Cyclistic Bike-Share Case Study

"How Can a Bike-Share Company Convert Casual Riders into Members?"

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Executive Summary

- Cyclistic, a bike-share company in Chicago, wants to grow its customer base by converting more casual riders into annual members. This analysis examines how casual and member riders differ in terms of ride behavior, duration, bike type usage, and patterns across time.
- Using 12 months of real ride data, I found that casual users take longer rides, mostly on weekends and during summer months, often using electric bikes. Members ride more frequently, consistently across the year, and primarily on weekdays for shorter durations.
- Based on these findings, I will provide data-driven recommendations to help the marketing team create targeted campaigns that encourage casual riders to become loyal annual members.

Ask Phase

➔ **Business Task:**
Cyclistic, a bike-share company in Chicago, aims to convert casual riders into annual members. My role as a junior data analyst is to analyze past ride behavior to identify how casual riders differ from members, so the marketing team can develop data-driven campaigns to improve membership conversions.

➔ **Key Stakeholders:**

- **Lily Moreno** – Director of Marketing
- **Cyclistic Marketing Team**
- **Executive Team** – Interested in revenue growth through memberships

➔ **Guiding Questions:**

- How do annual members and casual riders use Cyclistic bikes differently?
- What behavioral trends can be used to influence casual riders to convert?
- What business strategies can be recommended based on these insights?

Prepare Phase

- **Data Source:**

  I used public Cyclistic ride data (via Divvy) from January 2024 to December 2024, made available through 12 individual .csv files.

- **Description:**

  Each file includes ride-level details such as:
  - Rider type
  - Timestamps
  - Bike type
  - Start and end stations
  - Location coordinates

- **Tools Used:**
  - Python: Pandas, Seaborn, Matplotlib
  - Jupyter Notebook

Process Phase

- ➔ **Cleaning Steps:**
    - ➢ Removed null values
    - ➢ Removed duplicate entries and invalid records
    - ➢ Filtered out negative ride durations
    - ➢ Converted time fields to datetime format

- ➔ **Feature Engineering:**

  I added the following fields:
    - ➢ ride_duration (minutes)
    - ➢ day_of_week
    - ➢ month
    - ➢ start_hour
- The cleaned dataset was saved as **cleaned_ride_dataset.csv** and is available in the GitHub repository.

Analyze Phase

After preparing the data, I explored user behavior by comparing members and casual riders across several dimensions, including ride frequency, duration, bike preferences, and time patterns.

- ➔ **Key Observations:**
  1. **Ride Volume:**
     I grouped the dataset by user type and counted total rides. Members took over 3.7 million rides, while casual users took 2.1 million — suggesting stronger loyalty and frequent use among members.
  2. **Ride Duration:**
     By calculating the duration of each ride and then finding the average per user type, I found that casual riders take longer rides on average (~21 minutes), while members average around 12 minutes. This indicates casual riders may use bikes more for leisure, and members for commuting.
  3. **Bike Type Preferences:**
     I grouped the data by user type and bike type to compare preferences. Both groups favored electric bikes slightly more than classic bikes. Electric scooters made up a very small portion of total rides for either group.
  4. **Time of Week Patterns:**
     Grouping rides by user type and day of the week revealed that casual riders are most active on weekends (especially Saturdays), while members are more consistent on weekdays — peaking midweek (Wednesdays). This pattern reflects differing purposes between the two groups (leisure vs. commuting).
  5. **Monthly Seasonality:**
     I aggregated total ride counts by user type and month. Casual usage increased sharply during summer, especially in September, whereas member usage remained relatively steady throughout the year.

Jupyter Notebook – Full Code and Output

The following section contains the full Python notebook used to complete this analysis. It includes:

Data loading and exploration

Data cleaning and transformation

Exploratory analysis and visualizations

These steps correspond to the work described in the Process and Analyze phases of this report.

0.1 Loading the Data Set

[1]:
```python
import os
import pandas as pd

# Set the folder path where all the CSV files are stored
folder_path = r"C:\Users\asrao\OneDrive\Documents\Desktop\Case_Study"

# Listing all files that end with .csv in the folder
csv_files = [file for file in os.listdir(folder_path) if file.endswith('.csv')]

# Creating an empty list to store DataFrames
combined_data = []

# Loop through each file and try to read it
for file in csv_files:
    file_path = os.path.join(folder_path, file)
    try:
        df = pd.read_csv(file_path, engine='python')
        combined_data.append(df)
        print("Loaded:", file)
    except Exception as e:
        print("Error reading", file, ":", e)

# Combining all successfully loaded DataFrames into one
final_df = pd.concat(combined_data, ignore_index=True)

# To show the first few rows to verify
print(final_df.head())
```

```
Loaded: 202401-divvy-tripdata.csv
Loaded: 202402-divvy-tripdata.csv
Loaded: 202403-divvy-tripdata.csv
Loaded: 202404-divvy-tripdata.csv
Loaded: 202405-divvy-tripdata.csv
Loaded: 202406-divvy-tripdata.csv
Loaded: 202407-divvy-tripdata.csv
Loaded: 202408-divvy-tripdata.csv
```

```
Loaded: 202409-divvy-tripdata.csv
Loaded: 202410-divvy-tripdata.csv
Loaded: 202411-divvy-tripdata.csv
Loaded: 202412-divvy-tripdata.csv
            ride_id  rideable_type           started_at             ended_at  \
0  C1D650626C8C899A  electric_bike  2024-01-12 15:30:27  2024-01-12 15:37:59
1  EECD38BDB25BFCB0  electric_bike  2024-01-08 15:45:46  2024-01-08 15:52:59
2  F4A9CE78061F17F7  electric_bike  2024-01-27 12:27:19  2024-01-27 12:35:19
3  0A0D9E15EE50B171   classic_bike  2024-01-29 16:26:17  2024-01-29 16:56:06
4  33FFC9805E3EFF9A   classic_bike  2024-01-31 05:43:23  2024-01-31 06:09:35

           start_station_name start_station_id          end_station_name  \
0            Wells St & Elm St     KA1504000135   Kingsbury St & Kinzie St
1            Wells St & Elm St     KA1504000135   Kingsbury St & Kinzie St
2            Wells St & Elm St     KA1504000135   Kingsbury St & Kinzie St
3       Wells St & Randolph St     TA1305000030  Larrabee St & Webster Ave
4  Lincoln Ave & Waveland Ave            13253   Kingsbury St & Kinzie St

  end_station_id  start_lat  start_lng    end_lat    end_lng member_casual
0   KA1503000043  41.903267 -87.634737  41.889177 -87.638506        member
1   KA1503000043  41.902937 -87.634440  41.889177 -87.638506        member
2   KA1503000043  41.902951 -87.634470  41.889177 -87.638506        member
3          13193  41.884295 -87.633963  41.921822 -87.644140        member
4   KA1503000043  41.948797 -87.675278  41.889177 -87.638506        member
```

