Google Data Analytics Capstone

Cyclistic Case Study

;

Cyclistic: How can a bike-sharing company maximize their annual memberships?

A case-study/project authored by

Waqar Shaozab

15 September, 2023

Introduction

Greetings! This case study comes from the **Google Data Analytics Professional Certificate** capstone project. It offers an in-depth exploration of the six critical stages of the data analysis process: **Ask, Prepare, Process, Analyze, Share, and Act.**

Allow me to introduce Cyclistic, a fictitious bike-sharing company based in Chicago, Illinois. In the year 2016, Cyclistic launched an innovative bike-share program, boasting an impressive fleet of **over 5,800 bicycles** and an extensive network of **600** docking stations. Setting itself apart from other bike-sharing companies, Cyclistic proudly provides a large selection of different bike options, including reclining bikes, hand tricycles, and cargo bikes. We want our bikes to be as inclusive and accessible for individuals with disabilities. Despite these options, only **8 percent** of riders use of these assistive features.

;

Bikes stationed in Chicago - Divvy

Furthermore, a substantial **30 percent** of Cyclistic's riders use the service for their daily work commutes, indicating that the majority of users primarily use our bikes leisurely. Cyclistic's current marketing strategy centers around creating a broad brand awareness and appealing to a wide consumer base. This strategy is dependant on the implementation of flexible pricing plans, encompassing single-ride passes, full-day passes, and annual passes. Customers who opt for single-ride and full-day passes fall into the category of

casual riders, while those who choose the annual passes are considered *Cyclistic members.*

Despite the efficacy of these pricing plans in attracting a diverse consumer base, it's important to note that **Lily Moreno, the Director of Marketing**, firmly believes that focusing on converting casual riders into annual members will provide substantial growth Cyclistic. Finance analysts at Cyclistic have also concluded that annual members contribute to a higher profit margin compared to casual riders. As a result, instead of initiating a marketing campaign targeting new customers, Moreno is confident that we can successfully transition casual riders into Cyclistic members.

Table of Contents

Chapter 1

ASK

Asking the right questions are essential to the first phases of data analysis. If your questions are **S**pecific, **M**easurable, **A**ction-**O**riented, **R**elevant, **T**ime-**B**ound, or **S.M.A.R.T.**, then you know your answers will be as thorough and accurate as possible. This will then lead to a complete and actionable analysis.

1.1 Key Tasks

- Identify the business task
- Consider key stakeholders

1.2 Deliverable

☐ Clear statement of the business task

1.3 Business Task

Design marketing strategies aimed at converting casual riders into annual members.

1.4 Business Objectives

- 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?

1.5 Case-Study Deliverables

1. A clear statement of the business task.
2. A description of all data sources used.
3. Documentation of any cleaning or manipulation of data.
4. A summary of analysis.
5. Supporting visualizations and key findings.
6. Three recommendations based on the analysis.

1.6 Key Stakeholders

- Lily Moreno Director of Marketing and Manager: Responsible for developing and implementing initiatives and campaigns for the bike-share program.
- Cyclistic marketing analytics team: A team of data analysts guiding Cyclistics marketing strategy.
- Cyclistic executive team: Any new marketing programs are subject to approval by the highly-detailed executive team.

Chapter 2

PREPARE

2.1 Key Tasks

- Download data and store it appropriately
- Identify how it's organized
- Sort and filter data

2.2 Deliverable

☐ Description of all data sources used.

2.3 Information on Data Source

- The data is stored **here** via 57 datasets saved as **.CSV (comma-separated values)** files ranging from years **2013-2023.**
- The datasets are publicly available for this case-study by Motivate International Inc. under this **license.**https://www.overleaf.com/project/64a57b0b8f766fab10728056
- The original attributes that were captured include: *ride_id*, *rideable_type*, *started_at*, *ended_at*, *start_station_name*, *start_station$_i$d*, *end_tation_name*, *end_station_id*, *start_lat*, *start_lng*, *end_lat*, *end_lng*, *member_casual* with a total of 13 columns.
- Downloaded and unzipped all 12 files that corresponded to the year 2022.
- Housed the original files in a separate folder.
- Created sub-folders for .CSV files and .XLXS files with appropriate naming conventions.

2.4 Limitations of Data

- Data-privacy issues forbids us from accessing riders' personally identifiable information. That means I am unable to connect pass purchases to credit card numbers to determine some indicators like rider home location to Cyclistic services or if they purchased multiple single passes.
- Of the historical bike trip data, we are only using datasets that correspond to the last **12 months.**

2.5 Is The Data ROCCC?

A credible data source is **ROCCC** which stands for **R**eliable, **O**riginal, **C**omprehensive, **C**urrent, and **C**ited.

1. **Reliable** - YES - Large sample size; representative of population.
2. **Original** - YES - Primary source of data comes internally from Cyclistic.

3. **Comprehensive** - MED - Data can be easily deciphered; does contain null values but not enough to lead to an incomplete analysis.

4. **Current** - YES - The most relevant data is available; entirety of the 2022 calendar year.

5. **Cited** - YES - Sources comes directly from internal databases; no third-party was involved.

Chapter 3

PROCESS

Work in Process

3.1 Key Tasks

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

3.2 Deliverable

☐ Documentation of any cleaning and manipulation of data.

The process phase is an essential part for high-level decision making. This means cleaning and transforming data from dirty to clean in order to prepare for analysis. But the cleaner your data is, the better and more effective your analysis will be. Dirty data will lead to unreliable insights.

A number of tools can be used to process data like spreadsheets, SQL, and R. For this case-study, we'll start by cleaning the data using **Microsoft Excel** and then move over to coding in **R** due its ability to process large datasets.

Below will outline data cleaning process in Excel:

3.3 Removed Duplicates

1. $Data \rightarrow Data\,Tools \rightarrow Remove\,Duplicates \rightarrow Select\,Columns \rightarrow Ok$

3.4 Checked Spelling

1. $Select\ \ Column \rightarrow Review \rightarrow Proofing \rightarrow Spelling$

3.5 Searched for Null Values

1. $Home \rightarrow SelectSheet \rightarrow Editing \rightarrow Find\,and\,Select \rightarrow GoTo\,Special \rightarrow Blanks \rightarrow Highlight\,Blanks\,Yellow$

Note: Null values fall under columns: *start_station_name start_station_id end_station_name end_station_id end_lat*, and *end_lng*. This could be due to customers not retrieving and docking their bikes at an appropriate station.

