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

Scenario:

You are 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, your team wants to **understand how casual riders and annual members use Cyclistic bikes differently**. From these insights, your team will design a new marketing strategy to **convert casual riders into annual members**. First, Cyclistic executives must approve your recommendations, so they must be backed up with compelling data insights and professional data visualizations.

Characters and teams:

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.

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.

Cyclistic marketing analytics team

- A team of data analysts who are responsible for collecting, analyzing, and reporting data that helps guide Cyclistic marketing strategy. You joined this team six months ago and have been busy learning about Cyclistic's mission and business goals — as well as how you, as a junior data analyst, can help Cyclistic achieve them.

Cyclistic executive team

- The notoriously detail-oriented executive team will decide whether to approve the recommended marketing program.

About the company

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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.

Until now, Cyclistic's marketing strategy relied on building general awareness and appealing to broad consumer segments.

One approach that helped make these things possible was the flexibility of its pricing plans: **single-ride passes**, **full-day passes**, and **annual memberships**. Customers who purchase single-ride or full-day passes are referred to as casual riders. Customers who purchase annual memberships are Cyclistic members.

Cyclistic's finance analysts have concluded that annual members are much more profitable than casual riders. Although the pricing flexibility helps Cyclistic attract more customers, **Moreno believes that maximizing the number of annual members will be key to future growth.** Rather than creating a marketing campaign that targets all-new customers, Moreno believes there is a very good chance to convert casual riders into members. She notes that casual riders are already aware of the Cyclistic program and have chosen Cyclistic for their mobility needs.

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.

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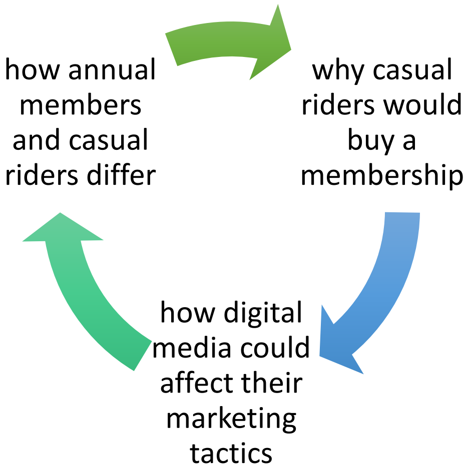
Step 1: ASK

We need to understand these three points:



<u>Guiding questions:</u>

What is the problem you are trying to solve?

How can your insights drive business decisions?

<u>Key tasks:</u>

What is the difference between the casual riders and annual members?

The task involves verifying the assumption of the director of marketing Lily Moreno that it is possible for casual riders to become annual members and that making profitable results comes from maximizing the number of annual members.

<u>Key stakeholders:</u>

The director of marketing Lily Moreno, Cyclistic marketing analytics team and Cyclistic executive team

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Step 2: PREPARE

You will use Cyclistic's historical trip data to analyze and identify trends. (Note: The datasets have a different name because Cyclistic is a fictional company. For the purposes of this case study, the datasets are appropriate and will enable you to answer the business questions. The data has been made available by Motivate International Inc. under this license.) This is public data that you can use to explore how different customer types are using Cyclistic bikes. But note that data-privacy issues prohibit you from using riders' personally identifiable information. This means that you won't be able to connect pass purchases to credit card numbers to determine if casual riders live in the Cyclistic service area or if they have purchased multiple single passes.

The data is made by **Motivate International Inc**; it uses the historical trip data for the purpose of analysing and identifying trends. As for questions about credibility, we assume that it is credible since it is used by the giant search engine Google.

```
> feb_2022 <- read_csv("C:/Users/KHAWLA/OneDrive/Bureau/Data- capstone
 project/tripdata/202202-divvy-tripdata.csv")

-- Column specification ------------------------------------------------
cols(
  ride_id = col_character(),
  rideable_type = col_character(),
  started_at = col_datetime(format = ""),
  ended_at = col_datetime(format = ""),
  start_station_name = col_character(),
  start_station_id = col_character(),
  end_station_name = col_character(),
  end_station_id = col_character(),
  start_lat = col_double(),
  start_lng = col_double(),
  end_lat = col_double(),
  end_lng = col_double(),
  member_casual = col_character()
)
```

```
> colnames(mar_2021)
 [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"
> colnames(may_2021)
 [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"
> colnames(dec_2021)
 [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"
```

The data frames contain the same columns names (13 variables) with the same order. In addition, there is no irregularity among the type of variables of each table, which leads us to the possibility of combining the 12 tables into one data frame (from March 2021 to February 2022).

