BIKE-SHARE DATA ANALYSIS CASE STUDY

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Introduction

As a junior data analyst on the marketing analyst team at Cyclistic[i], I am excited to present this comprehensive analysis of how casual riders and annual members use Cyclistic bikes differently. Cyclistic, a bike-share company based in Chicago, is at a pivotal point in its journey to increase annual memberships, which are crucial for its long-term success.

Our marketing director, Lily Moreno, has tasked my team with uncovering key insights into the behaviours and preferences of our diverse user base. By understanding the distinct patterns between casual riders and annual members, we aim to devise a targeted marketing strategy to convert more casual riders into loyal annual members.

Cyclistic is a Chicago-based bike-share program with over 5,800 bicycles and 600 docking stations. It offers traditional bikes and inclusive options like reclining bikes, hand tricycles, and cargo bikes. While most riders use traditional bikes, 8% opt for assistive options. About 30% of users commute to work, while others ride for leisure.

Through this analysis, I will leverage data insights and professional visualisations to support our strategic initiatives and help propel Cyclistic towards a future of sustained growth and success.

To develop compelling marketing strategies that convert casual riders into annual members, it's vital to understand the distinct behaviours of both groups and what motivates casual riders to consider purchasing a membership.

Three questions will guide the future of the marketing program:

1. How do annual members and casual riders use Cyclistic bikes differently?
2. Why would casual riders buy Cyclistic annual memberships?
3. How can Cyclistic use digital media to influence casual riders to become members?

As the data analytics team, we were tasked with answering the first question. Our mission is clear: analyse past data to uncover how annual members and casual riders use our bikes differently. By understanding these distinct usage patterns, we aim to craft targeted strategies that enhance membership conversion and improve overall user satisfaction.

***Note**: The datasets have a different name because Cyclistic is a fictional company. The datasets, however, are appropriate for answering business questions we have here. The data has been made available by Motivate International Inc. under this license.*

We have used Microsoft Excel to familiarise ourselves with the data and to perform the initial investigations. From all the variables available, we were interested in the duration of each ride and the day of the week each of the rides was opted for.

We begin in Microsoft Excel by exploring the data. We accessed the data for the past year, starting from the July of 2023 to the last month, June 2024. This ensured that the data satisfies timeliness. The data was segregated over months.

Our dataset from Cyclistic includes essential variables such as *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*, and *member_casual*. These variables provide detailed information on bike rides, including ride details, station locations, timestamps, and user type (whether the user is a member or casual rider).

The dataset captures approximately 500,000 rides each month, providing extensive insights into bike usage patterns, user behaviours, and station activity.

We started with the July 23 dataset, added a new column, *ride_length* and calculated the duration of each ride from the difference between the timestamps of the beginning and end of each ride, using the columns *started_at* and *ended_at*. Then, we formatted that cell to the format of Time (37:30:55) and populated the column ride_length by double-clicking the fill handle.

Similarly, we added a new column, day_of_week, which basically consisted of the day of the week the ride started. This was performed using the column *started_at and* using the function =WEEKDAY(C2,1). The function generated the numbers 1 to 7, corresponding to the weekdays starting from Sunday, respectively. Then, we formatted the cell into a Number with no decimal.

The datasets of all the months were pre-processed in this manner, each at a time, with utmost caution. Now that our data has been processed appropriately and prepared for analysis, we put it to work using Python.

```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import drive
import datetime
import statistics
drive.mount('/content/drive')

#Reading the files for each months
jul = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202307-divvy-
tripdata.csv')
aug = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202308-divvy-
tripdata.csv')
sep = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202309-divvy-
tripdata.csv')
```

```python
oct = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202310-divvy-tripdata.csv')
nov = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202311-divvy-tripdata.csv')
dec = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202312-divvy-tripdata.csv')
jan = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202401-divvy-tripdata.csv')
feb = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202402-divvy-tripdata.csv')
mar = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202403-divvy-tripdata.csv')
apr = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202404-divvy-tripdata.csv')
may = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202405-divvy-tripdata.csv')
jun = pd.read_csv('/content/drive/MyDrive/AA Cyclistic/202406-divvy-tripdata.csv')

# merging the data of all months to form a single data for the past year
df = pd.concat([jul, aug, sep, oct, nov, dec, jan, feb, mar, apr, may, jun], ignore_index=True)
df.reset_index(drop=True, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5740211 entries, 0 to 5740210
Data columns (total 18 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
 13  ride_length         object
 14  day_of_week         int64
 15  Unnamed: 15         float64
 16  Unnamed: 16         float64
 17  Unnamed: 17         float64
```

