr[QS^{D_2} = U]} \leq \varepsilon$$

DP allows only aggregate queries, e.g., count, sum.

L_1 -**sensitivity**:

Given neighboring datasets D_1 and D_2 , the sensitivity of query set *QS* is the the maximum change in their query results

$$\sigma(QS) = \max_{D_1, D_2} \sum_{i=1}^{q} | QS(D_1) - QS(D_2) |$$

[Dwork'06] shows that it is sufficient to achieve $\mathcal{E}$-*DP* by adding random Laplace noise with mean $\lambda = \sigma(QS) / \varepsilon$

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Privacy Framework

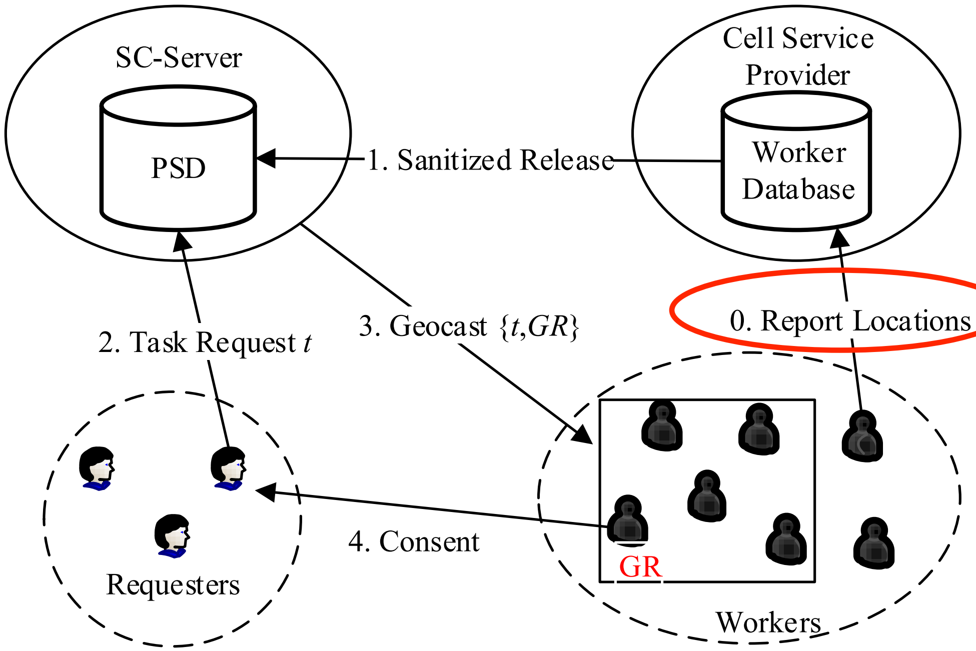
0. Workers send their locations to a trusted CSP

1. CSP releases a PSD according to ε . PSD is accessed by SC-server

2. SC-server receives tasks from requesters

3. When *SC-server* receives task *t*, it queries the PSD to determine a *GR* that enclose sufficient workers. Then, *SC-server* initializes geocast communication to disseminate *t* to all workers within *GR*

4. Workers confirm their availability to perform the assigned task



Workers trust SCP

Workers do not trust SC-server and requesters

Focus on *private task assignment* rather than post assignment

Design Goal and Performance Metrics

Protecting worker location may reduce the effectiveness and efficiency of worker-task matching, captured by following metrics:

Assignment Success Rate (ASR): measures the ratio of tasks accepted by workers to the total number of task requests

Worker Travel Distance (WTD): the average travel distance of all workers

System Overhead: the average number of notified workers (***ANW***). *ANW* affects both *communication overhead* required to geocast task requests and the *computation overhead* of matching algorithm

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Adaptive Grid (Worker PSD)

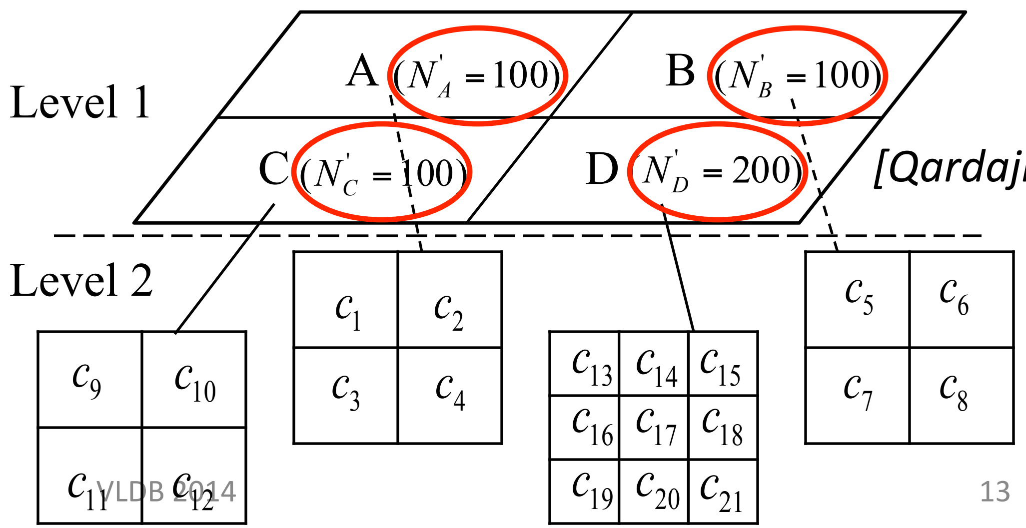
Creates a coarse-grained, fixed size $m_1 \times m_1$ grid over data domain. Then issues m_1^2 count queries for each level-1 cell using ε_1

$$m_1 = \max\left(10, \left\lceil \frac{1}{4}\sqrt{\frac{N \times \varepsilon}{k_2}} \right\rceil\right)$$

Partitions each level-1 cell into $m_2 \times m_2$ level-2 cells, m_2 is adaptively chosen based on noisy count N' of level-1 cell

$$m_2 = \left\lceil \frac{1}{4}\sqrt{\frac{N' \times \varepsilon_2}{k_2}} \right\rceil$$

$$\varepsilon = \varepsilon_1 + \varepsilon_2$$



[Qardaji'13]

