Price-aware Real-time Ride-sharing at Scale - An Auction-based Approach

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USC Viterbi School of Engineering

IMSC Integrated Media Systems Center

Motivation


co2
save
environmentally-friendly
tolls
share
stress
driving
pollution
ridesharing
mileage
commute
money
dollars
insurance
traffic
sustainability
fuel
parking
congestion
socializing
air
carpools
the new
cool

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- Increasing popularity of commercial ride-sharing platforms

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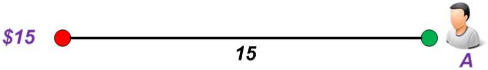

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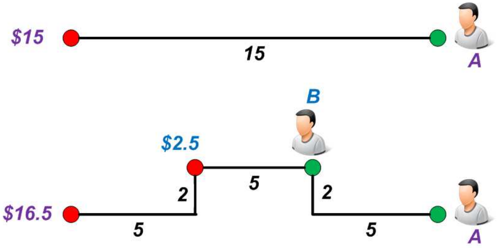

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    - Do not account for the service provider's incentive

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Driver's Income ***Rider's Fare***

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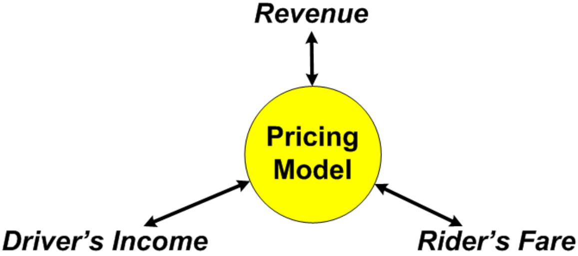

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- Scalability

Match
Riders to Drivers

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Schedule
Trips for Drivers

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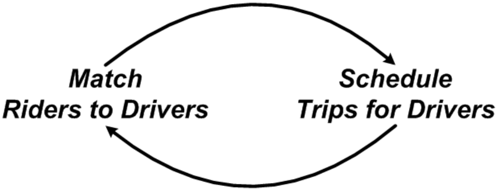

Outline

Definitions

Ride Request

A ride request r is represented as $\langle s, e, w, \epsilon, f \rangle$ where:

- s: pickup point
- e: dropoff point
- w: max wait time
- ϵ: max detour
- f: rider's profile

Definitions

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Driver

A driver v is represented as $\langle L, n, g \rangle$ such that:

- L: list of assigned requests
- n: max simultaneous passengers
- g: driver's profile

Definitions

Schedule

For a set L with n requests, a schedule $S = \langle x_1, x_2, ..., x_2 n \rangle$ is an ordered set of pickup and dropoff points of the requests in L.

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We call S a *valid* schedule if it satisfies these constraints:

- for every $r \in L$, $r.s$ precedes $r.e$ in S
- the rider's waiting time and detour
- the driver's capacity

Outline

Fair Pricing

For every pricing model:

- How much should the rider pay?
- How much should the driver be compensated?
- What's the revenue of the ride-sharing platform?

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In a *fair* system:

- the rider should receive a *discount* proportional the the detour incurred to his trip
- a driver's compensation should increase proportional to the distance of his trip

Rider's Fare

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- $\Delta d_r = d'_r - d_r$

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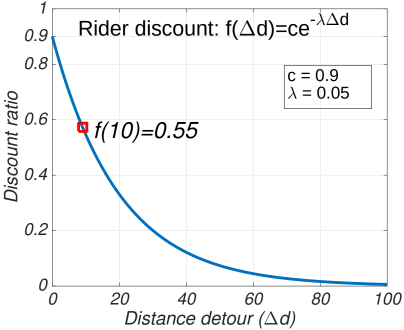

$$fare(r) = F(d_r)f_r(\Delta d_r)$$

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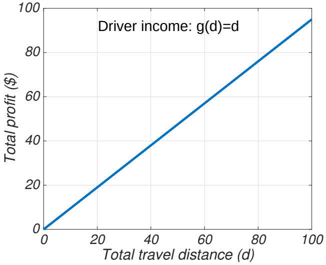