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```
> compare_df_cols(mar_2021, apr_2021,may_2021,jun_2021, jul_2021, aug_2021, sep_2021, oct_2021, nov_2021, dec_2021, jan_2022, feb_2022, return = "mismatch")
 [1] column_name mar_2021    apr_2021    may_2021    jun_2021
 [6] jul_2021    aug_2021    sep_2021    oct_2021    nov_2021
[11] dec_2021    jan_2022    feb_2022
<0 lignes> (ou 'row.names' de longueur nulle)
```

all_trip_data <- bind_rows(mar_2021, apr_2021,may_2021,jun_2021, jul_2021, aug_2021, sep_2021, oct_2021, nov_2021, dec_2021, jan_2022, feb_2022)

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
CFA86D4455AA1030	classic_bike	2021-03-16 08:32:30	2021-03-16 08:36:34	Humboldt Blvd & Armitage Ave	15651	Stave St & Armitage Ave	13266	41.91751	-87.70181	41.91774	-87.69139	casual
30D9DC61227D1AF3	classic_bike	2021-03-28 01:26:28	2021-03-28 01:36:55	Humboldt Blvd & Armitage Ave	15651	Central Park Ave & Bloomingdale Ave	18017	41.91751	-87.70181	41.91417	-87.71676	casual
846D87A15682A284	classic_bike	2021-03-11 21:17:29	2021-03-11 21:33:53	Shields Ave & 28th Pl	15443	Halsted St & 35th St	TA1308000043	41.84273	-87.63549	41.83066	-87.64717	casual
994D05AA75A168F2	classic_bike	2021-03-11 13:26:42	2021-03-11 13:55:41	Winthrop Ave & Lawrence Ave	TA1308000021	Broadway & Sheridan Rd	13323	41.96881	-87.65766	41.95283	-87.64999	casual
DF7464FBE92D8308	classic_bike	2021-03-21 09:09:37	2021-03-21 09:27:33	Glenwood Ave & Touhy Ave	525	Chicago Ave & Sheridan Rd	E008	42.01270	-87.66606	42.05049	-87.67782	casual
CEBA8516FD17F8D8	classic_bike	2021-03-20 11:08:47	2021-03-20 11:29:39	Glenwood Ave & Touhy Ave	525	Chicago Ave & Sheridan Rd	E008	42.01270	-87.66606	42.05049	-87.67782	casual
297268586B79588B	classic_bike	2021-03-20 14:10:41	2021-03-20 14:22:13	State St & Kinzie St	13050	Lake Shore Dr & North Blvd	LF-005	41.88919	-87.62775	41.91172	-87.62680	member
F39301858B6077DD	electric_bike	2021-03-23 07:56:51	2021-03-23 08:05:50	Shore Dr & 55th St	TA1308000009	Ellis Ave & 60th St	KA1503000014	41.79523	-87.58083	41.78522	-87.60108	member
D297F199D875BABE	electric_bike	2021-03-31 15:31:19	2021-03-31 15:35:58	Clinton St & Lake St	13021	Franklin St & Jackson Blvd	TA1305000025	41.88555	-87.64173	41.87729	-87.63616	member
36B877141175ED7E	classic_bike	2021-03-11 17:37:37	2021-03-11 17:52:44	Michigan Ave & Lake St	TA1305000011	Racine Ave & Washington Blvd	654	41.88602	-87.62412	41.88307	-87.65695	member
1728D115DBBDF01C	classic_bike	2021-03-13 13:00:02	2021-03-13 13:18:16	Damen Ave & Madison St	13134	Federal St & Polk St	SL-008	41.88137	-87.67493	41.87208	-87.62954	member
42179FE11265F287	electric_bike	2021-03-13 10:06:56	2021-03-13 10:22:34	Damen Ave & Madison St	13134	Federal St & Polk St	SL-008	41.88141	-87.67490	41.87213	-87.62995	member
3D5DD6B1D9211403	classic_bike	2021-03-01 17:37:12	2021-03-01 18:00:18	Halsted St & 21st St	13162	Halsted St & Clybourn Ave	331	41.85378	-87.64660	41.90967	-87.64813	member
ABCB727F5E85170A	classic_bike	2021-03-28 10:03:01	2021-03-28 10:10:17	McCormick Place	TA1305000004	Michigan Ave & 18th St	13150	41.85138	-87.61883	41.85781	-87.62455	member
549D2D8DD5BB2016	classic_bike	2021-03-18 13:34:49	2021-03-18 13:38:17	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member
33AEFB46E4E039D4	classic_bike	2021-03-11 16:38:19	2021-03-11 16:41:50	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member
3D35F5B177C731A8	electric_bike	2021-03-22 11:51:25	2021-03-22 11:53:57	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01281	-87.66586	42.01593	-87.66855	member
CD66C6FA57F8FB3B	classic_bike	2021-03-22 15:48:20	2021-03-22 15:51:44	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member
5BBAF72C8A8BACFF	classic_bike	2021-03-21 08:53:42	2021-03-21 08:56:46	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member
671A6081644C1708	classic_bike	2021-03-13 08:44:39	2021-03-13 08:48:07	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member
85ADE77E501AC55B	classic_bike	2021-03-04 16:37:26	2021-03-04 16:40:45	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member
BE704F143C6D2D3F	classic_bike	2021-03-04 13:38:13	2021-03-04 13:41:07	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member
7EF1C02098621AA1	classic_bike	2021-03-14 08:31:19	2021-03-14 08:34:17	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member
7F16E75F1A71716B	classic_bike	2021-03-05 16:29:04	2021-03-05 16:32:39	Glenwood Ave & Touhy Ave	525	Greenview Ave & Jarvis Ave	520	42.01270	-87.66606	42.01596	-87.66857	member

Step 3: PROCESS

Key tasks:

- Check the data for errors
- Choose your tools
- Transform the data so you can work with it effectively
- Document the cleaning processing.

```
> colnames(all_trip_data)
 [1] "ride_id"            "rideable_type"      "started_at"         "ended_at"
 [5] "start_station_name" "start_station_id"   "end_station_name"   "end_station_id"
 [9] "start_lat"          "start_lng"          "end_lat"            "end_lng"
[13] "member_casual"
```

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The column names of the combined table (all_trip_data) contains 13 variables/columns and 5667986 rows. The same goes for the structure of the dataset, all 12 tables have the same structure.

