A Spatiotemporal approach to micromobility

Grant McKenzie[1], Carlos Baez[2]

[1] Department of Geography, McGill University, Canada

[2.] Department of Geography, University of California, Santa Barbara, USA

Introduction

Micromobility services provide short-term access to a shared fleet of light weight personal transportation vehicles. Admittedly, defining these types of services is a bit like hitting a moving target as the transportation landscape is very much in flux with new mobility technologies disrupting the market every few months. In Chapter 12 of this book, Shaheen & Cohen provide a broad overview of the policies and practices associated with shared micromobility. In this chapter we limit our discussion to those micromobility services with vehicles that (a) involve electricity in some capacity, be it solely electric powered, or electric-assisted and (b) are dockless, meaning that users are not required to lock or dock them at a designated station, but can (in most cases) leave them in any public space (e.g., sidewalk). The two vehicle types most often associated with dockless, electric micromobility are electric scooters (e-scooters), and electric-assist bicycles (e-bikes). Both service types currently operate in a similar fashion with users identifying the location of an available vehicle through a mobile application, unlocking the vehicle by scanning a vehicle's matrix bar-code and riding the vehicle to their destination. Upon arriving, the user parks the vehicle (typically using a kickstand) and locks it through their mobile application, thus completing the trip. When these services were first launched in the United States, they typically cost $1 USD to unlock and $0.15 - $0.30 USD per minute depending on the city.

Over the last couple of years, these micromobility vehicles have flooded urban centres around the world. Replacing many of the non-electric, dockless bicycles that came before them, cities like Santa Monica and Washington, DC adopted these services in early 2018, paving the way for a range of operators to establish micromobility services in hundreds of cities world wide. The start-up companies operating these services, many funded or acquired by large automotive or ride-hailing companies, advertise them as a low-cost way to get around the city, an alternative to traditional motorised vehicle, bicycle, or even walking. Advocates see these vehicles as a method of alleviating traffic, reducing pollution and greenhouse gas emissions, and an alternative transportation option that is energy efficient and suitable for 'last mile' transportation (Gössling, 2020). On the other hand, critics see them as a health and safety nuisance (e.g., injuries, irresponsible riding) that simply adds additional congestion to an already struggling urban transportation network.

Overall, the introduction of micromobility services has been marred with controversy as operators often entered the market without official approval from local authorities. This has left little time for urban and transportation planners to conduct thorough assessments. The ensuing conflict between micromobility operators and local authorities was further complicated by several factors related to (1) a lack of micromobility specific regulations and (2) conflicts with jurisdictional authority. In mid-2018, for instance, only six U.S. states specifically regulated e-scooters (Agrawal et al., 2019). California has taken a hands-off approach, allowing e-scooters to operate legally since at least 2000 (and has gradually added statutes to further regulate their operation) while in the State of New York they remained illegal to operate through 2020. In the meantime, cities have nonetheless begun developing comprehensive micromobility regulatory programs that include permitting processes, data-sharing requirements, use and operational restrictions, and equity and sustainability initiatives.

Despite their recent introduction, micromobility has grown substantially worldwide. The National Association of City Transportation Officials (NACTO) estimated that 38.5 million e-scooter trips took place in 2018, with a fleet of over 85,000 e-scooters in 100 U.S. cities (NACTO, 2019). Of these trips, 40% took place in Los Angeles; San Diego and Austin. By comparison, NACTO reported 36.5 million station-based bikesharing trips, 9 million dockless bikesharing trips, and 6.5 million e-bike trips (up from 2.4 million total trips in 2011). An early survey reported that micromobility service users are typically younger males (Krizek and McGuckin, 2019), a demographic trend also found with more traditional non-e-bikeshare usage (Singleton and Goddard, 2016). Similar results were found in further studies for Portland (Orr et al., 2019), Santa Monica (City of Santa Monica, 2019), and San Francisco (San Francisco Municipal Transportation Agency, 2019).

Why conduct spatiotemporal analysis?

While analyses based on trip count and demographic statistics are useful from a policy and regulatory perspective, they only tell one part of the story. Crucially, they omit the spatial and temporal dimensions of activity/travel patterns that occur within the city. Understanding the dimensions of where and when people use these services is important for practical reasons such as public health and safety, measuring the local impacts that these services are having on neighbourhoods and urban infrastructure, and how these new services operate in relation to existing transportation options within a city. Furthermore, they help develop our scientific understanding of human mobility including the rationale for travel related motivations and decisions.

