# Data Analysis of Electric Scooter and Bicycle Usage

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## Abstract

Electric scooters or bicycles have gained significant popularity as a mode of transportation, although opinions about them are mixed. This study examines aggregated usage data and provides basic analysis from five American cities: Chicago, Louisville, Los Angeles and Austin and one Canadian - Toronto.

The study reveals patterns and trends based on day of the week, time of day, and seasonality. The analysis also considers the impact of the COVID-19 pandemic on rentals and explores gender and age differences in bike share usage. Additionally, popular locations and commuting patterns are examined through visualization. A prediction model for scooter trip destinations in Chicago is developed. Overall, this analysis provides valuable insights into the utilization of electric scooters and bicycles in urban environments.

## 1 Introduction

Electric scooters and bicycles have rapidly gained popularity in various cities worldwide. However, their widespread adoption has resulted in diverse reactions from the public. From a positive standpoint, these scooters are seen as a promising addition to the transportation system, potentially contributing to sustainability by complementing public transport, walking, and cycling options. They are viewed as an appealing alternative to private car ownership.

On the other hand, there are negative aspects to consider. E-tranport may compete with public transport, walking, and cycling rather than complementing them. They could also contribute to increased traffic congestion and accidents. Additionally, the short lifespan of these scooters or bicycles has a negative impact on the environment. Improper parking and abandonment of scooters in unsuitable locations are common issues. While some cities and operators have designated specific parking spots, many still allow scooters to be left anywhere.

To comprehend the role of electric scooters and bicycles within the transportation system, it is crucial to understand their usage patterns. This approach aims to provide insights into utilization rates, trip durations, distances traveled, and when and where these scooters are predominantly used.

## 2 Datasets' Information

For data mining on e-scooter and bicycle trips, we used datasets from various major cities in America and one in Canada. They had a lot more information (features) that we needed, so we selected only some of them.

### 2.1 E-Scooter Chicago Trips 2019

[3]

- from 15 June 2019 to 16 October 2019
- 710839 rows × 19 columns
- columns: Start Time, End Time, Trip Distance, Start Community Area Number, End Community Area Number, Start Community Area Name, End Community Area Name, Start Centroid Latitude, Start Centroid Longitude, End Centroid Latitude, End Centroid Longitude.

### 2.2 Bicycle Divvy Trips in Chicago 2019

[4]

- from 1 January 2019 to 31 December 2019
- 3818004 rows × 25 columns
- columns: Start Time, End Time, From Station ID', 'From Station Name', To Station ID, To Station Name, Gender, Birthyear, UserType.

### 2.3 E-Scooter Chicago Trips 2020

[5]

- from 12 August 2020 to 12 December 2020
- 630816 rows × 17 columns
- columns: Start Time, End Time, Trip Distance, Vendor, Start Community Area Number, End Community Area Number, Start Community Area Name, End Community Area Name, Start Centroid Latitude, Start Centroid Longitude, End Centroid Latitude, End Centroid Longitude.

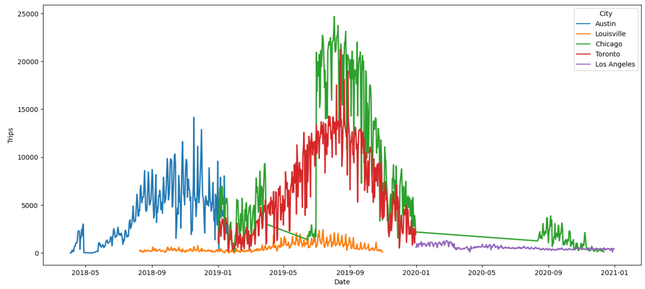


Figure 1: Periods for data relative to cities.

### 2.4 Austin Dockless Mobility 2018

[7]

- from 3 April 2018 to 16 January 2019
- 1969575 rows × 23 columns
- columns: Vehicle Type, Trip Distance, Start Time, End Time, Origin Cell ID, Destination Cell ID.

### 2.5 Bike Share Toronto 2019

[6]

- from 1 January 2019 to 31 December 2019
- 2439517 rows × 11 columns
- columns: Start Station ID, Start Time, Start Station Name, End Station ID, End Time, End Station Name, User Type.

### 2.6 Los Angeles Trip Data 2020

[2]

- from 1 January 2020 to 31 December 2020
- 209974 rows × 21 columns
- columns: Start Time, End Time, Start lat, Start lon, End lat, End lon, Bike Type, Start Location Name, End Location Name.

### 2.7 City Lousiville escooter trip data 2018/2019

[1]

- from 9 August 2018 to 31 October 2019
- 434582 rows × 12 columns
- columns: TripDistance, Vehicle Type, Start Time, End Time.

| City | Total trips |
|---|---|
| Chicago | 3007282 |
| Toronto | 2428208 |
| Austin | 1160193 |
| Louisville | 254379 |
| Los Angeles | 209895 |

Table 1: Total trips for all cities.

## 3 Data Preparation

We started data preparation by removing unnecessary columns or those that were too little information to know what they meant. Then we renamed them so that they are common to all dataframes to facilitate future work, e.g. in connecting dataframes.

We moved on to changing column types. The most obvious was changing the date columns from 'object' to 'data'. For the 2020 Chicago dataframe, we changed 'Trip Distance' from string to float, removing the comma that separates thousands from the rest.

One of the columns we designated was 'Trip Duration' expressed in minutes (it may be different in different datasets).

Then, incorrect records were removed - if the start time of the trip was later than its end or when the time was equal to 0, which could be related to its cancellation.

Columns have been added to make it easier to work with visualization and prediction later - 'City', 'Day of week', 'Hour' and 'Month'.

Wherever possible, the distance was calculated in a straight line on the map - thanks to this, it was possible to determine whether the user was driving in a circle, returned to the starting point or did not move at all.

