FlowCasting: A Dynamic Machine Learning based Dashboard for Bike-Sharing System Management

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***Abstract*—Prompted by increasing citizens' demand, the rapid evolution of smart- and micro-mobility continues to shape the landscape of urban transportation services. In light of their practical benefits in terms of environmental sustainability, public health, and traffic congestion mitigation, smart cities manage mobility services by tracking user demand and service utilization over time. Leveraging this data is crucial for discerning current patterns and anticipating future trends, thus improving service provision. In this context, we propose a new interactive dashboard for the advanced analysis of spatio-temporal data acquired from bike-sharing systems. Our goal is to show on an interactive map the city areas with the highest current and future users' demand and a simulation of the routes suitable for redistributing bikes across stations according to their predicted occupancy level. We leverage a clustering algorithm to identify the areas with currently highest bike demand and a forecasting approach to predict users' demand trends. Thanks to multi-resolution time and path management, end-users can exploit the dashboard to support their decisions regarding resource shaping. We showcase the FlowCasting's capabilities on a opensource dataset collecting BlueBikes data in Boston (U.S.). The online demo is available at the following link: https://flowcasting.streamlit.app/**

***Index Terms*—Interactive Dashboard, Data Analytics, Machine Learning, Smart Mobility**

I. INTRODUCTION

Smart mobility and micro-mobility services are becoming increasingly popular in urban areas as citizens look for convenient, eco-friendly alternatives to traditional means of transport, especially for short-distance travels. By primarily using bicycles and scooters, whether electric or traditional, people can reduce their carbon footprint on air pollution, which negatively impacts the quality of life in urban areas [1], and lower their stress level caused by traffic congestion [2], [3]. This underscores the significance of developing modern urban transportation services that accommodate the increasing citizens' demands, paying particular attention to road safety and policies to overcome the potential barriers [4].

Bike-sharing systems are one of the most popular smart mobility solutions. Although the diffusion of cycling is influenced by the presence of well-organized infrastructure and specific services, such as bike paths and docking stations, the recent advent of electric vehicles and bikes has brought forth a new dimension to urban mobility, increasing the diffusion due to their ease of use but also requiring additional features, such as recharging stations.

Moreover, the switching process from ownership to an access-based consumption model is a strong factor that influences the available market and the allocation of resources [5]. Different kinds of bike-sharing systems have been proposed in recent years, including Station-based Bike-Sharing (SBBS) and Free-Floating Bike-Sharing (FFBS) [6], [7]. Such a new mobility paradigm is enabled by the spread of digital services, which allow smart citizens to interact with the systems, exchange data, and get feedback [8]–[10].

However, as service demand grows, it becomes increasingly important to monitor resource usage to ensure that service provision remains effective, efficient, and sustainable. Data mining models and Business Intelligence are nowadays a cornerstone to understand users' behaviour, profile services, and detect users' demand evolution over time. For example, the analysis of historical service usage data could help to identify anomalies, inefficiencies, or common citizens' habits. On the other hand, detecting recurrent patterns from past data could enable the prediction of future users' demand and the early identification of potentially critical paths.

The important challenge of transforming historical spatio-temporal mobility data into actionable knowledge requires advanced analysis techniques and effective tools to enhance system planning, demand monitoring and maintenance operations [11], [12]. Based on this need to support the growth of Intelligent Transportation Systems, our work proposes FlowCasting, an interactive machine learning based dashboard to visualize relevant city areas, predict upcoming service usage trends and suggest viable routes according to the bike-sharing station occupancy levels (Figure 1). The dashboard is dynamic, highly customizable, and designed for service managers who are in charge of shaping bike-sharing services and defining resource allocation.

The main features of our interactive dashboard for visual bike-sharing data analytics are summarized as follows:

- **Clustering**: group nearby bike-sharing stations with high current users' demand.
- **Forecasting**: predict the upcoming users' demand trends.
- **Path Manager**: simulate the redistribution of bikes across stations to reallocate the system resources, thus optimizing service provision.