Stepping outside of an individual city, spatiotemporal analyses also permits us to more deeply examine how ridership varies between cities and even countries. Identifying activity trends have the potential to inform decision makers on how these services may operate in new markets and suggest regulations to ensure that these services complement existing transportation options (rather than compete with them). As such, in this chapter we provide an overview of spatiotemporal analysis techniques that are currently being used in identifying activity patterns of micromobility services. The objectives of this chapter are:

- to introduce the reader to electric micromobility services, namely e-scooters, and e-bikes.
- to present a number of quantitative analysis techniques for identifying spatial and temporal activity patterns within the data.

Analysing micromobility Data: A spatiotemporal approach

In this section we introduce a range of spatial and temporal analysis techniques to explore a sample of micromobility data with the goal of demonstrating how these techniques may provide insight into how these services are used. The data used in these analyses are trip origins and destinations for the month of July 2019 for two different micromobility services in two different cities, namely *Lime e-scooters* in Washington, DC, and *Jump e-bikes* in Montreal. These two sets of data were chosen as they represent micromobility services at two very different stages. In the short history of micromobility services in the United States, Washington was an early adopter. These services have operated within the District for roughly two years at time of writing and consist of multiple service operators. The novelty of interacting with micromobility vehicles in Washington, DC has worn off for most citizens, and the service operators now rely on a robust and consistent user base. The data from Montreal, on the other hand, are from the first month of Montreal's micromobility pilot project. As one of the first cities in Canada to allow Jump e-bikes, these data reflect a service in its infancy with a limited number of vehicles and a user base that has limited experience with micromobility vehicles. Additionally, the Montreal data are for e-bikes, a very different vehicle type than e-scooters. These data represent two ends of the spectrum for micromobility service type, novelty, user-reliance, and trip volume.

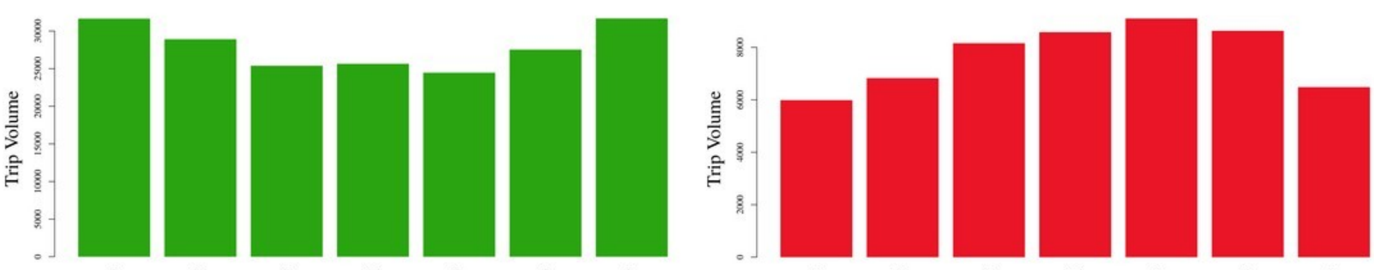
First, we compare some basic statistics for the two micromobility services (Table 1). There is a notable difference in the number of trips, number of vehicles in use per day, and average number of trips per day. The City of Montreal's pilot project restricted the number of vehicles which explains the difference in the first three rows. The variation in average trip duration and trip distance suggests that the average speed of a Jump e-bike is faster than a Lime e-scooter. This can be explained given that the speed of electric-assist bicycles are limited only by the pedal-power of the user. In general, these values are inline with similar reporting on this topic (Krizek and McGuckin, 2019; San Francisco Municipal Transportation Agency, 2019).

Table 1: Counts and averages for two micromobility services in two cities. Means are reported were appropriate with medians in parentheses.

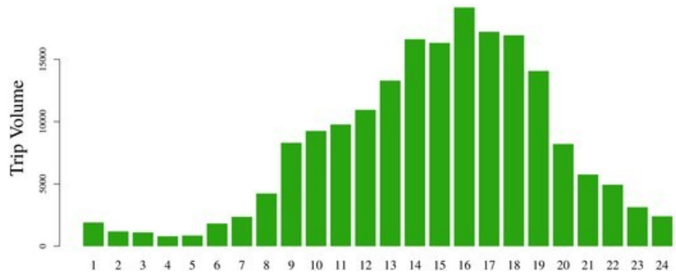
	Lime e-scooter (Washington, DC)	Jump e-bike (Montreal)
Number of trips	192,313	34,387
Average number of vehicles in use per day	731 (729)	272 (252)
Average number of trips per day	6,204 (5,940)	1,075 (1,028)
Average trip duration	25.1 (19) mins	19.5 (14) mins
Average trip distance	1,347.3 (1,055) m	3,482.5 (2,831) m