0.2 Data Inspection

[2]:
```python
# To check the shape of the combined dataset (rows, columns)
print("Shape of the dataset:", final_df.shape)

# column names
print("Column names:", final_df.columns)

# data types of each column
print("Data types:")
print(final_df.dtypes)

# Checking for missing values
print("Missing values:")
print(final_df.isnull().sum())
```

```
Shape of the dataset: (5860568, 13)
Column names: Index(['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'],
      dtype='object')
Data types:
```

```
ride_id                object
rideable_type          object
started_at             object
ended_at               object
start_station_name     object
start_station_id       object
end_station_name       object
end_station_id         object
start_lat             float64
start_lng             float64
end_lat               float64
end_lng               float64
member_casual          object
dtype: object
Missing values:
ride_id                     0
rideable_type               0
started_at                  0
ended_at                    0
start_station_name    1073951
start_station_id      1073951
end_station_name      1104653
end_station_id        1104653
start_lat                   0
start_lng                   0
end_lat                  7232
end_lng                  7232
member_casual               0
dtype: int64
```

0.3 Data Cleaning and Manipulation

[3]:

```python
import pandas as pd

# Removing duplicate rows
final_df.drop_duplicates(inplace=True)

# Converting started_at and ended_at to datetime
final_df['started_at'] = pd.to_datetime(final_df['started_at'], errors='coerce')
final_df['ended_at'] = pd.to_datetime(final_df['ended_at'], errors='coerce')

# Drop rows with missing or invalid dates
final_df.dropna(subset=['started_at', 'ended_at'], inplace=True)

# Create ride duration (in minutes)
final_df['ride_duration'] = (final_df['ended_at'] - final_df['started_at']).dt.
 ↪total_seconds() / 60
```

```python
# Drop rows with negative durations
final_df = final_df[final_df['ride_duration'] >= 0]

final_df.dropna(subset=['end_lat', 'end_lng'], inplace=True)


# Reset index after all cleaning
final_df.reset_index(drop=True, inplace=True)

# final shape and missing values after cleaning
print("Shape after cleaning:", final_df.shape)
print("\nMissing values:\n", final_df.isnull().sum())
```

```
Shape after cleaning: (5853109, 14)

Missing values:
 ride_id                     0
rideable_type               0
started_at                  0
ended_at                    0
start_station_name    1073823
start_station_id      1073823
end_station_name      1097267
end_station_id        1097267
start_lat                   0
start_lng                   0
end_lat                     0
end_lng                     0
member_casual               0
ride_duration               0
dtype: int64
```

[4]:
```python
# Summary statistics
print(final_df.describe())

# Value counts of member types
print(final_df['member_casual'].value_counts())

# Count of rides per bike type
print(final_df['rideable_type'].value_counts())
```

```
          start_lat     start_lng       end_lat       end_lng  ride_duration
count  5.853109e+06  5.853109e+06  5.853109e+06  5.853109e+06   5.853109e+06
mean   4.190219e+01 -8.764623e+01  4.190258e+01 -8.764644e+01   1.548589e+01
std    4.473420e-02  2.748243e-02  5.598340e-02  1.136844e-01   3.284965e+01
min    4.164000e+01 -8.791000e+01  1.606000e+01 -1.440500e+02   0.000000e+00
25%    4.188096e+01 -8.766000e+01  4.188096e+01 -8.766000e+01   5.539483e+00
```

```
50%    4.189738e+01 -8.764182e+01  4.189776e+01 -8.764288e+01   9.700000e+00
75%    4.193000e+01 -8.762952e+01  4.193000e+01 -8.762954e+01   1.720782e+01
max    4.207000e+01 -8.752000e+01  8.796000e+01  1.525300e+02   1.509367e+03
member    3707427
casual    2145682
Name: member_casual, dtype: int64
electric_bike       2980384
classic_bike        2728388
electric_scooter     144337
Name: rideable_type, dtype: int64
```

[5]:

```python
# Add day of the week
final_df['day_of_week'] = final_df['started_at'].dt.day_name()
print(" Added 'day_of_week' column. Unique values:", final_df['day_of_week'].
 ↪unique())

# Add month
final_df['month'] = final_df['started_at'].dt.month_name()
print(" Added 'month' column. Unique values:", final_df['month'].unique())

# Add start hour
final_df['start_hour'] = final_df['started_at'].dt.hour
print(" Added 'start_hour' column. Range:", final_df['start_hour'].min(), "to",␣
 ↪final_df['start_hour'].max())

# Add day of the month
final_df['day'] = final_df['started_at'].dt.day
print(" Added 'day' column.")
```

```
 Added 'day_of_week' column. Unique values: ['Friday' 'Monday' 'Saturday'
'Wednesday' 'Sunday' 'Thursday' 'Tuesday']
 Added 'month' column. Unique values: ['January' 'February' 'March' 'April'
'May' 'June' 'July' 'August'
 'September' 'October' 'November' 'December']
 Added 'start_hour' column. Range: 0 to 23
 Added 'day' column.
```

