Analysis Of The Covid-19 Pandemic's Impact On Montreal's Bike Sharing Network, BIXI

Under Peer Review, Not yet published

Zéphir Lorne[1] and Jules César Niyonkuru[2]

[1] *Computer Science & Neuroscience, McGill University, Montreal, Canada. Email: zephir.lorne@mail.mcgill.ca*
[2] *Computer Science, McGill University, Montreal, Canada. Email: jules.niyonkuru@mail.mcgill.ca*

Abstract

Montreal, with its booming growth, is a great demonstration of the urban mobility challenge: with congestion, construction, parking difficulties, weather and environmental conditions to cite a few. To support circumventing this challenge, *BIXI*, the first large-scale bike sharing network in North America at the time, was launched in May 2009. With over 5 million annual rides, it has been without doubt contributing positively to the city's development. However, with its increasing adoption, the network has become frustrating to use, with stations often being empty when you need a bike, or full when you need to return one at peak usage times. Through this project, we explore the tens of thousands of BIXI daily bikes trips to extract environmental and socio-economic insights, better understand the habits of Montrealers and understand how this phenomenon occurs. In addition, we analyse how the pandemic impacted these habits and the BIXI network. To do so, we use degree, betweenness and eigenvector centrality measures as well as Louvain and Fast Modularity community detection algorithms. By comparing our results from the 2019, 2020 and 2021 generated graphs, we are able to observe how the BIXI network shifted from being used mainly during commuting hours between residential and business districts pre-pandemic, to being more spread throughout the day and within each neighbourhood during the pandemic.

Our code is open source and can be found on our Github at https://rebrand.ly/BIXI-study-github[1]. In addition, all the graphs are interactive and can be further visualized on our website at https://rebrand.ly/BIXI-study-web (note: it doesn't work with Safari).

Keywords: Network science, Network Centrality Measures, Network Community Detection, Temporal Graph Networks, Bike-Sharing

1 Introduction

1.1 Background

For the past decades, we have seen a tremendous shift towards urbanization, along with population growth and environmental changes. Among the many challenges this paradigm shift brings, there is urban mobility. Montreal, which has been experiencing a booming growth for the past decades, is a great demonstration of this challenge: with congestion, construction, parking difficulties, weather and environmental conditions as only a few examples[2].

To contribute fighting this challenge, the *Public Bike System Company* launched *BIXI* in May 2009, the first large-scale bike sharing network in North America[3]. Today, this organization works as a non-profit after being sold to the city of Montreal[4]. With over 5 million rides every year, this shared green mobility transportation method provides an additional method for residents to travel to their destinations in a sustainable and engaging way. According to BIXI's website[3], the network is composed of over 9,000 bikes and 680 stations, though these numbers change every year as more stations and bikes are added to better serve the Montreal community.

The tens of thousands daily bicycle trips made by users induce a directed dynamic network with edges as trips and nodes as stations. As each trip is begun and concluded, the edge appears

MSURJ (2022)

Corresponding author
Zéphir Lorne

and disappears, creating a very time-dependent system. This network data can be used to provide various insights into the particularities of the Montreal bike-sharing system, with aspects ranging from community patterns, travel habits, geography and more.

An additional complexity of the bike-sharing system is the rebalancing of bicycles at each station. Trips made might not be properly balanced throughout the day, thus additional rebalancing by the BIXI organization is required to ensure the bikes are sufficiently spread out to all stations.

With the rise of the Covid-19 pandemic in 2020, many restrictions were repeatedly created and lifted in Quebec. This impacted the life of all Montrealers and in turn the BIXI bike sharing system.

1.2 Motivation

The use of BIXI does not come without inconveniences and challenges for users. Each BIXI station only has a fixed number of bike racks available, and one can run into an issue if they are all empty or all filled. If each bike rack is filled with a BIXI bicycle, then a user is unable to drop off theirs and needs to travel to another station and try again. Similarly, if all the racks are empty, a user who wants to use a bicycle will need to walk to another station or find another method of transportation. This can lead to frustration for the user and is indeed an inconvenience of the system. It is worth noting that the real-time availability of BIXI bicycles is provided on the BIXI app for each station, but it can still be exasperating for the user to not know ahead of time where they might be able to get a bike or drop one off.

In order to curb these user issues, BIXI re-balances stations by using trucks which take bikes from one station to another. However, improvements are still to be made as the issue is still ongoing.

Through this project, we want to analyze the BIXI network and understand how this phenomenon occurs and see if it is a local pattern, or global to Montreal. Furthermore, we want to study how the extent of the pandemic's impact on the BIXI network.

1.3 Related work

In the literature, studies have been conducted on the BIXI network using data from 2019 and before to evaluate how time, location and weather affects bicycle flows in the network. It has been found that peak usage varies between weekdays and weekends. During weekdays, peak activity is mostly found to occur at work commuting times in the morning and afternoon, with opposing in or out flow correlation between densely populated hubs and job hubs. This highlights how the demand of bikes and slots differ depending on time and location. On the other hand, the activity distribution on weekends is smoother. Studies also found that weather has an influence on the network, with increased activity correlated with warmer or sunny weather[5,6].

