Google Data Analytics Professional Certificate Capstone Project

Case Study: How Does a Bike-Share Navigate Speedy Success?

This project is part of the Google Data Analytics Professional Certification. Cyclistic, a bike-share company in Chicago has been chosen as the subject of the project. The project is aimed at finding the usage trends of annual and casual users.

The company has a fleet of over 5800 geotagged bikes and a network of over 600 stations across Chicago. The service offers 3 types of plans: A single ride pass; a full-day pass; and annual memberships. Single-ride and full-day customers are called Casual Riders while Annual plan customers are Cyclistic Members

Annual Members have been identified as much more profitable than Casual Riders. The management has outlined that the flexibility of products will help attract more customers overall, but real growth will only be seen with more members.

Rather than spending money on attracting all-new customers who have not heard of and/or never tried the service, it will be more efficient and beneficial to convert the existing Casual Riders who already know and trust Cyclistic

The goal of this project is to understand how casual riders and annual members differ. Why Casual Riders would be willing to upgrade to a membership.

The data is provided by Motivate International Inc with the following licence: https://www.divvybikes.com/data-license-agreement The data includes ride details of all the rides done on the bikes of the company during the calendar year 2022. No personal or customer data was shared. This means we can not identify the members or even the number of each category of rider. We can only classify the rides into categories.

1. Preparing the data

Loading and verifying data

```
# Importing the libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
sns.set_style("dark")

# Importing all 12 files
df1 = pd.read_csv('202201-divvy-tripdata.csv')
df2 = pd.read_csv('202202-divvy-tripdata.csv')
```

```
df3 = pd.read_csv('202203-divvy-tripdata.csv')
df4 = pd.read_csv('202204-divvy-tripdata.csv')
df5 = pd.read_csv('202205-divvy-tripdata.csv')
df6 = pd.read_csv('202206-divvy-tripdata.csv')
df7 = pd.read_csv('202207-divvy-tripdata.csv')
df8 = pd.read_csv('202208-divvy-tripdata.csv')
df9 = pd.read_csv('202209-divvy-tripdata.csv')
df10 = pd.read_csv('202210-divvy-tripdata.csv')
df11 = pd.read_csv('202211-divvy-tripdata.csv')
df12 = pd.read_csv('202212-divvy-tripdata.csv')

# Combining all 12 dataframes into 1 dataframe
tripdata = pd.concat([df1, df2, df3, df4, df5, df6, df7, df8, df9,
df10, df11, df12])

# Verifying the dataframe
tripdata.head()
```

```
            ride_id  rideable_type           started_at
ended_at  \
0  C2F7DD78E82EC875  electric_bike  2022-01-13 11:59:47  2022-01-13
12:02:44
1  A6CF8980A652D272  electric_bike  2022-01-10 08:41:56  2022-01-10
08:46:17
2  BD0F91DFF741C66D   classic_bike  2022-01-25 04:53:40  2022-01-25
04:58:01
3  CBB80ED419105406   classic_bike  2022-01-04 00:18:04  2022-01-04
00:33:00
4  DDC963BFDDA51EEA   classic_bike  2022-01-20 01:31:10  2022-01-20
01:37:12

              start_station_name start_station_id  \
0       Glenwood Ave & Touhy Ave              525
1       Glenwood Ave & Touhy Ave              525
2  Sheffield Ave & Fullerton Ave     TA1306000016
3       Clark St & Bryn Mawr Ave     KA1504000151
4    Michigan Ave & Jackson Blvd     TA1309000002

                end_station_name end_station_id  start_lat  start_lng
\
0          Clark St & Touhy Ave         RP-007  42.012800 -87.665906

1          Clark St & Touhy Ave         RP-007  42.012763 -87.665967

2  Greenview Ave & Fullerton Ave   TA1307000001  41.925602 -87.653708

3      Paulina St & Montrose Ave   TA1309000021  41.983593 -87.669154

4         State St & Randolph St   TA1305000029  41.877850 -87.624080
```

```
     end_lat    end_lng member_casual
0  42.012560 -87.674367        casual
1  42.012560 -87.674367        casual
2  41.925330 -87.665800        member
3  41.961507 -87.671387        casual
4  41.884621 -87.627834        member
```

```
# Checking the shape of the dataset
print("The combined dataset has",tripdata.shape[0],"records
and",tripdata.shape[1],"columns.")
```

```
The combined dataset has 5667717 records and 13 columns.
```

```
# Checking the data types
tripdata.dtypes
```

```
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
```

