Optimizing Impression Counts for Outdoor Advertising

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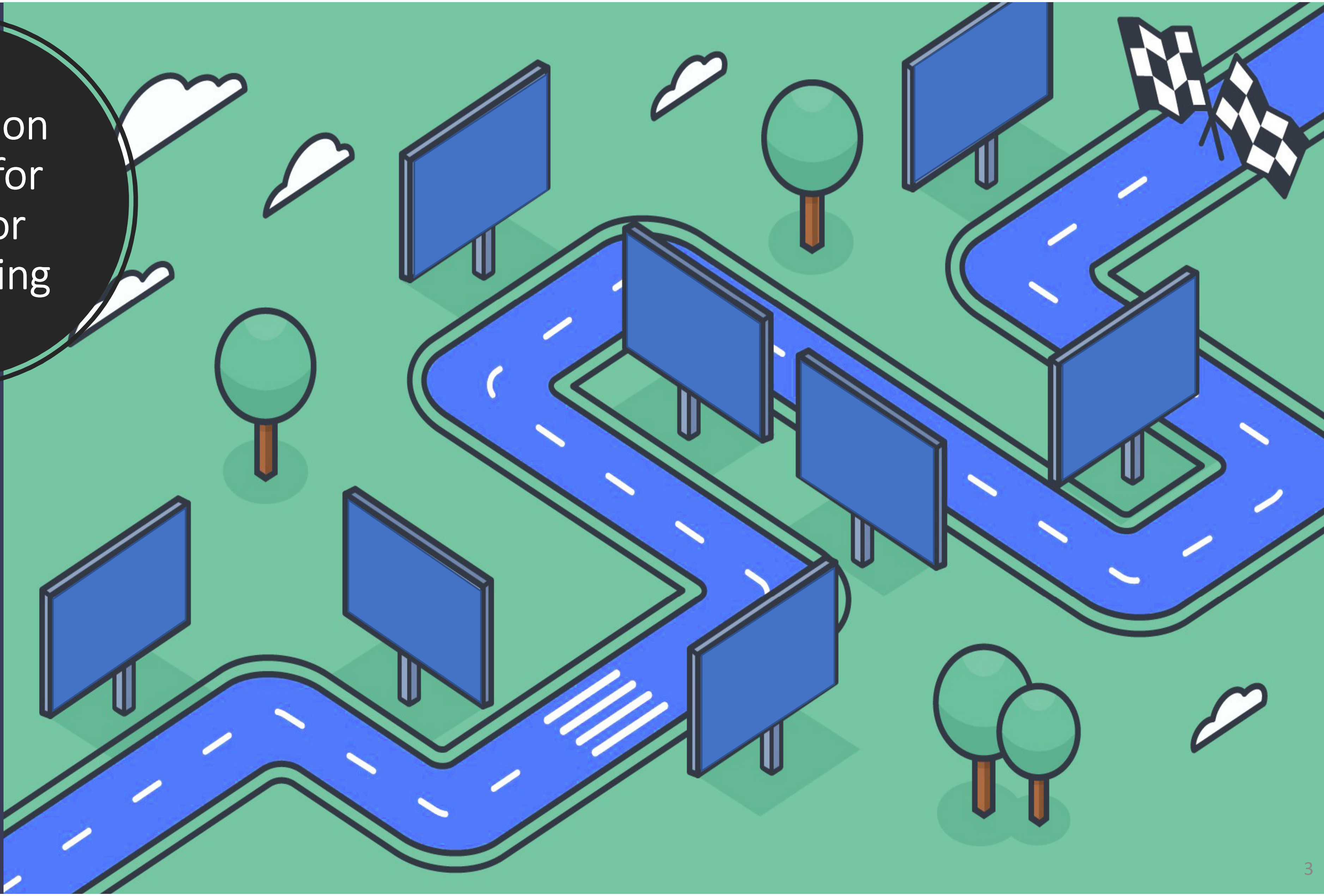
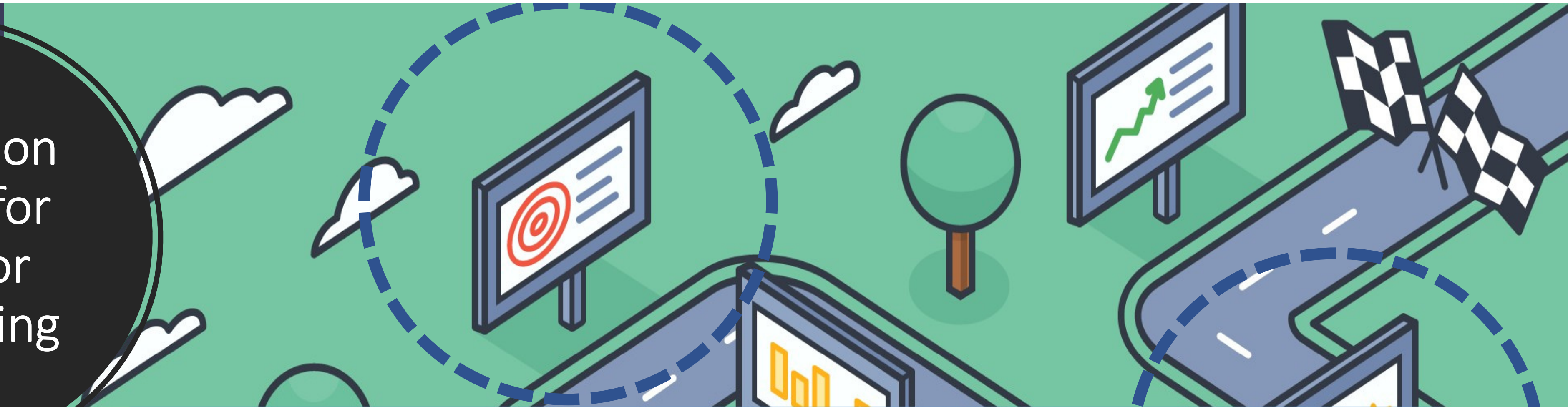
$30 Billion

80%

Impression Counts for Outdoor Advertising



Trajectory Billboards Budget



Impression
Counts for
Outdoor
Advertising

Trajectory

Billboards

Budget

Input:

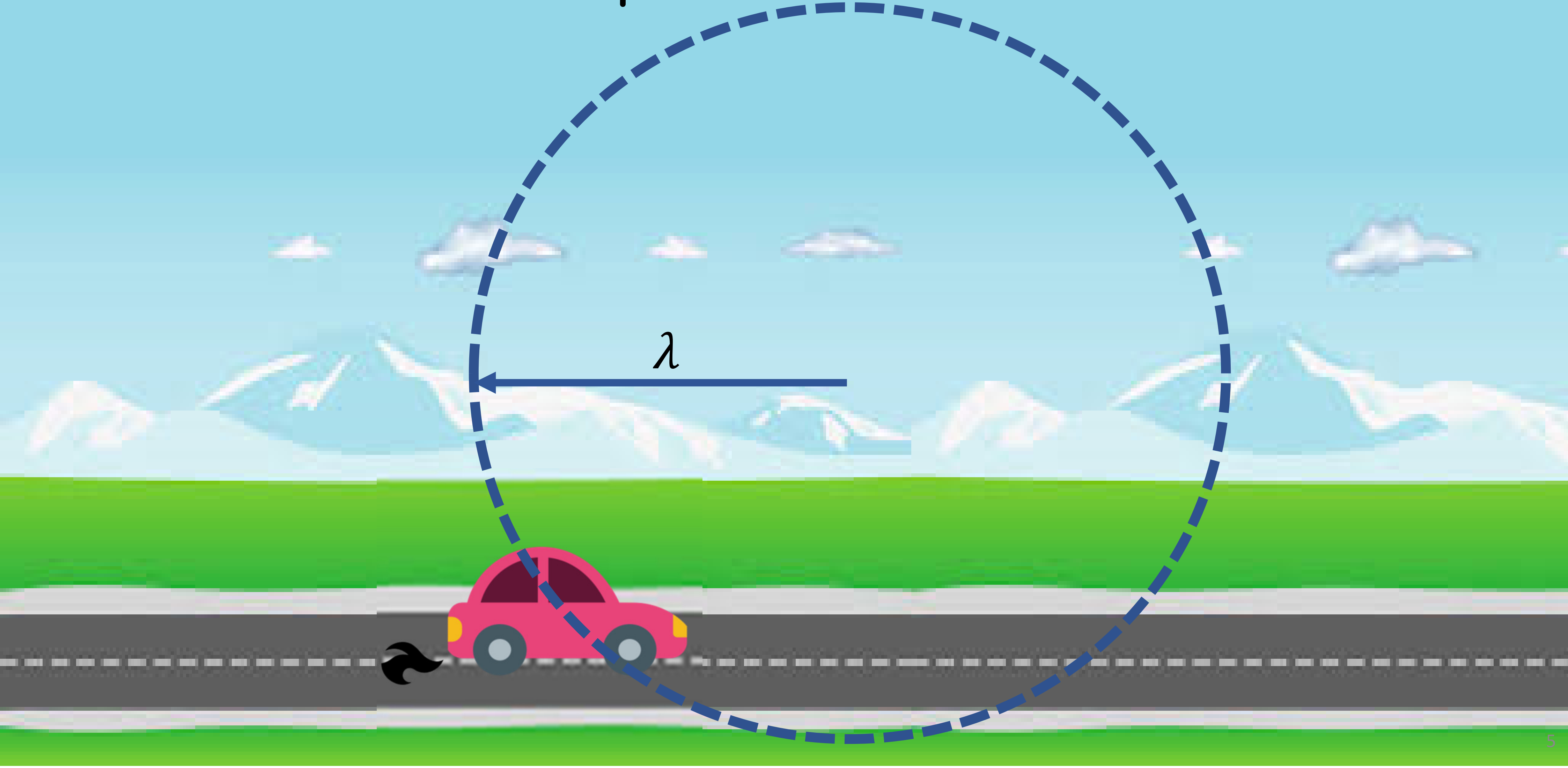
(1) Billboard database ***U***; (2) Trajectory database ***T***; (3) Budget constraint ***B***; (4) Influence Measurement ***I(S)***

Output:

Subset ***S*** $\subseteq$ ***U*** that maximizes the overall influence of S such that the total cost of S does not exceed B.

