

Cyclitic Bike Sharing Data Analysis



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Abstract

The bike share analysis case study presented here and brings the real world scenario of the nature of bike riders, i.e. Annual member riders and non-member Casual riders in Chicago. Data for this analysis has been provided by Motivate International Inc. for 692 stations across Chicago.

Cyclitic Bike Share it's a bike share program who offers more than 5,800 bicycles and 600 dock stations in Chicago's City. Cyclitic sets itself apart by offering different kind of bicycles making

bike-share more inclusive to people with disabilities and riders who can't use a standard two-wheels bike. Cyclitic offers a flexible plan which include casual and annual memberships.

The main goal of this work is to ensure design marketing strategies that would convert casual riders into annual members. Therefore, the focus will be centred on the nature of bike riders for a period of 12 months.

Dataset contains the detail of the last 12 months (from 01-2021 to 12-2021) of bike-trips in Chicago's City throw Cyclitic bicycle share program. The data has information about start station and end station (name, longitude and latitude), start and end time, type of bicycle used and type of customer. This data could be used to analyse the differences between casual riders and members and get insights which helps to develop marketing strategies in order to increase the number of annual members.

Tools: Python

Library: Pandas, Numpy, matplotlib, date

Github Account Link:

Vansh Patel:

<https://github.com/Vanshpatel-data/DAB402-Cyclistic-Project>

Jalat Patel:

https://github.com/JalatPatel/DAB402-Cyclistic-Bike-Sharing-Analysis/blob/main/Capstone_Cyclistic_Project-checkpoint.ipynb

RESEARCH QUESTIONS:

Q1: How do annual members and casual riders use Cyclitic bikes differently?

Q2: How can we causal riders into annual members?

Q3: How do annual members and casual riders use Cyclitic bikes differently?

Q4. How can cyclitic use digital media to influence casual riders to become member?

LITERATURE REVIEW

The bike share analysis case study presented here and brings the real-world scenario of the nature of bike riders, i.e., Annual member riders and non-member Casual riders in Chicago. Data for this analysis has been provided by Motivate International Inc. for 692 stations across Chicago. Bike-sharing systems are an emerging form of sharing-mobility in many cities worldwide. The travel patterns of users that take advantage of smart devices to ride a shared-bicycle in two large cities (Chicago and Budapest) have been investigated, with analysis of approximately 1 million transaction data records associated with bike trips made over a three-month period in each location. Several aspects of user travel behaviour—such as day and time of travel, frequency of usage, duration of usage, seasonal and peak/off-peak variations, major origin/destinations—have been included in this analysis.

Bicycle-sharing system refers to a public transportation service system in urban areas offering bicycles for shared use to individuals in a relatively short period of time (about 3045 minutes) for free or with very low charges [10]. In bicycle sharing systems, people can borrow bikes from stations near them and return the bike to any stations in the city, which can be used as a short-distance trip supplement for private vehicles as well as regular public transportation (e.g., buses and metro trains). Bicycle-sharing system is green and of low carbon, and each bike can be used by several people per day. What's more, due to the widely spread branches and stations available in the city, people can usually borrow and return the bikes very conveniently without wasting time on waiting (needed for the public transportation) or concerns about parking issues in cities (of private vehicles). As a result, bicycle-sharing systems are becoming more and more popular nowadays, which have been adopted in many large cities, e.g., Chicago (Divy Bike), New York (Citi Bike), San Francisco (Bay Area Bike Share), Washington, D.C. (Capital Bikeshare). Bicycle-

sharing system allows people to borrow bikes with either “one-day pass” or “annual subscribed membership”. “One-day pass” is usually preferred by people for temporary usages, e.g., tourist for short-time sightseeing, but the charges per day are slightly higher. Meanwhile, “subscribed membership” is a great option for people with frequent travel needs, e.g., office worker and students. Generally, trips completed by one-day pass/membership holders within 30 minutes are included in the pass/membership, but trips longer than 30- minutes may incur overtime fees. More information about the detailed pricing rules is available at Divvy’s official website¹. Unlike traditional fixed-route public transportation at prescheduled time, services provided by bicycle-sharing systems are more flexible and can meet the daily travel needs of different categories of users. Bicycle-sharing system provides a more microscopic perspective to understand individuals’ travel behaviours, which include various aspects about the trips, e.g., trip origin station and start time, as well as trip destination stations and end time. Generally, the travel behaviours of different categories of people with various travel purposes can be quite different. For instance, tourists with one-day pass tend to use the bike to travel among attraction spots, while registered subscribers (like workers and students) mainly travel between companies/schools and homes with the bike. Meanwhile, for stations located at different places in the city, the bike usage can be quite skewed and imbalanced [7]. Some stations that individuals like to borrow bikes from will lack enough bikes for people to check out, while some other stations that people normally return the bikes to will get jammed easily without enough docks for upcoming bikes. To support such a claim, we also analyse the real-world bicycle-sharing system data and count the numbers of bikes borrowed from/returned to each stations respectively. According to the analysis results, among all the 474 stations, 470 of them have historical usage records: 235 stations have more bikes being checked out, 234 of them have more returned bikes and only one station has balanced usages. Therefore,

one of the most challenging task for the effective operations of bicycle-sharing systems is to manually shift and rebalance the bikes from the jammed stations to the empty ones. Monitoring the bike usage and inferring the potential destinations of individuals' trips in advance (e.g., at the moment when individuals borrow a bike and start their trips) can help the service providers schedule the manual bike re-dispatch beforehand. Problem Studied: In this paper, we propose to predict the potential destination station and arriving time when people start their trips and check out bikes from the origin station at the very beginning. The problem is formally defined as the "trip prediction" problem.