3.6 Ensured *started_at* and *ended_at* Columns Had Consistent Timestamp Format

1. $Home \rightarrow Number \rightarrow FormatCells \rightarrow Time/Date \rightarrow dd-mm-yyyyhh:mm:ss \rightarrow Ok$

3.7 Used *=TRIM()* Function to Eliminate Extra Spaces

1. $Insert\ \ Column \rightarrow = TRIM(A2,\ B3\, etc...) \rightarrow Drag\, Values\, Down \rightarrow Copy\, New\, Column \rightarrow Use\, Paste\, Special\, on\, Old\, Column \rightarrow Values \rightarrow Ok \rightarrow Delete\, New\, Column$

3.8 Used *=TRIM()* and *=PROPER()* Functions

1. To be done on columns *start_station_id* and *end_station_id*
2. This is to eliminate spaces and format correctly
3. $Insert\ \ Column \rightarrow = TRIM(PROPER(F2)) \rightarrow Drag\, Values\, Down \rightarrow Copy\, New\, Column \rightarrow Use\, Paste\, Special\, on\, Old\, Column \rightarrow Values \rightarrow Ok \rightarrow Delete\, New\, Column$

3.9 Created New Column called *ride_length*

1. Calculated Length of Each Ride by Subtracting *started_at* From the *ended_at* Columns
2. *=(D2-C2)*
3. Formatted Time as HH:MM:SS (37:30:55)
4. $Home \rightarrow Number \rightarrow Format\, Cells \rightarrow Time \rightarrow HH:MM:SS(37:30:55)$

3.10 Created New Column Called *day_of_week*

1. Calculated Day of Week Each Ride Began Using the $=WEEKDAY$ Command.
2. *=WEEKDAY(C2,1)*
3. Formatted as Number With No Decimals
4. $Home \rightarrow Number \rightarrow Format\, Cells \rightarrow Number \rightarrow Decimal\, Places:\ 01 = Sunday, 7 = Saturday$

These steps are to be done for each .CSV file.

Below will outline the data cleaning/manipulation process in R.

Chapter 4

ANALYZE

5. 

4.1 Key Tasks

1. Aggregate your data so it's useful and accessible.
2. Organize and format your data.
3. Perform calculations.
4. Identify trends and relationships.

4.2 Deliverable

☐ Summary of analysis

4.3 Process and Analyze In R

```
# Install and load all required packages
```{r}
install.packages("tidyverse")
install.packages("lubridate")
install.packages("ggplot2")
install.packages("dplyr")

library(tidyverse)
library(lubridate)
library(ggplot2)
library(dplyr)
library(hms)

```
```

```
## Collect Data
# Upload Cyclistic datasets (csv files) here
```{r}
JAN_2022.csv <- read_csv("JAN_2022")
FEB_2022.csv <- read_csv("FEB_2022")
MAR_2022.csv <- read_csv("MAR_2022")
APR_2022.csv <- read_csv("APR_2022")
MAY_2022.csv <- read_csv("MAY_2022")
JUN_2022.csv <- read_csv("JUN_2022")
JUL_2022.csv <- read_csv("JUL_2022")
AUG_2022.csv <- read_csv("AUG_2022")
SEP_2022.csv <- read_csv("SEP_2022")
OCT_2022.csv <- read_csv("OCT_2022")
NOV_2022.csv <- read_csv("NOV_2022")
DEC_2022.csv <- read_csv("DEC_2022")
```
```

```
## Wrangle Data and Combine into a Single File
# Compare column names for each of the files
```{r}
colnames(JAN_2022)
colnames(FEB_2022)
colnames(MAR_2022)
colnames(APR_2022)
colnames(MAY_2022)
colnames(JUN_2022)
colnames(JUL_2022)
colnames(AUG_2022)
colnames(SEP_2022)
colnames(OCT_2022)
colnames(NOV_2022)
colnames(DEC_2022)
```
```

```
 [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"      "ride_length"        "day_of_week"
 [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"      "ride_length"        "day_of_week"
 [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"      "ride_length"        "day_of_week"
 [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"      "ride_length"        "day_of_week"
 [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"      "ride_length"        "day_of_week"
 [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...11"       "end_lat...12"
[13] "end_lng"            "member_casual"      "ride_length"
[16] "day_of_week"
 [1] "ride_id"            "rideable_type"      "started_at"
 [4] "ended_at"           "start_ride_station" "start_station_id"
 [7] "end_station_name"   "...8"               "start_lat"
[10] "start_lng"          "end_lat"            "end_lng"

[10] "start_lng"          "end_lat"            "end_lng"
[13] "member_casual"      "ride_length"        "day_of_week"
 [1] "ride_id"            "rideable_type"      "started_at"
 [4] "ended_at"           "start_station_name" "start_station_id"
 [7] "end_station_name"   "...8"               "start_lat"
[10] "start_lng"          "end_lat"            "end_lng"
[13] "member_casual"      "ride_length"        "day_of_week"
 [1] "ride_id"            "rideable_type"      "started_at"
 [4] "ended_at"           "start_station_name" "start_station_id"
 [7] "end_station_name"   "...8"               "start_lat"
[10] "start_lng"          "end_lat"            "end_lng"
[13] "member_casual"      "ride_length"        "day_of_week"
 [1] "ride_id"            "rideable_type"      "started_at"
 [4] "ended_at"           "start_station_name" "start_station_id"
 [7] "end_station_name"   "end_sation_id"      "start_lat"
[10] "start_lng"          "end_lat"            "end_lng"
[13] "member_casual"      "ride_length"        "day_of_week"
 [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"      "ride_length"        "day_of_week"
 [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"      "ride_length"        "day_of_week"
```

```
# Inspect the dataframes and look for incongruencies
```{r}
str(JAN_2022)
str(FEB_2022)
str(MAR_2022)
str(APR_2022)
str(MAY_2022)
str(JUN_2022)
str(JUL_2022)
str(AUG_2022)
str(SEP_2022)
str(OCT_2022)
str(NOV_2022)
str(DEC_2022)
```
```

