Network analysis reveals fare-free shared bike system improves community integration in Boston

Keywords: Network analysis; urban informatics; income inequalities; urban policy making; social vulnerability

Extended Abstract

Affordable public transport plays a crucial role in serving low-income communities, improving their mobility, and promoting social integration [1]. To improve rider equity in transit systems, agencies worldwide have been prioritizing cheaper or fare-free public transport to lessen commuters' financial burdens. These policies have gained even more prominence in the aftermath of the COVID-19 pandemic, where economic instability and vulnerability are at a historic high [2]. Despite these efforts, previous research has yielded mixed evidence whether these attempts have successfully improved the mobility of low-income residents [3]. In addition to traditional transit systems, shared bike programs have emerged as a novel alternative transit option in recent years. However, it also remains unclear whether shared-bike systems can effectively enhance the mobility disadvantaged and vulnerable populations [4].

In light of these gaps, our study aims to explore whether a fare-free bike-sharing system can benefit broader communities in Boston. To achieve this, we utilize a network-based approach that quantifies the bike-sharing systems' demand change among different income groups under a fare-free service. We also identify which transit-dependent regions are more likely to utilize fare-free transit systems. Our study uses open-source bike ridership data from Bluebikes, Boston's bicycle sharing system. We build a weighted and undirected network in which each node represents a Bluebikes station, and the weight on an edge between two nodes is the number of trips taken between them. We build two networks for comparison purpose. The first network is based on the ridership data between July 19 to August 19, 2022, before the fees were waived. The second network is based on the data between August 19 and September 19, 2022, during which fare-free services were provided to Bostonians due to the repair and maintenance of the city's orange line. In addition, we use Boston-Cambridge-Newton Metro Area median household income data [5] to divide Boston tracts into four quantiles: low (<$63,438), medium-low ($63,438-$94,352), medium-high ($94,352-$124,875), and high income (>$124,875). We assigned this classification as node attributes depending on the stations' location.

Our analysis begins with community detection conducted using the Greedy modularity maximization algorithm [6]. This method matches node groups with other communities based on a modularity optimization strategy until further increase in modularity is no longer possible. We obtain 6 communities *(Figure 1)* and treat each as destinations paired with low- or high-income station origins. We then use the network portrait divergence (PD) approach to quantify the dissimilarity between these origin-destination pairs under normal-service conditions and fare-free service. Jensen-Shannon divergence between graph-invariant probability distributions is applied as the comparison measure, thus focusing on network topology [7]. The cumulative portrait divergence in low-income groups is 1.59, which is 44% higher than that of the high-income ones. This indicates that fare-free service brought more topological changes in the network for low-income groups *(Figure 2),* suggesting that their travel patterns changed more. We also measure the degree centrality (DC) [8] in each step to capture the level of connectivity changes. The low-income groups changed their travel patterns by 0.47, 91% higher than the increase observed in the high-income groups.

To understand fare-free service utilization changes in a regional scale with different transit sub-groups around the city, we conduct Hamming distance analysis [9][10]. We separately took each of the city's 146 bus routes and identified Bluebikes stations in their proximity of 800 meters (*Figure 3.*). We analyzed these 146 node groups as separate sub-graphs, comprising trips taken only within the group. As they are a substitute for already established travel routes defined by bus lines, these groups can define mobility behavior changes on a regional scale. Hamming distance changes to an evenly connected stage (ΔHD_0) are calculated between two time periods for each group. The average ΔHD_0 is 10.7% (std = 5.8%) for the two lower-income groups and only 4.1% (std = %3.1) for the two higher-income groups. This indicates that lower-income groups became more evenly connected than the higher-income ones *(Figure 4)*. Therefore, the fare-free service has an immediate impact on sub-groups with higher lower-income populations, significantly increasing the connectivity of their mobility networks.

Overall, our approach offers valuable insights into the feasibility of a fare-free bike-sharing system in Boston and its potential to benefit diverse communities across the city. The results also indicate that Bluebikes in Boston is an important and effective alternative transportation mode that supplements bus lines. Fare-free transportation services should be considered more as a means to improve the social integration of communities.

