Shared micro-mobility patterns as measures of city similarity

Position Paper

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ABSTRACT

Micro-mobility services, such as dockless e-scooters and e-bikes, are inundating urban centers around the world. The mass adoption of these services, and ubiquity of the companies operating them, offer a unique opportunity through which to compare cities. In this position paper, a series of spatiotemporal measures are proposed based on activity data collected from shared micro-mobility services. The purpose of this paper is to identify a number of ways that these new mobility services can serve to augment existing city similarity approaches.

CCS CONCEPTS

• Applied computing → Transportation; **• Information systems → Location based services**.

KEYWORDS

shared mobility, micro-mobility, e-scooter, e-bike

ACM Reference Format:

Grant McKenzie. 2019. Shared micro-mobility patterns as measures of city similarity: Position Paper. In *1st ACM SIGSPATIAL International Workshop on Computing with Multifaceted Movement Data (MOVE'19), November 5, 2019, Chicago, IL, USA.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3356392.3365221

1 INTRODUCTION

The dynamics of a city are often best identified and understood through relative comparison with other cities. Comparison allows us to understand what aspects of a city are unique, and what facets of a city contribute to its identity [13]. Comparison is often conducted through assessing the similarities of different properties, or dimensions, of a city such as the population demographics [11] or urban structure [4]. More recently, researchers have made use of the plethora of user-contributed content pertaining to cities turning to place descriptions [6] and even tourist photographs [15] to quantify differences and similarities between urban centers. This topic of city similarity has been a focus of research for many academics, urban planners, and policy makers as the ability to quantify these similarities allows for a range of possibilities including inferring the future of cities, identifying travel recommendations, and better understanding how a specific policy might impact a certain city.

The purpose of this short paper is to highlight these data and propose a new set of measures for assessing similarity based on the mobility patterns exhibited by users of shared short-range vehicles, namely e-scooters and e-bikes. While these platforms are similar in some ways to existing modes of transportation such as traditional bike-share, the rapid influx of these new services have changed the transportation landscape. The global coverage of these companies (e.g., `Bird` e-scooters are in 120 cities [14]) means that data are being collected through a common platform for users across many different cities. These data all reflect micro-mobility users within different cities, yet the commonality of the platform and method of data collection make it particularly useful for similarity analysis. While a city may or may not have an existing bike-share platform, and the metro services may range with respect to data availability, the data provided through these shared mobility services offer an unprecedented opportunity to compare the exact same services across a number of urban centers and populations.

What I present here is a vision for how these data could be used to assess similarity of cities, namely through trajectory analysis, as well as inclusion of contextual data for a city. A number of measures are proposed with the hope that they be further explored as additional dimensions on which to augment or enhance existing urban similarity measures.

2 SHARED MICRO-MOBILITY SERVICES

For the purposes of this short paper I define shared micro-mobility services as those services that provide short term electric rental vehicles to the general public for a fee. The vehicles tend to be dockless[1] and on average the trips are shorter than those of traditional vehicle travel (e.g., automobile or metro trips). Specifically, the services described here are operated by multi-national, for profit companies (not local or regional governments). Examples of such platforms are `Lime`[2] and `Jump`.[3]

Shared mobility services have been the focus of a number of different studies (see [3] for an overview) from parking etiquette [5] and health impacts [9], to vehicle distribution optimization [2] and the development of efficient e-scooter batteries. A recent study out of Paris, France surveyed scooter-share users in the city and discovered that scooters are used by a very narrow demographic of the population [1], a finding that speaks to the applicability of certain similarity measures. Our own work on this topic identified

MOVE'19, November 5, 2019, Chicago, IL, USA

ACM ISBN 978-1-4503-6951-0/19/11…$15.00
https://doi.org/10.1145/3356392.3365221

[1] As opposed to the more traditional docking station based services
[2] https://li.me
[3] https://jump.com - Owned by Uber

some of the nuanced differences between these new services and existing government-funded bike-share systems [7].

Micro-mobility services are a multi-billion dollar industry (e.g., `Lime` was recently valued at $2.4 billion), rapidly expanding into new urban markets. How these services are used in different cities reflects both the urban structure and population that inhabit the city. The usage behavior, including the trajectories of users on these vehicles, offer an novel dimension on which to compare urban regions. Below I provide further details on how this might work in practice.

