

Cyclistic Bike-Share Case Study

How Annual Members and Casual Riders Use Cyclistic Bikes Differently

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1. Business Task

- **Statement of the Business Task**

As a junior data analyst on the Cyclistic marketing analytics team, I have been tasked to answer the following business question:

- **how casual riders and annual members use Cyclistic bikes differently?**

The goal is to get insights based on the riders data, which will help my team to design a new marketing strategy to convert casual riders into annual members.

- **Stakeholders**

- Lily Moreno (Director of Marketing)
- Cyclistic Marketing Analytics Team
- Cyclistic Executive Team.

2. Data sources

- **Data Used**

I used data that represent 1 year time frame to make the analyzing process more accurate. The data that was used:

- [202410-divvy-tripdata](#)
- [202411-divvy-tripdata](#)
- [202412-divvy-tripdata](#)
- [202501-divvy-tripdata](#)
- [202502-divvy-tripdata](#)
- [202503-divvy-tripdata](#)
- [202504-divvy-tripdata](#)
- [202505-divvy-tripdata](#)
- [202506-divvy-tripdata](#)
- [202507-divvy-tripdata](#)
- [202508-divvy-tripdata](#)
- [202509-divvy-tripdata](#)
- [202510-divvy-tripdata](#)

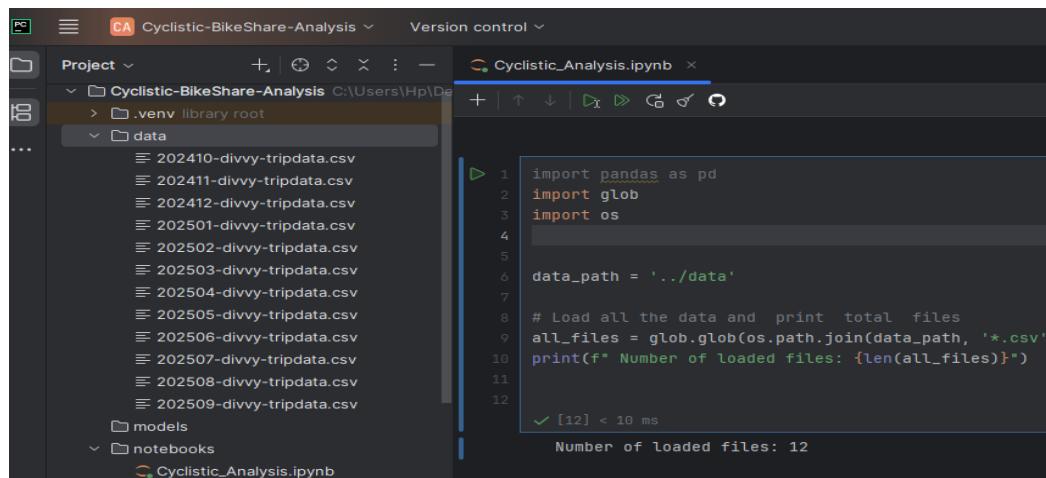
These datasets are public trip records provided by the City of Chicago and Motivate International Inc. under the [Divvy Data License Agreement](<https://www.divvybikes.com/data-license-agreement>) (open data for non-commercial use). Note that the files are named "Divvy" instead of "Cyclistic" because Cyclistic is a fictional company in this case study, but the data is equivalent and suitable for analysis.

- **Data Organization and Integrity (ROCCC Evaluation):**

- **Reliable**: Sourced from official Divvy records (City of Chicago), with consistent structure across files.
- **Original**: First-hand trip logs from the bike-share system.
- **Comprehensive**: Covers 5–6 million trips, including start/end stations, bike types, and user types (no personally identifiable information for privacy).
- **Current**: Latest available data up to October 2025.
- **Cited**: All files from <https://divvy-tripdata.s3.amazonaws.com/index.html>.

- **Privacy and Accessibility Notes**

- No personally identifiable information
- Data is freely accessible.