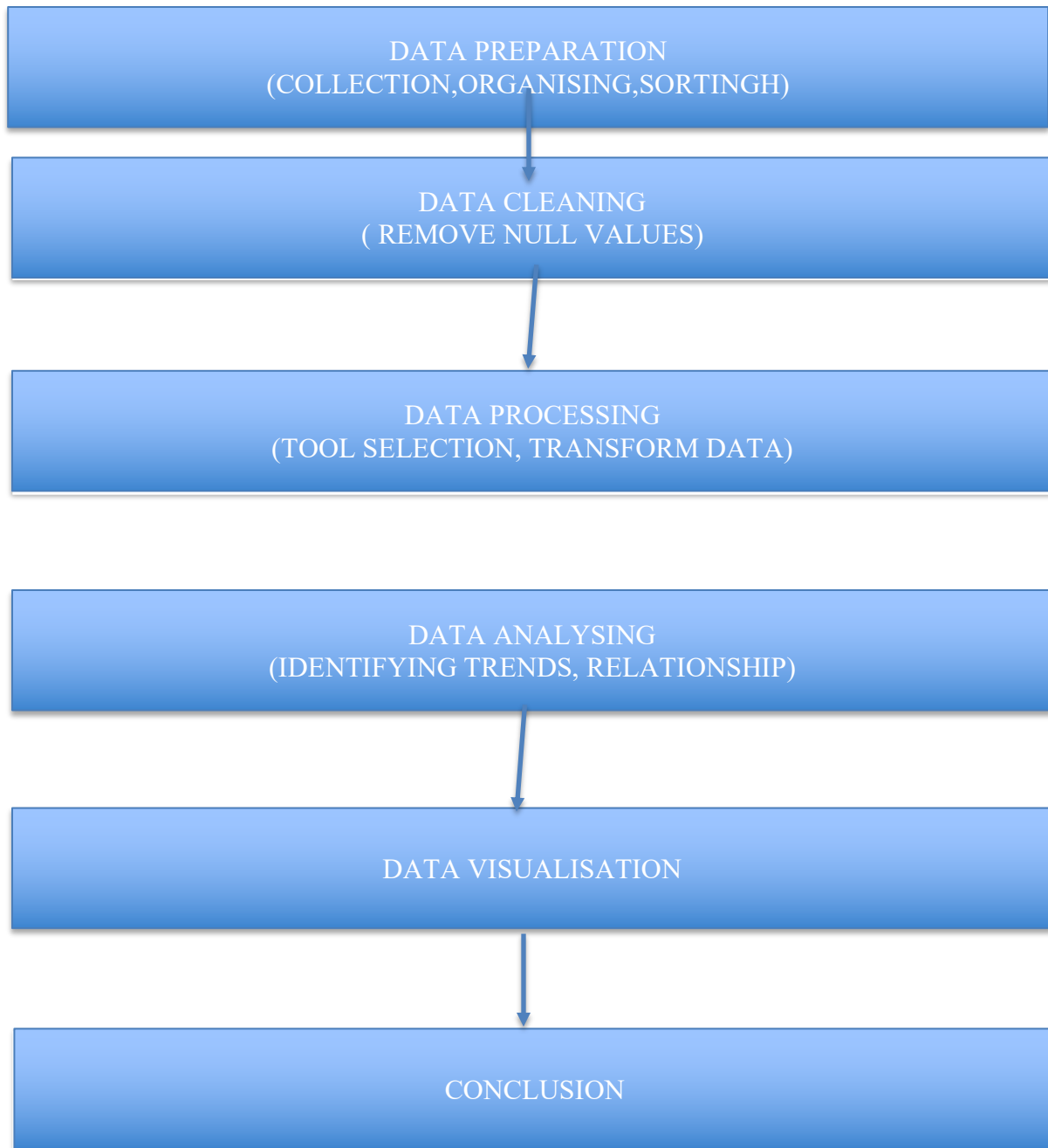
Being a type of non-motorized transport, a Bike-Sharing System (BSS) is a travel alternative that brings significant benefits to its users and society: overall, it has potential impacts in reduction of car use, positive effects on the environment, and health benefits (Shaheen, 2010). As the urban population of the world is increasing, the congestion in cities both on its roads and its public transport system will increase (Rudolph and Mátrai, 2018; Saif, 2018), thereby providing an opportunity for BSS to emerge as a viable, sensible, healthy and environmentally sustainable transport option. In essence, a BSS can be defined as 'shared use of a bicycle fleet' (Shaheen, 2010). It provides shared bicycles that allow cyclists to travel from their origin to their destination. Users are able to pick-up and drop-off bikes between different self-service docking stations within a short-term rental time (Fishman, 2016). This definition could be extended to the newly emerging type of dockless BSS, where the bikes can be picked up and dropped off at any location within a predefined service area. Several distinct features are needed to provide a seamless BSS experience which includes: suitable provision of bicycles between places (i.e. via docking stations); a technology application used for system management; appropriate and practical rental duration; and an efficient, affordable payments method. Technological applications allow BSS operators to keep

track both of the docking station status (i.e. available bicycles and racks) and users' movements through the network (Fishman, 2013). In terms of the pricing and payment method, the pricing models can vary considerably. In general, the aim is to maximize the utilization rate of vehicles, with services normally free for the first 30 or 60 min (DeMaio 2009; Vogel 2016). Users can use credit cards to pay additional fees that arise for further time usage of the system. Although BSS operation principles might seem quite simple, they have passed through a long development process before reaching their current state as a comprehensive system. BSS performances usually can be assessed by different indicators. One of them is the usage rate, probably the most common metric used for evaluating performances of BSS in different cities. User frequency is another equally important indicator, often mentioned in studies by different scholars such as Rojas-Rueda et al. (2011), Buck et al. (2013), Fishman et al. (2014), Médard de Chardon and Caruso (2015), Fishman (2016), Saif et al. (2018) and Soltani et al. (2019).

