Divvy Company
Data Analytics Team

Final Report on Divvy Case Study

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July 18, 2024

Content

1 Problem Statement

The primary objective of this report is to generate answers and recommendations to the following question made by the Divvy director of marketing: How do annual members and casual riders use Divvy differently ?

2 Data Description

All data is available for public use by divvy corporation and is taken directly from the azure cloud. The dataset is then store locally on my machine as well as google bigquery and google drive. The data is collected from January to March of 2024 and contains the following attributes.

- ride_id : unique identifier of user
- ridable_type : the type of bikes being used
- started_at : start time
- ended_at : end time
- start_station_name : start station name
- start_station_id : unique identifier of station
- end_station_name : end station name
- end_station_id : unique identifier of station
- start_lat : start latitude
- start_lng : start longitude
- end_lat : end latitude
- end_lng : end longitude
- member_casual : membership type

3 Data Cleaning and Manipulation

I will be doing general manipulation and feature engineering in Google sheets and finish cleaning up in Google BigQuery using SQL. Let's start from Google sheets first:

1. Make a copy of January data

ride_id	rideable_type	started_at	ended_at	start_station_nai	start_station_id	end_station_nan	end_station_id	start_lat	start_lng	end_lat	end_lng	member_casual
C1D650626C8C	electric_bike	2024-01-12 15:3	2024-01-12 15:3	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.90326738	-87.63473678	41.88917683	-87.63850577	member
EECD38BDB25	electric_bike	2024-01-08 15:4	2024-01-08 15:5	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.9029365	-87.63444017	41.88917683	-87.63850577	member
F4A9CE78061F	electric_bike	2024-01-27 12:2	2024-01-27 12:3	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.90295133	-87.63447033	41.88917683	-87.63850577	member
0A0D9E15EE50	classic_bike	2024-01-29 16:2	2024-01-29 16:5	Wells St & Rand	TA1305000030	Larrabee St & W	13193	41.884295	-87.633963	41.921822	-87.64414	member
33FFC9805E3E	classic_bike	2024-01-31 5:43	2024-01-31 6:09	Lincoln Ave & W	13253	Kingsbury St & K	KA1503000043	41.948797	-87.675278	41.88917683	-87.63850577	member
C96080812CD2	classic_bike	2024-01-07 11:2	2024-01-07 11:3	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.903222	-87.634324	41.88917683	-87.63850577	member
0EA7CB313D4F	classic_bike	2024-01-05 14:4	2024-01-05 14:5	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.903222	-87.634324	41.88917683	-87.63850577	member
EE11F3A3B39C	electric_bike	2024-01-04 18:1	2024-01-04 18:2	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.90336812	-87.63486135	41.88917683	-87.63850577	member
63E83DE8E327	classic_bike	2024-01-01 14:4	2024-01-01 14:5	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.903222	-87.634324	41.88917683	-87.63850577	member
800568286912	electric_bike	2024-01-03 19:3	2024-01-03 19:4	Clark St & Ida B	TA1305000009	Kingsbury St & K	KA1503000043	41.8760335	-87.630866	41.88917683	-87.63850577	member
22B85E685AE0	electric_bike	2024-01-03 7:39	2024-01-03 7:47	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.90302617	-87.6346065	41.88917683	-87.63850577	member
133CDC03CA43	classic_bike	2024-01-03 17:0	2024-01-03 17:1	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.903222	-87.634324	41.88917683	-87.63850577	member
32D57BF92858	electric_bike	2024-01-10 17:0	2024-01-10 17:1	Wells St & Elm S	KA1504000135	Kingsbury St & K	KA1503000043	41.90314517	-87.63457883	41.88917683	-87.63850577	member

2. Reformat alignment
3. Highlight headers
4. Drop all blank feature in latitude and longitude columns as it would affect calculations of new features
5. Generate new features including:
    - ride_length: the time the user rode a bike
    - week_day: the day bikes were used
    - distance_travelled: the distance travelled by the bike
    - day_time: the time of the day in 3 categories: Morning (4-12AM), Afternoon (1-5PM) and Evening (6-3PM)

ride_id	rideable_type	week_day	day_time	started_at	ended_at	ride_length
C1D650626C8C899A	electric_bike	Friday	Evening	Friday, January 12, 2024, 3:30:27 PM	Friday, January 12, 2024, 3:37:59 PM	0:07:32
EECD38BDB25BFCB0	electric_bike	Monday	Afternoon	Monday, January 8, 2024, 3:45:46 PM	Monday, January 8, 2024, 3:52:59 PM	0:07:13
F4A9CE78061F17F7	electric_bike	Saturday	Evening	Saturday, January 27, 2024, 12:27:19 PM	Saturday, January 27, 2024, 12:35:19 PM	0:08:00
0A0D9E15EE50B171	classic_bike	Monday	Afternoon	Monday, January 29, 2024, 4:26:17 PM	Monday, January 29, 2024, 4:56:06 PM	0:29:49
33FFC9805E3EFF9A	classic_bike	Wednesday	Morning	Wednesday, January 31, 2024, 5:43:23 AM	Wednesday, January 31, 2024, 6:09:35 AM	0:26:12
C96080812CD285C5	classic_bike	Sunday	Morning	Sunday, January 7, 2024, 11:21:24 AM	Sunday, January 7, 2024, 11:30:03 AM	0:08:39
0EA7CB313D4F456A	classic_bike	Friday	Afternoon	Friday, January 5, 2024, 2:44:12 PM	Friday, January 5, 2024, 2:53:06 PM	0:08:54
EE11F3A3B39CFBD8	electric_bike	Thursday	Evening	Thursday, January 4, 2024, 6:19:53 PM	Thursday, January 4, 2024, 6:28:04 PM	0:08:11
63E83DE8E3279F15	classic_bike	Monday	Afternoon	Monday, January 1, 2024, 2:46:53 PM	Monday, January 1, 2024, 2:57:02 PM	0:10:09
8005682869122D93	electric_bike	Wednesday	Evening	Wednesday, January 3, 2024, 7:31:08 PM	Wednesday, January 3, 2024, 7:40:05 PM	0:08:57
22B85E685AE0D490	electric_bike	Wednesday	Morning	Wednesday, January 3, 2024, 7:39:20 AM	Wednesday, January 3, 2024, 7:47:12 AM	0:07:52
133CDC03CA430172	classic_bike	Wednesday	Afternoon	Wednesday, January 3, 2024, 5:03:11 PM	Wednesday, January 3, 2024, 5:13:15 PM	0:10:04

