
# A Comparative Approach to Resurrecting the Market of MOD Vehicular Crowdsensing

Chaocan Xiang, Yaoyu Li, Yanlin Zhou, Suining He, Yuben Qu,
Zhenhua Li, Liangyi Gong, Chao Chen


# Outline

- **Motivation**
- **System Design**
- **Evaluation**
- **Conclusion**

# Mobility-on-Demand (MOD) vehicles: a big market




Over 1 million Uber/lyft drivers in the U.S. [1]

150 million DiDi drivers. [2]

MOD market size is reaching $228 billion by 2022.[3]

[1] Statista's reports: "How many uber drivers are there?" , https://therideshareguy.com/how-many-uber-drivers-are-there,2021.
[2] Statista's reports: https://new.qq.com/rain/a/20211211A075OJ00,2021.
[3] Statista's reports: "Global mobility on demand market forecast & opportunities by 2022," https://www.techsciresearch.com/report/global-mobility-on-demand-market/1254.html,2017

# MOD market is facing challenges

- MOD Drivers are earning less.

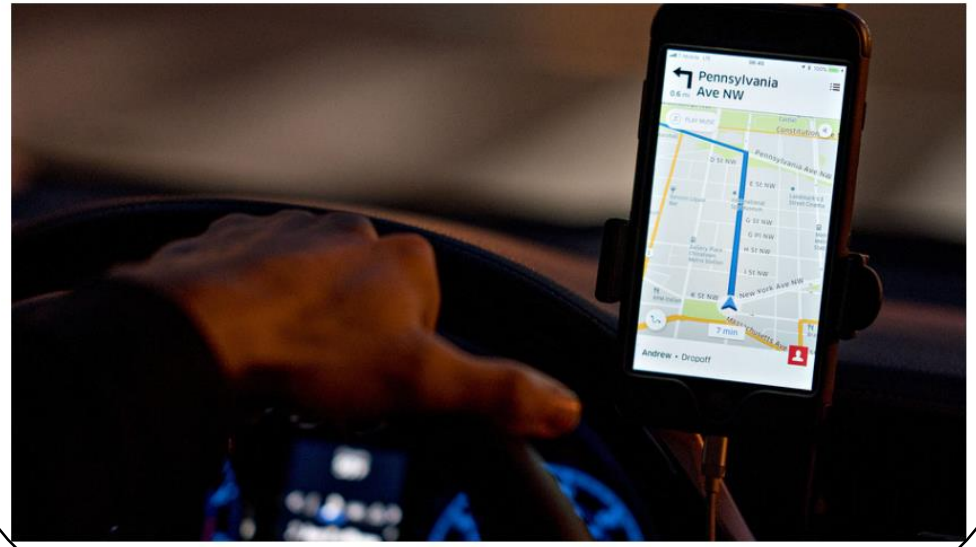
**Drivers for Uber, Lyft are earning less than half of what they did four years ago, study finds**

Published: Sept. 25, 2018 at 8:42 a.m. ET

By Elisabeth Buchwald

33

Drivers earned 53% less in 2017 than they did in 2013




- The situation is getting much worse due to COVID-19.

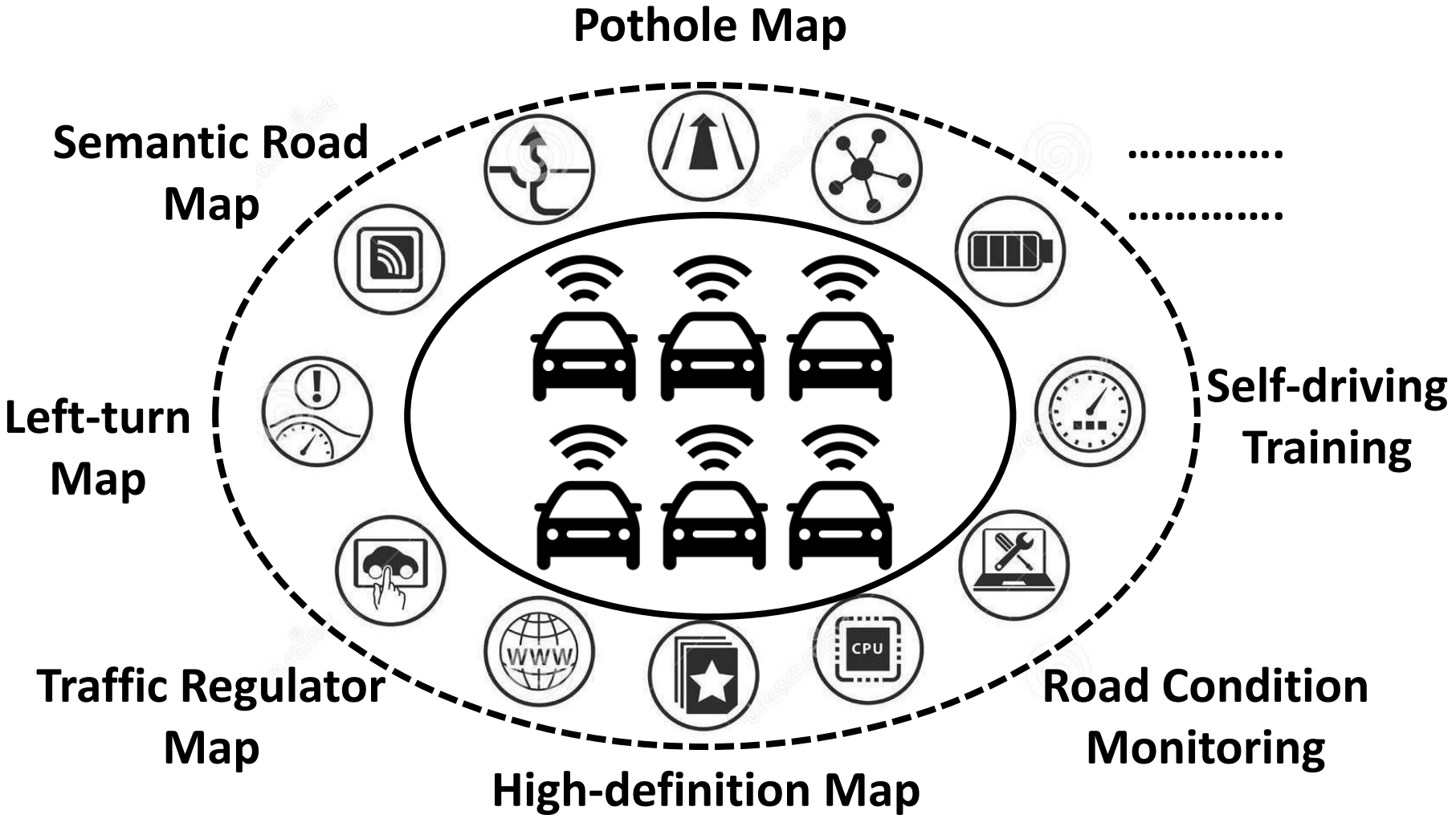
**Uber and Lyft are getting less unprofitable, but COVID-19 is still a drag on their business**

*Uber lost $6.7 billion in 2020, while Lyft lost $1.8 billion*

By Andrew J. Hawkins | @andyjayhawk | Feb 11, 2021, 4:40pm EST

SHARE

# A new earning market: MOVE-CS

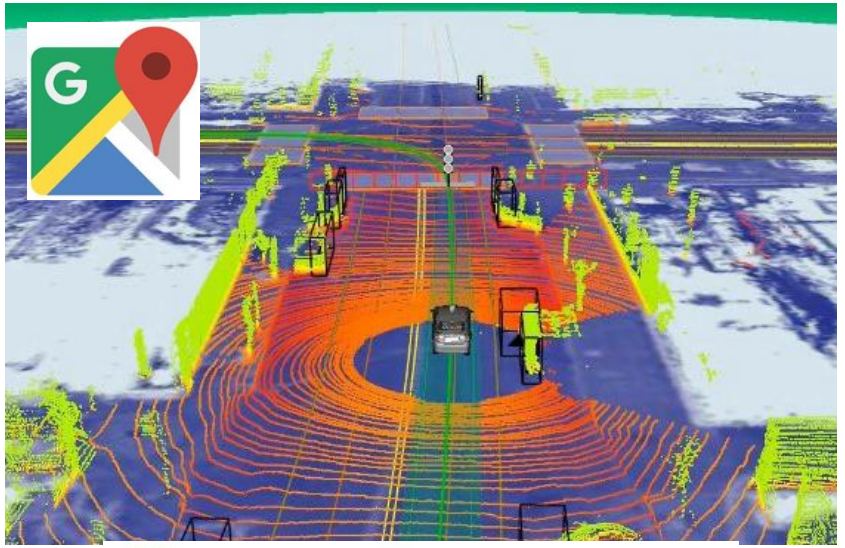



MOD-Vehicular-CrowdSensing (MOVE-CS) applications

# MOVE-CS: achieving win-win collaboration

- For Uber and Lyft drivers, installing a dashboard camera can boost their earnings by 5% to 15%.

- Selling road data to map companies (e.g., Google Maps and lvl5).



Win-win situation between MOVE-CS platform and drivers.

# However, MOVE-CS failed after two-year operation.

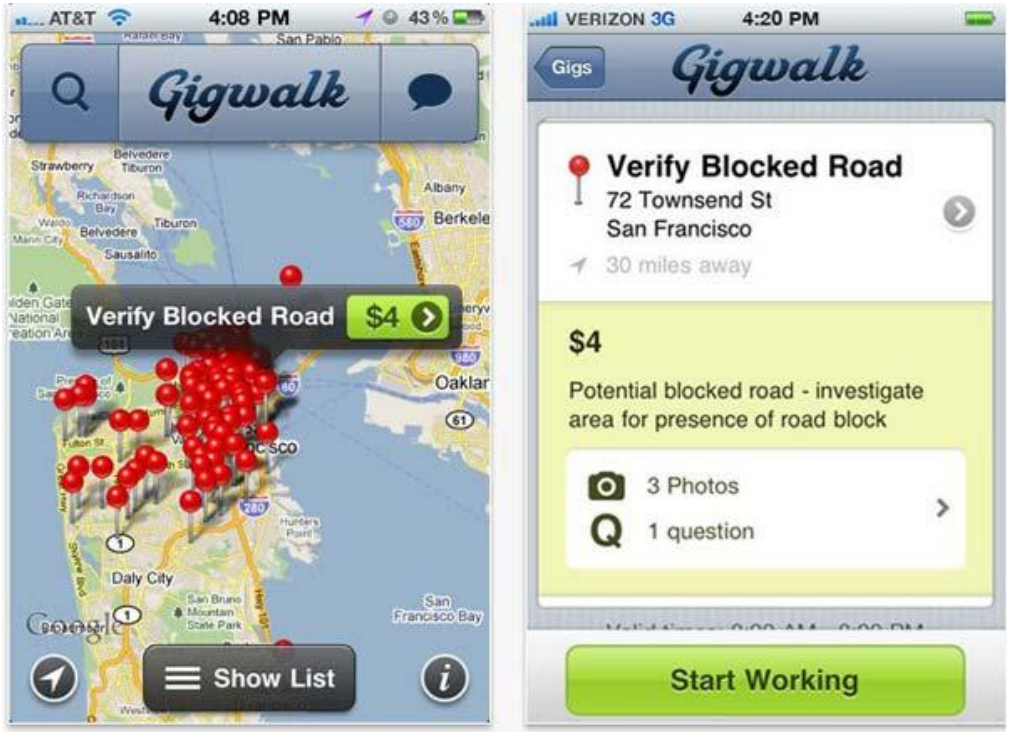
- Payver pays the drivers to collect road data on the move, which is effective at the beginning, but after two years, payver had to bankrupt itself in April 2019.



Can we resurrect the MOVE-CS market?

