MEXICO CITY ECOBIKES

PROJECT 4
BOOTCAMP
TEAM 3
BYRONT URCID
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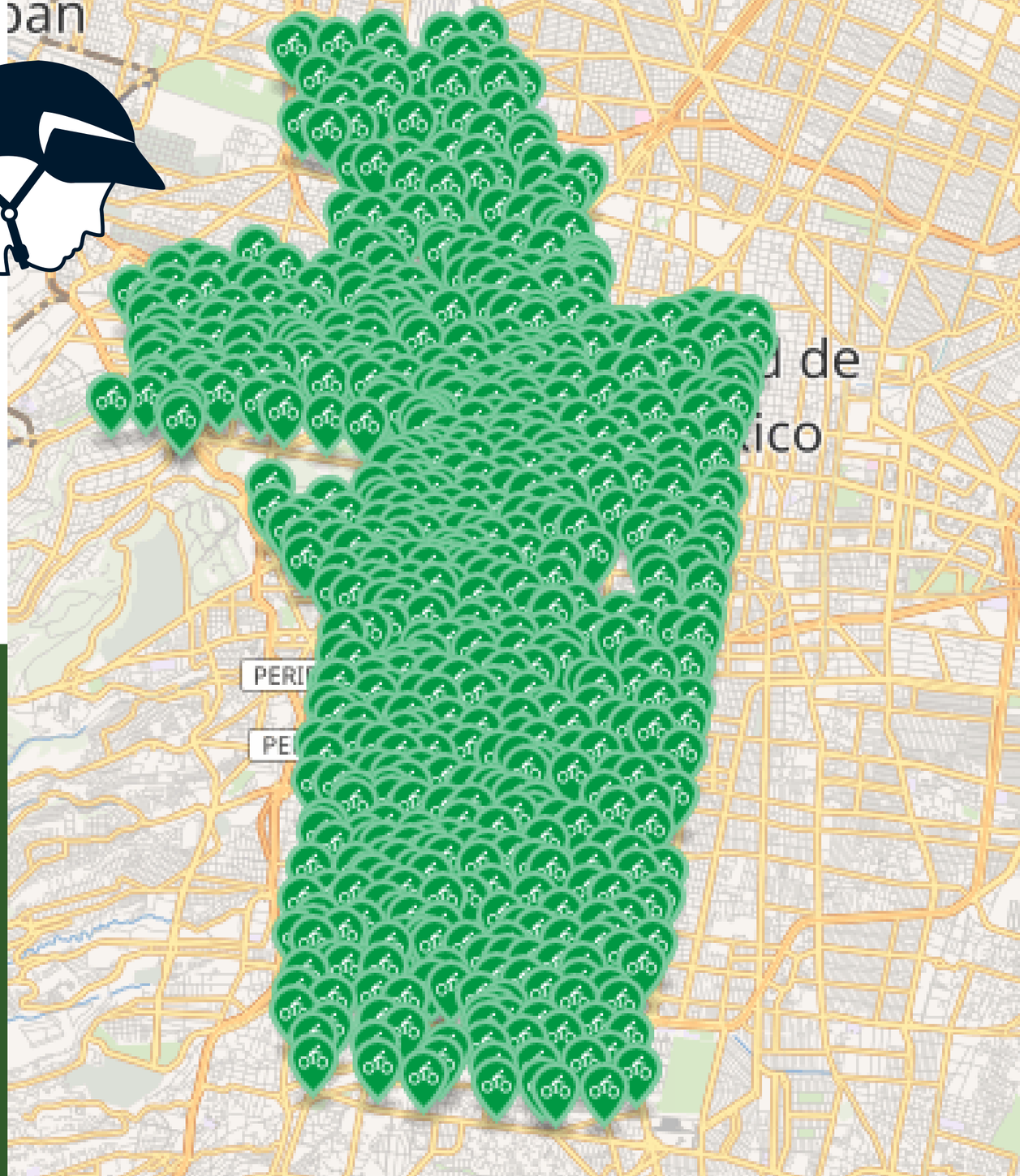
ECOBICI: Mexico City's Bike-Sharing System

- **Launched in 2010** with 85 stations and 1,114 bicycles
- **Operated by** Mexico City's government through the Ministry of Mobility
- **Goal**: To integrate bicycles into the public transport system as a sustainable and efficient option

How ECOBICI Has Grown

2025 stats:

- 689 stations
- 9,300 bicycles
- 70,000 average weekday trips
- Over 165,000 active yearly memberships
- **Coverage**: Active in 4 boroughs: Cuauhtémoc, Miguel Hidalgo, Benito Juárez, and Coyoacán



Where Our Data Comes From

Source: Datos Abiertos CDMX (Mexico City Open Data Portal)

Dataset: ECOBICI trip data

Includes:

- Start & end time, duration
- Origin & destination stations
- User type (annual/pass, occasional)
- Gender and age (when available)

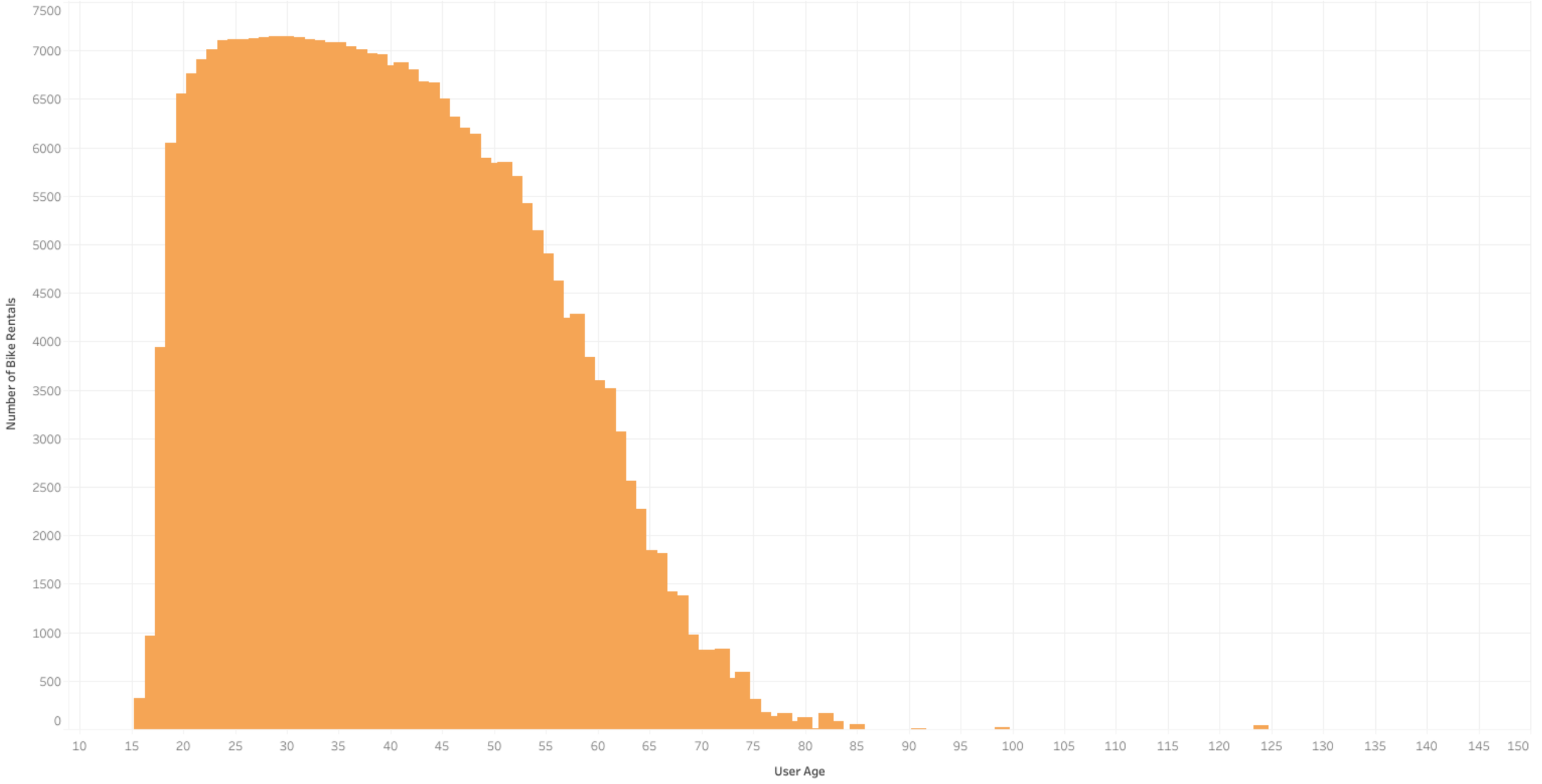
Time ranges used:

- 1 year of data for machine learning models
- 1 month of data for Tableau visualizations

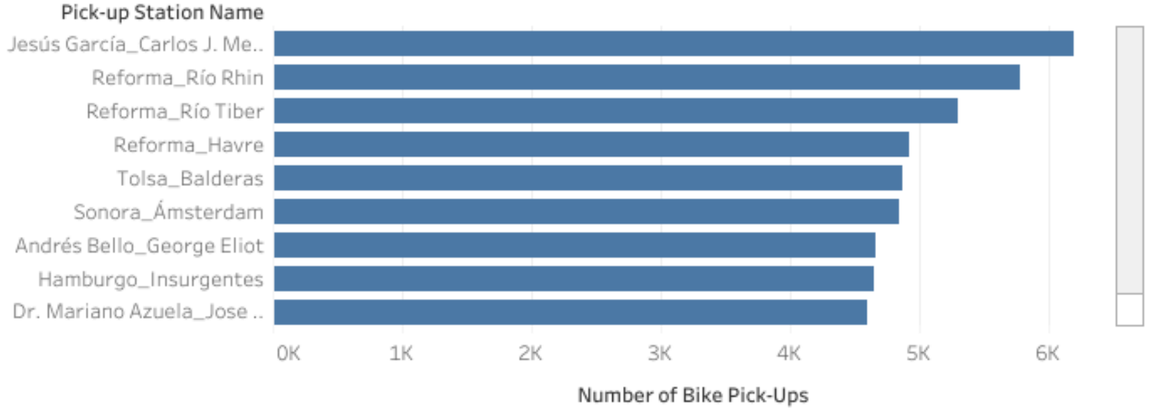
How is ECOBICI being used?

