MAY 2025

Divvy Trip Data *Analysis*

Losstng

This presentation is made as an example to showcase my ability and as part of Coursera Google Data Analytics Program.

Agenda

MAY 2025

- 01 Purpose
- 02 Data
- 03 Findings
- 04 Challenges
- 05 Recommendations
- 06 Reflection

Presentation's Purpose

Purpose

To analyze user behavior and ride patterns within Divvy's bike-sharing system—
with the goal of uncovering strategic insights that drive membership conversion, optimize operational efficiency, and inform targeted marketing efforts.

Current casual vs member population ratio: **71.26% vs 28.4%**

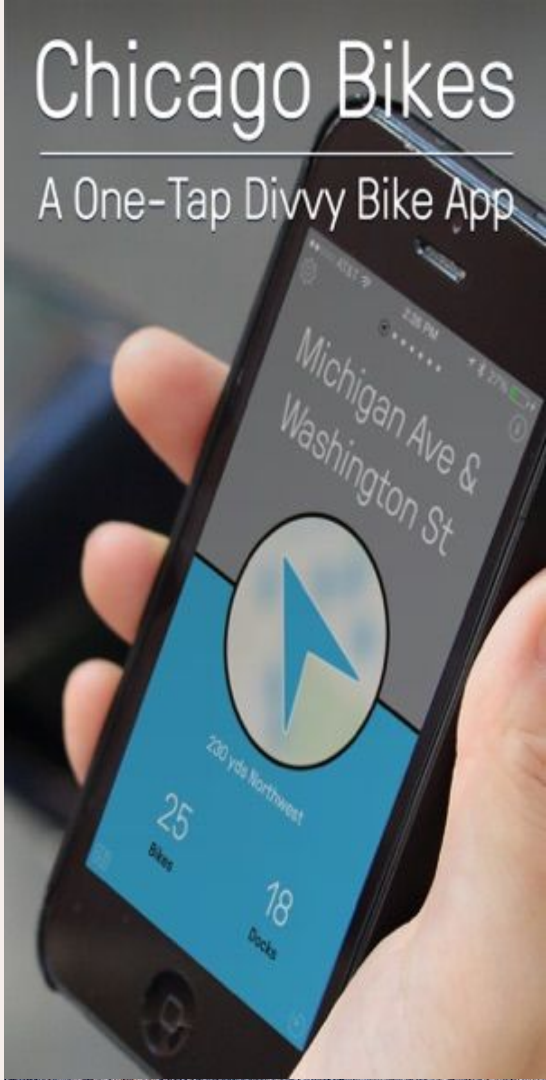
Objectives

Identify temporal trends (e.g., weekday vs. weekend usage)