References

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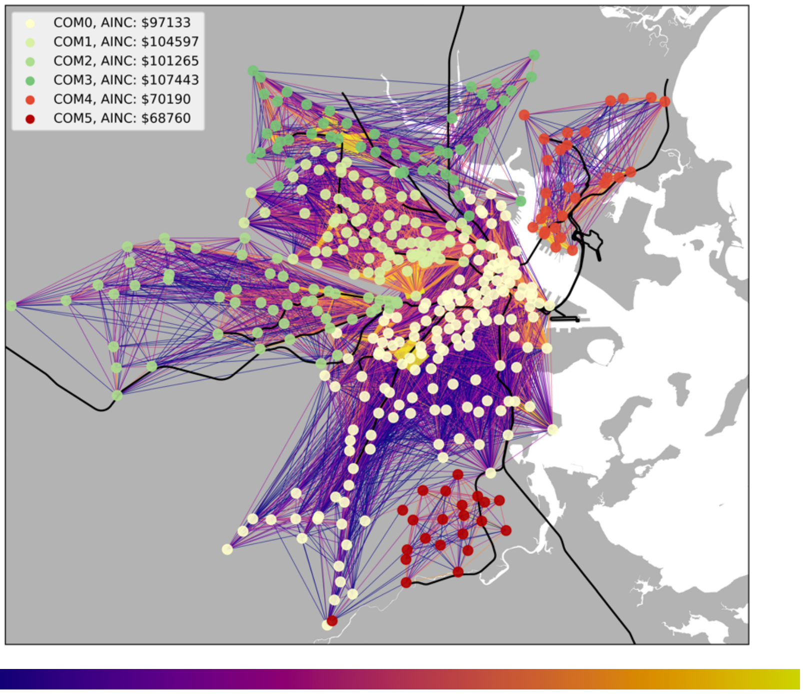

Figure 1. Community detection conducted by Greedy modularity maximization (COM: Community, AINC: Average Median Household Income)

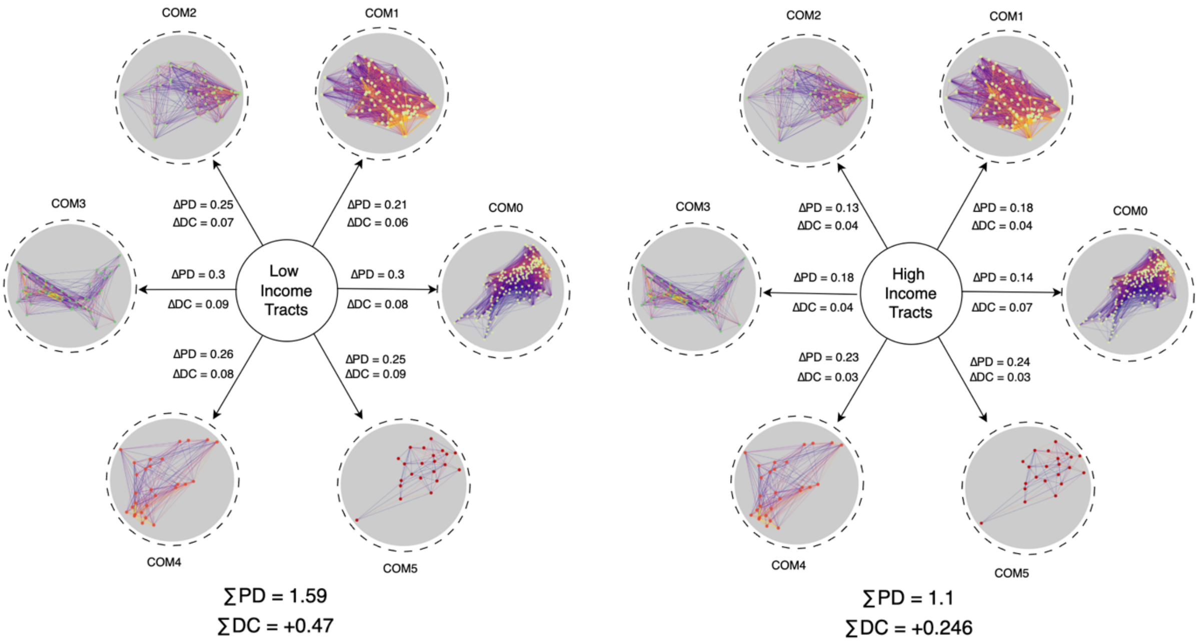

Figure 2. The left panel is low-income and the right panel is high-income nodes paired with each identified community which are visualized in surrounding circles. On the links, "PD" represent Network Portrait Divergence and "DC" represents degree centrality change between subgraphs of each income-community pairs taken within the networks built in 07/19/22 – 08/19/22 and 08/19/22 – 09/19/22 intervals.