ride_id	start_station_name	start_station_id	end_station_name	end_station_id	start_lat	start_lng	end_lat	end_lng	distance_travelled	member_casual
C1D650626C8C899A	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90326738	-87.63473678	41.88917683	-87.63850577	0.00000	member
EECD38BDB25BFCB0	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.9029365	-87.63444017	41.88917683	-87.63850577	1.56657	member
F4A9CE78061F17F7	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90295133	-87.63447033	41.88917683	-87.63850577	1.56765	member
0A0D9E15EE50B171	Wells St & Randolph St	TA1305000030	Larrabee St & Webster Ave	13193	41.884295	-87.633963	41.921822	-87.64414	4.25696	member
33FFC9805E3EFF9A	Lincoln Ave & Waveland Ave	13253	Kingsbury St & Kinzie St	KA1503000043	41.948797	-87.675278	41.88917683	-87.63850577	7.29428	member
C96080812CD285C5	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.903222	-87.634324	41.88917683	-87.63850577	1.59965	member
0EA7CB313D4F456A	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.903222	-87.634324	41.88917683	-87.63850577	1.59965	member
EE11F3A3B39CFBD8	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90336812	-87.63486135	41.88917683	-87.63850577	1.60657	member
63E83DE8E3279F15	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.903222	-87.634324	41.88917683	-87.63850577	1.59965	member
8005682869122D93	Clark St & Ida B Wells Dr	TA1305000009	Kingsbury St & Kinzie St	KA1503000043	41.8760335	-87.630866	41.88917683	-87.63850577	1.59246	member
22B85E685AE0D490	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.90302617	-87.6346065	41.88917683	-87.63850577	1.57343	member
133CDC03CA430172	Wells St & Elm St	KA1504000135	Kingsbury St & Kinzie St	KA1503000043	41.903222	-87.634324	41.88917683	-87.63850577	1.59965	member

6. Create 6 pivot tables including:
    - SUM and AVERAGE ride_length of each type of user
    - Distribution of types of user into each type of bikes
    - Distribution of types of user into day time
    - Distribution of types of user into week day
    - SUM and AVERAGE distance_travelled of each type of user
    - Distribution of user types

member_casual	SUM of ride_length	AVERAGE of ride_length
casual	9:59:15	0:14:48
member	11:40:53	0:11:33
Grand Total	**21:40:08**	**0:12:06**

COUNTA of ride_id	rideable_type		
member_casual	classic_bike	electric_bike	Grand Total
casual	10344	14009	24353
member	65893	54339	120232
Grand Total	**76237**	**68348**	**144585**

COUNTA of ride_id	day_time			
member_casual	Afternoon	Evening	Morning	Grand Total
casual	9564	8122	6667	24353
member	46790	32737	40705	120232
Grand Total	**56354**	**40859**	**47372**	**144585**

Morning: 4AM-12AM
Afternoon: 1PM-5PM
Evening: 6PM-3AM

COUNTA of ride_id	week_day							
member_casual	Friday	Monday	Saturday	Sunday	Thursday	Tuesday	Wednesday	Grand Total
casual	3098	4022	2514	2363	4388	3401	4567	24353
member	13754	19751	9696	9011	22666	18887	26467	120232
Grand Total	**16852**	**23773**	**12210**	**11374**	**27054**	**22288**	**31034**	**144585**

member_casual	AVERAGE of distance_travelled	SUM of distance
casual	1.53639	37415.75966
member	1.72892	207871.03887
Grand Total	**1.69649**	**245286.79853**

member_casual	COUNTA of ride_id
casual	24353
member	120232
Grand Total	**144585**

After getting a hold of the schema and how the data is structured let's move to Google BigQuery:

1. Combined 3 tables from 3 months into 1 table and remove all null values from columns latitude and longitude as it could mess with calculations

2. Query user by type, months and count

```
SELECT member_casual, EXTRACT(MONTH FROM started_at) AS month, COUNT(*) AS user_count FROM `keen-acolyte-427907-d1.data.Q1New`
GROUP BY member_casual, month
ORDER BY member_casual, month;
```

Row	member_casual	month	user_count
1	casual	1	24353
2	casual	2	46963
3	casual	3	82268
4	member	1	120232
5	member	2	175883
6	member	3	219023

3. Query user by type, months average length ride and sum of length ride

```
SELECT member_casual, EXTRACT(MONTH FROM started_at) AS month, SUM(ended_at - started_at) AS sum_ride_length, AVG(ended_at - started_at) AS avg_ride_length FROM `keen-acolyte-427907-d1.data.Q1New`
GROUP BY member_casual, month
ORDER BY member_casual, month;
```

Row	member_casual	month	sum_ride_length	avg_ride_length
1	casual	1	0-0 0 6009:59:15	0-0 0 0:14:48.430788
2	casual	2	0-0 0 14801:11:45	0-0 0 0:18:54.601814
3	casual	3	0-0 0 27271:48:17	0-0 0 0:19:53.398368
4	member	1	0-0 0 23147:40:53	0-0 0 0:11:33.090466
5	member	2	0-0 0 34931:4:53	0-0 0 0:11:54.974687
6	member	3	0-0 0 40863:23:27	0-0 0 0:11:11.656433

4. Query user by type, months average length distance and sum of length distance

```
SELECT member_casual,
  SUM(ST_DISTANCE(
    ST_GEOGPOINT(start_lng, start_lat),
    ST_GEOGPOINT(end_lng, end_lat)
  )/1000) AS total_distance_in_kilometers, AVG(ST_DISTANCE(
    ST_GEOGPOINT(start_lng, start_lat),
    ST_GEOGPOINT(end_lng, end_lat)
  )/1000) AS avg_distance_in_kilometers,  EXTRACT(MONTH FROM started_at) AS month
FROM
  `keen-acolyte-427907-d1.data.Q1New`
GROUP BY member_casual, month
ORDER BY member_casual, month;
```

Row	member_casual	total_distance_in_kil	avg_distance_in_kilo	month
1	casual	37415.72263008...	1.536390696427...	1
2	casual	85134.21030914...	1.812793269364...	2
3	casual	156412.6343547...	1.901257285393...	3
4	member	207872.8236365...	1.728930930505...	1
5	member	341722.1877295...	1.942894922929...	2
6	member	435487.7733763...	1.988319826576...	3

5. Query user by type, bike type and user count

```
SELECT member_casual, rideable_type, EXTRACT(MONTH FROM started_at) AS month, COUNT(*) AS user_count
FROM `keen-acolyte-427907-d1.data.Q1New`
GROUP BY member_casual, rideable_type, month
ORDER BY member_casual, month;
```

Row	member_casual	rideable_type	month	user_count
1	casual	classic_bike	1	10344
2	casual	electric_bike	1	14009
3	casual	electric_bike	2	19352
4	casual	classic_bike	2	27611
5	casual	classic_bike	3	39332
6	casual	electric_bike	3	42936
7	member	classic_bike	1	65893
8	member	electric_bike	1	54339
9	member	electric_bike	2	63498

6. Query user by type, month and day of the week

```
SELECT member_casual, EXTRACT(MONTH FROM started_at) AS month, FORMAT_TIMESTAMP('%A', started_at) AS day, COUNT(*) AS user_count
FROM `keen-acolyte-427907-d1.data.Q1New`
GROUP BY member_casual, rideable_type, month, day
ORDER BY member_casual, month, day;
```

Row	member_casual	month	day	user_count
1	casual	1	Friday	1250
2	casual	1	Friday	1848
3	casual	1	Monday	1655
4	casual	1	Monday	2367
5	casual	1	Saturday	1145
6	casual	1	Saturday	1369
7	casual	1	Sunday	1072
8	casual	1	Sunday	1291
9	casual	1	Thursday	1711