[6]:

```python
# Save the cleaned data set
final_df.to_csv("cleaned_ride_data.csv", index=False)

print(" Cleaned dataset saved as 'cleaned_ride_data.csv'")
```

```
 Cleaned dataset saved as 'cleaned_ride_data.csv'
```

0.4 Exploratory Data Analysis

[7]:
```python
# Compare ride counts by user type

ride_counts = final_df.groupby('member_casual')['ride_id'].count().reset_index()
ride_counts.columns = ['user_type', 'total_rides']
print(ride_counts)
```

```
  user_type  total_rides
0    casual      2145682
1    member      3707427
```

[8]:
```python
# Compare average ride duration by weekday

avg_duration_by_day = final_df.groupby(['member_casual',␣
↪'day_of_week'])['ride_duration'].mean().reset_index()
avg_duration_by_day.columns = ['user_type', 'day_of_week',␣
↪'avg_ride_duration_min']
day_order = ['Sunday', 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
↪'Saturday']
avg_duration_by_day['day_of_week'] = pd.
↪Categorical(avg_duration_by_day['day_of_week'], categories=day_order,␣
↪ordered=True)
avg_duration_by_day = avg_duration_by_day.sort_values(['user_type',␣
↪'day_of_week'])
print(avg_duration_by_day)
```

```
   user_type day_of_week  avg_ride_duration_min
3     casual      Sunday              24.385497
1     casual      Monday              20.439848
5     casual     Tuesday              18.160923
6     casual   Wednesday              18.637061
4     casual    Thursday              18.371659
0     casual      Friday              20.420535
2     casual    Saturday              23.931365
10    member      Sunday              13.600799
8     member      Monday              11.693118
12    member     Tuesday              11.712192
13    member   Wednesday              11.937110
11    member    Thursday              11.733214
7     member      Friday              11.923176
9     member    Saturday              13.556212
```

[9]:
```python
# Analyze bike type preferences

bike_type_by_user = final_df.groupby(['member_casual',␣
↪'rideable_type'])['ride_id'].count().reset_index()
```

```
bike_type_by_user.columns = ['user_type', 'bike_type', 'ride_count']
print(bike_type_by_user)
```

```
  user_type         bike_type  ride_count
0    casual       classic_bike      969076
1    casual      electric_bike     1091391
2    casual  electric_scooter       85215
3    member       classic_bike     1759312
4    member      electric_bike     1888993
5    member  electric_scooter       59122
```

[10]:
```
# Study monthly rides trends

# Define correct month order
month_order = ['January', 'February', 'March', 'April', 'May', 'June',
               'July', 'August', 'September', 'October', 'November', 'December']

# Group by user type and month
rides_by_month = final_df.groupby(['member_casual', 'month']).size().
 ↪reset_index(name='ride_count')

# Convert 'month' column to ordered categorical type
rides_by_month['month'] = pd.Categorical(rides_by_month['month'],␣
 ↪categories=month_order, ordered=True)

# Sort by user type and then by month order
rides_by_month = rides_by_month.sort_values(['member_casual', 'month']).
 ↪reset_index(drop=True)

# Display the cleaned output
print(rides_by_month)
```

```
   member_casual      month  ride_count
0         casual    January       24351
1         casual   February       46961
2         casual      March       82251
3         casual      April      131410
4         casual        May      230436
5         casual       June      300195
6         casual       July      319583
7         casual     August      317563
8         casual  September      345879
9         casual    October      215956
10        casual   November       92825
11        casual   December       38272
12        member    January      120214
13        member   February      175880
```

```
14         member      March      219015
15         member      April      283078
16         member        May      378368
17         member       June      409411
18         member       July      428284
19         member     August      437263
20         member  September      474285
21         member    October      399759
22         member   November      241909
23         member   December      139961
```

[11]:

```
# Finding the popular day of the week or preffered day of the week for rides

# Define correct day order (optional if needed for later visuals)
day_order = ['Sunday', 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
↪'Saturday']
final_df['day_of_week'] = pd.Categorical(final_df['day_of_week'],␣
↪categories=day_order, ordered=True)

# Get the most popular (mode) day of week for each user type
popular_day = final_df.groupby('member_casual')['day_of_week'].agg(lambda x: x.
↪mode()[0]).reset_index()
popular_day.columns = ['user_type', 'most_popular_day']

# Sort alphabetically by user_type and reset index
popular_day = popular_day.sort_values('user_type').reset_index(drop=True)

# Display the cleaned output
print(popular_day)
```

```
  user_type most_popular_day
0    casual         Saturday
1    member        Wednesday
```

[12]:

```
# summary of the main findings

# Total rides and average duration by user type
summary_stats = final_df.groupby('member_casual').agg({
    'ride_id': 'count',
    'ride_duration': 'mean'
}).reset_index().rename(columns={
    'ride_id': 'total_rides',
    'ride_duration': 'avg_ride_duration_min'
})
print(summary_stats)
```

```
  member_casual  total_rides  avg_ride_duration_min
0        casual      2145682              21.110668
```