```
> dim(all_trip_data)
[1] 5667986      13
> nrow(all_trip_data)
[1] 5667986
```

```
> str(all_trip_data)
Classes 'spec_tbl_df', 'tbl_df', 'tbl' and 'data.frame':       5667986 obs. of  13 v
ariables:
 $ ride_id           : chr  "CFA86D4455AA1030" "30D9DC61227D1AF3" "846D87A15682A284"
 "994D05AA75A168F2" ...
 $ rideable_type     : chr  "classic_bike" "classic_bike" "classic_bike" "classic_bik
e" ...
 $ started_at        : POSIXct, format: "2021-03-16 08:32:30" "2021-03-28 01:26:28"
 "2021-03-11 21:17:29" ...
 $ ended_at          : POSIXct, format: "2021-03-16 08:36:34" "2021-03-28 01:36:55"
 "2021-03-11 21:33:53" ...
 $ start_station_name: chr  "Humboldt Blvd & Armitage Ave" "Humboldt Blvd & Armitage
 Ave" "Shields Ave & 28th Pl" "Winthrop Ave & Lawrence Ave" ...
 $ start_station_id  : chr  "15651" "15651" "15443" "TA1308000021" ...
 $ end_station_name  : chr  "Stave St & Armitage Ave" "Central Park Ave & Bloomingdal
e Ave" "Halsted St & 35th St" "Broadway & Sheridan Rd" ...
 $ end_station_id    : chr  "13266" "18017" "TA1308000043" "13323" ...
 $ start_lat         : num  41.9 41.9 41.8 42 42 ...
 $ start_lng         : num  -87.7 -87.7 -87.6 -87.7 -87.7 ...
 $ end_lat           : num  41.9 41.9 41.8 42 42.1 ...
 $ end_lng           : num  -87.7 -87.7 -87.6 -87.6 -87.7 ...
 $ member_casual     : chr  "casual" "casual" "casual" "casual" ...
```

We notice that there are variables like the length of the ride that shows negative values.

```
> summary(all_trip_data)
   ride_id          rideable_type        started_at                      ended_at                  
 Length:5667986     Length:5667986     Min.   :2021-03-01 00:01:09   Min.   :2021-03-01 00:06:28  
 Class :character   Class :character   1st Qu.:2021-06-13 11:41:58   1st Qu.:2021-06-13 12:09:22  
 Mode  :character   Mode  :character   Median :2021-08-07 19:12:50   Median :2021-08-07 19:35:11  
                                       Mean   :2021-08-10 07:33:56   Mean   :2021-08-10 07:55:41  
                                       3rd Qu.:2021-10-02 14:16:11   3rd Qu.:2021-10-02 14:38:59  
                                       Max.   :2022-02-28 23:58:44   Max.   :2022-03-01 08:55:17  

 start_station_name start_station_id   end_station_name   end_station_id       start_lat    
 Length:5667986     Length:5667986     Length:5667986     Length:5667986     Min.   :41.64  
 Class :character   Class :character   Class :character   Class :character   1st Qu.:41.88  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character   Median :41.90  
                                                                             Mean   :41.90  
                                                                             3rd Qu.:41.93  
                                                                             Max.   :45.64  

   start_lng         end_lat          end_lng       member_casual     
 Min.   :-87.84   Min.   :41.39   Min.   :-88.97   Length:5667986    
 1st Qu.:-87.66   1st Qu.:41.88   1st Qu.:-87.66   Class :character  
 Median :-87.64   Median :41.90   Median :-87.64   Mode  :character  
 Mean   :-87.65   Mean   :41.90   Mean   :-87.65                     
 3rd Qu.:-87.63   3rd Qu.:41.93   3rd Qu.:-87.63                     
 Max.   :-73.80   Max.   :42.17   Max.   :-87.49                     
                  NA's   :4617    NA's   :4617                       
```

In the meantime, we will calculate some additional variables such as the ride length, the day of the week and extract month, day and year to facilitate the aggregation.

First, we calculate the ride length and the day of the week using spreadsheet or Excel. {“**ride_length”=”ended_at” – “started_at”**} and {“**day_of_week”** which returens a number between 1 and 7 who indicate the day of the week}.As we go through the data set of the previous twelve month, we that the variables “**start_station_id”** and “**end_station_id”** is not similar for the rest of the rows there are integer types and there are character one. Moreover, we notice the presence of missing values.

```
all_trip_data$date <- as.Date(all_trip_data$started_at)
all_trip_data$month <- format(as.Date(all_trip_data$started_at), "%m")
all_trip_data$year <- format(as.Date(all_trip_data$started_at), "%y")
all_trip_data$day <- format(as.Date(all_trip_data$started_at), "%d")
all_trip_data$day_of_week <- format(as.Date(all_trip_data$started_at), "%A")
all_trip_data$ride_length <- difftime(all_trip_data$ended_at, all_trip_data$started_at)
```

Since the table is very large, we could not work with Excel so we moved on to R for the third step of the data analysis.

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```
> str(all_trip_data)
Classes 'spec_tbl_df', 'tbl_df', 'tbl' and 'data.frame':        5667986 obs. of
8 variables:
 $ ride_id           : chr  "CFA86D4455AA1030" "30D9DC61227D1AF3" "846D87A15682A
4" "994D05AA75A168F2" ...
 $ rideable_type     : chr  "classic_bike" "classic_bike" "classic_bike" "classi
bike" ...
 $ started_at        : POSIXct, format: "2021-03-16 08:32:30" "2021-03-28 01:26:
8" "2021-03-11 21:17:29" "2021-03-11 13:26:42" ...
 $ ended_at          : POSIXct, format: "2021-03-16 08:36:34" "2021-03-28 01:36:
5" "2021-03-11 21:33:53" "2021-03-11 13:55:41" ...
 $ start_station_name: chr  "Humboldt Blvd & Armitage Ave" "Humboldt Blvd & Armi
ge Ave" "Shields Ave & 28th Pl" "Winthrop Ave & Lawrence Ave" ...
 $ start_station_id  : chr  "15651" "15651" "15443" "TA1308000021" ...
 $ end_station_name  : chr  "Stave St & Armitage Ave" "Central Park Ave & Bloomi
dale Ave" "Halsted St & 35th St" "Broadway & Sheridan Rd" ...
 $ end_station_id    : chr  "13266" "18017" "TA1308000043" "13323" ...
 $ start_lat         : num  41.9 41.9 41.8 42 42 ...
 $ start_lng         : num  -87.7 -87.7 -87.6 -87.7 -87.7 ...
 $ end_lat           : num  41.9 41.9 41.8 42 42.1 ...
 $ end_lng           : num  -87.7 -87.7 -87.6 -87.6 -87.7 ...
 $ member_casual     : chr  "casual" "casual" "casual" "casual" ...
 $ month             : chr  "03" "03" "03" "03" ...
 $ year              : chr  "21" "21" "21" "21" ...
 $ day               : chr  "16" "28" "11" "11" ...
 $ day_of_week       : chr  "mardi" "dimanche" "jeudi" "jeudi" ...
 $ ride_length       : 'difftime' num  244 627 984 1739 ...
```