To better understand how the system is being used across the city, we analyzed recent usage data. We explored user behavior, peak hours, the most active stations, and user demographics.

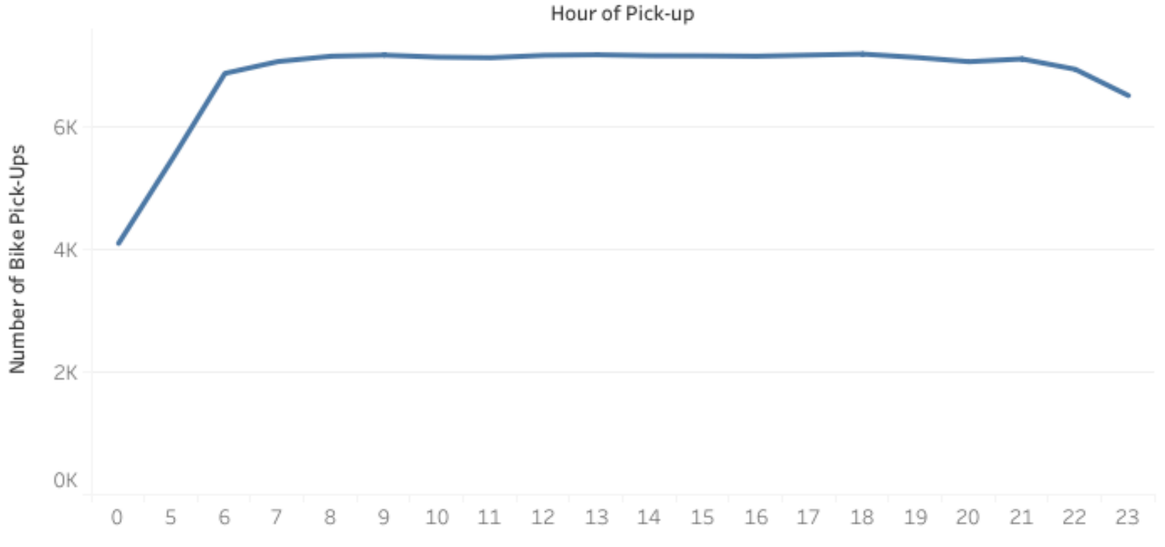
Age Distribution of Bike Share Users



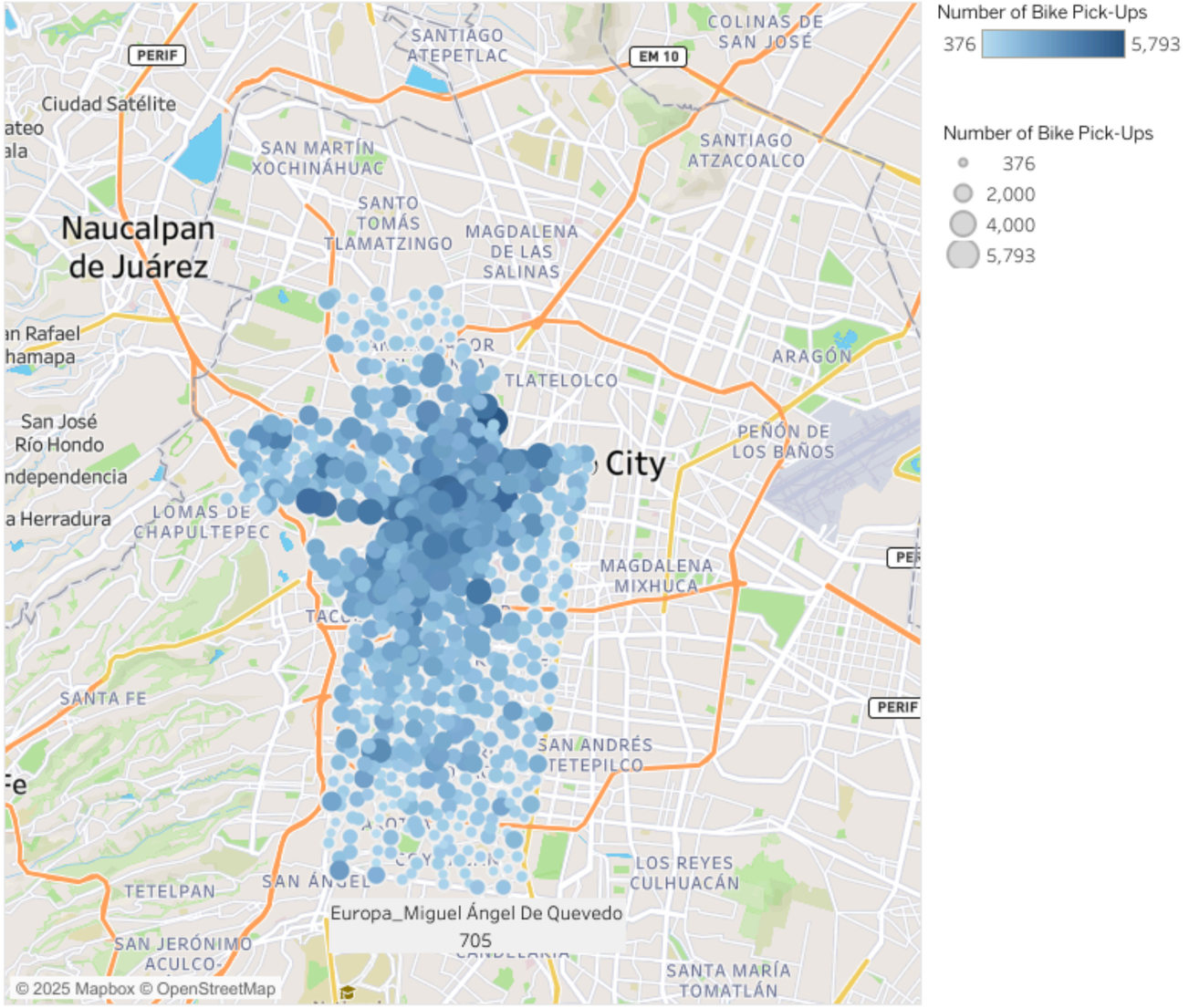
Top 10 Most Frequent Bike Pick-Up Stations