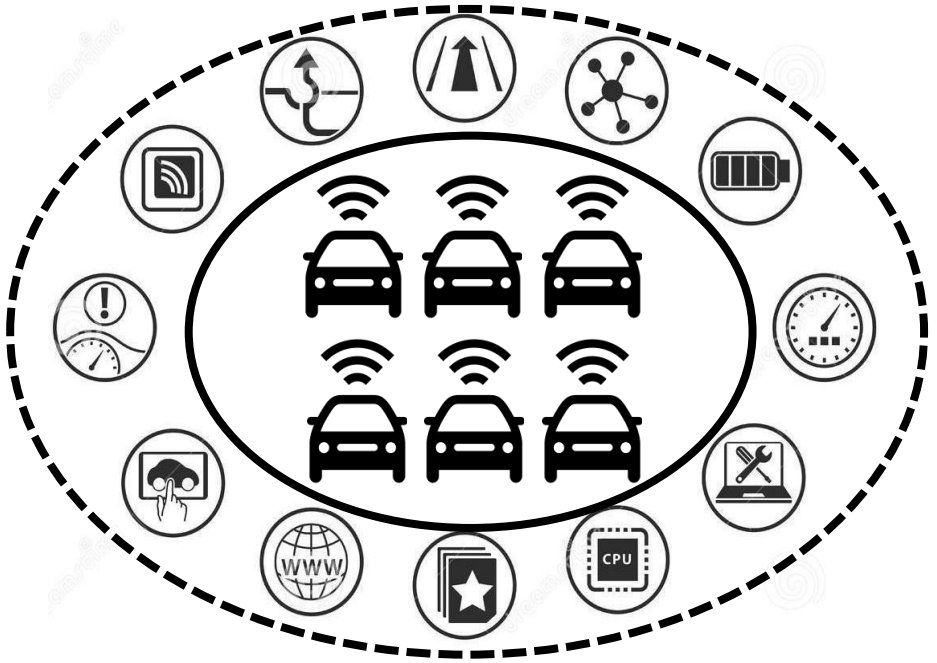
# MOMAN-CS: a similar but successful market

- A similar market named MOD-Human-Crowdsensing (MOMAN-CS) led by Gigwalk preserve its success since 2010.




Applied?

MOVE-CS market




Can we apply the model of MOMAN-CS to resurrect the MOVE-CS market?

# MOMAN-CS: a similar market led by Gigwalk

- Two central questions need to be answered.

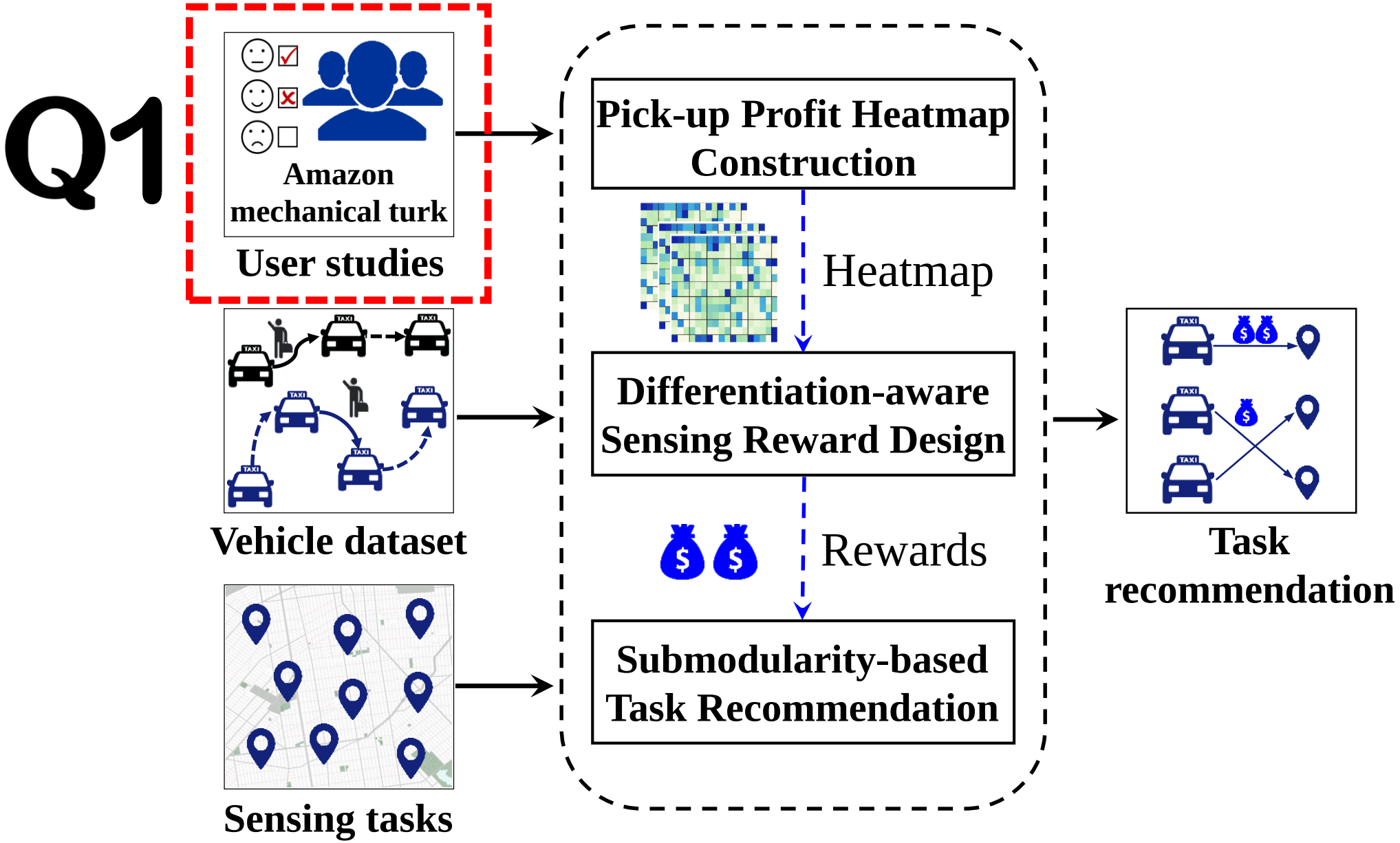
## Q 1

Why MOVE-CS failed but MOMAN-CS is still successful?

## Q 2

How to apply the MOMAN-CS model to the MOVE-CS market?

# User Studies

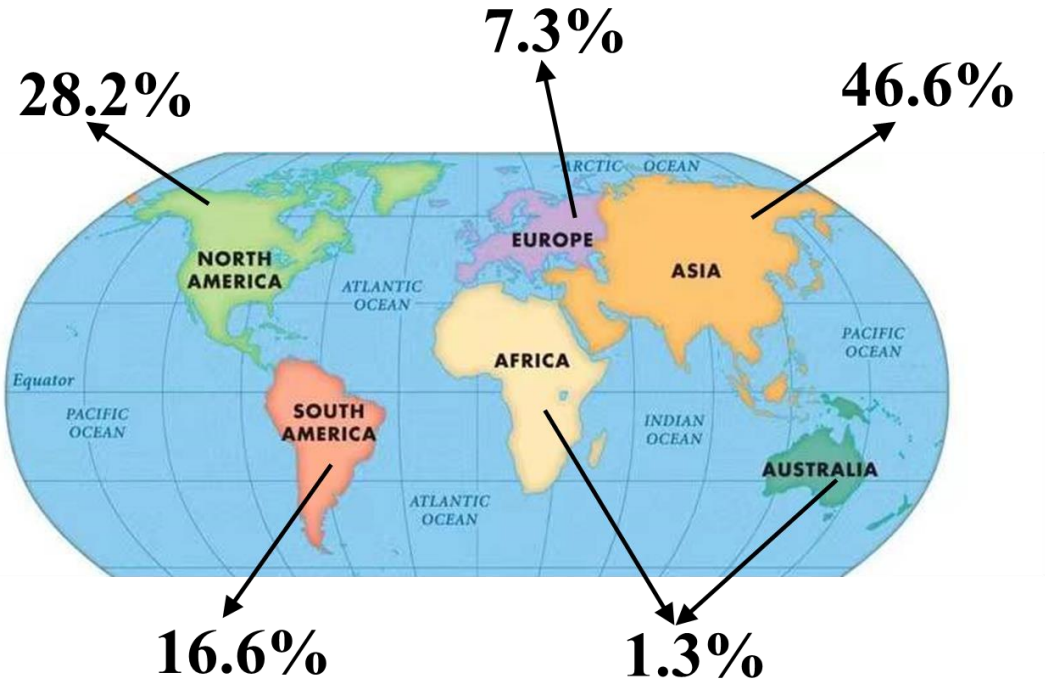


# Crowdsourcing-based User Studies

amazon mechanical turk

Surveying 581 drivers on Amazon MTurk

**Drivers' Distribution**



# Crowdsourcing-based User Studies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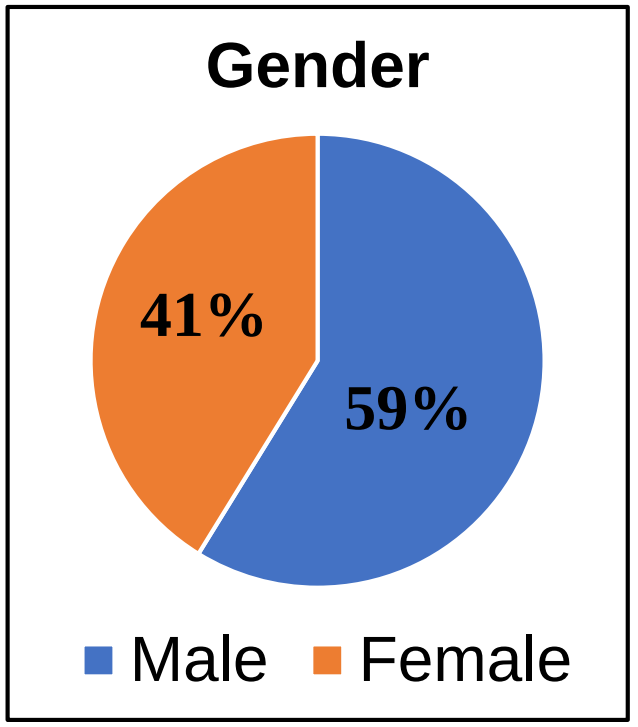
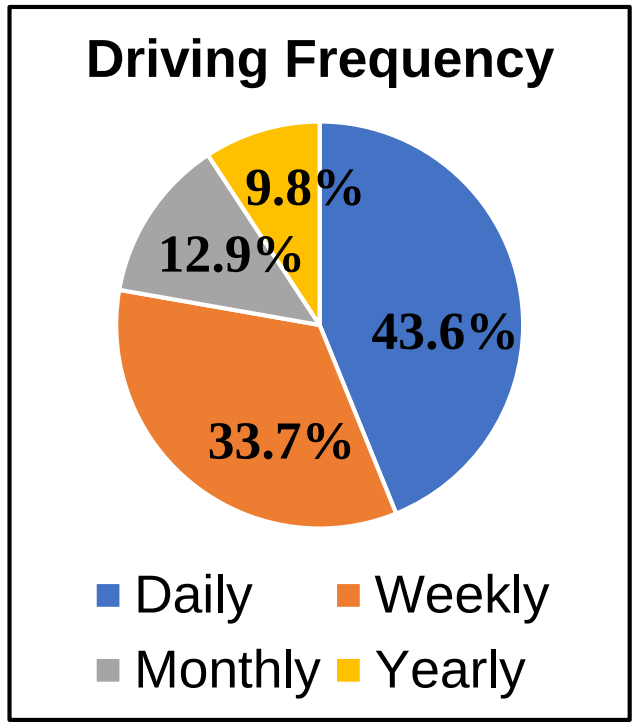
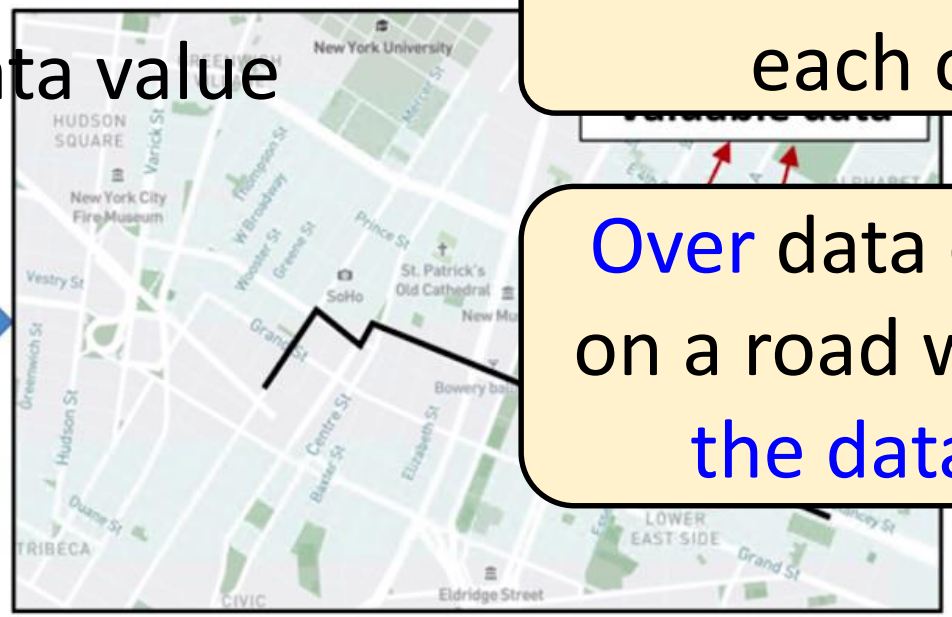