The screenshot shows a Jupyter Notebook environment with the following details:

- Project View:** The left sidebar displays a project structure with a folder named "Cyclistic-BikeShare-Analysis". Inside this folder are sub-folders ".venv", "data", "models", and "notebooks". The "data" folder contains 12 CSV files, each named "202410-divvy-tripdata.csv", "202411-divvy-tripdata.csv", etc., up to "202509-divvy-tripdata.csv".
- Notebook Cell:** The main area shows a code cell with the following Python code:

```
import pandas as pd
import glob
import os

data_path = '../data'

# Load all the data and print total files
all_files = glob.glob(os.path.join(data_path, '*.csv'))
print(f" Number of loaded files: {len(all_files)}")
```
- Output:** The code cell has run successfully, with the output "Number of loaded files: 12" displayed below it.

Figure 1: Showing 12 CSV files loaded

3. Data Cleaning & Preparation

- Tools Used

I used pandas - Python Data Analysis Library in Jupyter Notebook

- Initial Data Overview

The data contains 5,539,521 rows, which represent the total trips over a year.

There are also 13 Columns: ride_id, rideable_type, started_at, ended_at, start_station_name, start_station_id, end_station_name, end_station_id, start_lat, start_lng, end_lat, end_lng, member_casual.

The screenshot shows a Jupyter Notebook environment with the following details:

- Project Structure:** The left sidebar displays the project structure: `Cyclistic-BikeShare-Analysis` containing `.venv`, `data` (with multiple CSV files), `models`, and `notebooks` (containing `Cyclistic_Analysis.ipynb`).
- Notebook Content:** The right pane shows the `Cyclistic_Analysis.ipynb` notebook. The code cell contains the following Python script:

```
import pandas as pd
import glob
import os

data_path = '../data'

# Load all the data and print total files
all_files = glob.glob(os.path.join(data_path, '*.csv'))
#print(f" Number of loaded files: {len(all_files)}")

# Append all data in files to a single list
df_list = []
for file in all_files:
    temp_df = pd.read_csv(file)
    df_list.append(temp_df)

# Get number of rows and columns
df = pd.concat(df_list, ignore_index=True)
print(f" Rows and columns: {df.shape}")

[16] 11s 878ms
```
- Output:** The output of the code cell is visible at the bottom, showing the result of the `print(f" Rows and columns: {df.shape}")` command: `Rows and columns: (5539521, 13)`.

Figure 2: Successful merge all data (5539521 columns, 13 rows)

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5539521 entries, 0 to 5539520
Data columns (total 13 columns):
 #   Column            Dtype  
 ---  --  
 0   ride_id           object 
 1   rideable_type     object 
 2   started_at        object 
 3   ended_at          object 
 4   start_station_name object 
 5   start_station_id  object 
 6   end_station_name  object 
 7   end_station_id   object 
 8   start_lat          float64
 9   start_lng          float64
 10  end_lat           float64
 11  end_lng           float64
 12  member_casual     object 
dtypes: float64(4), object(9)
memory usage: 549.4+ MB
None
```

Figure 3: Columns and their data types

Some rows have outliers as follow:

- started_at & ended_at are strings not datetime
- Many null values
- Some trips' duration is seconds or days

- **Cleaning Steps**

Cleaning Steps Performed:

1. Converted "started_at" and "ended_at" columns to a datetime format
2. Calculated ride duration in minutes in a new column: "ride_length_min"
3. Exclude rides shorter than 1 minute and longer than 24 hours
4. Added "day_of_week", "month", and "hour" columns to make analysis easier.

```
df['started_at'] = pd.to_datetime(df['started_at'])
df['ended_at'] = pd.to_datetime(df['ended_at'])

print(df.info())

✓ [33] 30s 76ms

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5539521 entries, 0 to 5539520
Data columns (total 13 columns):
 #   Column           Dtype    
--- 
 0   ride_id          object    
 1   rideable_type    object    
 2   started_at       datetime64[ns]
 3   ended_at         datetime64[ns]
 4   start_station_name  object    
 5   start_station_id object    
 6   end_station_name  object    
 7   end_station_id   object    
 8   start_lat         float64  
 9   start_lng         float64  
 10  end_lat          float64  
 11  end_lng          float64  
 12  member_casual    object    
dtypes: datetime64[ns](2), float64(4), object(7)
memory usage: 549.4+ MB
None
```

Figure 4: Converted 'started_at' & 'ended_at' columns to datetime

