A Data-Driven Approach to Manage Curbside Ride-hailing Pick-ups and Drop-offs

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Outlines

- Introduction
- Methodology
- Numerical Experiment
- Conclusion
- Q&A

Introduction

- In addition to roads & intersections, **curb spaces** where multiple traffic flows meet and conflict.
- **More popular ride-hailing services**, more taxi orders, more frequent pick-up/drop-off, **more congested** curb spaces.
- Ride-hailing services could congest the city.
  - Cruising (Xu et al. 2019)
  - **Pick-ups and drop-offs (PUDO)**
- The number of PUDO is negatively correlated with speed significantly (Goodchild et al. 2019)
- Pricing policy implemented to manage pick-up/drop-off in many cities (New York, Washington D.C.)

Credit: City & State New York

Credit: The Wall Street Journal

Motivation

- **Learning effect** of PUDO on traffic state.
  - require RVs (Ride-hailing Vehicles) leave and rejoin traffic stream frequently.
  - occupy curb space inducing extra delays and wasteful cruising.

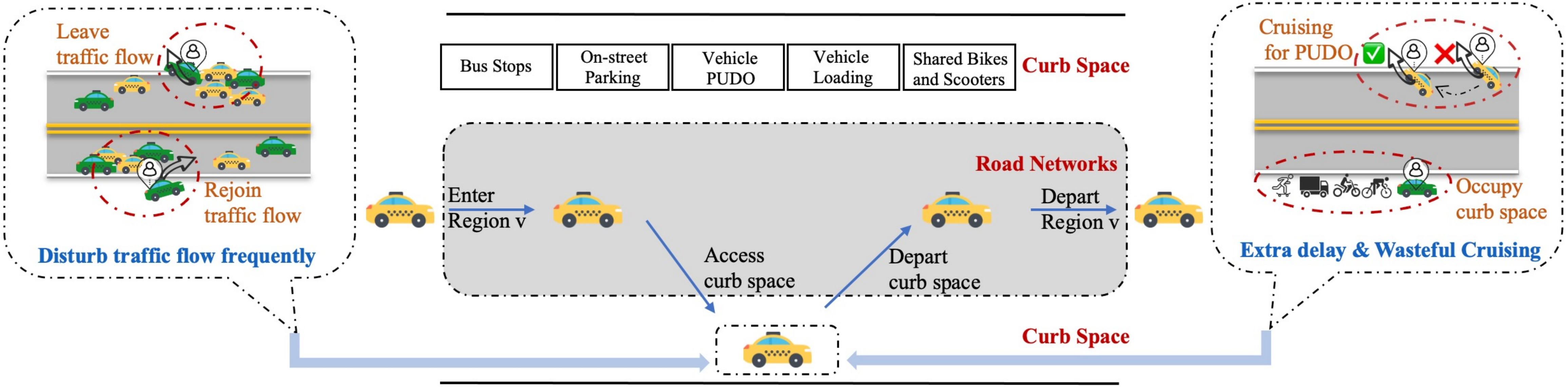

Fig 1. Illustration of the congestion effect of PUDO's number on traffic state

Challenges

- **Significant negative correlation of** Number of PUDO vs. Traffic speed : More PUDO, lower speed, more congestion;
- **Correlation is not causality.** There is a latent factor: **travel demand**
  - PUDO induced
  - Demand induced: higher travel demand, more PUDO, lower speed
- Can we also learn the **congestion effect(causality)** by machine learning ?

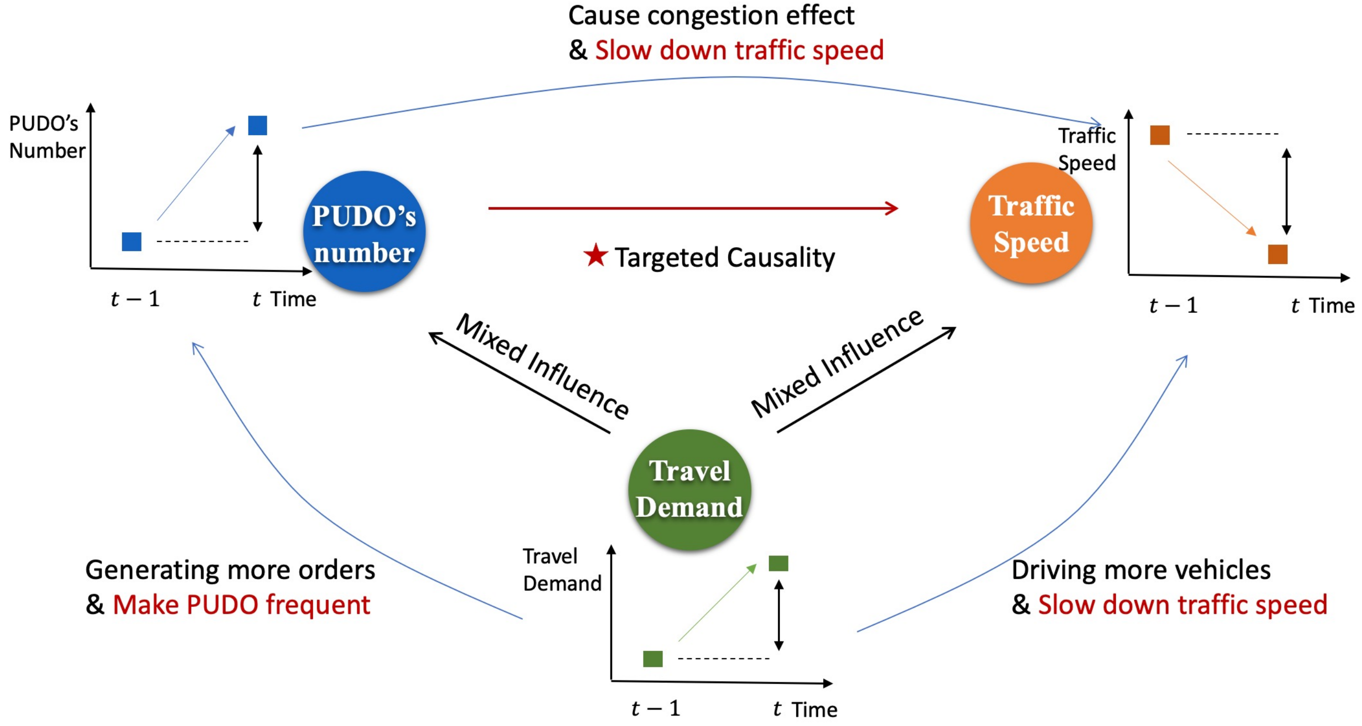

Fig 2. Illustration of causality among travel demand, PUDO's number, traffic state

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Causal Graph

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- Assumption: given a specific region, the congestion effect $\boldsymbol{\theta_v}$ of PUDO is negative and constant.
- Biased Modeling: Partially linear regression with strong assumption on function, inducing biased estimation.
- Spatial-temporal causality: Traffic state is varied with **time** and **space**, which makes causality estimation more complex.

$$y_v^t = \theta_v d_v^t + \varphi_v(\cdot) + \epsilon_v^t$$

$$d_v^t = \psi_v(\cdot) + \xi_v^t$$

- $\boldsymbol{y_v^t}$: traffic speed in the region v at time t;
- $\boldsymbol{\varphi_v}$: function to capture influence of factors on y_v^t;
- $\boldsymbol{\epsilon_v^t}$: error.
- $\boldsymbol{d_v^t}$: number of PUDO in the region v at time t;
- $\boldsymbol{\psi_v}$: function to capture influence of factors on d_v^t.
- $\boldsymbol{\xi_v^t}$: error.