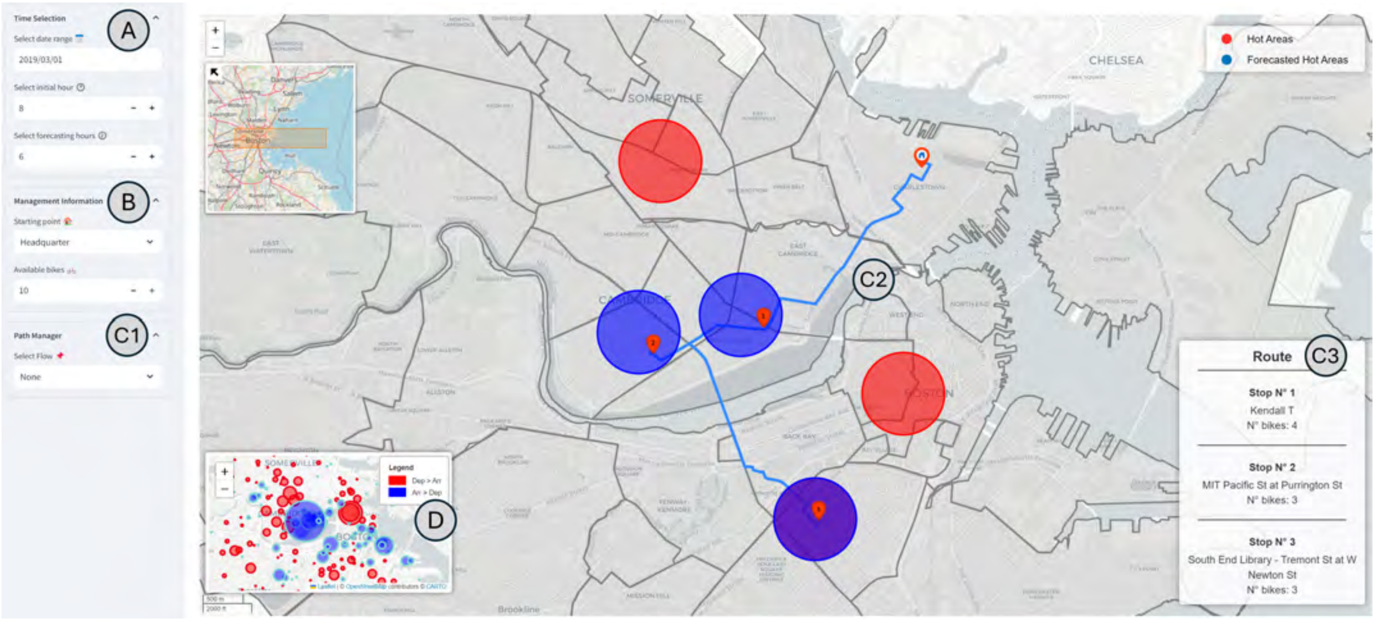

Fig. 1: **FlowCasting** is an interactive dashboard to visualize the current and future (estimated) trends of the utilization of bicycle sharing stations across the city area as well as a viable plan of bicycle redistribution across urban stations. FlowCasting incorporates four main visual components: (A) **Time-based Map**: a view of the current and future city areas with the highest users' demand, (B) **Management Information system**: a selector of the starting point of the service and the number of bikes to deploy, (C) **Path Manager**: a planner of the bike redistribution routes, and (D) **Density Map**: a visualization feature offering a better contextualization of bike movements.

II. Related works

Numerous studies have explored the use of machine learning techniques to explore and visualize bike-sharing data. The common goal is to support either system managers in decision-making or end-users to browse related content or explore the outcomes of ad hoc predictors [13]–[15]. Figure 2 shows the position of the present work, namely FlowCasting, in the related literature. [1] It is at the intersection of four complementary research areas that are mostly relevant to bike-sharing systems. It features all the separate contributions in a single, interactive dashboard.

a) Forecasting: The use of machine learning techniques to predict future users' demand based on historical data is established [16]–[23], where most common algorithms vary from RandomForest to LSTM neural networks and ARIMA models. They are indispensable tools to analyze time-evolving trends within large bike-sharing datasets.