The scope of this study is limited to exploring the travel pattern characteristics of bike-sharing users. The BSSs investigated in this chapter—Divvy, in Chicago and MOL Bubi, in Budapest—belong to the 4th generation of bike-sharing (Mátrai and Tóth 2016). The demographic features (i.e. gender and age), of users and their membership type have been also discussed.

Chicago has a successful story to tell in running its bike-sharing program, 'Divvy'. Chicago covers an area of 600km² and sits 176m above sea level, on the southwestern shore of Lake Michigan. The city is traversed by the Chicago and Calumet Rivers. Chicago's extensive parklands (about 3000 ha) attract an estimated 86 million visitors annually. Chicago is also recognized across the United States as a very passionate sports town. 'Divvy' is a BSS serving the City of Chicago and two adjacent suburbs and is operated by Motivate for the Chicago Department of Transportation. The name "Divvy" is a playful reference to sharing ("divvy it up").

Methodology:



Data Dictionary

Table 1 : Column Names And Datatypes

| Column Name | Datatype |
|--------------------|-------------|
| started_at | Datetime |
| ended_at | Datetime |
| start_station_name | |
| start_station_id | Int64 |
| end_station_name | |
| end_station_id | Int64 |
| member_casual | Categorical |
| day_week_start | Categorical |
| Duration | Time |
| Distance | Numerical |

Data Dictionary

Table 2: Data Dictionary Of Categorical Values

| Attribute Name of Categorical | Description | Number of Categorical Values | Values |
|----------------------------------|-------------------------|------------------------------------|--|
| rideable_type | Types of bike | 3 | Docked_bike Electric_bike Classic_bike |
| Member | Type of member | 2 | Casual member Annual member |
| Day_week_start | Name of the day of week | 7 | Monday Tuesday Wednesday Thursday Friday Saturday Sunday |

Data Dictionary Of Datetime

Table 3: Data Dictionary of Datetime

| Attribute Name In Datetime | Description | Number of Values | Value |
|-------------------------------|-------------------------|---------------------|--------------|
| Started_date | Start date of bike ride | 2 | 2020 2021 |
| ended_date | End date of bike ride | 2 | 2020 2021 |

Data Dictionary of Integer Values

Table 4: Data Dictionary Of Integer Values

| Attribute Name In Integer | Description | Number Of Integer Values | Value |
|------------------------------|--------------------------------------|-----------------------------|-------|
| Start_station_id | Id of start station of bike ride. | Int64 | 238 |
| End_station_id | Id of end station of bike ride | Int64 | 307 |

Table 5: Data Dictionary Of Numeric Values

| Attribute Name | Description | Data | Values |
|----------------|------------------------------|-----------|--------|
| Distance | Distance between the station | Numerical | 8525 m |

Descriptive Analysis

Table 5: Descriptive Analysis

| | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|----------|----------|--------------|--------------|----------|--------------|--------------|--------------|---------------|
| Distance | 891254 | 23671.300222 | 18712.910508 | 0.010000 | 10746.630000 | 18442.400000 | 31429.450000 | 304295.320000 |
| Duration | 8.912540 | 4.715277 | 1.334435 | 1.000000 | 8.020000 | 1.585000 | 5.118000 | 8.875942 |

Table 6: Descriptive Analysis of Annual Members

| | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|----------|--------|--------------|--------------|----------|--------------|--------------|--------------|---------------|
| Distance | 555275 | 22939.023892 | 22939.023892 | 0.010000 | 10376.900000 | 17769.060000 | 30404.110000 | 234232.330000 |

| | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Duration | 5.552750 | 2.619576 | 1.192097 | 1.000000 | 6.750000 | 1.222000 | 3.271000 | 8.869764 |

Table 7: Descriptive Analysis of Casual Riders

| | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|----------|----------|--------------|--------------|----------|--------------|--------------|--------------|---------------|
| Distance | 335979 | 24881.538777 | 20160.100234 | 0.010000 | 11511.730000 | 19741.350000 | 32983.900000 | 304295.320000 |
| Duration | 3.359790 | 8.178858 | 1.541120 | 1.000000 | 1.195000 | 2.528000 | 6.790000 | 8.875942 |