Temporal Patterns

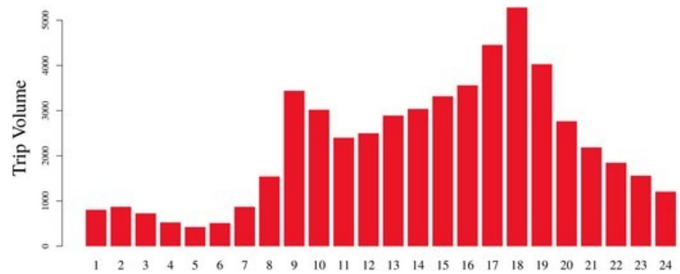
The first dimension of the activity patterns we'll discuss is temporal. The average trip duration, as reported in Table 1, only tell part of the story. We can further explore micromobility usage patterns by identifying when the services are most and least popular. First we aggregate trip start times by an appropriate temporal resolution, such as the hour of a typical day, or day of a typical week. These are reasonable resolutions given the average duration of a trip. The daily temporal patterns for Lime e-scooters in Washington, DC and Jump e-bikes in Montreal are calculated by counting the total number of trips by day of the week across the entire month of July 2019 (Figure 1a & 1b).



(a) Lime e-scooters in Washington, DC (b) Jump e-bikes in Montreal



(c) Lime e-scooters in Washington, DC



(d) Jump e-bikes in Montreal

Figure 1: Trip volume by day (a,b) of the week and Hour of the Day (c,d)

Even through this basic aggregation analysis, we can see that the two cities/services show very different temporal usage patterns. Notably, Lime usage in Washington, DC is highest on the weekends with low usage mid-week which contrasts Montreal's Jump activity showing increased usage during the week with the lowest activity on the weekends. This is consistent with the findings from the National Association of City Transportation Officials (2019). Increasing our temporal resolution, we can explore these same aggregated trip start times as hours of a day (Figure 1c & 1d).

While arguably more similar than the daily activity patterns, we do find some important differences between these two hourly temporal patterns. The most notable difference is the morning peak in the Jump data and lack of peak in the Lime data. This peak in the Jump temporal patterns reflects those user that rely on a Jump e-bike as part of their morning commute. This same peakedness has been identified in a number of other studies (Chang et al., 2019; Liu et al., 2019). The lack of a peak in the Lime data suggests that the Lime service as a whole is used less by people commuting for work. Similarly, the highest usage of the Jump service in Montreal is found between 5pm and 6pm (typical evening commute hours) while Lime usage in Washington, DC is identified around 4pm. All of these differences suggest that these two micromobility services cater to different types of users with varying mobility purposes. In this example, while we are comparing two services between cities, these same differences in temporal patterns are also observed between micromobility services in the same city.

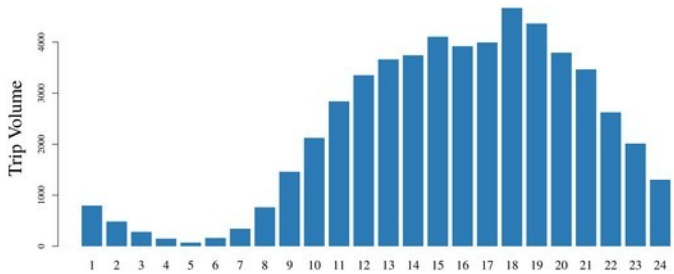
What the temporal patterns above do not show us is how the same micromobility service might vary between cities. For instance, how do the temporal patterns of Jump e-bikes usage differ between Montreal and Berlin? We can answer this question by first aggregating trip start activity patterns to hours of a typical week for both cities. To account for the magnitude of difference in trip volume between the two cities,[1] each city's temporal pattern is normalised by the maximum hourly trips. Berlin's aggregate temporal pattern is then subtracted from Montreal's. The resulting pattern indicates that, Berlin's Jump e-bike users are even more commuter focused than Montreal's, with higher activity during the weekday morning and evening commuting times and relatively less activity in the early mornings and afternoons.

Further research has explored the underlying land use associated with micromobility trips. Our previous work (McKenzie, 2019) explored the temporal distribution of trip origins and destinations by land use type in Washington, DC and found that the percentage of trips starting in residential land use regions did not change significantly from weekdays to weekends (roughly 24%). The largest difference was identified between commercial and recreational regions. Weekend trips originating in recreational areas made up a substantially larger percentage of overall trips compared with those originating in commercial regions.

