Demand-Aware Route Planning for Shared Mobility Services

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Outline

- Motivation
- Problem Formulation
- Algorithms
- Evaluations

Background

Development of ***shared*** mobility.

- Food delivery
- Ridesharing
- Crowdsourced parcel delivery

Online platforms for shared mobility

- Cainiao
- Meituan
- Uber
- Didi
- …

Route Planning for Shared Mobility

- A **large** amount of **dynamically** arriving requests

- A **large** amount of workers

Route Planning for Shared Mobility

- A **large** amount of possible route allowing share

- **Limited** response time

Route Planning for Shared Mobility

- **Large** amount of **dynamically** arriving requests
- **Large** a
- **Large** a … e
- **Limited** response time

effective / efficient
route planning strategy

Keep the Balance of Demand-Supply

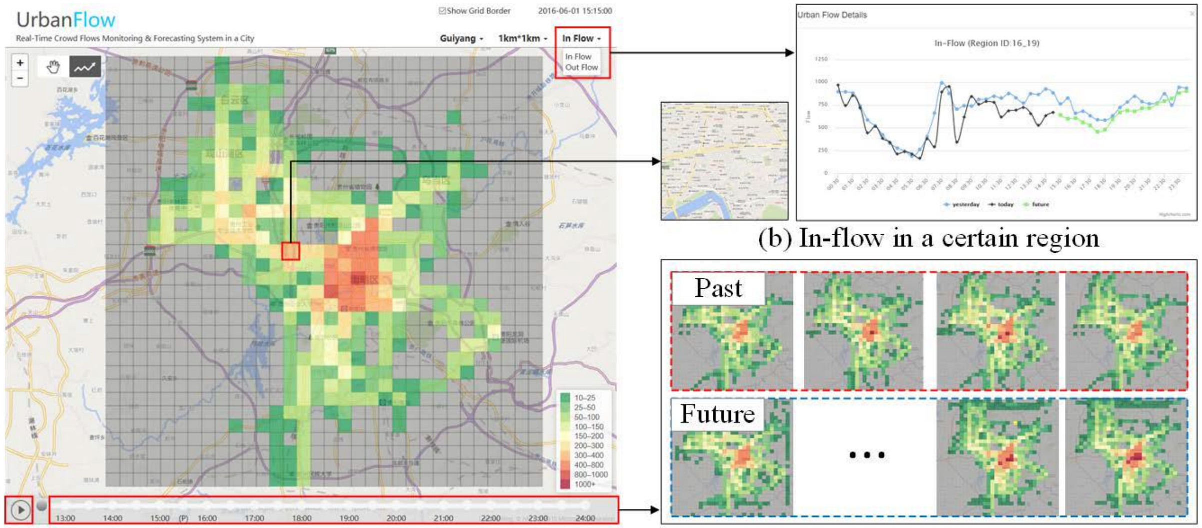
Great profit loss from ***unmatched*** distribution of ***demand*** and ***supply***

- **Rush hour** **(ridesharing)**
  - Morning: rural areas → center of the city
  - Evening: center of the city → rural areas

- **Lunch and supper time** **(food delivery)**
  - Tons of orders sent to business central

Prediction of Demand

Derive demands in different areas/timesteps accurately using **spatiotemporal** prediction. (e.g. DeepST*)



(a) User interface of UrbanFlow

(b) In-flow in a certain region

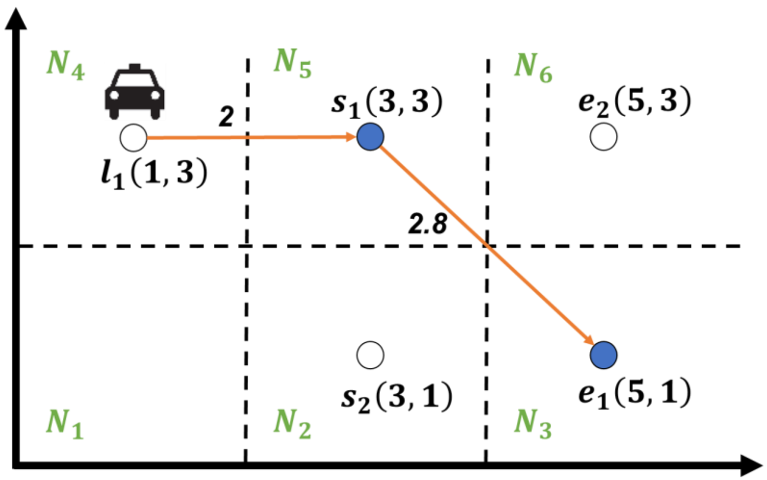
(c) Heatmaps in past & future

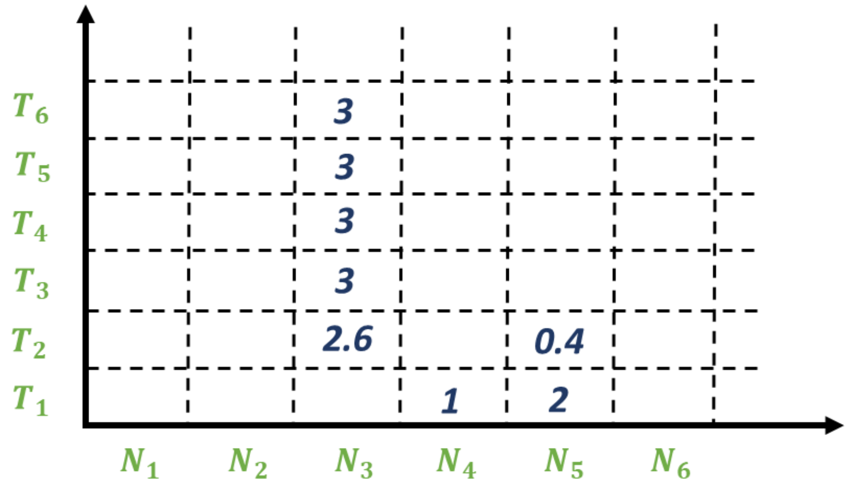
*Figure is Provided by Junbo Zhang

How to use it to benefit route planning for shared mobility?

Supply Organization

In each **area** and **time span**, a larger total **time duration** of workers leads to a higher probability to serve a request.