Further bike-sharing network analyses have also been conducted on the Helsinki bike sharing network, which has similar operating period to Montreal's BIXI network (it also is unavailable in the Winter due to weather conditions). A study analyzing Helsinki's bike network data from 2016 to 2020 found similar patterns compared to the Montreal studies, with most intensive bike usage occurring from 6:00 to 8:00 and from 16:00 to 18:00 on weekdays, and a smoother distribution centered around the late afternoon in weekends[7]. Centrality measures have also been applied to this network at different periods to identify important nodes and relationships between them. Degree centrality was used to identify hubs, betweenness centrality to identify 'bridge' and potentially-bottleneck nodes, as well as closeness centrality to identify intermediary stations connected to many others. Eigenvector centrality was also used as another way of evaluating the importance of a station considering adjacent stations, which can be significant when one considers dense and sparse station distributions. Additionally, several clustering techniques like the Combo Method, Louvain, and Fluid Community were used to detect communities which helped in understanding bike patterns and determining better pricing models[8].

All this data can further be used to predict bike flow patterns to design effective station rebalancing systems. To do so, P. Hulot et al. used a combination of reduction/reconstruction methods (K-means, SVD), prediction methods (Linear regression, MLP, Random Forest), and probability distributions on the BIXI network to predict the hourly demand for rentals and returns at each station of the system and propose a re-balancing system[9]. Another study approached the problem using a modified travelling salesman problem on a particular neighbourhood of Montreal[10]. Finally, a study observed that adding a BIXI station has a predominantly stronger impact on bicycle flows compared to increasing station capacity, something BIXI and policy makers should consider when adding new stations. Indeed, it has been shown that adding BIXI stations increase the value of nearby properties by about 2.7% in a studied neighbourhood[6,11].

Studies have also used other modality transportation networks to better design bike networks in urban areas. For example, a study used data from a taxi network to identify community clusters and build a simulated bike network based on the extracted leaders of the found communities[12].

These works show the variety of methods to analyse bike-sharing networks such as BIXI. Our study focuses on using network analysis methods for this particular bike-sharing network.

2 Study

2.1 Project Definition

This study analyzes the BIXI network in multiple ways.

First, a general analysis of the data is done by using exploratory data analysis tools such as heat-maps to discover habits of BIXI users over time. Then we apply different centrality measures and community detection algorithms to better understand local and global patterns in Montreal's bike-sharing network, and overlay results on a map of Montreal. This gives a better understanding of how and why stations become full or empty. In addition to date, time, and location; the effects of weather and localisation of metro stations are also analysed.

Moreover, we focus more particularly on the trips from 2019, 2020 and 2021 in order to analyze the impact of the COVID-19 pandemic outbreak on the Montreal's bike-sharing network.

Finally, we present dynamic visualizations of the BIXI network with interactive maps.

2.2 Datasets

The principal data used for this study are the trip history of the BIXI network which is openly available on the BIXI website at https://bixi.com/en/open-data[13].

The obtained BIXI data are structured in two datasets. The first contains a list of stations including: station code, station name, latitude, and longitude [Figure 1]. The second contains the list of rides with: start date and time, start station, end date and time, end station, duration, and if the user has a BIXI membership [Figure 2]. Currently, data are available from 2014 to 2020 between April and November during BIXI's operating period and from April to October in 2021. Some analysis is conducted with respect to the data for multiple years, while for others the analysis is restricted to a shorter time period. For many analysis points, the year 2019 is used as it is the most representative year with the most trips, pre-pandemic.

This data is then converted into a labeled simple directed graph network for each year, with the Networkx python package. In this network, nodes correspond to bike stations. Directed edges correspond to trips between stations, with the number of trips between the given 2 stations during a specific time-frame *(ex: a year)* as weights, and average trip duration and euclidean distance as other edge features. All the trips are therefore first aggregated and concatenated on top of each other to create one time-frame for the year. In addition, we similarly further created hourly graphs, but by selecting only trips occurring between set times, in order to analyse the network differently based on the time of the day and identify potential commuting patterns.

pk	name	latitude	longitude
10	Métro Angrignon (Lamont / des Trinitaires)	45.44691	-73.60363
13	Métro de l'Église (Ross / de l'Église)	45.462726	-73.565959
17	Tolhurst / Fleury	45.544149	-73.66752
21	St-Christophe / Cherrier	45.52029	-73.568119
31	Lespérance / de Rouen	45.538839	-73.552779
38	Métro Vendôme (de Marlowe / de Maisonneuve)	45.473868	-73.604538
43	Métro Université de Montréal (Édouard-Montpetit / Louis-Collin)	45.50367	-73.61848
47	Métro Guy-Concordia (Guy / St-Catherine)	45.495045	-73.57783
65	Bel Air / St-Antoine	45.482778	-73.584621

Figure 1. Snapshot of BIXI stations in April 2021

start_date	emplacement_pk_start	end_date	emplacement_pk_end	duration_sec	is_member
2021-04-09 07:54:26.237	262	2021-04-09 08:09:55.273	410	929	1
2021-04-09 07:59:40.044	171	2021-04-09 08:04:38.485	148	298	1
2021-04-09 08:02:23.059	636	2021-04-09 08:12:13.563	392	590	1
2021-04-09 08:03:03.069	636	2021-04-09 08:30:24.336	785	1641	1
2021-04-09 08:06:21.594	907	2021-04-09 08:18:38.855	152	737	1
2021-04-09 08:06:58.553	566	2021-04-09 08:52:00.672	365	2702	1
2021-04-09 08:07:36.824	262	2021-04-09 08:18:51.081	246	674	1
2021-04-09 08:08:23.442	247	2021-04-09 08:51:22.492	409	2579	1
2021-04-09 08:09:41.041	158	2021-04-09 08:17:25.541	686	464	0
2021-04-09 08:10:42.639	237	2021-04-09 08:30:36.420	237	1193	1
2021-04-09 08:11:17.625	636	2021-04-09 08:16:28.386	636	310	1
2021-04-09 08:13:13.165	158	2021-04-09 08:26:21.059	788	787	1
2021-04-09 08:13:21.384	225	2021-04-09 08:34:08.994	522	1247	1

