capstone project trips-2024

Raul 2025-09-25

Cyclist bike-share Analysis

Case Study for Google Data Analytics Professional Certificate. Data use for this case study obtained from the fictional company Cyclist bike-share. The I will follow the analisis process that consist of 7 Steps: Ask, Prepare, Process, Analyze, Share and Act

ASK

Business Task: Design a marketing strategies aimed at converting casusal riders into members by answering the following question. How do members and casual riders use Cyclist bike differently?

PREPARE

Data obtained from DIVV-TripData License

- Tools use
 - Exploring Data
 - RStudio
 - Data Cleaning and Transforms Data
 - RStudio
 - Data visualizacion
 - RStudio

PROCESS

1. Data Exploration

- The first step of my work is to check if tables are consistent with each other
- This is achieved by looking at the columns and the data type each column contains

So first let's see if all the columns are equal

January

```
[1] "ride_id" "rideable_type" "started_at"
[4] "ended_at" "start_station_name" "start_station_id"
[7] "end_station_name" "end_station_id" "start_lat"
[10] "start_lng" "end_lat" "end_lng"
[13] "member_casual"
```

•	February [1] "ride_id" [4] "ended_at" [7] "end_station_name" [10] "start_lng" [13] "member_casual"	"rideable_type" "start_station_name" "end_station_id" "end_lat"	"started_at" "start_station_id" "start_lat" "end_lng"
•	March [1] "ride_id" [4] "ended_at" [7] "end_station_name" [10] "start_lng" [13] "member_casual"	"rideable_type" "start_station_name" "end_station_id" "end_lat"	"started_at" "start_station_id" "start_lat" "end_lng"
•	April [1] "ride_id" [4] "ended_at" [7] "end_station_name" [10] "start_lng" [13] "member_casual"	"rideable_type" "start_station_name" "end_station_id" "end_lat"	"started_at" "start_station_id" "start_lat" "end_lng"
•	May [1] "ride_id" [4] "ended_at" [7] "end_station_name" [10] "start_lng" [13] "member_casual"	"rideable_type" "start_station_name" "end_station_id" "end_lat"	"started_at" "start_station_id" "start_lat" "end_lng"
•	June [1] "ride_id" [4] "ended_at" [7] "end_station_name" [10] "start_lng" [13] "member_casual"	"rideable_type" "start_station_name" "end_station_id" "end_lat"	"started_at" "start_station_id" "start_lat" "end_lng"
•	July [1] "ride_id" [4] "ended_at" [7] "end_station_name" [10] "start_lng" [13] "member_casual"	"rideable_type" "start_station_name" "end_station_id" "end_lat"	"started_at" "start_station_id" "start_lat" "end_lng"
•	August [1] "ride_id" [4] "ended_at" [7] "end_station_name" [10] "start_lng" [13] "member_casual"	"rideable_type" "start_station_name" "end_station_id" "end_lat"	"started_at" "start_station_id" "start_lat" "end_lng"

• September

[1]	"ride_id"	"rideable_type"	"started_at"
[4]	"ended_at"	"start_station_name"	"start_station_id"
[7]	"end_station_name"	"end_station_id"	"start_lat"
[10]	"start_lng"	"end_lat"	"end_lng"
[13]	"member_casual"		

October

[1]	"ride_id"	"rideable_type"	"started_at"
[4]	"ended_at"	"start_station_name"	"start_station_id"
[7]	"end_station_name"	"end_station_id"	"start_lat"
[10]	"start_lng"	"end_lat"	"end_1ng"
[13]	"member_casual"		

November

[1]	"ride_id"	"rideable_type"	"started_at"
[4]	"ended_at"	"start_station_name"	"start_station_id"
[7]	"end_station_name"	"end_station_id"	"start_lat"
[10]	"start_lng"	"end_lat"	"end_lng"
[13]	"member_casual"		

