

Google's Cyclistic Bike-Share Case Study

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Role: Junior Data Analyst

Overview and Objective:

About Cyclistic

• Cyclistic is a Chicago-based bike-share company with a fleet of over 5,800 bicycles and more than 600 docking stations. The service supports both recreational and commuting needs, with about 30% of riders using bikes for work commutes.

Project Objective

- The Cyclistic marketing team aims to increase annual memberships by converting more casual riders into long-term members.
- This project analyzes 12 months of historical ride data to identify key behavioral patterns between rider types and generate data-driven insights to support targeted marketing strategies.

Data Source:

Cyclistic's 12-month ride data, split into 4 quarterly CSV files from the year 2019.

- Divvy_Trips_2019_Q1.csv
- Divvy_Trips_2019_Q2.csv
- Divvy_Trips_2019_Q3.csv
- Divvy_Trips_2019_Q4.csv

Tools Used:

- Python (Pandas, Seaborn, Matplotlib)
- Jupyter Notebook
- CSV file handling
- Data Cleaning & Preprocessing
- EDA & Visualization

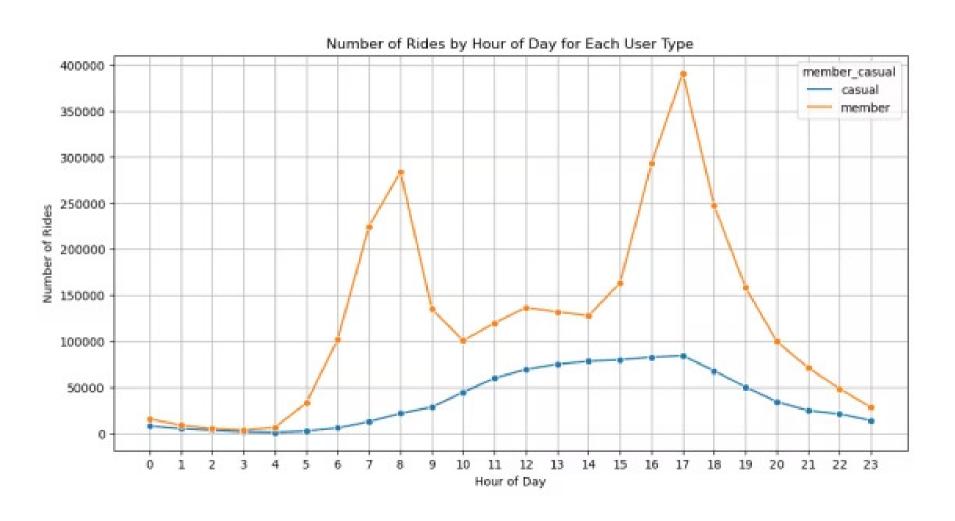
Process Overview:

- Data Cleaning: Standardized mismatched column names across quarters.
- Merging: Combined all quarters into one complete dataset.
- Feature Engineering: Extracted trip duration, ride hour, day, month, etc.
- Exploratory Data Analysis: Uncovered patterns using visualizations.
- Insights & Recommendations: Based on rider behavior.

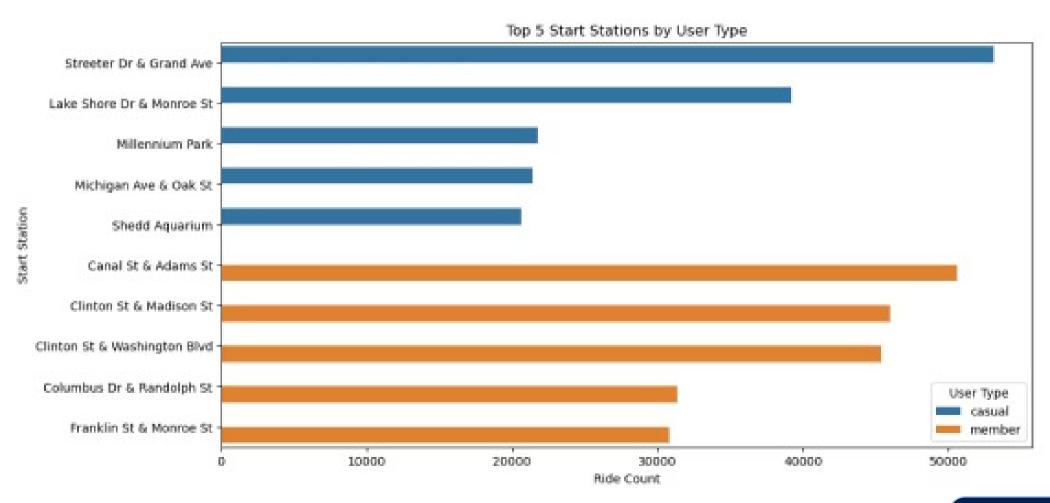
Key Business Questions Answered:

- How do annual members and casual riders use Cyclistic bikes differently?
- When do members and casual riders typically ride?
- What are the most popular stations?
- What is the average ride duration per user type?
- Which days and times are most popular?
- What do seasonal trends tell us?
- What are the peak usage hours?
- Can we predict rider type based on ride behavior?