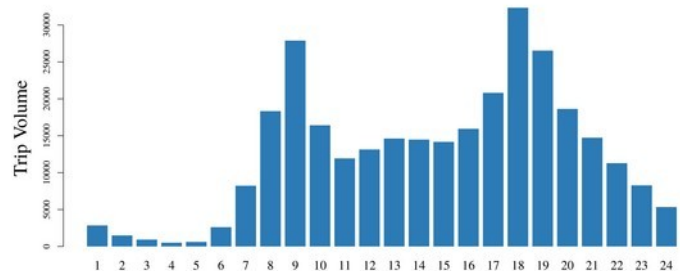
1 We identified 157,243 trips in Berlin for July 2019

How do these compare to docking station-based bikeshare?

Next, we compare the temporal patterns for our two micromobility services to those of the more traditional, and often government funded, docking station-based bikeshare services. This topic has been addressed in a number of studies (McKenzie, 2018; Li et al., 2019). Using the aggregation technique discussed in previous sections, we again identify temporal patterns, but this time for Washington DC's Capital Bikeshare (CaBi)[2] and Montreal's Bixi[3] programs. Both of these systems have been in use for at least a decade and offers two payment types. *Members* pay a monthly or yearly subscription fee whereas *Casual* users pay for a one way trip or weekend pass. The hourly temporal patterns for Capital Bikeshare in Washington, DC are shown in Figure 2, split into member and casual user trips. The temporal patterns for Montreal's Bixi are very similar.



(a) Casual Users



(b) Members

Figure 2: Capital Bikeshare temporal activity (hours of a day) for July 2019 split by members and casual users.

These two bikeshare patterns show striking differences. Membership usage reflects traditional commuting patterns with high usage during the morning and evening weekday commute. By comparison, temporal patterns for casual users do not display this same commuting behaviour. The daily temporal patterns show a similar pattern with lower usage for members on the weekends compared to casual users. These patterns are supported by the findings from the National Association of City Transportation Officials (2019), who conducted similar analysis across numerous cities in the United States. When we compare these two docking station-based bikeshare patterns to the temporal patterns for our micromobility services (shown in Figure 1) we identify clear similarities. Visually, the Lime e-scooter patterns appear to be more similar to the casual bikeshare usage patterns whereas the Jump e-bike patterns show more similarity to the member bikeshare usage, representing dominant weekday commuting behaviour. Statistical analysis of these patterns through the use of methods such as Watson's Two sample test of homogeneity and cosine similarity confirm this visual assessment (see McKenzie, 2020 for further details). The NACTO asserts that station-based bikeshare trips have a higher proportion of trips motivated by travel to and from work, connecting to transit, and social reasons while e-scooters have higher proportions for recreation/exercise reasons (NACTO, 2019), an argument that supports our findings here.

Spatial Patterns

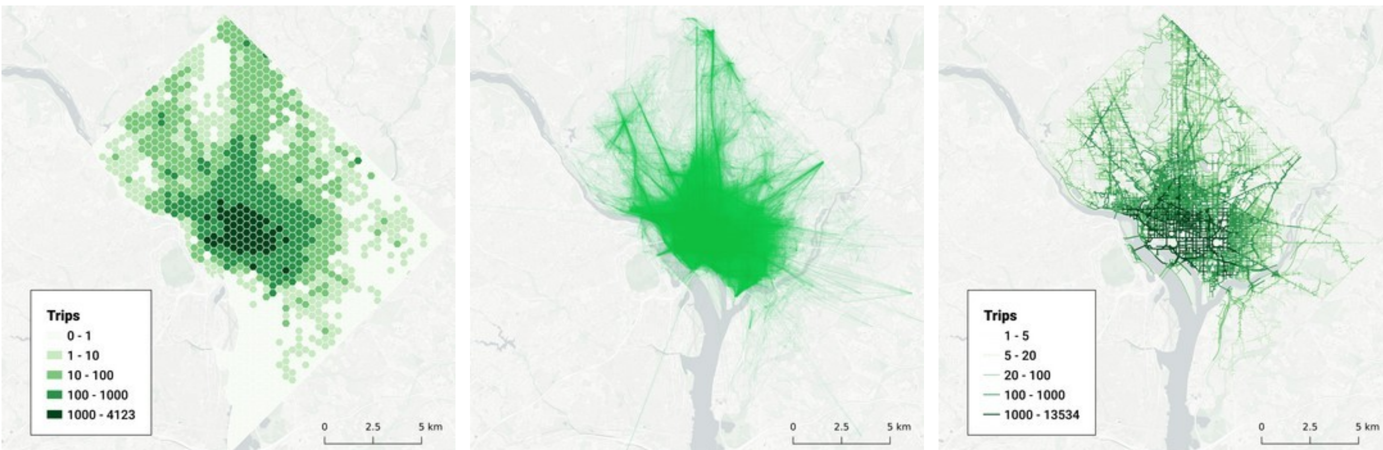
Next, we explore micromobility activity using spatial analysis techniques to identify common spatial patterns in the data. As was the case with temporal data exploration, the resolution at which the data is aggregated plays an important role. Figure 3 shows our two datasets, Lime e-scooters in Washington, DC and Jump e-bikes in Montreal using three different methods of spatial aggregation.