December

[1]	"ride_id"	"rideable_type"	"started_at"
[4]	"ended_at"	"start_station_name"	"start_station_id"
[7]	"end_station_name"	"end_station_id"	"start_lat"
[10]	"start_lng"	"end_lat"	"end_lng"
[13]	"member_casual"		

Now let's see that all the data is consistent

"character"

"character"

January

ended_at	started_at	rideable_type	ride_id
"character"	"character"	"character"	"character"
end_station_id	end_station_name	start_station_id	start_station_name
"character"	"character"	"character"	"character"
end_1ng	end_lat	start_lng	start_lat
"numeric"	"numeric"	"numeric"	"numeric"
			member_casual

February

ended_at	started_at	rideable_type	ride_id
"character"	"character"	"character"	"character"
end_station_id	end_station_name	start_station_id	start_station_name
"character"	"character"	"character"	"character"
end_1ng	end_lat	start_lng	start_lat
"numeric"	"numeric"	"numeric"	"numeric"
			member casual

•	March				
	ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"	
•	April ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"	
•	May ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"	
•	June ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"	
•	July ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"	
•	August ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"	

•	September ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"
•	October ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"
•	November ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"
•	ride_id "character" start_station_name "character" start_lat "numeric" member_casual "character"	rideable_type "character" start_station_id "character" start_lng "numeric"	started_at "character" end_station_name "character" end_lat "numeric"	ended_at "character" end_station_id "character" end_lng "numeric"

The data is consistent, so we can continue to the next step

2. Data Combination

The data combinated of January 2024 to Diciember 2024, is join by *bind_rows* in RStudio.

^	ride_id	rideable_type	started_at	ended_at	start_station_name	start_station_id	end_station_name	end_station_id	start_lat	start_Ing [©]	end_lat ÷	end_Ing [©]	member_casual
1	C1D650626C8C899A	electric_blke	2024-01-12 15:30:27	2024-01-12 15:37:59	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzle St	KA1503000043	41.90327	-87.63474	41.88918	-87.63851	member
2	EECD38BDB25BFCB0	electric_blke	2024-01-08 15:45:46	2024-01-08 15:52:59	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzle St	KA1503000043	41.90294	-87.63444	41.88918	-87.63851	member
3	F4A9CE78061F17F7	electric_blke	2024-01-27 12:27:19	2024-01-27 12:35:19	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90295	-87.63447	41.88918	-87.63851	member
4	0A0D9E15EE50B171	classic_bike	2024-01-29 16:26:17	2024-01-29 16:56:06	Wells St & Randolph St	TA1305000030	Larrabee St & Webster Ave	13193	41.88430	-87.63396	41.92182	-87.64414	member
5	33FFC9805E3EFF9A	classic_bike	2024-01-31 05:43:23	2024-01-31 06:09:35	Lincoln Ave & Waveland Ave	13253	Kingsbury St & Kinzie St	KA1503000043	41.94880	-87.67528	41.88918	-87.63851	member
6	C96080812CD285C5	classic_bike	2024-01-07 11:21:24	2024-01-07 11:30:03	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90322	-87.63432	41.88918	-87.63851	member
7	0EA7CB313D4F456A	classic_bike	2024-01-05 14:44:12	2024-01-05 14:53:06	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90322	-87.63432	41.88918	-87.63851	member
8	EE11F3A3B39CFBD8	electric_bike	2024-01-04 18:19:53	2024-01-04 18:28:04	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90337	-87.63486	41.88918	-87.63851	member
9	63E83DE8E3279F15	classic_bike	2024-01-01 14:46:53	2024-01-01 14:57:02	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90322	-87.63432	41.88918	-87.63851	member
10	8005682869122D93	electric_bike	2024-01-03 19:31:08	2024-01-03 19:40:05	Clark St & Ida B Wells Dr	TA1305000009	Kingsbury St & Kinzie St	KA1503000043	41.87603	-87.63087	41.88918	-87.63851	member
11	22B85E685AE0D490	electric_blke	2024-01-03 07:39:20	2024-01-03 07:47:12	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzle St	KA1503000043	41.90303	-87.63461	41.88918	-87.63851	member
12	133CDC03CA430172	classic_bike	2024-01-03 17:03:11	2024-01-03 17:13:15	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzle St	KA1503000043	41.90322	-87.63432	41.88918	-87.63851	member
13	32D57BF92858025D	electric_blke	2024-01-10 17:04:09	2024-01-10 17:11:40	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzle St	KA1503000043	41.90315	-87.63458	41.88918	-87.63851	member
14	B110B5685C38D69B	electric_blke	2024-01-12 12:35:14	2024-01-12 12:43:34	Clark St & Ida B Wells Dr	TA1305000009	Kingsbury St & Kinzie St	KA1503000043	41.87585	-87.63093	41.88918	-87.63851	member
15	B6608710B5FA0938	electric_bike	2024-01-07 08:00:19	2024-01-07 08:06:46	Clark St & Ida B Wells Dr	TA1305000009	Kingsbury St & Kinzie St	KA1503000043	41.87557	-87.63078	41.88918	-87.63851	member
16	E7A33AC59F174164	electric_bike	2024-01-24 08:28:31	2024-01-24 08:32:13	Clark St & Randolph St	TA1305000030	Kingsbury St & Kinzie St	KA1503000043	41.88417	-87.63209	41.88918	-87.63851	member
17	BAC650B3CFE6160E	electric_bike	2024-01-13 11:18:54	2024-01-13 11:25:16	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90303	-87.63462	41.88918	-87.63851	member
18	C6CC4B54F874526D	electric_bike	2024-01-24 18:52:19	2024-01-24 19:04:16	Sheffield Ave & Kingsbury St	13154	Aberdeen St & Randolph St	18062	41.91062	-87.65314	41.88411	-87.65426	member
19	A7BDDCFEDF01FC88	classic_bike	2024-01-27 13:12:24	2024-01-27 13:19:35	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90322	-87.63432	41.88918	-87.63851	member
20	E247F34BF1F9D880	electric_bike	2024-01-05 13:15:24	2024-01-05 13:21:41	Clark St & Randolph St	TA1305000030	Aberdeen St & Randolph St	18062	41.88530	-87.63225	41.88411	-87.65426	member