The dataset contains 5.7 million (5,740,211) records across 18 columns. The appearance of unnamed columns in the DataFrame is typically due to data import issues, empty fields, or parsing errors during the dataset extraction or formatting process. We will remove these in the next step.

```python
# dropping the irrelevant columns
df.drop(columns = ['Unnamed: 15', 'Unnamed: 16', 'Unnamed: 17'], inplace=True)
```

```
df.head()
```

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	ride_length	day_of_week
9340B064F0AEE130	electric_bike	07/23/23 20:06	07/23/23 20:22	Kedzie Ave & 110th St	20204	Public Rack - Racine Ave & 109th Pl	877	41.692406	-87.700905	41.694835	-87.653041	member	0:16:30	1
D1460EE3CE0D8AF8	classic_bike	07/23/23 17:05	07/23/23 17:18	Western Ave & Walton St	KA1504000103	Milwaukee Ave & Grand Ave	13033	41.898418	-87.686596	41.891578	-87.648384	member	0:13:30	1
DF41BE31B895A25E	classic_bike	07/23/23 10:14	07/23/23 10:24	Western Ave & Walton St	KA1504000103	Damen Ave & Pierce Ave	TA1305000041	41.898418	-87.686596	41.909396	-87.677692	member	0:09:36	1
9624A293749EF703	electric_bike	07/21/23 8:27	07/21/23 8:32	Racine Ave & Randolph St	13155	Clinton St & Madison St	TA1305000032	41.884112	-87.656943	41.882752	-87.641190	member	0:04:56	6
2F68A6A4CDB4C99A	classic_bike	07/08/23 15:46	07/08/23 15:58	Clark St & Leland Ave	TA1309000014	Montrose Harbor	TA1308000012	41.967088	-87.667291	41.963982	-87.638181	member	0:11:26	7

```
# check for missing values
df.isna().sum()
```

```
ride_id                    0
rideable_type              0
started_at                 0
ended_at                   0
start_station_name    933350
start_station_id      933350
end_station_name      980959
end_station_id        980959
start_lat                  0
start_lng                  0
end_lat                 7936
end_lng                 7936
member_casual              0
ride_length                0
day_of_week                0
```

There are missing values in the columns *start_station_name*, *start_station_id*, *end_station_name*, *end_station_id*, *end_lat* and *end_lng*. For now, we will focus on the ride's duration and the day of the week.

So, we will not drop the missing values in the columns start_station_name, start_station_id, end_station_name, and *end_station_id* as it would remove the lion's share from our data.

Since there are no missing values in the columns we focus on, which are *ride_length* and *day_of_week*, we go ahead without dropping the above missing values.

However, we impute the columns *end_lat* and *end_lng* using the mean.

```
# impute end_lat and end_lng using mean
df['end_lat'] = df['end_lat'].fillna(df['end_lat'].mean())
df['end_lng'] = df['end_lng'].fillna(df['end_lng'].mean())

# confirm the imputation
df.isna().sum()
```

```
ride_id                    0
rideable_type              0
started_at                 0
ended_at                   0
start_station_name    933350
start_station_id      933350
end_station_name      980959
end_station_id        980959
start_lat                  0
start_lng                  0
end_lat                    0
end_lng                    0
member_casual              0
ride_length                0
day_of_week                0
```

```
# check for duplicates
df.duplicated().sum()
```
We see that there are no duplicate records in our data.