$$\underset{cost(S)\leq B}{\operatorname{argmax}} I(S)$$

1. How a billboard impresses an audience?



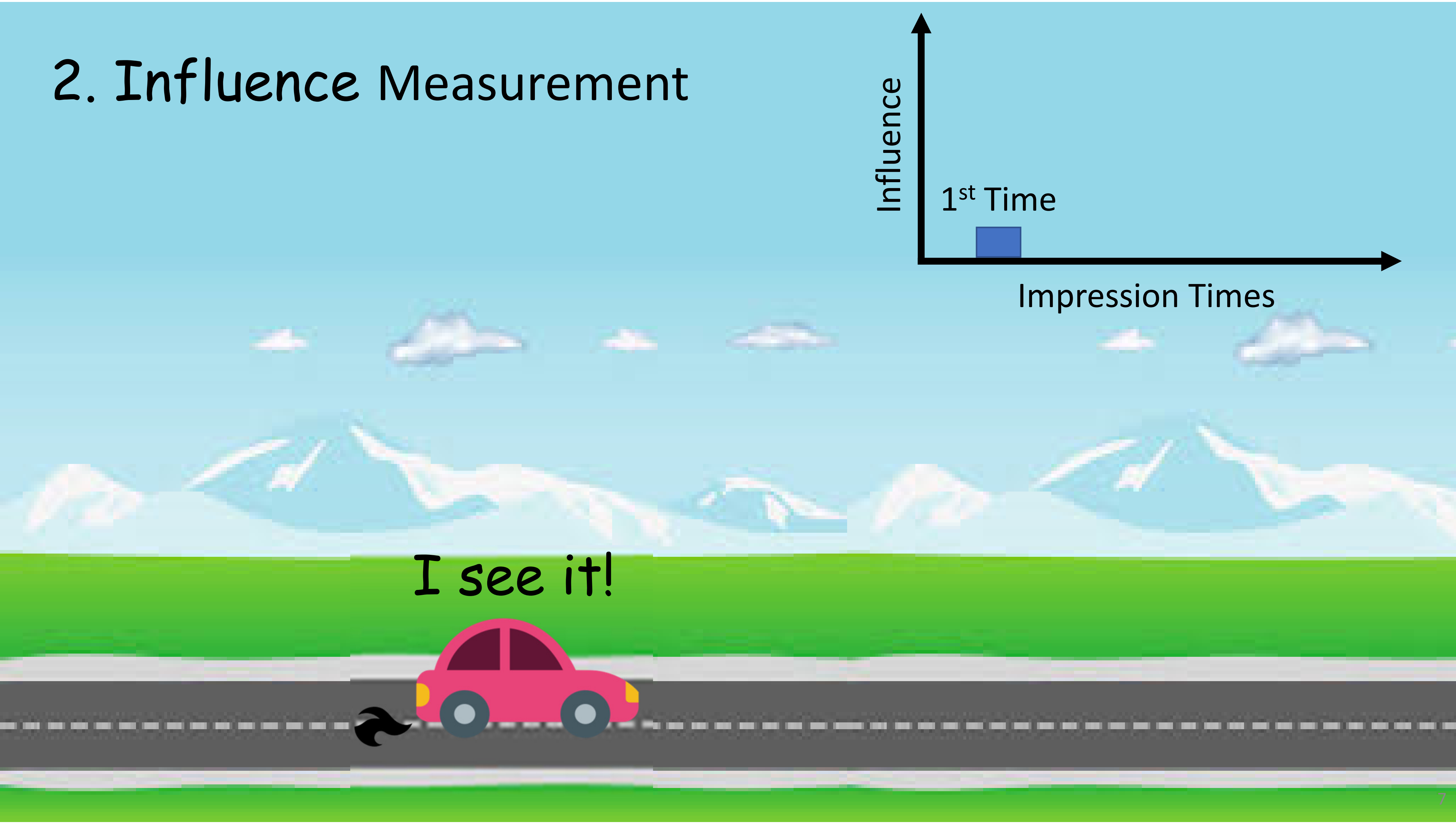
2. Influence Measurement

$$\underset{cost(S)\leq B}{\operatorname{argmax}}\ I(S)$$

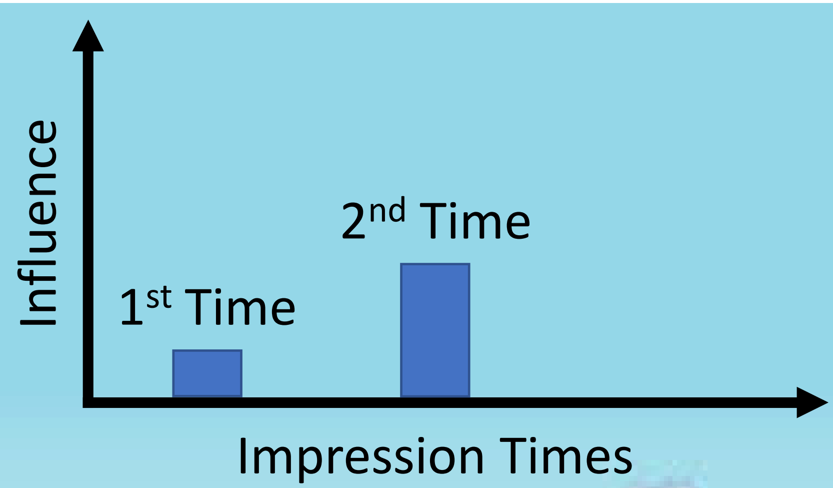
$$I(S) = \sum\nolimits_{t_j \in T} I(S, t_j)$$ *(Ping et al., SIGKDD 2018 [1])*

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
Influence
1st Time
Impression Times
I see it!

2. Influence Measurement



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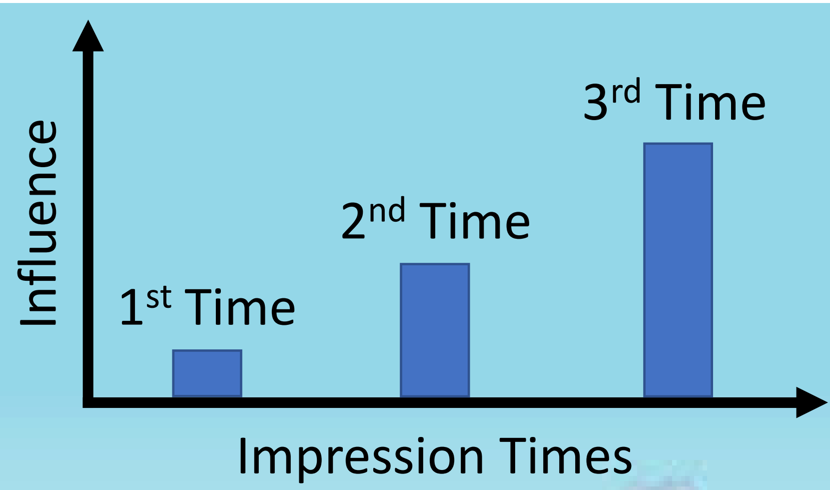
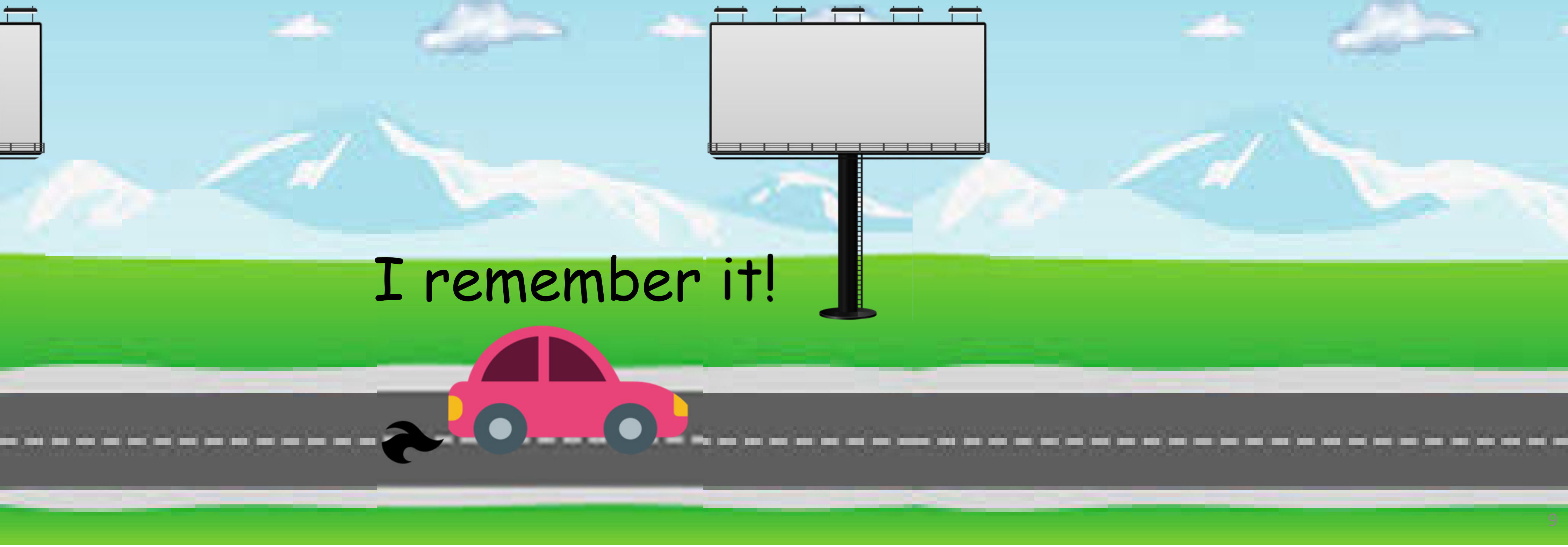
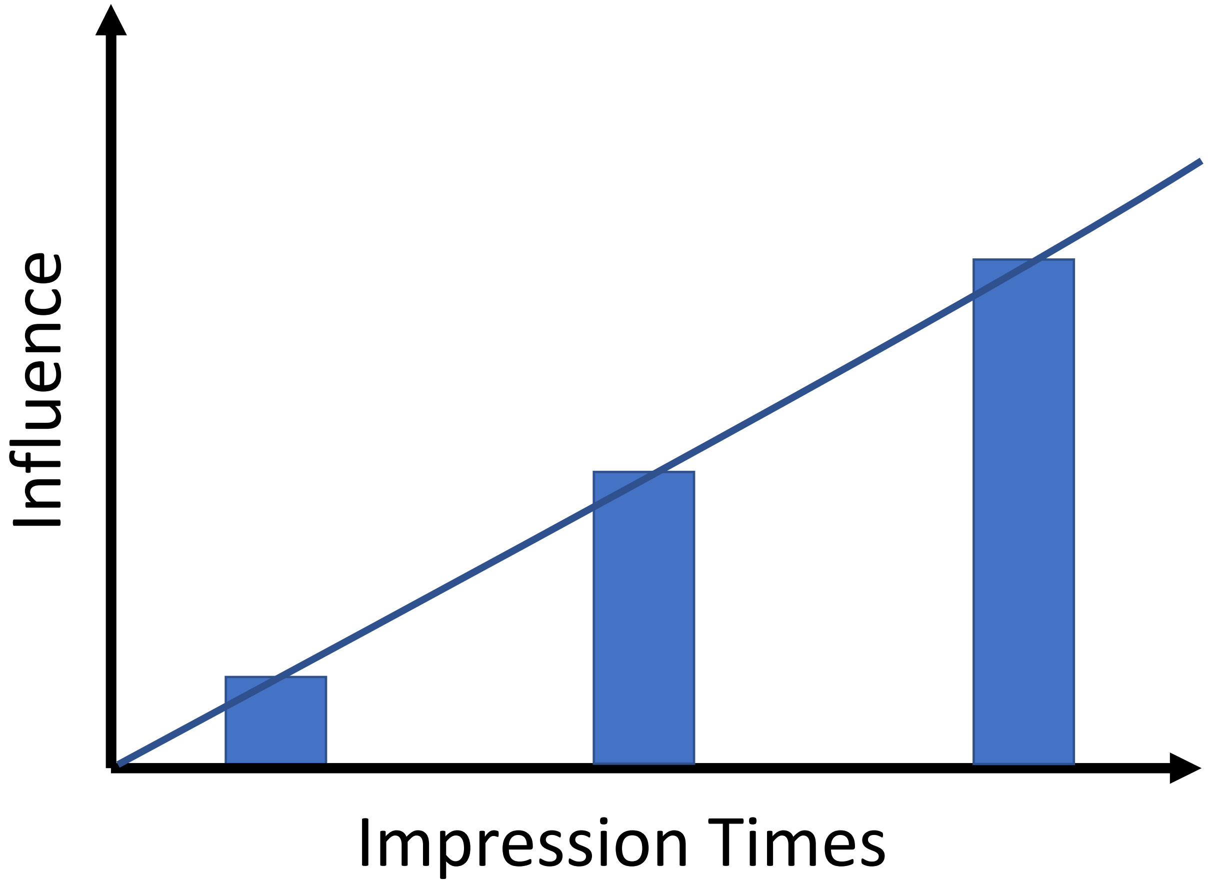
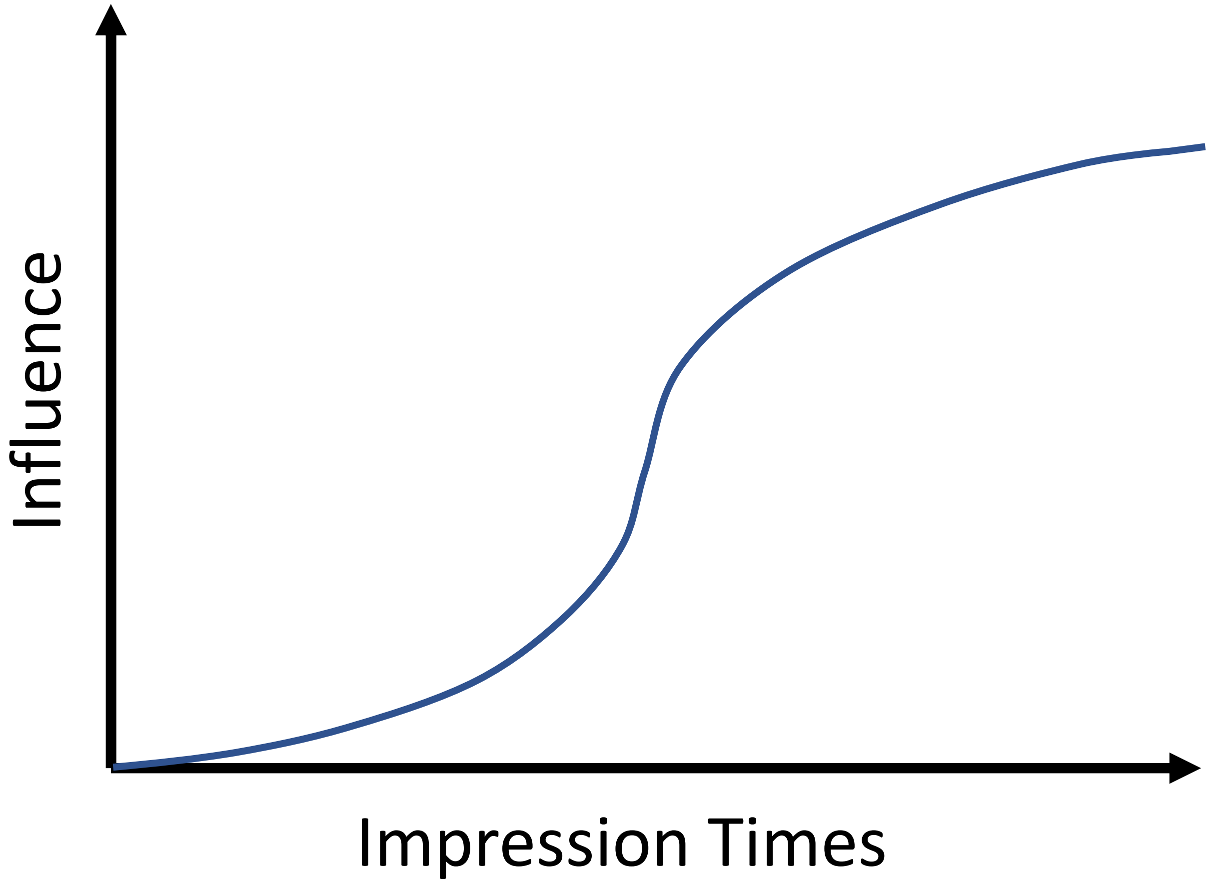