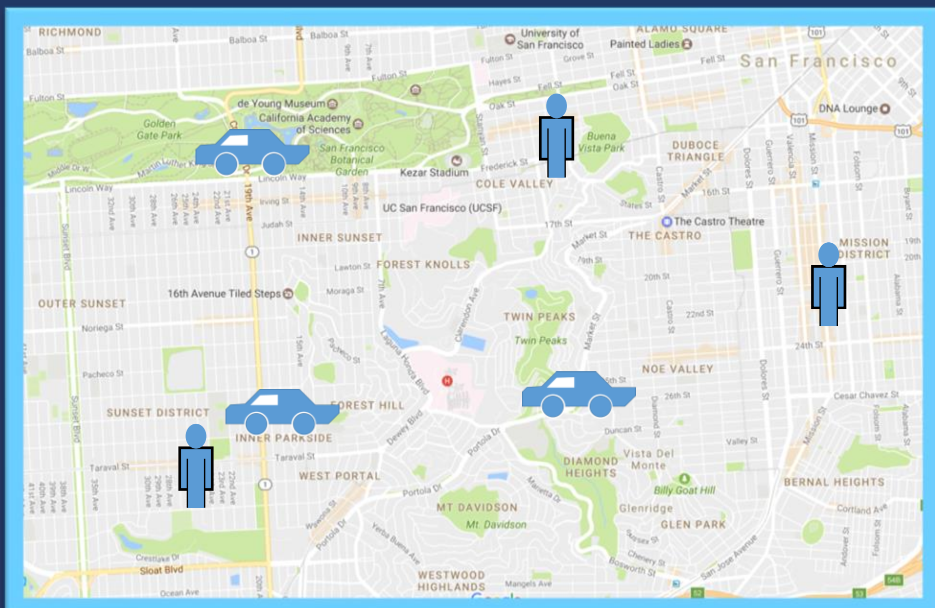


Different **route planning** strategy

→ → Different **distribution of supply**

Organize **supply** according to **demand** to maximize profit.

Motivation



Design an algorithm to **improve the effectiveness** of *route planning* for shared mobility through:

Evaluating the effect of **supply** during route planning based on **demand**.

The **overall profit** of the platform is **improved**.

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Workers and Requests

Workers

$$W = \{w_1, w_2, \dots, w_n\}$$

w_i

- current location l_i
- capacity a_i

Requests

$$R = \{r_1, r_2, \dots, r_m\}$$

r_j

- start/end loc. s_j/e_j
- release time tr_j
- deadline td_j
- rejection penalty p_j
- capacity a_j

Workers and Requests

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Workers and Requests

Workers

$$W = \{w_1, w_2, \dots, w_n\}$$

Requests

$$R = \{r_1, r_2, \dots, r_m\}$$

Route S_i, a sequence of s_j / e_j

w_i Planning routes to serve requests. r_j

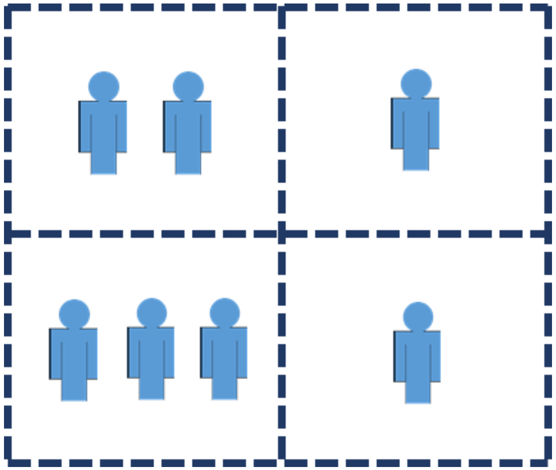
Existing work* handles the **distance** related cost.

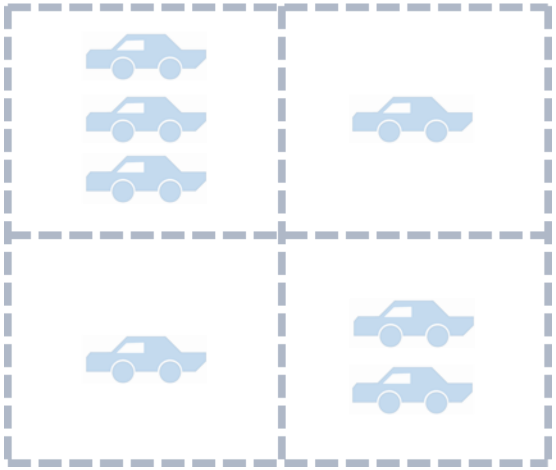
*Yongxin Tong et al.: A Unified Approach to Route Planning for Shared Mobility. Proc. VLDB Endow. 11(11): 1633-1646 (2018)

Quantize Demand-Supply Balance

1. Demand number map (DN)

- **Number of requests** in each time span and area
- Predicted using deep learning model*





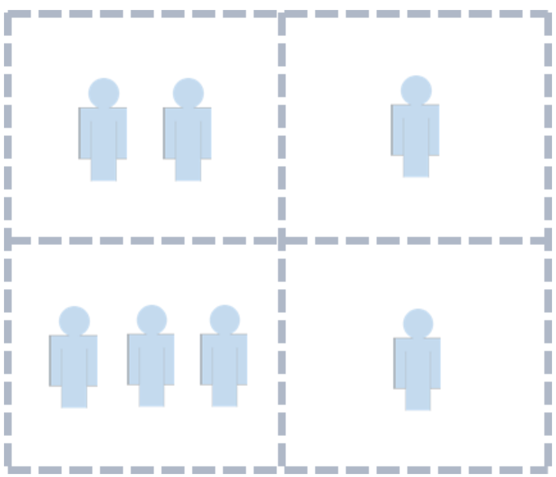
*Junbo Zhang, Yu Zheng, Dekang Qi, Ruiyuan Li, Xiuwen Yi: DNN-based prediction model for spatio-temporal data. SIGSPATIAL/GIS 2016: 92:1-92:4

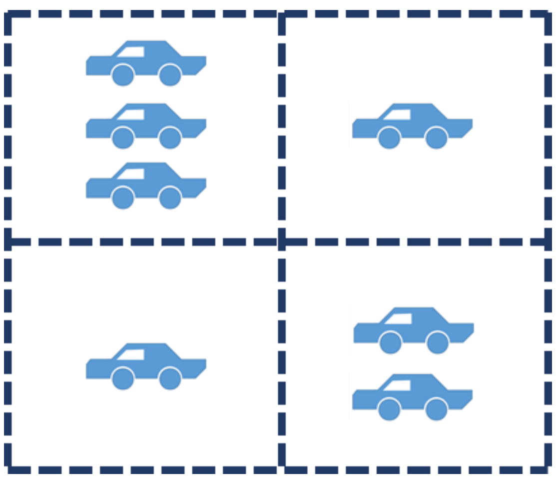
Quantize Demand-Supply Balance

1. Demand number map (DN)
2. Supply number map (SN)
   - **Number of workers** in each time span and area
   - Updated according to route planning