# Payver: a failed MOVE-CS platform

Model of Payver:

1. Collect data on the move
2. Get paid according to the data value

Drivers are invisible to each other

Over data collection on a road will reduce the data value

**66%**

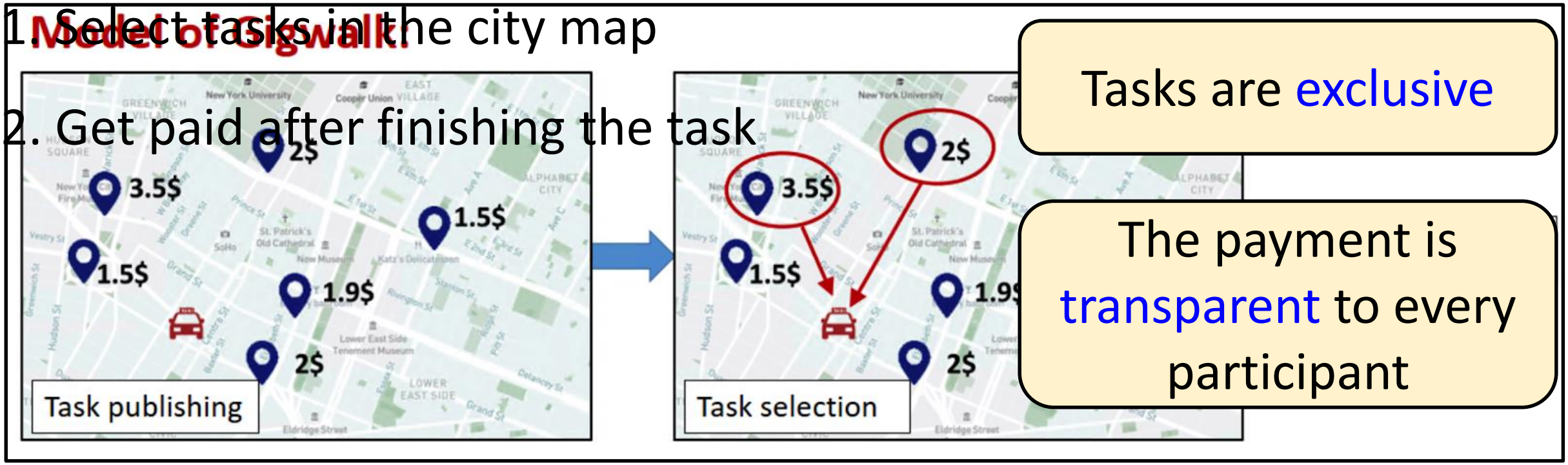
**Blind competitive model**

**94%**

Simple operation model based on blindly competitive rewards

# MOMAN-CS: a similar market led by Gigwalk

1. Select tasks in the city map
2. Get paid after finishing the task

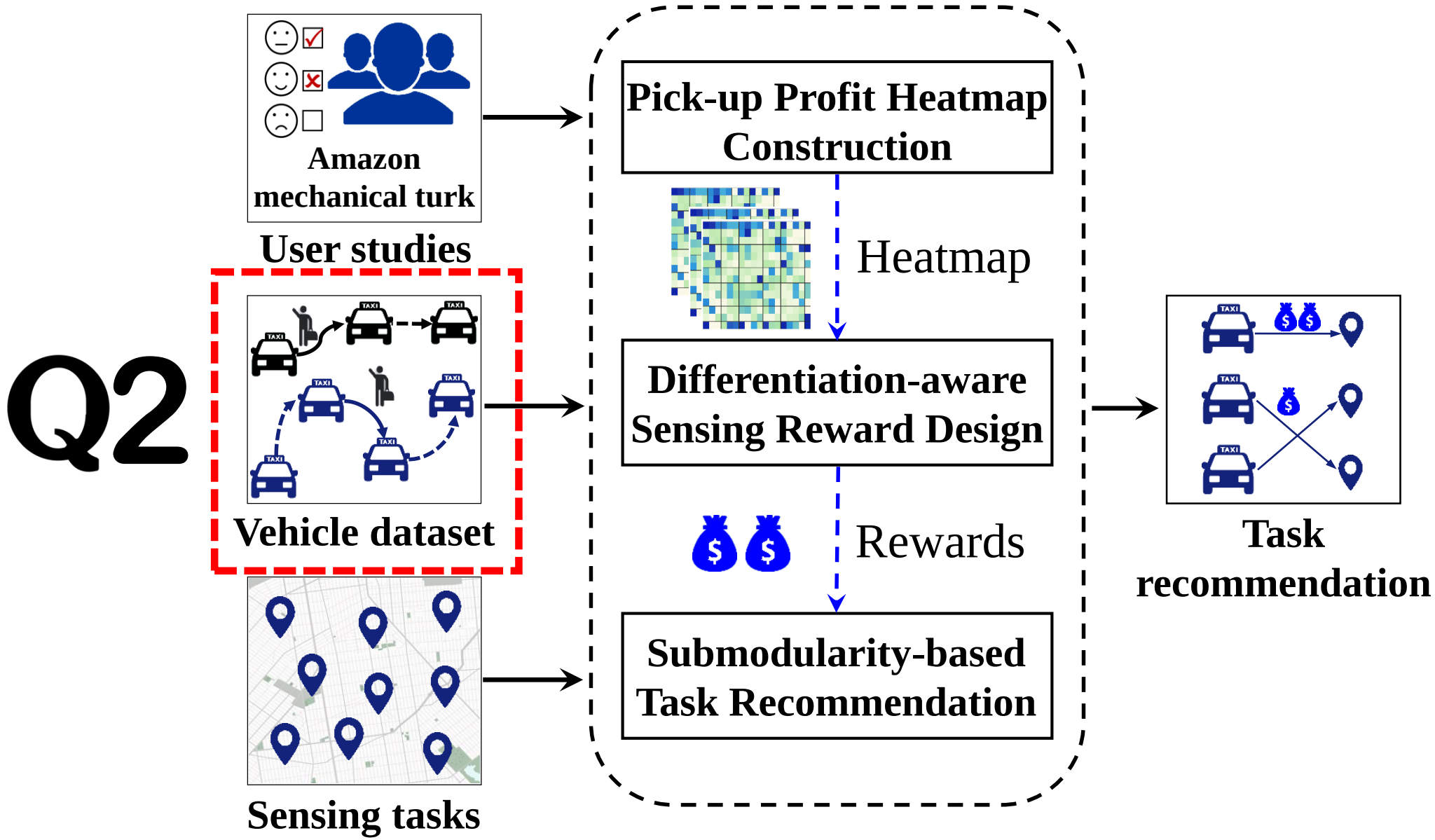



95%

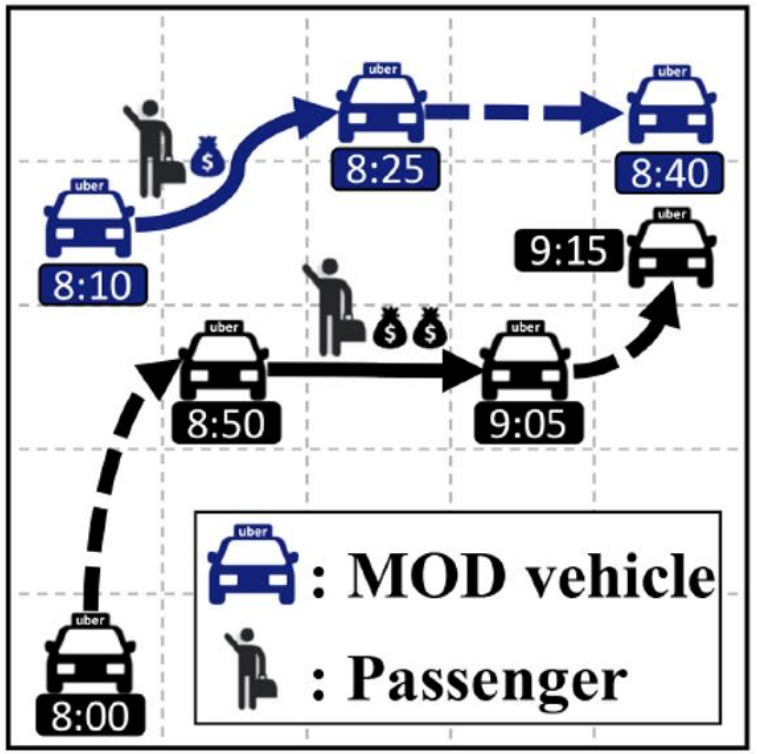
**Exclusive tasks** 81%

**Transparent reward** 70%

# System Overview



# Analyzing a large-scale vehicle dataset



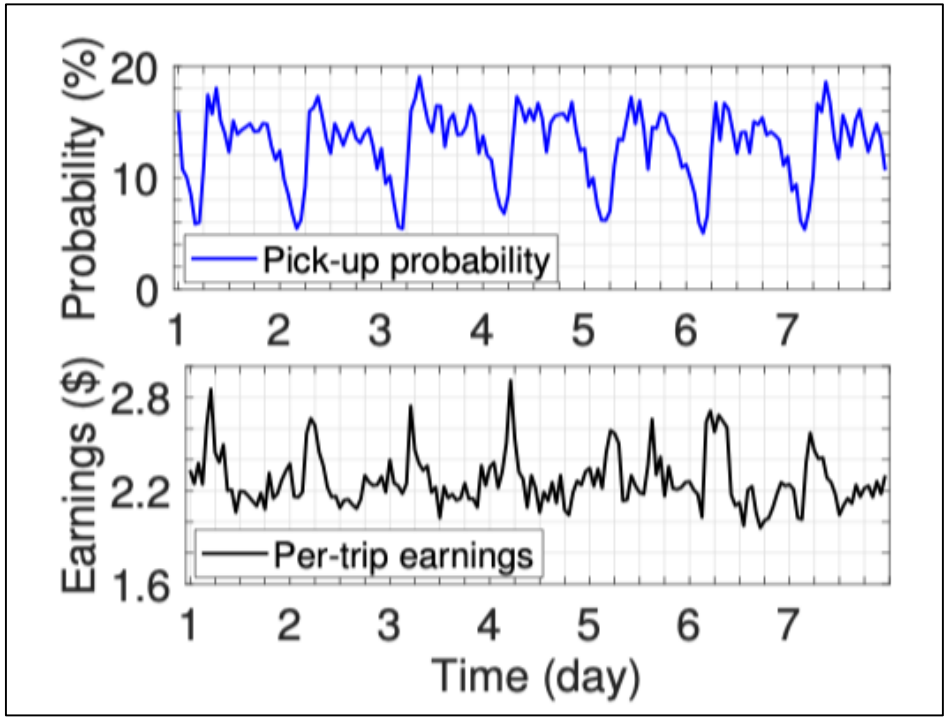

Trajectory