A link for the str() tibble can be found here file:///Users/waqarshaozab/Downloads/str.tibble.html

```
# Convert ride_id and rideable_type to character so that they can stack
correctly
```{r}
JAN_2022 <- mutate(JAN_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
FEB_2022 <- mutate(FEB_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
MAR_2022 <- mutate(MAR_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
APR_2022 <-  mutate(APR_2022,ride_id =
as.character(ride_id),rideable_type = as.character(rideable_type))
MAY_2022 <- mutate(MAY_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
JUN_2022 <- mutate(JUN_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
JUL_2022 <- mutate(JUL_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
AUG_2022 <- mutate(AUG_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
SEP_2022 <- mutate(SEP_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
OCT_2022 <- mutate(JAN_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
NOV_2022 <- mutate(JAN_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
DEC_2022 <- mutate(DEC_2022,ride_id = as.character(ride_id),rideable_type
= as.character(rideable_type))
```
```

```
# Stack individual month's data frames into one big data frame
```{r}
all_trips <- bind_rows(JAN_2022,FEB_2022,MAR_2022,APR_2022,MAY_2022,JUN_2
022,JUL_2022,AUG_2022,SEP_2022,OCT_2022,NOV_2022,DEC_2022)
```
```

```
##Clean Up Data to Prepare for Analysis
# Inspect the new table that has been created
```{r}
colnames(all_trips)
nrow(all_trips)
dim(all_trips)
head(all_trips)
tail(all_trips)
str(all_trips)
summary(all_trips)
```
```


```
                                                    Max.   :7.000

 end_lat...11      end_lat...12     start_ride_station
Min.   :42        Min.   :-88       Length:4978837
1st Qu.:42        1st Qu.:-88       Class :character
Median :42        Median :-88       Mode  :character
Mean   :42        Mean   :-88
3rd Qu.:42        3rd Qu.:-88
Max.   :42        Max.   :-88
NA's   :4210688   NA's   :4210688
    ...8
Length:4978837
Class :character
Mode  :character
```

ride_id <chr>	rideable_type <chr>	started_at <chr>
C2F7DD78E82EC875	electric_bike	1/13/2022 11:59
A6CF8980A652D272	electric_bike	1/10/2022 8:41
BD0F91DFF741C66D	classic_bike	1/25/2022 4:53
CBB80ED419105406	classic_bike	1/4/2022 0:18
DDC963BFDDA51EEA	classic_bike	1/20/2022 1:31
A39C6F6CC0586C0B	classic_bike	1/11/2022 18:48

ended_at <chr>	start_station_name <chr>
1/13/2022 12:02	Glenwood Ave & Touhy Ave
1/10/2022 8:46	Glenwood Ave & Touhy Ave
1/25/2022 4:58	Sheffield Ave & Fullerton Ave
1/4/2022 0:33	Clark St & Bryn Mawr Ave
1/20/2022 1:37	Michigan Ave & Jackson Blvd
1/11/2022 18:51	Wood St & Chicago Ave

start_station_id <chr>	end_station_name <chr>
525	Clark St & Touhy Ave
525	Clark St & Touhy Ave
Ta1306000016	Greenview Ave & Fullerton Ave
Ka1504000151	Paulina St & Montrose Ave
Ta1309000002	State St & Randolph St
637	Honore St & Division St

end_station_id <chr>	start_lat <dbl>	start_lng <dbl>	end_lat <dbl>
Rp-007	42.01280	-87.66591	42.01256
Rp-007	42.01276	-87.66597	42.01256
Ta1307000001	41.92560	-87.65371	41.92533
Ta1309000021	41.98359	-87.66915	41.96151
Ta1305000029	41.87785	-87.62408	41.88462
Ta1305000034	41.89563	-87.67207	41.90312

member_casual <chr>	ride_length <S3: hms>	day_of_week <dbl>	end_lat...11 <dbl>
casual	00:03:00	5	*NA*
casual	00:05:00	2	*NA*
member	00:05:00	3	*NA*
casual	00:15:00	3	*NA*
member	00:06:00	5	*NA*
member	00:03:00	3	*NA*

ride_id <chr>	rideable_type <chr>	started_at <chr>
7BDEDE9860418B53	classic_bike	12/7/2022 6:52
43ABEE85B6E15DCA	classic_bike	12/5/2022 6:51
F041C89A3D1F0270	electric_bike	12/14/2022 17:06
A2BECB88430BE156	classic_bike	12/8/2022 16:27
37B392960E566F58	classic_bike	12/28/2022 9:37
2DD1587210BA45AE	classic_bike	12/9/2022 0:27

ended_at <chr>	start_station_name <chr>
12/7/2022 6:56	Sangamon St & Washington Blvd
12/5/2022 6:54	Sangamon St & Washington Blvd
12/14/2022 17:19	Bernard St & Elston Ave
12/8/2022 16:32	Wacker Dr & Washington St
12/28/2022 9:41	Sangamon St & Washington Blvd
12/9/2022 0:35	Southport Ave & Waveland Ave

start_station_id <chr>	end_station_name <chr>	end_station_id <chr>
13409	Peoria St & Jackson Blvd	13158
13409	Peoria St & Jackson Blvd	13158
18016	Seeley Ave & Roscoe St	13144
Ka1503000072	Green St & Madison St	Ta1307000120
13409	Peoria St & Jackson Blvd	13158
13235	Seeley Ave & Roscoe St	13144

start_lat <dbl>	start_lng <dbl>	end_lat <dbl>	end_lng <dbl>	member_casual <chr>
41.88316	-87.65110	41.87764	-87.64962	member
41.88316	-87.65110	41.87764	-87.64962	member
41.94998	-87.71402	41.94340	-87.67962	member
41.88314	-87.63724	41.88186	-87.64926	member
41.88316	-87.65110	41.87764	-87.64962	member
41.94815	-87.66394	41.94340	-87.67962	casual

ride_length <S3: hms>	day_of_week <dbl>	end_lat...11 <dbl>	end_lat...12 <dbl>
00:04:00	4	*NA*	*NA*
00:03:00	2	*NA*	*NA*
00:13:00	4	*NA*	*NA*
00:05:00	5	*NA*	*NA*
00:04:00	4	*NA*	*NA*
00:08:00	6	*NA*	*NA*

Convert "ride_length" from Factor to numeric so we can run calculations on the data

```{r}
is.factor(all_trips$ride_length)
all_trips$ride_length <- as.numeric(all_trips$ride_length)
is.numeric(all_trips$ride_length)

```

```
[1] FALSE
[1] TRUE
```

Conduct descriptive analysis

Descriptive analysis on ride_length

```{r}
summary(all_trips$ride_length)

```

```
    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
       0     360     660    1088    1140  359640     711 
```

Compare members and casual users

```{r}
aggregate(all_trips$ride_length ~ all_trips$member_casual, FUN = mean)
aggregate(all_trips$ride_length ~ all_trips$member_casual, FUN = median)
aggregate(all_trips$ride_length ~ all_trips$member_casual, FUN = max)
aggregate(all_trips$ride_length ~ all_trips$member_casual, FUN = min)