Compare ride behavior between casual vs. member users

Assess preferences by bike type and station location

Recommend data-driven actions to improve user experience and resource allocation



Dataset Overview

MAY 2025

Base Attributes

ride_id — *Unique identifier for each trip*

rideable_type — *Type of bike used (e.g., classic, electric)*

started_at, ended_at — *Timestamps of trip initiation and completion*

start_station_name, end_station_name — *Text labels for station names*

start_station_id, end_station_id — *Unique station IDs*

start_lat, start_lng, end_lat, end_lng — *Coordinates of trip start and end*

member_casual — *Rider type: member or casual*

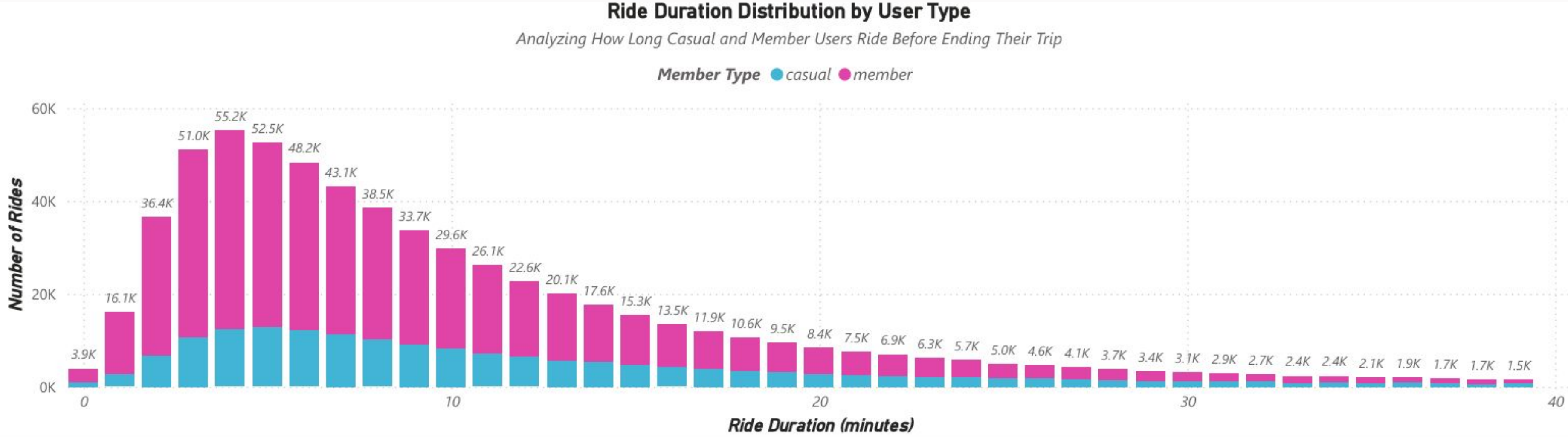
Calculated Fields

duration — *Total ride time (in minutes)*

weekday — *Day of the week on which the ride was taken*

This analysis utilizes cleaned ride data from *Divvy's bike-share program*, focusing on the months of **March** *(293,290 observations)* and **April** *(365,125 observations)*.

Findings - Duration x User Type



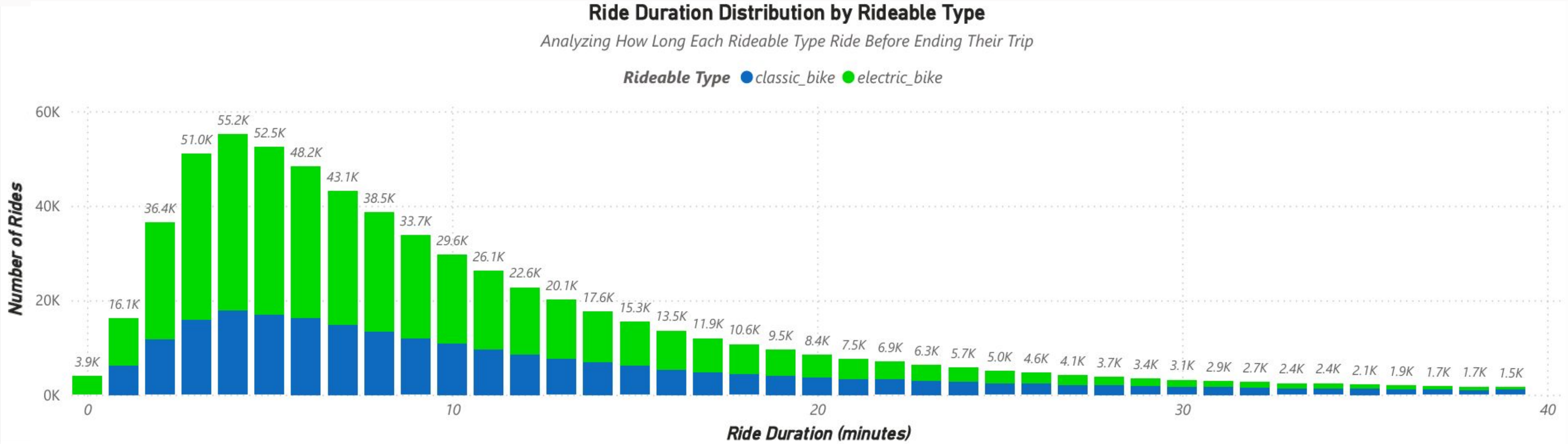
Key Findings – Ride Duration by User Type

➛ **Casual users are rare below 3 minutes**, suggesting deterrence from unlock fees.

➛ **Members dominate trips under 25 minutes**, indicating frequent short rides, likely for commuting.

➛ After 25 minutes, **ride volumes converge**, showing similar behavior for longer trips.

Findings - Duration x Rideable Type



Key Findings – Ride Duration by Rideable Type

➢ **Electric bikes dominate short trips**, suggesting users favor convenience and quicker access for shorter distances.

