Journal of Engineering Sciences
Vol 11, Issue 4, APRIL /2020
ISSN NO:0377-9254

UTILIZATION-AWARE TRIP ADIVSOR IN BIKE SHARING SYSTEMS BASED ON USER BEHAVIOUR ANALYSIS

Bhargavaaditya Sivalenka[1], Gaurav Parakh[2], Madapuri Lokeshwar[3], N. Sai Charan[4],
K.L.Narasimha Rao[5]

[1,2,3,4] *Department of Computer Science And Engineering, Gitam University, Hyderabad, India.*

[5] *Assistant Professor, Department of Computer Science And Engineering, GitamUniversity, Hyderabad, India.*

***Abstract*— The rapid development of bike-sharing systems has brought people enormous convenience during the past decade. On the other hand, high transport flexibility gives rise to problems for both users and operators. For users, dynamic distribution of shared bikes caused by uneven user demand often leads to the check in or check out service unavailable at some stations. For operators, unbalanced bike usage comes with more bike broken and growing maintenance cost.**

In this project, we consider enhancing user experiences and rebalance bike utilization by directing users to different stations with a higher success rate of rental and return. We will devise a trip advisor that recommends bike check-in and check-out stations with joint consideration of service quality and bicycle utilization. To ensure service quality, we firstly predict the user demand of each station to obtain the success rate of rental and return in the future.

To rebalance bike usage, from historical data, we identify that biased bike usage is rooted from circumscribed bike circulation among few active stations. Therefore, with defined station activeness, we optimize the bike circulation by leading users to shift bikes between highly active stations and inactive ones. We extensively evaluate the performance of our design through real-world datasets.

***Keywords*— Trip Advisor, Bike sharing system, Transport, Network, User**

1. INTRODUCTION

With the development of the economy, pollution and destruction caused by human activities to the natural environment were becoming more and more severe in recent years, and sustainable development has therefore become a consensus of the international community. In this circumstance, bike-sharing systems (BSS) are developed as a replacement for short vehicle journeys due to its low pollution, low energy consumption and high flexibility. In addition to the reduction of need for personal vehicle trips, public bike-sharing systems can not only extend the reach of transit and walking trips, providing people with a healthy transportation option, but also trigger greater interest in cycling, and increase cycling ridership. By the end of 2016, over 1,100 cities actively operated automated bike-sharing systems deploying an estimate of 2,000,000 public bicycles worldwide . With bike-sharing systems, a user can easily rent a bike with a smart card at a nearby station and return it at another station.

However, the advantages cannot cover up the increasingly prominent issues. For stations, the user demand is ever-changing and unbalanced, which often leads to the check in or check out service unavailable at some stations and has a negative impact on user experience. For bikes, the usage frequency of each bike is unevenly distributed, posing a problem for both riders and system operators. On the one hand, due to the high flexibility of bike sharing system, the system typically ends up with an uneven distribution of bikes across the different stations (due to the uncontrolled, uneven demand), often rendering the check in or check out service unavailable at some stations where bicycle docks are either fully occupied or empty. During peak periods, user demand characteristics differ among stations in certain areas. For example, rental demand usually gets larger in the morning near residential areas, whereas return demand gets larger near commercial districts. At present, operators perform bike redistribution based on monitor video and user complaints. However, this method has exposed the serious lag. It is usually when service unavailable events occur that operators start to give some scheduling. When the vehicle arrives, service unavailable events may have passed for some time, which makes it difficult to meet the needs of users at rush hour. To increase service availability and enhance user experience, studies have been conducted to improve these bike redistribution strategies based on bicycle mobility models and predictions. The majority of previous work focuses on bike usage patterns and rental volume forecasts for each station without considering online information. Less attention has been devoted to demand prediction of each cluster from the view of bike flow mobility patterns On the other hand, a small part of bikes is used much more frequently than others. Bikes that are used too much are vulnerable and hence increase repair bills and lead to potential denied service. The very first bicycle from Hangzhou BSS is reported to be rented for over 6,000 times and ridden for more than 20,000 kilometers in 3 years. Similarly, the most tireless bicycle from 2016 has been rented for 5,616 times, over 15 times on average each day. According to Hangzhou public bike-sharing company, the average life of their bicycles is less than 4 years due to longtime high load operation and lack of timely renewal and maintenance. On the contrary, the average life of private bicycles is 10 years and above. Meanwhile, the cost of repair and labor accounts for a large proportion in the overall operating expenses. In 2012, the repair cost of the Hangzhou bike-sharing system was nearly 6 million yuan . In Washington, D.C., the annual maintenance cost was $200 to $300 per bike in the year of 2012. Intuitively, operators can balance bike usage by leading users to use those unpopular bikes based on usage counts of each bike. However, directing users to rent a specific bike is not practical. Based on our analysis on a real bike-sharing dataset from Hangzhou, we observe that bikes located in some stations are much more likely to be used and moved to another active station. Hence, by introducing the station property of activeness, we transform the original problem of picking bikes to recommending check-in and check-out stations. By using the proposed trip advisor, we aim to guide users to ride bicycles between stations with different levels of activeness, therefore avoiding circumscribed circulation. Among active stations. For users, an advisor can not only help them choose stations with adequate bicycles, but also ensure a higher success rate when returning bikes. Also, different incentive mechanisms can be leveraged to better prompt the balancing process.