Route plan affects Supply Contribution

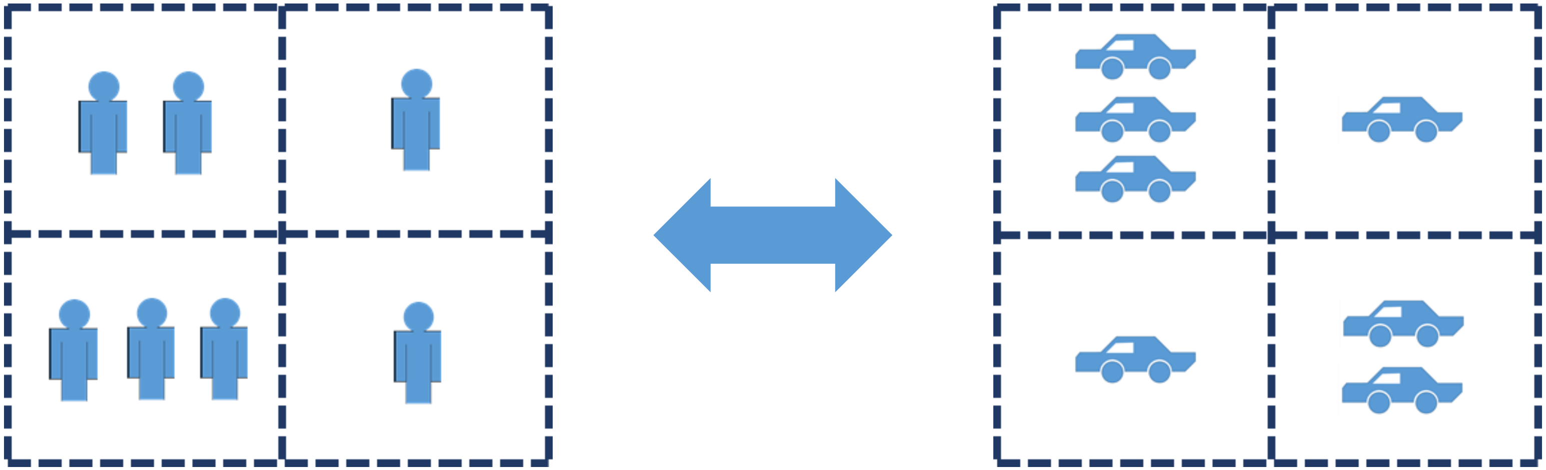
$$\text{Supply number } SN(N_x, T_y) = \sum_{w_i \in W} \sum_{k=1}^{|S_{w_i}|-1} SC_{xy}(l_k, l_{k+1}, arr_i[l_k])$$





Quantize Demand-Supply Balance

1. Demand number map (DN)
2. Supply number map (SN)
3. Demand-Supply Balance Score (DSB)
   - ➢ Each route plan affects future supply and balance
   - ➢ Statistically analyze the expected **profit** of the balance



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Local Balance $LB(\lambda, sn)$
(Expected # of matchings)

Local demand (λ) and supply (sn)

$$
\begin{aligned}
E(Y) &= \sum_{k=0}^{\lfloor sn \rfloor - 1} k \frac{\lambda^k}{k!} e^{-\lambda} + \sum_{k=\lfloor sn \rfloor}^{\infty} \lfloor sn \rfloor \frac{\lambda^k}{k!} e^{-\lambda} \qquad (3) \\
&= \sum_{k=0}^{\lfloor sn \rfloor - 1} (k - \lfloor sn \rfloor) \frac{\lambda^k}{k!} e^{-\lambda} + \sum_{k=0}^{\infty} \lfloor sn \rfloor \frac{\lambda^k}{k!} e^{-\lambda} \\
&= \sum_{k=0}^{\lfloor sn \rfloor - 1} (k - \lfloor sn \rfloor) \frac{\lambda^k}{k!} e^{-\lambda} + \lfloor sn \rfloor
\end{aligned}
$$

Analyzed based on ***Poisson distribution***

$$
DSB = \sum_{x=1}^{|\mathcal{N}|} \sum_{y=1}^{|\mathcal{T}|} \beta_y \left(sn'_{xy} - sn_{xy} \right) \cdot \boxed{\Delta_{LB}(\lambda_{xy}, sn_{xy})}
$$

Change of LB

Demand-Aware Route Planning (DARP) Problem

Given a set of workers W, a set of requests R, a demand number map DN, the DARP Problem is to find the sets of routes S for all the workers to minimize **Demand-Aware Cost (DAC)**:

Cost from workers' moving distances

Cost from Demand-Supply Balance

Cost from rejection

$$DAC(W, R, DN) = \boxed{\alpha \sum_{w_i \in W} D(S_{w_i})} - \boxed{DSB(\beta, S, DN)} + \boxed{\sum_{r_j \in \bar{R}} p_j}$$

Such that:

1. at any time the total capacity of requests of any worker should not exceed its **capacity** a_i;
2. each request meets its **deadline**;
3. an assigned request cannot be assigned to another; a rejected request cannot be revoked.