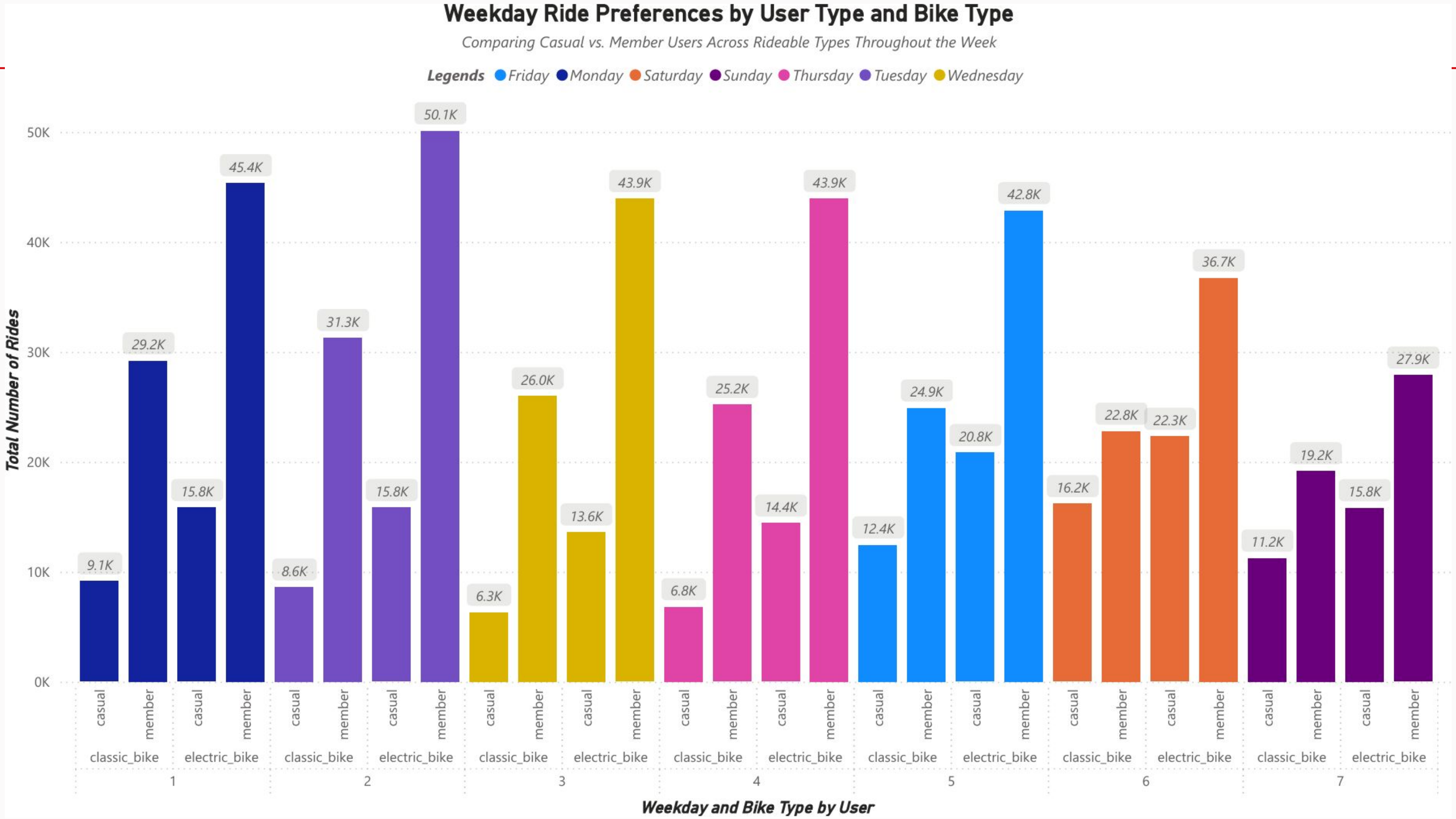
➢ **Classic bike usage grows with duration**, indicating they're preferred for longer, leisurely rides.

➢ **Electric bike volume sharply declines after 20 minutes,** likely due to battery limits or pricing structure disincentives.