4 Analysis Summary

Now that we have use spreadsheets as well as google bigquery to take a quick look as well as making a few pivot table now we can do our statistical analysis in Python. I am going to import the whole csv file to Kaggle for analysis:

- Document a few first observation

  Looking at the few first rows, i have a few observations:

  - Each rows seem to represent a time where customers uses a Divvy Bike
  - Customer can choose from electric_bike or classic_bike
  - Each rows also have location of start point and endpoint as well as the time
  - Each rides have an unique id
  - Each station have an unique id

- Create an info table

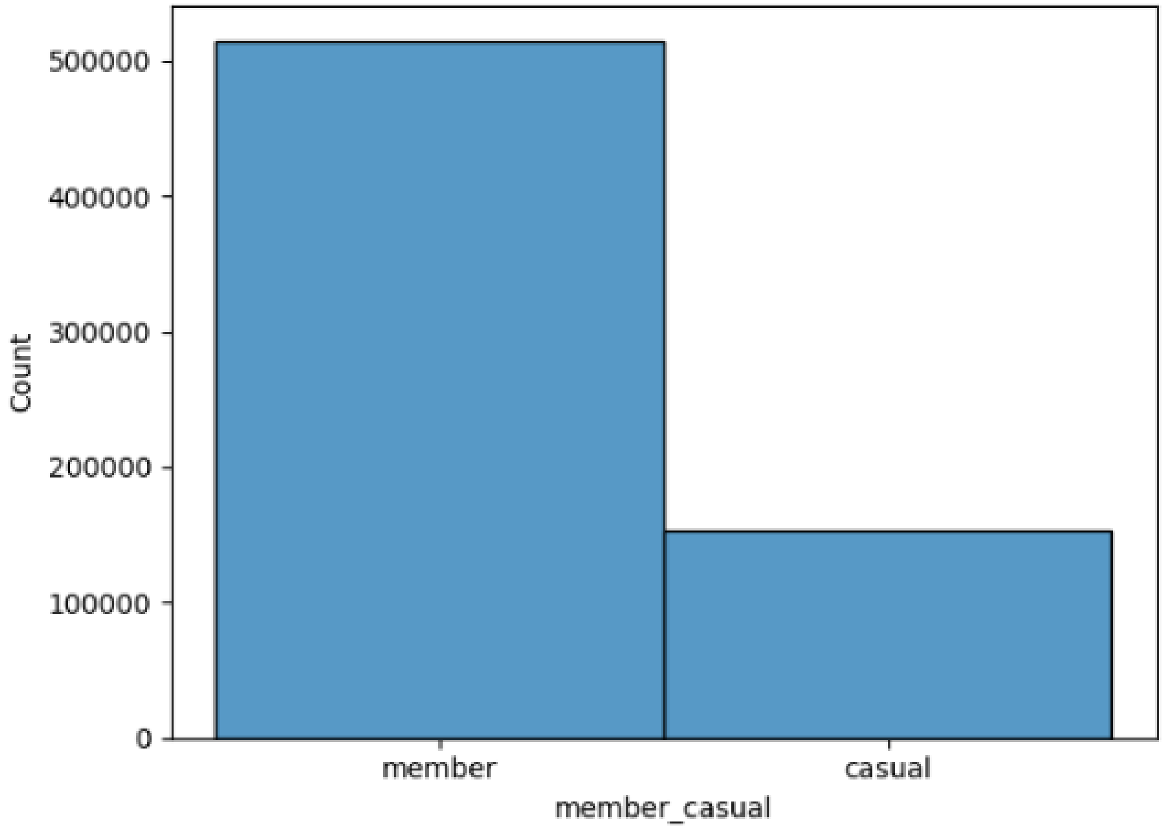
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 668722 entries, 0 to 668721
Data columns (total 19 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   ride_id                668722 non-null  object
 1   rideable_type          668722 non-null  object
 2   started_at             668722 non-null  object
 3   ended_at               668722 non-null  object
 4   start_station_name     581884 non-null  object