Now, Going for the descriptive analysis, we have,

```
# Summary statistics for the entire dataset
print("Summary Statistics for the Entire Dataset:")
print(df.describe())

# Summary statistics for annual members
print("\nSummary Statistics for Annual Members:")
print(df[df['member_casual'] == 'member'].describe())

# Summary statistics for casual riders
print("\nSummary Statistics for Casual Riders:")
print(df[df['member_casual'] == 'casual'].describe())
```

```
Summary Statistics for the Entire Dataset:
          start_lat     start_lng       end_lat       end_lng   day_of_week
count  5.740211e+06  5.740211e+06  5.740211e+06  5.740211e+06  5.740211e+06
mean   4.190288e+01 -8.764667e+01  4.190325e+01 -8.764689e+01  4.088204e+00
std    4.517871e-02  2.729548e-02  4.853924e-02  4.570883e-02  2.002692e+00
min    4.163000e+01 -8.794000e+01  0.000000e+00 -8.812000e+01  1.000000e+00
25%    4.188096e+01 -8.766000e+01  4.188103e+01 -8.766000e+01  2.000000e+00
50%    4.189897e+01 -8.764336e+01  4.189993e+01 -8.764395e+01  4.000000e+00
75%    4.193000e+01 -8.762963e+01  4.193000e+01 -8.762979e+01  6.000000e+00
max    4.207000e+01 -8.746000e+01  4.219000e+01  0.000000e+00  7.000000e+00

Summary Statistics for Annual Members:
          start_lat     start_lng       end_lat       end_lng   day_of_week
count  3.688363e+06  3.688363e+06  3.688363e+06  3.688363e+06  3.688363e+06
mean   4.190232e+01 -8.764741e+01  4.190261e+01 -8.764756e+01  4.053541e+00
std    4.473588e-02  2.612114e-02  4.488737e-02  2.618676e-02  1.908489e+00
min    4.163000e+01 -8.794000e+01  4.162000e+01 -8.799000e+01  1.000000e+00
25%    4.188033e+01 -8.766014e+01  4.188033e+01 -8.766028e+01  2.000000e+00
50%    4.189820e+01 -8.764436e+01  4.189897e+01 -8.764445e+01  4.000000e+00
75%    4.193000e+01 -8.763058e+01  4.193000e+01 -8.763083e+01  6.000000e+00
max    4.207000e+01 -8.746000e+01  4.215000e+01 -8.752000e+01  7.000000e+00

Summary Statistics for Casual Riders:
          start_lat     start_lng       end_lat       end_lng   day_of_week
count  2.051848e+06  2.051848e+06  2.051848e+06  2.051848e+06  2.051848e+06
mean   4.190389e+01 -8.764533e+01  4.190441e+01 -8.764567e+01  4.150514e+00
std    4.594690e-02  2.924069e-02  5.447266e-02  6.789699e-02  2.160333e+00
min    4.164000e+01 -8.792000e+01  0.000000e+00 -8.812000e+01  1.000000e+00
25%    4.188114e+01 -8.766000e+01  4.188186e+01 -8.766000e+01  2.000000e+00
50%    4.190000e+01 -8.764000e+01  4.190070e+01 -8.764000e+01  4.000000e+00
75%    4.193000e+01 -8.762596e+01  4.193125e+01 -8.762603e+01  6.000000e+00
max    4.207000e+01 -8.752000e+01  4.219000e+01  0.000000e+00  7.000000e+00
```

Annual members tend to use the service slightly more consistently throughout the week, with a mean day of the week of 4.05 compared to casual riders' 4.15. This suggests a slightly more varied usage pattern among casual riders.

Casual riders show higher variability in trip destinations, as indicated by the larger standard deviation in end latitude and longitude values. This variability could mean broader use cases like tourism or recreational activities.

Of the 5.74 million rides, annual members have approximately 3.69 million rides, whereas casual rides amount to approximately 2.05.

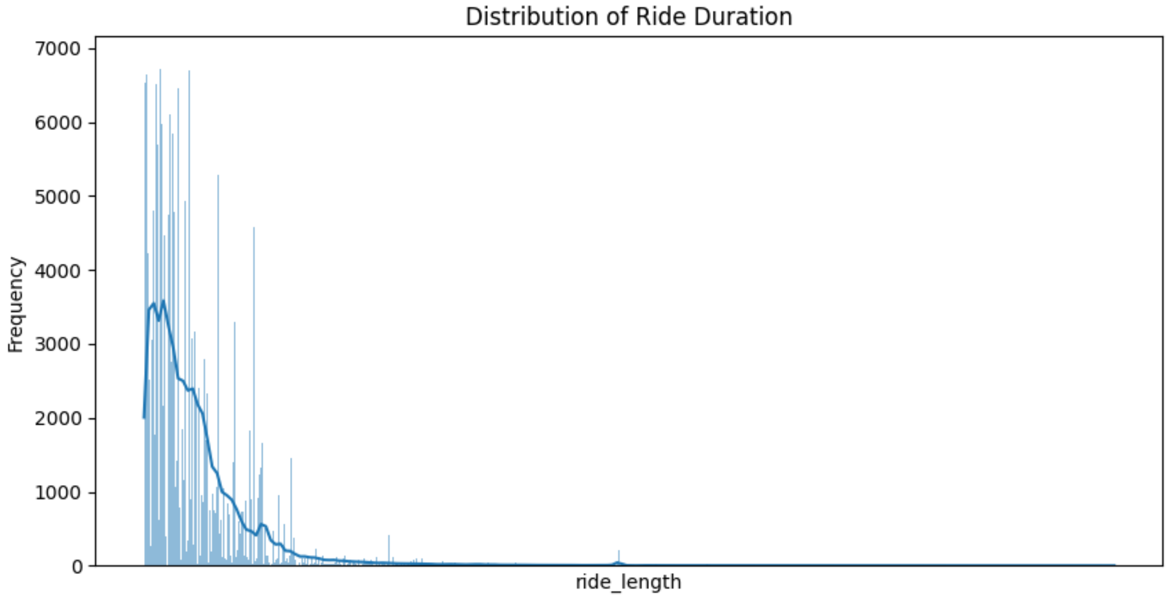
The average day of the week for rides is around Thursday, with a slight shift for casual riders indicating they might ride more on weekends. However, Thursday cannot be the most frequent day.

