Herbert Wertheim College of Engineering
UNIVERSITY of FLORIDA

POWERING THE NEW ENGINEER TO TRANSFORM THE FUTURE

Department of Civil & Coastal Engineering

Machine Learning Aided Transportation System Analysis, Management, and Decision Making

Lili Du, Ph.D., Associate Professor

University of Florida

SE Florida FSUTMS meeting on September 16th 2022

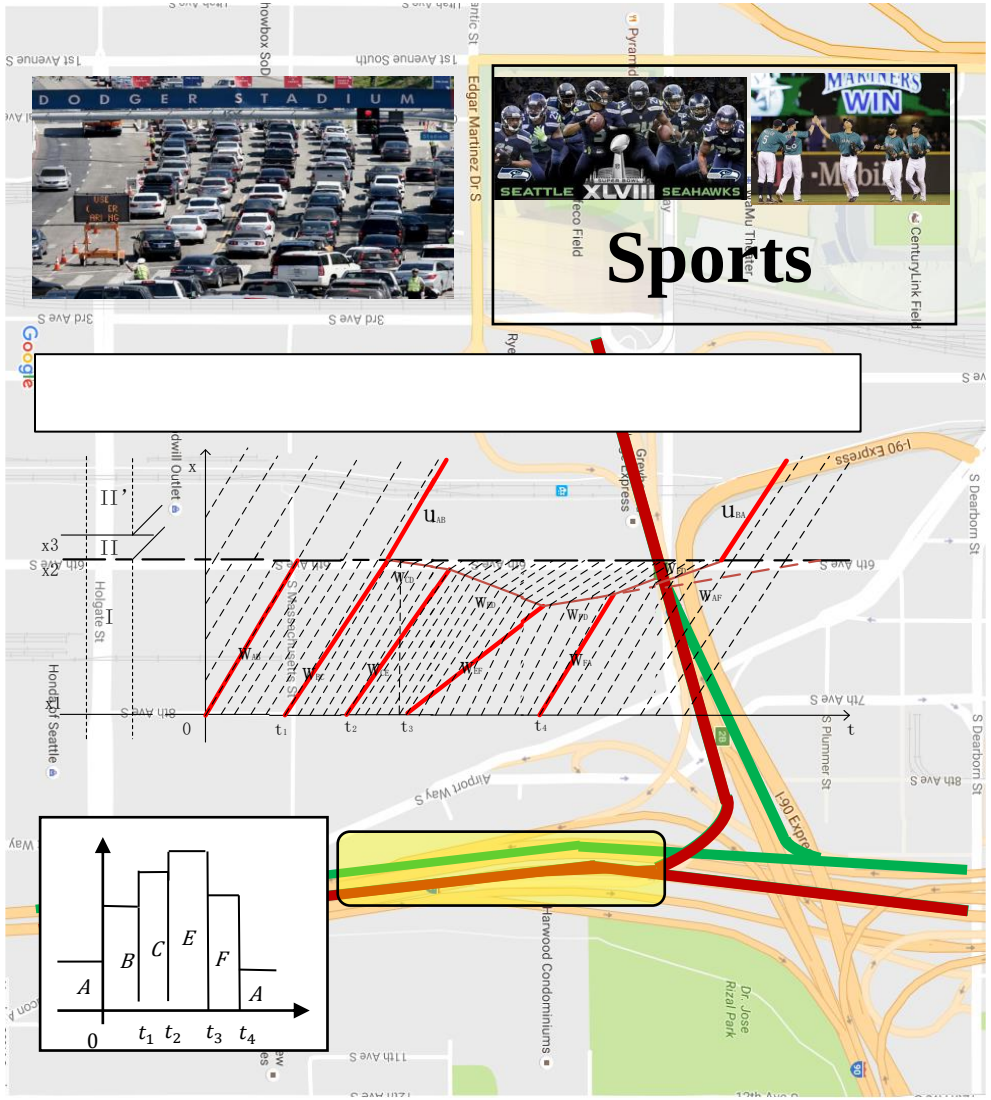
ML Aided Transportation System Management Decision Making

- **Data in Transportation System**
  - Huge and diverse spatiotemporal traffic data
    - Fixed point traffic data from loop, camera.
    - Trajectory data from probe vehicles.
    - Traffic data communication through V2V or V2I.
    - Mobility from mobile apps
- **ML Research (Data + ML + Domain Knowledge)**
  - Traffic anomaly detection and prediction: sports; construction; accidents.
  - Hybrid Mobility Service design.
  - Connected and autonomous vehicle control.
  - Traffic congestion mitigation: routing; ridesharing; information provision strategy.

Traffic Domain Knowledge

Early Alerting a Coming Public Event and Its Traffic Impact

- **Public Event and Its Unique Impacts**
  - Sports, concerts, special festivals.
  - Traffic congestion mainly occurs before the event starts or after it comes to the end.
  - Traffic impacts evolve in a large area and last over a relatively long time; proactive congestion is desired.
  - Highway segment near to the ramp leading to the local venue of the event is a critical point to sense and detect the event.
  - **Shockwave diagrams carry more features of the impacts than point data only showing traffic demand fluctuation.**
  - Develop shockwave generation/detection algorithm according to **traffic flow theory**

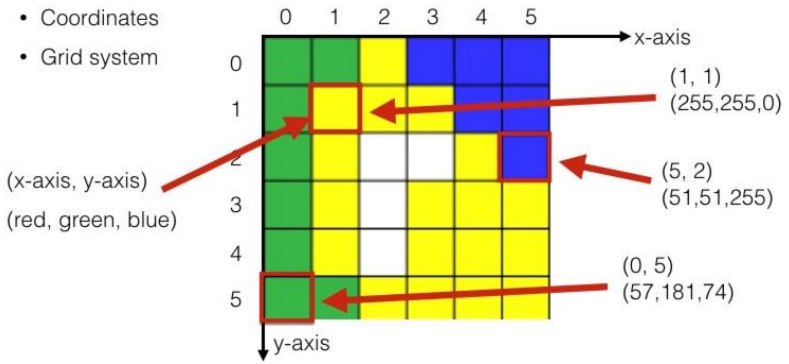


Yang, Hanyi, Lili Du, and Jamshid Mohammadi (2021). A shock wave diagram-based deep learning model for early alerting an upcoming public event. Transportation Research Part C: Emerging Technologies 122: 102862

Early Alerting a Coming Public Event and Its Impact

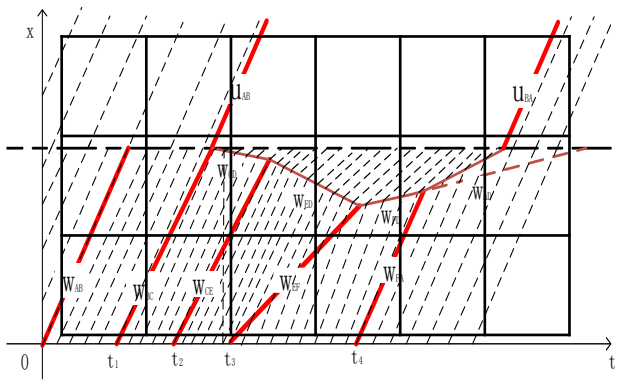
Encoding shockwaves

An Image



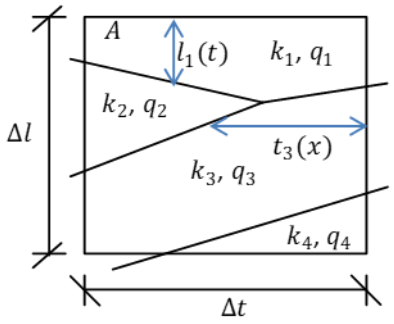
- An image can be stored as digital numbers by computers
- Formation: pixel grid system. And, each pixel represents its color
- Color encoding: (Red, Green, Blue) $\Longrightarrow$ a pixel

A Shock wave diagram



- Shock wave diagrams can also be stored as digital numbers by computers
- Formation: pixel grid system. And, each pixel represents traffic state
- Traffic state encoding: (Flow, Density) $\Longrightarrow$ a pixel