```

all_trips$member_casual <chr>	all_trips$ride_length <dbl>
casual	1536.8251
member	773.3823

all_trips$member_casual <chr>	all_trips$ride_length <dbl>
casual	780
member	540

all_trips$member_casual <chr>	all_trips$ride_length <dbl>
casual	359640
member	93600

all_trips$member_casual <chr>	all_trips$ride_length <dbl>
casual	0
member	0

See the average ride time by each day for members vs casual users

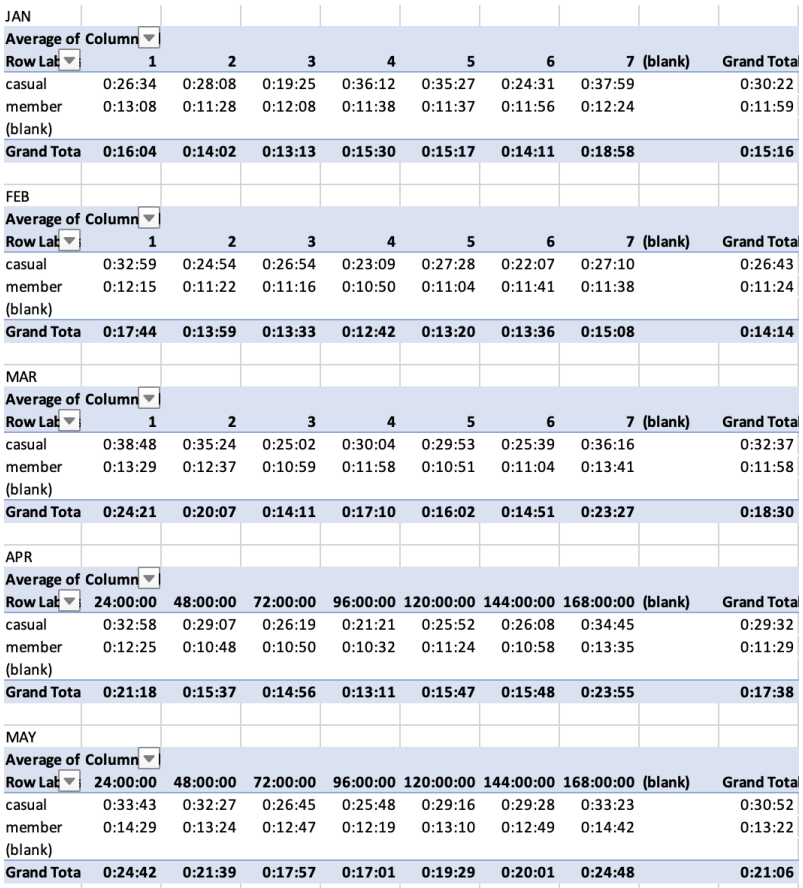
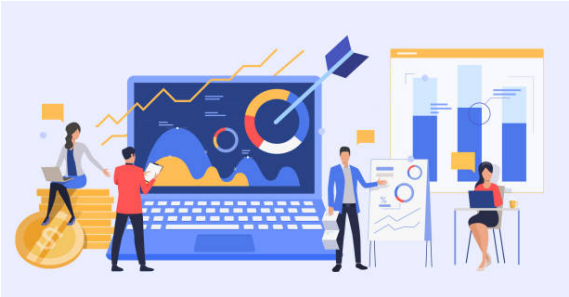
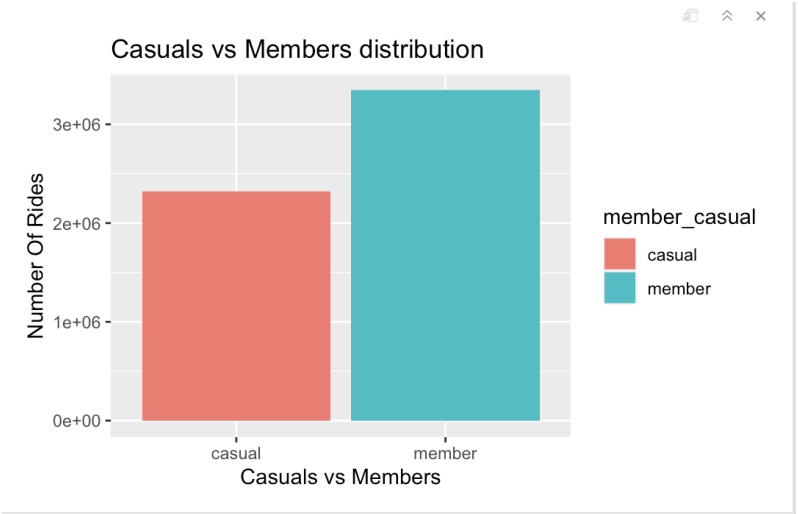
```{r}
aggregate(all_trips$ride_length ~ all_trips$member_casual +
all_trips$day_of_week, FUN = mean)
```

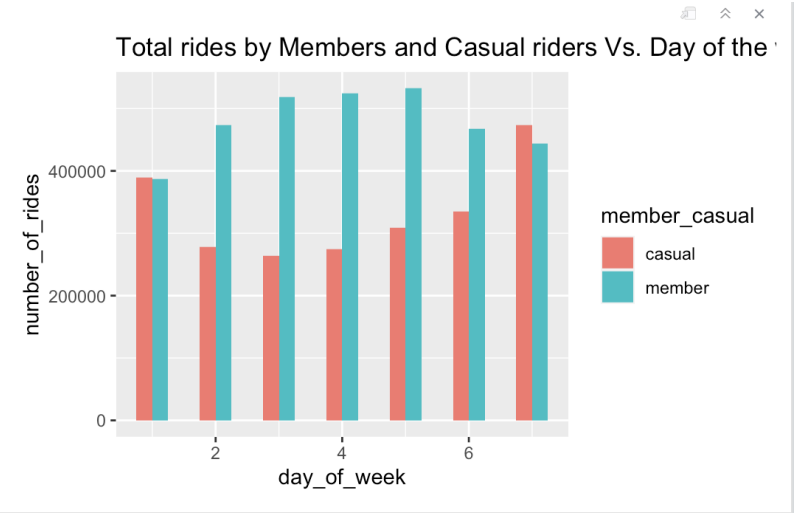
all_trips$member_casual <chr>	all_trips$day_of_week <dbl>
casual	1
member	1
casual	2
member	2
casual	3
member	3
casual	4
member	4
casual	5
member	5

all_trips$member_casual <chr>	all_trips$day_of_week <dbl>
casual	6
member	6
casual	7
member	7

all_trips$day_of_week <dbl>	all_trips$ride_length <dbl>
1	1723.1598
1	841.8464
2	1526.6171
2	736.1577
3	1345.3279
3	727.7927
4	1283.9093
4	726.3266
5	1338.5988
5	737.5799

all_trips$day_of_week <dbl>	all_trips$ride_length <dbl>
6	1414.0916
6	751.9322
7	1657.4400
7	848.3786

