Docked vs. Dockless Bike-sharing: Contrasting Spatiotemporal Patterns

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Abstract

U.S. urban centers are currently experiencing explosive growth in commercial dockless bike-sharing services. Tens of thousands of bikes have shown up across the country in recent months providing limited time for municipal governments to set regulations or assess their impact on government-funded dock-based bike-sharing programs. Washington, D.C. offers an unprecedented opportunity to examine the activity patterns of both docked and dockless bike-sharing services given the history of bike-sharing in the city and the recent availability of dockless bike data. This work presents an exploratory step in understanding how dockless bike-sharing services are being used within a city and the ways in which the activity patterns differ from traditional dock station-based programs.

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1 Introduction

Cities in the United States are in the midst of a bike-share revolution of sorts [8]. Seemingly overnight, GPS-enabled bicycles have popped up in urban centers from Seattle to Miami, offering access to inexpensive, mobile-payment-based, one-way rentals. Users simply unlock a bike with their mobile device, cycle to their destination, park and lock it on any public land, and walk away. These new dockless bike-share services sell themselves as low cost alternatives to traditional dock-based bike-sharing programs, allowing users the freedom to park a bike virtually anywhere in contrast to the traditional model of designated docking stations.

There is no shortage of companies entering the U.S. dockless bike-sharing space. While dockless programs are quite common in much of Asia and Europe, the U.S. has recently seen substantial investment from companies such as Mobike, Spin, Jump, and LimeBike (Figure 1a). In October of 2017, just as it entered the Washington, D.C. market, *LimeBike*[1] (LB), reported 300,000 unique users and $225 million in funding [2]. Similar to other dockless services, LimeBike offers 30 minute rentals for $1 USD and operates on any public space within the metro Washington D.C. area.

Bike-sharing in general is not new to the U.S. and one of the oldest bike-share programs in the country, *Capital Bikeshare* (CB), currently serves the greater metro D.C. area. Originally started under the name SmartBike DC in 2008, it boasts an annual ridership of over 2.1 million[2] and costs either $2 USD per 30 min rental or access through membership subscription. CB is a dock-based bike-sharing service where users lock and unlock bicycles from docking stations distributed around the city (Figure 1b). Importantly, and in contrast to the dockless

[1] http://www.limebike.com/
[2] https://www.capitalbikeshare.com

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(a) LimeBike (Dockless).

(b) Capital Bikeshare (Docked).

Figure 1 Docked vs. dockless bike-sharing platforms. Photographs: Wikimedia / CC License.

bike-share companies mentioned previously, Capital Bikeshare is owned by the municipal governments it serves (i.e., D.C., Virginia, and Maryland).

There have been numerous studies aimed at the social impact [5] and mobility patterns [10, 9] of bike-sharing programs as well as method for intelligently redistributing bikes throughout urban centers [6]. However, very little research has compared traditional dock-based models to new dockless systems. Given the dramatic influx of dockless bike-sharing companies in the U.S. over the last six months [1], this study is one of the first to compare and contrast the spatial and temporal usage patterns in a city that supports both. One important factor contributing to the novelty of this work is that the public is just now gaining access to much of these data.[3] The vast majority of these new dockless bike-sharing companies do not share data related to the locations of their fleet. As far as I am aware, Washington, D.C.'s Department of Transportation (DDOT) is the only U.S. city requiring these companies to provide a publicly accessible application programming interface (API) showing the current location of any dockless bicycles available for rent.[4]

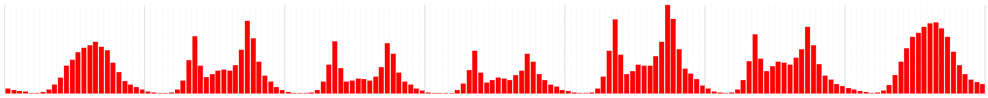
This short paper takes a first step in better understanding the differences in activity patterns between docked and dockless bike-sharing programs. The insight gained through this exploratory research can be used to better inform urban planners, transportation engineers, and the general public on how cyclists and citizens interact with their city.

2 Data

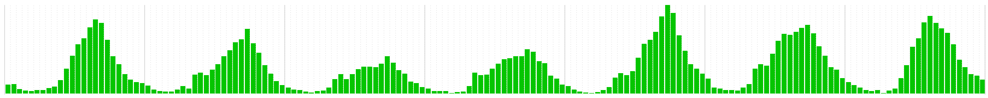
Capital Bikeshare trips for the month of March, 2018 were accessed for this work,[5] a total 238,936 individual trips. Attribute information for these trips include bike ID, time stamps for the start and end of the trip (to the nearest second), and start and end station IDs. Station IDs were matched with point locations through data available from DC.gov's open data portal. All stations outside of D.C., namely those in Maryland and Virginia, were removed thus restricting trips to only those within the district. This reduced the number of accessible stations from 499 to 269 and number of trips to 209,973. To permit comparison between the two bike-sharing services, the CB data was rounded to the nearest five minute interval.

