

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

## Background

Cyclistic launched a successful bike-share offering with a fleet of 5,824 bicycles that are geotracked and locked into a network of 692 stations across Chicago. The bikes can be unlocked from one station and returned to any other station in the system anytime.

Cyclistic's pricing plans include: single-ride passes, full-day passes, and annual memberships. Customers who purchase single-ride or full-day passes are referred to as casual riders. Customers who purchase annual memberships are Cyclistic members.

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

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## Business task

What are the best marketing strategies to convert casual riders into annual members?

Break down of the business task with three questions:

1. How do annual members and casual riders use Cyclistic bikes differently?
2. Why would casual riders buy Cyclistic annual memberships?
3. How can Cyclistic use digital media to influence casual riders to become members?

This analysis will focus on the first question:

How do annual members and casual riders use Cyclistic bikes differently?

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## Data sources

The dataset can be found [here](#). User data is from a 12 month period from January 2022 - December 2022. (Cyclistic is a fictional company and the dataset has been made publicly available by Motivate International Inc. via license). Riders' personal data is unavailable and prohibited.

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## Data cleaning

```
# load libraries used for analysis
library(tidyverse)
library(lubridate)
library(ggplot2)

# load datasets
df_202201 <- read_csv('202201-divvy-tripdata.csv')
df_202202 <- read_csv('202202-divvy-tripdata.csv')
df_202203 <- read_csv('202203-divvy-tripdata.csv')
df_202204 <- read_csv('202204-divvy-tripdata.csv')
df_202205 <- read_csv('202205-divvy-tripdata.csv')
df_202206 <- read_csv('202206-divvy-tripdata.csv')
df_202207 <- read_csv('202207-divvy-tripdata.csv')
df_202208 <- read_csv('202208-divvy-tripdata.csv')
df_202209 <- read_csv('202209-divvy-tripdata.csv')
df_202210 <- read_csv('202210-divvy-tripdata.csv')
df_202211 <- read_csv('202211-divvy-tripdata.csv')
df_202212 <- read_csv('202212-divvy-tripdata.csv')

# combine all dataframes into one dataframe
df_2022 <- bind_rows(df_202201,df_202202,df_202203,df_202204,df_202205,df_202206,
                     df_202207,df_202208,df_202209,df_202210,df_202211,df_202212)
head(df_2022)

# check for missing data
colSums(is.na(df_2022))

# remove columns that are not needed
df_2022 <- df_2022 %>%
  select(-c(start_lat,start_lng,end_lat,end_lng,
            start_station_id,end_station_id,start_station_name,end_station_name))

# column names of the dataframe
colnames(df_2022)

# dimensions of the dataframe
dim(df_2022)

# structure of the dataframe
str(df_2022)

# summary analysis of the dataframe
summary(df_2022)

# check for number of member/casual and rideable type
table(df_2022$member_casual)
table(df_2022$rideable_type)
```

```

# add separate columns for date and time
df_2022$date <- as.Date(df_2022$started_at)
df_2022$month <- format(as.Date(df_2022$date), '%m')
df_2022$day <- format(as.Date(df_2022$date), '%d')
df_2022$year <- format(as.Date(df_2022$date), '%Y')
df_2022$day_of_week <- format(as.Date(df_2022$date), '%A')
df_2022$time <- format(as.POSIXct(df_2022$started_at), format='%H:%M')

# create ride_length column to show the time length of each unique ride
df_2022$ride_length <- (difftime(df_2022$ended_at, df_2022$started_at, units='mins'))
df_2022$ride_length <- as.numeric(as.character(df_2022$ride_length))

# check for negative ride lengths and delete them
table(df_2022$ride_length < 0)

# delete negative ride lengths
df_2022 <- df_2022[!(df_2022$ride_length < 0),]

# check summary of new column
summary(df_2022$ride_length)

```

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## Data analysis

```

# calculate the mean, median, max, min for each type of customer
aggregate(df_2022$ride_length ~ df_2022$member_casual, FUN = mean)

##   df_2022$member_casual df_2022$ride_length
## 1                casual          29.14572
## 2                member          12.71401

aggregate(df_2022$ride_length ~ df_2022$member_casual, FUN = median)

##   df_2022$member_casual df_2022$ride_length
## 1                casual          13.000000
## 2                member           8.833333

aggregate(df_2022$ride_length ~ df_2022$member_casual, FUN = max)

##   df_2022$member_casual df_2022$ride_length
## 1                casual         41387.25
## 2                member          1559.90

aggregate(df_2022$ride_length ~ df_2022$member_casual, FUN = min)

##   df_2022$member_casual df_2022$ride_length
## 1                casual              0
## 2                member              0