Null Values In Dataset

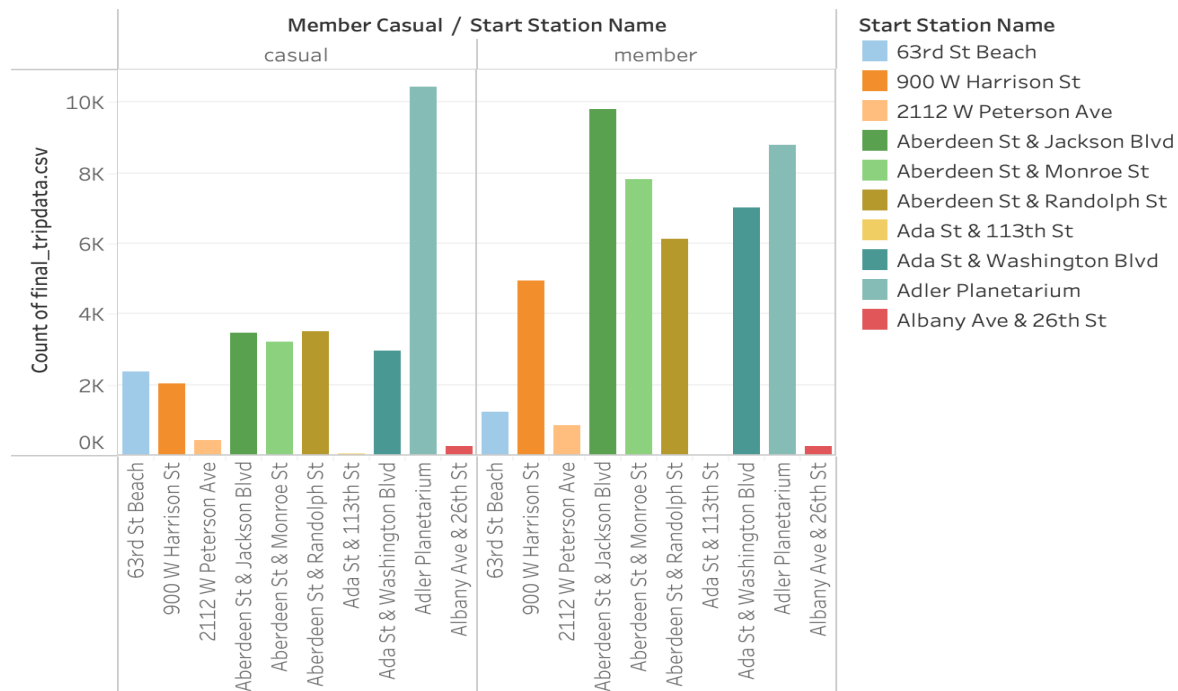
Table 6: Null Values In Dataset

| Attribute Name | Null Values |
|----------------|-------------|
| Duration | 2090 |
| Distance | 81554 |

Graphical Representation:

1.

Sheet 11



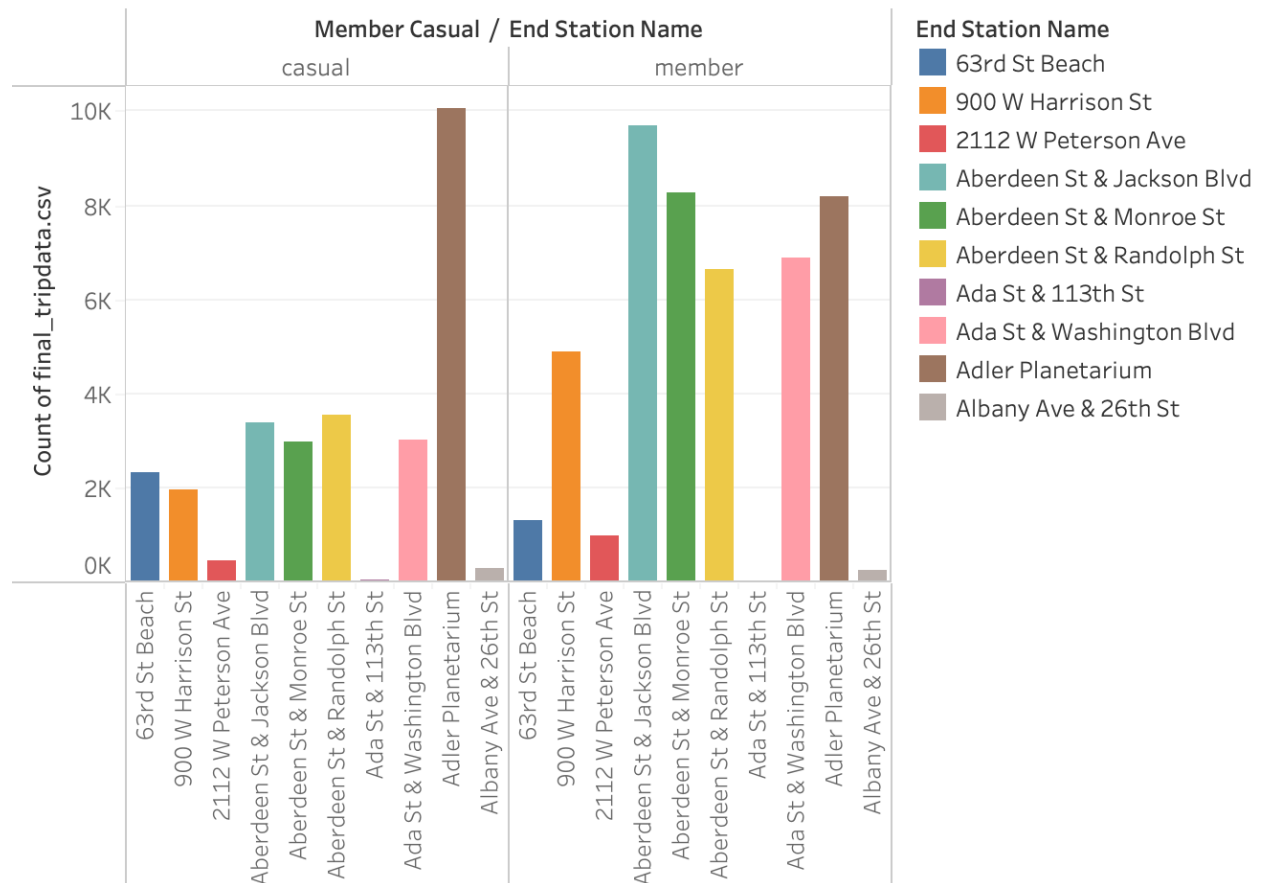
Count of final_tripdata.csv for each Start Station Name broken down by Member Casual. Color shows details about Start Station Name. The view is filtered on Start Station Name, which keeps 10 members.