```

40
44
45 # Exclude rides shorter than 1 minute and longer than 24 hours
46 validTrips = (df['duration_minutes'] > 1) & (df['duration_minutes'] < 1440)
47 df_filtered = df[validTrips]
48
49 print(f"Count original rows: {len(df)}")
50 print(f"Count Rows after applying the filter: {len(df_filtered)}")
51 print(f"Count deleted rows: {len(df) - len(df_filtered)}")
52
✓ [38] 33s 699ms

    Count original rows: 5539521
    Count Rows after applying the filter: 5397554
    Count deleted rows: 141967

```

Figure 5: Results after applying the filter (Exclude rides shorter than 1 minute and longer than 24 hours)

```

# Adding 3 new rows day_of_week, month, hour
df['day_of_week'] = df['started_at'].dt.day_name()
df['month']      = df['started_at'].dt.month_name()
df['hour']        = df['started_at'].dt.hour

# ordering the days
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
df['day_of_week'] = pd.Categorical(df['day_of_week'], categories=day_order, ordered=True)

# Print the new columns
print("The new columns: ")
print(df[['ride_duration_mins', 'day_of_week', 'month', 'hour']].head(10))
✓ [43] 20s 929ms

    The new columns:
    ride_duration_mins day_of_week     month  hour
0           6.874200    Monday  October     3
1           5.426067   Sunday  October    19
2           7.230283   Sunday  October    23
3          11.974250    Monday  October     2
4           1.619617   Sunday  October    19
5           7.077433    Monday  October     6
6           4.770633    Monday  October     9
7           3.173750    Friday  October    21
8           1.950767   Saturday  October   11
9           0.349867   Saturday  October   12

```

Figure 6: Display the first 10 rows of the new columns.

- **Result**

After applying the filter, 141,967 rides removed and the final dataset = 5,397,554 rides

- **Handling Missing Values**

I found some missing fields in start/end station names, and I decided to keep the rows since they still contain valid duration and user type information, which are still useful in the analysis.

4. Analysis & Key Findings

– Total Rides by User Type

We have 5,397,554 total rides:

3,479,797 (64.5%) of them are Annual Members.

1,917,757 (35.5%) of them are Casual Riders.

Insight: Annual members dominate overall usage.

– Average Ride Duration

The overall average trip duration is: 14.9 minutes