Grid Design



$$M=\{(\bar{k},\bar{q})\}_{mn}$$

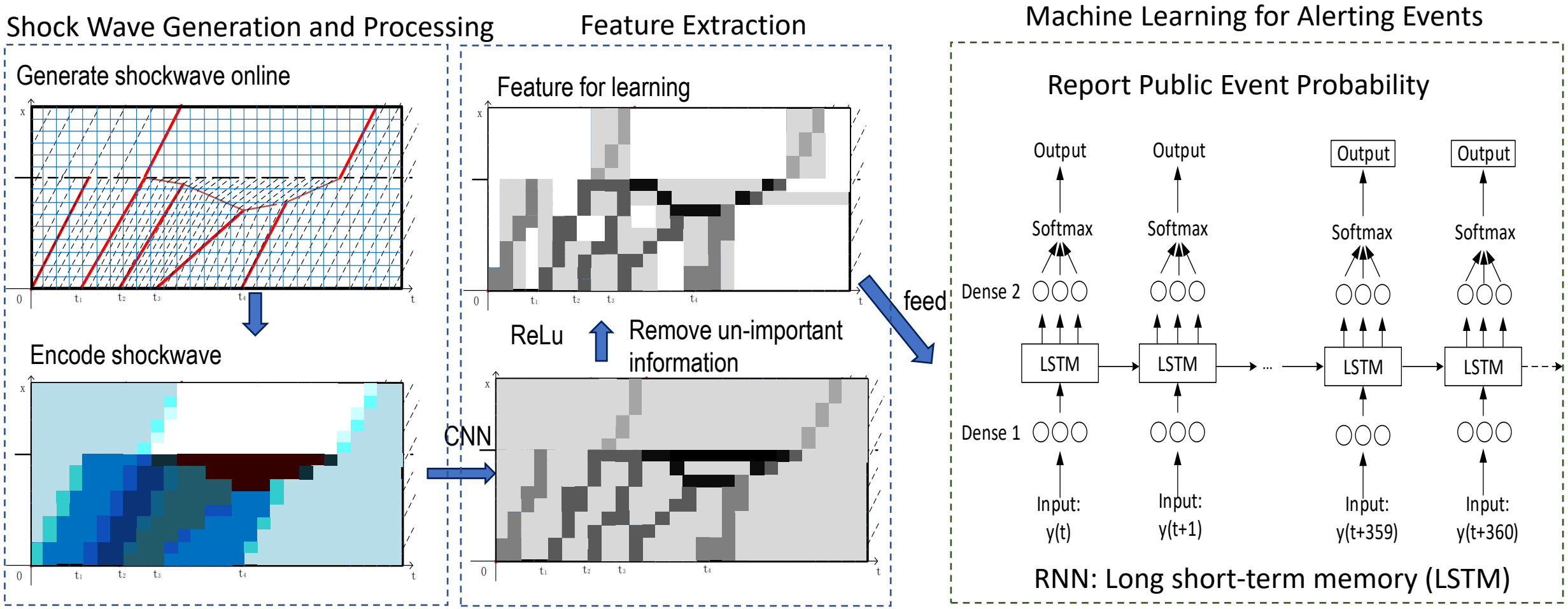
$$\bar{k}(A)=\frac{t(A)}{|A|}=\frac{\sum_i^N k_i\int_0^{\Delta t} l_i(t)dt}{\Delta l*\Delta t}$$

$$\bar{q}(A)=\frac{d(A)}{|A|}=\frac{\sum_i^N q_i\int_0^{\Delta l} t_i(x)dx}{\Delta l*\Delta t}$$

The optimization model searches for the best grid design to keep data resolution and computation efficiency

Early Alerting a Coming Public Event and Its Impact

Shock Wave Diagrams Fed Deep Learning Model (SW-DLM)



Grid is optimally designed to keep data resolution and computation efficiency

Early Public Event Prediction and Impact Alarming

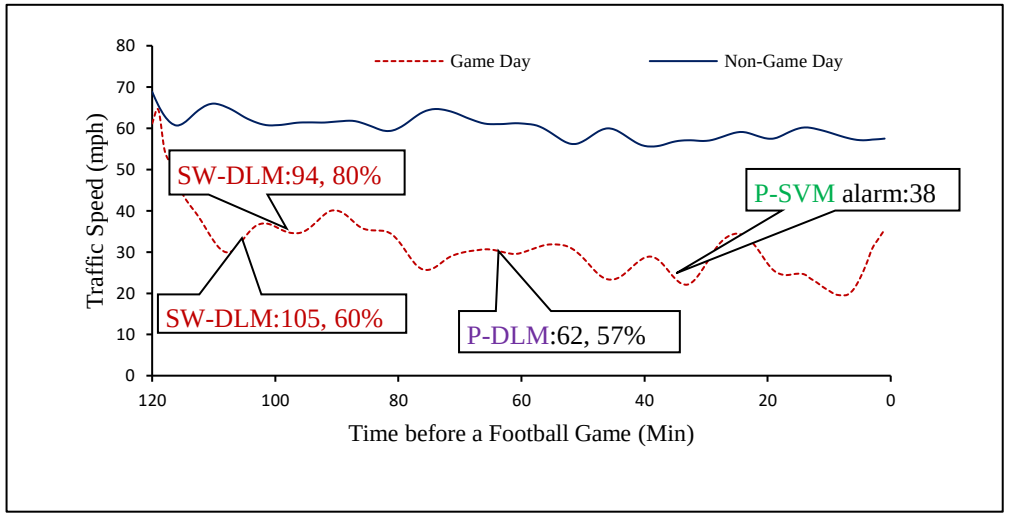
Experiment

- **Sports Game from 1PM-3PM, raining 11am-12pm**
  - T-Mobile Park and CenturyLink Field in Seattle, Washington State.
- **Report Event and Impacts**
  - SW-DLM: Senses traffic impacts 105 (or 94) mins before the game and predicts the coming game with 60% (or 80%) accuracy.
  - P-DLM: alarms the event 62 mins before the game with 57% accuracy.
  - P-SVM: alarms the event 38 minutes before the game.

Traffic impact report on Sep 25, 2011; Event from 1pm-3pm

Time	Free flow	Congestion	Event	Rain
7:00	Y	N	X	X
8: 00	Y	N	X	X
9:00	Y	N	X	X
10:00	Y	N	X	X
11:00	N	Y	√	√
12:00	N	Y	√	X
13:00	N	Y	E	X
14:00	N	Y	E	X
15:00	Y	N	X	X

√: impact alarmed by SW-DLM (event prediction with 50% confidence)



Can be extended to predict/detect other events such as traffic accidents or work zones which induce traffic anomalies

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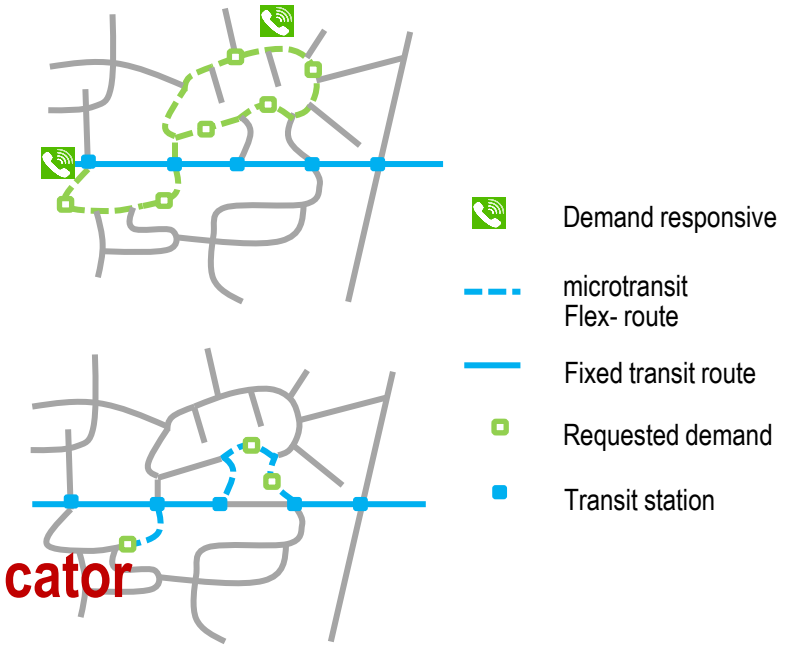
Data-driven Hybrid Mobility Service Design

- **Ridesharing and Transit**
  - Complicated competition and complementary relationship between transit and ridesharing.
  - None of them can fully satisfy mobility needs.
- **Hybrid urban mobility services**
  - Integrate transit with on-demand services, e.g. microtransit and ridesharing.
  - Inject flexibility into transit system.
- **Challenges**
  - **Where** are the good connections between transit and on-demand services?
  - **How** service gaps evolve over time?
- **Joint ridesharing and transit trajectories: a good indicator**



Trajectory Data Presentation

- **Analyzes Joint Transit and Ridesharing Trajectories in a 3-D space (x-y-time).**

- **Presentation Difficulties**
  - Scrambly; non-additive curves.
  - Hard to analysis; hard to see patterns by AI directly.

- **STEP I:** Optimal 3D discretization presentation
  - Optimal discretization of the time axis.
  - Optimal discretization of x-y plane.