2. LITERATURE SURVEY

A. Bike-sharing: History, Impacts, Models of Provision, and Future

Bike-sharing, or public bicycle programs, have received increasing attention in recent years with initiatives to increase cycle usage, improve the first mile/last mile connection to other modes of transit, and lessen the environmental impacts of our transport activities. Originally a concept from the revolutionary 1960s, bike-sharing's growth had been slow until the development of better methods of tracking bikes with improved technology.This development gave birth to the rapid expansion of bike-sharing programs throughout Europe and now most other continents during this decade. Since the publication of "Will Smart Bikes Succeed as Public Transportation in the United States?" (DeMaio 2004), much has happened in the nascent field ofbike-sharing.While the previous paper discussed the conditions for a successful program, this paper discusses the history of bike-sharing, provides a detailed examination of models of provision with benefits and detriments of each, examines capital and operating expenses, and concludes with a look into the future of bike-sharing through a discussion about what a 4th generation bike-sharing program could be.

B. Sensing and Predicting the Pulse of the City

City-wide urban infrastructures are increasingly reliant on network technology to improve and expand their services. As a side effect of thisdigitalization, large amounts of data can be sensed and analyzed to uncover patterns of human behavior. In this paper, we focus on the digital footprints from one type of emerging urban infrastructure: shared bicycling systems.We provide a spatiotemporal analysis of 13 weeks of bicycle station usage from Barcelona#39;s shared bicycling system, called Bicing. We apply clustering techniques to identify shared behaviors across stations and show how these behaviors relate to location, neighborhood, and time of day. We then compare experimental results from four predictive models of near-term station usage.Finally, we analyze the impact of factors such as time of day and station activity in the prediction capabilities of the algorithms.Observing and modeling human movement in urban environments is central to traffic forecasting, understanding the spread of biological viruses, designing location-based services, and improving urban infrastructure. However, little has changed since Whyte (1980) observed in his "Street Life Project " that the actual usage of New York 's streets and squares clashed with the original ideas of architects and city planners. A key difficulty faced by urban planners, virologists, and social scientists is that obtaining large, real-world observational data of human movement is challenging and costly (Brockman et al., 2006).As websites have evolved to offer geo-located services, new sources of real-world behavioral data have begun to emerge. For example, Rattenbury et al. (2007) and Girardin et al. (2008) used geo-tagging patterns of photographs in Flickr to automatically detect interesting real-world events and draw conclusions about the flow of tourists in a city. In addition, as city-wide urban infrastructures such as buses, subways, public utilities, and roads become digitized, other sources of real-world datasets that can be implicitly sensed are emerging. Ratti et al. (2006) and González et al. (2008) used cellular network data to study city dynamics and human mobility.McNamara et al. (2008) used data collected from an RFID-enabled subway system to predict co-location patterns amongst mass transit users.

C. Urban cycles and mobility patterns: Exploring and predicting trends in a bicycle-based public transport system

Public bike sharing services are becoming more and more popular in the

past few years. A still a growing list of cities which provide such service systems can be found at the Bike sharing world map.1 Since 2007 the city of