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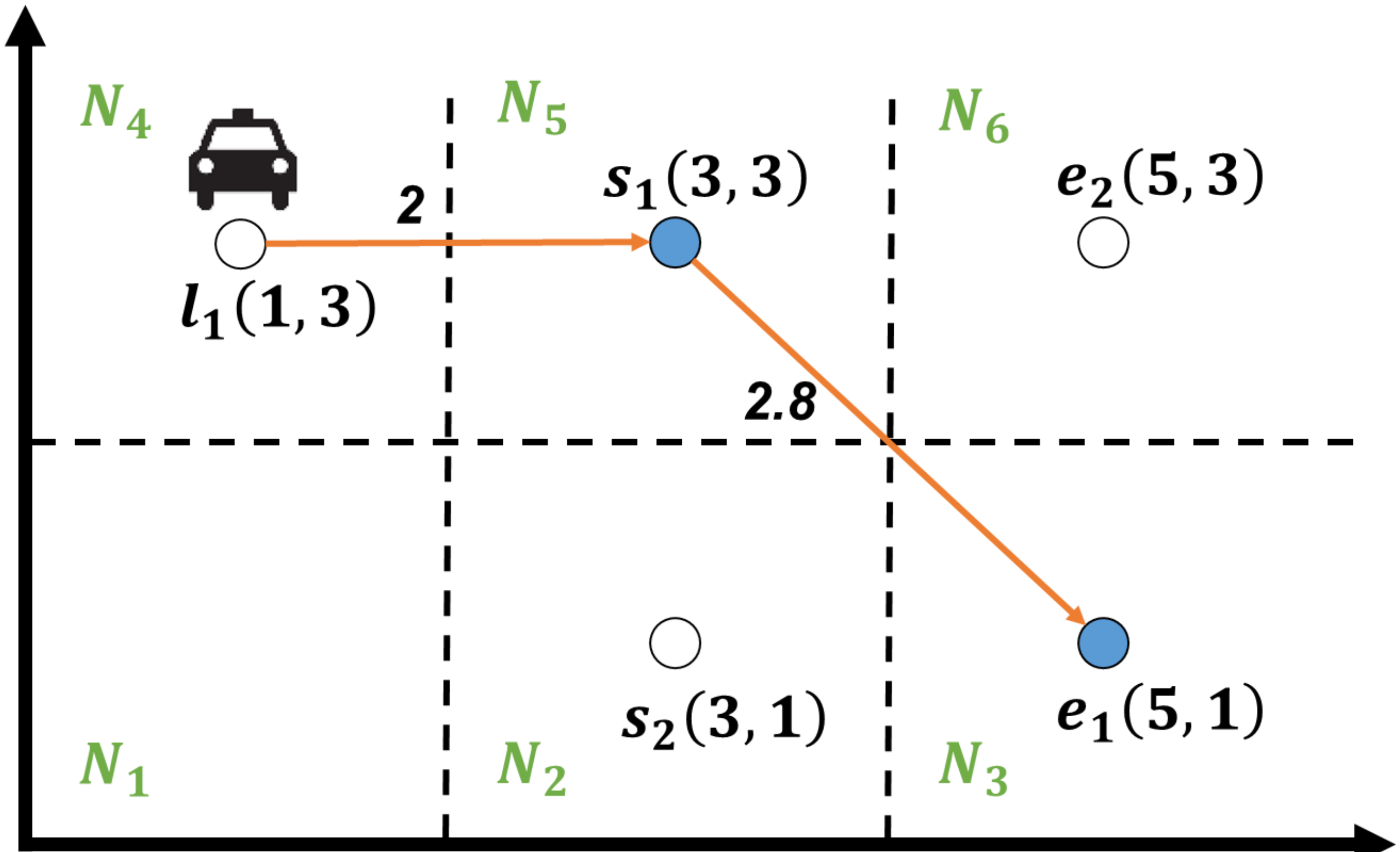
We prove the DARP problem is **NP-hard** by reducing it from the basic route planning problem* for shareable mobility services. We further show that **no** deterministic nor randomized algorithm can guarantee a **constant Competitive Ratio**

*Yongxin Tong, et al.: A Unified Approach to Route Planning for Shared Mobility. Proc. VLDB Endow. 11(11): 1633-1646 (2018)

Running Example

Time spans $[0\sim3, 3\sim6, \cdots, 15\sim18]$
Areas $[N_1, N_2, \cdots, N_6]$



w_1 <l_1, 0> r_1 <s_1, 0, e_1, 11> ← r_2 <s_2, 0, e_2, 11>

How to derive cost if we assign request r_2?

Running Example

Time spans $[0\sim3, 3\sim6, \cdots, 15\sim18]$
Areas $[N_1, N_2, \cdots, N_6]$

Table 1: Supply Number Map

$\mathcal{T}$ \ $\mathcal{N}$	N_1	N_2	N_3	N_4	N_5	N_6
T_1	1.7	3.8	2.5	2.3	0.5	1.3
T_2	3.3	2.1	1.7	1.1	3.2	2.9
T_3	3.5	3.3	2.0	0.7	3.8	1.4
T_4	3.6	1.3	2.4	3.0	1.2	2.6
T_5	0.5	2.5	1.4	1.3	1.6	2.3
T_6	3.4	2.0	1.0	3.7	2.2	3.8

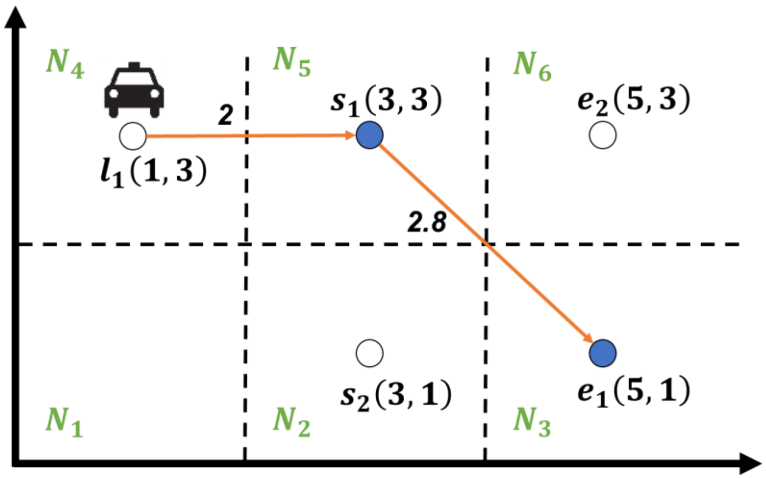
Table 2: Demand Number Map

$\mathcal{T}$ \ $\mathcal{N}$	N_1	N_2	N_3	N_4	N_5	N_6
T_1	2	3	5	2	4	3
T_2	3	2	4	2	3	2
T_3	3	3	4	2	2	2
T_4	3	1	4	3	2	2
T_5	4	2	4	3	1	3
T_6	3	2	3	4	2	2

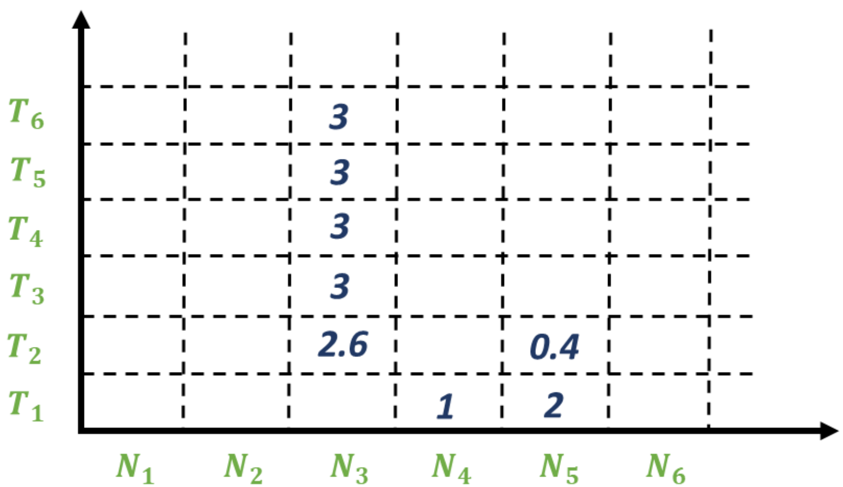
Supply number map **(SN)** and Demand number map **(DN)** are required for cost of Demand-Supply Balance **(DSB)**