Occupancy status

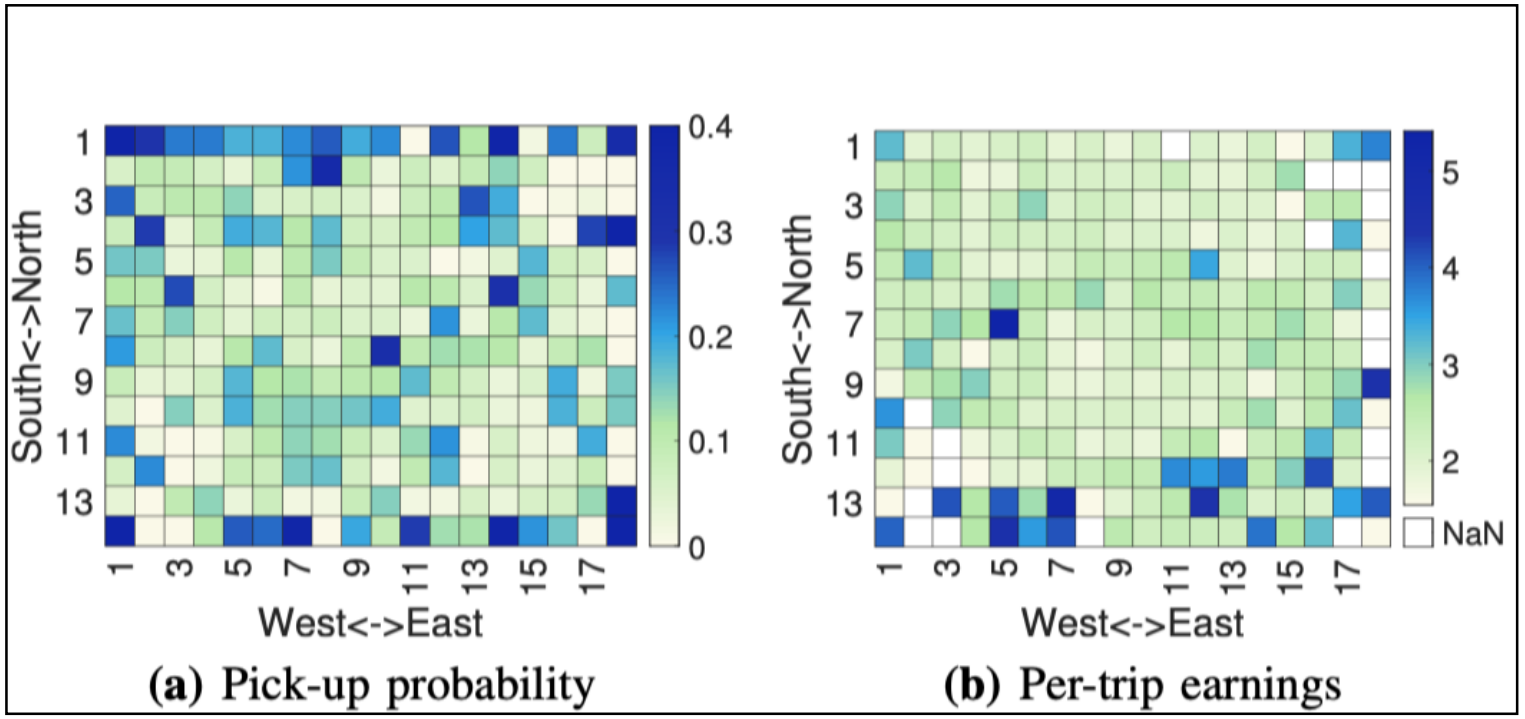
Profits

- 4,400 $km^2$ metropolitan area
- 12,493 MOD vehicles
- 15 seconds interval, 92 GB data

# Pick-up profit analysis via spatial-temporal dimension



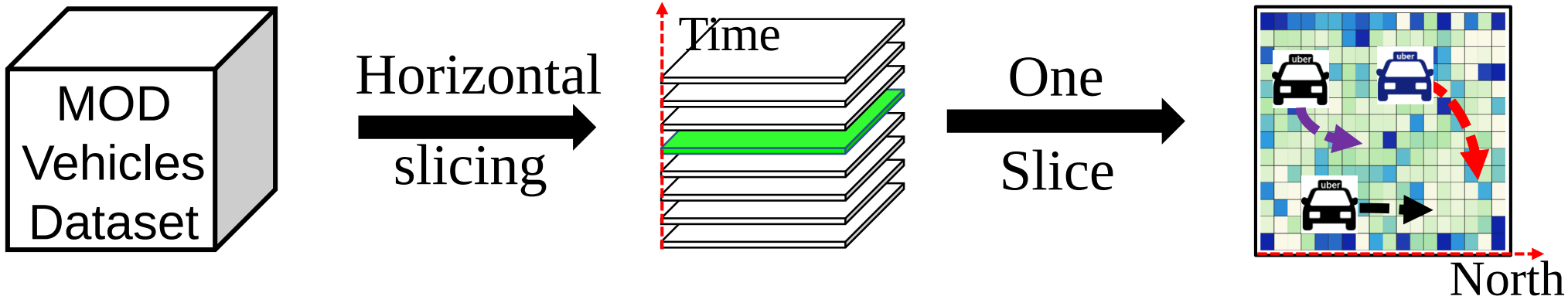

**Temporal diversity**

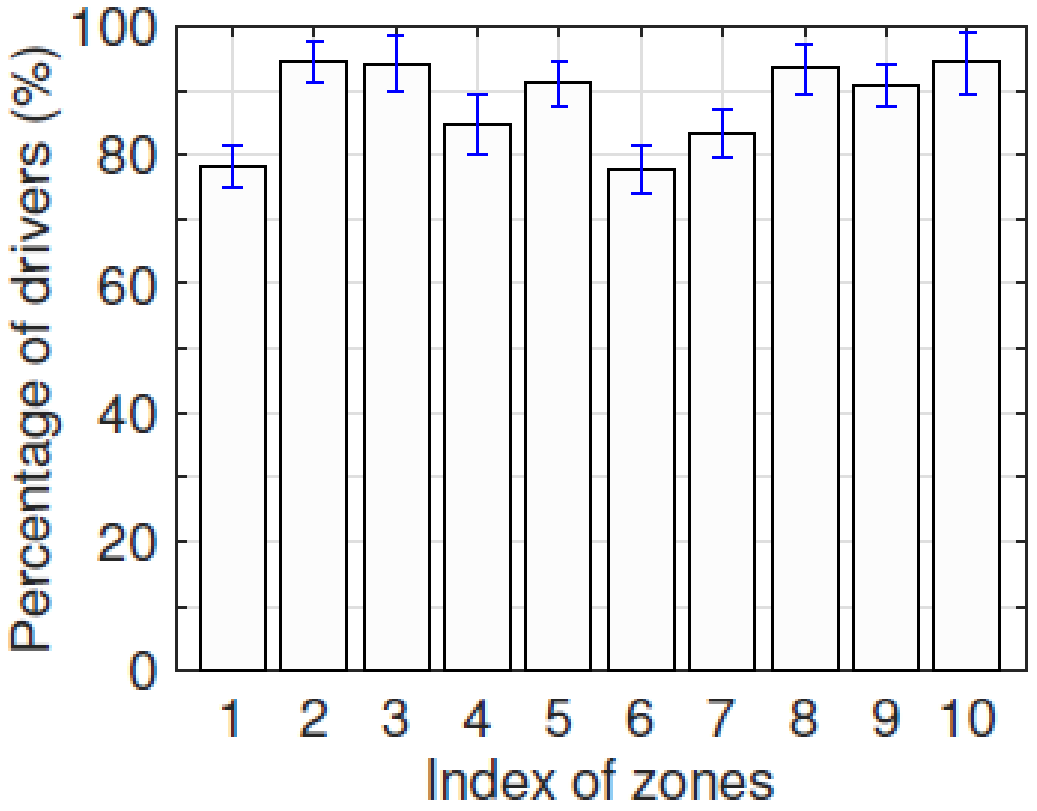



**Spatial diversity**

Pick-up profits of MOD drivers have huge **spatial-temporal differences** in different **zones** and **time periods**.

# MOD drivers' behavior analysis via 2D slicing

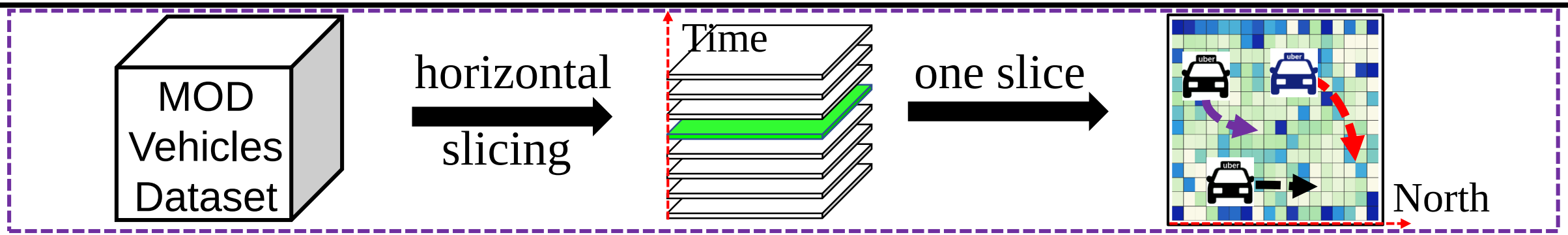


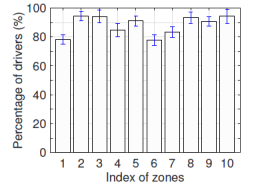



(a) Drivers' short-term behavior analysis

Most drivers (about 88.2%) in low-yield zones have a tendency of moving out (towards higher-yield zones).