Customized AG

Expected #workers (noisy count) in level-2 cells $\bar{n} = N' / m_2^{\ 2} = k_2 / \varepsilon_2$

large $\bar{n}$ leads to high communication cost

$N' = 100$

ε	ε_2	m_2	$\bar{n}$
1	0.5	3	**11**
0.5	0.25	2	**25**
0.1	0.05	1	**100**

☹ **Original AG** $(k_2 = 5)$

ε	ε_2	m_2	$\bar{n}$
1	0.5	6	**2.8**
0.5	0.25	5	**5.6**
0.1	0.05	2	**28**

☺ **Customized AG** $(k_2 = \sqrt{2}, p_h = 88\%)$

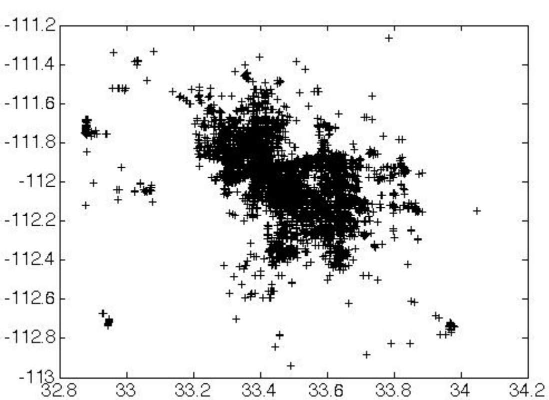
Increase m_2 to decrease overhead, but only to the point where there is at least one worker in a cell

The probability that the real count is larger than zero:

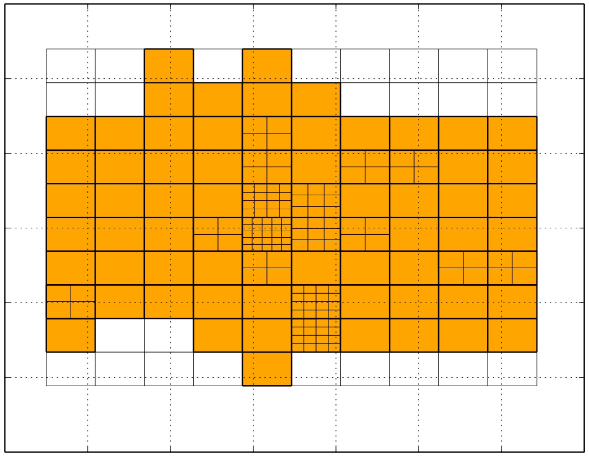
$$p_h = 1 - \frac{1}{2}\exp\left(-\frac{count_{PSD}}{1/\varepsilon_2}\right)$$

Customized AG

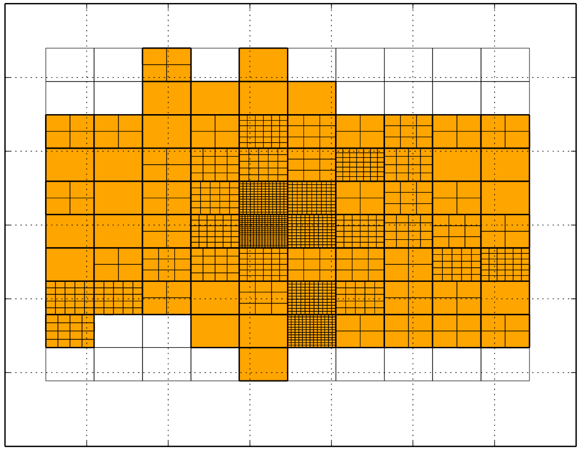
- Original AG and Customized AG adapts to data distributions
- Original AG minimizes overall estimation error of region queries while customized AG increases the number of 2nd level cells



Yelp Dataset



Original AG



Customized AG

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Analytical Utility Model

We define *Acceptance Rate* as a decreasing function of task-worker distance (e.g. *linear, Zipian*)

$$p^a = F(d); 0 \le p^a \le 1$$

SC-server establishes an *Expected Utility (EU)* threshold, which is the targeted success rate for a task. $EU > p^a$.

X is a random variable for an event that a worker accepts a received task

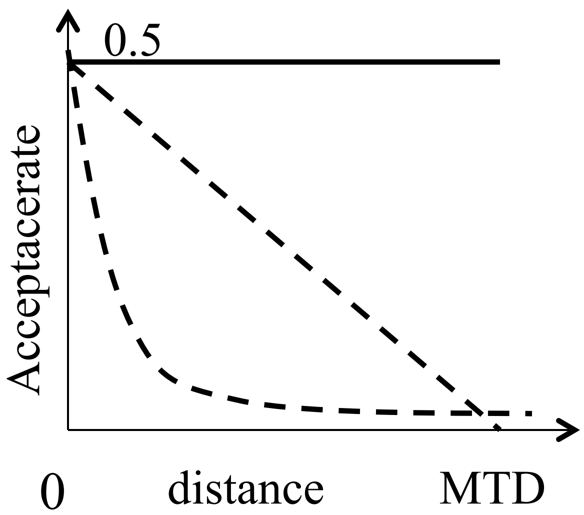
$$P(X = True) = p^a; P(X = False) = 1 - p^a$$

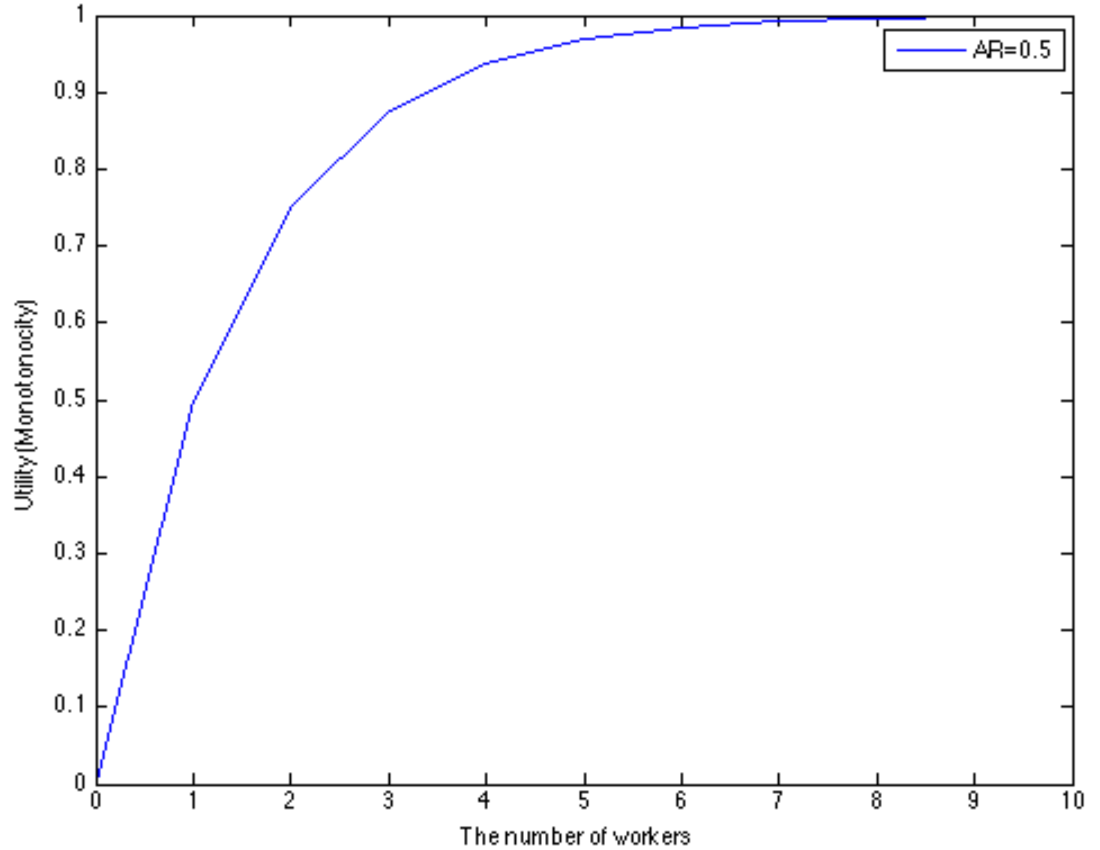
Assuming w independent workers. U is the probability that at least one worker accepts the task