Barcelona has been operating one of the largest bike sharing systems called Bicing, with about 6000 bikes distributed in about 400 stations across the entire city. The system was very successful with more than 180 000 subscribers in 2009 according to a recent study performed by Barcelona#39;s city council Lopez . However, the same study also addresses the result of a consumer satisfaction study, which shows still some room for improvements. The two biggest problems detected, which cause user frustration, are (a) the impossibility to find a bike when a user wants to start his/her journey and (b) the impossibility to leave the bike in the users#39;s destination due to empty or full stations. Without oversizing the system, there are basically two ways to solve these problems: Inform the user in advance about the best places to pick up or leave the bikes and improve the redistribution of bikes from full to empty stations. In this study we aim to contribute to the solution of these problems via the analysis of cyclic mobility patterns which lead to short term predictions of the number of available bikes in the stations. Such predictions would allow us to improve the current web-service of Bicing and in turn increase users#39;

satisfaction with the system. Once this type of information is available, users may use mobile devices to access it. Knowledge of those patterns could lead to an optimization of the Bicing system itself, allowing the operator to predict shortage or overflow of bicycles in certain stations well in advance and adapt its

redistribution schedule accordingly on the fly. Furthermore, we intend to show that this type of data also allows us to infer the activity cycles of Barcelona#39;s population as well as the spatio-temporal distribution of their displacements

3. EXISTING SYSTEM

With bike-sharing systems, a user can easily rent a bike with a smart card at a nearby station and return it at another station. However, the advantages can not cover up the increasingly prominent issues. For stations, the user demand is ever-changing and unbalanced, which often leads to the check in or check out service unavailable at some stations and has a negative impact on user experience. For bikes, the usage frequency of each bike is unevenly distributed, posing a problem for both riders and system operators. On the one hand, due to the high flexibility of bike sharing system, the system typically ends up with an uneven distribution of bikes across the different stations (due to the uncontrolled, uneven demand), often rendering the check in or check out service unavailable at some stations where bicycle docks are either fully occupied or empty. During peak periods, user demand characteristics differ among stations in certain areas. For example, rental demand usually gets larger in the workday morning near residential areas, whereas return demand gets larger near commercial districts. At present, operators perform bike redistribution based on monitor video and user complaints. However, this method has exposed the serious lag. It is usually when service unavailable events occur that operators start to give some scheduling instructions. When the vehicle arrives, service unavailable events may have passed for some time, which makes it difficult to meet the needs of users at rush hour. At present, operators perform bike redistribution based on monitor video and user complaints. However, this method has exposed the serious lag. It is usually when service unavailable events occur that operators start to give some scheduling instructions. When the vehicle arrives, service unavailable events may have passed for some time, which makes it difficult to meet the needs of users at rush hour.

4. PROPOSED SYSTEM

The trip advisor that recommends the optimal pair of stations to rent and return bikes. Through Guiding the actions of users, it can help balance bike usage, reduce operation cost and enhance user experience. Firstly, to make sure users can find bikes and available lockers, success rates of rental and return should be predicted for each station. Different from traditional demand prediction methods, we present probabilistic forecast methods on a minute timescale instead of predicting the exact stock number on sub-hour granularity. Secondly, in order to balance bike usage through station recommendation, a station property must be associated with bike usage frequency. These two parts constitute the core content of the trip advisor framework. Advantages of proposed system is By using the proposed trip advisor, we aim to guide users to ride bicycles between stations with different levels of activeness, therefore avoiding circumscribed circulation among active stations. For users, an advisor can not only help them choose stations with adequate bicycles, but also ensure a higher success rate when returning bikes. Also, different incentive mechanisms can be leveraged to better prompt the balancing process.

5. METHODOLOGY

The first time, we devise a trip advisor that recommends bike check-in and check-out stations with joint consideration of service quality and bicycle utilization. To ensure service quality, we firstly predict the user demand of each station to obtain the success rate of rental and return in the future. Experiments indicate that the precision of our method is as much as 0.826, which has raised by 25.9% as compared with that of the historical average method. To rebalance bike usage, from historical data, we identify that biased bike usage is rooted from circumscribed bicycle circulation among few active stations.

5.1. SYSTEM DESIGN

The purpose of the design phase is to plan a solution of the problem specified by the requirement document. This phase is the first step in moving from the problem domain to the solution domain. In other words, starting with what is needed, design takes us toward how to satisfy the needs. The design of a system is perhaps the most critical factor affecting the quality of the software; it has a major impact on the later phase, particularly testing, maintenance. The output of this phase is the design document. This document is similar to a blueprint for the solution and is used later during implementation, testing and maintenance. The design activity is often divided into two separate phases System Design and Detailed Design.System Design also called top-level design aims to identify the modules that should be in the system, the specifications of these modules, and how they interact with each other to produce the desired results. At the end of the system design all the major data structures, file formats, output formats, and the major modules in the system and their specifications are decided.During, Detailed Design, the internal logic of each of the modules specified in system design is decided. During this phase, the details of the data of a module is usually specified in a high-level design description language, which is independent of the target language in which the software will eventually be implemented.In system design the focus is on identifying the modules, whereas during detailed design the focus is on designing the logic for each of the modules. In other works, in system design the attention is on what components are needed, while in detailed design how the components can be implemented in software is the issue.Design is concerned with identifying software components specifying relationships among components. Specifying software structure and providing blueprint for the document phase. Modularity is one of the desirable properties of large systems.