# MOD drivers' behavior analysis via 2D slicing

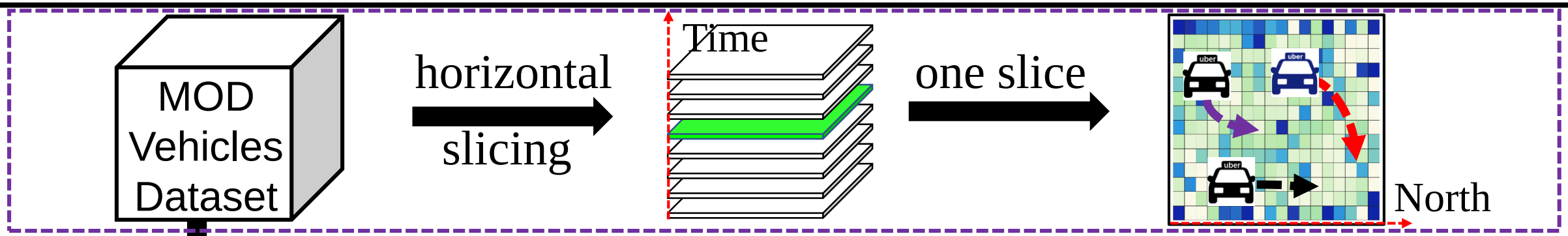


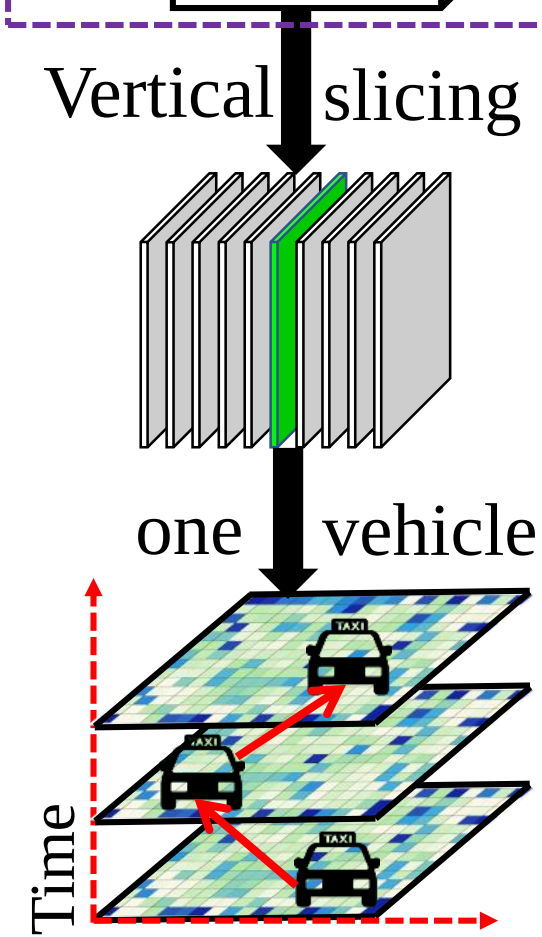



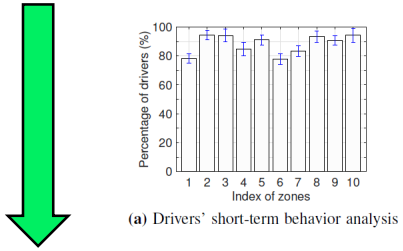

(a) Drivers' short-term behavior analysis

Drivers have **explicit preference** for **short-term, immediate gains**.

# MOD drivers' behavior analysis via 2D slicing

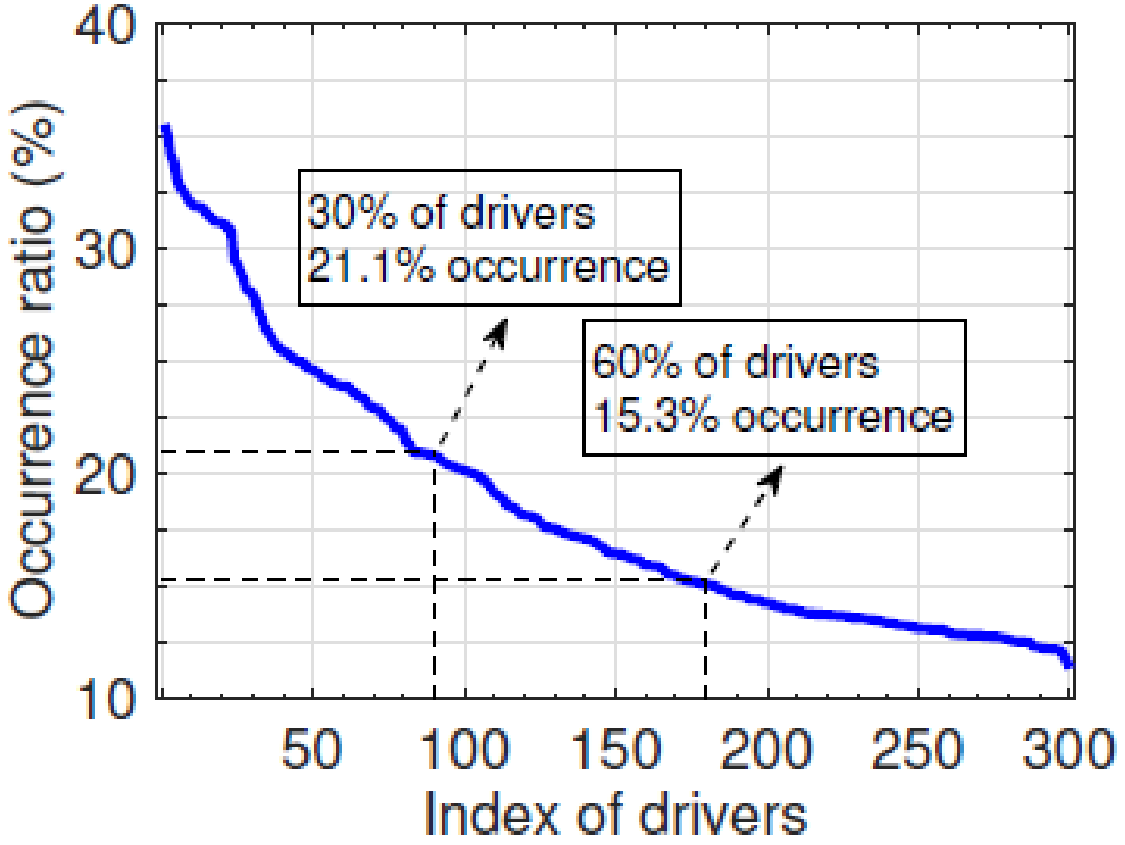


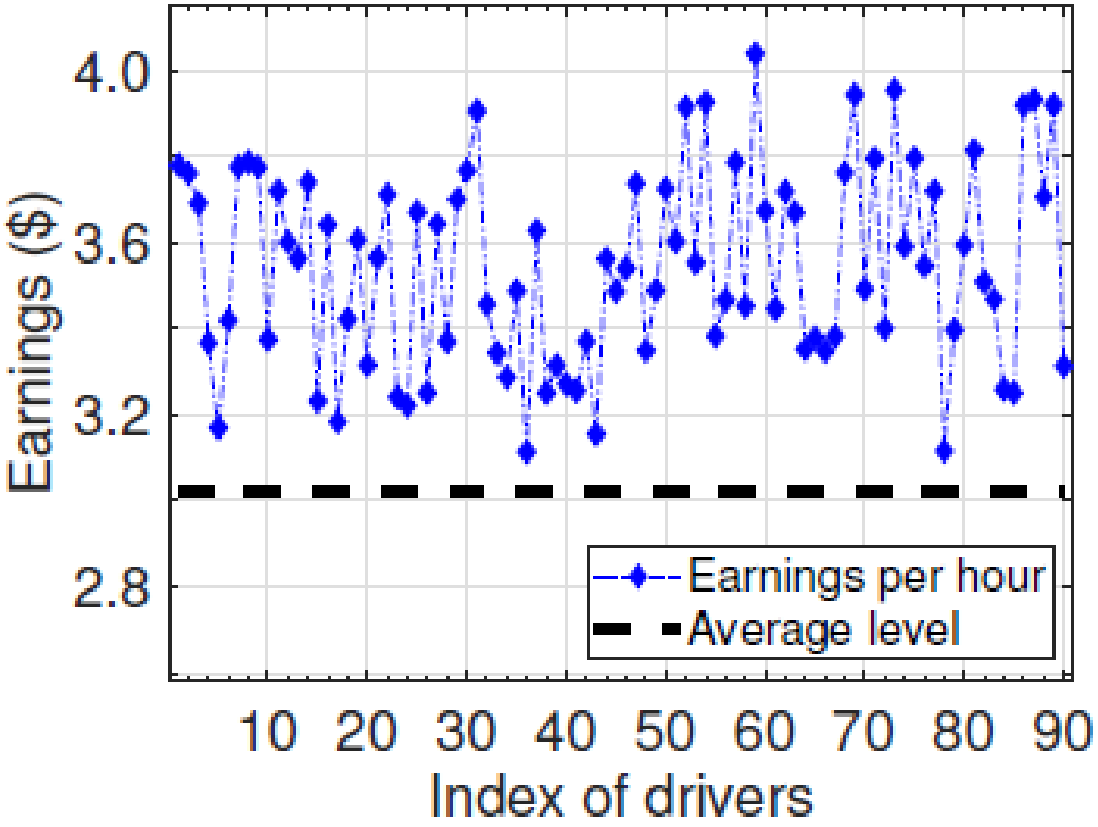




(a) Drivers' short-term behavior analysis

Drivers have **explicit preference** for **short-term, immediate gains**.

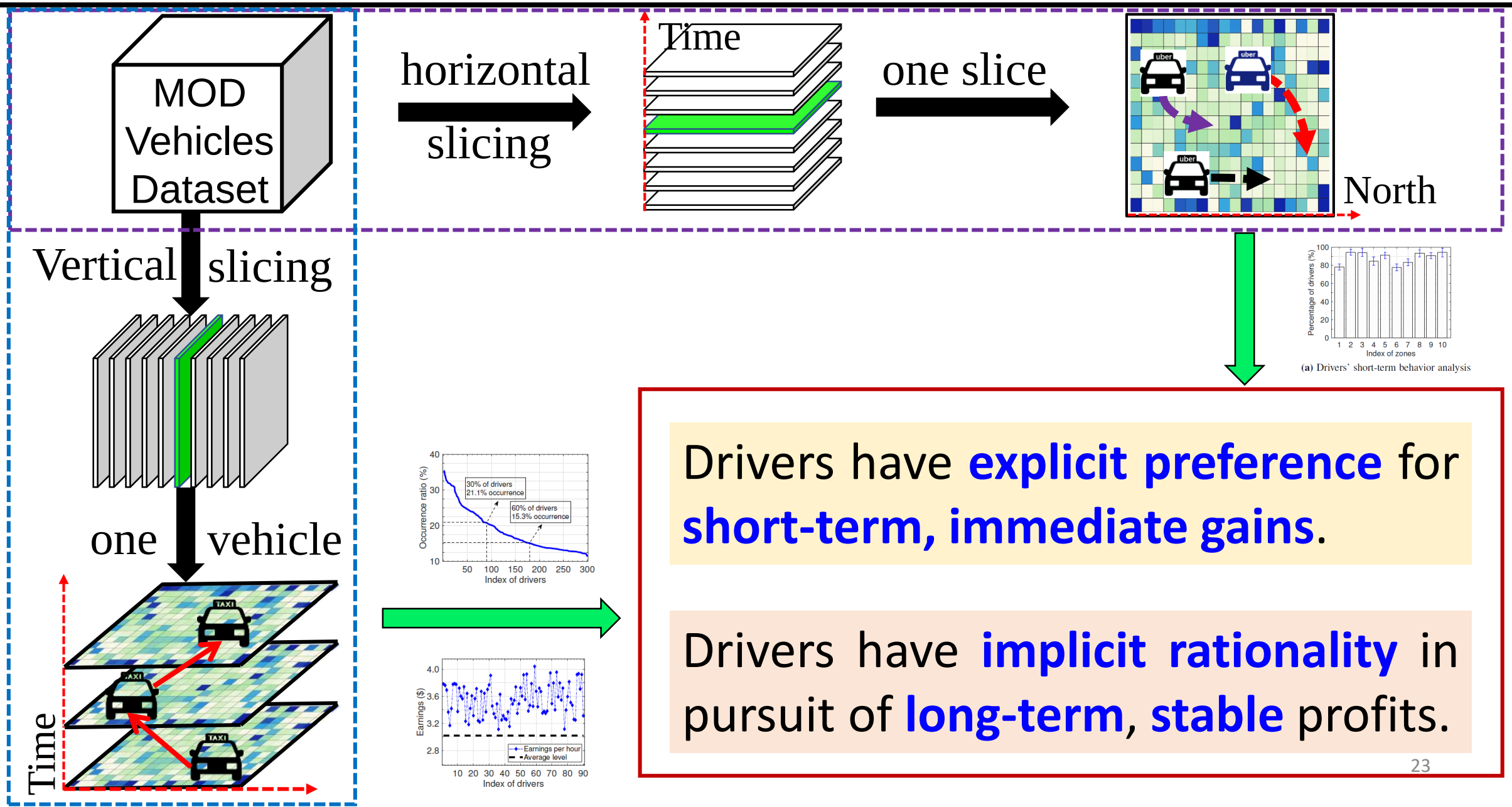



A considerable portion (30%) of drivers drive from high-yield zones to low-yield zones for picking up passengers with a high occurrence (21.1%).