Influence
Impression Times

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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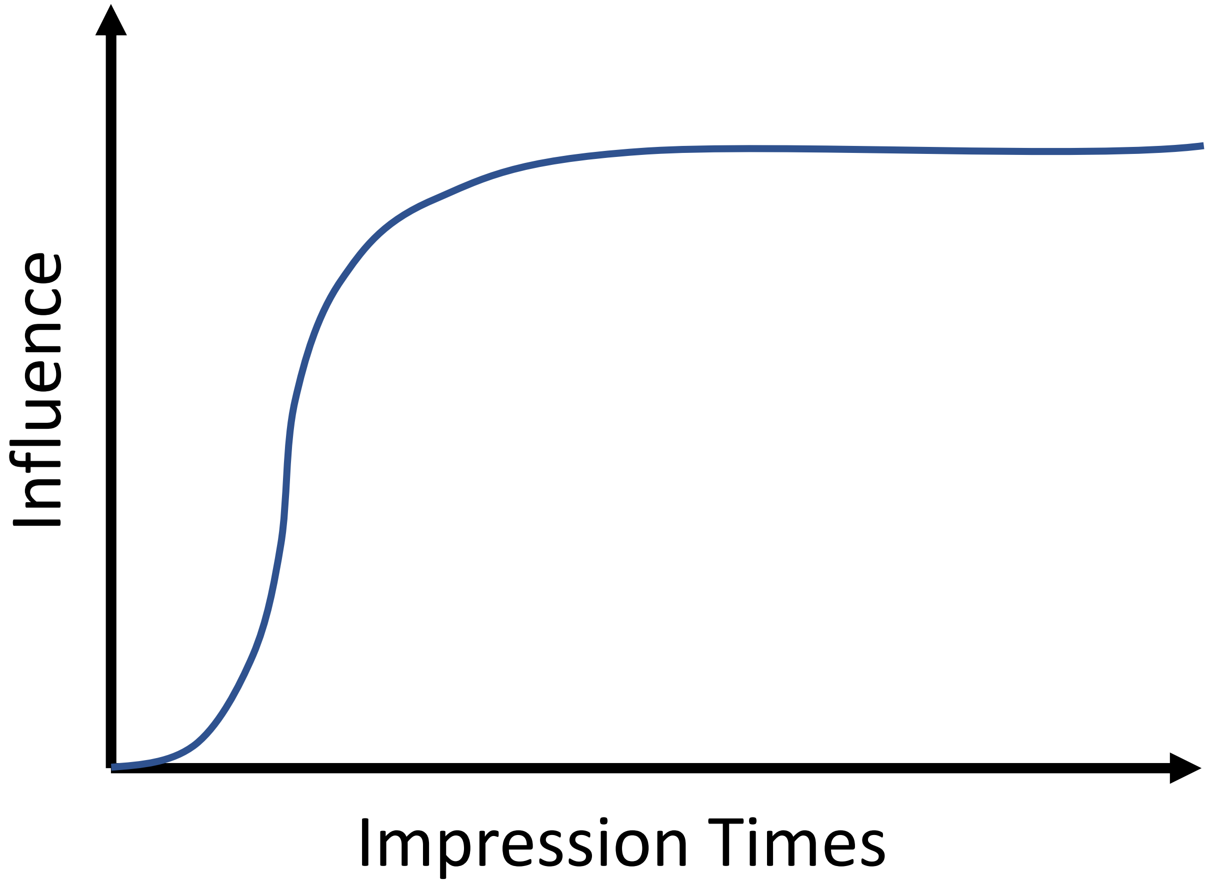

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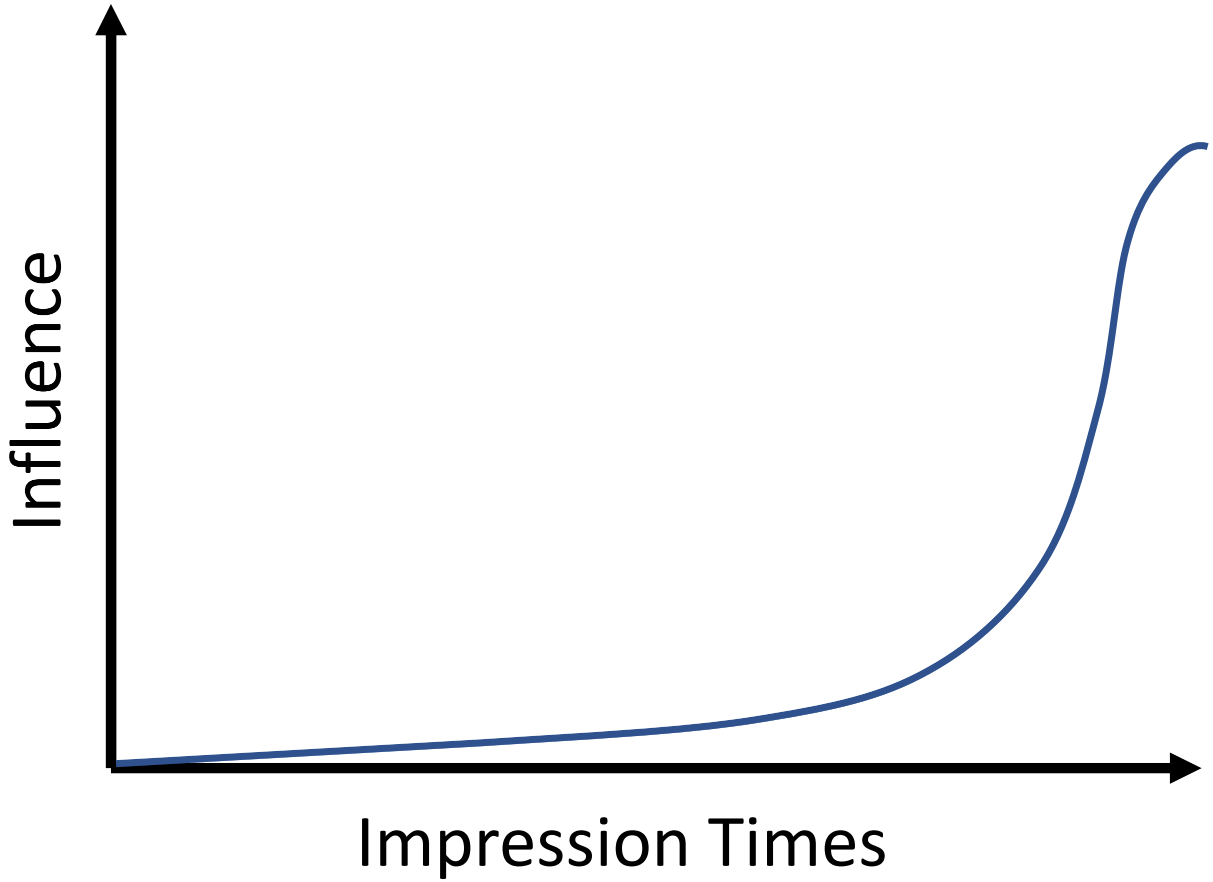
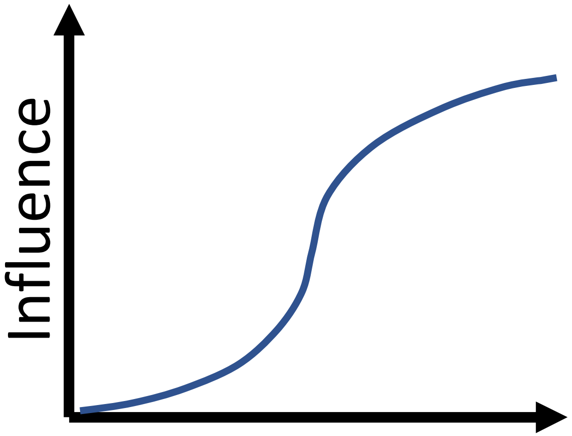


Influence Measurement



$$p(S,t) = \begin{cases} \frac{1}{1+exp\{\alpha-\beta\cdot\boxed{\Sigma_{o_i\in S} I(o_i,t)}\}} & if \;\; \exists o_i \in S \; \boxed{I(o_i,t) = 1} \\ 0 & otherwise \end{cases}$$

$$I(S) = \sum_{t_j \in T} p(S,t_j)$$

1. Influence Measurement is not submodular

- No approximation ratio for a greedy-based algorithm

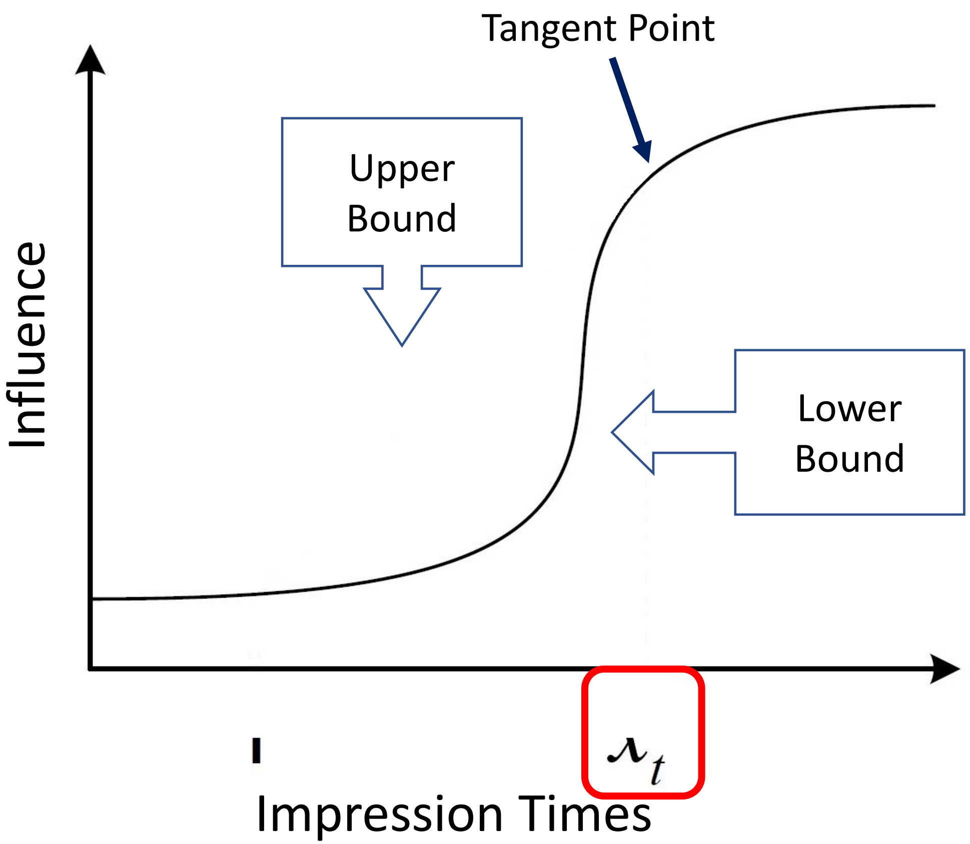
Upper-bound Estimation (submodular)