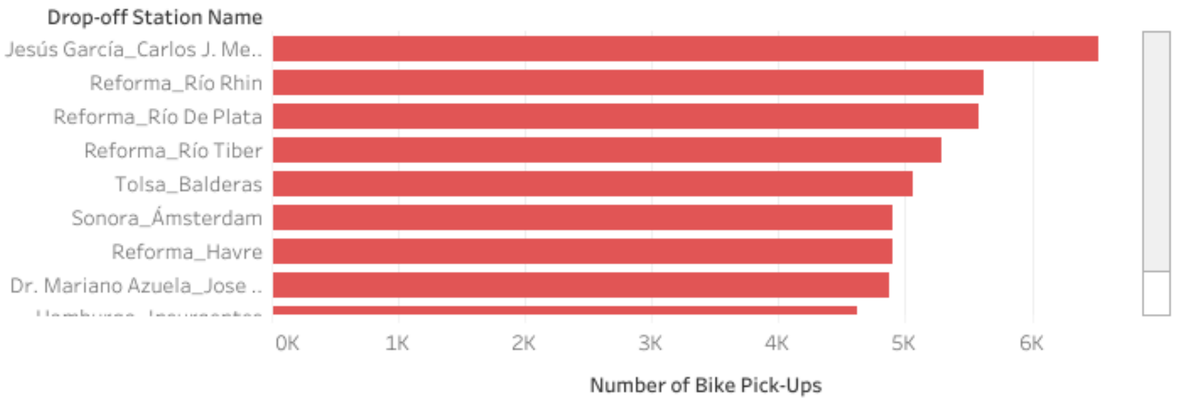
Hourly Distribution of Bike Pick-Ups



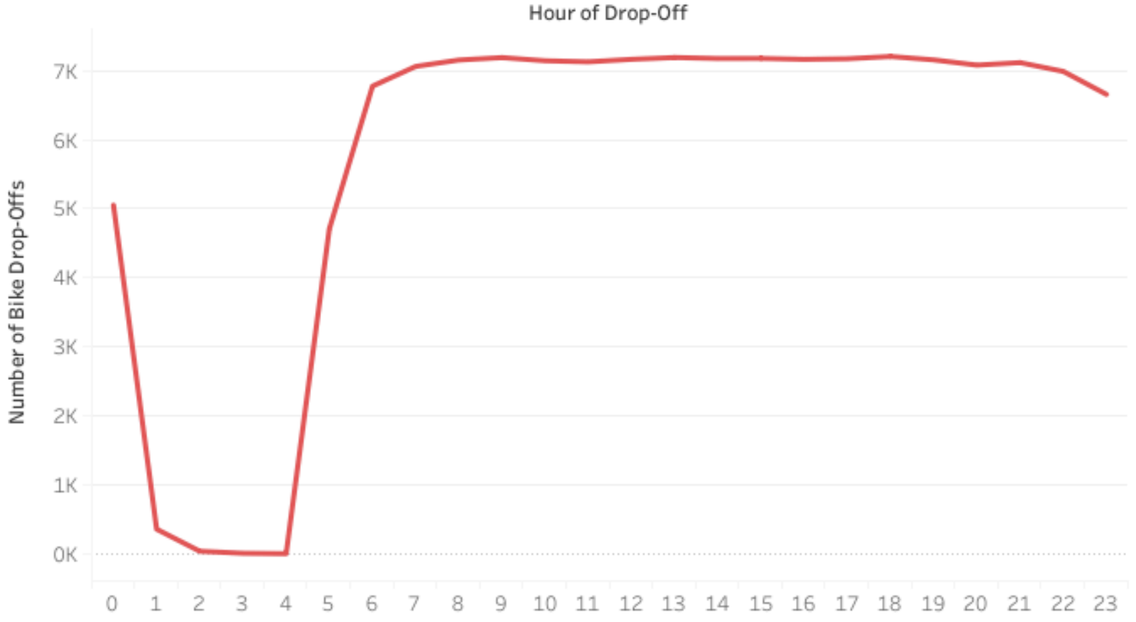
Spatial Distribution of Bike Pick-Ups in Mexico City



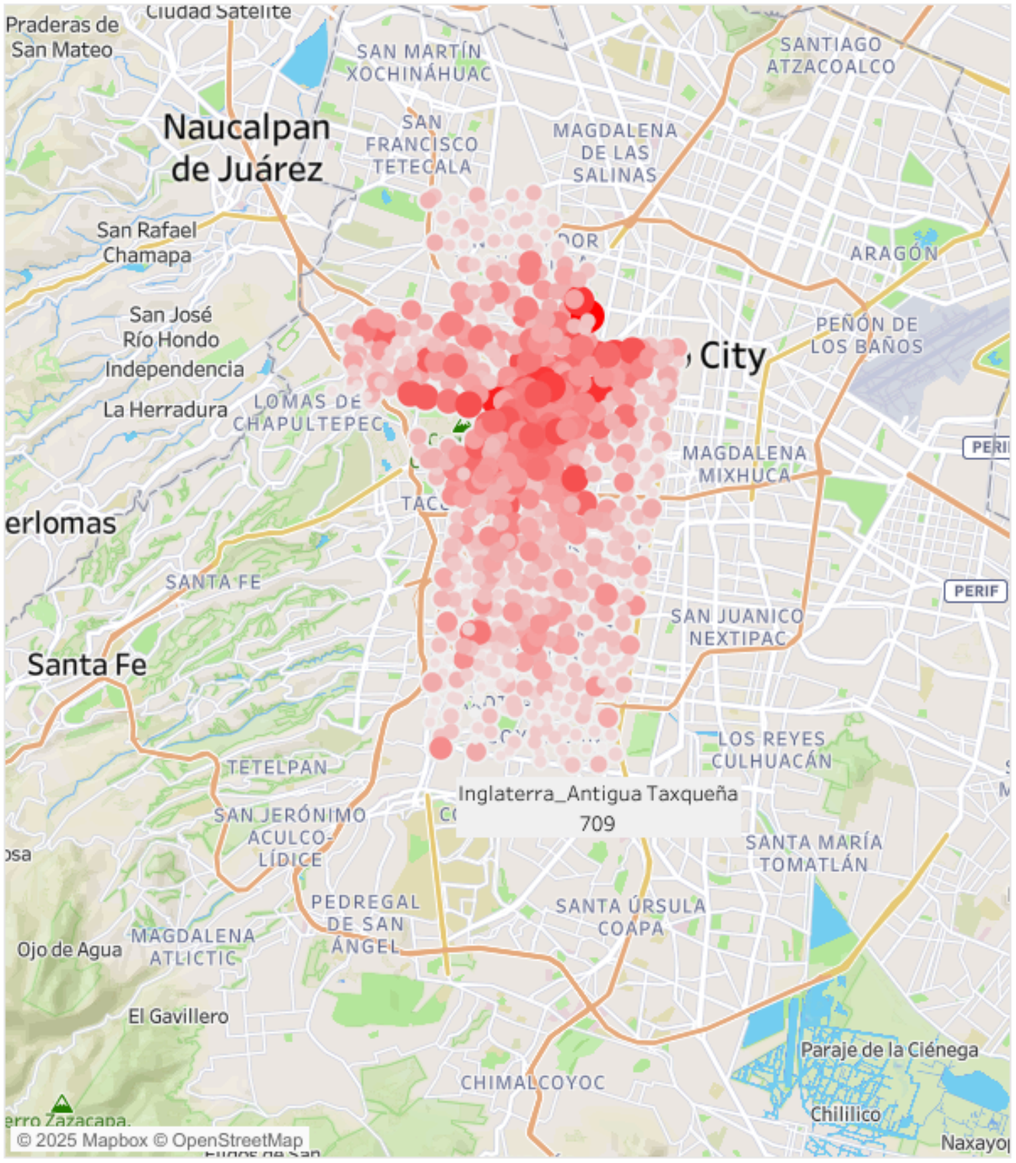
Top 10 Most Frequent Bike Drop-Off Stations

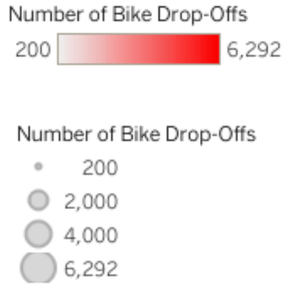


Hourly Distribution of Bike Drop-Offs



Spatial Distribution of Bike Drop-Offs in Mexico City





Machine Learning Applications

1. Bicycle Demand Prediction: Analyzes pickup and drop-off patterns to predict which stations will require the most bikes at certain times of the day.

2. Route Analysis: We will attempt to create a profile of the most used routes and how they vary by time of day, which could help improve the station system.

3. User Classification: Uses demographic data (gender and age) to predict user categories and usage patterns (for example, is a younger user more likely to use a bike at night?).

4. User Segmentation: Groups users into different segments based on their usage behavior, which can help with marketing campaigns or service improvements.

5. Trip duration. Predicting trip duration, we could explore factors influencing ride length, such as distance, time of day, or user experience

