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McGill

An Optimization Framework For Online Ride-sharing Markets

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Motivation I: Ride-sharing

- Emergence and rapid development of **online ride-sharing services**

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Taxi



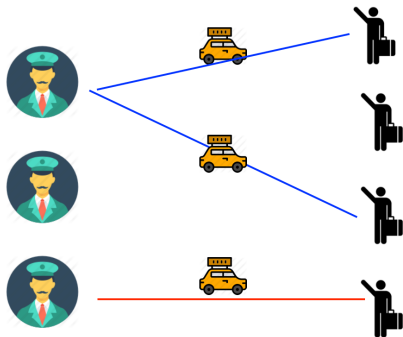
Delivery



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Motivation II: Two-sided Market

- Two-sided market configuration \Rightarrow Drivers and Customers
- Existing algorithms are mostly offline heuristics to apply in one-sided market



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Motivation III: Inefficiency

Efficiency of the services are limited by the sub-optimal and imbalanced matching

- Imbalance between supply and demand (e.g. No match or congestion)
- Long waiting time \Rightarrow Real-time response
- High cost \Rightarrow Surge Pricing



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- **Scalability:** Deal with a large number of workers and customers, can partition the map in **city's scale** (i.e. travel across the entire city)
- **Real-time:** Always need the platform to give real-time responses to the customers \Rightarrow Making **online** algorithms essential

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- Generalized economic models for both Internet taxi and product delivery markets
- A deterministic approximation algorithm with a **tight theoretical bound**
- Two heuristic online algorithms
- Verify the algorithms with theoretical analysis and trace-driven simulations

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Two-sided Market with both Temporal and Spatial information

- **Drivers** - The users who provide taxi or delivery services
- **Customers** - The users who receive the services
- **Tasks** - The taxi and delivery services ordered by the customers
- **Task Maps** - DAGs to demonstrate the relationship between the drivers and tasks in the market

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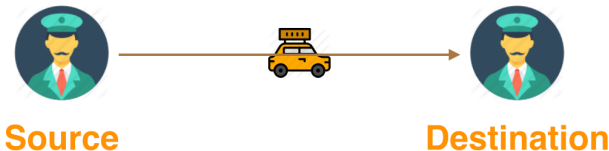
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of drivers: N , and for each driver $n \in [N]$:

- **Source** - location: $s_n = (u_n^-, v_n^-)$, time: t_n^-
- **Destination** - location: $d_n = (u_n^+, v_n^+)$, time: t_n^+



Problem Model

Customers and Tasks

of tasks: M , and for each task $m \in [M]$:

- **Source** - location: $\bar{s}_m = (\bar{u}_m^-, \bar{v}_m^-)$, time: \bar{t}_m^-
- **Destination** - location: $\bar{d}_m = (\bar{u}_m^+, \bar{v}_m^+)$, time: \bar{t}_m^+
- **Price** - p_m (calculated by the platform)
- **Publishing time** - \bar{t}_m : $\bar{t}_m^- < \bar{t}_m < \bar{t}_m^+$



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An example of driver's task map

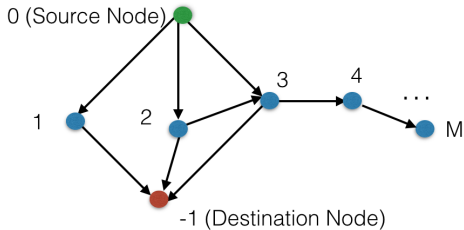


Figure: shows a simple example task map of driver n . The driver can take one task among task 1, task 2 and task 3. She can also take two tasks, and that is to take task 3 after finishing task 2.

Indicator $h_{n,m,m'} \in \{0, 1\}, \forall n \in [N], m, m' \in [\hat{M}]$ denotes whether there is an arc from m to m' in driver n 's task map.

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- $\hat{l}_{n,m}, \hat{c}_{n,m}$ - travel time/cost of the same task m for driver n
- $l_{n,m,m'}, c_{n,m,m'}$ - travel time/cost of driving empty from m to m' for driver n
- $\hat{h}_{n,m}$ - whether driver n can take task m , with $\hat{h}_{n,m} = 1$ indicating a "yes" as follows:

$$\hat{h}_{n,m} = 1 \Leftrightarrow (\hat{l}_{n,m} \leq \bar{t}_m^+ - t_m^-), \forall n \in [N], m \in [M]. \quad (1)$$



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For the arcs from the source (labeled 0) to any task m ,

$$h_{n,0,m} = 1 \Leftrightarrow \hat{h}_{n,m} \wedge (l_{n,0,m} \leq \bar{t}_m^- - t_n^-) \wedge (l_{n,m,-1} \leq t_n^+ - \bar{t}_m^+), \quad \forall n \in [N], m \in [M]. \quad (2)$$