In the end, we combined the data into two dataframes - for Chicago and all, while maintaining information common to all cities. In the Figure 1 you can see the distribution of obtained data in time. In Table 1 the total trips for each city are listed.

## 4 Impact of Day of the Week and Time of Day on Rentals

In this chapter, we will explore the correlations between the number of bicycle and electric scooter rentals and the day of the week, time of the day and month. The data on the usage of these vehicles provides valuable insights into user preferences and habits, allowing us to understand the dynamics of urban transportation services.

In the subsequent sections of this chapter, we will present the results of our analysis, including graphs, tables, and statistics that will aid in comprehending the relationships between the day of the week, time of day, and rental volumes.

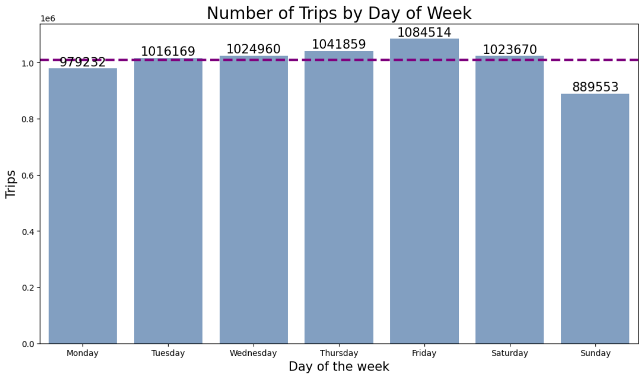


Figure 2: Number of trips by day of week and mean value for the full data set.

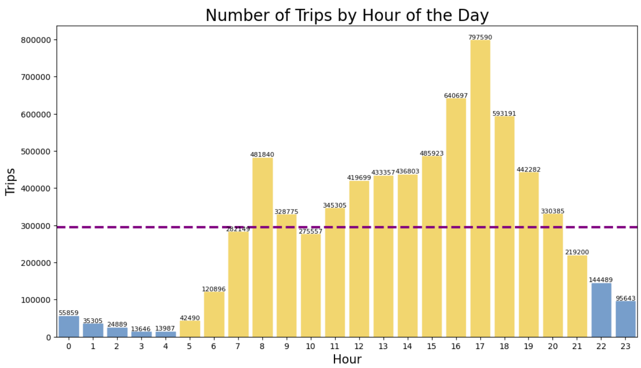


Figure 3: Number of trips by hour and mean value for the full data set.

## 4.1 Number of trips by day of week

The distribution of rentals throughout the week provides valuable insights into the patterns of bike and electric scooter usage.

From Figure 2 it is evident that Friday stand out as the peak day for rentals, surpassing the overall weekly average by approximately 10%. This observation suggests a higher demand for bikes and electric scooters during the end of the workweek. The increased popularity of rentals during these days could be attributed to various factors, such as leisure activities and reduced work commitments at the end of the week.

## 4.2 Number of trips by hour

The analysis of rental patterns also extends to exploring the distribution of trips throughout the day. Figure 3 presents a comprehensive view of the number of trips based on the hour of the day, revealing distinct peaks and trends.

Figure 3 indicates a particularly high demand for rentals at 8 AM and 5 PM. These specific time slots suggests a correlation with rush hours and commuting patterns. The increased usage during these hours could be attributed to individuals commuting to work or school, seeking alternative transportation options, or engaging in leisure activities during peak evening hours.

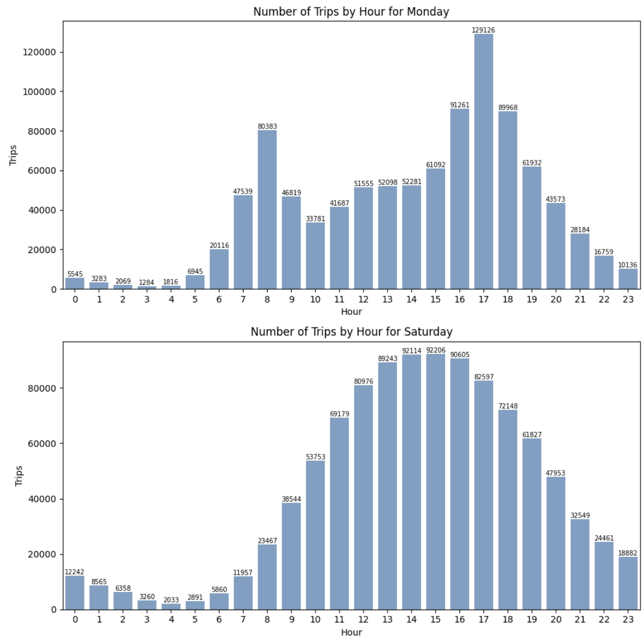


Figure 4: Comparison of number of trips by hour on weekday (Monday) and weekend (Saturday).

Figure 4 provides 2 histograms comparing the number of trips by hour on Monday and Saturday. First histogram highlights that on weekdays there is a notable spike in demand at 8 AM and 5 PM, similar to the overall pattern observed in Figure 3. This observation suggests that commuting patterns and work-related activities significantly influence rentals on weekdays. In contrast the second histogram shows the rental demand on Saturdays, which exhibits a gradually increasing trend throughout the day, reaching its peak around 3-4 PM. This pattern suggests a different usage pattern on weekends, potentially driven by recreational activities, sightseeing, and leisurely outings during the day.

## 4.3 Number of Trips by Month

In this chapter, we examine the distribution of trips across different months of the year for the whole dataset. The analysis aims to uncover any seasonal patterns in bicycle/scooter usage. A histogram depicting the number of trips by month can be found in the Figure 5.

Notably, the histogram illustrates a peak during the summer and early autumn months, specifically in July, August, September, and October. The number of trips during this period surpasses the annual average, indicating a heightened demand for bike/scooter share services. The most rentals took place in August.