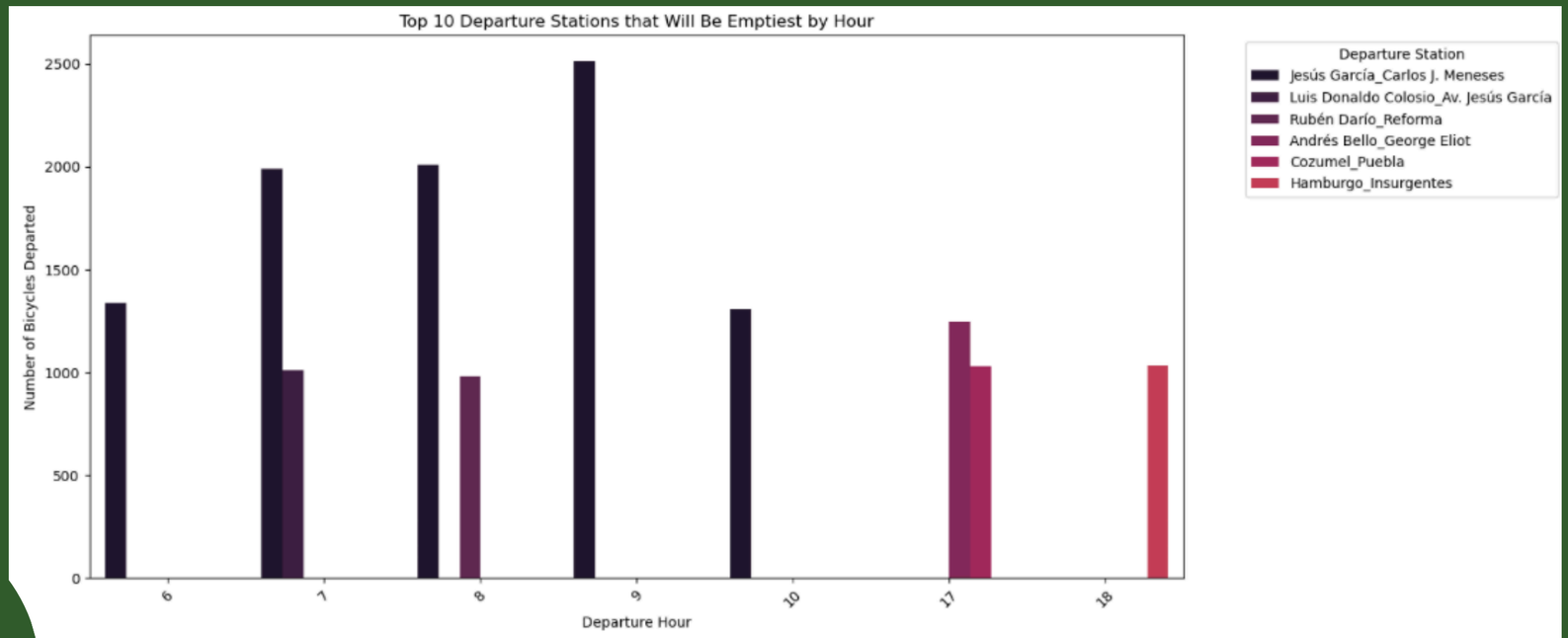
1. Bicycle Demand Prediction

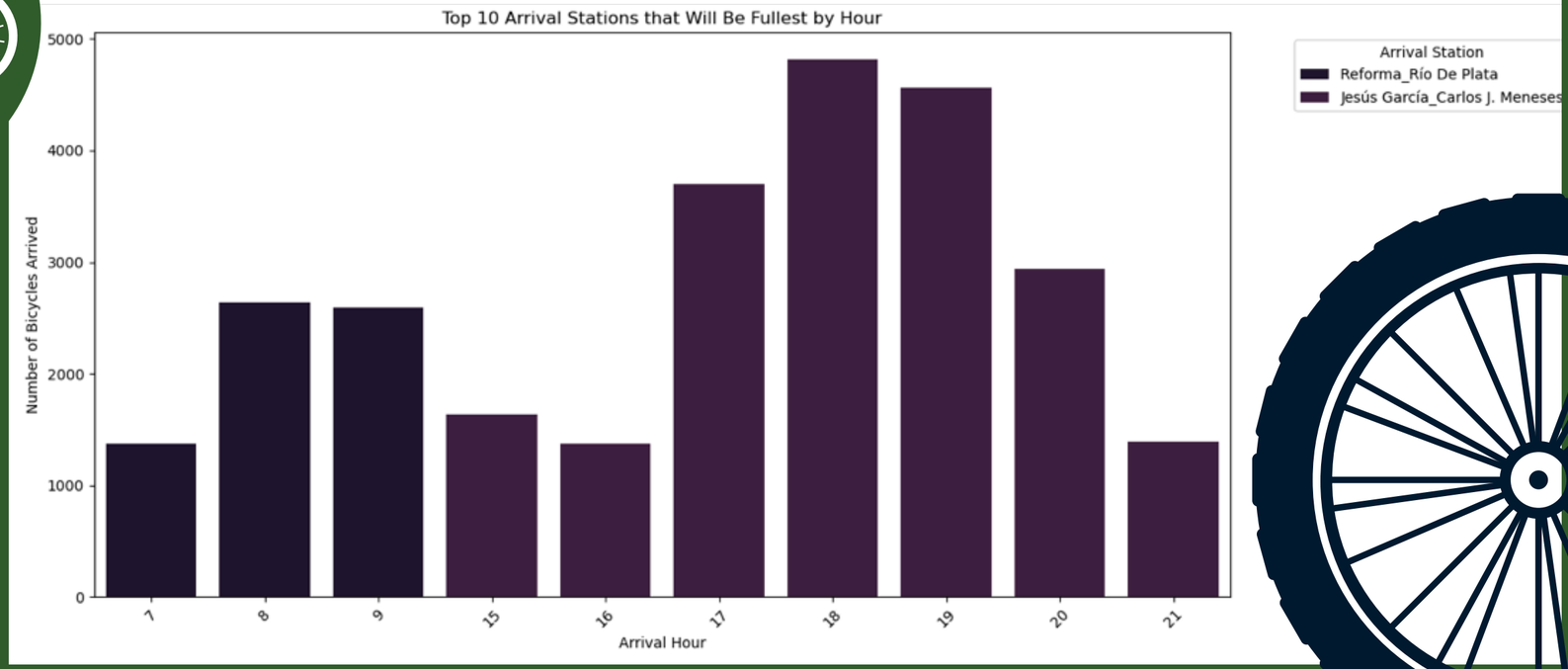
For this model we used the Random Forest Regressor Method

The model was trained with information of 1,745,620 millions of trips

Departure Stations Model Accuracy: **77%**

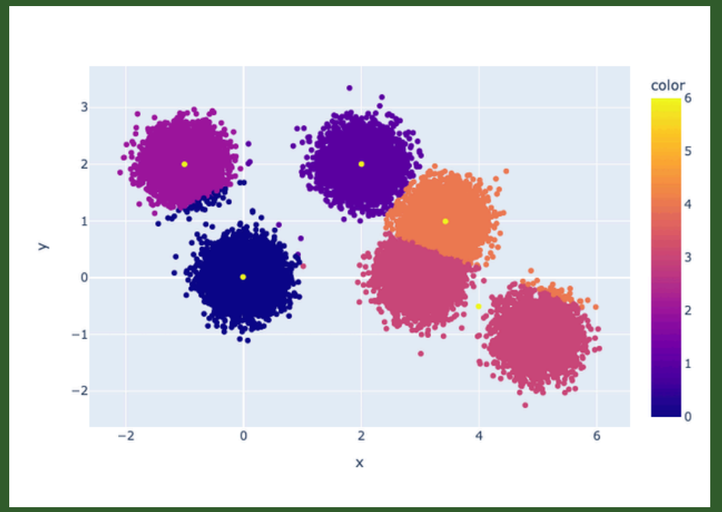
Arrival Stations Model Accuracy: **83%**



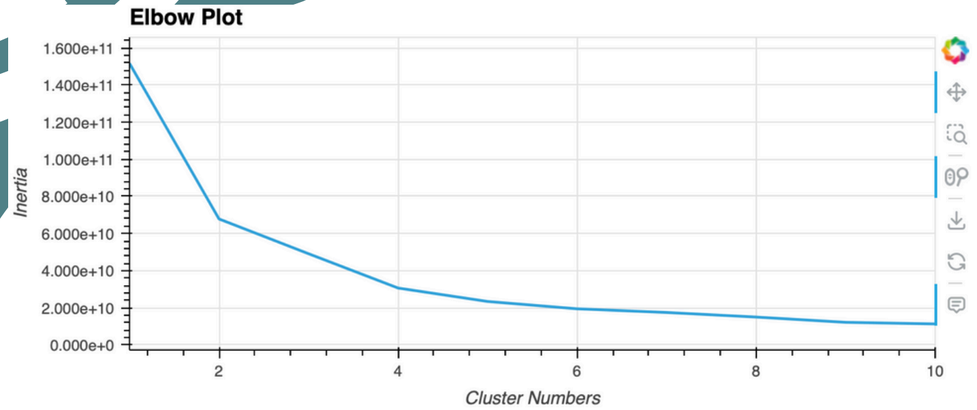


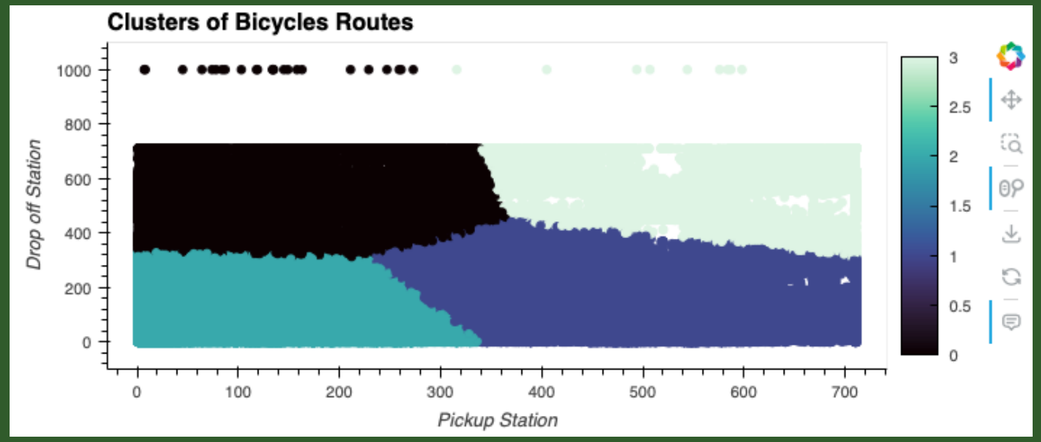
2. Route Analysis

For this model we used the K Means clustering model.



