Bike-Sharing is Transit: Building Tools to Plan and Optimize Bike-Sharing Networks

A thesis presented by

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Presented to

The Department of Computer Science

And

The Department of Government

In partial fulfillment of the requirements

For the degree with honors

Of Bachelor of Arts

April 3, 2020

Chapter 1

Introduction

Urban America is infamous for its broader lack of public transit connectivity. [1] Millions of Americans are termed as “transit-dependent”, which means they do not have immediate access to a vehicle or otherwise cannot drive and must use an alternative means of transportation. [2] About 11% of Americans commute with public transit every day [3] and in general 10-12% of Americans do not have access to a car, rendering them transit-dependent. These Americans are likely barred from vital services and getting to work. [4] Unfortunately, even getting to public transit options can be a struggle for many urban residents as “first/last mile connectivity”, defined by the physical distance from the trip origin to the public transit station, can be poor in many urban environments. [5] Too many Americans live in so-called “transit deserts”, areas where transportation demand significantly exceeds supply even in dense environments. [6] As urban populations grow, the importance of sustainable, accessible urban transportation options grows, and bike-sharing systems provide an effective solution to both, offering an environmentally friendly, healthy, and congestion-limiting option for commuters.

Bike-sharing systems are a subset of “micro-mobility” more broadly where some set of light-weight personal vehicles are distributed around a region as a form of mobility. Micro-mobility vehicles include bicycle, electronically assisted bicycles (e-bikes), scooters, and mopeds. Such systems are often designed to complement or even replace existing transit solutions like buses and metro-rail, and they could help transit deserts bloom. However, bike-sharing is still a relatively young concept with limited established planning tools. Planners can be unsure as to how to effectively design and plan these systems. [7] Bike-sharing systems as a result are decried as unreliable, inaccessible by low-income communities, and cost-ineffective.

Thus, an innovative way to plan and model bike-sharing systems could yield useful results, improving unit economics and shaping national municipal policies.

This thesis identifies inequities in the way transit is currently planned and how those approaches have negatively impacted bike-sharing planning. Through interviews and modeling, this thesis shows that bike-sharing should be treated as a form of public transit and will offer tools to help plan and understand how bike-sharing systems can complement existing public transit networks. In order to do so, this paper uses the City of Boston as a case study and, in particular, evaluates the Boston Bluebikes system using Boston Public Schools (BPS) teachers as a proxy for potential commuters to non-traditional destinations that may not be serviced by public transit. Public transportation networks are traditionally planned as hub-spoke networks, assuming that commutes will begin from suburbs in the periphery and end in urban Central Business Districts (CBDs). Schools, however, are geographically distributed around residential neighborhoods, which means that BPS teacher commutes would not be between suburbs and CBDs but rather would be between residential neighborhoods, rendering them as non-traditional commutes. [8]

As the City of Cambridge offers free Bluebikes subscriptions to city employees, including public school teachers, so the City of Boston could implement such a policy to incentivize bike-sharing. [9] Further, since schools, particularly in Boston, are located in non-traditional locations and are driven by communities, such commutes would be non-traditional commutes. However, there until now existed no method to clearly evaluate the efficacy of such a policy.

This thesis also presents BikePath, a simulation model that effectively visualizes, tracks, and follows the routes that teachers would potentially use, as well as model van-based redistribution for bikes around the city. This thesis shows that the Bluebikes network will likely be able to provide enough bikes in the right places for Boston Public School teachers with an initial distribution of bikes if the network were balanced efficiently throughout the day.

This thesis further uses cell-phone GPS tracking data to identify locations with heightened demand for transportation by presenting a method to identify trips. In doing so, this thesis presents a method for identifying a more effective distribution of bike-sharing stations based on the density of identified trips and expands this to evaluate the efficacy of bike-sharing stations placed at specific locations, in this case Boston Public Schools.

Informed by literature and interviews with bike-sharing operators, this chapter beings by exploring the importance of equitable transit planning and the role that interest groups play. Then, it dives into the values and pitfalls of bike-sharing programs. Finally, it concludes by claiming that bike-sharing must be treated as a form of public transit.

Necessity of Equitable Transit Planning

Value of Equitable Transit Accessibility

Defining access to transit is a contentious topic with several useful key metrics. Several factors influence this including proximity to transit, quality of walking and biking connections, parking, and the type and amount of transit offered at a given point. [10] Most existing aggregate metrics try to take into account the spatial and temporal availability of transit, basing access on the proximity of stations to origins and destinations, the frequency of service, and the service hours. [11] Some also account for the presence of pedestrian access and wait times. [12] The Local Index of Transit Availability score measures transit access through route coverage, frequency, and vehicle capacity. [13] Notably, none of these metrics include equity or transit dependence, although some cities have begun optimizing routes to take into account the potential cost of ridership.[1]

Nevertheless, cities with effective and equitable public transit systems, namely buses and rail, have been shown to be more diverse in terms of income and race. [14] In many cases where transit is not sufficiently distributed around a city, however, this diversity is replaced with displacement and gentrification in transit rich neighborhoods. Proximity to transit is one of the main causes of increasing property values. Wealthier tenants move into transit rich neighborhoods, bringing with them increasing car ownership, and, as a result, potential transit riders are crowded out by car owners. At the end of the day, transit stations do not reach their full potential. Pollack et al. describe this as a cycle of unintended consequences. [15] As incomes and ages increase, the probability of using automobiles rises in conjunction, while living in denser areas has a negative effect on income and positive effect on automobile usage. [16]

The lack of effective public transportation is a major factor in the lack of upward mobility. Chetty et al. show that upward mobility is inversely correlated with commute times and urban sprawl, [17] while Levitas et al. show that the lack of mobility creates barriers for lower income groups as they are unable to access resources and participate in community activities. [18] The lack of transit planning for such communities aggravates latent issues. Lower income and transit dependent communities rely on public transportation disproportionally and have lower vehicle ownership rates. Lacking alternative means of transportation limits accessible job opportunities, propagating the feedback loop. [19] In fact, the typical job is only accessible by transit to only 27% of the workforce within 90 minutes, and accessibility is worse in suburbs

[1] Interview with Laurel Paget-Seekins - MBTA

where transit coverage is poorer. [20] As sprawl rises, and the poor as displaced to lower-density neighborhoods, disadvantaged groups face further spatial barriers in accessing job centers. For city residents, access to transportation is shown to have a stronger influence on job access than actual spatial proximity to those jobs. [21] Improving access to transportation has been shown to alleviate the spatial distribution of poverty and create more equitable neighborhoods. [22] Further, access to subsidized transit has experimentally facilitated job search opportunities and intensity, showing that the lack of transit depresses job opportunity. [23]

Concerns with Bicycle Infrastructure

It is not clear whether cycling could be an alternative equitable transportation mode. Bicycle infrastructure can systematically lead to gentrification and displacement for non-white races, as it is primarily used by wealthy white males. [24] In fact, in cities like San Francisco, young tech professionals (like the author of this thesis) seek certain lifestyles and expect specific requirements to be met, which includes safe bicycle infrastructure, often crowding out infrastructure development for lower income groups. That is, investment in bicycle infrastructure disproportionately benefits the wealthy, reducing available funding for other forms of transit. [25] When bicycle infrastructure does exist in lower income communities, it is used. However, it is unclear whether bicycle infrastructure is used equally amongst various demographics. In Brooklyn, NY, riders on bicycle infrastructure in the area were 54% non-white and 80% male, with bicycle riders even finding better health outcomes. Although diverse, these proportions are not representative of the demographics of Brooklyn. [26] Further, cultural and physical constraints mean that women and inexperienced riders, often from lower income backgrounds, find infrastructure to be unsafe or uninviting. Wheeler et al. find that such cyclists require longer times to cross intersections at traffic lights, even with bicycle infrastructure. [27]

Unfortunately, analyses of docked bike-sharing networks show that the networks are also primarily used by white, upper-class residents. Individuals of color are highly unlikely to use bike-sharing networks, even when controlling for income. In Washington, DC, only 18% of high-income people of color have ridden bike-sharing systems, while 29% of high-income white residents have. [28] In New York, Babagoli et al. showed that Citi Bike stations were primarily located in low-poverty census tracts, even throughout expansion periods in the mid 2010s. While cycling rates have increased across racial and ethnic groups, income segregation disallows potential riders from having access to the network. Further, when controlling for spatial equity, factors such as cost, required credit or debit cards, and lack of familiarity reduce bike-sharing accessibility to lower income communities. [29]

As Harvard professor Anne Lusk states, even though most cyclists under the income range of $50,000 are non-white, infrastructure is not designed for those neighborhoods, often cutting corners and costs. Lower-income residents are more likely to get tickets for unlawful riding and are more likely to be targeted for bike-related crimes. Cities could work to build sufficient, safe bike networks for these neighborhoods. [30] Often riders have financial barriers, are afraid to ride, or simply do not know how to ride bikes. Offering cash payment systems and education programs that teach residents how to use bike-sharing programs could help incentivize ridership. [31]

Political Stakeholders in Transit Planning

As with any policy, there are several stakeholders that play important roles in local transportation planning. In the seminal work *Who Governs?*, Robert Dahl argues that the power dynamics in local governmental policy processes are such that power is dispersed amongst active groups who are willing to assert their views. While the most citizens are relatively apathetic, some interest groups emerge who actively will push for certain policies that are particularly important to them. As Dahl writes, "the political stratum is easily penetrated by anyone whose interests and concerns attract him to the distinctive political culture of the stratum." (92) Particularly at the local level, interest groups can have significant impacts on policy. [32]

In studying the importance of interest groups on local policy, Cooper et al. find that business associations and neighborhood associations have some of the largest levels of influence on local policy, along with cultural organizations and unions. [33] As a result, historically, policy decisions have been driven by business groups and homeowners. With a history of institutional racism, these interest groups have helped push transportation policy and urban planning towards a low-density, land-oriented planning approach that reduced the likelihood non-white Americans could move in and also increased property tax collection. Instead of expanding their dense cores after World War II, American cities de-densified, with broad populations out in the suburbs. These populations then continued to exert pressure on planning authorities. [34] Transportation projects that cities take on will primarily be focused on building ways for suburbanites to commute to the city rather than intra-city transit projects as building highways and commuter rail is often just easier. [35] However, as a result of these policies, even though low-income residents would benefit more from public transit subsidies, Iseki and Taylor find that transit "the benefits of subsidies disproportionately accrue to those least in need of public assistance". [36]

As localities grow more organized and educated on an infrastructure project, they are more and more likely to oppose them. Groups known as NIMBYs (Not In My Backyard) are more likely to form, reducing investment in transportation in general. [37] NIMBYs are primarily concerned about threats from "undesirables", given the "othering" of transit. NIMBYs cite potential increases in crime and decreases in the quality of life and, as a result, lower property values. Opposition increases when citizens feel as though they are not involved in the planning process. Such frustrations, as Dear writes, makes it impossible for cities to construct vital facilities. [38] Opponents of transit often paint transit users and transit dependent communities as communities that are “very different from them in status, ethnicity, and even morality”. This otherization, along with a general sense of anti-urbanism, begets a strong negative sentiment around development in general, slowing transit development and construction. [39] Much of this anti-urban sentiment may stem from racial prejudices and, in particular, an ideal of separating oneself from the “others” around one in what has been termed spatial “secession”. [40]

Further, in transportation planning, equity is often relegated to one criterion in a slew of criteria, which ends up being insufficient. [41] Such decisions are colored by local community engagement, but this can be infeasible or unrepresentative of the realities of larger populations. In particular, people of color and lower income communities are disproportionally left out of public involvement engagements. [42] And, access has been notably decreasing in some communities, such as in Portland, OR, where residential patterns are rooted in discriminatory real estate practices historically, which have persisted till now. [21] Luna writes that these tensions are exacerbated by the lack of representation, with white, suburban districts being overrepresented in Metropolitan Planning Organizations (MPOs), like the Metropolitan Area Planning Council, where the transit authority disproportionately represents white resident. Given its one government, one vote system, white suburbs are over-represented. There are inherent tensions in transportation interests between the urban core and suburban communities, as some are automobile-dependent, while others are transit-dependent. Racial segregation and geographic divide exacerbate these issues, particularly as transit agencies face declining revenues, escalating costs, and mounting debt. [43] Often decisions are made in political environments in order to maximize profits for developers or other capital interest groups, which further removes the local community from the requirements. [44] Matricardi points to grassroots efforts from transit dependent and local communities in New York and Atlanta as examples of communities rallying and still failing to advocate effectively for themselves. [45] Certain communities lack the voice and tools to advocate for improved transportation options.

Figure 1. The MBTA public transportation network

For these reasons, public transit routes are generally planned around the hub-and-spoke model. These are designed to get commuters from the suburbs into downtown for work. Figure 1 depicts the Boston MBTA public transportation network, clearly showing how commuter rail and rapid transit feed into three main hubs in downtown Boston: North Station, South Station, and Downtown Crossing. The intermediate routes are connected to each other via buses with a clear one-seat policy, which means that no transfers are required to get from popular origins to popular destinations. [46] However, MBTA bus service is notably infrequent and, worse, unreliable. [47] While its reliability has since risen 10% from a low 65% in 2017, there remains a space for consistent, granular transit routes. The MBTA's own reanalysis of its Bus routes noted that access to public transit has been poor in the lower-income Boston neighborhoods of Roxbury, Dorchester, and Mattapan, including limited access to/from high-demand areas like Kendall Square and the Seaport District. [46]

Transportation planning is affected significantly by the Spatial Mismatch Hypothesis, that racial segregation has pushed job centers out from the city into the suburbs. [48] Sprawl has been shown to reduce upward mobility from a direct effect on job accessibility, significantly mediated by income segregation. [49] Even as dense, urban neighborhoods are renewed and residents return to cities, this gentrification and "revitalization" has attracted high-income households to previously low-income neighborhoods, changing the dwellings and changes in lifestyles. This has led to negative externalities of traffic congestion, increased commute times, and displacement. [16]

Proximity to public transportation can be vital to social mobility, and thus, the importance of transportation equity cannot be overstated offering equal opportunity to particularly transit-dependent communities. Fan et al. note that proximity to light rail and bus stations is associated with significant increases in accessibility to low-wage jobs. [50] Further, Ruiz et al. find that simply increasing the frequency of buses can have significant impacts on social equity, without significant cost increases. [51]

Worse still, Linovski et al. find that in Canadian cities, equity is rarely taken into account when planning networks as the definition of transportation equity can be unclear. Rather than focusing on transit-dependent commuters, cities focus on distributing transit equally around the city, which may not benefit transit-dependent communities as much as may be required. Transit is viewed as a tool to revitalize neighborhoods and increase development, rather than simply a form of transportation, which misaligns the incentives amongst political stakeholders. Politicians, private developers, and planners alike often hope to build up the city. [52] Thus, there remains a tension amongst politicians, planners, developers and grassroots communities.

Interviews with Operators

In order to understand the current state of bike-sharing in North America, over the past few months, I have conducted over twenty interviews with bike-sharing officials at innovative micro-mobility providers and municipal governments from around the country including: Cambridge, Boston, Central Florida, Las Vegas, Portland, San Francisco, Detroit, Salem, Minneapolis, Pittsburgh, Omaha, Austin, Washington, DC, and Boise. These municipalities were chosen for myriad reasons. San Francisco, Washington, DC, and Portland were targeted as they are all in part operated by Lyft, which also operates Boston Bluebikes. Las Vegas, Omaha, Boise, and Salem were chosen as they have smaller networks in areas with few alternative transit options. Finally, Pittsburgh, Austin, and Minneapolis were chosen as they also have relatively robust transit networks, and also have competing micro-mobility providers. In all of these interviews, themes of unsurety, misaligned incentives, and concerns about "communities of concern" emerged. Simultaneously, the officials celebrated how effective current planning strategies have been, even if many of them are bespoke solutions, difficult to generalize out of specific neighborhood contexts.

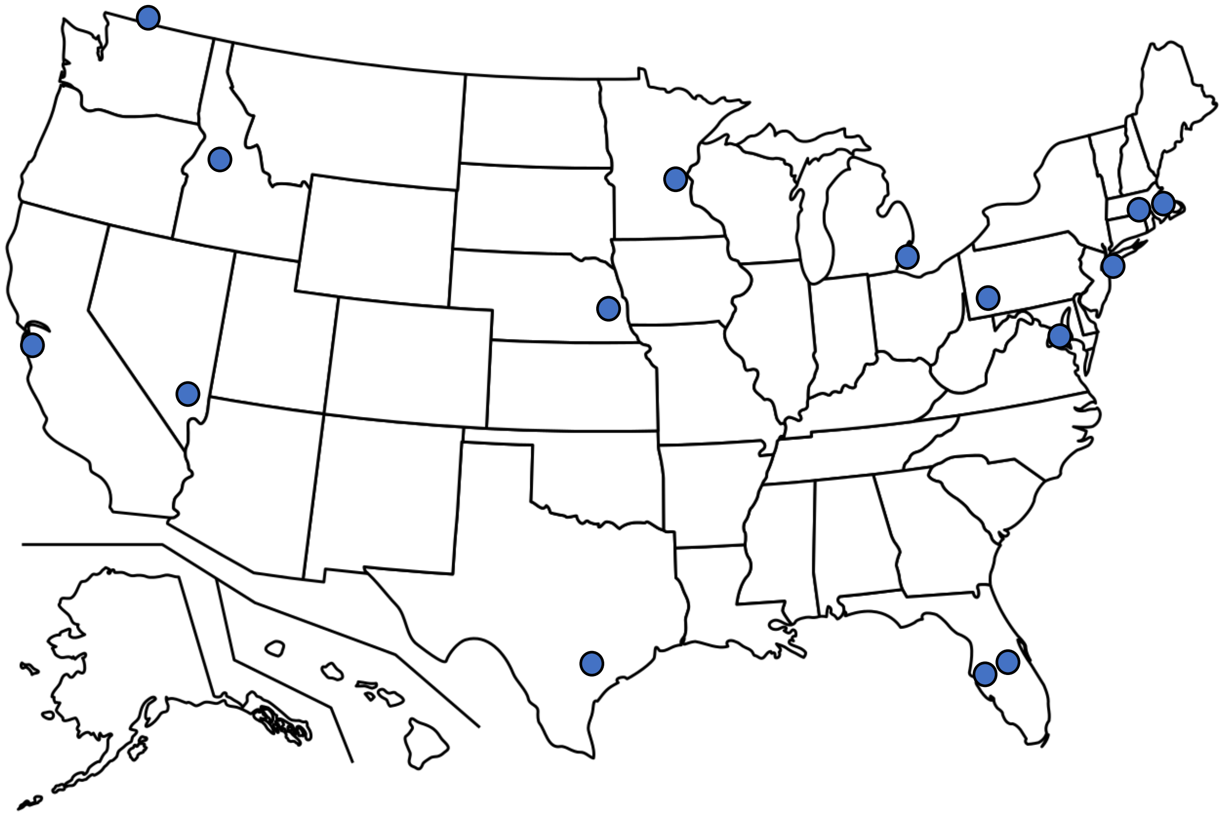

Figure 2. Operators and Cities Interviewed

Comment	Cities
ADA Issues with Dockless	Boston, New York City, Washington, DC
App Opens for Conversion Operations	Boston, New York City, Washington, DC
Bike Lanes Planning	Boston, New York City, Washington, DC, Minneapolis, New Haven, Hoboken, West Palm Beach, New Rochelle
City Does Planning	Tampa, Orlando, St. Petersburg, Vancouver
Clustered Start-Stops for Planning	Tampa, Orlando, St. Petersburg, Vancouver, Las Vegas, Los Angeles, Philadelphia
Community Education Required	Las Vegas, Los Angeles, Philadelphia, Portland, Pittsburgh
Crime Problem	Tampa, Orlando, St. Petersburg, Vancouver
Demand Heatmap/Hot-Spot Planning	Las Vegas, Los Angeles, Philadelphia, Portland, Washington, DC
Divide into Grid Planning	Boston, New York City, Washington, DC, Boston
Dockless Requires Regulation	Salem
E-Bikes Necessary	Boston, New York City, Washington, DC, Minneapolis

Equity Analysis/Demographics Planning	Boston, New York City, Washington, DC
GIS Modeling Planning	New Haven, Hoboken, West Palm Beach, New Rochelle
Government Regulation Unnecessary	Washington, DC
Heat/Sweating/Weather Issues	Tampa, Orlando, St. Petersburg, Vancouver, Las Vegas, Los Angeles, Philadelphia, Austin
Heavy Bikes	Tampa, Orlando, St. Petersburg, Vancouver
Helps Transit Deserts	New Haven, Hoboken, West Palm Beach, New Rochelle
Hybrid Bike-Sharing	Tampa, Orlando, St. Petersburg, Vancouver, Portland, Boise, New Haven, Hoboken, West Palm Beach, New Rochelle
In-House Rebalancing Software	Salem, Boston, New York City, Washington, DC, Pittsburgh
Job Density Planning	Boston, New York City, Washington, DC, Boston, Salem, Detroit, Boise, New Haven, Hoboken, West Palm Beach, New Rochelle
Lack of Actual Data	New Haven, Hoboken, West Palm Beach, New Rochelle
Need Dense Coverage of Network	Washington, DC, New Haven, Hoboken, West Palm Beach, New Rochelle
Not Enough Data Issue	Portland
Not enough bikes	Tampa, Orlando, St. Petersburg, Vancouver
Not enough trips per bike	Portland
Parking Access an Issue	Boston, New York City, Washington, DC
Physical Observation/Experience Planning	Las Vegas, Los Angeles, Philadelphia, Salem, Lincoln, New Haven, Hoboken, West Palm Beach, New Rochelle, Austin
Poor Government Relationship	Portland, Salem, Pittsburgh, Boise, Washington, DC
Poor Maintenance Issues	Boise
Population Density Planning	Las Vegas, Los Angeles, Philadelphia, Boston, New York City, Washington, DC, Salem, Detroit, Boise, New Haven, Hoboken, West Palm Beach, New Rochelle
Public/Community Outreach Planning	Tampa, Orlando, St. Petersburg, Vancouver, Boston, New York City, Washington, DC, Portland, Pittsburgh, Lincoln, Detroit, New Haven, Hoboken, West Palm Beach, New Rochelle
Redistribution Ratio Operations	Tampa, Orlando, St. Petersburg, Vancouver, Las Vegas, Los Angeles, Philadelphia, Austin, Portland, Tampa
Replace Bus Trips	New Haven, Hoboken, West Palm Beach, New Rochelle
Right of Way Planning	Detroit
Safety Issue	Salem
Scooters Cannibalized Trips	Boise, Austin
Self-Redistribution Works	Washington, DC
Station Density (300-500m) Planning	Boston, New York City, Washington, DC, Portland, Tampa, Orlando, St. Petersburg, Vancouver

Station Downtime/Outage for Reliability	Las Vegas, Los Angeles, Philadelphia, Pittsburgh, Lincoln
Stations/Docks Necessary	Minneapolis
Topography Planning	Boston, New York City, Washington, DC
Traffic Congestion Reduction	Boston, New York City, Washington, DC, Boston
Transit Proximity Planning	Boston, New York City, Washington, DC, New Haven, Hoboken, West Palm Beach, New Rochelle
Transportainment	Tampa, Orlando, St. Petersburg, Vancouver, Las Vegas, Los Angeles, Philadelphia, Salem, Boise
Unpredictable Redistribution	Tampa, Orlando, St. Petersburg, Vancouver
Use Qucit	Tampa, Orlando, St. Petersburg, Vancouver
Van Access for Stations Necessary	Boston, New York City, Washington, DC
Wealthy, Young, White Ridership	Las Vegas, Los Angeles, Philadelphia, Boise

Figure 3. Overview of Comments from Interviews

Benefits of Bike-Sharing

Micro-mobility offers an incredible opportunity for cities to avail health, environmental, and economic benefits while increasing public transportation options for commuters. Almost 500 cities have already built up such systems, since the first modern network, Velib, in Paris, after the storied 1965 creation of the Amsterdam Witte Fiesten bike-sharing system. [53] Figure 4. Shows the proliferation of bike-sharing in the United States.

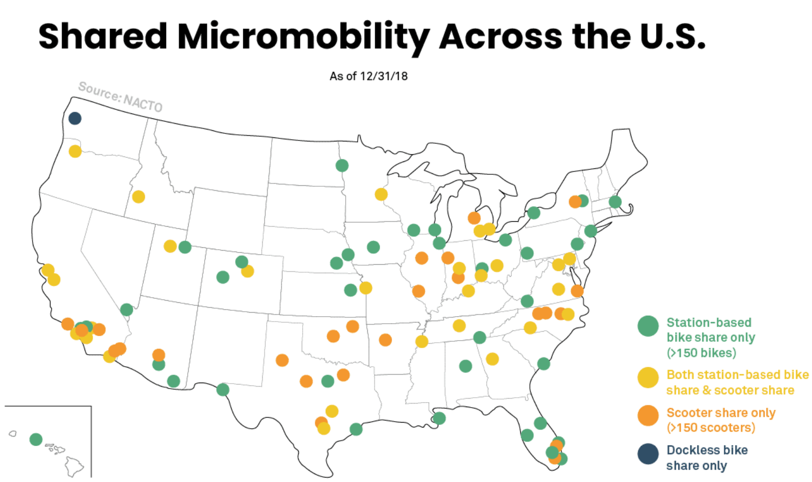

Figure 4. A NACTO map of bike and scooter sharing systems in the US as of 12/31/2018 [54]

There are two main types of bike-sharing: "docked" and "dockless". Docked bike-sharing is station-based, which means that bikes are docked at stations in clusters of 5-20 bikes per station around a city. Bikes must be picked up and dropped off at stations. Dockless bike-sharing systems, on the other hand, do not have stations. Bikes can be picked up and dropped off anywhere within a pre-specified region as bikes are GPS-tracked. Limited fixed physical infrastructure is required for dockless bike-sharing. [55] For the purposes of this analysis, the focus will primarily be on docked systems as the Bluebikes bike-sharing network in the City of Boston is a docked network.

As a form of "Active Transportation", defined as any mode of transportation that is self-propelled and human-powered, bike-sharing offers significant health benefits. [56] An analysis of Barclays London Cycle Hire found a significant reduction in transportation related injuries throughout the city, although most cycling trips replaced walking or transit. [57] A larger study of twelve European cities found a direct relationship between saving lives and bike-sharing due to the reduction in car-based trips, which helped increase bicycle safety, reduce pollution, and generally increase rider health. [58] However, health benefits may be overstated for women as women are more at risk for injury in cycling accidents. [59]

Further, by reducing trips taken in private vehicles, bike-sharing can offer significant environmental benefits. In DC, such networks resulted in an upwards of 4% reduction in traffic congestion in neighborhoods near the Capital Bikeshare stations. [60] In Barcelona, significant reductions in pollution and increases in road safety were noted. [61] In Shanghai and Denver, significant reductions in CO_2 emissions were noted, with Denver shedding over a million tons of

CO_2 emissions due to its B-Cycle network.[2] [62] That said, the effect on the environment could be overstated. In Vancouver, for example, reductions in CO_2 emissions were so minute, that the city will no longer tout that as a benefit. [63] Further, it is unclear whether the benefits of active biking can simply be ascribed to bike-sharing itself or broader trends influencing an increase in bicycling as a whole, including improved bicycling infrastructure like bike lanes. [64]

Bike-sharing even offers economic benefits both to local businesses and individuals. In Dublin, bike-sharing reduced the density of economic activity, yielding an increase in economic activity throughout the city. [65] In Washington, DC, a survey of riders found that 20% of local businesses reported increased income due to the introduction of the Capital Bikeshare program and 61% reported an improvement in their local neighborhood with only 1% and 2% of businesses reporting negative effects, respectively. The same study found that 25% of riders primarily used the bike-sharing network as it was cheaper than their regular commute and 73% reported that it was faster than their regular commute. [66] Sobolevsky et al. broke down the costs and benefits for the CitiBike network in New York City, noting that the main benefits came from reduced emissions from saved gas, increases in economic activities, and health benefits from increased activity. They found a benefit-cost ratio between 3 and 8, depending on the subscription fee, coupled with a 700-ton reduction in CO_2 emissions. [67]

Broadly, bike-sharing trips in Boston complement walking, generally serving different purposes as bike-sharing trips are generally much longer. Most walking trips are short and within neighborhoods, while most bike-sharing trips are either commuting from residential areas to commercial areas or are connected to major transit hubs. [68] This lines up with previous studies

[2] Incidentally, the B-Cycle system has recently been shut down and is slated to be replaced with another provider: https://www.thedenverchannel.com/news/local-news/b-cycle-ends-operations-in-denver-as-city-looks-for-replacement

that find that bike-sharing often works in tandem with, or in lieu of, existing transit options. Martin and Shaheen find in Washington, DC and Minneapolis that bike-sharing enables increased access to transit for those living in less dense areas but replaces bus trips for those living in denser urban cores. [69] With a longitudinal study of 22 American metro areas, Graehler et al. show an increase in both heavy and light rail, but a 1.8% decrease in bus ridership. [70] This implies that bike-sharing can be leveraged to replace bus routes as a last-mile connectivity option, particularly to/from rail stations. Interviewing an official in Hoboken revealed that bike-sharing can help alleviate transit deserts, offering more options to commuters and expanding the reach of existing transit options, like New Jersey Transit, going so far as noting that such trips would often replace bus trips.[3] With significant health, environmental, and economic, bike-sharing can act as an effective form of transit somewhere in between walking and buses, ultimately supplementing existing transit networks.

Struggles with Bike-Sharing

Navigating and managing a bike-sharing network is, of course, not without its difficulties. Docked bike-sharing systems, in particular, suffer from hardware limitations that can complicate access to bike-sharing networks broadly. In particular, there are two main issues that a bike-sharing rider will inevitably face. Either the station that the rider hopes to pick up a bike from will be completely empty, forcing the rider to find another station to pick up a bike from or to drop the trip altogether, or the rider will find that the station that is nearest to their ultimate destination is full, pushing the rider to find another nearby station to dock the bike at. Mitigating these possibilities, collectively referred to as “outages”, is the main responsibility of any bike-

[3] Interview with planner in Hoboken

sharing operations team outside of vehicle and station maintenance. Bike-sharing operators work to balance their networks throughout the day with a process known as “rebalancing”. Operators will use vans or trailers to move up to 30 bikes around their city to balance based on demand. [71] This can be an expensive, labor-intensive task that cuts into the potential profitability of these networks.

Figure 5. The Boston Bluebikes System [72]

Infrastructure Bottlenecks

Interviews with officials from around the nation indicate that the unit economics of bike-sharing need to be improved to increase its feasibility, with many decrying that the system is imbalanced and unsupported by current infrastructure bottlenecks, particularly as infrastructure is controlled by city limitations. Networks seem as though they are both oversubscribed and undersubscribed simultaneously. At peak hours, in the Boston Bluebikes system, around 30% of potential riders are either not able to pick up bikes or are not able to drop their bikes where they would like. Goh and Yan measured this effect by creating rider agents that pick up a bike from a dock using a ranking-based choice model based on ridership data and rider-expressed rankings of stations based on proximity, access to destination, and other exogenous factors like weather. This analysis further shows how network effects absorb supply shocks to the system, particularly as stations proximate to each other (such as South Station or Kendall Square) can handle increases in demand from stations that are stocked out outside of the system. [73] Some parts of the networks are heavily utilized, while others are rarely utilized at all. In this imbalance, cities often find metrics difficult to measure and quantify and often rely on individuals' "feels" on city networks. In Las Vegas, for example, 48% of the bike stations that had been constructed had to be relocated in order to induce increased ridership at those stations. Moving these stations by just a block increased both ridership and revenue. However, these stations were moved primarily by the way of "gut feelings" as opposed to a data-driven approach. While the relocation was clearly successful, measuring, quantifying, and generalizing such strategies can prove to be difficult.[4] Ridership is not always low, but still emerges as a primary concern for micro-mobility operators.

One potential solution would be to infuse more bikes into the system to ensure network availability. There are about 3,300 bikes in the Boston Bluebikes system, however, shockingly, at any given time, at maximum, around 300 are ever being ridden. This means that fewer than 10% of the bikes are ridden at any given time, even in peak ridership areas. [74] In Portland, this number may rise to around 40%, or about 6 trips per bike per day, on days of special events and particularly nice weather. However, such days are exceptions, with most days maintaining an average usage of around 10%, or 1 trip per bike per day. Such a low utilization rate particularly pushes the idea that there may be a sufficient number of bikes in the system, particularly as Portland estimates that their system cannot be profitable until usage is consistently 4-5 trips per bike per day.[5] Bikes generally idle all day.

[4] Interview with operator in Las Vegas
[5] Interview with operator from Portland

This research lends credence to the idea that maximizing individual bike usage may be more effective in terms of cost-maximization for cities themselves. Further, it may seem that purchasing more cycles is the answer, but each bicycle can cost $1,200 each and adding docks can cost $50,000 each, which means that costs can escalate greatly to increase capacity. [75]

Interviews reveal that often cities own their entire systems, limiting the expenditure and subsidies available for investing in the system as the funds must come from miscellaneous transit outlays rather than dedicated road infrastructure budgets or large-scale venture capital funds.

This is particularly salient in smaller networks in smaller cities. In Boise, for example, operators referred to the network as the “red-headed step-child of the Valley Regional Transit Authority”, concerned about how few resources are devoted to the network, bottlenecking the growth of the system. Boise’s network primarily relies on government funding, often supplemented by federal and state funding, which is generally provisioned as grants. In order to combat resource shortages, cities will come up with cost-effective workarounds, such as Boise creating stations out of pre-existing bike racks by simply geo-tagging them and labelling them on the map, such that riders can dock bicycles there without being charged a fee for not docking at an official station.[6]

Operations

In Boston and San Francisco, rebalancing is driven by “rideability”, which is the number of available bikes to available docks at a bike station. The value is calculated for every bike station in the system, and target values are set for each individual station depending on demand. Bikes are rebalanced around the network using vans that are able to carry around thirty bikes.

[6] Interview with an official in Boise

These vans are routed around the city primarily focused on taking bikes away from full stations (stations that no longer have any open docks; stations where the rideability score is too high) to stations where there are not enough bikes (stations with too many open docks; stations where the rideability score is too low). Boston and San Francisco generally target a rideability score of 0.6, which means a little less than half of their docks are empty.[7] In such cities, of course, there are stations that will inevitably "self-rebalance", which highlights the importance of understanding the network effects of how bikes are distributed across them. Bikes in high-demand areas will sometimes return to those areas throughout the day, particularly in mixed-use areas surrounded by residential and commercial areas alike.[8]

Medium tier networks, such as those in Austin, Hoboken, and Los Angeles, are able to use their experience and visual data analytics to rebalance their networks. Operators will pore over ridership in previous months and years to estimate how many bikes may be useful at stations throughout the city. They will also calculate rebalancing ratios similar to those in larger cities, generally looking to have about half of their docks free. That said, operators in the field may make gut-feel decisions to override those targets based on their intuitions.[9] In Pittsburgh, the operator described rebalancing as a balance between data-driven predictions and their own knowledge of how the city operates. Of course, this knowledge varies amongst their team, so often inconsistencies may occur in bicycle placement.[10]

Networks in smaller cities are craftier and nimbler. In Las Vegas, given that there are only 21 stations, limited by their Regional Transportation Commission, maintenance and

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[7] Interviews with operators in Boston and San Francisco
[8] Interview with planner in San Francisco
[9] Interviews with operators in Austin, Hoboken, and Los Angeles
[10] Interview with operator in Pittsburgh

rebalancing can be done on an ad hoc basis. The network does not have to be managed by a team of rebalancers and mechanics, but rather is managed by a single person who hops in his van when bikes need to be collected or moved around. The flip side is that ridership is likely hampered by a lack of supply.[11] The operator of the small operations in Tampa, Orlando, and St. Petersburg said that ridership was artificially held back by the lack of capital to expand their networks. The local transportation authorities were not willing to invest in the development of bike-sharing networks or other cycling infrastructure.[12]

Insufficient Planning Methods

Current planning methods, such as those recommended by the Institute for Transportation and Development Policy, are broad and based primarily on population density. Interviews with officials around the country support this thought approach, with many identifying that their planning processes focus on mapping population centers and job centers on top of current transit networks, bike infrastructure, and transportation patterns. These areas are often job-centers, commercial business districts, and tourist attractions or other points of interest like schools and large businesses. [13] In the smaller cities of Tampa, St Petersburg, Las Vegas, and Orlando, along these lines, it is clear that most rides originate from a locus of 10% of stations, often clustered in the same area. In larger cities, like Washington, DC and Boston, there are generally multiple ridership generating centers, reflecting multiple residential, leisure, and commercial centers.[14]

Generally, bike-sharing systems are planned simply by identifying locales with sufficient density. Demand models are generated by estimating factors such as the Price-Elasticity of

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[11] Interview with operator in Las Vegas
[12] Interview with operator in Tampa, Orlando, and St. Petersburg
[13] Interviews with operators in Portland, Boston, and Las Vegas
[14] Interviews with planners and operators in Washington, DC and Boston

Demand, for which uptake rate is often a proxy. In general, the Institute for Transportation Development Policy recommends about 10-30 bikes per 1000 people, and 2-2.5 docks per bike. These somewhat arbitrary metrics are based on the idea that bike-sharing docks should generally be half full such that riders are always able to dock or park their bike comfortably. [76]

In many cases, planners break down cities into “wards” that each must be provided a station. The logic here is that every ward must have a station in it to ensure a dense network where potential riders do not have to travel too far to be able to access a station. This set up varies in every city. New York City was broken up into 200-meter grid sections where docks were required to be placed in each section; San Francisco was broken up into 1000-feet grid sections where a bike must be available within walking distance (about a quarter mile) of any position in the city. In Portland, the city was broken up into about 100 wards and each ward had three sites identified as potential locations for bike stations. Each of those three potential station locations was then vetted based on several criteria, primarily along the lines of the number of houses nearby, the quality of the local bike-infrastructure, distance from transit lines, and curb use.[15] Stations are also vetted for access for rebalancing vans, to ensure that vans have a nearby location where they can park and load/unload bikes to the stations.[16]

Planning Around Trip Generators

Many systems are also designed around the express purpose of “transportainment”. As a planner from Tampa, St Petersburg, and Orlando explained, a significant proportion of riders will use the network not as a transit tool, but as an entertaining form of transportation to get around the cities. For this reason, many smaller networks in particular, such as Boise, Las Vegas, and

[15] Interview with operator in Portland
[16] Interview with operators in Paris and Tampa

the Floridian networks, will plan networks to optimize for points of interest, tourism, and entertainment with stops at dedicated hotspots like restaurants, along park routes, and large parking lots.[17] In Boise, overall ridership is primarily clustered around the Boise River Greenbelt, a 25-mile bike path around the Boise River, and thus much of the network is planned around the Greenbelt.[18] Similar observations were made in the larger city of Portland where planners note that such rides often will start and end at the same station, making it difficult to track exactly where the riders went exactly. However, since the rides start and end at the same station, the rides are most likely for leisure. Weather ends up being a major factor for these systems, in particular with concerns about sweat dissuading riders from commuting in the mornings. The cooler evenings often have higher ridership in such networks.[19]

While many initially assumed that bike-sharing networks will primarily supplement traditional transit systems, such as buses and metro-rail, smaller networks in cities without strong rail transit networks find that ridership is primarily centered around point-to-point transit systems. In other words, bike-sharing is not a last-mile connectivity solution in cities without rail networks. In Las Vegas, since taking the bus seems to have a stigma, users rarely use the infrastructure specifically constructed for bus transfers at transit centers; most rides do not start or end at transit stations.[20] Similarly, in Boise, while ridership is high at stations near transit centers, this is primarily because those transit centers are in dense neighborhoods with several ride-generators. In fact, the bike station nearest to the transit center, is not as frequented as others in that area.[21] Even though Hoboken has a relatively small bike-sharing network, its most

[17] Interview with operator in Tampa, St. Petersburg, and Orlando
[18] Interview with operator in Boise
[19] Interview with operator in Portland
[20] Interview with operator in Detroit
[21] Interview with operator in Boise

frequently used stations are near the New Jersey Transit rail stop. This indicates that the size of the network is not the predictor, but rather bike-sharing supplants the smaller trips that people would have otherwise made on buses and supplements trips that people will continue on rail.[22]

In larger cities like Boston, however, planners have found transfers to the transit network to be quite frequent, often as a primary use case of the Bluebikes bike-sharing network. Even in this case, the bikes are replacing bus trips that could have acted as feeders to the T metro-rail network in the city.[23] Other large cities like Washington, DC and New York City report similar observations.[24] While nearness to other transit hubs is used as a primary metric for planning bike-sharing stations, they will likely only be trip-generators if they are rail stations.

Local Community Involvement

Cities will further then incorporate different forms of community-driven information such as having conversations with locals on where exactly they would like to go and why they would like to go there. To that end, conversations will involve understanding the needs that current transportation methods fulfill and do not currently fulfill, which requires both accepting the wants of current residences as well as inferring where commuters and travelers may actually want to travel. Community residents often ask for specific alterations such as specific numbers of bikes or station locations. They may also demand bike infrastructure such as bike lanes and bike paths as a prerequisite.[25]

Feasibility studies from Wilmington, DE and Asheville, NC show similar approaches as well, but extend them to include community involvement. Wilmington used Facebook likes to

[22] Interview with operator in Hoboken
[23] Interviews with planners and operators in Boston
[24] Interviews with operators in Washington, DC and New York City
[25] Interview with operator in Boston

help rank which stations they should prioritize and used data on employment and population density, public attractions, transit, and minority population distributions to calculate a “suitability score” for stations to maximize equity and access. [77] Asheville similarly set out to balance maximizing ridership and coverage and created demand models based on proximity to population, employment, education, leisure, and commuting centers. [78]

The primary concerns of residents often come down to on-street parking in big and small cities. As planners from Lyft discussed, on-street parking is a free and unlimited, fully subsidized amenity for Boston residents, while Boston Bluebikes, although owned by the Cities of Boston, Somerville, Cambridge, and Brookline, is operated by Lyft and charges a fee. So, when bike infrastructure gets in the way of street parking, residents will, to say the least, complain.[26] When expanding the Boston Bluebikes system in 2019, the Boston Transportation Department held 42 public meetings in order to hear from various neighborhoods. [79] At the end of the day, as Laurent Mercat, Founder of French micro-mobility company Smoove, outlined, planning stations is more of a political decision than a planning decision, in particular when businesses get involved.[27]

Businesses often undervalue the economic value that bikes may provide. While research shows that replacing parking with bicycle infrastructure almost always increases consumer spending and traffic, [80] businesses generally chafe at the idea of supplanting parking spaces with bike infrastructure like bike lanes, bike parking spaces, and, in particular, docked bike-sharing stations. Businesses will complain that the stations block access to commuters, bring unwanted attention, or limit delivery options to the business. Such concerns need to be mitigated

[26] Interview with planners in Boston
[27] Interview with Laurent Mercat, founder of Smoove

and confronted by planners very directly in order to facilitate both community involvement with and usage of the bike-sharing systems.

Advocacy groups and public meeting attendees, however, can often misrepresent the demographics of a neighborhood. Einstein et al. find that attendees to such events are generally older, male, longtime residents. [81] In a subsequent study, they found that attendees are also predominantly white. In fact, in Boston, 95% of attendees were white. Attendees also tend to be NIMBYs, fierce advocates against any sort of development. [82] This could misrepresent the needs of a community, particularly in larger cities.