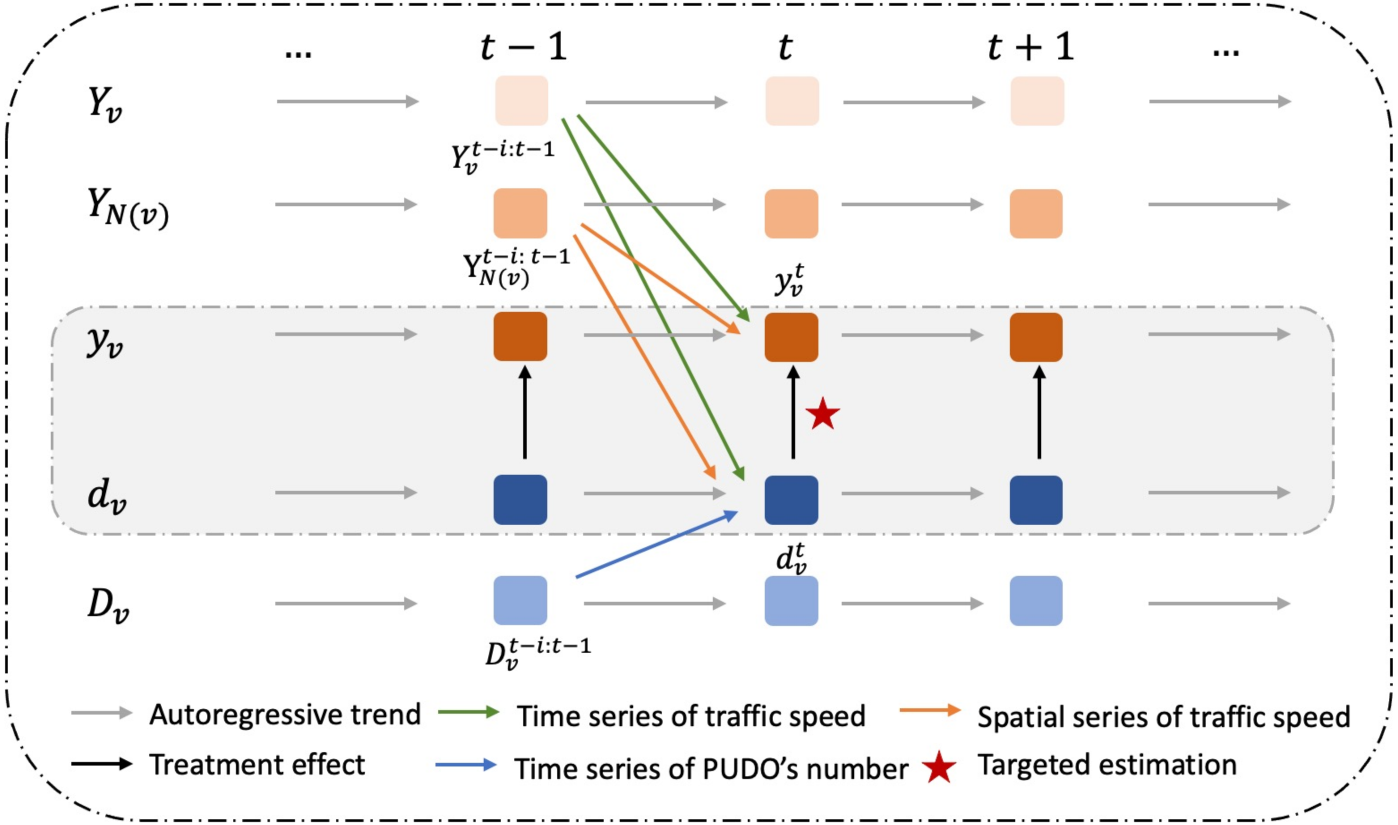

Fig 3. Causal graph between the number of PUDO and traffic speed

DSML: Double and Separated ML

- DSML consist of 3 components: first two non-linear parts and one linear part.
- **Model Y:** predict speed y_v^t by ML.
- **Model D:** predict number of PUDO d_v^t by ML.
- **Model Z:** estimate θ_v based on residuals of Model Y and Model D by LR.
- **Frisch–Waugh–Lovell Theorem**: residuals-on-residuals

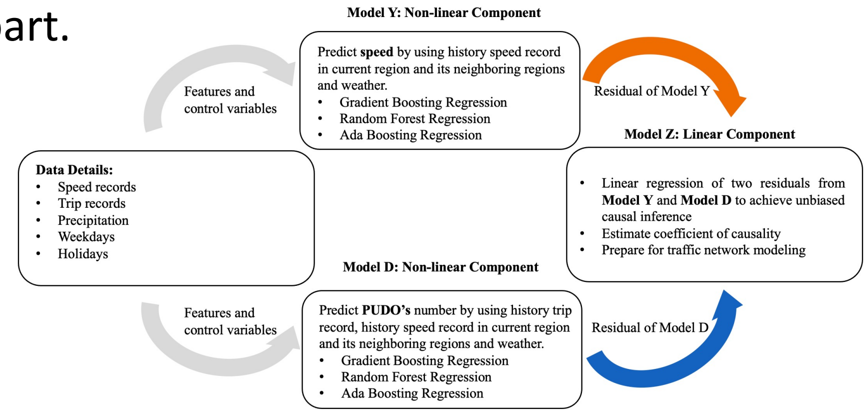

Fig 4. Framework of DSML

Model Y $$y_v^t = \varphi_v(\mathbf{Y}_v^{t-i:t-1}; \mathbf{Y}_{\mathcal{N}(v)}^{t-i:t-1}; w_v^t) + \epsilon_v^t, \quad \mathbb{E}[\epsilon_v^t | \mathbf{Y}_v^{t-i:t-1}; \mathbf{Y}_{\mathcal{N}(v)}^{t-i:t-1}; w_v^t] = 0$$