Figure 2. Snapshot of BIXI trips in April 2021

We also used external weather data to analyze BIXI usage depending on the precipitation and temperature [Figure 3]. This data are obtained from the Government of Canada's hourly weather historical database https://climate.weather.gc.ca[14]. We selected the McTavish station next to McGill University as it is the most central weather station in Montreal with hourly data available between 2014 and 2021. The data was downloaded as a csv file with a simple command line by following these instructions from the Government of Canada: https://drive.google.com/drive/folders/1WJCDEU34c60IfOnG4rv5EPZ4IhhW9vZH[15].

Longitude (x)	Latitude (y)	Station Name	Climate ID	Date/Time (LST)	Year	Month	Day	Time (LST)	Temp (°C)	Dew Point	Rel Hum (%)	Precip. Amount (mm)	Wind Dir (10s deg)	Wind Spd (km/h)	Stn Press (kPa)
-73.58	45.50	MCTAVISH	7024745	2021-10-02 00:00	2021	10	2	00:00	12.5	8.1	74	0.0	17	2	101.04
-73.58	45.50	MCTAVISH	7024745	2021-10-02 01:00	2021	10	2	01:00	11.9	9.0	83	0.0	23	2	101.01
-73.58	45.50	MCTAVISH	7024745	2021-10-02 02:00	2021	10	2	02:00	11.7	10.0	89	0.0	10	2	100.96
-73.58	45.50	MCTAVISH	7024745	2021-10-02 03:00	2021	10	2	03:00	11.7	10.9	95	1.3	17	1	100.92
-73.58	45.50	MCTAVISH	7024745	2021-10-02 04:00	2021	10	2	04:00	11.6	10.8	95	0.9		0	100.89
-73.58	45.50	MCTAVISH	7024745	2021-10-02 05:00	2021	10	2	05:00	11.5	10.8	95	1.6	16	4	100.85
-73.58	45.50	MCTAVISH	7024745	2021-10-02 06:00	2021	10	2	06:00	11.1	10.5	96	2.3	16	3	100.80
-73.58	45.50	MCTAVISH	7024745	2021-10-02 07:00	2021	10	2	07:00	11.3	10.7	96	0.6	16	4	100.78
-73.58	45.50	MCTAVISH	7024745	2021-10-02 08:00	2021	10	2	08:00	11.5	10.9	96	0.6	17	5	100.76
-73.58	45.50	MCTAVISH	7024745	2021-10-02 09:00	2021	10	2	09:00	11.4	10.7	95	0.3	15	5	100.72
-73.58	45.50	MCTAVISH	7024745	2021-10-02 10:00	2021	10	2	10:00	11.2	10.5	95	0.3	15	3	100.69
-73.58	45.50	MCTAVISH	7024745	2021-10-02 11:00	2021	10	2	11:00	11.3	10.4	95	0.6	9	5	100.69
-73.58	45.50	MCTAVISH	7024745	2021-10-02 12:00	2021	10	2	12:00	11.4	10.8	96	1.2	16	5	100.63

Figure 3. Hourly weather data for McTavish station Snapshot obtained from the Government of Canada[14,15]

Finally, to analyze the relation between BIXI usage and metro usage, we obtained the name and geolocalisation data of metro stations and their entrance points through STM's developer web-page at https://www.stm.info/en/about/developers[16] and filtered the dataset to include only metro stations as mean of transport [Figure 4].

stop_id	stop_code	stop_name	stop_lat	stop_lon	stop_url	location_type	parent_station	wheelchair_boarding
STATION_M118	10118	STATION ANGRIGNON	45.446466	-73.603118		1		2
43	10118	Station Angrignon	45.446466	-73.603118	http://www.stm.info/fr/infos/reseaux/metro/angrignon	0	STATION_M118	2
43-01	10118	Station Angrignon	45.446319	-73.603835		2	STATION_M118	2
STATION_M120	10120	STATION MONK	45.451158	-73.593242		1		2
42	10120	Station Monk	45.451158	-73.593242	http://www.stm.info/fr/infos/reseaux/metro/monk	0	STATION_M120	2
42-01	10120	Station Monk - Édicule Nord (B)	45.451307	-73.593128		2	STATION_M120	2
42-02	10120	Station Monk - Édicule Sud (A)	45.451007	-73.593380		2	STATION_M120	2
STATION_M122	10122	STATION JOLICOEUR	45.457010	-73.581691		1		2
41	10122	Station Jolicoeur	45.457010	-73.581691	http://www.stm.info/fr/infos/reseaux/metro/jolicoeur	0	STATION_M122	2
41-01	10122	Station Jolicoeur	45.456787	-73.582115		2	STATION_M122	2

Figure 4. STM Bus and metro stations Snapshot obtained from STM's developer website[16]

2.3 Methodology

To analyse the network, we used a combination of three key network centrality measures: Degree centrality (1), Eigenvector centrality (2), and Betweenness centrality (3).