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For the arc from one node of task m to the next task m' , driver n should have enough time to travel from the destination of task m to the source of task m' :

$$h_{n,m,m'} = 1 \Leftrightarrow \hat{h}_{n,m} \wedge \hat{h}_{n,m'} \wedge (l_{n,m',-1} \leq t_n^+ - \bar{t}_{m'}^+) \wedge (l_{n,m,m'} \leq \bar{t}_{m'}^- - \bar{t}_m^+), \forall n \in [N], m \in [M], m' \in [M]. \quad (3)$$

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If $h_{n,m,m'} = 1$ then also set $h_{n,m',-1} = 1$, there is an arc from m to m' and another arc from m' to -1 .

It will take $(M^2 + 2M)$ iterations to calculate all the values of $h_{n,m,m'}$ for driver $n \Rightarrow$ Complexity to construct the task map of all the N drivers is $O(NM^2)$.



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Drivers' Profits Maximization: Objective

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Our Goal: Maximize drivers' total profits \Rightarrow Total Revenue - Total Excess Cost (Shown in (4))

Decision variables:

- $x_{n,m}$ - If task m is assigned to driver n in the market
- $y_{n,m,m'}$ - If driver n takes task m' after finishing task m .

$$\begin{aligned} Z : \text{maximize} \quad & \sum_{n \in [N]} \sum_{m \in [M]} x_{n,m} p_m - \left(\sum_{n \in [N]} \sum_{m \in [M]} x_{n,m} \hat{c}_{n,m} \right. \\ & \left. + \sum_{n \in [N]} \sum_{m \in [\hat{M}]} \sum_{m' \in [\hat{M}]} y_{n,m,m'} h_{n,m,m'} c_{n,m,m'} - \sum_{n \in [N]} c_{n,0,-1} \right). \end{aligned} \quad (4)$$

Problem Model I:

Drivers' Profits Maximization: Constraints

s.t.

$$\sum_{n \in [N]} x_{n,m} \leq 1, \quad \forall m \in [M]; \quad (5a)$$

$$\sum_{m \in [M]} x_{n,m} p_m \geq \sum_{m \in [\hat{M}]} \sum_{m' \in [\hat{M}]} y_{n,m,m'} h_{n,m,m'} c_{n,m,m'} \quad (5b)$$

$$+ \sum_{m \in [M]} x_{n,m} - c_{n,0,-1}, \quad \forall n \in [N];$$

$$\sum_{m' \in [\hat{M}]} h_{n,0,m'} y_{n,0,m'} = 1, \quad \forall n \in [N]; \quad (5c)$$

$$\sum_{m \in [\hat{M}]} h_{n,m,-1} y_{n,m,-1} = 1, \quad \forall n \in [N]; \quad (5d)$$

(5a): task allocation, (5b): individual rationality

(5c)-(5d): flow conservation for sources and destinations

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Problem Model I:

Drivers' Profits Maximization: Constraints (Cont'd)

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$$\sum_{m \in [\hat{M}]} h_{n,m,m'} y_{n,m,m'} = x_{n,m'}, \forall n \in [N], m' \in [M]; \quad (6a)$$

$$\sum_{m' \in [\hat{M}]} h_{n,m,m'} y_{n,m,m'} = x_{n,m}, \forall n \in [N], m \in [M]; \quad (6b)$$

$$x_{n,m} \in \{0, 1\}, \quad \forall n \in [N], m \in [M]; \quad (6c)$$

$$y_{n,m,m'} \in \{0, 1\}, \quad \forall n \in [N], m \in [\hat{M}], m' \in [\hat{M}]. \quad (6d)$$

(6a)-(6b): flow conservation for internal nodes

(6c) - (6d): decision variables

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b_m : Customers' willingness-to-pay for task m

$$\hat{Z} : \text{maximize } \sum_{n \in [N]} \sum_{m \in [M]} x_{n,m} b_m - \left(\sum_{n \in [N]} \sum_{m \in [M]} x_{n,m} \hat{c}_{n,m} + \sum_{n \in [N]} \sum_{m \in [\hat{M}]} \sum_{m' \in [\hat{M}]} y_{n,m,m'} h_{n,m,m'} c_{n,m,m'} - \sum_{n \in [N]} c_{n,0,-1} \right). \quad (7)$$

s.t

Previous Constrains +

$$\sum_{n \in [N]} x_{n,m} (b_m - p_m) \geq 0, \forall m \in [M]. \quad (8)$$

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- Solving (4) or (7) is NP-hard
- In the real markets, it is hard to formulate the social welfare, since it is hard to estimate b_m
- Optimizing the drivers' total profits is enough to improve the efficiency of the ride-sharing markets
- Relax to LP and get an upper bound of OPT