2. Processing the data

Cleaning Data

```
# Checking for empty values
tripdata.isnull().sum()
```

```
ride_id                    0
rideable_type              0
started_at                 0
ended_at                   0
start_station_name    833064
start_station_id      833064
end_station_name      892742
end_station_id        892742
start_lat                  0
start_lng                  0
end_lat                 5858
end_lng                 5858
```

```
member_casual             0
dtype: int64
```

```python
# Dropping records with null values
tripdata.dropna(subset=['start_station_name'], inplace=True)
tripdata.dropna(subset=['start_station_id'], inplace=True)
tripdata.dropna(subset=['end_station_name'], inplace=True)
tripdata.dropna(subset=['end_station_id'], inplace=True)
tripdata.dropna(subset=['end_lat'], inplace=True)
tripdata.dropna(subset=['end_lng'], inplace=True)

# Verifying that all records with empty values are removed
tripdata.isnull().sum()
```

```
ride_id               0
rideable_type         0
started_at            0
ended_at              0
start_station_name    0
start_station_id      0
end_station_name      0
end_station_id        0
start_lat             0
start_lng             0
end_lat               0
end_lng               0
member_casual         0
dtype: int64
```

Records that reflect test or maintainence rides should be removed

```python
# Dropping records with station names containing 'Base'
tripdata = 
tripdata[~tripdata['start_station_name'].str.contains('Base')]
tripdata = 
tripdata[~tripdata['end_station_name'].str.contains('Base')]

# Dropping records with station ids containing 'DIVVY'
tripdata = 
tripdata[~tripdata['start_station_name'].str.contains('DIVVY')]
tripdata = 
tripdata[~tripdata['end_station_name'].str.contains('DIVVY')]

# Dropping records with station ids containing 'TEST'
tripdata = 
tripdata[~tripdata['start_station_id'].str.contains('TEST')]
tripdata = tripdata[~tripdata['end_station_id'].str.contains('TEST')]

# Dropping records with station ids containing 'charging'
tripdata = 
```

```
tripdata[~tripdata['start_station_id'].str.contains('charging')]
tripdata =
tripdata[~tripdata['end_station_id'].str.contains('charging')]

# Keeping only rides with a valid ride_id of 16 characters
tripdata = tripdata[tripdata['ride_id'].str.len()==16]
```

Transforming Data

Fields like started_at and ended_at need to be converted to computable time. And trip length will be calculated.

```
# Transforming the started and ended columns into datetime
tripdata['started_at'] = pd.to_datetime(tripdata['started_at'],
format='%Y-%m-%d %H:%M:%S')
tripdata['ended_at'] = pd.to_datetime(tripdata['ended_at'],
format='%Y-%m-%d %H:%M:%S')

tripdata['month'] = pd.DatetimeIndex(tripdata["started_at"]).month

# Adding the new column for triplength
tripdata['trip_length'] = tripdata['ended_at'] -
tripdata['started_at']

# Adding a new column of trip_seconds for calculations
tripdata['trip_seconds'] = tripdata['trip_length'].dt.total_seconds()

# Adding the new column for day of the week
tripdata['day_of_week'] = tripdata['started_at'].dt.day_name()
```

The latitude and longitude values are rounded to 3 places after the decimal so that they can be groupped and plotted on a map in a more intuitive way. https://blis.com/precision-matters-critical-importance-decimal-places-five-lowest-go/#:~:text=So%2C%20as%20you%20can%20see,six%20can%20identify%20a%20person states that the distance between 2 points with the precision of 3 places after the decimal is about 100 meters.

```
# Rounding the latitude and longitude values to 3 places after the
decimal for the required accuracy
tripdata['start_lat'] = tripdata['start_lat'].round(3)
tripdata['start_lng'] = tripdata['start_lng'].round(3)
tripdata['end_lat'] = tripdata['end_lat'].round(3)
tripdata['end_lng'] = tripdata['end_lng'].round(3)
```

To keep the data relevent, we will remove the records that have a ride length of more than 24 hours and less than 1 minute.

```
# Checking how many records are valid and invalid based on the
trip_length constraint
valid = tripdata[(tripdata['trip_length'] >= '0 days 00:01:00') &
```

```
(tripdata['trip_length']<'1 days 00:00:00')]
invalid = tripdata[(tripdata['trip_length'] < '0 days 00:01:00') &
(tripdata['trip_length']>='1 days 00:00:00')]
print("There are ",len(valid), " valid and ",len(invalid), "invalid
records based on the trip length constraint.")
```

```
There are  4222071  valid and  0 invalid records based on the trip
length constraint.
```

```
# Keeping only the rides that have a trip length of more than 1
minutes
tripdata = tripdata[tripdata['trip_length']>'0 days 00:01:00']

# Keeping only the rides that have a trip length of less than 24 hours
tripdata = tripdata[tripdata['trip_length']<'1 days 00:00:00']
```

The trips with the same start and end station and a ride shorter than 2 minutes will be filtered out.

```
# Identifying the rides with same start and end station
tripdata['same_station'] = tripdata['start_station_id'] ==
tripdata['end_station_id']

# Filtering out records with same start and end station and less than
2 minute ride
tripdata = tripdata[~(tripdata['same_station'] &
(tripdata['trip_length'] < pd.Timedelta('0 days 00:02:00')))]

# Dropping the same_station column as it is no longer needed
tripdata = tripdata.drop(columns=['same_station'])

# Checking the shape of the dataset after all cleaning and
transformation.
print("The combined dataset has",tripdata.shape[0],"records
and",tripdata.shape[1],"columns.")
```

```
The combined dataset has 4198497 records and 17 columns.
```