Model D $$d_v^t = \psi_v\left(\mathbf{D}_v^{t-i:t-1}, \mathbf{Y}_v^{t-i:t-1}, \mathbf{Y}_{\mathcal{N}(v)}^{t-i:t-1}, w_v^t\right) + \xi_v^t \quad \mathbb{E}[\xi_v^t | \mathbf{D}_v^{t-i:t-1}; \mathbf{Y}_v^{t-i:t-1}; \mathbf{Y}_{\mathcal{N}(v)}^{t-i:t-1}; w_v^t)] = 0$$

Model Z $$\hat{\theta}_v = \arg\min_{\theta \in \Theta} \mathbb{E}[(y_v^t - \varphi_v(\mathbf{Y}_v^{t-i:t-1}; \mathbf{Y}_{\mathcal{N}(v)}^{t-i:t-1}; w_v^t) - \theta_v \cdot \mathbb{E}[(d_v^t - \psi_v(\mathbf{D}_v^{t-i:t-1}; \mathbf{Y}_v^{t-i:t-1}; \mathbf{Y}_{\mathcal{N}(v)}^{t-i:t-1}; w_v^t)]$$

Rerouting

- Consider travelers from node 1 to node 5
- Concentrated pick-ups (node 1) and drop-offs (node 5), specifically in shopping mall/ office buildings
- Can we encourage walking to spread the pick-ups and drop-offs to minimize the total travel time?

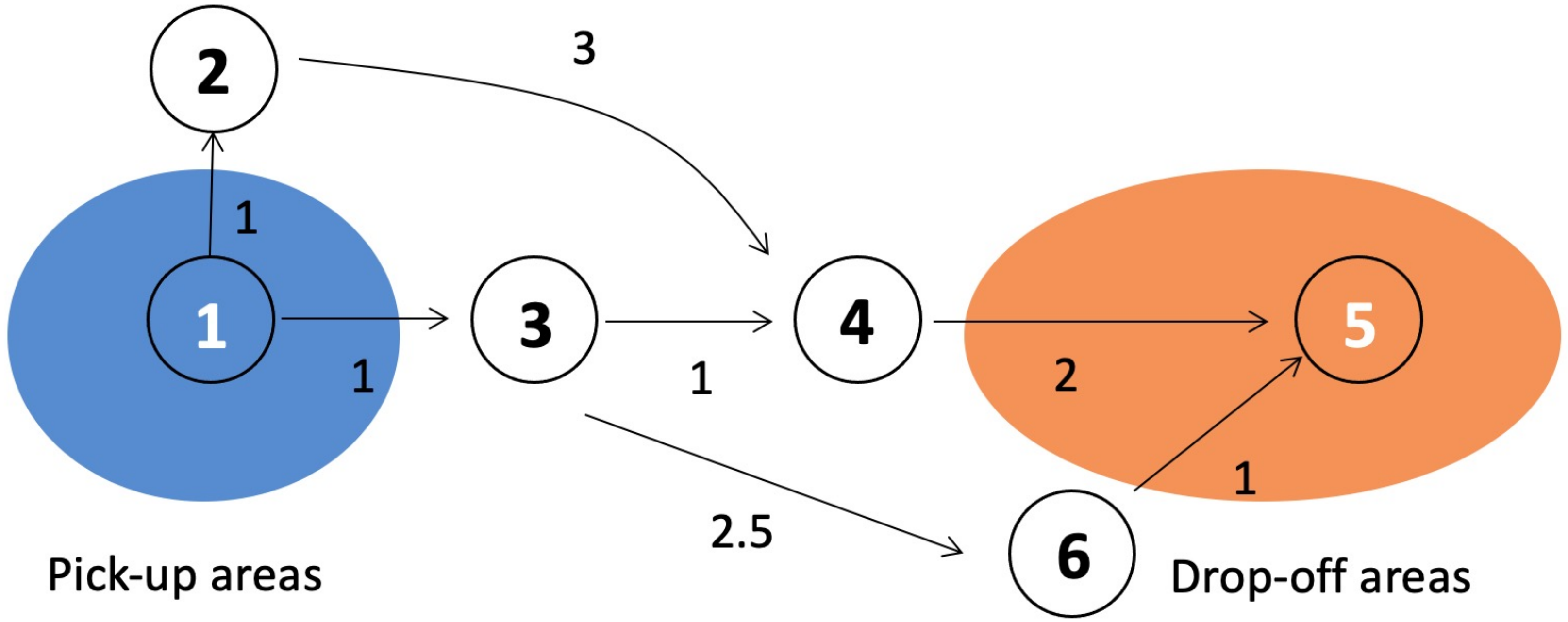

Fig 5. Illustration of the distribution of PUDO by rerouting

Rerouting Formulation

- **Decision variables:** $\widetilde{\mathbf{f}^t_{rs}}$ traffic flow from r to s directly; $\widetilde{\mathbf{h}^t_{rsn}}$ traffic flow from r to $\mathrm{n}, n \in N(s)$ firstly and continue to walk to s at time t.
- **Objective function:** minimize total travel time
- **Constraints:**
  - Conservation of traffic flow before and after rerouting;
  - Limit range of changed traffic flow;
  - Non-negative constraints of traffic flow.

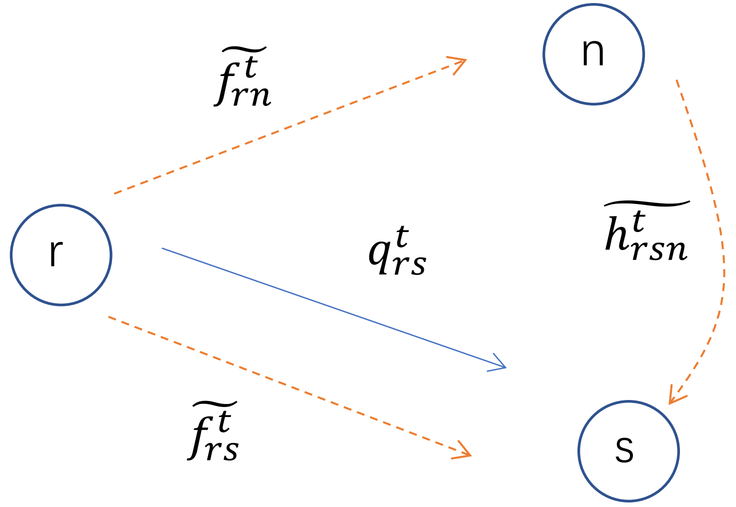

Fig 6. Illustration of rerouting traffic flow

$$
\begin{aligned}
\min_{\tilde{f}^t_{rs}, \tilde{h}^t_{rsn}} \quad & \sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{R}} \tilde{f}^t_{rs} \tilde{m}^t_{rs} + \sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{R}} \sum_{n \in \mathcal{N}(s)} \tilde{h}^t_{rsn} \tilde{c}^t_{rsn} \\
\text{s.t.} \quad & \tilde{f}^t_{rs} + \sum_{n \in \mathcal{N}(s)} \tilde{h}^t_{rsn} = \lambda q^t_{rs} \quad \forall n \\
& \beta d^t_s \le \tilde{d}^t_s \le \gamma d^t_s \\
& 0 \le \tilde{f}^t_{rs} \quad \forall r, s \\
& 0 \le \tilde{h}^t_{rsn} \quad \forall r, s, n
\end{aligned}
$$

Solving Algorithm

- Solving algorithm of the non-linear programming:
  - given time cost t,
  - shift itself into one linear programming,
  - update parameters based on optimized value,
  - For loop until it converges.