Figure 1: Member_Casual Origin Station

The above bar graph shows, the top 10 Stations from where both the casual and annual members have started their respective rides.

2.

Sheet 12



Count of final_tripdata.csv for each End Station Name broken down by Member Casual. Color shows details about End Station Name. The view is filtered on End Station Name, which keeps 10 members.

Figure 2: Member_Casual destination Station

The above bar graph shows, the top 10 Stations from where both the casual and annual members have ended their respective rides.

3.

Number of rides per month by ride type

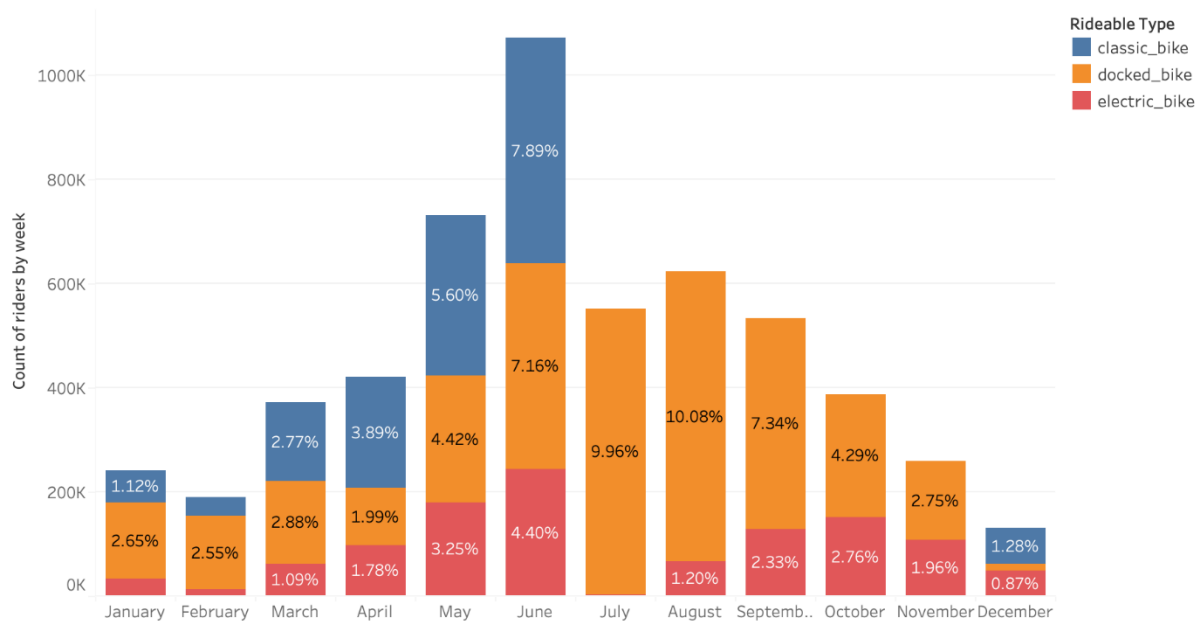
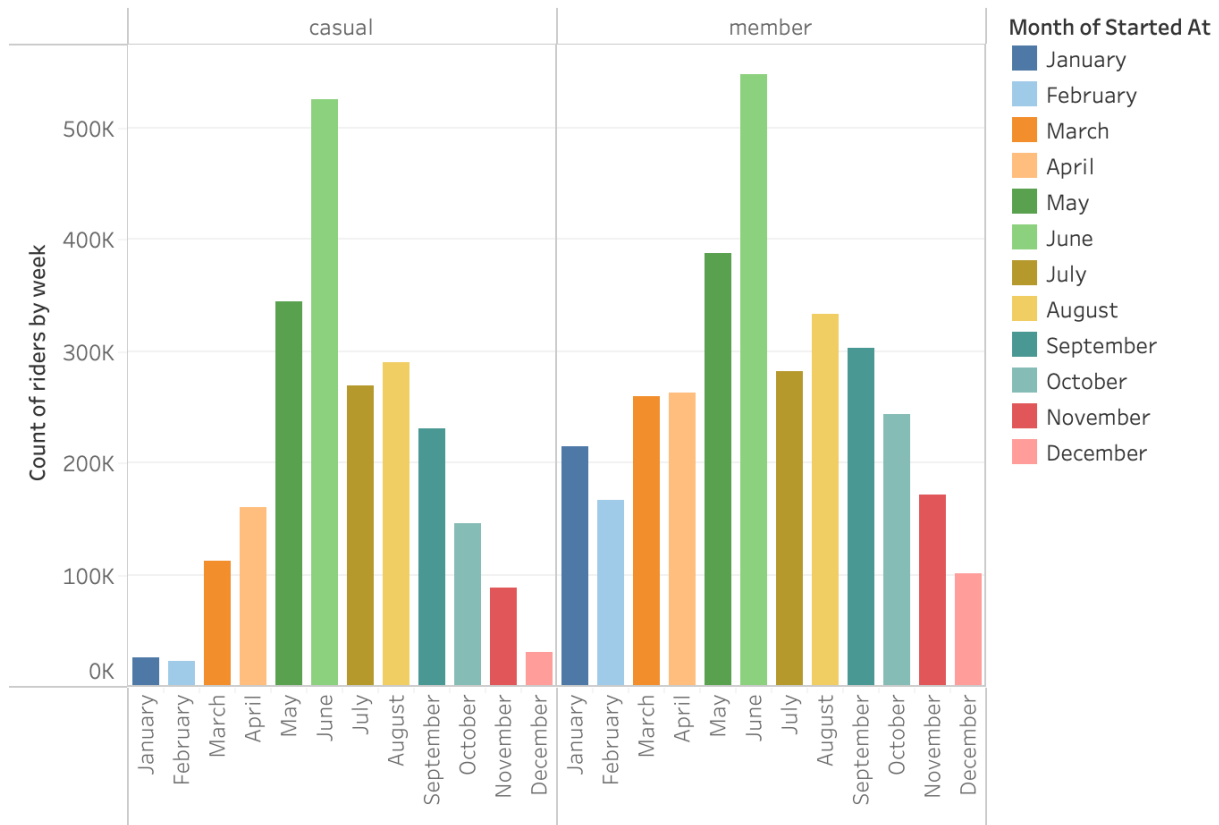