Now that the data preparation and transformation is over, we can proceed to analyse it

3. Analysing the data

Distribution of rides among user type

```
tripdata.describe(include=[np.number])
```

```
          start_lat     start_lng       end_lat       end_lng
month  \
count  4.198497e+06  4.198497e+06  4.198497e+06  4.198497e+06
4.198497e+06
mean   4.190198e+01 -8.764467e+01  4.190230e+01 -8.764495e+01
```

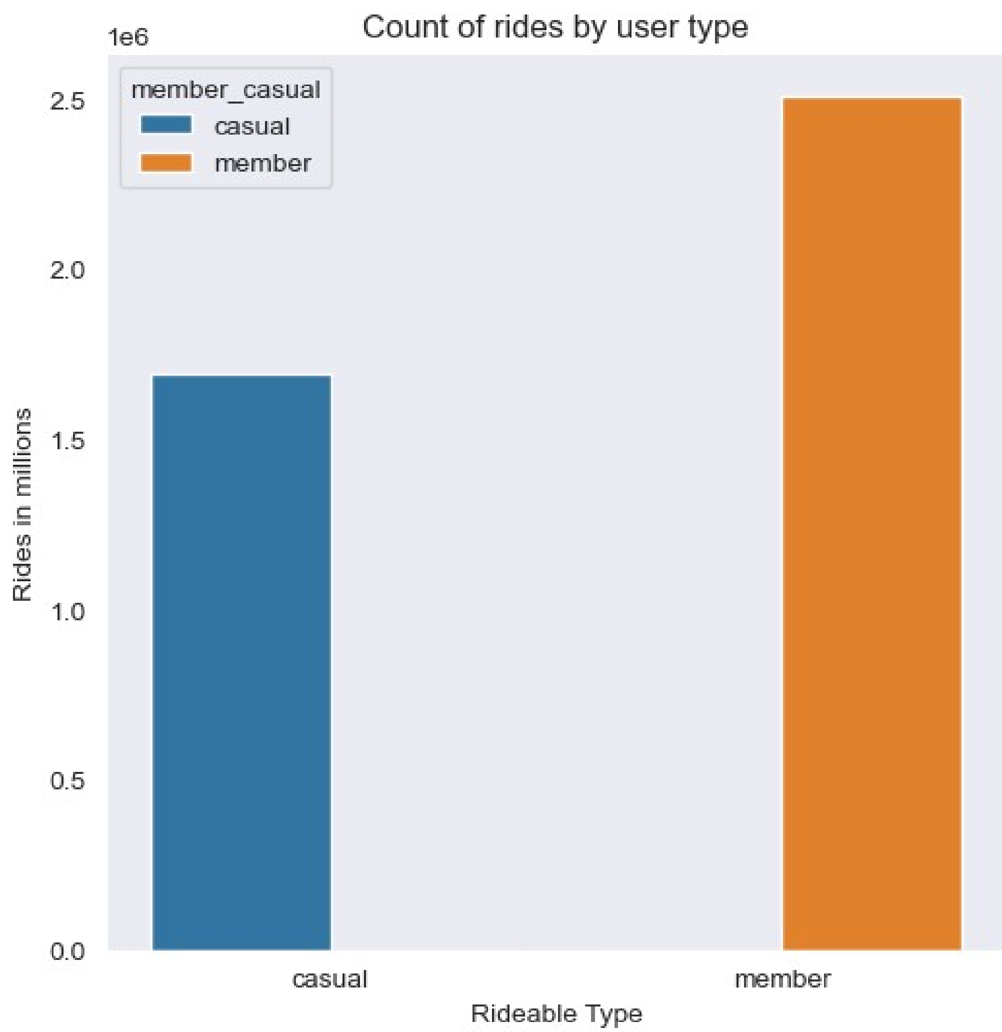
```
7.070903e+00
std    4.267613e-02  2.485534e-02  4.286484e-02  2.505811e-02
2.518611e+00
min    4.164900e+01 -8.783000e+01  4.164900e+01 -8.783000e+01
1.000000e+00
25%    4.188100e+01 -8.765800e+01  4.188100e+01 -8.765800e+01
5.000000e+00
50%    4.189700e+01 -8.764100e+01  4.189800e+01 -8.764200e+01
7.000000e+00
75%    4.192900e+01 -8.762800e+01  4.192900e+01 -8.762800e+01
9.000000e+00
max    4.206500e+01 -8.752500e+01  4.206500e+01 -8.752800e+01
1.200000e+01

                     trip_length  trip_seconds  day_of_week_index
count                    4198497  4.198497e+06       4.198497e+06
mean   0 days 00:17:24.097305535  1.044097e+03       3.048397e+00
std    0 days 00:31:02.342903210  1.862343e+03       1.980192e+00
min              0 days 00:01:01  6.100000e+01       0.000000e+00
25%              0 days 00:06:19  3.790000e+02       1.000000e+00
50%              0 days 00:10:52  6.520000e+02       3.000000e+00
75%              0 days 00:19:24  1.164000e+03       5.000000e+00
max              0 days 23:59:22  8.636200e+04       6.000000e+00
```

```
# Checking the number of users in each type over past 12 months
member_type = tripdata["member_casual"].value_counts()
member_type
```

```
member    2509187
casual    1689310
Name: member_casual, dtype: int64
```