Surprisingly, their hourly earnings are 17.5% more than the average level ($126.6 monthly raise).

# MOD drivers' behavior analysis via 2D slicing




Drivers have **explicit preference** for **short-term, immediate gains**.

Drivers have **implicit rationality** in pursuit of **long-term**, **stable** profits.


# Outline

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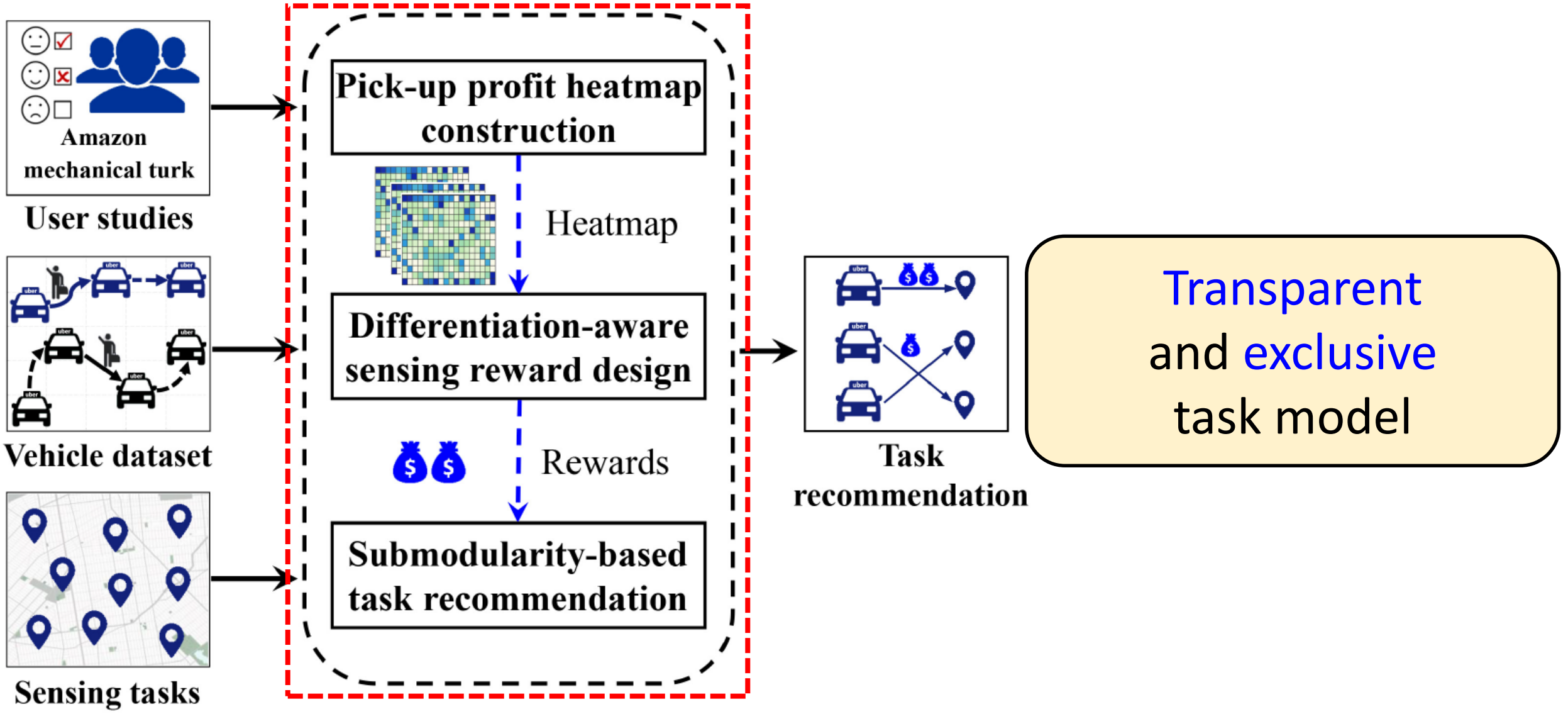
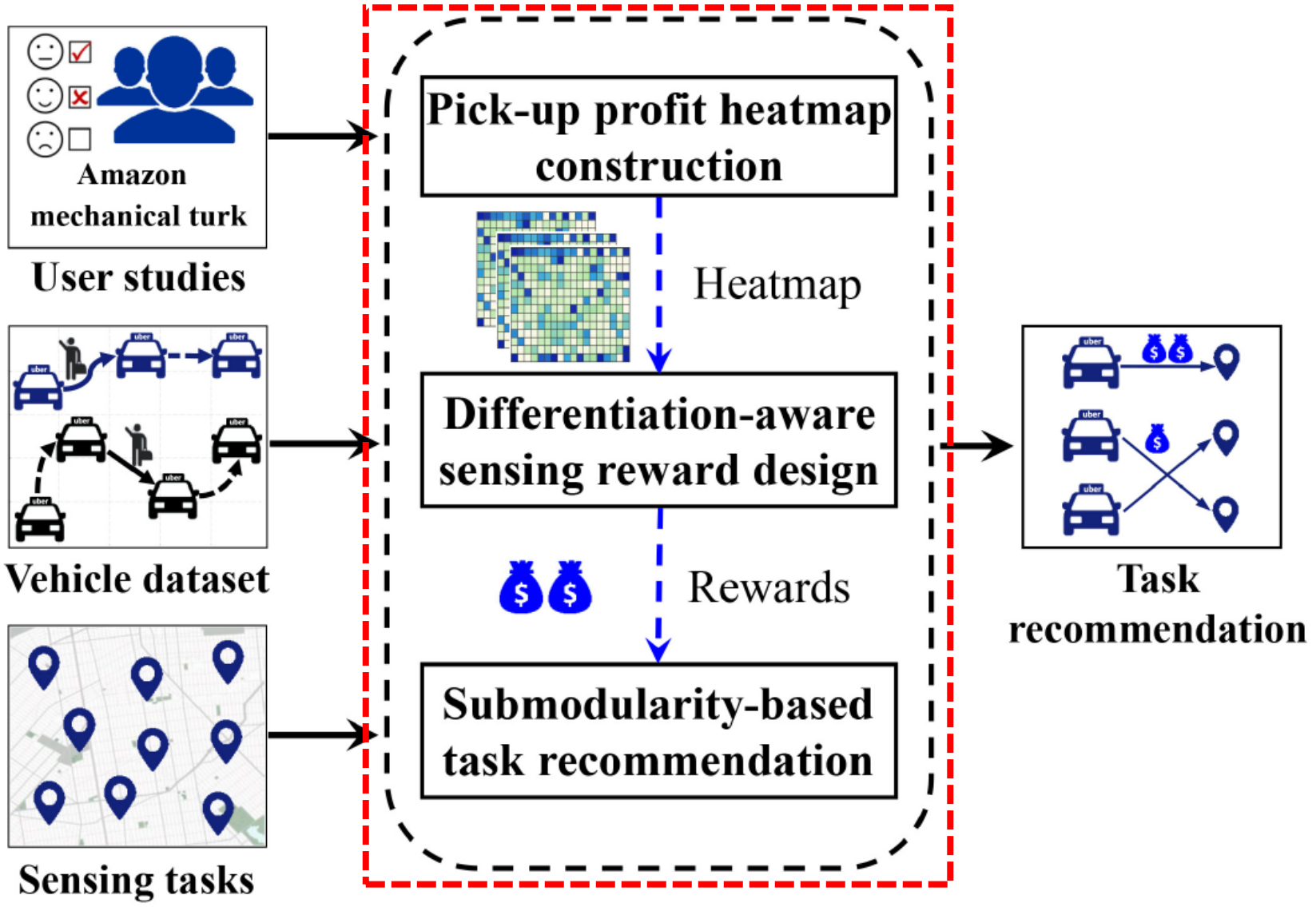
# Basic idea


Amazon mechanical turk
User studies
Vehicle dataset
Sensing tasks
Pick-up profit heatmap construction
Heatmap
Differentiation-aware sensing reward design
Rewards
Submodularity-based task recommendation
Task recommendation
Transparent and exclusive task model

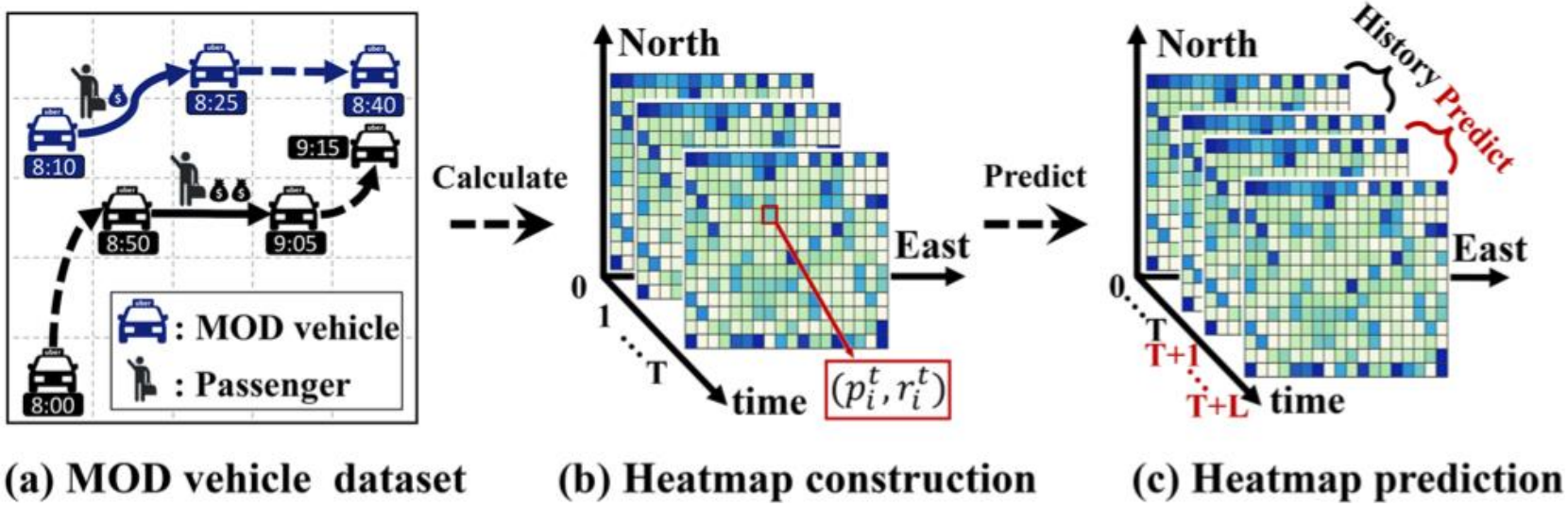
# Basic idea




Recommendation scheme by the professional platform considering drivers' short-term and long-term profits.

