# Network Analysis of ’MiBici’ Public Bike Service in Guadalajara’s Metropolitan Area

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***Abstract*—WORK IN PROGRESS**

***Index Terms*—WORK IN PROGRESS**

## I. Introduction

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## II. Related work

The exploration of public bicycle systems through network analysis has garnered significant attention in recent literature, offering insights into system structure, dynamics, and user behaviors. Wei, Xu, and Ma [1] demonstrated the applicability of complex network theory and shortest path analysis in characterizing the public bicycle network structure in Yixing, China. Yao et al. [2] focused on analyzing urban bike-sharing systems using real-time data from the Nanjing public bicycle system. Dobrzyńska and Dobrzyński [3] conducted a comprehensive analysis of the BiKeR public bike-sharing system in Białystok, Poland, emphasizing the dynamics of network topology changes and station location choices. Jurdak [4] investigated the impact of cost and network topology on urban mobility using data from public bicycle share systems in two U.S. cities. Xiao et al. [5] addressed the challenge of short-term demand prediction in public bike-sharing programs, proposing a spatio-temporal graph convolutional network (STGCN) approach. Builes-Jaramillo and Lotero [6] conducted spatial-temporal network analysis of the public bicycle sharing system in Medellín, Colombia.

These studies collectively contribute to advancing knowledge on public bicycle systems, offering insights into network structure, dynamics, user behaviors, and planning strategies, which are instrumental in promoting sustainable urban transportation.

## III. Dataset

### A. Source

The dataset used in this analysis is a public dataset from Kaggle, specifically sourced from the MiBici public bike service in Guadalajara’s metropolitan area (ZMG) in Jalisco, Mexico. It spans from December 2014 to January 2024, covering 110 months in total. The dataset comprises 25,863,690 public bike trips and includes information on 372 public bike stations [8].

### B. Data Description

The dataset comprises two main components: the Nomenclature dataset and the MiBici dataset. The Nomenclature dataset consists of 372 entries, providing information about bike station locations within the Guadalajara Metropolitan Area. Each entry includes details such as station ID, name, location, latitude, longitude, and status. The MiBici dataset contains 25,863,690 entries and records bike trip information spanning from 2014 to 2024. It includes trip IDs, user IDs, demographics (sex, birth year), trip start and end times, origin and destination station IDs, user age, and trip duration.

### C. Data Preprocessing

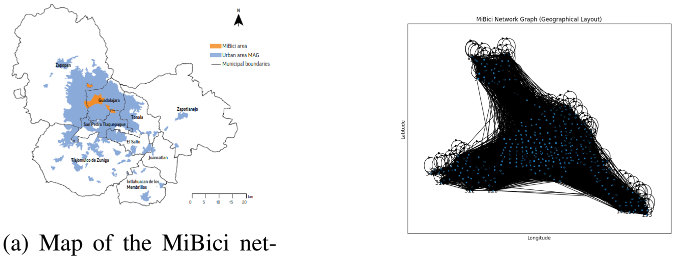
The raw dataset was pruned to improve efficiency due to its large size, reducing it to approximately 1/10th of its original size. The pruned dataset was then exported to a CSV file named ’mibici_compact.csv’ that you will be able to find on our github page.

Stations marked as ’NOT_IN_SERVICE’ were removed from the ’nomenclature’ dataset to ensure that only active stations were included. Additionally, columns such as ’obcn’, ’location’, and ’status’ were dropped from the ’nomenclature’ dataset as they were deemed unnecessary for the analysis.

In the pruned ’MiBici’ dataset, datetime columns (’Trip_start’ and ’Trip_end’) were converted to datetime objects to facilitate temporal analysis. The ’Duration’ column, representing the duration of each bike trip, was converted to numerical format (seconds) for easier computation. Additional features, such as ’Day_of_week’, ’Hour_of_day’, and ’Month’, were extracted from the datetime columns to provide more granular insights into temporal patterns. Finally, unnecessary columns such as ’Unnamed: 0’, ’User_Id’, ’Sex’, ’Birth_year’, and ’Age’ were dropped from the pruned ’MiBici’ dataset to streamline further analysis (those will be reinserted later on for prediction algorithms purposes if times allow it).

### D. Constructing the Network

The network was constructed by creating a directed and weighted graph to represent the ’MiBici’ public bike service in Guadalajara. Nodes, corresponding to bike stations, were added using data from the ’nomenclature’ dataset, including station ID, name, latitude, and longitude. Edges representing bike trips between stations were derived from the pruned ’MiBici’ dataset. For each trip record, if an edge didn’t exist already, it was created. Otherwise the edge weight was incremented to reflect the number of trips between stations. To facilitate analysis and identify patterns, graphs could be generated based on specific criteria such as years or days of the week later on. The network graph was visualized with nodes positioned according to geographical coordinates to illustrate the spatial layout of bike stations and trip connections (see Figure 1).



