Case study: How does a bike-share navigate speedy success ‘Cyclistic’

2025-05-11

Library Installation and Explanation

dplyr

```
install.packages("dplyr")
library(dplyr)
```

This code installs and loads the dplyr package, which is part of the tidyverse collection. dplyr provides a set of tools for data manipulation in R. It allows you to:

- Filter rows of data (filter()),
- Select columns (select()),
- Arrange data (arrange()),
- Mutate data by creating new columns or modifying existing ones (mutate()),
- Summarize data to get statistical summaries (summarize()).

ggplot2

```
install.packages("ggplot2")
library(ggplot2)
```

ggplot2 is a powerful visualization package. It allows you to create complex and beautiful charts such as bar plots, line graphs, and scatter plots using a layered approach.

here

```
install.packages("here")
library(here)
```

The here package makes file paths easier to manage. It finds the root of your project automatically, helping you avoid hard-coded pat

skimr

```
install.packages("skimr")
library(skimr)
```

skimr provides an easy way to view summary statistics of your dataset, such as min, max, mean, and number of missing values.

janitor

```
install.packages("janitor")
library(janitor)
```

The janitor package helps clean messy data. For example, it can standardize column names and detect duplicate rows or missing values

scales

```
install.packages("scales")
library(scales)
```

The scales package is mainly used with ggplot2 to format numbers, percentages, currency, and more in your charts.

lubridate

```
install.packages("lubridate")
library(lubridate)
```

lubridate makes it easier to work with dates and times in R. You can extract or modify components like year, month, and day easily.

Importing CSV Data

```
trip_data_2019 <- read_csv("Divvy_Trips_2019_Q1.csv")
trip_data_2020 <- read_csv("Divvy_Trips_2020_Q1.csv")
```

The code above loads two datasets into R using the read_csv() function from the readr package.

- trip_data_2019 refers to the data from Divvy_Trips_2019_Q1.csv
- trip_data_2020 refers to the data from Divvy_Trips_2020_Q1.csv

These datasets were downloaded from the following link: Divvy Trip Data Repositoryn

