A Privacy-Preserving Order Dispatch Scheme for Ride-Hailing Services

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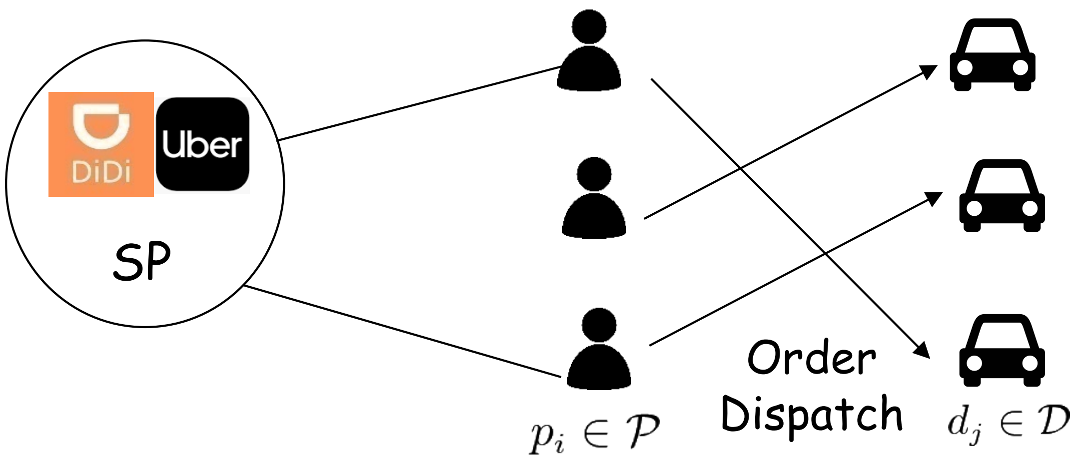
1. Introduction

- Ride-hailing system
  - Service Provider (SP): Uber and Didi
  - Order dispatch: matching passengers (P) and drivers (D)

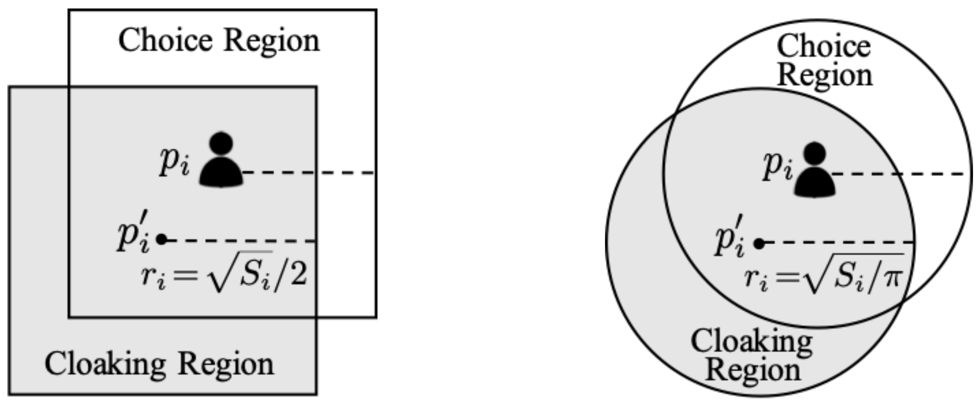


- Privacy concerns
  - Passenger locations are exposed to the SP
  - SP could infer passengers' habits [1].

[1] Shokri, R., Theodorakopoulos, G., Le Boudec, J. Y., and Hubaux, J. P., Quantifying Location Privacy (IEEE SSP '11)

Motivation

- Cloaking region S_i (for privacy protection)
  - Passenger p_i sends a fake location p_i' to SP
  - SP cannot infer passenger's exact location in S_i