Most used routes prediction

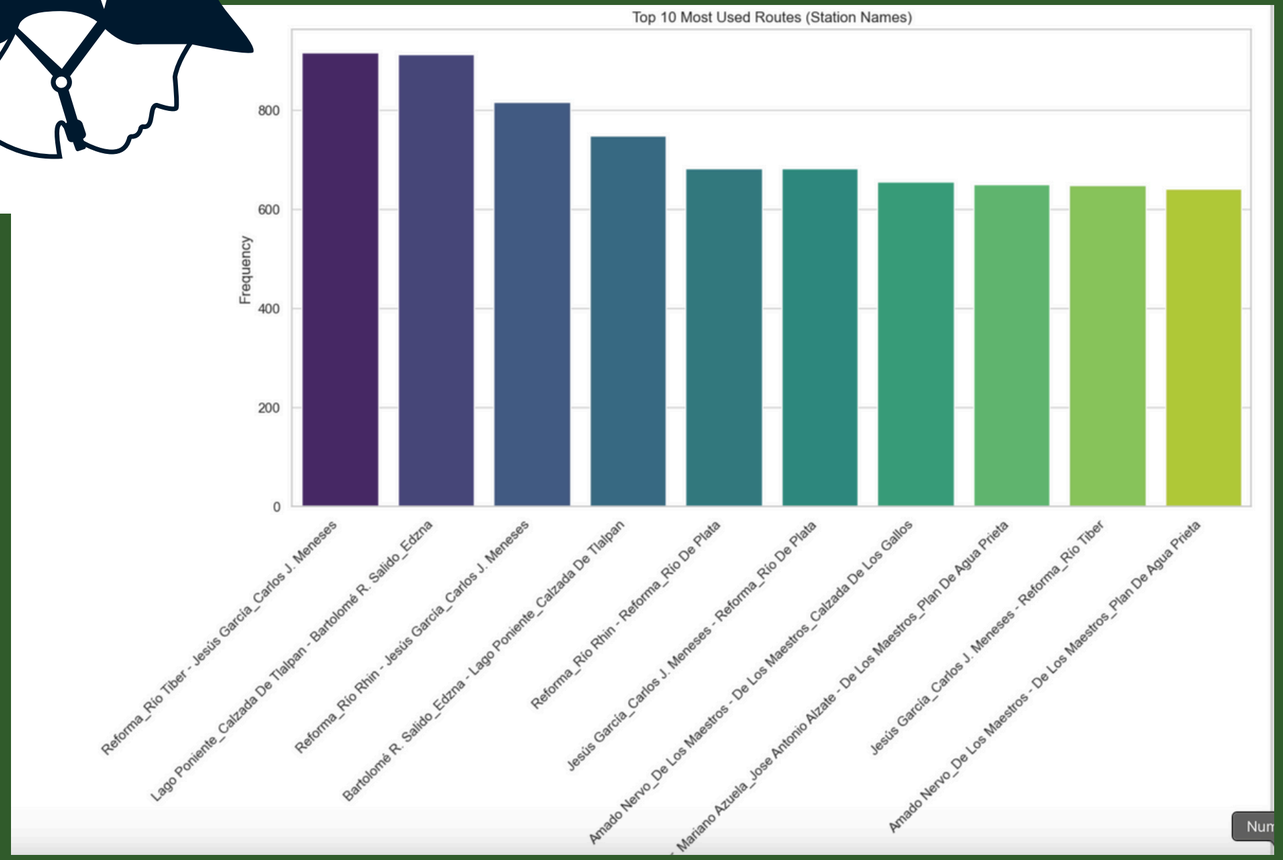




Top 10 Most used predicted routes by the model

TOP 10 ROUTES	Frequency
Route_Names	**Frequency**
Reforma_Río Tiber - Jesús García_Carlos J. Meneses	917
Lago Poniente_Calzada De Tlalpan - Bartolomé R. Salido_Edzna	913
Reforma_Río Rhin - Jesús García_Carlos J. Meneses	817
Bartolomé R. Salido_Edzna - Lago Poniente_Calzada De Tlalpan	748
Reforma_Río Rhin - Reforma_Río De Plata	683
Jesús García_Carlos J. Meneses - Reforma_Río De Plata	682
Amado Nervo_De Los Maestros - De Los Maestros_Calzada De Los Gallos	656
Dr. Mariano Azuela_Jose Antonio Alzate - De Los Maestros_Plan De Agua Prieta	651
Jesús García_Carlos J. Meneses - Reforma_Río Tiber	648
Amado Nervo_De Los Maestros - De Los Maestros_Plan De Agua Prieta	642

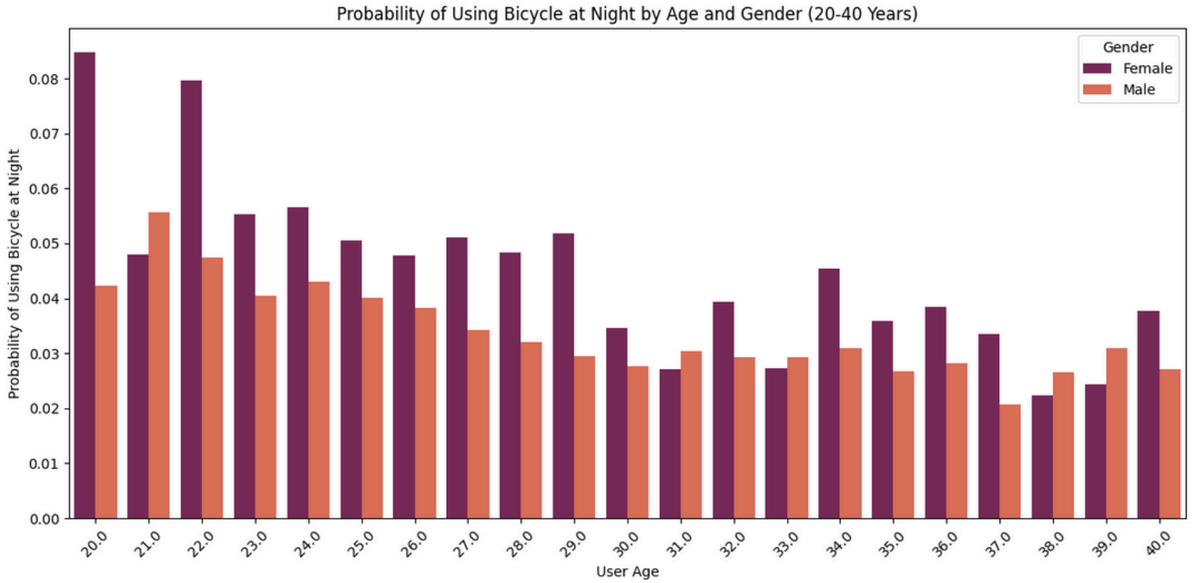
Accuracy of the K Means model: **67%**



3. User Classification

For this model we used the Random Forest Regressor Method

Usage Patterns predictions by demographics

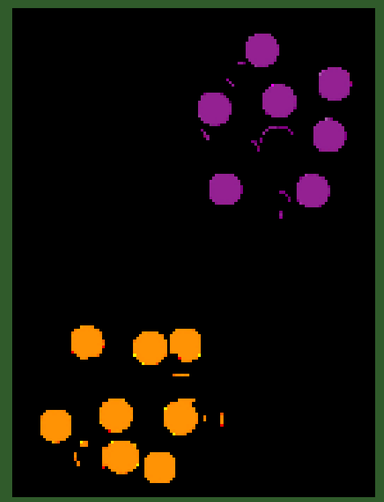


To better understand how the system is being used across the city, we analyzed recent usage data. We explored user behavior, peak hours, the most active stations, and user demographics.