Algorithm 2: system optimal rerouting algorithm based on non-linear programming

Routing$\left(\tilde{f}^t_{rs}, \tilde{h}^t_{rsn}\right)$;

Input : driving time cost m^t_{rs}, sum of driving and walking time cost c^t_{rsn}, path flow q^t_{rs}, drop-off demand d^t_s, speed y^t_s

, treatment effect θ_s, set of passing regions $\mathcal{L}_{rs}$;

Output: Rerouted path flow $\tilde{f}^t_{rs}$ and $\tilde{h}^t_{rsn}$

Initialize f^t_{rs} and h^t_{rsn} by gradient projection ;

Calculate $\tilde{d}_s = \sum_{rs} \tilde{f}^t_{rs} + \sum_r \sum_{\mathcal{N}(s)} \tilde{h}^t_{rsn}$;

Calculate $\Delta^t_s = d^t_s - \tilde{d}^t_s$;

Calculate original total travel time $\sum_{rs} q^t_{rs} m^t_{rs}$;

Initialize m = 0;

while $m < looptimes$ **do**

- Initialize decision variables $\tilde{f}^t_{rs}$ and $\tilde{h}^t_{rsn}$;
- Update $\tilde{y}^t_s = y^t_s + \theta_s\ \Delta_s$;
- Update $\tilde{m}^t_{rs}$ and $\tilde{c}^t_{rsn}$ with changed $\tilde{y}^t_s$ as shown in Eq. 15 ;
- Calculate optimized objective function $\sum_r \sum_s \tilde{f}^t_{rs}\tilde{m}^t_{rs} + \sum_r \sum_s \sum_n \tilde{h}^t_{rsn}\tilde{c}^t_{rsn}$;
- Solve the linear programming given $\tilde{m}^t_{rs}$ and $\tilde{c}^t_{rsn}$;
- Obtain optimized value $\tilde{f}^t_{rs}$ and $\tilde{h}^t_{rsn}$;
- Update $\tilde{f}^t_{rs}$ and $\tilde{h}^t_{rsn}$ by Gradient Descent with Momentum ;
- Update $\tilde{d}^t_s = \sum_{rs} \tilde{f}^t_{rs} + \sum_r \sum_{\mathcal{N}(s)} \tilde{h}^t_{rsn}$;
- Update $\Delta_s = d_s - \tilde{d}_s$;
- Update $m = m + 1$;

end

$$
\begin{aligned}
\min_{\tilde{f}^t_{rs}, \tilde{h}^t_{rsn}} \quad & \sum_{r\in\mathcal{R}} \sum_{s\in\mathcal{R}} \tilde{f}^t_{rs}\tilde{m}^t_{rs} + \sum_{r\in\mathcal{R}} \sum_{s\in\mathcal{R}} \sum_{n\in\mathcal{N}(s)} \tilde{h}^t_{rsn}\tilde{c}^t_{rsn} \\
\text{s.t.} \quad & \tilde{f}^t_{rs} + \sum_{n\in\mathcal{N}(s)} \tilde{h}^t_{rsn} = \lambda q^t_{rs} \quad \forall n \\
& \beta d^t_s \le \tilde{d}^t_s \le \gamma d^t_s \\
& 0 \le \tilde{f}^t_{rs} \quad \forall r, s \\
& 0 \le \tilde{h}^t_{rsn} \quad \forall r, s, n \\
& d^t_s = \sum_{r\in\mathcal{R}} q^t_{rs} \\
& \tilde{d}^t_s = \sum_{r\in\mathcal{R}} \tilde{f}^t_{rs} + \sum_{r\in\mathcal{R}} \sum_{n\in\mathcal{N}(s)} \tilde{h}^t_{rsn} \\
& \Delta^t_s = \tilde{d}^t_s - d^t_s \\
& \tilde{y}^t_s = y^t_s + \hat{\theta}_s \Delta^t_s \\
& m^t_{rs} = \sum_{v\in\mathcal{L}_{rs}} l_v / y^t_v \\
& \tilde{m}^t_{rs} = \sum_{v\in\mathcal{L}_{rs}} l_v / \tilde{y}^t_v \\
& w_{ns} = \sum_{v\in\mathcal{L}_{rs}} l_v / k
\end{aligned}
$$

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Data

- Feb 2019 to Jun 2020 on Manhattan island, 5 min resolution
  - TLC Trip Record Data （Pick-up/drop-offs, d_v^t）
  - NYC public traffic speed data (Traffic Speed, y_v^t)
  - Weather/ Weekdays/ Weekends (Control variables w_v^t)

Table 3: Data details

Data Sets	Time	Resolution	Amount	Description
NYC Traffic Speed	Feb 2019 - Jun 2020	in 5 min	404351029	TMC, road speed, reference speed, time stamp
TCL Trip Record	Feb 2019 - Jun 2020	in 5 min	18157071	Pick-up region ID, drop-off region ID, time stamp
IEM	Feb 2019 - Jun 2020	in 1 h	11987	precipitation, time stamp