```

```

# order the days of week
df_2022$day_of_week <- ordered(df_2022$day_of_week,
                               levels=c('Sunday', 'Monday', 'Tuesday', 'Wednesday',
                                           'Thursday', 'Friday', 'Saturday'))

# average ride time by day of week
aggregate(df_2022$ride_length ~ df_2022$member_casual + df_2022$day_of_week, FUN = mean)

##      df_2022$member_casual df_2022$day_of_week df_2022$ride_length
## 1          casual          Sunday          34.05795
## 2          member          Sunday          14.03124
## 3          casual          Monday          29.18736
## 4          member          Monday          12.27011
## 5          casual          Tuesday          25.82287
## 6          member          Tuesday          12.12949
## 7          casual          Wednesday          24.75085
## 8          member          Wednesday          12.10489
## 9          casual          Thursday          25.54792
## 10         member          Thursday          12.29273
## 11         casual          Friday          28.04425
## 12         member          Friday          12.53077
## 13         casual          Saturday          32.61408
## 14         member          Saturday          14.14006

# analyze by type of customers and days of the week
df_2022 %>%
  mutate(weekday=wday(started_at,label=TRUE)) %>%
  group_by(member_casual,weekday) %>%
  summarise(number_of_rides=n(),average_duration=mean(ride_length)) %>%
  arrange(member_casual,weekday)

## # A tibble: 14 x 4
## # Groups:   member_casual [2]
##   member_casual weekday number_of_rides average_duration
##   <chr>          <ord>          <int>          <dbl>
## 1 casual        Sun            389011          34.1
## 2 casual        Mon            277671          29.2
## 3 casual        Tue            263731          25.8
## 4 casual        Wed            274354          24.8
## 5 casual        Thu            309327          25.5
## 6 casual        Fri            334698          28.0
## 7 casual        Sat            473185          32.6
## 8 member        Sun            387208          14.0
## 9 member        Mon            473335          12.3
## 10 member       Tue            518618          12.1
## 11 member       Wed            523867          12.1
## 12 member       Thu            532255          12.3
## 13 member       Fri            467083          12.5
## 14 member       Sat            443274          14.1

```

```
# analyze by type of customers and month
print(df_2022 %>%
  group_by(member_casual,month) %>%
  summarise(number_of_rides=n(),average_duration=mean(ride_length)) %>%
  arrange(member_casual,month),n=24)
```

```
## # A tibble: 24 x 4
## # Groups:   member_casual [2]
##   member_casual month number_of_rides average_duration
##   <chr>          <chr>          <int>          <dbl>
## 1 casual        01             18520           30.4
## 2 casual        02             21416           26.7
## 3 casual        03             89880           32.6
## 4 casual        04            126417           29.5
## 5 casual        05            280414           30.9
## 6 casual        06            369044           32.1
## 7 casual        07            406046           29.3
## 8 casual        08            358917           29.3
## 9 casual        09            296694           28.0
## 10 casual       10            208988           26.4
## 11 casual       11            100747           21.3
## 12 casual       12             44894           22.3
## 13 member       01             85250           12.0
## 14 member       02             94193           11.4
## 15 member       03            194160           12.0
## 16 member       04            244832           11.5
## 17 member       05            354443           13.4
## 18 member       06            400148           14.0
## 19 member       07            417426           13.7
## 20 member       08            427000           13.4
## 21 member       09            404636           13.0
## 22 member       10            349693           12.0
## 23 member       11            236947           11.1
## 24 member       12            136912           10.6
```