LimeBike data were accessed through their API[6] every five minutes from March 10th through March 31, 2018. These data include the bike ID, geographic coordinates (to roughly the nearest meter), and time stamp of the available bicycle (at a five minute temporal

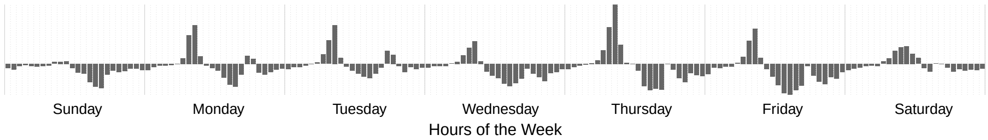
[3] LimeBike's D.C. API was made public on February 6, 2018.
[4] `https://github.com/ubahnverleih/WoBike/issues/9#issuecomment-355047664`
[5] Data are available at `https://www.capitalbikeshare.com/system-data`
[6] `https://lime.bike/api/partners/v1/bikes`



(a) Capital Bikeshare.



(b) LimeBike.



(c) LimeBike subtracted from Capital Bikeshare temporal patterns. Y-axis ranges from 0.6 to -0.2.

Figure 2 Temporal signatures for Capital Bikeshare and LimeBike in Washington, D.C. aggregated to hours of a standard week.

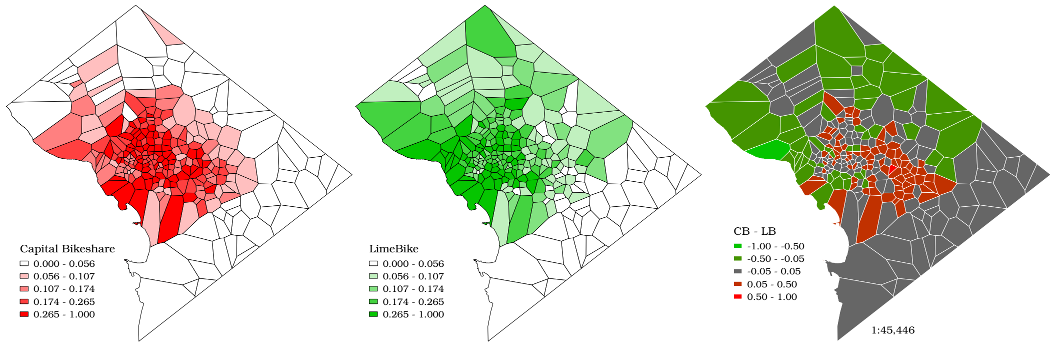
resolution). Further steps were necessary to convert the LB bike *availability data* into trips. The data snapshots captured every five minutes were sorted in order and a trip was recorded as the last time stamp that a bike ID was marked as available, to the next time stamp that the same bike ID reappeared in the data. Assuming GPS accuracy errors within an urban setting, only those bike IDs that moved more than 50 meters were recorded as trips. In total, 154,024 trips were taken by LimeBike users over this time period within the district boundary.

3 Temporal Differences

The mean duration of a trip for both services was approximately 18 minutes though CB showed a median duration of 11 minutes while LB reported 5 minutes (the temporal resolution of data collection). The tendency towards longer trips by CB users is significant and may be partially due to the necessity of finding a docking station instead of leaving the bike in any public space.

The temporal popularities of the two bike-sharing services are shown in Figure 2. This shows bike trip start times aggregated to the nearest hour of a week and independently normalized to account for the larger number of CB trips. We see an expected diurnal pattern with the majority of trips taking place during daylight hours for both services. One difference is the weekday morning peak in Figure 2a, notably missing from Figure 2b. Figure 2c shows the LB temporal pattern subtracted from the CB pattern. The weekday morning peak in CB activity is more apparent here and most pronounced at 8 a.m. This also shows that LB is more popular in the early and late afternoons. Note, however, that there is a negligible difference between the two bike-share services at 5 p.m. on weekdays, peak of the evening commute.

An assessment, based purely on temporal patterns within these data, suggests that the docked CB is used more for commuting to and from work than the dockless LB. Contrarily, CB is used more frequently outside of commuting hours and particularly in the mid-afternoon.