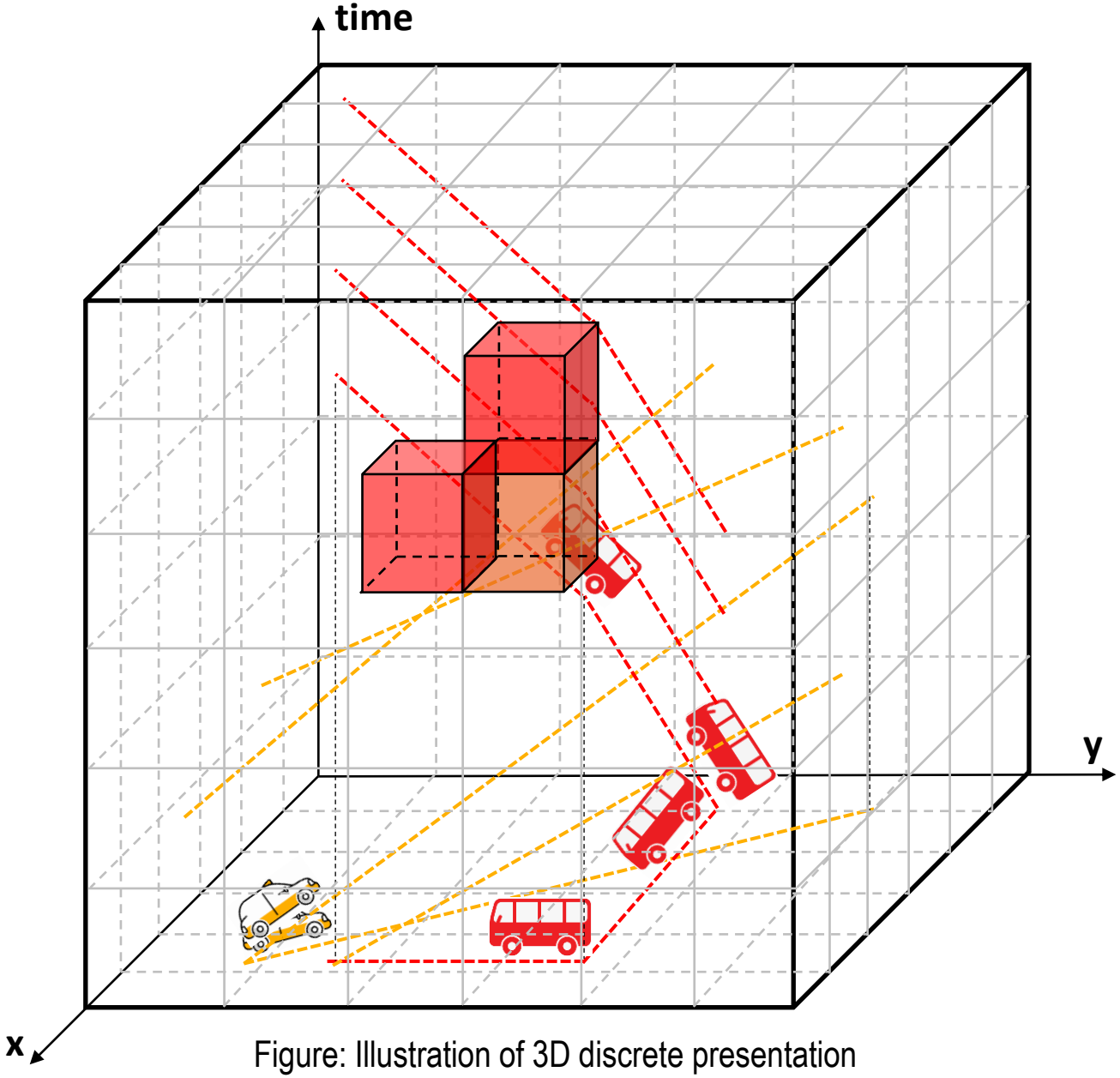
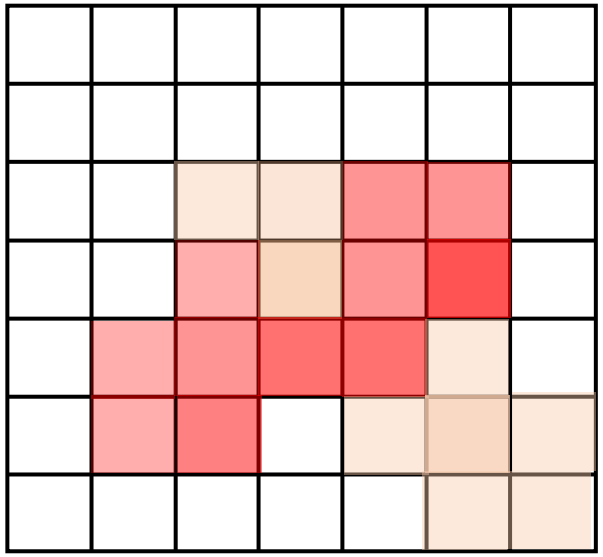


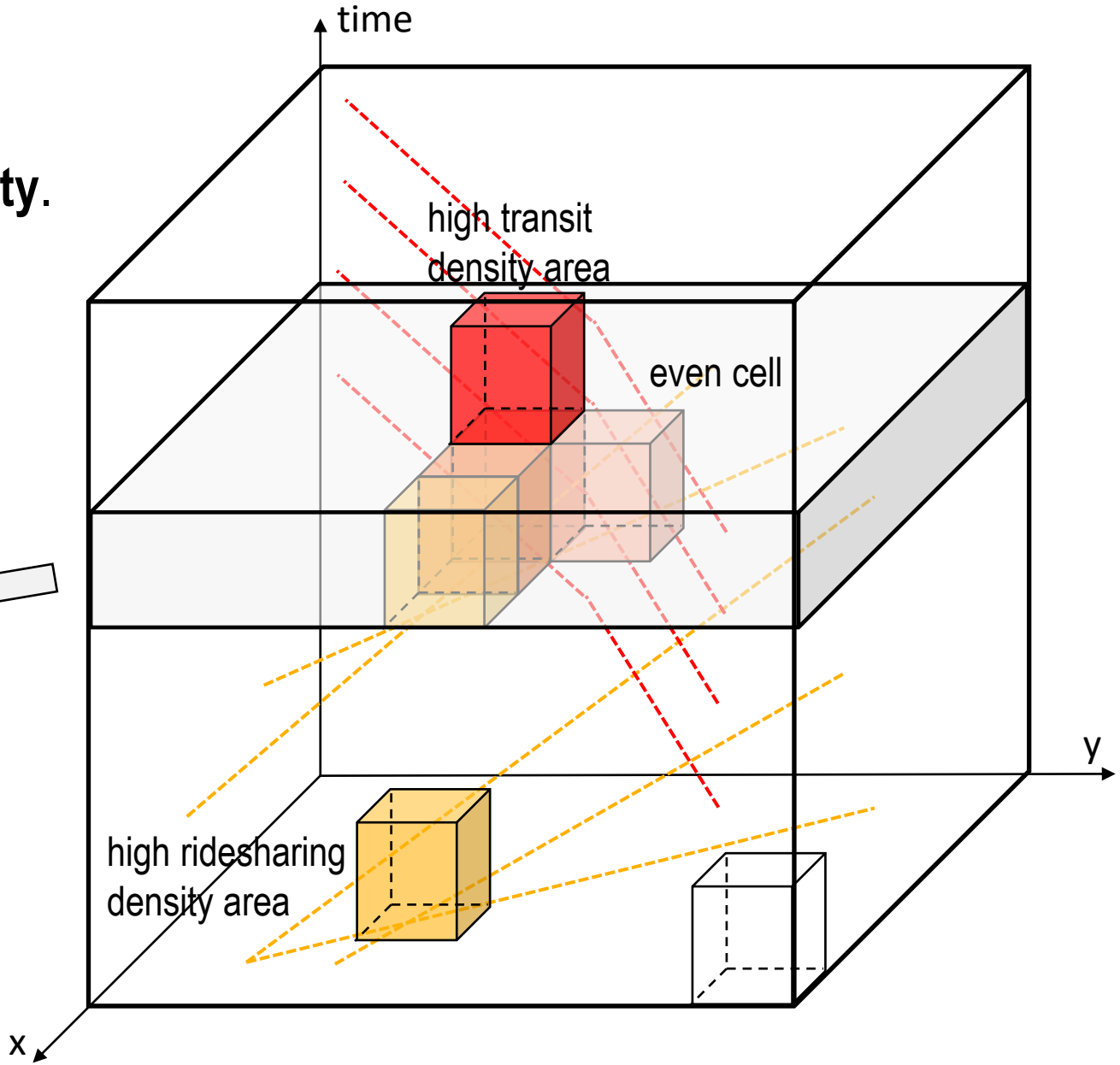
Figure: Illustration of 3D discrete presentation

Data-driven Transit Service Design - Trajectory Data Presentation

- **STEP II: Heatmap Generation and Analysis**
  - **Ridesharing (R_r)** and **transit (R_t) trip density**.
  - Transit or ridesharing trajectory dominant, or even cell
  - **Generate Heatmap (Many)**



Heatmap of each time interval



Data-driven Transit Service Design - Pattern Recognition and Learning

Pattern Recognition by Clustering Algorithm

- **"Sandwich" patterns (A-B-A) correlates to First/last Mile Zones**
  - B zones is with high transit station density.
  - A zones attract or generate significant traffic demand (land use analysis).
  - Many ridesharing orders in A zones, e.g. $A_1 \rightarrow A_2$, $A_1 \rightarrow B$, or $A_2 \rightarrow B$.