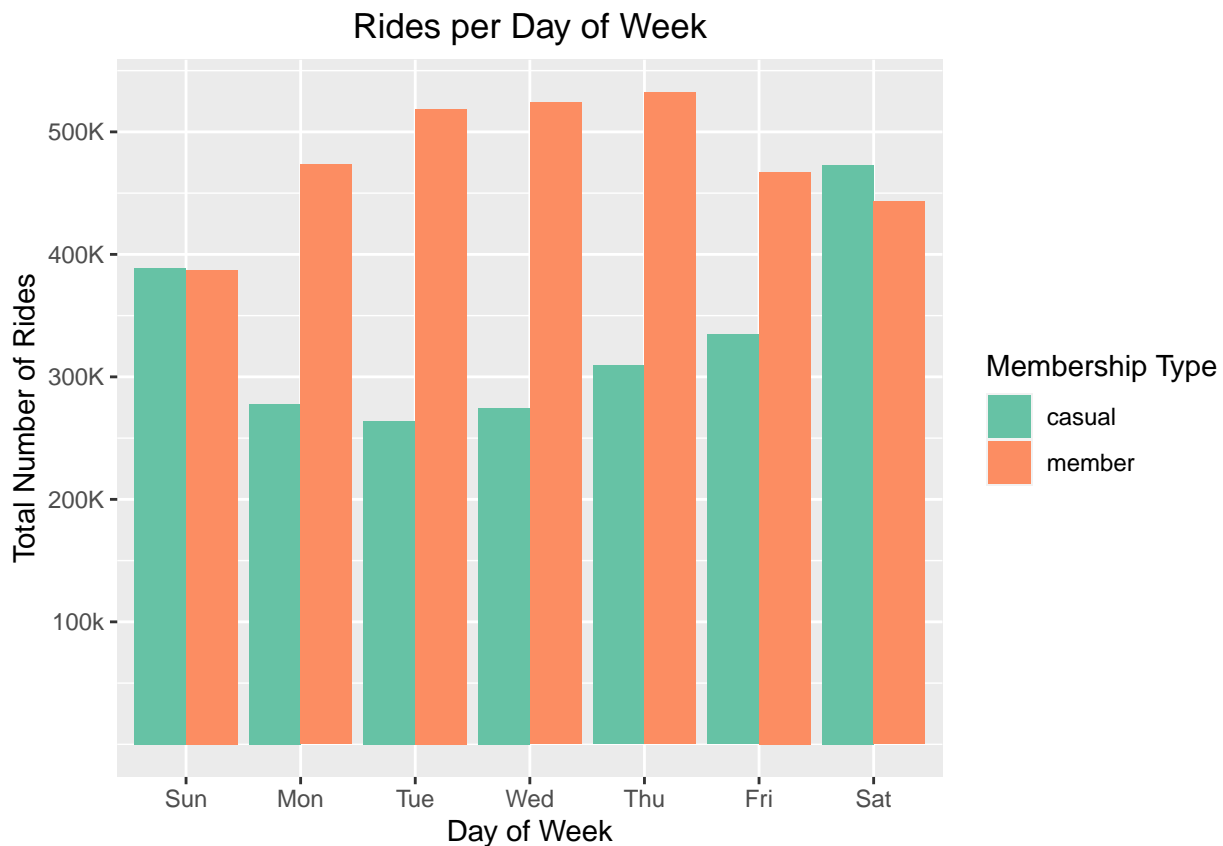
```
# analyze by type of bike
df_2022 %>%
  group_by(member_casual,rideable_type) %>%
  summarise(number_of_rides=n(),average_duration=mean(ride_length)) %>%
  arrange(member_casual,rideable_type)
```

```
## # A tibble: 5 x 4
## # Groups:   member_casual [2]
##   member_casual rideable_type number_of_rides average_duration
##   <chr>          <chr>          <int>          <dbl>
## 1 casual        classic_bike      891443           28.8
## 2 casual        docked_bike      177474           123.
## 3 casual        electric_bike    1253060           16.2
## 4 member        classic_bike     1709743           13.9
## 5 member        electric_bike    1635897           11.5
```