2. NP-hard to approximate within any constant factor

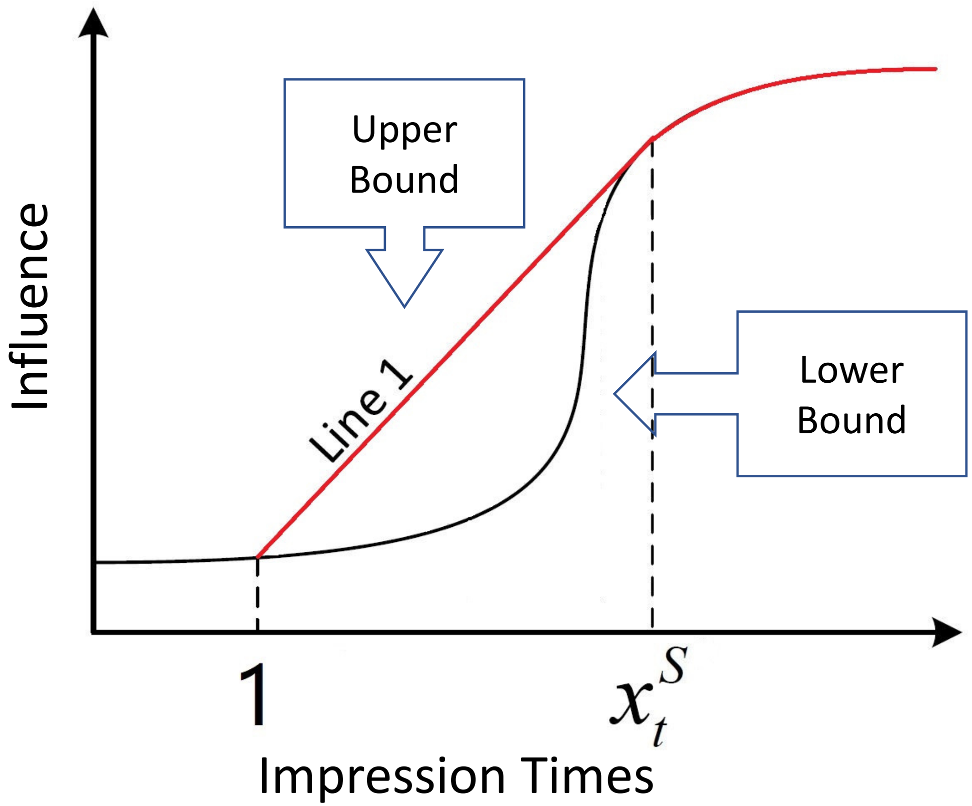
Branch-and-Bound Framework

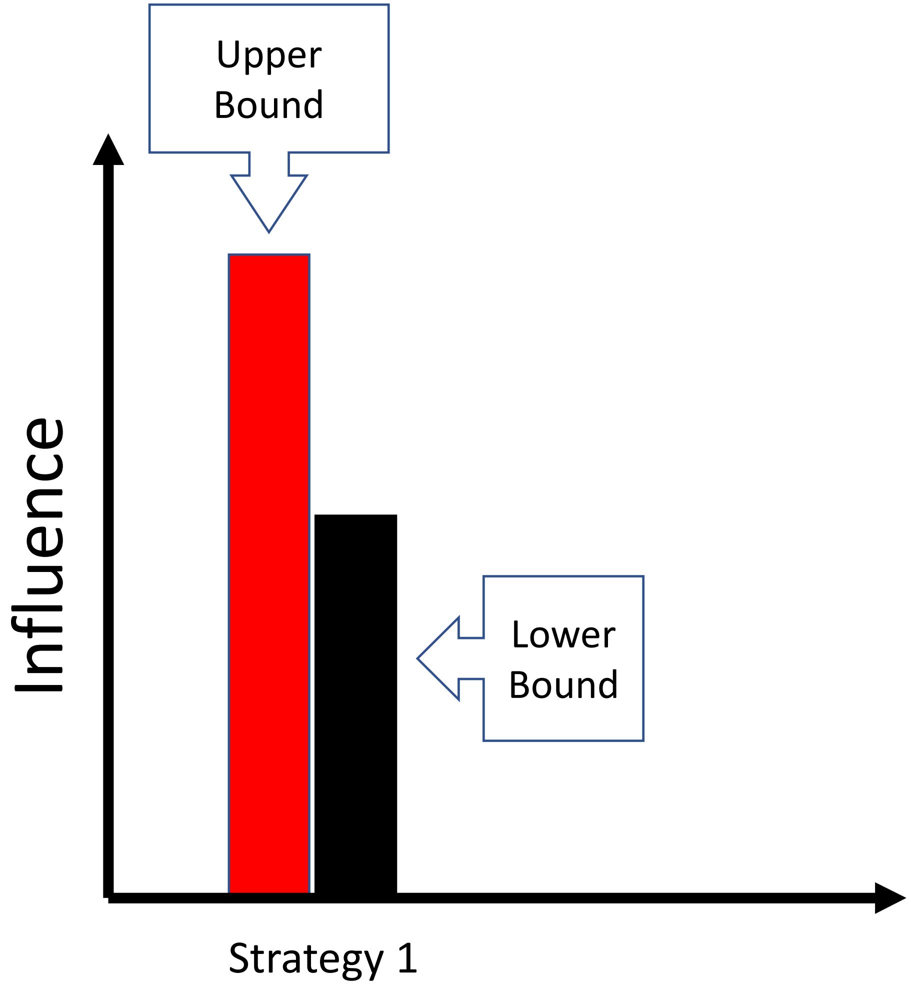
Challenges

Upper-bound Estimation

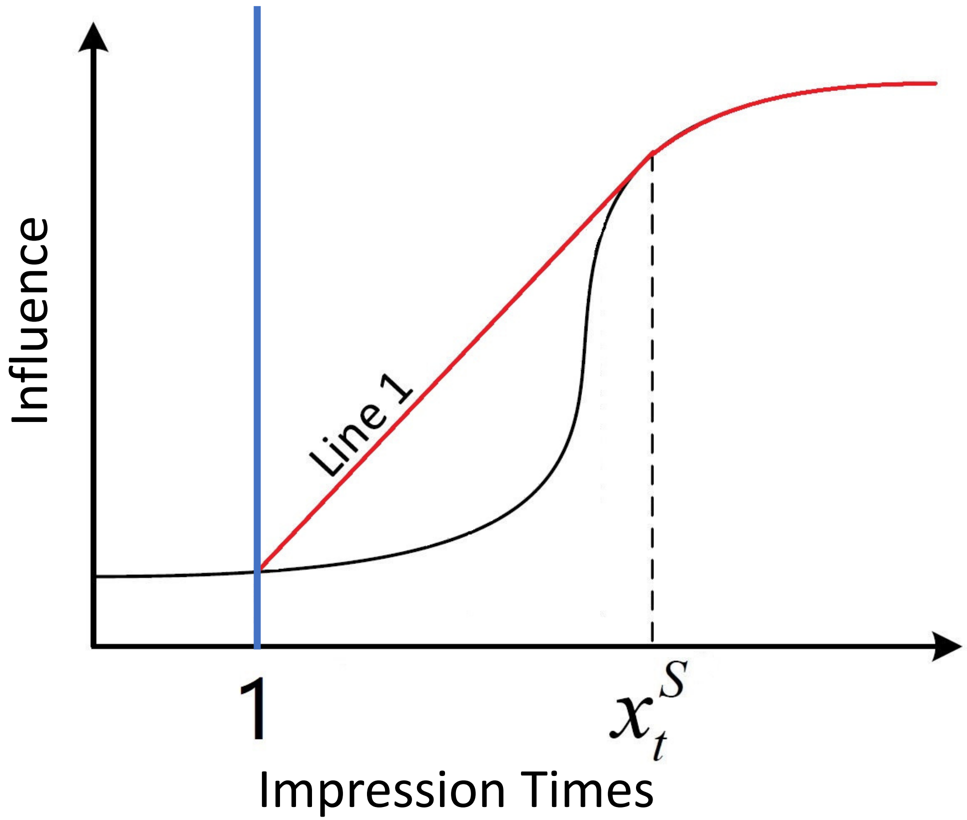


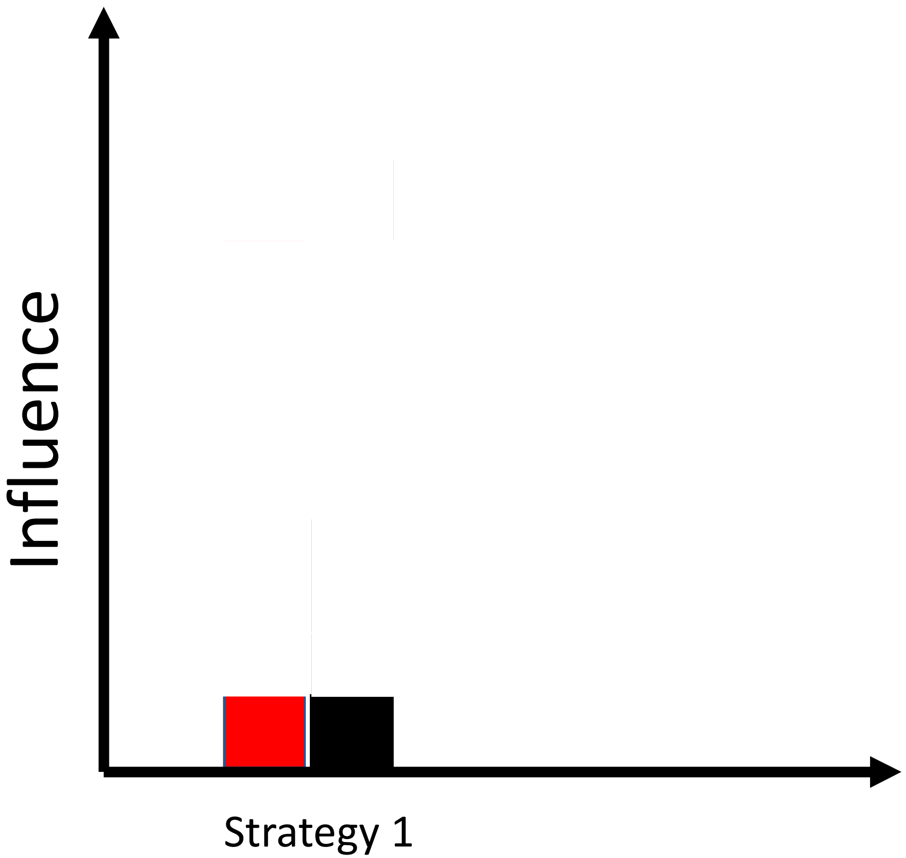
Upper-bound Estimation



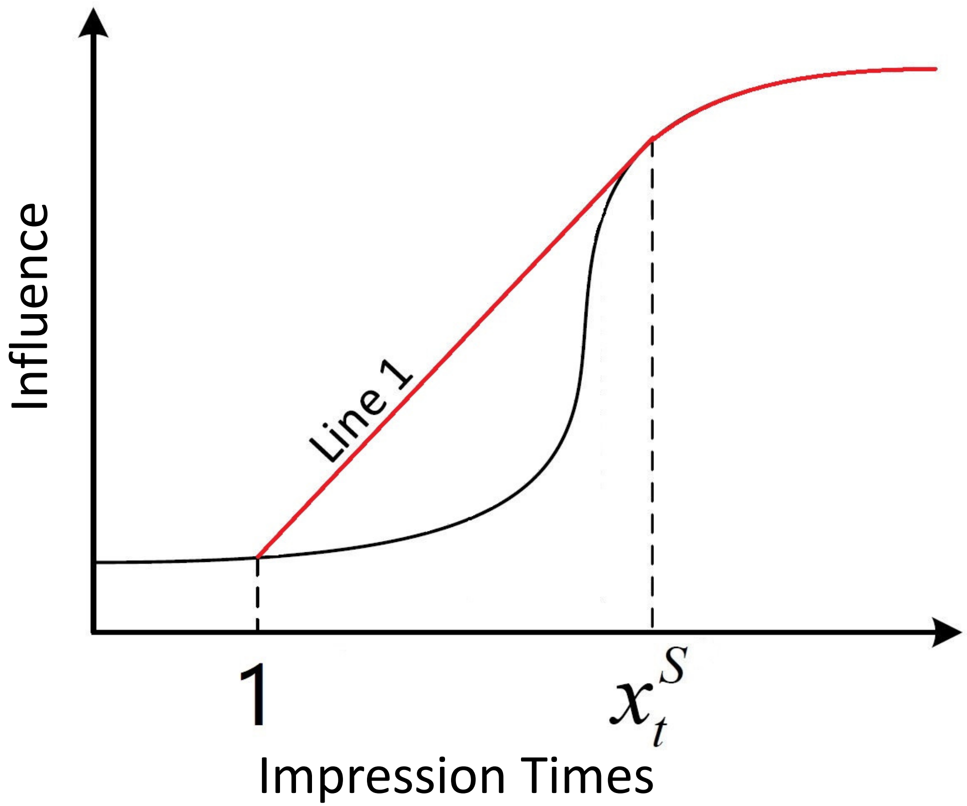


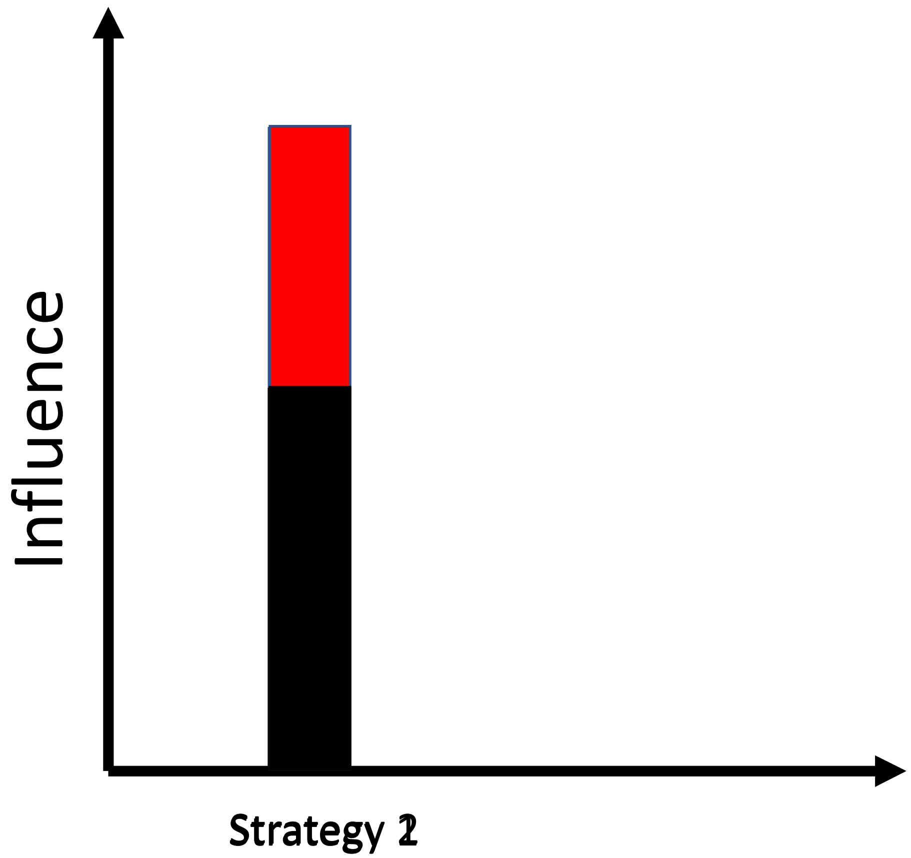
Upper-bound Estimation



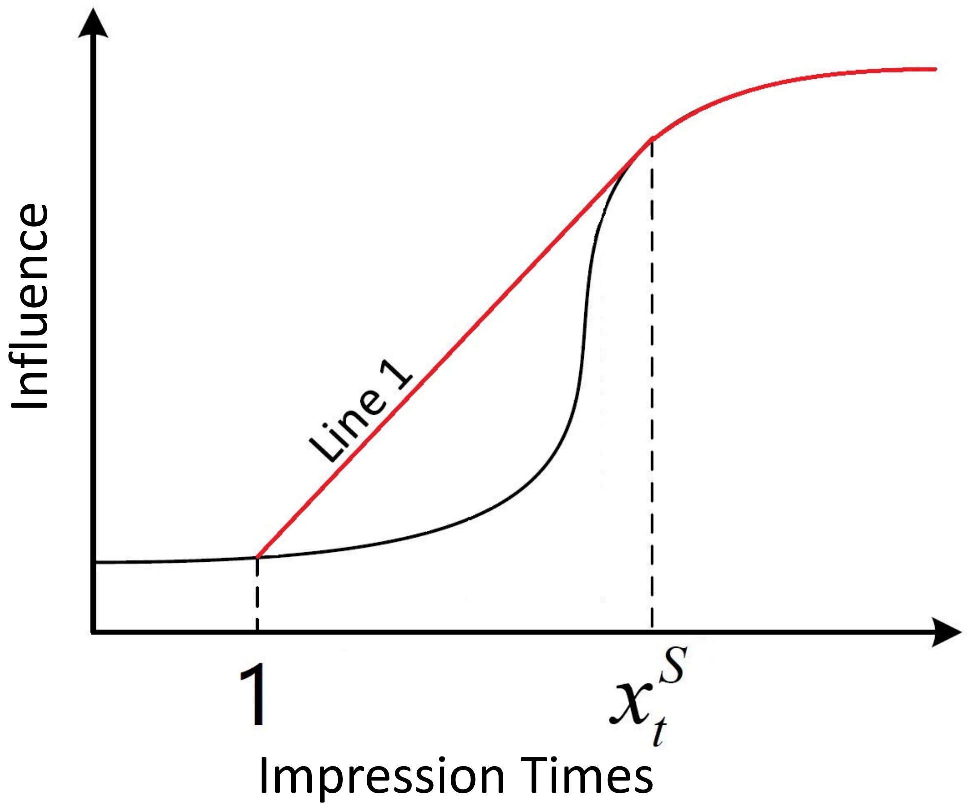


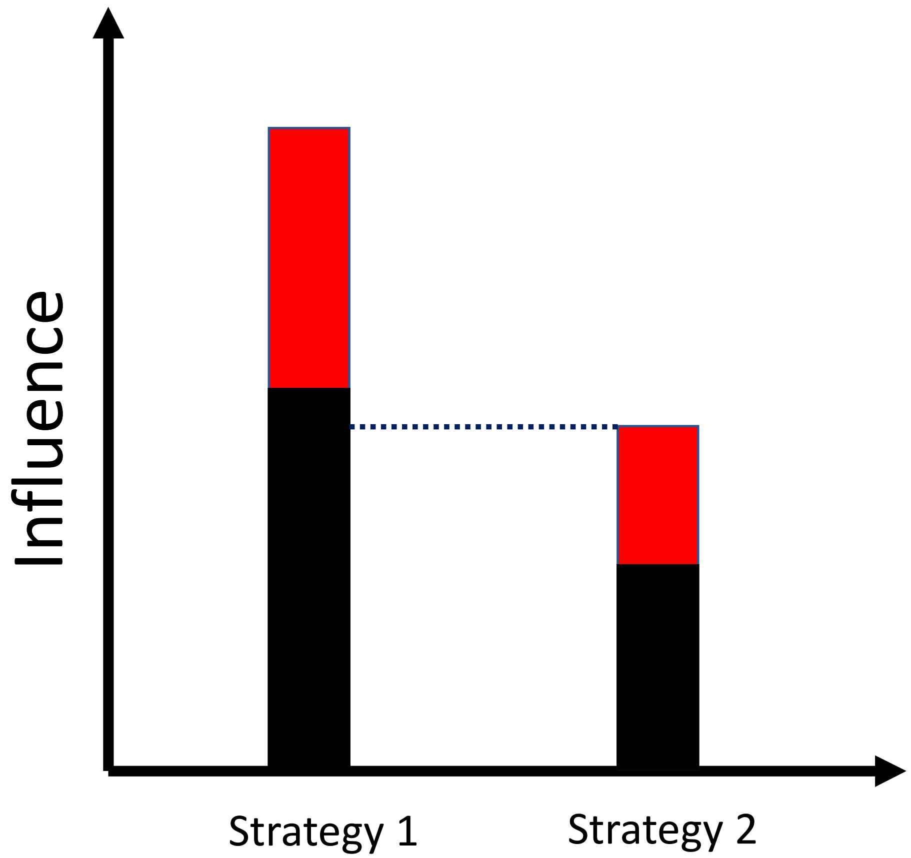
Upper-bound Estimation





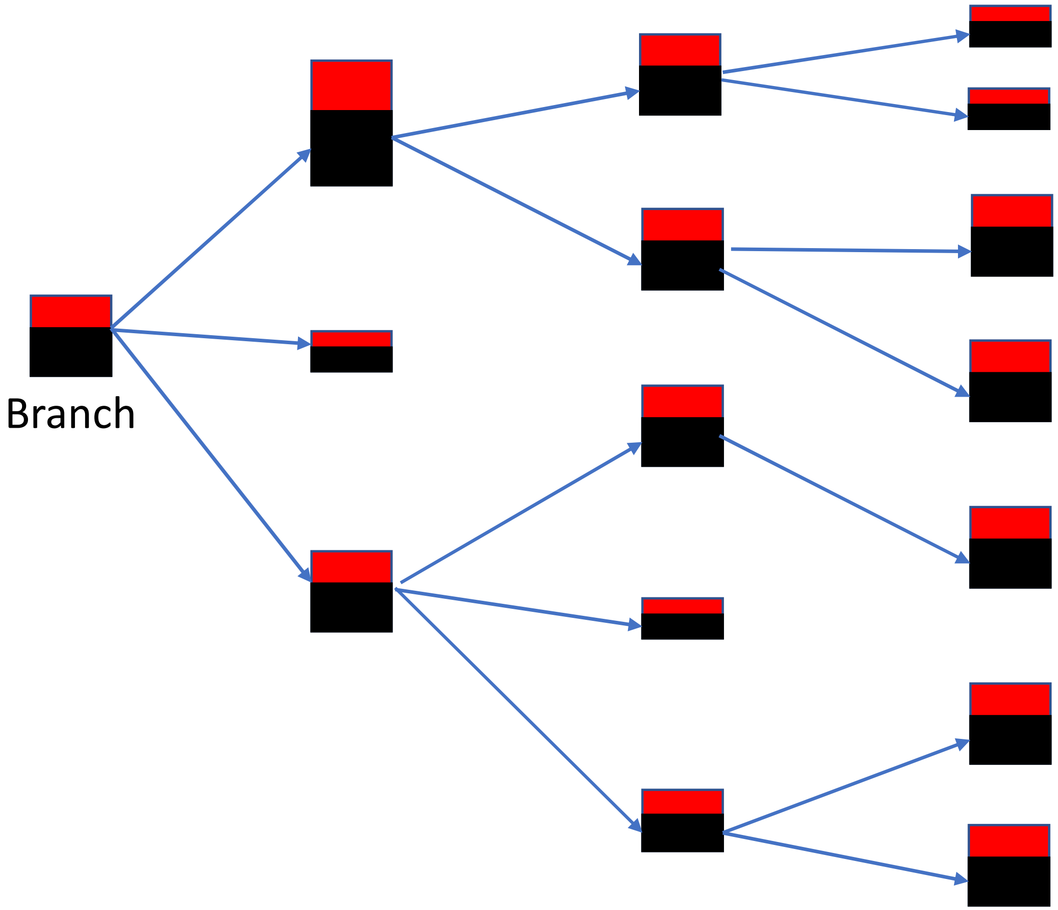