Ride_Length

```
# Cleaning the ride_length column - Ensure all entries are in HH:MM:SS format
# Using regex to filter out invalid entries
valid_format = df['ride_length'].str.match(r'^\d+:\d{2}:\d{2}$')
df = df[valid_format]

# Convert 'ride_length' to timedelta
df['ride_length'] = pd.to_timedelta(df['ride_length'])
df['ride_length'].describe()
```

```
count                        5739542
mean      0 days 00:18:19.193484950
std       0 days 02:38:40.112531189
min                  0 days 00:00:00
25%                  0 days 00:05:33
50%                  0 days 00:09:44
75%                  0 days 00:17:16
max                 68 days 09:29:04
Name: ride_length, dtype: object
```

```
# plotting the distribution of Ride duration
plt.figure(figsize=(10, 5))
sns.histplot(df['ride_length'], kde=True)
plt.title('Distribution of Ride Duration')
plt.gca().set_xticks([])
plt.ylabel('Frequency')
plt.show()
```



From the above analyses, we have the following findings,

The average ride length is approximately 18 minutes and 19 seconds (0 days 00:18:19.193484950), and the standard deviation is about 2 hours, 38 minutes, and 40 seconds (0 days 02:38:40.112531189), indicating a high variability in ride lengths.

The median ride length is about 9 minutes and 44 seconds (0 days 00:09:44). This means that half of the rides are shorter than 9 minutes and 44 seconds, and half are longer.

The majority of rides are relatively short, as indicated by the 25th, 50th, and 75th percentiles, which are all under 20 minutes. The mean ride length being higher than the median suggests that there are some very long rides that skew the average upwards.

There is a high standard deviation, which indicates significant variability in ride lengths. This could be due to a mix of different use cases, such as short commutes versus longer leisure rides.

The graph shows that a significant number of bike rides have short durations. This suggests that many users use bikes for quick trips or short distances. The peak around shorter duration suggests that the company's bikes are well-suited for short trips, such as within a city centre or for last-mile transportation.

While short rides dominate, a tail still extends to the right, indicating longer ride durations as well. To optimise bike availability and maintenance, Cyclistic could focus on ensuring a sufficient number of bikes for short rides while also catering to users who need longer durations.

```
# average ride_length for members and casual riders
avg_member_ride_length = df[df['member_casual'] ==
'member']['ride_length'].mean()
avg_casual_ride_length = df[df['member_casual'] ==
'casual']['ride_length'].mean()

print("Average member ride length:", avg_member_ride_length)
print("Average casual ride length:", avg_casual_ride_length)
```

```
Average member ride length: 0 days 00:12:59.164767768
Average casual ride length: 0 days 00:27:54.506756186
```

On average, annual members ride for about 12 minutes and 59 seconds per ride. While this is the case, casual riders ride for about 27 minutes and 54 seconds per ride on average.

Members tend to take shorter rides compared to casual riders, with an average ride duration of just under 13 minutes. This could suggest that members might use the service for shorter commuting or regular short trips.

