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

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# Company

In 2016, Cyclistic launched a successful bike-share offering. Since then, the program has grown to a fleet of 5,824 bicycles that are geotracked and locked into a network of 692 stations across Chicago. The bikes can be unlocked from one station and returned to any other station in the system anytime. This is a hypothetical company made for this case study.

#Stakeholders * Cyclistic executive team: The notoriously detail-oriented executive team will decide whether to approve the recommended marketing program * Lily Moreno: The director of marketing and your manager. Moreno is responsible for the development of campaigns and initiatives to promote the bike-share program. These may include email, social media, and other channels.

# Marketing Design Team Objective

The director of marketing, Lily Moreno, has set a clear goal: Design marketing strategies aimed at converting casual riders into annual members. In order to do that, however, the marketing analyst team needs to better understand how annual members and casual riders differ, why casual riders would buy a membership, and how digital media could affect their marketing tactics. Moreno and her team are interested in analyzing the Cyclistic historical bike trip data to identify trends.

Three questions will guide the future marketing program: * How do annual members and casual riders use Cyclistic bikes differently? * Why would casual riders buy Cyclistic annual memberships? * How can Cyclistic use digital media to influence casual riders to become members?

#Business Task The business task assigned to me is to analyze the data cysclistic data from the last 12 months, cylcistic data from December 2021 - November 2022, to figure out the difference between annual members and casual riders.

#Data Source Cyclistic's historical trip data from the past 27 months is accessible link. This is a public, open dataset provided by Motivate International Inc. under the Data License Agreement. Note that the purchases in the data set are not linked to credit card information to ensure privacy of users.

#Data Cleaning/Manipulation This will be all done within R Studio, through the R language. The reason for this is because the R language have many packages and tools that could be used for the cleaning, manipulation, and visualization of the data.

Steps for the Data Cleaning Process: *Gather the data within R Studio and check its characteristics

```
data_2021_12 <- read.csv("202112-divvy-tripdata.csv")
```

```
data_2022_01 <- read.csv("202201-divvy-tripdata.csv")
```

```
data_2022_02 <- read.csv("202202-divvy-tripdata.csv")
```

```
data_2022_03 <- read.csv("202203-divvy-tripdata.csv")
```

```
data_2022_04 <- read.csv("202204-divvy-tripdata.csv")
```

```
data_2022_05 <- read.csv("202205-divvy-tripdata.csv")
```

```
data_2022_06 <- read.csv("202206-divvy-tripdata.csv")
```

```
data_2022_07 <- read.csv("202207-divvy-tripdata.csv")
```

```
data_2022_08 <- read.csv("202208-divvy-tripdata.csv")
```

```
data_2022_09 <- read.csv("202209-divvy-tripdata.csv")
```

```
data_2022_10 <- read.csv("202210-divvy-tripdata.csv")
```

```
data_2022_11 <- read.csv("202211-divvy-tripdata.csv")
```

*Then take all frame gathered data and stack them together into one single data frame.

```
united_data <- bind_rows(data_2021_12, data_2022_01, data_2022_02, data_2022_03, data_2022_04, data_2022_05, data_2022_06, data_2022_07, data_2022_08, data_2022_09, data_2022_10, data_2022_11)
```

*Check for NA values and remove them

```
united_data <- drop_na(united_data)
```

##

*The data also lacks the data of day, month, and year. Which will be added as another column

```
united_data["date"] <- as.Date(united_data$started_at)
```

```
united_data["month"] <- format(as.Date(united_data$date), "%m")
```

```
united_data["day"] <- format(as.Date(united_data$date), "%d")
```

```
united_data["year"] <- format(as.Date(united_data$date), "%Y")
```

```
united_data["day_of_the_week"] <- format(as.Date(united_data$date), "%A")
```

*We need a calculated field for the length of ride called ride_length and convert it to a numeric value

```
united_data["ride_length"] <- difftime(united_data$ended_at, united_data$started_at)
```

```
as.character(united_data$ride_length)
```

```
united_data$ride_length <- as.numeric(united_data$ride_length)
```

```
is.numeric(united_data$ride_length)
```