$$X \sim Binomial(w, p_a)$$

$$\Rightarrow U = 1 - (1 - p^a)^w$$

Acceptance Rate Functions





Geocast Region Construction

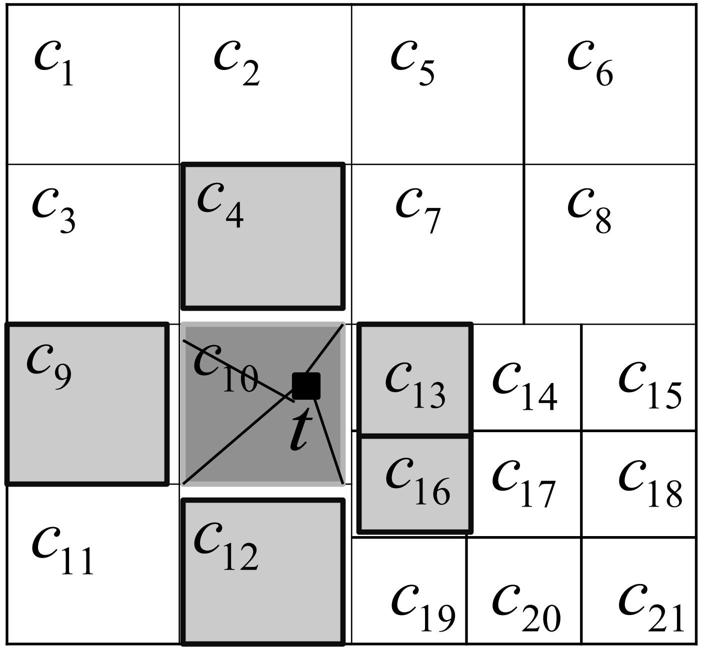
Determines a *small* region that contains *sufficient* workers

Greedy Algorithm (GDY)

1. Init *GR* = {}, *max-heap* Q of candidates

   Q = { the cell that contains t }

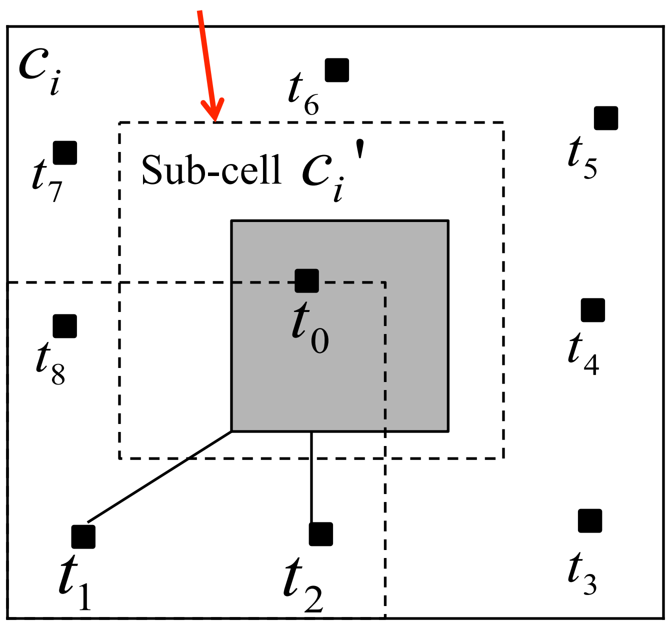
2. $c_i \leftarrow Q$
3. $U \leftarrow 1-(1-U)(1-U_{c_i})$
4. If $U \geq EU$, return *GR*
5. $neighbors = \{c_i\text{'s } neighbors\} - GR \cap MTD$
6. $Q = Q \cup neighbors$; *Go to 2.*



