Google Data Analytics Cyclistic Bike Share Case Study

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Introduction

Welcome to my Cyclistic bike-share analysis case study! In this case study, I work as a junior data analyst for a fictional company, Cyclistic, a bike-share program that features more than 5,800 bicycles and 600 docking stations. Cyclistic sets itself apart by also offering reclining bikes, hand tricycles, and cargo bikes, making bike-share more inclusive to people with disabilities and riders who can't use a standard two-wheeled bike. The majority of riders opt for traditional bikes; about 8% of riders use the assistive options. Cyclistic users are more likely to ride for leisure, but about 30% use them to commute to work each day.

Scenario

I am a junior data analyst working in the marketing analyst team at Cyclistic, a bike-share company in Chicago. The director of marketing believes the company's future success depends on maximizing the number of annual memberships. Therefore, my team wants to understand how casual riders and annual members use Cyclistic bikes differently. From these insights, my team will design a new marketing strategy to convert casual riders into annual members. But first, Cyclistic executives must approve my recommendations, so they must be backed up with compelling data insights and professional data visualizations.

Key Questions

Three questions will guide the future 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?

Solutions

STEP 1: COLLECT DATA

```
#Installing packages
library(tidyverse) #helps wrangle data
library(lubridate) #helps wrangle date attributes
library(ggplot2) #helps visualize data
library(dplyr)#helps manipulate data
library(janitor)#helps clean data
library(scales)#helps for plotting data
```

```r
# Upload Divvy datasets (csv files) here
q2_2019 <- read_csv("Divvy_Trips_2019_Q2.csv")
q3_2019 <- read_csv("Divvy_Trips_2019_Q3.csv")
q4_2019 <- read_csv("Divvy_Trips_2019_Q4.csv")
q1_2020 <- read_csv("Divvy_Trips_2020_Q1.csv")
```

STEP 2: WRANGLE DATA AND COMBINE INTO A SINGLE FILE

```r
colnames(q3_2019)
colnames(q4_2019)
colnames(q2_2019)
colnames(q1_2020)

# Rename columns to make them consistent with q1_2020
# (as this will be the supposed going-forward table design for Divvy)
(q4_2019 <- rename(q4_2019
                  ,ride_id = trip_id
                  ,rideable_type = bikeid
                  ,started_at = start_time
                  ,ended_at = end_time
                  ,start_station_name = from_station_name
                  ,start_station_id = from_station_id
                  ,end_station_name = to_station_name
                  ,end_station_id = to_station_id
                  ,member_casual = usertype))
(q3_2019 <- rename(q3_2019
                  ,ride_id = trip_id
                  ,rideable_type = bikeid
                  ,started_at = start_time
                  ,ended_at = end_time
                  ,start_station_name = from_station_name
                  ,start_station_id = from_station_id
                  ,end_station_name = to_station_name
                  ,end_station_id = to_station_id
                  ,member_casual = usertype))
(q2_2019 <- rename(q2_2019
                  ,ride_id = "01 - Rental Details Rental ID"
                  ,rideable_type = "01 - Rental Details Bike ID"
                  ,started_at = "01 - Rental Details Local Start Time"
                  ,ended_at = "01 - Rental Details Local End Time"
                  ,start_station_name = "03 - Rental Start Station Name"
                  ,start_station_id = "03 - Rental Start Station ID"
                  ,end_station_name = "02 - Rental End Station Name"
                  ,end_station_id = "02 - Rental End Station ID"
                  ,member_casual = "User Type"))

# Inspect the dataframes and look for incongruencies
str(q1_2020)
str(q4_2019)
str(q3_2019)
```

```
str(q2_2019)


# Convert ride_id and rideable_type to character
# so that they can stack correctly
q4_2019 <- mutate(q4_2019, ride_id = as.character(ride_id)
                  ,rideable_type = as.character(rideable_type))
q3_2019 <- mutate(q3_2019, ride_id = as.character(ride_id)
                  ,rideable_type = as.character(rideable_type))
q2_2019 <- mutate(q2_2019, ride_id = as.character(ride_id)
                  ,rideable_type = as.character(rideable_type))

# Stack individual quarter's data frames into one big data frame
all_trips <- bind_rows(q2_2019, q3_2019, q4_2019, q1_2020)

# Remove lat, long, birthyear, and gender fields
# since this data was dropped beginning in 2020
all_trips <- all_trips %>%
  select(-c(start_lat, start_lng, end_lat, end_lng, birthyear, gender
  , "01 - Rental Details Duration In Seconds Uncapped"
  , "05 - Member Details Member Birthday Year"
  , "Member Gender"
  , "tripduration"))
```

