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'Cyclistic' Customer Analysis: How Does A Bike-Share Navigate Speedy Success?



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For this case study, I assume the role of a junior data analyst working in the marketing and analytics team at *Cyclistic*, a bike-share company in Chicago. The director of marketing believes that the company's future success depends on maximizing the number of member riders. Therefore, my team is tasked to suggest marketing strategies to convert casual riders into member riders. However, we need to first understand (1) how casual and member riders differ, (2) why casual riders would buy a membership, and (3) how digital media could affect their marketing tactics. I was specifically assigned to solve the first problem.

To accomplish my task, I will follow the steps of the data analysis process: **Ask, Prepare, Process, Analyze, Share, and Act**.

Tools: Spreadsheet (Microsoft Excel), SQL (BigQuery), Tableau

Visualization: Go to my [Tableau profile](#).

Documentation: Visit my [GitHub profile](#).

Step 1: Ask

I. Context

In 2016, Cyclistic launched a successful bike-share offering. Since then, the program has grown to a fleet of 5,824 bicycles that are geo-tracked and locked into a network of 692 stations across Chicago.

Cyclistic offers three pricing plans: single-ride passes, full-day passes, and annual memberships. Customers who purchase the first two are called **casual riders**, and the rest are considered **member riders**.

II. Task

I will analyze how casual and member riders differ in terms of using Cyclistic bikes. This will involve exploring the following specific points:

- Proportion of casual and member riders;
- Number of rides by bike type;
- Frequency of rides by month (season);
- Frequency of rides by day of the week;
- Frequency of rides by hour within a day; and
- Average ride duration by day of the week.

Then, I will present recommendations for Cyclistic's marketing strategy.

Step 2: Prepare

I. Access the data

I was instructed to use Cyclistic's historical trip data only for the year 2022. Access the dataset through this [link](#).

II. Collect the data

The dataset is composed of several CSV files containing monthly data since 2004.

Name	Type	Size	Date created
202201-divvy-tripdata	Microsoft Excel Comma Separated Values File	18,567 KB	2/1/2022 11:40 AM
202202-divvy-tripdata	Microsoft Excel Comma Separated Values File	20,638 KB	3/2/2022 10:46 AM
202203-divvy-tripdata	Microsoft Excel Comma Separated Values File	50,533 KB	4/5/2022 1:00 PM
202204-divvy-tripdata	Microsoft Excel Comma Separated Values File	65,341 KB	5/3/2022 9:28 AM
202205-divvy-tripdata	Microsoft Excel Comma Separated Values File	114,780 KB	6/3/2022 6:43 PM
202206-divvy-tripdata	Microsoft Excel Comma Separated Values File	140,228 KB	7/14/2022 11:04 AM
202207-divvy-tripdata	Microsoft Excel Comma Separated Values File	149,306 KB	8/5/2022 2:31 PM
202208-divvy-tripdata	Microsoft Excel Comma Separated Values File	142,148 KB	9/8/2022 11:56 AM
202209-divvy-tripdata	Microsoft Excel Comma Separated Values File	138,135 KB	10/6/2022 4:18 PM
202210-divvy-tripdata	Microsoft Excel Comma Separated Values File	109,293 KB	11/8/2022 10:40 AM
202211-divvy-tripdata	Microsoft Excel Comma Separated Values File	66,348 KB	12/2/2022 1:09 PM
202212-divvy-tripdata	Microsoft Excel Comma Separated Values File	35,612 KB	1/3/2023 10:27 AM

I only downloaded 12 files (1 GB in total) corresponding to the months of January to December 2022.

III. Examine the data

I inspected the files in Microsoft Excel and found that all have the following attributes or headers:

Header	Description
ride_id	unique id of the ride
rideable_type	type of bike ridden
started_at	date and time the ride started
ended_at	date and time the ride ended
start_station_name	name of the ride's starting station
start_station_id	id of the ride's starting station
end_station_name	name of the ride's ending station
end_station_id	id of the ride's ending station
start_lat	latitude coordinate of the ride's starting station
start_lng	longitude coordinate of the ride's starting station
end_lat	latitude coordinate of the ride's ending station
end_lng	longitude coordinate of the ride's ending station
member_casual	membership type: member for annual membership riders or casual for casual riders

Additionally, each file has the following number of observations or rows:

Table		Rows
1	January	103,771
2	February	115,610
3	March	284,043
4	April	371,250
5	May	634,859
6	June	769,205
7	July	823,489
8	August	785,933
9	September	701,340
10	October	558,686
11	November	337,736
12	December	181,807
Total		5,667,729

Step 3: Process

I. Clean the data with spreadsheet

I initially cleaned each file in Microsoft Excel to reduce its size before uploading it to BigQuery (limited to 100 MB).

1. I checked for incomplete values in all columns using the COUNTBLANK function. I found a significant number of missing values in **start_station_name**, **start_station_id**, **end_station_name**, and **end_station_id**, making them unreliable for data analysis. Thus, I decided to delete them from each table.