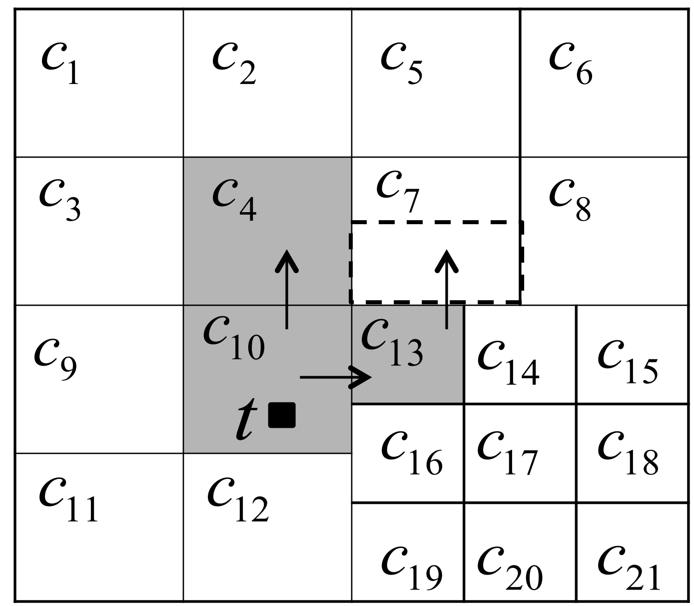
Partial Cell Selection

☹ The number of workers can still be large with AG, especially when ε_2 small

Allow ***partial cell inclusion*** on the lastly added cell c_i



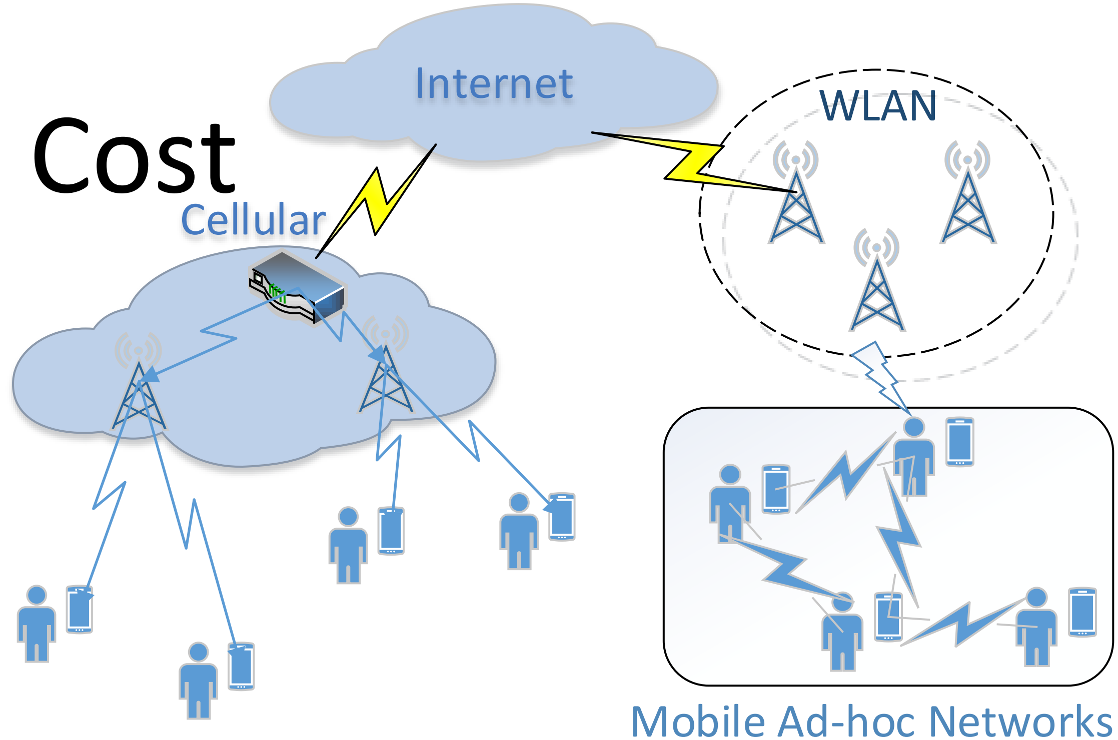
Splitting c_i



Splitting c_7

Communication Cost

The more ***compact*** the *GR*,
the lower the cost



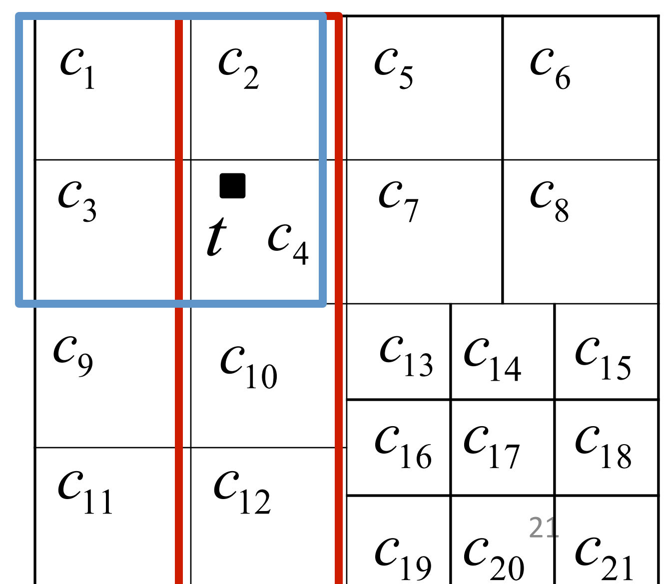
Infrastructure-based Mode v.s Infrastructure-less Mode

Digital Compactness Measurement [Kim'84]

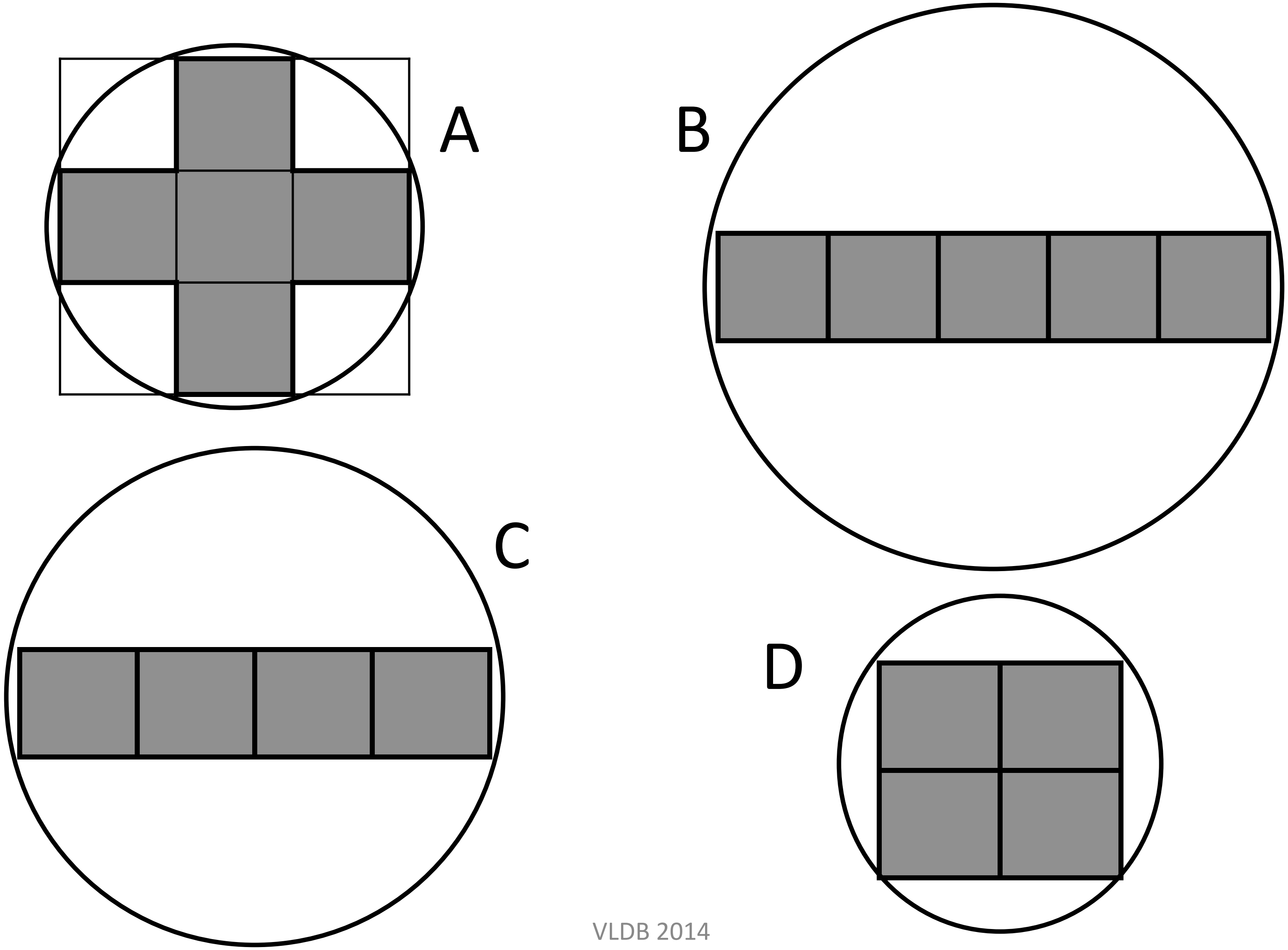
$$DCM = \frac{area(GR)}{area(MIN\ BALL)}$$

