Examining the impact of new metro services on dockless bike sharing mobility patterns

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Abstract

Dockless bike sharing schemes provide an efficient transport alternative for short distance trips in cities. They have been shown to help solve the "first/last mile" problem for public transit systems, for example, getting people from metro stations to their final destinations. But the relationships between bike sharing and metro systems are not well understood. This paper develops a spatial analysis that seeks to quantify this relationship in order to inform the planning of non-motorized transportation, service extensions for other modes of public transit, and to improve flexibility of transportation. In this study, spatial statistics and graph theory are used to quantify the changes in dockless bike trips arising from newly opened metro lines and stations. The results demonstrate a number of different impacts that transportation system developments have on dockless bike sharing mobility patterns.

Keywords: dockless bike sharing, mobility, transit system, metro.

1 Introduction

Bike sharing can contribute towards improving air quality and reducing congestion in cities as a part of a sustainable travel infrastructure (Lovelace et al., 2011). Its popularity has increased in the last few years globally mainly due its advantages in cost and convenience over owning a bike and other forms of transport. With the development of 'Internet of Things', dockless bike sharing schemes first emerged around 2015. Unlike traditional bike sharing schemes where bikes can only be borrowed and returned at docking stations, the dockless schemes allow users to use smartphone apps to locate and borrow bicycles and leave them at a large number of public locations in a predefined geographic area. The smart lock system and GPS unit on the bikes creates a large quantity of spatiotemporal data at the individual level to support the management of the scheme, which also provides new opportunities to reveal urban dynamics and individual non-motorised mobility patterns.

Bike sharing schemes are considered to enhance the effectiveness of public transport by providing an "extension service" for the "first/last mile" of journeys, for example, the distance between home/workplace and public transport that is too far to walk (Shaheen et al., 2010; Saberi et al., 2018; Susan et al., 2010). But very few studies in literature have investigated the impact of public transportation infrastructures on bike sharing schemes using a quantitative approach (Saberi et al., 2018).

This paper aims to measure, understand, and characterise the interdependencies between metro and dockless bike sharing schemes. The case study is based on data from Nanchang, located in southeast China around the time when a new metro line came into operation. The associated changes in bike usage and mobility patterns are analysed using spatial statistics and graph theory.

2 Literature Review

This history of bike sharing can be traced back to the 1960s. Its development has gone through three stages (generations): free usage, a coin-deposit system and IT-based systems. The second-generation (coin deposit) first introduced docking stations into the scheme to prevent theft and to aid in the management of bike fleets. The use of docking stations also facilitated data collection of bike usage (Fishman, 2016, Shaheen et al., 2010), allowing the analysis of cycling mobility patterns.

A large body of work to date has concentrated on individual cycling behaviour and mobility patterns in order to improve the management and service of schemes. For example, Vogel, et al. (2011) and O'Brien et al. (2014) examined the geographical clustering of docking stations based on temporal bike usage patterns. By analysing the patterns in usage, bike fleet rebalancing strategies were developed and implement for different types of stations. Daddio (2012) presented a regression approach that related surrounding land-use characteristics with station demand, showing that commercial zones have a positive effect on the usage of station-based bike sharing. Such studies have mainly focused on demand and rebalancing bike provision, while the relationship, and the impact of events that happens between bike sharing and other transportation is less quantified and discussed. Saberi et al. (2018) compared various spatio-temporal statistics and network (graph) properties of docking stations to reveal the impact of Tube strikes in London on bike sharing. The strike was shown to greatly increase the usage of bike sharing both in terms of the number of trips and the average distance of these. It was shown that there was a remarkable and long-term influence on the network of cycling activity.

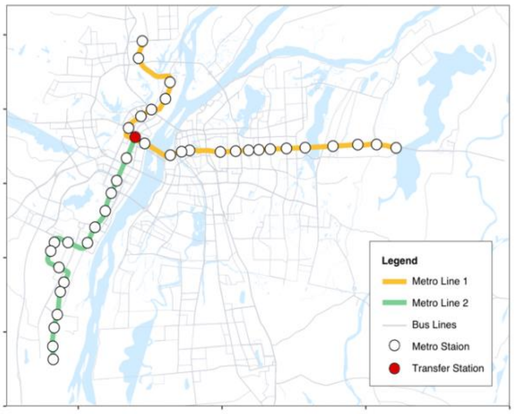
The studies outlined above were all generated by using data from the 3rd generation of bike sharing (i.e. IT-based system). The data used are: (1) the available bike count at each docking station, and (2) the flows of bike from one station to another (O'Brien et al., 2014; Kaltenbrunner et al., 2010). This means that the analyses and inference are limited to station-based data and locations.