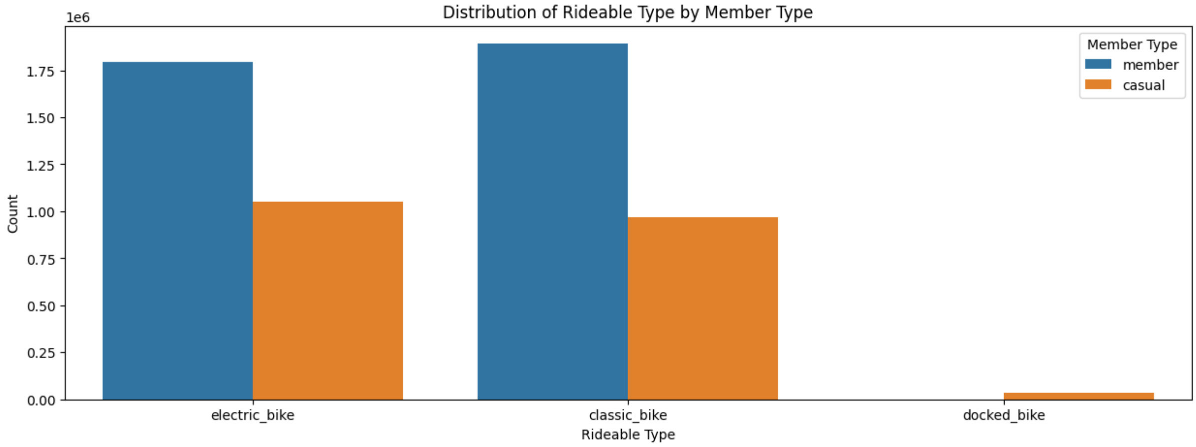
On the other hand, casual riders take longer rides on average, almost 28 minutes per ride. This longer duration might indicate that casual riders use the service for leisurely rides, sightseeing, or longer trips compared to members.

These insights into average ride lengths can be used to make informed decisions related to service offerings, pricing strategies, or resource allocation within the bike-sharing system.

Rideable Type

```
# Distribution of rideable type
plt.figure(figsize=(15, 5))
sns.countplot(data=df, x='rideable_type', hue='member_casual')
plt.title('Distribution of Rideable Type by Member Type')
plt.xlabel('Rideable Type')
```

```
plt.ylabel('Count')
plt.legend(title='Member Type', loc='upper right')
plt.show()
```



The above bar plot illustrates the distribution of rideable bike types among annual members and casual users. We have three types of bikes: electric bikes, classic bikes, and docked bikes.

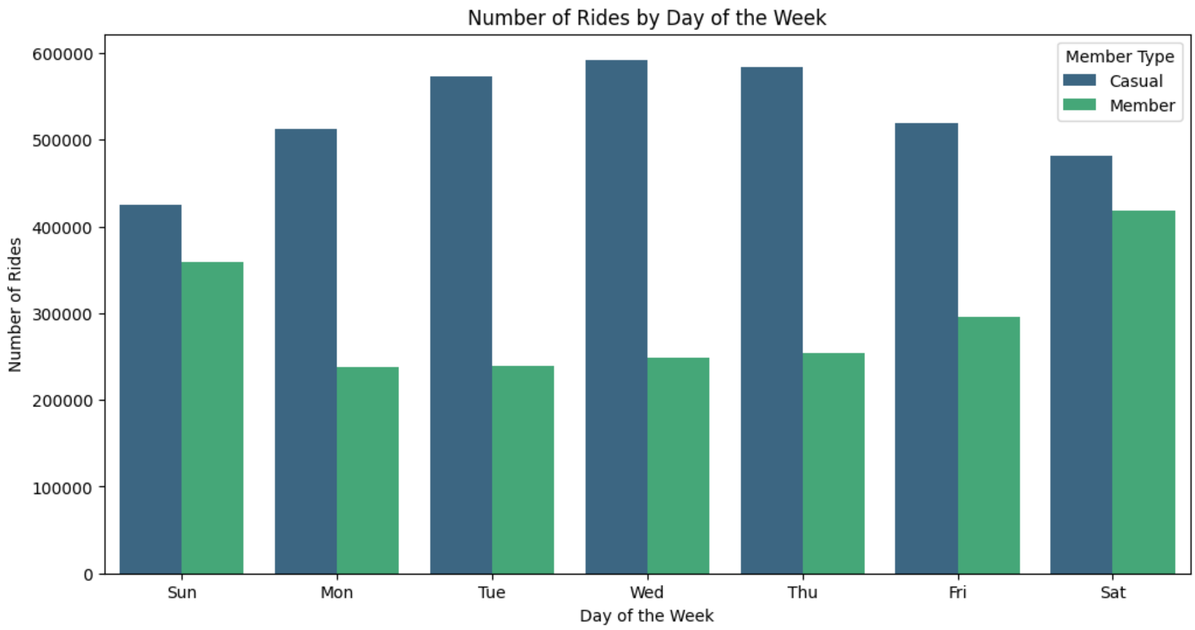
Both annual members and casual riders use electric bikes frequently, but annual members use them more. Classic bikes are the most popular type among both members and casual riders, with members again showing higher usage. Docked bikes are bikes that must be picked up from and returned to designated docking stations. Docked bikes are the least popular option for both groups, indicating a strong preference for electric and classic bikes.