Figure 3: Ride per month by ride type

From the above bar chart, we see that highest number of usages of classic bike in month of June with 7.89% which is followed by docked and electric bike with 7.16% and 4.40% respectively. In the summer time riders ride percentage is significantly increased as we see from the May to September.

4.

Number of rides per month by members



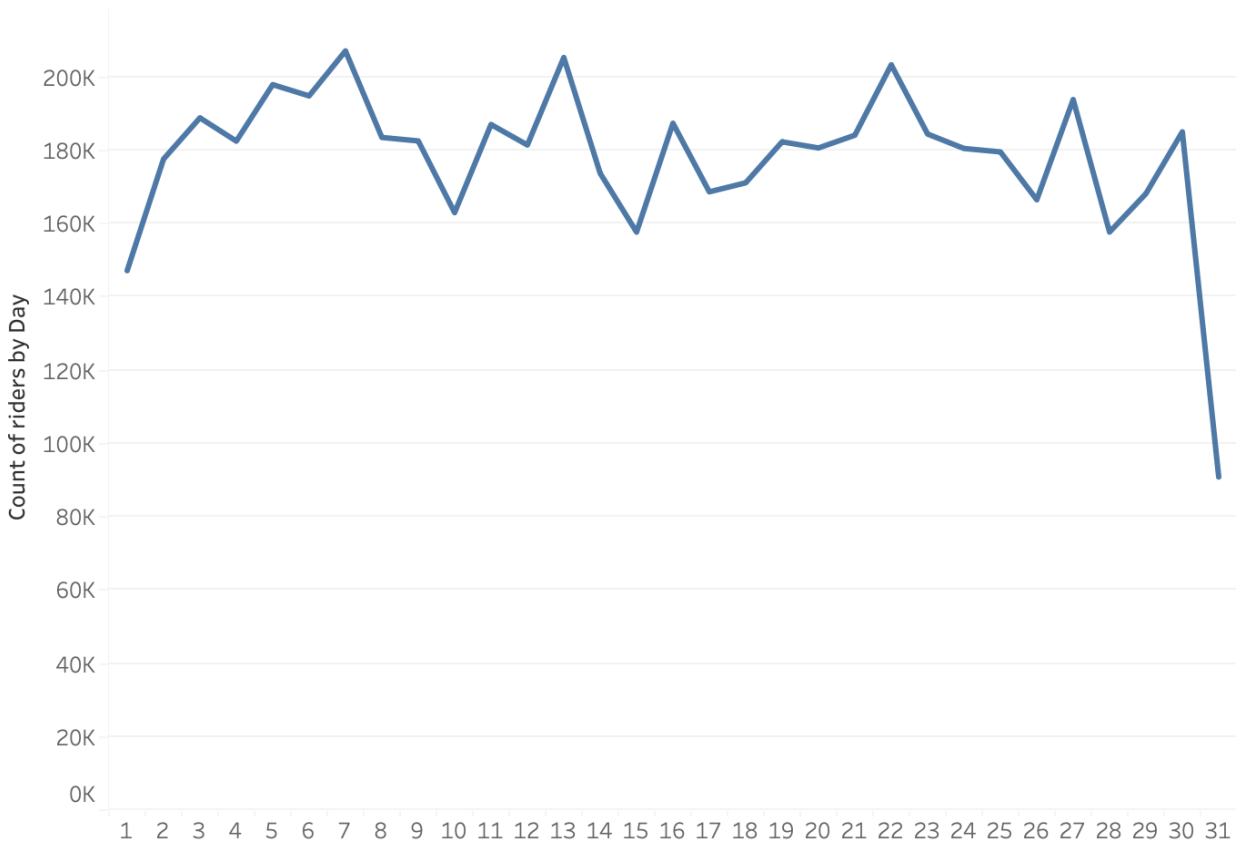
Count of final_tripdata.csv for each Started At Month broken down by Member Casual. Color shows details about Started At Month.

Figure 4: Number Of rides per month by riders

From the above graph we see that there is almost a similar number of riders type between the month of May to August while there is a significant drop in terms of casual rider number as we can see in the winter season months.

5.

Number of rides per day



The trend of count of final_tripdata.csv for Started At Day.

Figure 5: Number of rides per day by riders

There was a correlation between the days and riders' behaviour. The trend displayed in the line chart above shows how riders use cyclistics service on daily basis per whole year. We observe that how the average number of riders of rise weekend days as well as it fell drastically around 90k on 31st date due to a smaller number of 31st date in one calendar year.

6.