The result of the combined data is 5,860,568 rows and 13 columns

3. Data Cleaning and Transforming

- Transform the started_at and ended_at columns from char to POSIXct to perform the following calculation
- Calculate the duration of the rides

```
# Transform data type (char to POSIXct)
all_trips_24\started_at <- ymd_hms(all_trips_24\started_at)
all trips 24\$ended at <- ymd hms(all trips 24\$ended at)
# Calculate the ride length
all_trips_24$ride_length <- as.numeric(difftime(all_trips_24$ended_at,
all trips 24\$started at, units="secs"))
all trips 24 %>%
  select(started_at, ended_at, ride_length) %>%
  head()
##
              started at
                                    ended at ride length
## 1 2024-01-12 15:30:27 2024-01-12 15:37:59
                                                      452
## 2 2024-01-08 15:45:46 2024-01-08 15:52:59
                                                      433
## 3 2024-01-27 12:27:19 2024-01-27 12:35:19
                                                      480
## 4 2024-01-29 16:26:17 2024-01-29 16:56:06
                                                     1789
## 5 2024-01-31 05:43:23 2024-01-31 06:09:35
                                                     1572
## 6 2024-01-07 11:21:24 2024-01-07 11:30:03
                                                      519
```

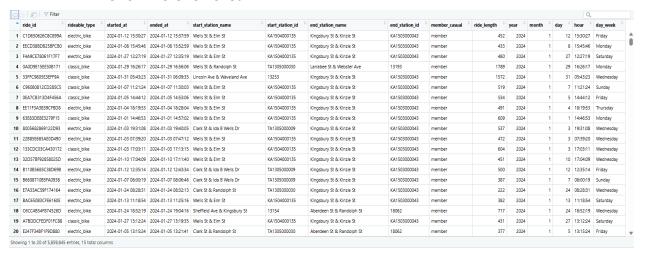
• We create new columns from the started_at column, where we obtain the year, month, day, hour, and day of the week.

