Order Dispatching in Ride-Sharing Platform under Travel Time Uncertainty: A Data-Driven Robust Optimization Approach (Paper ID: 40)

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Outline

- Introduction to Ride-Sharing in Mobility on Demand Systems
- Problem Description
- Methodology and Formulation
- Experimental Results
- Conclusions and Future Work

Introduction to Ride-Sharing in Mobility on Demand Systems

- Ride-sharing platforms such as Uber, Lyft, and Didi have reshaped the transportation mode.
- Ride-sharing is a transportation mode where the travelers have similar itineraries in mobility on demand systems.
- Merits and advantages for both riders (demand side) and drivers (supply side). Reduce cost by sharing, reduce traffic congestion by decreasing fleet, etc.

Source: https://disrupt-africa.com/2016/12/20/ride-sharing-platform-gawana-to-launch-in-rwanda/

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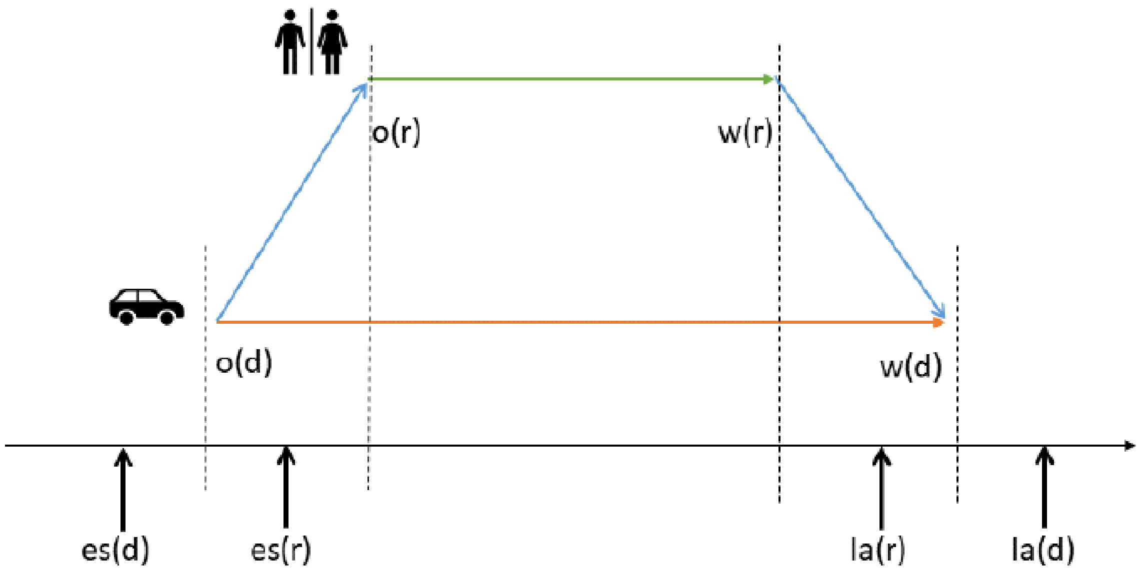
Problem Description

- A set of drivers, a set of riders, and a central operator for the ride-sharing platform
- Travelers (drivers / riders) claim their origins and destinations (coordinates) as well as their earliest departure times and latest arrival times
- Travel time is considered under uncertainty
- One-to-one matching to find the optimal solutions such that the overall travel time savings is maximized under worse-case scenario (maximum travel time delay)



$$dist(o(d), w(d)) - dist(o(d), o(r)) - dist(w(r), w(d))$$

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Methodology and Formulation

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- Robust optimization. To maximize the overall travel time saving under worst-case scenario (maximum travel time delay), while a group of constraints must be satisfied.
- The construction of uncertainty set. The nominal travel time and travel time deviation are assumed to be time-series data. Therefore, time-series forecasting approach (ARIMA in this work) is introduced.

$$U_1 = \{\xi \mid \|\xi\|_1 \le \Gamma\} = \left\{\xi \mid \sum_{j \in J_i} |\xi_j| \le \Gamma\right\}$$

- The derived uncertainty set will be used as the input for the robust optimization model.

TABLE I: Notation Table for Mathematical Models

Sets	Description
$\mathcal{D}^k$	A set of drivers at time k, indexed by d
$\mathcal{R}^k$	A set of riders at time k, indexed by r
$\mathcal{L}$	A set of regions indexed by i and j
$\mathcal{A}^k$	A set of travelers at time k, indexed by a, $\mathcal{A}^k = \mathcal{D}^k \cup \mathcal{R}^k$
$\mathcal{T}$	A set of time slots, indexed by k
$\mathcal{U}$	The uncertainty set of travel time between regions
Parameters	**Description**
$t_{i,j}$	The realized travel time from region i to j, $t_{i,j} = \bar{t}_{i,j} + \xi_{i,j}\tilde{t}_{i,j}$
$\bar{t}_{i,j}$	The nominal travel time from region i to j
$\tilde{t}_{i,j}$	The travel time deviation from region i to j
Γ	The uncertainty degree of the polyhedral uncertainty set
$o(a)$, $w(a)$	The origin and destination of a, $o(a), w(a) \in \mathcal{L}$
$es(a), la(a)$	The earliest starting time and latest arrival time of a)
Variables	**Description**
$x_{d,r} \in \{0,1\}$	Matching status that is equal to 1 if driver d and rider r is matched
$dt_d \in \mathbb{R}_+$	The departure time of driver d
$\xi_{i,j} \in \mathcal{U}$	Random variables whose values vary in the given uncertainty sets