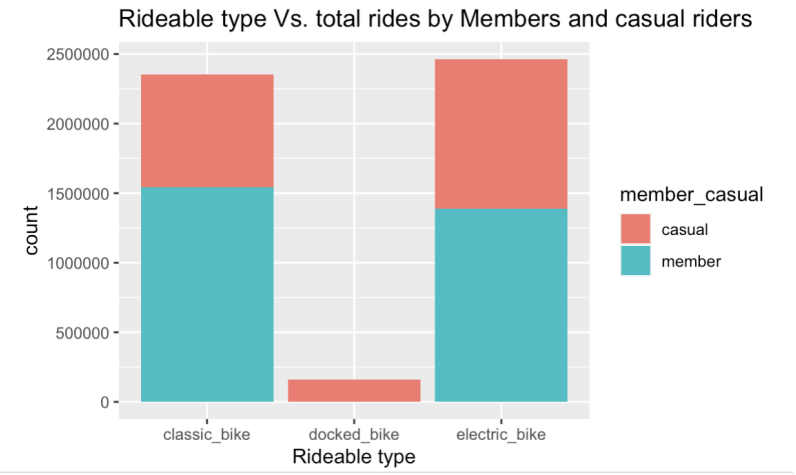
```
#Finally lets create a .csv file that we will visualize in Tableau
```{r}
write.csv(all_trips,"C:/Users/waqarshaozab/Desktop/csv_files/all_trips.csv",
row.names =FALSE)
```
```

4.4 Analyze in Excel

Given my proficiency in data manipulation using Excel, I've chosen to export the R data frame to a .csv file. Once this is completed, I'm poised to conclude the analysis and transition into the data visualization phase. Below, I'll provide a detailed account of the steps executed in Excel.

4.5 Create Pivot Table 1

1. *Select Column member_casual and ride_length* $\rightarrow$ *Insert* $\rightarrow$ *Pivot Table* $\rightarrow$ *New Worksheet* $\rightarrow$ *Drag member_casual to Rows Section* $\rightarrow$ *Drag ride_length to Value Section*

2. Formatted Time as HH:MM:SS (37:30:55)

3. *Home* $\rightarrow$ *Number* $\rightarrow$ *Format Cells* $\rightarrow$ *Time* $\rightarrow$ $HH:MM:SS(37:30:55)$

4. Right click each table and set the measure to 'average' and repeat for each month

JAN		FEB	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:30:22	casual	0:26:43
member	0:11:59	member	0:11:24
(blank)		(blank)	
Grand Tota	**0:15:16**	**Grand Tota**	**0:14:14**

MAR		APR	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:32:37	casual	0:29:32
member	0:11:58	member	0:11:29
(blank)		(blank)	
Grand Tota	**0:18:30**	**Grand Tota**	**0:17:38**

MAY		JUN	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:30:52	casual	0:32:06
member	0:13:22	member	0:14:00
(blank)		(blank)	
Grand Tota	**0:21:06**	**Grand Tota**	**0:22:41**

JUL		AUG	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:29:17	casual	0:29:19
member	0:13:43	member	0:13:23
(blank)		(blank)	
Grand Tota	**0:21:23**	**Grand Tota**	**0:20:39**

SEP		OCT	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:27:59	casual	0:26:23
member	0:12:59	member	0:11:57
(blank)		(blank)	
Grand Tota	**0:19:20**	**Grand Tota**	**0:17:21**

NOV		DEC	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:21:18	casual	0:22:18
member	0:11:08	member	0:10:37
(blank)		(blank)	
Grand Tota	**0:14:10**	**Grand Tota**	**0:13:30**

JAN		FEB	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:30:22	casual	0:26:43
member	0:11:59	member	0:11:24
(blank)		(blank)	
Grand Tota	**0:15:16**	**Grand Tota**	**0:14:14**

MAR		APR	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:32:37	casual	0:29:32
member	0:11:58	member	0:11:29
(blank)		(blank)	
Grand Tota	**0:18:30**	**Grand Tota**	**0:17:38**

MAY		JUN	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:30:52	casual	0:32:06
member	0:13:22	member	0:14:00
(blank)		(blank)	
Grand Tota	**0:21:06**	**Grand Tota**	**0:22:41**

JUL		AUG	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:29:17	casual	0:29:19
member	0:13:43	member	0:13:23
(blank)		(blank)	
Grand Tota	**0:21:23**	**Grand Tota**	**0:20:39**

SEP		OCT	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:27:59	casual	0:26:23
member	0:12:59	member	0:11:57
(blank)		(blank)	
Grand Tota	**0:19:20**	**Grand Tota**	**0:17:21**

NOV		DEC	
Row Lab	Average of ride_length	Row Lab	Average of ride_length
casual	0:21:18	casual	0:22:18
member	0:11:08	member	0:10:37
(blank)		(blank)	
Grand Tota	**0:14:10**	**Grand Tota**	**0:13:30**

4.6 Create Pivot Table 2

1. *Select Column* member_casual, *ride_length*, and day_of_week → *Insert* → *Pivot Table* → *New Worksheet* → *Drag member_casual to Rows Section* → *Drag ride_length to Value Section, and Drag day_of_week to Column Section*

2. Formatted Time as HH:MM:SS (37:30:55)

3. *Home* → *Number* → *Format Cells* → *Time* → $HH:MM:SS(37:30:55)$

4. Right click each table and set the measure to 'average' and repeat for each month



JAN									
Average of Column									
Row Lab	1	2	3	4	5	6	7	(blank)	Grand Total
casual	0:26:34	0:28:08	0:19:25	0:36:12	0:35:27	0:24:31	0:37:59		0:30:22
member	0:13:08	0:11:28	0:12:08	0:11:38	0:11:37	0:11:56	0:12:24		0:11:59
(blank)									
Grand Tota	0:16:04	0:14:02	0:13:13	0:15:30	0:15:17	0:14:11	0:18:58		0:15:16