Members and casual riders both prefer classic bikes the most, followed by electric bikes, with docked bikes being the least preferred. Members consistently show higher usage of both electric and classic bikes compared to casual riders.

Cyclistic has to focus more on maintaining and increasing its fleet of electric and classic bikes due to their high demand. Understanding the reasons behind the low popularity of docked bikes might reveal opportunities for service improvements or fleet optimisation.

Day of the Week

```
# Plotting the distribution of rides by day of the week
plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='day_of_week', hue='member_casual',
palette='viridis')
plt.title('Number of Rides by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Number of Rides')
plt.legend(title='Member Type', loc='upper right', labels=['Casual',
'Member'])
plt.xticks([0, 1, 2, 3, 4, 5, 6], ['Sun', 'Mon', 'Tue', 'Wed', 'Thu',
'Fri', 'Sat'])
plt.show()
```



Annual Members take more bike rides on weekends (Saturday and Sunday). This suggests that weekends are popular for leisurely rides or recreational biking. They are consistent on weekdays (Monday to Friday), possibly for commuting or regular transportation. The consistent weekday usage by Members suggests that they rely on bikes for daily transportation needs.

On weekdays, casual riders consistently outpace Casual riders, suggesting that they use bikes for daily transportation needs. They comprise more bikes than annual members, even on weekdays. The higher number of rides on weekends indicates that people use bikes for non-work-related activities during their free time.

The company can allocate more bikes on weekdays to meet the increased demand. Weekend bike availability should cater to Members' commuting needs. Marketing efforts could encourage casual riders to use bikes on weekends.

```
# Dictionary mapping numeric day of week-to-day names
day_mapping = {
    1: 'Sunday',
    2: 'Monday',
    3: 'Tuesday',
    4: 'Wednesday',
    5: 'Thursday',
    6: 'Friday',
    7: 'Saturday'
}

# Calculate the mode of day_of_week
mode_day_of_week = statistics.mode(jul['day_of_week'])
mode_day_name = day_mapping[mode_day_of_week]
print("Mode day of week:", mode_day_name)
```

```
Mode day of week: Saturday
```

This suggests that Saturday has the highest frequency of bike usage compared to any other day, likely reflecting increased recreational or leisure activities during the weekend. Cyclistic can use this insight to ensure that more bikes are available on Saturdays to accommodate the higher demand.

```
# number of rides for users by day_of_week
rides_by_day = jul.groupby('day_of_week')['ride_id'].count()

# Dictionary mapping numeric day of week to day names
day_mapping = {
    1: 'Sunday',
    2: 'Monday',
    3: 'Tuesday',
    4: 'Wednesday',
    5: 'Thursday',
    6: 'Friday',
    7: 'Saturday'
}

# Print the number of rides for each day of the week
for day, count in rides_by_day.items():
    day_name = day_mapping[day]
    print(f"Number of rides on {day_name}: {count}")
```

```
Number of rides on Sunday: 116825
Number of rides on Monday: 122535
Number of rides on Tuesday: 101697
Number of rides on Wednesday: 81886
Number of rides on Thursday: 104125
Number of rides on Friday: 104026
Number of rides on Saturday: 136556
```

As we saw earlier, Saturday has the highest number of rides, with **136,556** rides. Then, Sunday follows with **116,825** rides. This indicates that the bike-sharing service is most popular on weekends, likely due to people having more free time for leisure activities and outings.

The number of rides tends to be lower in the middle of the week, particularly on Wednesday , which has the lowest count of **81,886** rides. Tuesday and Thursday also have relatively lower numbers compared to the start and end of the work week, with **101,697** and **104,125** rides, respectively.

A pattern can be seen at the beginning and end of each week. Mondays see a significant number of rides, with **122,535** rides, suggesting a busy start to the work week, with people possibly commuting to work or starting their week with activities. Similarly, at the end of the week, Friday also has a relatively high number of rides at **104,026**, which may reflect people preparing for the weekend or winding down their work week.

Given the high usage on weekends, targeted promotions or special offers could be implemented to further capitalise on this peak period. Strategies to boost mid-week usage, such as mid-week discounts, special events, or partnerships with local businesses to incentivize riding, could be beneficial.