Now with 5 columns added to the dataset.

```
all_trip_data2<- all_trip_data %>%
  filter(all_trip_data$ride_length > 0)
```

We remove the observations with a length ride less than 0 seconds and we go to a table with 5667333 observations and 19 variables.

Finally, in order to remove the missing values and clean the dataset, which leaves us with 4630904 observations, we use the function:

```
all_trips_data_v2<- na.omit(all_trip_data2)
```

```
> summary(all_trips_data_v2)
   ride_id          rideable_type        started_at                    ended_at                  
 Length:4630904     Length:4630904     Min.   :2021-03-01 00:01:09   Min.   :2021-03-01 00:06:28  
 Class :character   Class :character   1st Qu.:2021-06-10 21:24:13   1st Qu.:2021-06-10 21:49:35  
 Mode  :character   Mode  :character   Median :2021-08-03 18:20:24   Median :2021-08-03 18:39:32  
                                       Mean   :2021-08-06 03:49:49   Mean   :2021-08-06 04:11:26  
                                       3rd Qu.:2021-09-26 17:58:30   3rd Qu.:2021-09-26 18:22:36  
                                       Max.   :2022-02-28 23:58:44   Max.   :2022-03-01 08:55:17  
 start_station_name start_station_id   end_station_name   end_station_id        start_lat       start_lng     
 Length:4630904     Length:4630904     Length:4630904     Length:4630904     Min.   :41.65   Min.   :-87.83  
 Class :character   Class :character   Class :character   Class :character   1st Qu.:41.88   1st Qu.:-87.66  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character   Median :41.90   Median :-87.64  
                                                                             Mean   :41.90   Mean   :-87.64  
                                                                             3rd Qu.:41.93   3rd Qu.:-87.63  
                                                                             Max.   :45.64   Max.   :-73.80  
    end_lat         end_lng        member_casual           date               month              year          
 Min.   :41.65   Min.   :-87.83   Length:4630904     Min.   :2021-03-01   Length:4630904     Length:4630904    
 1st Qu.:41.88   1st Qu.:-87.66   Class :character   1st Qu.:2021-06-10   Class :character   Class :character  
 Median :41.90   Median :-87.64   Mode  :character   Median :2021-08-03   Mode  :character   Mode  :character  
 Mean   :41.90   Mean   :-87.64                      Mean   :2021-08-05                                        
 3rd Qu.:41.93   3rd Qu.:-87.63                      3rd Qu.:2021-09-26                                        
 Max.   :42.17   Max.   :-87.52                      Max.   :2022-02-28                                        
     day            day_of_week        ride_length     
 Length:4630904     Length:4630904     Length:4630904    
 Class :character   Class :character   Class :difftime   
 Mode  :character   Mode  :character   Mode  :numeric    
```

Step 4: ANALYZE

Key tasks:

- Aggregate your data so it's useful and accessible,
- Organize and format your data,

- Perform calculations,
- Identify trends and relationships.

```
> summary(all_trips_data_v2$ride_length)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
      1     412     725    1298    1315 3356649
```

The summary represents the descriptive analysis of the ride length variable, with a mean of 1298 seconds of ride length.

For this part, we compare the ride length for each membership type (member or casual)

Casual members exceeds annual members with a difference of 1161.607

```
> aggregate(all_trips_data_v2$ride_length~all_trips_data_v2$member_casual, FUN = mean)
  all_trips_data_v2$member_casual all_trips_data_v2$ride_length
1                          casual                     1944.2624
2                          member                      782.6554
> aggregate(all_trips_data_v2$ride_length~all_trips_data_v2$member_casual, FUN = median)
  all_trips_data_v2$member_casual all_trips_data_v2$ride_length
1                          casual                           995
2                          member                           576
> aggregate(all_trips_data_v2$ride_length~all_trips_data_v2$member_casual, FUN = max)
  all_trips_data_v2$member_casual all_trips_data_v2$ride_length
1                          casual                       3356649
2                          member                         89738
> aggregate(all_trips_data_v2$ride_length~all_trips_data_v2$member_casual, FUN = min)
  all_trips_data_v2$member_casual all_trips_data_v2$ride_length
1                          casual                             1
2                          member                             1
```

```
> aggregate(all_trips_data_v2$ride_length~all_trips_data_v2$member_casual+all_trips_data_v2$day_of_week, FUN = mean)
   all_trips_data_v2$member_casual all_trips_data_v2$day_of_week all_trips_data_v2$ride_length
1                           casual                      dimanche                     2253.3859
2                           member                      dimanche                      902.8666
3                           casual                         lundi                     1953.5265
4                           member                         lundi                      755.1151
5                           casual                         mardi                     1719.9626
6                           member                         mardi                      734.3252
7                           casual                      mercredi                     1694.9199
8                           member                      mercredi                      738.8411
9                           casual                         jeudi                     1688.6325
10                          member                         jeudi                      734.2611
11                          casual                      vendredi                     1843.2278
12                          member                      vendredi                      762.3497
13                          casual                        samedi                     2078.0141
14                          member                        samedi                      879.7124
```

```
> aggregate(all_trips_data_v2$ride_length~all_trips_data_v2$member_casual+ all_trips_data_v2$rideable_type, FUN = length)
  all_trips_data_v2$member_casual all_trips_data_v2$rideable_type all_trips_data_v2$ride_length
1                          casual                     classic_bike                       1262644
2                          member                     classic_bike                       1997064
3                          casual                      docked_bike                        310951
4                          casual                    electric_bike                        479152
5                          member                    electric_bike                        581093
```

From the results of the analysis, we can conclude that on average, casual users are greater than member riders are. In addition, for both types of riders the time spent on the ride is less on Mondays and grows throughout the week until it get to the peak on Sundays.