The newly emergent and increasingly popular dockless bike sharing scheme provides new opportunities as well as challenges to non-motorised mobility studies. Because bikes are significantly more evenly distributed in urban spaces rather than only being available or having to be returned to docking stations. The spatiotemporal usage patterns and travel flows of dockless bikes are more complex to analyse compared with the more fixed docking station schemes. A new approach to studying the usage and the mobility patterns of the dockless schemes is wanted in order to understand evolving urban dynamics. Currently, dockless bike sharing studies are still in their infancy. Existing studies of dockless bike sharing are very limited and have focused on the management of bike fleets (Pal et al., 2017) or the planning of cycling infrastructures (Bao et al., 2017). There is much more novel research that can be done focussing on mobility pattern of dockless bike sharing. An important aspect of this is the relationship between dockless bike sharing combined with the use of other public transit systems.

3 Study Area and Data

Nanchang, located in southeast China, is the capital city of Jiangxi province. It has two metro lines as of September 2017. The new line of 17 stations, Metro Line 2, opened and started running a daytime service on August 18, 2017. Figure 1 shows the transit map of Nanchang revealing the Gan river running through the city, and the two metro lines (Metro Line 2 is located on the west side of the river).

Figure 1: Nanchang Transit Map.



Mobike is one of the biggest dockless bike sharing companies in China, it operated in the Nanchang area with around 80,000 cycles around the time of the opening of Metro Line 2.

A program was set up to collect data on the availability of Mobike bikes using the Mobike API. The Mobike API has in built limits such that a request for bike availability at a point location returns information (bike identifiers and coordinates) for the nearest 30 bikes that are available for hire. The program written to collect data on bike availability iterates through the whole urban area collecting data on bike availability on a raster grid of 0.0015 degrees in a longitude and latitude coordinate system. Most, but perhaps not all bike locations of available bikes across Nanchang are thus captured approximately every four minutes. The time taken for each iteration varies depended on the speed at which the Mobike API processed each request and communicated the results back to the program which waited a reasonable time before resending requests and making additional request so as not to overload Mobike with too many simultaneous requests. The time stamp of each result dataset was captured and the gridded results were aggregated into single coverages for the Nanchang area.

Trips were identified by using the bike identifiers and examining the changes in location when these bikes became available. For this study, the threshold value of a trip is 100 metres. If the change in location of a bike between two timestamps exceeded this threshold, then the two records are linked as a trip, the former one provides the origin coordinates, and the latter one is the destination of the trip. There are a number of assumptions and limitations to this approach of identifying trips and it is interesting to study the sensitivity of the results to the frequency of bike availability surveying and the threshold distance of 100 metres.

Extreme weather conditions have been found to have significant negative effects on cycling activity (El-Assi et al., 2017). To eliminate this potential weather influence, only data from rain-free days are used and in this study data from the 5 weekdays before and the 5 weekdays after the operation of metro system were analysed (Weather data obtained from wunderground.com).

4 Spatial Analysis

The duration, start and end of Mobike trips were spatially and temporally heterogeneous. Figure 2 indicates the average number of daily trips (count based on trip origins) before the operation of the new metro line. Each hexagon grid cell is approximately 1 square kilometre. Areas with the highest trip density are located around the middle zones of Line 1 (Bayi Square) – the main central business district of Nanchang.

After the opening of Metro Line 2, changes in the pattern of bike rides and ridership is evident. The service catchments around Metro Line 2 show increases in trip amount (Figure 3). Most areas experienced an increase of 40% to 120% while some show increases of over 120% and others over 500%. Figure 3 shows the spatial heterogeneity of the impact with areas associated with the highest increase in usage concentrating around the middle part of Metro Line 2.

Figure 2: Trip amount (Trip origins)

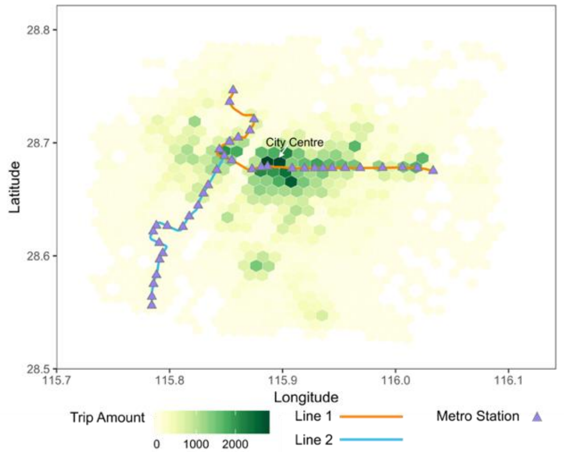
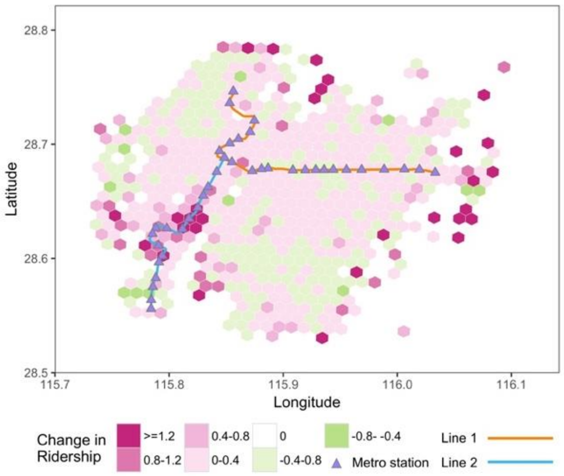
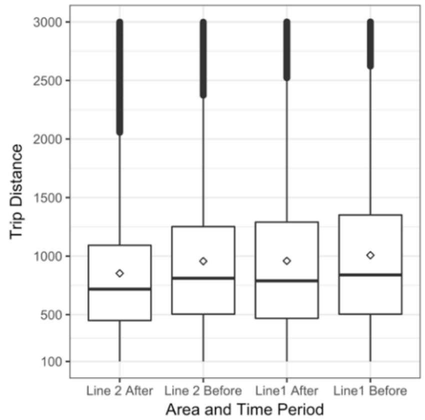