 5   start_station_id       581884 non-null  object
 6   end_station_name       576684 non-null  object
 7   end_station_id         576684 non-null  object
 8   start_lat              668722 non-null  float64
 9   start_lng              668722 non-null  float64
 10  end_lat                668722 non-null  float64
 11  end_lng                668722 non-null  float64
 12  member_casual          668722 non-null  object
 13  month                  668722 non-null  int64
 14  ride_length_secs       668722 non-null  int64
 15  ride_length_mins       668722 non-null  int64
 16  distance_in_kilometers 668722 non-null  float64
 17  day_of_week            668722 non-null  object
 18  started_hour           668722 non-null  int64
dtypes: float64(5), int64(4), object(10)
memory usage: 96.9+ MB
```

- Validate and change a few columns datatypes

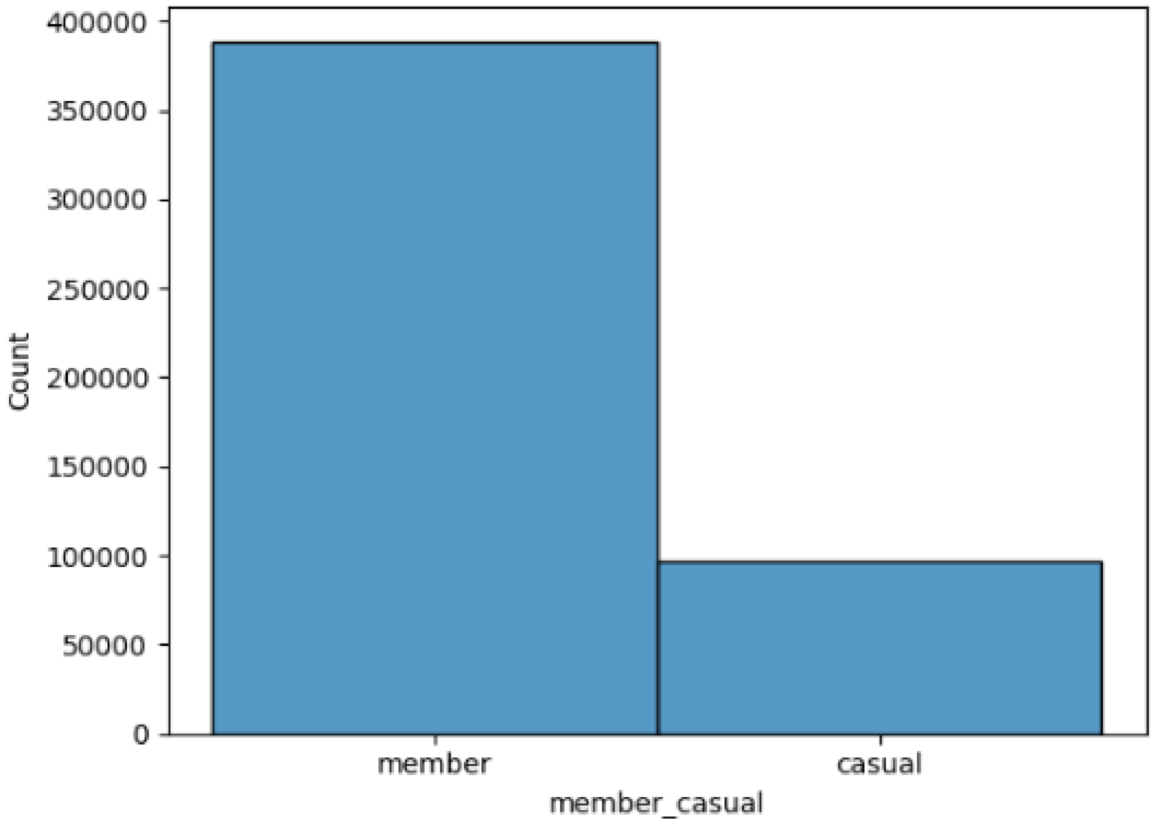
- Create description table containing mean, median, quartile,...etc

	start_lat	start_lng	end_lat	end_lng	month	ride_length_secs	ride_length_mins	distance_in_kilometers	started_hour