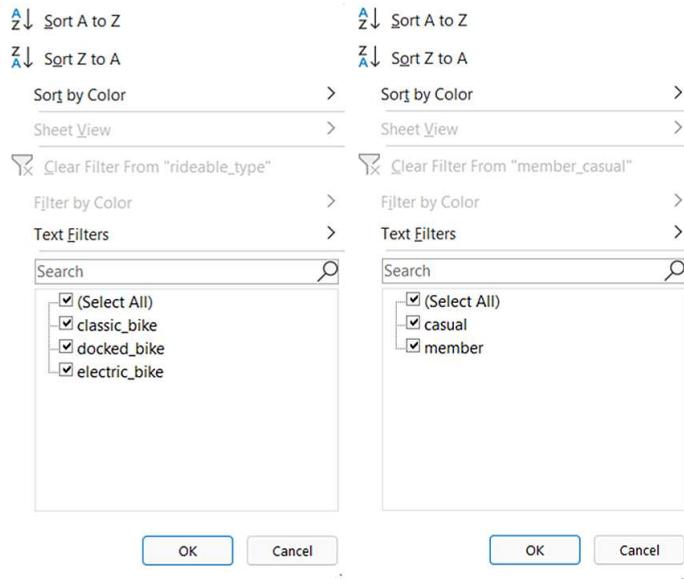
Missing Values														
15														
16	ride_id	rideable_type	started_at	ended_at	start_station_name	start_station_id	end_station_name	end_station_id	start_lat	start_lng	end_lat	end_lng	member_casual	
17	January	0	0	0	0	16,260	16,260	0	17,924	0	0	86	86	0
18	February	0	0	0	0	18,580	18,580	0	20,359	20,359	0	77	77	0
19	March	0	0	0	0	47,246	47,246	51,157	51,157	0	266	266	0	
20	April	0	0	0	0	70,887	70,887	75,288	75,288	0	317	317	0	
21	May	0	0	0	0	86,704	86,704	93,171	93,171	0	722	722	0	
22	June	0	0	0	0	92,944	92,944	100,152	100,152	0	0	1,055	0	
23	July	0	0	0	0	112,031	112,031	120,951	120,951	0	947	947	0	
24	August	0	0	0	0	122,037	122,037	120,522	120,522	0	843	843	0	
25	September	0	0	0	0	103,780	103,780	111,185	111,185	0	712	712	0	
26	October	0	0	0	0	91,355	91,355	96,617	96,617	0	475	475	0	
27	November	0	0	0	0	51,957	51,957	54,259	54,259	0	230	230	0	
28	December	0	0	0	0	29,283	29,283	31,158	31,158	0	128	128	0	
29	Total	0	0	0	0	833,064	833,064	892,742	892,742	0	5,658	5,658	0	0.00000%
30	%	0.00000%	0.00000%	0.00000%	0.00000%	14,69837%	14,69837%	15,75132%	15,75132%	0.00000%	0.00000%	0.10336%	0.10336%	0.00000%

2. I checked for irrelevant values in the remaining columns and noticed that `start_lat`, `start_lng`, `end_lat`, and `end_lng` are unlikely to be useful in addressing my specific tasks. Hence, I decided to also delete them.

3. I checked for duplicate values in `ride_id` using the Remove Duplicates feature. No duplicate values were found in each file.

effield Ave & Fullerton Ave	TA1306000016
ark St & Bryn Mawr Ave	KA1504000151
chigan Ave & Jackson Blvd	TA1309000002
ood St & Chicago Ave	637
ckley Ave & Irving Park Rd	8
effield Ave & Fullerton Ave	6
cine Ave & 15th St	13304
Salle St & Jackson Blvd	4
Salle St & Jackson Blvd	4
arendon Ave & Leland Ave	9
effield Ave & Fullerton Ave	TA1306000016
sh St & Superior St	15530
chigan Ave & Jackson Blvd	TA1309000002
colin Park Conservatory	LP-
Salle St & Jackson Blvd	TA1309000004

4. I checked for invalid values in `rideable_type` and `member_casual`. No invalid values were found in each file: bike type only includes `classic_bike`, `docked_bike`, and `electric_bike`, and rider type only includes `casual` and `member`.



5. Since I intend to compare the ride duration of casual and member riders, I inserted a column named `ride_length` computed as `ended_at` minus `started_at`. Then, I converted the column into TIME (HH:MM:SS) format.

6. I checked for outliers in `ride_length` using the Custom Filter feature. I retrieved values less than 00:01:00 (one minute) or greater than 24:00:00 (24 hours) and deleted the rows containing those values.