External Stakeholders

Along with local concerns, planners must take into account external stakeholders. The Bluebikes system itself is owned by a collaboration of the cities of Boston, Brookline, Cambridge, Everett, and Somerville. Thus, the infrastructure is municipally owned. However, the operations are outsourced to a private organization, Lyft, which owns and operates the app, rebalancing, and maintenance. Curiously, Lyft's ride-sharing operations may directly compete with its micro-mobility ambitions. While the actual contract is not in the public domain, a revenue share is discussed in the Request for Proposal that the City of Boston put out while implementing the initial bike-sharing system. The system's Title Sponsorship is health insurance provider BlueCross BlueShield, which led to the rebranding of the original moniker of Hubway to Bluebikes. Sponsors often expect certain numbers of bikes at stations near their locations which may imbalance bike-sharing networks.[28] Such a convoluted web is repeated throughout the country with municipal stakeholders.

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[28] Interview with planner in Boise

A significant portion of micro-mobility systems are also funded by venture capitalists (VCs) expecting a return on investment. Billions of dollars have flooded the micro-mobility space. Micro-mobility provider, Lime, has raised around $765 million for its scooter-sharing business, and it is but one of at least a dozen different domestic operators. [83] Lyft entered the bike-sharing space by purchasing Motivate for around $250 million. [84] Uber purchased bike-sharing company JUMP for $200 million. [85] Investors expect the movement of young professionals to cities to drive the growth in bike and scooter sharing and anticipate that upward price adjustments and system optimizations could yield significant profits. [86] This throws another wrench in the works: these companies need to make a profit. There is a tug-of-war amongst municipalities, communities, and private operators as operators strive for profits, municipalities hope for system-wide reliability, and communities focus on their own needs.

Bike-sharing is Not Profitable

Unfortunately, bike-sharing operations have not been raking in the fortunes that venture capitalists have expected so far. As Small writes, "even with a maximal level of ridership, cities typically need to find some way to subsidize a bike share system through corporate sponsorship, federal dollars, or both." The Pronto bike-share network in Seattle shut down in 2015 as ridership numbers were so low that even corporate sponsorships could not keep it afloat and the federal TIGER grant that the Seattle Department of Transportation had requested did not come through. [87] A similar story almost played out in Boise where over the course of these past few months, the Boise Greenbike network lost one of its main corporate sponsors and the Valley Regional Transit Authority had to bail out the network to help keep it afloat.[29] In recent months,

[29] Interview with operator in Boise

micro-mobility companies Lime, Zagster, and Bird have seen a string of layoffs and valuation cuts. [88] [89] Even in China, where cycling is a cultural staple and bike-sharing companies raised billions of yuan, almost every bike-sharing firm went bankrupt over the last four years. [90] As Shaheen et al. found, in a survey of all North American bike-sharing operators willing to offer data, only two reported making a profit (although most did not report operating costs). [91] Without the revenue to be self-sustaining, bike-sharing networks cannot cover costs and thus require subsidies.

Working with Communities of Concern

In the Boston Bluebikes network, the stations in the majority non-white Bowdoin have about a tenth of the trips of the majority white Oak Square neighborhood. [92] As of 2016, only 7.1% of African-Americans had access to bike-sharing in Boston, where as 42% of white Americans did. Only 14% of lower-income residents had access, while 18.6% of high-income residents had access. Boston showed a statistically significant disparity for race and income. This is paralleled across several cities in the US, except Washington, DC which has much more strict policy regulations for balancing bike-sharing placement. [93]

The City of Boston has a slew of data reporting mechanisms that keep track of system metrics such as ridership and reliability. [94] [95] Some governments, to maintain certain service levels throughout the city, mandate data reporting standards, fleet size minimums and maximums, and vehicle deployment numbers in certain neighborhoods. For example, in Washington, DC, underserved neighborhoods must always have pre-specified numbers of bikes available to ride. Cities also mandate reliability and maintenance standards for those neighborhoods. [96]

Additionally, Detroit, Portland, and Las Vegas have found success in bringing lower income residents onto their network through community outreach programs. The biggest issue that lower income communities face is the literal lack of access to stations as bike-sharing stations are often not located near enough to lower income communities. However, even when stations and bikes were available, three main issues emerged as barriers for access for lower income residents: 1) Inability to pay with bank cards; 2) Limited understanding of the way bike-sharing systems work; 3) Lack of safety throughout the local network. In order to combat these issues, Detroit, Portland and Las Vegas each have instituted unique strategies. In Detroit, representatives from the Detroit MoGo bike-sharing system partnered with local community leaders to help educate riders and offer heavily discounted passes to lower income riders with cash payment options. This has been shown to significantly increase ridership in Detroit, ensuring that educational programs and community-driven initiatives have helped funnel new users into the system, improving their physical, urban, and social mobility.[30] Similarly, in Portland, lower income residents actually see significantly higher trip rates than other members as many have grown to depend on the network. Biketown4All (Portland's discounted ridership pass for eligible riders) pass users generally ride up to five times a day as compared with the regular members' one ride a day. Planners ascribe this discrepancy to bike-sharing's utility across the city, with other options like ride-sharing available to upper income users.[31] In Las Vegas, certain lower income housing complexes are near some of the most popular stations in the entire network. Initially some of these stops were under-utilized, but Las Vegas set up multiple events where riders were offered free rides and were taught exactly how to use the

[30] Interview with operator in Detroit
[31] Interview with operator in Portland

system by members of their communities. Initial interest converted to actual memberships and ridership then grew organically through word-of-mouth for local riders.[32]

Unfortunately, some systems often are too small or resource-strapped to effectively pursue social-equity focused initiatives, even if they want to. Most smaller networks, particularly those that lack the backing of larger operating organizations, have poor data and metrics for measuring how many members of "communities of concern" their networks reach. While many deliberately quantify and track their efficacy in these fields, most are only able to count how many users of their discounted/free bike passes there are. Some are even unable to bring underrepresented riders onto their networks due to the lack of infrastructure and other resources. Even after Philadelphia's campaign to improve access by allowing cash payments and significant membership discounts, Caspi and Noland find, while controlling for factors such as transit access and bicycle lane access, that lower income neighborhoods still have not produced more trips. [97]

In order to get around the inability to bring users onto their normal bike-sharing network, operators in Boise are implementing novel, unique approaches. With retired bicycles acquired from Boise's sister bike-sharing network in Topeka, operators are setting up a bike-sharing "library" for Boise's homeless, so that they are able to travel and reach job opportunities with alternative mobility options.[33] While bike-sharing networks may not equitably reach all in cities, most municipalities are particularly concerned about ensuring equitable transportation access throughout their networks as a priority. Boston also has a history of working with communities, in organizing events centered around education, maintenance, and group rides. These, however,

[32] Interview with operator in Las Vegas
[33] Interview with operators in Boise

are often centered around current subscribers and frequent riders, rather than necessarily reaching communities of concern. Generally, this is left to the municipalities themselves to organize, rather than the Bluebikes network itself. [98]

Treating bike-sharing as another public transportation option, integrating it as an active and accessible solution could expand social mobility and transit options for communities of concern around myriad urban environments. Thus, effective planning mechanisms and tools are required in order to do so efficiently and equitably.

Policy Diffusion in Bike-Sharing

No one city is tackling bike-sharing on its own. Local governments around the nation and around the world are all working to bring mobility into the 21st century, to tackle social equity concerns, and to leverage new technology-enabled mobility options. Thus, local governments will look to each other and learn from each other, diffusing insights and learnings around the world. Gilardi et al. define “policy diffusion” as “the process by which policymaking in one government affects policymaking in other governments”. They write that as policies are adopted in some cities, they are perused and explored in other cities, often with different “policy frames”. Policy frames are defined as “the presentation or discussion of an issue from a particular view-point to the exclusion of alternate viewpoints”. [99] The way a policy is framed can affect how it is understood and adopted at the local level through the downstream stages. Local governments learn from previous policy frames and the implications of those frames and right size them for their own municipal goals. Thus, Gilardi et al. conclude that policy frames significantly impact the way policies are adopted and implemented in cities, finding that understanding the implications of a policy help highlight which concerns are more important and which are not. In this way, as policies diffuse, their policy frames grow more complex but also better defined.

[100] An incredible benefit of this model is that localities are less likely to succumb to one-size-fits-all policies. Local governments are more likely to pull policy ideas from cities that share similar characteristics and leverage local interest groups and stakeholders to shape the policy frame with which policies should be formed. [101]

When different policy frames are taken into account, explored policies change. These policy frames are influenced not only by internal factors, but also by external factors. As Johnson and White found in Kansas City, while transportation planners focus on automobile planning, when presented with the trade-offs of water quality and public health, their interest in sustainable transportation options increases. Peer cities and regional organizations are able to have significant impacts on policy decisions and priorities. [102] As a policy diffuses, it begins affecting conversations well before policies are even actively considered, shaping policy frames as well. [103] In this way, the outlooks that policy makers have on prioritizing and evaluating policies are shaped by the ramifications of those policies around the nation.

As Midlarsky noted, much of policy diffusion is centered around smaller cities copying larger cities. [104] Shipan and Volden find that, as a result, local governments for smaller cities have a significant disadvantage. While larger cities can experiment and deliberately enact policies, smaller cities are more likely to simply copy policies from larger cities and are less capable of learning from the policy choices and implications of larger cities. [105] Smaller cities may have fewer full time staff to explore alternative legislative options, or simply cannot afford to invest in exploring options; copying is easier and cheaper. [106] As Einstein et al. note, while cities will surely look to similar cities for policy inspiration, they will look to larger cities as "highly respected" sources of inspiration. [107] Thus, it seems that policy diffuses primarily from the top down.

Regional and national interest groups often facilitate the diffusion of ideas by pre-creating policy frames with which local governments can evaluate and enact policies. As Boushey writes, “The spread of policy innovation is often driven by the dedicated work of policy entrepreneurs and interest-group activists who appeal to local, state, and national governments to secure legislative change.” Boushey continues that interest groups do not acquiesce to incremental policy frames that could spread through diffusion, but rather actively advocate for specific policy frames that fit their own objectives. Such groups will try to form policy frames that draw on a sliding scale ranging from national themes to local trends depending on what topics would draw grassroots support. [108] Interest groups will not only form the policy frames, but also the legislation itself. Such groups will literally write the bill for legislators and such specific language would then diffuse around the nation. [109] Interest groups and the policy entrepreneurs that interest groups influence can thus become policy drivers and expedite diffusion.

The story of bike-sharing follows a very similar route. Parkes et al. track the early story of policy diffusion in bike-sharing. They outline how bike-sharing first took shape in Europe and slowly began to spread as other cities looked to pioneers like Amsterdam, Paris, and Lyon. After a few years, bike-sharing crept into the United States, with the first major success being Capital Bikeshare in Washington, DC. As the network in Washington grew in size and ridership, local governments and planners noticed and sought to bring such networks to their own cities. Private operators that were running networks in other cities helped shape this growth as large and small cities alike took the opportunity to create new transportation options. [110] External bike-sharing associations then formed including the North American Bike Share Association (NABSA). Bill Dossett, a founding member and former President of NABSA, cited that while the initial concerns with bike-sharing were centered around rider safety, vandalism, and capital expenditure, the main question in legislators' minds was: will people ride it? Of course, people did. Cities have still been loath to integrate planning these networks in their own transit networks, letting individual operators plan the networks themselves.

As a result, planning such networks in myriad and variegated cities then became a challenge. Particularly initially, planners had to find ways to adapt planning methods used in Washington, DC and New York City to Minneapolis and Tulsa. Where Washington and New York are dense cities where stations every 1000 feet are warranted, Minneapolis and Tulsa have small urban cores surrounded by single-family homes that do not require as many stations to accommodate demand.[34] Further, capital expenditure concerns emerged. As an operator in Pittsburgh noted, Lexington, KY cannot plan the same way New York City can because Lexington cannot afford that many stations. And yet, cities try to employ the same planning processes.[35]

Organizations like NABSA, ITDP, and Transportation for America (T4A) try to prescribe bike-sharing business plans and planning guides as national interest groups pushing bike-sharing norms and standards. Distinctions between public bike-sharing providers and private, dockless bike-sharing providers means that bike-sharing networks have disparate incentives. Further, network design is influenced by myriad factors including weather and geography that such national organizations ignore by offering middle-of-the-road advice. While these are frequently beneficial, and sometimes offer conditional recommendations, the one-size-fits-all approach may not be an optimal planning standard for bike-sharing networks. [111] [76] [112] Networks end up

[34] Interview with Bill Dossett from Minneapolis
[35] Interview with operator in Pittsburgh

unoptimized and imbalanced by going simply off of these recommendations. Overall, nevertheless, bike-sharing has grown around America primarily as a function of policy diffusion, with private operators and national organizations helping spread infrastructure and planning techniques.

Bike-sharing as Transit

Bike-sharing grew as an experimental transportation system that has not been effectively integrated into local transit planning. This leads to an unclear understanding of its goals and outcomes. While some stakeholders hope for increased public access, others hope for profit-maximization. That said, given the required public subsidies and its importance as a public good, bike-sharing should be treated as a form of public transit, used primarily to alleviate transit deserts and improve access to active transportation.

The goal of bike-sharing then grows clearer: increase access to riders on routes that are currently not well-served and increase ridership around the city. This starts at the planning level. New, innovative planning mechanisms will be required to identify methods to maximize ridership and minimize required infrastructure in custom ways for individual bike-sharing networks. A method that can analyze, predict, and quantify the impacts of adding demand and changing capacity to a system could reform how micro-mobility is managed in the US. Such a method will be presented in the following chapter.

Chapter 2

Introduction

If bike-sharing is to be viewed as a public good, cost-efficient methods are required to gauge its efficacy. As discussed in the previous chapter, bike-sharing operators in particular lack methods to effectively utilize the data they gather. A framework for both translating data into useful insights as well as a system to preview and understand changes to the network could prove to be significantly useful for bike-sharing operators as they could preview both changes in supply and demand without deploying extra infrastructure, saving on time and expense.

Bike-sharing operators have expressed qualms with being able to grapple with contextualizing and accounting for future demand, particularly from large demand shocks, such as a greater cohort of members joining all at once. Further, the potential efficacy of bike-sharing on non-traditional transit routes, such as those between residential neighborhoods, has not been studied or quantified. Finally, given the racial and income demographic breakdowns of most bike-sharing riders, a window into the potential usability of the network by middle income users could prove insightful.

Thus, this chapter presents a potentially generalizable method for translating bike-sharing data to predict ridership based on exogenous information for a given day, as well as simulating the impacts of changing network parameters. Finally, this chapter presents a method for predicting the impacts of adding additional ridership from particular neighborhoods and evaluating its impacts. As a case study, this chapter explores analyzing the effects of offering the option to all Boston Public School teachers who are on the Bluebikes network the opportunity to commute to work via the Boston Bluebikes network, which would thus explore how such a model may work with non-traditional transit routes.

Literature Review

Previous research in simulating bike-sharing models has generally focused on rebalancing networks. Chemla et al. showed that measuring rider access, wait times, and vehicle utilization requires modelling riders, stations, and bikes. By modelling the City of Paris as a network of nodes using OADLIBSim, the authors were able to design a short time-frame algorithm for rebalancing bicycles. This redistribution model can serve effectively as an outline for how the bike-sharing network must be reasonably modeled in order to simulate the environment. [113] Statistical modeling has found that increasing bike-sharing capacity will decrease congestion. Saltzman and Bradford modeled the bike-sharing program in San Francisco as a Poisson process using the mean of the ridership data with riders willing to wait no more than two minutes. Again, the authors modeled the riders, stations, and bikes as agents that can be simulated, with the particular insight that riders will be willing to wait no more than two minutes. They concluded that increasing the number of bikes and docks at certain stations by about 4% will reduce congestion by 30%, where congestion was measured by the number of riders still waiting at the station. However, the authors did not look at the impacts of decreasing capacity. [114]

Freund et al. outline some of the primary metrics that Lyft systems currently use for bike-sharing rebalancing and dock allocation, calculating how many docks should be allocated for each station around a municipality. Using data from New York City in particular, the authors first develop a non-linear integer program that iteratively optimizes the network based on a defined objective (or evaluation) function. This objective function was defined as the number of station outages, which is when the station is out of bikes to pick up. Interestingly, this algorithm is used by Lyft throughout the nation to plan dock allocation but does not take into account outages for when the stations are full, as in bikes can no longer be parked. Using the concept of gradient descent, at each iteration, the algorithm can find a slightly better solution by altering one variable, leading to the evaluation function. If the current solution was not as good as the previous one, the algorithm will change another variable and continue the loop. If the current solution evaluated better than the previous solution, then the algorithm will maintain its course. Local optima are further proven as global optima. The second finding is an analysis of the rider-led rebalancing program, Bike Angels, which rewards individuals for moving bikes from stations with too many to stations with too few. This finding shows that the system in fact can be rebalanced by such individuals at a much cheaper rate than van rebalancing system, but at a fraction of the cost. [115]

Pan et al. applied a similar approach to dockless bike-sharing systems, treating the network as a Markov Decision Process built with spatial and temporal features. The researchers model their reward function as number of successful rides and optimize the network with a novel deep reinforcement learning algorithm, which iteratively updates based on an adversarial actor-critic approach. Using data from the Chinese Mobike, the authors are able to show that their Hierarchical Reinforcement Pricing model outperforms current rebalancing modeling algorithms, optimizing the network across the entire Chinese market while maintaining budget constraints. [116] Li et al. use another deep reinforcement learning approach in order to rebalance micro-mobility systems, creating clusters with inner-balancing, simulating internal rebalancing with reinforcement learning to limit customer loss, and then simulating cross-cluster rebalancing to train a deep neural network. With real world Citi Bike data, the authors then confirm that their algorithm results in an optimal solution. [117] Lozano et al. compare several machine learning approaches to land on a Random Forest Regression approach given a balance between performance and speed, building out a web application that allows users to input data, visualize their bicycle networks, and then predict demand. [118]

Teacher Trip Determination

In order to evaluate the efficacy of offering Boston Public Schools teachers free or subsidized ridership on the Boston Bluebikes network, data must be gathered and translated into artificial trip data that can be implemented into the simulation analysis.

Gathering Teacher Data

The City of Boston publishes data for all of its city employees, including their first name, last name, home zip code, income, and workplace in their annual Employee Earnings Report.[36] Of course, the privacy of such datasets is quite suspect. As Sweeney showed, with only someone's gender, date of birth, zip code, their full name and address can be found. [119] Armed with all of this information as well as the teachers' full names, I was able to gather teachers' home addresses.

In order to do this, a data aggregator called TruePeopleSearch was scraped.[37] As the name implies, TruePeopleSearch allows users to input an individual's full name and zip code and yield information about them, including, but not limited to, their home address, relatives, and phone number. For the purposes of this paper, only their home address was required. Given this, a web scraper with the Selenium Python package[38] that pulled up the TruePeopleSearch result for each of the 5,542 individual teachers and thus was able to gather their home addresses. Around 2,000 teachers were not found in the database. Thus, their information was discarded, and those teachers were removed from the dataset.

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[36] https://data.boston.gov/dataset/employee-earnings-report
[37] https://truepeoplesearch.com/
[38] https://selenium-python.readthedocs.io

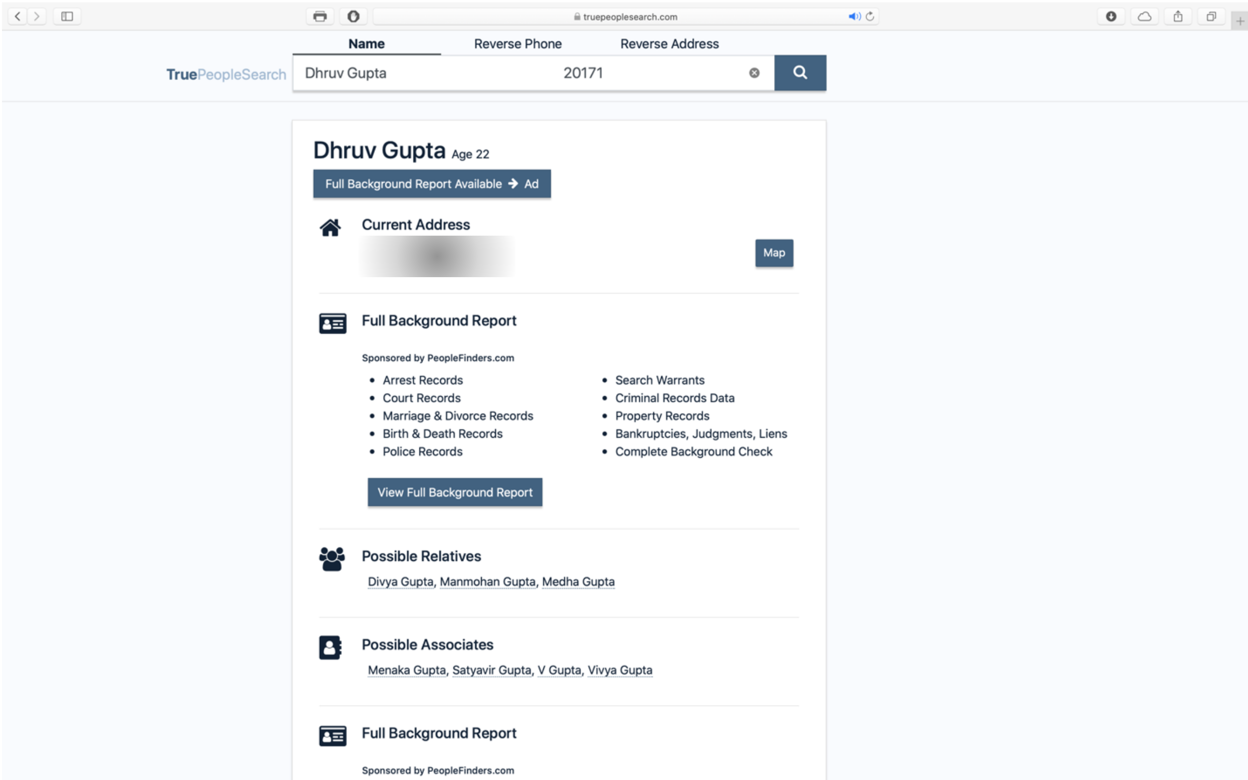

Figure 1. The TruePeopleSearch result for the author

In order to avoid this exact use case, where the privacy of an entire dataset of individuals is violated, and likely to force users to pay for its premium service, TruePeopleSearch limits the number of requests that can be made from a single IP address. Thus, a workaround was created that used the ProxyMesh tool to alter the IP address that ProxyMesh received. Since TruePeopleSearch only accepts American IP addresses, IP address pools from California and Washington were used and cycled through, randomly switching to another pool every time TruePeopleSearch would throw an error. This was an inherently time-consuming process, that was only somewhat sped up by multi-threading the system since the proxies used by the pools would rotate at staggered rates throughout the day.[39]

[39] https://www.proxymesh.com/faq/

Geographic Distribution of Teachers

Figure 2 depicts a choropleth map outlining the distribution of the homes of Boston Public Schools teachers in the United States. While employees in the City of Boston are generally required to live within the City, the Boston Teachers Union has been granted an exception to the rule. [120] Nevertheless, a significant portion of (1041 of the 5542) teachers were identified as living within 500 meters of stations in the Bluebikes network, as depicted in Figure 3. This number may be higher, however, data for a significant number of teachers was not found. Finally, Figure 4 depicts the locations of Boston Public Schools. Boston Public Schools teachers were chosen as a case study as the data was readily available and because the trip origins and destinations could be easily determined; teachers will commute to school in the mornings and return home in the evenings. Further, their trips will likely not follow traditional transit routes as schools are located in neighborhoods rather than central business districts. As can be visually noted here, the locations of teachers and schools are in primarily residential areas and are dispersed around city in local neighborhoods.

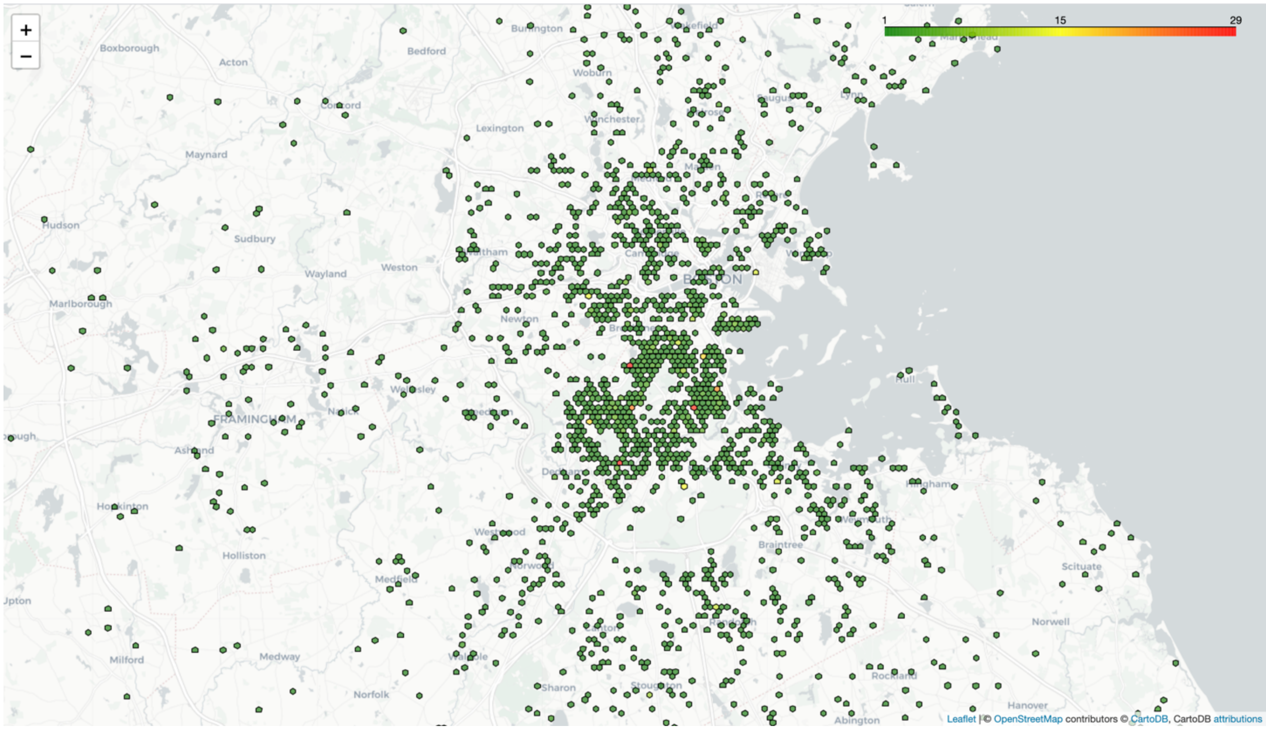

Figure 2. Locations of All BPS Teachers in Boston Metropolitan Area

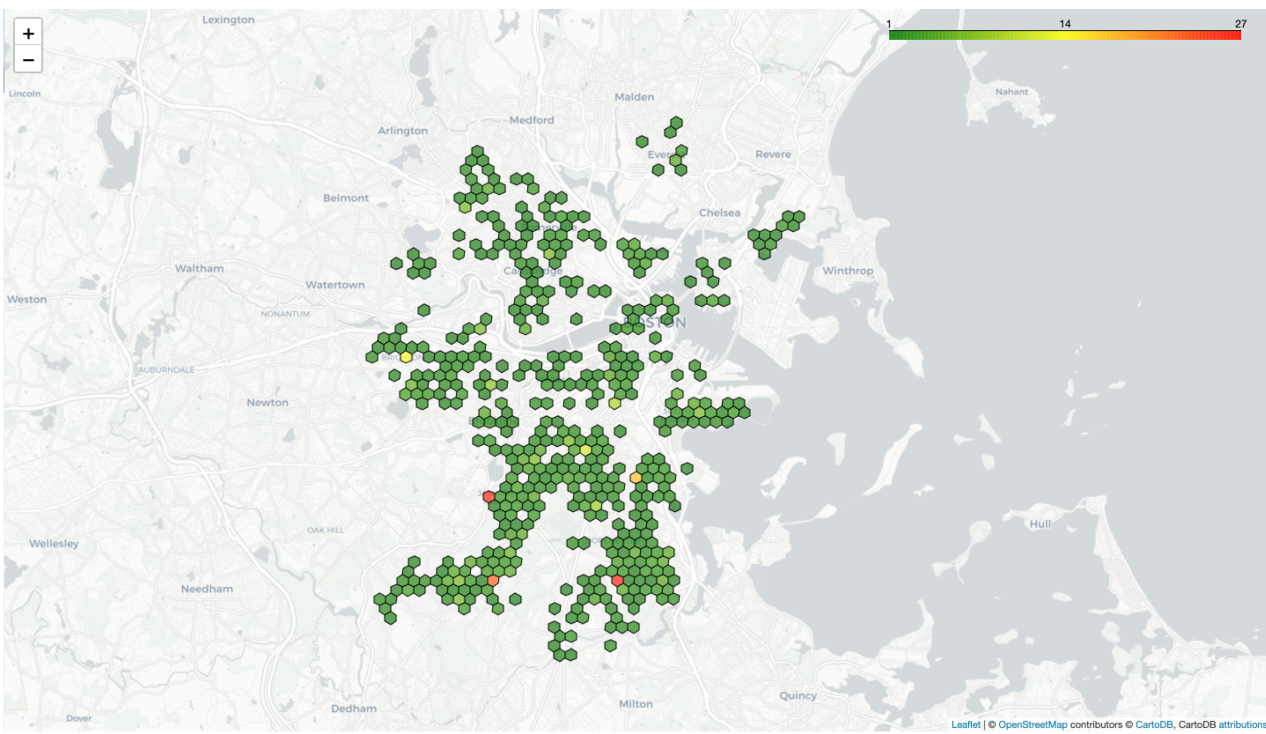

Figure 3. Locations of BPS Teachers within 500m of Bluebikes Stations

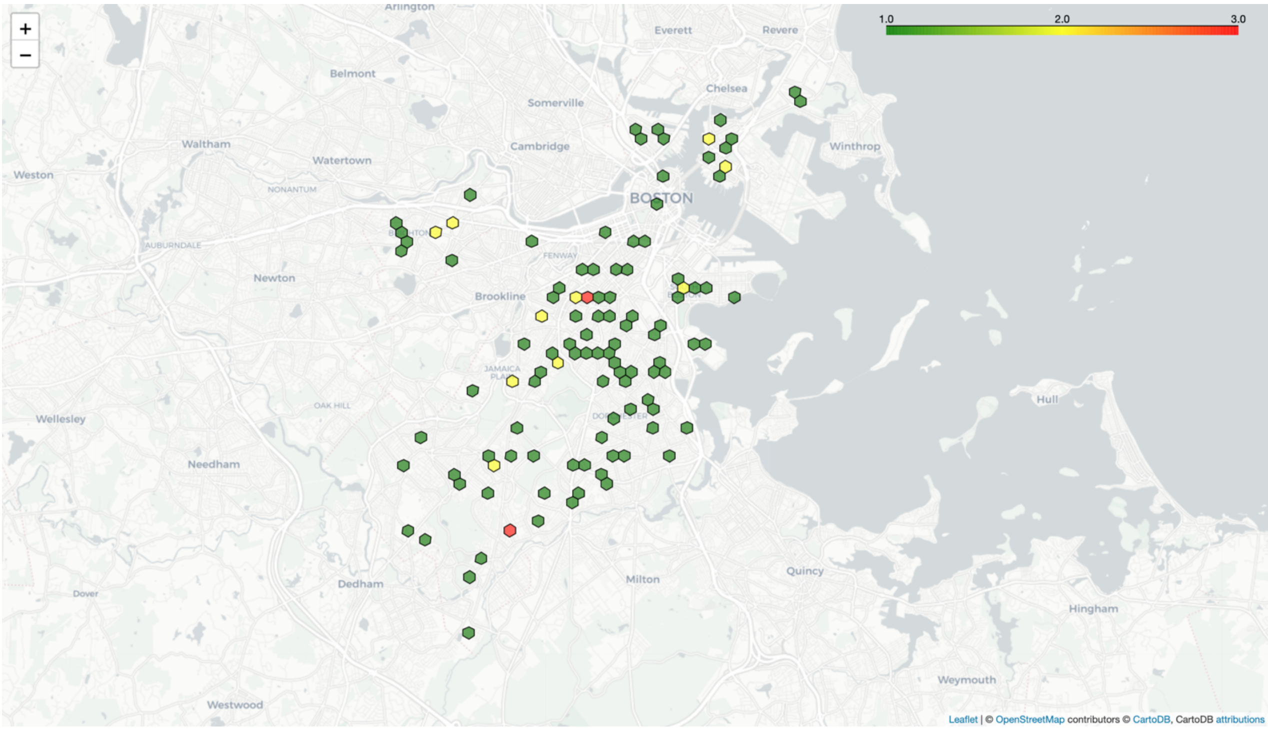

Figure 4. Locations of Boston Public Schools

Artificially Creating Trips

Once the teacher addresses were collected, the addresses were then associated with their latitude and longitude using the Geocodio service.[40] Then, the Google Maps API[41] was used to route the teachers to their schools via the Bluebikes network. As it turns out, all schools but one had Bluebikes stations within 500 meters of them, so the teachers were always routed within a 5-minute walk of the school. These trips were randomly set to start in between 6 AM and 8 AM in the morning and between 2 PM and 4 PM in the afternoon as schools in the Boston area start and end around those times.[42] In order to do so, first the teachers' home addresses were geocoded as their geo-coordinate pairs, and then were associated with their nearest bike-sharing station in the

[40] https://www.geocod.io
[41] https://developers.google.com/maps/documentation
[42] https://www.bostonpublicschools.org/Page/7017

Bluebikes network using the SciPy Python package[43]. The same was done for all of the schools in the Boston Public Schools system. Then, using the Google Maps API again, the length of a bike trip between the two stations both with respect to time and distance was calculated. A pair of trips was generated for each teacher. The first was from the home to the school, associated with starting at a random time between 6am and 8am, and the second was from the school returning home, associated with starting at a random time between 2pm and 4pm. In this way, trips were created for all of the teachers such that they could simply be inputted into the simulation model as artificial but pre-defined “riders”.

Ridership Demand Prediction

The goal of this model is to evaluate the effectiveness of a bike-sharing system given varied parameters. This approach accomplishes this goal by allowing for modeling a “simulated” day based on given exogenous parameters about some arbitrary or potential day of ridership. In order to effectively model a simulated day, all trips with similar exogenous parameters were clustered together and then a certain number of trips was sampled, weighted by distance of the specified set of parameters from the clusters. This number was calculated by a regression which predicts the total ridership demand for a day given its exogenous parameters. These exogenous parameters include weather (temperature, pressure, wind speed, precipitation), whether the day is a holiday or not, and whether the day is over the weekend or not. With this approach, a set of artificial trip data based on real trips and exogenous parameters can be simulated.

Clustering Trips by Parameters

[43] https://docs.scipy.org/doc/scipy/reference/spatial.distance.html

The Boston Bluebikes network offers a dataset of trip-level data which offers a set of attributes, including the starting station and time, ending station and time, and duration of trip. Weather data were collected from the National Oceanic and Atmospheric Administration's climate.gov datasets.[44] These data were then associated with the Pandas Python package[45] at an hourly granularity with the all of the trip data from 2019, which Bluebikes makes publicly available.[46] Using the Holidays Python package[47] and the datetime Python module[48], all trips were also associated with Booleans that indicate whether they are holidays or weekends.

All of these data were then fed into a K-means Nearest Neighbor clustering algorithm with six clusters via the Scikit-Learn Python package.[49] The determination to use only six clusters was made with the ELBO method, noting a significant change in the sum of squared distances at six clusters. Thus, as a result, all of the trip data were sorted into six clusters.

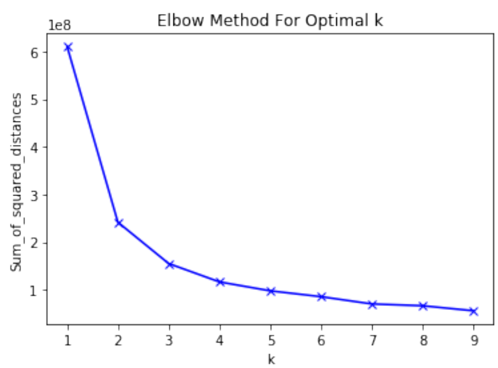

Figure 5. Elbow Method for Optimal Number of Clusters

Predicting Total Trip Demand

[44] https://www.climate.gov/maps-data/dataset/past-weather-zip-code-data-table
[45] http://pandas.pydata.org/
[46] https://www.bluebikes.com/system-data
[47] https://pypi.org/project/holidays/
[48] https://docs.python.org/3.7/library/datetime.html
[49] https://scikit-learn.org/stable/

In order to construct a simulated day, particularly with sampled trips, a prediction of how many trips there should be is required. Thus, inspired by Lozano et al. [118], a regression was designed that takes in the aforementioned exogenous parameters for a hypothetical day, and outputs a predicted number of trips. The following equation was fit:

$$y = \mathbf{w} \cdot \mathbf{x}^{\boldsymbol{T}} + \alpha + \epsilon$$

where $\mathbf{x}$ is the vector of exogenous variables which are temperature, air pressure, wind speed, precipitation, and Booleans for whether the day is a weekend or a holiday; $\mathbf{w}$ is a vector of the assigned weights; α is a constant; and, ϵ is an error term. The output of the regression is the number of trips for that given day. The trip data were aggregated and grouped by day based on the start date, and the total number of trips for each day was calculated as training data.

Three different regression approaches were used an compared against each other: simple Linear Regression, Random Forest, and Gradient Boosted Regression. These approaches were trained with a 70% of the data as a training set and the rest of the dataset as a validation set. Of these, the Random Forest approach consistently outperformed the others, and thus was chosen for the model. Note that the error for calculating Mean Squared Error reported in Figure 6 is determined by the difference in the actual number of trips on a validated day from the predicted number of trips. Interestingly, as Figure 7 shows, temperature was determined to be the greatest predictor of the number of rides per day by far, distantly followed by precipitation, air pressure, wind speed, and whether the day was a weekend or not.

	Mean Squared Error
Random Forest	7484414.90
Linear	7672583.65
Gradient Boosted	7709645.45

Figure 6. Comparison of Regression Approaches

	Weekend	Holiday	Temperature	Precipitation	Pressure	Wind Speed
Weight	0.044	0.003	0.775	0.076	0.056	0.046

Figure 7. Weights of Parameters for Number of Trips Prediction

Sampling Trips

Armed with a set of clustered trips and a model for predicting the number of trips per day, a weighted sampling method was created that takes in the exogenous parameters of a day and outputs a day's worth of trip data. Given a set of exogenous parameters, the number of trips for that day was predicted. Then, those exogenous parameters were fit in the clusters calculated with the K-Means model. The distances of these parameters were calculated from each of the clusters in the model, and those distances were associated with each of the trips in the clusters in the trip data set. This way, each trip was associated with a weight that indicated how relevant the trip was to the hypothetical exogenous parameter set. These weights were then normalized and used as parameters in a simple weighted sample, where the weights were the probabilities of being selected. In order to ensure that trips that were associated with exogenous parameters that were quite different from the hypothetical exogenous parameters had lower chances of being selected, the reciprocals of the weights were used before normalizing them. A limitation of this approach is that it inserts an element of randomness. Each run of the simulation could yield fairly different results. In future studies, this could be mitigated by taking an aggregate over multiple simulations of the same parameters.

Simulation

Overview of Architecture

This thesis has chosen to use a dynamic, simulation-based approach as such an approach is better suited for bike-sharing than static modeling where only statistical methods are used.

Boyles et al. found that static modeling has a tendency to significantly underestimate network congestion and demand levels. [121] On the other hand, Kryvobokov et al. noted that static and dynamic urban modeling frameworks may still generate similar empirical results. [122] Since the focus of this paper is on network congestion and the network effects of adding different sets of ridership to the network. A simulation approach allows for modeling the impacts increased ridership at individual stations on each other as agents move amongst those stations, affecting usage throughout the network. Modeling individual bikes, rather than predicting their locations, allows for viewing a clear, rather than an aggregate, picture of network movement.

The BikePath platform is built on the Mesa Python package[50] and uses agent-based stations, bicycles, and riders. And geospatial data for the City of Boston is modeled via OpenStreetMap, using the OSMNX and NetworkX Python packages[51]. Stations are placed on the map and keep track of their bicycle capacities and the number of bicycles currently there. Bicycles are generated at the stations and maintain information on their destination, speed, rider, and path. Finally, riders keep track of whether they're at a station or on a bicycle, where they started, and what their destination is.

Station	Bike Capacity	Current Number of Bikes	Location Node	Connected Streets	Station ID	
Bike	Destination	Speed	Current Rider	Path	Direction	Current Station
Rider	Current Station	Current Bike	Start Station	Destination Station	Start Time	End Time

Figure 8. Agents and their associated attributes in the BikePath model

[50] https://mesa.readthedocs.io/
[51] http://osmnx.readthedocs.io/

Bicycles are generated at stations and, if there is a rider at the station, are randomly assigned to a rider. Riders are preprogrammed with starting points and destinations based on the sampled trip-level data. Should a bicycle be available to a rider, the rider's destination is then given to the bicycle, which uses the built-in path-finding algorithm based on Dijkstra's algorithm to calculate the shortest path to the next station. Once the rider checks out a bicycle from the station, they both follow the pre-specified path until they reach the destination station. The rider then disappears. If a station's capacity is full when the bicycle reaches the station, the bicycle will remain there until the station opens up. Since rider data is determined from real trip-level data, the rider does not become available until it is time for their ride. Riders remain available at the station until they are picked up by a bicycle.

Step-1: Bicycles and Stations generated

Step-2: All Riders generated based on trip data

Step-3: As time increments, every rider not already on a trip checks if it is time for the ride to start and if a bike is available

```
{   if (cur_time <= rider.start_time && rider.cur_station.has_bike() == True)
        bike ← rider.cur_station.choose_bike()
        rider.cur_bike ← bike
        bike.cur_rider ← rider
        bike.path ← calculate_path_to_destination(bike)
}
```

Step-4: At every time increment, rider-bike pairs move towards their destination with a speed based on the total duration of the trip and travel distance.

Step-5: When a rider-bike pair approach the destination station, if the station capacity is full, the rider-bike pair idles for fifteen minutes. If the station is still not full, the ride is counted as a missed ride and the bike is reallocated to the nearest station. When a dock opens, the rider is destroyed and the bike docks at the station ready for a new rider.