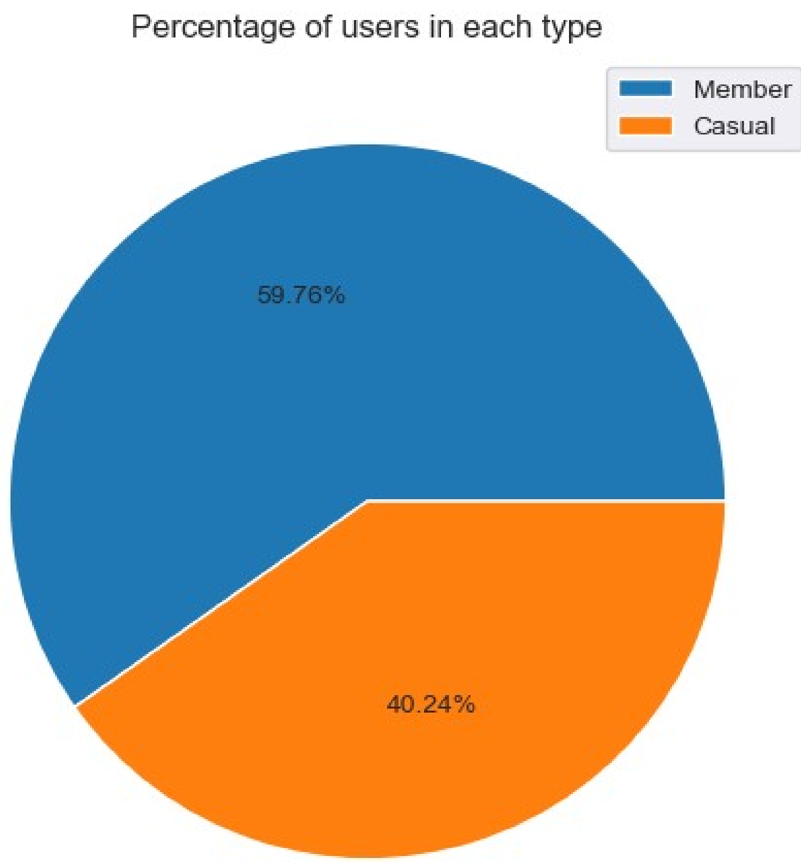
```
# Plotting the count of Member and Casual rides
plt.figure(figsize=(6, 6))
ax = sns.countplot(x='member_casual', hue='member_casual',
data=tripdata)
ax.set_title("Count of rides by user type")
ax.set_xlabel("Rideable Type")
ax.set_ylabel("Rides in millions")
```

```
Text(0, 0.5, 'Rides in millions')
```




```python
# Plotting a pie chart of users in each type
plt.figure(figsize=(8, 6))
plt.pie(member_type.values, autopct="%1.2f%%")
plt.title("Percentage of users in each type")
plt.legend(member_type.index, labels= ["Member", "Casual"])
plt.show()
```

```
C:\Users\HAL9K\AppData\Local\Temp\ipykernel_39924\1612470138.py:5:
UserWarning: You have mixed positional and keyword arguments, some
input may be discarded.
  plt.legend(member_type.index, labels= ["Member", "Casual"])
```



Just shy of 60% of the rides were done by members and only about 40% of the rides were casual riders, meaning that the company is in a relatively good health.