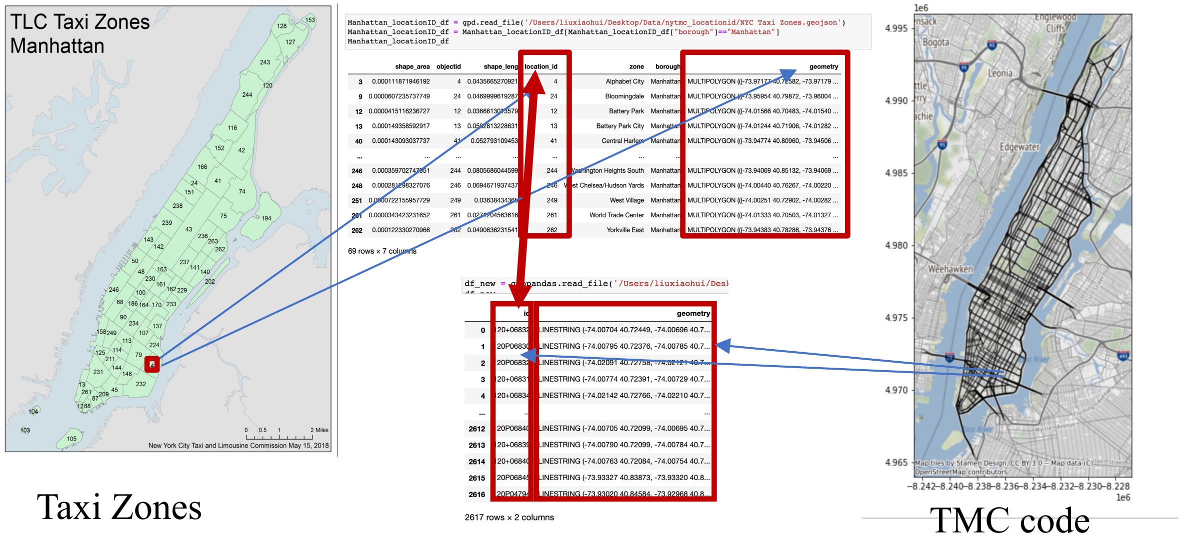


Fig 7. Details of data set

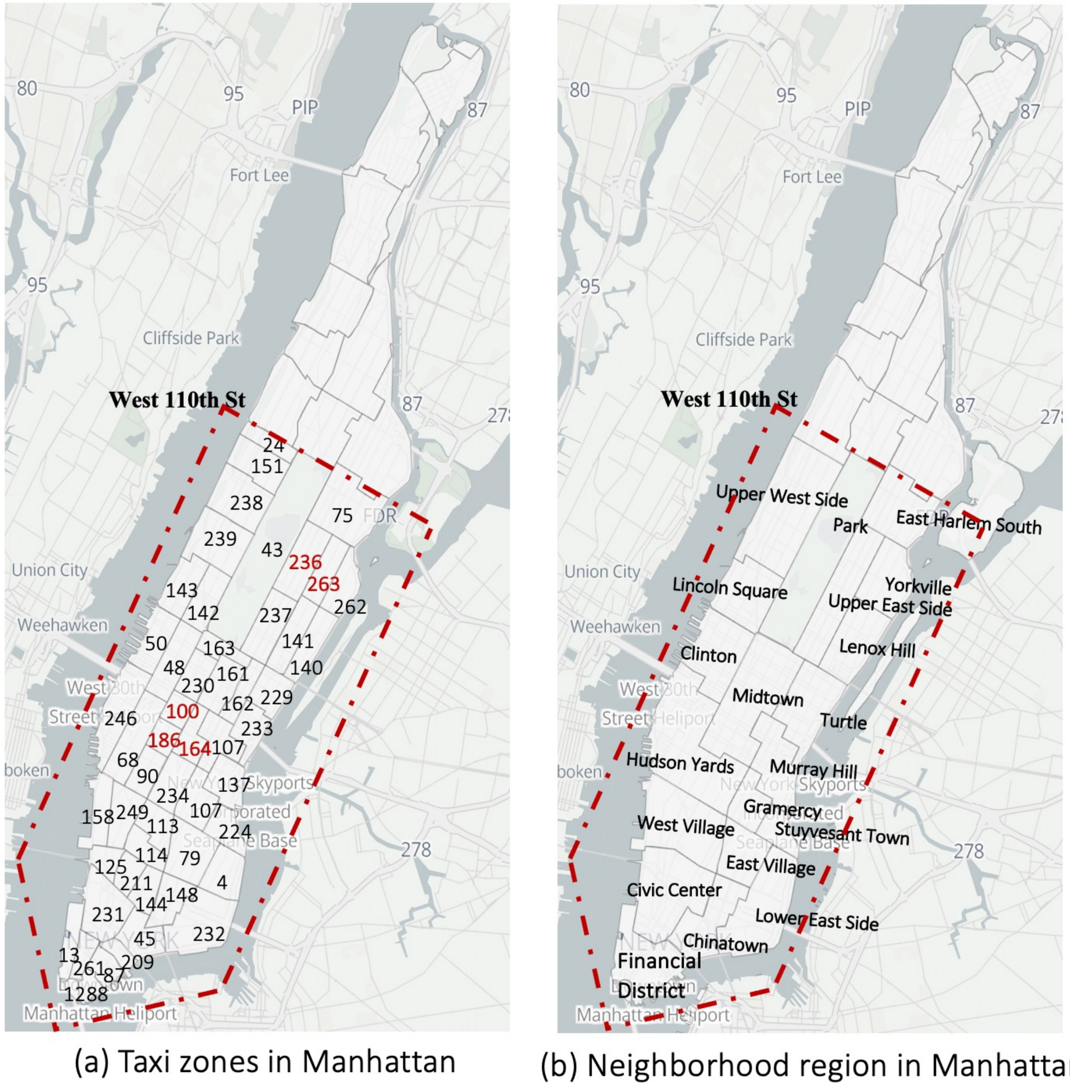


Fig 8. Taxi zone & neighborhood region in Manhattan

Numerical Experiment

- Model Y & Model D: Random Forest Regression/ Gradient Boosting Regression/ Ada Boosting Regression
- Model Z: Linear Regression