Figure 9. Bike and rider journey algorithm

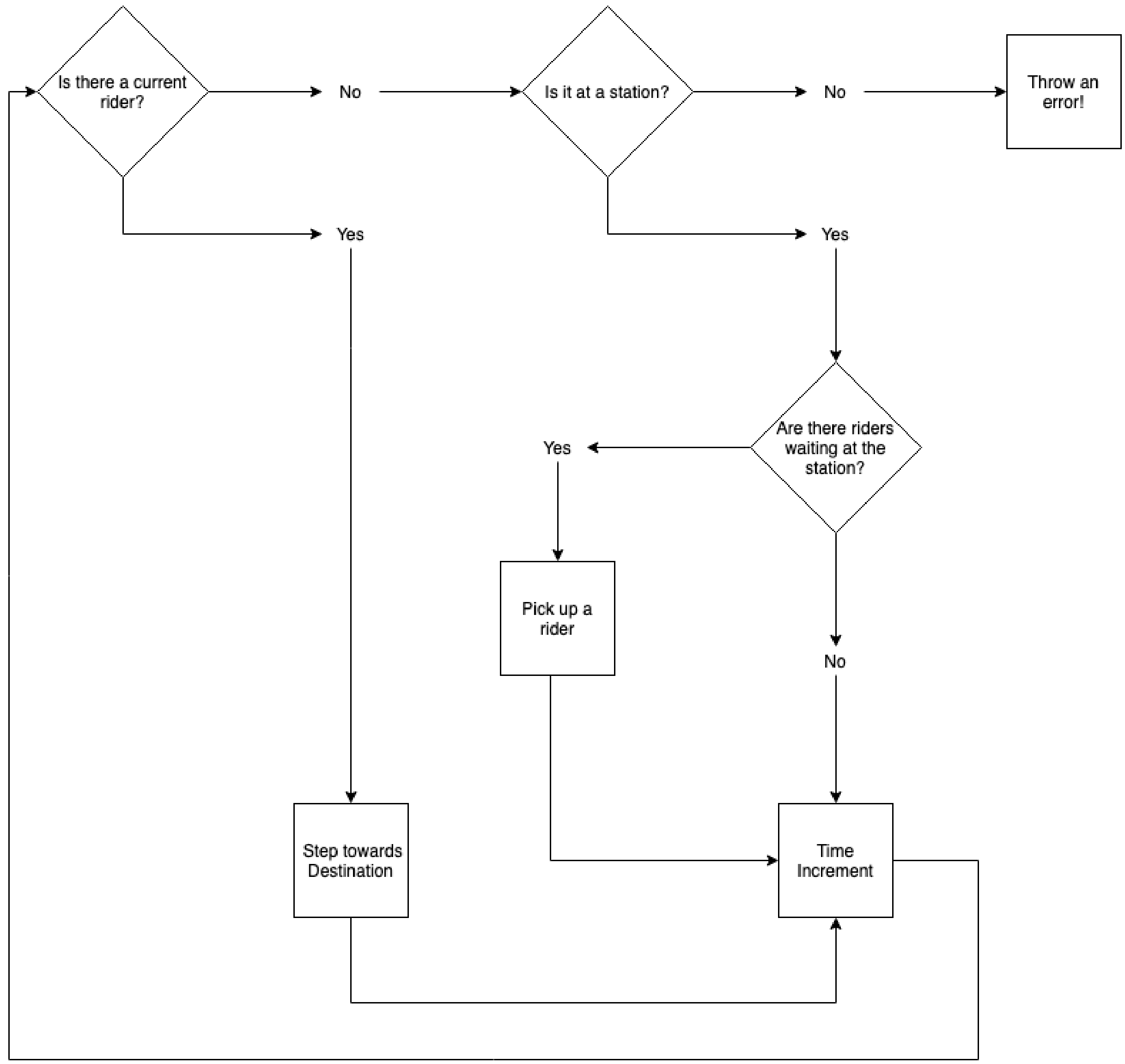

Figure 10. Decision process of bike agent

The broader workflow is as follows. The exogenous daily parameters are inputted, and the sampled data is outputted using the KNN-Random Forest model described above. Then, a randomized subset of teachers is added to the sampled data in order to form a combined set of trip data for the sampling method. Then, this trip dataset is converted into BikePath rider objects, which are then run through the network over a period of a day. The outputted data is pre-calculated and visualized via a web application.

Initial Placement of Bikes

The initial placement of the bicycles was determined through a prediction and optimization algorithm developed in conjunction with another student, Soumil Singh, and inspired by Liu et al. The 30 most similar days from trip data from 2019 are found based on the inputted weather parameters and ridership for each station is averaged across those days. For each station, the hourly net flow is calculated, which comes from the number of bicycles drop-offs at that station subtracted by the number of bicycle pickups. From there, for each possible number of bikes at each station, the potential missed rides are calculated based on these net flows. [123] In essence, this calculation determines how many bikes would be necessary at each station to minimize the number of missed rides. Finally, an integer program, constrained by the capacities of the stations and the total number of bikes in the system, calculates an optimal placement of bikes around the network minimizing the overall number of missed rides for each station. In this way, the initial placement of bikes around the network is not random, but rather based on a prediction model.

Web Application

The Django backend (PathFinder), React frontend (Pioneer) web application allows users to easily simulate, visualize, and analyze the model. The Django backend houses the BikePath simulation model and stores this data in a Postgres database on Amazon RDS. The React front-end, run off of Amazon S3, allows users to visualize the network as time progresses via the Leaflet Javascript module, lets users input and start new simulations via API calls to the Django backend, and view data metrics about the simulation.

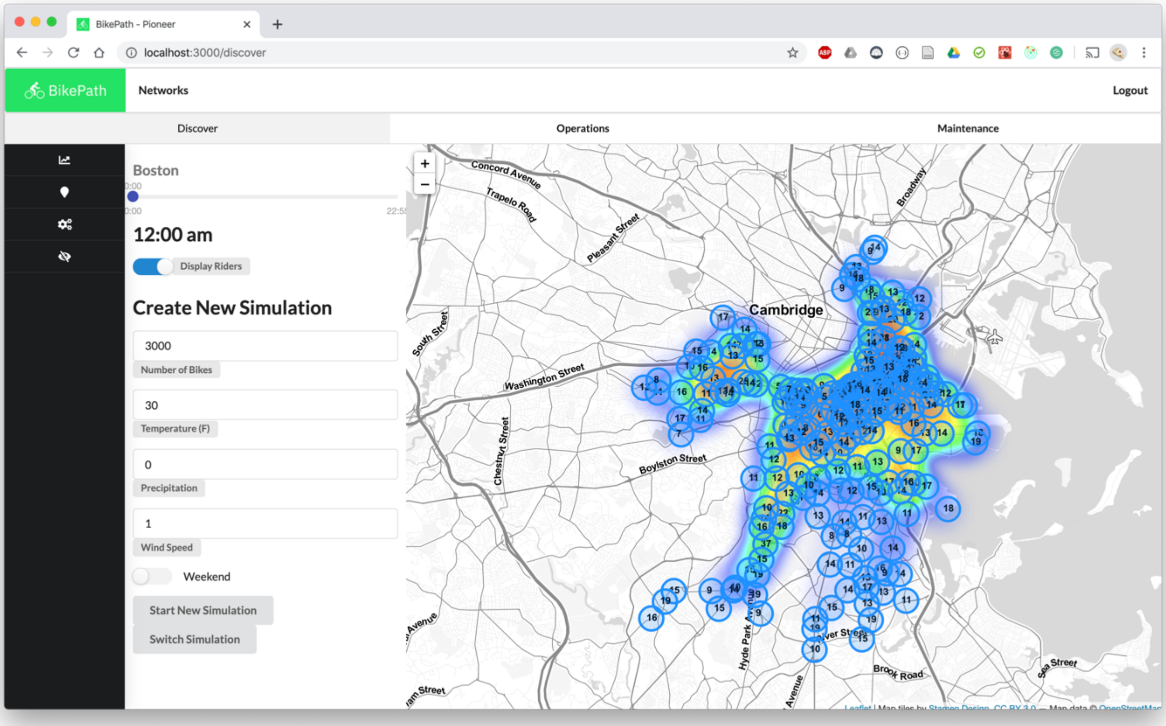

Figure 11. Screenshot of BikePath web application

Tracked Metrics

The simulation model keeps track of a heatmap of routes used by ridership throughout the day. Secondly, the simulation model keeps track of missed rides, which measures the number of predicted trips that were unable to be completed as a rider was unable to get on a bike at a station. This is incremented when a rider that is attempting to leave a station at its start time must wait more than 15 minutes. That ride is then terminated and the missed ride counter rises. The number of intended rides, rides that were predicted to occur, was calculated over time and mapped against the number of actually completed rides. The difference between these two metrics is the number of missed rides. Finally, the number of active rides was noted over the period of the simulation.

Simulation Results

The simulations were broken down into two different categories such that varying parameters were tested both with and without the addition of teachers into the Boston network. As a result, 32 different scenarios were tested with varying degrees of temperatures and bike capacities, as well as 8 scenarios with precipitation. As other parameters were shown to have little effect on ridership, they were not simulated. This is a limitation of this study as those parameters could affect the types of rides (i.e. the distribution of origins and destinations) that are taken on different days such as weekends. Future studies should also compare such scenarios. The temperatures 30°, 50°, and 70° were chosen as they roughly correspond to the average temperatures in Boston in the Winter, Spring/Fall, and Summer. Half an inch of precipitation was chosen as it is roughly the average daily precipitation in the Spring and Fall in Boston.[52]

With Teachers

	3000 bikes			2000 bikes			1000 bikes			500 bikes		
	Intended	Completed	Missed	Intended	Completed	Missed	Intended	Completed	Missed	Intended	Completed	Missed
30°	2616	972	1644	2635	833	1802	2616	546	2070	2618	332	2286
50°	4255	1298	2957	4193	994	3199	4260	701	3559	4249	322	3927
50°, 0.5” rain	3046	1037	2009	2991	879	2112	2956	613	2343	3055	334	2721
70°	5874	1404	4470	5765	1038	4727	5841	732	5109	5793	351	5442

Figure 12a. Ridership from Simulations with BPS Teachers

Without Teachers

	3000 bikes			2000 bikes			1000 bikes			500 bikes		
	Intended	Completed	Missed	Intended	Completed	Missed	Intended	Completed	Missed	Intended	Completed	Missed
30°	1047	496	551	1032	420	612	1037	347	690	1009	209	800
50°	2643	862	1781	2702	726	1976	2639	465	2174	2659	259	2400
50° and 0.5” rain	1487	549	938	1419	517	902	1440	375	1065	1395	234	1161
70°	4214	1002	3212	4252	771	3481	4254	543	3711	4257	273	3984

Figure 12b. Ridership from Simulations without BPS Teachers

[52] https://www.usclimatedata.com/climate/boston/massachusetts/united-states/usma0046

Figure 13a. Missed Rides by Scenario with Teachers

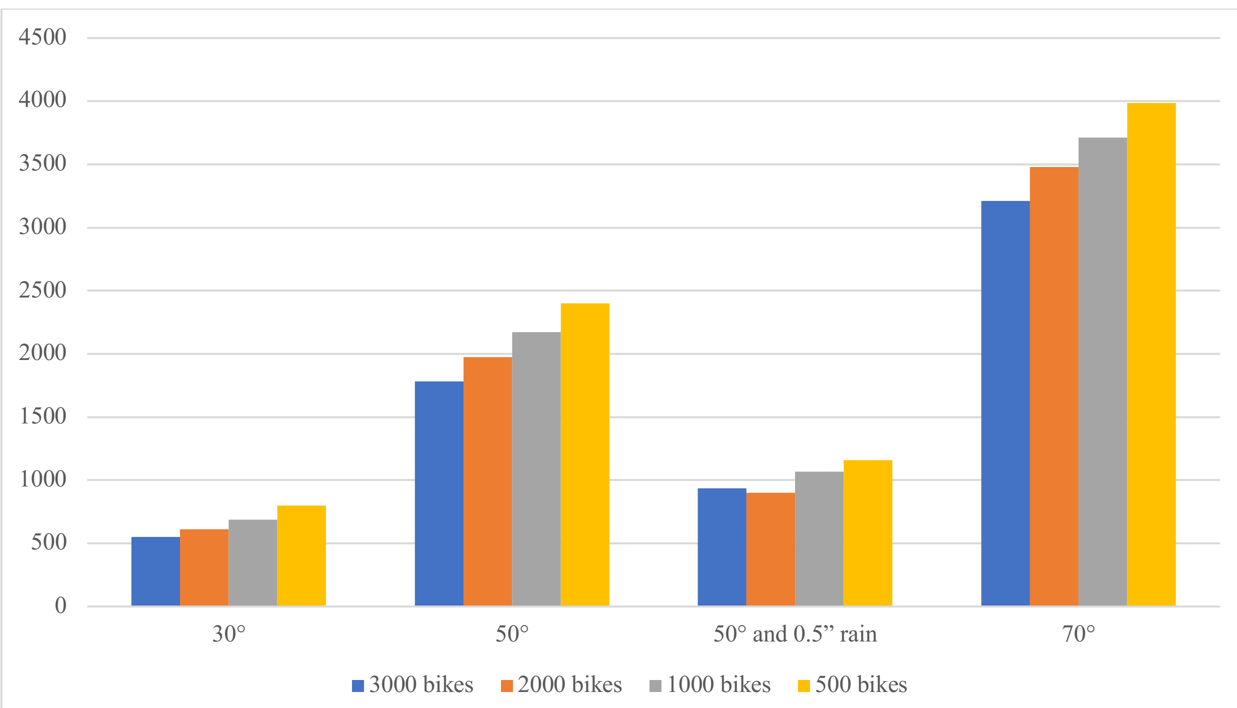

Figure 13a. Missed Rides by Scenario without Teachers

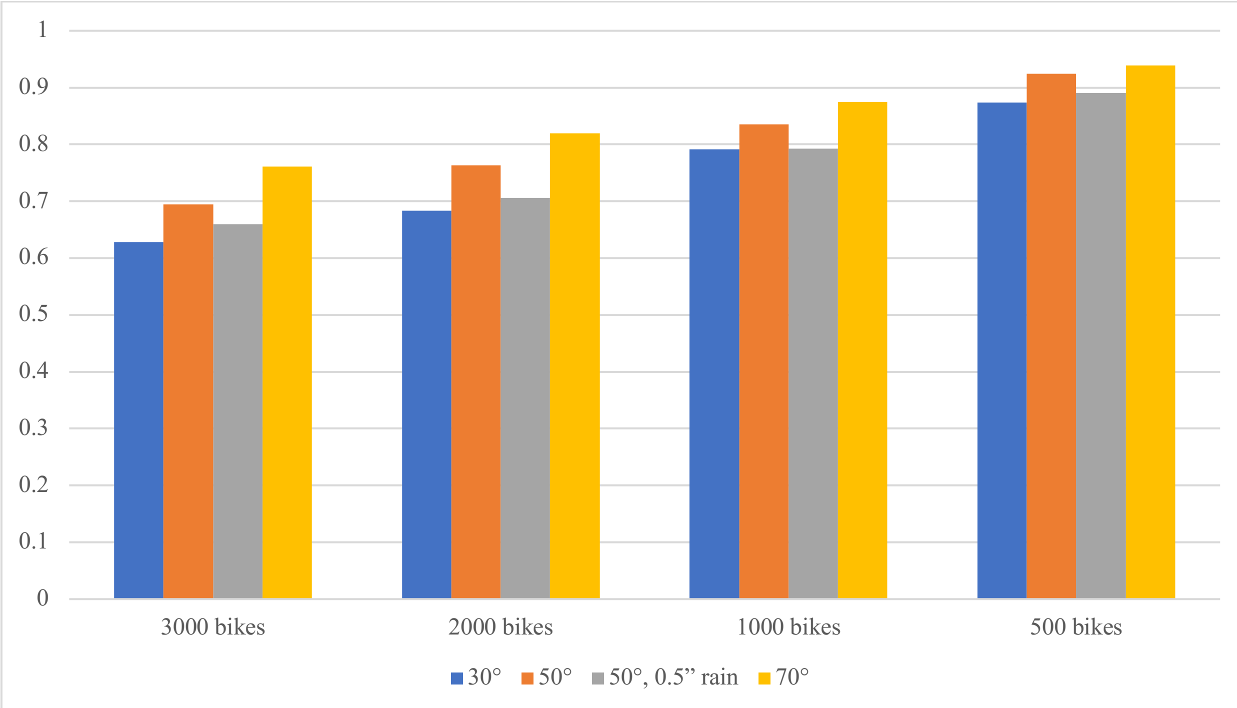

Figure 14a. Missed Rides as a Fraction of Intended Rides by Number of Bikes with Teachers

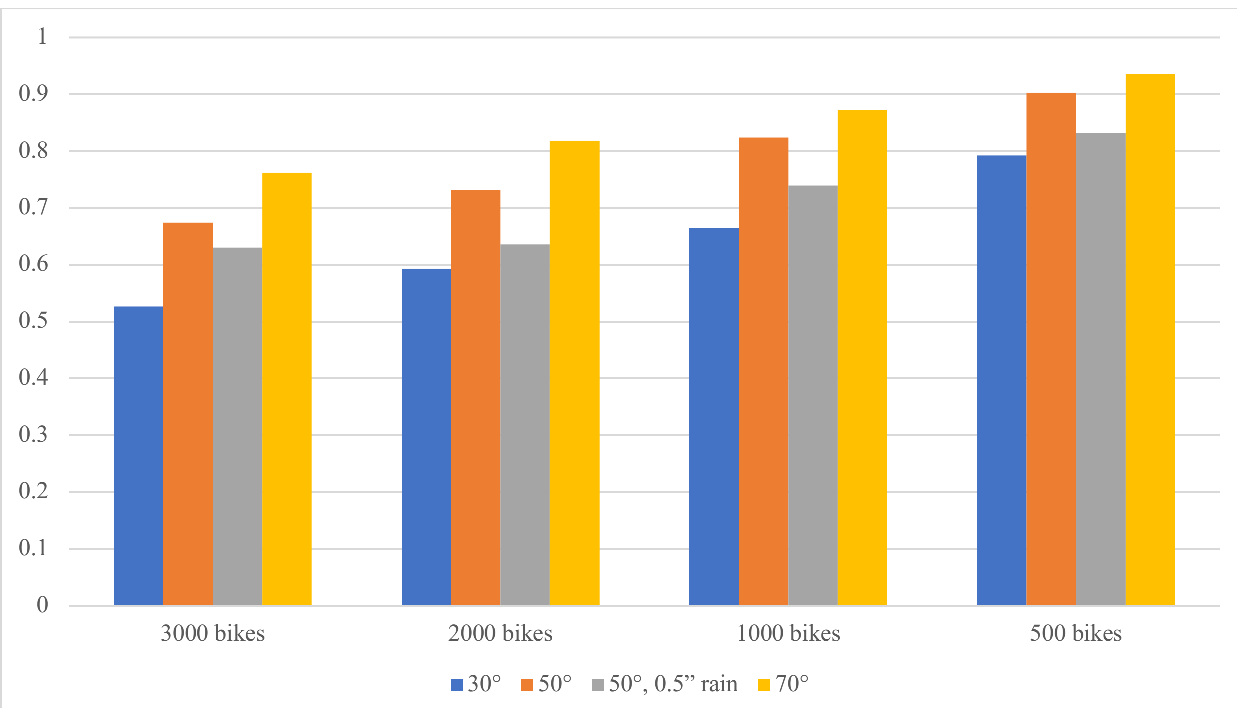

Figure 14b. Missed Rides as a Fraction of Intended Rides by Number of Bikes without Teachers

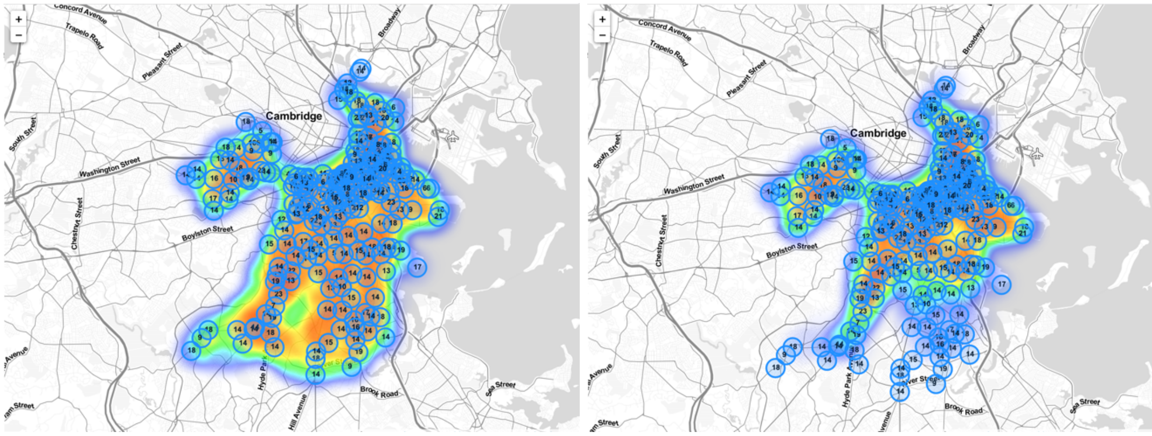

Figure 15. Heatmaps of the 50° Scenario with 3000 bikes with Teachers (left) and without Teachers (right)

Discussion

The results show a few key points, some of which offer validity to the model, while others offer new insights, albeit tempered by a major limitation. Amongst the four different weather-based scenarios, we note that the ridership is inversely proportional to the temperature and drops when there is precipitation. Further, we see a significant increase in ridership and a resulting increase in missed rides, both in absolute and relative terms, when teachers are added to the network, which of course makes sense as 1000 trips were artificially inserted into the system with the assumption that all teachers that could use the Bluebikes network to commute to school would do so.

We also note an increased number of missed rides as the number of bikes falls in the network. This also makes intuitive sense; if riders cannot get on bikes, they cannot complete rides. However, the proportion of missed rides from all rides does not rise significantly between corresponding scenarios if the number of bikes is slashed in the network, dropping from 0.628 to 0.68, for example, in the 30° scenario with teachers as the number of bikes goes from 3000 to 2000. This could be because too many bikes in the network would lead to missed rides when the rider attempts to dock the bike at a station and the station is already full. A future analysis of individual station capacities and outages could be useful in this case.

Nevertheless, this brings up two key limitations in this study. An assumption of static rebalancing was made in this simulation, which is when the network is only rebalanced once at the beginning of the day. This apportionment was informed by ridership data from 2019 that could not account for the increase in demand from teachers. The increased demand and also unpreparedness of the network could account for the increased missed rides rates for teachers.

Further, modeling a dynamic rebalancing system, where the network is rebalanced multiple times throughout the day, could make a significant impact in showing whether reduced numbers of bikes could account for ridership throughout the day. [124] This is likely why the number of missed rides is so high for the scenario without teachers as well. Those rides could have been completed given a dynamic rebalancing system. Future studies should explore and simulate such a system.

The heatmaps in Figure 15 tell a striking story. Ridership when teachers were added in corridors around Brookline, Jamaica Plain, and Dorchester skyrocketed. A significant plurality of teachers lives in these neighborhoods (Figure 3) and would commute to the schools in those neighborhoods (Figure 4). These are residential neighborhood to residential neighborhood routes. Such a route would require taking three different buses even though the distance is only about three miles, whereas bike-sharing is able to enable this route.[53] Interestingly, demand, and even for bike-sharing in general, was limited in these neighborhoods without the insertion of the teachers. Given the lower density and lack of cycling infrastructure, these routes may not be

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[53] https://www.mbta.com/trip-planner

amenable to cycling at the moment. However, this simulation shows that there is in fact latent demand and significant potential ridership for routes between these residential neighborhoods that is satisfied currently likely through cars.

This simulation model shows how resilient the Bluebikes network could be to an increase in demand on routes. It also shows that there could be significant ridership on certain routes that do not currently have the requisite infrastructure for bike-sharing. That said, the simulation model also leaves some open questions as it does not model dynamic rebalancing throughout the day. Further, without a station-level analysis of whether stations are full or empty, it is unclear where the missed rides are coming from. Nevertheless, modeling bike-sharing as a transit network to enable ridership around the city through simulation is a generalizable solution that could help offer planners new tools and methods to understand the true potential of their network.

Chapter 3

Introduction

The previous chapter explored how the current bike-sharing network would be affected should more Boston Public Schools teachers commute to work with the Bluebikes system in Boston, in service of showing that non-traditional transit routes could be supplemented with micro-mobility offerings. However, current planning methods, as discussed in previous chapters, are insufficient for planning around such routes. Planning methods prioritize those who are vocal in community meetings and can unfortunately leave segments of demand out as they may simply not capture them

The goal of this chapter, as a result, is to identify how bike-sharing systems would have to change in order to accommodate this potential latent demand. The main motivating tenet here is to build bike-sharing such that it meets people where they are by using available GPS data in order to so. Thus, this chapter breaks down into two different sub-goals.

The first sub-goal of this chapter is to identify the scope of demand at a given bike-sharing station. In other words, if there were a bike-sharing station at a certain location, how many people would use it? To accomplish this goal, an algorithm has been developed that uses GPS logging data from cellphone usage in order to identify how many trips there may be within a walking distance (500m) of a bike-sharing station. In this way, the efficacy and size of a bike-sharing station can be gauged.

The second sub-goal tries to answer the opposite side of this problem: where should the stations go in the first place? While in the previous two sub-goals, the station location was given, in this sub-goal, the actual locations of the stations are identified automatically by noting clusters of stations. Locations with sufficient clusters of trip origins and destinations would likely be strong contenders for bike-sharing station locations. Such locations can be identified through the cellphone GPS location data, as these data can be segmented, as in the previous step, to show origins and destinations of trips, which then allow locations to be determined.

Literature Review

Traditional Planning Methods

As discussed in Chapter 1, the primary way that bike-sharing stations are planned is through community conversations, population density analytics, and trip-generation calculations. Given the focus on trip-generation in this chapter, this literature review will focus on trip-generation. The Institute of Transportation Engineers is the primary source of trip data analytics in the United Stations. American urban planners will take a look at the buildings and points of interest in regions that they are planning for, look up those locations in the ITE *Trip Generation Manual* handbook, and literally add up the number of trips. This manual tells users how many trips there will be and what each transportation mode will be for different times of day. As Figure 1 shows, a neighborhood of Single-Family Homes with 235 houses would generate 2234 total trips a day, for example. Urban planners and researchers will literally go outside and count the number of vehicles they see moving around at various intersections. These data are then aggregated and averaged into the reports that the ITE *Manual* publishes. [125]

		Trip Rates			**Directionality**					**TRIP ENDS**			**Directionality**			
Description/ITE Code	**Units**	**Week day**	**AM**	**PM**	**AM In**	**AM Out**	**PM In**	**PM Out**	**Dwelling Units**	**Daily**	**AM**	**PM**	**AM In**	**AM Out**	**PM In**	**PM Out**
Single Family Homes 210	DU	9.52	0.75	1.00	25%	75%	63%	37%	**235**	**2234**	**176**	**235**	**44**	**132**	**148**	**87**
Condo/Townhouse 230	DU	5.81	0.44	0.52	17%	83%	67%	33%	**126**	**734**	**56**	**66**	**9**	**46**	**44**	**22**
									361	**2968**	**232**	**300**	**53**	**178**	**192**	**109**

Source: ITE Trip Generation Manual, 9th ed.

Figure 1. An example of the information the ITE *Trip Generation Manual* offers

These ITE Schools in particular have been shown to generate varying levels of trips, however, that can be different from the ITE in a way that may significantly misrepresent trips. For example, Slipp and Hummer find that trip generation for high schools may actually be significantly higher in some regions, particularly urban countries of North Carolina, given unclear and different socioeconomic parameters of the ITE data. [126] Criticism of the usage of this data as a catch-all that is broadly applied to all trip-generators has led to several municipalities and transportation authorities collecting their own data to use as more closely accurate sources of information. [127] The prevailing issue with the ITE data is that it seems to ignore temporal, special, and social contexts by generally offering a suburban view leading to an overestimation of automobile trips. [128]

Cellphone Trip Data Usage

New technologies have promised to disrupt this planning process, particularly GPS location tracking of cellphones, which has offered a prime honeypot of data that could reveal the true movement of people around a region. This data is collected by apps on mobile cellphones and is sold to data aggregators who then parse this data and sell it for analytics. Several companies in this space, like Foursquare, IBM, and Safegraph (which provided data for this paper) aggregate this data, have taken criticism for potentially violating the privacy of individuals. While this information is not released with individual names or phone numbers, unique IDs are still associated with each location endpoint, which can be de-anonymized in order to identify the exact movements of individuals. [129]

That said, identifying the exact movements of individuals is an incredibly valuable asset in understanding where people are going and where transportation options are insufficient. Los Angeles has been redesigning its entire transit network based on these data by mapping the data over time and noting spikes in travel. The analysts noted the obvious bi-modal distribution of trips, with spikes in the morning and evening rush hour periods, but there was also a third peak in the off-peak hours where individuals may be running errands. Researchers were also able to upturn the traditional planning method of planning for commuting, rather finding that trips were primarily short hops within smaller neighborhoods instead of long commuting routes. [130]

The researchers in this study showed that grid-based clustering algorithms and point-based clustering algorithms can thus help identify where individual trips actually originate and terminate. A grid-based clustering algorithm involves dividing a region into 100m long cells and then clumping all the local location captures of an individual user together over a short period of time. A point-based algorithm, on the other hand, clusters individuals by clustering individual points based on their maximum distance from each other on a time horizon of ten minutes. In both methods, an understanding of where a user has *stopped* traveling can be calculated, which the identifies the beginning or end of a trip. Given this information, travel demand can thus be calculated for origins and destinations. [131]

Calculating and analyzing transportation mode can be a difficult challenge in that it can often be unclear whether the data are Single-Mode Trajectories or Mixed-Mode Trajectories. That is to say, as Yang et al. point out, there is a significant difference in trying to understand whether individuals are walking somewhere for the entire length of the collected location data or if they switch transportation modes from, for example, walking to biking back to walking. The previous paragraph discussed how an MMT dataset may break up data into segments by clustering movements, which then turns the MMT data into SMT segment data. Thus, given then SMT segments, research has shown that Support Vector Machine algorithms can be sufficient for predicting mode-share, as well as various forms of decision trees, ensemble methods, and neural network models. Generally, the parameters used are speed, bearing, time, and distance. [132]

Jiang et al. were further able to build a model with an Recurrent Neural Network that achieved a 98% classification accuracy focusing only on the individual speed per point and average speed per segment. [133] Graells-Garrido et al. were able to infer the beginning of trips by thresholding against the change in trajectory for an individual person, and thus, given the segments, used the point speed to calculate mode share. [134]

Trip Segmentation

Cellphone GPS data from November 16, 2016 provided by Safegraph was used to predict where trips originated and terminated. This GPS data captured the latitude, longitude, accuracy, timestamp, and user ID for each GPS ping. This allowed for uniquely tagging individuals and their travel patterns as their GPS points could be tracked throughout the day. Given that this data is over three years old, its applicability may be limited. Although smart phone ownership varies by income, Wesolowski et al. find that this does not significantly skew broader estimates of mobility. [135]

Trip segments were created for each user by taking individual GPS points and noting if the change in speed was less than one meter per second, if there were a time difference between trips of 3 minutes, or if the distance between points was less than 10 meters. The speed of the trip was calculated by dividing the distance between each GPS datapoint and its predecessor from the same user by the corresponding time. All determined trips with only one datapoint were discarded as they would not capture movement. This method was adapted from Zhou et al. [136] About 1.5 million trips were identified in the Safegraph GPS data for November 16, 2016 through this process.

Virtual Station Method

Methodology

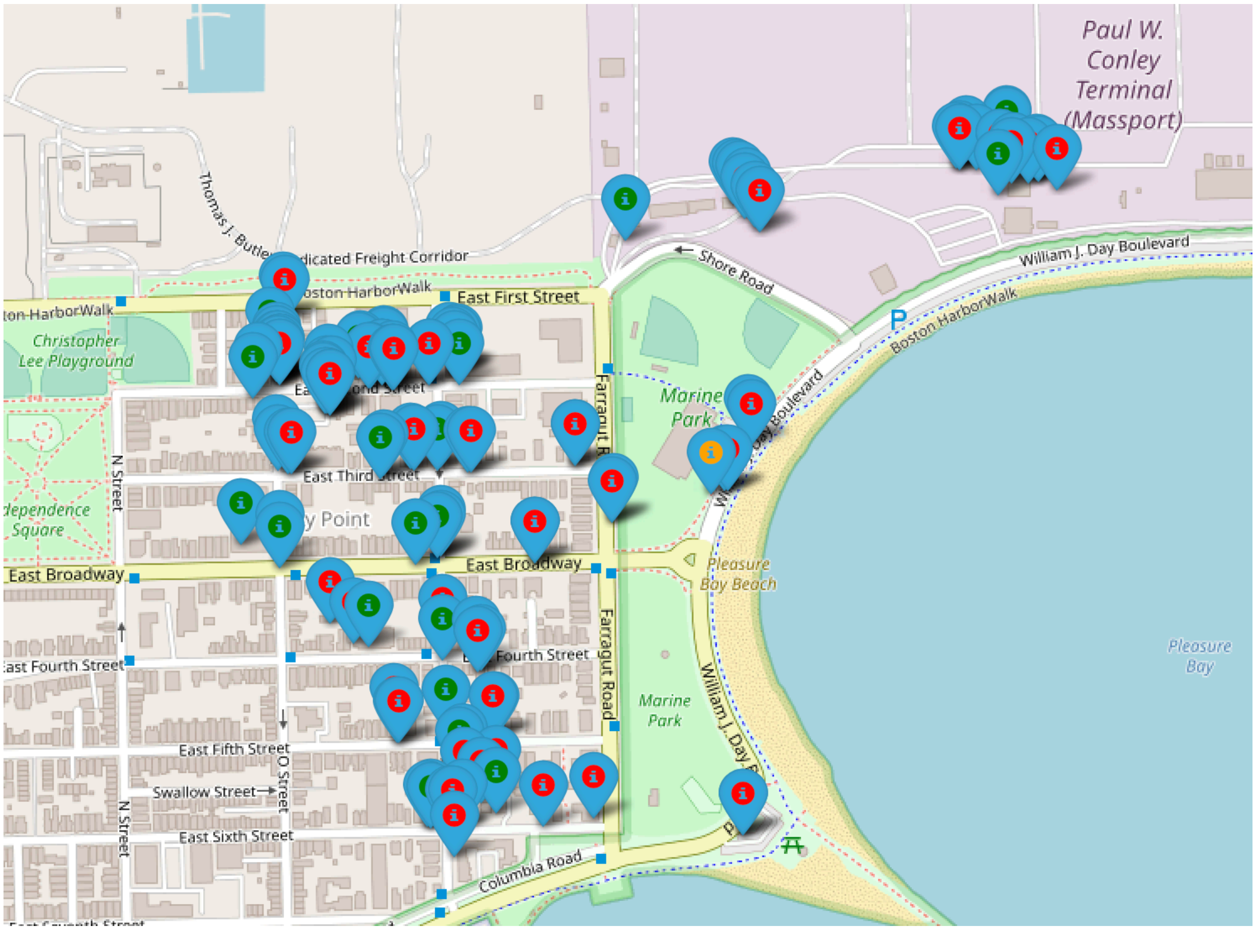

Figure 2. Trip Starts (Green) and Ends (Red) Around the Murphy Skating Rink Bluebikes Station (Orange)

In November of 2016, there were 167 Bluebikes stations, while there are 330 stations in March of 2020. With the trip segmentation, 1,503,429 trips were identified for November 16, 2016. On that same day, there were 4,404 Bluebikes trips. This method will use GPS data and ridership data at the stations in 2016 to extrapolate what ridership would have been for the stations that have been added since. This generalizable method would be able to thus extrapolate what ridership may look like around any point where a bike-sharing station may be added.

As Figure 2 shows, a radius of 500 meters was created around each station and the number of trip segments originating and terminating within that radius was determined. Then, the numbers of historical trip origins and destinations were determined for each station. Finally, the ratios of the historical trip origins and destinations to GPS data trip origins and destinations were calculated. Given these ratios, the projected ridership at the new stations could be calculated.

Results

Ratio for actual starts to cell phone starts –

Metric	**Ratio**
Mean	0.042577
Standard Deviation	0.044989
Minimum	0.001414
25% Percentile	0.015867
50% Percentile	0.028935
75% Percentile	0.052517
Maximum	0.309735
Median	0.028935

Figure 3a. Ratio of Historical Ridership to Cellphone Trip Origins

Metric	**Ratio**
Mean	0.041162
Standard Deviation	0.042908
Minimum	0.001504
25% Percentile	0.016733
50% Percentile	0.030568
75% Percentile	0.046195
Maximum	0.313364
Median	0.030568

Figure 3b. Ratio of Historical Ridership to Cellphone Trip Origins

In both cases, the median is around 0.03 so the cellphone trip origins and destinations were scaled by 0.03 to estimate predicted ridership. Incidentally, 0.03 is near the actual 2016 cycling mode share in Boston of 2.4%. [137] A subset of the predictions for stations is replicated here while the full table of predicted trips is in the Appendix.

Station	Starts	Ends
St Mary's	22.17	22.26
Broadway at Central St	7.92	7.89
East Somerville Library (Broadway and Illinois)	11.91	12.12
Assembly Square T	7.65	7.92
Community Path at Cedar Street	4.02	4.23
Park St at Norwell St	6.72	6.60
Gallivan Blvd at Adams St	4.44	4.53
Washington St at Bradlee St	8.55	8.49
Fields Corner T Stop	15.27	14.55
Ashmont T Stop	9.30	9.33
Shawmut T Stop	7.41	7.47
Forest Hills	15.51	15.36
Williams St at Washington St	9.75	9.45
Main St at Baldwin St	8.67	8.55
Stony Brook T Stop	6.87	7.02
Farragut Rd at E. 6th St	1.20	1.35
Ames St at Broadway	22.56	22.71
84 Cambridgepark Dr	12.39	12.66
Main St at Thompson Sq	17.88	18.42

Figure 4. Subset of New Stations with Trip Predictions

Station Identification

Methodology

In order to identify where demand for bike-sharing is throughout the city, all trip origins and destinations were visualized around the city using the Uber H3 visualization package. This bucketing mechanism creates a hierarchical indexing system with various distance resolutions. The system creates a global hexagonal grid that gauges the demand within each hexagon.[54]

In this case, all the Safegraph GPS trip origins and destinations from November 16, 2016 were visualized with the H3 package. Several cluster resolutions were visualized in order to

[54] https://eng.uber.com/h3/

visualize overall demand, as Figure 5 shows, to highlight where bike-sharing stations could be useful. In future studies, further constraint optimizations could be used in order to mandate station capacities and station densities throughout the network, to ensure a dense enough network for bike-sharing access. Also, the newly identified stations could be inputted back into the simulation model from the previous chapter in order to identify how the new stations could handle bike-sharing demand. Station capacities for the simulation model could be determined by modeling the number of trips that are predicted to start and end at that station.

Results

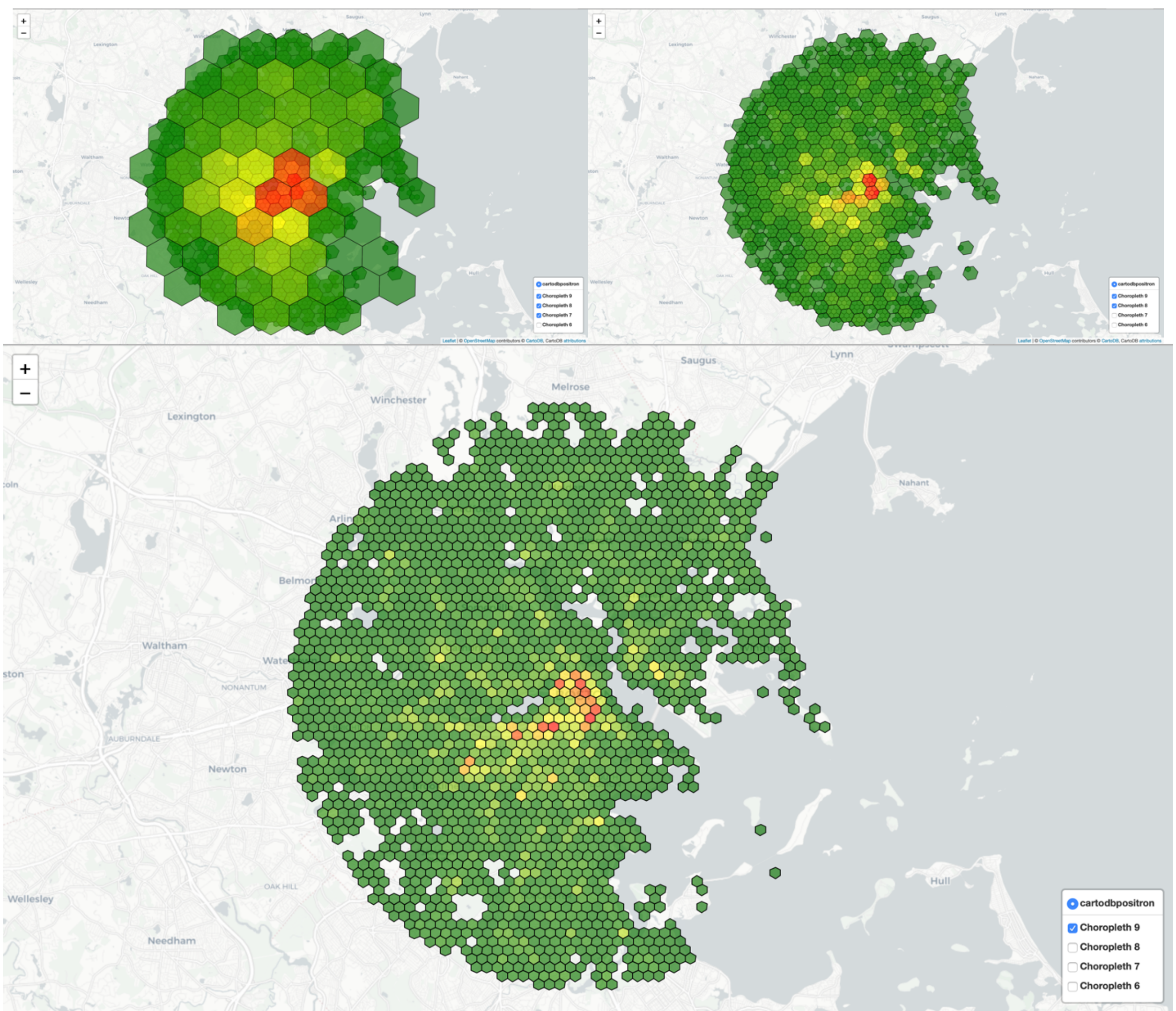

Figure 5. Cellphone GPS Trip Origins and Destinations at Resolutions of 3.23km (Top-Left), 1.22km (Top-Right), and 0.46km (Bottom)

Figure 5 shows the GPS trip origins and destinations identified from the Safegraph GPS data at various resolutions. At the most granular resolution, it grows clearer that while, of course, much of the demand is centered around the central business districts, there are also some hotspots in Cambridge, Everett, Brookline, and Dorchester, among others.