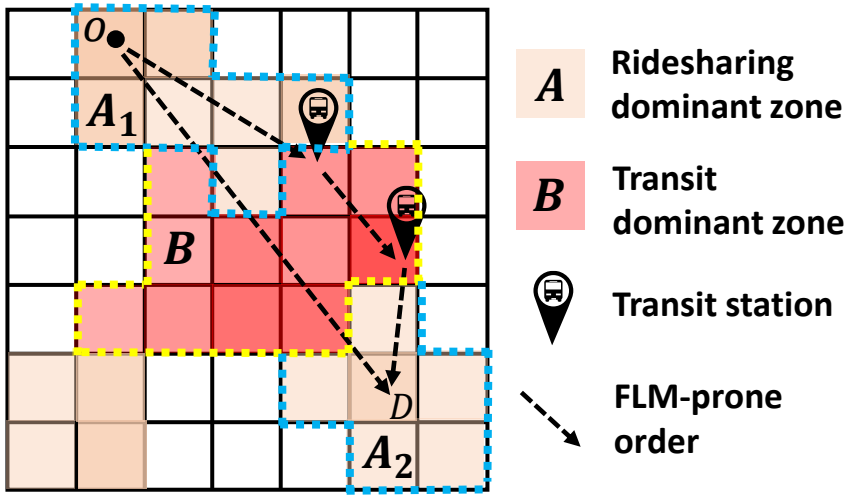


Figure 3. Illustration of "sandwich" patterns.

Convolution LSTM Spatiotemporal Learning

- Heatmaps as time series training data.
- Find future "Sandwish Pattern" and
- Predict FLM zones hour by hour.

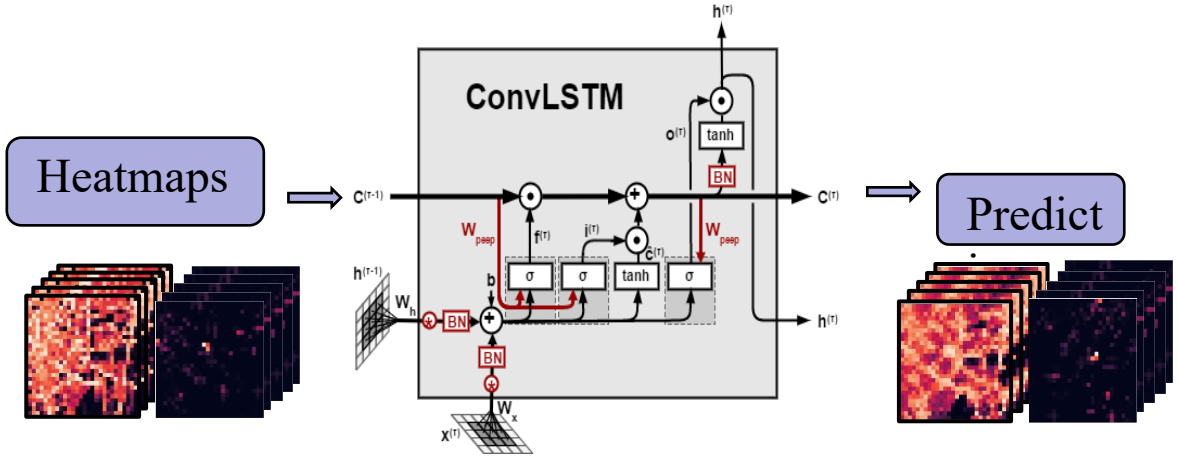
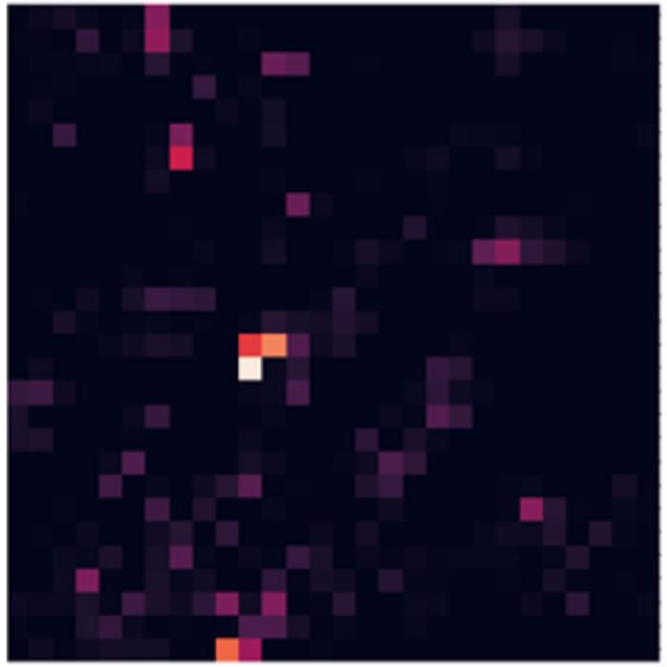


Figure: Illustration of ConvLSTM to predict FLM zones.

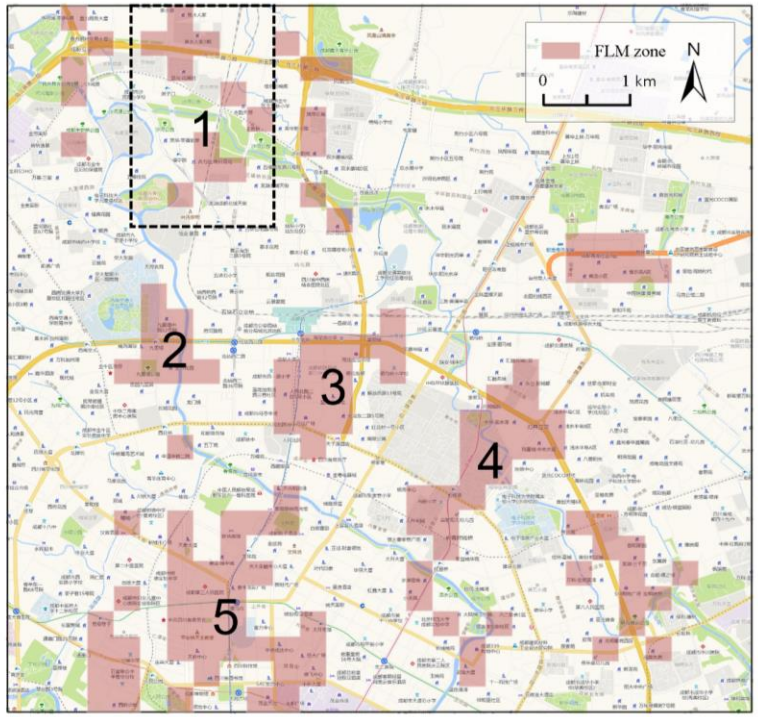
Result of Case Study

Transit First/Last Mile (FLM) Zones Validation in Second Ring of Chengdu city, China

(a) FLM zones on the heatmap: Light color inside pixel represents a high probability of FLM gaps.

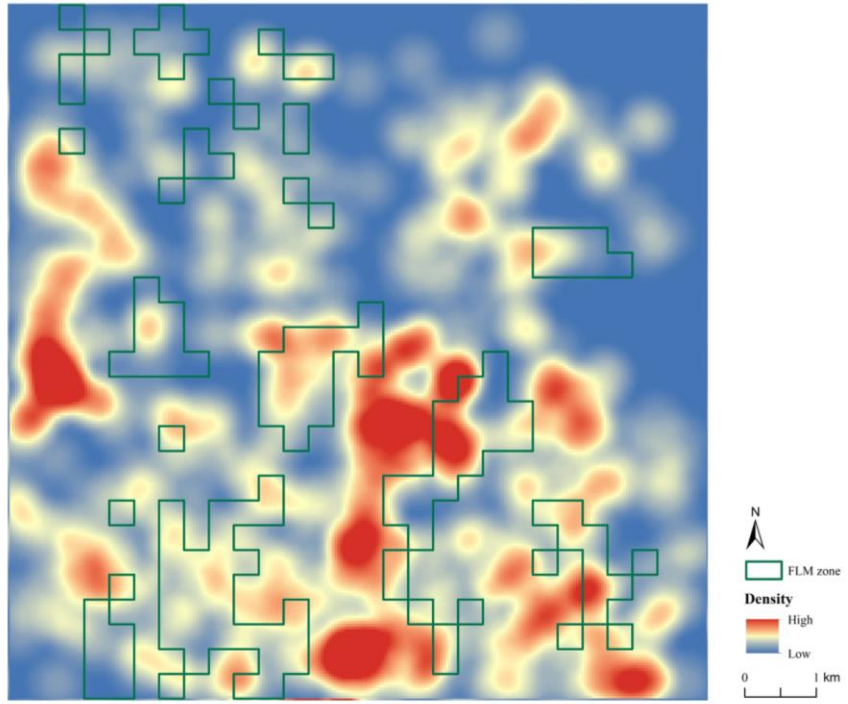


(b)FLM zones on the map: covering big residential areas or commercial areas with significant traffic demand.