$$C_{\mathrm{D}}(v) = \sum_{\substack{k=1 \\ (v \neq t \in V)}}^{N} x_{vt} \quad (1) \qquad C_{\mathrm{E}}(v) = \alpha \sum_{\substack{k=1 \\ (v \neq t \in V)}}^{N} x_{vt} C_{\mathrm{D}}(t) \quad (2) \qquad C_{B}(v) = \sum_{(s \neq v \neq t \in V)} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (3)$$

Where *s, t, v* are the *source*, *target*, and *measured* nodes from the set of nodes *V* in the network. x_{vt} is the edge between *v and t*, α is a scaling factor, σ_{st} is the shortest path between *s and t*.[17]

(1) **Degree centrality** is the simplest measure and works by calculating the the number of *(weighted)* edges of each node: their degree[17]. As an *edge* represent a *trip* between two *station nodes*, the more edges a station has, the higher its degree centrality. Thus this measure enables us to quickly identify the most important individual stations in term of bike flow and usage.

(2) **Eigenvector centrality** is a bit more complex in a sense that it also takes into account the importance of neighboring nodes. Connections to nodes with high-scoring eigenvector centrality contribute more to the score than an equal number of connections to low-scoring nodes. As a result, a node may have a low Eigenvector score if all of its connections are with low-score nodes despite having a large number of connections[17]. Therefore, this measure allows us to better assess geographical areas and neighborhoods as opposed to degree centrality which only focuses on single stations. This is important in bike sharing networks as multiple stations are often located close to each other, like hubs.

(3) As for **betweenness centrality**, it measures the extent to which node lies on the path between other nodes (shortest path based)[17]. Therefore, this measure is helpful to identify bridges between communities as well as potential flow bottleneck nodes. As betweenness centrality normally uses distance as weights between two nodes to give more importance to closer nodes; however, in our case we use the reciprocal of the number of trips between two stations as the weight to asses the connection strength.

Furthermore, we used two community detection algorithms: **Fast Modularity**[18] and **Louvain**[19] to identify biking communities and neighbourhoods within Montreal. Both methods are agglomerative and tend to produce super-communities. In Fast Modularity, every node is initialized as a cluster and then gets merged. Louvain works by repetitively moving nodes around (through their links) and aggregating clusters.

2.4 Experiment Setup

To conduct our study, we coded python scripts in a jupyter notebook environment, which we open sourced on our Github at https://rebrand.ly/BIXI-study-github[1].

The rundown of our experiment is the following:

- `Obtaining the raw datasets`
  - `BIXI trips from BIXI open data`[13]
  - `Weather data from the Government of Canada`[14]
  - `Metro stations from the STM`[16]

- `Cleaning and preparing of the raw datasets`
  - `Converting csv files to python panda dataframes for manipulation`

- Renaming, re-ordering, casting data types and formats for consistency and ease of use
- Filtering datasets
  * BIXI - Filtering out trips related to missing stations and self-loops
  * Weather - Filtering out unneeded weather data, keeping only temperature and precipitation data; writing 0 when no data
  * STM - Filtering out bus stations, keeping only metro stations
- Concatenating time frames by time and date (hours, day of the week, years)

• Creating networkx simple directed weighted graph (SDG) from processed panda dataframes

• Computing network features
- Calculating centrality measures on SDG
  * Degree centrality (1), including net-in-out-degree
  * Eigenvector centrality (2)
  * Betweenness centrality (3)
- Computing communities
  * Fast modularity[18]
  * Louvain[19]

• Creating visualisations of network features
- Creating plots from panda dataframes
  * Daily number of BIXI trips over years line plot
  * Number of BIXI trips vs Temperature histogram
  * Number of BIXI trips Day of the week vs Hour of the day heat-map
- Overlaying network features on top of a map of Montreal using Kepler.gl[20].
  * Net-Degree, Eigenvector, and Betweenness Centrality measure heat-maps
  * Net-Degree, Eigenvector, and Betweenness Centrality measure point-maps
  * In-Out-Degree Centrality dynamic point-maps
  * Fast modularity and Louvain community point-maps

Given that the data from 2019 was the most representative of the network pre-pandemic, we used that time-frame (rather than all time-frames) for the main results. We also used the 2020 dataset as a representative of the pandemic outbreak period and the 2021 dataset for the pandemic recovery period to analyze the impact of the COVID-19 pandemic outbreak on the Montreal's bike-sharing network and draw conclusions.

2.5 Results and Discussion

First of all, we plotted the daily number of BIXI bike trips between 2014 and 2021 to get an initial quick overview of BIXI usage [Figure 5] from the processed data. This showed a continued growth from 2014 until 2019, with year 2020 showing a decline in bike usage while the number of bikes available as well as stations kept increasing over time. There are several possible reasons why bike trips declined in 2020, the most likely being the impact of circulation restrictions due to the COVID-19 pandemic outbreak. This is further validated considering how the daily bike trips increased again in 2021 as the COVID-19 pandemic restrictions eased gradually.