STEP 3: CLEAN UP AND ADD DATA TO PREPARE FOR ANALYSIS

```
# Inspect the new table that has been created
colnames(all_trips) #List of column names
nrow(all_trips) #How many rows are in data frame?
dim(all_trips) #Dimensions of the data frame?
head(all_trips) #See the first 6 rows of data frame.
tail(all_trips) #See the last 6 rows of data frame.
str(all_trips) #See list of columns and data types (numeric, character, etc)
summary(all_trips) #Statistical summary of data. Mainly for numerics
```

In this data cleaning section there are 4 problems to be resolved:

1) In the “member_casual” column, there are two names for members (“member” and “Subscriber”) and two names for casual riders (“Customer” and “casual”). We will need to consolidate that from four to two labels.

```
# In the "member_casual" column, replace "Subscriber" with "member" and
"Customer" with "casual"
# Begin by seeing how many observations fall under each usertype
table(all_trips$member_casual)

# Reassign to the desired values (we will go with the current 2020 labels)
all_trips <- all_trips %>%
  mutate(member_casual = recode(member_casual
                                ,"Subscriber" = "member"
                                ,"Customer" = "casual"))
```

```
# Check to make sure the proper number of observations were reassigned
table(all_trips$member_casual)
```

2) The data can only be aggregated at the ride-level, which is too granular (too deep). We will want to add some additional columns of data – such as day, month, year – that provide additional opportunities to aggregate the data.

```
# Add columns that list the date, month, day, and year of each ride
# This will allow us to aggregate ride data for each month, day, or year ... before completing
# these operations we could only aggregate at the ride level
# The default format is yyyy-mm-dd
all_trips$date <- as.Date(all_trips$started_at)
all_trips$month <- format(as.Date(all_trips$date), "%m")
all_trips$day <- format(as.Date(all_trips$date), "%d")
all_trips$year <- format(as.Date(all_trips$date), "%Y")
all_trips$day_of_week <- format(as.Date(all_trips$date), "%A")
```

3) We will want to add a calculated field for length of ride since the 2020Q1 data did not have the "tripduration" column. We will add "ride_length" to the entire dataframe for consistency.

```
# Add a "ride_length" calculation to all_trips (in seconds)
all_trips <- mutate(all_trips,
ride_length=difftime(all_trips$ended_at,all_trips$started_at, units = "secs"))

# Inspect the structure of the columns
str(all_trips)

# Convert "ride_length" from Factor to numeric so we can run calculations on the data
is.factor(all_trips$ride_length)
all_trips$ride_length <- as.numeric(as.character(all_trips$ride_length))
is.numeric(all_trips$ride_length)
```

4) There are some rides where tripduration shows up as negative, including several hundred rides where Divvy took bikes out of circulation for Quality Control reasons. We will want to delete these rides.

```
# Remove "bad" data
# The dataframe includes a few hundred entries when bikes were taken out of docks and
# checked for quality by Divvy or ride_length was negative
# We will create a new version of the dataframe (v2) since data is being removed
all_trips_v2 <- all_trips[!(all_trips$start_station_name == "HQ QR" |
all_trips$ride_length<0),]
```