Furthermore, the histogram shows a notable difference in the number of trips between months with 31 days and those with fewer days, such as 30 or 28/29 in the case of February. For instance, the number of trips in January exceeds that of February but is also similar to March. This observation suggests that the number of trips in the winter time remains constant and the variations are derived from the number of days in a

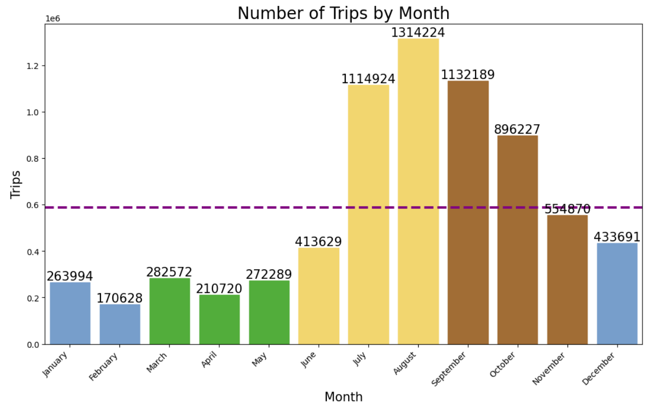


Figure 5: Number of trips by month and mean value for the full data set.

month.

The underlying reasons for the observed patterns in the histogram can be attributed to several factors. Firstly, the higher number of trips during the summer and early autumn months can be attributed to more favorable weather conditions, making using a bike/scooter a popular choice for commuting and leisure activities. Additionally, these months often coincide with vacations and holidays, leading to increased tourism and recreational opportunities, which may contribute to the higher demand for bike share services.

# 5 The impact of the pandemic on bike share

In the previous chapter we showed the distribution for the whole dataset, containing trips in all cities. If we display the charts for individual cities, where we have data for the entire calendar year, we can see that the characteristics of overall distribution does not hold for the city of Los Angeles. When we look at the Figure 6 with the data for Toronto in 2019, as expected, the most rentals occurred during the summer, but not for LA. One of the reasons for this outcome could be that in LA there are comfortable weather conditions throughout the whole year.

We also notice an unexpected decrease of rentals in March 2020. The possible reason for this change could be the COVID-19 virus pandemic, which hit America and Europe at a similar time, i.e. in March in 2020. At that time, moving around and leaving the house was limited, hence the reduction of bicycle rental by over 10,000.

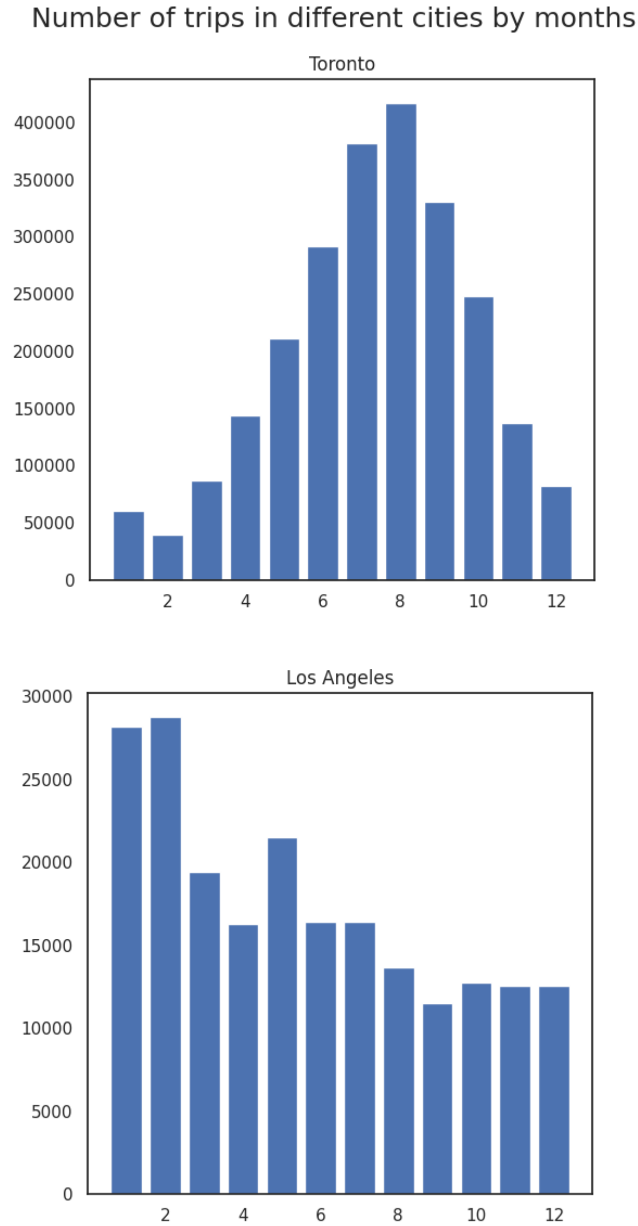


Figure 6: Number of trips by month for Toronto (2019) and Los Angeles (2020).

| Year | Average speed [m/s] |
|---|---|
| 2019 | 3,13 +/- 1,66 |
| 2020 | 2.62 +/- 1,62 |

Table 2: Average speeds for electric scooters in Chicago.

# 6 Calculating Average Speed of Electric Scooters

In this chapter, we will focus on analyzing the speeds of electric scooters in Chicago, comparing the data from the years 2019 and 2020. It is important to analyze the speeds of electric scooters as it significantly impacts the safety of both users and other road participants. Comparing data from different years will allow us to assess whether any changes in the regulations concerning electric scooter speeds had any effect on the average speeds in Chicago.

Figure 7 provides histograms depicting the distributions of average speeds per trip in years 2019 and 2020, respectively. Table 2 presents the average speeds of electric scooters in Chicago for the years 2019 and 2020.