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Methodology and Formulation

$$\max \sum_{d\in\mathcal{D}^k}\sum_{r\in\mathcal{R}^k}\left(\overline{T}^0_{d,r}x_{d,r}+\min_{\xi\in\mathcal{U}}\xi^0_{d,r}\widetilde{T}^0_{d,r}x_{d,r}\right) \quad (2)$$

s.t.

$$\overline{T}^0_{d,r}+\min_{\xi\in\mathcal{U}}\xi^0_{d,r}\widetilde{T}^0_{d,r}+H(1-x_{d,r})\geqslant 0, \forall d\in\mathcal{D}^k, \forall r\in\mathcal{R}^k, \quad (2a)$$

$$dt_d \geqslant es(d), \quad \forall d\in\mathcal{D}^k, \quad (2b)$$

$$dt_d+\overline{t}_{o(d),o(r)}+\min_{\xi\in\mathcal{U}}\xi_{o(d),o(r)}\tilde{t}_{o(d),o(r)}+H(1-x_{d,r}) \geqslant es(r), \forall d\in\mathcal{D}^k, \forall r\in\mathcal{R}^k, \quad (2c)$$

$$dt_d+\overline{T}^1_{d,r}+\min_{\xi\in\mathcal{U}}\xi^1_{d,r}\widetilde{T}^1_{d,r}\leqslant la(r)+H(1-x_{d,r}), \forall d\in\mathcal{D}^k, \forall r\in\mathcal{R}^k, \quad (2d)$$

$$dt_d+\overline{T}^2_{d,r}+\min_{\xi\in\mathcal{U}}\xi^2_{d,r}\widetilde{T}^2_{d,r}\leqslant la(d)+H(1-x_{d,r}), \forall d\in\mathcal{D}^k, \forall r\in\mathcal{R}^k, \quad (2e)$$

$$\sum_{r\in\mathcal{R}}x_{d,r}\leqslant 1, \quad \forall d\in\mathcal{D}^k, \quad (2f)$$

$$\sum_{d\in\mathcal{D}}x_{d,r}\leqslant 1, \quad \forall r\in\mathcal{R}^k, \quad (2g)$$

$$x_{d,r}\in\{0,1\}, \quad \forall d\in\mathcal{D}^k, \forall r\in\mathcal{R}^k, \quad (2h)$$

$$dt_d\in\mathbb{R}_+, \quad \forall d\in\mathcal{D}^k, \quad (2i)$$

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Experimental Results

- Experiment setup. Python 3.7, Gurobi 9.0, Intel Core i7 CPU, 32 GB RAM, Win 10
- Data sets. New York taxi trip records, January 2017 – June 2017. Seven regions and six time slots are selected.

TABLE II: The total number of riders and drivers in the ride-sharing regions during the given time slots

Time Slots No.	1	2	3	4	5	6
Num. of Rider	33	209	102	158	67	153
Num. of Drivers	40	251	123	190	81	184

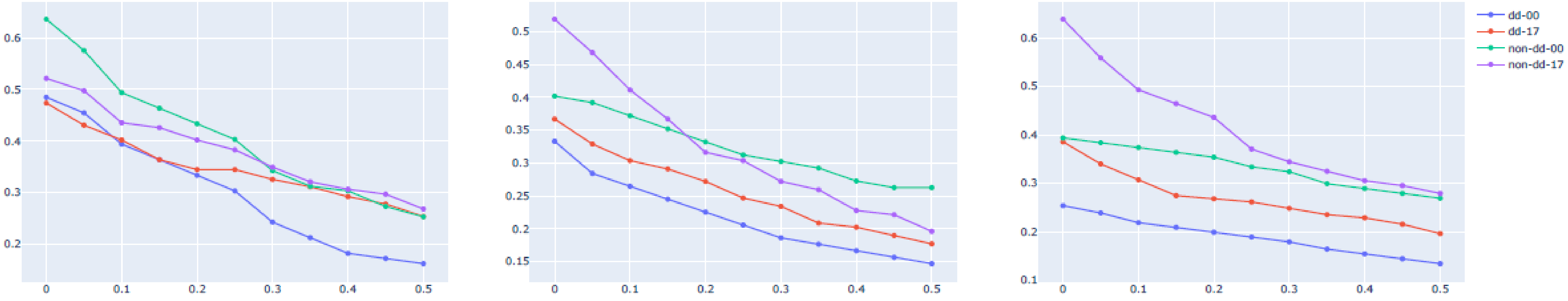
The comparison of average travel time savings

TABLE IV: The comparison of average travel time savings for the ride-sharing systems (in minutes) by data-driven and non-data-driven robust optimization under different levels of uncertainty degree. For each time slot, the top row is derived from data-driven robust optimization, the bottom row is derived from non-data-driven robust optimization, and the change compared to non-data-driven robust optimization is in the middle in italics.