Running Example

Route before insertion



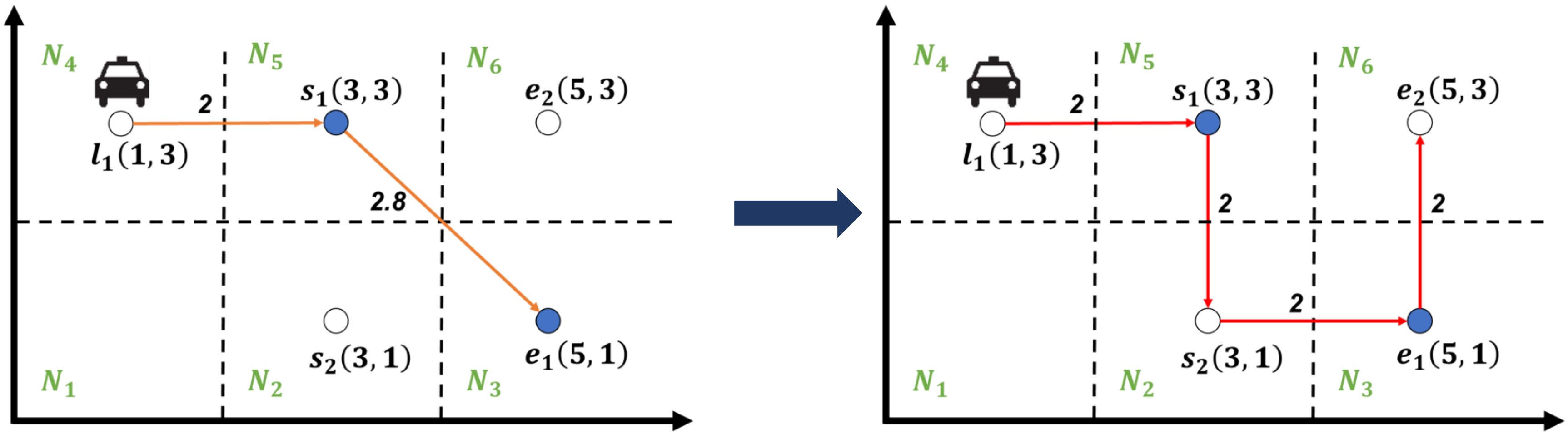
Time duration of w_i in spatiotemporal cells of **SN** before insertion



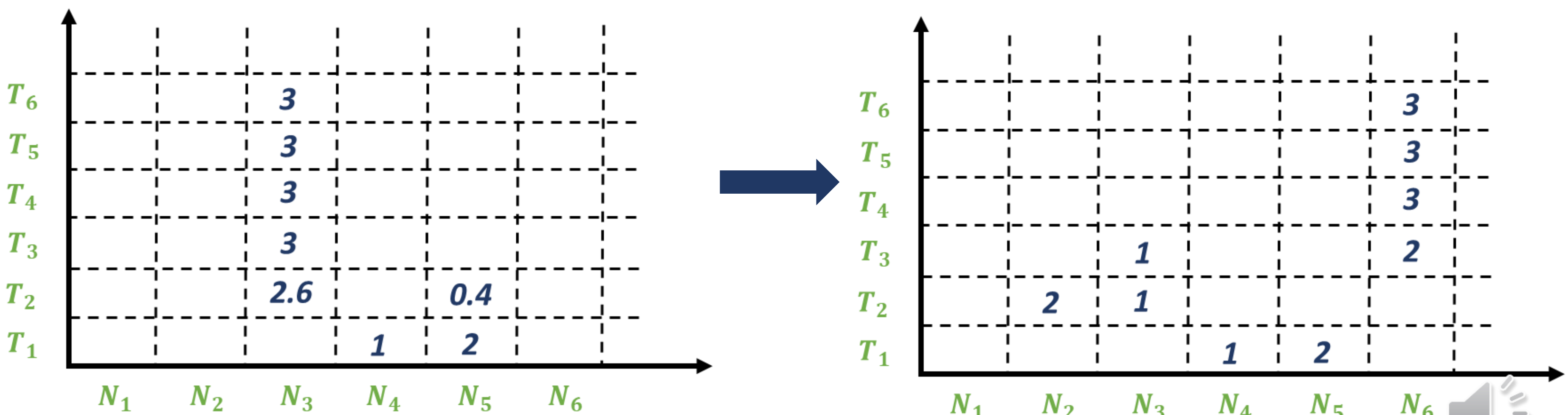
Running Example

A possible insertion

Route before/after insertion



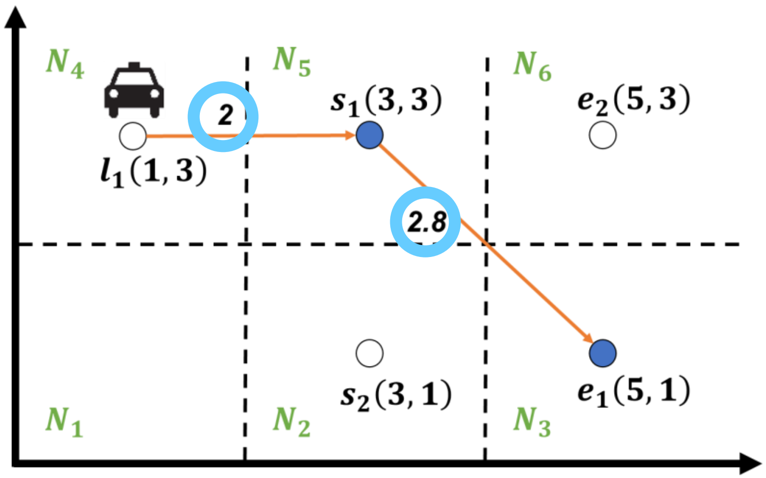
Time duration of w_i in spatiotemporal cells of **SN** before/after insertion

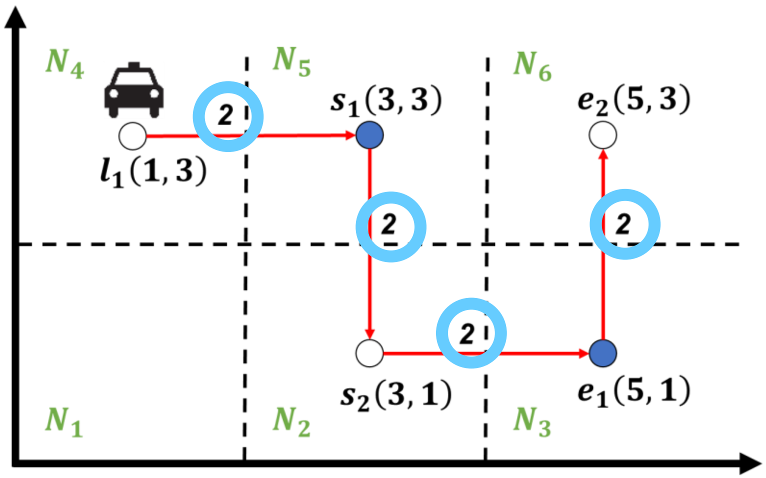


Running Example

A possible insertion

Route before/after insertion





Shortest distance to finish original route
2+2.8

Shortest distance to finish inserted route
2+2+2+2

Cost from workers' moving distances
is derived according to the difference of finishing time