The data reveals a decline in the average speed from 3.13 m/s in 2019 to 2.62 m/s in 2020, representing a decrease of approximately 16.3% in average speed. The decline in average speed and the shift in the distribution towards lower speeds suggest that there might have been changes in the operating conditions, rider behavior, or scooter characteristics during the examined period.

Possible factors that could have influenced the decrease in average speed and the observed distribution include the implementation of speed restrictions or increased emphasis on safety. Also technological advancements in electric scooters could have played a role. Manufacturers might have introduced models with improved safety features or performance characteristics that naturally limit the maximum speed achievable.

# 7 Analysis of Bike Share Users

In this chapter, we investigate the variety of bike share users, focusing on age and gender distribution. The data used for this analysis includes only individuals aged 18 and above.

Figure 8 presents a histogram illustrating the distribution of age and gender among bike share users. Notably, the histogram reveals significant differences in bike usage patterns between males and females. Man appear to use the bike share services approximately three times more often than woman.

Furthermore, the histogram provides insights into age-related trends among bike share riders. It shows that bikes are particularly popular among individuals in their late 20s and early 30s. Surprisingly, the histogram also indicates a relatively lower participation

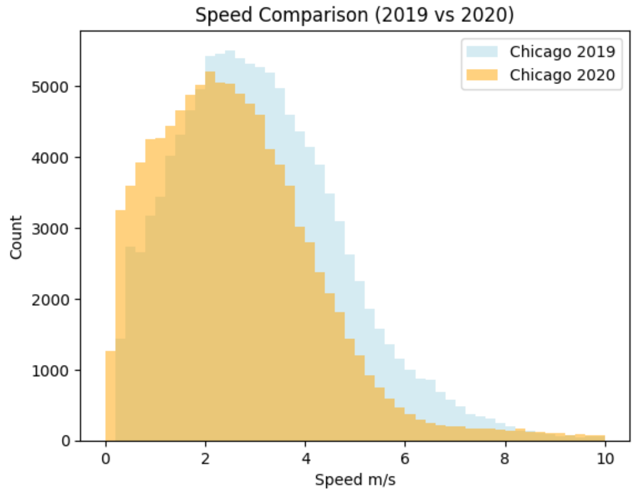


Figure 7: Distribution of average speeds per trip of electric scooters in Chicago, comparison 2019 and 2020

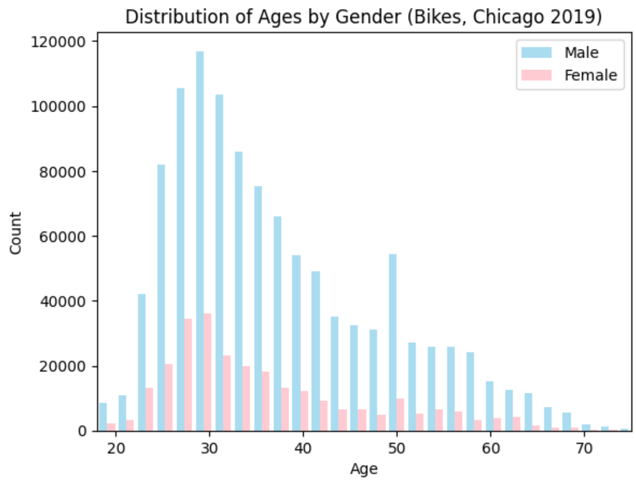


Figure 8: Distribution of age and gender among Bike Share users

rate among individuals below the age of 25.

# 8 Most frequented places

For Chicago, Los Angeles and Toronto cities, we may check the most frequent end trips stations:

| End Location Name | percentage |
|---|---|
| York St / Queens Quay W | 1.272649 |
| Union Station | 1.055743 |
| Bay St / Queens Quay W (Ferry Terminal) | 0.992021 |
| Bathurst St/Queens Quay(Billy Bishop Airport) | 0.953097 |
| Adelaide St W / Bay St - SMART | 0.799417 |

Table 3: Most frequented places for Toronto

For Toronto, you can easily see in the Figure 9 that the most frequented places are at the shore of the lake or near it. These clusters are typically places frequented by people, like the old town, which is full of the main attractions of the city.

| End Location Name | percentage |
|---|---|
| Streeter Dr & Grand Ave | 1.905548 |
| WEST TOWN | 1.565122 |
| Clinton St & Washington Blvd | 1.229889 |
| Canal St & Adams St | 1.219268 |
| NEAR WEST SIDE | 1.174369 |

Table 4: Most frequented places for Chicago

For Chicago, you can easily see in the Figure 9 a similar affliction to Toronto. The most frequented places are located on or near the coast. There are plenty of restaurants, shops, cafes and cultural places where you can meet friends or family.

| End Location Name | percentage |
|---|---|
| 7th & Flower | 4.172086 |
| Figueroa & 8th | 3.493652 |
| Metro Bike Share Free Bikes | 2.018152 |
| Virtual Station | 2.015293 |
| Union Station West Portal | 1.956216 |

Table 5: Most frequented places for Los Angeles

In the case of Los Angeles, we have places that are a bit more dispersed and specific, so the visualisation would not result in defined clusters like in Toronto or Chicago. The LA dataset shows some concentrations of trips destinations near metro stations. After further research we discovered that a lot of bike stations are located close to these metro stations. This arrangement enables users to swiftly access public transportation, facilitating an easier commute to work.