Measurement:

$$Hop\ count = \frac{\text{Farthest distance between two workers}}{2 \times Communication\ range}$$



Geocast Regions



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Experimental Setup

- Datasets

Name	#Tasks	#Workers	MTD (km)
Gowalla	151,075	6,160	3.6
Yelp	15,583	70,817	13.5

- Assumptions
  - Gowalla and Yelp users are workers
  - Check-in points (i.e., of restaurants) are task locations
- Parameter settings $\varepsilon = \{0.1, 0.4, 0.7, 1\}$

$$EU = \{0.3, 0.5, 0.7, 0.9\}$$

$$MaxAR = \{0.1, 0.4, 0.7, 1\}$$

- 1000 random tasks x 10 seeds

GR Construction Heuristics (Gow.-Linear)

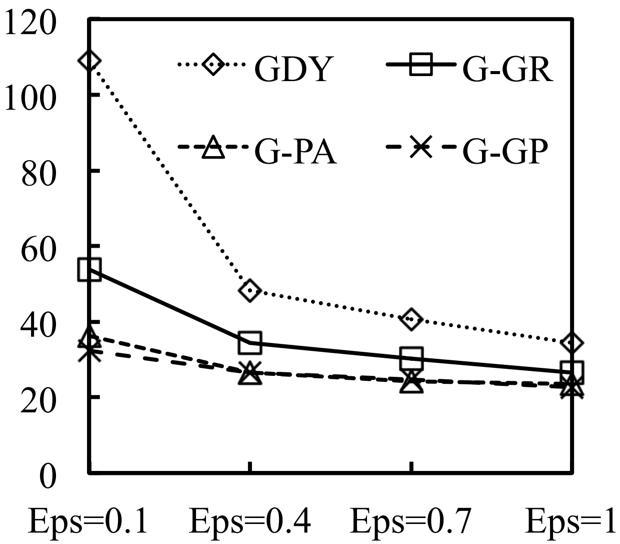
GDY = geocast (GREedy algorithm) + original Adaptive grid (AG) *[Qardaji'13]*

G-GR = geocast + AG with customized GRanularity

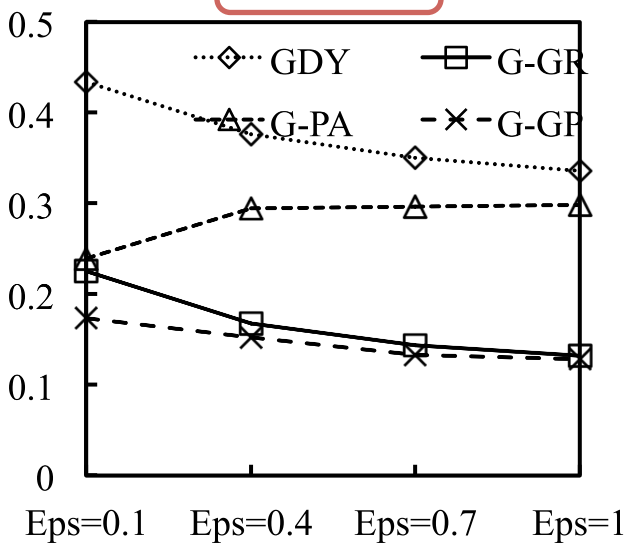
G-PA = geocast with PArtial cell selection + original Adaptive grid (AG)