Running Example

A possible insertion

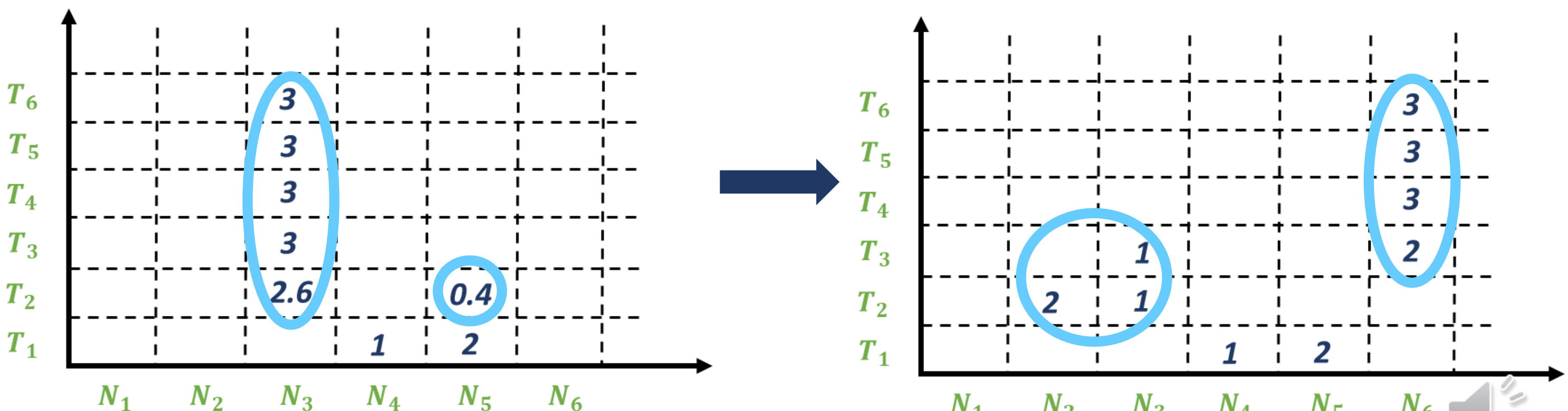
Cost from Demand-Supply Balance (DSB)

Predicted Demand Number Map (DN)

Supply Number Map (SN)

Change of time duration affects the supply in each spatiotemporal cell

Time duration of w_i in spatiotemporal cells of **SN** before/after insertion



Running Example

Cost from Demand-Supply Balance (DSB)

The total cost of a valid insertion

Cost from workers' moving distances
is derived according to the difference of finishing time

Outline

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- Evaluations

Proposed Approaches

To solve the DARP problem, we proposed

Insertion algorithm (single request)

- **Basic** insertion
- **Dynamic programming**-based insertion

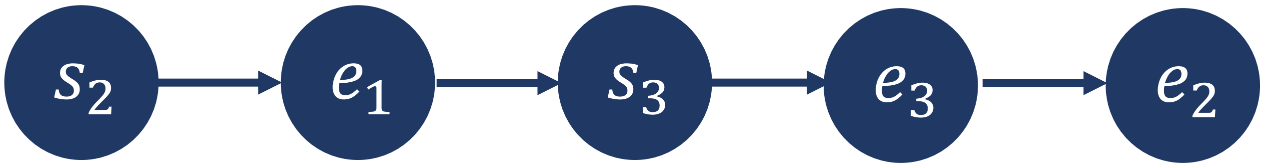
Solution for DARP problem

- Insertion-based **dual-phase framework**

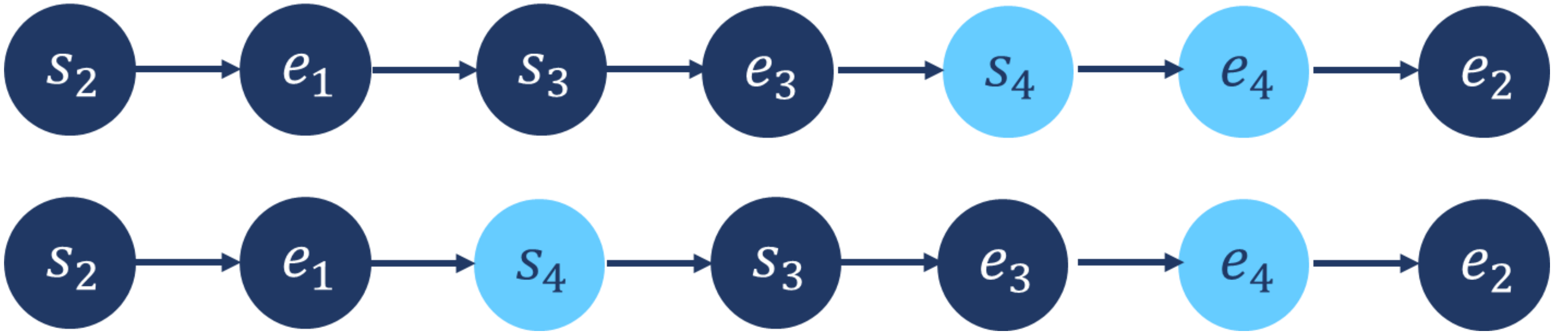
Insertion

Insertion: one request → one worker's route

effective and efficient approach



Original nodes are in the **same order** (search space ↓):



Insertion

Naturally: $\boldsymbol{O}(\boldsymbol{N}^3)$ time complexity

Distance-related cost: $\boldsymbol{O}(\boldsymbol{N})$.

Existing work* reduces its cost as: additional distances from inserting source and destination are **separable**.