count	668722.000000	668722.000000	668722.000000	668722.000000	668722.000000	668722.000000	668722.000000	668722.000000	668722.000000
mean	41.899286	-87.646908	41.899570	-87.647032	2.234337	791.495584	12.703267	1.890240	13.721573
std	0.047142	0.027405	0.047261	0.027491	0.782206	2259.494942	37.656501	1.734732	4.702697
min	41.648501	-87.844110	41.630000	-87.870000	1.000000	-2617.000000	-43.000000	0.000000	0.000000
25%	41.879569	-87.660984	41.880000	-87.661198	2.000000	289.000000	4.000000	0.824857	10.000000
50%	41.894733	-87.643819	41.895501	-87.643948	2.000000	487.000000	8.000000	1.381710	14.000000
75%	41.928773	-87.630000	41.928887	-87.630000	3.000000	843.000000	14.000000	2.401104	17.000000
max	42.070000	-87.528232	42.080000	-87.460000	3.000000	90562.000000	1509.000000	31.124978	23.000000

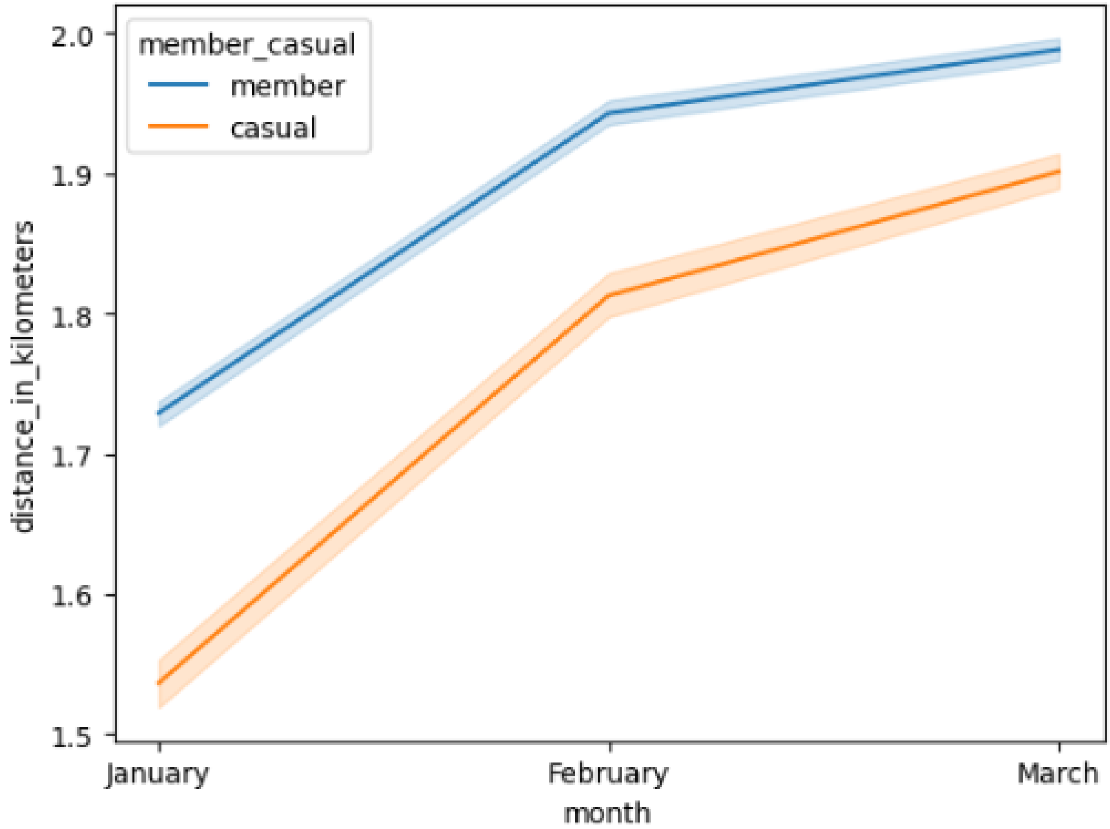
- Visuallize the amount of casual and member riders

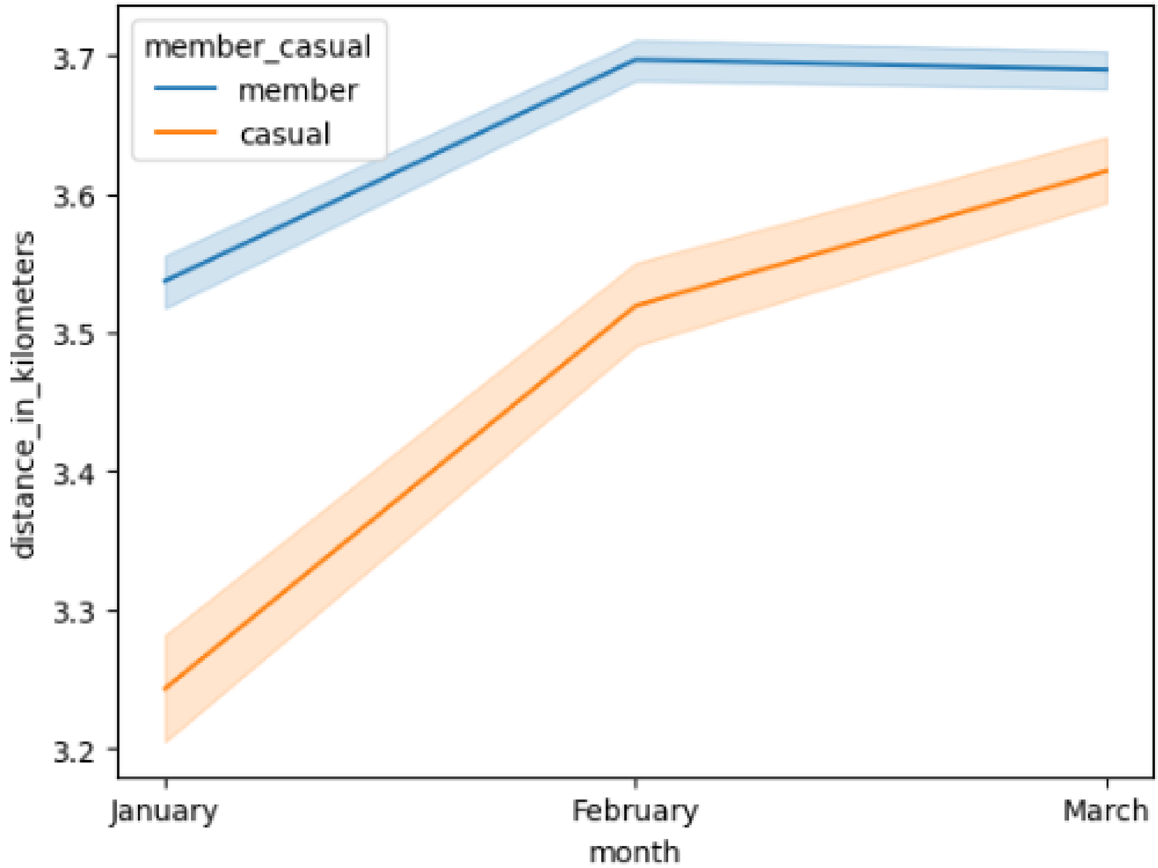


- Visuallize and calculate the percentage of member and casual riders riding above mean distance

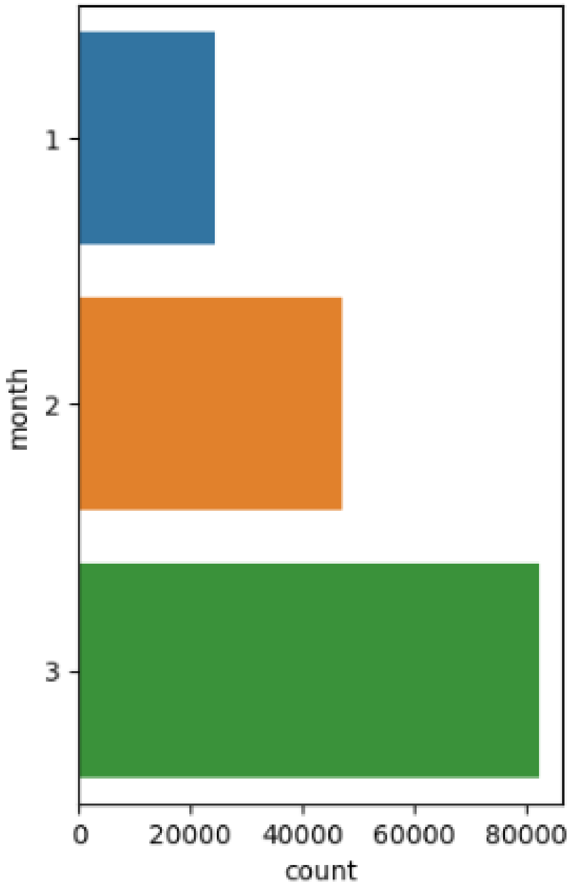


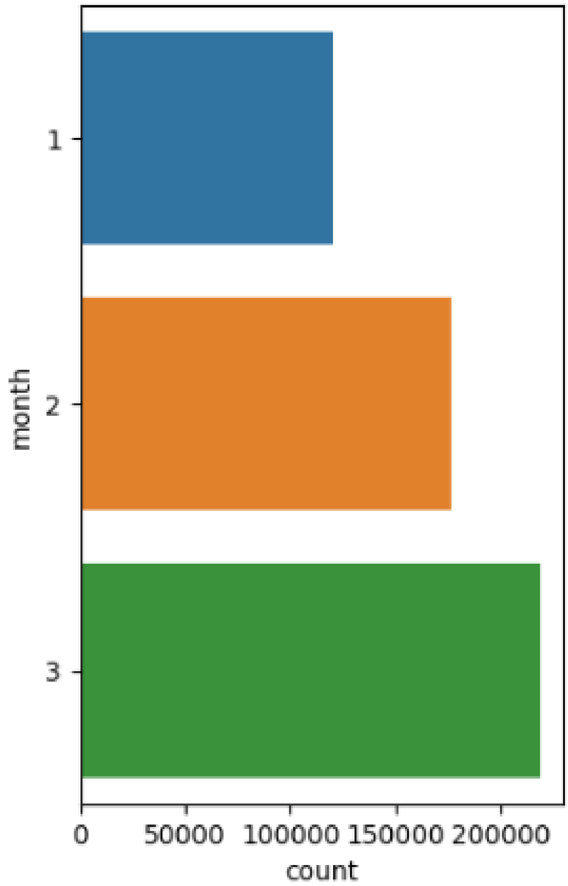