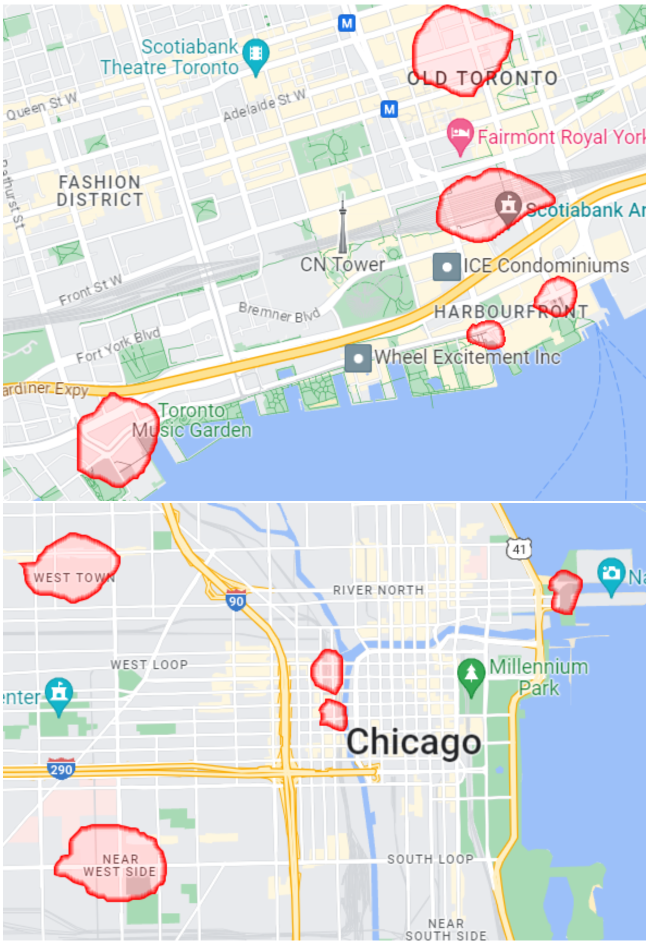


Figure 9: Most frequented places for Toronto and Chicago

## 9 Visualization of trip routes on the map

For visualization on the map, we took into account two cities - Chicago and Los Angeles, because of their information on latitude and longitude, as they were the most precise. First, we focused on the city of Chicago. On the map, using arrows, we visualized 200 routes for 8 AM and 5 PM, which had the most trips for different times of the day.

First picture in the Figure 10 shows that several clusters have appeared on the map, to which the travel routes were directed. Most of them are streets full of shops or shopping centers, which probably means the arrival of employees. The most interesting clusters are shown in the Figure 11, i.e. cluster 2, which has a park with lots of sports, cluster 8, which has a community center, and cluster 7, which has the most arrows, but it doesn't look like anything special on the map other than houses.

Fewer clusters appeared in Chicago at 5 PM (Figure 10). However 3 clusters out of 4 also appeared at 8 AM. These are still places full of shops, restaurants or a community center with meeting places. It indicates that people use scooters/bikes to go shopping, for dinner, to work or to meet friends.

The visualization of the routes for Los Angeles on Figure 12 is not as clear as for Chicago, and no clusters appear except for one, which is downtown LA. The reason is that the company has distributed its bikes in three large clusters in the city, one of which is the cluster shown. Between 8 AM and 5 PM the movements do not change significantly except that in the afternoon there are more routes outside the center, when probably some people go back to their homes.