It implies that the system is divided into several parts. In such a manner , the interaction between parts is minimal and clearly specified.During the system design activities , Developers bridge the gap between the requirements specification , produced during requirements elicitation and analysis , and the system that is delivered to the user. Design is the place where the quality is fostered in development . Software design is a process through which requirements are translated into a representation of software.

5.2. DATA MINING

The past two decades has seen a dramatic increase in the amount of information or data being stored in electronic format. This accumulation of data has taken place at an explosive rate. It has been estimated that the amount of information in the world doubles every 20 months and the size and number of databases are increasing even faster.

Data storage became easier as the availability of large amounts of computing power at low cost i.e. the cost of processing power and storage is falling, making data cheap. There was also the introduction of new machine learning methods for knowledge representation based on logic programming etc. in addition to traditional statistical analysis of data. The new methods tend to be computationally intensive hence a demand for more processing power.

Database Management systems gave access to the data stored but this was only a small part of what could be gained from the data. Traditional on-line transaction processing systems, OLTPs, are good at putting data into databases quickly, safely and efficiently but are not good at delivering meaningful analysis in return. Analysing data can provide further knowledge about a business by going beyond the data explicitly stored to derive knowledge about the business. This is where Data Mining or Knowledge Discovery in Databases (KDD) has obvious benefits for any enterprise.

5.3. MACHINE LEARNING

Machine learning is the automation of a learning process and learning is tantamount to the construction of rules based on observations of environmental states and transitions. This is a broad field which includes not only learning from examples, but also reinforcement learning, learning with teachers, etc. A learning algorithm takes the data set and its accompanying information as input and returns a statement e.g. a concept representing the results of learning as output. Machine learning examines previous examples and their outcomes and learns how to reproduce these and make generalisations about new cases.

5.4. CLUSTER ANALYSIS

Clustering and segmentation basically partition the database so that each partition or group is similar according to some criteria or metric. Clustering according to similarity is a concept which appears in many disciplines. If a measure of similarity is available there are a number of techniques for forming clusters. Membership of groups can be based on the level of similarity between members and from this the rules of membership can be defined. Another approach is to build set functions that measure some property of partitions i.e. groups or subsets as functions of some parameter of the partition. This latter approach achieves what is known as optimal partitioning.

5.5. SOFTWARE REQUIREMENTS

Operating System: Windows 7
User Interface : HTML, CSS
Client-side Scripting: JavaScript
Programming Language : Java
Web Applications: JDBC, Servlets, JSP
IDE/Workbench: My Eclipse 8.6
Database: Oracle 11g
Server Deployment: Tomcat 7.0