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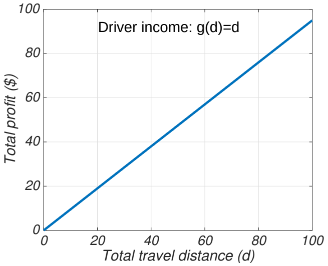
$$income_v = \int_{start_s}^{end_s} I\left(S_v(t) \neq \langle\rangle\right).g(d(t))dt$$

- $I()$: indicator function
- $S_v(t)$: driver's schedule at t.
- $start_s$: first pickup time of S_v
- end_s: last dropoff time of S_v
- $d(t)$ traveled distance of v at t



Revenue

A driver v's profit is:

$$profit_v = \sum_{r_i \in S_v} fare(r_i) - income_v$$

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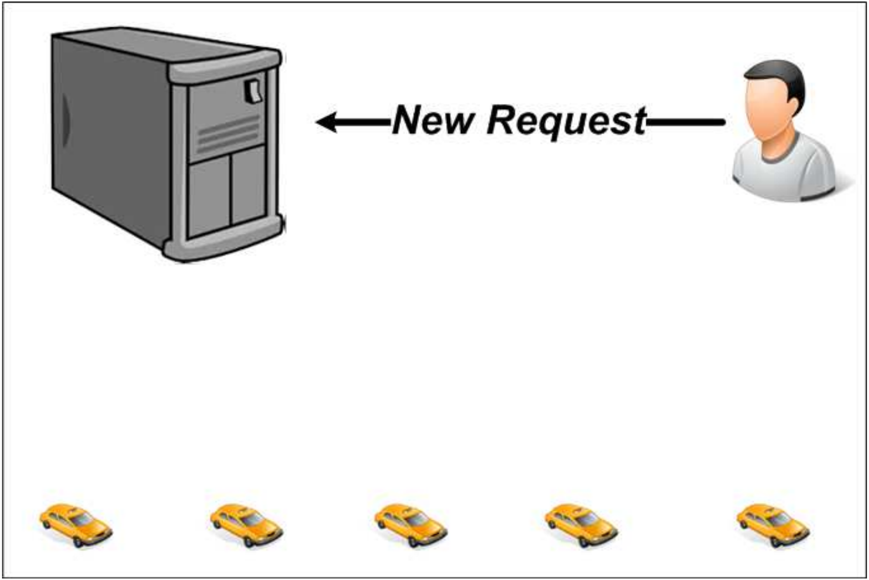
therefore,

$$revenue = \sum_{v \in V} profit_v$$

Outline

Overview



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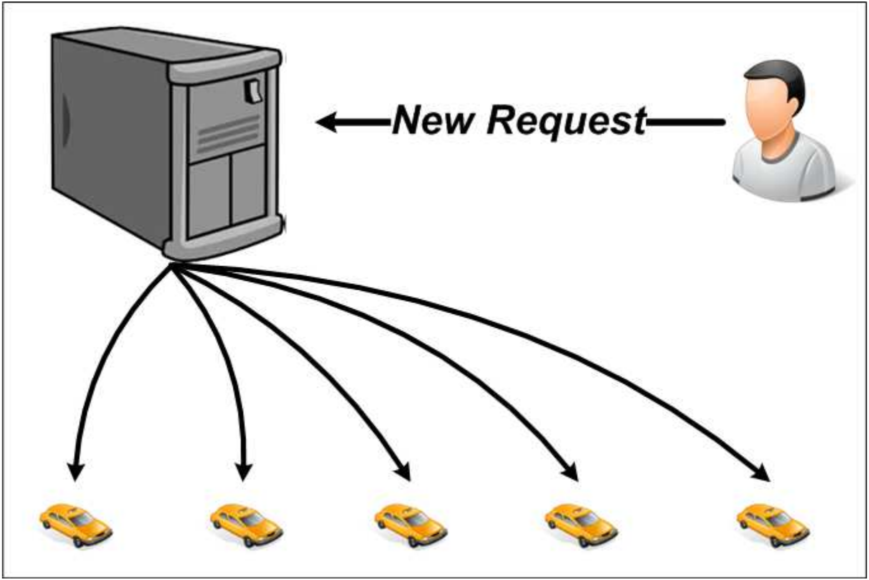