Extracting Trips

`Jump` and a number of other shared mobility services[4] offer applications programming interfaces (API) to access available vehicles in real-time. Each request to the API lists all available vehicles in the region along with unique vehicle identifier, geographic coordinates, and current battery percentage. Vehicle trips can be identified by requesting available vehicles from the API at a regular temporal frequency and calculating the distance that each unique vehicle moves between requests. For example a `Jump` e-bike may appear available at a specific location at $T = 0$, not appear in the *available vehicles* request at $T = 2$ and reappear in a different location at $T = 3$. These time stamps and geographic locations are then considered the origin and destination of a trip (at a temporal resolution of data collection).

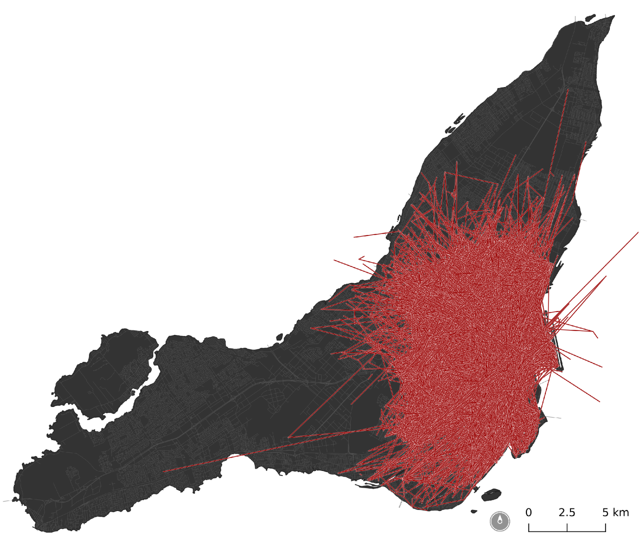


Figure 1: Lines between trip origins and destinations

The data are cleaned to remove erroneously identified trips due to GPS multipathing and company redistribution by removing all trips less than 100 meters, greater than 2 hours, average speed greater than 32 kph or slower than 5 kph. In addition, trips where the battery increased between origin and destination are removed as these indicate a *recharging* trip typically performed by a `Jump` staff member. Given origin and destination values, the route along each city's road network can be determined using Dijkstra's shortest path algorithm. While it is unlikely that all trips take place along the shortest path, on aggregate this approach is suitable for the task of determining network density.

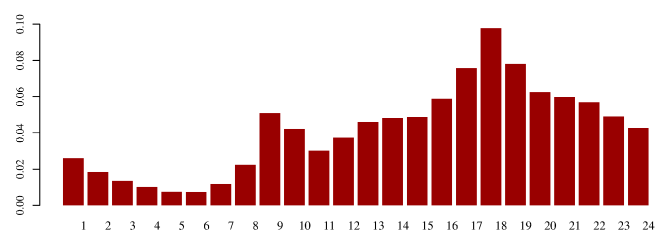
[4]See for example: https://ddot.dc.gov/page/dockless-api

3 MOBILITY AS THE BASIS FOR SIMILARITY

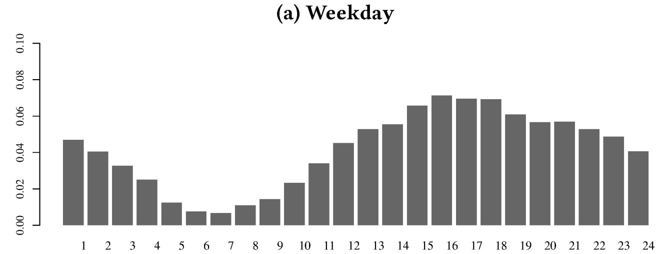
Here, a number of techniques are discussed for actually quantifying micro-mobility usage and for comparing values across cities.