5.6. HARDWARE REQUIREMENTS

Processor :Intel core i3 or above

Hard Disk :500GB or more

6.RESULTS

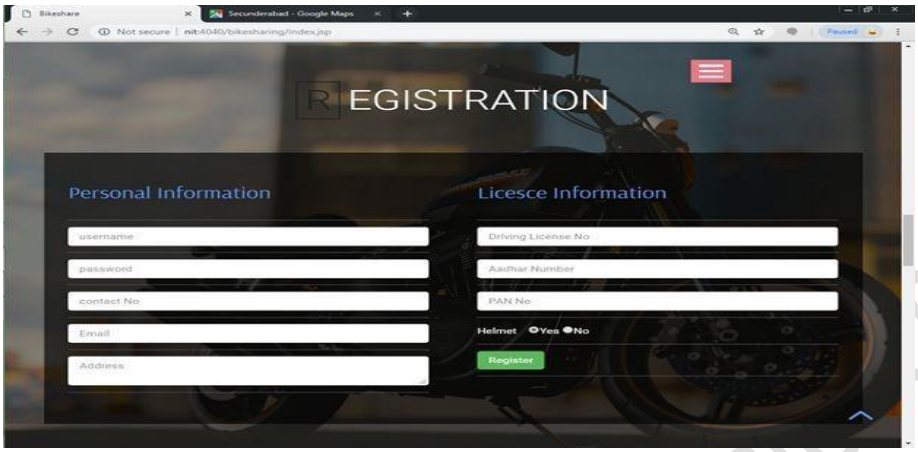

Figure 6.1: New Customer Registration

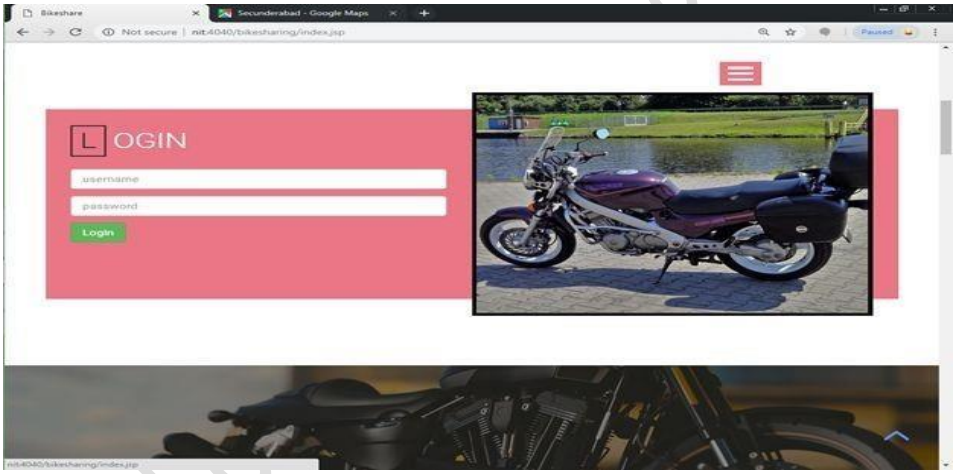

Figure 6.2: Existing Customer Login

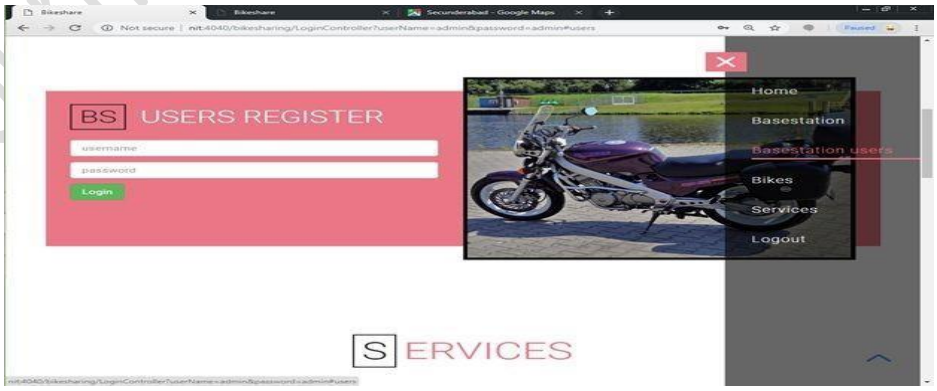

Figure 6.3: Balancing Bike Usage

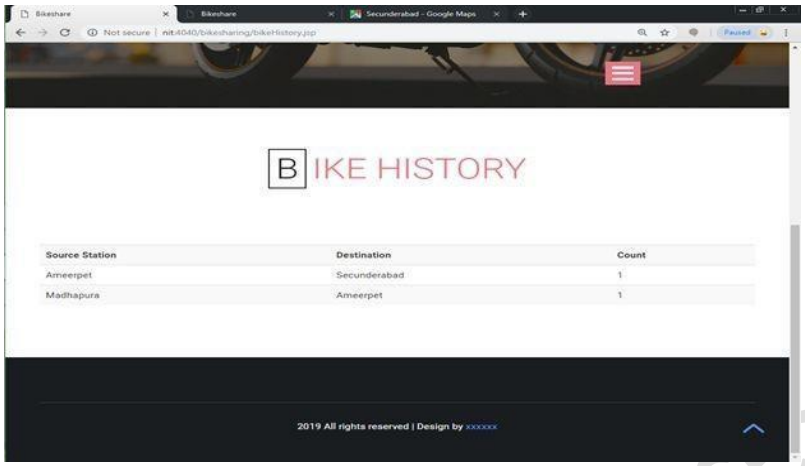

Figure 6.4: To Find the History of a Bike

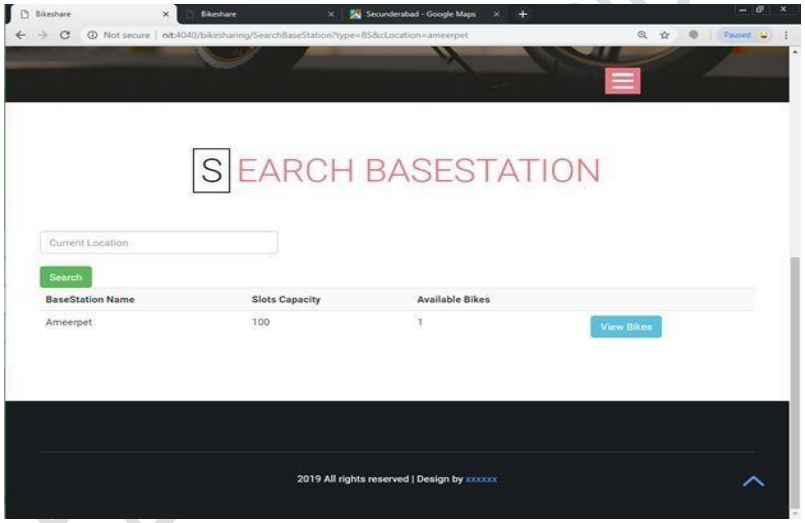

Figure 6.5: The List of Base Stations

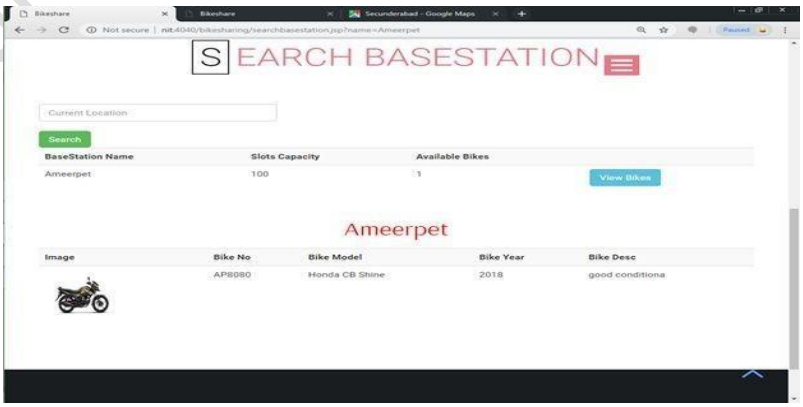

Figure 6.6: View the Bikes Available

7. CONCLUSION

In this project, we presented a study on user vitality ranking and prediction in social networking services such as microblog application. Specifically, we first introduced a user vitality ranking problem, which is based on dynamic interactions between users on social networks. To solve this problem, we developed two algorithms to rank users based on vitality. While the first algorithm works based on the developed two user vitality measurements, the second algorithm further takes into account the mutual influence among users while computing the vitality measurements. Then we presented a user vitality prediction problem and introduced a regression based method for the prediction task.