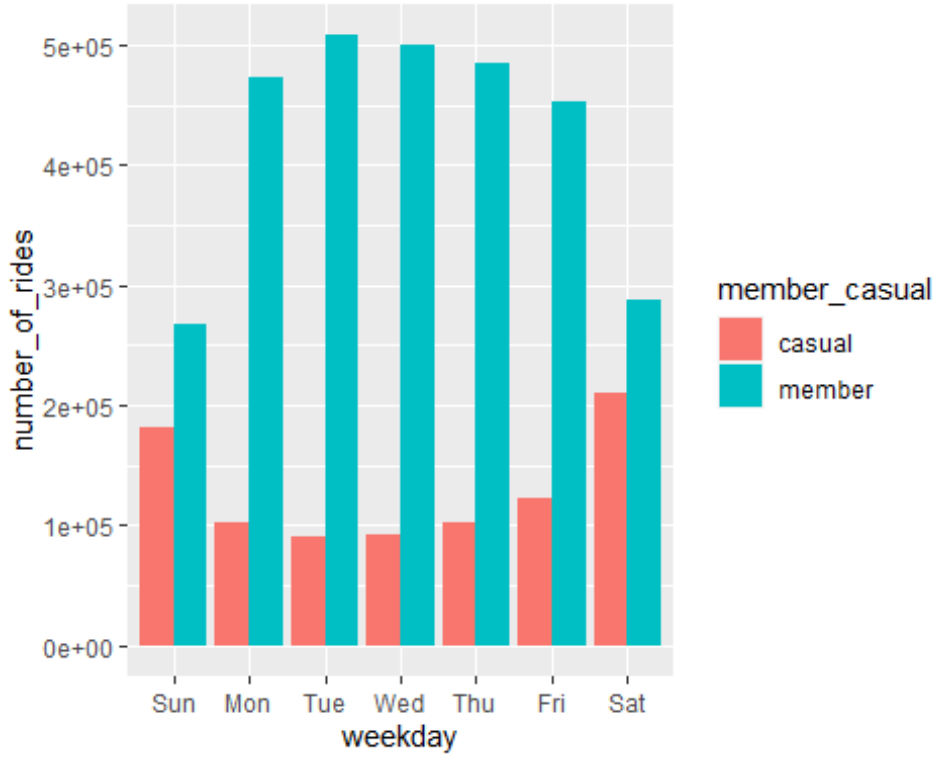
STEP 4: CONDUCT DESCRIPTIVE ANALYSIS

```
mean(all_trips_v2$ride_length) #straight average (total ride length / rides)
median(all_trips_v2$ride_length) #midpoint number in the ascending array of
```