- Visuallize and calculate the percentage of member and casual riders riding above mean ride duration

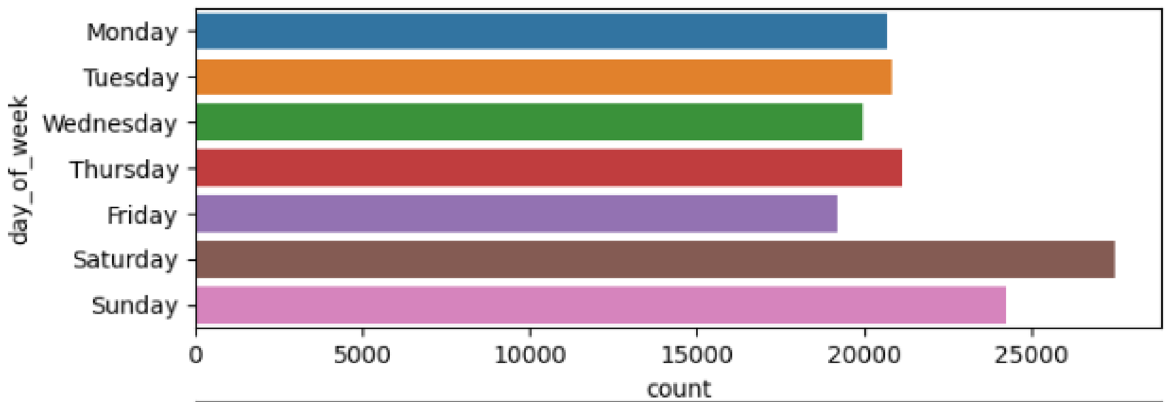


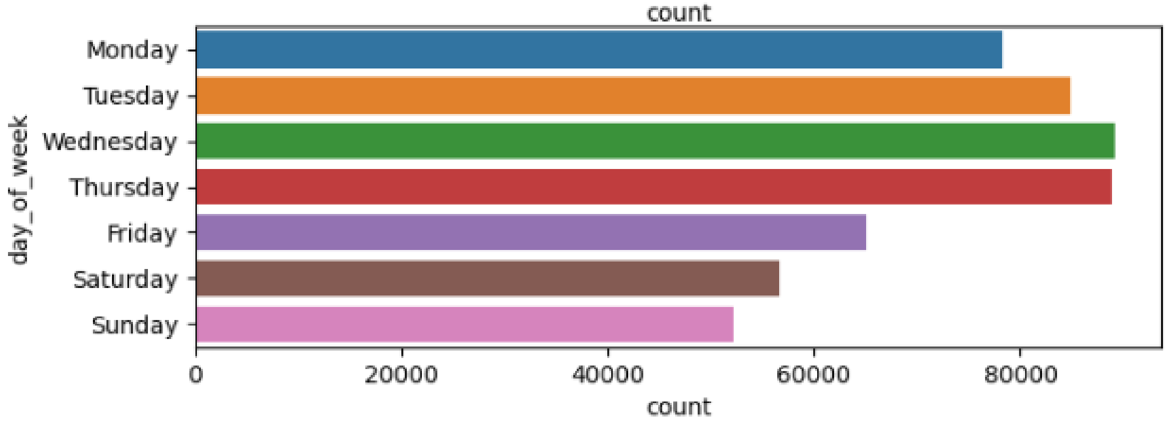


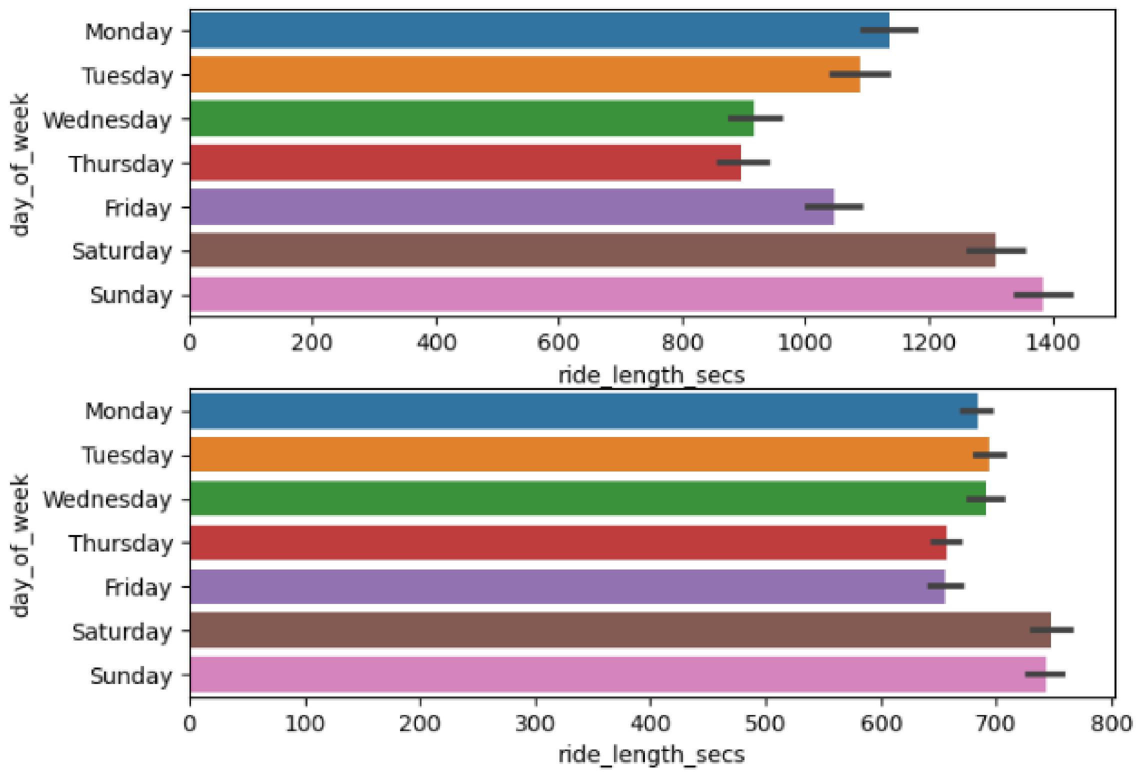
- Visuallize which month, date of the week member and casual riders prefer


1
2
3
month
0
20000
40000
60000
80000
count

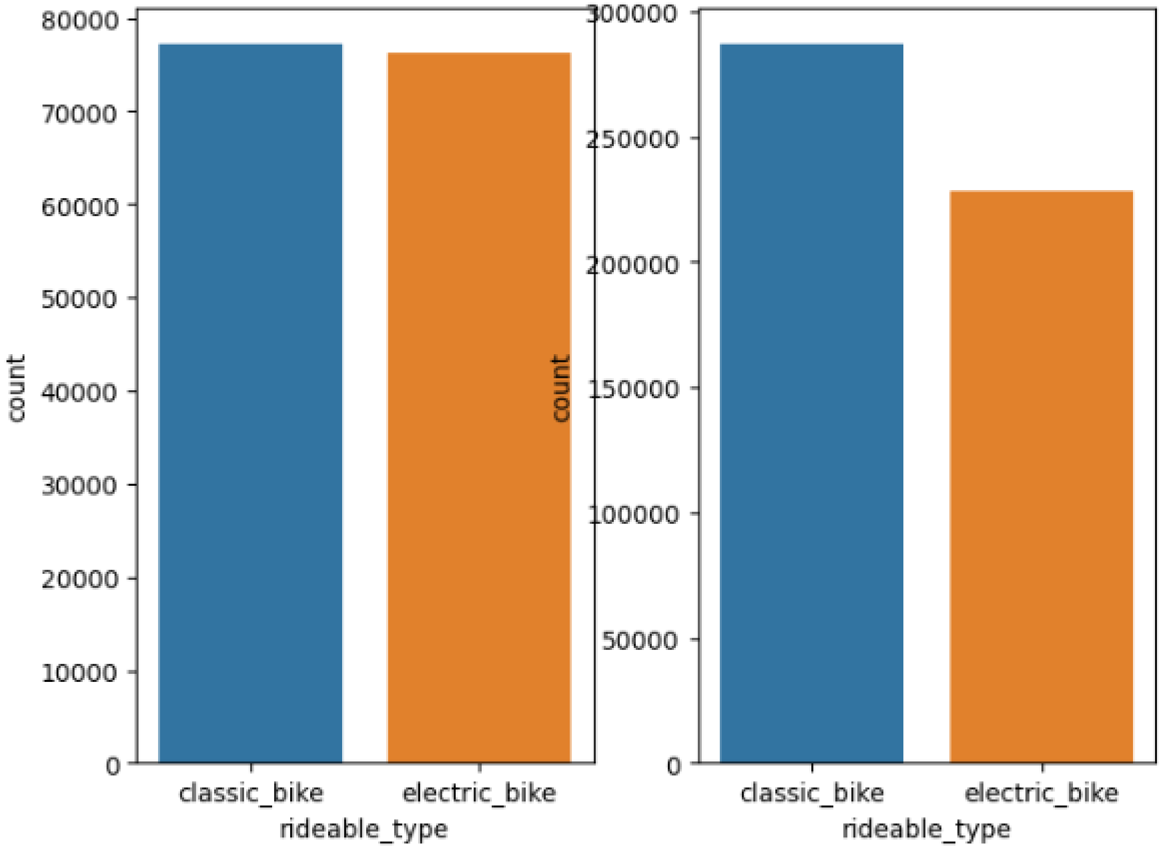

1
2
3
month
0
50000
100000
150000
200000
count

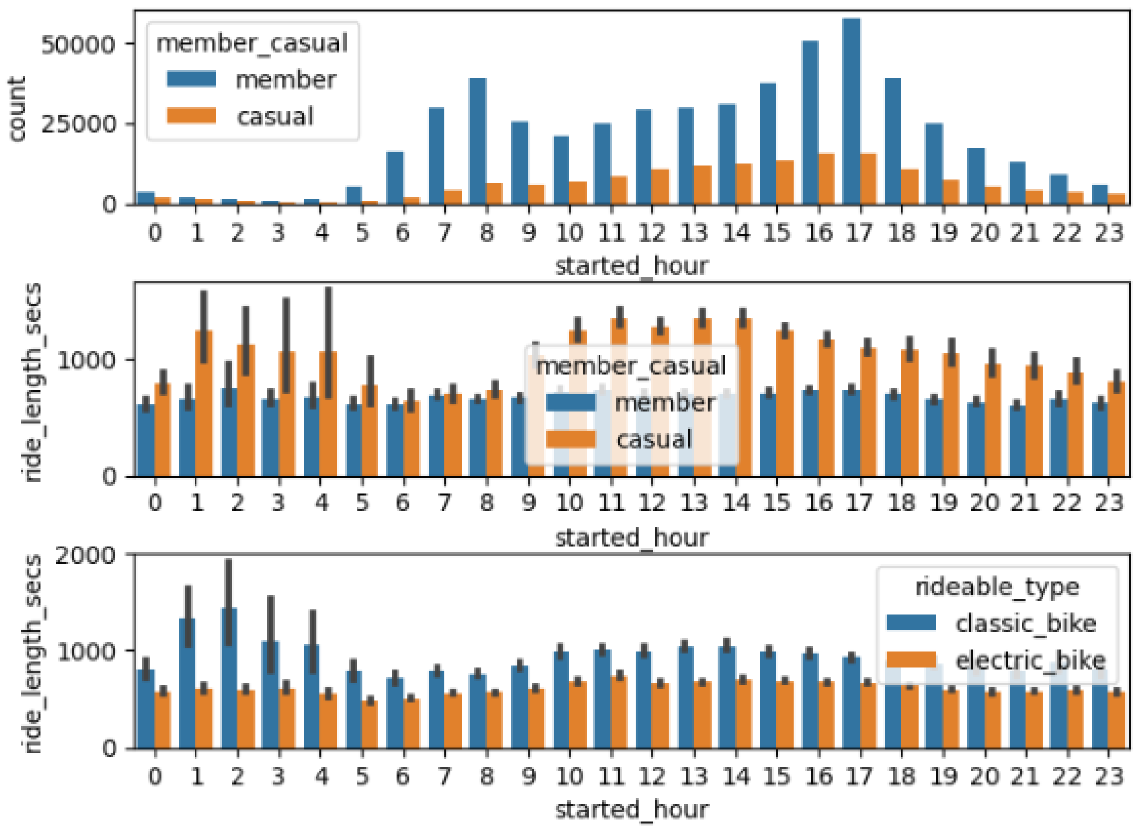

Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
day_of_week
0
5000
10000
15000
20000
25000
count


Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
day_of_week
0
20000
40000
60000
80000
count



- Visuallize which types of bikes and what hour member and casual riders enjoy riding

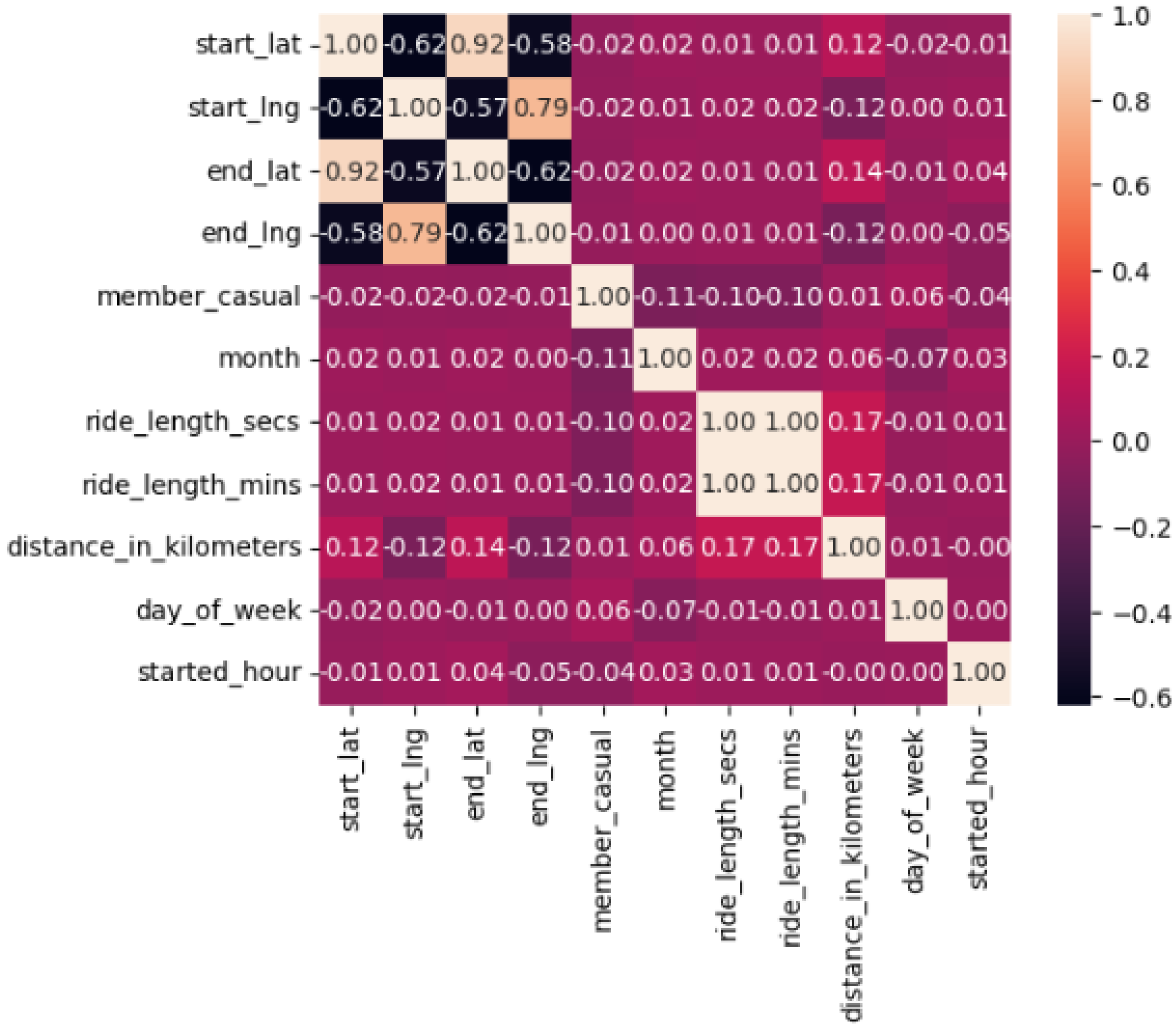




- Create a table display top 10 station prefered by member and casual riders and what bikes they used

	rideable_type	member_casual	start_station_name	end_station_name	started_rent(hour)	average_duration_trip
0	classic_bike	member	Lincoln Ave & Addison St	Clark St & Winnemac Ave	9	1481.0