In the first approach (Figures 3a and 3d) we aggregate all trip origins from our datasets into 500 meter radius hexagons and generate a choropleth map binning trip volume by colour saturation.

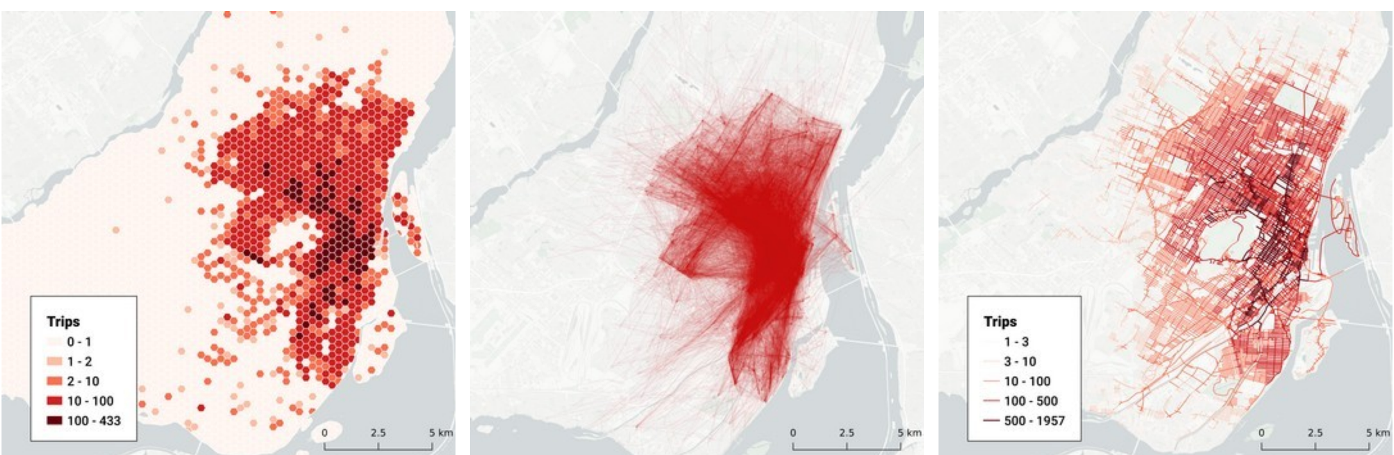
2 https://www.capitalbikeshare.com/

3 https://montreal.bixi.com/en

This cartographic technique is useful for identifying core operating regions (clusters) for each service in addition to exposing the spatial extent of each micromobility service in each city. Statistical techniques for quantifying and comparing these services involve autocorrelation functions and spatial clustering measures such as Moran's I or DB-scan as well as spatial similarity measures such as Earth Mover's Distance. We have used these, and other techniques, to successfully compare different services in the same city showing that there are significant differences in the spatial patterns of different micromobilty operators within the same region (McKenzie, 2020).



(a) Trip origin volume by 500m hexagons (b) Lines between Origin & Destination (c) Trip volume on road network (estimated)



(d) Trip origin volume by 500m hexagons (e) Lines between Origin & Destination (f) Trip volume on road network (estimated)

Figure 3: Three spatial representations of shared mobility activity over the month of July, 2019. Lime e-scooters in Washington, DC, USA (a,b,c) and Jump e-bikes in Montreal, Canada (d,e,f).

In the second set of maps (Figures 3b and 3e), we show all trips as individual lines drawn between each origin and destination. This approach ignores the underlying street networks and is useful primarily to demonstrate rough distances between points, identify clusters of origins and destinations outside the city cores, and generally represent all trips as a series of coarse nodes and edges. Each trip is represented by a thin line with a low opacity allowing overlapping lines to increase the density on the map, highlighting frequent trips between the same origins and destinations. For instance, in Washington, DC, we see a clear linear cluster linking the Northeast of the city to the downtown core. Further investigation of this cluster identified a high volume *juicing* location within the District.[4] From a spatial statistics perspective, origin-destination flow clustering techniques have been successfully employed to identify large clusters of trajectories in similar mobility datasets (Zhou, 2015).