Upper-bound Estimation





Upper-bound Estimation

Branch-and-Bound Framework

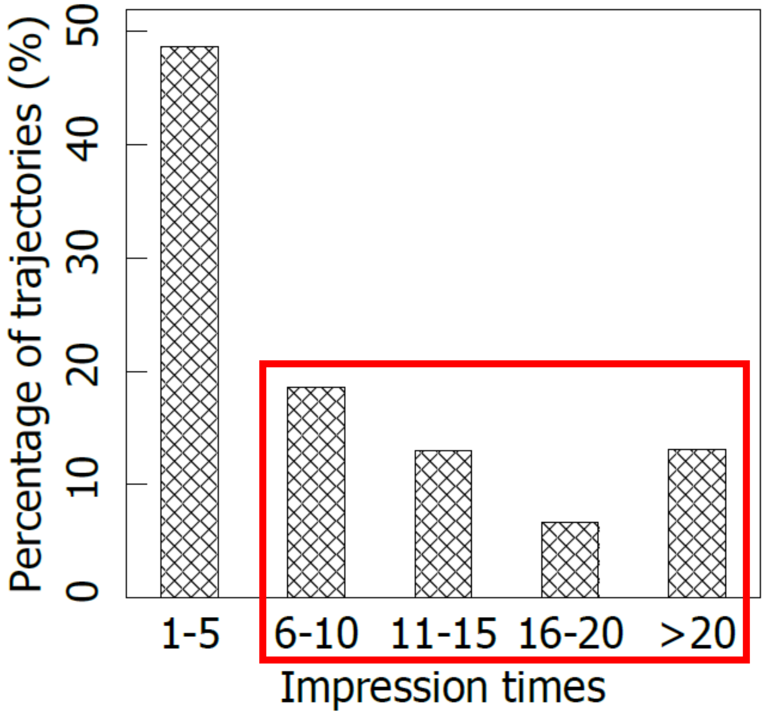


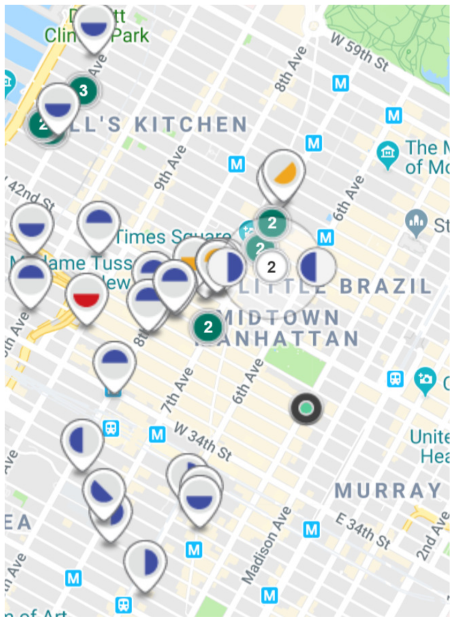
Optimization

	Approximation Ratio	Effectiveness	Efficiency
BBS: Branch–and–Bound Framework	$\frac{1}{2}(1-\frac{1}{e})$	1X	1X
PBBS: Branch-and-Bound Framework with Progressive Bound-Estimation	$\frac{\theta}{2}(1-\frac{1}{e}-\epsilon)$	0.92X	50X

Experiment - Statistics of datasets

	$\lvert\mathcal{T}\rvert$[1]	$\lvert\mathcal{U}\rvert$[2]	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]

Ping et al., SIGKDD 2018 [1]