In addition, before further graph analysis, we analyzed the link between weather and the use of BIXI bikes. Figure 6 illustrates that most of the rides occur when the air temperature is warmer, between 13 and 27 Celsius degrees. However, the BIXI network is only active between April and

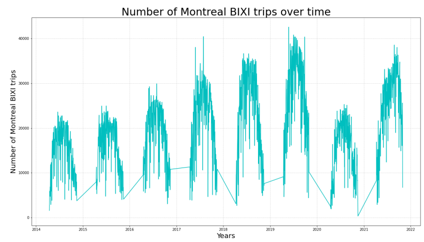


Figure 5. The daily number of BIXI bike trips between April 2014 and October 2021

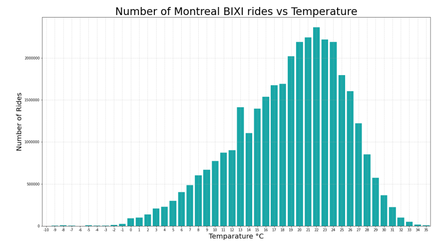


Figure 6. The number of Montreal BIXI rides vs average Temperature between April 2014 and October 2021

November and therefore the graph is biased toward the warmer temperatures of the summer. As for precipitation data, we unsurprisingly found that the overwhelming number of trips occurred when it wasn't raining. Therefore, this seems to confirm the idea that weather influences bike usage.

Taking into consideration how daily bike trips follow the same bell-shape pattern every year, we analyzed the network graphs per year, pre-in-post-pandemic between 2019 and 2021 (in this paper the *post-pandemic* term is used to refer to the gradual decrease of Covid-19-related prevalence and restrictions in 2021). As mentioned earlier, using stations as vertices and bike trips between them as edges, we created a directed weighted graph, with the distance between stations and the trip duration as edge attributes and the number of trips between stations as weights. For year 2019, we had a graph with 619 nodes and 221903 edges, which had a network density of 0.580.

The different types of relationships between the graph nodes gave us a lot of insight about the network structure and dynamics. As a result, we applied several centrality measures to the graph, analyzed the temporal network flow by comparing in-degree and out-degree centralities over time, and visualized the link between bikes usage and the Montreal Metro.

Degree centrality

By plotting these degree centralities on the map of Montreal, we can clearly see that the stations with the most trips associated are located around downtown and the Plateau [Figure 7]. This relates to the fact that the majority of stations are concentrated in that area, and with fewer stations and less BIXI usage closer to the periphery.

Furthermore, stations with the highest degree centrality are **'de la Commune / King'** with **84355** associated trips, followed by **'Métro Laurier (Rivard / Laurier)'** with **83476** while **'Métro Mont-Royal (Rivard / du Mont-Royal)'** completes the trio with **82594**. It makes sense that the **'de la Commune / King'** station is the most central one as it is located right next to Old Port of Montreal, one of the busiest spots in the city with many attractions, especially over the summer.

Eigenvector centrality

The eigenvector centrality measures a node's importance within the network while taking into account the centrality of its neighbours. The top stations **'de la Commune / King'** and **'de la Commune / Place Jacques-Cartier'** are located in the Old Port of Montreal, further showcasing its hub feature of providing access to a wide variety of surrounding summer leisure activities. Moreover, when plotting the measures on a map of Montreal, we can observe similar results to the degree centrality one. This makes sense as eigenvector centrality uses the degree of neighboring stations, which are often close by each other. Once again, the Residential-Work-Leisure trio of the Plateau, Downtown and the Old Port are the neighborhoods with the most central stations [Figure 8].

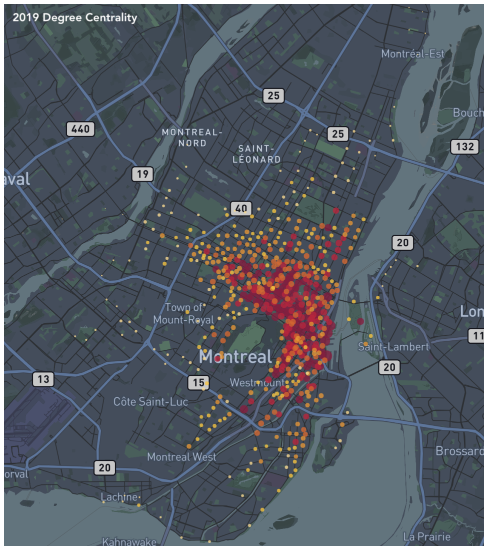


Figure 7. Degree centralities in 2019. Larger and redder nodes are more important. White points are metro stations

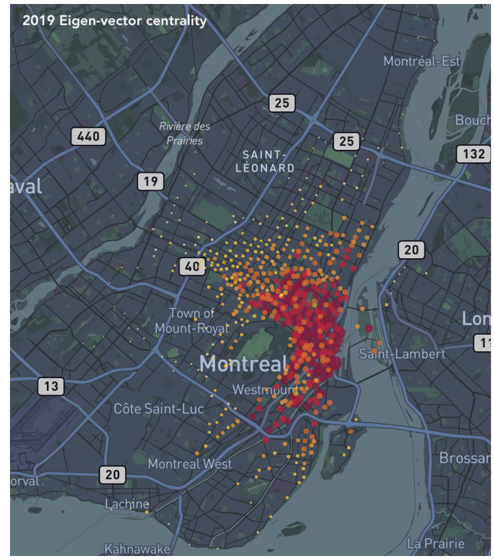


Figure 8. Eigenvector centralities in 2019. Larger and redder nodes are more important

Betweenness centrality

On the other hand, the **'BAnQ (Berri / de Maisonneuve)'** has the highest betweenness centrality, which was expected since the station is located next to Montreal's biggest metro station Berri-UQAM and betweenness centrality captures the number of shortest paths going through a target station [Figure 9]. This highlights how this station is an important bridge between different communities, with it being at the intersection of four communities out of six from the Louvain Community Detection algorithm [Figure 15].