Findings - Member Type x Rideable Type x Weekday

Key Findings

- **Members ride consistently throughout weekdays,** especially on Tuesday (50.1K) and Thursday (43.9K), aligning with likely work commutes.
- **Casual user volume spikes on weekends,** notably Saturday and Sunday, indicating leisure-based usage.

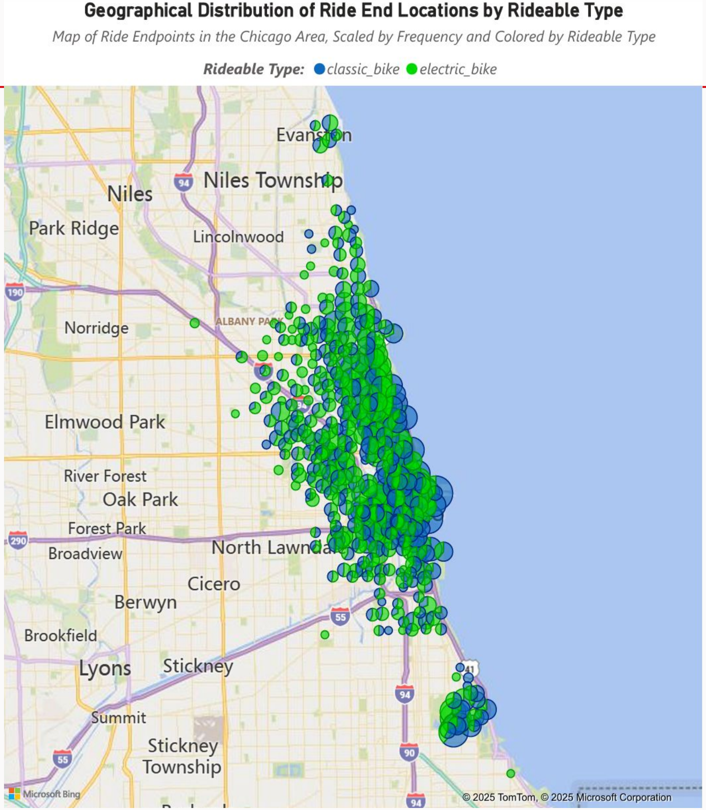


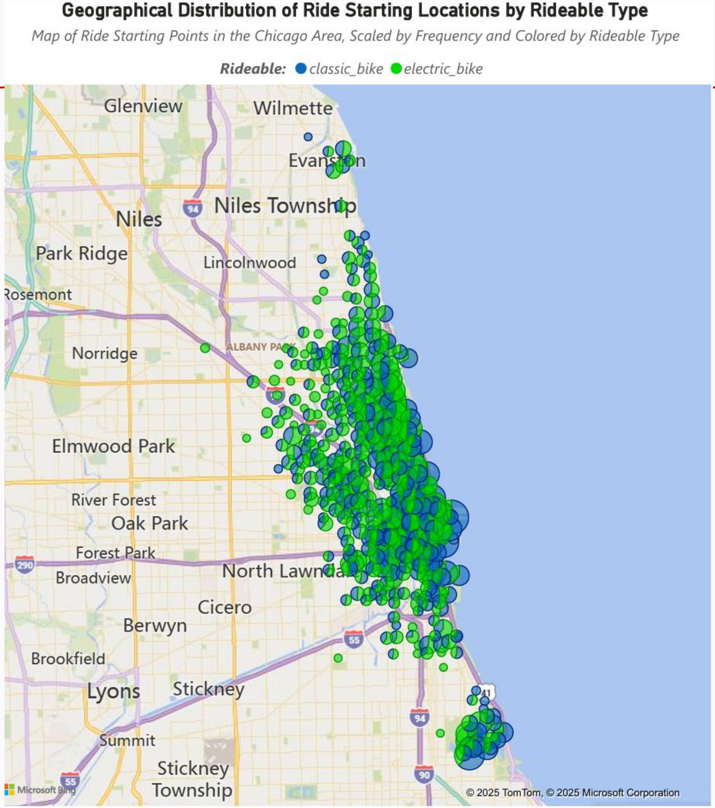
Findings - Location x Rideable Type x Frequency

Key Findings

- **Classic bikes dominate outer regions (e.g., Evanston in the north and South Shore),** which could be due to limited infrastructure.

- **Overall spatial distribution mirrors typical commuter corridors,** especially along the lakeshore and city center.