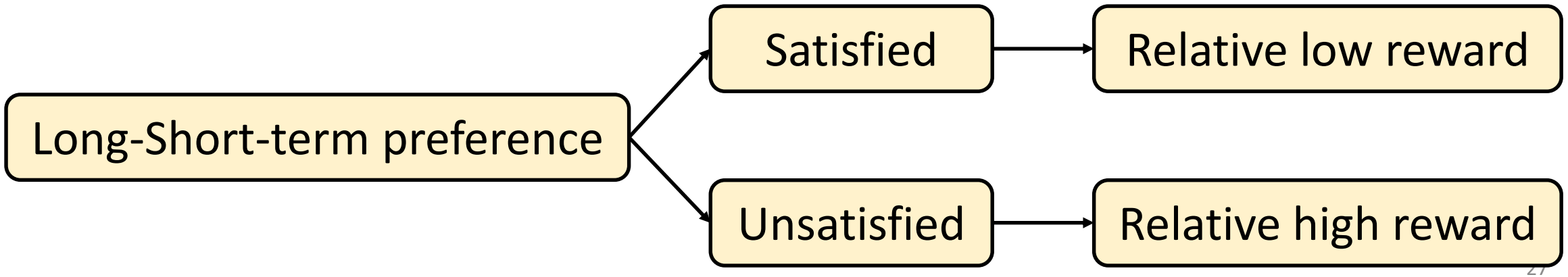
# System flow

- Pick-up heatmap construction by dual-attention RNN

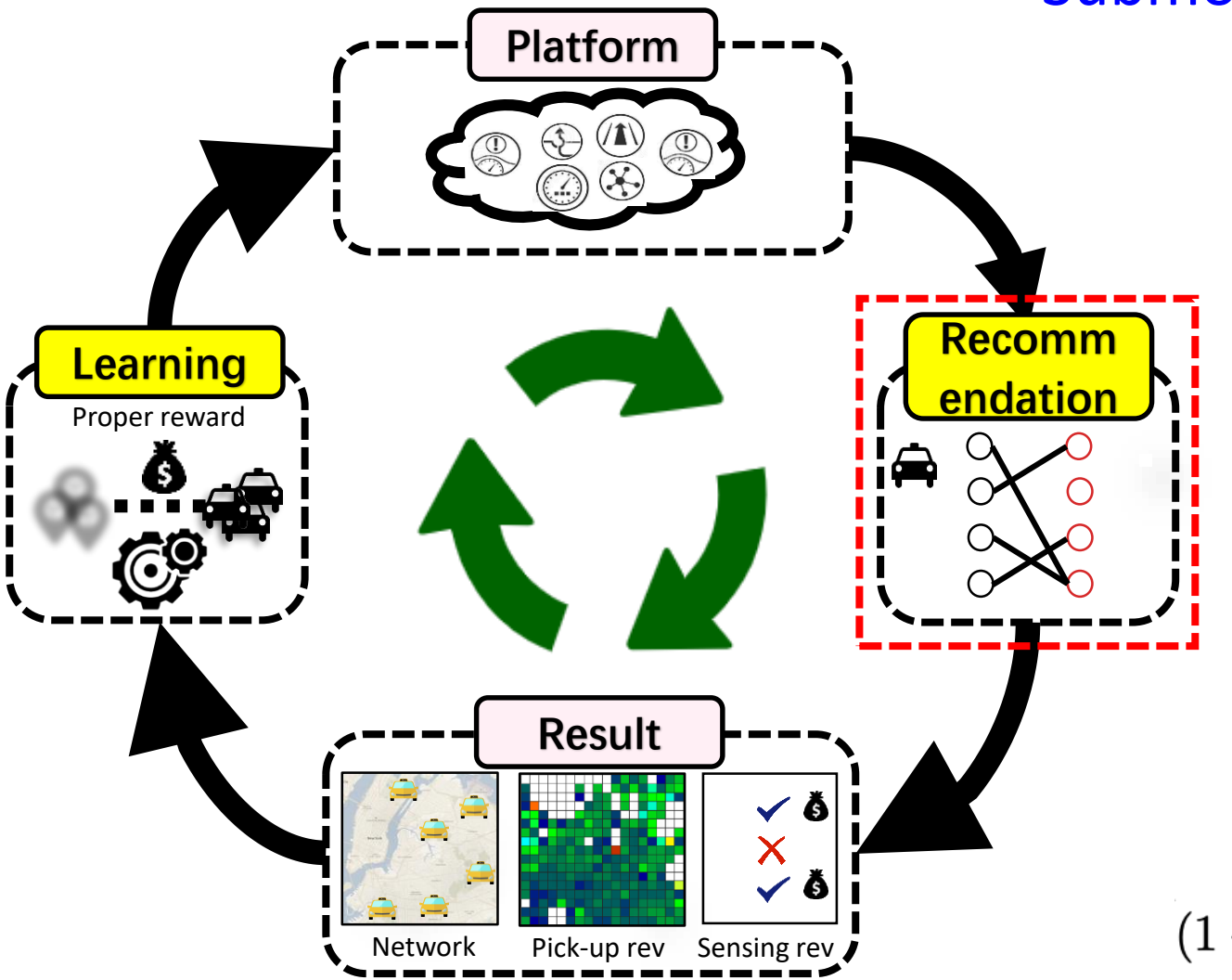



(a) MOD vehicle dataset (b) Heatmap construction (c) Heatmap prediction

- Adjust sensing reward to satisfy driver's preferences



# System flow




## Submodularity based task recommendation

**Algorithm 1:** Greedy Local Search-based Near-optimal Task Recommendation Algorithm.

**Input:** Task set $\mathcal{S}$; MOD driver set $\mathcal{M}$;
Sensing rewards set $\{c_{kj}\}$;
Set of drivers' acceptance probability $\{\rho_{kj}\}$;
Set of tasks' profits to the platform $\{u_j\}$; Budget $B$;
**Output:** Recommended task set $\{x_{kj}\}$; Platform profit $U$.

Initialize $\mathcal{A}_0 = \{v_0, v_1\}$, where $v_0 = \arg\max_{v \in \mathcal{V}} U(\{v\})$, $v_1 = \arg\max_{v \in \mathcal{V}\setminus\{v_0\}} U(\{v, v_0\}) - U(\{v_0\})$;
Initialize $n = 0$, and $swap = true$;
**while** $swap$ **do**
  $swap \leftarrow false$;
  $\mathcal{V}_s := \{(v_+, v_-) | \forall v_+ \in \mathcal{V}\setminus\mathcal{A}_n, \forall v_- \in \mathcal{A}_n \cup \{\emptyset\}\}$;
  **while** $(swap \neq true)$ && $(\mathcal{V}_s \neq \emptyset)$ **do**
    $(v_+^*, v_-^*) = \arg\max_{(v_+, v_-) \in \mathcal{V}_s} \pi(v_+, v_-)$;
    **if** $\mathcal{A}_n \setminus \{v_-^*\} \cup \{v_+^*\}$ satisfies constraints (7)(8) and $\pi(v_+^*, v_-^*) \geq \frac{\epsilon}{M^2 S^2}$ **then**
      $\mathcal{A}_{n+1} \leftarrow \mathcal{A}_n \setminus \{v_-^*\} \cup \{v_+^*\}$;
      $n \leftarrow n + 1$;
      $swap \leftarrow true$;
    $\mathcal{V}_s \leftarrow \mathcal{V}_s \setminus \{(v_+, v_-)\}$;
Set $\mathbf{x} \leftarrow \{x_{kj} = 1 | \forall k, \forall j, (k, j) \in \mathcal{A}_n\}$;
Compute $U(\mathbf{x})$ based on $\mathbf{x}$, $\{u_j\}$, and $\{\rho_{kj}\}$, according to Eq. (6);
**return** $\mathbf{x}$ and $U(\mathbf{x})$ .

$(1 - e^{-2})/2$ ratio near-optimal solution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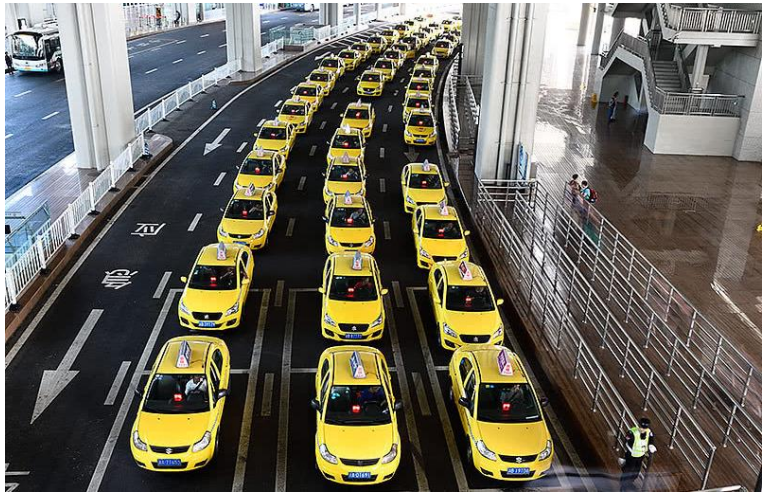
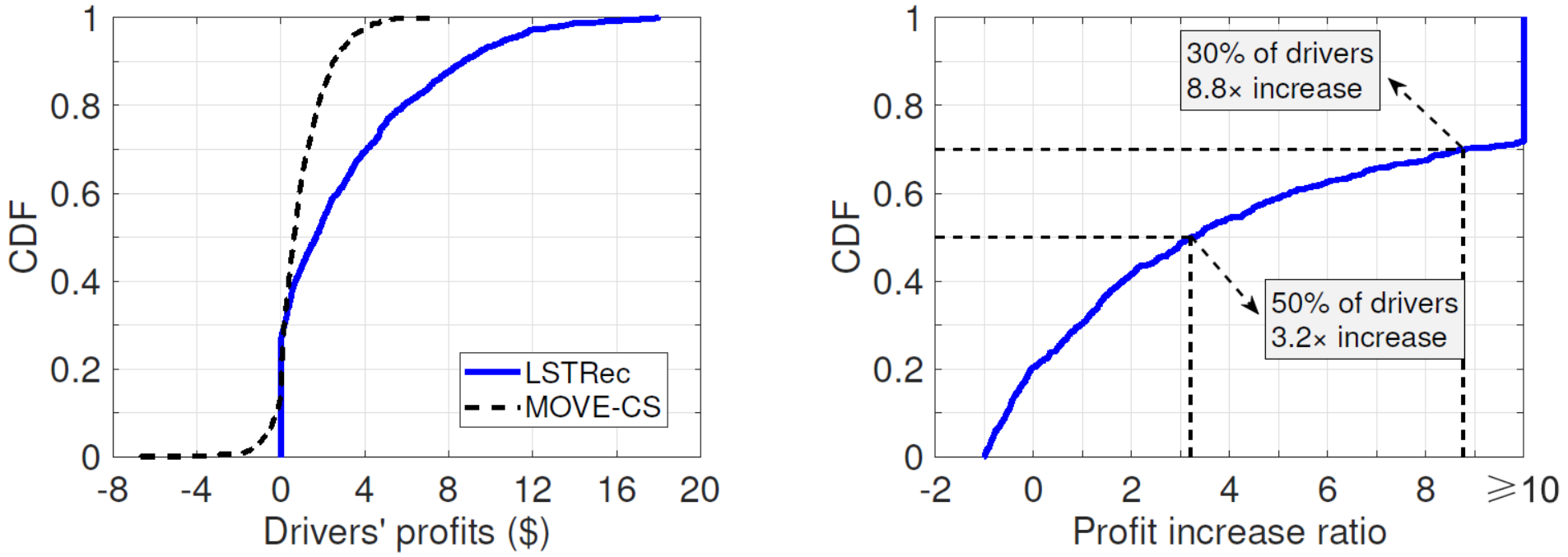
# Experimental Settings

- Real dataset
  - 1 month sensing data of 12493 MOD drivers (2017.3)
  - Sampling rate: 15 seconds
- Parameter settings
  - Sensing target: 878 road segments
  - Sensing profit: $2.5,1.5 and 0.5 per mile for the 3 times covering
- Evaluation Metrics
  - Drivers' profits
  - Platform's profit
  - Sensing coverage