REFERENCES

[1] eMaio, "Bike-sharing: History, Impacts, Models of Provision, and Future," Journal of Public Transportation,vol. 12, no. DeMaio 2004, pp. 41–56, 2009. [Online].Available: http://www.transitinformatics.org/test/nctr/wp-content/uploads/2010/03/JPT12-4DeMaio.pdf

[2] P. Midgley, "Bicycle-sharing schemes: enhancing sustainable mobility in urban areas," United Nations, Department of Economic and Social Affairs, pp. 1–12, 2011.

[3] MetroBike, "2016 Year-end wrap-up will appear at the end of January," http://bike-sharing.blogspot.com/2017/01/2016-year-end-wrap-up-will-appear-at.html.

[4] . Froehlich, J. Neumann, and N. Oliver, "Sensing and Predicting the Pulse of the City through Shared Bicycling," in IJCAI, 2009

[5] P. Vogel and D. C. Mattfeld, "Strategic and Operational Planning of Bike-Sharing Systems by Data Mining - A Case Study," in Computational Logistics, 2011, pp. 127–141.

[6] P. Borgnat, E. Fleury, C. Robardet, and A. Scherrer, "Spatial Analysis of

[7] Dynamic Movements of V´elo'v, Lyon's Shared Bicycle Program," in European Conference on Complex Systems (ECCS), 2009.

[8] Y. Li, Y. Zheng, H. Zhang, and L. Chen, "Traffic Prediction in a Bike Sharing System," in ACM SIGSPATIAL, 2015.