The relatively high number of rides on Monday and Friday suggests that many users might be using the service for commuting. Enhancing commuter-friendly features such as ensuring that bikes are readily available and in good condition during rush hours, planning maintenance schedules during non-peak hours and providing convenient docking stations near business districts could improve user satisfaction.

```
# average ride_length for users by day_of_week
avg_ride_length_by_day =
df.groupby('day_of_week')['ride_length'].mean()

# Dictionary mapping numeric day of week to day names
day_mapping = {
    1: 'Sunday',
    2: 'Monday',
    3: 'Tuesday',
    4: 'Wednesday',
    5: 'Thursday',
    6: 'Friday',
    7: 'Saturday'
}

# Print the average ride_length for each day of the week
for day, avg_length in avg_ride_length_by_day.items():
    day_name = day_mapping[day]
    print(f"Average ride length on {day_name}: {avg_length}")
```

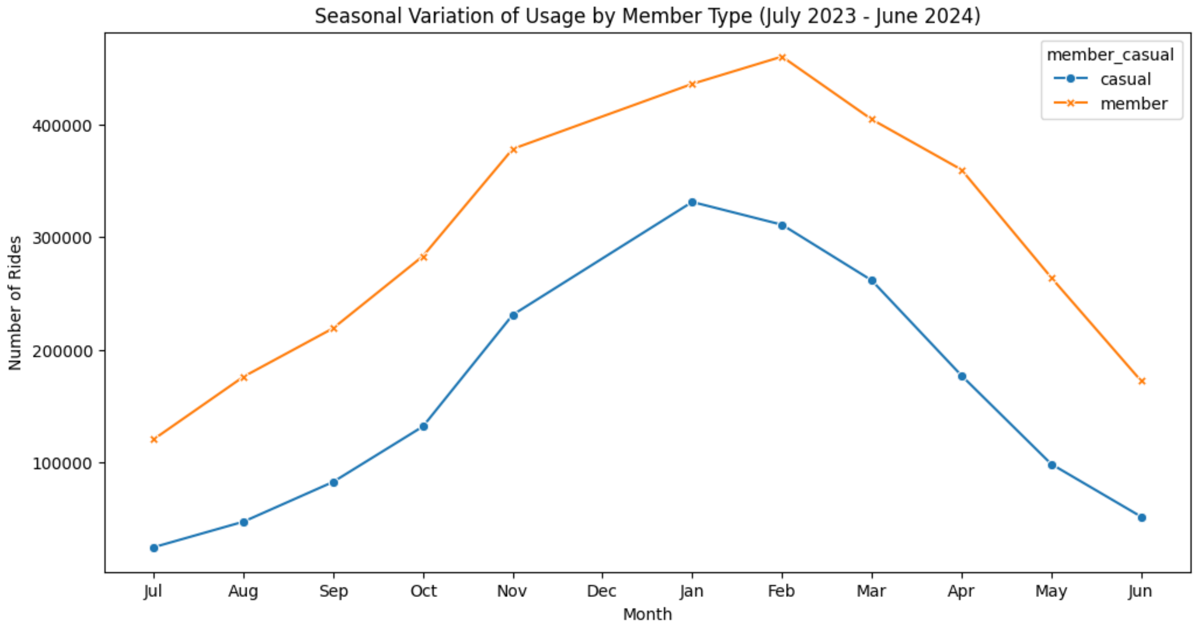
```
Average ride length on Sunday: 0 days 00:22:53.281846479
Average ride length on Monday: 0 days 00:17:08.447597836
Average ride length on Tuesday: 0 days 00:16:08.652066412
Average ride length on Wednesday: 0 days 00:16:02.092353046
Average ride length on Thursday: 0 days 00:16:00.786218339
Average ride length on Friday: 0 days 00:17:51.678901648
Average ride length on Saturday: 0 days 00:21:59.042420794
```

Sunday shows the longest average ride length at approximately 22 minutes and 53 seconds, followed closely by Saturday, with an average ride length of about 21 minutes and 59 seconds, reinforcing that weekends might see more leisurely or longer rides.

The weekdays generally have shorter average ride lengths ranging from about 16 to 18 minutes, indicating possibly more utilitarian or shorter-distance rides during weekdays than weekends. However, these days exhibit very similar average ride lengths. This consistency might indicate stable usage patterns or commuter behaviour with relatively predictable ride durations during the weekdays.