Table		Deleted Rows	Percentage
1	January	10,326	9.95%
2	February	15,924	13.77%
3	March	32,304	11.37%
4	April	45,822	12.34%
5	May	78,630	12.39%
6	June	98,490	12.80%
7	July	112,308	13.64%
8	August	110,058	14.00%
9	September	97,254	13.87%
10	October	81,456	14.58%
11	November	47,562	14.08%
12	December	29,478	16.21%
Total		647,304	13.40%

7. Finally, I sorted each table according to `started_at` in ascending order and saved it.

II. Transform the data with SQL

In BigQuery, I created a dataset named `cyclistic_2022` and uploaded the 12 cleaned tables. Then, I executed the following procedures:

1. I created a table named `all_months` to combine the rows from the 12 tables using the UNION ALL command.

```
CREATE TABLE awesome-tempo-374012.cyclistic_2022.all_months AS
SELECT *
FROM (
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.January`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.February`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.March`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.April`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.May`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.June`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.July`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.August`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.September`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.October`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.November`
UNION ALL
    SELECT *
    FROM `awesome-tempo-374012.cyclistic_2022.December`
);
);
```

2. From that table, I created a new table named **main_table** to add other columns necessary to accomplish my tasks. Since I intend to compare the frequency of rides by month, day, and hour, I inserted columns for such attributes using the CASE statement and the EXTRACT function. Since I also want to get the "average" ride duration and realized **ride_length** (TIME format) cannot be used for the AVG function, I also added a new column named **duration_mins** (INTEGER format) computed as the minute interval between **ended_at** and **started_at** using the DATE_DIFF function.

```

CREATE TABLE awesome-tempo-374012.cyclistic_2022.main_table AS
SELECT
    ride_id,
    rideable_type,
    started_at,
    ended_at,
    ride_length,
    member_casual,
    CASE
        WHEN EXTRACT(MONTH FROM started_at) = 1 THEN "January"
        WHEN EXTRACT(MONTH FROM started_at) = 2 THEN "February"
        WHEN EXTRACT(MONTH FROM started_at) = 3 THEN "March"
        WHEN EXTRACT(MONTH FROM started_at) = 4 THEN "April"
        WHEN EXTRACT(MONTH FROM started_at) = 5 THEN "May"
        WHEN EXTRACT(MONTH FROM started_at) = 6 THEN "June"
        WHEN EXTRACT(MONTH FROM started_at) = 7 THEN "July"
        WHEN EXTRACT(MONTH FROM started_at) = 8 THEN "August"
        WHEN EXTRACT(MONTH FROM started_at) = 9 THEN "September"
        WHEN EXTRACT(MONTH FROM started_at) = 10 THEN "October"
        WHEN EXTRACT(MONTH FROM started_at) = 11 THEN "November"
        ELSE "December"
    END AS month,
    CASE
        WHEN EXTRACT(DAYOFWEEK FROM started_at) = 1
            THEN "Sunday"
        WHEN EXTRACT(DAYOFWEEK FROM started_at) = 2
            THEN "Monday"
        WHEN EXTRACT(DAYOFWEEK FROM started_at) = 3
            THEN "Tuesday"
        WHEN EXTRACT(DAYOFWEEK FROM started_at) = 4
            THEN "Wednesday"
        WHEN EXTRACT(DAYOFWEEK FROM started_at) = 5
            THEN "Thursday"
        WHEN EXTRACT(DAYOFWEEK FROM started_at) = 6
            THEN "Friday"
        ELSE "Saturday"
    END AS day,
    EXTRACT(HOUR FROM started_at) AS hour,
    DATE_DIFF(ended_at, started_at, minute) AS duration_mins,
FROM `awesome-tempo-374012.cyclistic_2022.all_months`
ORDER BY started_at ASC;

```

This `main_table` shall be the final version of the data that will be used for analysis and visualization.

III. View the data

Here's a preview of the `main_table`:

Row #	ride_id	rideable_type	started_at	ended_at	ride_length	member_casual	month	day	hour	duration_mins
1	980355D9A9852B89	classic_bike	2022-01-01 00:00:00..	2022-01-01 00:01:00..	00:01:00	casual	January	Saturday	0	1
2	42178E850B92597A	electric_bike	2022-01-01 00:00:00..	2022-01-01 00:32:00..	00:31:00	casual	January	Saturday	0	31
3	04706C47F5BD03EE	electric_bike	2022-01-01 00:01:00..	2022-01-01 00:04:00..	00:03:00	casual	January	Saturday	0	3
4	46694335EACB022	classic_bike	2022-01-01 00:02:00..	2022-01-01 00:31:00..	00:29:00	casual	January	Saturday	0	29
5	6892C46E8FB5114C	classic_bike	2022-01-01 00:02:00..	2022-01-01 00:31:00..	00:29:00	casual	January	Saturday	0	29
6	AC1167BDCDD009..	electric_bike	2022-01-01 00:03:00..	2022-01-01 00:04:00..	00:01:00	member	January	Saturday	0	1
7	A5B05A4FD5D305414	electric_bike	2022-01-01 00:05:00..	2022-01-01 00:08:00..	00:03:00	member	January	Saturday	0	3
8	7BF8F3F3EAF9467DC	electric_bike	2022-01-01 00:05:00..	2022-01-01 00:25:00..	00:20:00	casual	January	Saturday	0	20
9	E93D5F426242BC48	electric_bike	2022-01-01 00:06:00..	2022-01-01 00:13:00..	00:07:00	casual	January	Saturday	0	7
10	0C9545A5FBAFCF60E	classic_bike	2022-01-01 00:06:00..	2022-01-01 00:09:00..	00:03:00	member	January	Saturday	0	3
11	22E39FF7ECA32D58	classic_bike	2022-01-01 00:06:00..	2022-01-01 00:16:00..	00:10:00	casual	January	Saturday	0	10
12	4049C74FB13C545F	electric_bike	2022-01-01 00:07:00..	2022-01-01 00:19:00..	00:12:00	casual	January	Saturday	0	12
13	C77847F089561C07	electric_bike	2022-01-01 00:07:00..	2022-01-01 00:19:00..	00:12:00	casual	January	Saturday	0	12
14	18E75495AE8901E	electric_bike	2022-01-01 00:07:00..	2022-01-01 00:19:00..	00:12:00	casual	January	Saturday	0	12
15	B8308F09A2EFA6FD	classic_bike	2022-01-01 00:07:00..	2022-01-01 00:24:00..	00:17:00	member	January	Saturday	0	17
16	138419B00043E534	electric_bike	2022-01-01 00:07:00..	2022-01-01 00:19:00..	00:12:00	casual	January	Saturday	0	12
17	8998F5F173D66543	classic_bike	2022-01-01 00:07:00..	2022-01-01 00:24:00..	00:17:00	member	January	Saturday	0	17
18	0A5DBE6FFA8E9299	classic_bike	2022-01-01 00:07:00..	2022-01-01 00:54:00..	01:47:00	casual	January	Saturday	0	107
19	3F775747FE2B6638	classic_bike	2022-01-01 00:07:00..	2022-01-01 00:24:00..	00:17:00	member	January	Saturday	0	17
20	C1151DFEDB0A1273	electric_bike	2022-01-01 00:08:00..	2022-01-01 00:19:00..	00:11:00	casual	January	Saturday	0	11

And here's the metadata for the `main_table`:

	Field name	Type	Mode	Collation	Default Value	Policy Tags	Description
□	ride_id	STRING	NULLABLE				
□	rideable_type	STRING	NULLABLE				
□	started_at	TIMESTAMP	NULLABLE				
□	ended_at	TIMESTAMP	NULLABLE				
□	ride_length	TIME	NULLABLE				
□	member_casual	STRING	NULLABLE				
□	month	STRING	NULLABLE				
□	day	STRING	NULLABLE				
□	hour	INTEGER	NULLABLE				
□	duration_mins	INTEGER	NULLABLE				

Step 4: Analyze

Once again, I used BigQuery to analyze the data and extract the values I need to carry out my tasks.

I. Proportion of casual and member riders

```

SELECT
    member_casual AS membership_type,
    COUNT(member_casual) AS total_rides,
    ROUND(COUNT(member_casual) / SUM(COUNT(member_casual)))
        OVER( ) * 100, 2) AS percentage
FROM
    `awesome-tempo-374012.cyclistic_2022.main_table`
GROUP BY
    member_casual
ORDER BY
    member_casual;

```

Row	membership_type	total_rides	percentage
1	casual	2269389	40.96
2	member	3271726	59.04

Here, I retrieved the total number of rides and its percentage taken by each rider type, sorted in alphabetical order. The percentage must be rounded to two decimal places.

II. Number of rides by bike type

```

SELECT
    rideable_type AS bike_type,
    member_casual AS membership_type,
    COUNT(rideable_type) AS total_rides,
    ROUND(COUNT(rideable_type) / SUM(COUNT(rideable_type)))
        OVER(PARTITION BY rideable_type) * 100, 2)
        AS percentage_per_bike_type
FROM
    `awesome-tempo-374012.cyclistic_2022.main_table`
GROUP BY
    rideable_type, member_casual
ORDER BY
    rideable_type, member_casual;

```

Row	bike_type	membership_type	total_rides	percentage_per_bike_type
1	classic_bike	casual	876031	34.23
2	classic_bike	member	1683293	65.77
3	docked_bike	casual	173919	100.0
4	electric_bike	casual	1219439	43.43
5	electric_bike	member	1588433	56.57

Here, I retrieved the total number of rides and its percentage taken by each rider type for each bike type, sorting the results first by bike type and then by rider type. The percentage must be rounded to two decimal places.

III. Frequency of rides by month (season)

```

SELECT
    month,
    member_casual,
    COUNT(month) AS total_rides,
    ROUND(COUNT(month) / SUM(COUNT(month))
        OVER(PARTITION BY month) * 100, 2)
        AS percentage_per_month
FROM
    `awesome-tempo-374012.cyclistic_2022.main_table`
GROUP BY
    month, member_casual
ORDER BY
    month, member_casual;

```

Row	month	member_casual	total_rides	percentage_per_month
1	April	casual	123796	34.05
2	April	member	239816	65.95
3	August	casual	350499	45.66
4	August	member	417090	54.34
5	December	casual	43649	24.68
6	December	member	133244	75.32
7	February	casual	20916	18.52
8	February	member	92039	81.48
9	January	casual	18125	17.76
10	January	member	83924	82.24

Here, I retrieved the total number of rides and its percentage taken by each rider type for each month, sorting the results first by month and then by rider type. The percentage must be rounded to two decimal places.