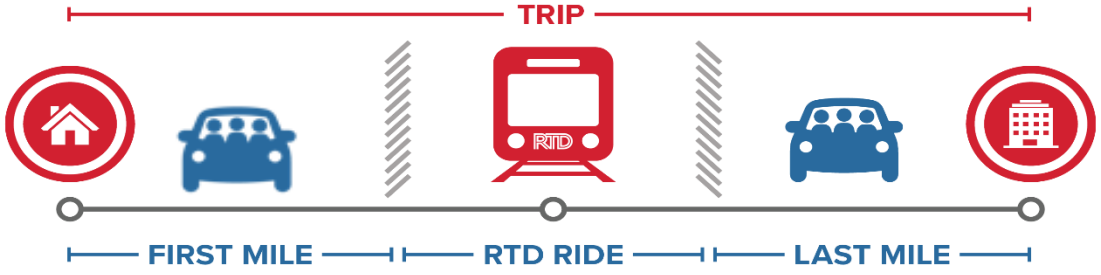
(c) Overlap FLM heatmap on the transit stop heatmap

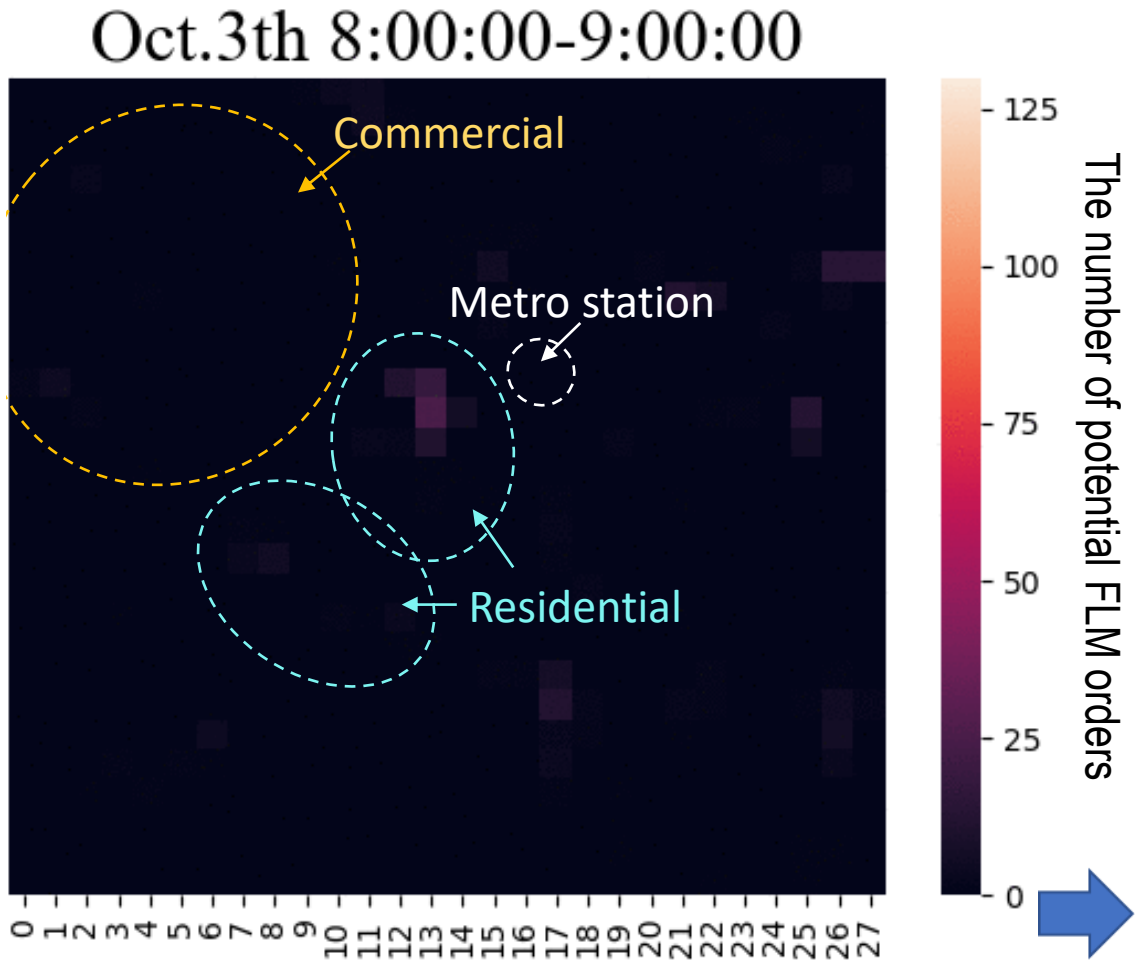
- FLM zones are near the areas that have high transit stop density.
- Transit service is low inside the FLM zones.



Data-driven Transit Service Design-Predict FLM

- **Transit First/Last Mile Zones Evolvement over A Day**
  - FLM zones in commercial areas are not active until 10am since Malls are closed.
  - FLM zones in residential areas near metro station are more active than other areas.
  - Help adaptively dispatch ridesharing or microtransit services.





Analyze the trajectory data of other modes, such as private auto, micro-mobility, to develop optimal transit design

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Community Learning Based Semi-Centralized Optimal AV Carpool/Ridesharing Scheme

Lili Du, Ph.D.
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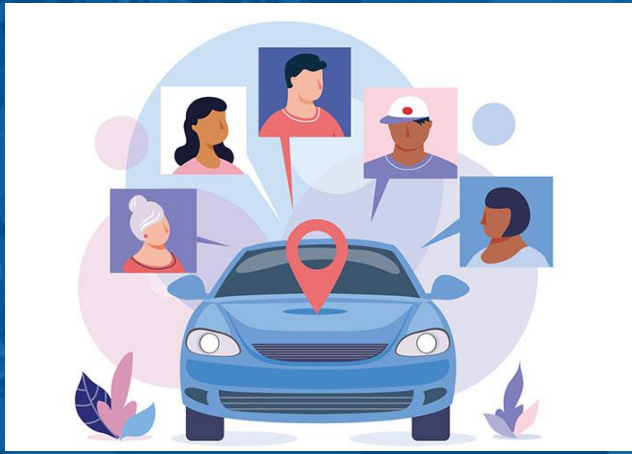

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Background and Motivation

- **Ridesharing (such as Uber and Lyft) improves mobility and reduces private car ownership rate**
- **Ride-hailing (solo trip) causes congestion**

Low occupancy leads to congestion

Solution: Promote Carpooling

- **The advantages of autonomous vehicles (AVs)**

Larger capacity

Route flexibility

Less Parking

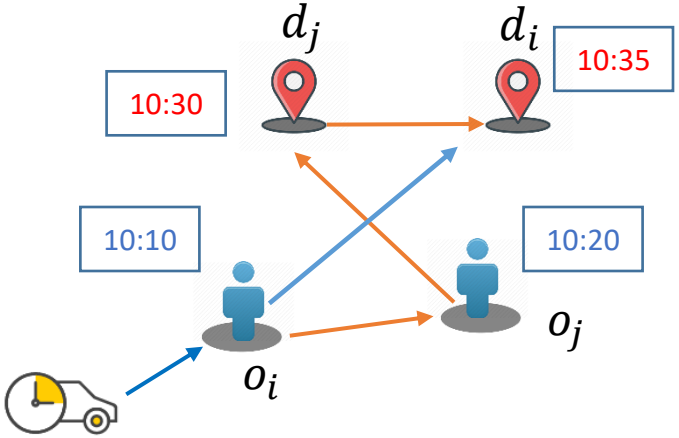
Increased safety

Peng, Wang, and Lili Du. "Investigating Optimal Carpool Scheme by a Semi-Centralized Ride-Matching Approach." IEEE Transactions on Intelligent Transportation Systems (2022). DOI: 10.1109/TITS.2021.3135648

Research Challenges

Research: Matching multiple riders with multiple AVs in Real Time

- **Riders have different timing and trip plans, thus hard to match**
- **Carpooling (i.e., ridesharing) may often cause detour, currently have low compliance**
- **TNC receives a large-scale real-time mobility service requests**
- **Performing real-time optimal matching leads to high computation challenges**



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Research Challenges

CSP-MIP:

$$min \sum_{v\in V}\sum_{n_1\in O\cup D}\sum_{n_2\in O\cup D}\tau_{n_1n_2}x^v_{n_1,n_2} + \sum_{v\in V}\sum_{n_2\in O}\tau_{n_vn_2}x^v_{n_v,n_2} \quad (1)$$

Subject to

$$x^v_{n_1,n_2} = 0, \forall v\in V, \forall n_1\in \tilde{N}, \forall n_2\in O\cup D, n_1 \neq n_v \quad (2)$$

$$x^v_{n_1,n_2} = 0, \forall v\in V, \forall n_1\in O\cup D\cup \tilde{N}, \forall n_2 \in \tilde{N} \quad (3)$$

$$\sum_{n\in O} x^v_{n_v,n} \leq 1, \forall v\in V \quad (4)$$

$$\sum_{v\in V}\sum_{n\in O\cup D\cup\tilde{N}} x^v_{n,o_i} = 1, \forall i\in I, n\neq o_i \quad (5)$$

$$\sum_{n_1\in O\cup D\cup n_v} x^v_{n_1,o_i} = \sum_{n_2\in O\cup D} x^v_{n_2,d_i}, \forall i\in I, \forall v\in V, n_1\neq o_i, n_2\neq d_i \quad (6)$$

$$\sum_{n_1\in\{O\backslash o_i\}\cup\{D\backslash d_i\}\cup\tilde{N}} x^v_{n_1,o_i} = \sum_{n_2\in\{O\backslash o_i\}\cup D} x^v_{o_i,n_2}, \forall i\in I, \forall v\in V \quad (7)$$

$$\sum_{n_1\in O\cup D} x^v_{n_1,d_i} \geq \sum_{n_2\in O\cup D} x^v_{d_i,n_2}, \forall i\in I, \forall v\in V, n_1\neq d_i, n_2\neq d_i \quad (8)$$