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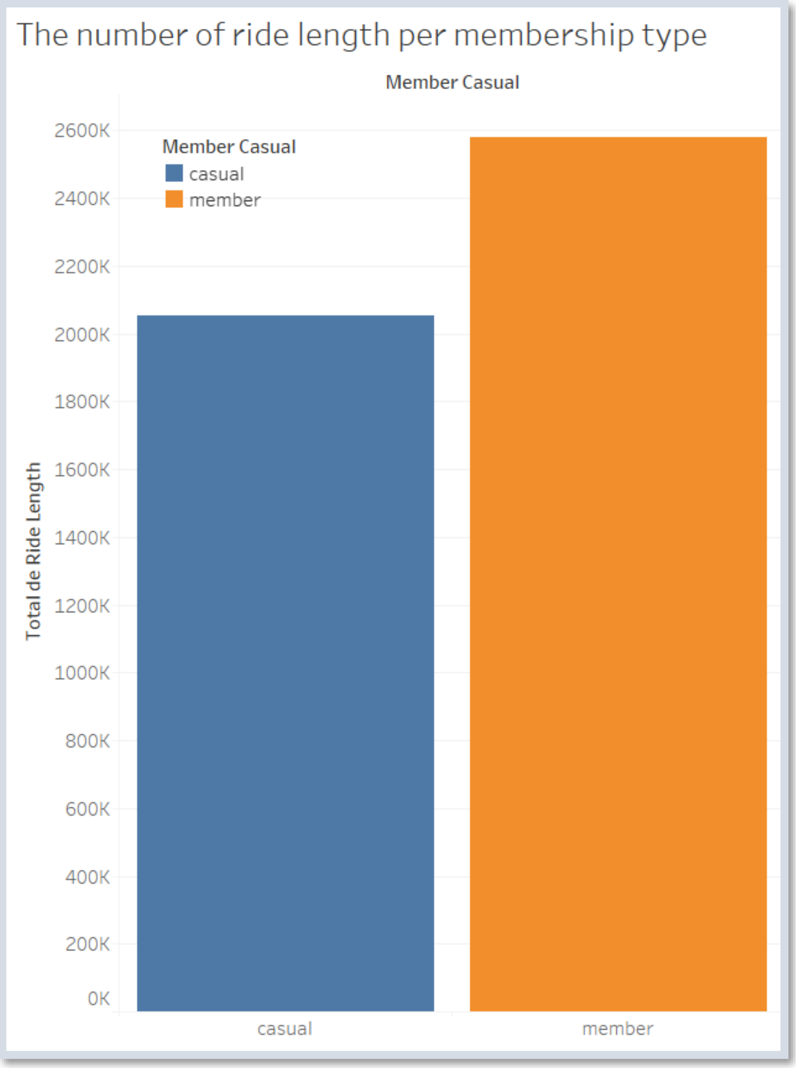
Step 5: SHARE

Key tasks:

- Determine the best way to share your findings.
- Create effective data visualizations
- Present your findings
- Ensure your work is accessible



The data visualization on the left demonstrate the number of rides per membership type (casual or member).

The number of annual riders (members) is higher than the casual ones.

The member rides counts 2 578 155 rides while casual riders counts 2 052 747.