*Check ride_length if it contains any negative value or HQ QR stations and remove them cause they do not signify any attempted riding.

```
united_data["ride_length"] <- difftime(united_data$ended_at, united_data$started_at)
```

*After cleaning is complete we export the full data for the analysis portion.

```
final_united_data <- united_data[!(united_data$start_station_name == "HQ QR" | united_data$ride_length<0),]
```

#Data Analysis/Visualization In this part we would start with taking the singular cleaned file and start the descriptive analysis by finding the mean, median, and max of the ride_length value. This will give us a better sense of the data layout:

```
mean(cyclist_data$ride_length)
```

```
median(cyclist_data$ride_length)
```

```
max(cyclist_data$ride_length)
```

```
min(cyclist_data$ride_length)
```

Then we will compare the ride_length between the Casual and Members with in the data using the aggregate function finding their overall means, median, min, and max of the casual and member individuals:

```
aggregate(cyclist_data$ride_length ~ cyclist_data$member_casual, FUN = mean)
```

```
aggregate(cyclist_data$ride_length ~ cyclist_data$member_casual, FUN = median)
```

```
aggregate(cyclist_data$ride_length ~ cyclist_data$member_casual, FUN = max)
```

```
aggregate(cyclist_data$ride_length ~ cyclist_data$member_casual, FUN = min)
```

In this we are comparing the different values between the members and casual riders through the median, mean, max, and min values of the ride_length. From this observation the mean and max value are massively larger with the casual riders than the member riders. But the medians are more close in value but the casual members still have the higher value and they both share the same min value of 0.

Then we will check the average ride time by each day for members vs casual users and we will also fix the order of the days of week because they are out of order. Then I will run the average ride time by each day for members vs casual users:

```
aggregate(cyclist_data$ride_length ~ cyclist_data$member_casual + cyclist_data$day_of_the_week, FUN = mean)
```

```
cyclist_data$day_of_week <- ordered(cyclist_data$day_of_the_week, levels=c("Sunday", "Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday"))
```

```
aggregate(cyclist_data$ride_length ~ cyclist_data$member_casual + cyclist_data$day_of_the_week, FUN = mean)
```

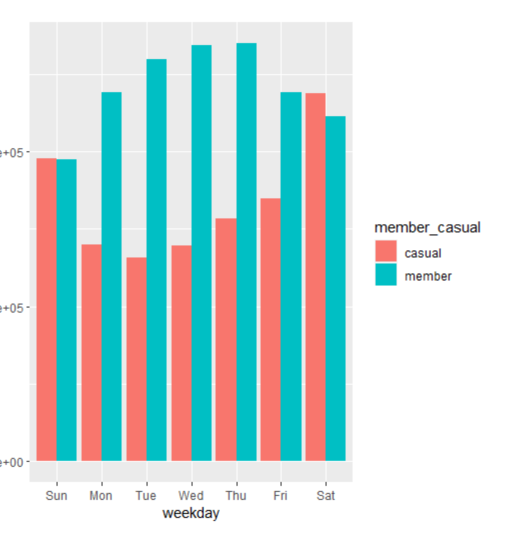
Then we will analyze the ridership data by viewing it through its type and weekday:

```
cyclist_data %>%
  mutate(weekday = wday(started_at, label = TRUE)) %>%
  group_by(member_casual, weekday) %>%
  summarise(number_of_rides = n()
          ,average_duration = mean(ride_length)) %>%
  arrange(member_casual, weekday)
```

Through this analysis it further shows that on a daily basis throughout the week, the casual riders have a longer average duration than the member riders.