G-GP = geocast with Partial cell selection + AG with customized Granularity

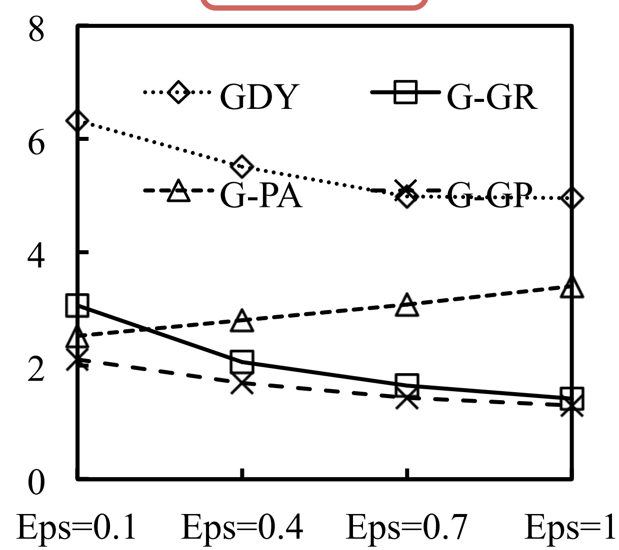
ANW



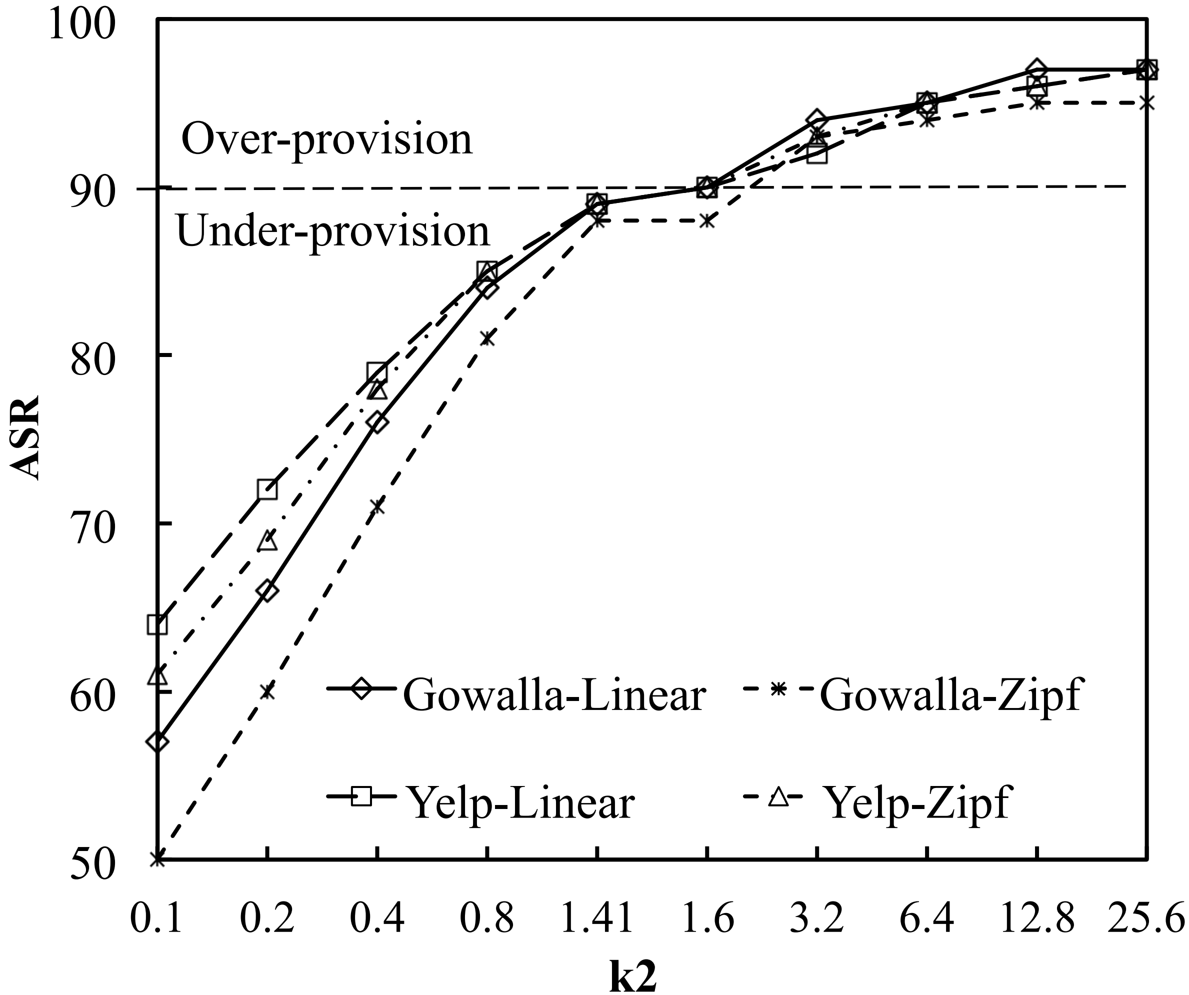
WTD-FC



HOP

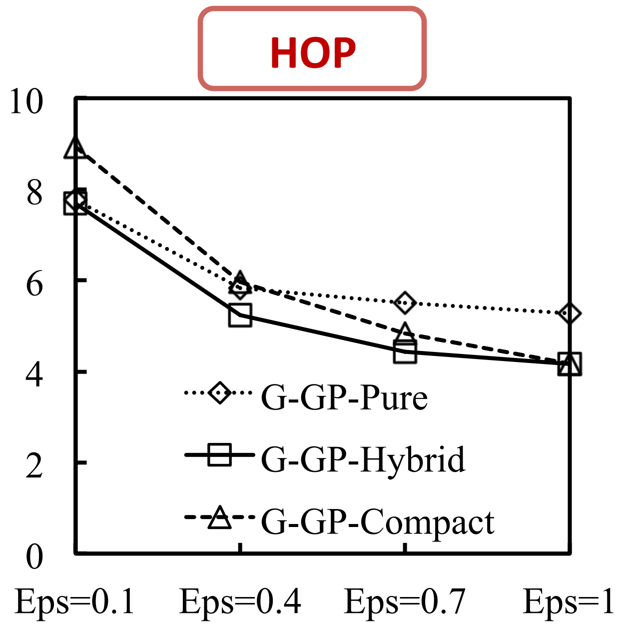