(a) Capital Bikeshare. **(b)** LimeBike. **(c)** LB subtracted from CB.

Figure 3 Normalized trip starts assigned to Capital Bikeshare station-based Voronoi polygons.

4 Spatial Patterns

While the temporal activity patterns of bike-sharing services is one dimension on which to assess their similarities and differences, spatial activity patterns offer a different perspective.

By definition, docked or dockless bike-sharing systems consist of fundamentally different architecture. These differences make it difficult to compare them spatially. While dockless bike locations are scattered throughout the city (where ever someone chooses to stop), CB bike trips are restricted to starting and ending at docking station. To compare these two datasets, a Voronoi tessellation was used to partition Washington, D.C. into polygons based on the locations of CB docking stations. In theory, each of these polygons represents the region to which a CB user was traveling based on their chosen docking station. Admittedly there are limitations to this approach (e.g., water body restrictions), but this analysis was deemed suitable for this short paper.

The number of CB trips starting from each station were summed across the dataset and matched to the appropriate Voronoi polygon. LB trip starting points were also intersected with these same polygons and summed. The total trip count for each bike-sharing service in each polygon was then normalized for each service independently. This was done to account for the larger number of CB trips thus allowing for comparison between the two services. Figures 3a and 3b show the spatial distribution of trip starting points for CB and LB respectively. Figure 3c demonstrates the difference between the two services as the LB value for each Voronoi polygon subtracted from the CB value.

These maps demonstrate that CB ridership is more focused on the central business district, of Washington, D.C. than LB. Intersecting these polygons with land use data from D.C.'s Office of Planning, we find the ratio of commercial, industrial, or mixed use buildings to residential housing is nearly double for CB (0.35) compared to LB (0.17). This supports the temporal pattern analysis that suggests that CB is used more frequently for commuting than LB.

These maps indicate that the southeastern portion of the district is less likely to use any bike-sharing service than anywhere else in the district. One possible explanation is that the 2015 American Community Survey reported these predominantly residential regions, namely Wards 7 and 8, as having both the lowest household income in the district and largest number of individuals below the federal poverty line. While relatively inexpensive, both of these bike-sharing services rely on credit cards as the basis for payment, making it less likely that lower income individuals can use these services.

From a combined *spatiotemporal* perspective, the largest trip volume difference between services, across Voronoi polygons is weekdays between 3 p.m. and 5 p.m. whereas the smallest overall difference is weekdays between 2 a.m. and 4 a.m. LB shows the largest temporal variance in trip volume to the west of the downtown core, near the Georgetown neighborhood with peak usage on Fridays at 2 p.m. In contrast, CB peaks at 5 p.m., Monday through Thursday in the downtown commercial region of the district.

4.1 Data-driven Dock Locations

Access to dockless bike-share data offers an opportunity for a docked bike-share company such as CB. Given that dockless bikes can be left virtually anywhere, we can assume that bikes are most often parked at the most convenient locations for their users. This information can be used to assess the optimality of current docking station locations.

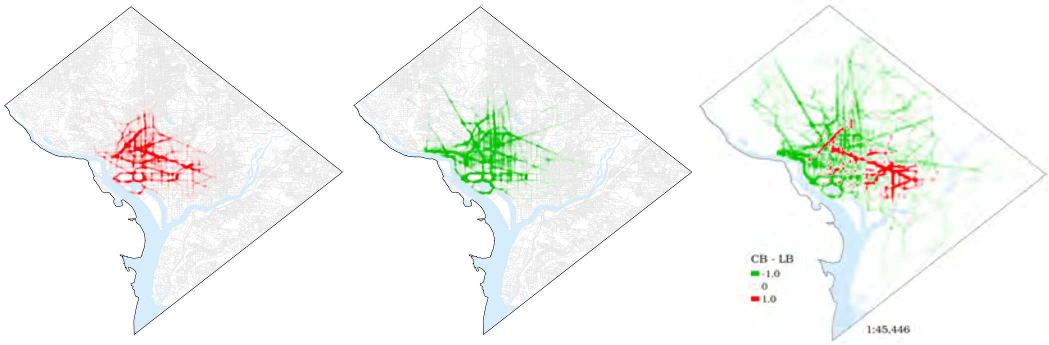
K-means [7] was used to cluster the dockless LB locations with a value of 269, the current number of DB stations in D.C., set as the number of clusters. Provided the weighted centers of these new clusters, the average distance between each cluster center and it's nearest existing CB station was computed. This resulted in a mean distance of 305.4 m with a median of 181.4 m).This clustering approach ignores buildings and roads, however, and since many DB docking stations are located near intersections, these new cluster centers were snapped to the nearest road intersection and the average distance to existing stations was calculated again. The snapping had a minimal impact reducing the mean distance to 300.1 m and median to 180.2 m. This median distance indicates that the existing DB docking stations, on average, are reasonably well situated throughout Washington, D.C., at least as reflected by LB users. This approach demonstrates that having access to dockless bike-share data can have a substantial impact on infrastructure planning, potentially saving a city considerable effort and financial investment [4].