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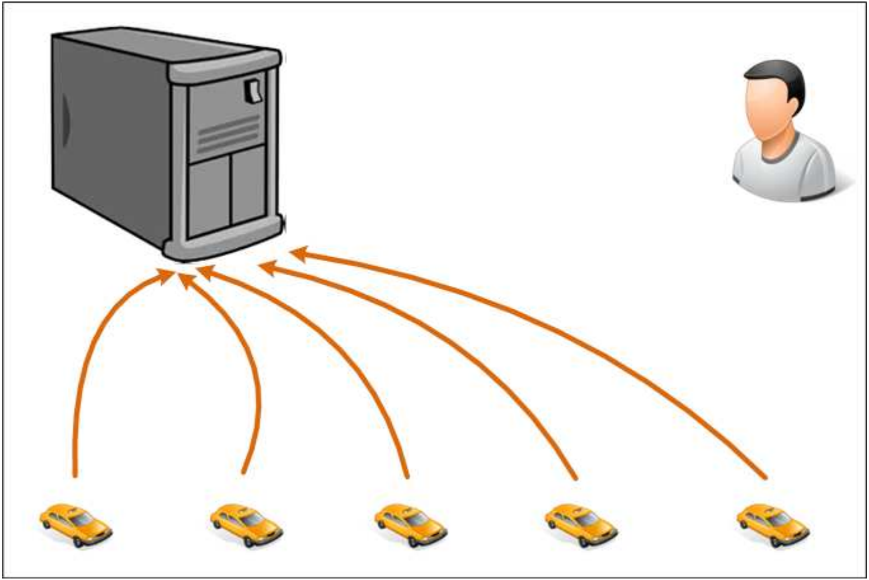

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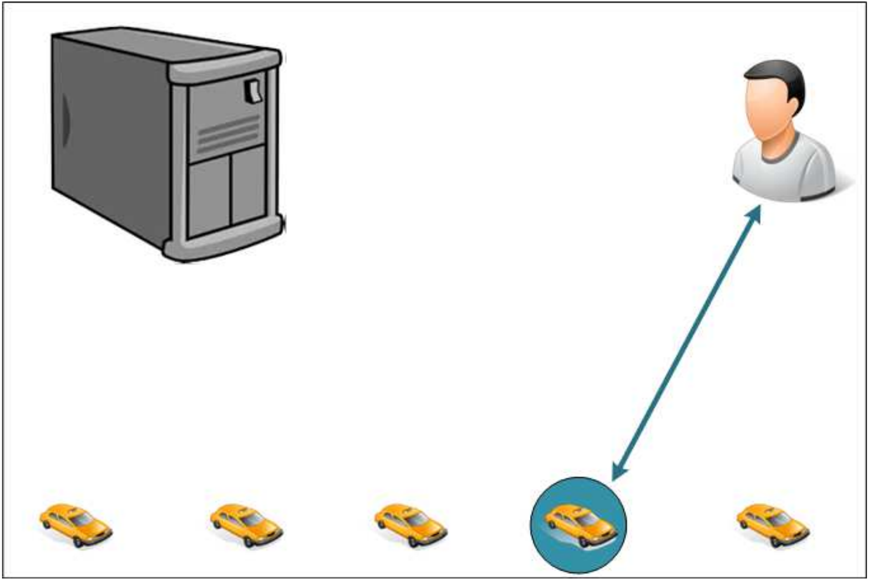
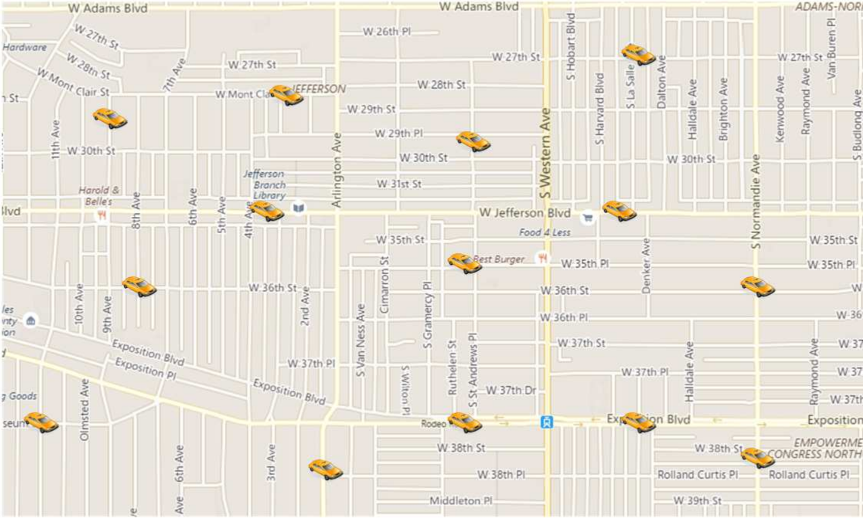