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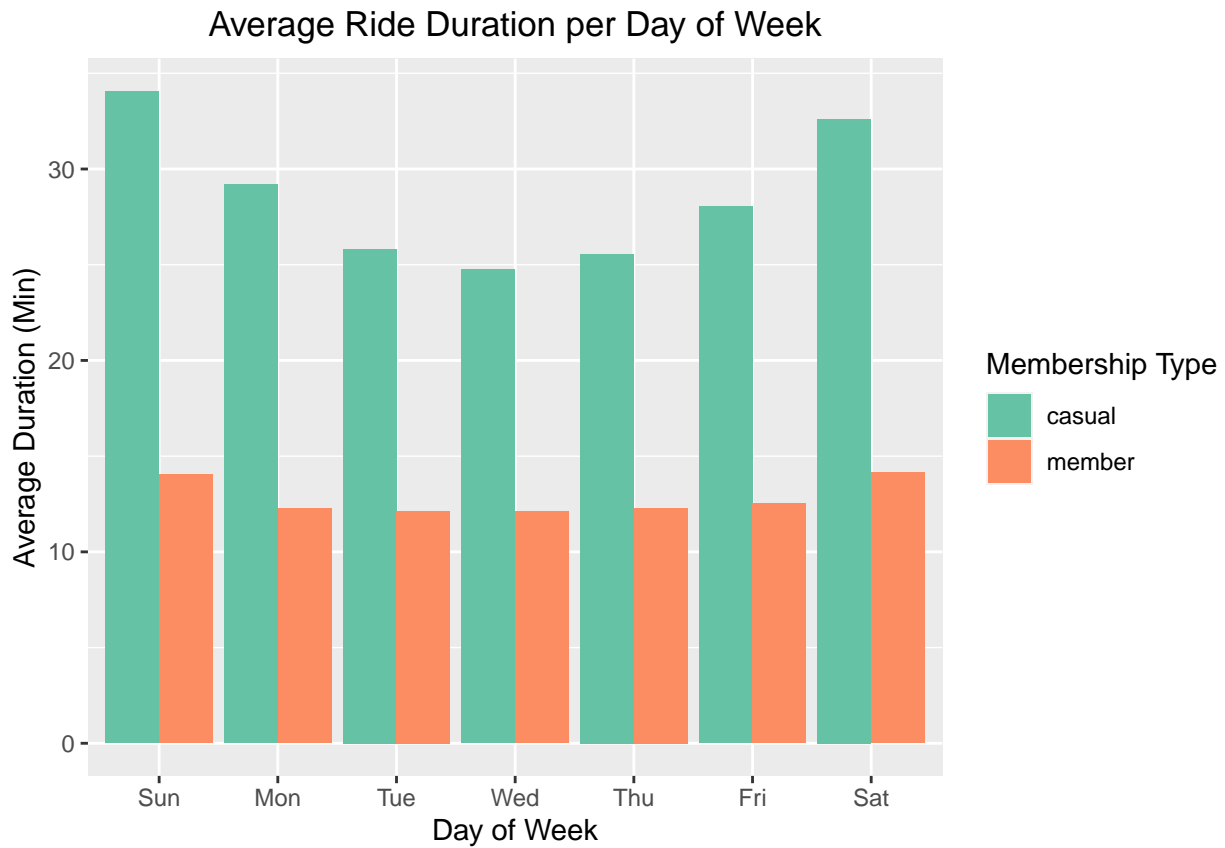
## Data visualizations

```
# bar chart of number of rides by day of week
df_2022 %>%
  mutate(weekday=wday(started_at,label=TRUE)) %>%
  group_by(member_casual,weekday) %>%
  summarise(number_of_rides=n()) %>%
  arrange(member_casual,weekday) %>%
  ggplot(aes(x=weekday,y=number_of_rides,fill=member_casual)) +
  geom_col(position='dodge') +
  labs(x='Day of Week',y='Total Number of Rides',title='Rides per Day of Week',
       fill='Membership Type') +
  theme(plot.title=element_text(hjust=0.5)) + scale_fill_brewer(palette='Set2') +
  scale_y_continuous(breaks=c(100000,200000,300000,400000,500000),
                    labels=c('100k','200K','300K','400K','500K'))
```