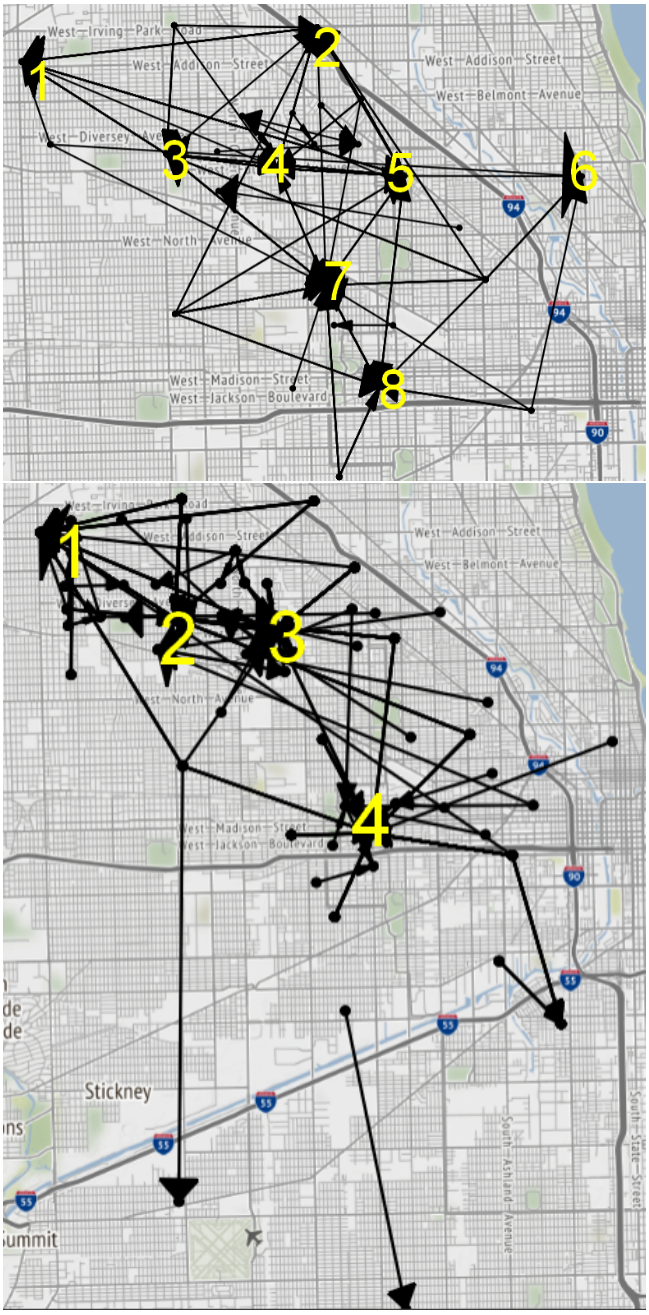


Figure 10: Visualization of trip routes for Chicago at 8 AM and 5 PM

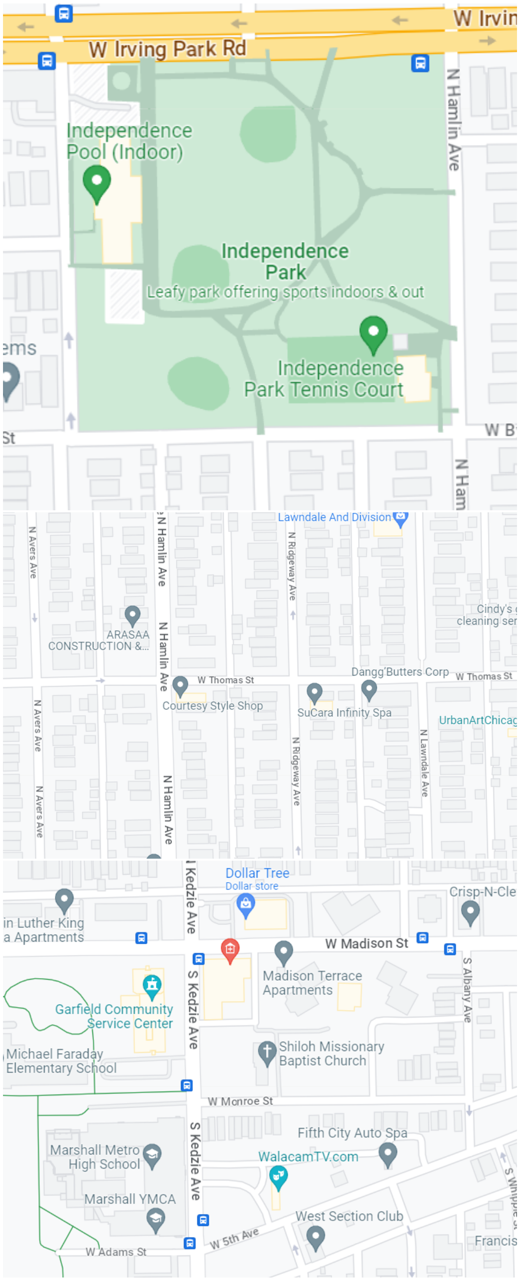


Figure 11: 2, 7 and 8 cluster in Chicago

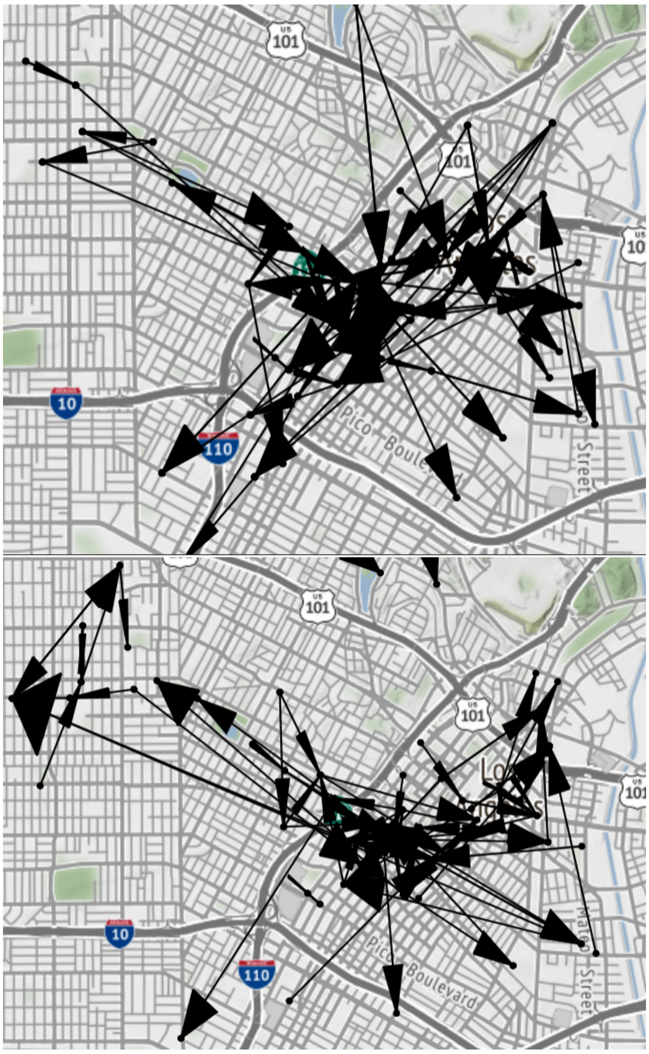


Figure 12: Visualization of trip routes for Los Angeles at 8 AM and 5 PM

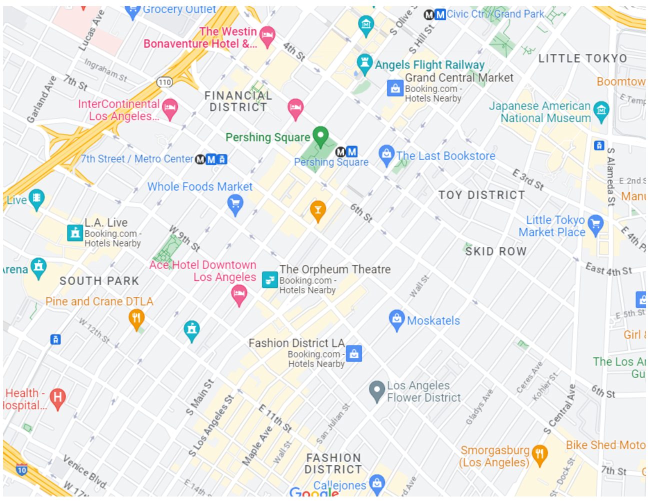


Figure 13: The Center of LA

# 10 Prediction Model for End Location

In the following chapter, we will focus on building a prediction model for the End Location Area of scooter trips. For that the dataset Chicago 2019 will be used.