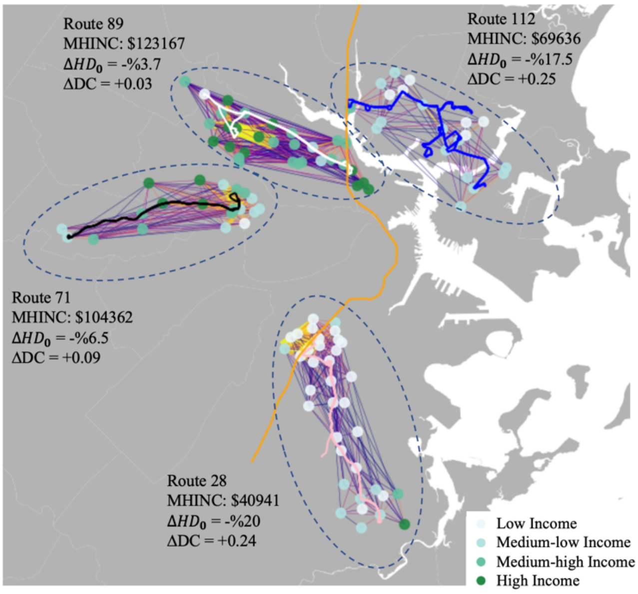

Figure 3. An example illustration for Hamming distance and degree centrality calculations over 4 bus routes, represented by pink, black, white and blue lines, and their averaged median household incomes. The orange line represents the metro service on repair during the 1-month fare-free Bluebikes services.

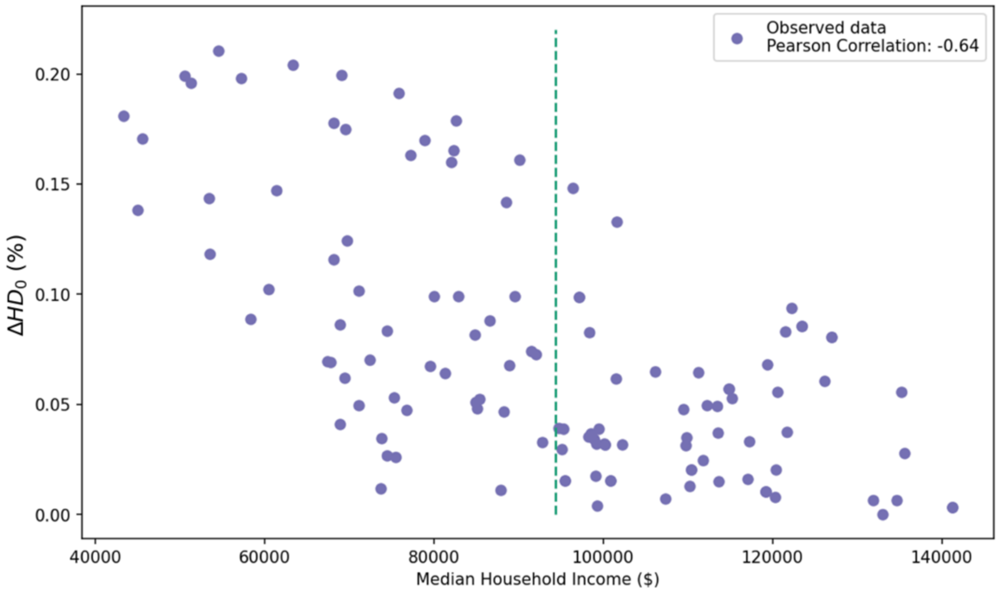

Figure 4. Resultant Hamming distance changes with their corresponding income averages. The dashed green line represents the $94,352 limit where data points are grouped as lower and higher income levels for averaging.