#Visualizing the Data Visualize the rides by rider types:

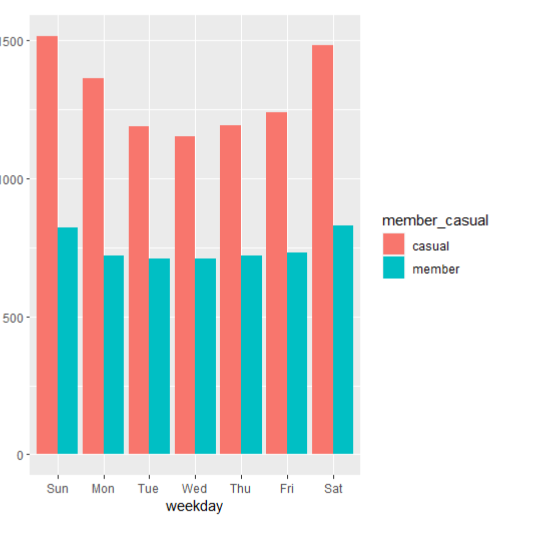
```
cyclist_data %>%
  mutate(weekday = wday(started_at, label = TRUE)) %>%
  group_by(member_casual, weekday) %>%
  summarise(number_of_rides = n()
          ,average_duration = mean(ride_length)) %>%
  arrange(member_casual, weekday)  %>%
  ggplot(aes(x = weekday, y = number_of_rides, fill = member_casual)) +
  geom_col(position = "dodge")
```




Through this visualization, it seems that throughout the week, the member riders seem to have more number of rides than the casual riders in this. Where number of rides is referencing the observable value within this group of member/casual riders.

Then I will create a visualization for average ride length duration throughout the week:

```
cyclist_data %>%
  mutate(weekday = wday(started_at, label = TRUE)) %>%
  group_by(member_casual, weekday) %>%
  summarise(number_of_rides = n()
          ,average_duration = mean(ride_length)) %>%
  arrange(member_casual, weekday)  %>%
  ggplot(aes(x = weekday, y = average_duration, fill = member_casual)) +
  geom_col(position = "dodge")
```



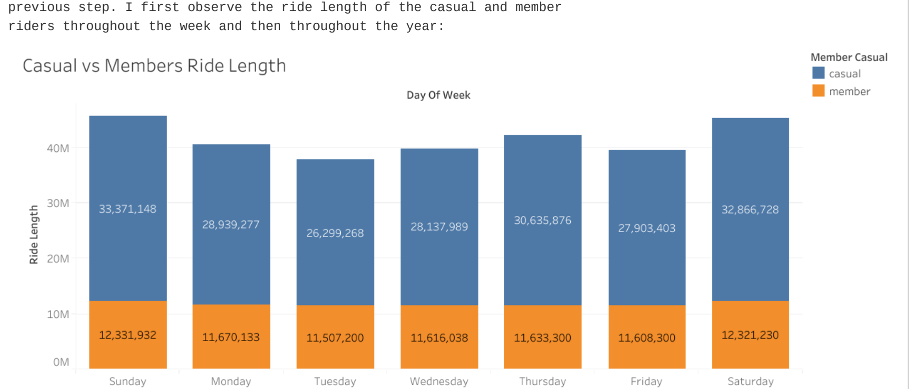

From this, we can see that the casual riders, while they have a smaller amount of rides, have a larger average amount of ride length than the member riders. Showing that the casual riders have done more riding that the member riders regardless on the amount of rides have for both groups.