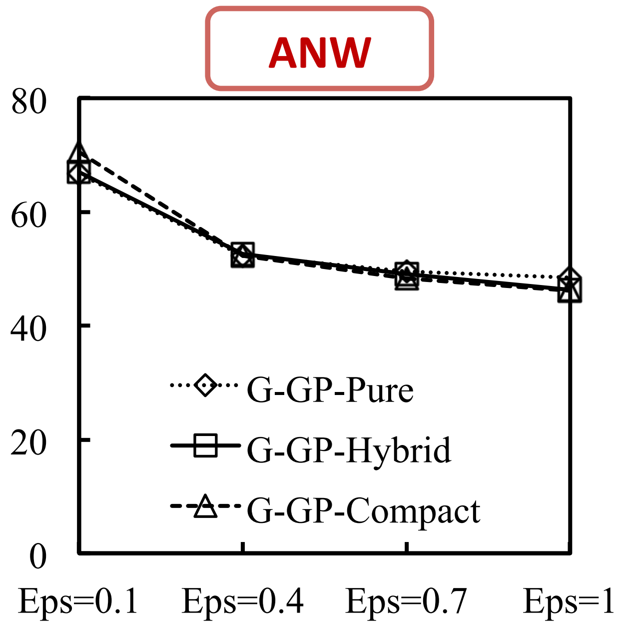
Effect of Grid Size to ASR



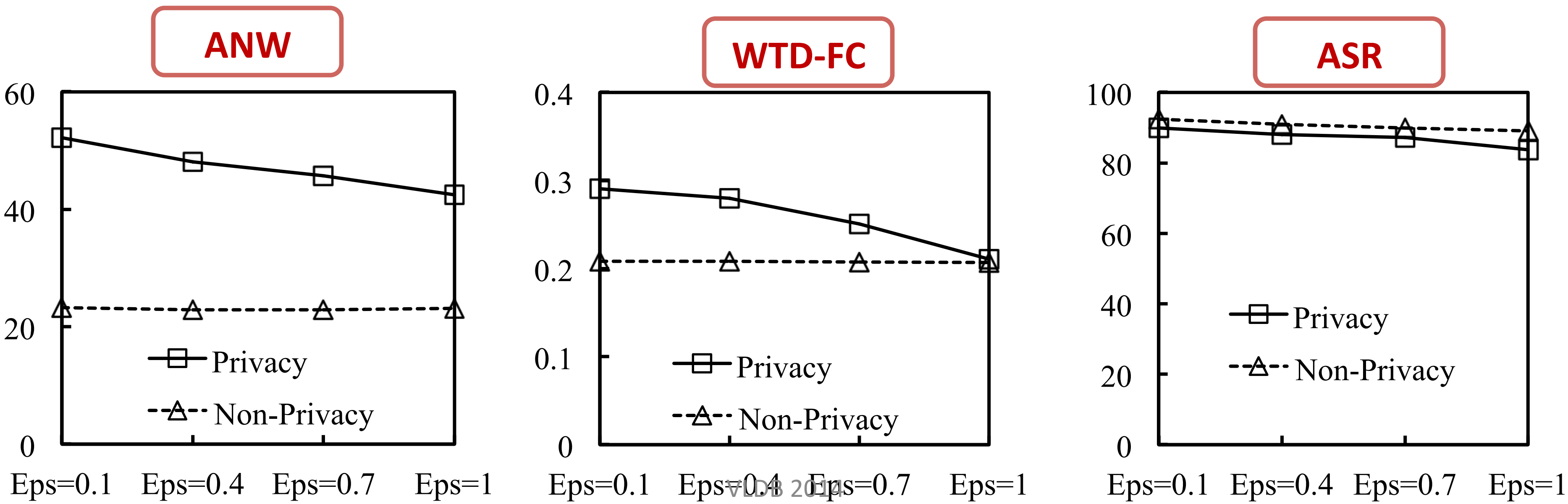
Average ASR over all values of budget by varying k2

Compactness-based Heuristics (Yelp-Zipf)