Given the longer average ride lengths on weekends (Sunday and Saturday), bike-sharing services might consider special promotions or incentives to attract more riders during these days. Similarly, understanding the shorter average ride lengths on weekdays could influence operational decisions such as bike deployment or service availability adjustments to cater to shorter, possibly commuter-focused rides.

```
# Filter data from July 2023 to June 2024
df_filtered = df[(df['started_at'] >= '2023-07-01') & (df['started_at']
<= '2024-06-30')]

# Specify the format of the 'started_at' column
df_filtered['started_at'] = pd.to_datetime(df_filtered['started_at'],
format='%m/%d/%y %H:%M', errors='coerce')

# Extract the month from the 'started_at' column
df_filtered['month'] = df_filtered['started_at'].dt.month

# Group data by month and member type
grouped_data = df_filtered.groupby(['month',
'member_casual'])['ride_id'].count().unstack()

# Create a line chart for ride patterns among casual and member riders
plt.figure(figsize=(12, 6))
sns.lineplot(data=grouped_data, markers=True, dashes=False)

# Set labels and title
plt.xlabel('Month')
plt.ylabel('Number of Rides')
plt.title('Seasonal Variation of Usage by Member Type (July 2023 - June
2024)')

# Label the months on the x-axis
plt.xticks(ticks=range(1, 13), labels=['Jul', 'Aug', 'Sep', 'Oct',
'Nov', 'Dec', 'Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun'])

# Show the plot
plt.show()
```



The line representing casual riders starts lower in July and gradually increases. The peak for casual riders occurs in December - January, suggesting higher usage during the holiday season. After the new year, the casual rider line declines and remains below the member line.

The member line peaks in July, possibly due to regular commuters. Members consistently have a higher number of rides compared to casual riders across all months. It gradually declines after November. Both the annual users and casual riders show more pronounced seasonal variation, with peaks in December and dips in summer.

Both member and casual rider usage shows a distinct seasonal pattern. There is a general increase in usage for both groups from July to January, followed by a steady decline from February to June.

The increase in bike usage during winter (November to January) might be influenced by favourable weather conditions, holidays, and potential seasonal promotions. The decline during the summer months (April to July) could be due to adverse weather conditions, vacations, or other factors reducing the need for bike usage.

Cyclistic can allocate more resources and bikes during peak months (November to January) to meet the higher demand. Implementing marketing strategies during the off-peak months (April to July) might help in balancing the usage throughout the year.

The consistent higher usage among members suggests that membership benefits are appealing. Cyclistic could highlight these benefits to encourage more casual riders to become members.

Understanding these trends allows Cyclistic to plan maintenance and operational activities during lower demand periods to minimise service disruptions.

Conclusions…

This analysis has provided valuable insights into the distinct behaviours and preferences of Cyclistic's annual members and casual riders. Here are the key findings:

- Annual members have an average ride duration of about 13 minutes, while casual riders average nearly 28 minutes per ride.
- Casual riders exhibit a high variability in ride lengths, suggesting diverse use cases such as leisure or sightseeing.
- Both annual members and casual riders prefer classic bikes, followed by electric bikes, with docked bikes being the least popular.
- Members consistently show higher usage of both electric and classic bikes compared to casual riders.
- Casual riders are more likely to use bikes on weekends, while annual members show consistent usage on weekdays, indicating daily commuting.
- Saturday has the highest number of rides, followed by Sunday, reflecting increased recreational activities on weekends.
- The lowest number of rides is on Wednesday, with a notable dip in mid-week usage.
- Members are more likely to use bikes for short, frequent trips, likely for commuting.
- Casual riders tend to use bikes for longer, less frequent rides, suggesting recreational use.

Recommendations:

1. **Targeted Marketing Strategies**: Focus marketing efforts on converting casual riders to annual memberships by highlighting the benefits of membership for frequent, shorter trips. Develop promotions and special offers aimed at weekend users to further capitalise on the peak usage period.
2. **Bike Availability and Maintenance**: Ensure a sufficient number of bikes are available for short rides during peak hours, particularly on weekends and Mondays. Focus maintenance efforts on non-peak hours to maximise bike availability during high-demand periods.
3. **Service Enhancements**: Improve commuter-friendly features, such as ensuring bikes are readily available near business districts and maintaining convenient docking stations. Address the low popularity of docked bikes by exploring opportunities for service improvements or fleet optimisation.
4. **Digital Media Campaigns**: Utilize digital media to promote the benefits of annual memberships and highlight the convenience and cost-effectiveness of regular users. Engage with casual riders through social media campaigns, emphasising the value of memberships for leisure and sightseeing activities.

These insights and recommendations will aid Cyclistic in developing effective strategies to increase annual memberships and enhance overall user satisfaction, ensuring sustained growth and success for the company, thereby answering the business question: How do annual members and casual riders use Cyclistic bikes differently?