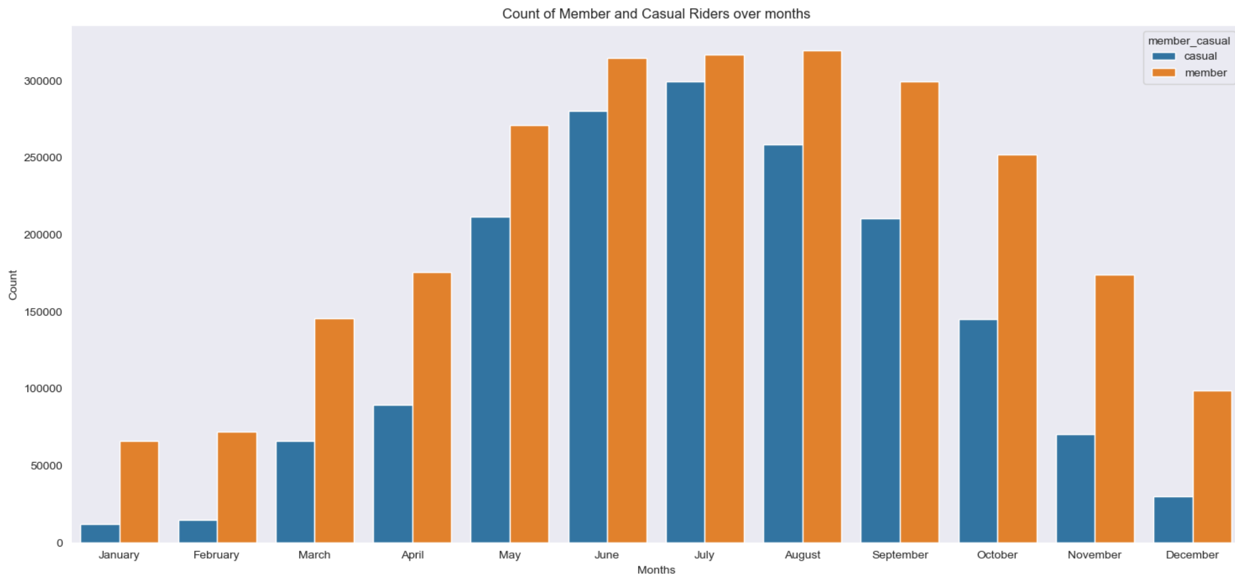
```
# Checking the number of users over months
users_over_month = tripdata.groupby("month")
["member_casual"].value_counts()
users_over_month

month  member_casual
1      member            66371
       casual            12387
2      member            72394
       casual            14869
3      member           146040
       casual            66016
4      member           176011
       casual            89562
5      member           271333
       casual           211691
6      member           315039
       casual           280463
```

```
7       member            317338
        casual            299459
8       member            319991
        casual            258482
9       member            299711
        casual            210857
10      member            252140
        casual            145024
11      member            174173
        casual             70479
12      member             98646
        casual             30021
Name: member_casual, dtype: int64
```

```
# Segregating the number of users into member or casual riders over
months
list_month = []
list_x = []
list_y = list(users_over_month.values)
for i, j in users_over_month.index:
    list_x.append(j)
    list_month.append(str(i))
```

```
# Plotting the count of Member and Casual riders over months
plt.figure(figsize=(18, 8))
ax = sns.countplot(x='month', hue='member_casual', data=tripdata)
ax.set_xticklabels(["January", "February", "March", "April", "May",
"June", "July", "August", "September", "October", "November",
"December"])
ax.set_title("Count of Member and Casual Riders over months")
ax.set_xlabel("Months")
ax.set_ylabel("Count")
```

```
Text(0, 0.5, 'Count')
```



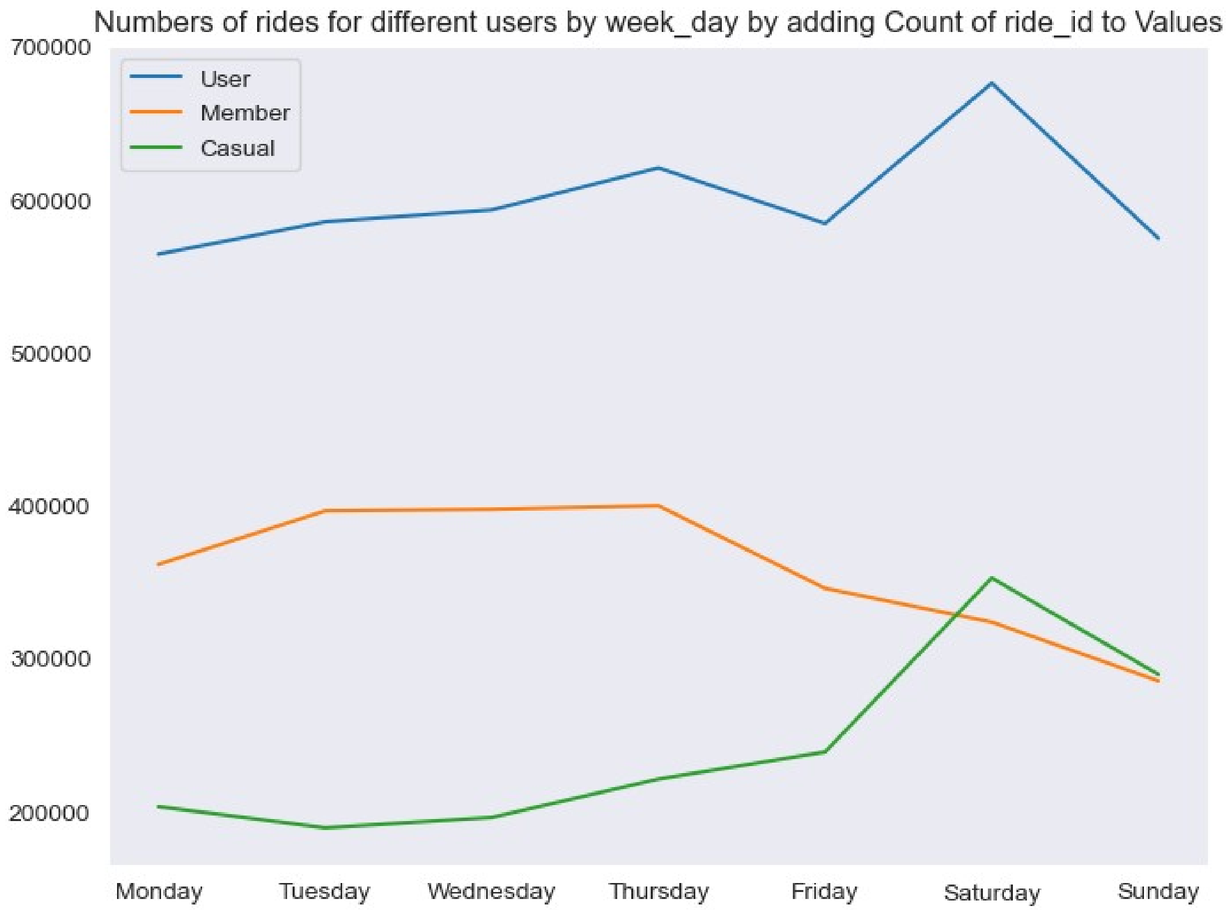
Clearly the most rides happen during the spring and summer seasons, from the months of May to September. The gap between members and casual riders also reduces drastically during this period. The good weather attracts local customers to use the bikes, and as this is a vacation season, many tourists might also use the bikes, presumably everyone of them using as a casual user.