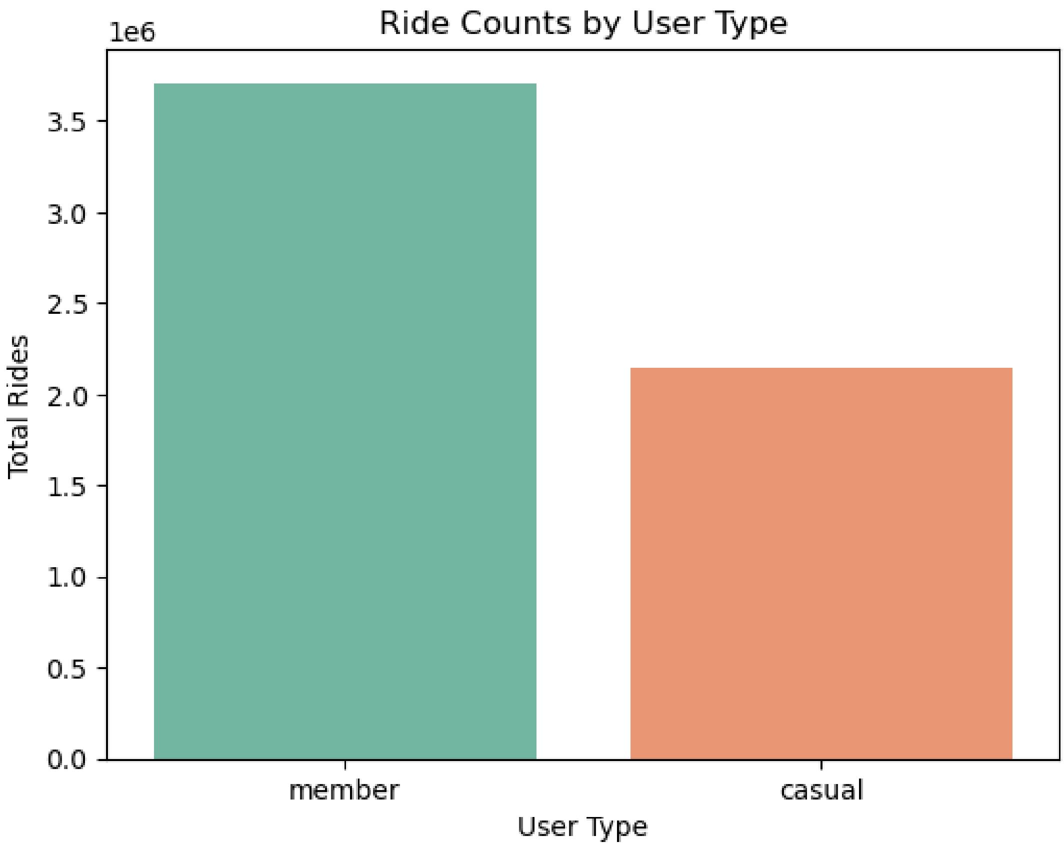
```
1         member      3707427               12.230541
```

0.5 Visualizations

[13]:
```python
#importing the libraries required for visualizations

import matplotlib.pyplot as plt
import seaborn as sns
```

Ride Counts by User Type

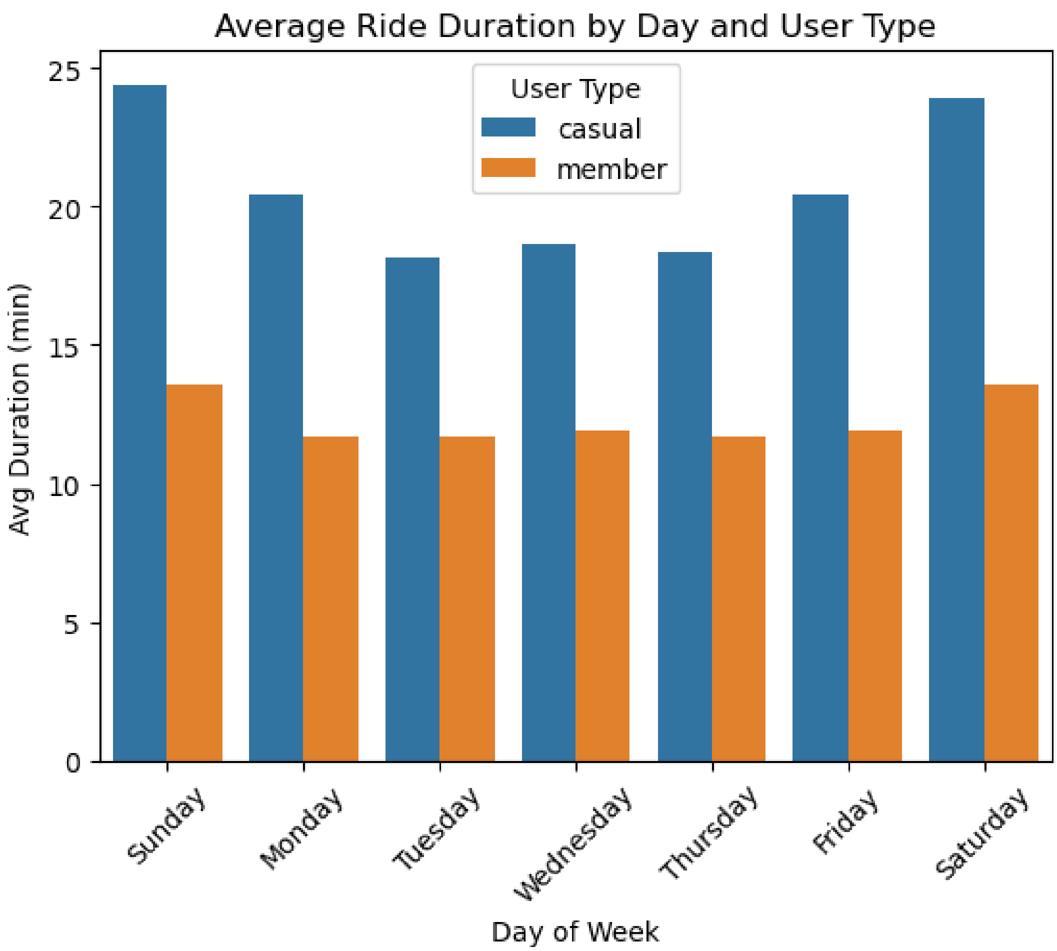
[14]:
```python
sns.countplot(data=final_df, x='member_casual', palette='Set2')
plt.title("Ride Counts by User Type")
plt.xlabel("User Type")
plt.ylabel("Total Rides")
plt.show()
```