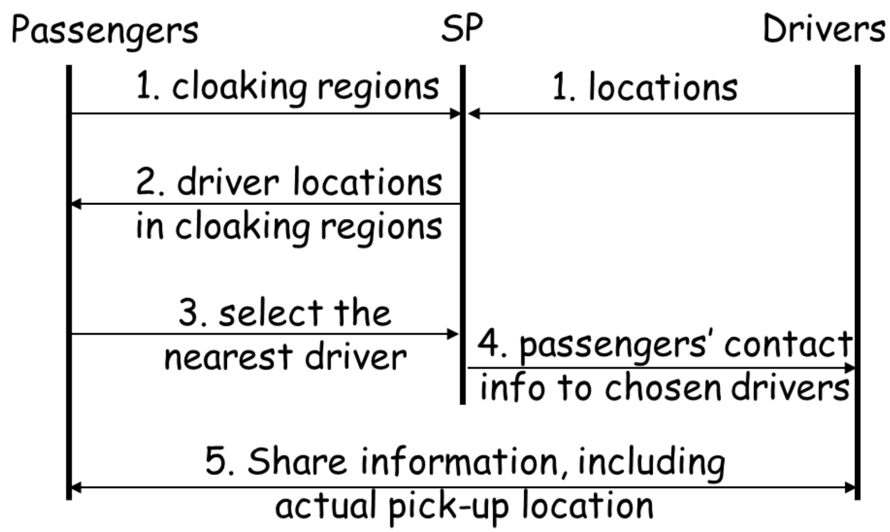


- How to perform order dispatch (for different S_i)?
  - Let passengers choose the nearest driver [2], or
  - Let SP match in a centralized manner (this paper)

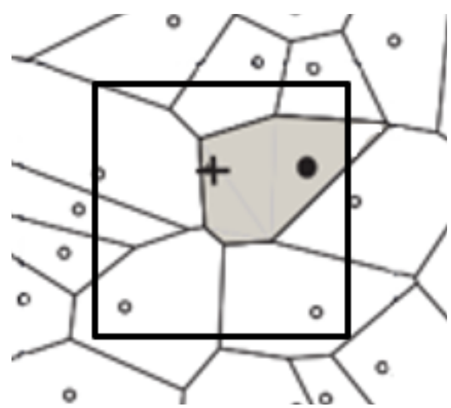
[2] Khazbak, Y., Fan, J., Zhu, S. and Cao, G., Preserving location privacy in ride-hailing service (IEEE CNS'18)

Privacy Attack

- Passenger choosing [2]



- Attack model [2]
  - Voronoi graph:

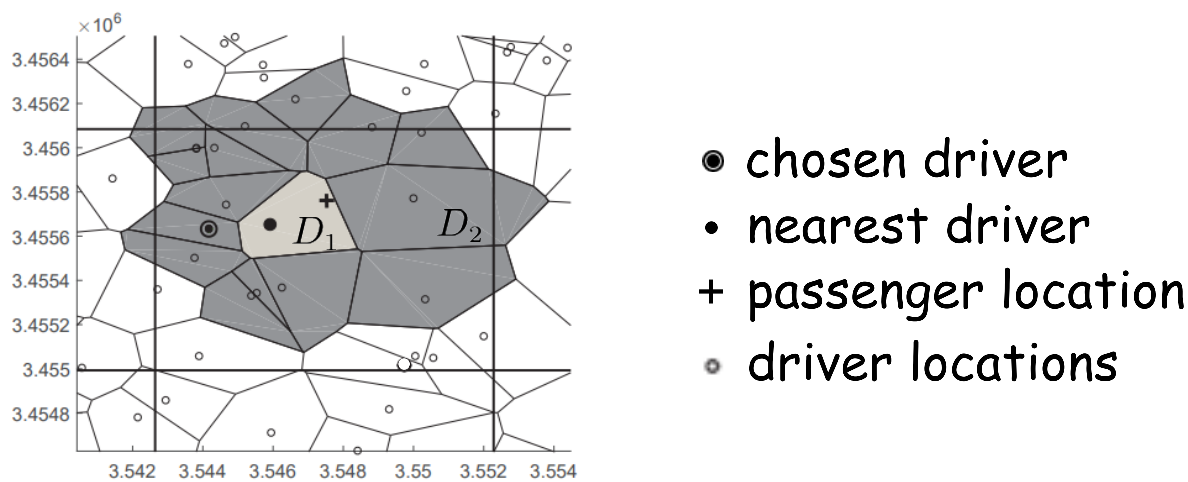


• nearest driver
+ passenger location
∘ driver locations

[2] Khazbak, Y., Fan, J., Zhu, S. and Cao, G., Preserving location privacy in ride-hailing service (IEEE CNS'18)