Dispatching Tasks



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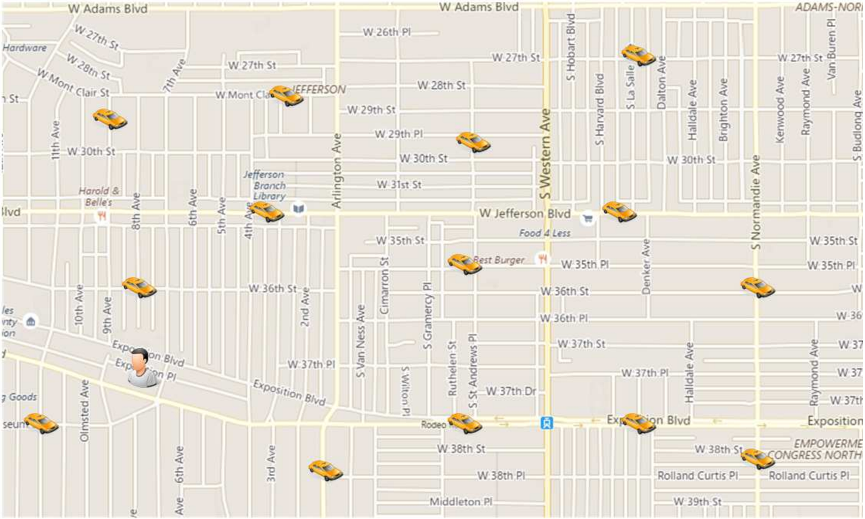

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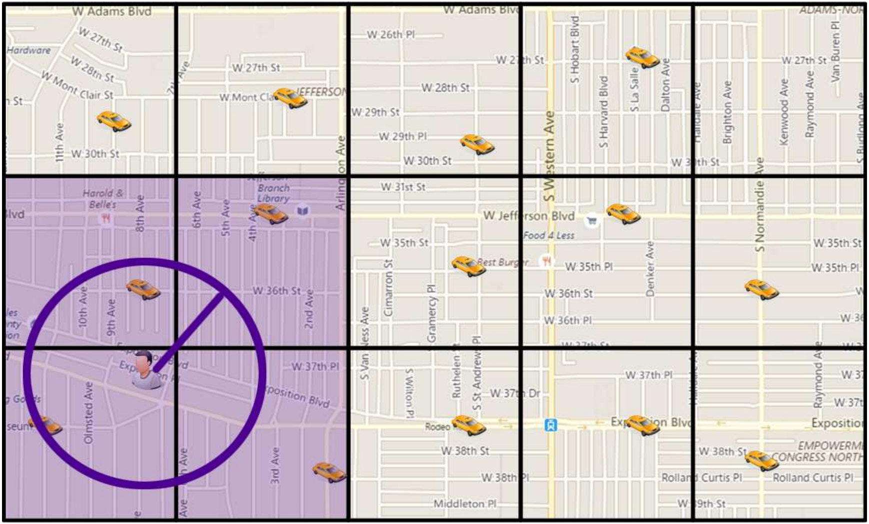