# Evaluation Results—*Compared with MOVE-CS*

➢Drivers' profit

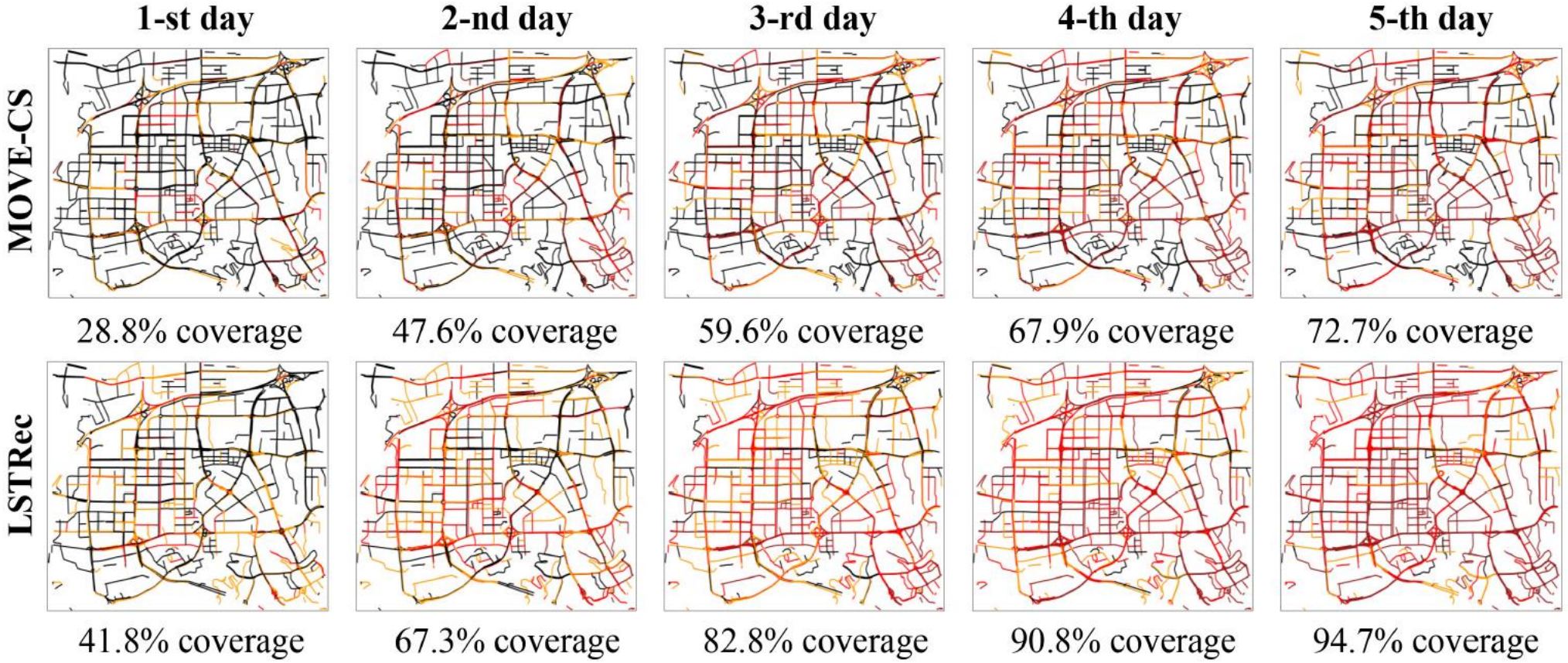



(a) Drivers' profits (b) Profit increase ratio

50% of drivers increase profits by 320%, 30% have an increase ratio of 880%, 20% suffer decreased profits

# Evaluation Results—*Compared with MOVE-CS*

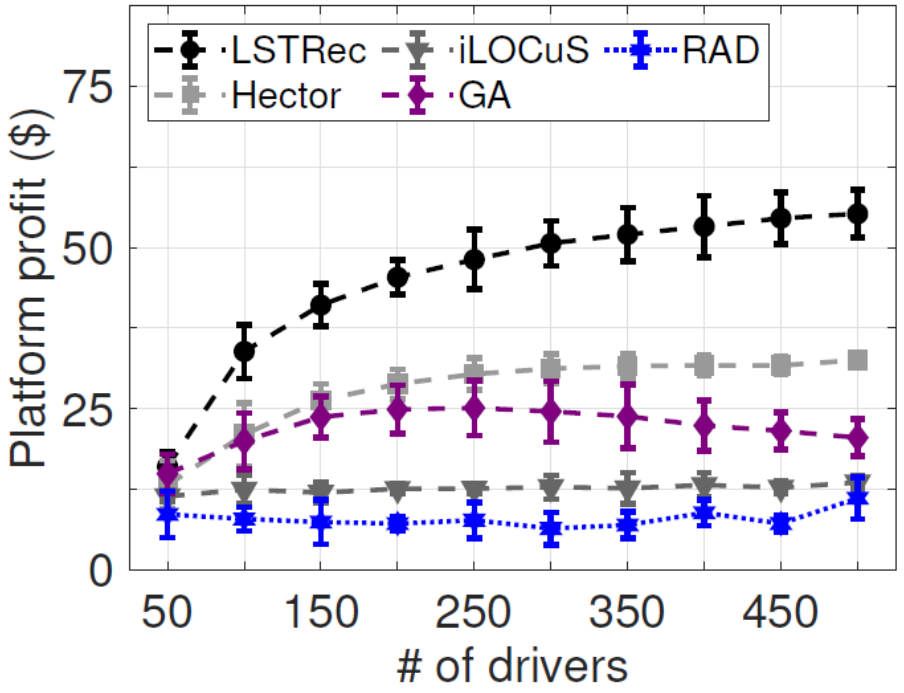
➢Sensing coverage



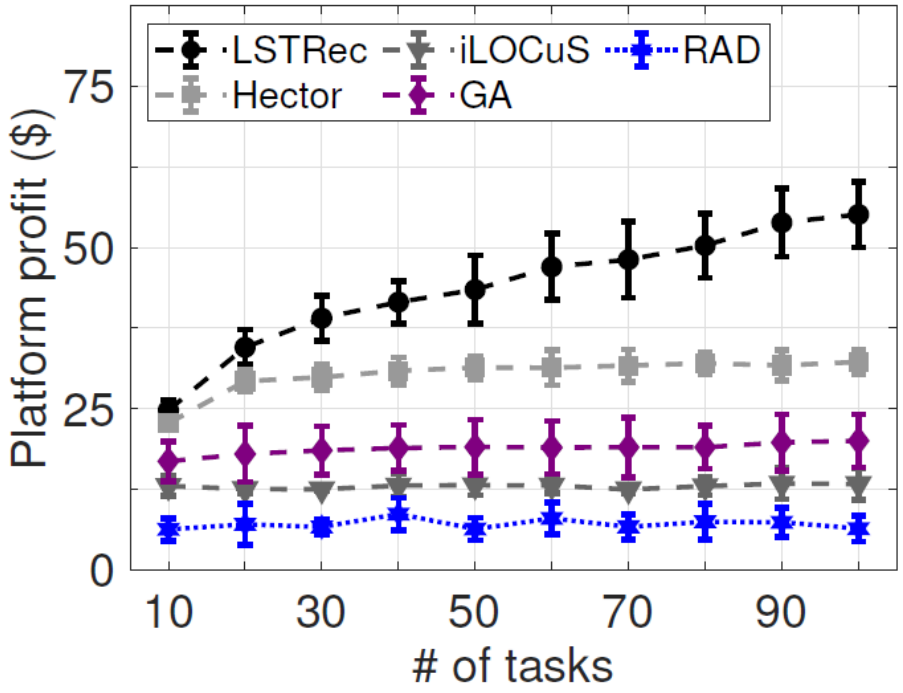

22% higher coverage than that in MOVE-CS, and the platform’ s profit increases by 34.3%

# Evaluation Results—*Compared with other baselines*

- Impacts of different number of drivers and tasks for platform




(a) Drivers' number



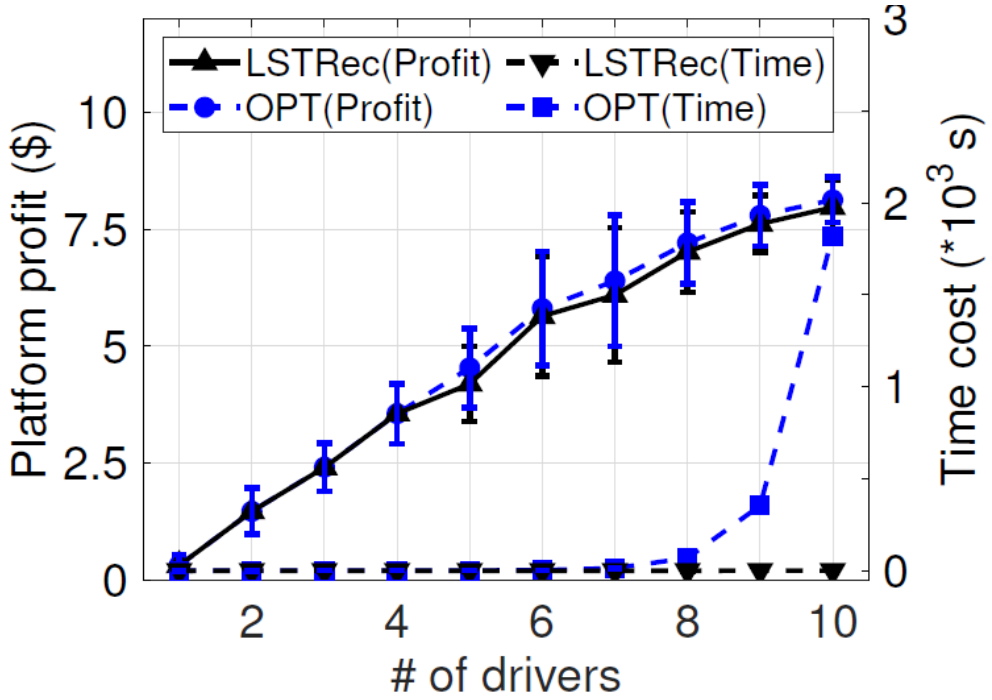

(b) Tasks' number

Outperforms by 61.7% compared with Hector on average

Outperforms by 44.4% compared with Hector on average

# Evaluation Results—*Compared with other baselines*

- Comparisons of near-optimality




(a) Near-optimality

Achieving 97.2% of optimal profit with only 0.004% of the time cost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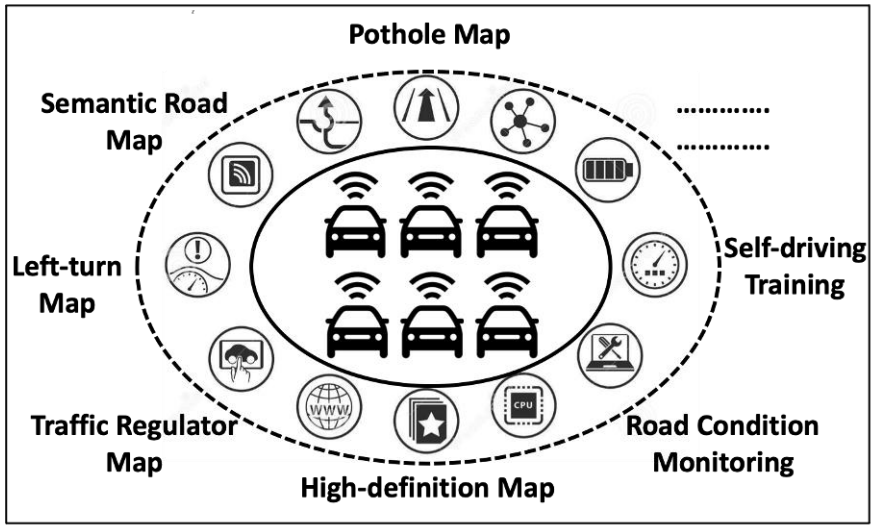
# Conclusions

- Figure out the root cause of MOVE-CS's failure by surveying 581 drivers and analyzing a 12,493 MOD vehicle dataset.
- Propose a novel operation model to satisfy both drivers' explicit preference for short-term gains and their implicit need of long-term profits.
- Conduct extensive emulations based on a large-scale dataset.



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Thank you! Q & A

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