Furthermore, by overlaying the metro stations on the same map, we can see how other BIXI station with high betweenness centralities correlate with locations of metro stations (sometimes hard to see on the map as the metro stations are plotted below the BIXI station centrality). This further highlights the bridge-like feature of nodes located next to important metro stations.

Figure 9. Betweenness centralities in 2019. Larger nodes are more important

Impact of the COVID-19 pandemic outbreak on the BIXI network

Finally, we analyzed the impact of the COVID-19 pandemic outbreak on the Montreal's bike-sharing network by comparing the usage patterns for year 2019, which is the most representative subset of the pre-pandemic datasets, year 2020 dataset as a representative of the pandemic outbreak period, and the 2021 dataset for the pandemic recovery period.

Link between BIXI usage and metro stations

To a greater extent, we analyzed the link between Montreal BIXI bikes usage and the Montreal metro using degree centrality heat-maps. Thanks to them, we hypothesized that the BIXI network plays a crucial role in alleviating the *last mile mobility problem* in the city. *Representing the distance a commuter needs to travel between a transit stop and their final destination, the last mile mobility problem is a key obstacle in public transport planning and development*[21]. Indeed, in 2019 [Figure 10] we observed that the 'hotter' nodes are all located next to metro stations.

However, when taking a look at the same heatmap in 2020 and 2021, the correlation is less visible, suggesting that people commuted less to metro stations (and employed public transport less frequently) as people were discouraged to commute during the pandemic [Figure 11].

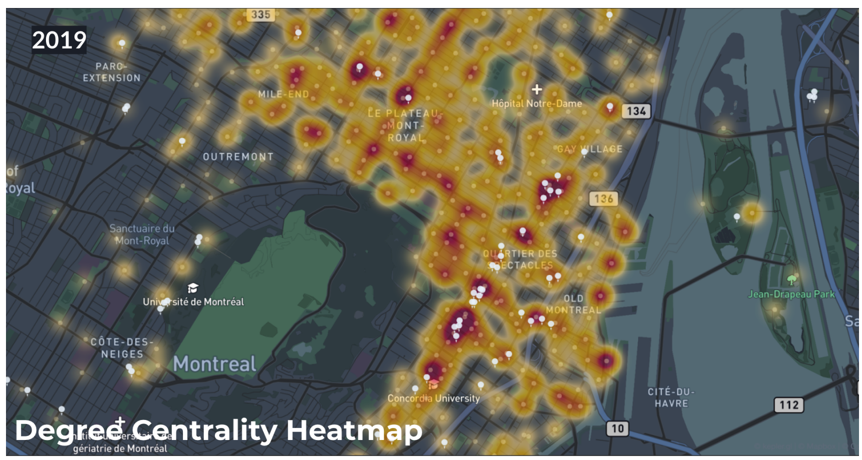


Figure 10. The Montreal BIXI network degree centrality heat-map with The Montreal Metro stations (white markers), in 2019

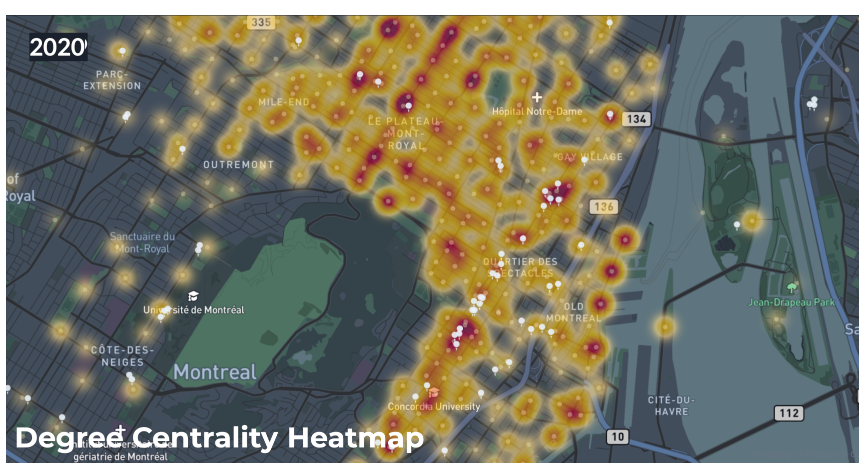


Figure 11. The Montreal BIXI network degree centrality heat-map with The Montreal Metro stations (white markers), in 2020

Hourly bike usage patterns within each day

Using time heat-maps, we realized that before the pandemic highest bike usage occurred between 7:00 and 9:00 in the morning and from 16:00 to 18:00 in the afternoon during business days. This highlighted how people used the BIXI network mainly for commuting purposes during the week. On the other hand, during weekends, the pattern changed. Montreal BIXI users tended to be more active in the afternoon, with a little more usage on Sundays, demonstrating how the BIXI network was also employed for leisure activities.

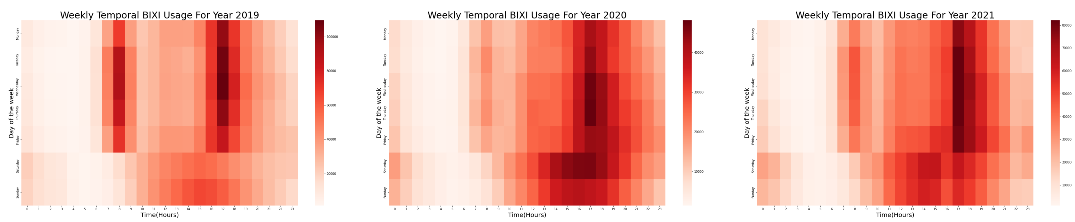


Figure 12. Montreal BIXI bike trips. Hour vs day of the week (2019, 2020, 2021).