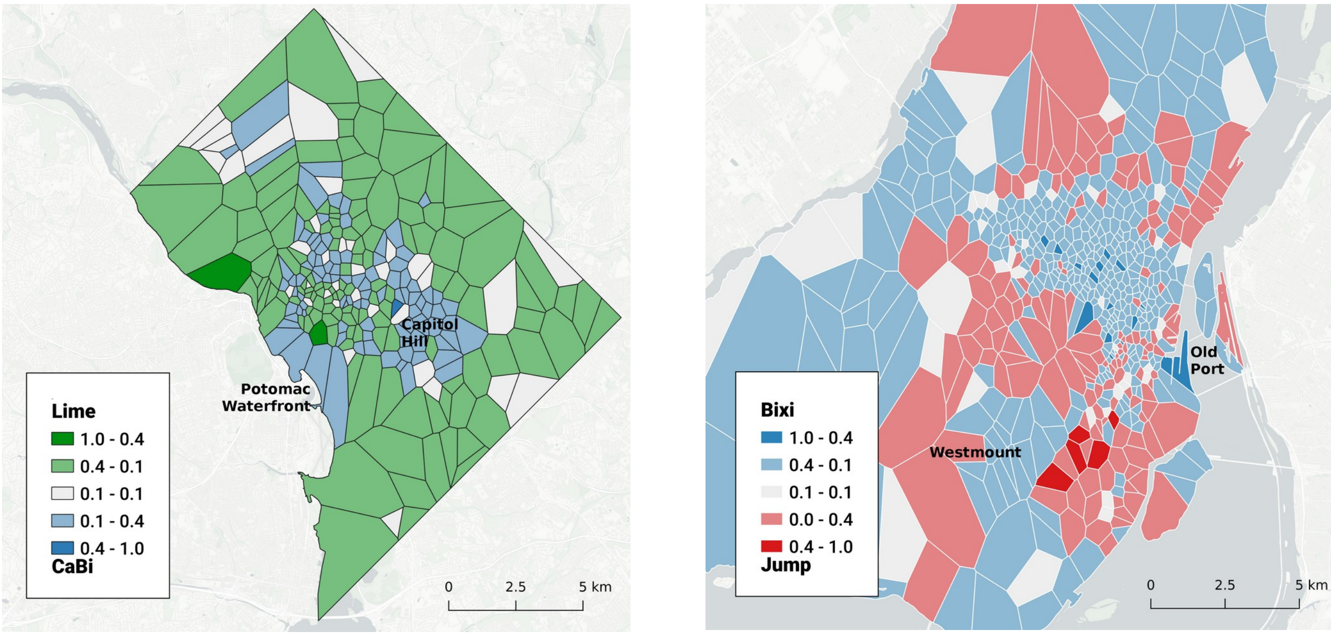
Finally, Figures 3c and 3f show the same sets of trips mapped to the local street network. In some cases, researchers have access to global navigation satellite system trajectory data (e.g., GPS tracks) and can snap these sequential points to the street network (Murphy et al., 2019). In other cases, researchers only have access to the origins and destinations of trips. In this latter case, an algorithm such as Dijkstra's (1959) can be used to calculate the shortest path between an origin and destination along a connected street network. The two street network maps shown here were generated in this manner. This is a useful technique for depicting trip volume along a real street network, using colour saturation and line width to indicate which streets are busier than others. While the origin density maps (Figures 3a and 3d) show the volume of trips based on trip origins, these maps show the *full trips* as a density value. Depending on the origins, destinations, and shortest path between the two, these two maps may differ in the regions of the city they show to be busiest. The data presented visually in these two figures can be analysed spatially in a number of ways. In comparing two or more service areas, Earth Mover's Distance can again be used, as well as network-based similarity and graph measures such as centrality and connectedness (Tantardini et al., 2019).

Compare with docking station-based bikeshare

The difficulty in a spatial comparison of micromobility services and docking station-based bikeshare is that the two services operate quite differently, resulting in two very different spatial footprints. While micromobility services are dockless, meaning trips may originate or finish anywhere, most existing bikesharing services, such as Capital Bikeshare and Bixi, are restricted to starting or ending a trip at a docking station. To properly conduct a spatial comparison, we generate a Voronoi tessellation from the docking station locations. A Voronoi tessellation is a partition of a plane into regions close to each of a given set of objects, in our case, docking stations. This tessellation approach produces regional polygons from point data thus associating all parts of a city with one station or another. We then intersect and aggregate all micromobility trip origins with these Voronoi polygons, producing a comparable set of geometries.

Another difficulty in comparing these two services is the difference in trip volume. Traditional docking station-based bikeshare usage remains quite high, compared to micromobility usage, in most North American cities that operate one. To identify which of the two services is relatively more popular in a given region, we first normalised each of the trip counts by dividing the count in each region (Voronoi polygon) by the maximum number of trips overall. The resulting normalised trip volumes means that we can subtract one service from another in each region producing the maps shown in Figure 4.