Before de next step in the process, i have to clean de the data:

Remove the columns that are not needed

And finally, we create another dataframe with all the clean data

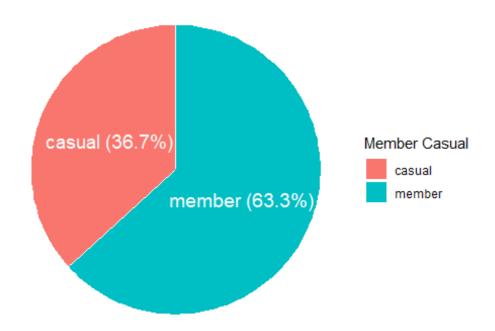
- The ride_length can not be negative so we have to exclude all rows that have negative values or 0 values
- The new and clean data frame is 5,859,845 row and 15 columns, which mean that
 723 row were removed



ANALYZE

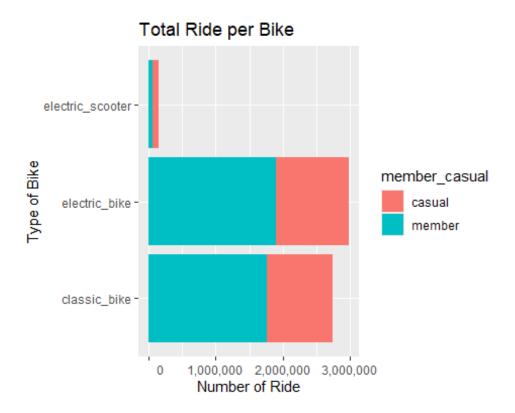
Question to analyze: How do members and casual riders use Cyclist bike differently?

To answer this question first let's see the percentage of casual and member used Percentage of ride by type of user



- Membership users have a higher use of bicycles compared to casual users
- Membership users use bicycles 63.3% more than casual users

In the following graph we can see which type are the most used bicycles



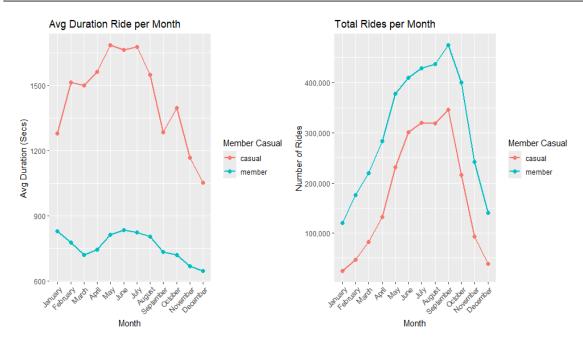
- We can see that all Cyclist users prefer bicycles over scooters
- The percentage of members who rent electric bikes is slightly higher than those who rent classic bikes
- The percentage of casual users who rent electric bikes is much higher than those who rent classic bikes

Now I will calculate the average duration of trips per month made by users with membership and casual users

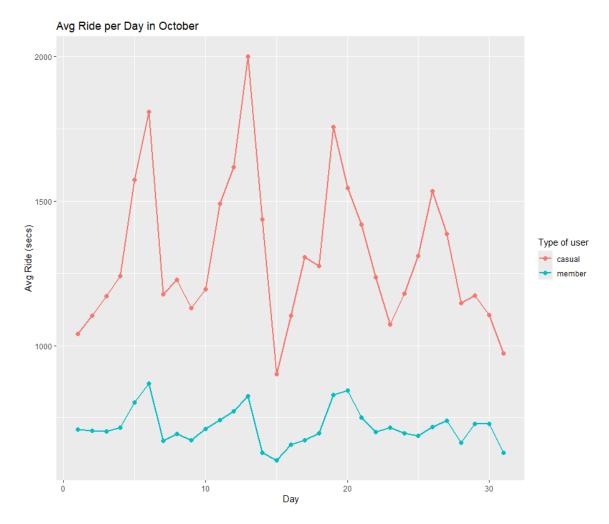
```
avg_duration_ride <- all_trips_24_v2 %>%
  group_by(member_casual, month) %>%
  summarise(avg_duration = mean(ride_length), .groups = "drop")
```