FEB									
Average of Column									
Row Lab	1	2	3	4	5	6	7	(blank)	Grand Total
casual	0:32:59	0:24:54	0:26:54	0:23:09	0:27:28	0:22:07	0:27:10		0:26:43
member	0:12:15	0:11:22	0:11:16	0:10:50	0:11:04	0:11:41	0:11:38		0:11:24
(blank)									
Grand Tota	0:17:44	0:13:59	0:13:33	0:12:42	0:13:20	0:13:36	0:15:08		0:14:14

MAR									
Average of Column									
Row Lab	1	2	3	4	5	6	7	(blank)	Grand Total
casual	0:38:48	0:35:24	0:25:02	0:30:04	0:29:53	0:25:39	0:36:16		0:32:37
member	0:13:29	0:12:37	0:10:59	0:11:58	0:10:51	0:11:04	0:13:41		0:11:58
(blank)									
Grand Tota	0:24:21	0:20:07	0:14:11	0:17:10	0:16:02	0:14:51	0:23:27		0:18:30

APR									
Average of Column									
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:32:58	0:29:07	0:26:19	0:21:21	0:25:52	0:26:08	0:34:45		0:29:32
member	0:12:25	0:10:48	0:10:50	0:10:32	0:11:24	0:10:58	0:13:35		0:11:29
(blank)									
Grand Tota	0:21:18	0:15:37	0:14:56	0:13:11	0:15:47	0:15:48	0:23:55		0:17:38

MAY									
Average of Column									
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:33:43	0:32:27	0:26:45	0:25:48	0:29:16	0:29:28	0:33:23		0:30:52
member	0:14:29	0:13:24	0:12:47	0:12:19	0:13:10	0:12:49	0:14:42		0:13:22
(blank)									
Grand Tota	0:24:42	0:21:39	0:17:57	0:17:01	0:19:29	0:20:01	0:24:48		0:21:06

JUN

Average of Column								
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:36:08	0:31:29	0:31:29	0:29:04	0:30:12	0:32:38	0:32:14		0:32:06
member	0:15:41	0:13:25	0:13:39	0:13:06	0:13:42	0:13:48	0:15:10		0:14:00
(blank)									
Grand Tota	0:27:24	0:21:24	0:21:02	0:19:42	0:20:59	0:23:06	0:24:51		0:22:41

JUL

Average of Column								
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:33:35	0:31:06	0:26:23	0:24:00	0:24:21	0:26:05	0:32:54		0:29:17
member	0:15:12	0:13:23	0:12:56	0:12:55	0:13:01	0:13:01	0:15:18		0:13:43
(blank)									
Grand Tota	0:25:42	0:21:41	0:18:34	0:17:33	0:17:59	0:19:16	0:25:31		0:21:23

AUG

Average of Column								
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:33:45	0:28:53	0:28:11	0:25:39	0:25:11	0:30:13	0:31:57		0:29:19
member	0:14:38	0:12:28	0:13:04	0:13:00	0:13:03	0:13:33	0:14:41		0:13:23
(blank)									
Grand Tota	0:24:44	0:19:06	0:19:08	0:18:05	0:18:11	0:21:46	0:24:22		0:20:39

SEP

Average of Column								
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:34:40	0:28:37	0:21:10	0:22:48	0:21:11	0:27:08	0:35:23		0:27:59
member	0:14:08	0:12:33	0:12:14	0:12:24	0:12:26	0:13:00	0:14:47		0:12:59
(blank)									
Grand Tota	0:24:28	0:18:55	0:15:17	0:16:04	0:15:42	0:19:11	0:25:58		0:19:20

OCT

Average of Column								
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:32:23	0:22:14	0:23:20	0:20:08	0:19:38	0:25:21	0:30:15		0:26:23
member	0:13:20	0:11:25	0:11:11	0:11:16	0:10:57	0:11:42	0:13:29		0:11:57
(blank)									
Grand Tota	0:22:17	0:14:52	0:14:37	0:13:53	0:13:41	0:16:42	0:21:25		0:17:21

NOV

Average of Column								
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:34:06	0:17:43	0:16:42	0:16:24	0:24:10	0:19:16	0:22:34		0:21:18
member	0:11:52	0:10:34	0:10:47	0:10:55	0:11:41	0:11:21	0:11:11		0:11:08
(blank)									
Grand Tota	0:20:07	0:12:18	0:12:18	0:12:25	0:15:37	0:13:55	0:15:22		0:14:10

DEC

Average of Column								
Row Lab	24:00:00	48:00:00	72:00:00	96:00:00	120:00:00	144:00:00	168:00:00	(blank)	Grand Total
casual	0:25:06	0:18:18	0:15:20	0:24:13	0:19:42	0:29:04	0:23:18		0:22:18
member	0:10:51	0:10:29	0:10:20	0:10:23	0:10:24	0:10:53	0:11:17		0:10:37
(blank)									
Grand Tota	0:15:13	0:12:06	0:11:23	0:13:26	0:12:33	0:15:44	0:15:03		0:13:30

4.7 Summary of Analysis

After analyzing the data using tools like R and Excel, we've uncovered valuable insights that can help us address the business task at hand: creating marketing strategies to turn casual riders into annual members. These insights directly address the three business objectives set by Lily Moreno, our Director of Marketing: 1. How do annual members and casual riders use Cyclistic differently? 2. Why would casual riders buy Cyclistic annual memberships? 3. How can Cyclistic use digital media to influence casual riders to become members?

Addressing the first objective, "How do annual members and casual riders use Cyclistic differently?" We should be able to differentiate the two groups by underscoring these three insights:

1. **Understanding Riding Behavior**: The data reveals that annual members and casual riders use Cyclistic bikes differently. In 2022, members took more rides overall than casual riders. However, when we look at daily usage patterns, both groups ride similarly on weekends. The key distinction arises on weekdays, where members significantly outpace casual riders in bike usage. This suggests that members likely use Cyclistic bikes for their daily commutes.

2. **Ride Duration**: When examining ride duration by month, casual riders spend considerably more time on bikes than members. The average ride duration for casual riders is approximately 28 minutes, while for members, it's around 12 minutes. Additionally, both casual riders and members tend to spend more time riding on weekends compared to weekdays. Notably, members reduce their weekday riding time.

3. **Bike Type Preferences**: Our analysis also revealed differences in bike type usage. Members primarily opt for classic bikes, while casual riders predominantly choose electric and docked bikes. Notably, docked bikes are exclusively used by casual riders, and these bikes require docking at a station to stop the meter.