4 Juicing is the term Lime uses to describe the process of a private citizen being paid to recharge one or more vehicles.



(a) Service dominance by Capital Bikeshare

(b) Service dominance by Bixi

Figure 4: Comparing normalised bikeshare trip volume to normalised micromobility service volume using station-based Voronoi polygons as the common geometry.

In Figure 4a the map indicates that, relatively speaking, Lime e-scooters are more popular than Capital Bikeshare outside of the downtown core and specifically in certain neighbourhoods to the west of the city such as Georgetown and along the National Mall. By comparison, Capital Bikeshare is more popular in the downtown core, along the Potomac waterfront, and in the Capitol Hill neighbourhood. While future analysis should compare these regions to their daytime demographics, these results, in combination with the temporal analysis, suggests that Capital Bikeshare is used more by commuters in getting to and from workspaces in the District whereas Lime e-scooters are more likely to be used for leisure and recreational activities. A similar pattern can be seen in Figure 4b with Bixi dominating the downtown core of the city and the Old Port and Jump e-bike more prevalent in some of the younger and more affluent neighbourhoods outside of the city core.

Compare with ride-hailing services

Another form of shared mobility that disrupted the urban transportation status-quo well before micromobility services hit the streets, is ride-hailing (e.g., Uber). In discussing the rise of micromobility services one is often asked how these two very different *sharing economy* services compare. Here we examine these two services with the goal of identifying which service is faster, and when.

Ride-hailing travel time data is publicly available for a number of cities through Uber's Movement dataset.[5] These data report hourly aggregated travel times between all pairs of Traffic Analysis Zones (TAZ) within a city, both for weekdays and weekends. Provided these data for a city such as Washington, DC, we aggregate our micromobility data at the same spatial and temporal resolution. Restricting our analysis to only adjacent TAZ, we calculate the difference in average travel time between ride-hailing services and micromobility services.

Splitting these spatial results into weekday and weekend maps, we observe that difference in travel time is temporally dependent. For instance, on weekdays in much of the downtown core, it is faster to take an e-scooter or e-bike than a ride-hailing service to get to a nearby location. On weekends, ride-hailing services are almost always faster. Further analysis of the temporal patterns at an

5 https://movement.uber.com/

hourly resolution demonstrates a continued trend. During the weekend, averaging across all regions, it is always faster to use a ride-hailing platform than a micromobility service, regardless of the hour. Similarly, during most hours of a weekday it is faster to use a ride-hailing service with the important exception of rush hour, from 8-9am and 5-6pm, when it is significantly faster to use a micromobility vehicle (McKenzie, 2020).

The Future of micromobility

As micromobility service operators rapidly expand into new markets around the world, many of the cities in which the services have been operating continue to wrestle with their long-term impacts. Concerns over the impact of this disruptive transportation model fuel discussions in the media, government offices, and on the streets. As is the case with many new technologies, regulatory agencies are often slow to react and two years after their launch, many local governments are just now beginning to fund research into to their impacts on health, safety, the environment, and urban infrastructure. It is an exciting time to be a researcher in this field.

In this chapter, we presented a spatiotemporal analysis approach to identifying nuanced activity behaviour of micromobility users. We demonstrated that raw trip count and demographics alone do not give a complete picture of how these services are used. Digging into the spatial and temporal patterns provides us with much more information on which to gain an understanding of both *why* and *how* these vehicles are being used. While informative, it is important to remember that the approaches presented in this work just begin to scratch the surface of what is possible. It is only through combining multiple analysis techniques that we can truly understand the role that micromobility plays in the urban sharing economy.

What is next?

The future of micromobility services is anything but clear. Though these services now represent a multi-trillion dollar industry, they continue to grapple with government regulations and societal push-back. In discussing the future of micromobility, one next step that we are likely to see relatively soon is the establishment of more formal partnerships between cities and commercial micromobility operators. With privately funded micromobility services pushing into the existing taxpayer funded bikesharing market, it is only a matter of time before cities replace existing docking-station based systems with dockless, electric modes of transportation. By flexing their regulatory muscles it is likely that local governments will strongly encourage public-private partnerships with these micromobility service operators, allowing cities to have a stronger role in all aspects of the business from fleet management to enforcing parking laws and safety standards. This will likely mean a more equitable distribution of vehicles with the city moving to include communities that currently do not have access to there services. Similarity, regulatory control may move from the city level to the county, state, or provincial level with the goal of standardizing access and regulations. This move will also permit greater multi-modal cooperation with existing urban transportation systems such as buses and trains. For instance, leading mapping platforms have recently added “scooter mode” to their navigation options suggesting it is just a matter of time before government-endorsed transportation applications add micromobility vehicles to their multi-modal route planning services. Access to data will play a pivotal role in all of this. A move towards open data and adoption of data standards will lead to more integrated planning which, in the end, will benefit all stakeholders.