IV. Frequency of rides by day

```

SELECT
    day,
    member_casual,
    COUNT(day) AS total_rides
FROM
    `awesome-tempo-374012.cyclistic_2022.main_table`
GROUP BY
    day, member_casual
ORDER BY
    day, member_casual;

```

Row	day	member_casual	total_rides
1	Friday	casual	327057
2	Friday	member	456795
3	Monday	casual	271500
4	Monday	member	463171
5	Saturday	casual	462323
6	Saturday	member	432759
7	Sunday	casual	380005
8	Sunday	member	378128
9	Thursday	casual	302431
10	Thursday	member	520667

Here, I retrieved the total number of rides taken by each rider type for each day, sorting the results first by day and then by rider type.

V. Frequency of rides by hour

```

SELECT
    member_casual,
    hour,
    COUNT(hour) AS total_rides
FROM
    `awesome-tempo-374012.cyclistic_2022.main_table`
GROUP BY
    member_casual, hour
ORDER BY
    member_casual, hour;

```

Row	member_casual	hour	total_rides
1	casual	0	45204
2	casual	1	29341
3	casual	2	18158
4	casual	3	10795
5	casual	4	7379
6	casual	5	12148
7	casual	6	28851
8	casual	7	50479
9	casual	8	68377
10	casual	9	70652

Here, I retrieved the total number of rides taken by each rider type for each hour of the day, sorting the results first by rider type and then by hour.

VI. Average ride duration by day

```
SELECT
    day,
    member_casual,
    ROUND(AVG(duration_mins), 2) AS avg_duration_mins
FROM
    `awesome-tempo-374012.cyclistic_2022.main_table`
GROUP BY
    day, member_casual
ORDER BY
    day, member_casual;
```

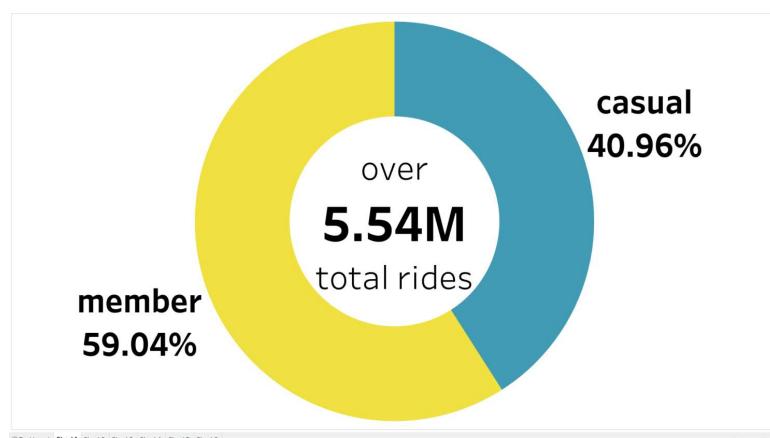
Row	day	member_casual	avg_duration_mins
1	Friday	casual	20.92
2	Friday	member	12.48
3	Monday	casual	22.79
4	Monday	member	12.23
5	Saturday	casual	25.02
6	Saturday	member	14.11
7	Sunday	casual	25.51
8	Sunday	member	13.99
9	Thursday	casual	19.9
10	Thursday	member	12.25

Here, I retrieved the average duration of rides (in minutes) taken by each rider type for each day, sorting the results first by day and then by rider type. The average duration must be rounded to two decimal places.

Step 5: Share

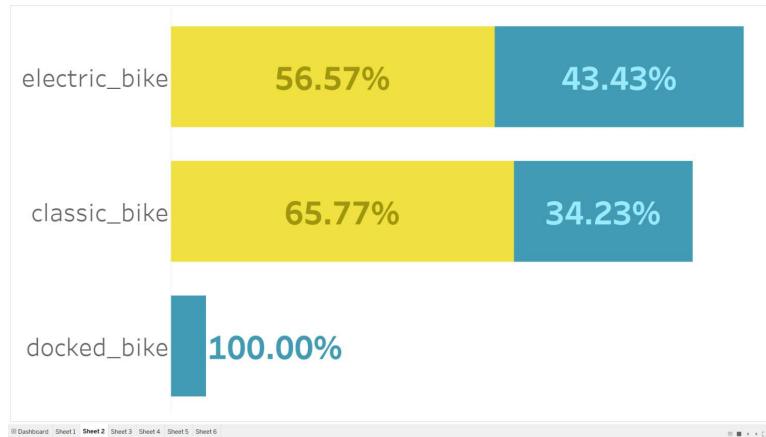
I used Tableau to visualize the results of my analysis. Visit my [Tableau profile](#) to check the data viz for this project.