From the overall ride activity, it's clear that members use the service much more than casual riders. There's a noticeable gap — with members logging over 3.7 million rides compared to just over 2.1 million by casual users. This suggests that member users are more consistent and engaged in their usage.

Average Ride Duration by Day and User Type

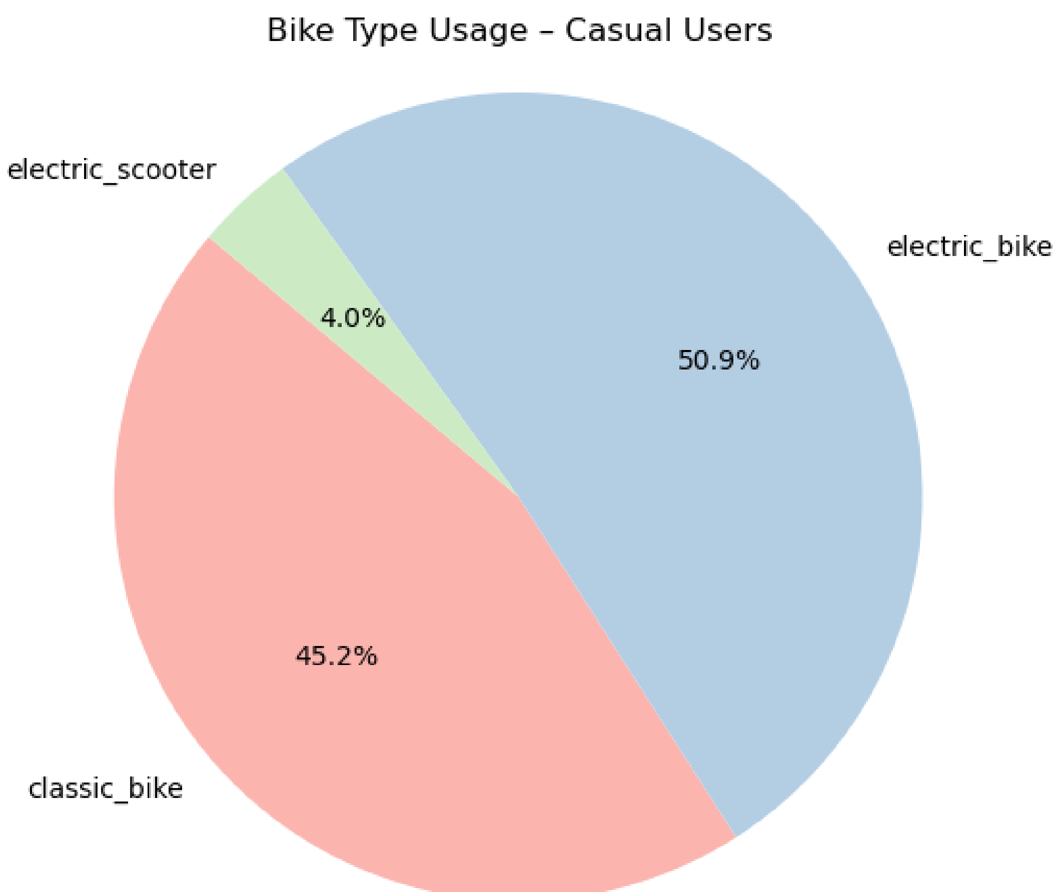
[15]:
```
sns.barplot(data=avg_duration_by_day, x='day_of_week',␣
↪y='avg_ride_duration_min', hue='user_type', palette='tab10')
plt.title("Average Ride Duration by Day and User Type")
plt.xlabel("Day of Week")
plt.ylabel("Avg Duration (min)")
plt.xticks(rotation=45)
plt.legend(title='User Type')
plt.show()
```



Looking at how long people ride, casual users consistently take longer trips than members. Their ride times spike over the weekend, especially on Saturdays and Sundays, which could point to recreational or leisure riding. Members, on the other hand, tend to ride for shorter durations and have steadier ride patterns across all weekdays — possibly using the service more for commuting.