Addressing the second objective, "Why would casual riders buy Cyclistic annual memberships?" We can effectively persuade casual riders to become members by highlighting two critical insights:

1. **Frequency vs. Duration**: Members ride more frequently than casual riders, particularly on weekdays. However, they spend less time per ride. This highlights Cyclistic's ability to offer an affordable and efficient means of commuting to work. Our ad campaign can emphasize this by showcasing how members save time and money while staying active.

2. **Health Benefits**: We can promote the benefits of exercise for physical, mental, and spiritual well-being. Linking exercise to improved productivity at work is a

persuasive angle. Given that many city dwellers prefer public transit, we should target this audience with a campaign designed for a general audience, using a third-grade reading level and vibrant graphics to engage Chicago residents. Additionally, we should highlight the bike options available, making cycling more accessible, even for people with disabilities.

Addressing the third objective, "How can Cyclistic use digital media to influence casual riders to become members?" I believe that the benefits of digital media can generate this impactful insight to fruition:

1. **Online Presence**: We can use digital media platforms like Facebook, Twitter, and Instagram to provide efficient tools for reaching a wider audience. Leveraging recommendation algorithms, we can ensure our advertisements are seen by the right people. By harnessing digital media effectively, we can confidently promote our product and extend our reach to potential customers.

Chapter 5

SHARE



5.1 Key Tasks

1. Determine the best way to share your findings
2. Create effective data visualizations
3. Present your findings
4. Ensure your work is accessible

5.2 Deliverable

☐ Supporting visualizations and key findings

5.3 Visualization in R

```
# Let's visualize the number of rides by rider type
```{r}
 ggplot(all_trips, aes(x = member_casual, fill=member_casual)) +
    geom_bar() +
    labs(x="Casuals vs Members", y="Number Of Rides", title= "Casuals vs
Members distribution")
```
```



As you can see, members take more rides then casuals. So based on the cyclistic data,

```
# Comparison between Members Causal riders depending on ride length
(mean, median, minimum, maximum)
```{r}
all_trips %>%
  group_by(member_casual) %>%
  summarise(average_ride_length = mean(ride_length, na.rm = TRUE),
            median_length = median(ride_length, na.rm = TRUE),
            max_ride_length = max(ride_length, na.rm = TRUE),
            min_ride_length = min(ride_length, na.rm = TRUE))
```
```

member_casual <chr>	average_ride_length <dbl>	median_length <dbl>
casual	1495.6630	780
member	762.8505	540

median_length <dbl>	max_ride_length <dbl>	min_ride_length <dbl>
780	359640	0
540	93600	0

```
# Lets visualize total rides data by type and day of week
```{r}
all_trips %>%
  group_by(member_casual, day_of_week) %>%
  summarise(number_of_rides = n(), .groups="drop") %>%
  arrange(member_casual, day_of_week)  %>%
  ggplot(aes(x = day_of_week, y = number_of_rides, fill = member_casual))
+
  labs(title ="Total rides by Members and Casual riders Vs. Day of the
week") +
  geom_col(width=0.5, position = position_dodge(width=0.5)) +
  scale_y_continuous(labels = function(x) format(x, scientific = FALSE))
```
```




```r
#Rideable type Vs. total rides by Members and casual riders
```{r}
all_trips %>%
    group_by(rideable_type) %>%
    summarise(count = length(ride_id))

ggplot(all_trips, aes(x=rideable_type, fill=member_casual)) +
    labs(x="Rideable type", title="Rideable type Vs. total rides by Members and casual riders") +
    geom_bar()
```
```

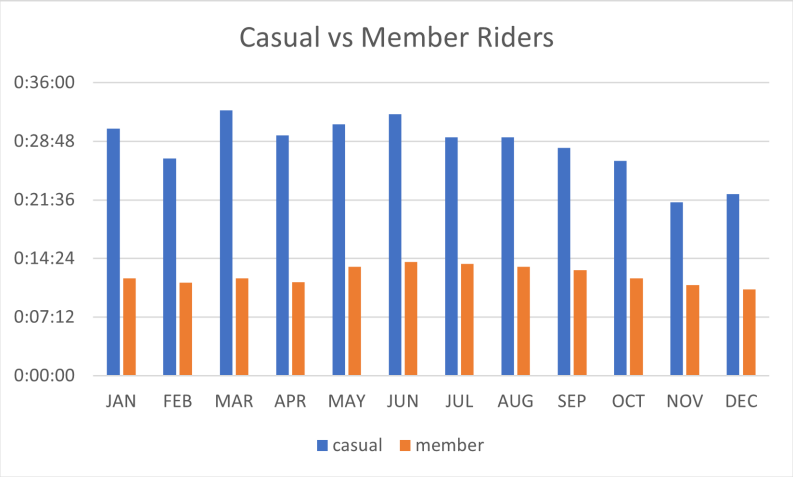
rideable_type <chr>	count <int>
classic_bike	2353187
docked_bike	160896
electric_bike	2464754



5.4 Visualization in Excel

This table was created from **Pivot Table 1** in order to create the first Excel visual

casual	member
0:30:22	0:11:59
0:26:43	0:11:24
0:32:37	0:11:58
0:29:32	0:11:29
0:30:52	0:13:22
0:32:06	0:14:00
0:29:17	0:13:43
0:29:19	0:13:23
0:27:59	0:12:59
0:26:23	0:11:57
0:21:18	0:11:08
0:22:18	0:10:37
0:28:14	**0:12:20**



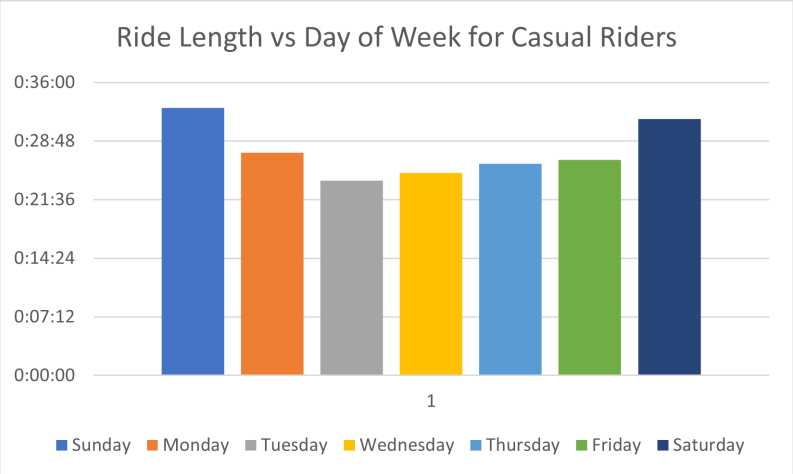
These tables were created from **Pivot Table 2** in order to create the next Excel visuals