Analysing the total rides across the days of the week

```
# Assigning numbers from 0 through 1 to the days of the week for
better sorting
week_day = { "Monday": 0, "Tuesday": 1, "Wednesday": 2, "Thursday": 3,
"Friday": 4, "Saturday": 5, "Sunday": 6}
tripdata["day_of_week_index"] = tripdata["day_of_week"].apply(lambda
y: week_day[y])

# Creating new dataframes with data of member and casual riders
separately
member = tripdata[tripdata['member_casual'].str.contains('member')]
casual = tripdata[tripdata['member_casual'].str.contains('casual')]

# Calculating the mode of day of the week
print("The most rides are on",tripdata['day_of_week'].mode())

The most rides are on 0    Saturday
Name: day_of_week, dtype: object

# Finding the mode of day of the week for member and cansual riders
print("Members most use the bikes on" ,member['day_of_week'].mode()),
print("Casual users most use the bikes on",
casual['day_of_week'].mode())

Members most use the bikes on 0    Thursday
Name: day_of_week, dtype: object
```

```
Casual users most use the bikes on 0    Saturday
Name: day_of_week, dtype: object

# Counting all users by day of week
users_week_day = tripdata.groupby("day_of_week_index")
["ride_id"].count()
users_week_day.sort_index()

day_of_week_index
0    564283
1    585418
2    593187
3    620674
4    584341
5    676055
6    574539
Name: ride_id, dtype: int64

# Counting member users by day of week
member_week_day = member.groupby("day_of_week_index")
["ride_id"].count()
member_week_day.sort_index()

day_of_week_index
0    361372
1    396324
2    397359
3    399702
4    345669
5    323614
6    285147
Name: ride_id, dtype: int64

# Counting casual users by day of week
casual_week_day = casual.groupby("day_of_week_index")
["ride_id"].count()
casual_week_day.sort_index()

day_of_week_index
0    202911
1    189094
2    195828
3    220972
4    238672
5    352441
6    289392
Name: ride_id, dtype: int64

# Plotting the graph of Weekday vs Number of Rides
plt.figure(figsize= (8,6))
plt.plot(users_week_day.index, users_week_day.values)
```

```
plt.plot(member_week_day.index, member_week_day.values)
plt.plot(casual_week_day.index, casual_week_day.values)
plt.title("Numbers of rides for different users by week_day by adding
Count of ride_id to Values")
plt.legend(["User", "Member", "Casual"])
labels = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
"Saturday","Sunday"]
plt.xticks(users_week_day.index, labels)
plt.show()
```



The weekly trends suggest that the rides go up towards the end of the week from Thursday and peaking at Saturday. But upon comparing the two types of users, the trend is drastically different. Members ride more during the working week and the casual riders ride more during the weekend.