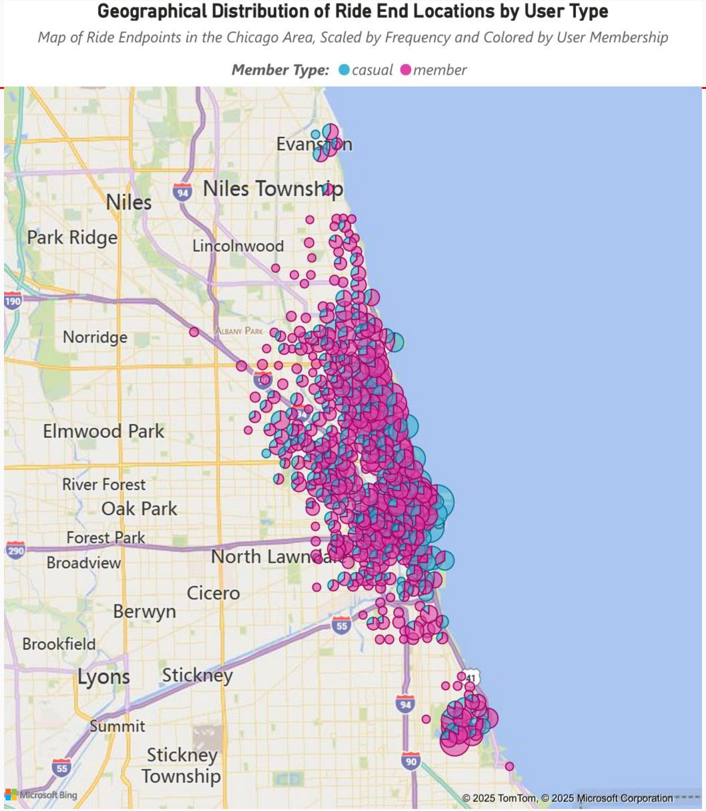


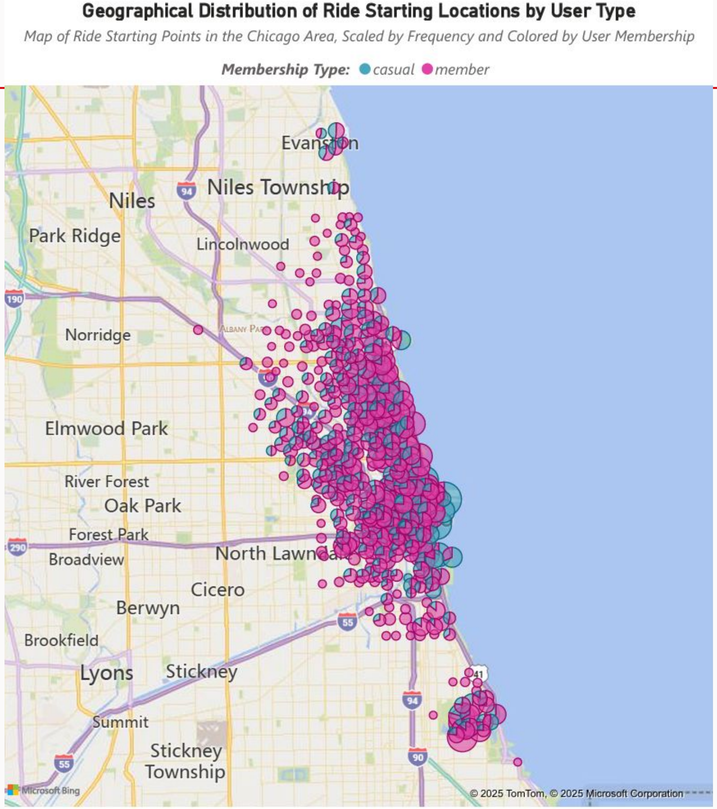
Findings - Location x Member Type x Frequency

Key Findings

- **Members dominate outer zones,** particularly in the far north and south, indicating more structured commuting patterns.