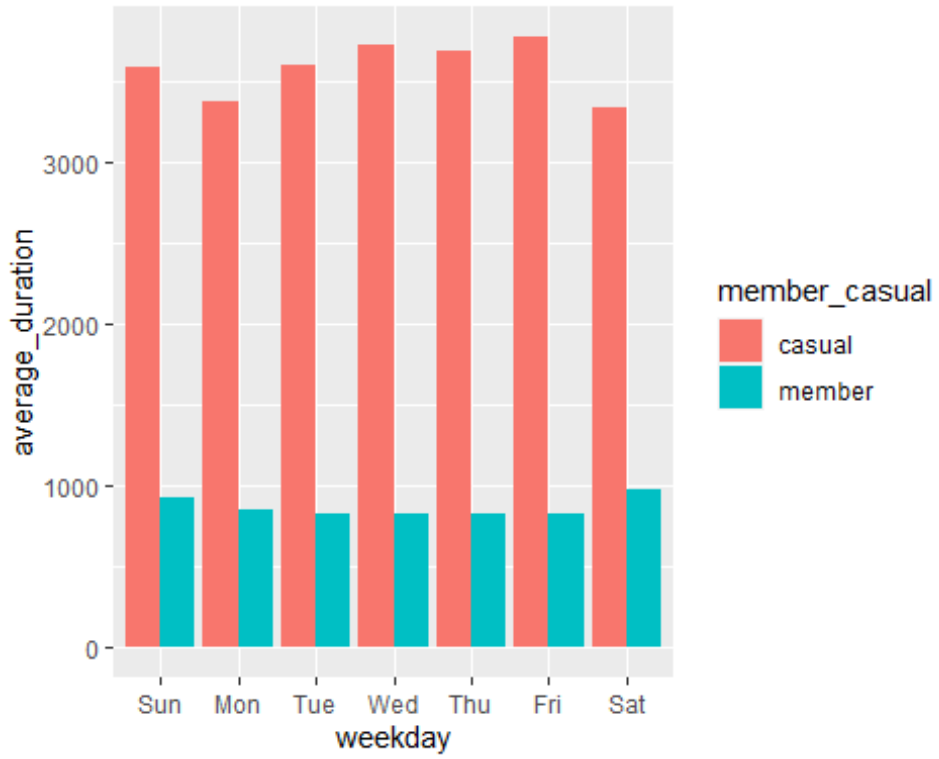
```r
ride lengths
max(all_trips_v2$ride_length) #longest ride
min(all_trips_v2$ride_length) #shortest ride

# Condensing the four lines above to one line using summary() on the specific
attribute
summary(all_trips_v2$ride_length)

# Compare members and casual users
aggregate(all_trips_v2$ride_length ~ all_trips_v2$member_casual, FUN = mean)
aggregate(all_trips_v2$ride_length ~ all_trips_v2$member_casual, FUN =
median)
aggregate(all_trips_v2$ride_length ~ all_trips_v2$member_casual, FUN = max)
aggregate(all_trips_v2$ride_length ~ all_trips_v2$member_casual, FUN = min)

# See the average ride time by each day for members vs casual users
aggregate(all_trips_v2$ride_length ~ all_trips_v2$member_casual +
all_trips_v2$day_of_week,
          FUN = mean)

# The days of the week are out of order so ordered() is used.
all_trips_v2$day_of_week <- ordered(all_trips_v2$day_of_week,
levels=c("Sunday"
          ,"Monday","Tuesday", "Wednesday", "Thursday", "Friday",
"Saturday"))

# Now we can clearly see the average ride time by each day for members vs
casual users
aggregate(all_trips_v2$ride_length ~ all_trips_v2$member_casual +
all_trips_v2$day_of_week,
          FUN = mean)

# Analyze ridership data by type and weekday
all_trips_v2 %>%
  mutate(weekday = wday(started_at, label = TRUE)) %>% #creates weekday field
using wday()
  group_by(member_casual, weekday) %>% #groups by usertype and weekday
  summarise(number_of_rides = n() #calculates the number of rides and average
duration
            ,average_duration = mean(ride_length)) %>% # calculates the
average duration
  arrange(member_casual, weekday) # sorting

# Also need to convert month to numeric
is.factor(all_trips_v2$month)
all_trips_v2$month <- as.character(as.numeric(all_trips_v2$month))
is.numeric(all_trips_v2$month)
all_trips_v2$month_name <- as.Date(cut(all_trips_v2$date, breaks = 'month'))
```