Analysing the trip length

```
# Finding the average ride length
print("The average ride length is ",tripdata['trip_length'].mean())

The average ride length is  0 days 00:17:24.097305535
```

```python
# Finding the maximum ride length
print("The maximum ride length is ",tripdata['trip_length'].max())
```

```
The maximum ride length is  0 days 23:59:22
```

```python
# Calculating the mean ride length for member and cansual riders
print("The average ride length for members is
",member['trip_length'].mean(), "and the average ride length of casual
riders is",casual['trip_length'].mean())
```

```
The average ride length for members is  0 days 00:12:43.439376180 and
the average ride length of casual riders is 0 days 00:24:20.967641818
```

```python
# Calculating the average ride_length for all users by day of week
user_avg_ride_len_week_day = tripdata.groupby("day_of_week_index")
["trip_length"].mean(numeric_only=False)
user_avg_ride_len_week_day
```

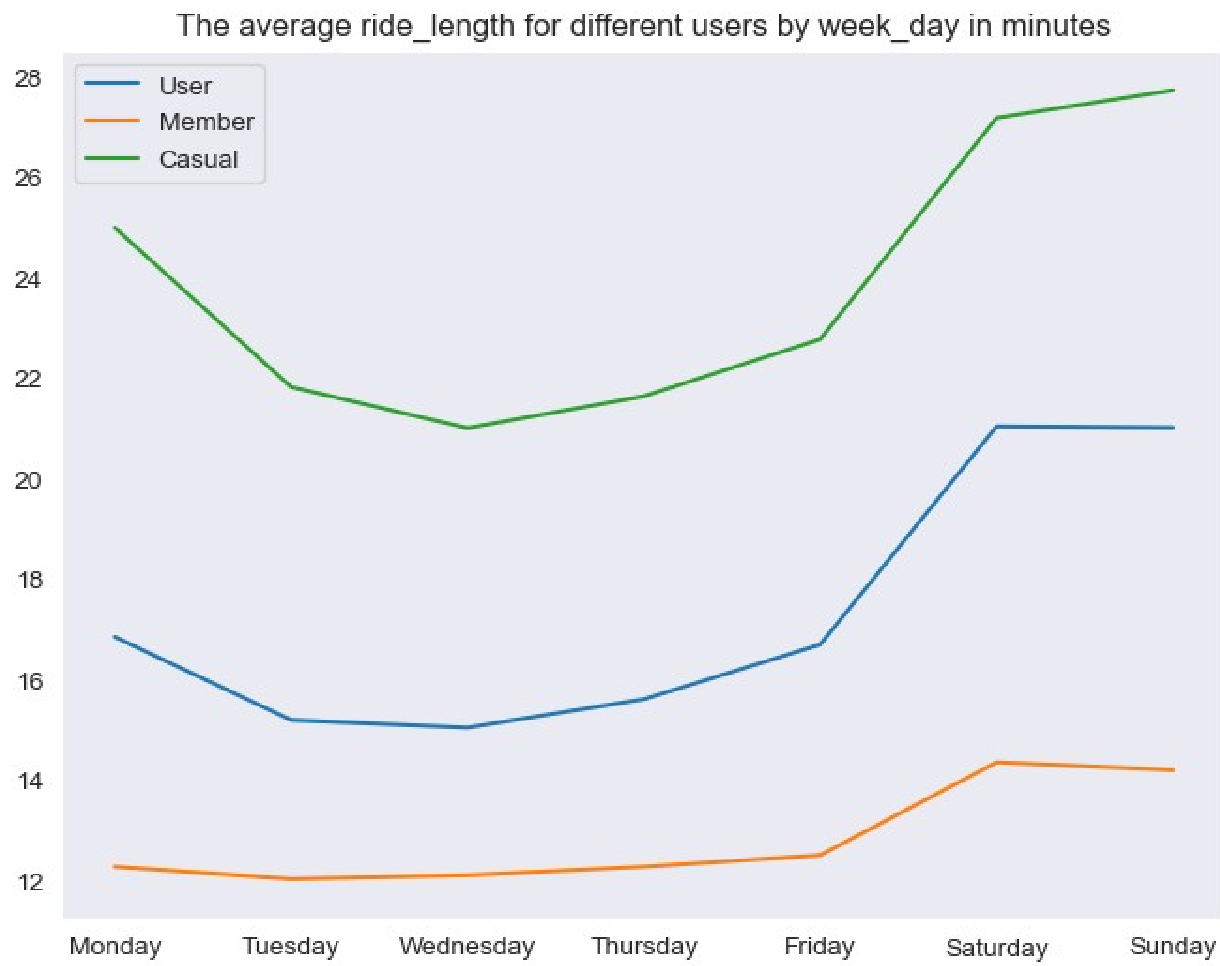
```
day_of_week_index
0   0 days 00:16:50.792625331
1   0 days 00:15:11.468685622
2   0 days 00:15:02.506585612
3   0 days 00:15:36.330041213
4   0 days 00:16:41.727782236
5   0 days 00:21:02.334441724
6   0 days 00:21:00.849348782
Name: trip_length, dtype: timedelta64[ns]
```

```python
# Calculating the average ride_length for members by week_day
member_avg_ride_len_week_day = tripdata[tripdata["member_casual"] ==
"member"].groupby(
    "day_of_week_index")["trip_length"].mean(numeric_only=False)
member_avg_ride_len_week_day
```

```
day_of_week_index
0   0 days 00:12:16.252310638
1   0 days 00:12:01.670623025
2   0 days 00:12:06.106973794
3   0 days 00:12:16.251407298
4   0 days 00:12:29.914172228
5   0 days 00:14:20.927051981
6   0 days 00:14:11.839121575
Name: trip_length, dtype: timedelta64[ns]
```