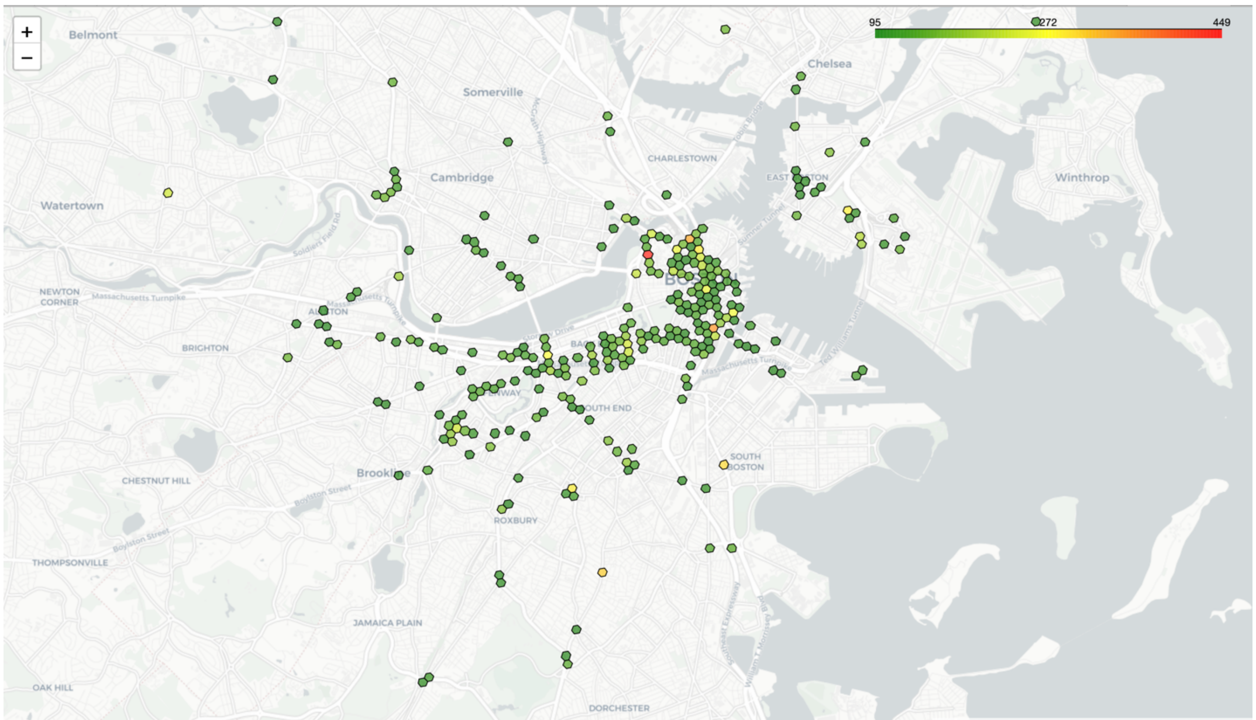

Figure 6a. The 300 Densest Areas at a Resolution of 0.46km

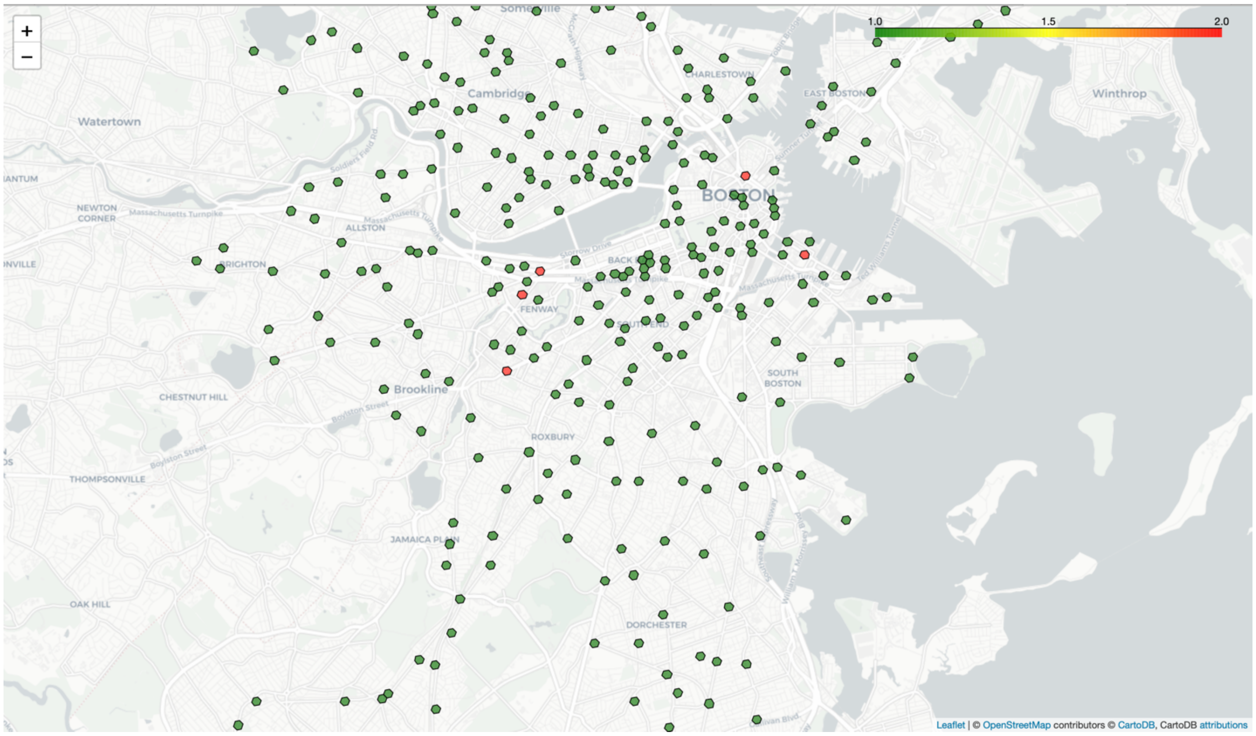

Figure 6b. The Existing Bluebikes Station Network

Figure 6a shows the densest areas identified at a resolution of 0.46km, which is about how long a pedestrian would walk to get to a bike-sharing station. When juxtaposed against the existing Bluebikes network, the importance of avoiding station clustering can be noted. Networks are often planned to with certain regional station densities in mind. Without spreading the stations out, going exclusively off of ridership, stations would be clustered in busy parts of the city without creating a comprehensive and accessible transit network.

Using cellphone GPS data to identify the potential ridership at stations and potential station locations is novel when applied to bike-sharing. This useful and generalizable tool, utilizing a new type of dataset, highlights the importance and value of effective demand prediction. Simultaneously, these visualizations tell a cautionary tale of basing station locations exclusively on projected ridership as stations could then grow clustered exclusively in high demand areas, barring stations from spreading out around a city in order to facilitate ridership across the city rather than in dense neighborhoods.

Conclusion

As established through this thesis, bike-sharing has the opportunity and the prerogative to be thought of as a form of public transportation that facilitates equitable mobility throughout a city. In order to develop such a network, new modeling and planning methods are required. This thesis presents two such models: a simulation model that allows for planners to understand the impacts of weather and variations in demand; and a GPS enabled, data-driven approach to identifying station usage. While both models are limited, they take steps towards establishing a new automated, data-driven paradigm in bike-sharing planning.

Through the simulation model, this thesis shows that, using the Boston Bluebikes network, ridership along non-traditional, residential-residential routes can be modeled. It further shows that adding teachers to the network does not significantly impact the proportion of missed rides, highlighting the flexibility of the Bluebikes network. Finally, the BikePath simulation model itself is a multi-agent, impact focused approach to modeling different weather scenarios, levels of demand, and static rebalancing.

Secondly, through the explorations of virtual stations and station identification, this thesis presents a novel technique for demand discovery using GPS movement data. This thesis shows how historical data can be leveraged to project the ridership at brand new stations and gauge the efficacy of new expansions to bike-sharing networks. Further, it presents a method to identify the potential locations of new stations through effective data visualization and modeling.

With data-driven, automated processes, bike-sharing can be made more cost-effective and accessible. Given these novel tools, bike-sharing and bike-sharing implementation can be revitalized as a form of equitable urban mobility, offering new ways to make bike-sharing safe and effective, and justifying its role as a form of transit on its own right.

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Appendix

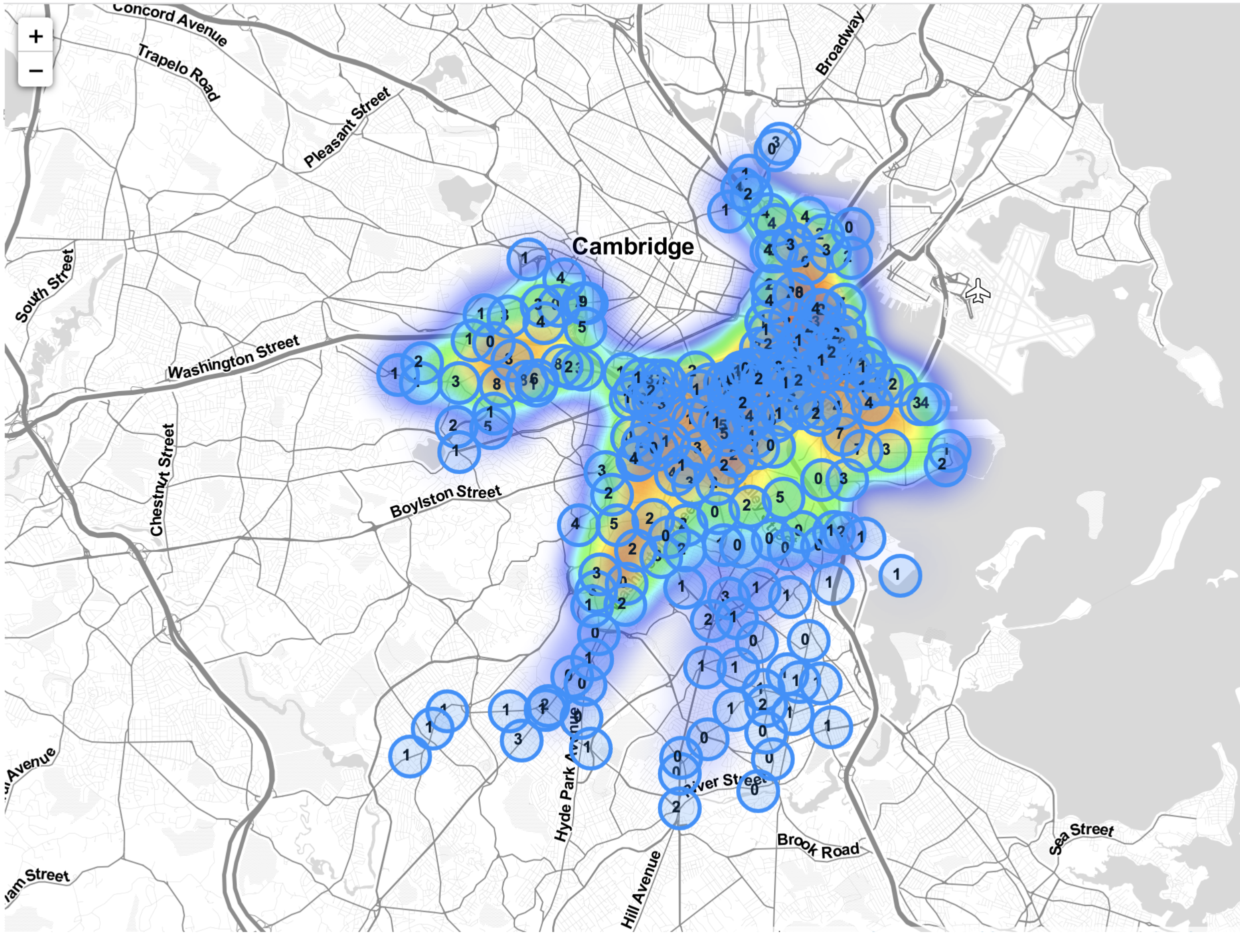
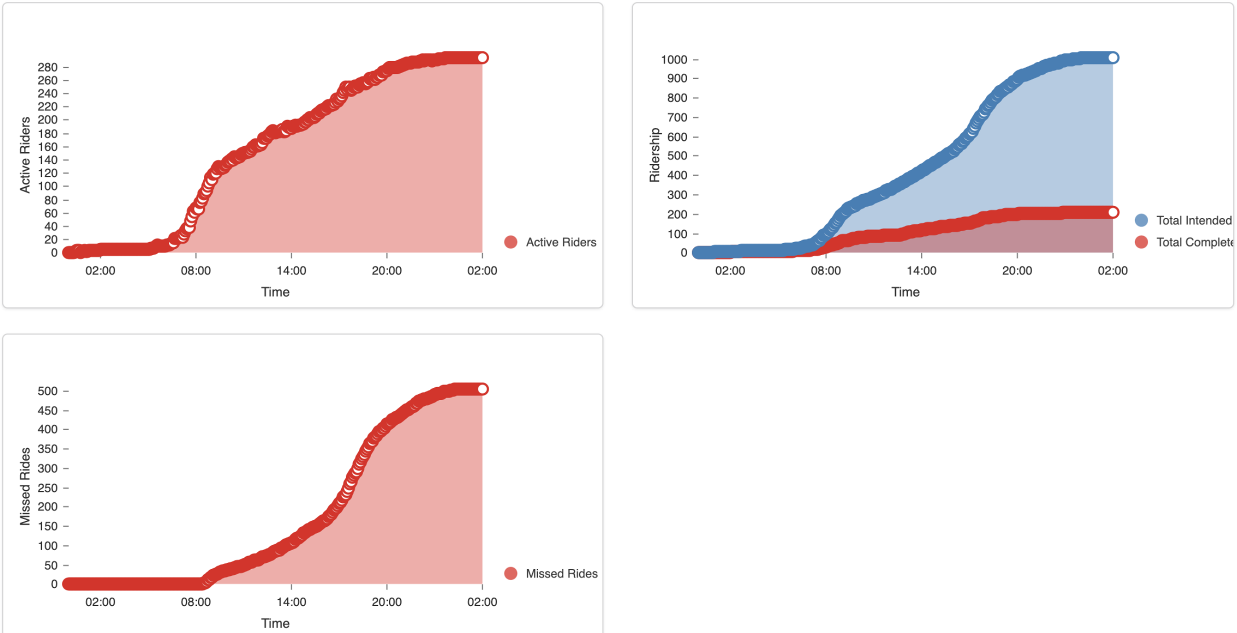


Figure A.1. 500 bikes, 30°, without teachers



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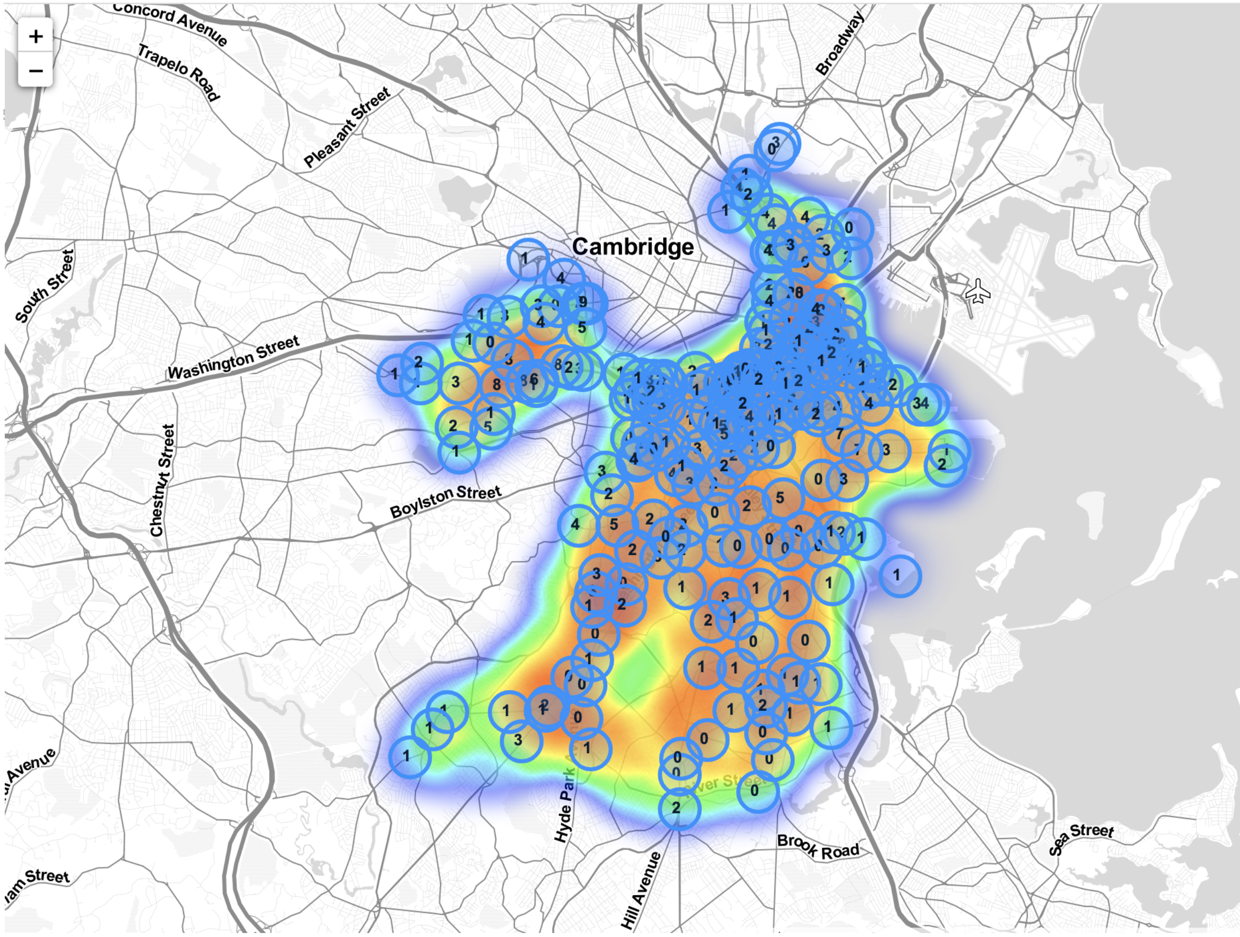

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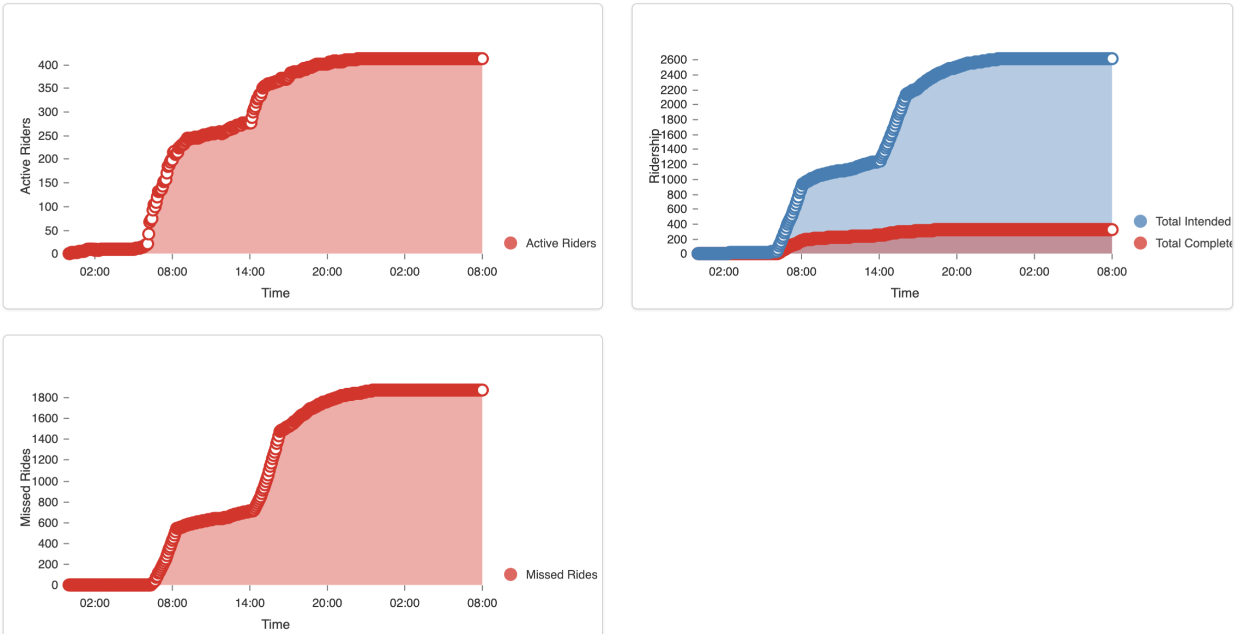

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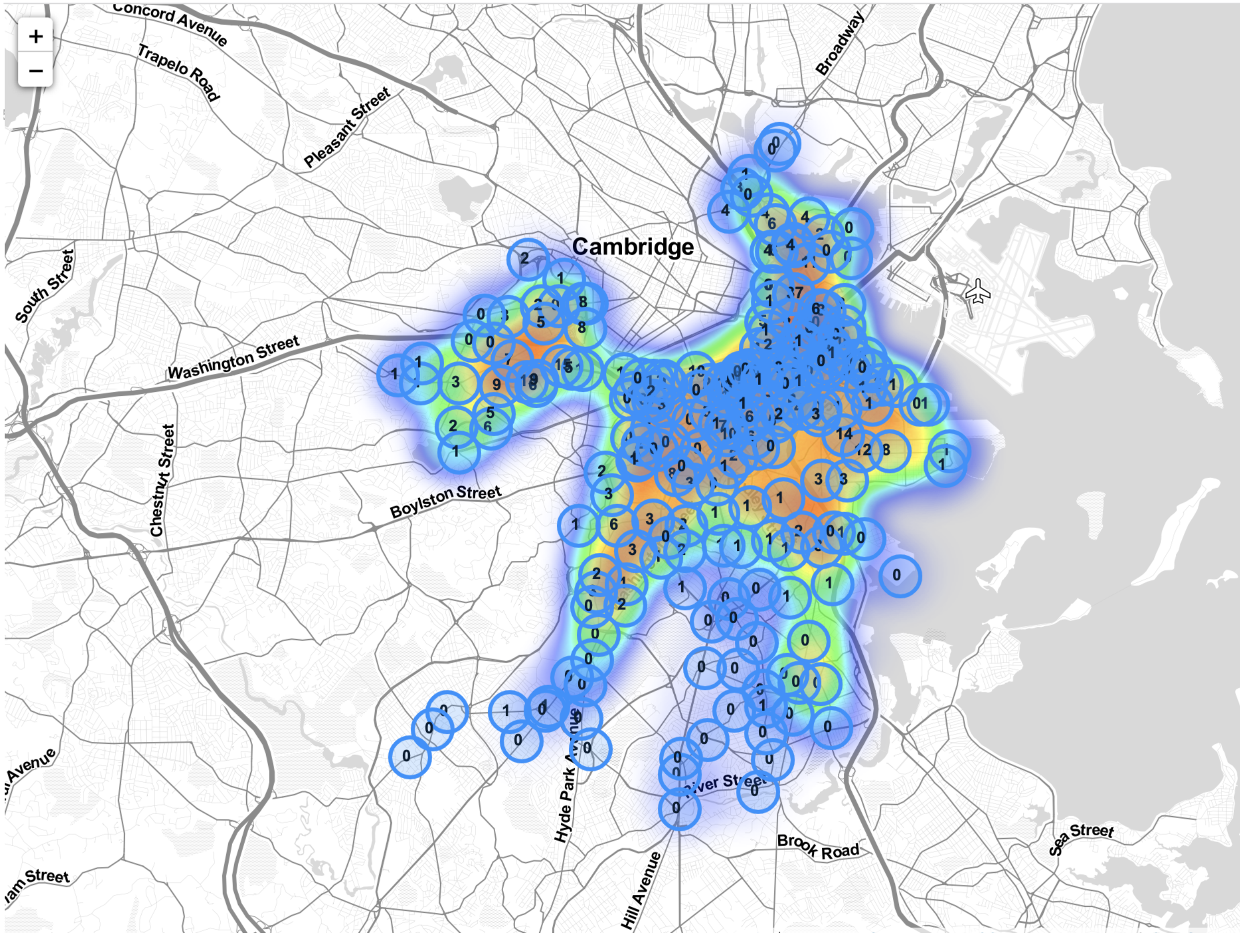
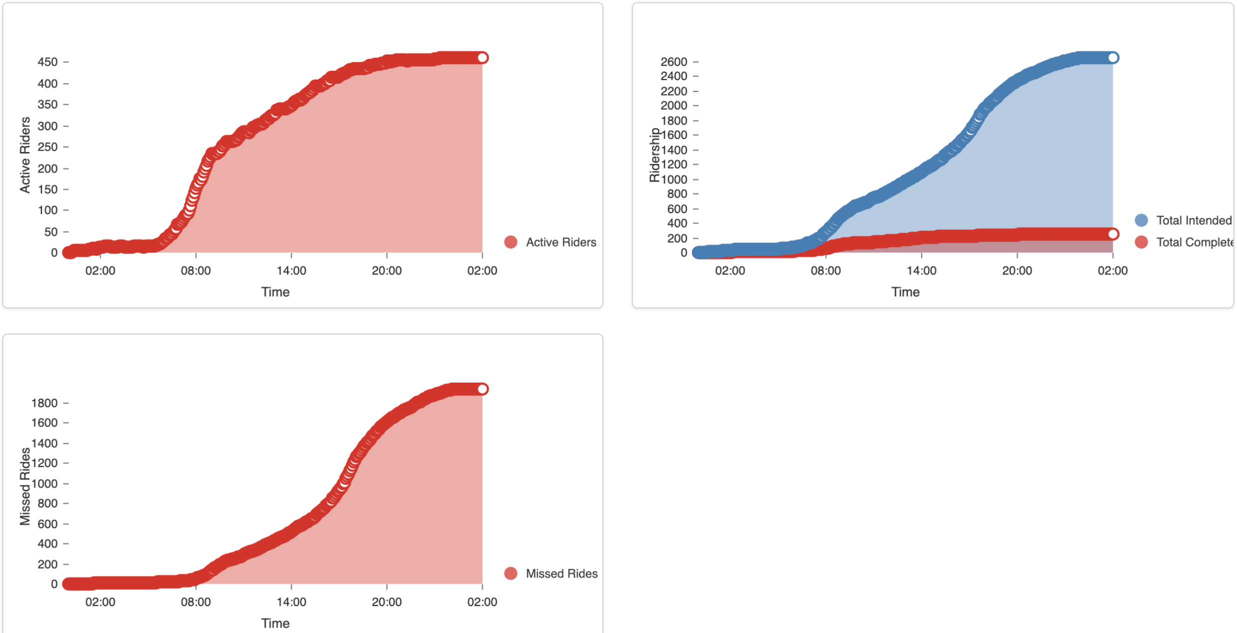


Figure A.5. 500 bikes, 50°, without teachers



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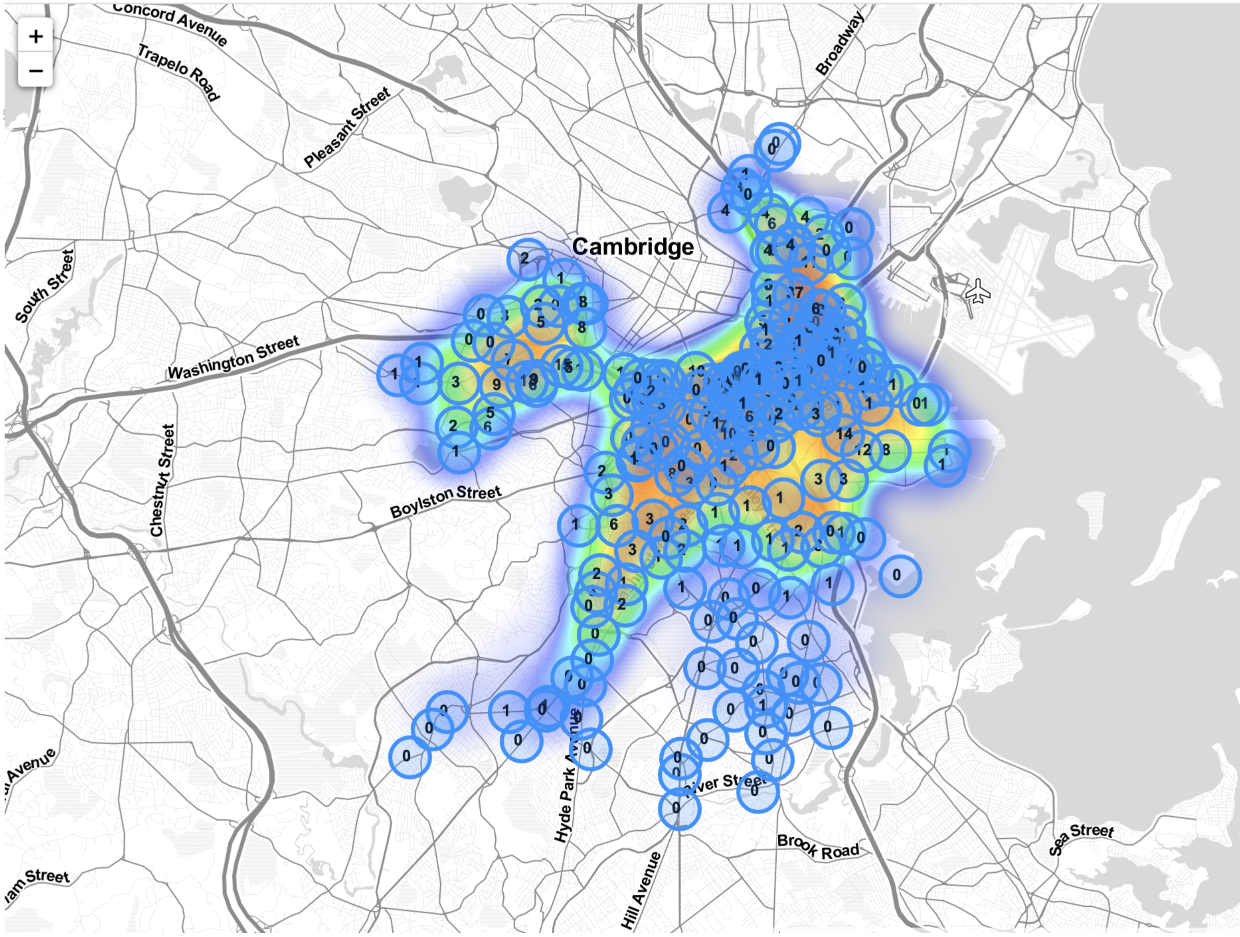
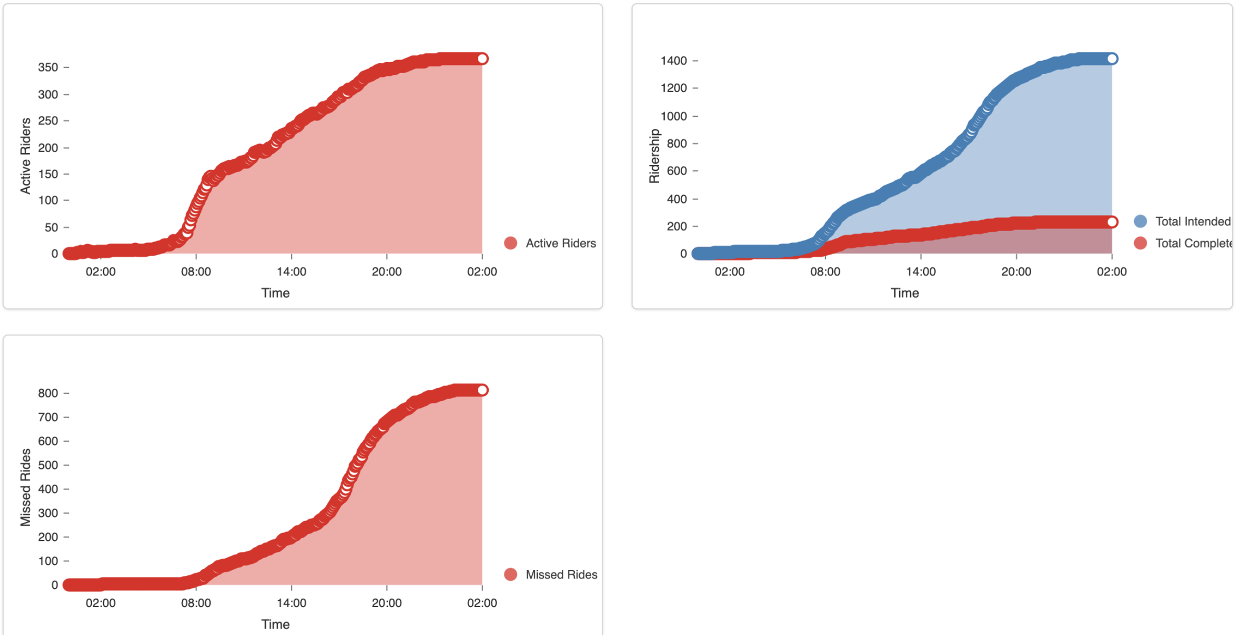


Figure A.7. 500 bikes, 50° and 0.5” precipitation, without teachers



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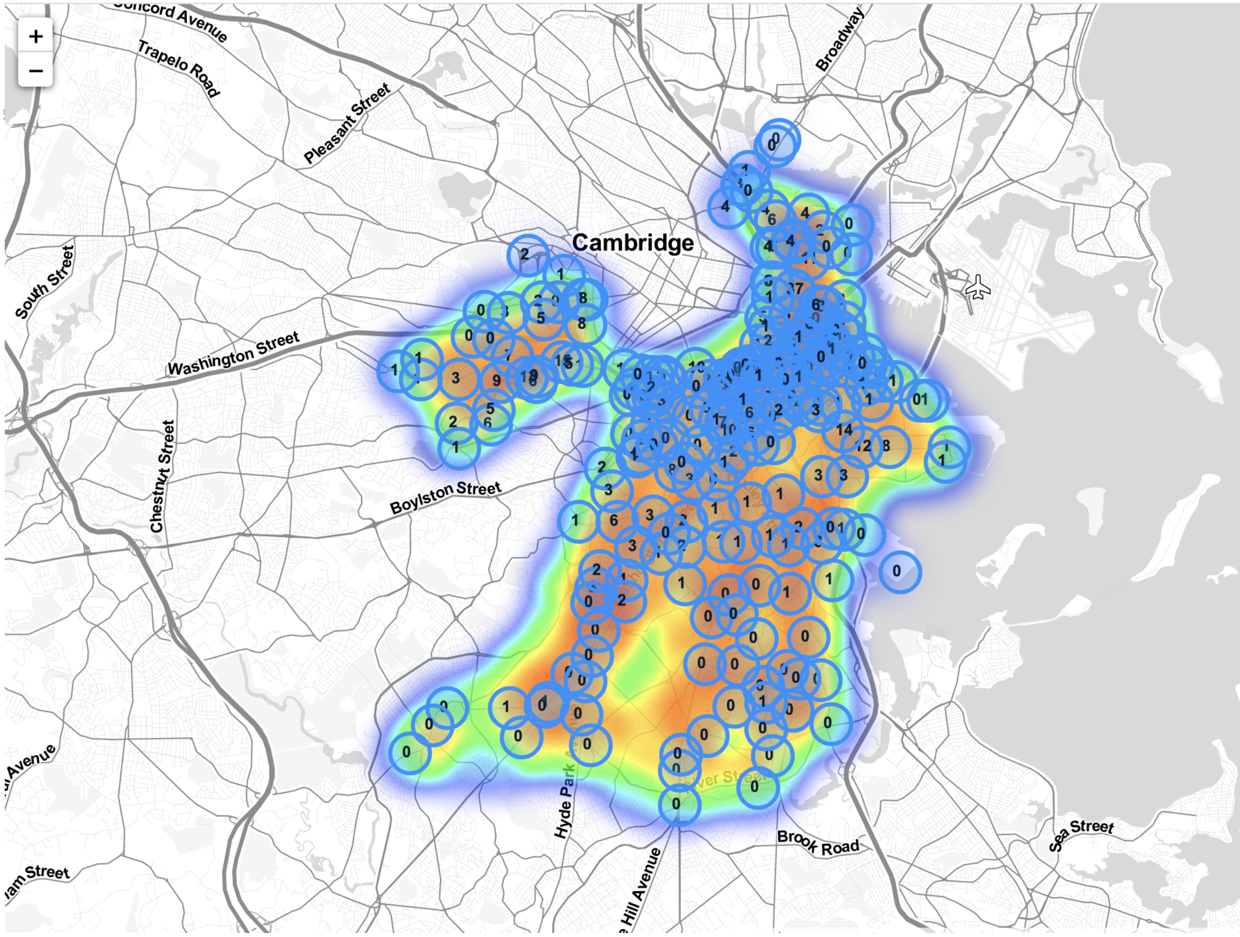


Figure A.9. 500 bikes, 50° and 0.5” precipitation, with teachers

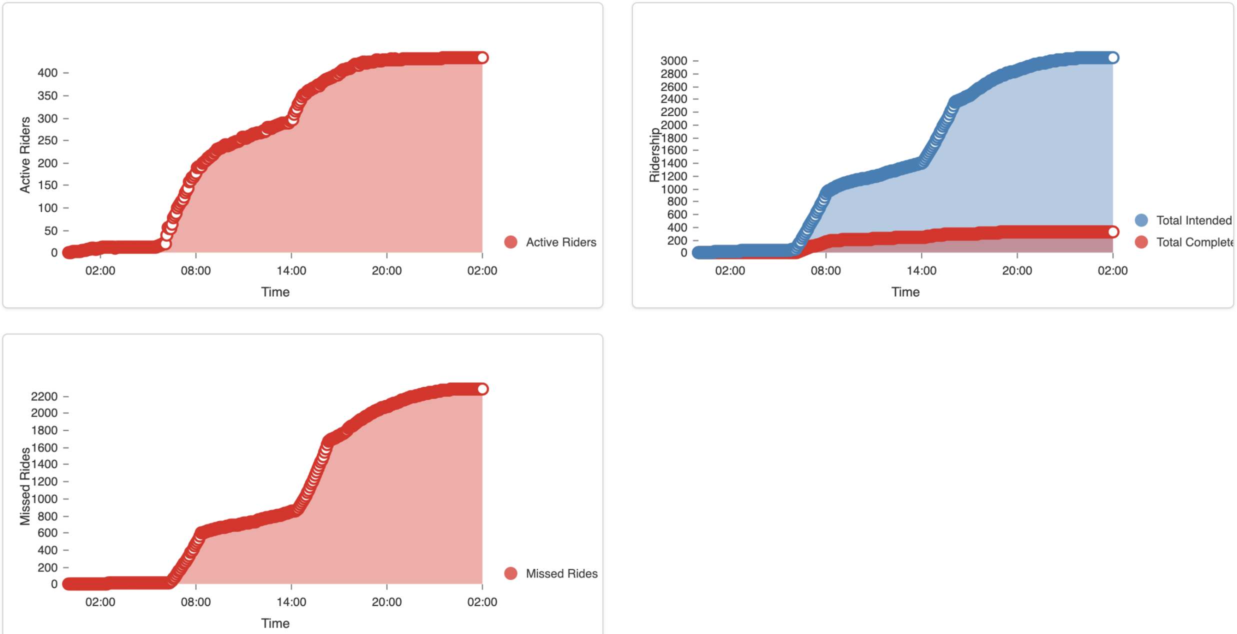
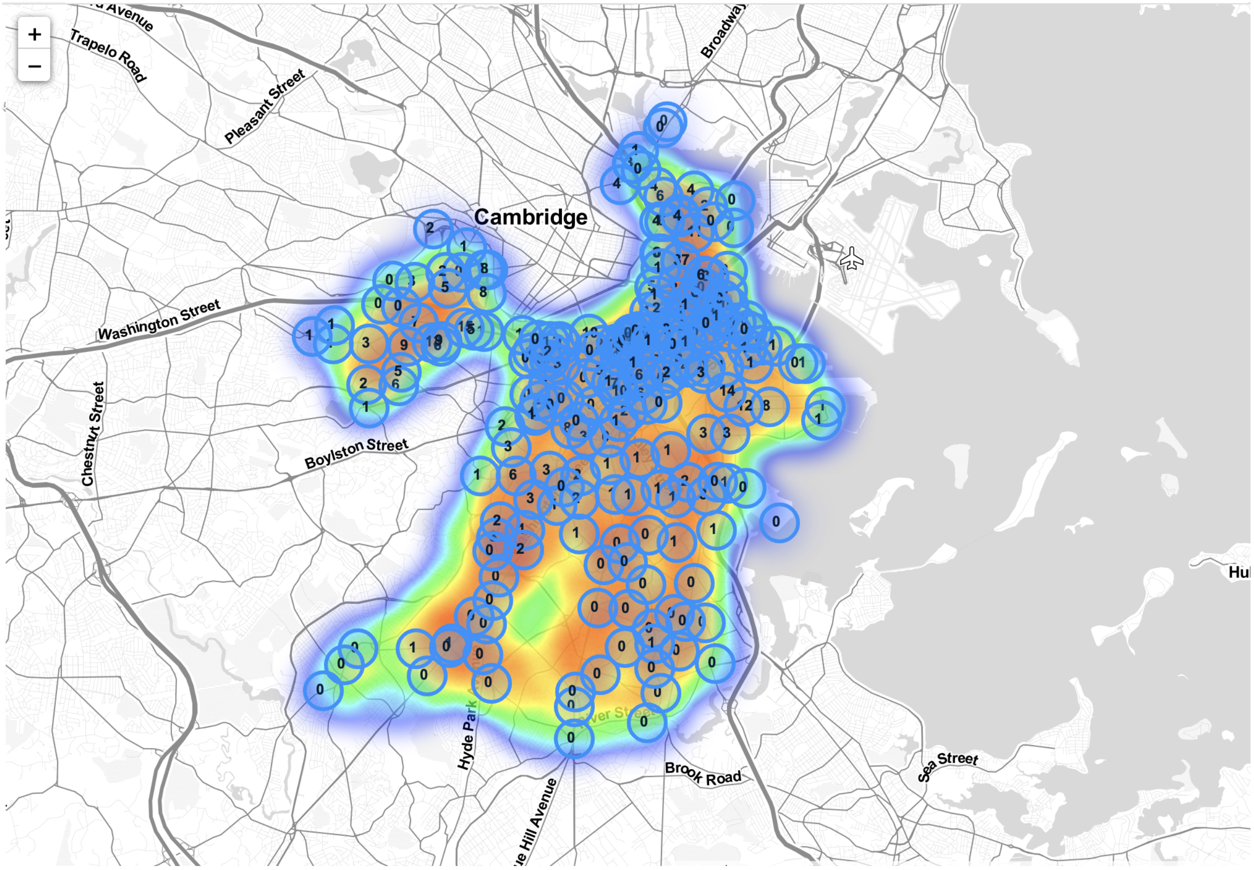