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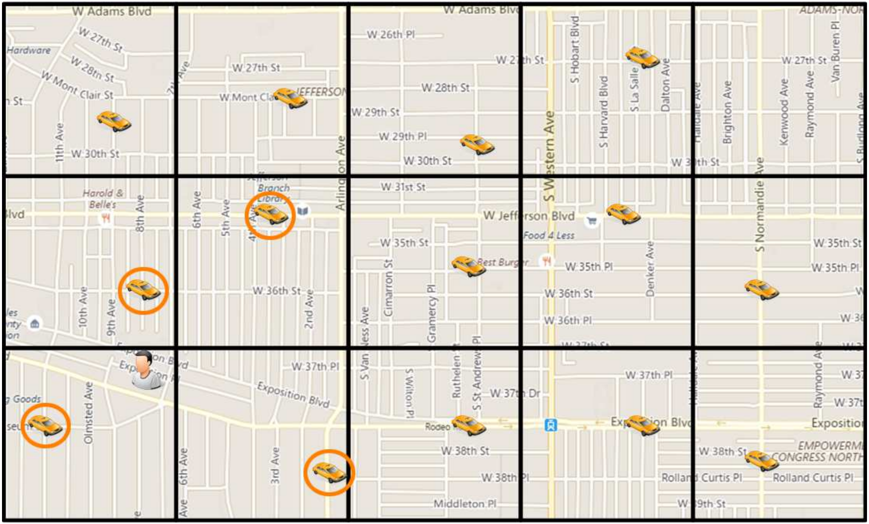
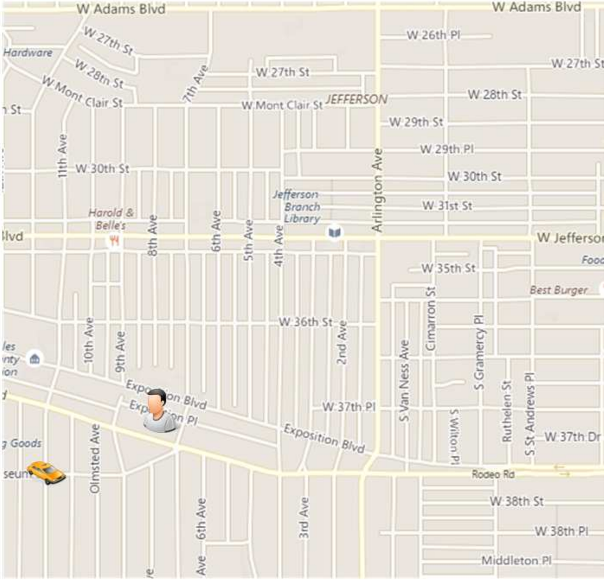


Bid Computation



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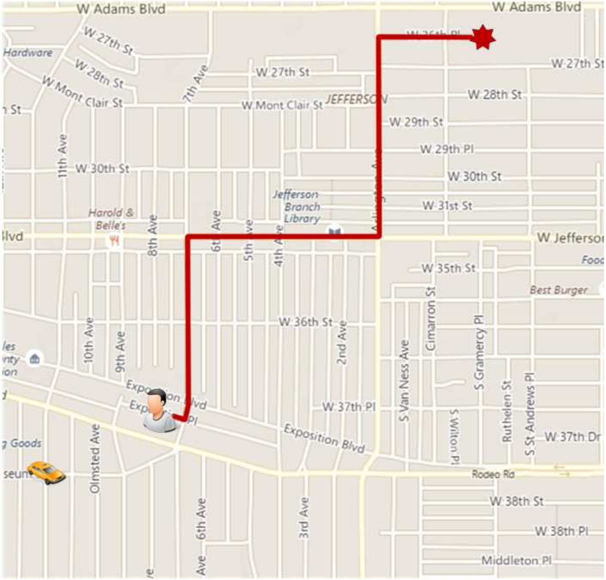
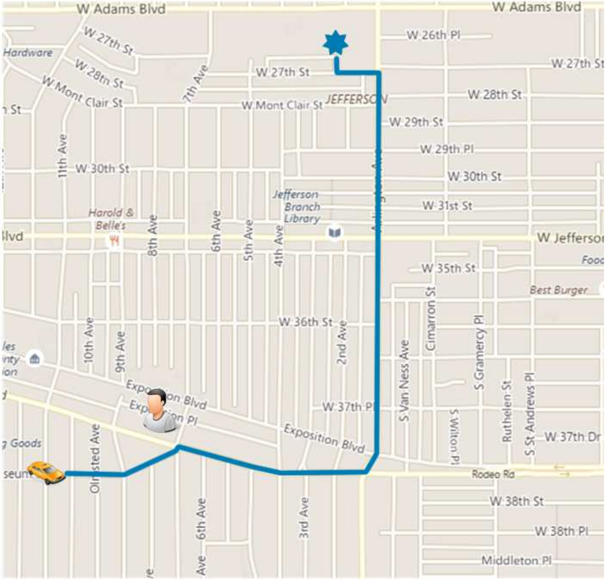