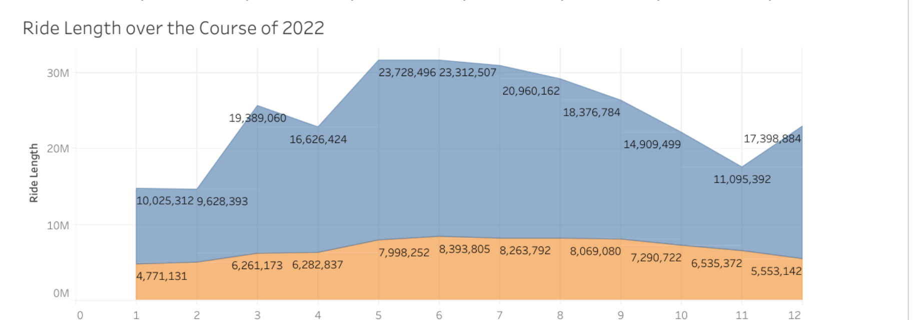
Finally i will export a summary .csv file to take the results and further visualization using the Tableau tool:

```
counts <- aggregate(cyclist_data$ride_length ~ cyclist_data$member_casual + cyclist_data$day_of_week, FUN = mean)
```

```
write.csv(counts, file = 'C:/Users/dexch/Documents/cyclist-data/avg_ride_length.csv')
```

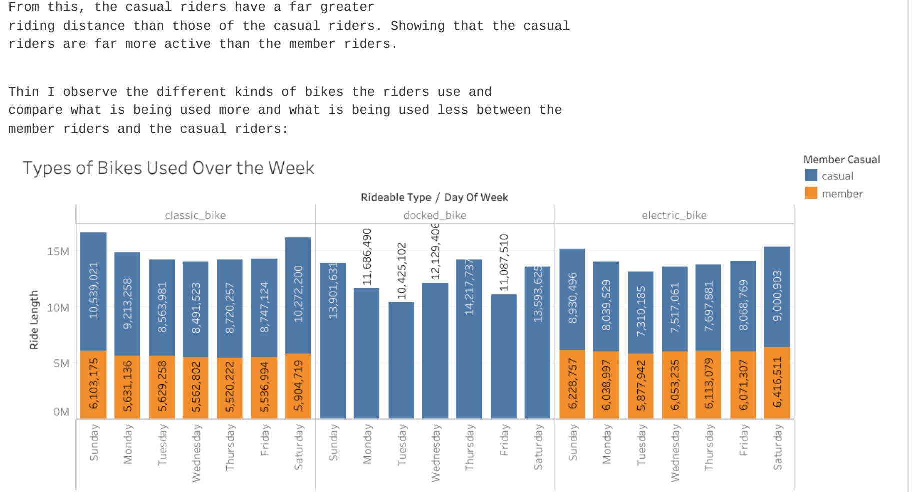
Using Tableau to visualize the summary data gathered from the previous step. I first observe the ride length of the casual and member riders throughout the week and then throughout the year:

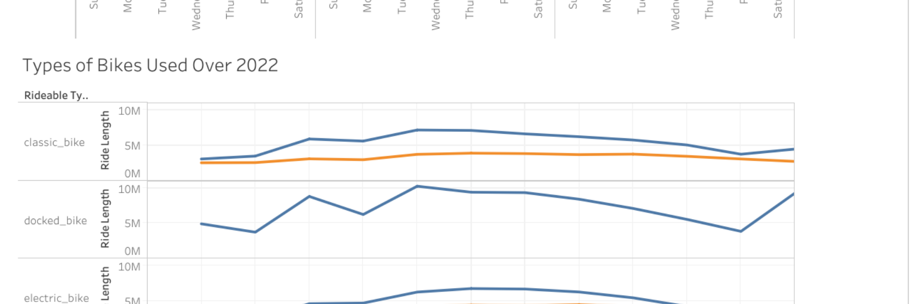



From this, the casual riders have a far greater riding distance than those of the casual riders. Showing that the casual riders are far more active than the member riders.