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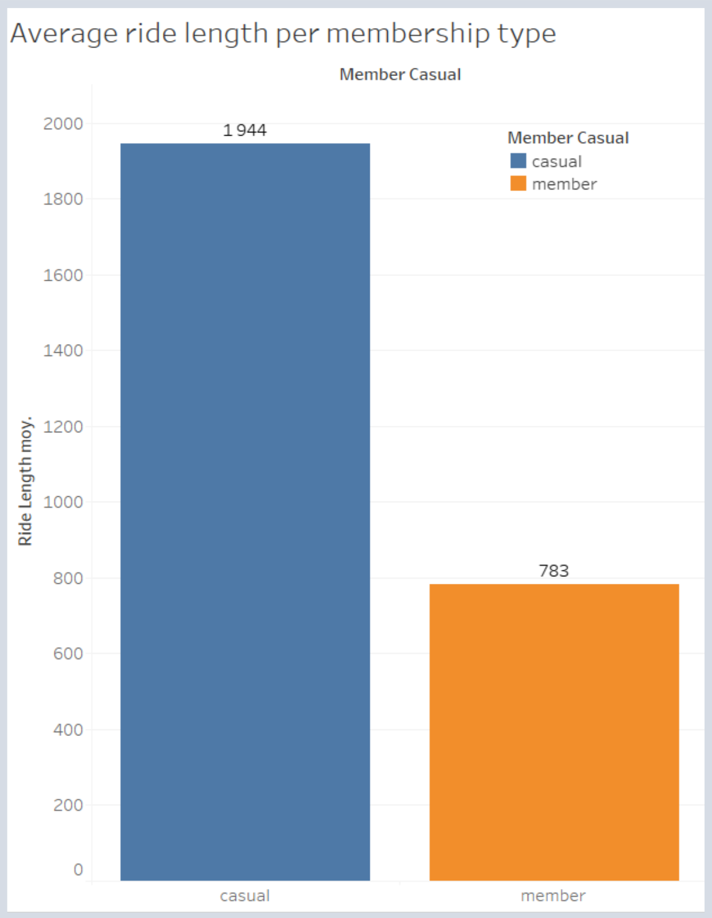
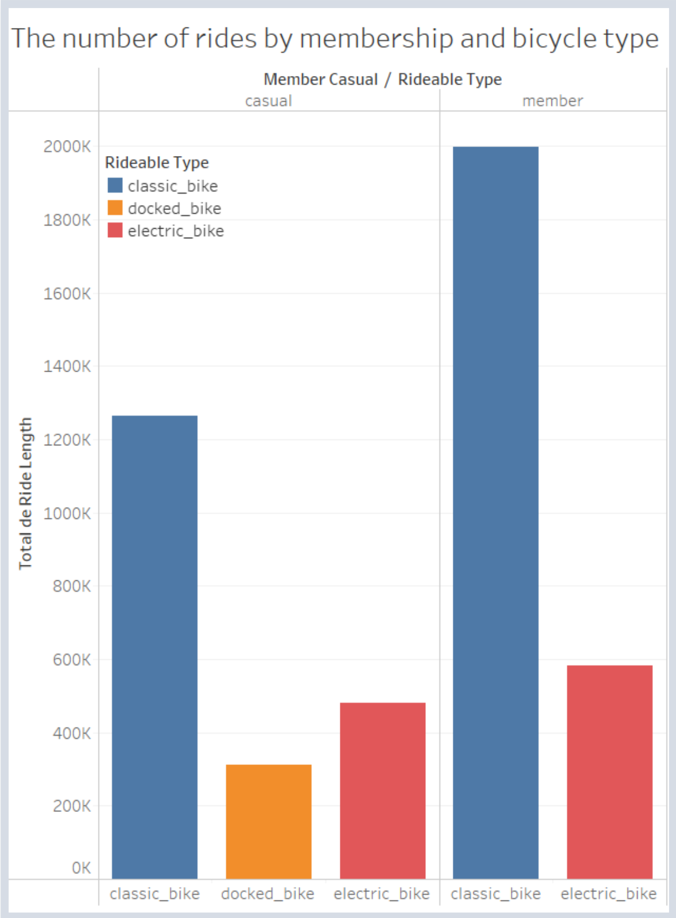
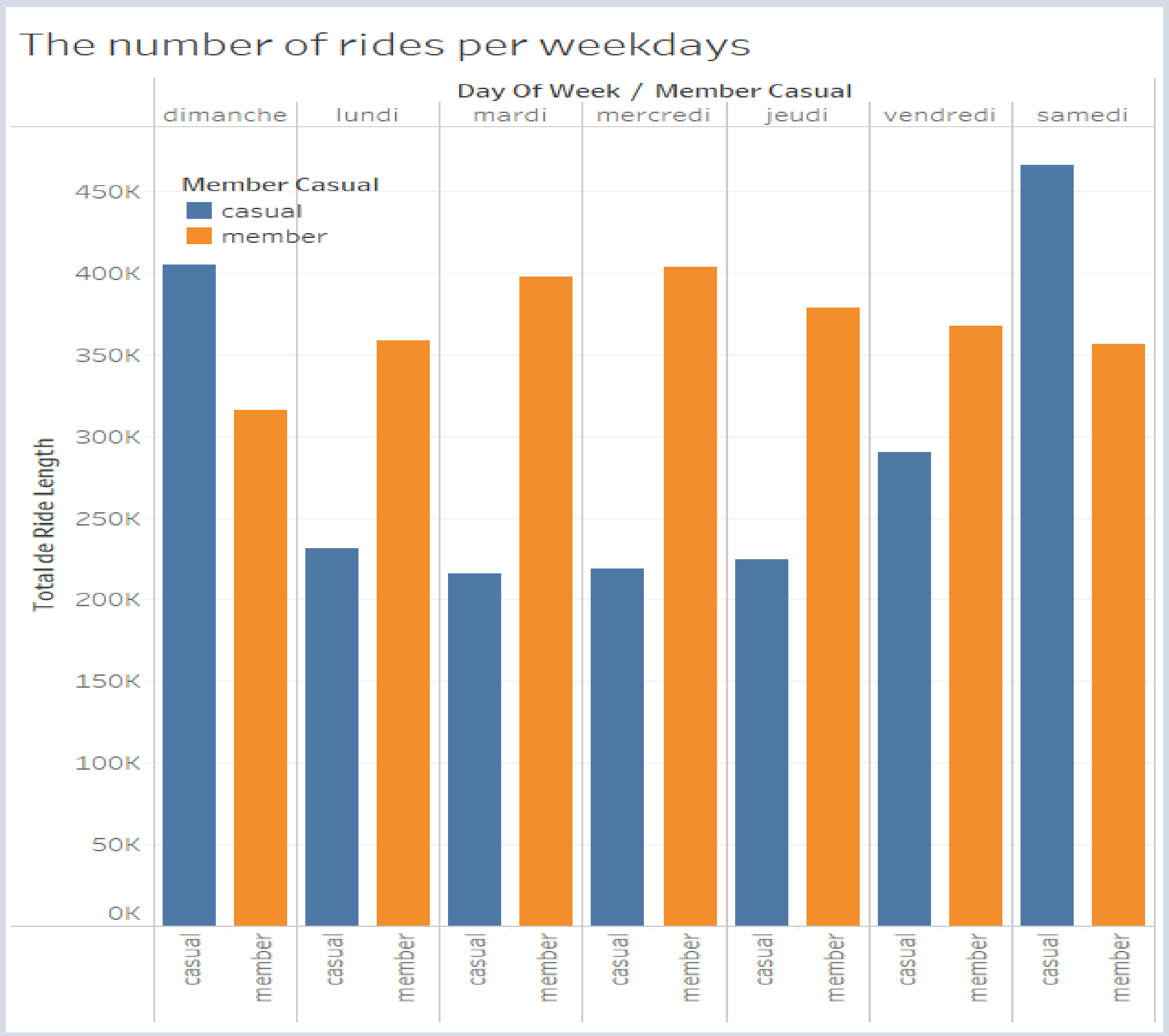




As for the average of ride length per membership type, the average of casual riders exceeds the member riders.