1	classic_bike	casual	McClurg Ct & Ohio St	Clark St & Lincoln Ave	18	1478.0
2	classic_bike	member	Lincoln Ave & Waveland Ave	Lincoln Ave & Roscoe St*	9	1472.0
3	classic_bike	member	DuSable Lake Shore Dr & Monroe St	McClurg Ct & Erie St	16	1467.0
4	classic_bike	member	Aberdeen St & Jackson Blvd	Delano Ct & Roosevelt Rd	18	1462.0
5	classic_bike	member	State St & 33rd St	Shields Ave & 28th Pl	13	1460.0
6	classic_bike	casual	Halsted St & Fulton St	Franklin St & Illinois St	16	1453.0
7	classic_bike	casual	Clark St & Armitage Ave	Sedgwick St & Webster Ave	13	1450.0
8	classic_bike	member	Kingsbury St & Kinzie St	Clark St & Elm St	15	1437.0
9	classic_bike	casual	Delano Ct & Roosevelt Rd	Dearborn St & Van Buren St	15	1429.0

- Dropping blank rows
- Evaluate outliers
- Visuallize correlation of multiple variables



- Do hypothesis testing on few findings

H_0: Casual members rides on average for a longer duration or equal than member riders

H_A: Casual members rides on average for a less duration than member riders

+ Code + Markdown

I would choose 5% as the significance level and proceed with a one-tailed two-sample t-test.