The goal is to assess the level of accuracy with which we can predict the End Location Area of scooter trips. By examining the accuracy of our predictions, we can see if there are many individuals that build a habit of using a scooter such as commuting between work and home.

## 10.1 Correlation Matrix

To see which features in the dataset are correlated with the target „End Community Area Number" the correlation matrix was created. To achieve that the function corr() (pandas library) was applied to the features of the dataset. The resulting correlation matrix was visualized using a heatmap shown in Figure 14.

The heatmap shows relatively high correlation between the „End Community Area Number" and the features which describe the starting location, precisely „Start Community Area Number", „Start Latitude", „Start Longitude". It may indicate that there are specific areas where commuting between them is popular, which could point to the existence of a pattern of movement between these locations.

The analysis reveals a moderate correlation between the "Trip Distance" and the "End Community Area Number" variables, although it is slightly weaker compared to the correlation with the starting point. The correlation coefficient between these factors is calculated to be -0.14. This negative correlation suggests that as the distance of the trip increases, there is a tendency for the end location to be associated with different community areas.

The correlation between "End Community Area Number" and the features "Hour" and "Day of week" is negligible but non-zero. This dependencies appear possibly due to the influence of factors such as work-related commuting patterns and other time-dependent movement trends but are not strong enough to establish a significant relationship.

## 10.2 Regression Model

A regression model is a statistical approach used to predict or estimate a continuous target variable based on one or more independent variables. It aims to establish a functional relationship between the predictors and the target variable, allowing for the prediction of the target variable for new or unseen data points. In the context of our analysis, we are using a regression model to predict the end location area of scooter trips based on various features and attributes associated with each trip.

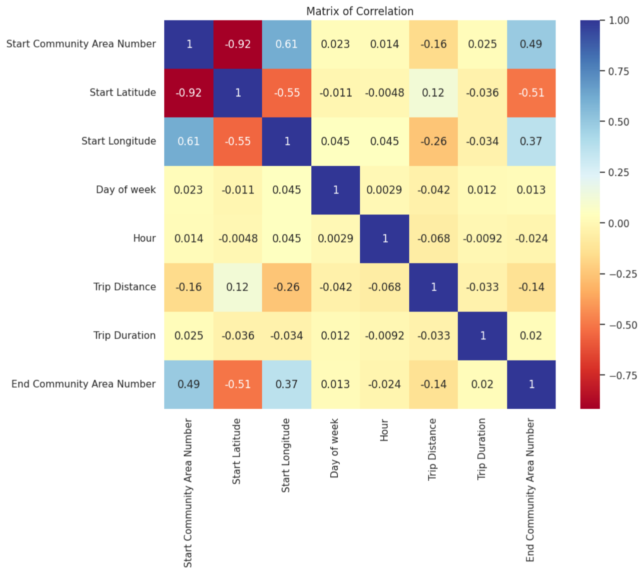


Figure 14: Correlation matrix of Features

### 10.2.1 Random Forest Classifier

The Random Forest Classifier model (sklearn) was selected as a suitable choice for regression in this scenario because it is capable of handling both categorical and numerical features effectively. Our dataset contains a combination of features such as 'Start Community Area Number' (categorical) and 'Trip Distance' (numerical). The Random Forest Classifier can handle such mixed data types without requiring extensive data preprocessing or feature engineering. This flexibility allows for a more straightforward implementation of the model on the given dataset.

The Random Forest Classifier is also known for its ability to handle complex relationships and interactions between features. It works by constructing multiple decision trees and aggregating their predictions to make final predictions. This ensemble approach helps capture non-linearities and interactions within the dataset, which can be beneficial in predicting the end community area number accurately. The randomization in the model's construction also helps to mitigate overfitting, leading to improved generalization on unseen data.

### 10.2.2 Creating the Regression Model

To create the regression model, the following steps were performed:

- The relevant features, including 'Start Community Area Number', 'Start Latitude', 'Start Longitude', 'Day of week', 'Hour', 'Trip Distance', and 'Trip Duration', were selected for training the model based on the correlations described in this chapter.
- Data standardization was applied to ensure that the features were on a similar scale and prevent any dominance of a particular feature.
- The dataset was split into training and testing sets.

- A Random Forest Classifier model, capable of handling both categorical and numerical features, was chosen and trained on the standardized training data.

### 10.2.3 Prediction Results

Predictions were generated on the standardized testing data using the trained model. The performance of the regression model was evaluated using metrics such as precision, recall, F1-score, and support for each class in the target variable. Classification results for selected community area numbers can be found in the Table 6. The average values of the results can be seen in the Table 7.

| Area No. | precision | recall | f1-score | support |
|---|---|---|---|---|
| 5.0 | 0.00 | 0.00 | 0.00 | 12 |
| 7.0 | 0.20 | 0.10 | 0.13 | 50 |
| 19.0 | 0.49 | 0.51 | 0.50 | 162 |
| 22.0 | 0.60 | 0.67 | 0.63 | 581 |
| 24.0 | 0.67 | 0.76 | 0.71 | 913 |

Table 6: Selected classification results of the Random Forest Classifier

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| accuracy | | | 0.59 | 3450 |
| macro avg | 0.32 | 0.28 | 0.30 | 3450 |
| weighted avg | 0.57 | 0.59 | 0.58 | 3450 |

Table 7: Summary of classification results of the Random Forest Classifier

The regression model achieved an overall accuracy of 0.59, indicating that approximately 59% of the instances in the testing set were correctly predicted by the model. This suggests a moderate level of accuracy in predicting the end community area number.