I. Proportion of casual and member riders



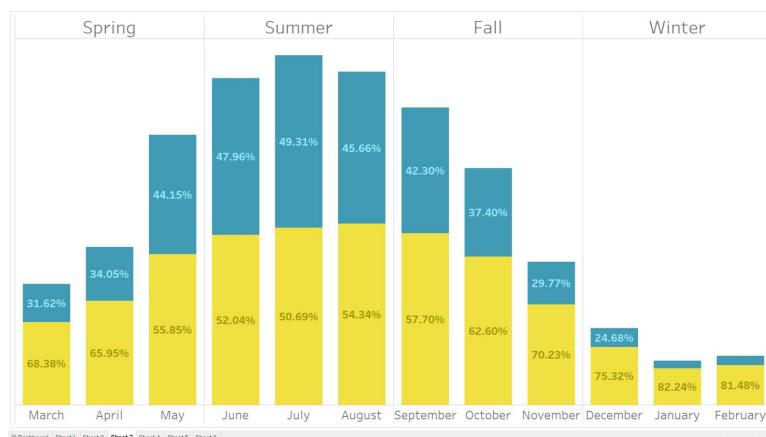
A majority of over 5.54 million total rides taken in 2022 were by member riders (59.04%).

II. Number of rides by bike type



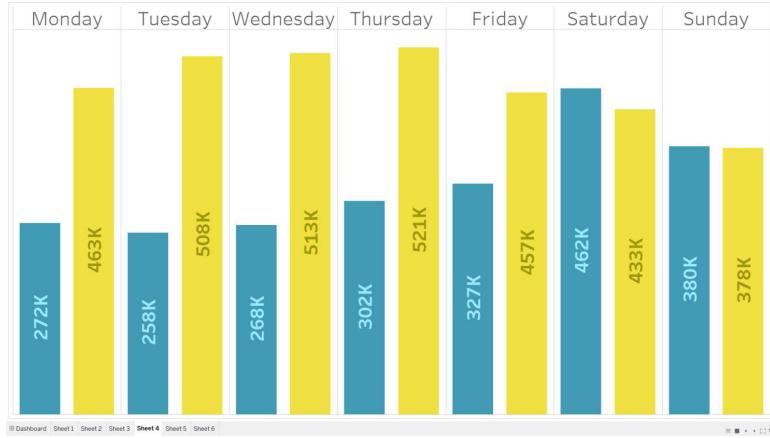
Classic bikes are preferred by member riders, while electric bikes are preferred by casual riders.

III. Frequency of rides by month (season)



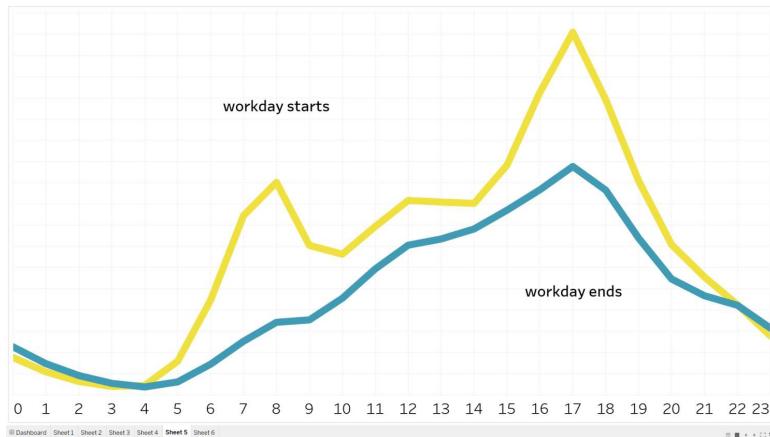
Cyclistic bikes are rented the most by both member and casual riders during summer (June to August), and the least during winter (December to January).

IV. Frequency of rides by day



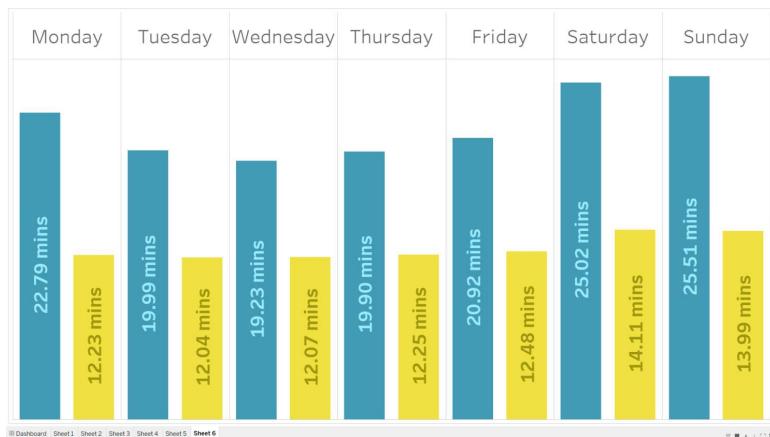
Member riders tend to rent bikes more during weekdays (Monday to Friday), while casual riders rent bikes more during weekends (Saturday and Sunday).

V. Frequency of rides by hour



Member riders rent bikes most frequently during rush hours (around 8 AM and 5 PM), while casual riders tend to rent bikes primarily around 5 PM.