Conversely, in 2020, bike usage was lower in the morning than 2019. Therefore, we infered how the pandemic affected BIXI usage patterns, with less people commuting due to the new remote work requirements. Nevertheless, the afternoon (16:00 to 18:00) bikes usage trend remained high, with higher usage during weekends than before, especially on Saturdays. This suggests that this time period became the right moment for most people that had been required to work remotely to go out and de-stress.

As of 2021, the success of the COVID-19 vaccination campaign in Quebec allowed gradual ease of pandemic related circulation restrictions, which is the main reason explaining why we expected daily bike trips to increase again in general. Meanwhile, we especially found that the BIXI usage has increased again over work commuting time (7:00 and 9:00) during business days.

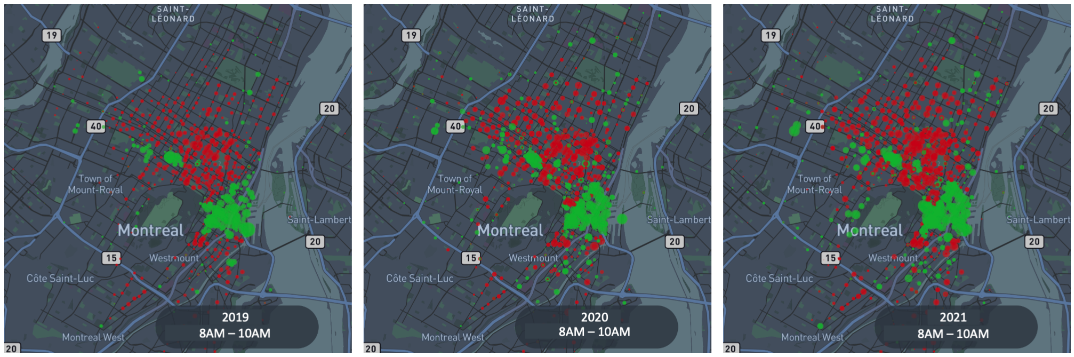
Hourly in-out degree weekday patterns

Furthermore, by plotting the net degree centrality of each stations (bikes arriving minus leaving a station) hourly during each weekday, we can indeed see how bikes flow from residential areas such as *The Plateau* to business districts *Downtown* and around the video game studio *Ubisoft Montreal* between 8AM and 10AM and vice versa between 4PM and 6PM [Figure 13]. This confirms the home-work-home commuting patterns we discussed above.

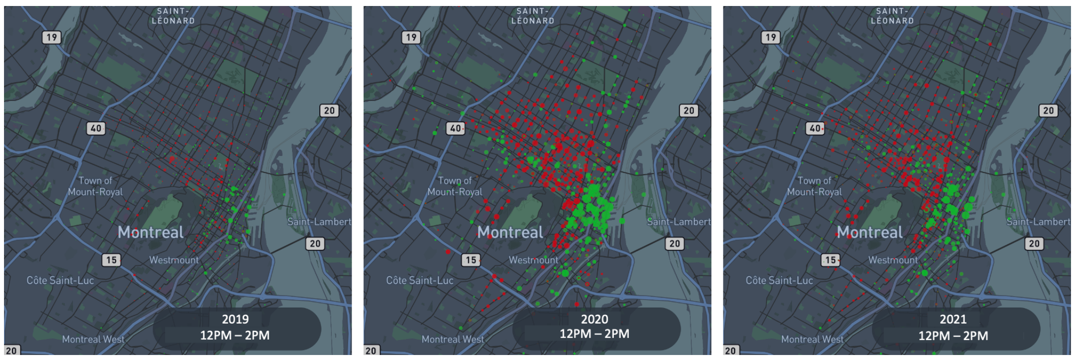
While this pattern can be observed both pre-pandemic and during the pandemic, it is a lot sharper in 2019 compared to 2020 and 2021. Indeed, this 24h gif https://rebrand.ly/BIXI-study-24h-gif showcases the morning, midday and afternoon net degrees, and we can observe that during the pandemic bike usage is a lot more evenly spread (both location and time wise) compared to before the pandemic, further highlighting how the pandemic introduced a shift in BIXI usage patterns.

Moreover, we can see that in 2021, the stations located near universities were relatively more busy compared to 2020, as universities started teaching in-person again.

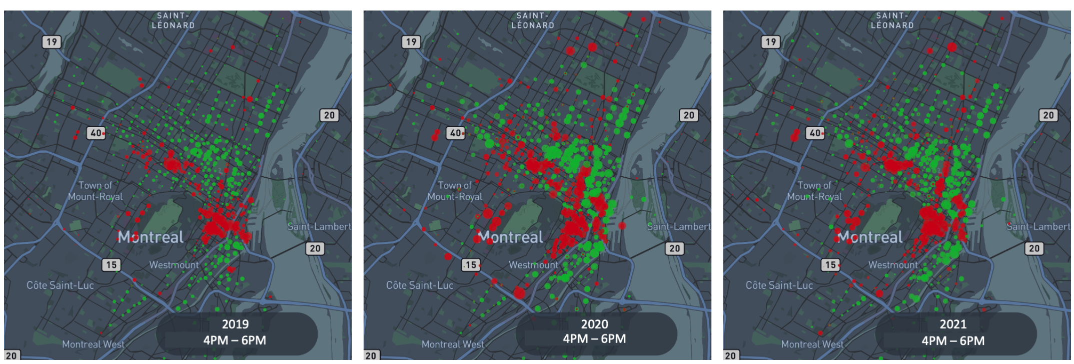
Therefore, we could suggest BIXI to make sure to have their trucks ready to work around the most central nodes at the busiest commuting hour timeframes to rebalance the stations the other way around.