Accuracy of the Random Forest Regression Model: **96%**

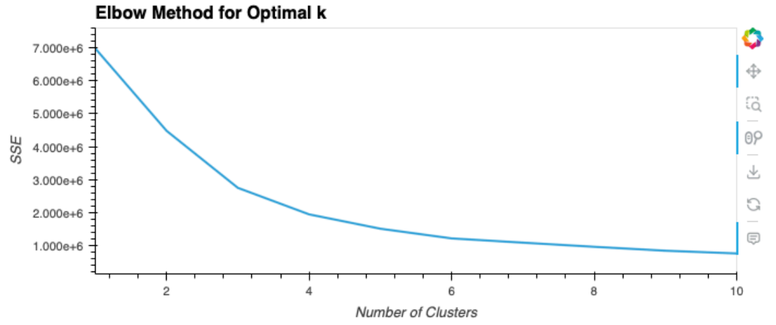
4. User Segmentation

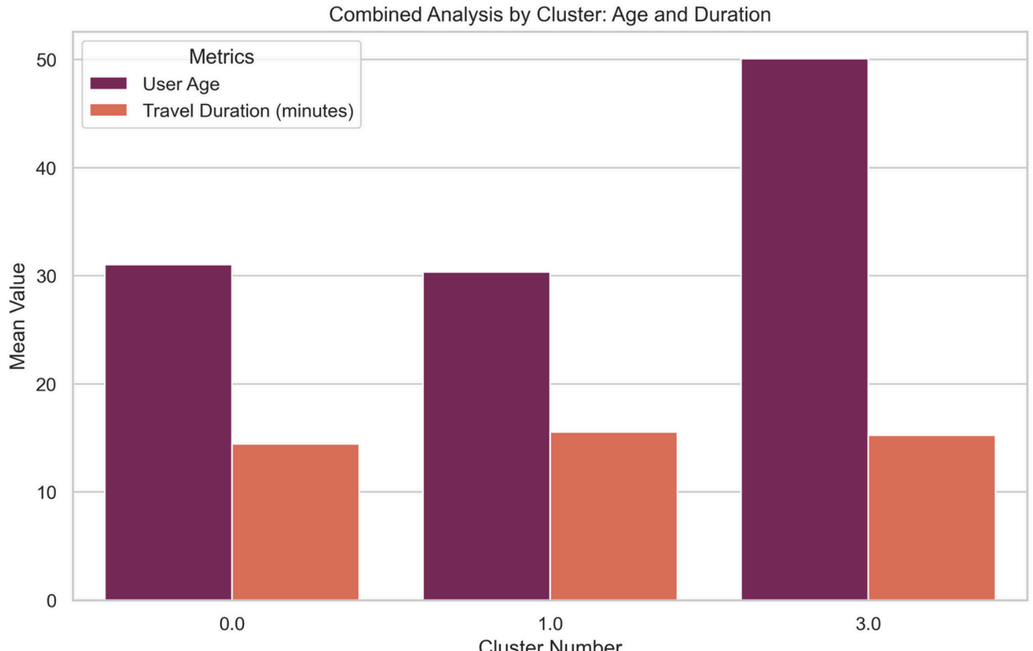
For this model we used the K Means clustering model.



User Segmentation

Groups users into different segments based on their usage behavior, which can help with marketing campaigns or service improvements.





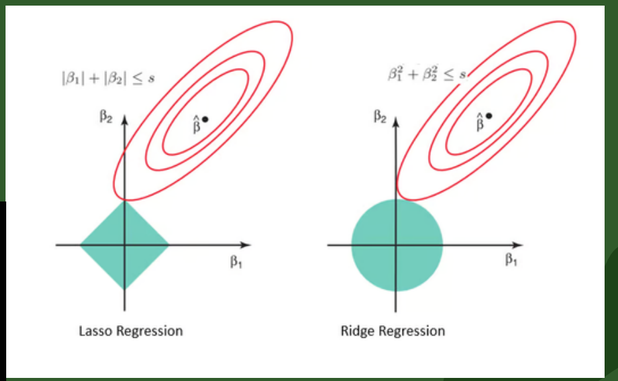
Accuracy of the K Means clustering model for user segmentation:

71%

5. Trip duration

For this intend we use 5 different approaches to get a different perspective:

a) Linear Regression
b) Ridge
c) Lasso Regression
d) Decision Tree Regression
e) Random Forest Regressor



SPLITTING THE DATASET

To compare how different machine learning models perform, we first split the dataset: one part for training and the other for testing.

pandas: For handling tabular data (reading CSVs, manipulating DataFrames, etc.).

LabelEncoder (from sklearn.preprocessing): Allows you to transform categorical variables into numeric values (e.g., convert 'M' / 'F' to 0 / 1).

train_test_split (from sklearn.model_selection): Facilitates randomly splitting a DataFrame (or arrays) into training and test sets.

After reading the dataset, information was taken from the trip start date and time columns, as well as the trip end date and time, to create a "trip duration" column.

Outlayers were removed from this dataset to improve travel time prediction results.

(Only trips longer than 10 minutes and shorter than 120 minutes)

Apply one-hot encoding to Hour_Day and Day_Week. This means that instead of having a column with numeric values (0–23 for the hour, 0–6 for the day), binary (dummy) columns are created that indicate "true/false" for each possible value.

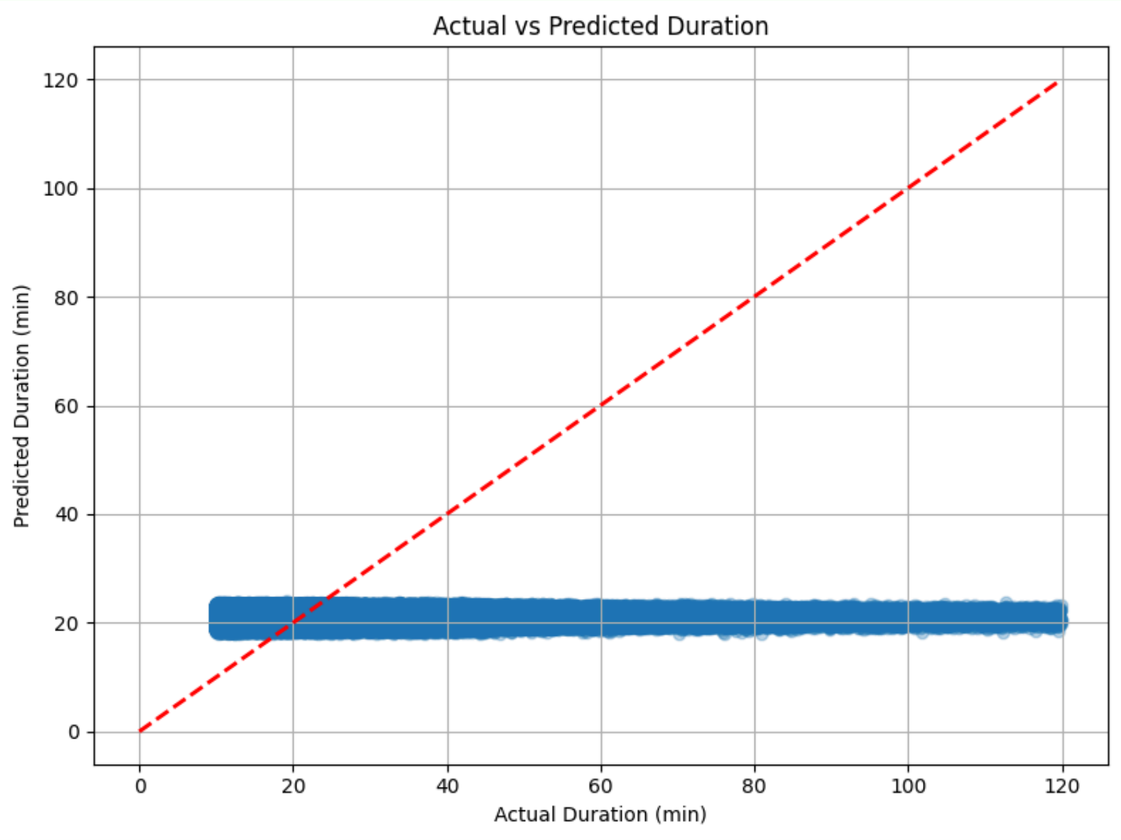
The data was split into 80% training (X_train, y_train) and 20% test (X_test, y_test).

The data was then exported into pickle files.

TRAINING SOME MODELS

LINEAR REGRESSION

MAE: 7.68 minutes
RMSE: 102.57 minutes
R^2 Score: 0.0091



MAE (Mean Absolute Error) shows average error in the same units.

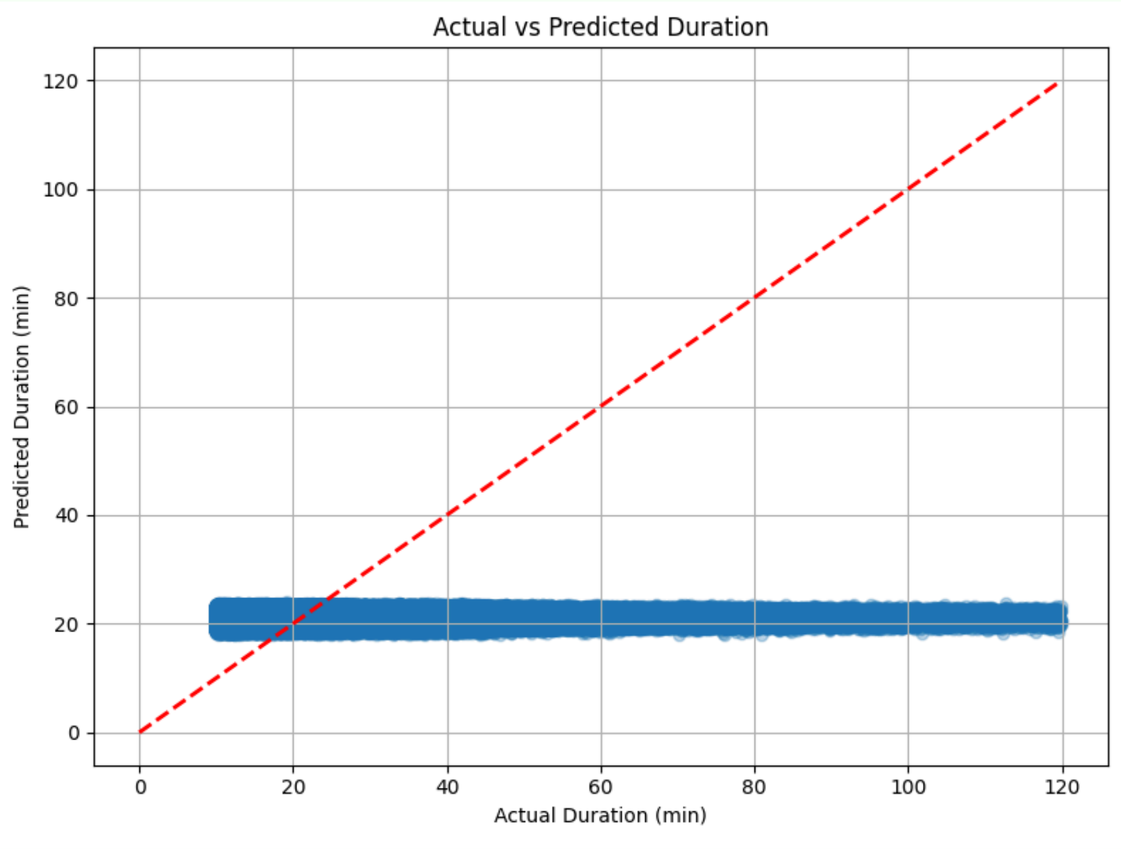
RMSE (Root Mean Squared Error) penalizes large errors more heavily.