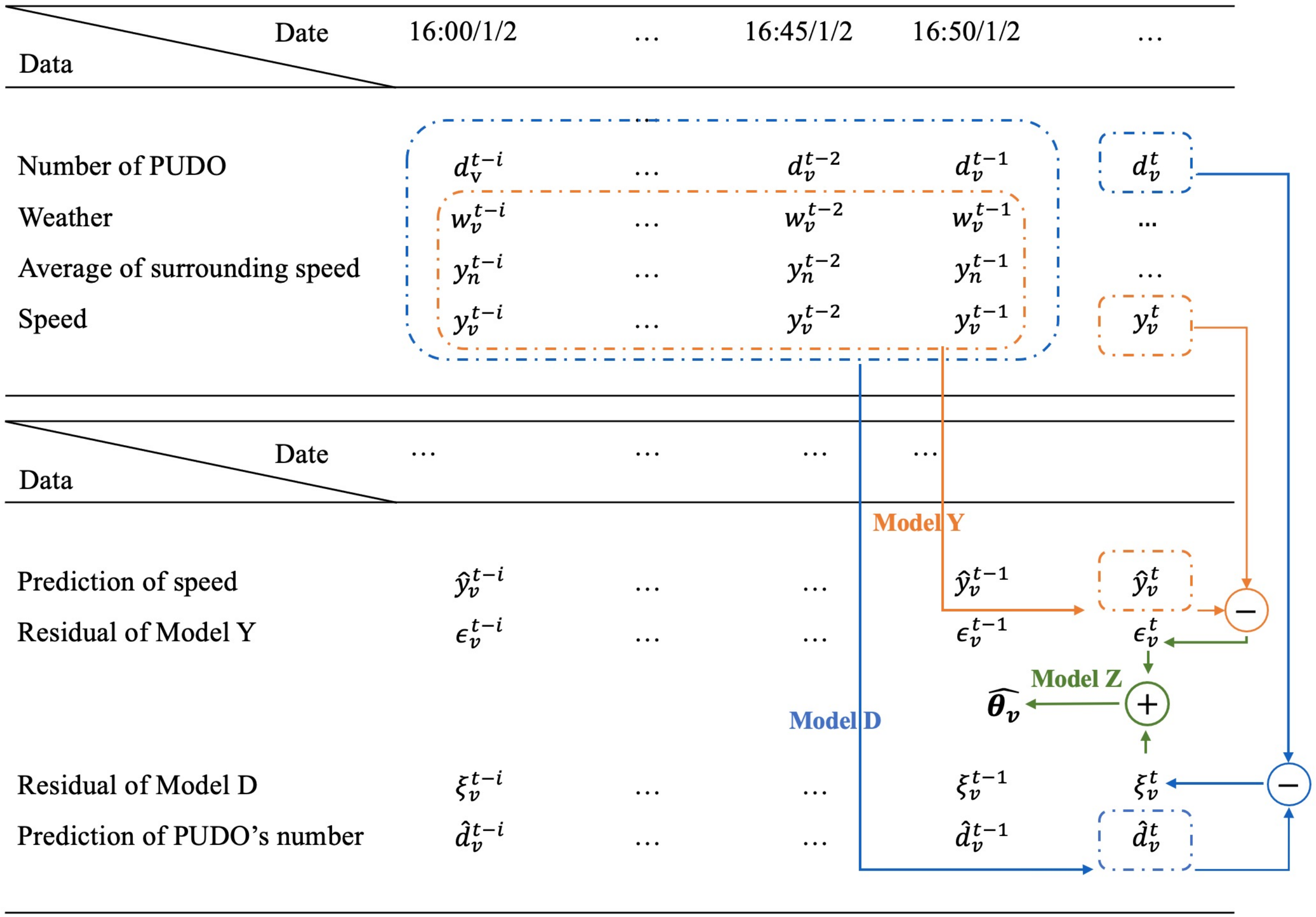
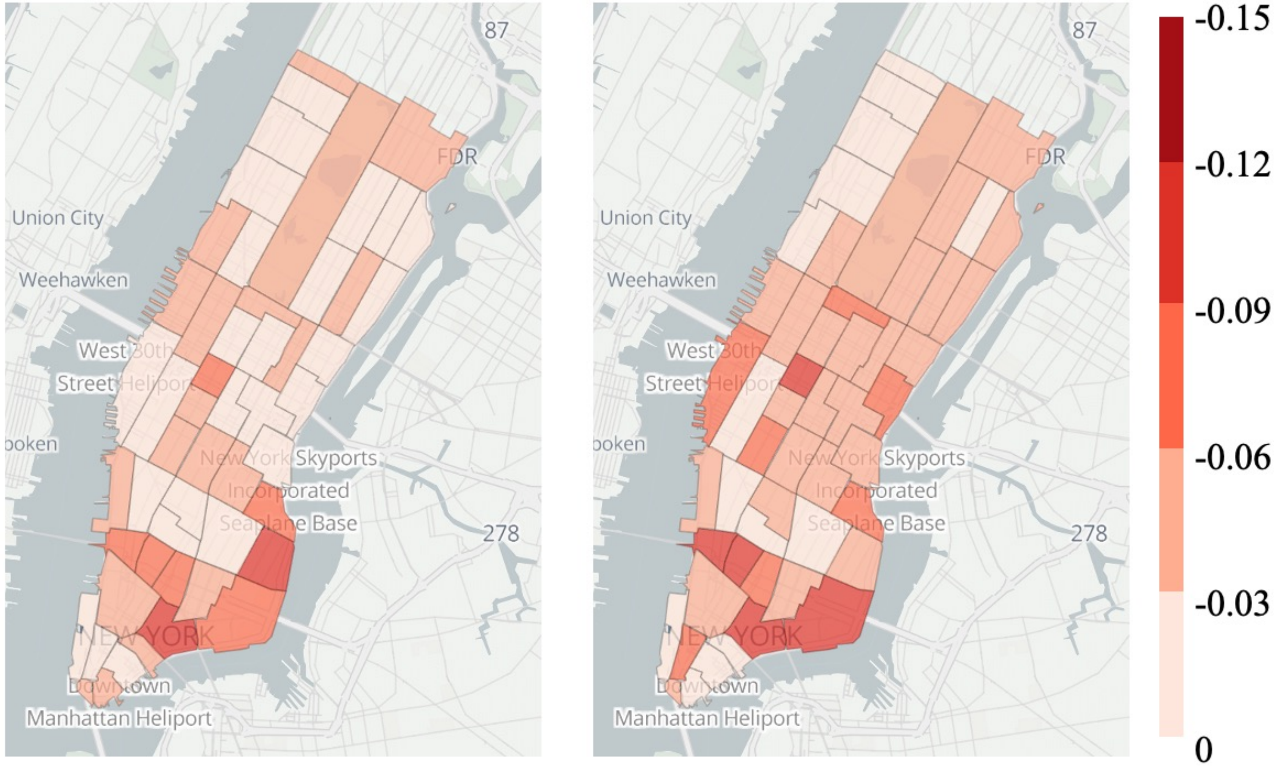


Fig 9. illustration of DSML in the numerical experiment

Effect Overview

- $\hat{\theta}$ = **-0.0370(weekdays) / -0.0454(weekends)** : more 100 PUDO reduce the average speed by 3.70/ 4.54 mph.
- Estimation result of θ is significant and consistent with common sense: the **busier** the region, the **bigger** the effect.
- Different travel pattens : bigger impacts on POI on **weekends** than **weekdays**.