VI. Average ride duration by day



On average, casual riders rent bikes for longer periods than member riders, particularly on weekends (Saturday and Sunday).

Step 6: Act

Based on these findings, I recommend the following strategies to help Cyclistic convert more casual riders into member riders:

I. Expand electric bike fleet

As casual riders tend to prefer electric bikes, Cyclistic could consider expanding its electric bike fleet to attract more casual riders. This could include offering discounts or promotions for new member riders who choose the electric bike option.

II. Promote summer riding

Since casual riders typically rent bikes the most during the summer, Cyclistic could develop a summer promotion campaign that offers discounts or other incentives to encourage them to become member riders during this peak season.

III. Offer flexible pricing plans

Since casual riders usually rent bikes more during weekends, Cyclistic could consider offering flexible pricing plans that allow weekend-only usage at a discounted rate. This could appeal to casual riders who may not want to commit to a full annual membership.

IV. Host events during peak hours

During peak hour periods (around 5 PM), Cyclistic could host events that cater to the needs of casual riders and promote the benefits of becoming a member rider. This could include commuter-focused events, such as group rides or bike safety classes, that help riders feel more comfortable using bikes for commuting purposes.

V. Offer bike storage solutions

Because casual riders tend to rent bikes for longer periods, Cyclistic could consider offering bike storage solutions (especially on weekends) to make it easier for casual riders to store their bikes safely and conveniently during longer rides or breaks.

This project was completed as part of the requirements for the [Google Data Analytics Professional Certificate](#) program.

Comments

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Johannes Moon · 1st

Reporting Engineer | Banking industry | Process Engineer | ad-hoc | SQL | ...

2y

...

Wow, Jhermien Paul Alejandria this is an awesome article! - You demonstrate a) how it's supposed to done, b) how you did it and c) documented it - absolutely killer work!

The dashboard looks clean and easily accessible!

Love · ❤️ 1 | Reply · 3 replies

 **Jhermien Paul Alejandria** ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Actio...

Hi **Johannes**! Thank you so much for your kind words and support! I'm glad you found the article awesome. Your feedback means a lot to me, and I appreciate you taking the time to read and comment on my work. 😊

Like · 🎉 1 | Reply | 56 impressions

 **Johannes Moon** • 1st
Reporting Engineer | Banking industry | Process Engineer | ad-hoc | ...

Sure thing, **Jhermien**! It's also the color choice that caught my eye (although also influenced by what's going on in Europe). - you may know by now that I'm writing a post series about how to improve dashboard designs with help of the community.

So stop by once in a while... your opinion counts!

Support · 🎉 1 | Reply

 **Jhermien Paul Alejandria** ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Actio...

Thank you for letting me know about your post series on improving dashboard designs! I will definitely check it out and provide my opinion.

Regarding the color scheme of my dashboard, I appreciate your observation and you're right that it does resemble the colors of Ukraine's flag. But I chose those colors because they are the official colors of Cyclistic, the company I created the dashboard for. Anyway, I'm glad the color combination caught your attention and I'm grateful for your feedback on my work. Thank you again for your kind words and support! ❤️

Like · 🎉 1 | Reply | 381 impressions

Collapse replies

 **Rakesh K** • 1st
Data Analyst

This is pretty awesome!

Love · ❤️ 1 | Reply · 1 reply

 **Jhermien Paul Alejandria** ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Actio...

Thank you so much, **Rakesh**! 😊

Like · 🎉 1 | Reply | 86 impressions

 **Chintan Sikotariya** ✅ • 1st
Expertise in Clinical Data Insights, Process Optimization & EPR Systems | ...

Hey **Jhermien Paul Alejandria**, Hope you are doing well, Thanks for sharing the project It has really helped me learn a couple of things which surely am gonna apply in my project as well..

Thanks for sharing.
Wish you have a great time ahead.

Support · 🎉 1 | Reply · 1 reply

 **Jhermien Paul Alejandria** ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Actio...

Hello, **Chintan**! Thank you so much for your comment and I'm happy that my project has been helpful to you. It's always great to hear that

my work has made an impact. If you have any questions or feedback, please don't hesitate to reach out. Thank you for your well wishes and I wish you all the best in your own projects too! ❤️

Like · 1 | Reply | 265 impressions

 Jouhari Abdelouhab • 1st
Junior Data Analyst

2y ...

Congratulations, Bro...
Nice and compleat analysis, I do almost the same things but using R.

Love · 1 | Reply · 1 reply

 Jhermien Paul Alejandria ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Action...

2y ...

Hey [Jouhari!](#) Thanks for checking out my post and for the congrats.
All the best for your R project! 😊

Like | Reply | 186 impressions

 Ayan Khan • 1st
Data Analyst • Excel | SQL | Python | Power BI | AWS • I smoke Data joints ...

2y ...

Perfectly executed work! Loved it [Jhermien Paul Alejandria](#) 🎉🔥

Love · 1 | Reply · 1 reply

 Jhermien Paul Alejandria ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Action...

2y ...