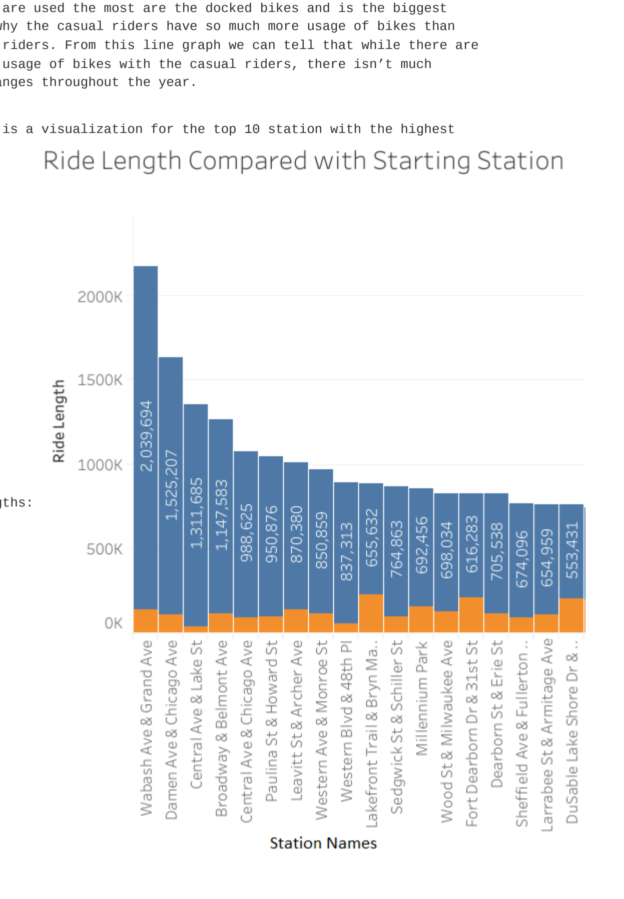
Thin I observe the different kinds of bikes the riders use and compare what is being used more and what is being used less between the member riders and the casual riders:




From this visualization, it seems that the type of bikes that are used the most are the docked bikes and is the biggest factor to why the casual riders have so much more usage of bikes than the member riders. From this line graph we can tell that while there are still more usage of bikes with the casual riders, there isn't much notable changes throughout the year.

Then there is a visualization for the top 10 station with the highest riding lengths:




This visualization further shows that the casual riders make up the majority of riders in the data but also shows that Wabash Ave & Grand Ave is the starting station with the most riding distance.

#Data Conclusion Conclusion for the business task: How do annual members and casual riders use Cyclistic bikes differently? *The key difference between the casual and member riders is that the casual riders tend to use more of the cyclistic bikes than the member riders.* The member riders seems to only use the classic and electric bikes where they don't use the docked bikes *The casual riders get more riding distance closer to the weekend while the member riders keep a close constant number of distance throughout the entire week.* Members riders distance tend to get lower when near the fall and winter season and increases in the summer season. *Casual riders also have a great increase of distance in the summer and decreases closer to the winter though it seem to have gotten an increase at the end of the year of 2022.

#Recommendations Recommendation from the data and conclusion: *Through social media or etc, we can advertise some form of a summer special deal to try increase the membership numbers. The reason for this is because the casual riders are much more active in the summer season. This would be more opportunity to gain more members. Along with more advertisements in this season, the larger number of people would end up seeing it and since it is the season to do such exercise, they are more prone to signing up as a member.* There can also be more advertisement in the weekends, potentially even some weekend deal for the casual riders. The data have shown that casual riders have more distance made in the weekend. Most likely that weekends tend to be off days from work or school. *More advertisement can also be placed at the the 10 most visited starting stations. Advertising the kind of company Bike share is and what they can do for their members and even the environment. Promoting a helping the Earth type of campaign to catch more of the casual rider eyes. Advertising more in these areas would catch more of the causal riders attention because these starting stations are some of the most visited from the data collected.

#Additional Data and Expansion Things that would have been helpful in this analysis is figuring out what time bikes were used during the weekday. With this information, we can potentially figure the reasons for why our members use bike-share and develop a strategy for the annual subscription.A survey can also be used to collect more data and ask about their preferences, taking a look a possible reason for why they have the membership. We would need to be careful with what words are used for the survey questions to eliminate any kind of bias that may occur when they answer the survey.

Potentially, I could have use SQL to clean and manipulate data since the process within SQL would be much more quicker since it is typically able to handle larger databases.