for Casual Riders: 20.2 minutes

for Annual Members: 12.0 minutes

Insight: Casual riders take longer trips

– Ride Patterns by Day of Week

Annual Members ride Patterns by Day of Week:

On Tuesday, there are 568165 trips = 16.33% of the total Annual members' trips.

On Thursday, there are 548303 trips = 15.76% of the total Annual members' trips

On Wednesday, there are 532789 trips = 15.31% of the total Annual members' trips

Casual Members ride Patterns by Day of Week:

On Saturday, there are 391845 trips = 20.43% of the total casuals' trips.

On Sunday, there are 323850 trips = 16.89% of the total casuals' trips.

On Friday, there are 301154 trips = 15.70% of the total casuals' trips.

Insight: Annual Members ride more during weekdays, Casual Members ride more during the weekends

– Ride Patterns by Hour

Annual members' ride patterns by hours:

17 o'clock, there are 371627 trips = 10.68% of the total annual members' rides

16 o'clock, there are 327242 trips = 9.40% of the total annual members' rides

18 o'clock, there are 287662 trips = 8.27% of the total annual members' rides

Casual members' ride patterns by hours:

17 o'clock, there are 182728 trips = 9.53% of the total casual members' rides

16 o'clock, there are 169503 trips = 8.84% of the total casual members' rides

18 o'clock, there are 156409 trips = 8.16% of the total casual members' rides

Insight: Peaks at 7–9 AM & 4–6 PM for members, Casual: afternoon/evening usage

– Bike Type Preference

Annual members' preferred bike type:

electric_bike = 2125579 trips (61.08%)

classic_bike = 1354218 trips (38.92%)

Casual members' preferred bike type:

electric_bike = 1200469 trips (62.6%)

classic_bike = 717288 trips (37.4%)

Insight: Electric bikes are more preferred

– Seasonal Trends

Seasonal Trends for Annual members:

In August, there are 443130 trips = 12.73%

In September, there are 440939 trips = 12.67%

In July, there are 430394 trips = 12.37%

Seasonal Trends for Casual Riders:

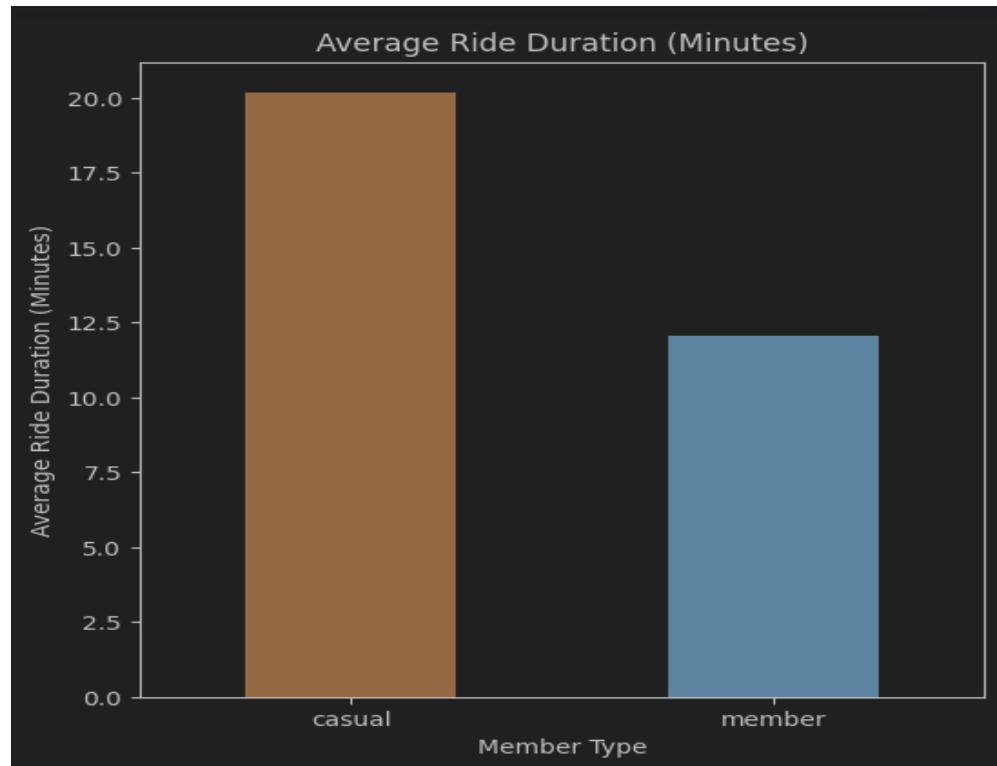
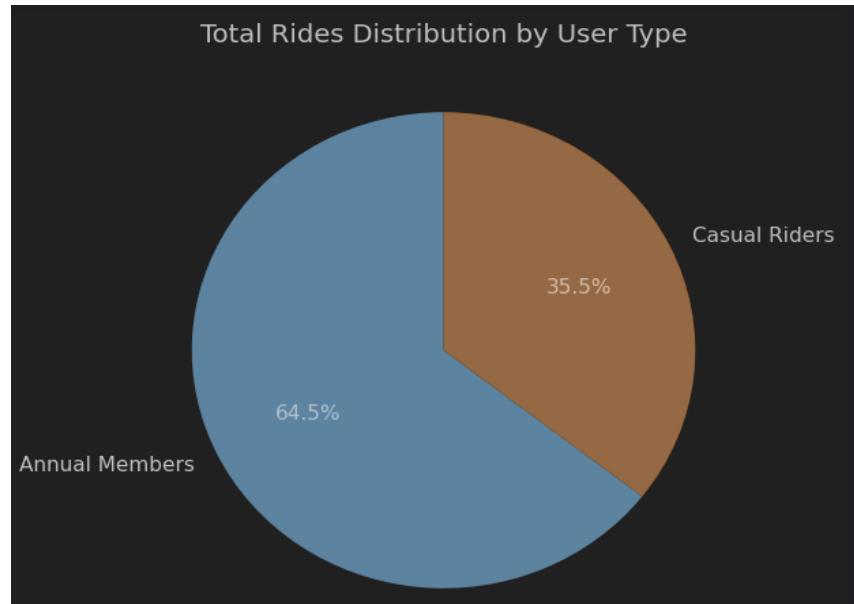
In August, there are 323533 trips = 16.87%

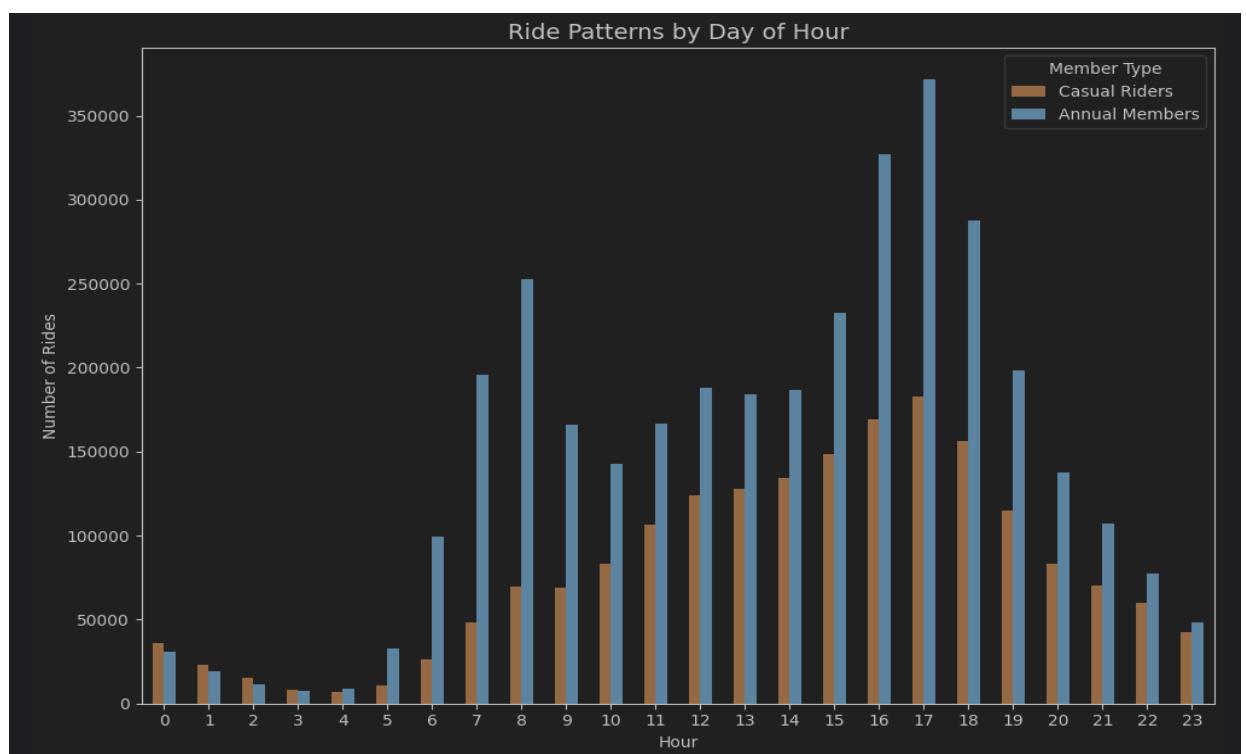
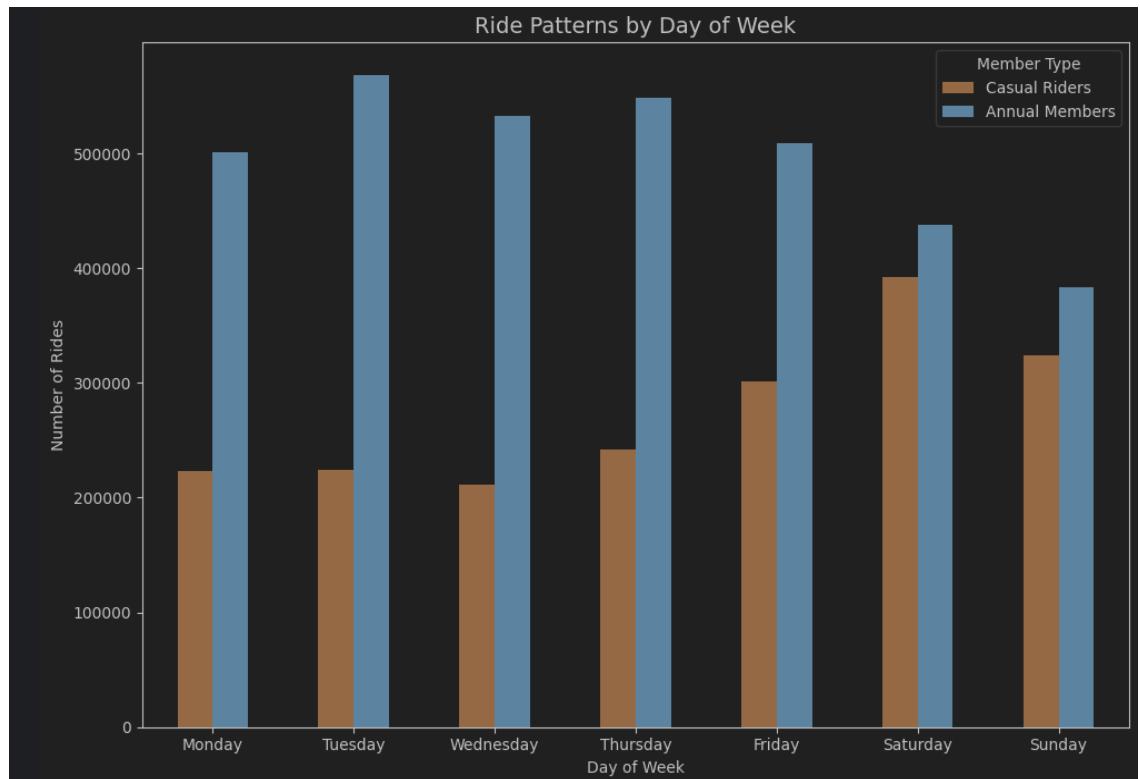
In July, there are 308446 trips = 16.08%

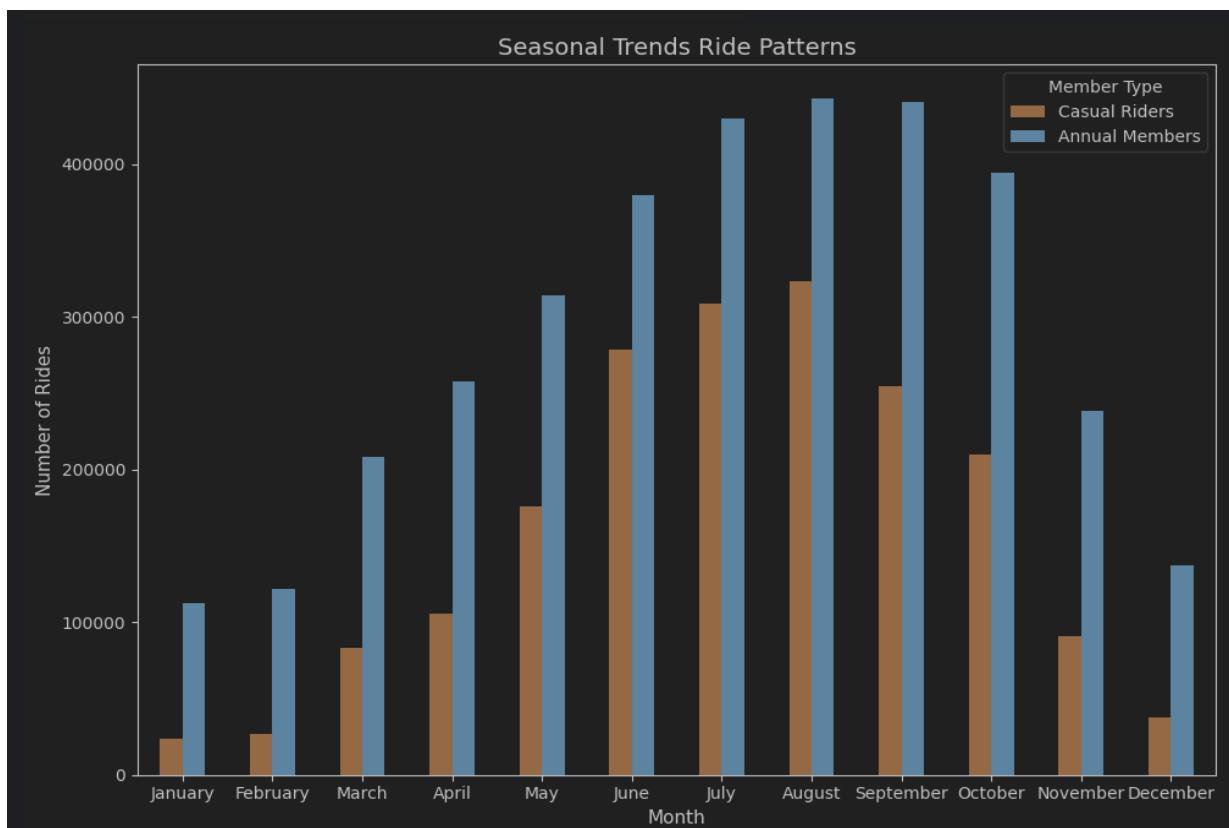
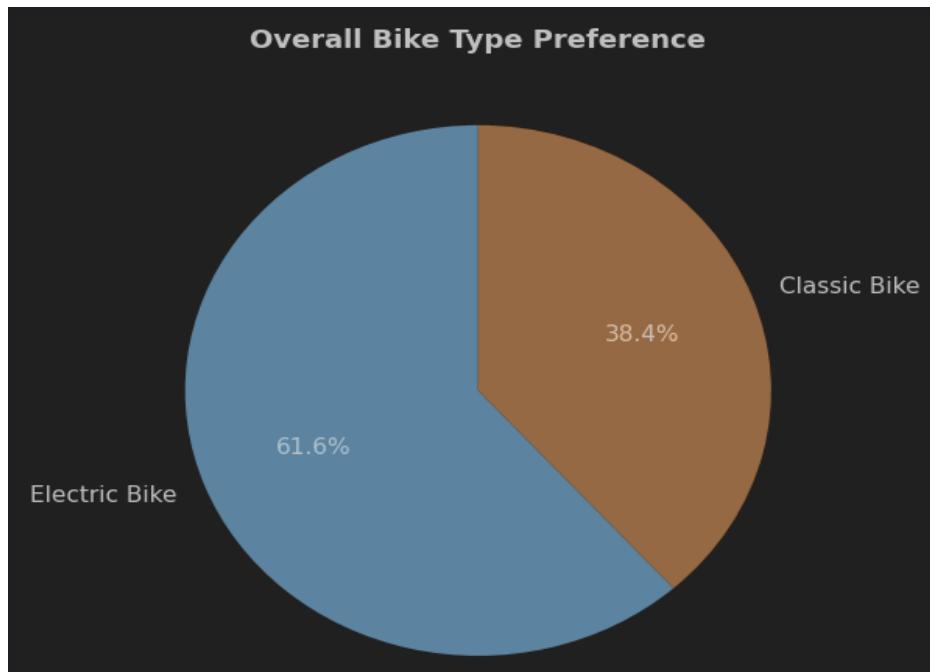
In June, there are 278702 trips = 14.53%

Insight: Peak months: Jul–Sep (summer), Lowest: Dec–Feb (winter). Weather is the biggest driver!

- Visualizations







5. Recommendations

1- Weekends discount

Casual peak rides are during the weekends; this can be an opportunity to convince them to upgrade to an annual membership by giving them X% discount for rides per weekend, with a maximum of X days per month.

2- Free rides in during summer.

As July to August (summer time) is the peak period for casual rides. Then, we can make a campaign to convince them to upgrade to an annual membership by giving them X free rides during the summer if they upgrade to an annual membership.

3- Electric bikes + Peak hours discount for the first month

As the preferred bike type is electric bikes, and the peak hours are between 12 and 18. Then, we can offer them a discount of X% on electric bike rides during the peak hours for the first month if they buy a membership.

6. Conclusion

I found that members use Cyclistic bikes differently: members for daily commuting, casuals for leisure on weekends and in summer.

In order to target casual riders to buy a membership. Then, we need to offer them discounts/free rides during weekends and summer