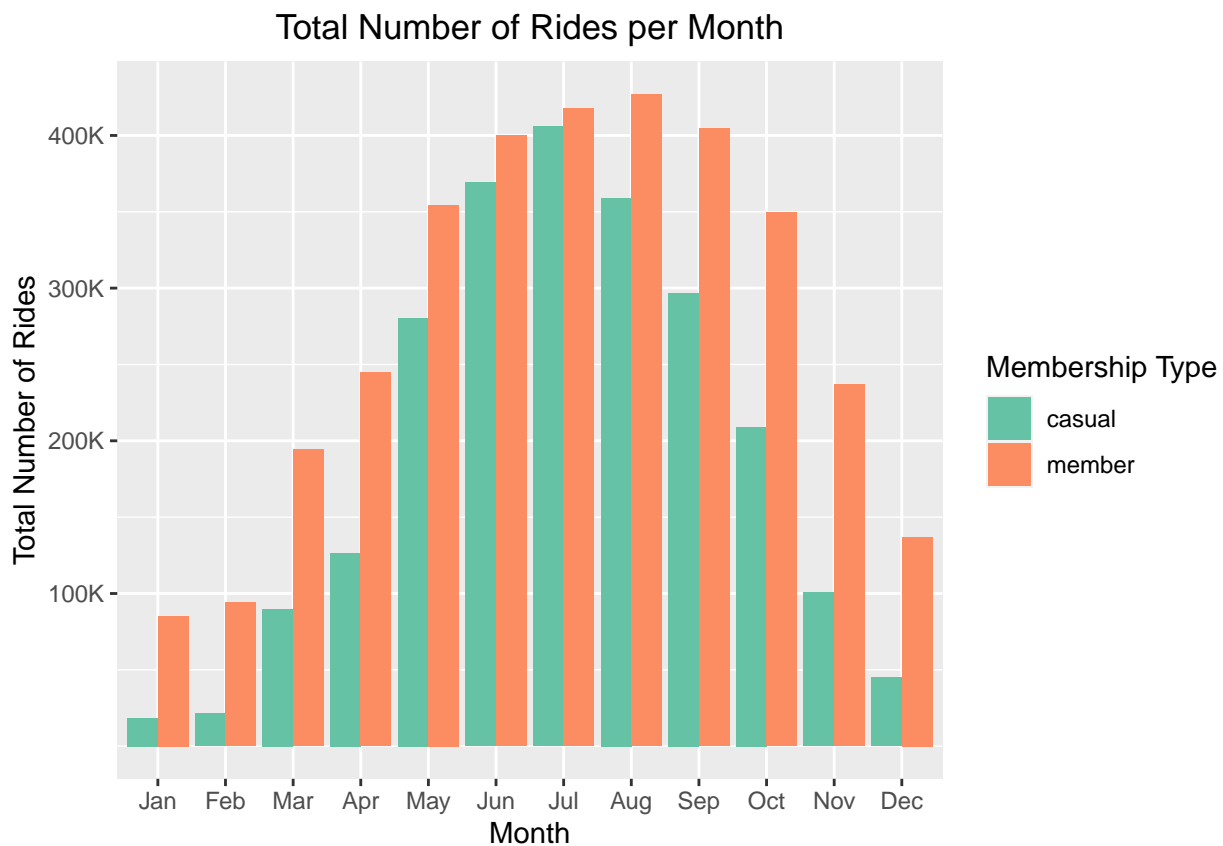
Casual riders bike usage peaks during the weekend while members bike usage peaks during the weekday. This indicates that members use the bike-share service more for commutes while casual riders use the bike-share service more for leisurely purposes on the weekends.

```
# bar chart of average duration of members/casuals
df_2022 %>%
  mutate(weekday=wday(started_at,label=TRUE)) %>%
  group_by(member_casual,weekday) %>%
  summarise(number_of_rides=n(),average_duration=mean(ride_length)) %>%
  arrange(member_casual,weekday) %>%
  ggplot(aes(x=weekday,y=average_duration,fill=member_casual)) +
  geom_col(position='dodge') +
  labs(x='Day of Week',y='Average Duration (Min)',
       title='Average Ride Duration per Day of Week',fill='Membership Type') +
  theme(plot.title=element_text(hjust=0.5)) + scale_fill_brewer(palette='Set2')
```



Overall, casual riders use the bike-share service fewer times but for longer rides while members use the bike-share service more often for shorter rides.