Figure A.10. 500 bikes, 50° and 0.5” precipitation, with teachers data



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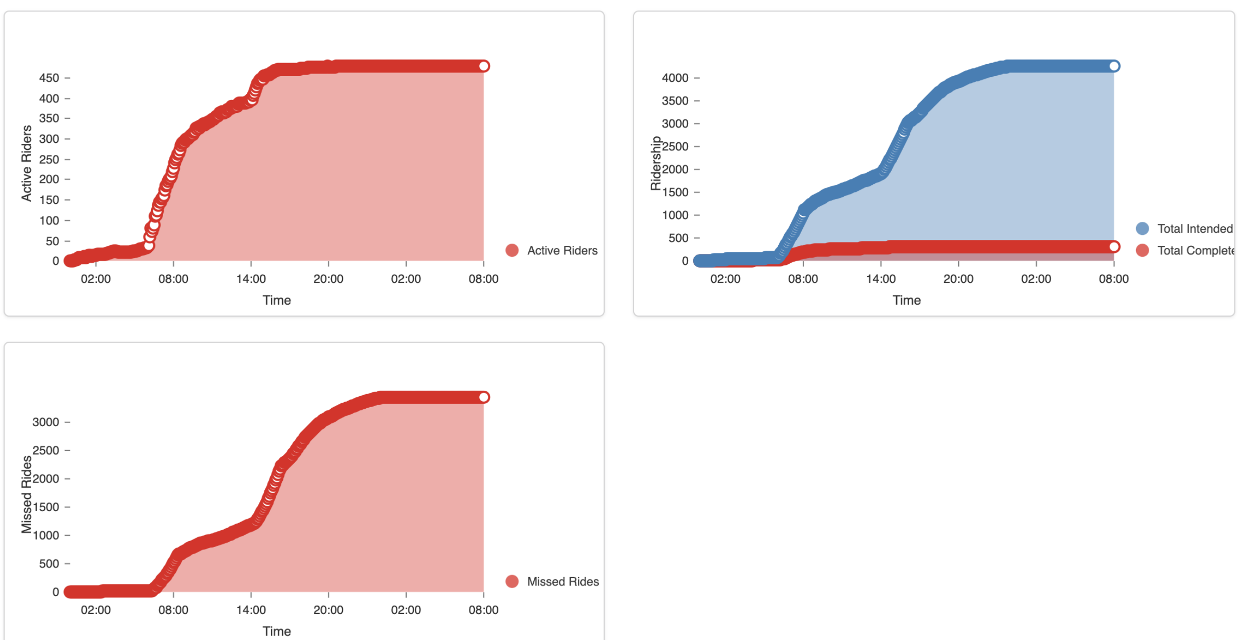

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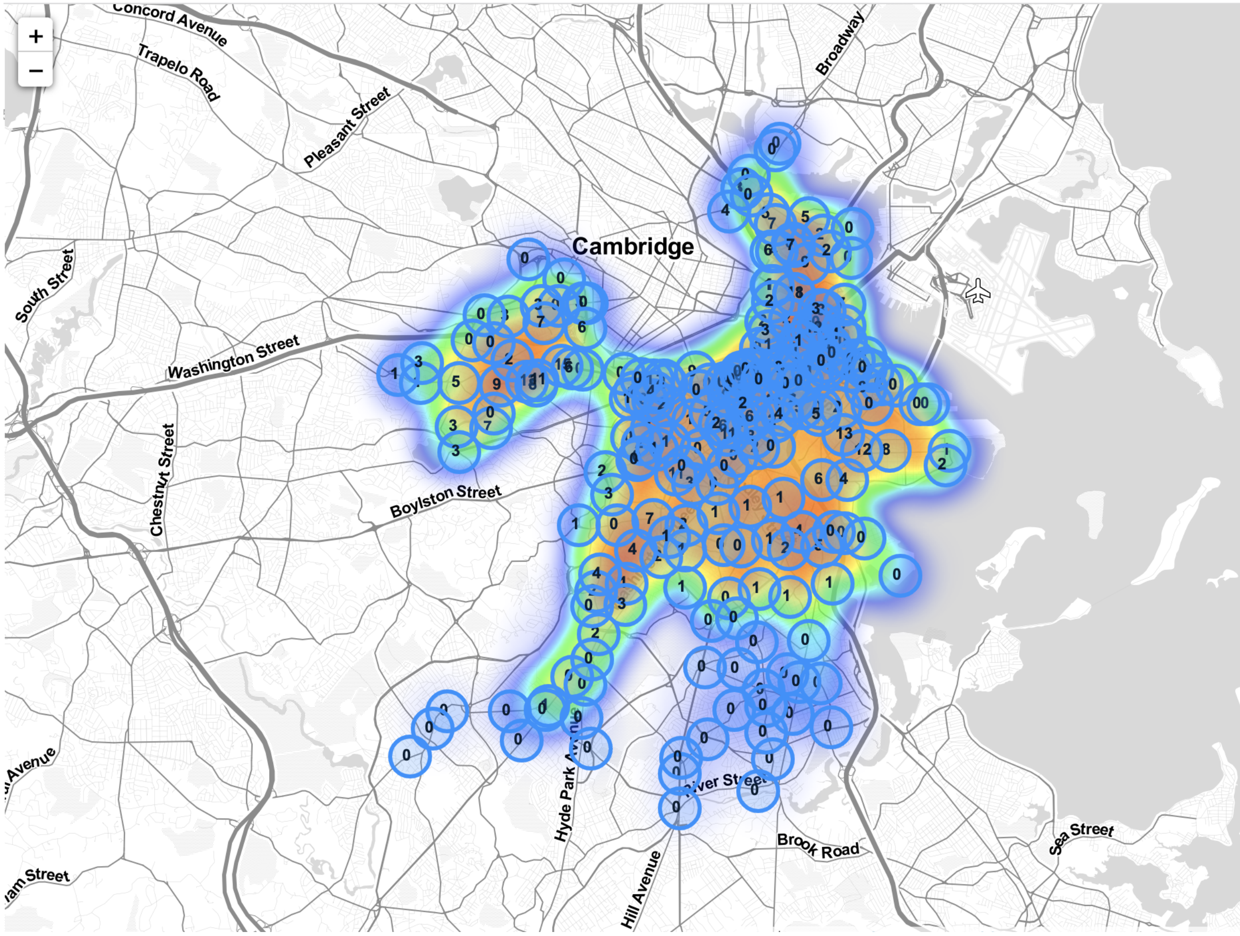

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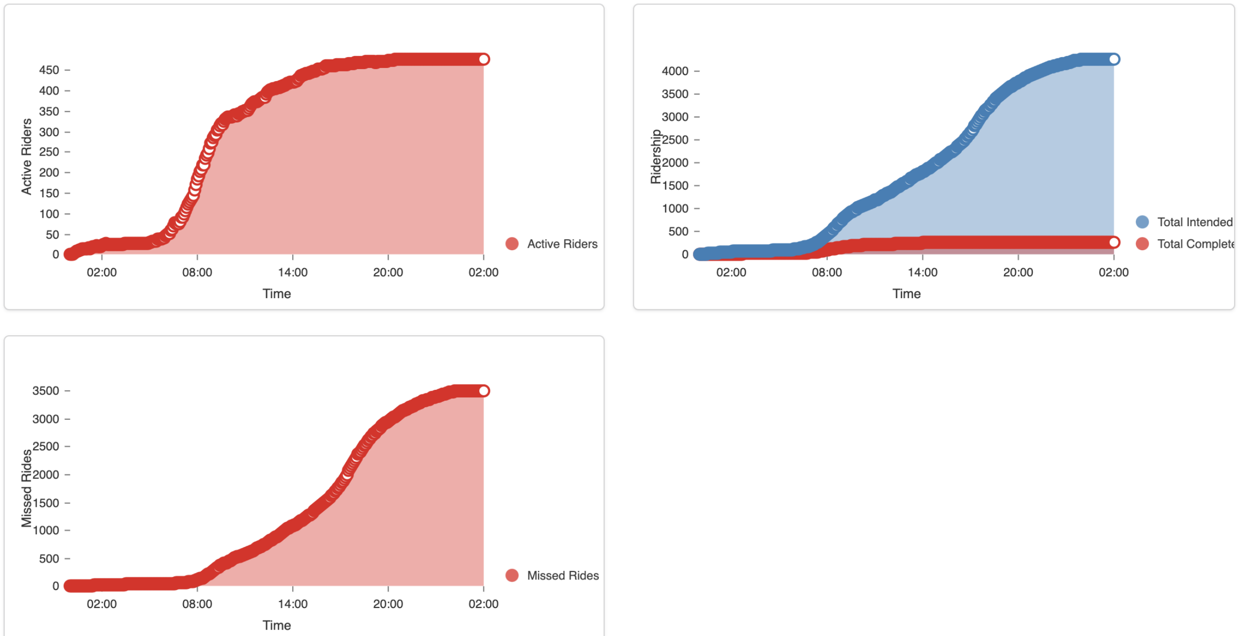

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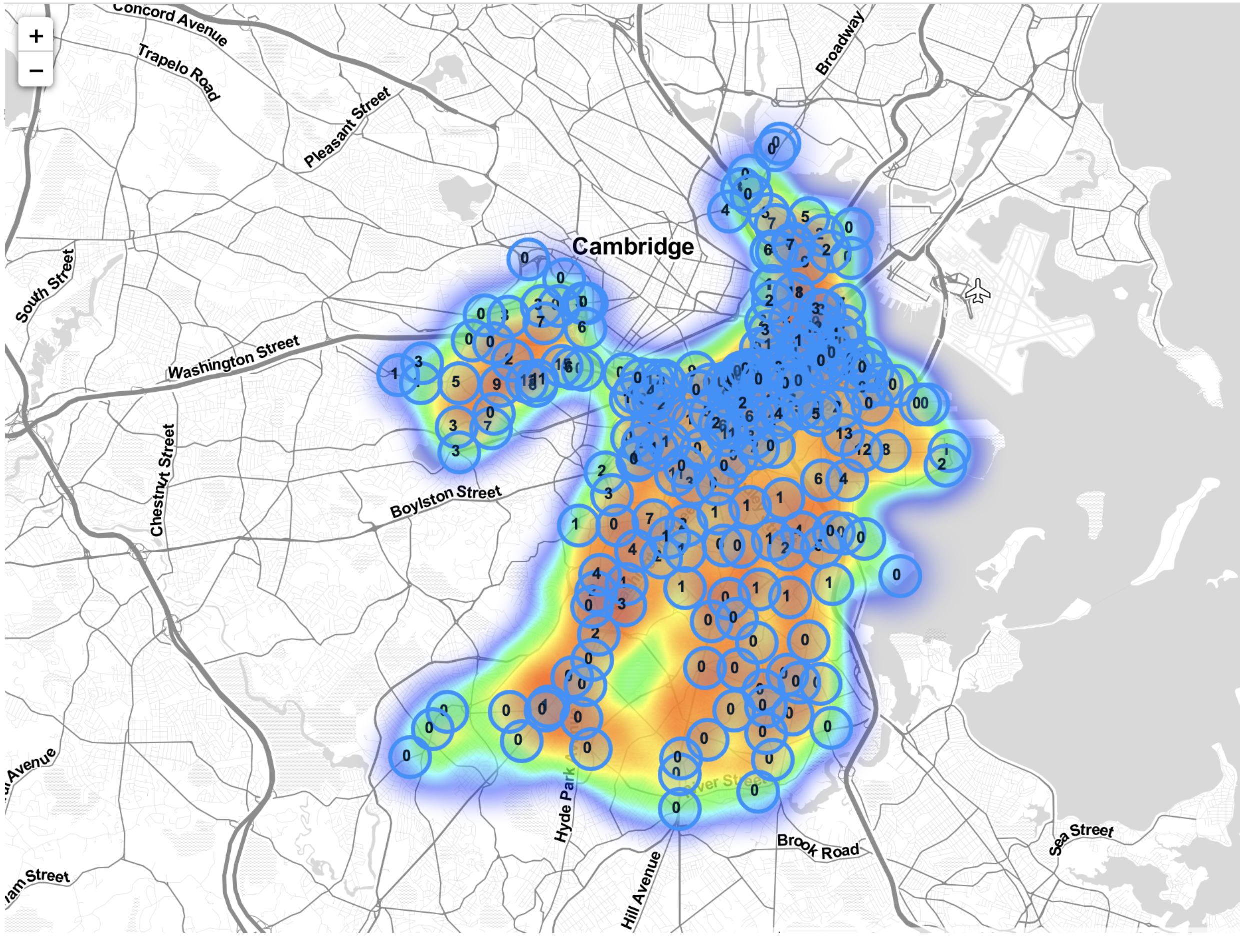

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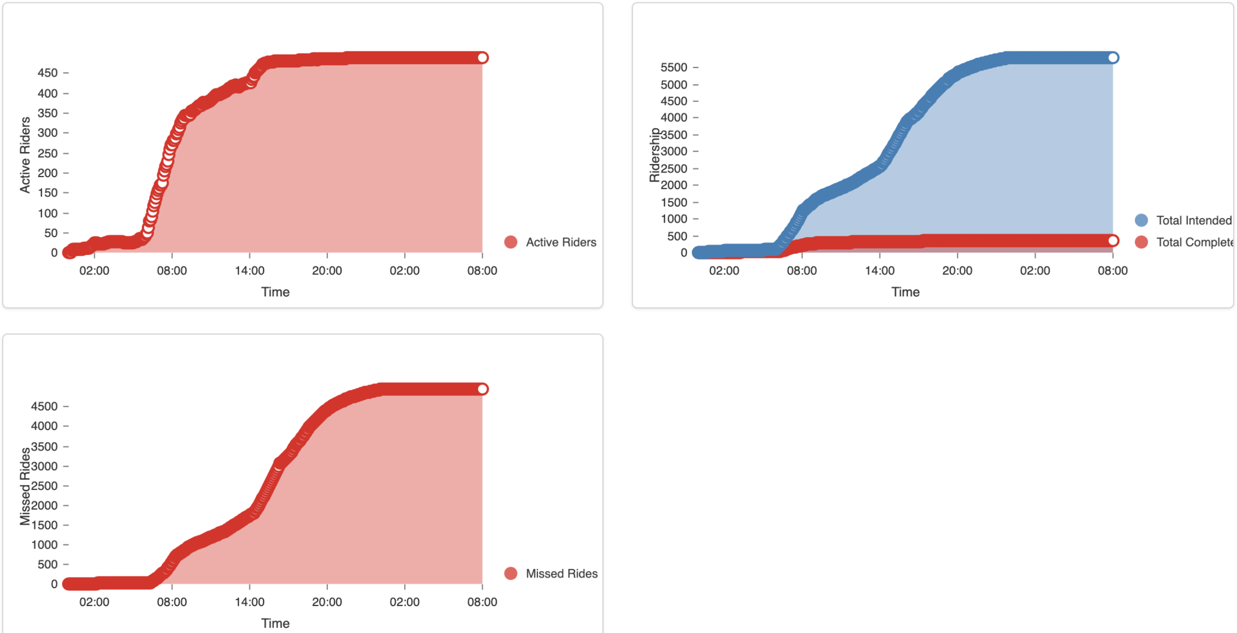

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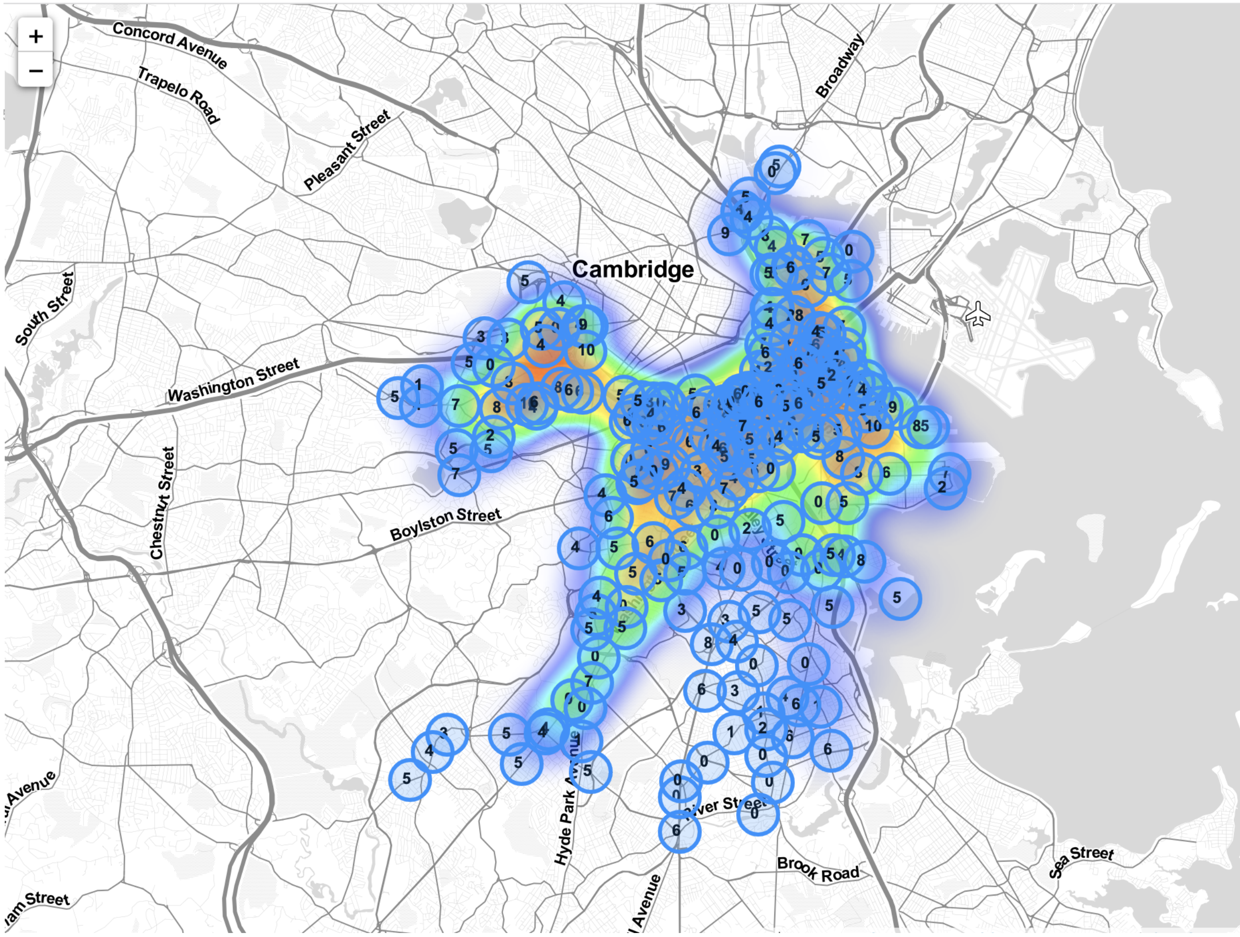
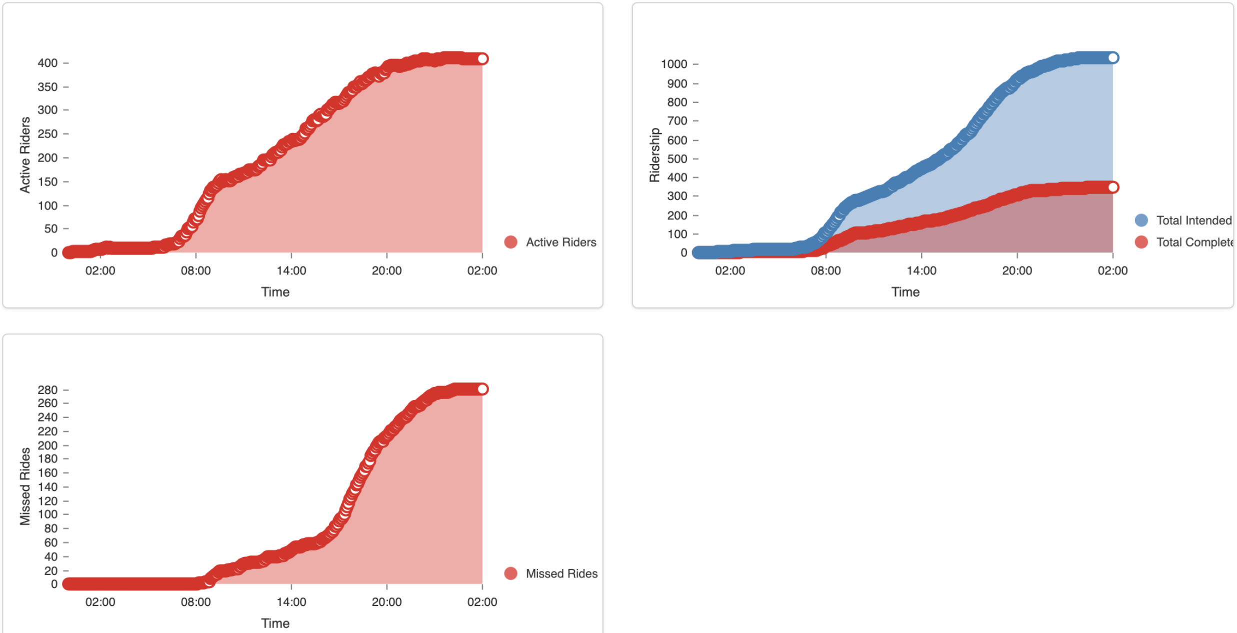


Figure A.17. 1000 bikes, 30°, without teachers



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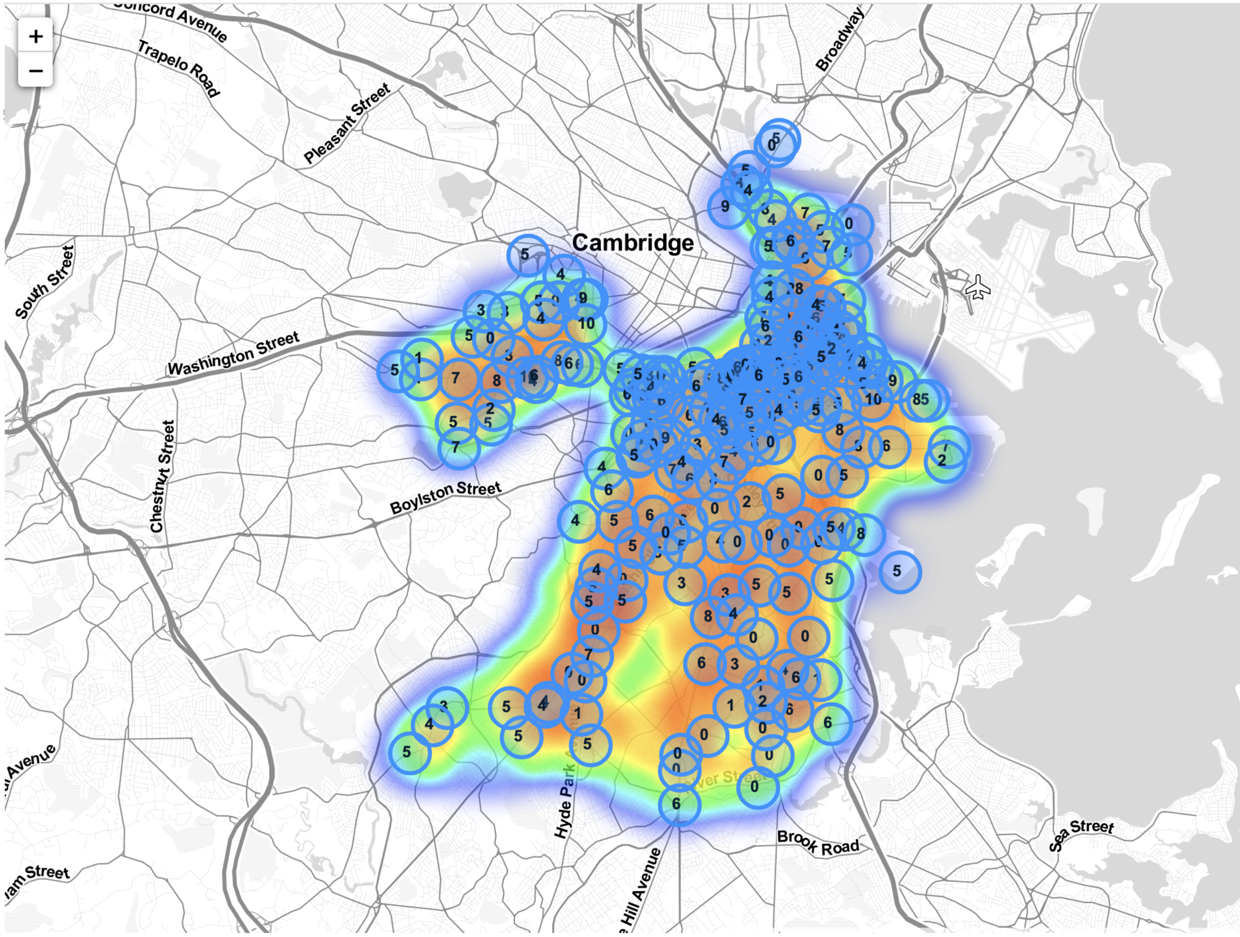

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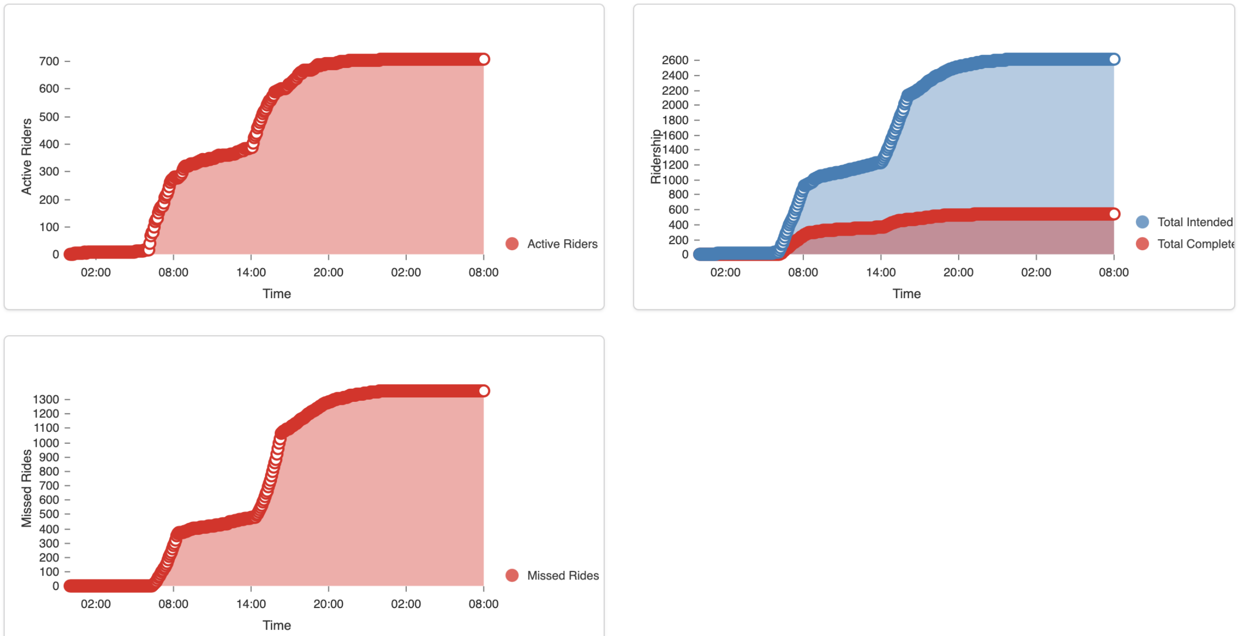

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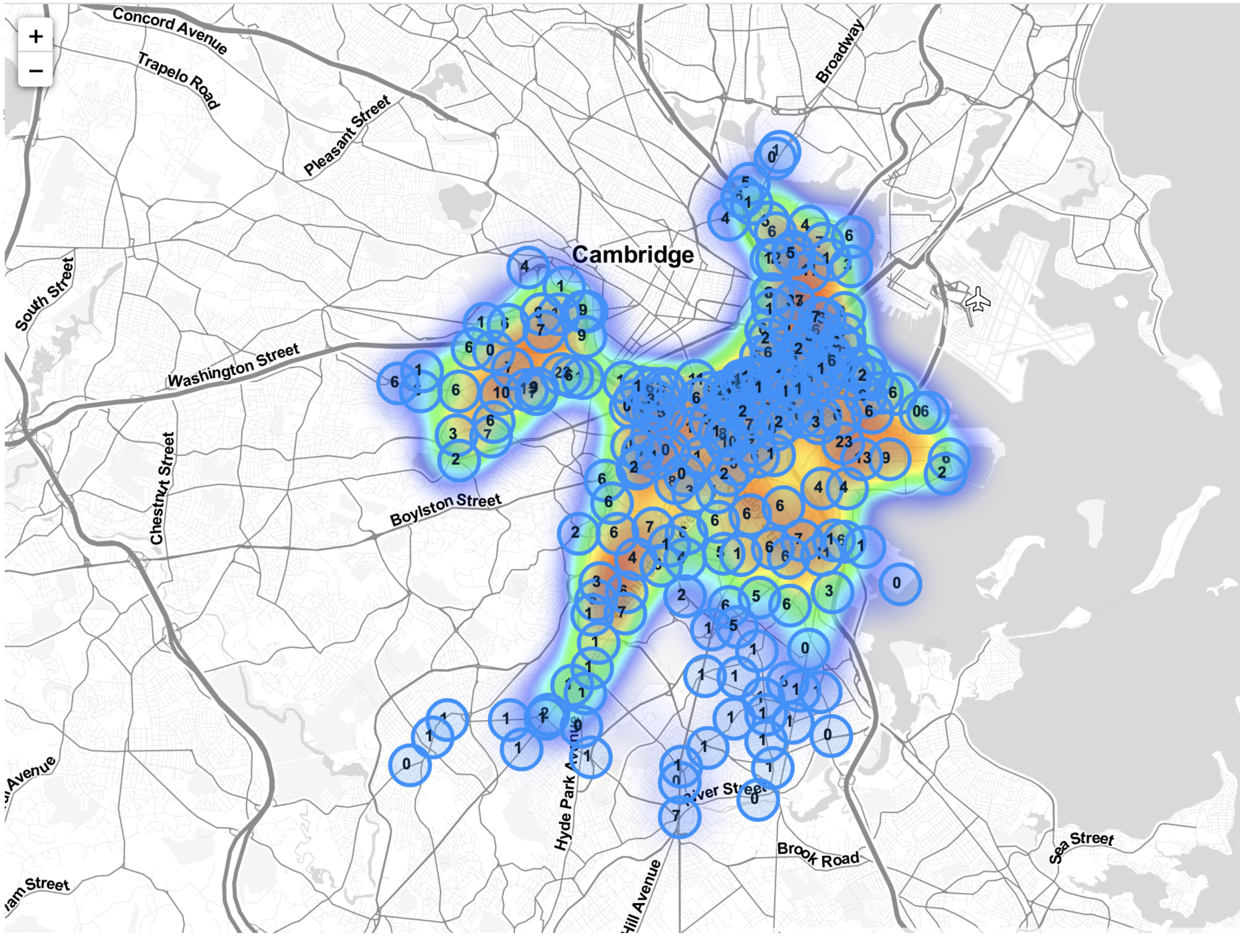

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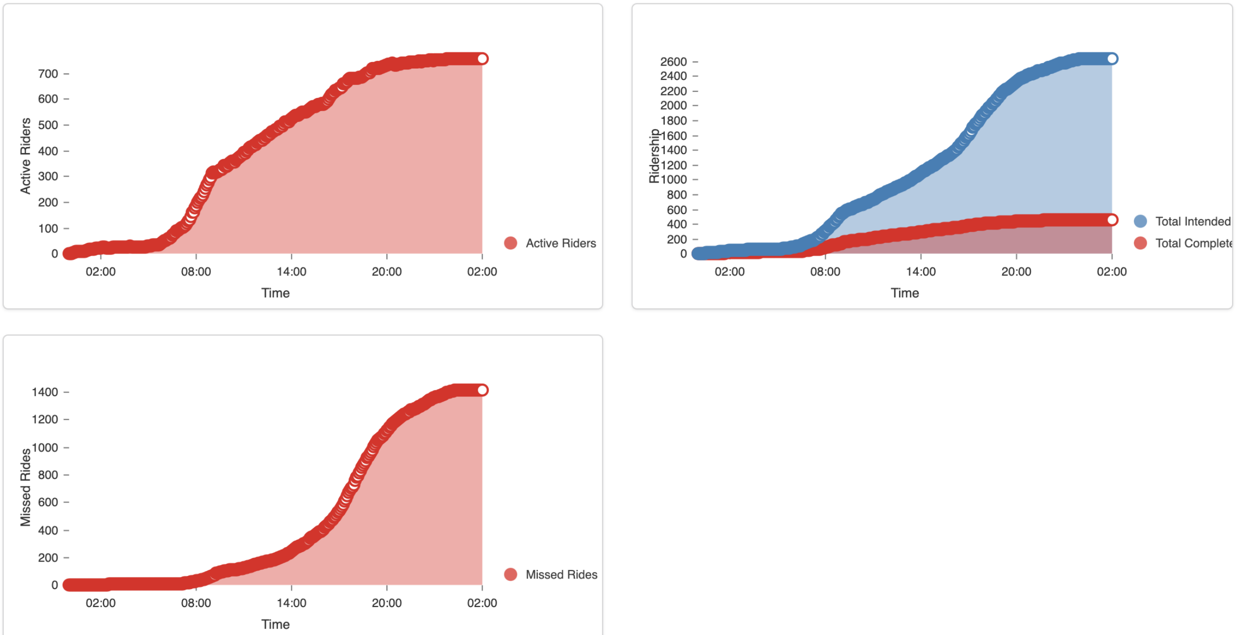

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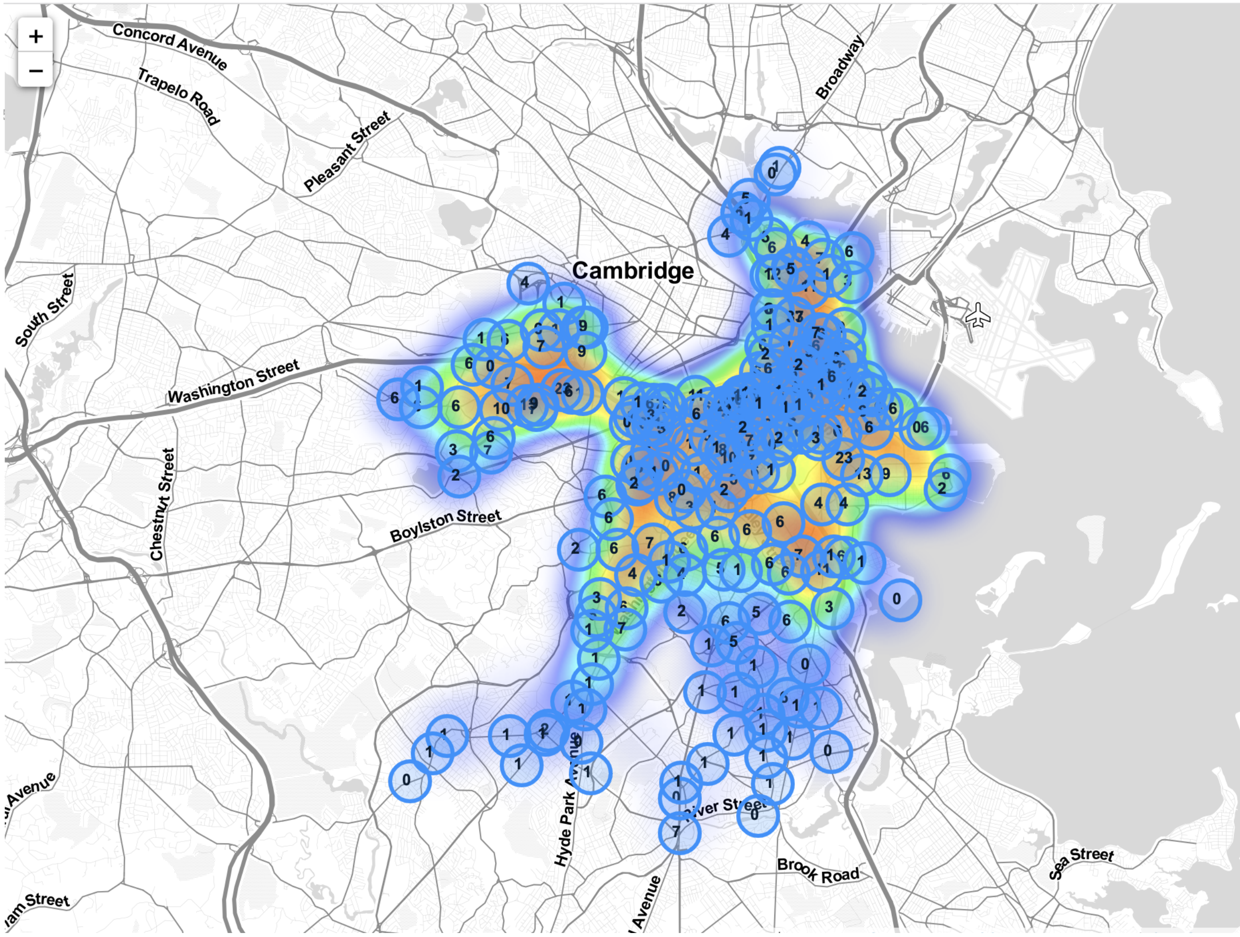

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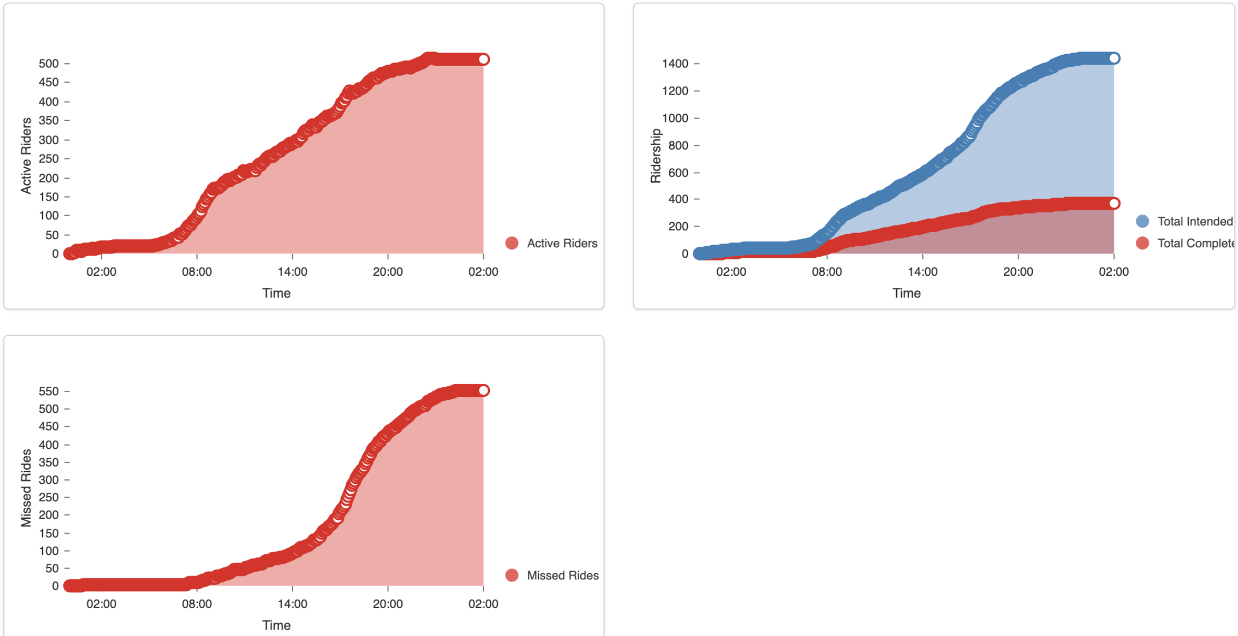

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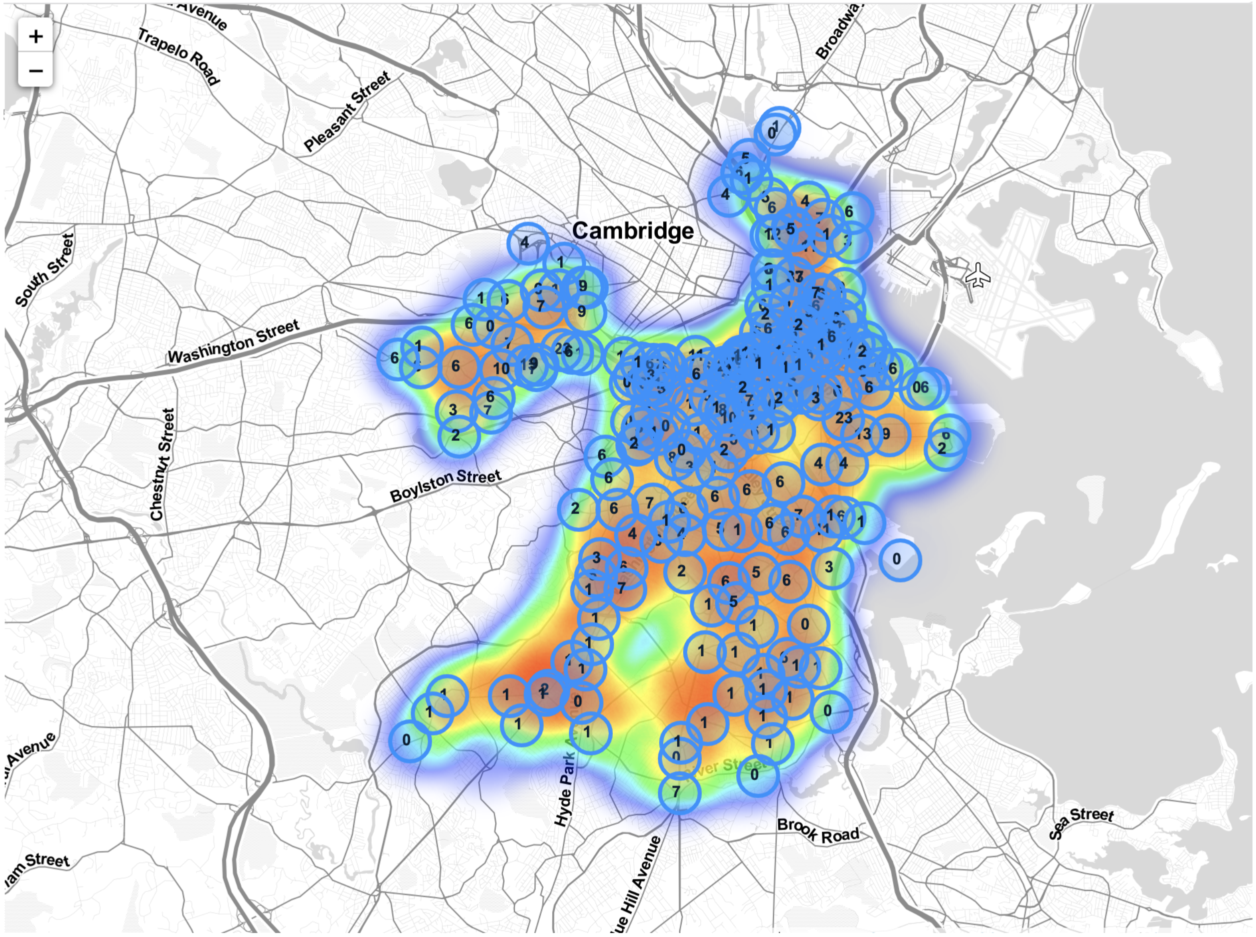