3.1 Temporal analysis

Trip frequencies can be aggregated to hours of the day and split by either weekday or weekend. Figure 2a shows typical weekday patterns for the city of *Montréal* where as Figure 2b shows typical weekend patterns. The weekday pattern clearly shows a maximum peak between 5pm-6pm and a smaller localized peak between 8am-9am. These reflect standard commute behavior for most cities and the smaller peak in the morning implies that commuters are less likely to use a `Jump` vehicle to travel to work as compared to home. While this pattern is apparent in most cities, there are slight differences between temporal patterns between cities. *Berlin* for example shows a much more pronounced peak during morning commute than *Montréal*. The similarity between city temporal patterns can be calculated through statistical measures such as Circular Earth Mover's Distance, Cosine Similarity, or Watson's two sample method of heterogeneity. These patterns have the potential to uniquely identify a city through shared mobility temporal usage behavior.



(a) Weekday



(b) Weekend

Figure 2: Hourly temporal usage patterns of Jump eBikes in Montréal, split by weekday and weekend.

3.2 Spatial analysis

The mobility patterns also exhibit unique spatial properties. These can be explored in three different ways, namely trajectory metrics, differences in origin and destinations (pick up and drop off points for vehicles), and trip volume distributed across a city's road network.

3.2.1 Trajectory metrics. A basic approach to quantifying shared micro-mobility is to explore some basic statistics of mobility usage within a city. A select few statistics for vehicle usage in three major cities are shown in Table 1. These statistics actually tell us quite a bit about each city. While the total number of vehicles is often limited by the company or city regulations, the adoption of the service, frequency of use, as well as average duration and distance are each representative of the inhabitants or visitors to a city. For example, the median trip distance of `Jump` users in *Berlin* is almost twice the distance of trips taken by users in *Los Angeles* or *Montréal*.

	Berlin	Los Angeles	Montréal
Number of Trips	286,508	184,921	75,640
Med. Vehicles in Use/Day	1,859	1,001	306
Med. Trip Duration (min)	14.2	11	13.2
Med. Trip Distance (m)	5,009	2,161	2,784

Table 1: Trip and vehicle statistics for three cities over 60 days.

Spatial descriptive statistics such as the radius, range, and major/min axes of an ellipse are also useful for exploratory analysis of a city as well as computing similarity between two or more cities. Further analysis might explore methods such as convex hull, gridded trip density, or point density (e.g., Kernel density estimation).

3.2.2 Origins & destinations. Analysis of trip origin and destinations can identify regions of popularity with a city. Using clustering methods such as *DBScan* allows us to identify *hotspots* within the city. Similarly, we can apply a Kernel Density Estimation (KDE) approach to identify areas of the city that show a high density of trip origins or destinations.

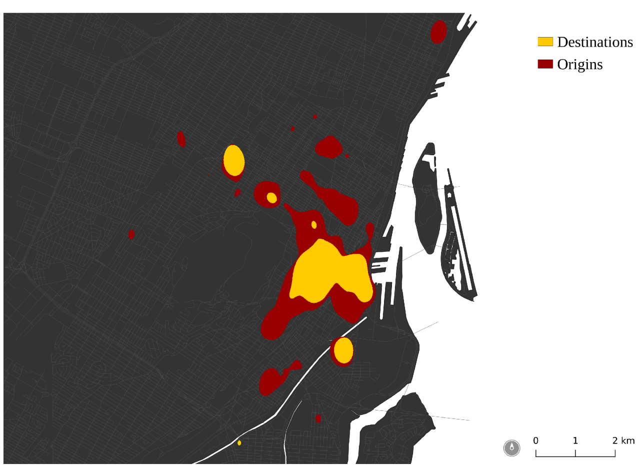


Figure 3: Kernel density estimated regions (median threshold) for morning weekday commute.

Ignoring the temporal component, these methods of analysis show regions of the city *to* and *from* which users travel. By focusing on specific temporal periods, we can better approximate residential and commercial regions of the city. For example, cluster analysis of trip origins between 8am-9am on weekdays (morning commute) is likely to identify residential regions of the city, and specifically those regions of the city that are high in the specific demographic that tend to use micro-mobility services. In contrast, if we focus on destination locations between 9a-10a, we see a very different pattern with clusters centered in the downtown core or business district of each city. Figure 3 shows an example of this using KDE (all values below the KDE median are removed) for the city of *Montréal*. The red regions shows the areas with the highest density of trip origins during the morning commute. Notably the total area of this region is much larger than the yellow destinations regions and correlates with residential land use more than the yellow regions.