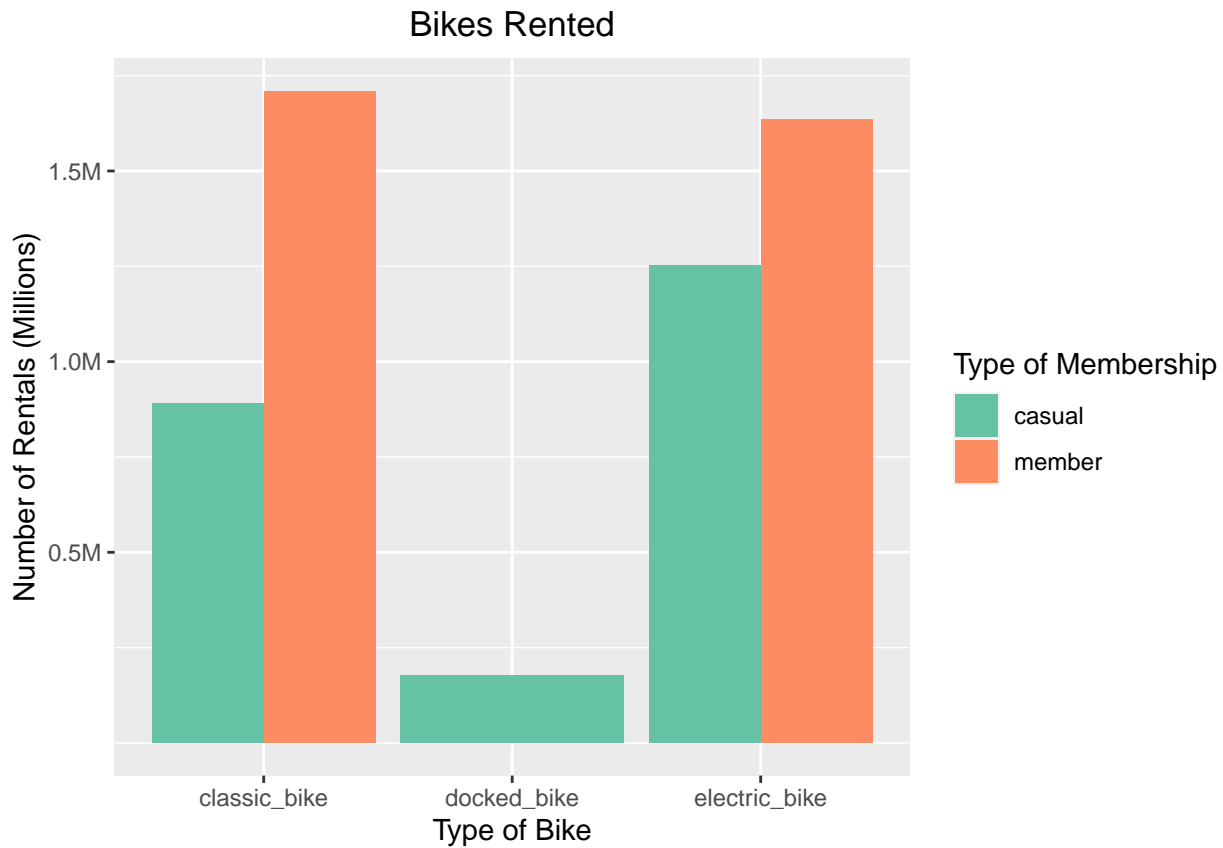
```
# bar chart of number of rides per month
df_2022 %>%
  group_by(member_casual,month) %>%
  summarise(number_of_rides=n()) %>%
  arrange(member_casual) %>%
  ggplot(aes(x=month,y=number_of_rides,fill=member_casual)) +
  geom_col(position='dodge') +
  labs(x='Month',y='Total Number of Rides',title='Total Number of Rides per Month',
       fill='Membership Type') +
  theme(plot.title=element_text(hjust=0.5)) + scale_fill_brewer(palette='Set2') +
  scale_x_discrete(labels=c('Jan','Feb','Mar','Apr','May','Jun',
                           'Jul','Aug','Sep','Oct','Nov','Dec')) +
  scale_y_continuous(breaks=c(100000,200000,300000,400000),
                    labels=c('100K','200K','300K','400K'))
```



For both casual riders and members, the number of rides peak during the warmer summer months of Chicago while the number of rides are fewer in the colder winter months of Chicago, with very few casual riders in the winter.



```
# bar chart of number of rentals by type of bike
df_2022 %>%
  ggplot(aes(x=rideable_type,fill=member_casual)) +
  geom_bar(position='dodge') +
  labs(x='Type of Bike',y='Number of Rentals (Millions)',title='Bikes Rented',
       fill='Type of Membership') +
  theme(plot.title=element_text(hjust=0.5)) + scale_fill_brewer(palette='Set2') +
  scale_y_continuous(breaks=c(500000,1000000,1500000),labels=c('0.5M','1.0M','1.5M'))
```



Most bikes rented are the classic bikes and the electric bikes by both casual riders and members. Members slightly favor the classic bikes while casual riders favor the electric bikes. Members do not ride docked bikes at all while very few casual riders use docked bikes.

## **Key Findings**

- There are more riders who are members than casual riders.
- Members use the bikes throughout the week but slightly more during the weekdays for their commutes but for shorter rides than casual riders.
- Casual riders use the bikes for longer rides and use it more during the weekends than the weekdays.
- The bikes overall are used more during the warmer months compared to the colder months with very few casual riders using the bikes during the winter months.
- Members use the classic bikes and electric bikes, slightly favoring the classic bike and do not use the docked bikes at all. Casual riders favor the electric bikes over the classic bikes with very few using the docked bikes.

## **Recommendations**

- Introduce monthly or seasonal membership options for casual riders for the warmer months but more costly per month than an annual membership.
- Raise prices on single-ride passes or full-day passes. This will push casual riders who use the bike-share service often to become annual members.