b) Clustering: These algorithms have been used to detect spatial and temporal correlations in urban environments [24]–[27]. Algorithms, such as K-Means, Minimum spanning tree, and hierarchical clustering, are not only useful for outlier detection [28] but also to plan bike redistribution actions [29], [30] and predict users' demand drift [31].

c) Path Management: Other methods have already studied the optimal bike distributions under varying conditions, using different machine learning algorithms, as Random Forest, Multilayer Perceptron, and clustering to forecast the bikes availability and support efficiently the rebalancing operations [23], [32]. The goal is to recommend the optimal routes or eco-friendly paths [33], [34] across the bike-sharing stations, thus simplifying planning and maintenance operations [35], [36].

d) Visualization: To guide the decision-making process, various interactive tools have been proposed in the context of bike-sharing systems. They propose specific visualizations and data encoding to detect spatio-temporal patterns for each station - including demand frequency and trips profiling - [37], the integration of data science tools for mobility data analysis with maps and trajectory visualizations [38], and the development of applications and dashboards to support users in advanced analytics [39], [40].

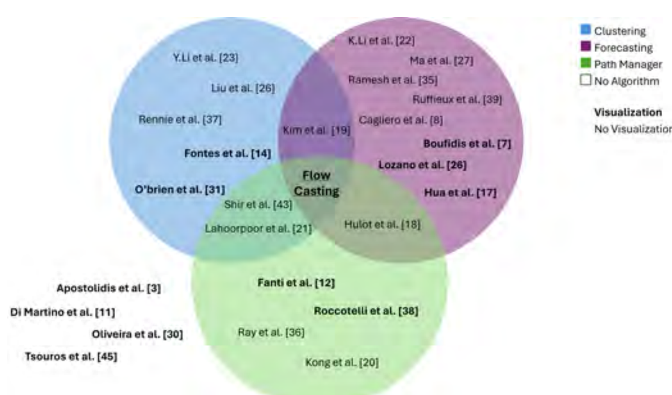

Fig. 2: Visual representation of the state of the art and of the position of the work in the related literature.

[1] We disregard the comparison between clustering and time series forecasting algorithms used in the literature, as it is out of the scope of the present study.

Unlike previous solutions, our approach integrates clustering, forecasting, path management, and visualization methods into a comprehensive system dashboard, offering a novel visualization tool for an effective understanding of the system status according to geographical areas of the city. In detail, FlowCasting provides an open and user-friendly framework to support managers in service monitoring and shaping.

III. Design Objectives and Requirements

According to the literature review we define the interactive dashboard requirements ensuring an enriched and more powerful bike-sharing data exploration. To fulfill the necessary design objectives, during our implementation we meet the following requirements in agreement with smart mobility experts:

a) ***R1*** *- Intuitive and easy-to-use application:* We prioritize user-centric design principles, including a simplified interface with clear navigation and interactive elements to facilitate data exploration. The main objective is to provide system managers with a user-friendly application to expedite the process of data monitoring and decision-making.

b) ***R2*** *- Visualization of time-evolving data:* This requirement involves implementing key strategies to enhance the clarity and usability of spatio-temporal data representations for highlighting moments of intense usage. Visualizations of time-evolving data, clusters, and predictive analytics are presented with a clear visual hierarchy, interactive map features, and real-time updates to enhance comprehension and responsiveness.

c) ***R3*** *- Support comparison between current and predicted critical areas:* This involves overlaying current and predicted areas with high users' demand on the map. The goal is to allow end-users to visually assess differences and emerging trends. Visual cues such as color coding enable users to identify and anticipate future demand shifts. Interactive controls enable users to select specific time frames for comparison, ensuring focused analysis based on user-defined criteria.

d) ***R4*** *- Optimization for live computation and customization of parameters:* Flexibility is a key aspect for data analytics. Thus, FlowCasting is expected to perform live computations according to the specific user input, allowing stakeholders to analyze several scenarios and study different solutions for bike management based on their preferences. In addition, it should provide multiple alternatives to understand the most convenient path to cover the predicted areas of interest.