Preventing Privacy Attack

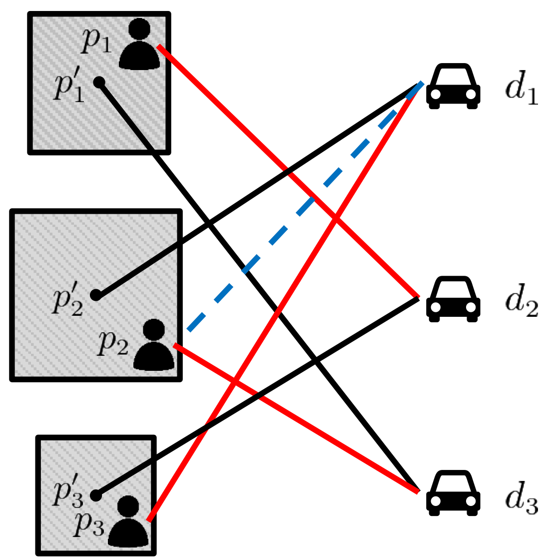
- A probabilistic mechanism [2]
  - Form and sort driver set D with *k* nearest drivers
  - Partition D into D_1 and D_2 based on distance
  - Pick a driver from D_1 (D_2) with a higher (lower) probability
- Guarantee privacy (based on prior probabilities)[2]
  - Problem: not optimize pick-up distances, locally nor globally



[2] Khazbak, Y., Fan, J., Zhu, S. and Cao, G., Preserving location privacy in ride-hailing service (IEEE CNS'18)

Our Approach

- Optimize social welfare
  - Minimize the total pick-up distance (bipartite matching)
- Performance loss
  - Travel fares + privacy fares – discount



Pick-up distance by matching : blue (based on p’) > red (based on p)

2. Social Welfare Optimization

- Social welfare: - $dis(p_i, d_j)$ (negation of pick-up distance)
- Privacy requirement: $|S_i|$

$$\boxed{\max \quad W = -x_{ij} dis(p_i, d_j)}$$

Maximize social welfare

$$\text{s.t.} \quad \sum_{d_j} x_{ij} = 1, x_{ij} \in \{0, 1\}, \forall p_i$$

All passengers matched

$$\sum_{p_i} x_{ij} \leq 1, x_{ij} \in \{0, 1\}, \forall d_j$$

Not all drivers matched

$$\|p_i - p_i'\|_\infty \leq \sqrt{S_i}/2, \forall p_i$$

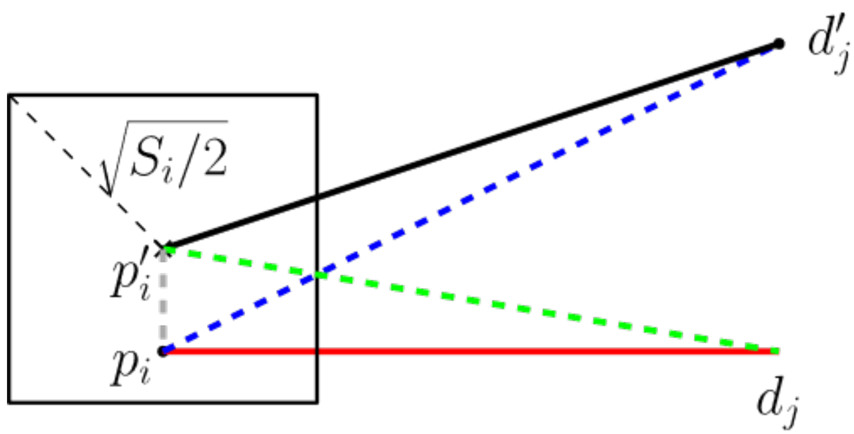
Privacy constraint

Bounded Performance Loss

Theorem: actual pick-up distance

$$\sum_{p_i} \text{blue} \leq \sum_{p_i} (\text{red} + \sqrt{2S_i})$$

- Proof sketch



Optimality of bipartite matching:

$$\sum_{p_i} \text{black} \leq \sum_{p_i} \text{green}$$

Triangle inequality:

$$\sum_{p_i} \text{blue} \leq \sum_{p_i} (\text{black} + \text{grey})$$

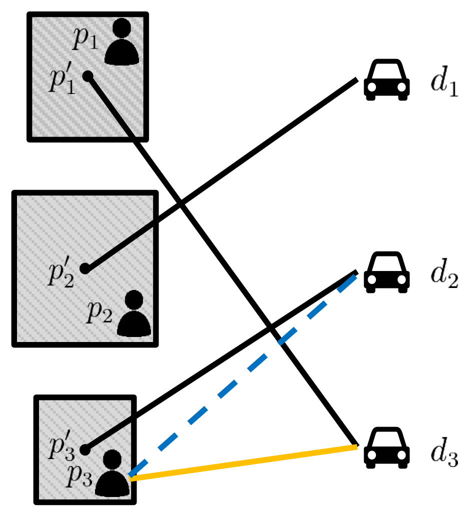
$$\sum_{p_i} \text{green} \leq \sum_{p_i} (\text{red} + \text{grey})$$

Combining:

$$\sum_{p_i} \text{blue} \leq \sum_{p_i} (\text{red} + 2\text{grey})$$

3. Discount Allocation

- Profit distribution
  - SP
  - Drivers in D (global)
  - Passengers in P (local + global)

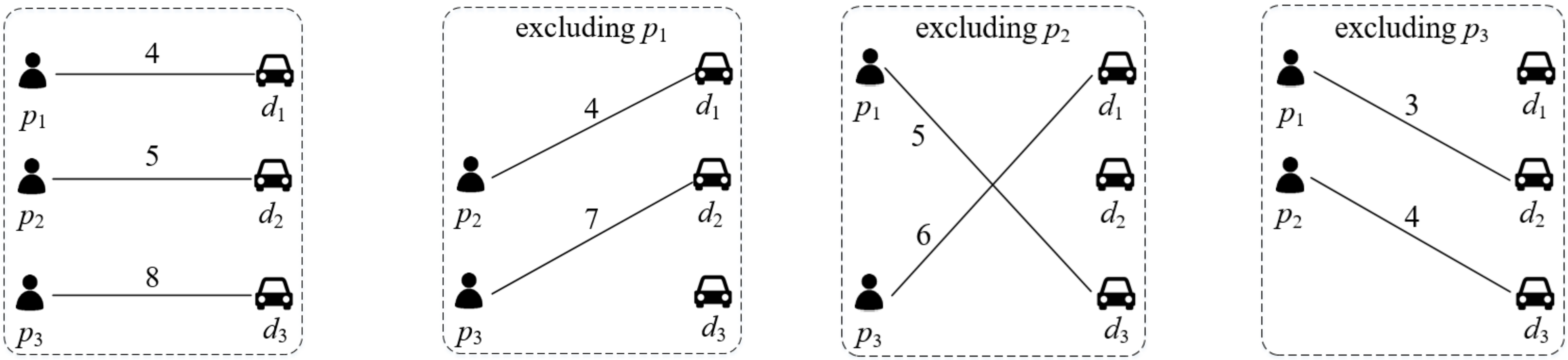


- Local distance loss (for P)
  - The difference between actual pick-up and nearest distance
  - p_3 local loss: blue line – yellow line (nearest)
- Global social welfare loss (for a party in P or D)
  - The difference between others' social welfare that includes and excludes this party [3]

[3] Krishna, V. and Motty, P., Efficient mechanism design (Available at SSRN 64934,1998).

Global Social Welfare Loss

Global social welfare (SW) loss for passengers/drivers based on VCG [3]



social welfare for p_2 and p_3 is -(5+8) = -13

social welfare for p_2 and p_3 is -(4+7) = -11

the SW loss of p_2 is -(5+6)-(-(4+8)) = 1

the SW loss of p_3 is -(3+4)-(-(4+5)) = 2

the SW loss of p_1 is the difference, i.e., -11-(-13) = 2

Passengers	Percentage
p_1	2/5
p_2	1/5
p_3	2/5

Drivers	Percentage
d_1	3/5
d_2	1/5
d_3	1/5

[3] Krishna, V. and Motty, P., Efficient mechanism design (Available at SSRN 64934,1998).