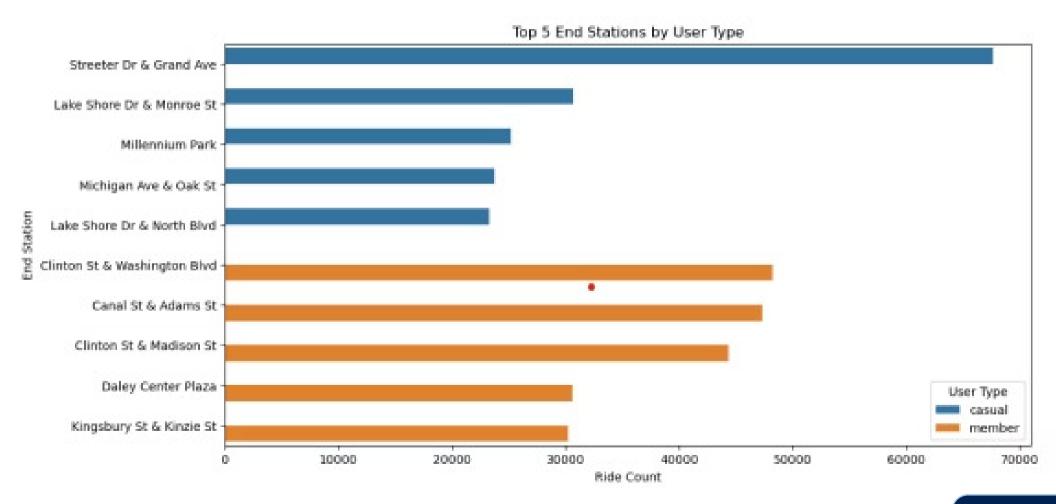
Q1) When do members and casual riders typically ride?



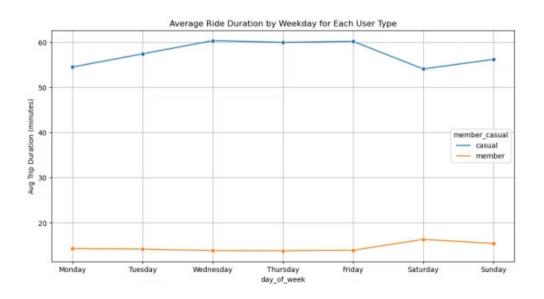
Q2) What are the most popular Start stations?



Q3) What are the most popular End stations?

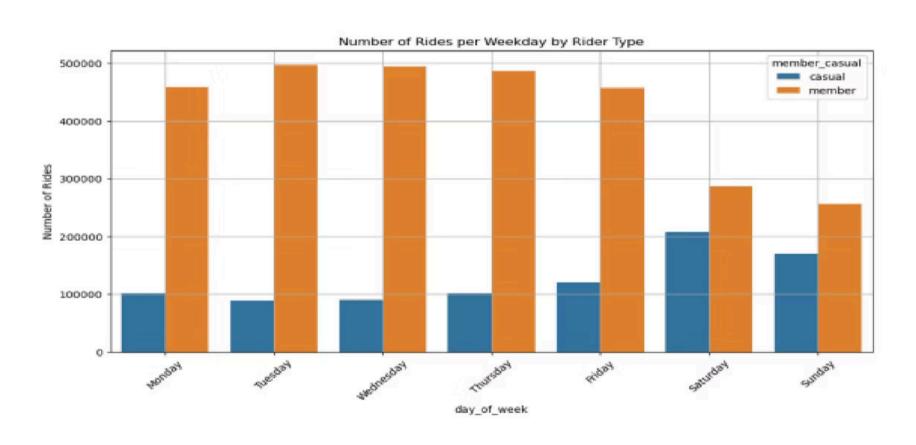


Q4) What is the average ride duration per user type?



	member_casual	day_of_week	avg_trip_minutes
0	casual	Monday	54.499889
1	casual	Tuesday	57.413284
2	casual	Wednesday	60.334066
3	casual	Thursday	59.951123
4	casual	Friday	60.175611
5	casual	Saturday	54.061110
6	casual	Sunday	56.181687
7	member	Monday	14.249284
8	member	Tuesday	14.152592
9	member	Wednesday	13.809845
10	member	Thursday	13.779792
11	member	Friday	13.897478
12	member	Saturday	16.302705
13	member	Sunday	15.401188

Q5) What days do riders ride the most?



Q6) How do ride trends change month-over-month?



Conclusion:

Rider Type Behavior:

- Members take more frequent but shorter rides, likely for commuting or quick errands.
- Casual riders take longer rides, often during weekends or holidays possibly for leisure or exploration.

Temporal Trends:

- Members ride more consistently during weekdays, especially during morning and evening peak hours (commute times).
- Casuals prefer afternoons and weekends, with activity peaking between 12 PM to 6 PM.

Conclusion:

Ride Duration

Casual riders consistently have higher average ride durations, which may indicate less familiarity with the system or more exploratory behavior.

Station Popularity

Certain stations appear frequently in both start and end points, showing high-traffic hubs — ideal for targeted promotions or better bike availability.

Seasonality

There is a clear rise in casual ridership during summer months, aligning with better weather and tourism.

Business Insights:

Opportunity to Convert Casuals to Members:

Casual riders exhibit regular behavior patterns — especially on weekends. Targeting these users with weekend-specific "limited trial memberships" could convert them.

Fleet and Station Optimization:

Since peak usage hours and stations are known, redistribution of bikes and staffing can be planned more efficiently.

Marketing Strategy:

Casual riders can be targeted with experience-based offers, like guided bike tours or weekend bundle packages.

Members can be retained by offering loyalty perks or work commute-related incentives.

Recommendations:

- Target casual riders who ride often but haven't converted offer promo codes and in-app nudges to try membership for a week.
- Strengthen inventory at high-demand stations during peak hours and seasons using predictive models.
- Run seasonal campaigns (e.g., summer rides, holiday-themed routes) focused on casual users.

Limitations:

- Missing values in 'gender' and 'birthyear' but does not affect our analysis.
- No geolocation data available for mapping analysis.