```
from scipy.stats import ttest_ind
member = new_df[new_df["member_casual"] == 1]["ride_length_secs"]
casual = new_df[new_df["member_casual"] == 0]["ride_length_secs"]

ttest, pval = ttest_ind(casual, member, alternative="less")

print("t-test",ttest)
print("p-value",pval)
```

```
t-test 72.58777514915464
p-value 1.0
```

Conclusion:

- p-value is larger than significance level so we can conclude that the ride duration of casual member is statistically significantly higher than member riders

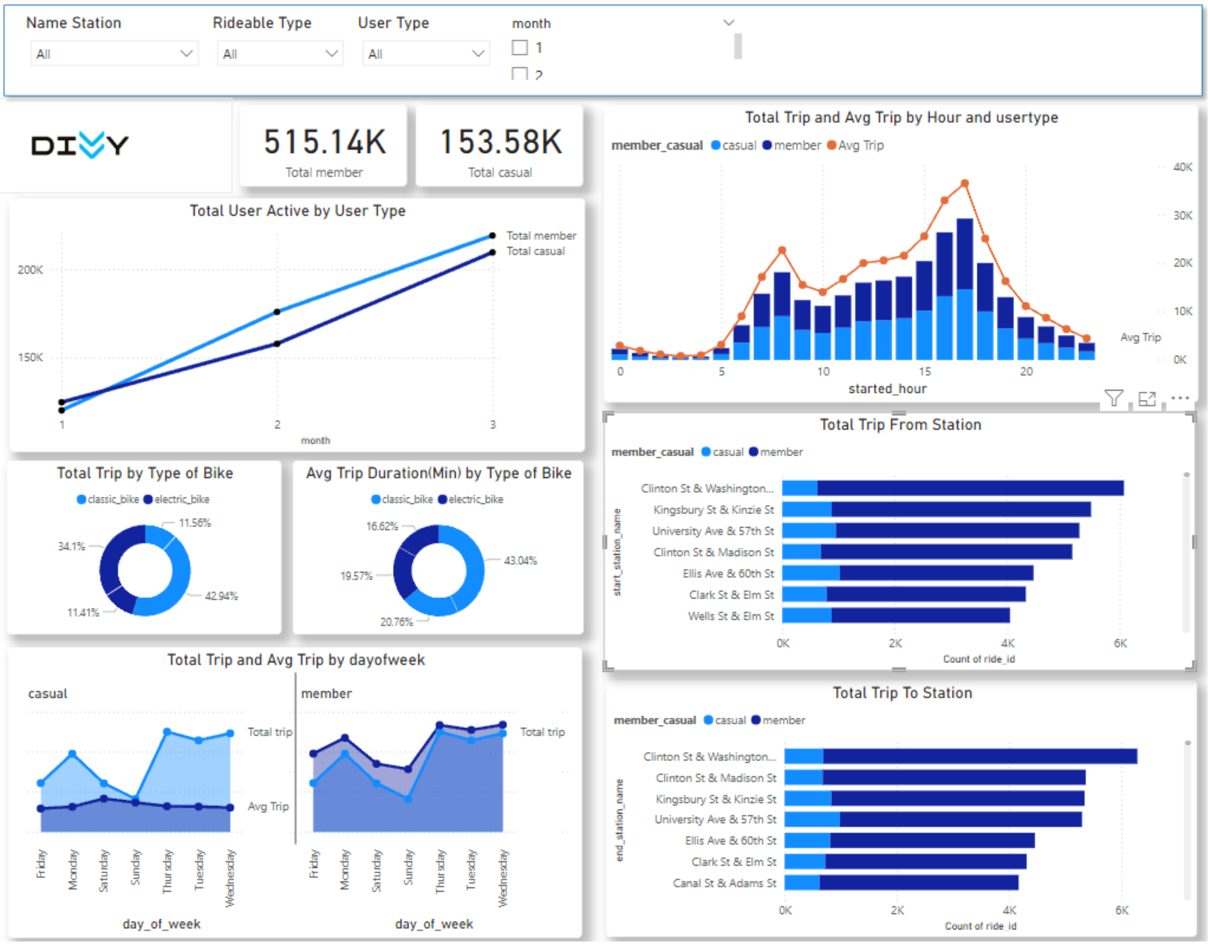
This is only a summary and few previews of the notebook. Please refer to the Kaggle notebook for a more detail analysis

5 Visualizations and Key Findings

Here are some key findings i manage to found:

- The number of member riders are exponentially higher than casual riders
- Casual riders on average ride for a longer time and longer distance
- More casual riders prefer riding in the afternoon
- Classic bikes are more popular with both riders
- March seems to have most casual and member riders alike
- Casual riders like riding on weekends and member like weekdays

Here is a report visualization build in Power BI:



6 Recommendations

Here are some recommendations based on the aforementioned data:

- Seasonal campaigns need to be done in March. By using inbound marketing techniques that utilize superior content from the benefits obtained from annual members to attract upgradability from regular members.

- Modified the comfort feature of classic bikes and electric bikes for casual riders so they would be more satisfied as casual are more likely to ride for longer distance and longer period of times than member
- On weekends the number of active users of regular members increases quite a lot compared to normal days. use email marketing to share interesting promos specifically for regular members who often rent and return bicycles at busy stations such as Streeter Dr & Grand Ave, DuSable Lake Shore Dr & Monroe St and DuSable Lake Shore Dr & North Blvd.