Discount Allocation Strategy

- For drivers in D
  - Discount is based on global social welfare (SW) loss

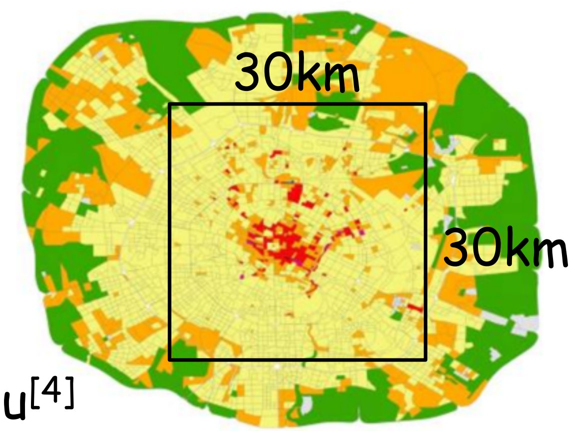
- For passengers in P
  1. Discount is based on global SW loss;
  2. Discount is based on local distance (LD) loss;
  3. Combine 1) and 2), i.e.,

$$\lambda \times LD + (1 - \lambda) \times SW$$

4. Experiment

- Synthetic and real-world dataset
  - Synthetic: p_i, d_j (uniform distribution)
  - Real-world (Didi passenger dataset):
    - p_i: Didi trace data in Chengdu; d_j : uniform distribution
  - Privacy settings: $S_i \sim \mathcal{N}(\mu, \mu/3)$ (normal distribution)
- Dataset statistics

Data Source	Didi's trajectory data
Time Span	11/1/2016 - 11/30/2016
Number of orders	691,269

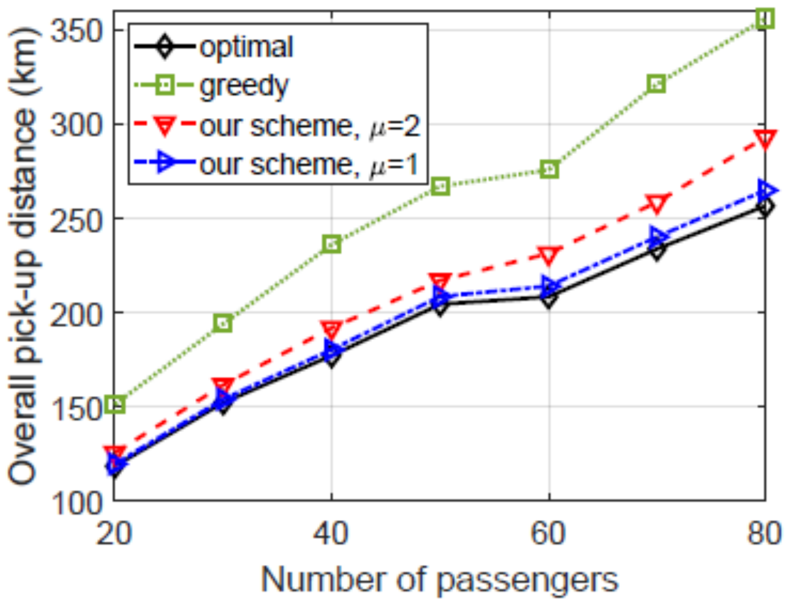


Chengdu[4]

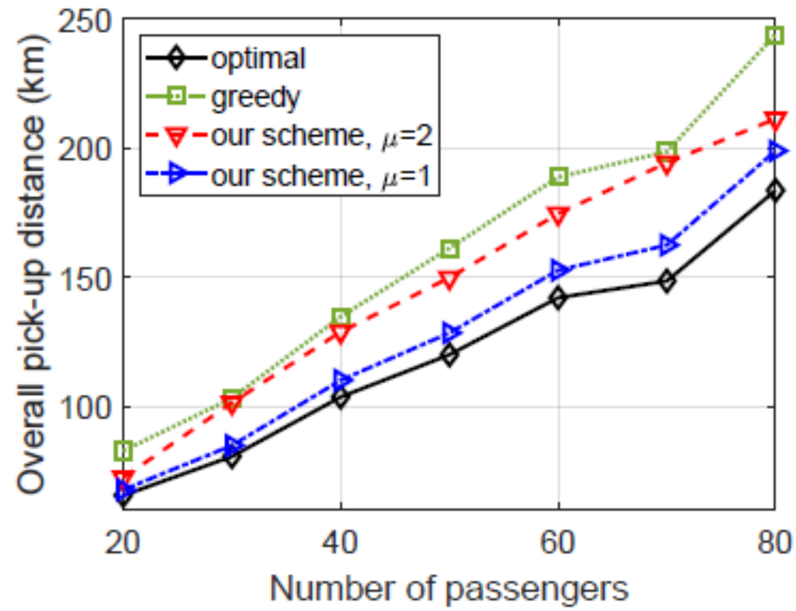
[4] Identification of urban regions' functions in Chengdu, China, based on vehicle trajectory data (NCBI)