IV. Framework Design

The overall architecture is illustrated in Figure 3. It shows the dashboard that is accessible through a web browser (**R1**). Users can perform analysis on bike-sharing datasets, interacting by adjusting time, management, and route parameters.

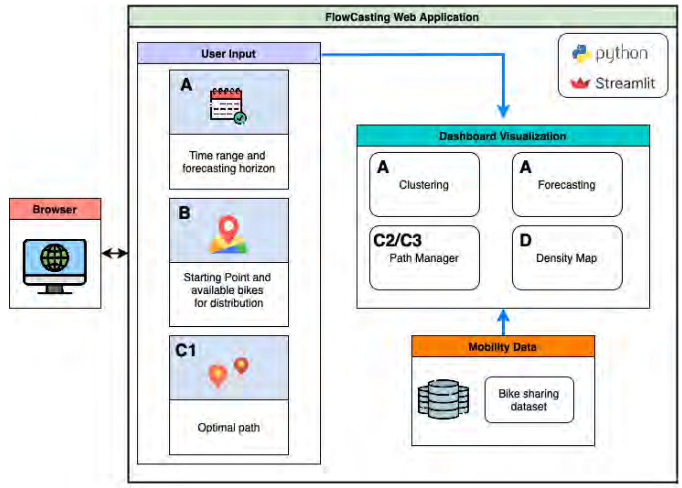

Fig. 3: Architecture overview describing the main components of FlowCasting. The application can be accessed using a simple browser. Based on the input and the historical mobility data, users can observe the customized visualizations.

Based on these selections, the data, the map displaying areas of interest and the suggested routes are dynamically updated.

Algorithms design. FlowCasting receives as input data storing records about trips of bike-sharing systems, including the arrival and departure station names, station positions, and time. On this data, we apply clustering to divide city areas according to bike-station positions (based on latitude and longitude coordinates). We employ the K-Means [41] algorithm, where the number of clusters K is chosen in accordance with the number of neighborhoods in the city under analysis. To compare current and future city areas of interest, we aim to identify short-term future bike-station utilization. This is implemented by forecasting the hourly bike demand for each station and detecting the expected most relevant clusters. In detail, the forecasts of the per-station occupancy levels are generated by the Autoregressive Integrated Moving Average (ARIMA) [42] model to leverage the stationary properties of the time series. The clustering and forecasting are computed each time user-defined values (see Section IV-A) are modified.

Dashboard design. The FlowCasting dashboard is developed as a web application with the Python language (**R1**). Specifically, the front-end interface is based on the Streamlit framework [2], while the maps are generated through the Folium library [3]. Additionally, the routes are generated using the OSMnx and NetworkX libraries [43], [44]. Broadly, our platform is designed with customization in mind. As such, the implementation of different clustering, forecasting, and routing algorithms can be tailored to specific use cases as needed. Moreover, by leveraging the web-browser properties, we natively support the most common screen resolutions such as 1080p, 1440p and 2160p, focusing mainly on the last two.

[2]https://streamlit.io

[3]https://python-visualization.github.io/folium/latest/

In the following, we describe the components of the interface as well as their interactions. The dashboard is made of a Time-based Map (A), a Management Information (B), a Path Manager (C) and a Density View (D) (Figure 1).

A. Time-Based Map (A)

The map in Figure 1 represents the city under examination. Notably, it highlights both current and predicted areas of interest for the upcoming time range (**R2, R3**). In our case study, these areas are determined based on the number of departures of the included stations, a critical factor in comprehending station utilization.

To access information on these relevant areas, users can select the desired date and departure time on the sidebar on the left (**R4**). This selection prompts the display of current areas of interest on the map (depicted in red). These areas of interest are determined through a clustering of bike stations. Indeed, from the perspective of the service provider, these zones are defined based on station density rather than geographic regions within the city. Conversely, specifying forecast hours from the current time reveals the predicted areas of interest (depicted in blue). This juxtaposition of significant zones enables the analysis of how these areas evolve over time.