Bibliography

Agrawal, Asha Weinstein, Kevin Fang, and Ashley M. Hooper. “Electric Kick Scooters on Sidewalks in Virginia but Not in California? A Review of How States Regulate Personal Transportation Devices." *Transportation Research Board*. No. 19-04299. (2019).

Chang, A., L. Miranda-Moreno, R. Clewlow, and L. Sun. "Trend or fad? deciphering the enablers of micromobility in the U.S*." SAE International.* Technical Report. (2019)

City of Santa Monica. "Shared mobility pilot program summary report." Technical report. (2019)

Dijkstra, Edsger W. "A note on two problems in connexion with graphs." *Numerische mathematik* 1, No. 1 269-271. (1959):

District Department of Transportation. "Dockless data and application programming interface." Technical report. (2020)

Dong, Y., Z. Yang, Y. Yue, X. Pei, and Z. Zhang. "Revealing travel patterns of sharing-bikes in a spatial-temporal manner using non-negative matrix factorization method." *CICTP 2018 : Intelligence, Connectivity, and Mobility.* (2015)

Gössling, Stefan. "Integrating e-scooters in urban transportation: Problems, policies, and the prospect of system change." *Transportation Research Part D: Transport and Environment* 79:102230 (2020)

Krizek, Kevin. J. and Nancy McGuckin. "Shedding NHTS light on the use of "little vehicles" in urban areas." *Transport Findings.* (2019)

Li, Haojie, Yingheng Zhang, Hongliang Ding, and Gang Ren. "Effects of dockless bike-sharing systems on the usage of the London Cycle Hire." *Transportation Research Part A: Policy and Practice* 130: 398-411. (2020)

Liu, Mingmin, Sonya Seeder, and Howell Li. "Analysis of E-Scooter Trips and Their Temporal Usage Patterns." *Institute of Transportation Engineers. ITE Journal* 89, no. 6: 44-49. (2019)

Los Angeles Department of Transportation. "Mobility data specification." Technical report. (2018).

Lyu, Xiongying, and Haixiao Pan. "Sharing Bicycle Riding Characteristics Analysis in Shanghai Based on Mobike Opening Data." *Shanghai Urban Planning Review* 2: 11. (2018)

Mathew, Jijo K., Mingmin Liu, and Darcy M. Bullock. "Impact of Weather on Shared Electric Scooter Utilization." In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, pp. 4512-4516. IEEE, (2019)

McKenzie, Grant. "Docked vs. Dockless Bike-sharing: Contrasting Spatiotemporal Patterns (Short Paper)." In *10th international conference on geographic information science (GIScience 2018)*. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, (2018)

McKenzie, Grant. "Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, DC." *Journal of transport geography* 78 (2019): 19-28.

McKenzie, Grant. "Urban mobility in the sharing economy: A spatiotemporal comparison of shared mobility services." *Computers, Environment and Urban Systems* 79: 101418. (2020)

Murphy, James, Yuanyuan Pao, and Albert Yuen. "Map matching when the map is wrong: Efficient on/off road vehicle tracking and map learning." In *Proceedings of the 12th ACM SIGSPATIAL International Workshop on Computational Transportation Science*, pp. 1-10. (2019)

National Association of City Transportation Officials. "Shared mobility in the U.S." Technical report. (2019)

North American Bikeshare Association. "General bikeshare feed specification." Technical report. (2019)

North American Bikeshare Association. “GBFS & Data Principles.” Technical report. (2020)

Orr, Briana, J. MacArthur, and J. Dill. “The Portland e-scooter experience.” *Portland Bureau of Transportation.* Technical report (2018).

San Francisco Municipal Transportation Agency. “Powered scooter share mid-pilot evaluation.” Technical report. (2019)

Singleton, Patrick A., and Tara Goddard. "Cycling by Choice or Necessity?: Exploring the Gender Gap in Bicycling in Oregon." *Transportation research record* 2598, no. 1: 110-118. (2016)

Tantardini, Mattia, Francesca Ieva, Lucia Tajoli, and Carlo Piccardi. "Comparing methods for comparing networks." *Scientific reports* 9, no. 1: 1-19. (2019)

Zhou, Xiaolu. "Understanding spatiotemporal patterns of biking behavior by analyzing massive bike sharing data in Chicago." *PloS one* 10, no. 10 (2015)