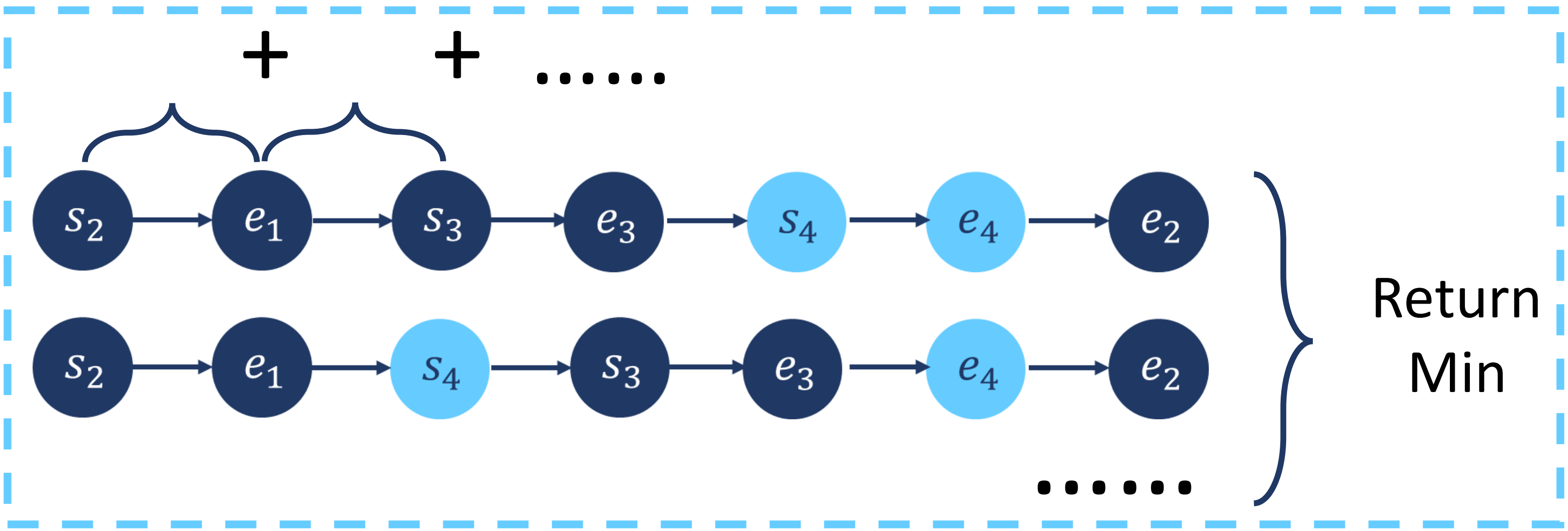
Demand supply balance cost: previous $\boldsymbol{O}(\boldsymbol{N}^2)$ and $\boldsymbol{O}(\boldsymbol{N})$ algorithms are **not** appliable

Detour of inserting source affects all the supply from latter nodes.

*Yongxin Tong, et al.: A Unified Approach to Route Planning for Shared Mobility. Proc. VLDB Endow. 11(11): 1633-1646 (2018)

The Basic Insertion Algorithm ($O(N^3)$)

1. **Enumerate** insertion pairs for a length-N route
   - $O(N^2)$ cases
2. For **each** new route, derive the cost
   - $N+1$ small paths. **Calculate** and **sum up** them cost $\boldsymbol{O}(\boldsymbol{N})$



3. Return the plan with **lowest** cost (Greedy)

The DP-Based Insertion Algorithm ($O(N^2)$)

1. **Enumerate** insertion pairs

- $O(N^2)$ cases

2. For each new route, derive the cost in $O(1)$ time

- **Distance**-related cost in $O(1)$: studied*
- Cost from Demand Supply Balance (**DSB**): how?

The DP-Based Insertion Algorithm ($O(N^2)$)

1. Dynamically derive a ***check-up table*** in $\boldsymbol{O(N)}$ ***time***
   - Derive the maximum time to delay for each node.
   - Divide it into a discretized space. Increasing **DSB** is stored with **time delay**.
2. Enumerate insertion pairs
   - O(N^2) cases
3. For each new route, derive the cost ***in*** $\boldsymbol{O(1)}$ ***time***
   - Distance-related cost in O(1): studied*
   - Cost from DSB: ***check in*** $\boldsymbol{O(1)}$ ***time according to time delay***
4. Return the plan with lowest cost

*Yongxin Tong, et al.: A Unified Approach to Route Planning for Shared Mobility. *Proc. VLDB Endow. 11(11): 1633-1646 (2018)*

The DAIF framework

- Assign requests **one-by-one**

- Quickly derive a ***lower bound*** of cost for each worker
  - In $\boldsymbol{O(N)}$ time + only ***1*** shortest path query.
  - Existing work* derive the lower bound for ***distance cost***
  - We efficiently derive a lower bound for ***balance cost***

    based on the property of Demand-Supply-Balance cost

- ***Sort*** → Calculate ***exact*** cost → ***Prune & insert***
  - Derive **exact** cost for each worker ordered by lower bound
  - If the lower bound is larger than current minimal cost, ***safely prune*** all the rest workers

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Experimental Setting

- Road Network
  - NYC (|V|=61,298, |E|=141,372)
- Real Dataset
  - Taxi Trips (2013) in NYC (427,093 trip records)
- Synthetic Dataset
  - Generated according to the distribution of NYC (452,116 trip records)

Experimental Setting

- Compared parameters
  - e_r: the deadline coefficient.
  - a_i: the capacity of workers.
  - α, β: the weight for distance/ balance cost.
  - γ: the factor that staying time duration of worker transfer to supply.
  - p_o: the ratio of penalty cost
  - $|W|$: number of workers
  - g: grid size

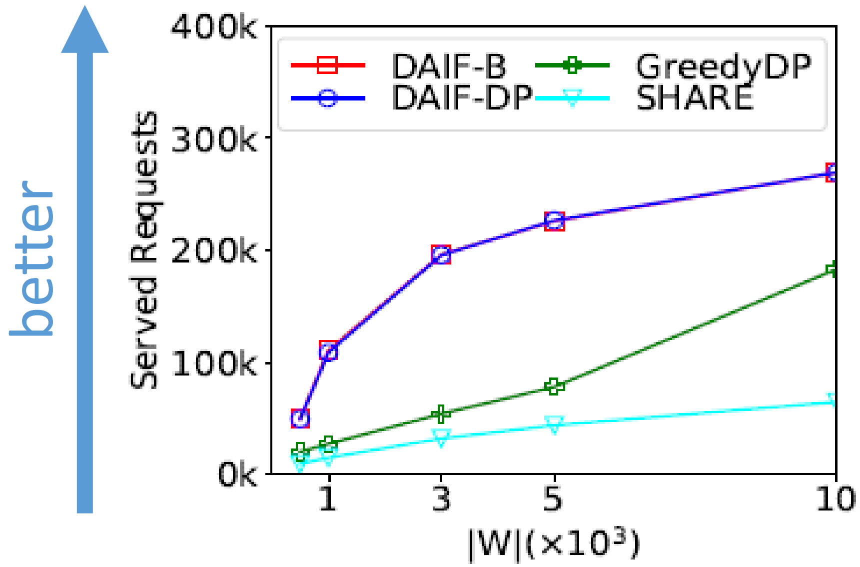
Parameters	Settings
Deadline Coefficient e_r	0.1, 0.2, **0.3**, 0.4, 0.5
Capacity a_i	2, **3**, 4, 7, 10
Distance Weight α	**1**
Balance Weight β	$\left[\boldsymbol{p_r^*}, \frac{\boldsymbol{p_r^*}}{\boldsymbol{e}}, \frac{\boldsymbol{p_r^*}}{\boldsymbol{e^2}}, \cdots, \frac{\boldsymbol{p_r^*}}{\boldsymbol{e^5}}\right]$
Supply Coefficient γ	**0.0016**
Penalty ratio p_o	**30**
Number of workers $\|W\|$	500, 1k, **3k**, 5k, 10k
Grid size g	1k×1k, **2k×2k**, 4k×4k