$$\tilde{t}^v_n \geq 0, n\in O\cup D\cup\tilde{N} \quad (9)$$

$$\tilde{t}^v_{n_2} - \tilde{t}^v_{n_1} - \tau_{n_1n_2} \geq M\left[x^v_{n_1,n_2} - 1\right], \forall v\in V, \forall n_1\in O\cup D\cup\tilde{N}, \forall n_2\in O\cup D, n_1\neq n_2 \quad (10)$$

$$\tilde{t}^v_{n_1} - \tilde{t}^v_{n_1} \geq \varepsilon \sum_{n_2\in O\cup D\backslash n_1} x^v_{n_1,n_2}, \forall v\in V, \forall n_1\in O\cup D\cup\tilde{N} \quad (11)$$

$$\tilde{t}^v_{o_i} \leq \tilde{t}^v_{d_i}, \forall i\in I, \forall v\in V \quad (12)$$

$$\tilde{t}^v_n \leq t^-(n) - t^+(n), \forall n\in O\cup D \quad (13)$$

$$\tilde{t}^v_{o_i} - \tilde{t}^v_{o_j} \leq M\psi^v_{o_i,o_j}, \forall i\in I, \forall j\in I, i\neq j \quad (14)$$

$$\tilde{t}^v_{o_i} - \tilde{t}^v_{o_j} \geq M\left(\psi^v_{o_i,o_j} - 1\right), \forall i\in I, \forall j\in I, i\neq j \quad (15)$$

$$\tilde{t}^v_{o_i} - \tilde{t}^v_{d_j} \leq M\psi^v_{o_i,d_j}, \forall i\in I, \forall j\in I, i\neq j \quad (16)$$

$$\tilde{t}^v_{o_i} - \tilde{t}^v_{d_j} \geq M\left(\psi^v_{o_i,d_j} - 1\right), \forall i\in I, \forall j\in I, i\neq j \quad (17)$$

$$\omega^v_{n_1,n_2,o_i} \leq x^v_{n_1,n_2}, \forall i\in I, \forall v\in V, \forall n_1\in\{O\backslash o_i\}\cup D, n_2\in O\cup D, n_1\neq n_2 \quad (18)$$

$$\omega^v_{n_1,n_2,o_i} \leq \psi^v_{o_i,n_1}, \forall i\in I, \forall v\in V, n_1\in\{O\backslash o_i\}\cup D, n_2\in O\cup D, n_1\neq n_2 \quad (19)$$

$$\omega^v_{n_1,n_2,o_i} \geq x^v_{n_1,n_2} + \psi^v_{o_i,n_1} - 1, \forall i\in I, \forall v\in V, n_1\in\{O\backslash o_i\}\cup D, n_2\in O\cup D, n_1\neq n_2 \quad (20)$$

$$\sum_{n_1\in\{O\backslash o_i\}}\sum_{n_2\in O\cup D}\omega^v_{n_1,n_2,o_i} + \sum_{n_5\in O\cup D\cup\tilde{N}\backslash o_i} x^v_{n_5,o_i} - \sum_{n_3\in D}\sum_{n_4\in O\cup D}\omega^v_{n_3,n_4,o_i} = y^v_{o_i}, \forall i\in I, \forall v\in V, n_1\neq n_2, n_3\neq n_4 \quad (21)$$

$$y^v_{o_i} \leq q^v, \quad \forall v\in V, \forall i\in I \quad (22)$$

$$x^v_{n_1,n_2} = \{0,1\}, \forall n_1\in O\cup D\cup\tilde{N}, \forall n_2\in O\cup D, n_1\neq n_2 \quad (23)$$

- **A large-scale mixed integer program**
  - Minimize AVs' total travel time or fleet size
  - Network topology constraints
  - Trip timeline constraints
  - Feasibility constraints
    - e.g., flow conservation; one visiting to each origin
- **Complexity**
  - $|V|$:# of AVs; $|I|$: # of riders
  - The number of variables: $O(|V||I|^2)$
  - The number of constraints: $O(|I||V|^2)$
  - NP hard problem and no efficient algorithms for a large-scale problem
- **Our Solution**
  - Scale down by decomposing riders
  - Transfer to network flow problem

Methodology

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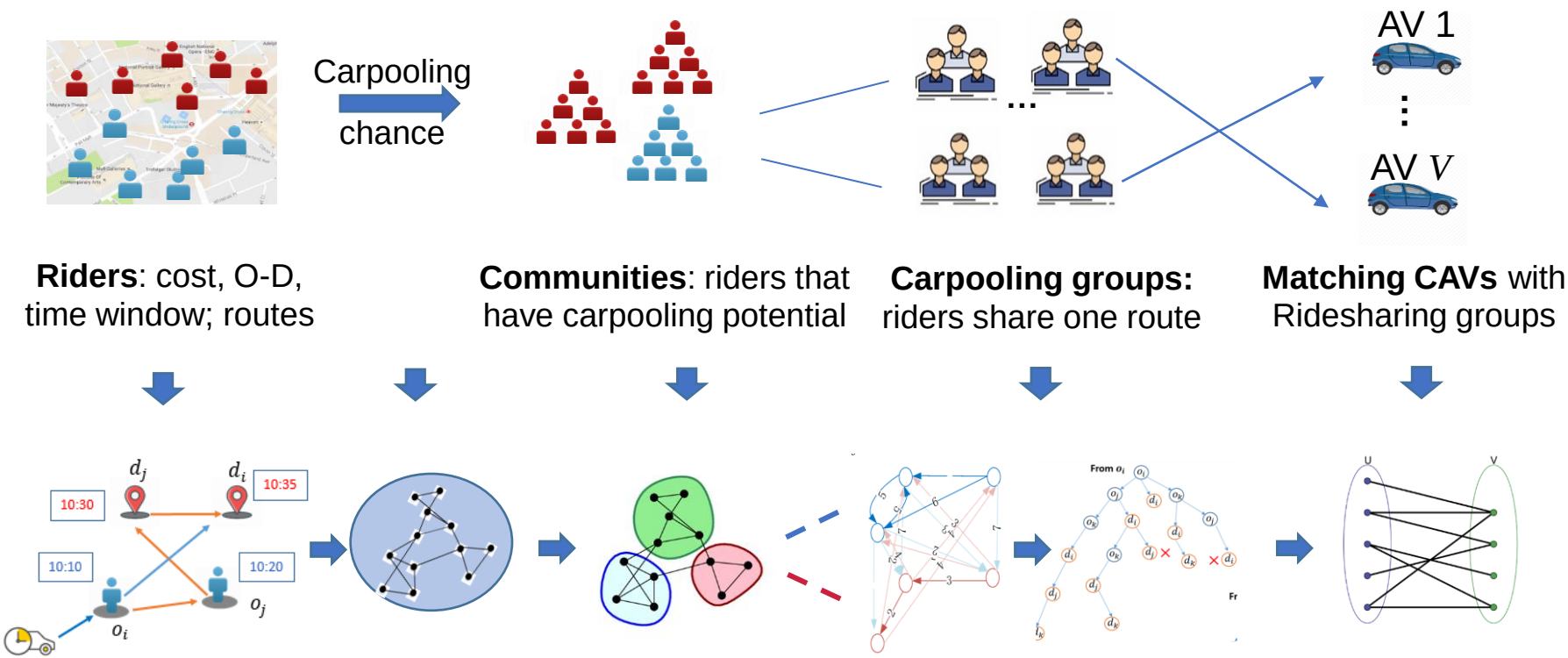
- **SCN: Semi-Centralized Community Learning based Ride-Matching Scheme Combined with Network Flow Approach**



Peng, Wang, and Lili Du. "Investigating Optimal Carpool Scheme by a Semi-Centralized Ride-Matching Approach." IEEE Transactions on Intelligent Transportation Systems (2022). DOI: 10.1109/TITS.2021.3135648

Methodology: Carpool Chance and Graph

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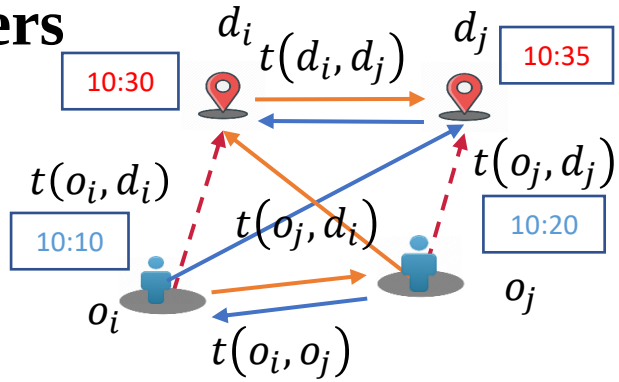
❖ Carpooling chances (C2) between two riders

- A carpool route must be feasible to the timeline requirements of riders
- Short waiting time ⇒ stronger C2
- More travel time saving ⇒ stronger C2
- More candidate carpooling routes ⇒ stronger C2