Experiment Results

- Overall pick-up distance



Synthetic dataset

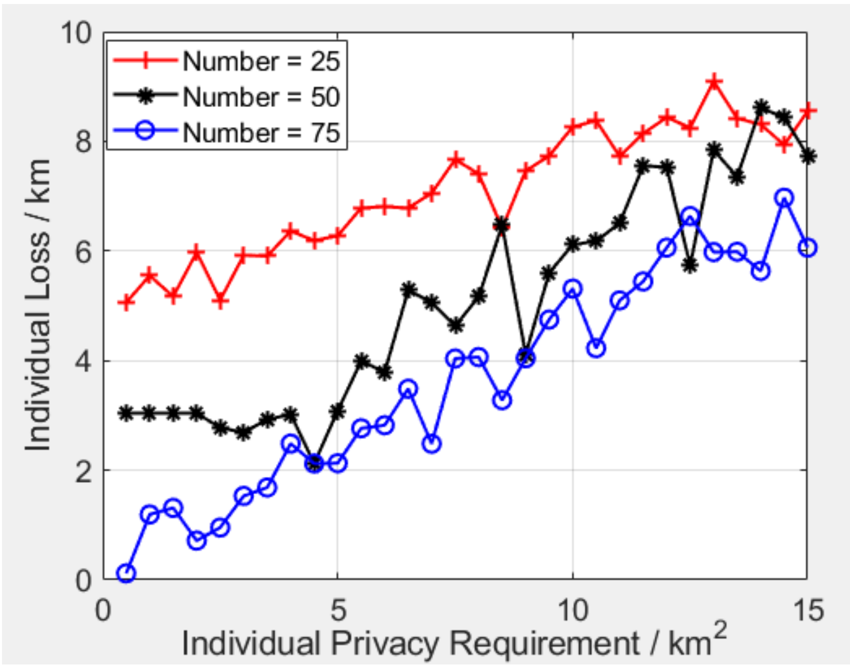


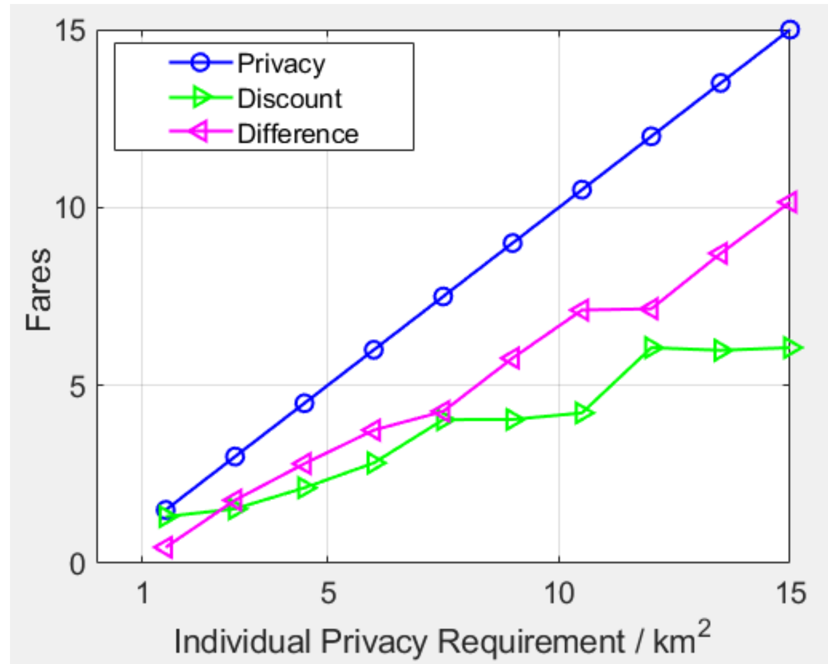
Didi passenger dataset

  - Greedy: each passenger greedily chooses the nearest driver
  - Optimal: SP matches based on real passenger & driver locations