3.2.3 Network density. Network density can be calculated by counting the number of trips that intersect with each road segment in the city. Figure 4 shows the traffic volume on Montréal roads as contributed by `Jump` users. Compared to the previous analysis which purely focused on the origins and destinations, this approach demonstrates the impact of these mobility services on a city's road infrastructure.

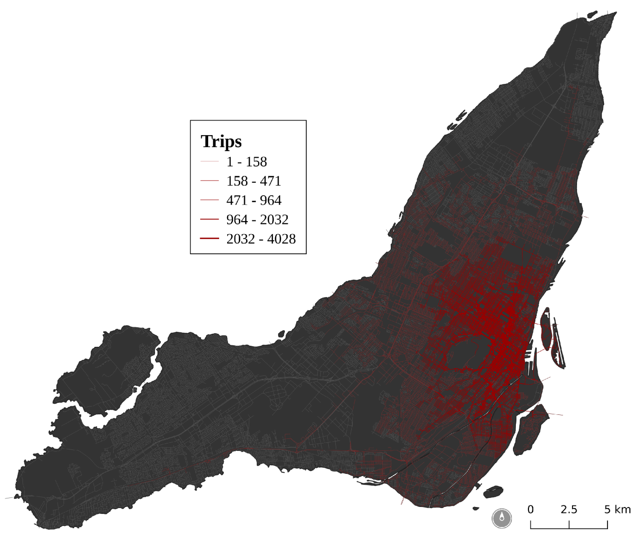


Figure 4: Road density based on trips.

This approach is useful when comparing to alternative modes of travel that share the same road network such as (traditional) bicycles, automobiles, or above ground public transit. This contributes to the identity of the city by highlighting not only pick up and drop off regions, but also those regions in the middle, along the trip, that are likely impacted by the use of this mode of travel.

3.3 Interaction with existing data dimensions

While the previous methods explicitly describe the micro-mobility activities themselves, additional insight can be gained through contextual analysis combining external data sources. A select few of these are described below.

3.3.1 Existing land use & zoning. Shared mobility data can be intersected with existing land use or zoning boundaries in order to show the percentage of trips originating or ending in the same or different land use types. Similarly, the combination of time of day, day of the week, and land use provides insight into the identity of a city particularly as compared to other cities that follow very different regional or network layouts. These data can also be compared to the regions identified in Section 3.2.2 either as validation (e.g., are the origin regions more likely to overlap with residential land use) or in identifying differences between authoritative land use datasets and those regions identified though micro-mobility user behavior.

3.3.2 Sociodemographic population data. Sociodemographic data clearly has a role to play in providing additional contextual information to shared mobility patterns. Data collected via national or regional censuses provide information regarding age, gender, race, income, etc. aggregated to regions within a city. These data have been shown to be highly spatially correlated and combining these data with shared mobility trajectories will highlight sociodemographic differences. Existing research has shown there are substantial differences in the populations that do or do not have access to these services [10]. This type of spatial equity analysis can be used to differentiate cities from one another with regards to access to shared mobility services. Lastly, a number of census platforms (such as the American Community Survey) provide data regarding dominant mode of travel for commuting. These values can be compared to shared mobility trajectories for the purpose of validation or identification of regions where the two datasets disagree.

3.3.3 Existing points of interest. Point of interest (POI) datasets (e.g., Google Places, Foursquare Venues) are immensely useful in providing contextual information related to the purpose of trips. While previous analysis may be able to identify trips originating or ending at work or home, POI data can tells us additional information regarding where a vehicle was dropped off or picked up. For instance, *bars* and *nightclubs* tend to cluster in specific areas of the city [8]. Inclusion of a POI *category* dataset in analysis of shared mobility patterns will allow us to determine if there is a relationship between vehicle use and activity (as proxied via POI category). For example, are Jump users more likely to head to an *entertainment* region of the city after work on Fridays than other days of the week?