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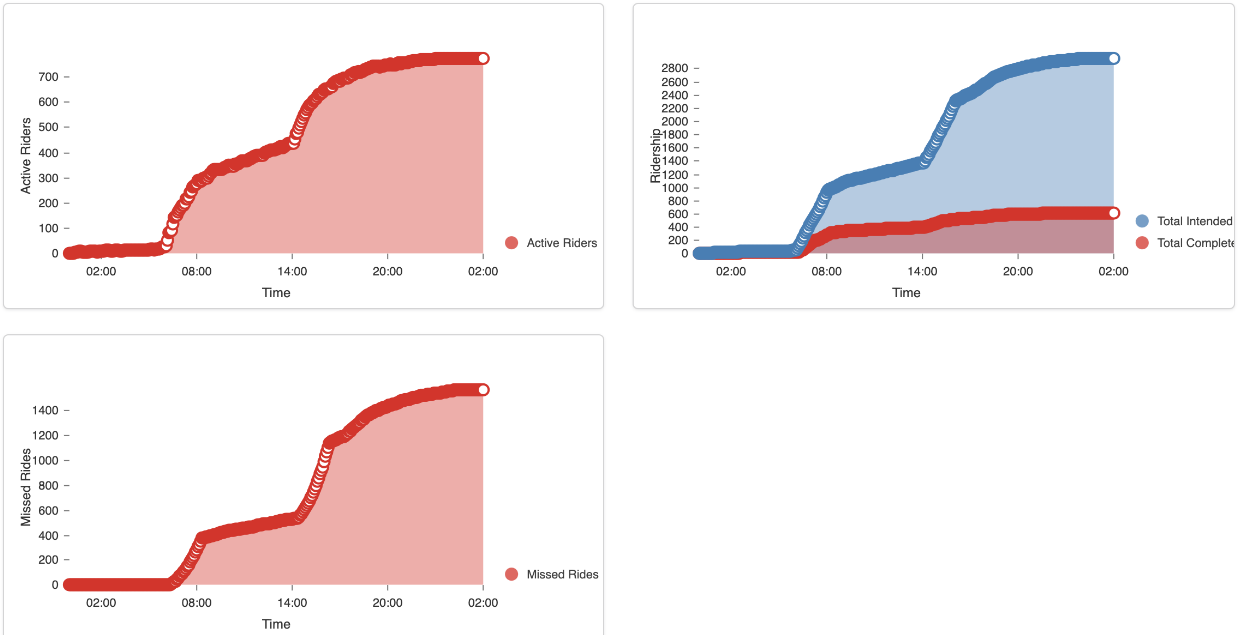

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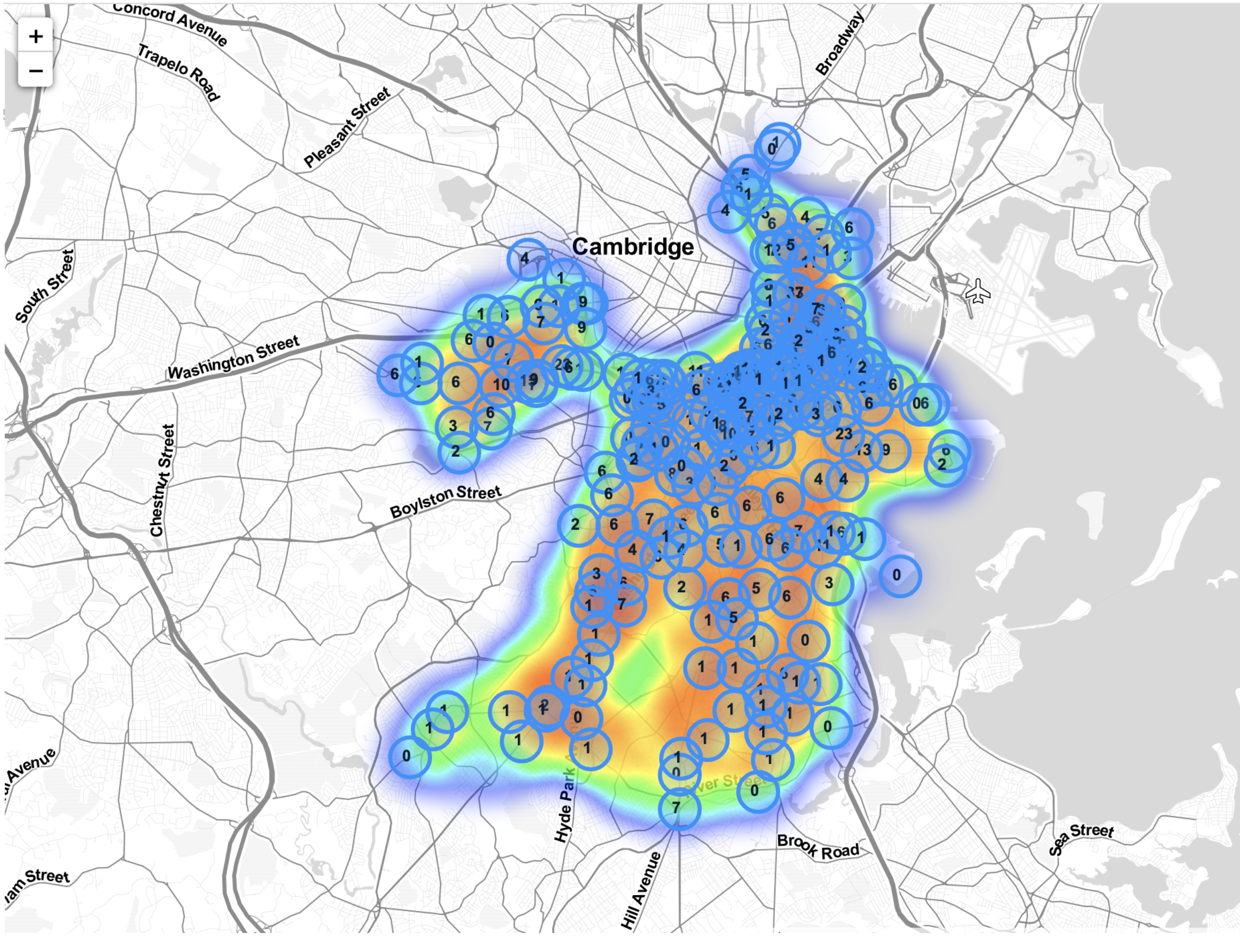

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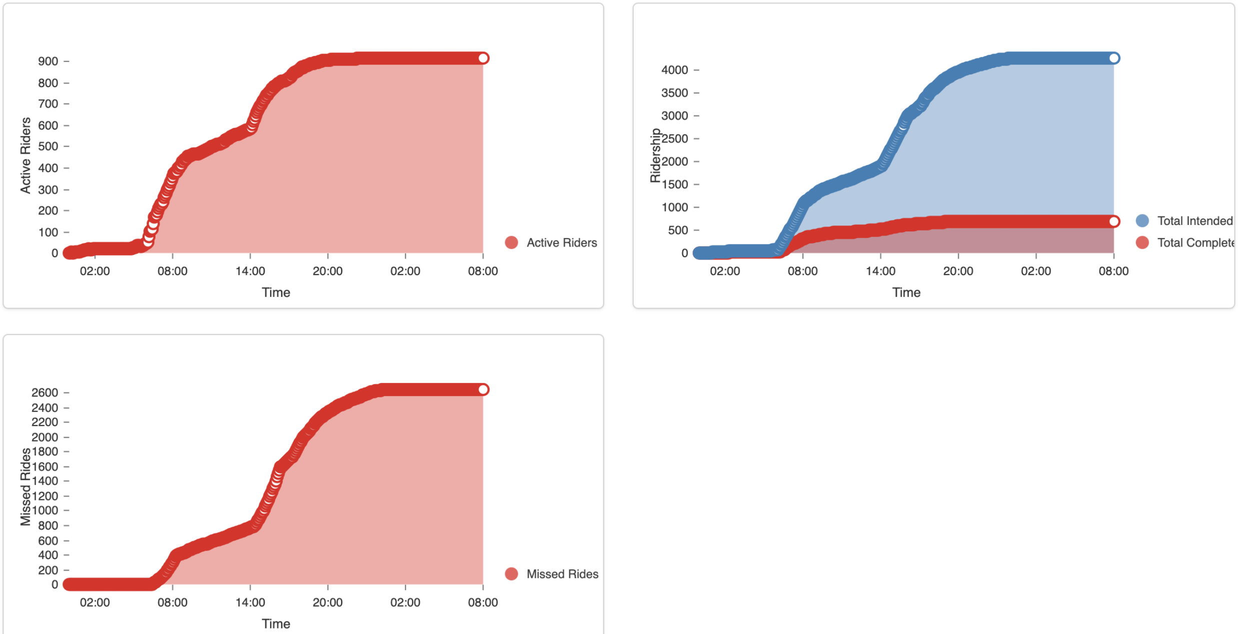

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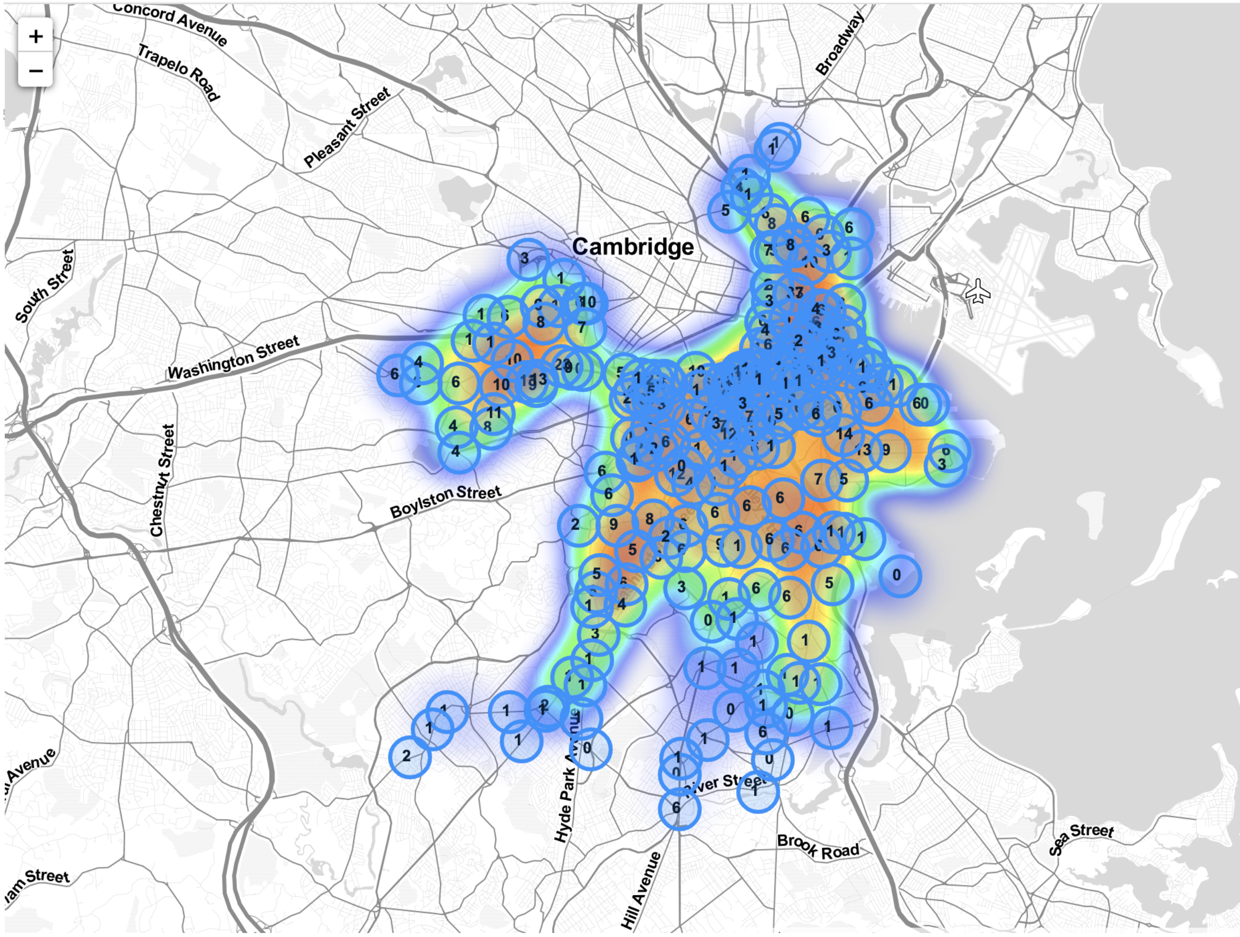

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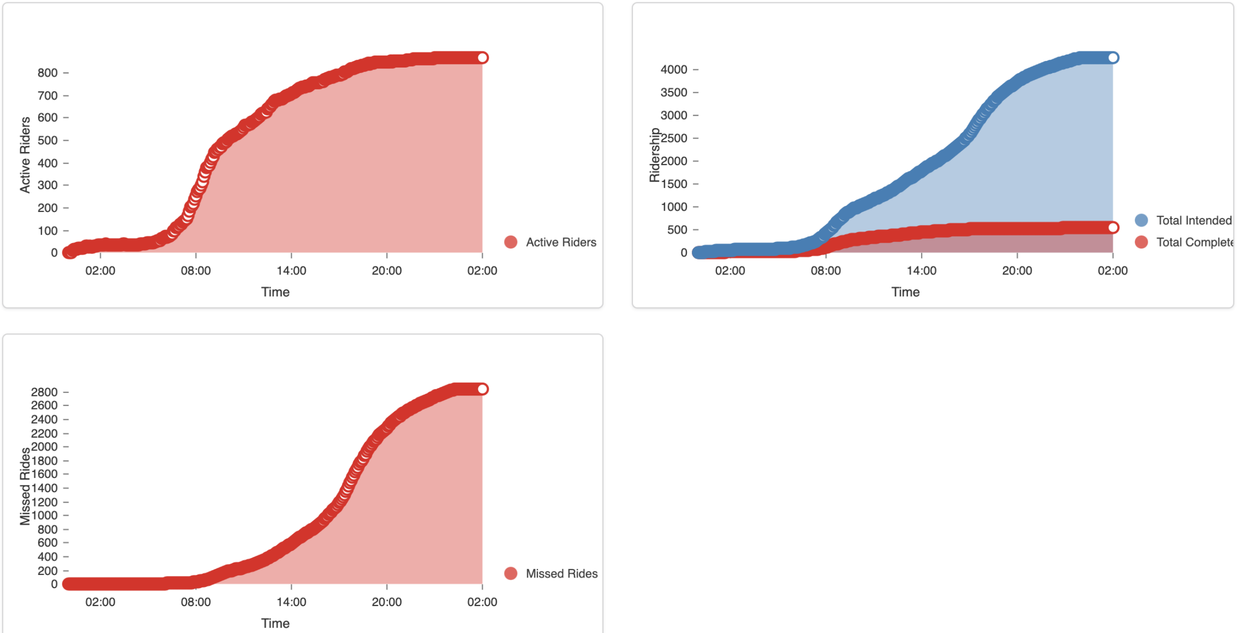

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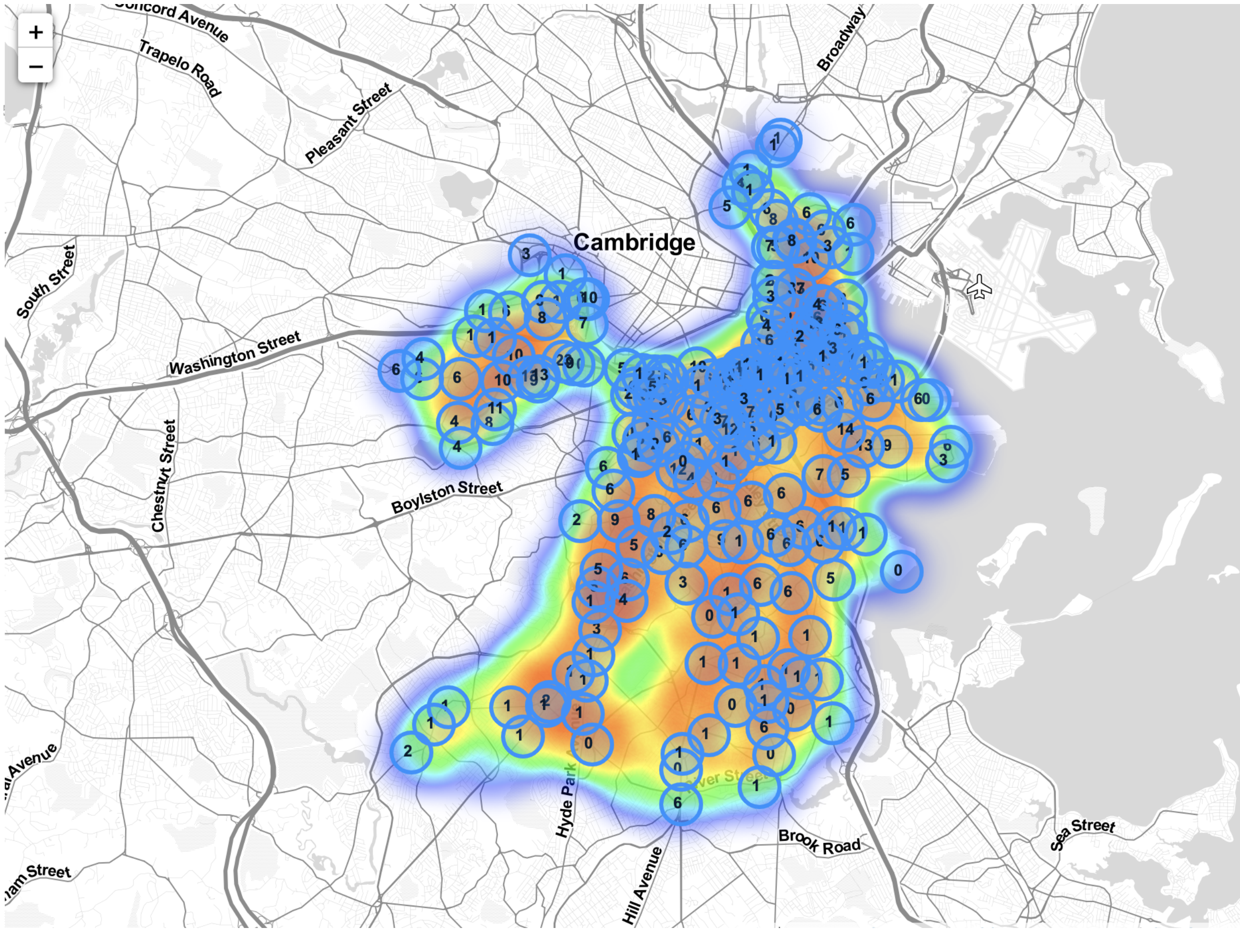

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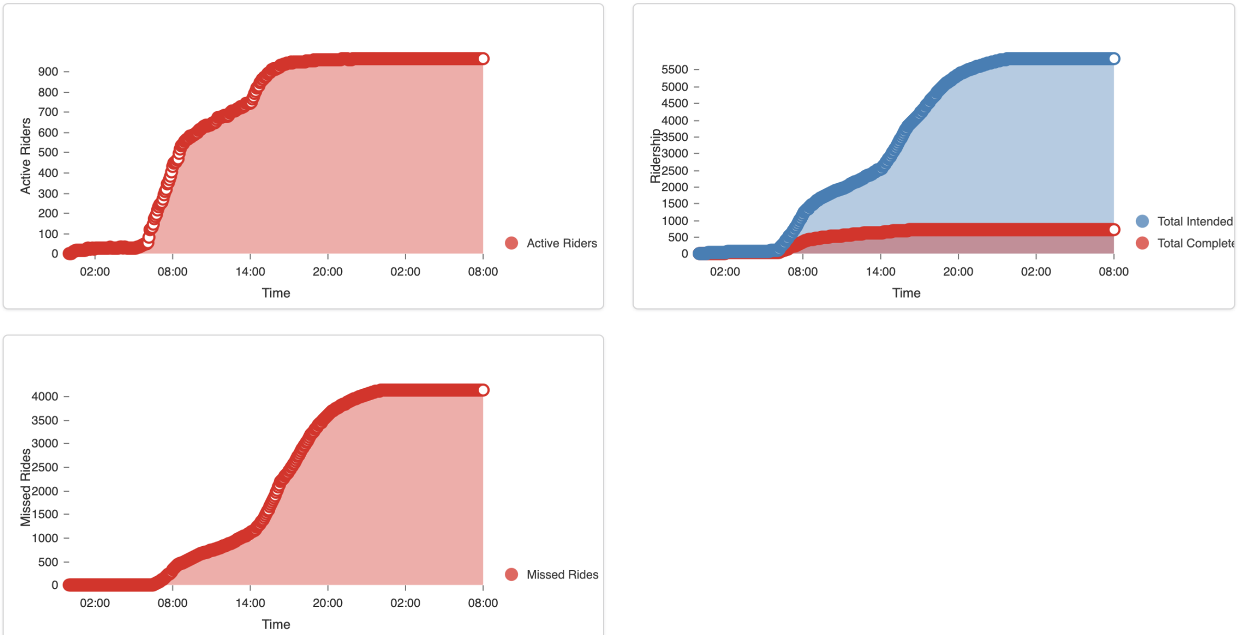

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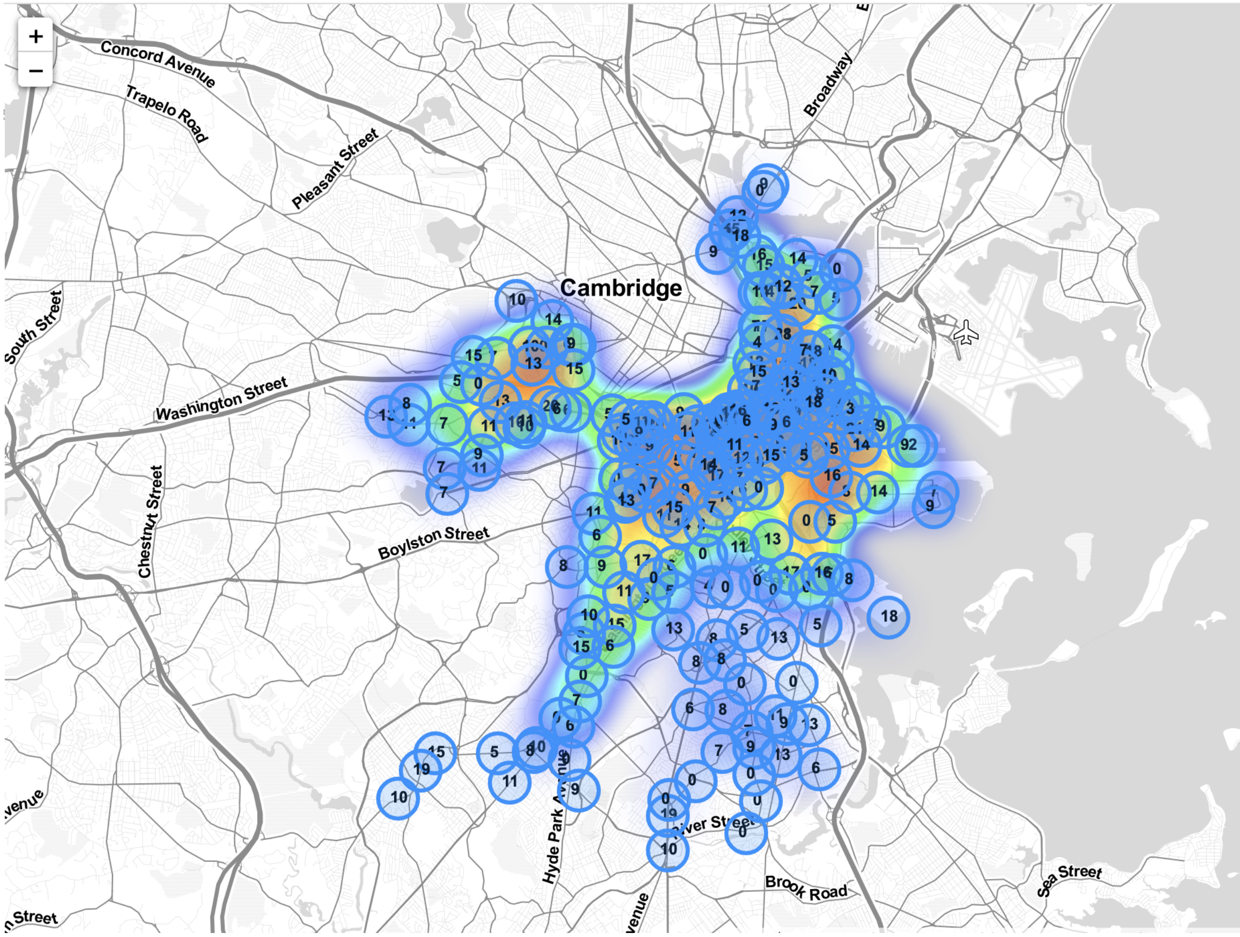

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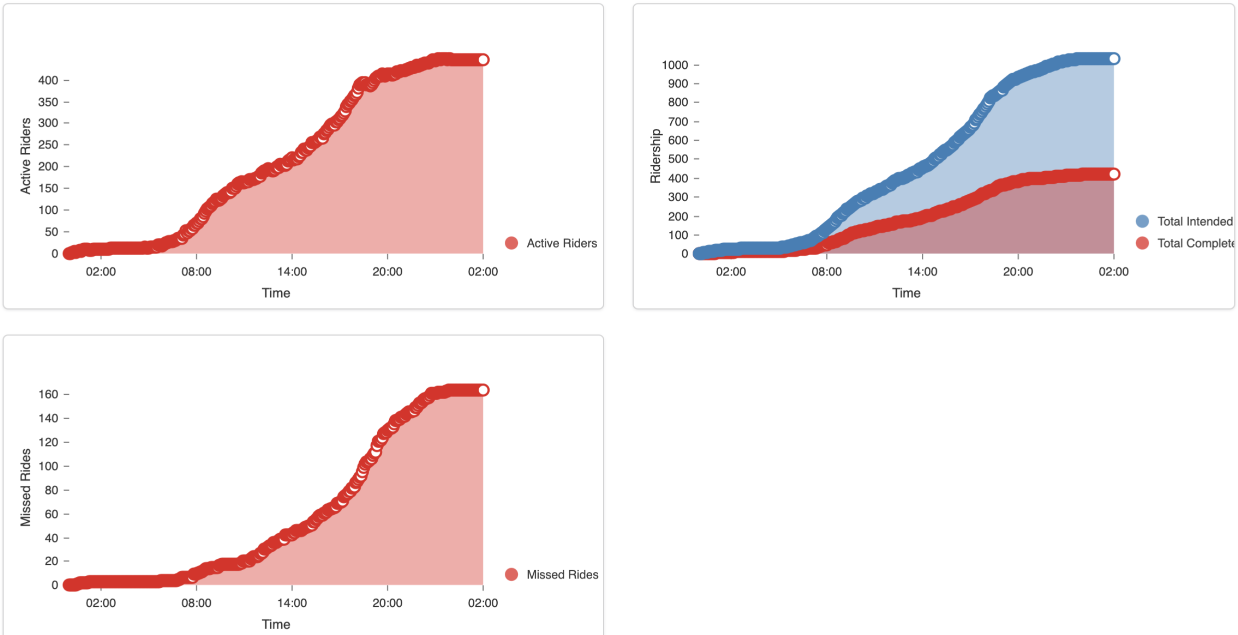

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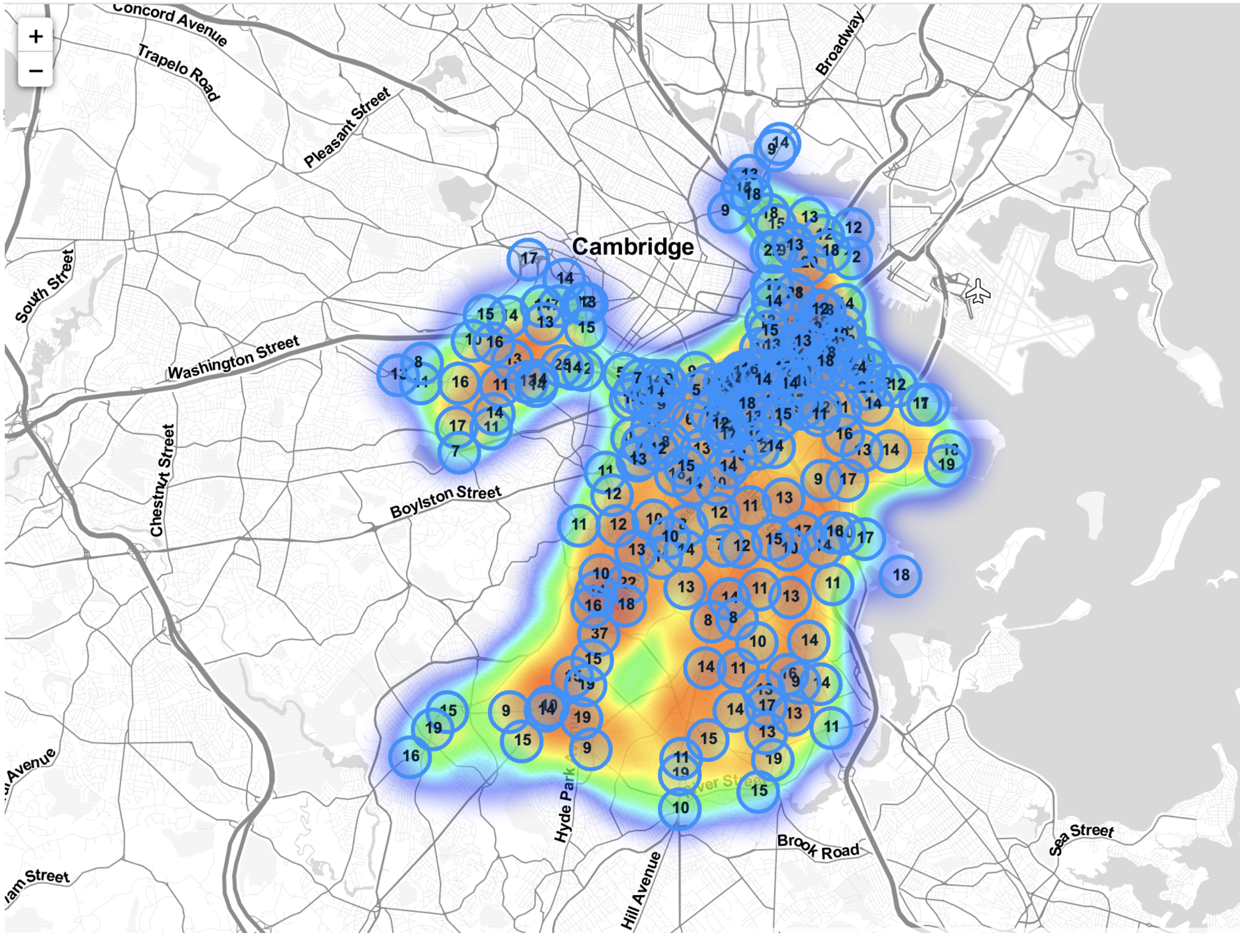

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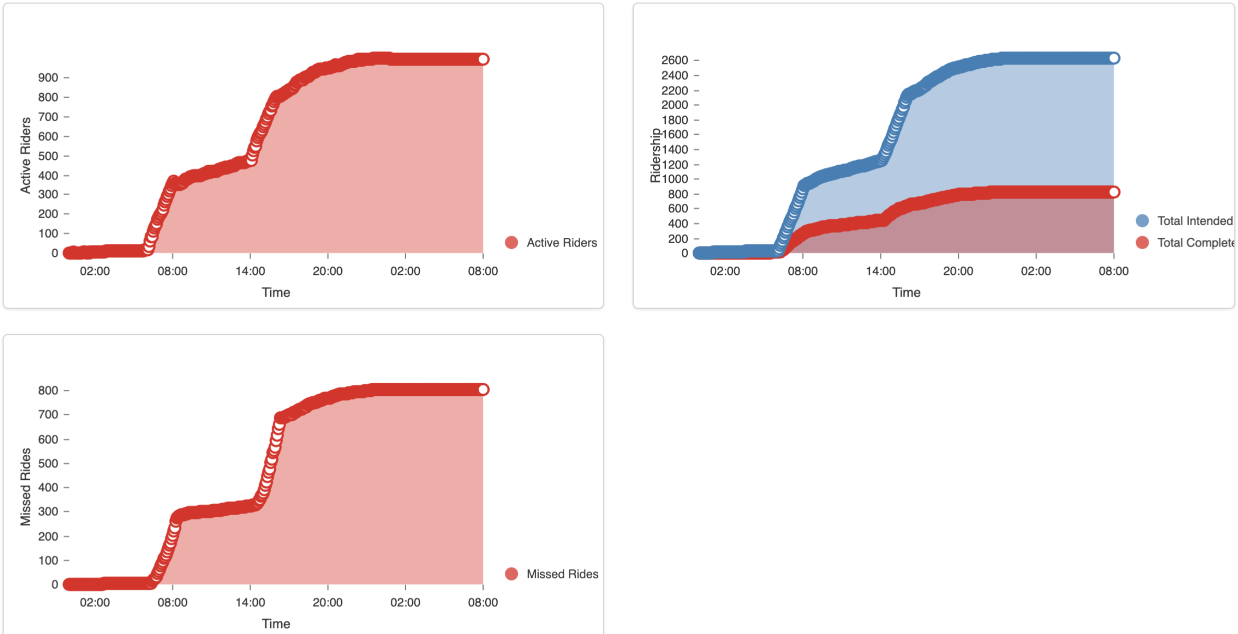

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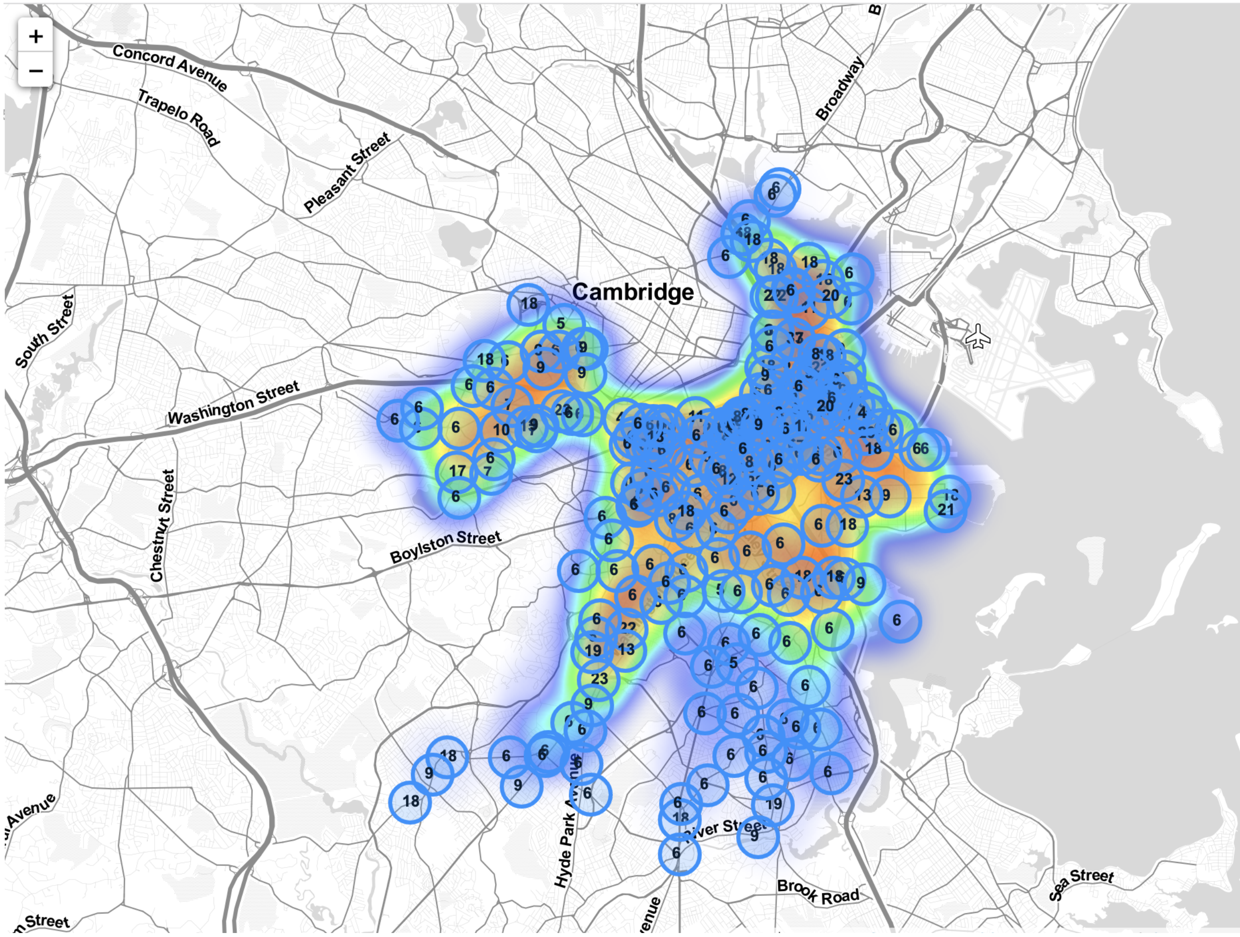

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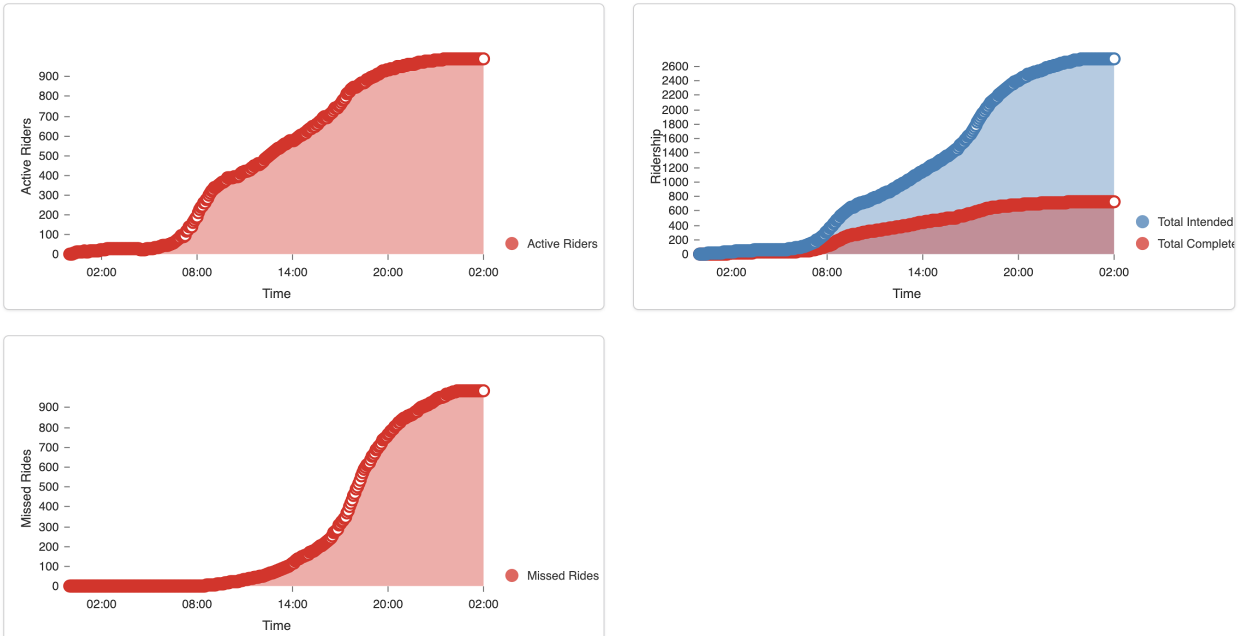

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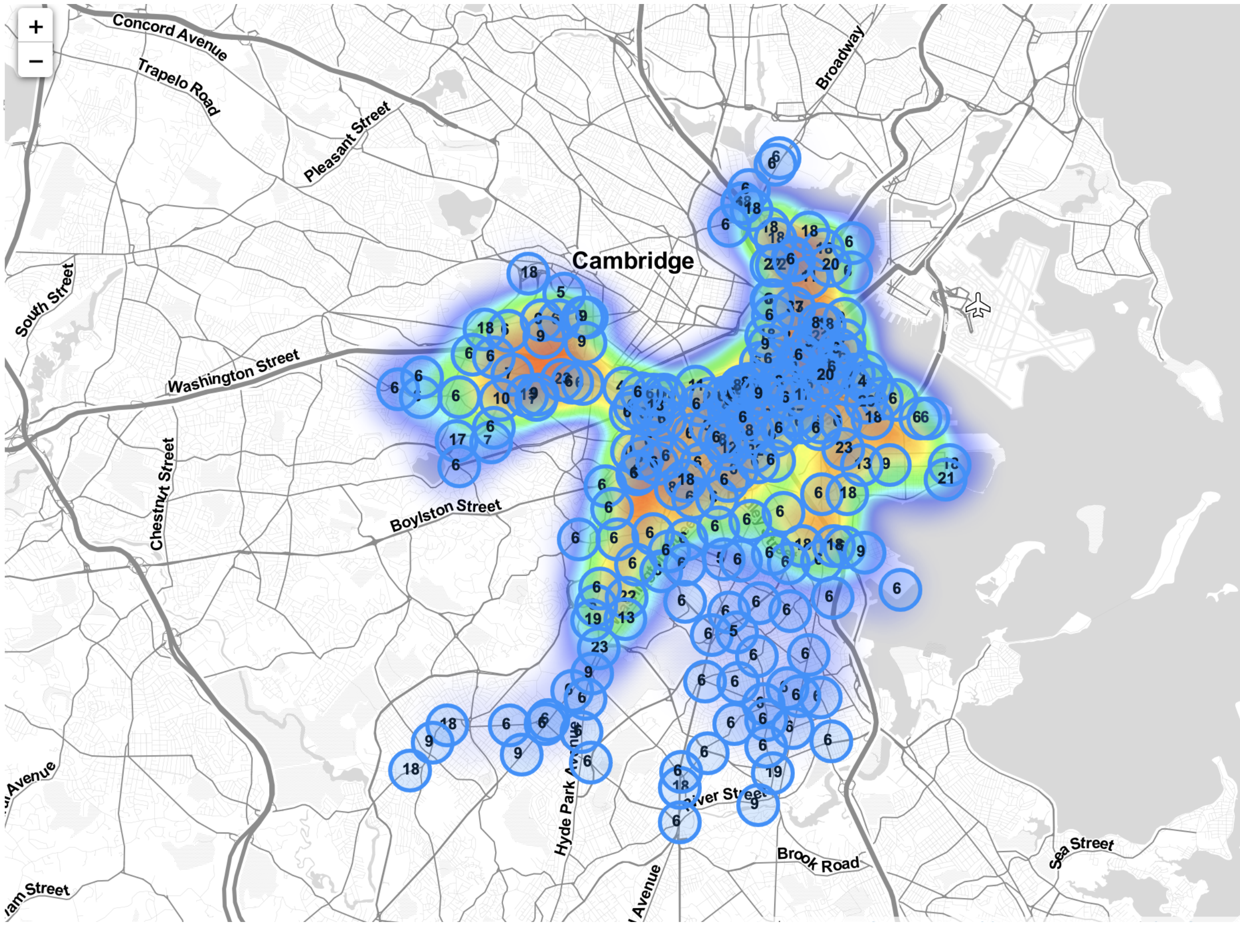