B. Management Information (B)

Bike-sharing system managers commonly need to schedule bike rebalancing actions or extensions of the currently offered services in different locations of the urban environment. To accommodate this, we allow managers to choose the starting points (*home* pin in the map) in the left sidebar, enabling diverse analyses and informed decisions (**R4**). Simultaneously, within the "*Management Information*" section, managers can specify the number of bikes that are expected to be relocated. These bikes may be relocated due to either maintenance action or the addition of new stations. The starting number can be interpreted as the maximum number of available bikes, which is commonly fixed by design. This value may change based on the number of bikes needing reassignment.

C. Path Manager (C)

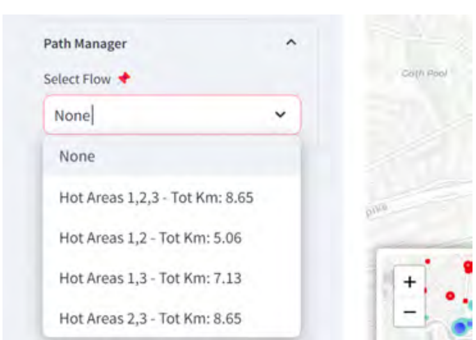

Fig. 4: Path Manager drop-down menu with the available routes associated to road distance. Each route includes the areas of interest and the road distance to cover.

Fig. 5: Patch of the map exemplifying the information provided when a path is selected. It shows the following elements: (1) home pin for the starting point, (2) the actual and predicted relevant areas, (3) the road route in blue, (4) the stopping point for each predicted area with a numerated pin, (5) the popup on the stopping point with the information on the station name and the number of bikes to deploy, (6) the summary with the route to follow for the reassignment.

The Path Manager of the FlowCasting dashboard shows the candidate paths for redistributing bikes across the stations.

In the left-hand drop-down menu (C1) within the "*Path Manager*" section (see Figure 4), users can choose among four possible paths (**R4**). Notably, the travelled distance (expressed in kilometers) is calculated based on the road route and immediately displayed alongside each path. We choose to provide four alternative options for bike relocation. Each option is associated with a path from the starting point to the destination areas, where the bikes are relocated to the selected stations within the destination area.

Upon selecting a route, the main map is dynamically updated (C2) to display the designated road (in blue), along with the designated stops (Figure 5). These stops are determined based on proximity to the predicted areas of interest relative to the departure location. They are shown on the map through numbered pinpoints, reflecting the sequence of stops. Regarding the selection of stations for bike insertion, we highlight the stations for which the gap between daily cumulative departures and arrivals at a specified point of time is positive (denoting a decreasing occupancy level trend). Each numbered marker on the map features a popup (on the left on Figure 5) displaying the station name and the number of bikes to be allocated. At the bottom right of the page (Figures 1 and 5) a report (C3) shows a comprehensive trip summary. It details the stops for each selected area of interest are shown, listing the stations (in sequential order) and the corresponding number of bikes to be assigned.

D. Density View (D)

This visualization element is designed to support the Time-Based Map, allowing a better generalization (**R2**). The density map (see Figure 6) allows end-users to explore and analyze areas of interest with higher departures (red) or arrivals (blue). To support targeted analysis, the density map is generated utilizing historical data corresponding to the same day of the week. This approach enhances the accuracy and relevance of the insights derived from the density map and, combined with

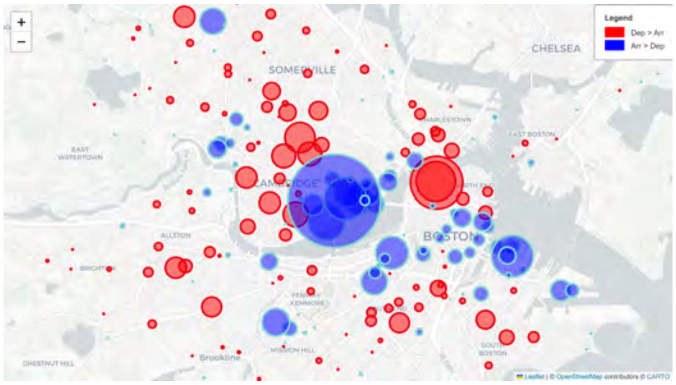

Fig. 6: Density Map. It shows areas with more departures (in red) or arrivals (in blue) on the same day of the week of the selected date. It allows a better generalization and contextualization of the ongoing situation for the chosen time parameters.

the information in the main map, it provides users with a more robust understanding of mobility patterns.