Varying the budget B

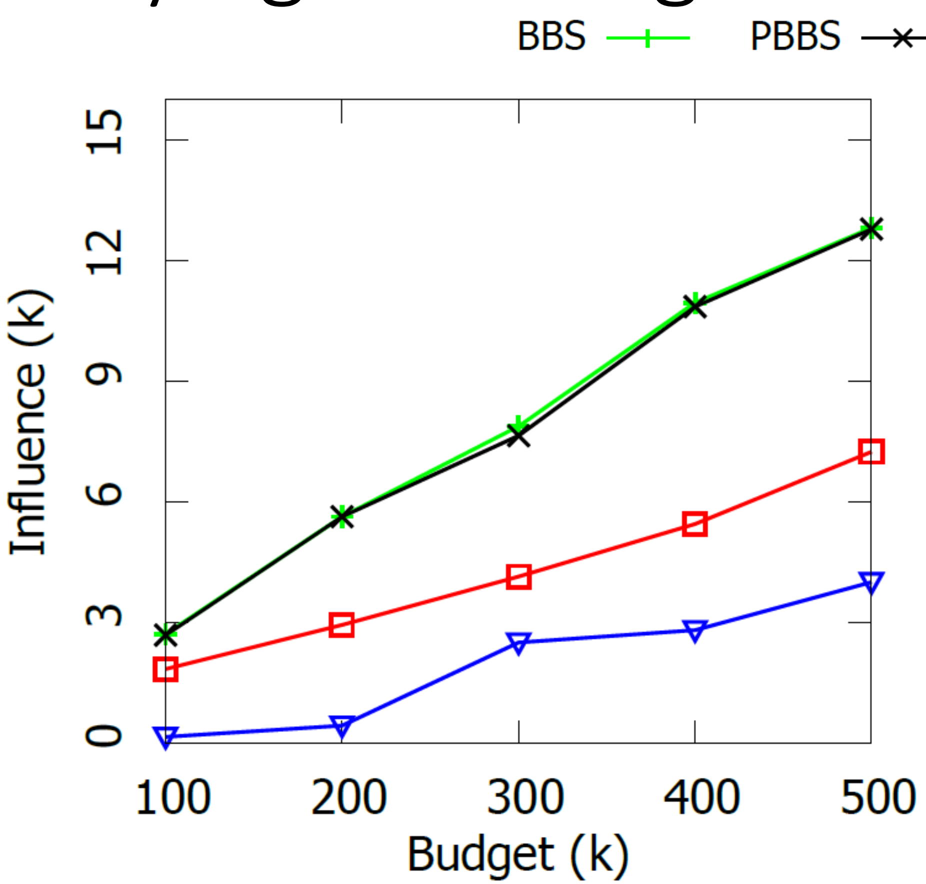


Figure 1: Influence in NYC

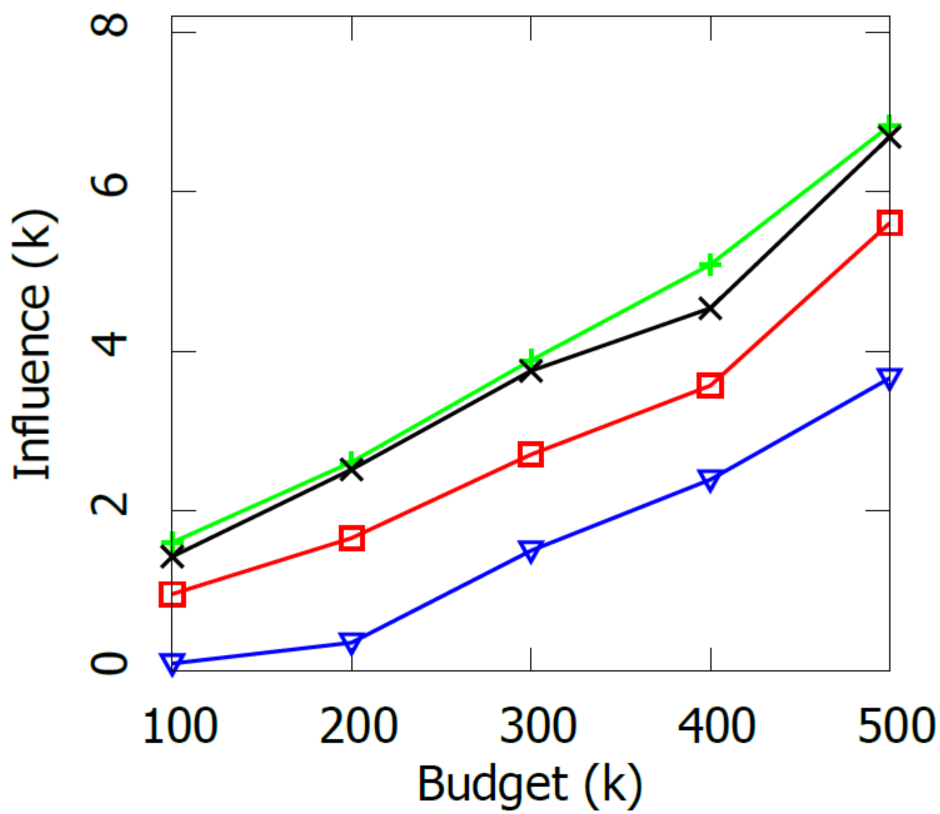


Figure 2: Influence in LA

Varying the number of trajectories $|T|$

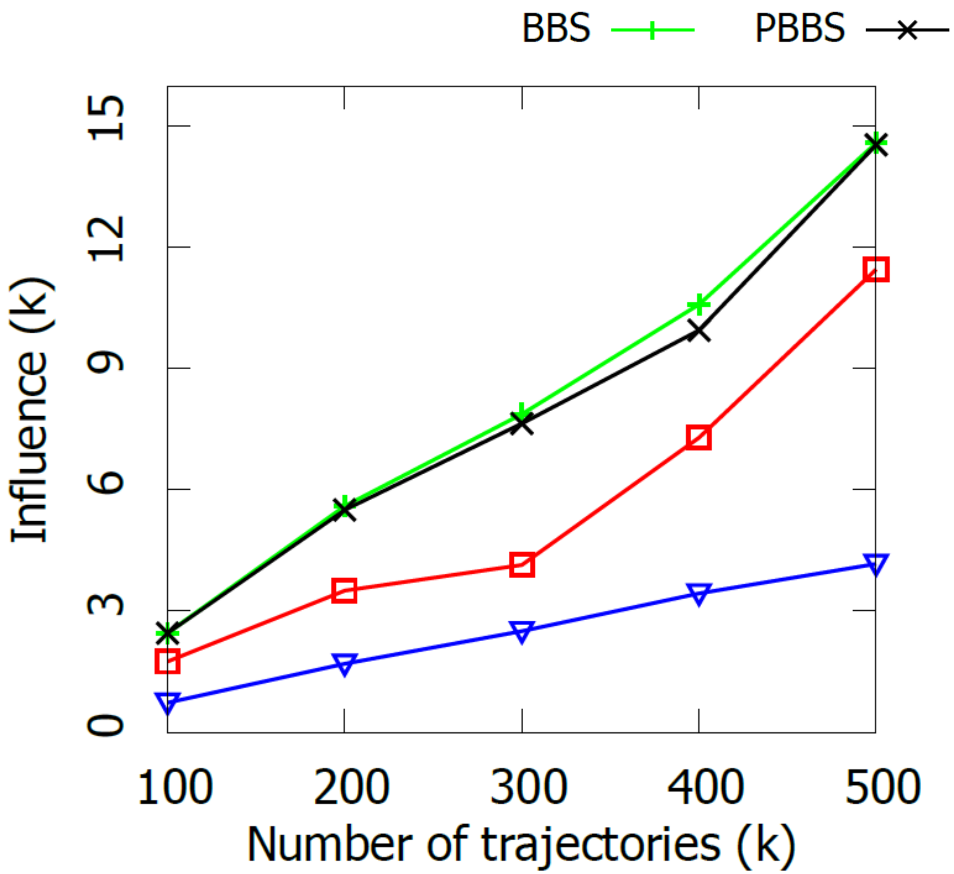


Figure 3: Influence in NYC

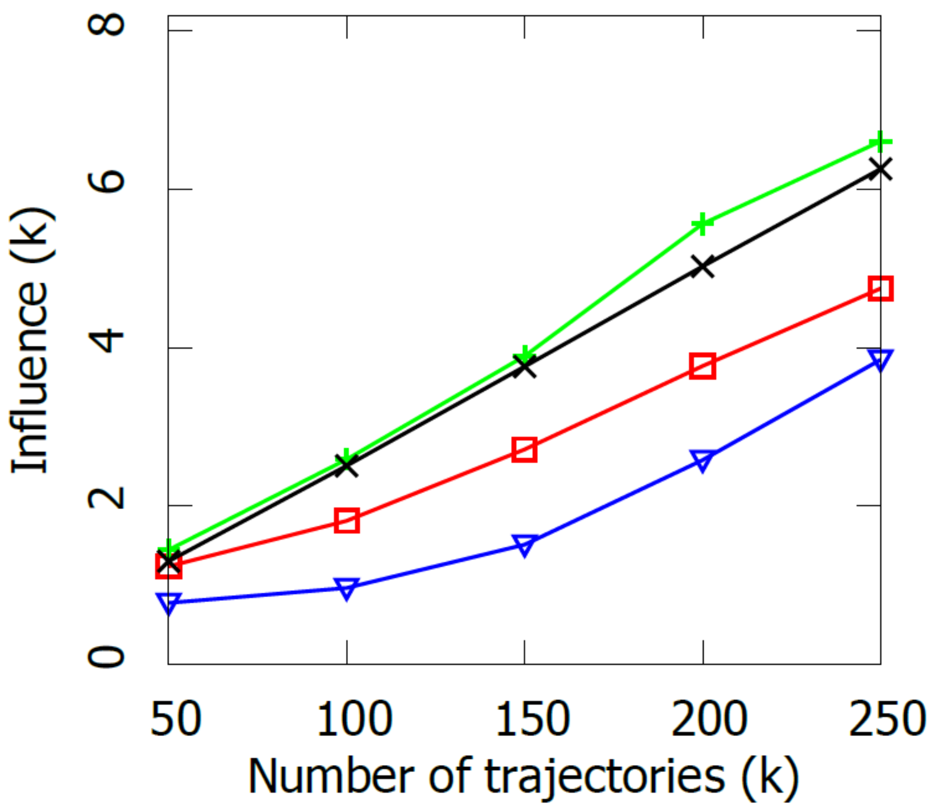
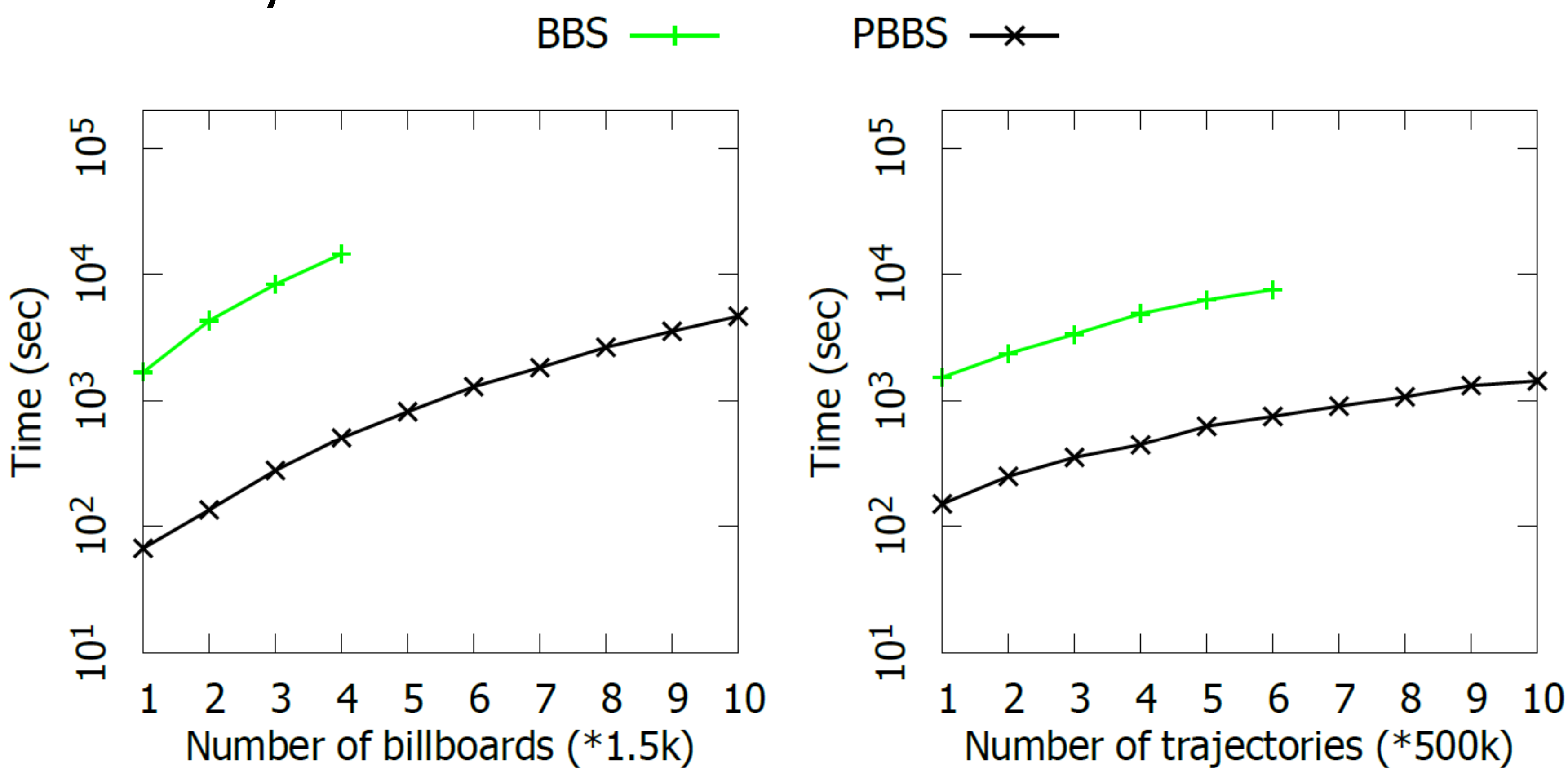