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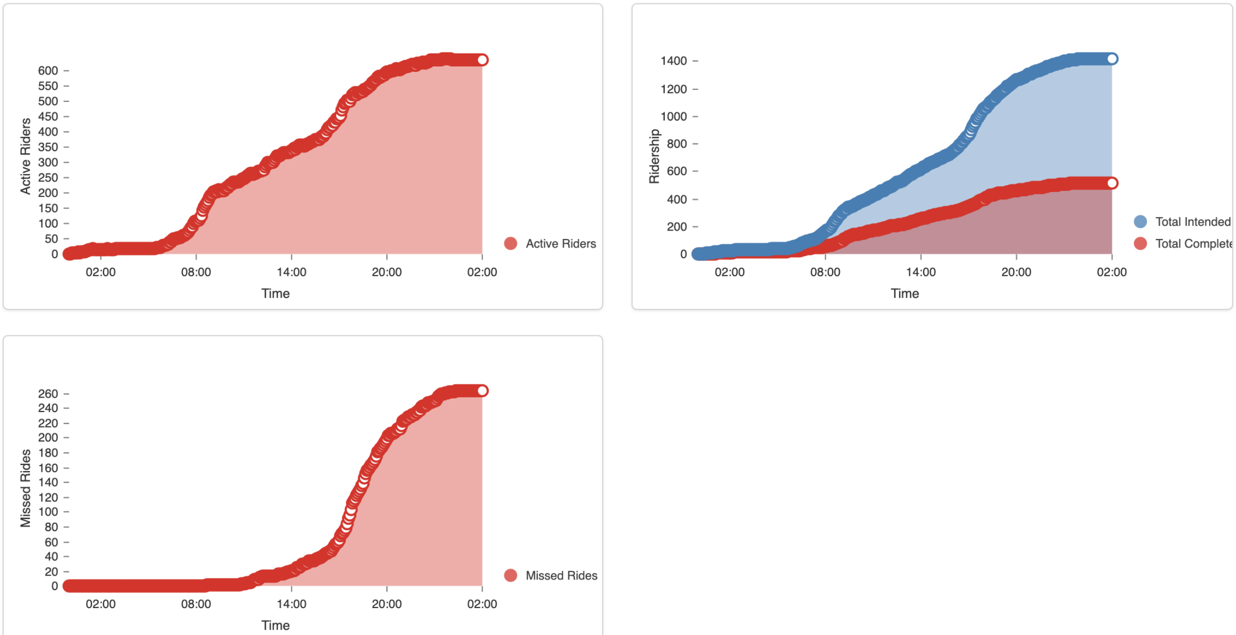

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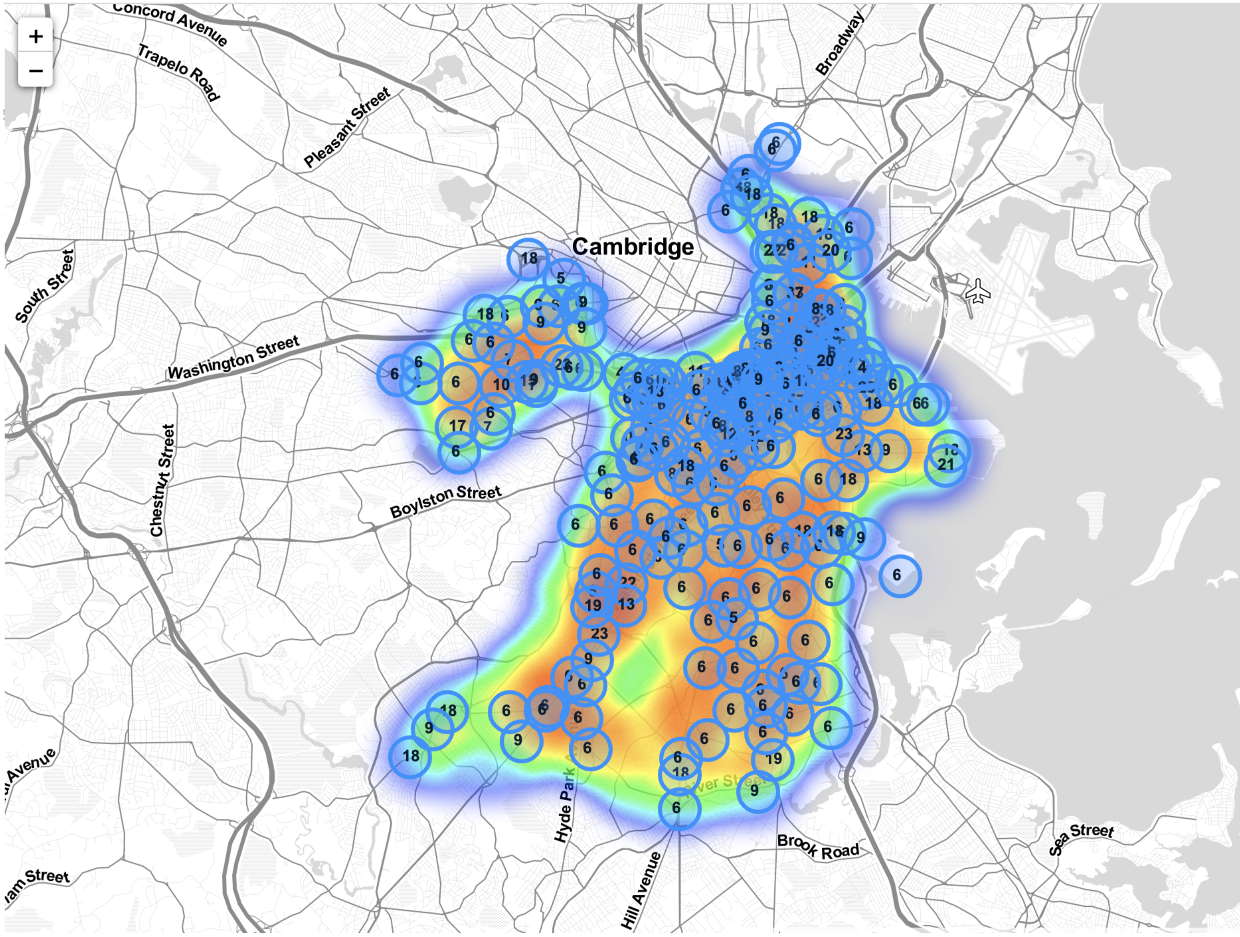

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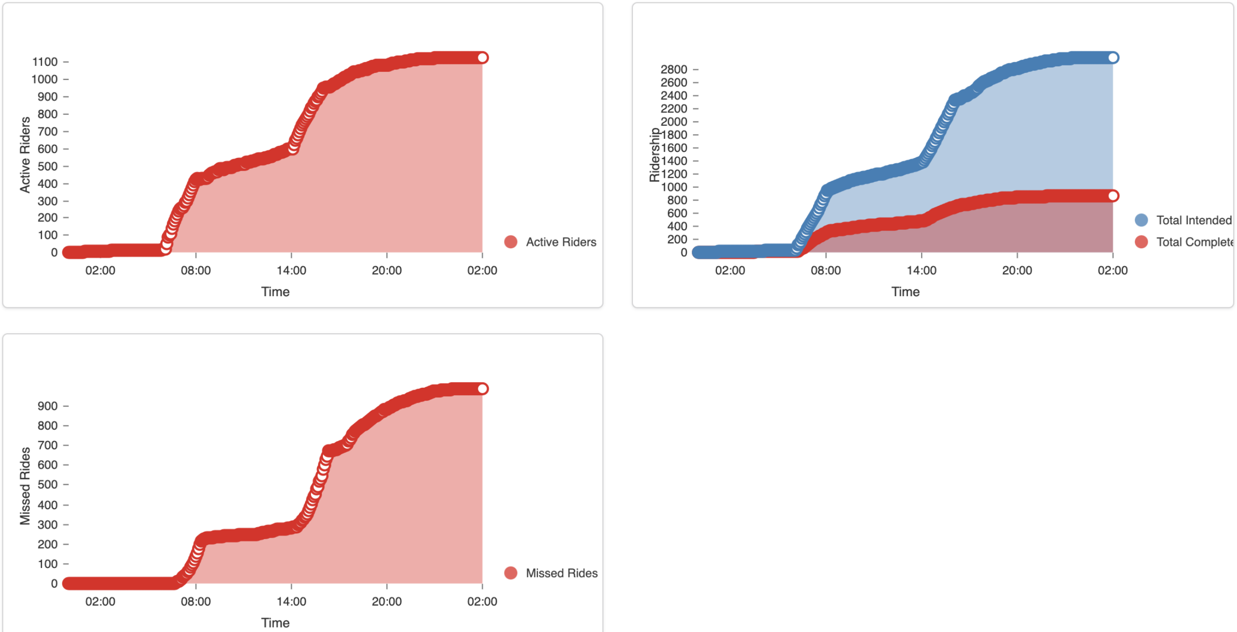

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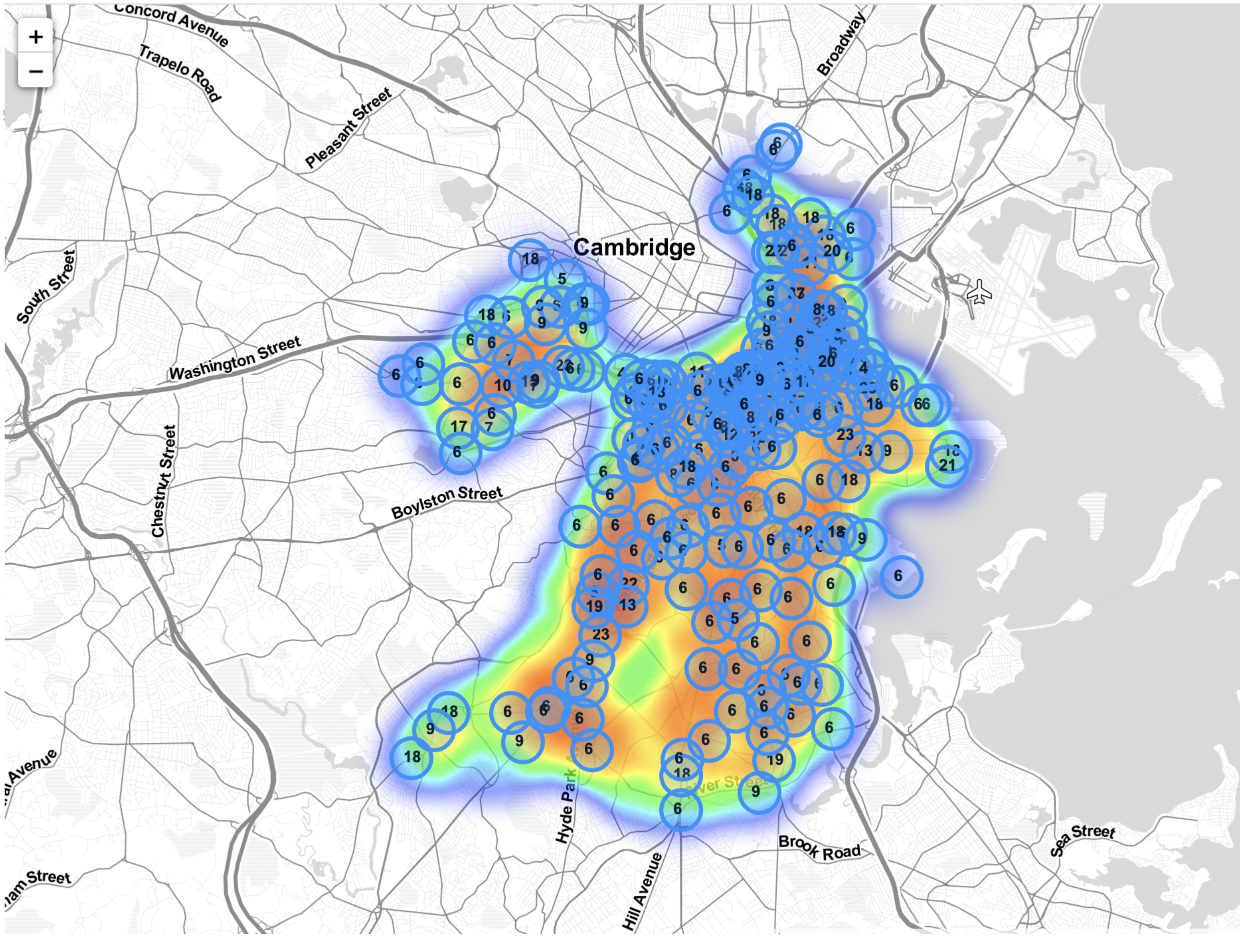

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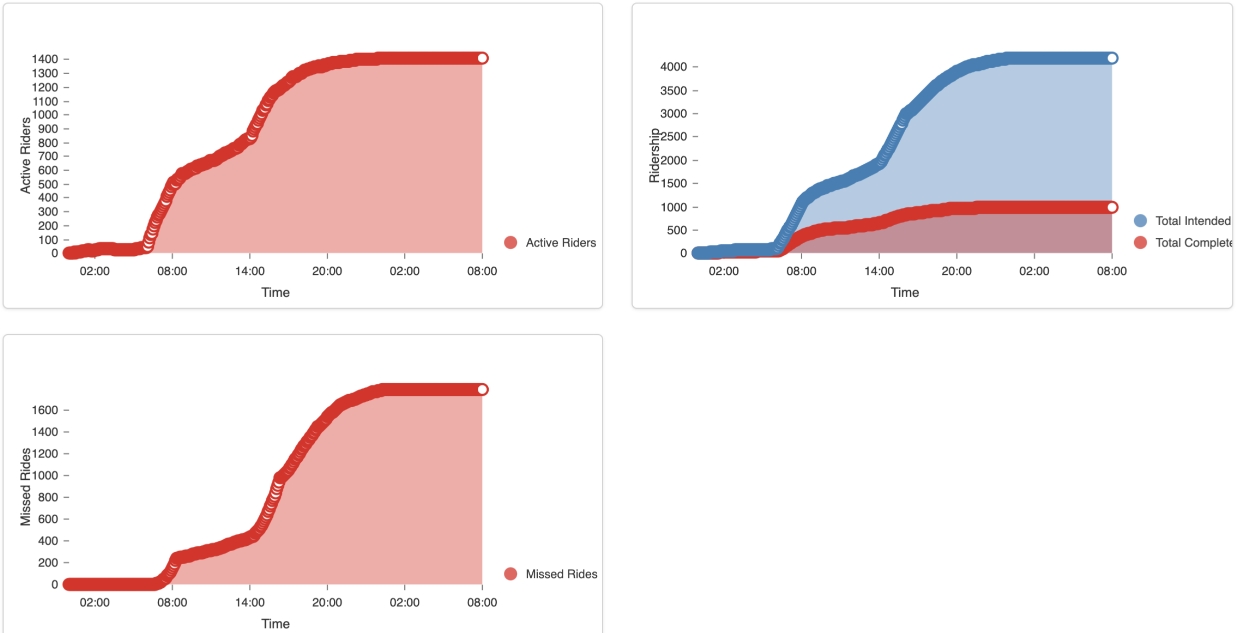

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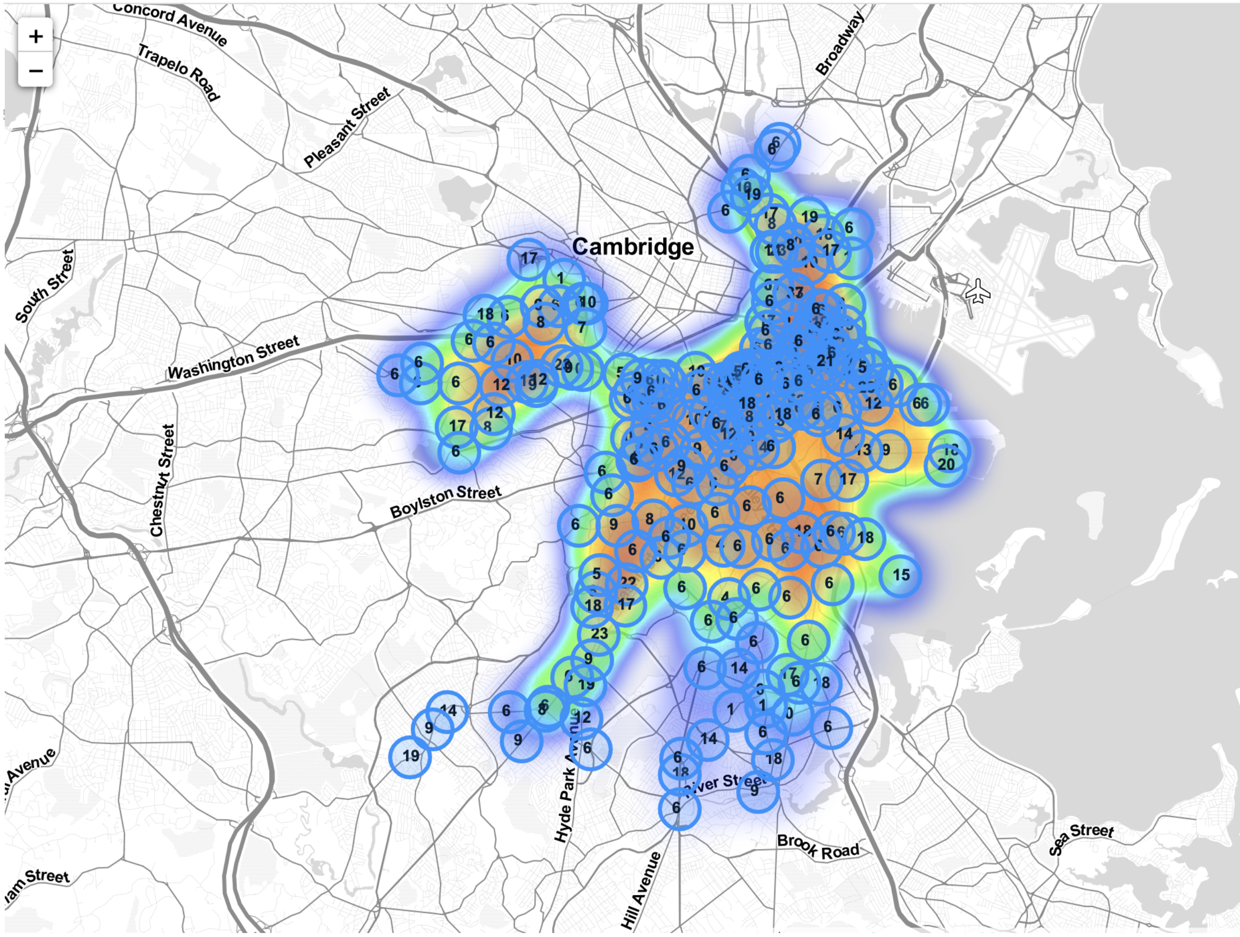

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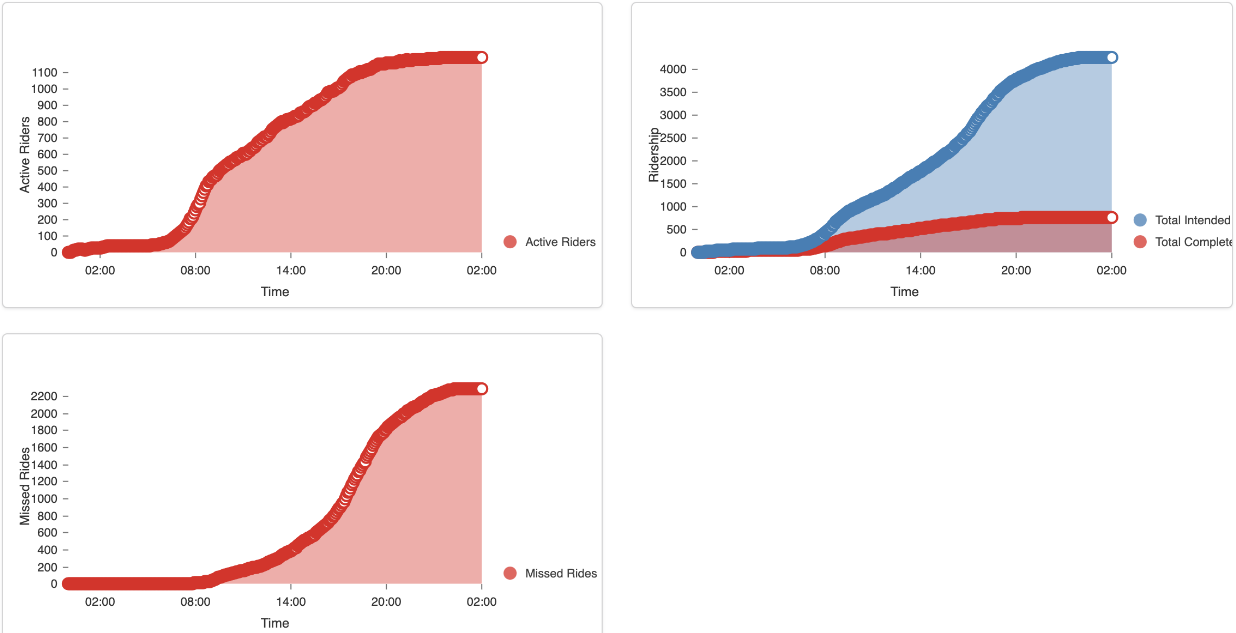

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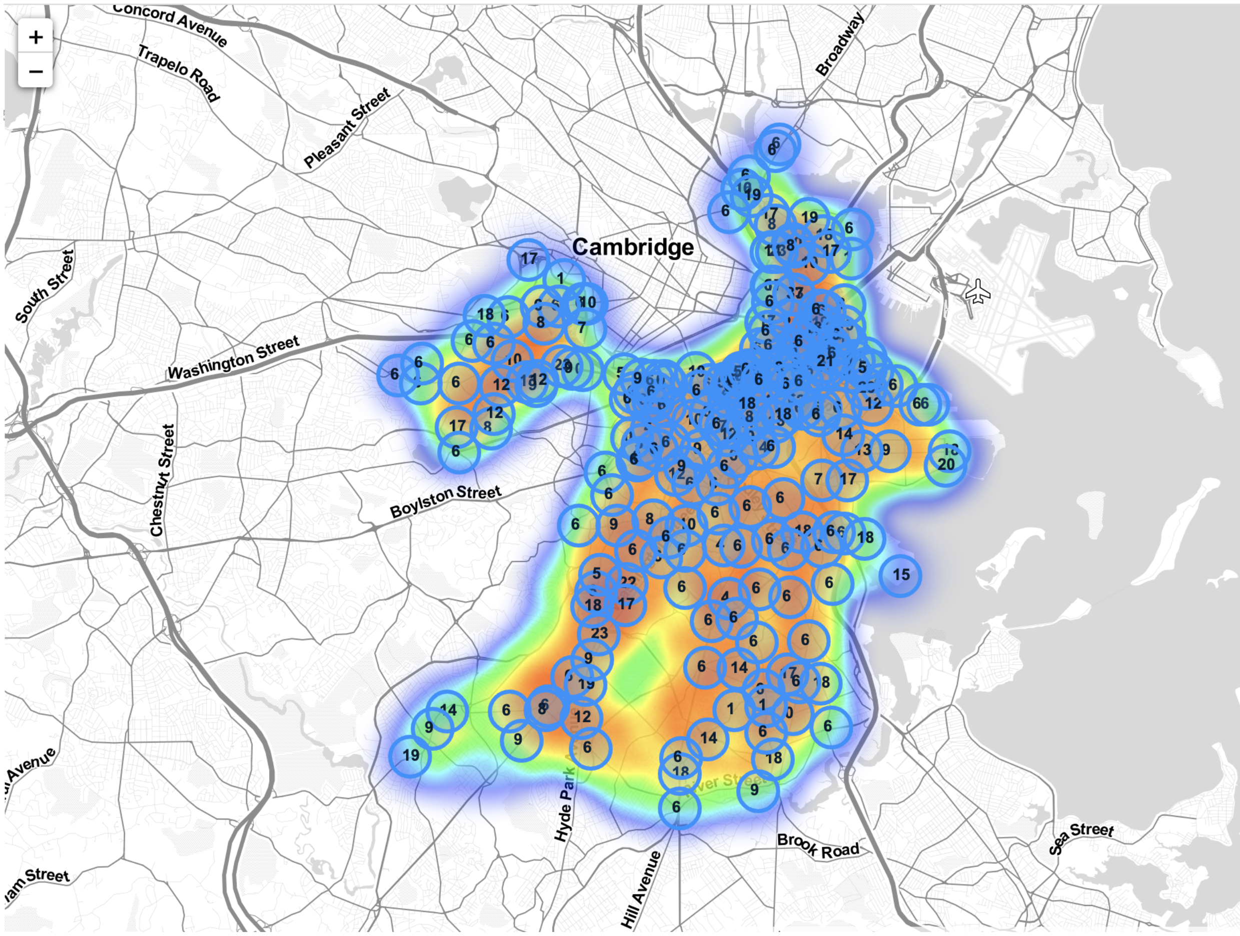

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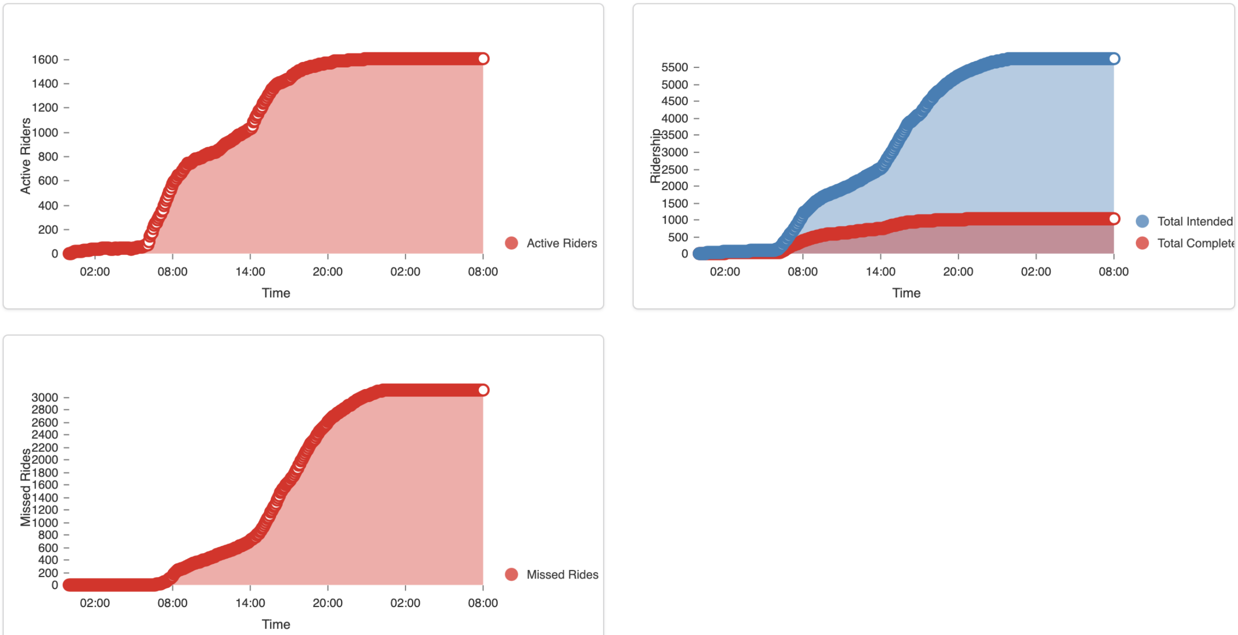

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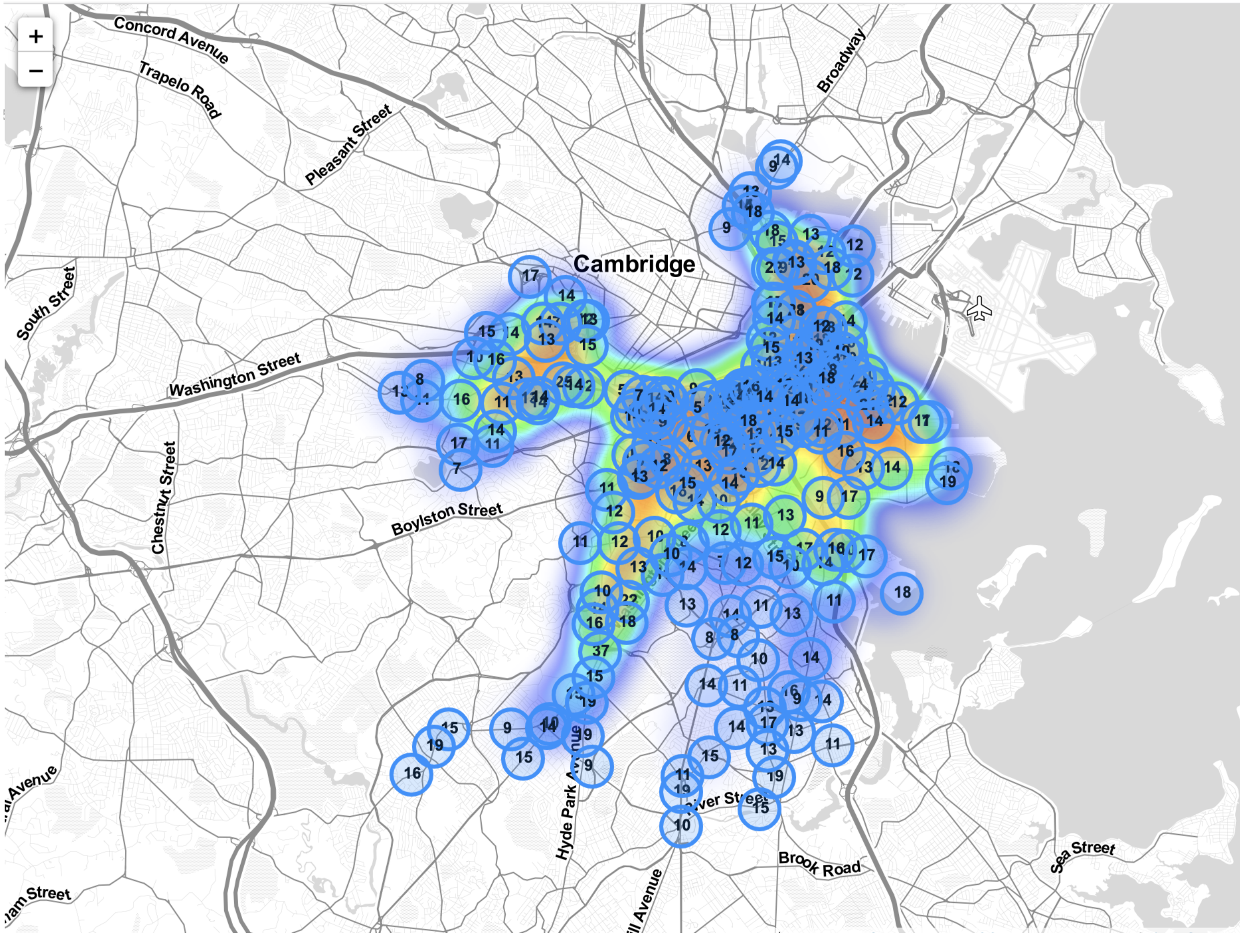