(a) Map of the MiBici network

(b) Constructed network

Fig. 1: Real network vs our network

### E. Descriptive Analysis of the network

The network comprises 359 nodes representing various entities interconnected by 37,031 edges, reflecting relationships between these entities. This network is directed and weighted. With an average path length of around 1.81, the network reveals numerous lightly utilized pathways between bike stations, contributing to the slightly lower average path length. A single large connected component signifies that all parts of the bike network are interconnected, ensuring comprehensive coverage across the city. However, with a density of approximately 0.29, only about 29% of all possible connections exist, implying that certain rides between specific stations are infrequent. This aligns with the logical expectation that riding between very close or distant stations may be less common. The high reciprocity, nearing 0.78, indicates a substantial number of mutual connections between nodes, likely reflecting regular commuting patterns such as travel to work or school. Furthermore, the clustering coefficient, approximately 0.68, suggests a tendency for nodes to cluster together, reflecting typical travel patterns where people frequently move between specific areas, creating traffic clusters, such as between city centers and residential zones.

## IV. Methodology

### A. Literature Review and Exploratory Data Analysis

The study will commence with a comprehensive literature review to comprehend the existing research landscape and to identify relevant features and patterns in the domain of interest. Concurrently, exploratory data analysis (EDA) will be conducted on the available dataset to gain insights into its structure, distribution, and potential relationships between variables.

### B. Data Preprocessing

Following EDA, data preprocessing will be performed to prepare the dataset for further analysis. This step will involve cleaning the data, handling missing values, and standardizing formats to ensure consistency and accuracy. Additionally, the dataset will be pruned to a tenth of its original size to facilitate efficient processing.

### C. Feature Selection

Based on insights gained from the literature review and EDA, relevant features will be selected for analysis. Features will be chosen based on their potential to contribute meaningful information to the study objectives. Information such as stations' names and coordinates, trips' origin, destination, datetime, and duration will be retained.

### D. Graph Construction

Using the selected features, a graph representation of the data will be constructed. Each bike station in the dataset will be represented as a node, and trips between stations will be represented as edges. The graph will provide a structured framework for analyzing relationships and patterns within the dataset.

### E. Exploratory Analysis of Graph

Basic descriptive analysis will be conducted on the constructed graph to gain a better understanding of its properties. Information such as average path length, density, and reciprocity will be computed to inform further analysis.

### F. Network Preprocessing

To ensure the integrity of the network analysis, preprocessing steps such as removing disconnected nodes or nodes with low edge connections will be performed. This step will help streamline the analysis and focus on meaningful network structures.

### G. Pattern Identification

Using exploratory techniques, interesting patterns within the network data will be identified. These patterns could include trends such as hourly, daily, or monthly variations, as well as differences between weekdays and weekends. Specific visualizations will be created to explore and analyze these patterns effectively.

### H. Network Property Analysis

For identified patterns, key network properties and metrics will be analyzed to understand their underlying characteristics and dynamics. This analysis will provide insights into the structural properties of the network and how they evolve over time.

### I. Result Interpretation

Finally, the results of the analysis will be interpreted, drawing conclusions and implications based on the observed patterns and network properties. This step will involve synthesizing findings from multiple analyses to provide a comprehensive understanding of the dataset and its underlying dynamics.

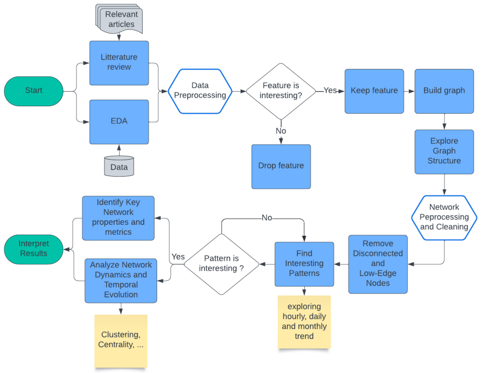

Relevant articles
Litterature review
Start
EDA
Data
Data Preprocessing
Feature is interesting?
Yes
No
Keep feature
Build graph
Drop feature
Explore Graph Structure
Network Peprocessing and Cleaning
Remove Disconnected and Low-Edge Nodes
Find Interesting Patterns
exploring hourly, daily and monthly trend
No
Pattern is interesting ?
Yes
Identify Key Network properties and metrics
Analyze Network Dynamics and Temporal Evolution
Clustering, Centrality, ...
Interpret Results

Fig. 2: Network analysis flowchart

## V. Results

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## VI. Conclusion

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## References

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[7] Torres, Arturo, Ortega, Andrea, Sudmant, Andrew, & Gouldson, Andy. (2021). Sustainable Mobility for Sustainable Cities: Lessons from Cycling Schemes in Mexico City and Guadalajara, Mexico.

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## VII. Github

The source code of the project can be viewed on Github at https://github.com/monthenry/Network-Science-Project.