using PATH we get the *base fare* for the new request

Bid Computation



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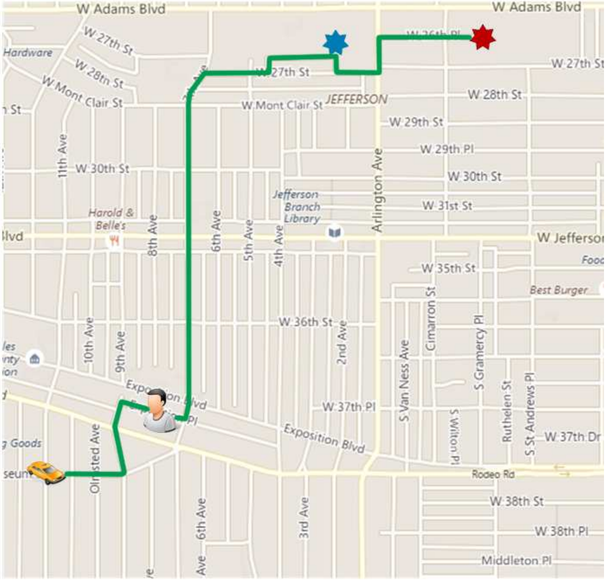

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diff(route, route) gives Δd for new request

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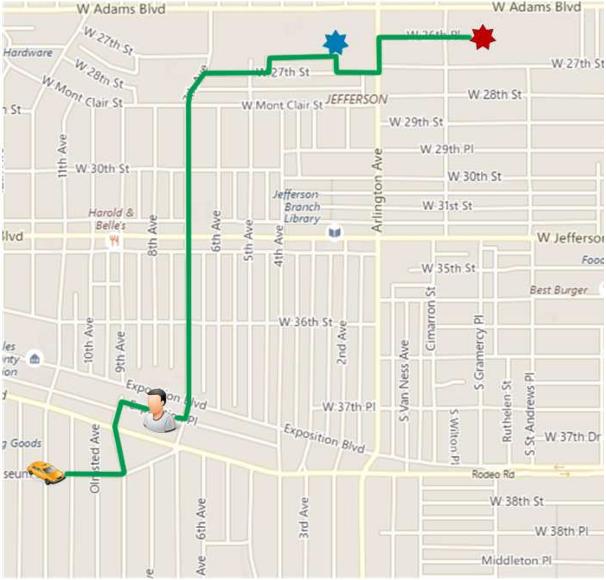

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diff(route, route) gives Δd for new request

Bid

new profit - current profit

Outline

Setup

- Data Set: New York City's Taxi data set
  - 40K drivers & 500K trips per day
  - pickup/dropoff points, request time

Setup

- Data Set: New York City's Taxi data set
- Algorithms:
  - APART
  - TREE (shortest traveled distance) [1]
  - NN (closest driver)

[1] Y. Huang, F. Bastani, R. Jin, and X. S. Wang, Large scale real-time ridesharing with service guarantee on road networks, Proceedings of the VLDB Endowment, vol. 7, no. 14, pp. 20172028, 2014.