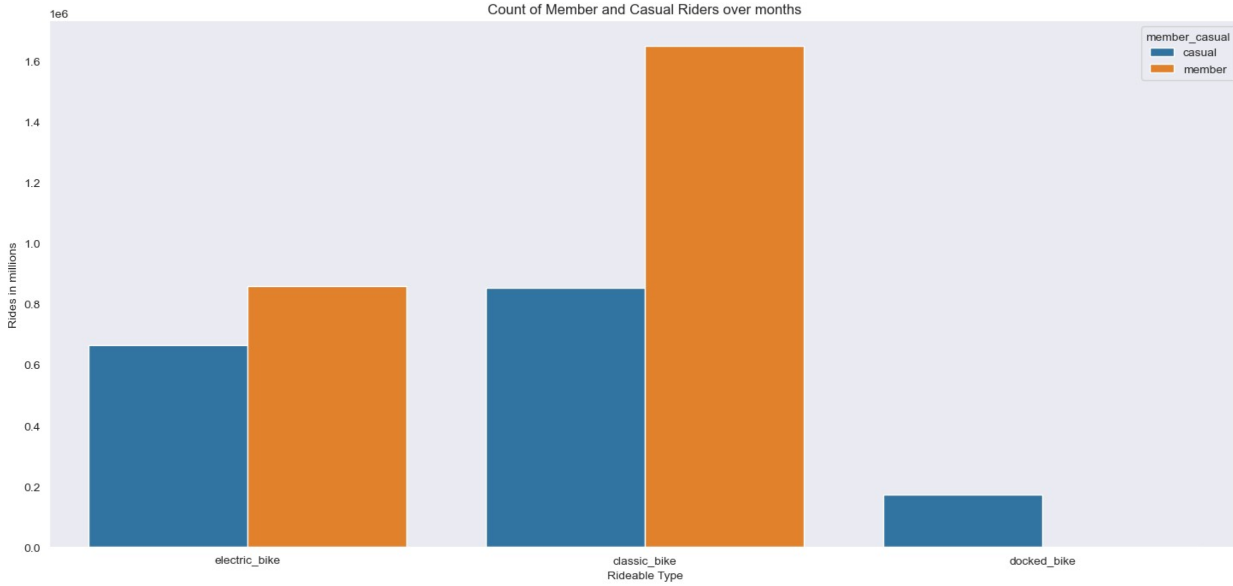
```python
# Calculating the average ride_length for members by week_day
casual_avg_ride_len_week_day = tripdata[tripdata["member_casual"] ==
"casual"].groupby(
    "day_of_week_index")["trip_length"].mean(numeric_only=False)
casual_avg_ride_len_week_day
```

```
day_of_week_index
0   0 days 00:24:59.732025370
1   0 days 00:21:49.268337440
2   0 days 00:21:00.443006107
3   0 days 00:21:38.239378744
4   0 days 00:22:46.429794864
5   0 days 00:27:10.909752270
6   0 days 00:27:43.859933930
Name: trip_length, dtype: timedelta64[ns]

# Plotting the graph of Weekday vs Average ride length
plt.figure(figsize=(8, 6))
plt.plot(user_avg_ride_len_week_day/pd.Timedelta(minutes=1))
plt.plot(member_avg_ride_len_week_day/pd.Timedelta(minutes=1))
plt.plot(casual_avg_ride_len_week_day/pd.Timedelta(minutes=1))
plt.title("The average ride_length for different users by week_day in 
minutes")
plt.legend(["User", "Member", "Casual"])
labels = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday", 
"Saturday","Sunday"]
plt.xticks(user_avg_ride_len_week_day.index, labels)
plt.show()
```



The average ride length follows the trend of the number of rides, peaking during the weekend. Upon comparing the users, it apears that the average ride length of members is almost half the average ride length of casual riders.

```
# Plotting the count of Member and Casual riders by rideable type
plt.figure(figsize=(18, 8))
ax = sns.countplot(x='rideable_type', hue='member_casual',
data=tripdata)
ax.set_title("Count of Member and Casual Riders over months")
ax.set_xlabel("Rideable Type")
ax.set_ylabel("Rides in millions")

Text(0, 0.5, 'Rides in millions')
```



Comparing the rideable types, classic bikes are most common, followed by electric bike and the docked bike has a minority share. The casual riders use electric and classic bikes almost equally, but the members seem to have a strong preference for classic bike over the electric bike.

```
tripdata.to_csv('tripdata_export')
```