Bike Type Usage - Casual Users

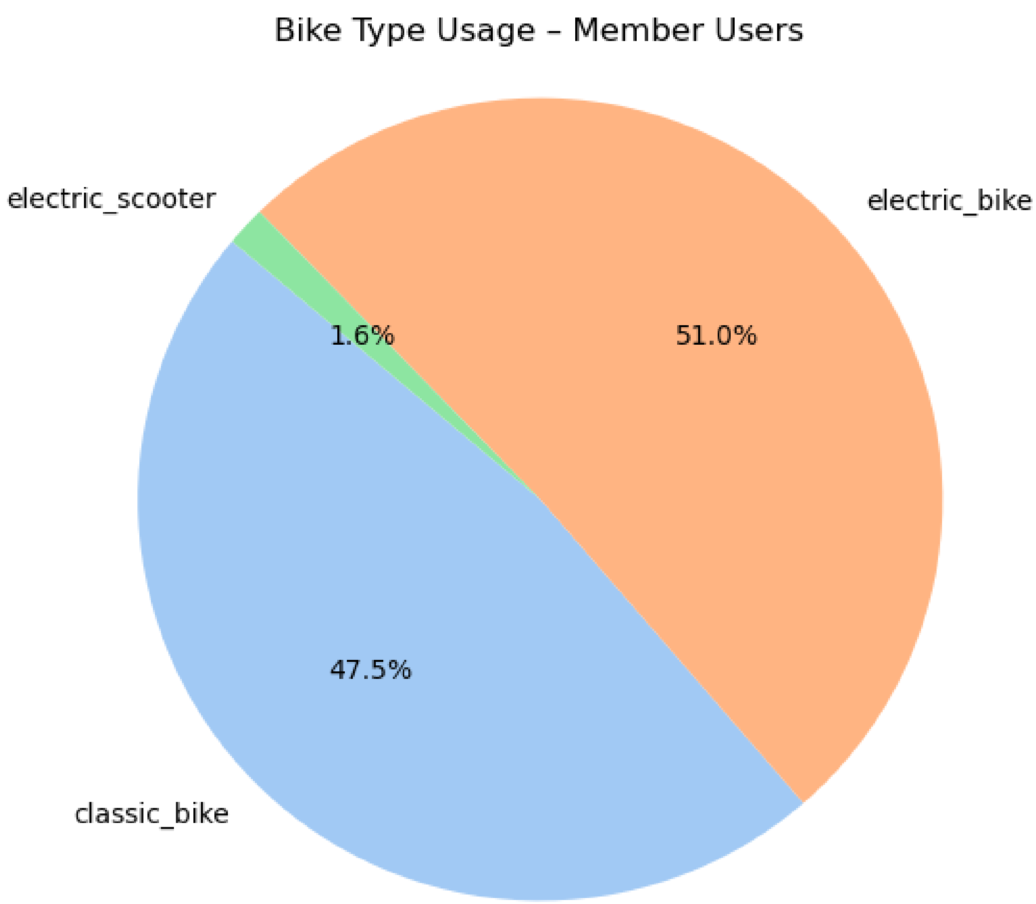
[16]:
```
# Filter data for casual users only
casual_data = bike_type_by_user[bike_type_by_user['user_type'] == 'casual']

# Plot pie chart
plt.figure(figsize=(6,6))
plt.pie(casual_data['ride_count'], labels=casual_data['bike_type'], autopct='%1.
↪1f%%', startangle=140, colors=sns.color_palette('Pastel1'))
plt.title('Bike Type Usage - Casual Users')
plt.axis('equal')
plt.show()
```



Among casual riders, electric bikes are slightly more popular than classic bikes. Around half of the rides are on electric bikes, followed closely by classic bikes. Interestingly, very few casual users opt for electric scooters — suggesting scooters may not be a preferred option for short-term or leisure use.

Bike Type Usage- Member Users

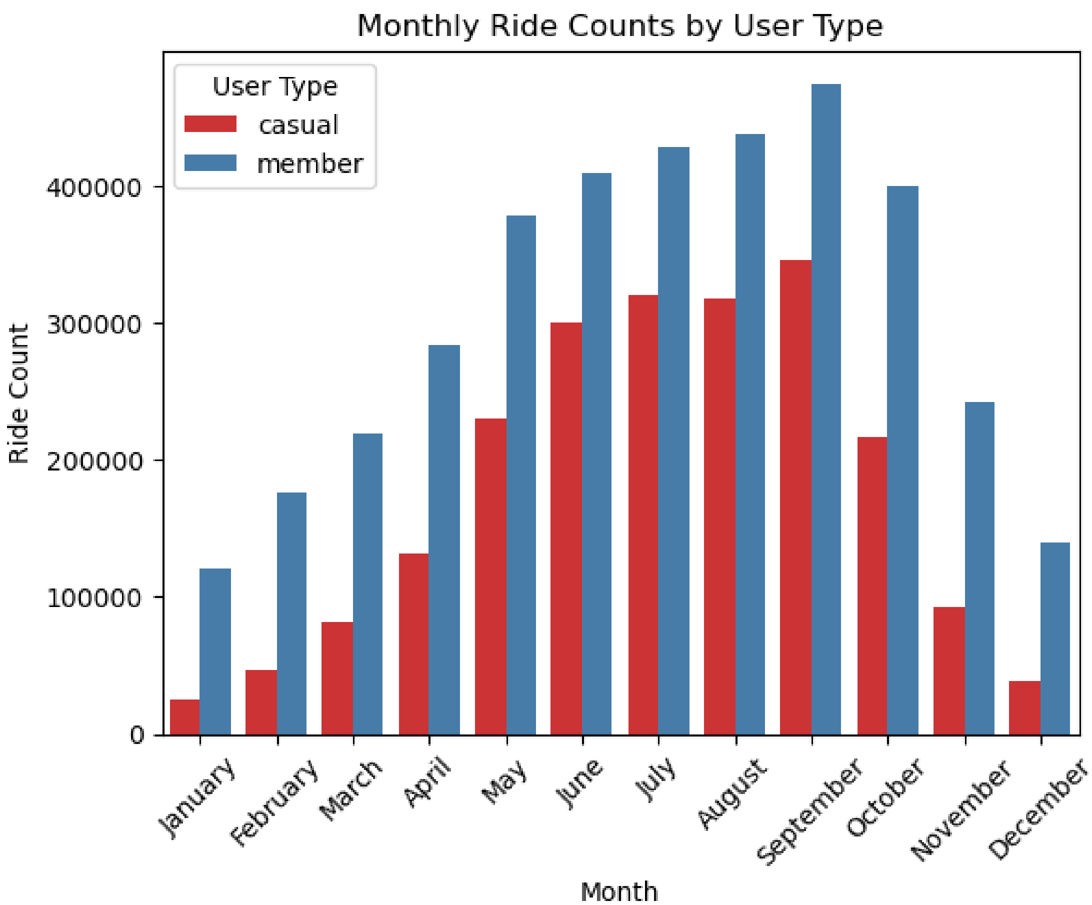
[17]:
```python
# Filter data for members
member_data = bike_type_by_user[bike_type_by_user['user_type'] == 'member']

# Plot pie chart
plt.figure(figsize=(6,6))
plt.pie(member_data['ride_count'], labels=member_data['bike_type'], autopct='%1.
↪1f%%', startangle=140, colors=sns.color_palette('pastel'))
plt.title('Bike Type Usage - Member Users')
plt.axis('equal')
plt.show()
```