Setup

- Data Set: New York City's Taxi data set
- Algorithms:
- Parameters:

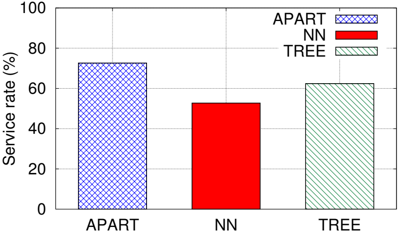
Parameter	Values
Max Wait Time (w)	3min, **6min**, 9min, 12min, 15min, 20min
# of Drivers	1000, 2000, **5000**, 10000, 20000
Max Passengers (n)	2, 3, **4**, 5, 6
Max Allowed Detour (ϵ)	25%, **50%**, 75%, 100%

Setup

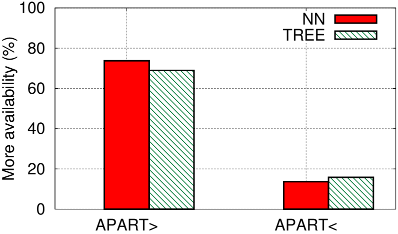
- Data Set: New York City's Taxi data set
- Algorithms:
- Parameters:
- Pricing Model:

$$F(d) = 2 \times d$$
$$\forall r, f_r(\Delta d_r) = 1 - (0.25 \times \Delta d_r^2)$$
$$\forall v, g_v(d) = 1.5 \times d$$

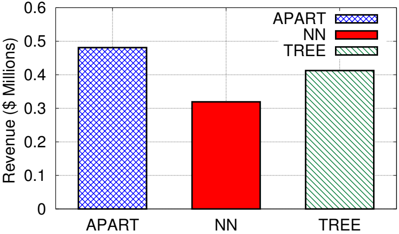
Algorithm Comparison



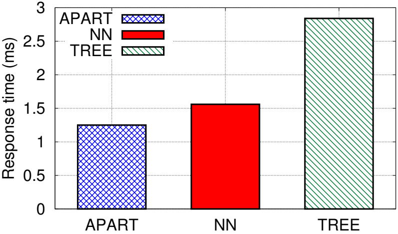
Service Rate



Driver Availability



Revenue

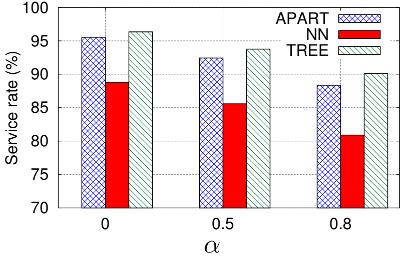


Response Time

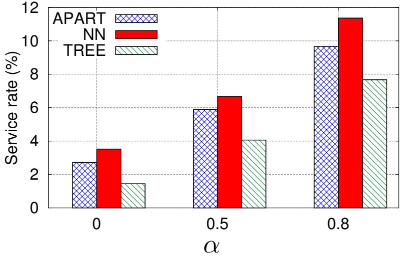
Pricing Model Comparison

If we use the frame work in [2]:

$$c.d_1 + (1+\alpha).c.d_2$$



Users that Saved Money

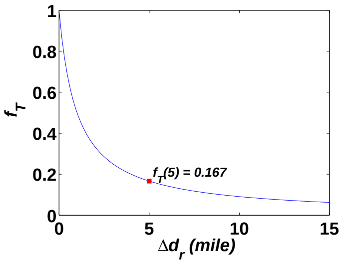


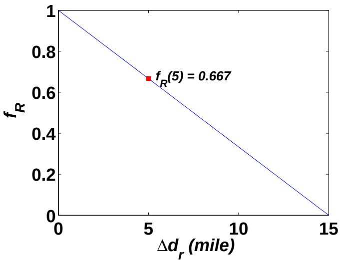
Users that Lost Money

[2] S. Ma, Y. Zheng, and O. Wolfson, T-share: A large-scale dynamic taxi ridesharing service, in Data Engineering (ICDE), 2013 IEEE 29th International Conference on

Effect of Profiles

- $APART_T$: $f_T(\Delta d_r) = \frac{1}{(\Delta d_r + 1)}$
- $APART_R$: $f_R(\Delta d_r) = 1 - (\frac{\Delta d_r}{max\delta})$





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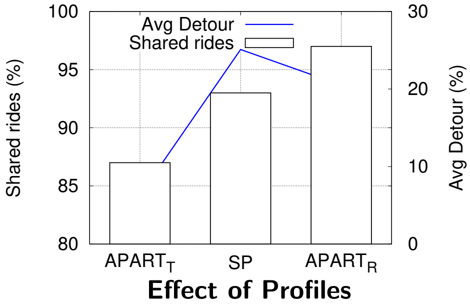

Questions