R^2 Score (coefficient of determination) shows how much variance in duration is explained by the model (1.0 is perfect, 0.0 means "as good as mean", negative means worse).

TRAINING SOME MODELS

RIDGE

MAE: 7.68 minutes
RMSE: 102.57 minutes
R^2 Score: 0.0091



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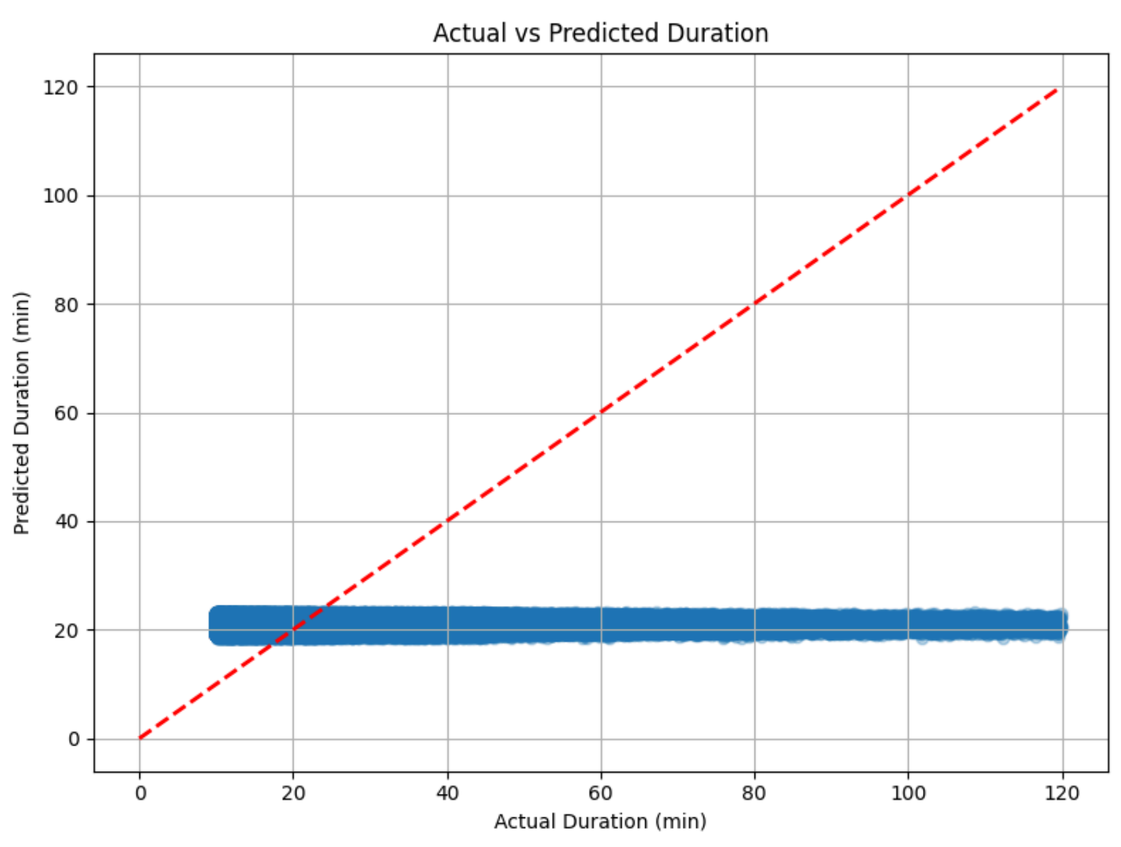
RMSE (Root Mean Squared Error) penalizes large errors more heavily.

R^2 Score (coefficient of determination) shows how much variance in duration is explained by the model (1.0 is perfect, 0.0 means "as good as mean", negative means worse).

TRAINING SOME MODELS

LASSO REGRESSION

MAE: 7.68 minutes
RMSE: 102.60 minutes
R^2 Score: 0.0088



MAE (Mean Absolute Error) shows average error in the same units.

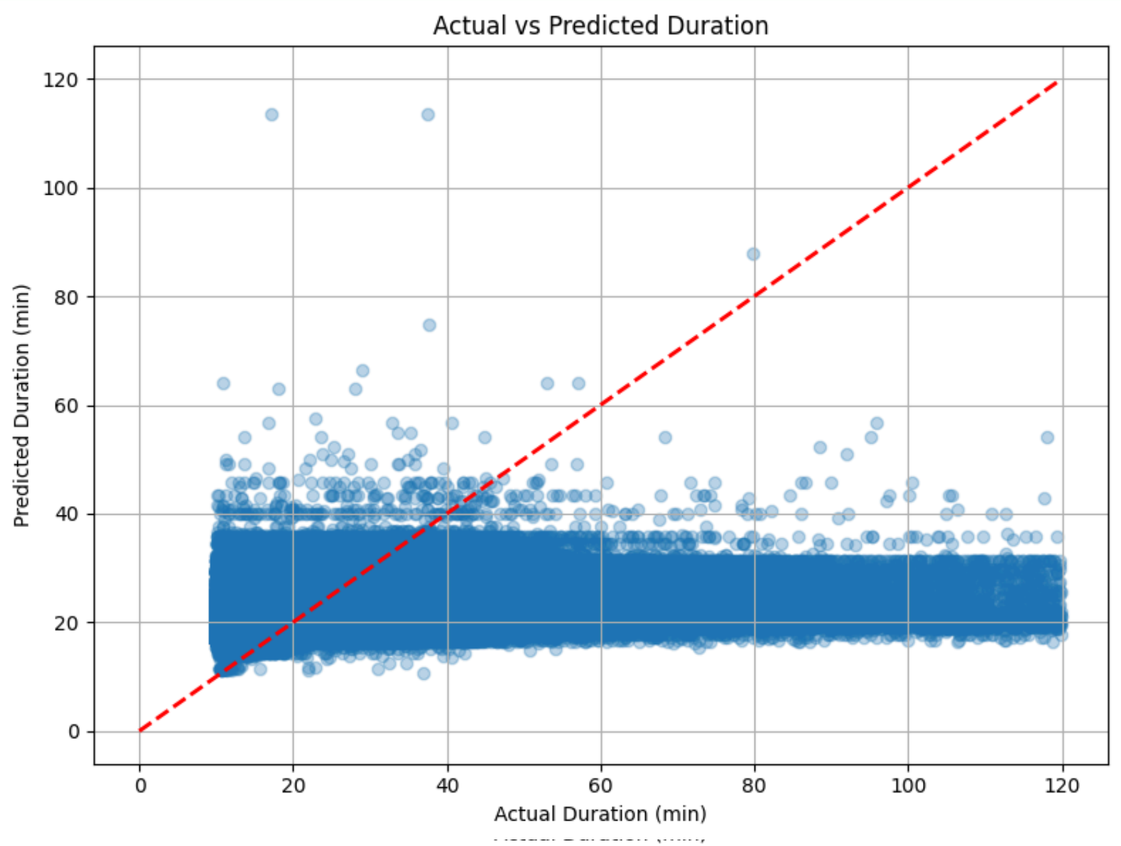
RMSE (Root Mean Squared Error) penalizes large errors more heavily.

R^2 Score (coefficient of determination) shows how much variance in duration is explained by the model (1.0 is perfect, 0.0 means "as good as mean", negative means worse).