Members show a similar preference trend, favoring electric bikes slightly more than classic bikes. Again, electric scooters make up a very small portion of the rides. This shows that across both groups, bikes (especially electric) are the go-to mode, while scooters are underutilized.

Monthly Ride Counts By User Type

[18]:
```
sns.barplot(data=rides_by_month, x='month', y='ride_count',␣
 ↪hue='member_casual', palette='Set1')
plt.title("Monthly Ride Counts by User Type")
plt.xlabel("Month")
plt.ylabel("Ride Count")
plt.xticks(rotation=45)
plt.legend(title='User Type')
plt.show()
```

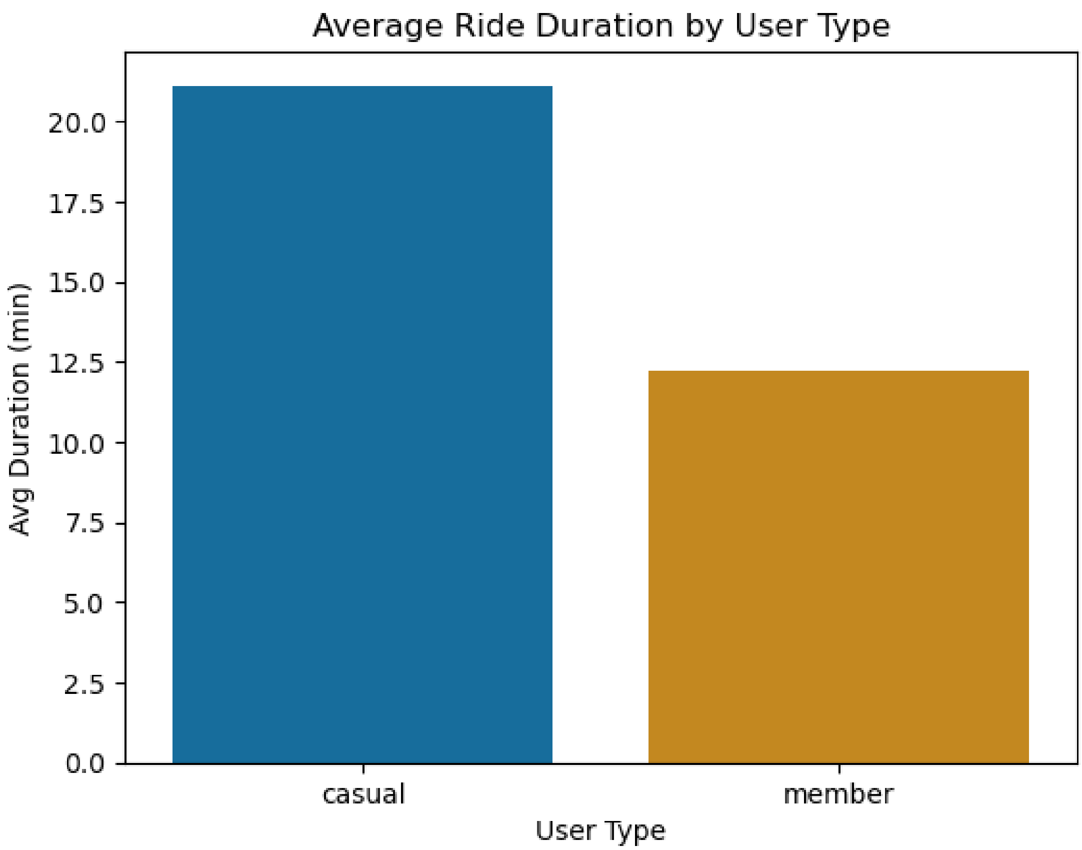


Rides by both user groups follow a seasonal pattern, increasing during the warmer months. Members tend to ride consistently from May to October, while casual users see the biggest spike during summer — especially in September. This highlights an opportunity to engage more casual users during seasonal peaks.

Average Ride Duration By User Type

[19]:
```
sns.barplot(data=summary_stats, x='member_casual', y='avg_ride_duration_min',␣
 ↪palette='colorblind')
plt.title("Average Ride Duration by User Type")
```

```python
plt.xlabel("User Type")
plt.ylabel("Avg Duration (min)")
plt.show()
```



When we compare how long each group rides on average, casual users ride nearly twice as long as members. This reinforces the idea that casual users are likely riding for fun or exploration, while members are using the bikes more for quick trips or daily errands.