It can be observed that precision recall and f1-score vary across different classes, indicating variations in the model's performance for different categories. These variations can be seen in Table 6. The results indicate poor predictions for the area numbers that were the least frequent destinations. The frequencies can be found in Figure 15

In order to improve the model, the data for the "End Community Area Number" column was restricted to those with at least 300 occurrences. Subsequently, classification was performed, and the results can be found in the Table 8. These results indicate an improvement in accuracy and a reduced discrepancy between the "macro average" and "weighted average" measures compared to the initial model. These findings demonstrate a higher quality of prediction for the model that only considered "End Community Area Numbers" with at least 300 occurrences.

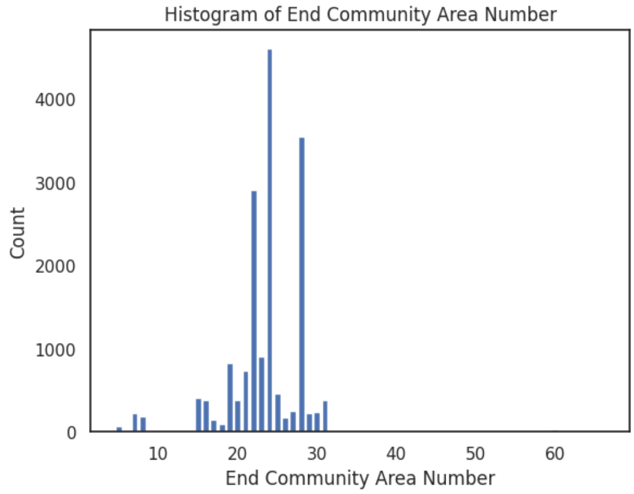


Figure 15: End Community Area Number frequencies.

| Area No. | precision | recall | f1-score | support |
|---|---|---|---|---|
| 15.0 | 0.45 | 0.45 | 0.45 | 97 |
| 16.0 | 0.30 | 0.31 | 0.30 | 59 |
| 19.0 | 0.61 | 0.57 | 0.59 | 171 |
| 20.0 | 0.32 | 0.31 | 0.32 | 74 |
| 21.0 | 0.40 | 0.31 | 0.35 | 139 |
| 22.0 | 0.66 | 0.67 | 0.66 | 587 |
| 23.0 | 0.50 | 0.41 | 0.45 | 186 |
| 24.0 | 0.69 | 0.76 | 0.72 | 918 |
| 25.0 | 0.51 | 0.45 | 0.48 | 85 |
| 28.0 | 0.79 | 0.79 | 0.79 | 718 |
| 31.0 | 0.57 | 0.40 | 0.47 | 81 |
| accuracy | | | 0.65 | 3115 |
| macro avg | 0.53 | 0.49 | 0.51 | 3115 |
| weight. avg | 0.65 | 0.65 | 0.65 | 3115 |

Table 8: Classification results of the Random Forest Classifier for Area Numbers with at least 300 occurrences.

# 11 Summary and conclusions

The analysis of usage data from electric scooters and bicycles in five American cities (Chicago, Louisville, Los Angeles, Austin) and one Canadian city (Toronto) provides valuable insights into the patterns and trends of their utilization within the transportation system. The following conclusions can be drawn from the study:

- The usage patterns of electric scooters and bicycles show variations based on the day of the week and time of day. Peak days for rentals are observed on Fridays, indicating higher demand during the end of the workweek and the start of the weekend. The analysis also reveals distinct peaks in rental volumes at 8 AM and 5 PM, correlating with rush hours and commuting patterns.

- The distribution of trips by month shows a peak in rentals during the summer and early autumn months, particularly in July, August, September, and October. This observation suggests a higher demand for bike and scooter share services during these months, potentially due to more favorable weather conditions, vacations, and increased tourism. The number of trips during winter remains relatively constant, with variations attributed to the number of days in a month.

- The COVID-19 pandemic has had a significant impact on bike share services. The analysis reveals a decrease in rentals after February 2020. The restrictive measures and limitations on movement implemented during the pandemic likely contributed to the reduction in bike and scooter rentals.

- The average speed of electric scooters in Chicago decreased from 3.13 m/s in 2019 to 2.62 m/s in 2020. This decline indicates possible changes in operating conditions, rider behavior, or scooter characteristics. Factors such as the implementation of speed restrictions, increased emphasis on safety, or technological advancements in scooter models could have influenced the observed decrease in average speed.

- The analysis of bike share users revealed significant differences in bike usage patterns between males and females. Males were found to use the bike share services approximately three times more often than females. Additionally, the age distribution of bike share riders showed a higher participation rate among individuals in their late 20s and early 30s, while individuals below the age of 25 had a relatively lower participation rate.

- The examination of the most frequented places in Chicago, Los Angeles, and Toronto cities highlighted popular locations for bike share users. In Chicago, the most frequented places were found to be located on or near the coast, with a concentration of restaurants, shops, cafes, and cultural attractions. Los Angeles showed a dispersed pattern with stations close to metro areas, indicating the use of bikes for commuting to and from the metro zone. Toronto also had popular locations along the lakeshore and in the old town, which attracted people to major attractions.

- The visualization of trip routes on the map provided insights into commuting patterns and popular destinations. In Chicago, clusters of routes were observed, particularly around streets with shops, shopping centers, and community centers. Los Angeles exhibited fewer clusters, mainly concentrated in the downtown area. The visualization indicated that people in both cities used bikes for various purposes, such as commuting, shopping, dining, and meeting friends.

- The prediction model for the end location area of scooter trips in Chicago was built using a Random Forest Classifier. The model utilized features such as start community area number, start latitude, start longitude, day of the week, hour, trip distance, and trip duration to predict the end location area. The correlation matrix showed significant correlations between the end community area number and the starting location features, indicating commuting patterns between specific areas. The regression model achieved an accuracy of 59% in predicting the end community area number, suggesting a moderate level of accuracy.

## References


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