(a) θ on weekdays (b) θ on weekends

Fig 10. Estimation result of DSML

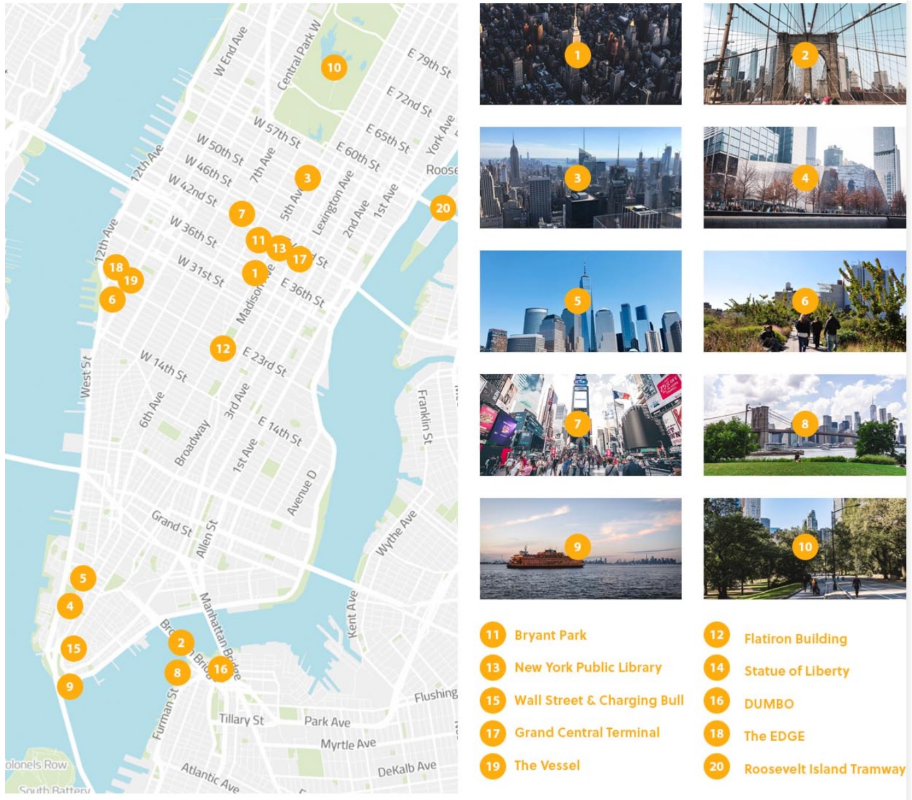


Fig 11. Attractions in Manhattan

Comparison and Significance Analysis

- DML (2018): cannot distinguish difference of effect in different regions.
- Partially LR: learn the correlation rather than causality.

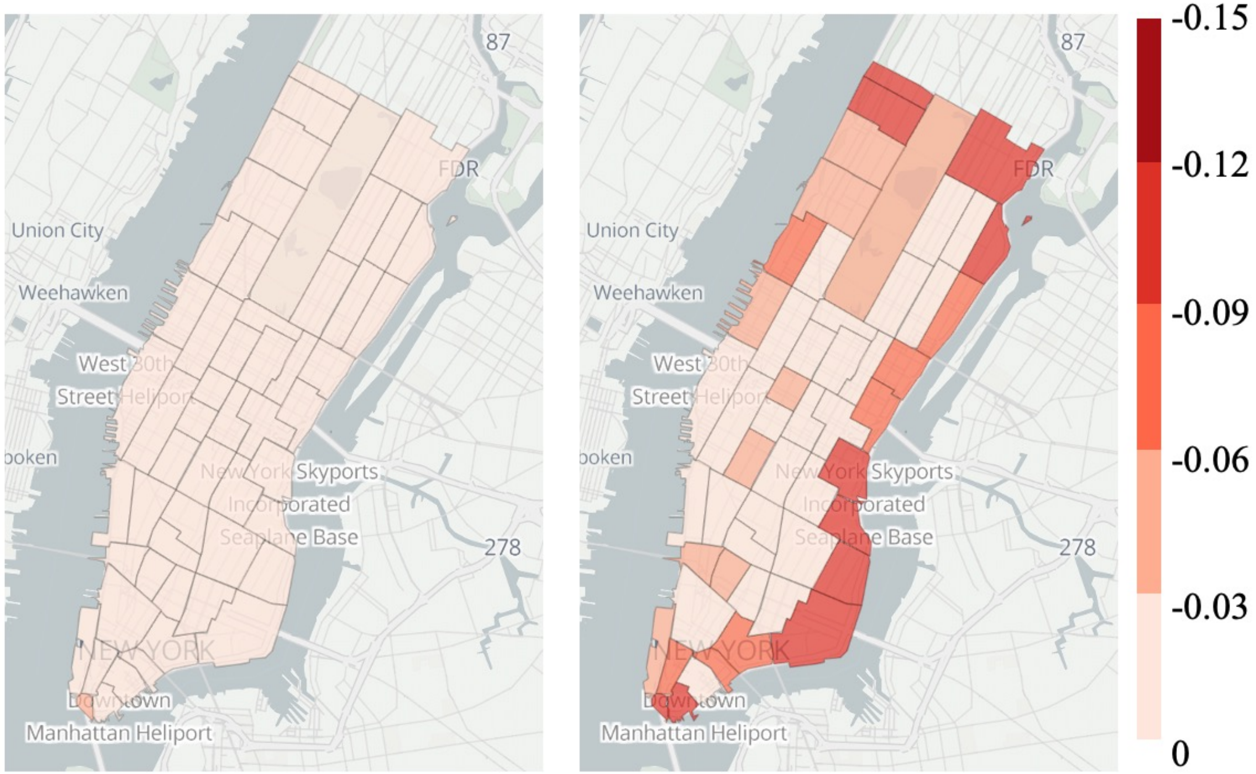
Table 4: Comparison of DSML, DML and LR

Models	Features	Outcome Variable	Methods
LR	D^r_{t+1}	Y^r_{t+1}	linear regression
DML	$\mathbf{D}^r_{t:t-i}$, $\mathbf{Y}^r_{t:t-i}$, $\mathbf{Y}^{\mathcal{N}(r)}_{t:t-i}$, $\mathbf{W}^r_{t+1}$	Y^r_{t+1}	machine learning methods
	$\mathbf{D}^r_{t:t-i}$, $\mathbf{Y}^r_{t:t-i}$, $\mathbf{Y}^{\mathcal{N}(r)}_{t:t-i}$, $\mathbf{W}^r_{t+1}$	D^r_{t+1}	machine learning methods
	η^r_{t+1}	τ^r_{t+1}	linear regression
DSML	$\mathbf{Y}^r_{t:t-i}$, $\mathbf{Y}^{\mathcal{N}(r)}_{t:t-i}$, $\mathbf{W}^r_{t+1}$	Y^r_{t+1}	machine learning methods
	$\mathbf{D}^r_{t:t-i}$, $\mathbf{Y}^r_{t:t-i}$, $\mathbf{Y}^{\mathcal{N}(r)}_{t:t-i}$, $\mathbf{W}^r_{t+1}$	D^r_{t+1}	machine learning methods
	η^r_{t+1}	τ^r_{t+1}	linear regression

Table 5: Comparison of estimation result of DSML, DML and LR

Regions ID	DSML		DML		LR	
	θ	p-value	θ	p-value	θ	p-value
4	-0.092	0.000***	-0.009	0.021*	-0.162	0.000***
12	-0.036	0.039*	-0.050	0.019*	-0.163	0.000***
13	-0.020	0.000***	-0.012	0.000***	-0.052	0.000***
24	-0.038	0.000***	-0.023	0.000***	-0.169	0.000***

[a] ***$p \leq 0.001$, highly significant
[b] **$p \leq 0.001$, very significant
[c] *$p \leq 0.005$, significant
[d] $p > 0.05$, not significant



(a) DML (b) PLR

Fig 12. Estimation result of DSML

Optimization Result

- Setting total number of vehicles can be controlled as 15 times of taxi vehicles.
- The optimized result at Midtown near 14.72% ; at Central Park around 4.16%.