Most Popular Day of the Week

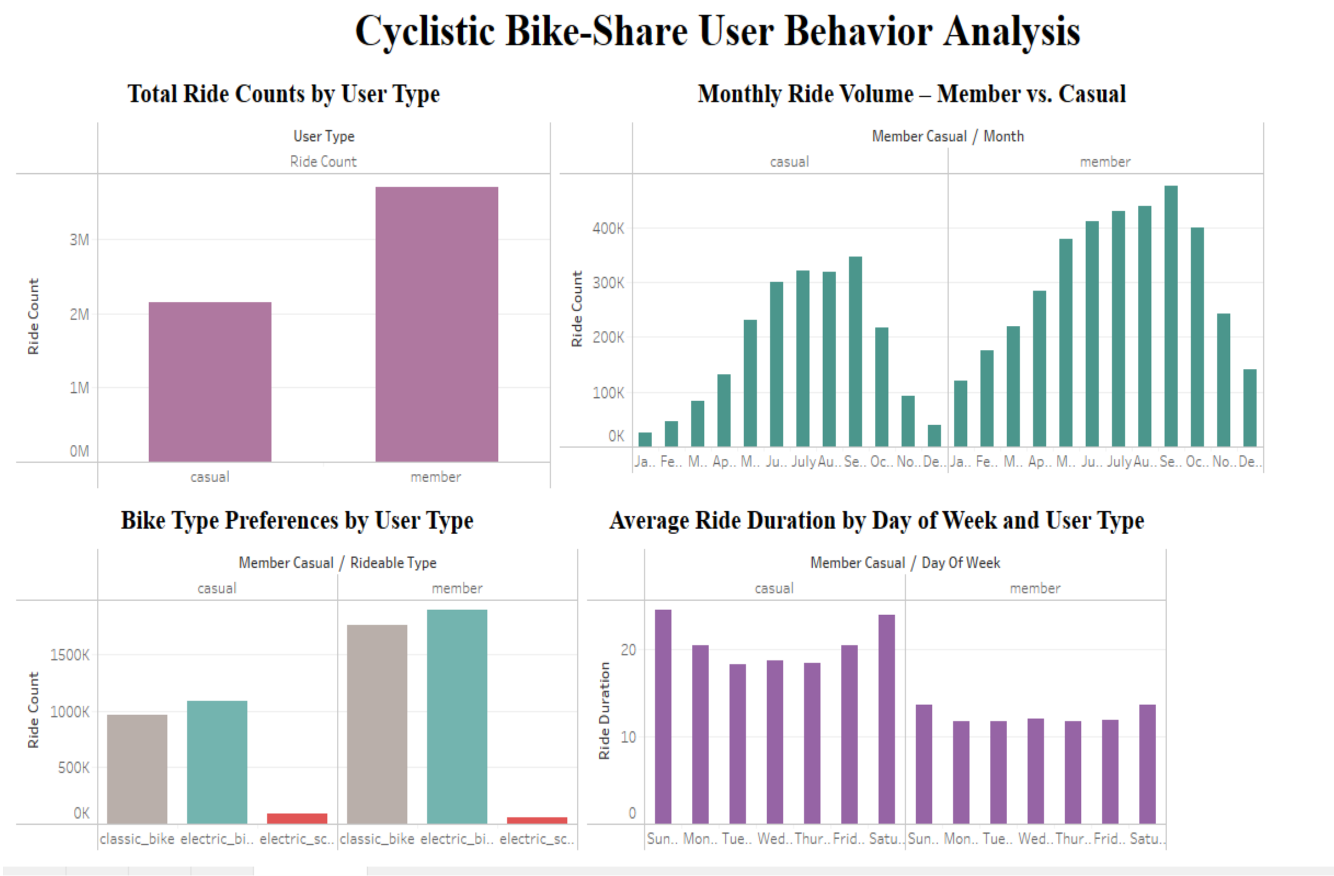
[20]:
```python
import pandas as pd
from IPython.display import display

# Manually create the summary
popular_day_table = pd.DataFrame({
    'User Type': ['Casual', 'Member'],
    'Most Popular Day': ['Saturday', 'Wednesday']
})

# Display the mini table
display(popular_day_table)
```

```
  User Type Most Popular Day
0    Casual         Saturday
1    Member        Wednesday
```

Casual riders ride the most on Saturdays, while members show peak activity on Wednesdays. This supports the pattern of casual users riding more on weekends and members being weekday commuters.

Tableau Dashboard

For an interactive overview of the same insights in a dashboard format, refer to the **Tableau dashboard** below:



Click the image to open the full interactive dashboard on Tableau Public.

Act Phase - Final Recommendations

Business Objective: Convert casual riders into annual members

Based on the findings, I recommend:

➔ **Launch a "Weekend to Weekday" Campaign**
  - **Why:** Casual riders are mostly active on weekends, especially Saturdays.
  - **Action:** Offer time-limited weekday passes or small rewards for riding during weekdays to shift behavior toward consistent usage — similar to members.

➔ **Promote the Value of Membership for Longer, Frequent Rides**
  - **Why**: Casual users ride longer and use electric bikes more, which can become expensive over time.
  - **Action**: Use app/email messaging to show casual riders how much they could save by switching to an annual plan, especially if they ride more than X(specific) times/month.

➔ **Introduce Summer Discount Plans for Casual Users**
  - **Why:** Casual usage spikes in summer months.
  - **Action:** Offer summer-exclusive "trial memberships" or discounts during peak months (June–Sept) to convert casual riders while usage is already high.

Appendix

Project Resources

- **Dataset Source:**
  [Divvy Trip Data Archive]
  (12 months of bike-share ride data used for analysis)

- **Interactive Dashboard:**
  View Tableau Dashboard – Cyclistic Case Study
  (Includes ride trends, user behavior, bike preferences, and ride duration insights)

- **Jupyter Notebook (Python Analysis)**:
  Cyclistic_analysis.ipynb
  (Complete data cleaning, EDA, and visualization code)

Tools Used

- **Python** – Pandas, NumPy, Seaborn, Matplotlib
- **Jupyter Notebook**
- **Tableau Public** – Interactive visual dashboard
- **GitHub** – Project hosting and version control
- **Google Docs / MS Word** – Report writing and formatting