4.2 Network Patterns

The previous section's comparison of trip starting points[7] is useful for understanding the different spatial distributions of bike-sharing services in D.C. An alternative approach is to examine the spatial distributions of trips on the D.C. road network. The shortest path was calculated between each start and end location along the D.C. road network using Dijkstra's algorithm [3] as implemented in pgRouting.[8] Once routing analysis was complete, point geometries were generated every 10 m along each of the resulting line geometries. Using these points, kernel density estimates were created for CB and LB independently, producing the two *heat* maps shown in Figures 4a and 4b. Normalizing the kernel density values, LB was subtracted from CB to produce Figure 4c.

These results depict a similar, but more nuanced pattern than the Voronoi polygons shown in Figure 3. While the results are based on a simple shortest-path approach to determining trip routes, the analysis does offer important insight into how urban cyclist interact with their city. LB shows relatively more activity outside the city core, towards historic Georgetown, around the Tidal Basin, and along the Potomac River, areas that cater to leisure activity and are not typically considered areas of business. CB, by comparison, dominates commercial centers, along Massachusetts Avenue, Union train station, and the streets around Capital Hill. These results again support the notion that Capital Bikeshare tailors more to commuters than dockless services such as LimeBike.

[7] Start points and end points since every end point is a start point for the next trip.
[8] `http://pgrouting.org/`



(a) Capital Bikeshare. **(b)** LimeBike. **(c)** LB subtracted from CB.

Figure 4 Start and end points of bike-share trips mapped to shortest path on the D.C. road network displayed as kernel density maps.

5 Conclusions & Next Steps

This work investigates the spatial and temporal dimensions of docked and dockless bike-share services in Washington, D.C. Though much of this analysis is exploratory, the findings suggest that there are clear difference in how these two services are used. Capital Bikeshare tends to be more commuter focused whereas LimeBike reflects more leisure or non-commute related activities. The results of these analyzes have important implications for urban planners, transportation safety boards, and transportation engineers as these findings may influence infrastructure budgeting, maintenance planning, and new development opportunities.

The results presented in this paper are preliminary since access to this spatial and temporal resolution of commercial bike-share data in the U.S. is still new and the recent influx of bike-share services in cities is disrupting the status quo. Analyzing more data over a longer time period will provide additional insight. Future work will examine the impact of new modes of dockless transportation (e.g., electric scooters), compare these patterns to light-rail ridership, and further examine the behavioral motivations for selecting one service over another.

References

1. Eliot Brown. Dockless bike share floods into U.S. cities, with rides and clutter. *The Wall Street Journal*, March 2018. Online; posted 26-03-2018.
2. Biz Carson. Limebike now valued at $225 million after investors go all in on bike-sharing craze. *Forbes*, October 2017. Online; posted 16-11-2017.
3. Edsger W Dijkstra. A note on two problems in connexion with graphs. *Numerische mathematik*, 1(1):269–271, 1959.
4. Leif Dormsjo. District of Columbia, Capital Bikeshare Development Plan. Technical report, Government of the District of Columbia, 09 2015.
5. Elliot Fishman, Simon Washington, and Narelle Haworth. Bike share: a synthesis of the literature. *Transport reviews*, 33(2):148–165, 2013.
6. Zhaoyang Liu, Yanyan Shen, and Yanmin Zhu. Inferring dockless shared bike distribution in new cities. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*, pages 378–386. ACM, 2018.
7. James MacQueen et al. Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, volume 1, pages 281–297. Oakland, CA, USA, 1967.

8 Felix Salmon. Bring on the bikocalypse. *Wired*, February 2018. Online; posted 01-02-2018.
9 Yu Shen, Xiaohu Zhang, and Jinhua Zhao. Understanding the usage of dockless bike sharing in singapore. *International Journal of Sustainable Transportation*, pages 1–15, 2018.
10 Jon Wergin and Ralph Buehler. Where do bikeshare bikes actually go? Analysis of capital bikeshare trips with GPS data. *Transportation Research Record: Journal of the Transportation Research Board*, 2662:12–21, 2017.