TRAINING SOME MODELS

DECISION TREE REGRESSOR

MAE: 7.49 minutes
RMSE: 98.83 minutes
R^2 Score: 0.0453



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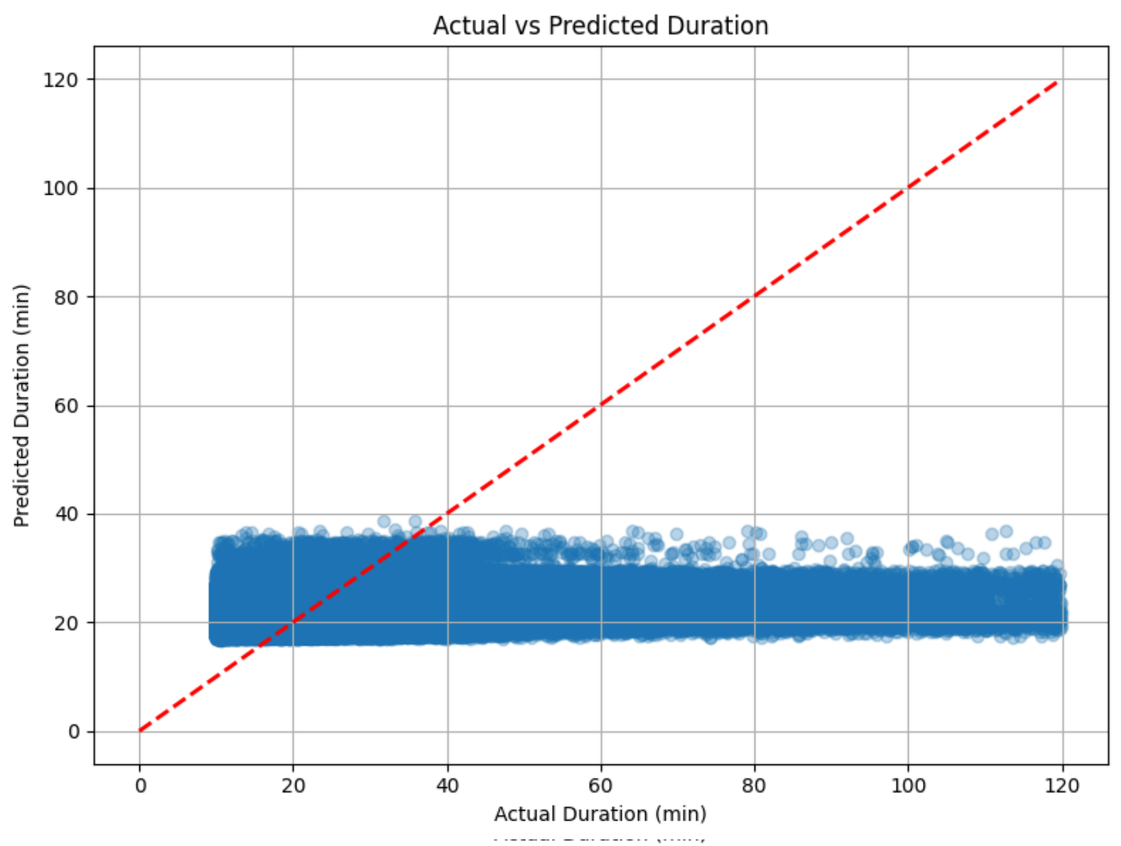
RMSE (Root Mean Squared Error) penalizes large errors more heavily.

R^2 Score (coefficient of determination) shows how much variance in duration is explained by the model (1.0 is perfect, 0.0 means "as good as mean", negative means worse).

TRAINING SOME MODELS

LGBM REGRESSOR

MAE: 7.46 minutes
RMSE: 98.25 minutes
R^2 Score: 0.0509



MAE (Mean Absolute Error) shows average error in the same units.

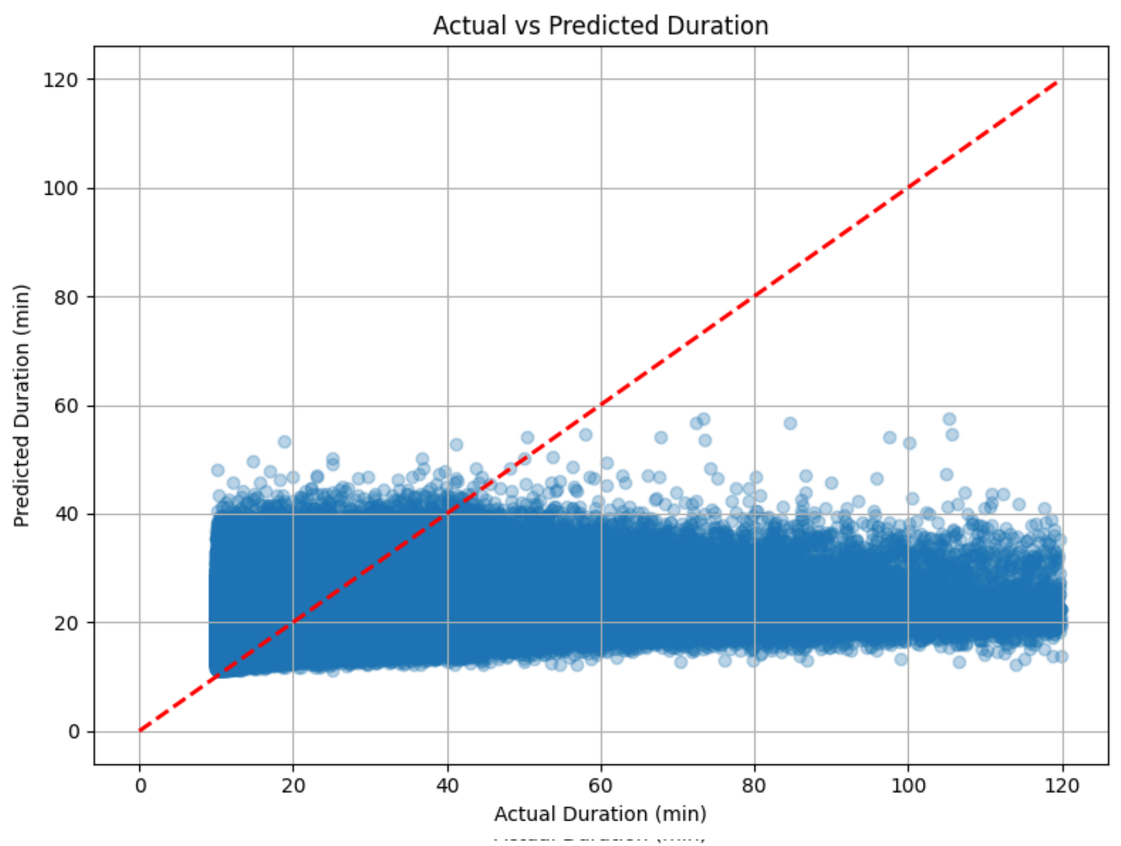
RMSE (Root Mean Squared Error) penalizes large errors more heavily.

R^2 Score (coefficient of determination) shows how much variance in duration is explained by the model (1.0 is perfect, 0.0 means "as good as mean", negative means worse).

TRAINING SOME MODELS

RANDOM FOREST REGRESSOR

MAE: 7.04 minutes
RMSE: 92.49 minutes
R² Score: 0.1065



MAE (Mean Absolute Error) shows average error in the same units.

RMSE (Root Mean Squared Error) penalizes large errors more heavily.

R² Score (coefficient of determination) shows how much variance in duration is explained by the model (1.0 is perfect, 0.0 means "as good as mean", negative means worse).

Conclusions

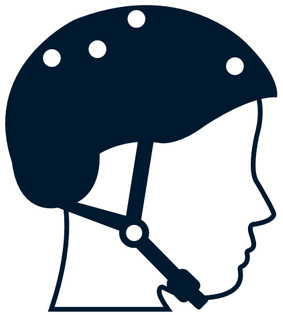
Based on the analysis carried out with the different machine learning models, these are some of the areas of opportunity that we believe can be obtained by training and improving the models presented.

Bicycle Demand Prediction

Understanding which stations tend to be used together or share usage patterns can help with transport logistics and bicycle redistribution.

Identification of high-demand areas

Areas with high concentrations of usage can be identified for the location of new stations or the adjustment of the size of current ones.



Ride Duration Insights

Predicting trip duration, we could explore factors influencing ride length, such as distance, time of day, or user experience, indicating potential areas for service improvements.

Targeted marketing

Understanding the demographics and patterns of users who use a group's stations can provide insights for more effective and targeted marketing campaigns.

RESOURCES PAGE

1. Gobierno de la Ciudad de México. (n.d.). Ecobici. https://ecobici.cdmx.gob.mx/
2. Gobierno de la Ciudad de México. (n.d.). Mapa de Ecobici. https://ecobici.cdmx.gob.mx/mapa/
3. ECOBICI. (n.d.). Datos abiertos. Gobierno de la Ciudad de México. https://ecobici.cdmx.gob.mx/datos-abiertos/
4. Wikipedia contributors. (n.d.). Ecobici (Ciudad de México). Wikipedia. https://es.wikipedia.org/wiki/Ecobici_(Ciudad_de_M%C3%A9xico)

THANK YOU!

https://github.com/lord-byront/ml-mexico-city-bikes/