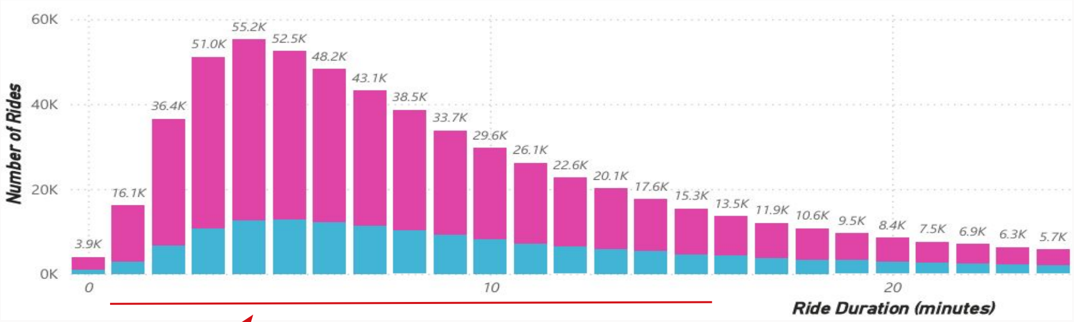
- **Casual users cluster in central city areas,** likely tied to leisure or tourist usage.





Inferred Challenges

The challenge, then, is not just to **increase usage**—but to **reshape how casual users experience and perceive value,** nudging them toward habitual, member-style behavior.



Problem 1

Low retention potential – casual riders take infrequent, leisure-based trips (mostly weekends, city center), indicating poor alignment with membership benefits.

Problem 2

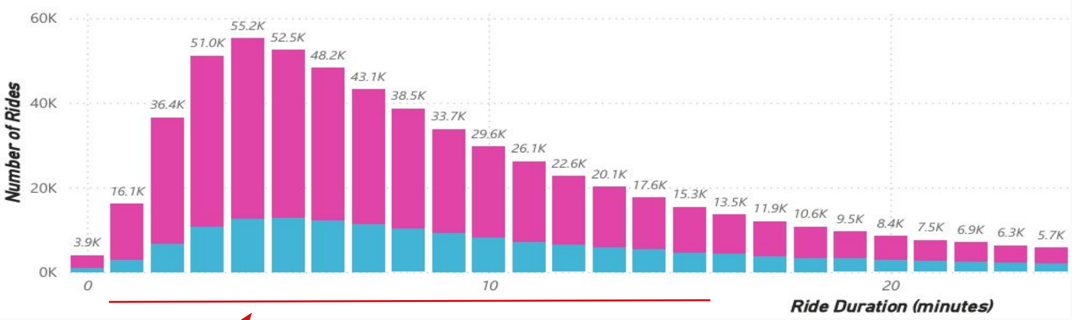
Cost sensitivity – brief trip durations, especially under 3 minutes, imply avoidance of unlock fees, suggesting pricing friction deters deeper usage.

Problem 3

Lack of peripheral exposure – casual riders are underrepresented in outlying zones where commuter demand and infrastructure are better aligned with membership value.

Recommendations

To convert casual users into committed members, we must **incentivize habitual usage by gradually aligning their behavior with that of current members.**



Solution 1

Geo-Targeted Campaigns - Promote special offers or trial memberships near central hotspots and fringe transition zones where casual activity is dense but member presence is weak—guiding users outward.

Solution 2

Progressive Conversion Triggers - Introduce a "Convert-as-you-go" model: after a threshold number of rides within a month, casual users receive a prorated discount toward an annual plan, making the transition feel earned and value-based.

Solution 3

Time-Based Micro-Incentives - Offer weekday discounts or off-peak bundles for casual rides under 25 minutes—where member usage is strongest—to simulate commuter-like patterns and reduce cost sensitivity.

*Reflections - **Personal***

What could have been done better, critically reviewed.

Problem 1

Comprehensive timeframe -
This problem lays in the limited capability of my computer hardware and the processing ability of Big Query.

Solution 1

Local environment > Cloud-based -
Installing R studio and using other solutions that are free.

Problem 2

The usage map could be better -
For reasons of the computer's limitation, the difficulty in calculating the location, and truthfully display the exact location.

Solution 2

Filter out unnecessary trips -
This could work as limiting to just trips in a certain duration time frame, however it would untruthfully reflect the data.[

Problem 3

Working Structure -
As a part of this program, this is my first ever case study and project on analytics therefore the workflow could be improved

Solution 3

Improved on this & work on more -
From this project now I have a clear understanding of the workflow, and will be able to better myself with future projects.

Thank You

MAY 2025

Losstng

This presentation is made as an example to showcase my ability and as part of Coursera Google Data Analytics Program.