Experiment Results (1)

- Impact of privacy requirement





settings: μ = 5 km for other passengers
with uniform distributions

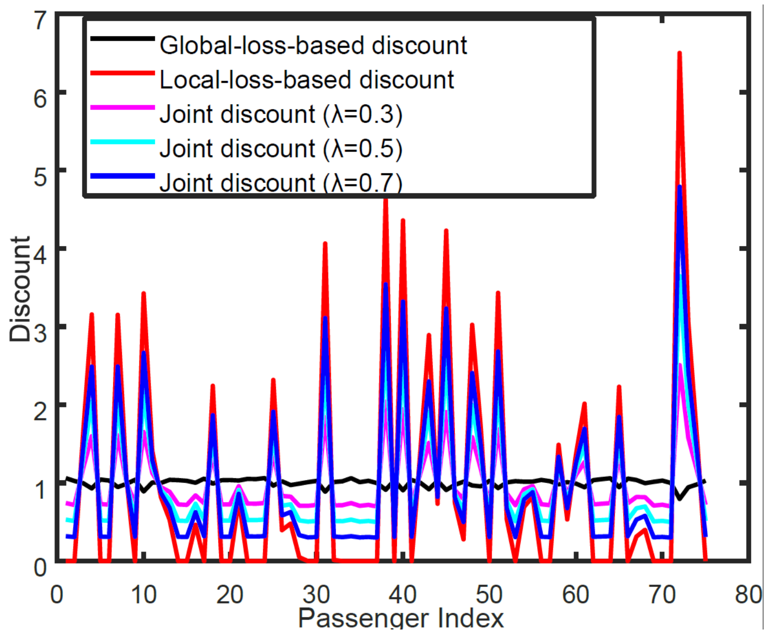
conclusion: the higher the privacy,
the more the local distance loss.

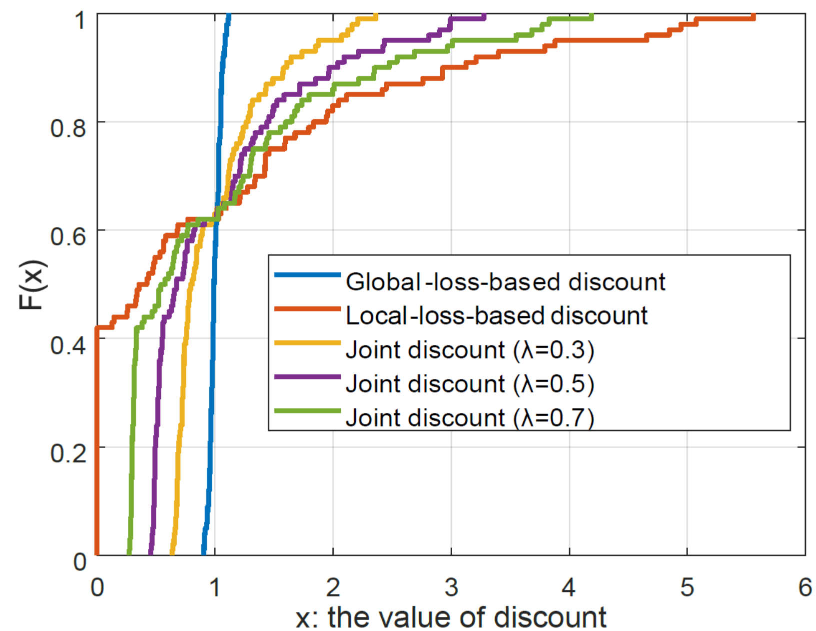
settings: Privacy: $|S_i|$
Difference = Privacy – Discount 2

conclusion: the higher the privacy,
the more the difference value.

Experiment Results (2)

- Evaluation on three discount allocation strategies





settings: number of passengers = 75, total distributed profits = 75, uniform distribution

conclusion: the values of global social welfare loss for all passengers are smoother than that of their local distance loss.

5. Summary

- Privacy-preserving order dispatch scheme
  - SP matches passengers and drivers with privacy requirement
- The trade-off between performance and privacy
  - Derive the bound of performance loss
  - Propose to allocate discounts to make up the loss
- Experiments on real-world/synthetic datasets
  - Show the matching performance with different settings
  - Evaluate the fares and discount with different settings

Thank you

Q & A