Data Driven Methods for Effective Micromobility Parking

Institute for Software Integrated Systems

Caleb Van Geffen

Department of Electrical Engineering and Computer Science, Vanderbilt University, Nashville, TN 37235

Background

Micromobility

- Urban micro-mobility is a growing transportation sector, useful for short on-demand trips.
- It is offering commuters a greener solution to their first and last mile trips.

Safety Concerns

- Hazardous sidewalk clutter; Americans with Disabilities Act (ADA) violations.
- Lack of helmet use.
- Sharing streets with cars and other high-speed vehicles can have deadly consequences for scooter and bike riders.

Policy Discussion

- Implementing fines to users parked outside designated areas.
- Fining companies as well for not managing their scooter parking.
- Incentives provided to users and companies that comply with parking.
- Mobile parking infrastructure that shifts upon current trends.

Unsupervised Machine Learning Algorithms

Various algorithms in Python used to group scooter trips into clusters for specific locations for scooter parking.

K-means

- One of the simplest clustering algorithms, separates groups based on the sums-of-squares between points.
- Takes one parameter, *n_clusters*, which specifies the amount of clusters to partition the dataset into.

DBSCAN

- A density-based clustering algorithm with the ability to discover clusters of arbitrary shape; does not cluster every point as some are considered noise.
- Takes two parameters, *MinPts* and *Epsilon*, which specify the minimum points needed for a cluster and the maximum radius for a cluster, respectively.

HDBSCAN

- Created as an extension to DBSCAN with using a hierarchical structure for grouping and less parameters.
- Takes one parameter, *min_cluster_size*, which specifies the amount of points needed to form a cluster.

Results

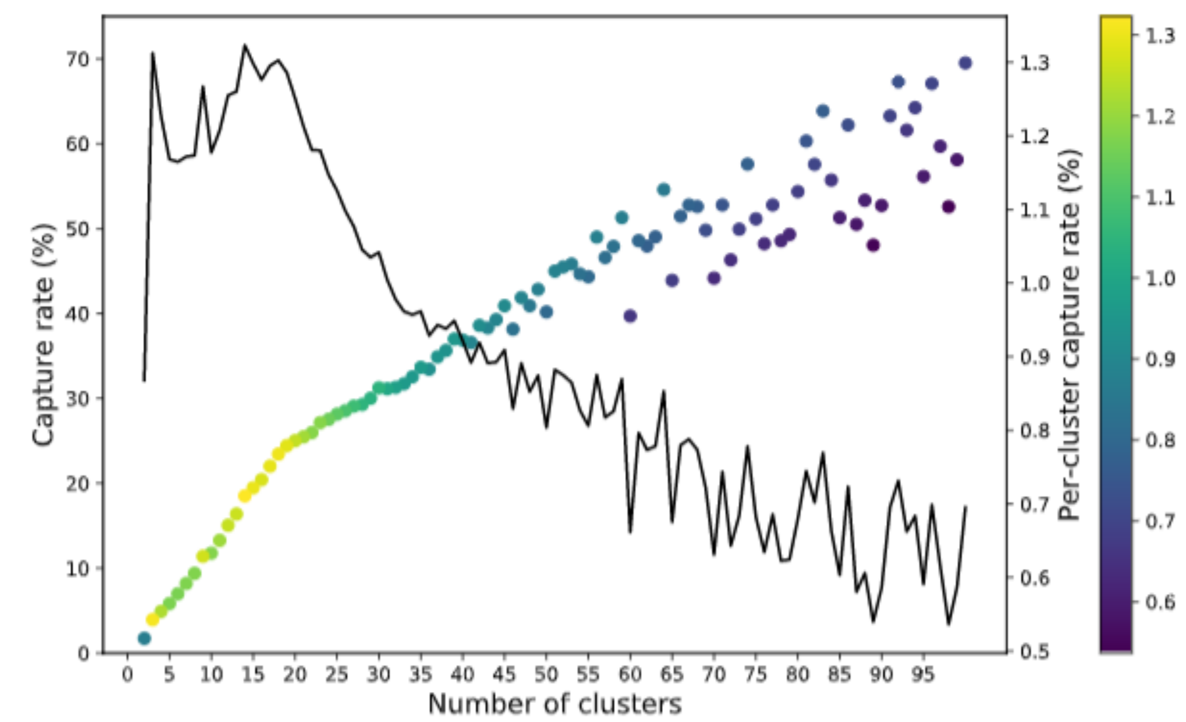

FIGURE 2: Relationship between total trip capture (colored points) and per-facility capture rates (i.e., capture efficiency) (black line) for DBSCAN facility placement. *Note: capture efficiency is given on the secondary y-axis.*