Figure 3: Change in ridership after the introduction of line 2



Not only did the number of trips increase, but also the average distances of these increased too. Each trip was located in buffer 1km zones around the Line 1 and Line 2 stations from which trip distances were calculated. The results are shown in Figure 4 using box plots.

Figure 4: Distribution of Trip distance.



Trip distance patterns in the older metro line (Line 1) areas are relatively consistent. The average trip distance in Line 1 buffer area only dropped by 31m from 1,250 to 1,219m, by contrast, in the new line area, the mean trip distance decreased by 168 m from 1,166 m to 998 m. Overall, the result confirm that a new metro service encourages more cycling activity while reducing bike trip distance.

5 Network Analysis

Conceptualising urban spaces as networks with flows can reveal interaction between different places and how people move around (Batty, 2013). Previous studies of public transit systems normally regard stations as nodes in the graph structure (Saberi et al., 2018; Zhong et al., 2014). However, dockless bike sharing do not have typical docking stations, and their availability around the city at any given time can be more dispersed or indeed concentrated. In general, the chances are that the nearest bike that would be available (at any location) in a dockless system would be closer than that for a docking station system ceteris paribus. Also, with dockless systems, the bike trips and travel flows are more complex and diverse because both origin and destinations are far less constrained.

In this study, small hexagonal grid cells were used to aggregate dockless bike trip flows. The grid covers buffer areas around new metro station (buffer width: 1200 m) and the side length of hexagon is 75m, the relatively small area of grid cells ensures their ability to capture the flows in study area. The flows from one grid cell to another are aggregated to build a network (graph structure), in which the grid cells are the nodes (vertices), and the links (edges) are the flows travel from one cell to another. Graph (network) properties are then quantified to reveal the properties of the system. They help to understand the local change as well as the relationship between different places. Figure 5 shows the distribution of node degree in the two periods. The degree of a node in a graph is defined as the number of other nodes that linked to it. The average degree increased from 18.5 to 20.8.

Figure 5：Node Degree of the two periods

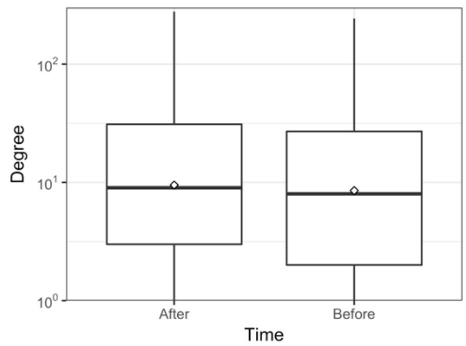
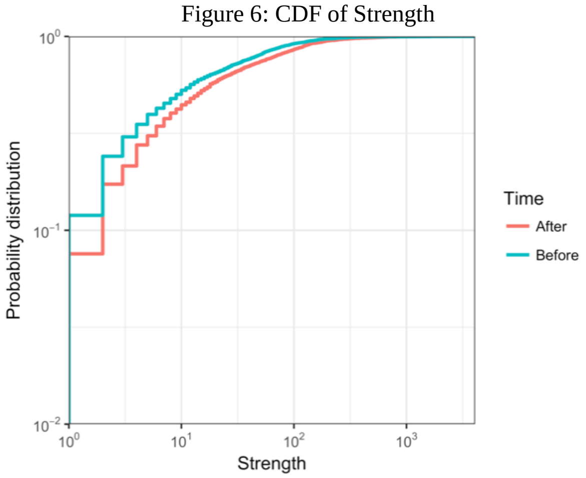


Figure 6 shows the CDF (Cumulative Distribution Function) of node strength, with strength defined as the weight of links between nodes. The results suggest that in the "after" period, new line areas have a higher probability of exhibiting stronger links. The average link strength increased from 32.2 to 49.4. The average centrality measure, betweenness centrality (Zhong et al., 2014), also increased from 3038.3 to 3406.8.

Overall, the changes indicate that structure of cycling network becomes more centralized, and interactions between areas are stronger.

Figure 6: CDF of Strength



6 Discussion and Future Work

This paper analysed the impact of new operated metro stations/lines on dockless bike sharing system. Important changes in trip amount, trip distance, as well as the graph structure of cycling flows were found. The new metro service has had significant positive impact on dockless bike sharing mobility patterns in a number of ways.

Future work will focus on analysing the finer spatiotemporal pattern change of bike usage and the relationship between cycling demand, population and urban land use.

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