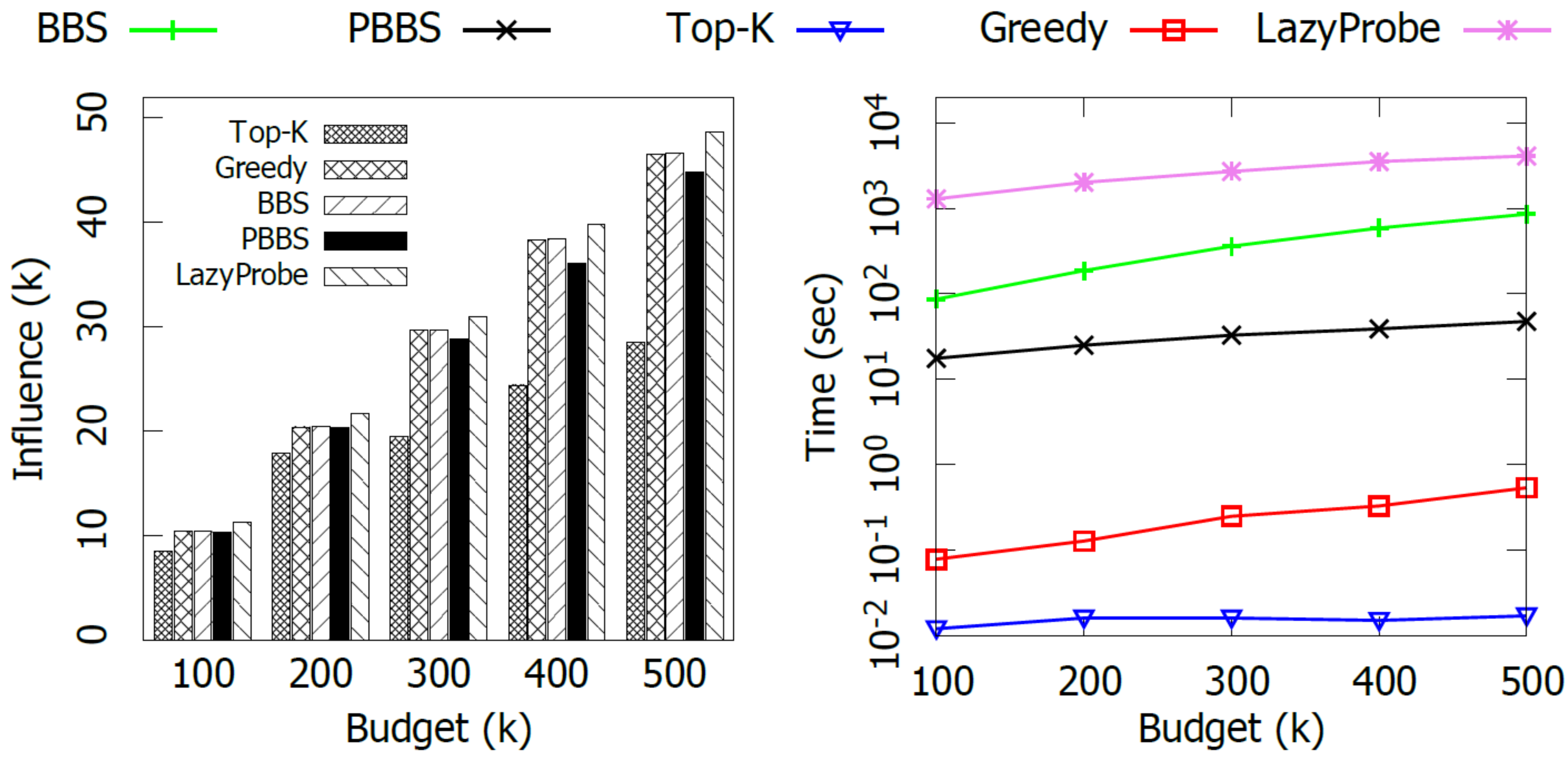
Figure 4: Influence in LA

Scalability test in NYC



(a) Varying $|\mathcal{U}|$ **(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

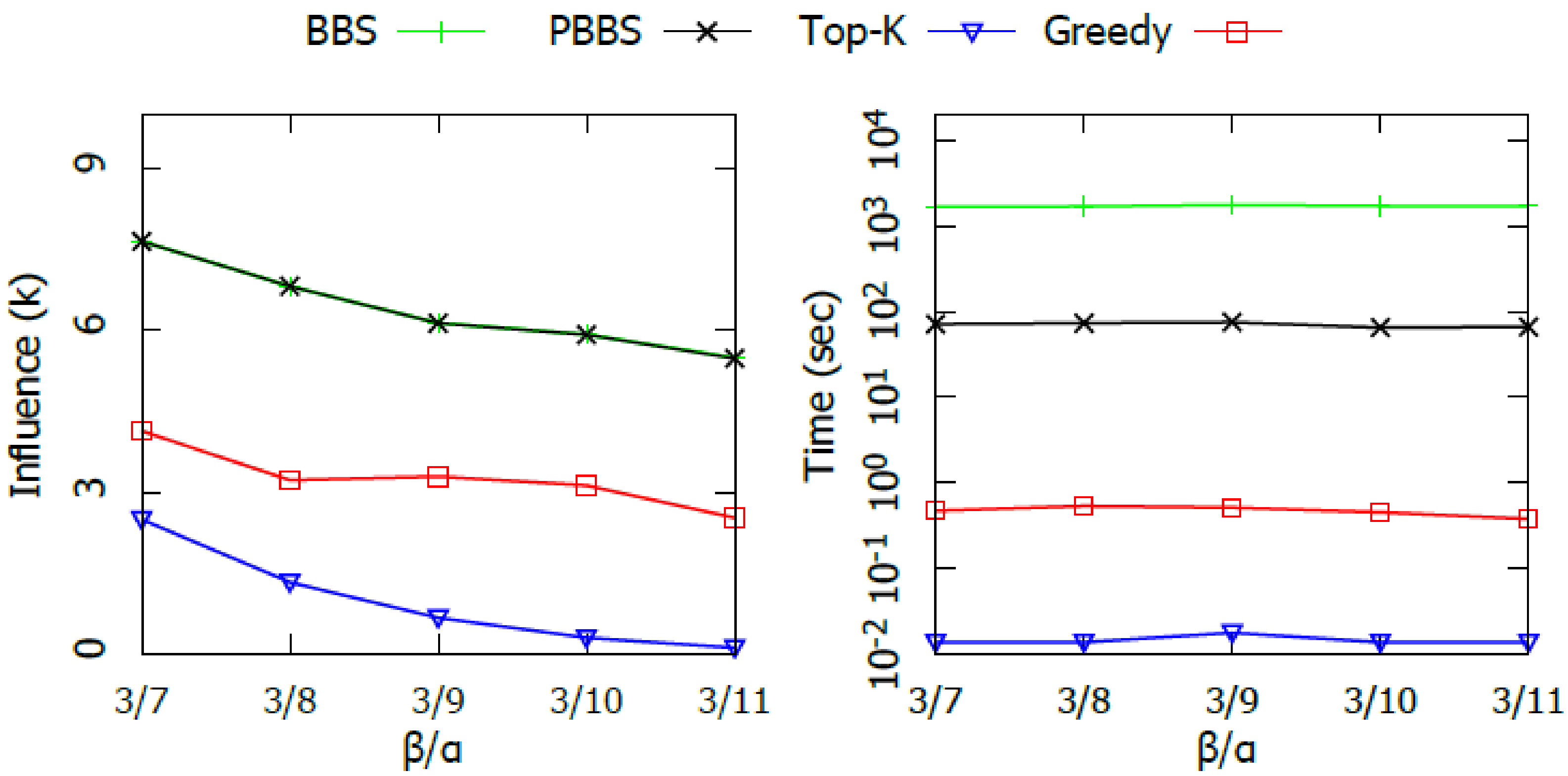
Takeaways

- Personal driving trajectories
- Personal identification of trajectories
- Digital Billboards

References

- [1] Ping Zhang, Zhifeng Bao, Yuchen Li, Guoliang Li, Yipeng Zhang, and Zhiyong Peng. 2018. Trajectory-driven Influential Billboard Placement. In SIGKDD. ACM, 2748–2757.
- [2] Feder, Richard E Just, and David Zilberman. 1985. Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change* 33, 2 (1985), 255–298.
- [3] William H Greene. 2003. *Econometric analysis*. Pearson Education India.
- [4] Margaret C Campbell and Kevin Lane Keller. 2003. Brand familiarity and advertising repetition effects. *Journal of consumer research* 30, 2 (2003), 292–304.
- [5] Johny K Johansson. 1979. Advertising and the S-curve: A new approach. *Journal of Marketing Research* (1979), 346–354.
- [6] John DC Little. 1979. Aggregate advertising models: The state of the art. *Operations research* 27, 4 (1979), 629–667.
- [7] Julian L Simon and Johan Arndt. 1980. The shape of the advertising response function. *Journal of Advertising Research* (1980).
- [8] LAMAR. 2017. National Rate Card. http://apps.lamar.com/demographicrates/content/salesdocuments/nationalratecard.xlsx