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Key Solving Ideas: Node-disjoint Path Problem

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- **Original Problem:** Allocate tasks to drivers for total profits maximization (temporal + spatial)
- Merge all the N task maps into one DAG (G). Assign each task to at most one driver (**Node-disjoint needed**).
- **Objective:** Find multiple *weighted node-disjoint paths* with maximum total value.
- **EDP:** Edge-disjoint paths (existing solutions)



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Node-disjoint Path Problem: Definitions

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Definitions:

- π : A path from a source to a destination
- \mathcal{P}_i : All the paths in the graph G from s_i to d_i for driver i
- f_π : Whether path π is selected in the solution
- r_π : Profit of the path - the summation of the total value of the tasks subtracting the excess cost (defined in Eq. (4))

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Node-disjoint Path Problem: Equivalent Formulation

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$$Z : \text{maximize } \sum_{\pi \in \cup_i \mathcal{P}_i} f_{\pi} r_{\pi}. \quad (9)$$

s.t.

$$\sum_{\pi \in \mathcal{P}_i} f_{\pi} = x_i, \forall i \in [N]; \quad (10a)$$

$$\sum_{i=1}^N \sum_{\pi \in \mathcal{P}_i: m \in \pi} f_{\pi} \leq 1, \forall m \in [M]; \quad (10b)$$

$$x_i \in \{0, 1\} \forall i \in [N]; \quad (10c)$$

$$f_{\pi} \in \{0, 1\}, \forall \pi \in \cup_i \mathcal{P}_i. \quad (10d)$$

- (9): Same as (4), for the drivers' total profits
(10a): Each driver may choose 1 or 0 task list
(10b): Node-disjoint guarantee

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The Greedy Algorithm: Pseudocode

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Initialization: Let $S = \emptyset$, $\Pi = \emptyset$, $X = \{1, 2, \dots, N\}$, $G' = G$
while there exists driver $i \in X$ and path $\pi \in \cup_i \mathcal{P}_i$ from s_i to d_i with strictly positive profit $r_\pi > 0$ **do**

(a) Find the path $\pi^* = \operatorname{argmax}_{\pi \in \cup_i \mathcal{P}_i} r_\pi$, such that π^* has the maximum profit in the current graph G' . Let π^* be the task list for driver i^* ;

(b) Remove the source and destination nodes (s_{i^*}, d_{i^*}) of driver i^* and all the task nodes in π^* from the current graph G' ;

(c) $S = S \cup i^*$, $\Pi = \Pi \cup \pi^*$, $X = X / i^*$;

end

Output the drivers in set S and the selected paths (i.e. task lists) in Π .



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Theorem

The Greedy Algorithm (i.e. GA) gives a feasible solution with $(\frac{1}{D+1})$ -approximation ratio in polynomial time, where D is the maximum number of nodes in a path (i.e. the diameter of the graph G). The ratio is tight.

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Lemma 1: *Complexity*

GA achieves a feasible solution of (4) within time complexity $O(N^2M^2)$.



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Lemma 2: *Lower Bound*

GA guarantees an approximation ratio of $(\frac{1}{D+1})$.

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- \mathcal{B} : Set of paths selected by GA
- \mathcal{O} : Paths selected by the optimal solution (i.e. OPT)
- GA terminates in K iterations, $\{\pi_k\}_{k=1,2,\dots,K}$ is the path selected by GA during the k -th iteration.

Proposition 1

Every path in \mathcal{O} must intersect with at least one path in \mathcal{B} .

Proposition 2

Every path in \mathcal{B} intersects with at most $(D + 1)$ paths in \mathcal{O} .



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\mathcal{O}_k : Set of paths in \mathcal{O} that intersect with π_k

Proposition 3

$$\mathcal{O} = \cup_{k=1}^K \mathcal{O}_k \quad (11)$$

Proposition 4

$$\sum_{\pi \in \mathcal{O}_k} r_{\pi} \leq (D + 1) \cdot r_{\pi_k}, \quad \forall k = 1, 2, \dots, K \quad (12)$$

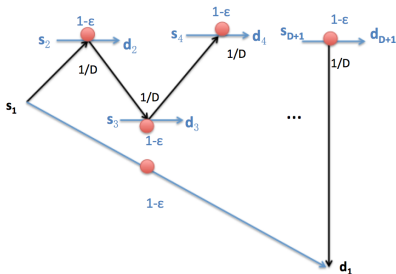
Offline Approximation Algorithm

Theoretical Analysis

Lemma 3: Upper Bound

$(\frac{1}{D+1})$ is also the upper bound to the approximation ratio.