Hi there, [Ayan!](#) Thank you very much for your kind words! I'm thrilled that you loved my work and appreciate your support. If you have any feedback or suggestions, please don't hesitate to let me know. Thank you again! 😊

Like | Reply | 204 impressions

 JEOFREY DE TORRES ✅ • 1st
Data Consultant | Power BI Developer | Data Analyst

2y ...

Thank you for this Jhermien Paul Alejandria! Well documented, nice work!

Love · 1 | Reply · 1 reply

 Jhermien Paul Alejandria ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Action...

2y ...

Thank you so much, [JEOFREY!](#) 😊

Like · 1 | Reply | 44 impressions

 Aljon Balanag • 1st
Aspirant Data Engineer

1y ...

This is very informative sir Jhermien. Thank you.

Love · 1 | Reply · 1 reply

 Jhermien Paul Alejandria ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Action...

1y ...

Thanks [Aljon!](#) 😊

Like | Reply | 34 impressions

 Huong (Tris) Nguyen • 1st
Data Analyst: SQL|Python|Excel| Data Viz // I translate data insights into ...

2y ...

Really good analysis [Jhermien Paul Alejandria](#). I am finishing my Google Data Certificate as well.

Love · 1 | Reply · 1 reply

 Jhermien Paul Alejandria ✅ Author
Data Analyst at Royal Caribbean • Transforming Big Data into Action...

2y ...

Hello, [Huong!](#) Thank you for your kind words, I appreciate your support! It's great to hear that you're also pursuing the Google Data Analytics Professional Certificate program. I wish you all the best in your studies and hope that you find the program both challenging

and rewarding. If you ever have any questions or want to discuss data analytics further, feel free to reach out to me anytime. 😊

Like | Reply | 207 impressions



Michael Smith • 1st

Radio Operator @ City of Cleveland | Python, R, Data Analysis

2y

...

Great capstone Jhermien. I didn't look at seasonal ridership as much as you did in your capstone. The way causal riders go up in the summer makes a lot of sense. Thanks for sharing.

Love · ❤️ 1 | Reply · 1 reply



Jhermien Paul Alejandria ✅ Author

Data Analyst at Royal Caribbean • Transforming Big Data into Action...

2y

...

You're welcome, **Michael!** It's really interesting to see how different factors can impact ridership patterns, and I'm glad you found my analysis helpful. 😊

Like | Reply | 97 impressions



Elijah Rosario ✅ • 1st

Production Data Analyst

12mo

...

Seeing the effort put into the design of your dashboards after you completed the google data analytics certificate inspires me to go the extra mile on my own portfolio projects.

It's very well done and makes the data so readable!

Support · 🙌 1 | Reply · 1 reply



Jhermien Paul Alejandria ✅ Author

Data Analyst at Royal Caribbean • Transforming Big Data into Action...

12mo

...

Thank you for the kind words, **Elijah!** I'm sure you'll be able to make fantastic portfolio projects. 😊

Like | Reply | 14 impressions



Stanley Ifedi • 1st

Data Analyst | Microsoft Excel | SQL | Tableau | PowerBI | BigQuery |

2y

...

The guidance i need to finish my own project. Great job **Jhermien Paul Alejandria**

Support · 🙌 1 | Reply · 1 reply



Jhermien Paul Alejandria ✅ Author

Data Analyst at Royal Caribbean • Transforming Big Data into Action...

2y

...

Hi **Stanley Ifedi!** I appreciate your comment! It's always great to hear that my work can help others. If you need any further guidance, feel free to let me know. 😊

Like · 🎉 1 | Reply | 85 impressions



Ben Smith • 2nd

Follow my journey to asset ownership!

2y

...

I've been looking for this project for a while!

It's so well done!

Could I be greedy and have you look at my first project, **Jhermien I** ...more

Love · ❤️ 1 | Reply · 3 replies

See previous replies



Jhermien Paul Alejandria ✅ Author

Data Analyst at Royal Caribbean • Transforming Big Data into Action...

2y

...

Thanks **Ben!** 😊

Like · 🎉 1 | Reply | 423 impressions



Vishwas Kshirsagar ✎ • Following

Data Analytics & Science | I Help You Land Your Dream Data Job

2y

...

Good work **Jhermien Paul Alejandria**

Love · 1 | Reply · 1 reply



Jhermien Paul Alejandria Author
Data Analyst at Royal Caribbean • Transforming Big Data into Action...

2y ...

Hi [Vishwas!](#) Thank you so much. I appreciate you! 😊

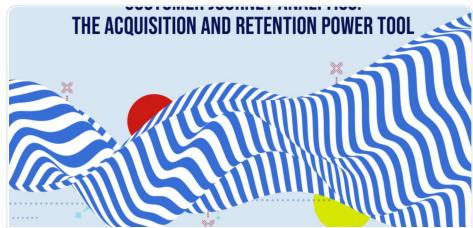
Like · 1 | Reply | 74 impressions



Jhermien Paul Alejandria

Data Analyst at Royal Caribbean • Transforming Big Data into Actionable Insights & Strategies PH

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