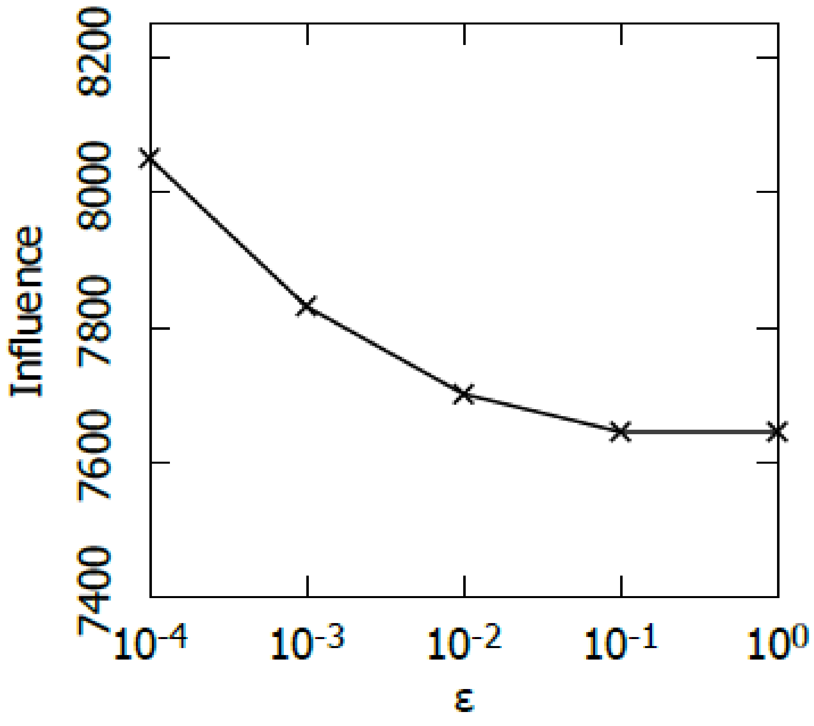
Varying β/α in NYC



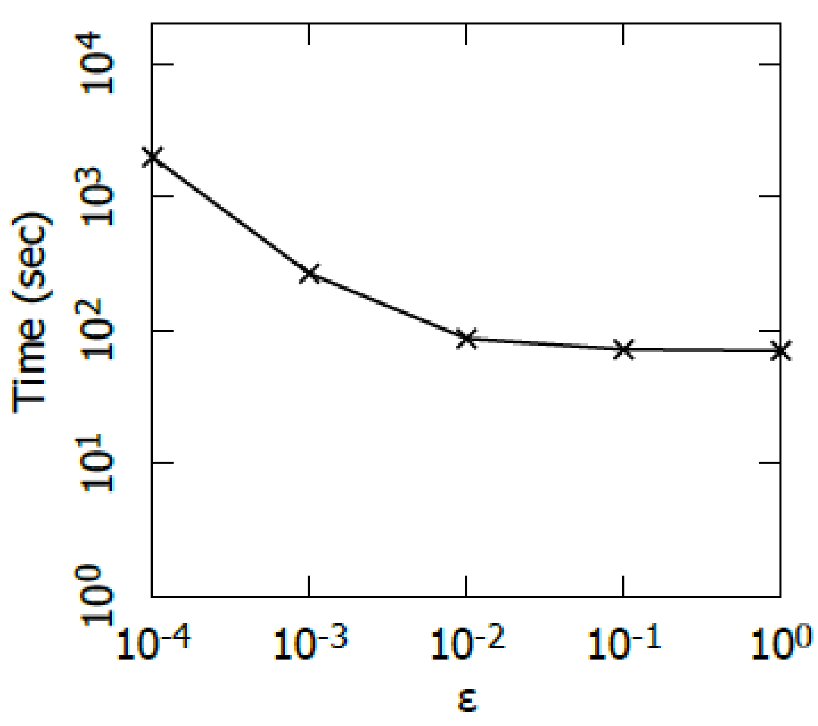
(a) Influence

(b) Time

Varying ϵ in NYC

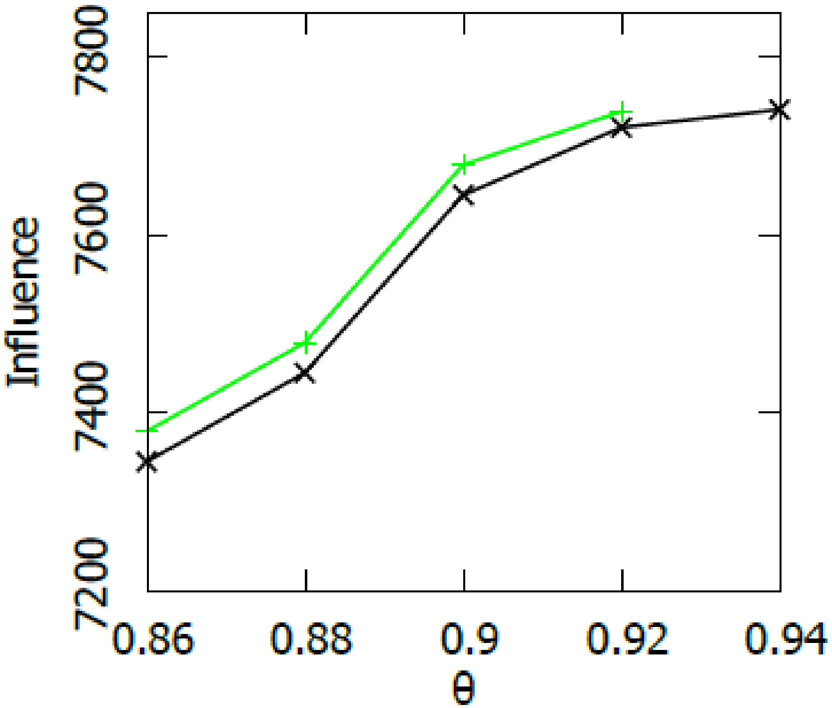


(a) Influence

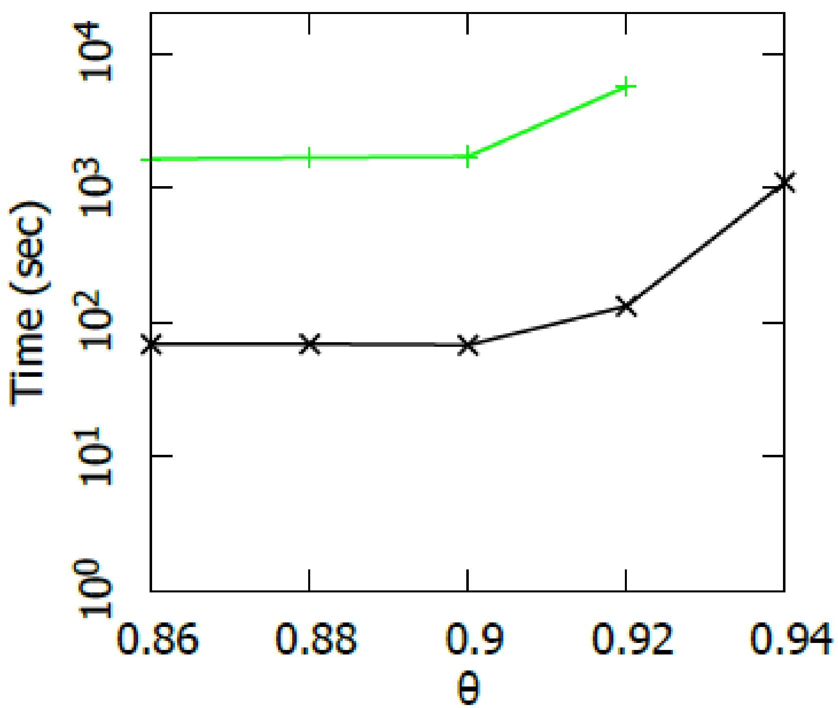


(b) Time

Varying θ in NYC

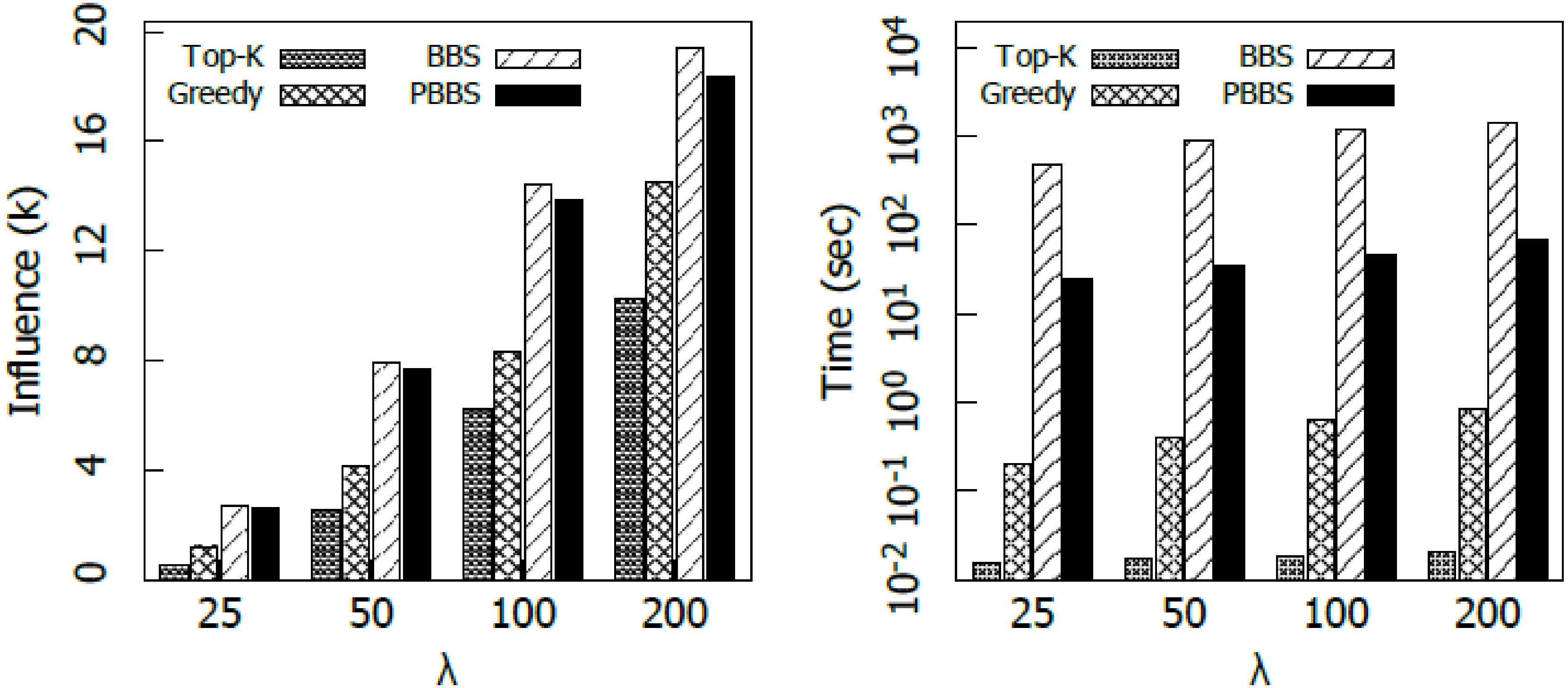


(a) Influence



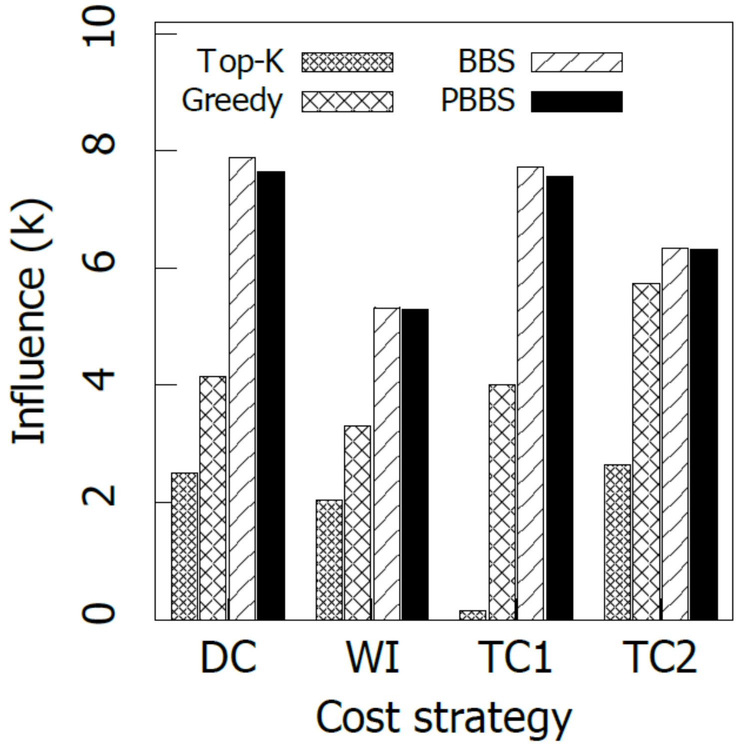
(b) Time

Varying λ in NYC



(a) Influence (b) Time

Test on different cost setting strategies



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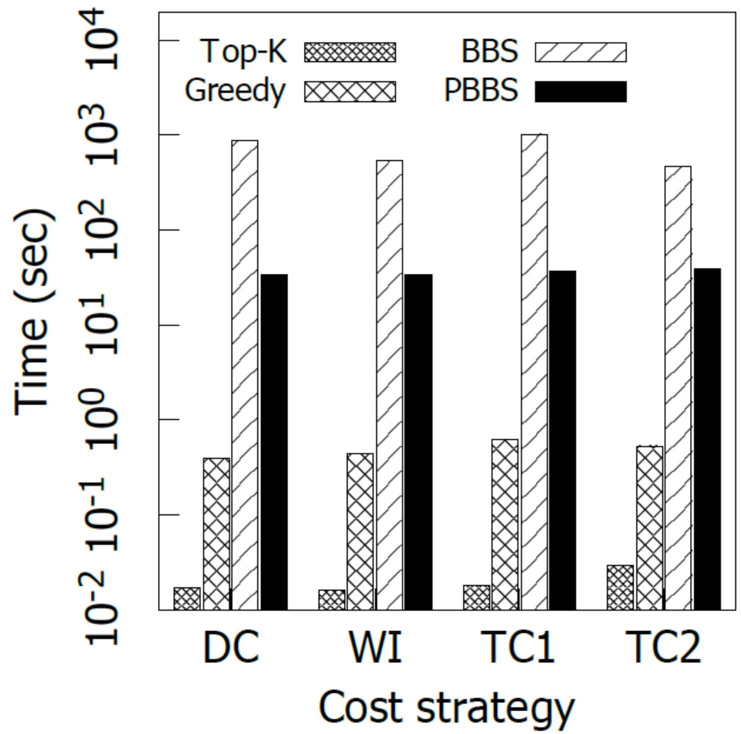
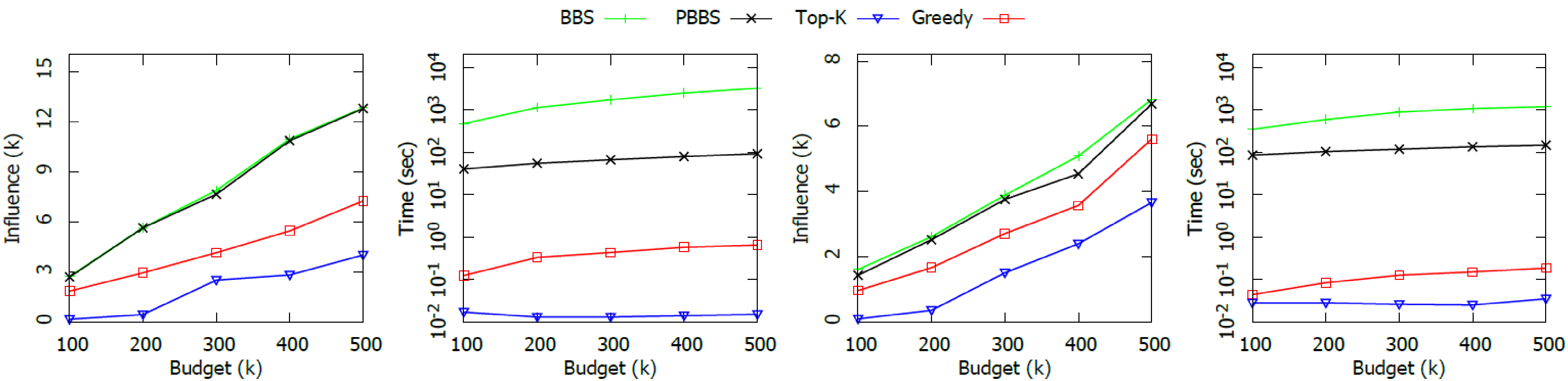


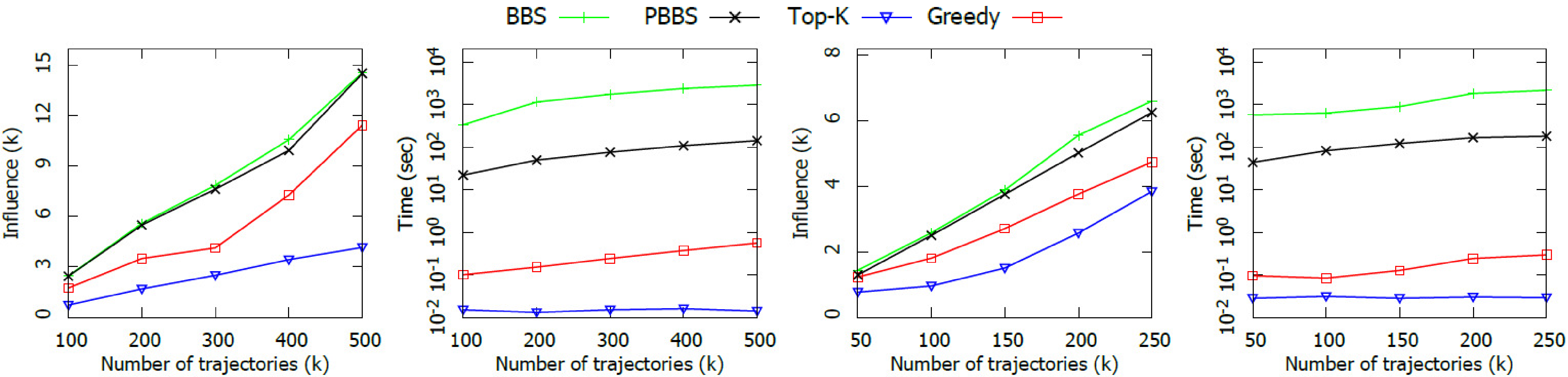
(b) Time

Varying the budget B



(a) Influence in NYC (b) Runtime in NYC (c) Influence in LA (d) Runtime in LA

Varying the number of trajectories $|T|$



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Thank You!