A Comparative Approach to Resurrecting the Market of MOD Vehicular Crowdsensing

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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]

MOD market is facing challenges

- MOD Drivers are earning less.
- The situation is getting much worse due to COVID-19.

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

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

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 | @andrewhawk | Feb 11, 2021, 4:42pm EST
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.

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

Q1

Pick-up Profit Heatmap Construction

Heatmap

Differentiation-aware Sensing Reward Design

Rewards

Submodularity-based Task Recommendation

Task recommendation

Sensing tasks

Vehicle dataset

User studies

Amazon mechanical turk
Crowdsourcing-based User Studies

Surveying 581 drivers on Amazon MTurk

Drivers’ Distribution

- North America: 28.2%
- Europe: 7.3%
- Asia: 46.6%
- South America: 16.6%
- Africa: 1.3%
- Australia: 7.3%
Crowdsourcing-based User Studies

Surveying 581 drivers on Amazon MTurk

Drivers’ Distribution

<table>
<thead>
<tr>
<th>Gender</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>41%</td>
<td>59%</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Driving Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
</tr>
<tr>
<td>Weekly</td>
</tr>
<tr>
<td>Monthly</td>
</tr>
<tr>
<td>Yearly</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>33.7%</td>
</tr>
<tr>
<td>43.6%</td>
</tr>
<tr>
<td>12.9%</td>
</tr>
<tr>
<td>9.8%</td>
</tr>
</tbody>
</table>

Surveying 581 drivers on Amazon MTurk
Payver: a failed MOVE-CS platform

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.

Road data collection

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

Tasks are exclusive
The payment is transparent to every participant

Exclusive tasks: 95%
Transparent reward: 70%
System Overview

Q2

User studies

Vehicle dataset

Sensing tasks

Amazon mechanical turk

Pick-up Profit Heatmap Construction

Differentiation-aware Sensing Reward Design

Submodularity-based Task Recommendation

Heatmap

Rewards

Task recommendation
Analyzing a large-scale vehicle dataset

- 4,400 km² metropolitan area
- 12,493 MOD vehicles
- 15 seconds interval, 92 GB data

Trajectory

Occupancy status

Profits
Pick-up profit analysis via **spatial-temporal** dimension

Pick-up profits of MOD drivers have huge **spatial-temporal differences** in different **zones** and **time periods**.
MOD drivers’ behavior analysis via 2D slicing

MOD Vehicles Dataset
Horizontal slicing
One Slice
Northern Direction
Time

18
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

Drivers have **explicit preference** for short-term, immediate gains.
MOD drivers’ behavior analysis via 2D slicing

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

• Motivation
• System Design
• Evaluation
• Conclusion
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

- Adjust sensing reward to satisfy driver’s preferences

Long-Short-term preference

- Satisfied: Relative low reward
- Unsatisfied: Relative high reward
Submodularity based task recommendation

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

1. Initialize $A_0 = \{v_0, v_1\}$, where $v_0 = \arg \max_{v \in V} U_0(v)$.
2. Initialize $n = 0$, and $swap = true$.
3. while $swap$ do
   4. $swap \leftarrow false$;
   5. $V_n := \{v_0 \ \forall v_0 \in V \ \forall v_0 \in A_n \ \forall v_0 \in A_n \cup \{v_0\}\}$;
   6. while ($swap$ is true) & ($V_n \neq \emptyset$) do
      7. $(v^*_+ , v^-_+) \leftarrow \arg \max_{v_+ \in V \ \forall v_0 \in A_n \cup \{v_0\}} \pi(v_+ , v_-)$;
      8. if $A_n \setminus \{v^-_+\} \cup \{v^*_+\}$ satisfies constraints (7)(8) and
         $\pi(v^*_+ , v^-_+) \geq \frac{\pi(v^*_+ , v^-_+)}{U_0(v^*_+ \cup v^-_+)}$ then
         9. $A_{n+1} \leftarrow A_n \setminus \{v^-_+\} \cup \{v^*_+\}$;
      10. $n \leftarrow n + 1$;
      11. $swap \leftarrow true$;
   12. $V_n \leftarrow V_n \setminus \{(v_+ , v_-)\}$;
13. Set $x = \{x_{k,j} = 1|k,j, (k,j) \in A_n\}$;
14. Compute $U(x)$ based on $x$, $\{v_0\}$, and $\{\rho_{k,j}\}$, according to
15. Eq. (6);
16. return $x$ and $U(x)$.

$$(1 - e^{-2})/2$$ 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
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**

<table>
<thead>
<tr>
<th>MOVE-CS</th>
<th>1-st day</th>
<th>2-nd day</th>
<th>3-rd day</th>
<th>4-th day</th>
<th>5-th day</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>28.8% coverage</td>
<td>47.6% coverage</td>
<td>59.6% coverage</td>
<td>67.9% coverage</td>
<td>72.7% coverage</td>
</tr>
<tr>
<td>LSTRec</td>
<td>41.8% coverage</td>
<td>67.3% coverage</td>
<td>82.8% coverage</td>
<td>90.8% coverage</td>
<td>94.7% coverage</td>
</tr>
</tbody>
</table>

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

**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

![Graph showing near-optimality](image)

(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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