Now let's compare the number of rides per month and the average duration of the rides between members and casual users

```
# Agrupamos los datos por mes y se calcula el numero total de rides
month_rides <- all_trips_24_v2 %>%
   group_by(member_casual, month) %>%
   summarise(number_of_ride = n(), .groups = "drop") %>%
   arrange(member_casual, month)
```



- It can be observed that users with memberships make more trips per month
- Casual users make longer trips
- We can also observe that there is a decrease in the number of trips in the month of September October
- It can be observed that in October there was an increase in the ride time of casual users, this may be due to the holidays, Let's see is there is a correlation



 As we can see in the graph, there is no correlation between the holidays and the time spent using the bikes

Now let's compare the number of rides per day and the average duration of the rides between members and casual user

Number of Rides per day



- We can see that member make more rides per day that casual
- We can see that Wednesdays are the days where members take the most rides
- Also, we can see that Saturdays are the days where casuals take the most rides

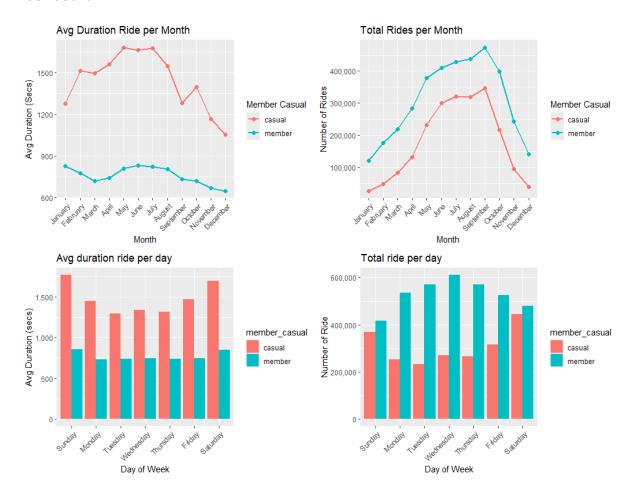
Avg Duration of Ride per day

Avg duration ride per day 1,500 1,000 1,000 Sunday Markey Restay Res

- In the graph, we can see that casual users take much longer rides than member users
- It can also be seen that the days with the longest average trips are Sundays, followed by Saturdays

Share

Dashboard



How do members and casual riders use Cyclist bike differently?

- Based on the analysis, we can see that members use bicycles more frequently during the week, while casual users use them on weekends, with a higher percentage on Saturdays
- This may be because casual users prefer to use bicycles as a means of tourism or touring, while members use them as a mode of transportation
- It can also be observed that there is a decrease in use starting in September by both types of users, this may be because it is the end of summer

Act

Recommendations

Based on the analysis done the marketing campaign to convert casual users to members users, my suggestions would be the following:

Create custom memberships

 Custom memberships can be created to target a different group of users, for example, a monthly or seasonal membership, since there is a large group of users who use the service during the summer and may be interested in obtaining a membership during that time only

Give a discount for adding friends

 As can be seen in the graphs, casual users use the Cyclist service on Saturdays, just like member users. It's very likely that in a large group of rides that take place on that day will include both member and casual users, so it would be a good strategy to offer discounts to member users for adding their casual user friends to the member users

Seasonal Campaigns

 Create seasonal campaigns, where prices can be lowered during periods such as winter, when membership and casual users use the Cyclist service less frequently. Launch promotions for weekends, holidays, or longer trips for members that encourage cycling

Social Media

 Based on the previous points, you can create marketing campaigns on social media that tell stories about how casual users and members use the Cyclist service. These stories can include how the Cyclist service has helped them get around the city or how it has served as a distraction from a stressful week at work