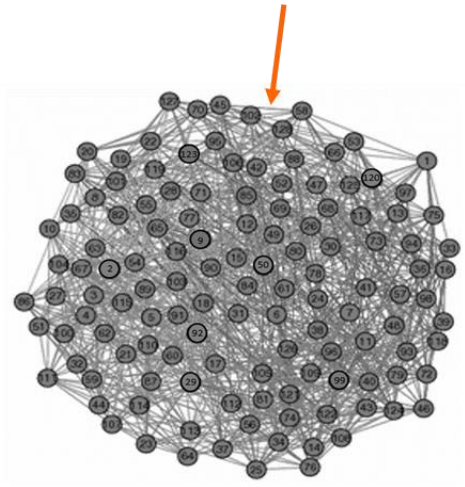
carpooling chance between *i* and *j*

$$c_{ij} = \sum_{U_{ij}} \left[\underbrace{\frac{\Delta u_{ij}^k}{t_{o_i d_i}} + \frac{\Delta u_{ij}^k}{t_{o_j d_j}}}_{\text{travel time saving ratio}} \right] \left[\underbrace{1 - \frac{\varpi_{u_{ij}^k}}{\hat{\varpi}_{u_{ij}^k}}}_{\text{waiting time ratio}} \right] \quad \forall i \neq j \in I$$

Candidate carpooling routes ➡ Network flow approach

❖ Carpool chances (C2) Graph

- Node: rider
- Connection with weight: carpool chance



Carpooling chance graph

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Methodology: Forming carpooling communities

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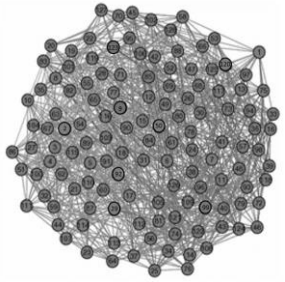
❖ Carpooling communities

- Partition the C2 graph into smaller carpooling coalitions
- Strong **C2** between riders within a carpooling community (strong inner-C2)
- Weak **C2** between riders in different carpooling communities (weak inter-C2)

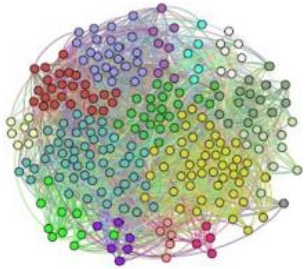
❖ Community Detection

- Modularity $Q = \frac{1}{2m}\sum_{ij}[c_{ij} - \frac{k_i k_j}{2m}]\,\delta(\pi_i, \pi_j)$
- Q increases ⇔ inner-C2 increases, or inter-C2 decreases
- Start with where every rider forms a community
- Merge two community leads to maximum increase of Q
- Stop when no operation improves Q

$\delta(\pi_i, \pi_j) = 1$ when riders i and j in one community; $\frac{k_i k_j}{2m}$: the expected weight of edges between riders i and j



Carpooling chance graph



Carpooling community

ridesharing groups/routs within each community?

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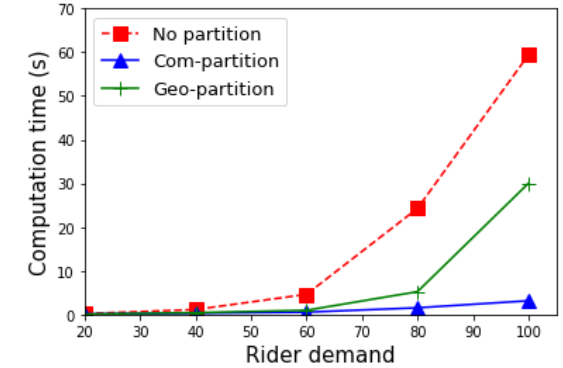
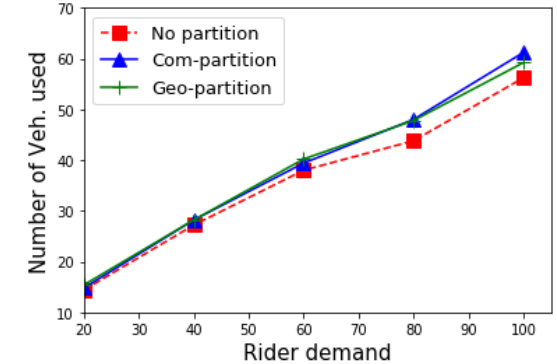
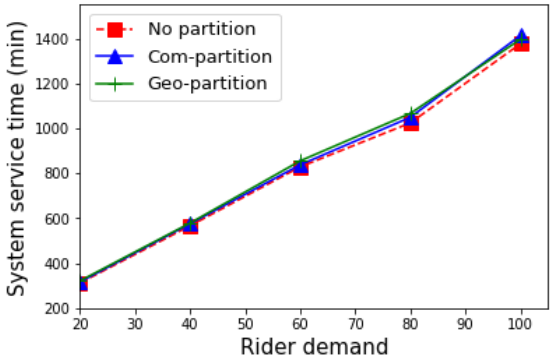
Experiments

❖ The Merit of Community Formation

- Community detection according to Carpooling chance significantly reduces the computation load from no-partition and Geo-partition (split riders according to TAZs/districts).
- Community detection slightly compromises system performance than no-partition, but performs slightly better than using geo-partition.
- Overall, Com-partition outperforms Geo-partition and No-partition while co-considering system performance and computation efficiency.







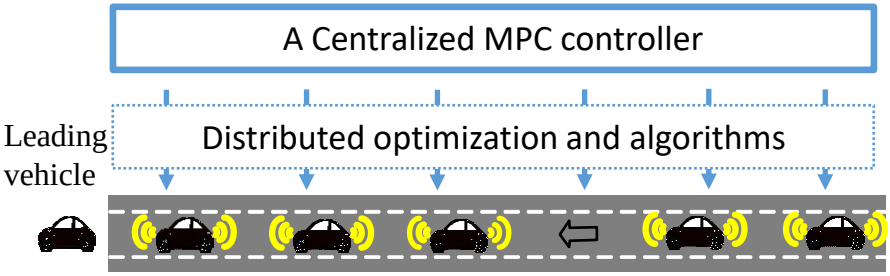
Peng, Wang, and Lili Du. "Investigating Optimal Carpool Scheme by a Semi-Centralized Ride-Matching Approach." IEEE Transactions on Intelligent Transportation Systems (2022). DOI:10.1109/TITS.2021.3135648

Platoon Centered Control (PCC)

- **System Optimal Platoon Centered Control (PCC) for CAV Car Following**

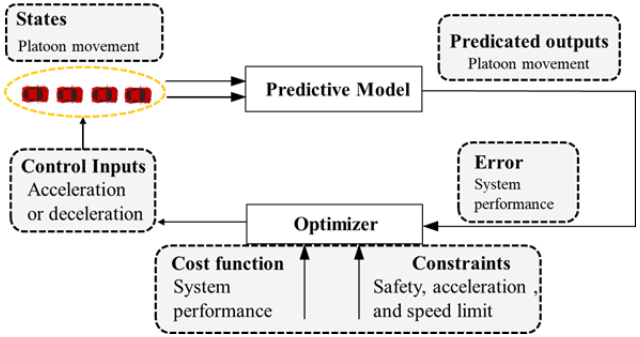
Consider entire platoon as system; uses a model predictive control (MPC) to determine platoon's movement to ensure safety, efficiency and traffic smoothness.

PCC



A large-scale Optimizer (NLP or MINLP)

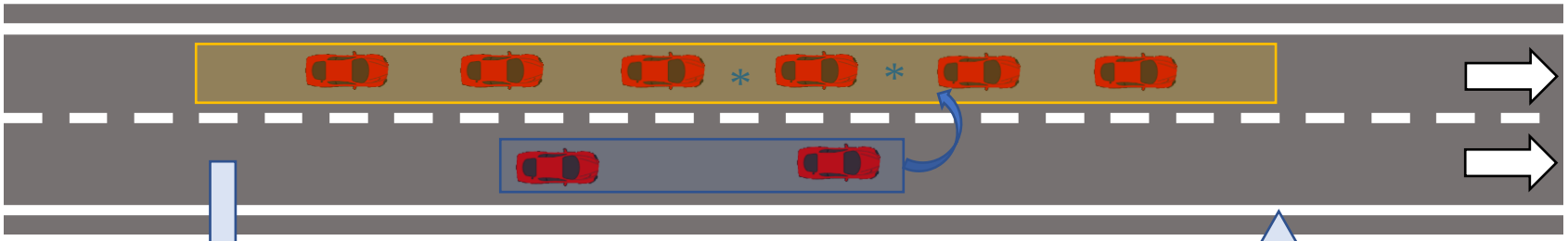
MPC



OPT-PCC $W = \frac{1}{2} z(k)^T Q_\alpha z(k) + \frac{1}{2} z'(k)^T Q_\beta z'(k) + \frac{\tau^2}{2} \lVert u(k-1) \rVert_2^2$	
s.t.	
$a_{min} \leq u_i(k-1) \leq a_{max}, \forall \mathrm{i} = 1, \cdots, \mathrm{n}$	Acceleration limit
$0 \leq v_i(k) \leq v_{max}, \forall \mathrm{i} = 1, \cdots, \mathrm{n}$	Speed limit
$x_{i-1}(k) - x_i(k) \geq L + v_i(k)\tau - (v_i(k) - v_{min})^2 / 2a_{min}, \forall\ \mathrm{i} = 1, \cdots, \mathrm{n}$	Safety
Vehicle dynamics; Other constraints under a special scenario, such as lane change (MINLP)	

AI aided Cooperative Lane Change for a Platoon under PCC

- The platoon under PCC determines the optimal spacings and timing to accommodate safe and smooth lane-change requests, while keeping traffic smoothness and efficiency.