Figure A.49. 3000 bikes, 30°, without teachers

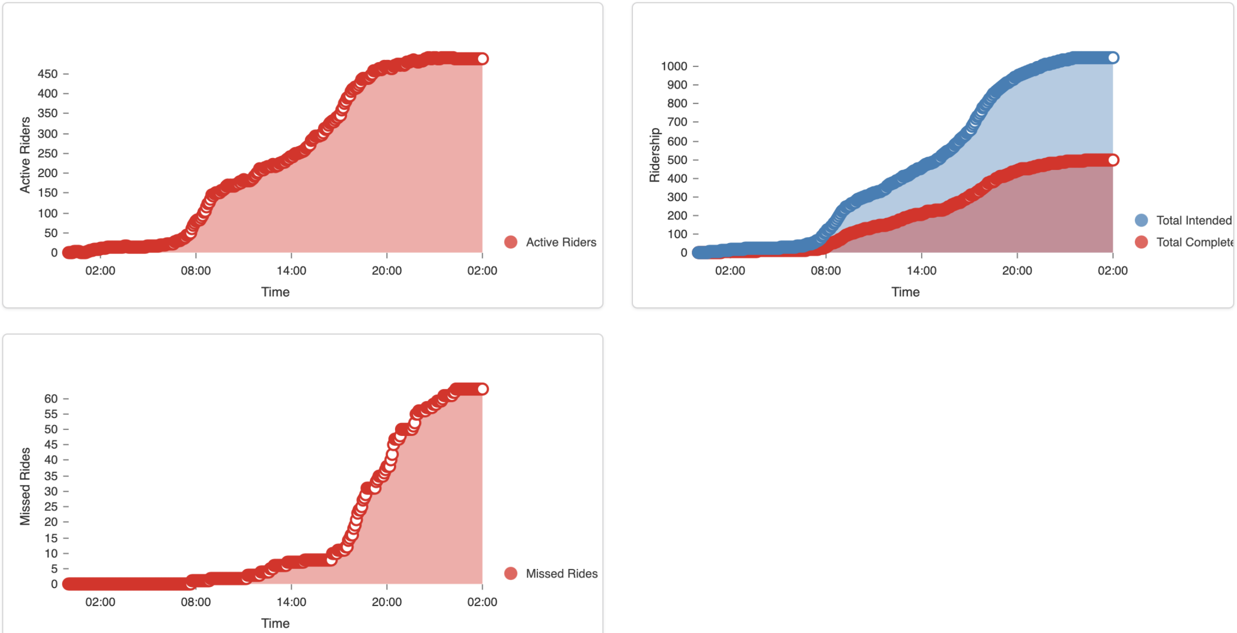

Figure A.50. 3000 bikes, 30°, without teachers data

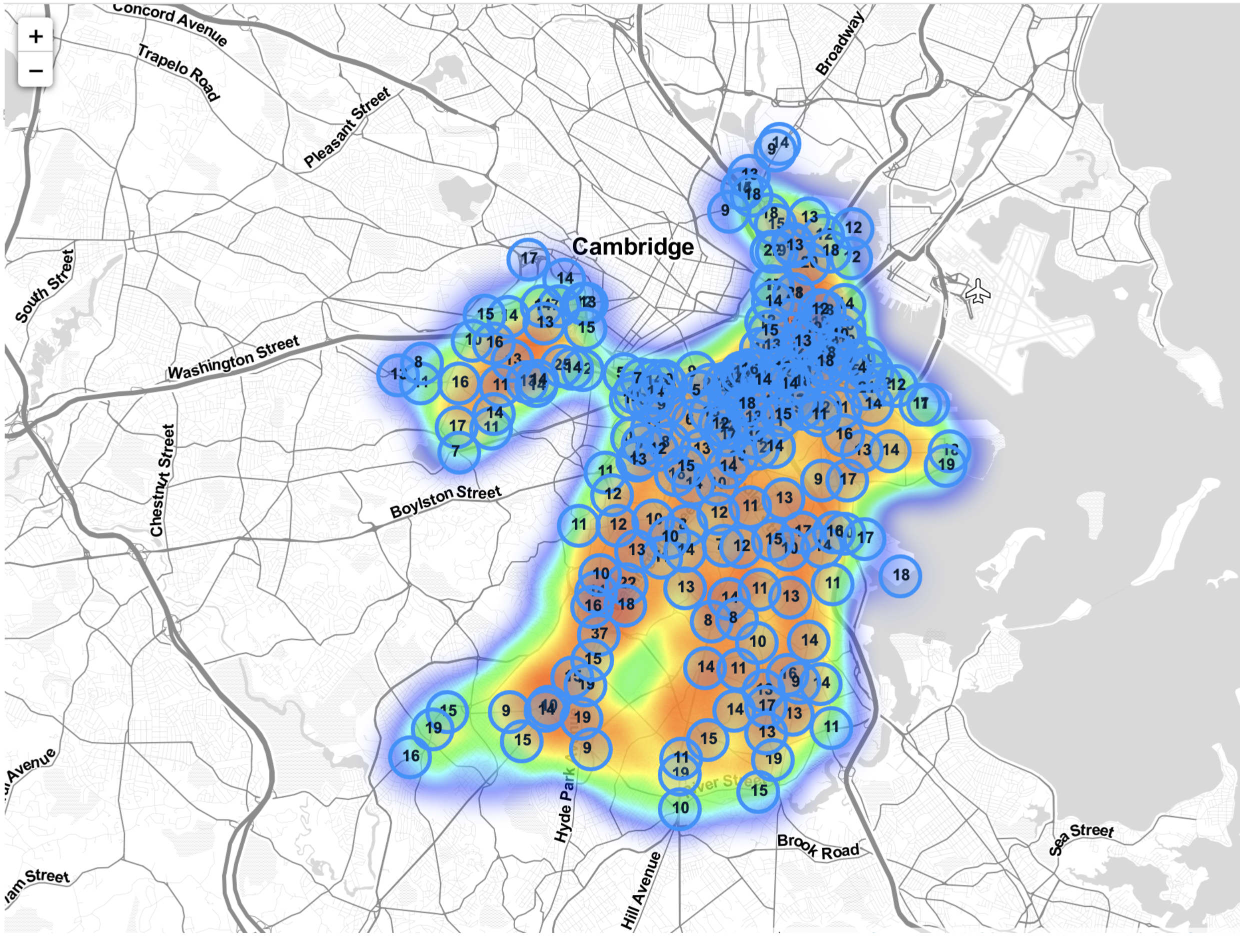

Figure A.51. 3000 bikes, 30°, with teachers

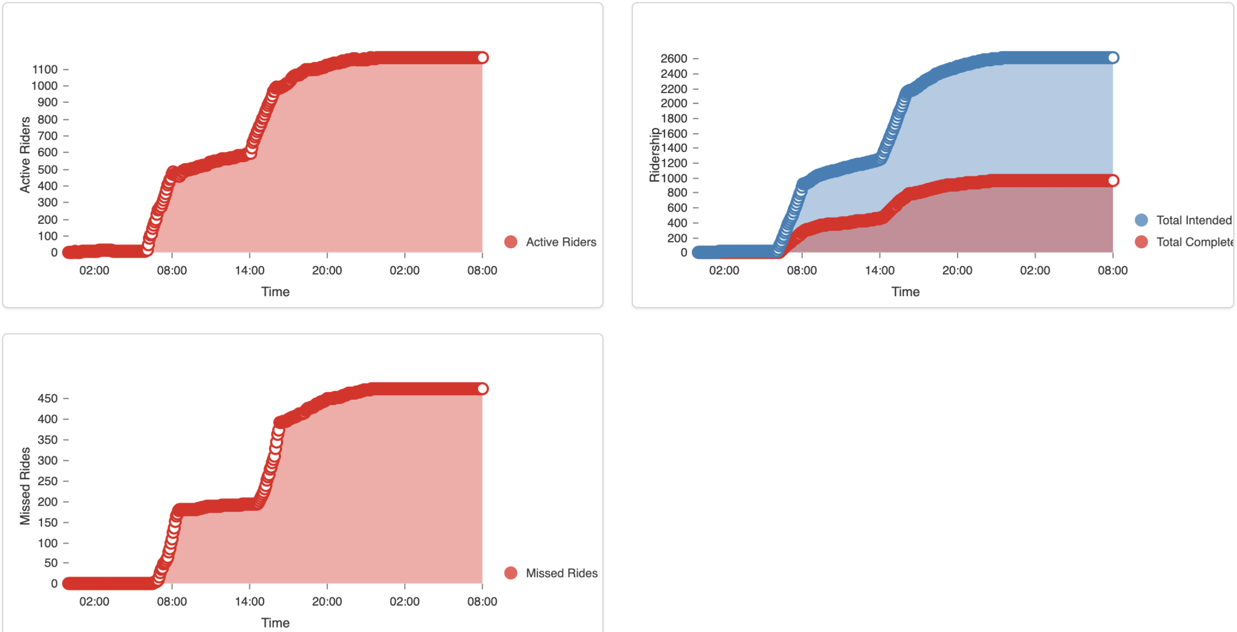

Figure A.52. 3000 bikes, 30°, with teachers data

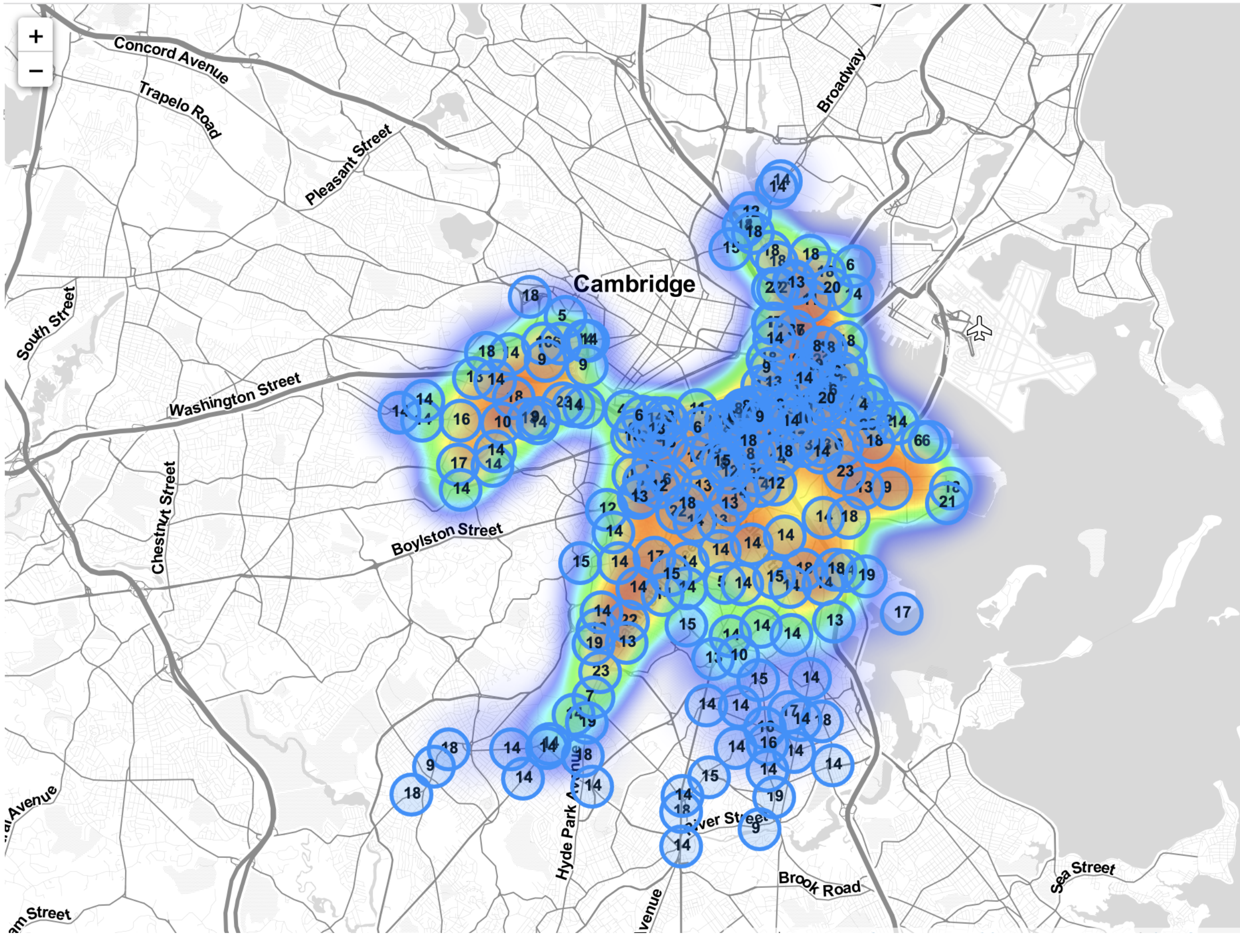

Figure A.53. 3000 bikes, 50°, without teachers

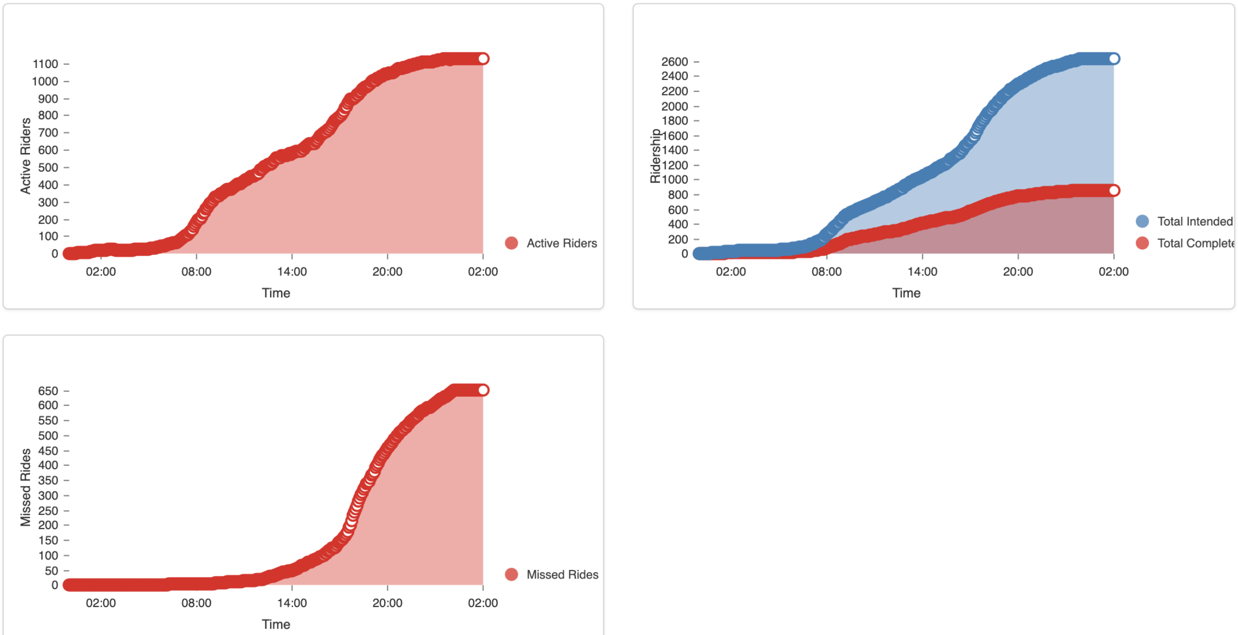

Figure A.54. 3000 bikes, 50°, without teachers data

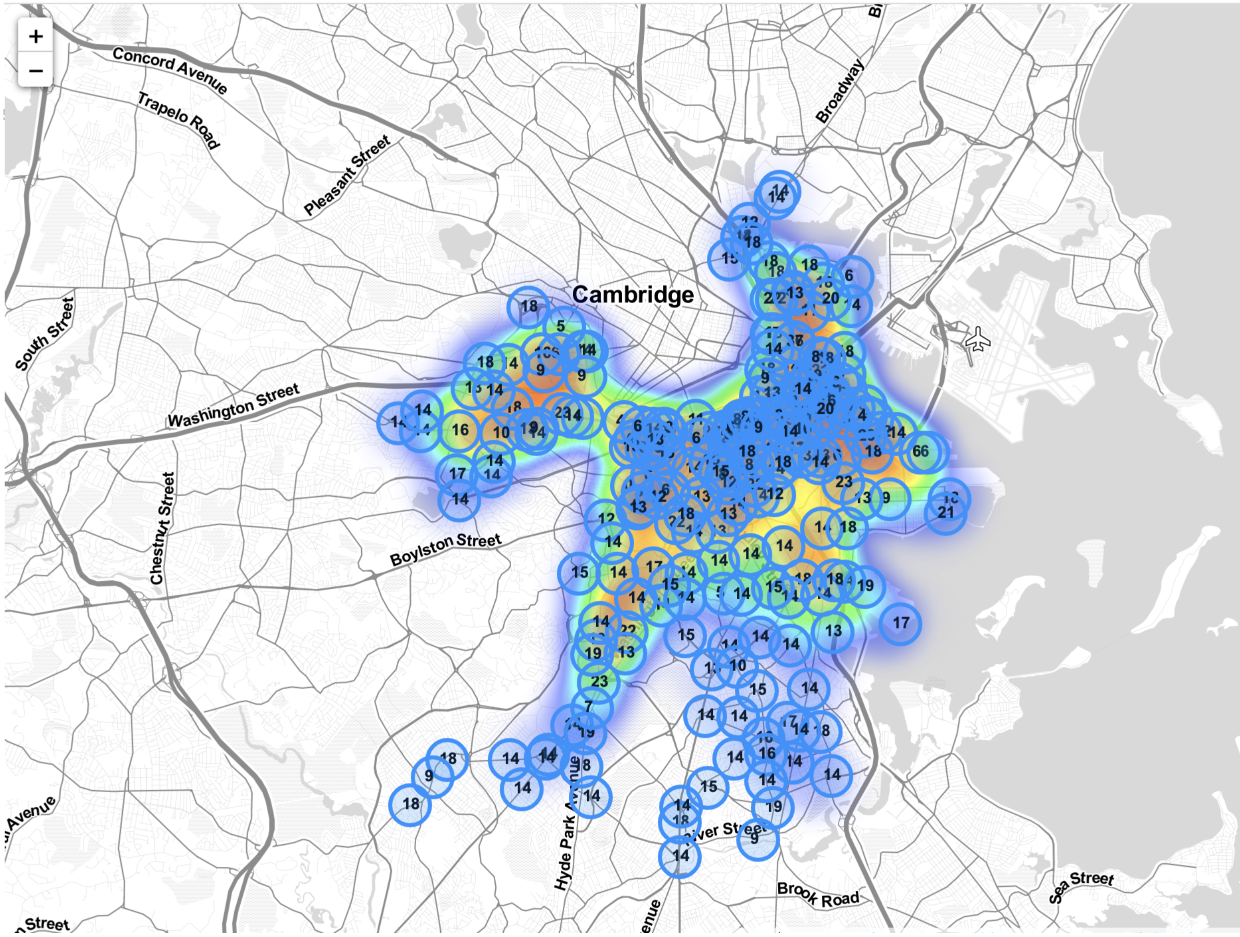

Figure A.55. 3000 bikes, 50° and 0.5” precipitation, without teachers

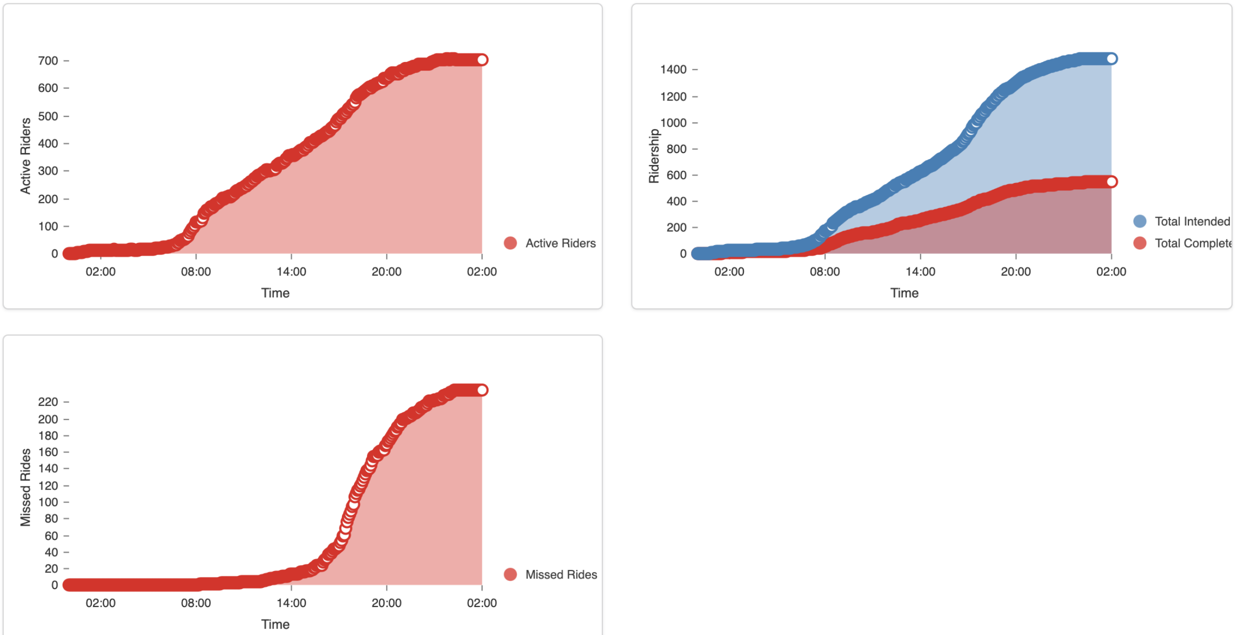

Figure A.56. 3000 bikes, 50° and 0.5” precipitation, without teachers data

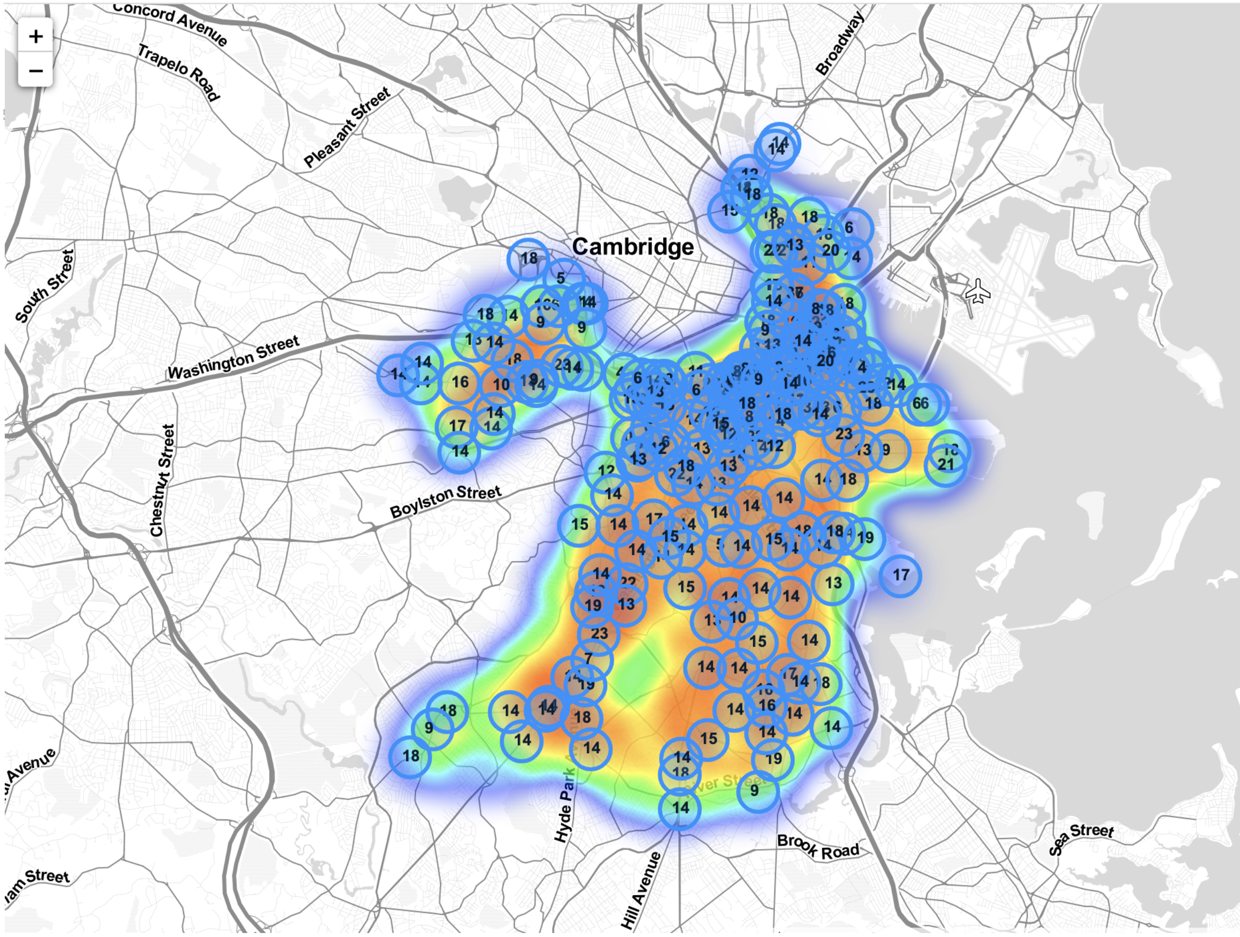

Figure A.57. 3000 bikes, 50° and 0.5” precipitation, with teachers

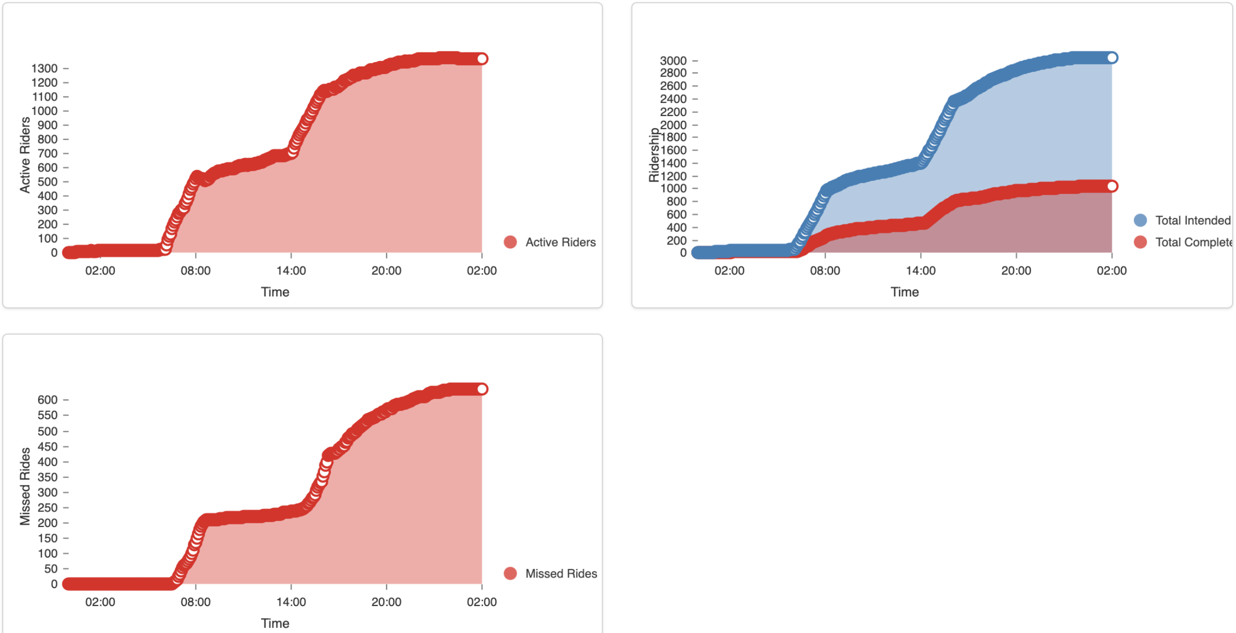

Figure A.58. 3000 bikes, 50° and 0.5” precipitation, with teachers data

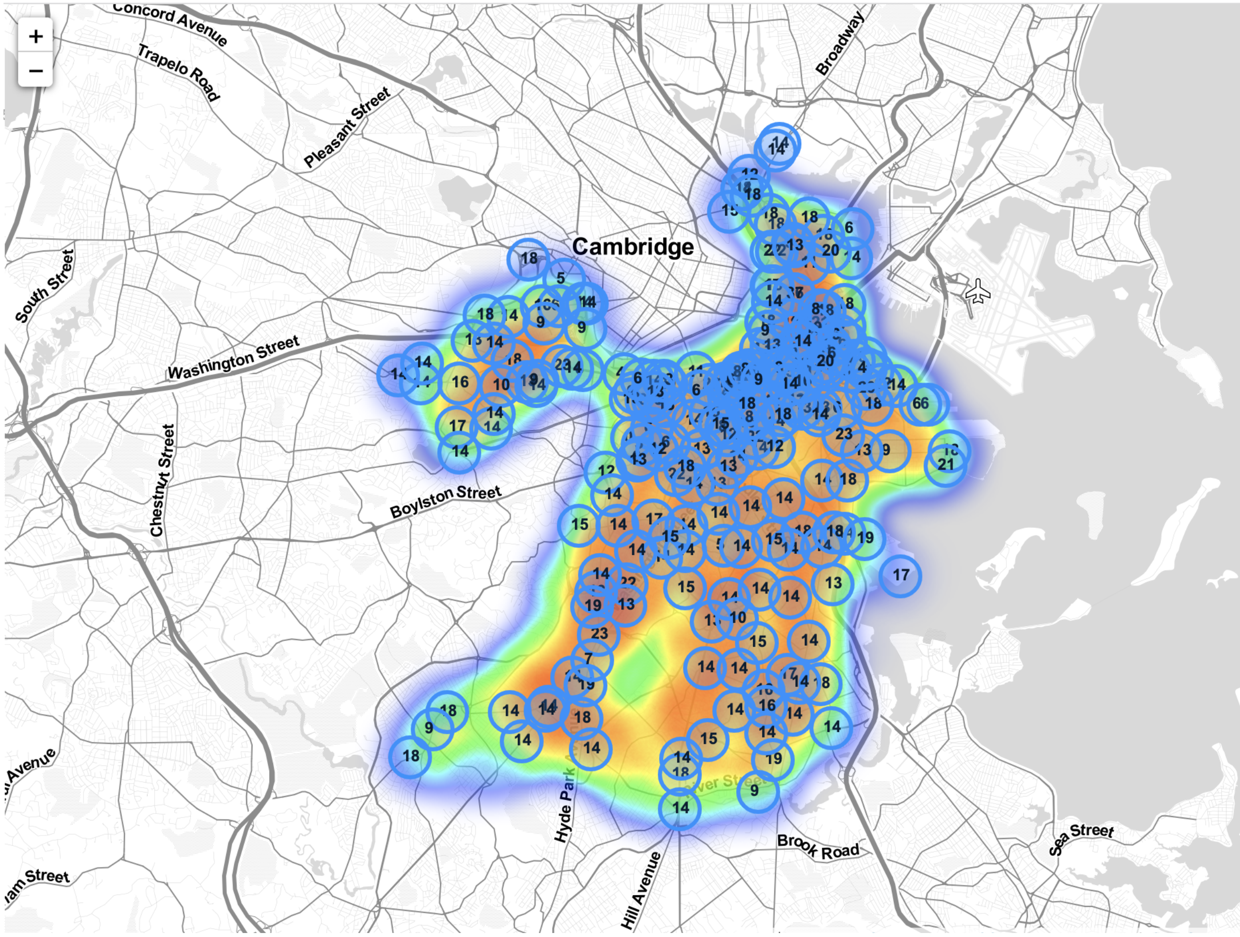

Figure A.59. 3000 bikes, 50°, with teachers

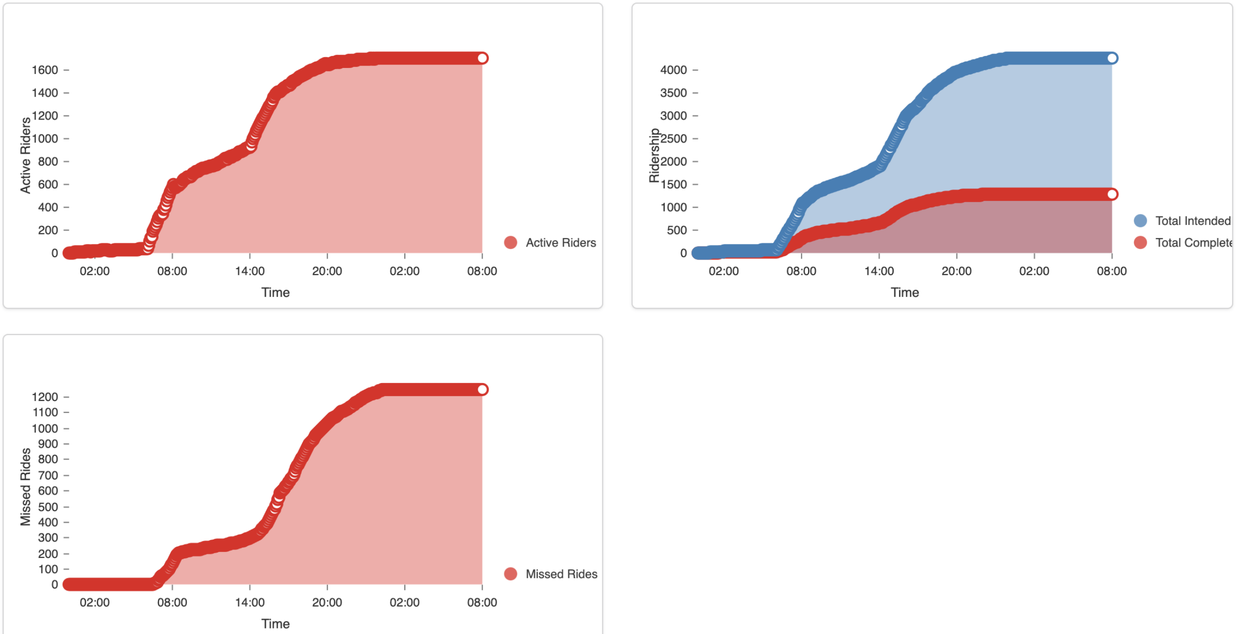

Figure A.60. 3000 bikes, 50°, with teachers data

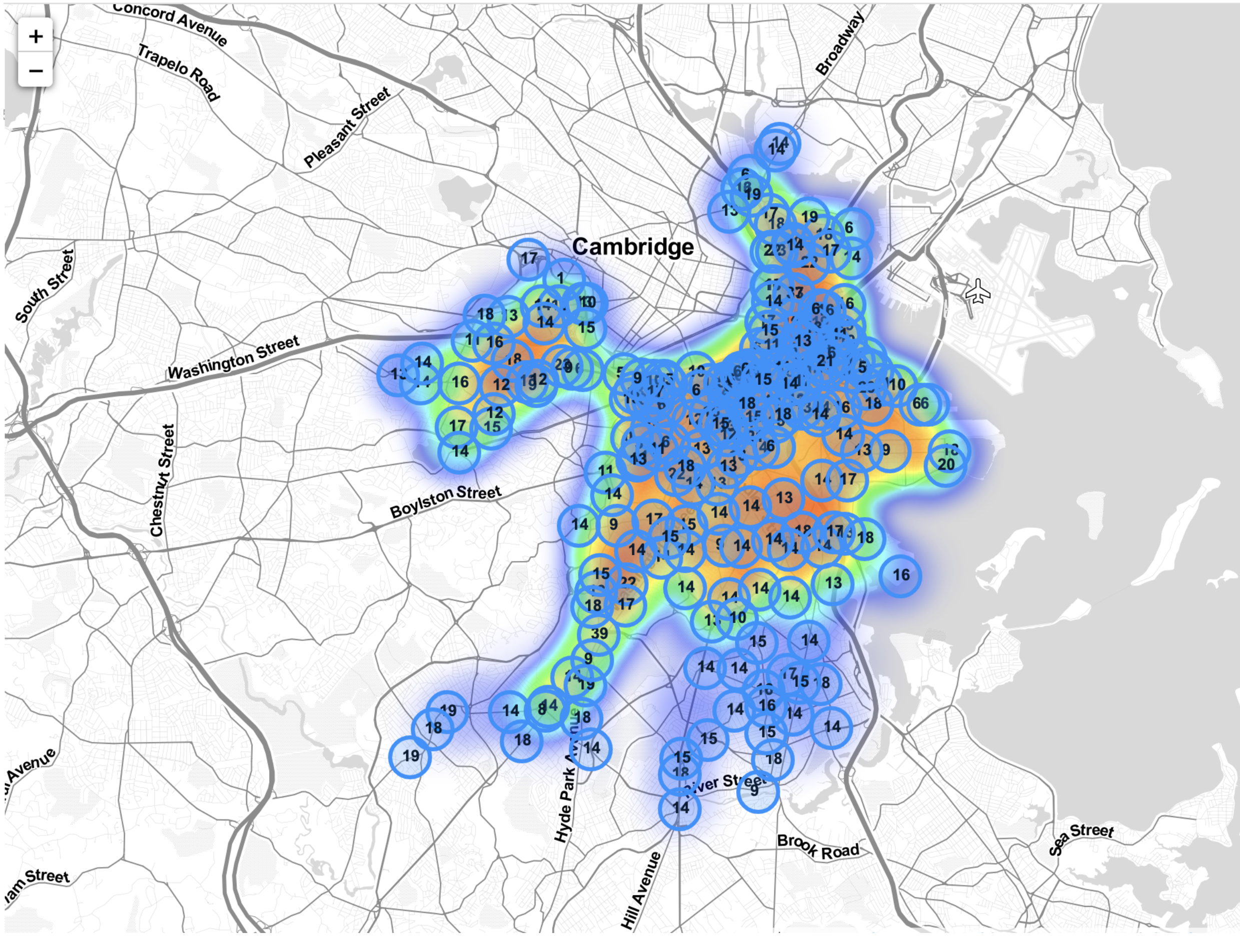

Figure A.61. 3000 bikes, 70°, without teachers

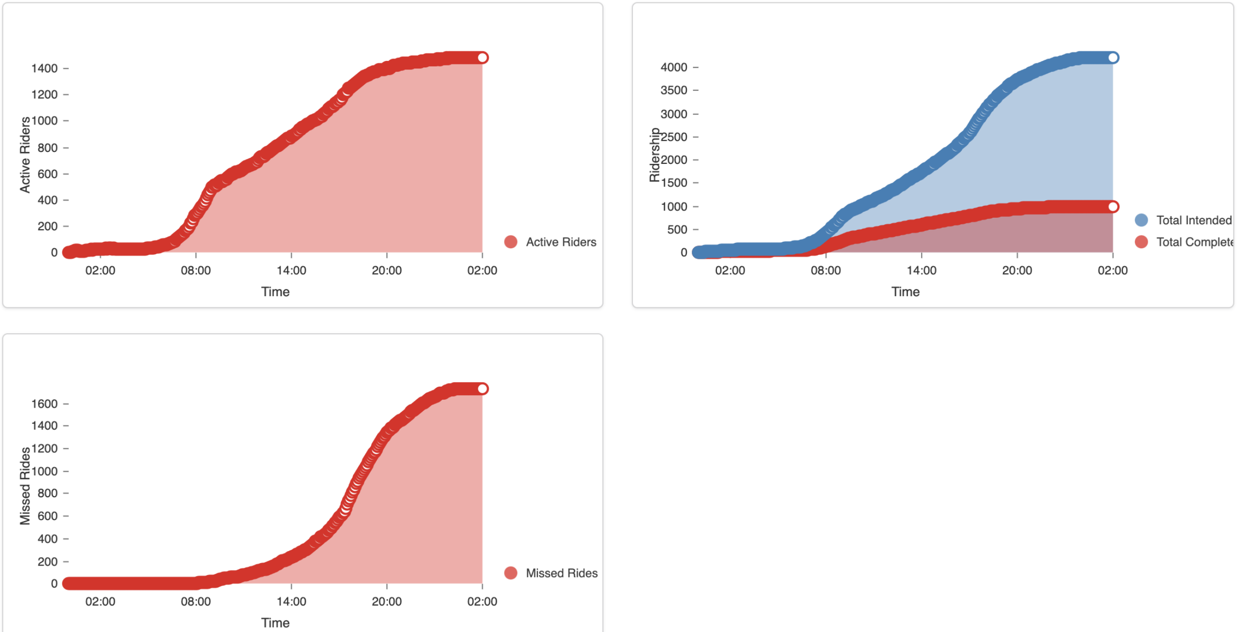

Figure A.62. 3000 bikes, 70°, without teachers data

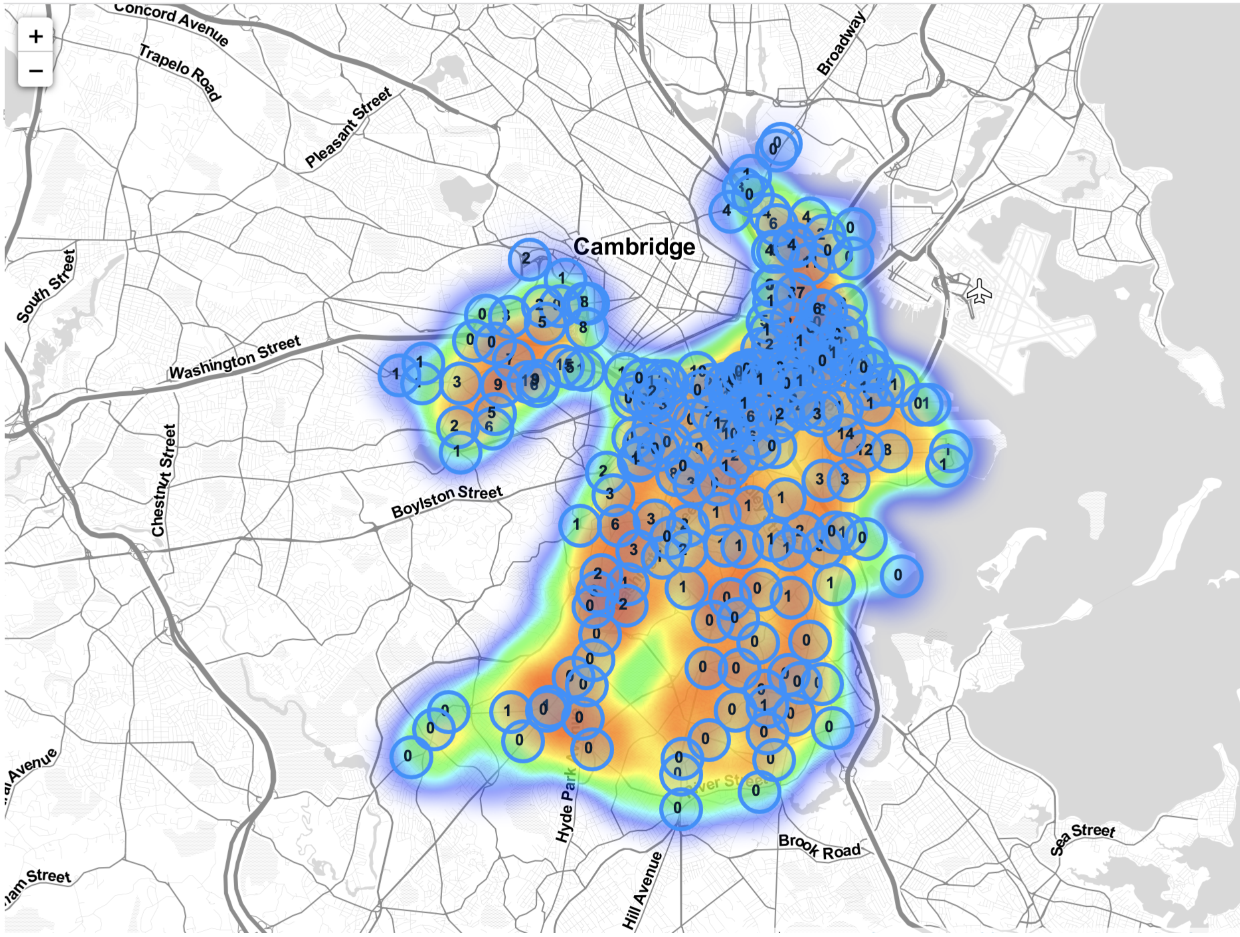

Figure A.63. 3000 bikes, 70°, with teachers

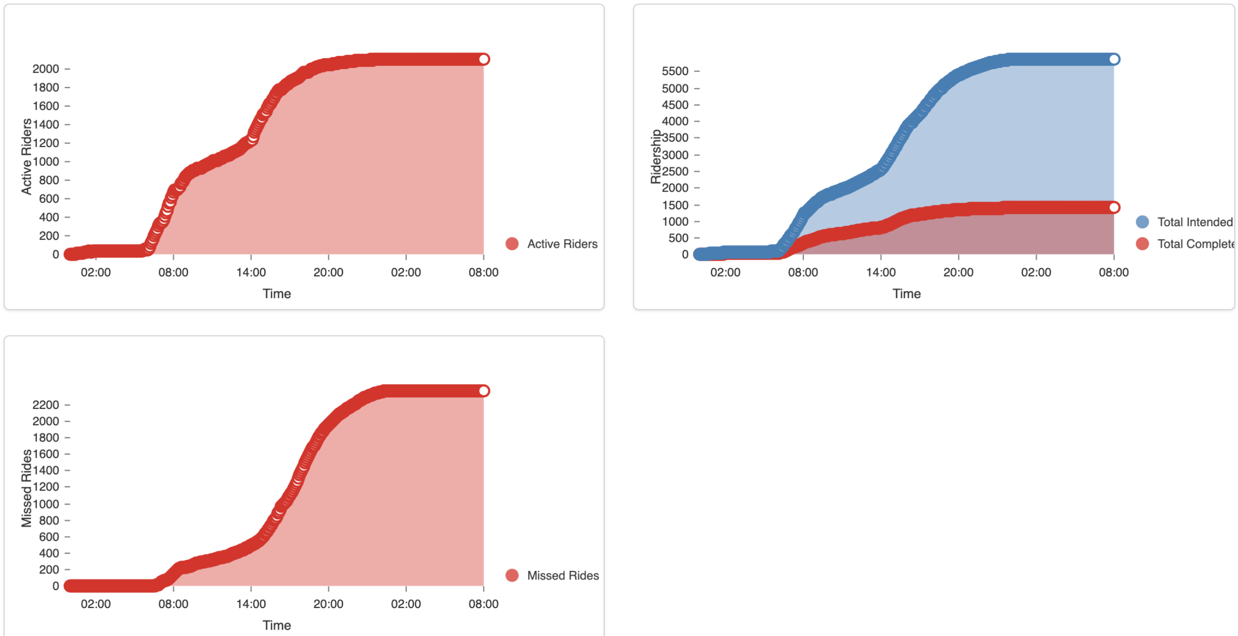

Figure A.64. 3000 bikes, 70°, with teachers data

Station	Predicted Starts	Predicted Ends
New Balance - 20 Guest St	9.12	9.27
Brookline Village - Station Street at MBTA	16.41	16.14
Ball Sq	4.68	4.5
Upham's Corner	14.25	14.28
Newmarket Square T Stop - Massachusetts Ave at...	10.77	11.25
Rogers St & Land Blvd	17.1	17.25
Murphy Skating Rink - 1880 Day Blvd	1.83	1.95
Somerville Hospital	5.49	5.64
Seaport Blvd at Sleeper St	37.65	37.44
Franklin Park - Seaver St at Humbolt Ave	5.13	5.37
Ryan Playground - Dorchester Ave at Harbor Vie...	15.81	15.96
Franklin Park Zoo - Franklin Park Rd at Blue H...	14.79	14.1
Huron Ave At Vassal Lane	2.55	2.55
Museum of Science	28.35	28.68
Alewife MBTA at Steel Place	10.83	10.98
Cypress St at Clark Playground	5.58	5.49
Foss Park	13.41	13.8
Tappan St at Brookline Hills MBTA	6.09	6.45

Columbia Rd at Ceylon St	8.52	8.85
Walnut Ave at Warren St	8.04	7.68
Bowdoin St at Quincy St	11.13	11.34
Government Center - Cambridge St at Court St	87.72	88.47
Chelsea St at Saratoga St	15.78	15.39
Piers Park	5.31	5.46
The Eddy - New St at Sumner St	8.37	8.97
Orient Heights T Stop - Bennington St at Sarat...	8.22	8.01
Verizon Innovation Hub 10 Ware Street	16.47	16.35
Troy Boston	30.27	29.79
Fresh Pond Reservation	2.1	2.28
Cambridge Dept. of Public Works -147 Hampshire...	16.32	16.05
Commonwealth Ave At Babcock St	18.9	18.6
Silber Way	24.33	24.48
One Memorial Drive	14.82	15.15
Four Corners - 157 Washington St	16.65	16.68
St Mary's	22.17	22.26
Broadway at Central St	7.92	7.89
East Somerville Library (Broadway and Illinois)	11.91	12.12
Assembly Square T	7.65	7.92
Community Path at Cedar Street	4.02	4.23
Park St at Norwell St	6.72	6.6
Gallivan Blvd at Adams St	4.44	4.53
Washington St at Bradlee St	8.55	8.49
Fields Corner T Stop	15.27	14.55
Ashmont T Stop	9.3	9.33
Shawmut T Stop	7.41	7.47
Forest Hills	15.51	15.36
Williams St at Washington St	9.75	9.45
Main St at Baldwin St	8.67	8.55
Stony Brook T Stop	6.87	7.02
Farragut Rd at E. 6th St	1.2	1.35
Ames St at Broadway	22.56	22.71
84 Cambridgepark Dr	12.39	12.66
Main St at Thompson Sq	17.88	18.42
Grove St at Community Path	6.42	6.57
Washington St at Myrtle St	4.83	4.56
30 Dane St	11.61	11.61

Huntington Ave at Mass Art	28.89	29.52
Harvard Ave at Brainerd Rd	18.96	18.66
699 Mt Auburn St	3.3	3.39
Mass Ave at Hadley/Walden	12.39	12.15
Harvard St at Greene-Rose Heritage Park	16.71	16.8
Mattapan T Stop	0	0
Roslindale Village - South St	4.23	4.23
Commonwealth Ave at Kelton St	12.66	12.51
Archdale Rd at Washington St	4.8	4.83
Blue Hill Ave at Almont St	5.82	6.15
Roslindale Village - Washington St	4.02	3.99
Boylston St at Jersey St	33	33.12
Morton St T	12.72	12.3
Commonwealth Ave at Chiswick Rd	10.62	10.62
Park Plaza at Charles St S.	58.17	58.47
Cleveland Circle	8.58	8.46
Thetford Ave at Norfolk St	6	6
Talbot Ave At Blue Hill Ave	9.9	9.84
Washington St at Talbot Ave	8.31	8.64
Codman Square Library	7.23	7.11
Faneuil St at Arlington St	5.16	4.92
Ring Rd	57.3	58.14
Mattapan Library	6.81	7.05
Washington St at Egremont Rd	8.64	9
Bennington St at Constitution Beach	7.71	7.5
Charlestown Navy Yard	5.76	5.67
Centre St at Seaverns Ave	8.07	8.34
Medford St at Charlestown BCYF	4.32	4.26
One Brigham Circle	34.41	35.28
Bartlett St at John Elliot Sq	14.94	14.76
Deerfield St at Commonwealth Ave	30.9	30.99
Columbia Rd at Tierney Community Center	11.01	11.22
Harrison Ave at Mullins Way	32.25	32.13
Tremont St at Northampton St	23.49	23.85
Harrison Ave at Bennet St	56.55	56.97
Broadway T Stop	23.67	22.68
Vassal Lane at Tobin/VLUS	3.33	3.36
Blue Hill Ave at Southwood St	14.94	14.67

Boston Public Market	83.58	83.64
Dartmouth St at Newbury St	63.21	64.38
700 Huron Ave	1.59	1.59
Boylston St at Exeter St	56.28	57.15
Belgrade Ave at Walworth St	0.42	0.27
Tremont St at Hamilton Pl	63.51	63.96
Honan Library	11.1	10.5
Perry Park	12.12	11.91
191 Beacon St	8.94	8.61
Tremont St at W. Dedham St	21.66	22.23
Mass Ave at Albany St	20.34	20.7
Inman Square at Springfield St.	13.32	13.47
Clarendon St at Newbury St	72.63	73.05
Albany St at E. Brookline St	24.63	25.68
Sennott Park Broadway at Norfolk Street	15.99	15.99
Norman St at Kelvin St	6.03	5.94
Main Street at Carter Street	9.27	8.79
Everett Square (Broadway at Chelsea St)	11.76	11.1
Broadway at Lynde St	8.37	8.49
Encore	2.94	2.97
Glendale Square (Ferry St at Broadway)	10.41	10.17
Ferry St at Pleasantview Ave	7.83	8.1
Broadway at Maple St	10.98	10.74
Chelsea St at Vine St	12.06	11.94
Main St at Beacon St	5.01	5.25
Broadway at Beacham St	9.09	8.88
75 Binney St	19.14	19.5
Shawmut Ave at Oak St W	50.73	51.3
Big Papi Station	38.19	38.07
High St at Cypress St	3.03	2.79
Washington St at Griggs Rd	8.58	8.73
Marion St at Harvard St	18.21	18.06
Mass Ave T Station	31.17	31.68
Sydney St at Carson St	21.06	20.82
Somerville City Hall Annex	8.82	8.79
Craigie at Summer St	7.29	7.74
Edgerly Education Center	9.9	9.75
Elm St at White St	12.9	12.81

Adams St at Lonsdale St	5.64	5.58
Dorchester Ave at King St	7.32	7.44
Washington St at Peters Park	28.05	27.81
Kennedy-Longfellow School 158 Spring St	8.1	8.22
Discovery Park - 30 Acorn Park Drive	3.39	3.39
Stuart St at Berkeley St	69.72	71.31
Blossom St at Charles St	47.73	48.75
Columbus Ave at W. Canton St	40.14	40.44
Central Square East Boston	23.97	24.57
Charles St at Pinckney St	33.84	34.59
Northbourne Rd at Hyde Park Ave	6.06	6
Cummins at American Legion	0.9	0.93
Mt. Hope St at Hyde Park Ave	6.27	6.39
Jamaica St at South St	10.23	10.71
The Dimock Center	16.95	16.38
Surface Rd at Summer St	77.91	77.85
Washington St at Denton Terr	0	0
Western Ave at Richardson St	6.57	6.75
Washington St at Walsh Playground	7.02	7.17
Washington St at Fuller St	5.7	5.79
Centre St at W. Roxbury Post Office	0	0
Centre St at Parkway YMCA	0	0
Spring St at Powell St	0	0
Central Ave at River St	6.6	6.21
Maverick St at Massport Path	17.7	17.94
Berkshire Street at Cambridge Street	7.2	7.23
Boston Landing	8.67	8.88
Sullivan Square	19.23	19.02
Hyde Park Ave at Walk Hill St	5.88	5.46
Whittier St Health Center	18.93	19.08
Geiger Gibson Community Health Center	4.92	4.98
700 Commonwealth Ave.	22.89	22.53

Figure A.65 Complete List of New Stations with Trip Predictions