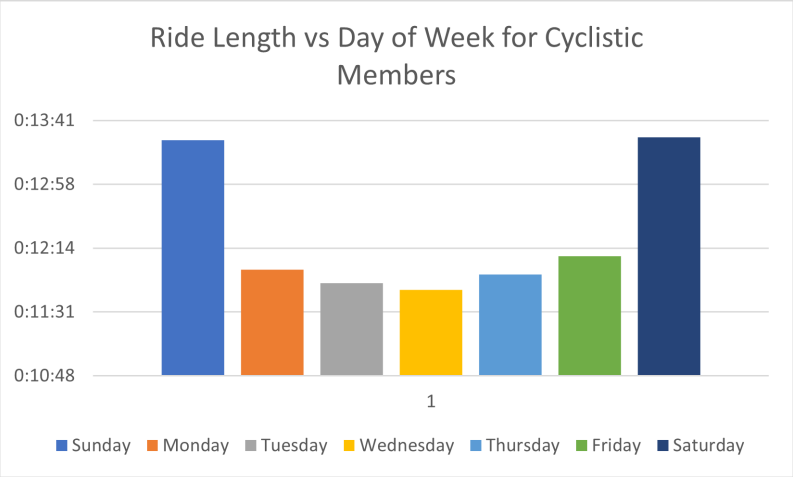
1_casual	2_casual	3_casual	4_casual	5_casual	6_casual	7_casual
0:26:34	0:28:08	0:19:25	0:36:12	0:35:27	0:24:31	0:37:59
0:32:59	0:24:54	0:26:54	0:23:09	0:27:28	0:22:07	0:27:10
0:38:48	0:35:24	0:25:02	0:30:04	0:29:53	0:25:39	0:36:16
0:32:58	0:29:07	0:26:19	0:21:21	0:25:52	0:26:08	0:34:45
0:33:43	0:32:27	0:26:45	0:25:48	0:29:16	0:29:28	0:33:23
0:36:08	0:31:29	0:31:29	0:29:04	0:30:12	0:32:38	0:32:14
0:33:35	0:31:06	0:26:23	0:24:00	0:24:21	0:26:05	0:32:54
0:33:45	0:28:53	0:28:11	0:25:39	0:25:11	0:30:13	0:31:57
0:34:40	0:28:37	0:21:10	0:22:48	0:21:11	0:27:08	0:35:23
0:32:23	0:22:14	0:23:20	0:20:08	0:19:38	0:25:21	0:30:15
0:34:06	0:17:43	0:16:42	0:16:24	0:24:10	0:19:16	0:22:34
0:25:06	0:18:18	0:15:20	0:24:13	0:19:42	0:29:04	0:23:18
0:32:54	**0:27:22**	**0:23:55**	**0:24:54**	**0:26:02**	**0:26:28**	**0:31:31**

Sunday	Monday	Tuesday	Wednesd	Thursday	Friday	Saturday
0:32:54	**0:27:22**	**0:23:55**	**0:24:54**	**0:26:02**	**0:26:28**	**0:31:31**

1_membe	2_membe	3_membe	4_membe	5_membe	6_membe	7_membe
0:13:08	0:11:28	0:12:08	0:11:38	0:11:37	0:11:56	0:12:24
0:12:15	0:11:22	0:11:16	0:10:50	0:11:04	0:11:41	0:11:38
0:13:29	0:12:37	0:10:59	0:11:58	0:10:51	0:11:04	0:13:41
0:12:25	0:10:48	0:10:50	0:10:32	0:11:24	0:10:58	0:13:35
0:14:29	0:13:24	0:12:47	0:12:19	0:13:10	0:12:49	0:14:42
0:15:41	0:13:25	0:13:39	0:13:06	0:13:42	0:13:48	0:15:10
0:15:12	0:13:23	0:12:56	0:12:55	0:13:01	0:13:01	0:15:18
0:14:38	0:12:28	0:13:04	0:13:00	0:13:03	0:13:33	0:14:41
0:14:08	0:12:33	0:12:14	0:12:24	0:12:26	0:13:00	0:14:47
0:13:20	0:11:25	0:11:11	0:11:16	0:10:57	0:11:42	0:13:29
0:11:52	0:10:34	0:10:47	0:10:55	0:11:41	0:11:21	0:11:11
0:10:51	0:10:29	0:10:20	0:10:23	0:10:24	0:10:53	0:11:17
0:13:27	**0:12:00**	**0:11:51**	**0:11:46**	**0:11:56**	**0:12:09**	**0:13:30**

Sunday	Monday	Tuesday	Wednesd	Thursday	Friday	Saturday
0:13:27	**0:12:00**	**0:11:51**	**0:11:46**	**0:11:56**	**0:12:09**	**0:13:30**




Ride Length vs Day of Week for Cyclistic Members
0:13:41
0:12:58
0:12:14
0:11:31
0:10:48
1
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday

Chapter 6

ACT

6.1 Key Tasks

1. Create recommendations for stakeholders

2. Add case study to portfolio

6.2 Deliverable

☐ Top three recommendations based on analysis

Once we've wrapped everything up, I'd like to share three suggestions with our stakeholders on how we can turn casual riders into Cyclistic members. These ideas come from our data

analysis and insights. I truly think that by implementing these three steps, we can increase Cyclistic's ability to increase member ridership.

6.3 Three Recommendations

1. Engage in a proactive effort to advertise the benefits becoming a member
2. Use the power of digital media
3.

Conclusion

In concluding this data analyst project centered around Cyclistic, I want to emphasize the significance of our findings and recommendations. Through a thorough analysis of the data, we've gained valuable insights that can greatly benefit our stakeholders as they attempt to convert casual riders into Cyclistic members.

Our analysis has given us insight on key trends, patterns, and user behaviors within the biking community. It has allowed us to identify actionable strategies that can enhance Cyclistic's appeal and encourage more riders to become members.

As we move forward, I am confident that the implementation of our recommendations will lead to a significant increase in membership. These suggestions are not educated guesses; they stem from real data and observations, making them practical and achievable.

By adopting these strategies, Cyclistic can effectively engage with its target audience, improve the overall rider experience, and ultimately boost membership numbers. We have a unique opportunity to inspire Chicago residents to choose Cyclistic as their preferred bike-sharing service.

In conclusion, our analysis and recommendations provide a roadmap for Cyclistic's growth in memberships. I'm enthusiastic about the impact these insights can have on our company, and I believe that they will allow our stakeholders to make informed decisions that will drive Cyclistic's success in converting casual riders into members.