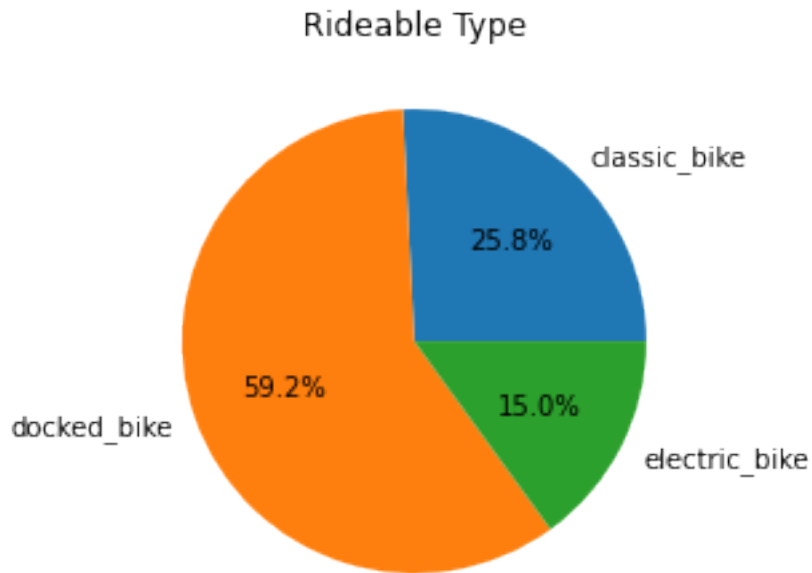


Figure 6: Type of ride by riders

Three different types of bikes used by the users on their preferences. Data shows that riders prefer the docked bike with the 59.2 % while the electric bike was the least preferred which covers 15% of total used bike type.

7.

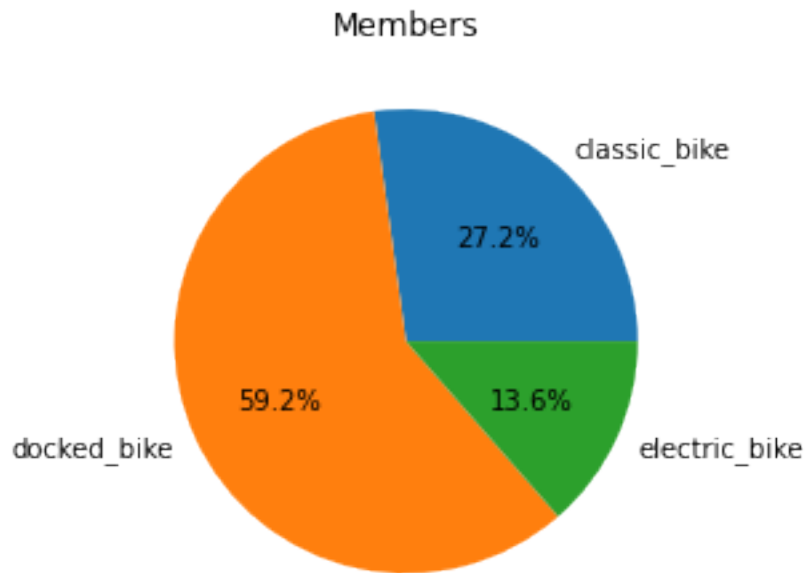


Figure 7: Type of ride by member riders

Annual membership holder used three types of bikes. Data shows that riders prefer the docked bike with the 59.2 % while the electric bike was the least preferred which covers 13.6% of total used bike type. So, we can determine from those Annual members more likely to used docked bike.

8.

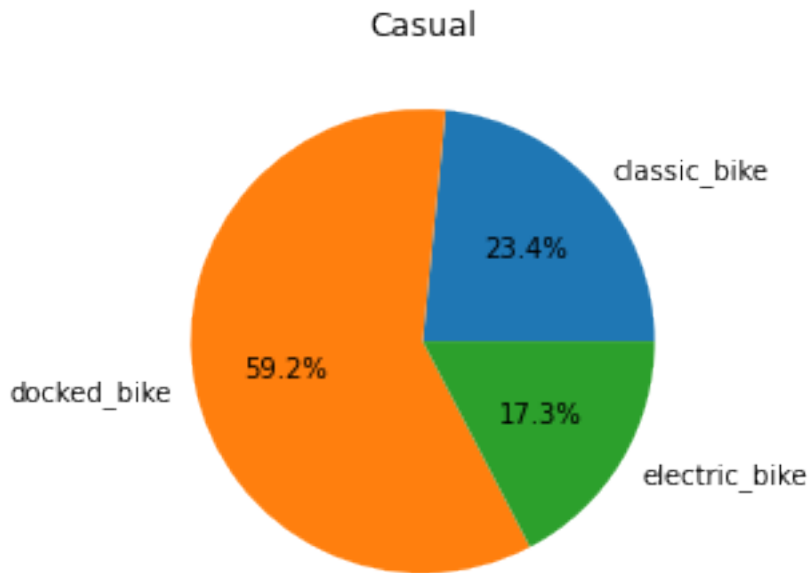


Figure 8: Type of ride by casual riders

Casual members also used three types of bikes. Data shows that riders prefer the docked bike with the 59.2 % while the electric bike was the least preferred which covers 17.3% of total used bike type. So, we can determine from those casual members more likely to used docked bike.

9.