Platoon features: speeds, spacings, etc

4 PCC enlarges platoon spacings & cut in

3 Optimal spacing & timing *

2 Optimal decisions: spacing & timing?

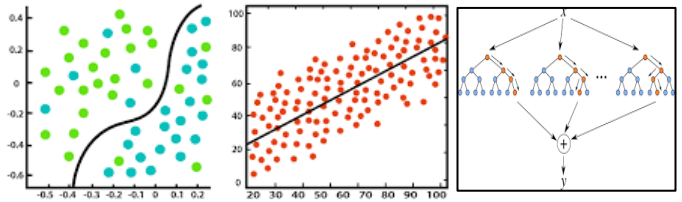
1 Lane-change requests

Optimization

Predicted lane change spacing & timing

Machine Learning Framework

Input



Classification Regression Random forests

Output

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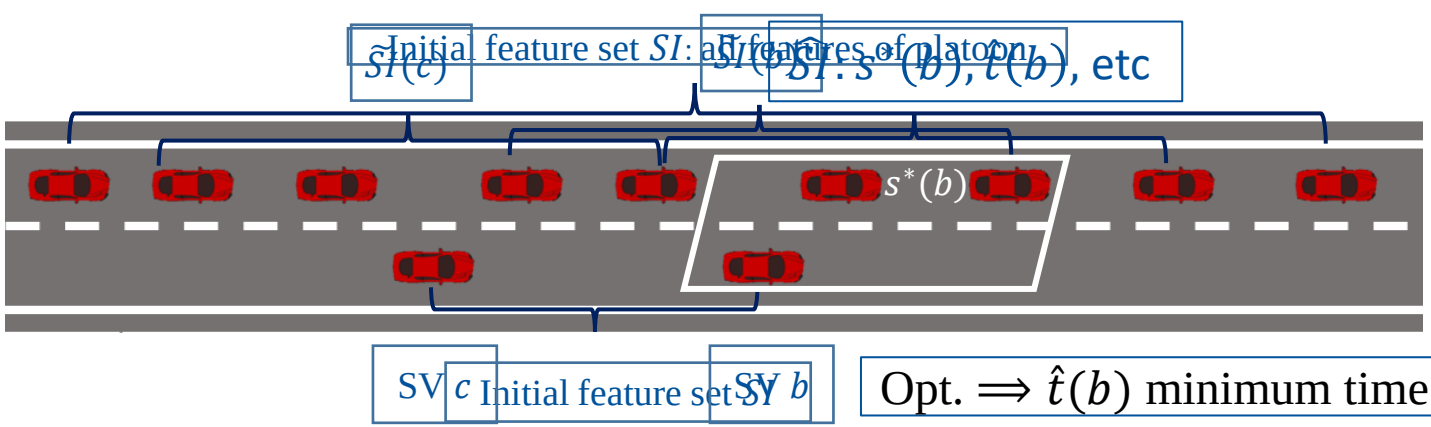
Solution Approach: ML-DBB Algorithm

- Challenges to find the optimal cut-in spots
  - Quickly solve the NP-hard MINLP-MPC model within a control sample interval (< 1sec) for the control smoothness and continuity.
- Key Ideas (ML-DBB)
  - Use a machine learning (ML) to predict candidate spots (spacing and time steps) ⇒ reduce integer solution space.
  - Use distributed branch and bound (DBB) to find out the optimal solution in the candidate pool ⇒ split computation loads.
- Machine Learning Procedures

SI(all features) → $\widetilde{SI}$(SV′s neigherhood) → $\widehat{SI}$(best spacing neighberhood)



Opt. ⟹ $\hat{t}(b)$ minimum time step

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Numerical Experiments: ML-DBB

- Computation performance: the case with two lance change vehicles

Solution optimality	ML-PP		ML-DBB-90	ML-DBB-99
Global optimal	38.79%		84.80%	94.00%
0-5% optimal	46.82%		10.60%	5.98%
5-10% optimal	8.91%		2.83%	0.02%
10-20% optimal	1.08%		0.40%	0.00%
Infeasible	4.40%		1.37%	0.00%
Total	100%		100%	100%
Computation performance	**Gurobi 8.0**	**ML-PP**	**ML-DBB-90**	**ML-DBB-99**
Computation time(s)	3.011	0.0632	0.1904	0.3292
The time includes both DSRC communication time (Kenney, 2011) and the computation time				

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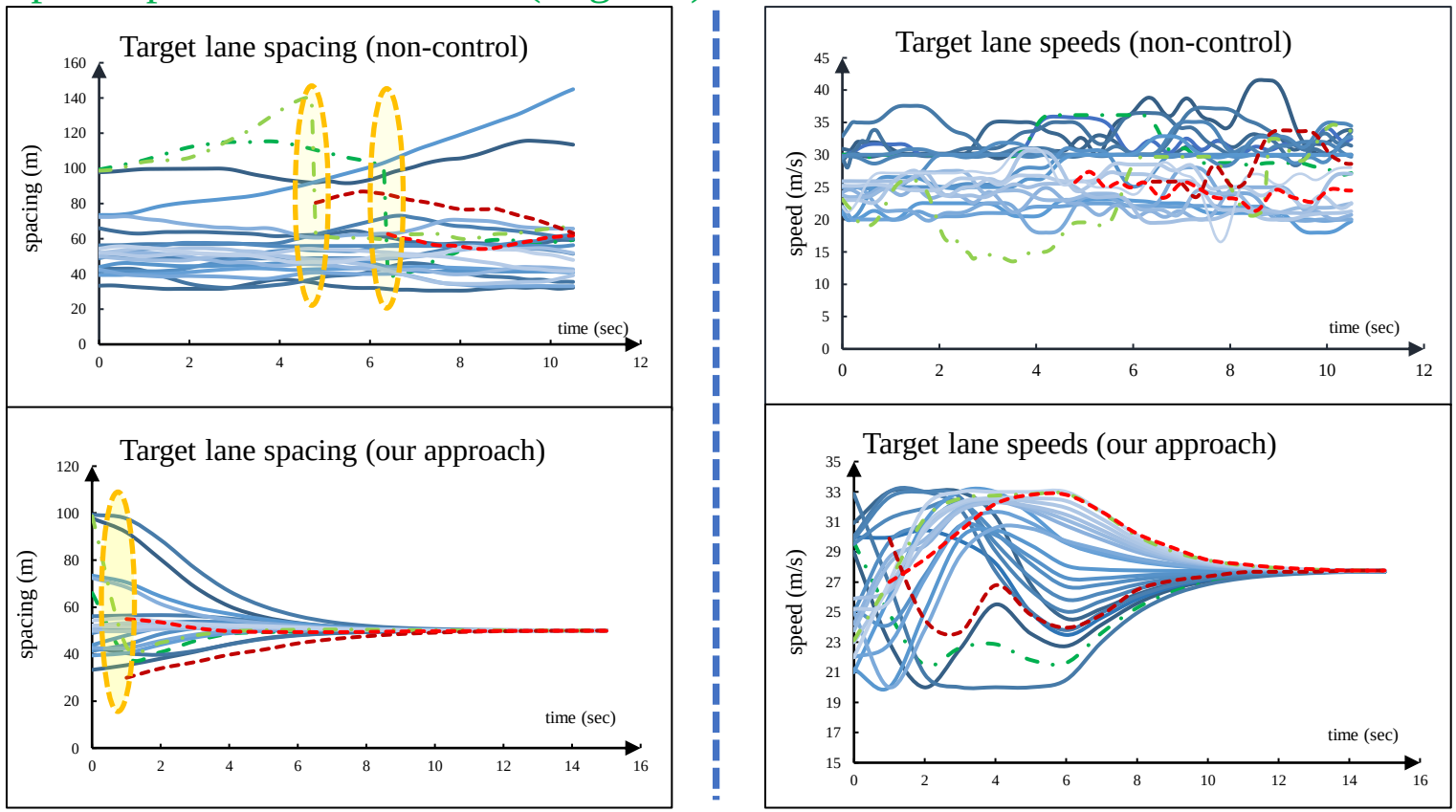
PCC based Cooperative Lane change: Experiments

- Two lane-change vehicles (in red) and 21 platoon vehicles (in blue); target space/speed of host vehicle (in green)



- PCC based cooperative lane change control can smoothen lane-change accommodation and then reduce traffic fluctuations as compared with the field traffic

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Summary

- Explosion of transportation data sources from persons, vehicles, and activity processes necessitates a new generation of methods and tools to analyze and visualize those data.
- Traditional approaches such as optimization, control, traffic flow analysis, dynamics, statistics, and more still function fundamentally.
- Machine Learning is a generic and powerful method– its value is largely dependent on the analyst's skill set and domain knowledge.
- The effectiveness of ML requires correctly integrating the variables and likely relationships by deeply understanding transportation domain knowledge.
- Hybrid approaches are more effective – combining sound physics with statistical rigor and machine learning power.

Thank you and Q &A

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