(a) Net Degree in the morning (8:00-10:00)



(b) Net Degree around Noon (12:00-14:00)



(c) Net Degree in the evening (16:00-18:00)

Figure 13. Net Degree Comparison in 2019, 2020, and 2021. Green and red nodes have respectively a higher in and out degree centrality.

Louvain and Fast Modularity Community Detection

Finally, using Louvain and Fast Modularity community detection algorithms, we managed to see that BIXI bikes' network communities remained almost the same regardless the COVID-19 pandemic impact on bikes usage preferences. For reference, the fast modularity community detection algorithm divided Montreal stations in two, with one in the North-West and the other in the South-East, which didn't give us much insight [Figure 14]. However, the Louvain algorithm is more insightful and was able to find 6 different communities, centered around *Le Plateau & Outremont, Verdun & South West, Downtown & Westmount, Cote des Neiges, Rosemont & Villeray, and Mercier-Hochelaga-Maisonneuve* [Figure 15], with the station having the highest betweenness centrality *'BAnQ (Berri / de Maisonneuve)'* as the center of four of these neighborhoods. This implies that bike usage *within* these six neighborhoods was higher than the bike usage *between* them, and that *'BAnQ (Berri / de Maisonneuve)'* was the main bridge point between these communities.

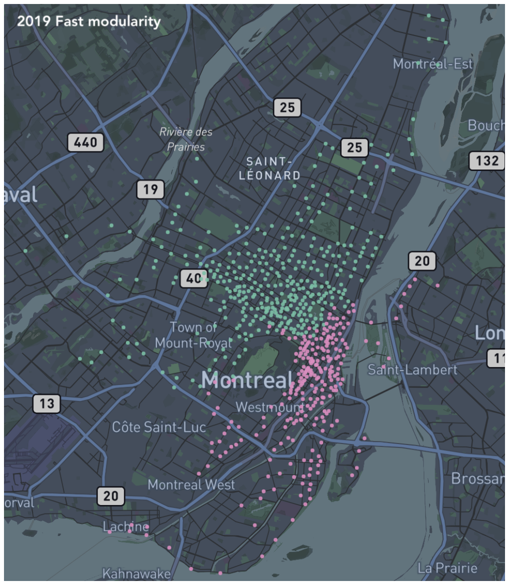


Figure 14. Fast Modularity community detection (2019)

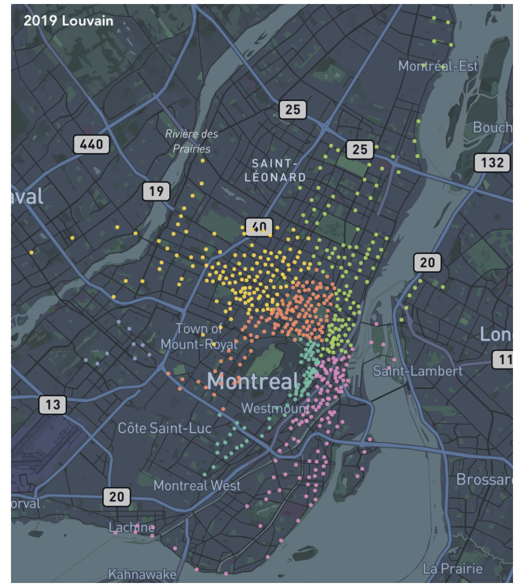


Figure 15. Louvain community detection (2019). The BAnQ BIXI station is at intersection of the red, blue, green and pink communities

3 Conclusion and Future Work

In conclusion, by using different centrality measures, we were able to identify the most important stations and potential bottlenecks in the Montreal BIXI network. More particularly, we found that the busiest nodes were often located next to metro stations, universities, as well as near the Montreal old port. This highlights how the BIXI network is used for both commuting and leisure. Therefore, we could suggest BIXI to make sure to have their trucks ready to work around these most central nodes at the busiest commuting hour timeframes to rebalance the stations the other way around effectively. We were also able to identify different communities and the main bridges between them.

In addition, we were able to clearly see the impact of the pandemic on Montrealers' circulation through the BIXI network and how usage habits shifted. Indeed, whereas BIXI bikes were mostly used during clear-cut commuting hours to go from residential areas to work areas and vice-versa pre-pandemic in 2019, this pattern was a lot less observed in 2020 and 2021. This highlights how people respected the work from home policy and used the BIXI network for other activities during the pandemic.

Future work could focus on using link prediction and machine learning models in order to propose better BIXI station re-balancing operations.

All of our code is open source and can be found on GitHub at https://rebrand.ly/BIXI-study-github. Feel free to reuse and build on top of our work to analyse the BIXI network further.

4 Acknowledgements

This study was performed during the *COMP599 Network Science* class at McGill University[22]. We thank our instructor Reihaneh Rabbany and teaching assistant Andy Huang for their support and feedback. We also thank our classmates for anonymously reviewing our paper.

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