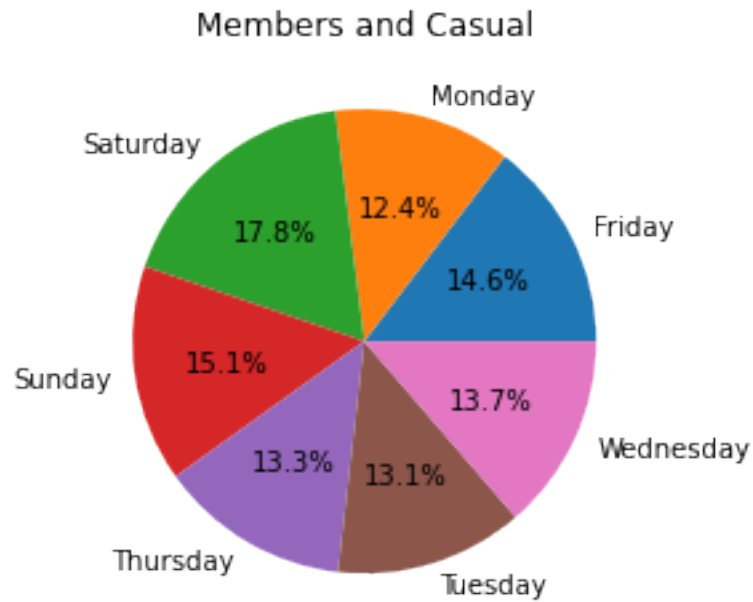


Figure 9: Day-wise rides

Though the number of trips taken by rides shown in the above pie chart. It shows highest number of riders ride on Saturday and Sunday with 17.8% and 15.1% respectively. On the weekdays riders number stay under the 15%.

10.

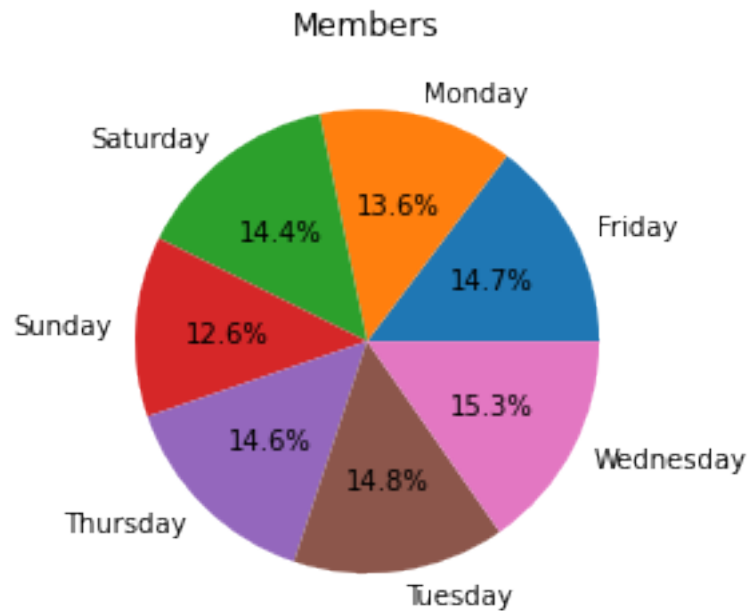


Figure 9: Day-wise rides

Through the number of percentage of trips taken by member riders on everyday same except Sunday. Sunday only 12.6% of members ride on that day while all other day percentage of ride between 13.6% to 15.3%. So, from that fact it illustrates that members mostly use the service to commute to and from work.

11.

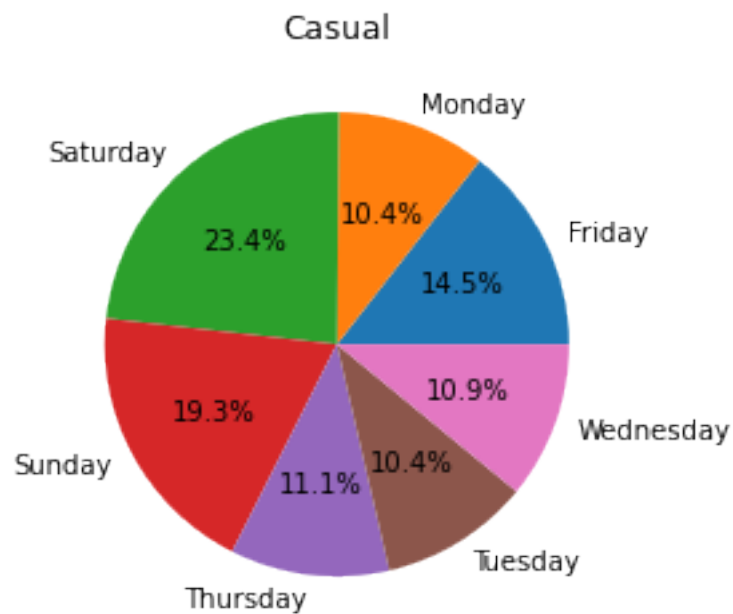


Figure 11: Day-wise rides by casual rider

Through the number of trips taken by casual riders on weekly day basis is significantly low compared to weekends. Almost double rides on weekends compared to weekdays by casual rides it almost touch to quarterly part of rides Saturday. This could be attributed to the fact that casual riders use the bikes for fun or exercise

Conclusion

Now that we have defined the key differences between members and casual riders, the marketing department is able to come up with some strategies that can help market the annual membership to casual riders and convert them into members.

We recommend launching a marketing campaign highlighting the benefits of having an annual membership pass. Rather than paying for each trip, Cyclistic should emphasize to casual riders the lower-cost per hour compared to not having an annual membership. We should offer exclusive benefits for members such as a priority access pass that enables them to secure a bike up to an hour in advance by making reservations through the app.

Cyclistic could also create a weekend membership pass providing casual riders with unlimited rides on the weekend. This could help persuade casual riders into purchasing an annual membership.

Lastly, we could launch tiered weekly and monthly passes to capture casual riders in the market who cannot commit to an annual pass. This could be especially appealing during the summer months when the ridership of casual riders exceeds that of annual members.

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