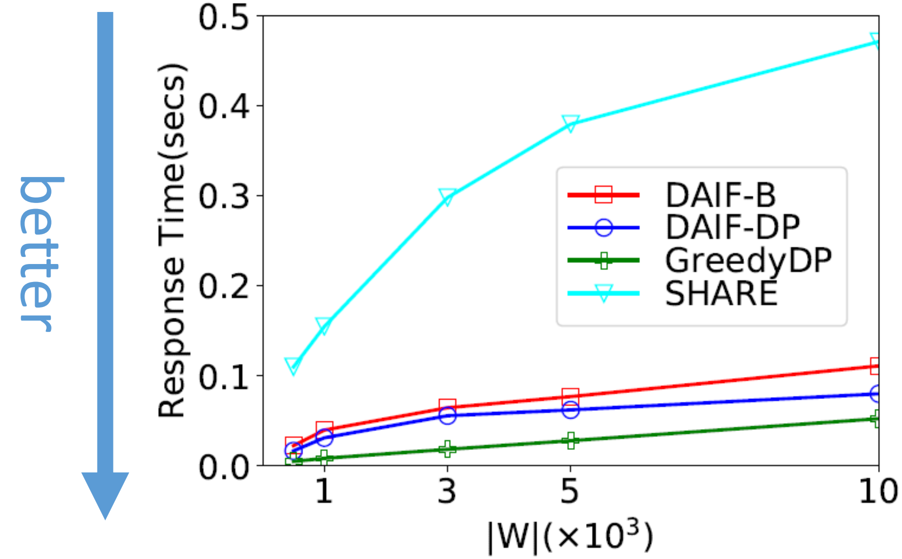
Experimental Setting

- Tested Algorithms
  - **GreedyDP***: the state-of-art route planning algorithm using insertion. No demand-related information is used.
  - **SHARE#**: It uses historical information of nodes to choose a route with a higher possibility to pick up passengers along the route
  - **DAIF-B**: our DAIF framework using Basic insertion
  - **DAIF-DP**: our DAIF framework using DP-based insertion

*Yongxin Tong, et al.: A Unified Approach to Route Planning for Shared Mobility. Proc. VLDB Endow. 11(11): 1633-1646 (2018)
#Chak Fai Yuen, et al.: Beyond Shortest Paths: Route Recommendations for Ride-sharing. WWW 2019: 2258-2269

Experimental Results





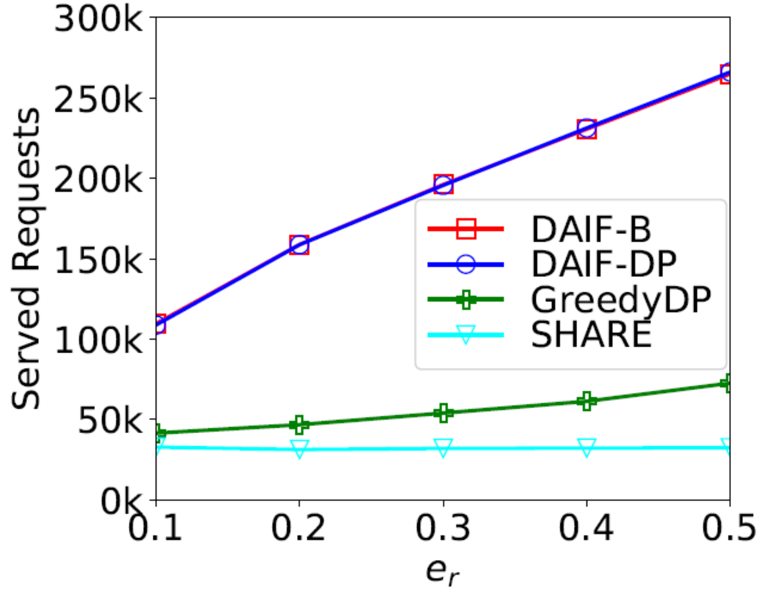
Serve ***47%*** to ***624%*** more requests

Response time < ***0.15s***

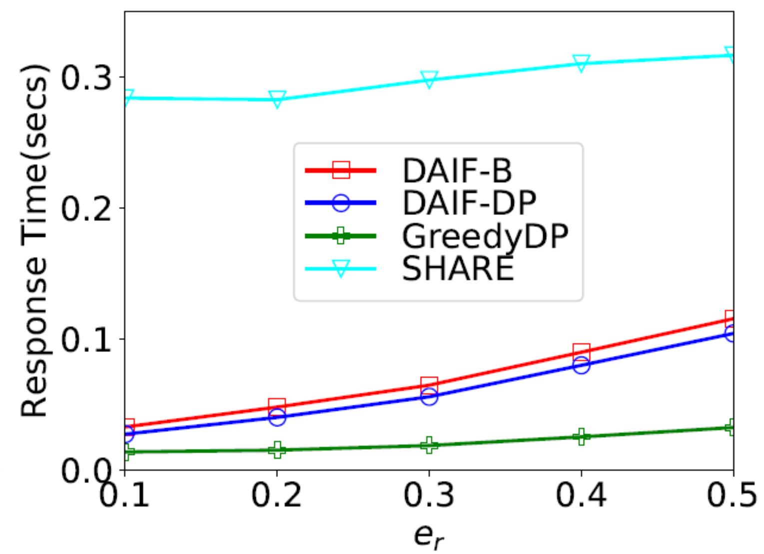
Performance of varying number of workers $|W|$

Experimental Results

better



better



Serve ***161.7%*** to ***718.1%*** more requests

Response time < ***0.15s***

Performance of varying deadline coefficient e_r

Thank You

Q&A

The code and datasets
https://github.com/dominatorX/DAIF