4 NEXT STEPS

This short position paper presents some preliminary thoughts on the use of shared micro-mobility patterns in assessing similarities between cities. The explosive growth of these services around the world offers an unprecedented opportunity to compare and contrast spatiotemporal mobility patterns within cities. Here I have presented some possible methods and techniques for analyzing these data and highlighted some of the ways these data can be of use to urban planners, transportation engineers, and policy makers.

Next steps will involve implementing many of the ideas presented in this paper and assessing the viability of the similarity approaches that have been proposed. We are still very much on the cusp of what is possible with data from these services and the limits of these data are yet to be fully explored.

ACKNOWLEDGMENTS

This research was supported by the Social Sciences and Humanities Research Council of Canada.

REFERENCES

[1] 6t-bureau de recherche. 2019. *Uses and Users of Free-floating Electric Scooters in France.* Technical Report. 6t. https://6-t.co/en/free-floating-escooters-france/
[2] Yi-Wen Chen, Chen-Yang Cheng, Shu-Fen Li, and Chung-Hsuan Yu. 2018. Location optimization for multiple types of charging stations for electric scooters. *Applied Soft Computing* 67 (2018), 519–528.
[3] Regina R Clewlow. 2019. The Micro-Mobility Revolution: The Introduction and Adoption of Electric Scooters in the United States. In *Proceedings of the Transportation Research Board 98th Annual Meeting*. 13.
[4] Paolo Crucitti, Vito Latora, and Sergio Porta. 2006. Centrality measures in spatial networks of urban streets. *Physical Review E* 73, 3 (2006), 036125.
[5] Kevin Fang, Asha Weinstein Agrawal, Jeremy Steele, John Joseph Hunter, and Ashley M Hooper. 2018. Where Do Riders Park Dockless, Shared Electric Scooters? Findings from San Jose, California. (2018).
[6] Junchul Kim, Maria Vasardani, and Stephan Winter. 2017. Similarity matching for integrating spatial information extracted from place descriptions. *International Journal of Geographical Information Science* 31, 1 (2017), 56–80.
[7] Grant McKenzie. 2019. Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. *Journal of Transport Geography* 78 (2019), 19–28. https://www.grantmckenzie.com/academics/McKenzie_JTG2019.pdf Journal Article.
[8] Grant McKenzie and Benjamin Adams. 2017. Juxtaposing thematic regions derived from spatial and platial user-generated content. In *13th International Conference on Spatial Information Theory (COSIT 2017)*, Eliseo Clementini, Maureen Donnelly, May Yuan, Christian Kray, Paolo Fogliaroni, and Andrea Ballatore (Eds.), Vol. 86. Dagstuhl, Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik, 20:1–20:14. https://doi.org/10.4230/LIPIcs.COSIT.2017.20 Conference Article.
[9] Gary Mitchell, Henry Tsao, Thomas Randell, Jacqueline Marks, and Prudence Mackay. 2019. Impact of electric scooters to a tertiary emergency department: 8-week review after implementation of a scooter share scheme. *Emergency medicine Australasia* (2019).
[10] Stephen J Mooney, Kate Hosford, Bill Howe, An Yan, Meghan Winters, Alon Bassok, and Jana A Hirsch. 2019. Freedom from the station: Spatial equity in access to dockless bike share. *Journal of Transport Geography* 74 (2019), 91–96.
[11] Gordon F Mulligan and Jason P Crampton. 2005. Population growth in the world's largest cities. *Cities* 22, 5 (2005), 365–380.
[12] Julien Rabin, Julie Delon, and Yann Gousseau. 2008. Circular Earth Mover's Distance for the comparison of local features. In *2008 19th International Conference on Pattern Recognition*. IEEE, 1–4.
[13] Müge Riza, Naciye Doratli, and Mukaddes Fasli. 2012. City branding and identity. *Procedia-Social and Behavioral Sciences* 35 (2012), 293–300.
[14] Will Yakowicz. 2019. 14 Months, 120 Cities, $2 Billion: There's Never Been a Company Like Bird. Is the World Ready? *Inc.* (2019).
[15] Bolei Zhou, Liu Liu, Aude Oliva, and Antonio Torralba. 2014. Recognizing city identity via attribute analysis of geo-tagged images. In *European conference on computer vision*. Springer, 519–534.