Optimizing Impression Counts for Outdoor Advertising

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$30 Billion

80%
Impression Counts for Outdoor Advertising

Trajectory
Billboards
Budget
Input:
(1) Billboard database \( U \); (2) Trajectory database \( T \); (3) Budget constraint \( B \); (4) Influence Measurement \( I(S) \)

Output:
Subset \( S \subseteq U \) that maximizes the overall influence of \( S \) such that the total cost of \( S \) does not exceed \( B \).

\[
\text{argmax } I(S) \quad \text{subject to } \text{cost}(S) \leq B
\]
1. How a billboard impresses an audience?
2. Influence Measurement

$$\arg\max_{I(S)} \text{ argmax } I(S)$$

$$\text{cost}(S) \leq B$$

$$I(S) = \sum_{t_j \in T} I(S, t_j)$$  \hspace{1em} (Ping et al., SIGKDD 2018 [1])

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Is It enough for impressing a person only one time?

One-time impression is not enough (Gershon et al., 1985[2]; William et al., 2003 [3])
2. Influence Measurement

I see it!

Impression Times

Influence

1st Time
2. Influence Measurement

It is familiar!
2. Influence Measurement

I remember it!
The logistic function (Advertising market and Customer behavior [4-7])

The effectiveness of advertisement repetition varies from one person to another.
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The effectiveness of advertisement repetition varies from one person to another.
Influence Measurement

\[ p(S, t) = \begin{cases} 
\frac{1}{1 + \exp\{\alpha - \beta \sum_{o_i \in S} I(o_i, t)\}} & \text{if } \exists o_i \in S \text{ such that } I(o_i, t) = 1 \\
0 & \text{otherwise}
\end{cases} \]

\[ I(S) = \sum_{t_j \in T} p(S, t_j) \]
1. Influence Measurement is not submodular
   - No approximation ratio for a greedy-based algorithm

   **Upper-bound Estimation (submodular)**

2. NP-hard to approximate within any constant factor

   **Branch-and-Bound Framework**
Upper-bound Estimation

Tangent Point

Upper Bound

Lower Bound

Influence

Impression Times

$\lambda_t$
Upper-bound Estimation

Upper Bound

Line 1

Lower Bound

Influence

Impression Times

Strategy 1

Upper Bound

Lower Bound
Upper-bound Estimation

Influence

Impression Times

Line 1

$x_t^S$

Strategy 1

Influence
Upper-bound Estimation

\[ \text{Influence} \]

\[ \text{Impression Times} \]

Line 1

\[ x_t^S \]

Strategy 2

Influence
Upper-bound Estimation

Influence

Impression Times

Strategy 1

Strategy 2
Upper-bound Estimation

Strategy 1
Branch-and-Bound Framework
<table>
<thead>
<tr>
<th>Optimization</th>
<th>Approximation Ratio</th>
<th>Effectiveness</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>BBS: Branch-and-Bound Framework</td>
<td>$\frac{1}{2}(1 - \frac{1}{e})$</td>
<td>1X</td>
<td>1X</td>
</tr>
<tr>
<td>PBBS: Branch-and-Bound Framework with Progressive Bound-Estimation</td>
<td>$\frac{\theta}{2}(1 - \frac{1}{e} - \epsilon)$</td>
<td>0.92X</td>
<td>50X</td>
</tr>
</tbody>
</table>
## Experiment - Statistics of datasets

|          | $|\mathcal{T}|$ | $|\mathcal{U}|$ | AvgDistance | AvgTravelTime | AvgPoint |
|----------|----------------|----------------|--------------|--------------|---------|
| NYC      | 600k           | 1500           | 2.9km        | 569s         | 159     |
| LA       | 250k           | 2500           | 2.7km        | 511s         | 138     |

1 TLC, 2 Lamar
Experiment - Algorithms

• Greedy: Maximum ratio of marginal influence gain to cost
• Top-k: Maximum number of trajectories
• BBS: Branch-and-bound framework
• PBBS: Branch-and-bound framework with progressive Bound Estimation
• LazyProbe: The best-performing method in [1]
Varying the budget $B$

Figure 1: Influence in NYC

Figure 2: Influence in LA
Varying the number of trajectories $|T|$
Scalability test in NYC

(a) Varying $|U|$  
(b) Varying $|\mathcal{T}|$
Comparison with LazyProbe

(a) Influence

(b) Time
Conclusion

• Real Problem
  • Meet more than one billboard in each travel (Impression Count)
  • Non-uniform cost of billboards
  • Budget

• Real Solution
  • While having the approximation guarantee

• Real-world Trajectory Dataset and Billboard Dataset

Takeaways

• Personal driving trajectories
• Personal identification of trajectories
• Digital Billboards
References


Varying $\beta/\alpha$ in NYC

(a) Influence

(b) Time
Varying $\varepsilon$ in NYC

(a) Influence

(b) Time
Varying $\theta$ in NYC
Varying $\lambda$ in NYC
Test on different cost setting strategies

(a) Influence

(b) Time
Varying the budget $B$
Varying the number of trajectories $|T|$