V. Case Study

A use case is thoroughly examined using the publicly available BluBikes Boston dataset [45] to validate the functionality and effectiveness of the dashboard in a real-world scenario, ensuring its reliability and applicability across diverse contexts. To assess the design choices of our development team, we collect feedback from six individuals expert in different fields ranging from computer engineering to design and transportation sector.

*a) **Dataset**:* We use the BlueBikes dataset collected on the city of Boston [45]. The selection of this dataset was driven by its comprehensive nature, notably the presence of geographic and temporal data including latitude, longitude, and date. Moreover, its extensive temporal coverage enables the execution of forecasting tasks, amplifying the depth and breadth of our analysis.

*b) **Algorithms Configuration**:* Considering the number of neighborhoods in the city of Boston where the BlueBikes [45] stations are located, we set the number K of clusters to 15. Given this dataset, after an exploration of the parameters, we found effective to employ the *ARMA* configuration for the forecasting, with the following parameters $p = 2, d = 0, q = 2$.

*c) **Design Peer Review**:* In our study, we conducted interviews with five participants from STEM backgrounds, including engineers and designers, as well as a representative from a local transportation company, to evaluate design choices for a dashboard. Participants were shown various graphical sketches and provided feedback on different aspects. All participants preferred placing user-modifiable elements on a sidebar rather than above or below the main map. Five participants felt that including a frequent flows map was not essential to the main analyses, with one being neutral. Four participants favored having immediate route changes on the map without intermediate views, and all agreed that reloading the map without preset paths from previous analyses would minimize confusion. Opinions were divided on whether to include information popups for station markers, leading to the addition of popups as complementary information. Five participants supported showing both actual and forecasted hot areas, considering it an interesting comparison, while one was neutral. When it came to the number of hot areas to display, three participants found three areas to be the most balanced choice. This feedback was crucial in shaping the design decisions for the dashboard.

*d) **Evaluation Peer Review**:* We evaluate the final dashboard on the same candidates as the *Design Peer Reviews*. Reviewers praised its intuitive interface, facilitating easy navigation and making it accessible to users. The dynamic visualizations, particularly the time-based maps and density views, were commended for effectively showcasing trends and areas of high demand. This enhances the decision-making processes with the support of the ability to visualize and plan bike redistribution routes efficiently. While the interface was generally user-friendly, reviewers - particularly the local company candidate - mentioned that certain advanced features required a steep learning curve, and the customization options seemed more accessible to users with technical backgrounds. However, they also highlighted how, after a brief explanation of the main concepts, the usability became more effective. There were also concerns about performance issues when handling large datasets, as the real-time computations could lead to slower response times. However, following several tests, the system proved to be consistent in performance.

VI. Discussion and Conclusion

Effectively interacting with temporal data poses a significant challenge, as creating a user-friendly interface that ensures readability is not a straightforward task. Furthermore, the management and optimization of services remain ongoing challenges of huge interest for service provider companies. In this context, we have developed FlowCasting, an intuitive machine learning based dashboard for bike-sharing data visualization and analytics. The application is driven by key objectives focused on usability, dynamic spatio-temporal data representation, comparison of current and predicted high demand areas, and path suggesstion for resource allocation. Pursuing these objectives, we have developed an interactive platform that enables users to efficiently and easily explore and analyze bike-sharing data. Our case study underscores these considerations, providing a practical application of the considered concepts and design choices.

As future work, our plan involves implementing a bike repositioning system to optimize service by redistributing bikes to areas of interest. Additionally, we aim to enhance management by integrating a navigation system directly into the platform to streamline redistribution efforts. We also seek to refine the prediction system by leveraging additional data to identify potential areas of interest with insufficient bike availability. Finally, we aim to extend our work to consider multiple cities.

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