- \mathcal{O} chooses Blue Edges $\Rightarrow (D + 1) \cdot (1 - \epsilon)$ (OPT)
- \mathcal{B} chooses Black Edges $\Rightarrow 1$ (GA)



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- Motivated by the EDP model, state-of-the-art bound:
 $O\left(\min(n^{2/3}, \sqrt{m})\right)$ for undirected graphs and
 $O\left(\min(n^{4/5}, \sqrt{m})\right)$ for directed graph.
- $\left(\frac{1}{D+1}\right)$ is a tight bound, and can apply well in real markets.
 D is small for ride-sharing. $D = 1$ and $\frac{1}{2}$ approximation ratio for Google's Waze Rider market.



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- When a task m arrives, chooses the driver who can arrive at the first time
- Update the information of tasks and drivers
- If no driver can take the task, then drop task m

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- Define the **marginal value**:

$$\delta_{n,m} = p_m - (c_{n,m,-1} + \hat{c}_{n,m} + c_{n,m',m} - c_{n,m',-1})$$

- When a task m arrives, chooses the driver n who can serve with the largest $\delta_{n,m}$
- Update the information of tasks and drivers
- If no driver can take the task, then drop task m

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- Dataset: ECML/PKDD 15 including a complete year (from 01/07/2013 to 30/06/2014) of the trajectories for all the 442 taxis running in the city of Porto, Portugal
- 1,000,000+ records with detailed information, including the timestamp of starting time and finishing time for each trip, **polyline of the trip trajectory**, and the driver ID



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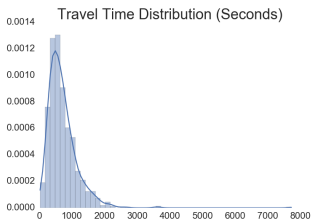


Figure: Travel Time Distribution

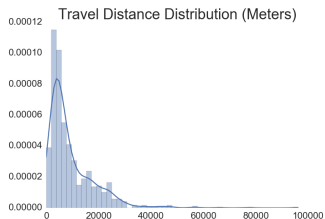


Figure: Travel Distance Distribution

Performance Evaluations

Results: Performance Ratios

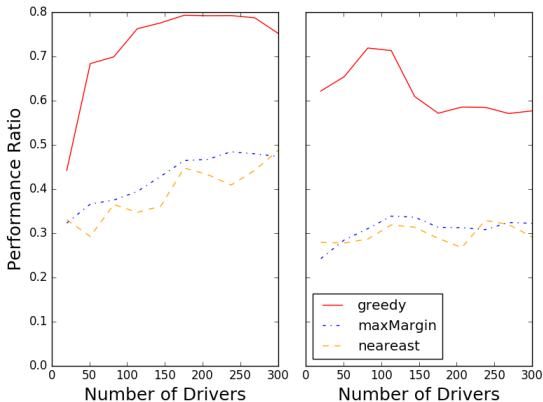


Figure: The left figure shows the performance ratio of the “hitchhiking” model and the right figure shows the performance ratio of the “home-work-home” model

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Results: More Insights

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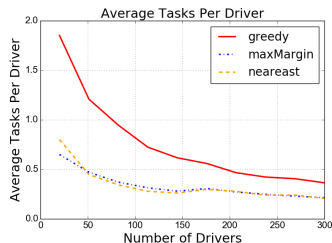
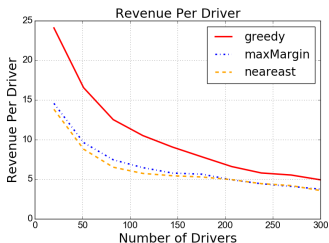
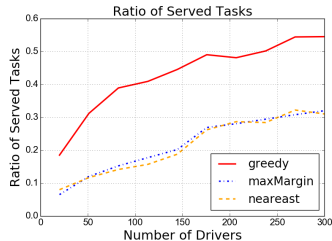
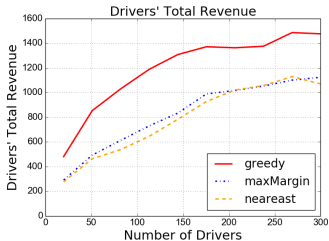
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Conclusion Remarks

- Propose generalized economic models for ride-sharing markets: Dynamic Scheduling based on **Temporal + Spatial** info
- A deterministic offline algorithm + Two online heuristics
- Application Specialization: **Limited # of tasks** within a period, our greedy algorithm works fine
- Future Work: Design deterministic online algorithms

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Thank You



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