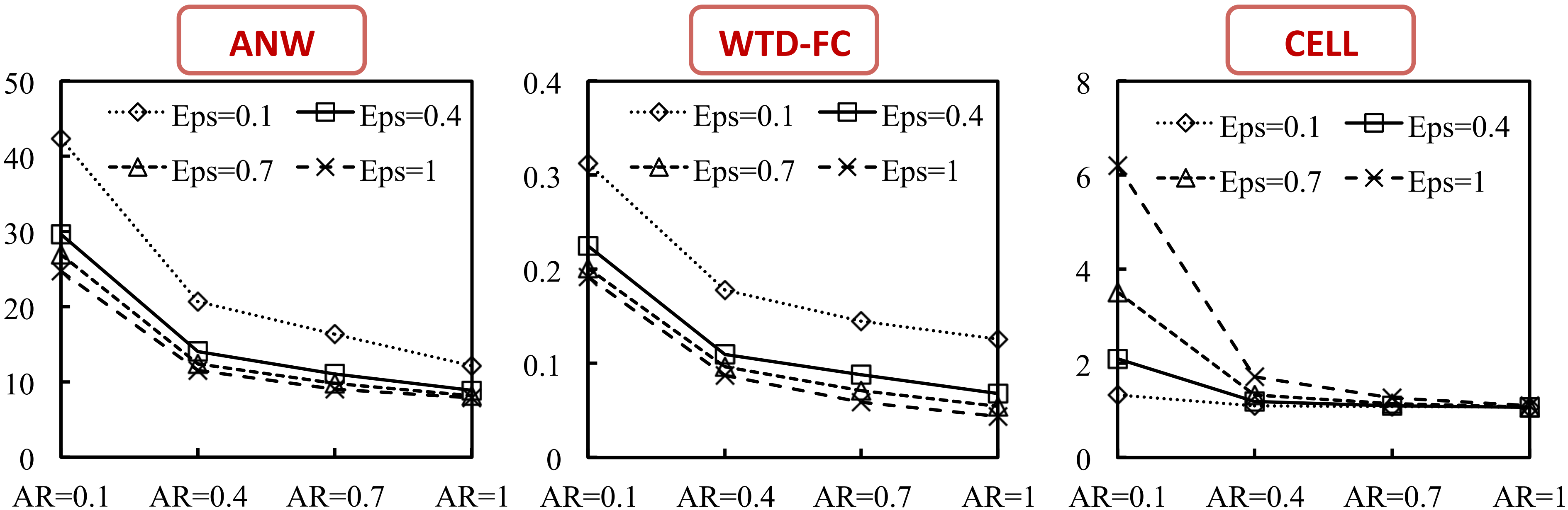




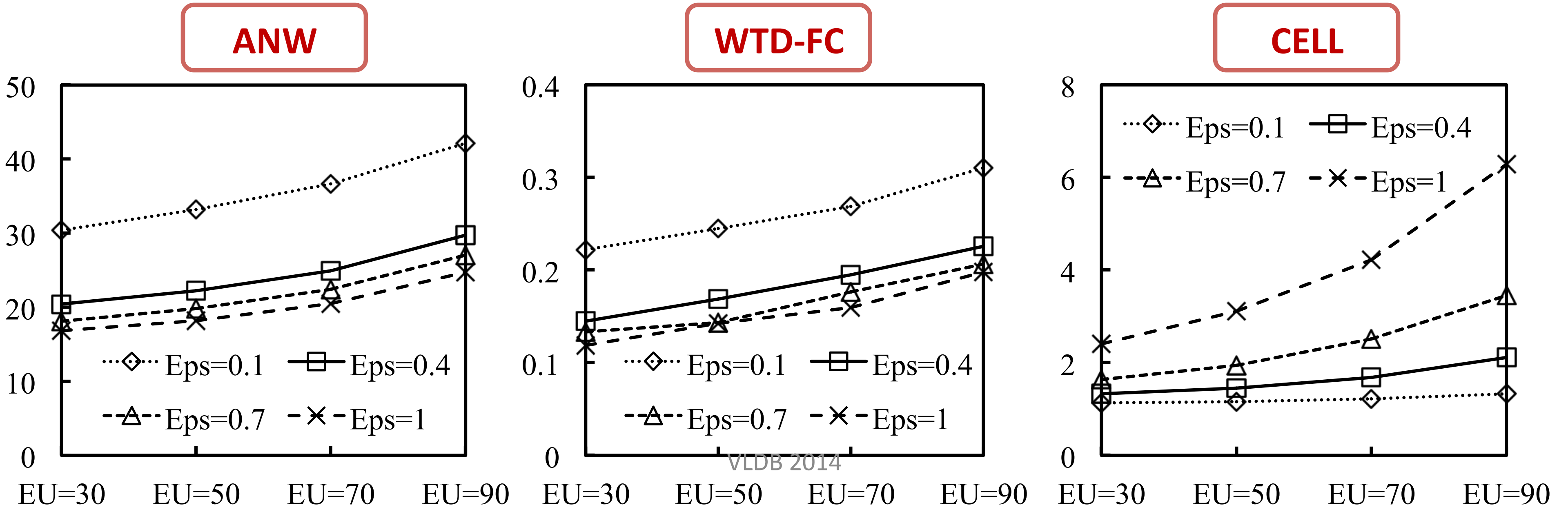
Overhead of Archieving Privacy (Gow.-Zipf)



Effect of Varying MAR (Yelp-Linear)

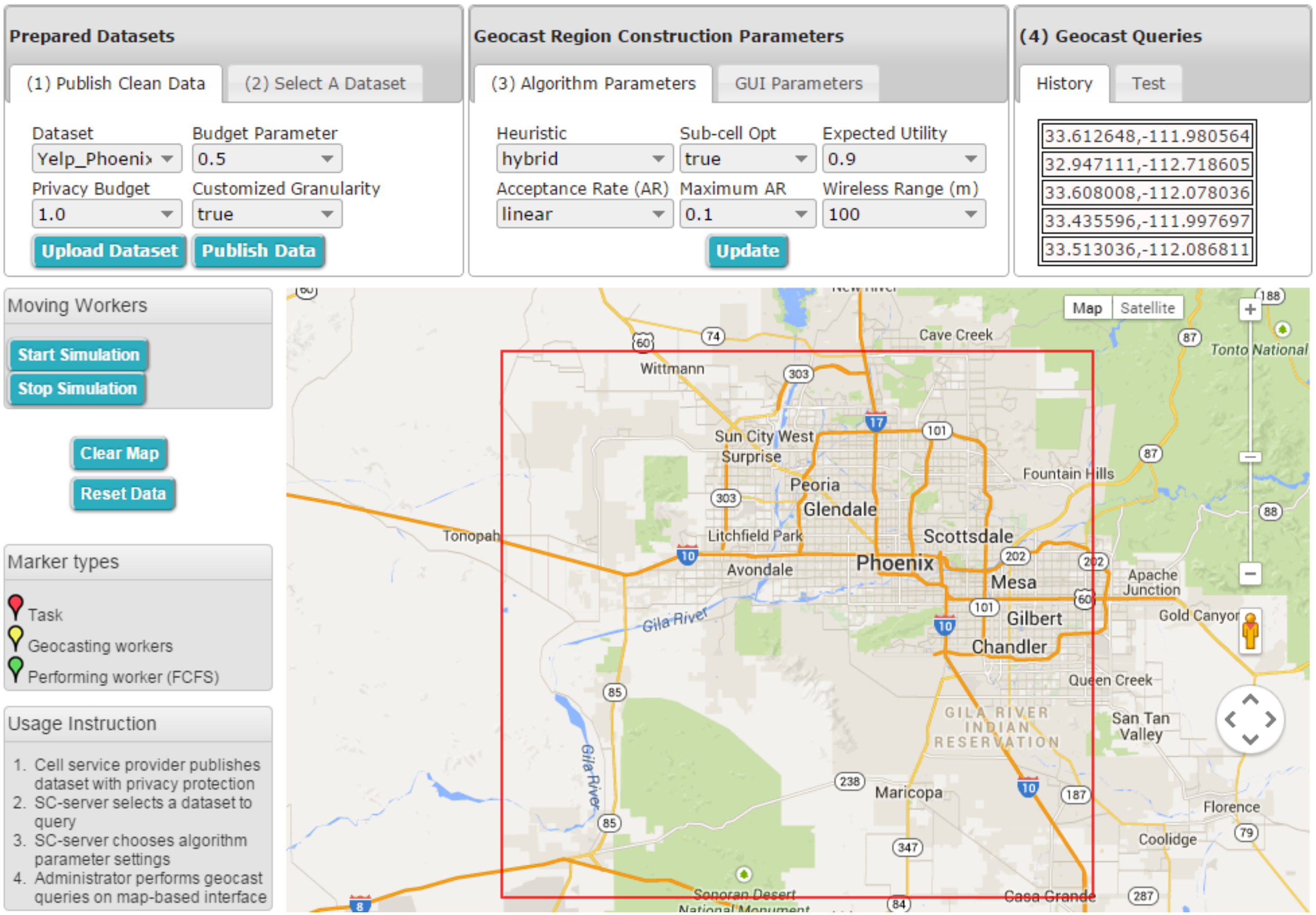


Effect of Varying EU (Yelp-Linear)



Demo

http://geocast.azurewebsites.net/geocast/



https://www.youtube.com/watch?v=4zkiJ9gk79s

Conclusion

Introduced a novel privacy-aware framework in SC, which enables workers participation without compromising their location privacy

Identified geocasting as a needed step to preseve privacy prior to workers consenting to a task

Provided heuristics and optimizations for determining effective geocast regions that achieve high assignment success rate with low overhead

Experimental results on real datasets shows that the proposed techniques are effective and the cost of privacy is practical

References

Hien To, Gabriel Ghinita, Cyrus Shahabi. *A Framework for Protecting Worker Location Privacy in Spatial Crowdsourcing.* In Proceedings of the 40th International Conference on Very Large Data Bases (VLDB 2014)

Hien To, Gabriel Ghinita, Cyrus Shahabi. *PriGeoCrowd: A Toolbox for Private Spatial Crowdsourcing.* (demo) In Proceedings of the 31st IEEE International Conference on Data Engineering (ICDE 2015)