Time Slots \ Γ	0%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
06/01/2017 00	1.88	1.85	1.73	1.69	1.50	1.49	1.21	0.93	0.74	0.62	0.52
	(16.8%)	*(22.5%)*	*(27.2%)*	*(74.2%)*	*(92.3%)*	*(112.8%)*	*(83.3%)*	*(60.3%)*	*(89.7%)*	*(87.9%)*	*(79.3%)*
06/01/2017 00	1.61	1.51	1.36	0.97	0.78	0.7	0.66	0.58	0.39	0.33	0.29
06/01/2017 17	1.57	1.55	1.53	1.47	1.44	1.41	1.35	1.26	1.15	1.05	0.91
	(3.3%)	*(2.6%)*	*(3.8%)*	*(1.0%)*	*(1.0%)*	*(2.2%)*	*(1.5%)*	*(3.3%)*	*(3.6%)*	*(18.0%)*	*(8.3%)*
06/01/2017 17	1.52	1.51	1.48	1.46	1.43	1.38	1.33	1.22	1.11	0.89	0.84
06/03/2017 00	1.79	1.76	1.74	1.73	1.72	1.69	1.57	1.51	1.33	1.17	1.02
	(42.1%)	*(44.3%)*	*(20.7%)*	*(54.5%)*	*(53.6%)*	*(70.7%)*	*(70.6%)*	*(64.1%)*	*(75.0%)*	*(77.3%)*	*(61.9%)*
06/03/2017 00	1.26	1.22	1.16	1.14	1.12	0.99	0.92	0.92	0.76	0.66	0.63
06/03/2017 17	1.77	1.77	1.75	1.64	1.58	1.54	1.48	1.31	1.23	1.17	0.99
	(1.1%)	*(4.7%)*	*(6.7%)*	*(6.5%)*	*(12.1%)*	*(17.5%)*	*(25.4%)*	*(25.9%)*	*(30.8%)*	*(48.1%)*	*(47.8%)*
06/03/2017 17	1.75	1.69	1.64	1.54	1.41	1.31	1.18	1.04	0.94	0.79	0.67
06/18/2017 00	2.21	2.20	2.18	2.13	2.12	2.10	2.08	2.04	1.94	1.81	1.57
	(28.5%)	*(27.9%)*	*(29.0%)*	*(27.5%)*	*(26.9%)*	*(29.6%)*	*(40.5%)*	*(53.4%)*	*(63.0%)*	*(60.2%)*	*(40.2%)*
06/18/2017 00	1.72	1.72	1.69	1.67	1.67	1.62	1.48	1.33	1.19	1.13	1.12
06/18/2017 17	1.87	1.83	1.81	1.79	1.76	1.76	1.68	1.66	1.58	1.55	1.47
	(27.2%)	*(26.2%)*	*(30.2%)*	*(30.7%)*	*(30.4%)*	*(33.3%)*	*(31.3%)*	*(40.7%)*	*(38.6%)*	*(46.2%)*	*(44.1%)*
06/18/2017 17	1.47	1.45	1.39	1.37	1.35	1.32	1.28	1.18	1.14	1.06	1.02
Avg.	1.85	1.83	1.79	1.74	1.69	1.67	1.56	1.45	1.33	1.23	1.08
Avg.	*(19.4%)*	*(20.4%)*	*(23.4%)*	*(27.9%)*	*(31.0%)*	*(36.9%)*	*(36.8%)*	*(39.4%)*	*(44.6%)*	*(51.9%)*	*(42.1%)*
Avg.	1.55	1.52	1.45	1.36	1.29	1.22	1.14	1.04	0.92	0.81	0.76

The comparison of violation rates

- The metric to measure the robustness of solution (the unmatched rates of rider)



(a) June 1st

(b) June 3rd

(c) June 18th

Fig. 3: Comparison of violation rates by data-driven robust optimization and non-data-driven robust optimization

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Conclusions and Future Work

- Conclusions. We propose a data-driven robust optimization approach to address order dispatching in ride-sharing platform. The framework organically integrates time-series predictor and robust optimization model.
- Future work.
  - To extend one-to-one driver and rider matching to one-to-many matching (i.e., one driver can pick up more than one rider).
  - To utilize different types of uncertainty sets to validate the performance of robust optimization models.

Thank you !

Questions?