The time spent on rides is higher for the casual riders who may spend rides for long distances.

For the bicycle type chosen by each rider, casual riders prefer classic bikes on the first hand with 1 262 644 rides, then electric bikes with 479 152 rides and lastly comes the docked bikes with 310 951 rides. For the annual members they prefer by far the use of classic bikes with 1 997 063 rides and 581 092 rides for electric bikes. On general, the classic bike is the best choice for both types of riders.



We notice that casual riders are higher in numbers on weekends and member riders are higher in number on weekdays.

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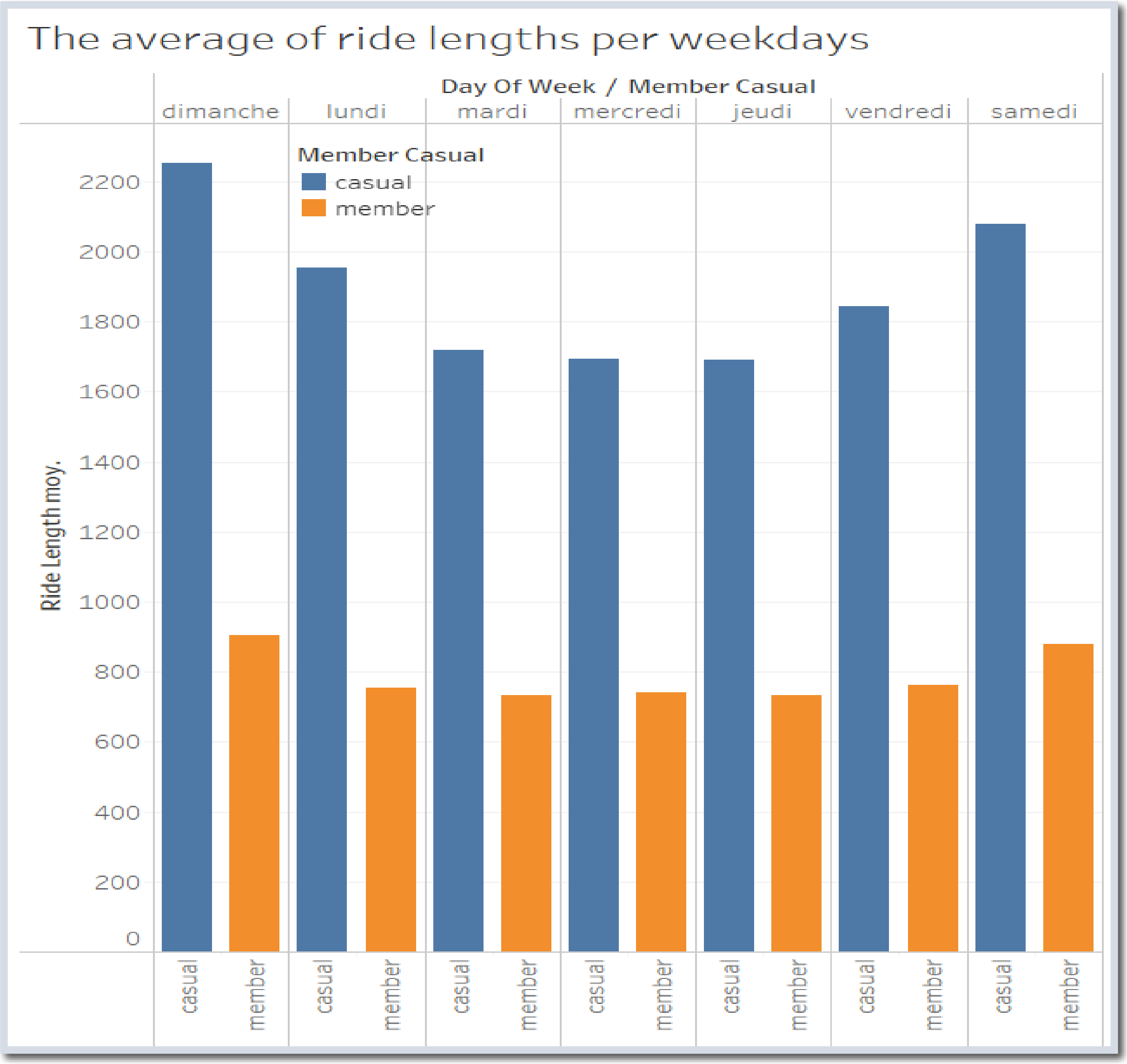

However, if we look at the average time spent on the rides, we find that the casual riders spend more time than the member riders do for all the days of the week.

While both riders spend more time on weekends.