Parking Location	Location Name
A	Rec. Center
B	21st Ave. (North Side)
C	Hillsboro Village
D	Rand Hall
E	Commons Center

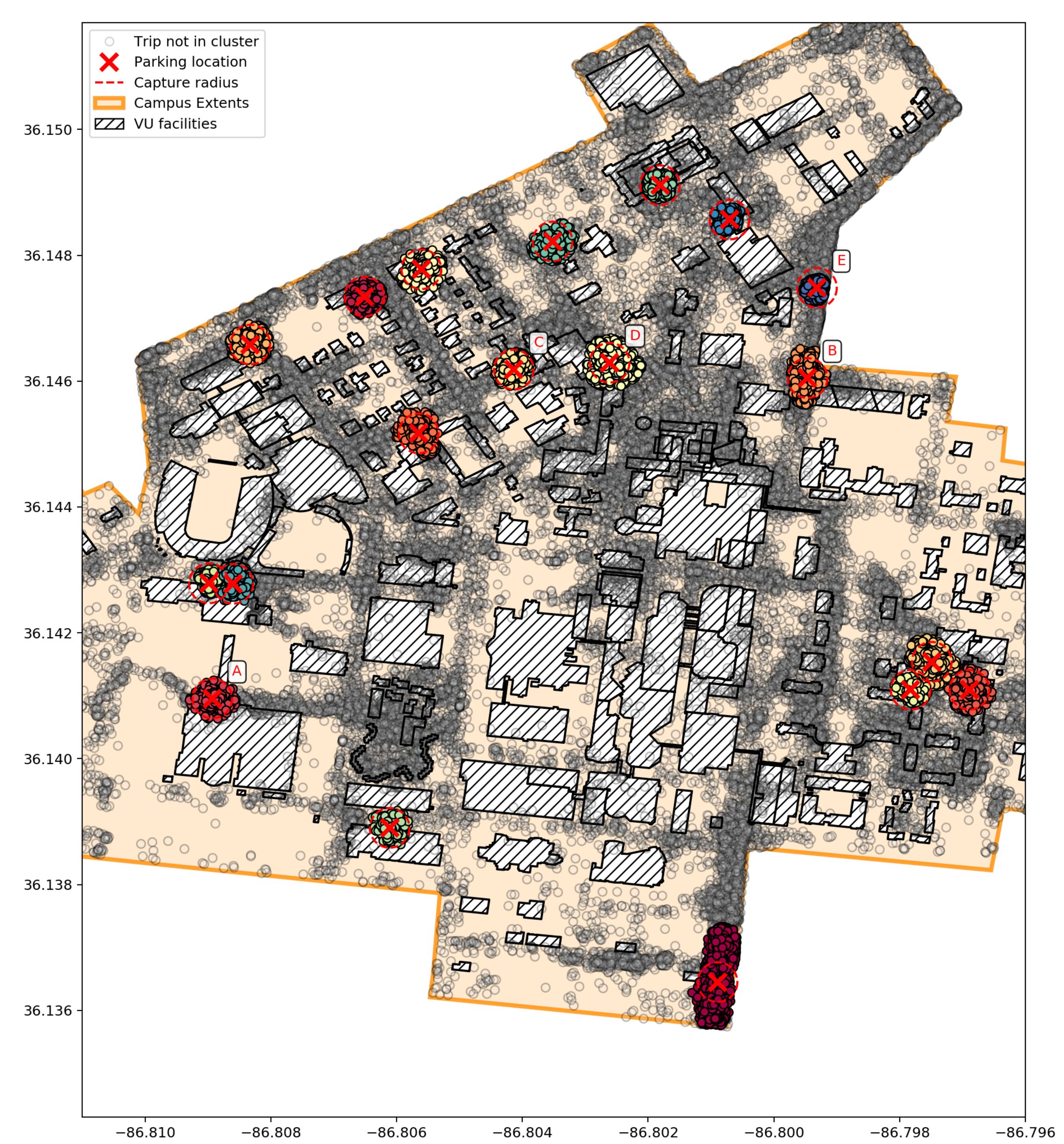

FIGURE 3: Map of 29 parking location (red X's) and capture radii of 100 feet (red dashed lines) generated by DBSCAN. The colored points at each parking location are the trip endpoints belonging to each cluster. Trip endpoints not belonging to a cluster are shown as light grey points.

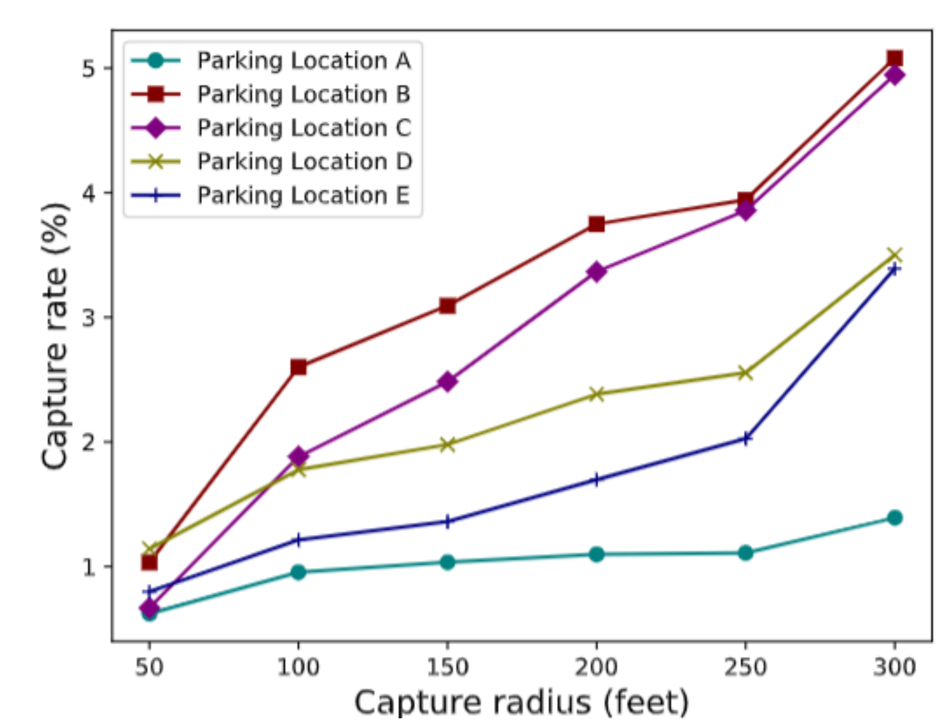

FIGURE 4: Growth in trip capture rates as a function of increasing capture radius.

Conclusions

- Data-driven placement of dedicated SUMD parking facilities to maximize their impact in terms of capture of trips.
- Using data-driven placement increases the likelihood that, under an optimal usage model, they are effective at convincing users to park because of locational proximity.
- Our case study showed that 19 of these locations has the potential to capture 25% of trip demand when evaluated on a testing dataset.
- Across those same 19 locations, peak capacity required to serve 98% of usage periods was only 6 devices on average.
- There were clear and obvious distinctions between usage patterns of these parking locations.
- Similar temporal fluctuations would be anticipated in other locales, and this data-driven approach allows all time to be considered rather than anecdotal judgements for decision making.

Future Directions

- Accounting for irregularly-shaped (non-circular) clusters of trip endpoints should be served by multiple parking facilities when capture radius cannot sufficiently cover all dense areas.
- Location determination should consider truly feasible facility locations that are free from obstructions such as buildings and roadways.
- Considering a capture zone that is non-circular in shape due to occlusion by buildings.
- A model to determine the likelihood of SUMD users to park in optional parking facilities based on location and other factors.

References

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