Table 6: Baseline of optimization result by controlling total vehicles amounts on weekdays ($\lambda = 15$)

	Original time cost ($\times 10^3$ hours)	Optimized time cost ($\times 10^3$ hours)	Improvement rate (%)
	In Midtown on weekdays		
Average	4.41 ± 2.82	3.75 ± 2.14	14.72 ± 2.21
16:00	4.60 ± 0.63	3.89 ± 0.47	15.17 ± 2.27
17:00	4.74 ± 0.75	3.99 ± 0.55	15.60 ± 2.40
18:00	4.50 ± 0.80	3.81 ± 0.61	15.07 ± 2.42
19:00	3.81 ± 0.84	3.32 ± 0.66	12.50 ± 2.47
	In Central Park on weekdays		
Average	3.63 ± 2.98	3.46 ± 2.67	4.16 ± 2.02
16:00	2.94 ± 0.56	2.79 ± 0.49	4.64 ± 2.33
17:00	3.75 ± 0.78	3.57 ± 0.70	4.41 ± 2.02
18:00	4.23 ± 0.90	4.03 ± 0.81	4.52 ± 2.29
19:00	3.57 ± 0.82	3.45 ± 0.76	3.02 ± 1.68

Fig 13. Neighborhoods Regions of Manhattan

Sensitivity Analysis

- The more amount of vehicles can be controlled, the more travel time can be saved.

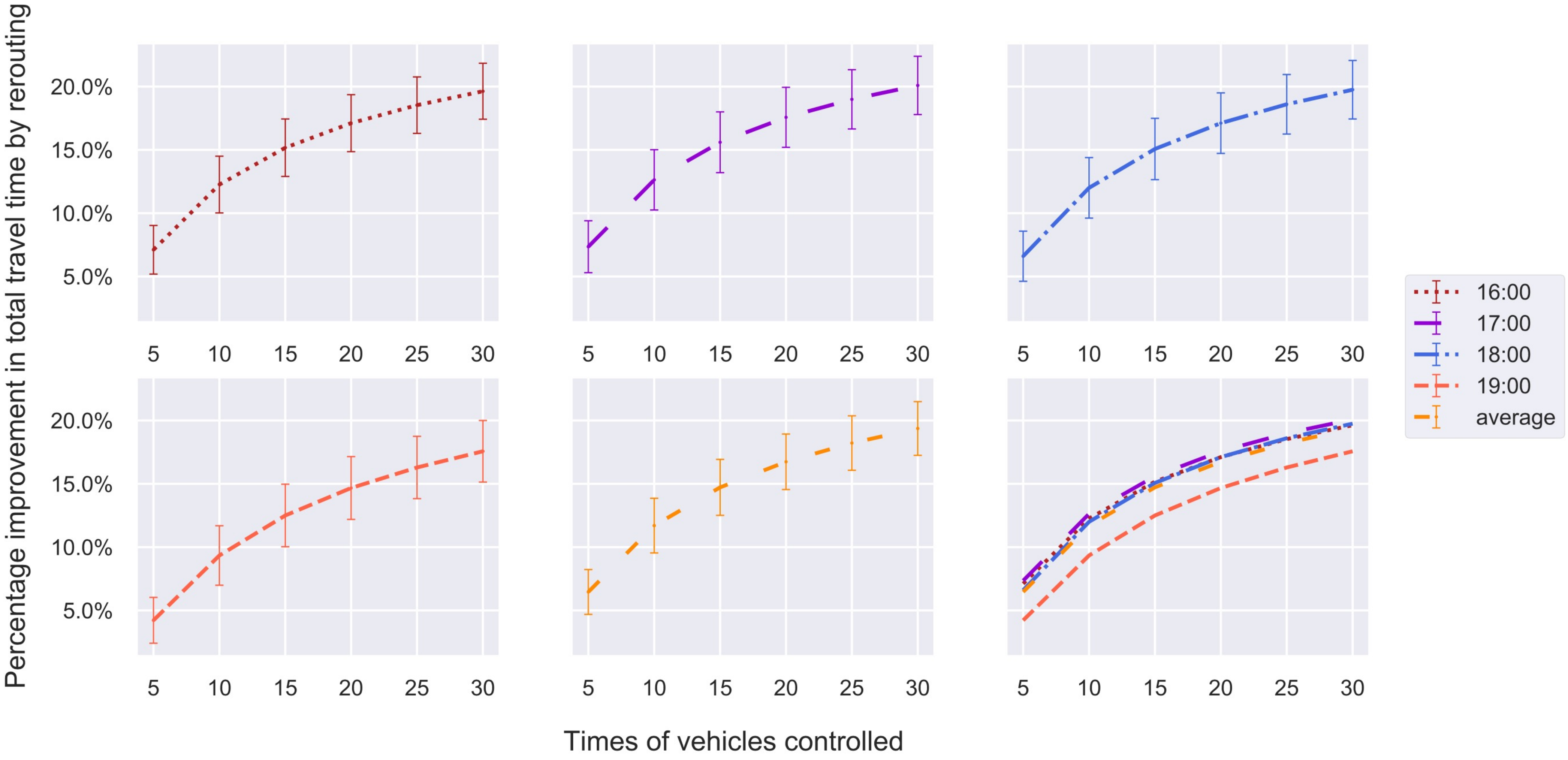


Fig 14. Improvement rate curve in MidTown on weekdays controlling vehicle amount

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Conclusion and Discussion

- **Causality Analysis:**
  - **DSML** model can obtain **valid estimation** of causality with considering varied time and space two dimensions
  - PUDO has **dynamic negative impact** on traffic state with time and space.
  - **100** additional PUDO will make speed decrease by **3.70 mph on weekdays**, while **4.54 mph on weekends** in Manhattan.

- **Rerouting programming:**
  - Rerouting based on difference of causality in different regions **works effectively** to minimize travel time.
  - The optimized rate at one **busy region** can arrive at **near 14.72%,** while that at one **less busy region** is around **4.16%**.

Thanks!