STEP 5: VISUALIZE THE DATA

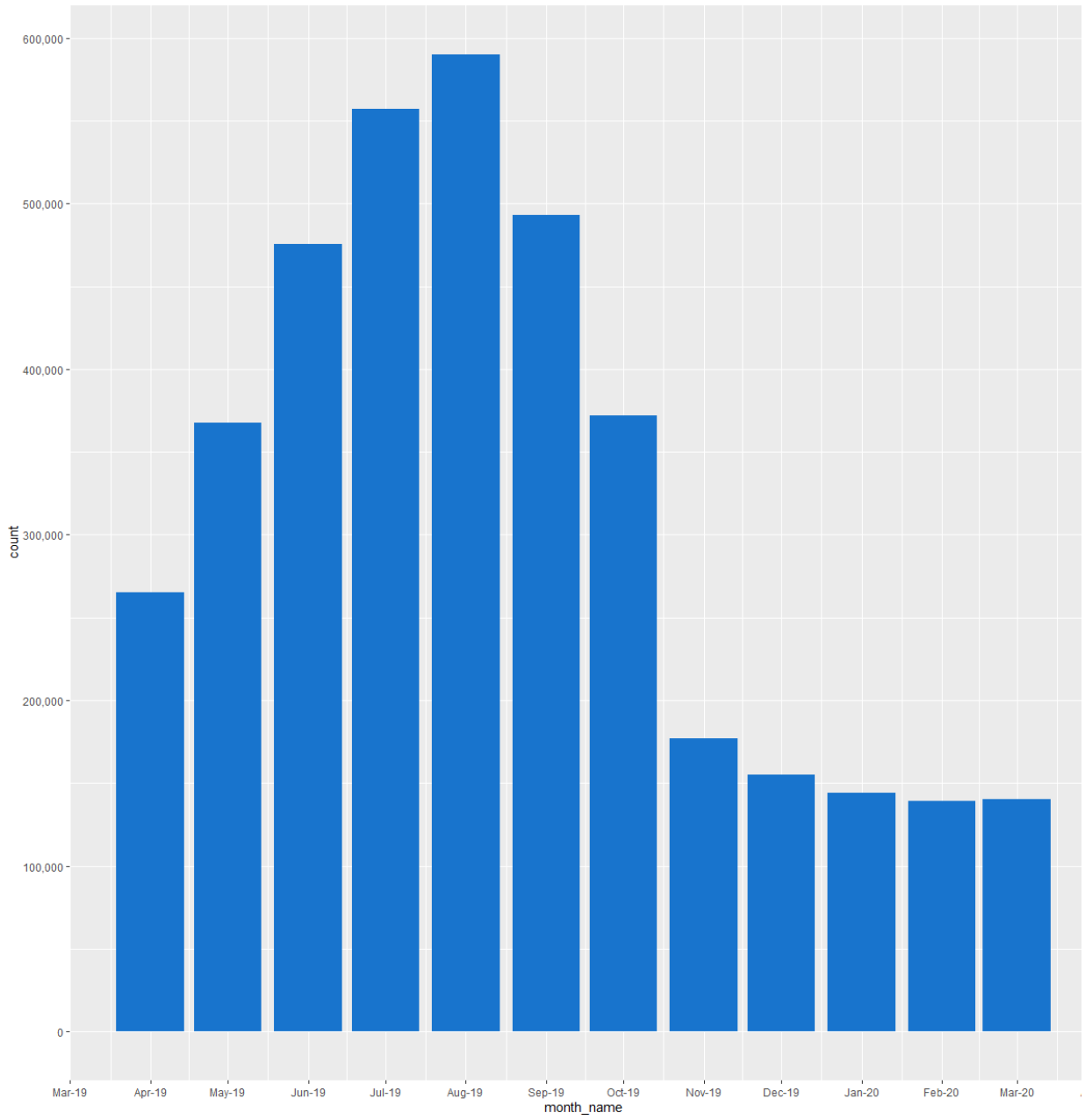
```
# Visualize the number of rides by rider type
all_trips_v2 %>%
  mutate(weekday = wday(started_at, label = TRUE)) %>%
  group_by(member_casual, weekday) %>%
  summarise(number_of_rides = n()
            ,average_duration = mean(ride_length)) %>%
  arrange(member_casual, weekday) %>%
  ggplot(aes(x = weekday, y = number_of_rides, fill = member_casual)) +
  geom_col(position = "dodge")
```




```
# Visualization for average ride duration
all_trips_v2 %>%
  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")
```




```
# Visualization for the total number of rides per month
ggplot(all_trips_v2, aes(month_name)) +
  geom_histogram(stat = "count",fill = "dodgerblue2") +
    scale_y_continuous(labels = comma, breaks = seq(0,6000000, 100000))+
      scale_x_date(labels = date_format("%b-%y"), breaks = "1 month")
```



Conclusion

Although subscribed riders tend to ride more overall, casual riders tend to ride more over the weekends. We can also see that the busiest months tend to be July and August. It is recommended that the marketing team focuses on weekend promotions to garner interest in casual riders during the months of July and August, while also encourage weekday incentives to convert them into subscribers.