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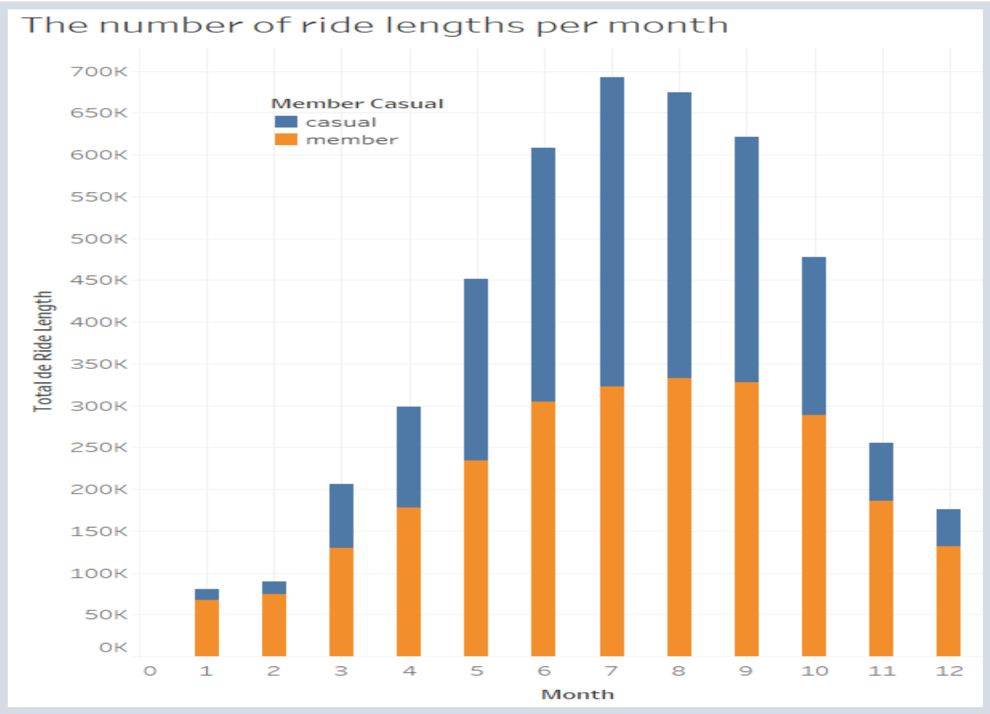
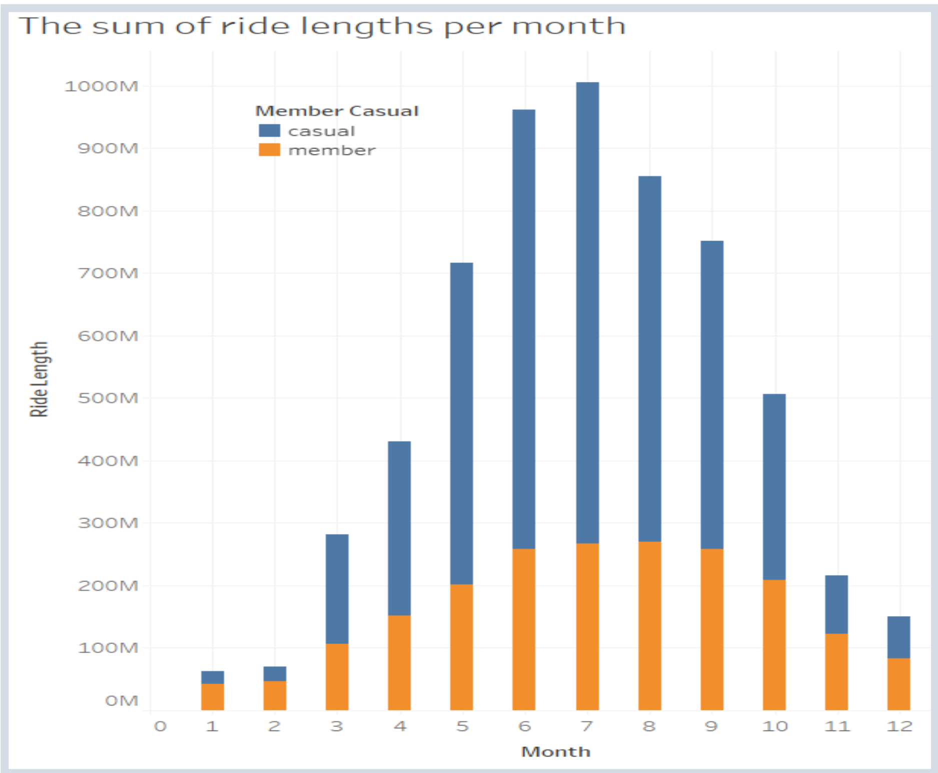


The visualization on the left side shows that the number of the member riders are higher than casual riders in the start of the year. These riders grow in number until the month of July where they get to the peak and start decreasing in numbers in comparison to the member riders who even though on January and February they are higher than casual riders they grow in numbers until they reach the peak on August and start decreasing but less importantly than casual riders do.

The chart show the same normal distribution as the last chart.

The time spent on cycle for the casual riders is less than the members are for January and February, the length of the ride start getting higher and higher until its peak in July and start decreasing until it reaches the minimum



amount of time in November and December. The same thing goes for the member riders whose ride length is higher in January and February, keeps growing until its peak on August, and starts decreasing in the last three months of the year. This may be due to the weather and the changes of the seasons. Riders use bicycles more when it has warm than when it is cold and chilly weather.

Step 6: ACT

Key tasks:

- Create your portfolio
- Add your case study
- Practice presenting your case study to your friend or family member.

To sum it up:

- The member rider are important in number than the casual ones but the average amount of time spent on rides is important for the casual riders.
- The classic bikes is the type of bicycles preferred for both types of riders.
- Regardless of the day of the week, the riders use bicycles however, the amount of rent is important on weekends especially on Saturdays.
- Member riders use bikes all the week with not much difference on the number.
- On average, for weekday's casual riders use bikes more than members do.
- Casual riders rent bikes on weekends and less on weekdays with Saturday as the peak.
- Riders regardless of the type, they spend the amount of time using a bike in dependence on the season and the weather.
- Riders use bikes less on winter, fall, and more on spring and summer.

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As rides peak on weekends and the minimum number of rides is on weekdays, we recommend using a strategy or a campaign for weekend users for example a type of membership for weekend riders with an encouraging price.

Since rides are more important in number and in time of the rides on spring and summer, we recommend using an attractive campaign for these two seasons.

Casual member use the bike renting regardless of the day of the week, we recommend using a campaign with an advantageous price for them to save up more money than in the normal membership and other utilities to promote them into annual members