Data Cleaning and Transformation

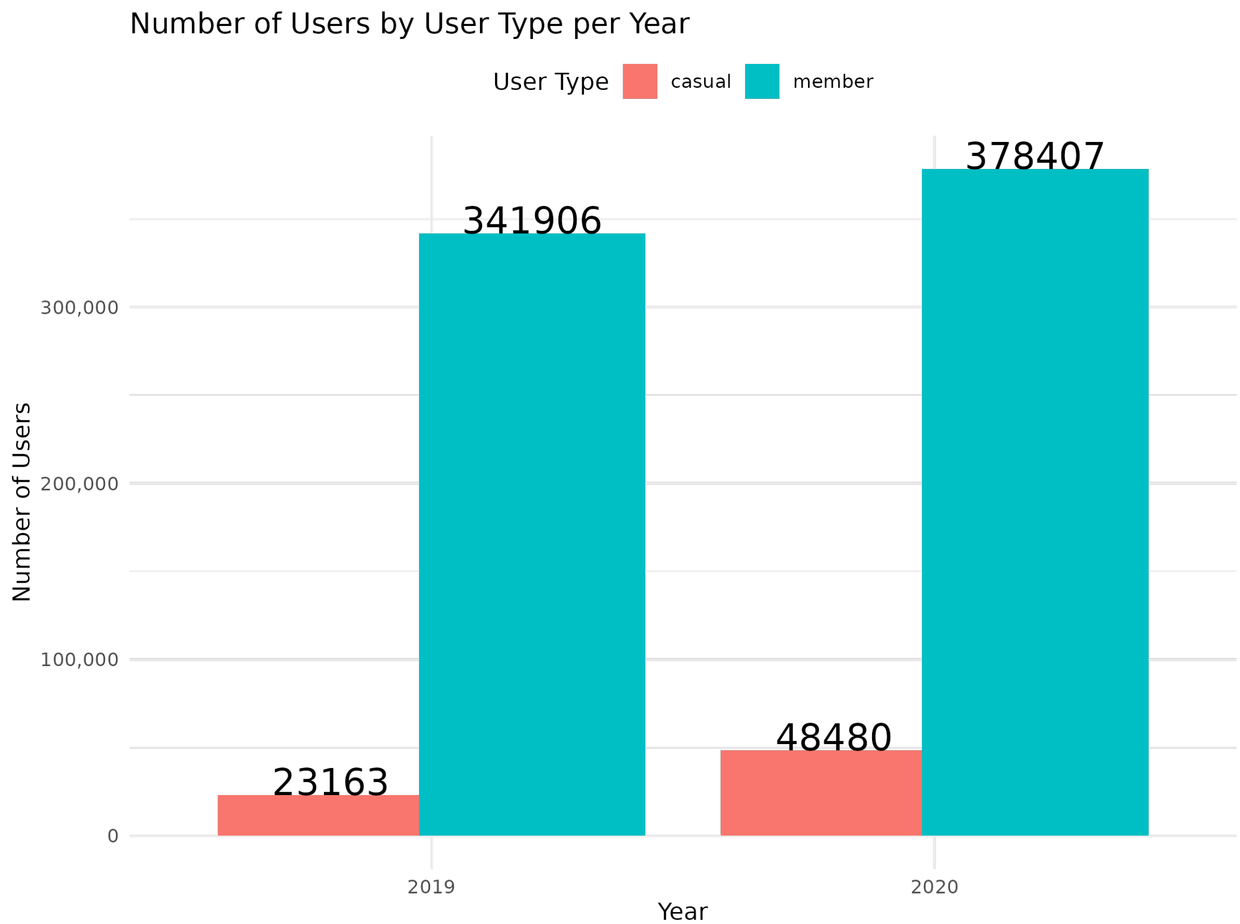
The following R code performs a series of data cleaning and transformation steps on the Divvy trip datasets for 2019 and 2020. This ensures the data is consistent, cleaned of missing values, and ready for analysis.

```
# Cleaning and processing 2019 data by updating usertype values
cleaned_data_2019 <- trip_data_2019 %>%
  select(trip_id, start_time, end_time, usertype) %>%  # Select necessary columns
  filter(!is.na(start_time) & !is.na(end_time) & !is.na(usertype)) %>%  # Remove rows with NA values
  mutate(
    # Calculate ride_length as the difference in time between start_time and end_time (in seconds)
    ride_length = as.numeric(difftime(end_time, start_time, units = "secs")),

    # Add day_of_week column based on start_time (day of the week)
    day_of_week = weekdays(as.Date(start_time)),

    # Replace usertype values: Subscriber becomes member, Customer becomes casual
    usertype = recode(usertype, "Subscriber" = "member", "Customer" = "casual")
  )
```

```r
# Cleaning and processing 2020 data
cleaned_data_2020 <- trip_data_2020 %>%
  # Rename columns to match the 2019 dataset
  rename(
    trip_id = ride_id,
    start_time = started_at,
    end_time = ended_at,
    usertype = member_casual
  ) %>%
  # Select necessary columns
  select(trip_id, start_time, end_time, usertype) %>%
  # Remove rows with NA values in the required columns
  filter(!is.na(start_time) & !is.na(end_time) & !is.na(usertype)) %>%
  # Add ride_length and day_of_week columns
  mutate(
    # Calculate ride_length as the difference in time between start_time and end_time (in seconds)
    ride_length = as.numeric(difftime(end_time, start_time, units = "secs")),

    # Add day_of_week column based on start_time (day of the week)
    day_of_week = weekdays(as.Date(start_time))
  )

# Convert trip_id in both datasets to the same data type (character)
cleaned_data_2019 <- cleaned_data_2019 %>%
  mutate(trip_id = as.character(trip_id))

cleaned_data_2020 <- cleaned_data_2020 %>%
  mutate(trip_id = as.character(trip_id))

# Combine cleaned_data_2019 and cleaned_data_2020 into a single dataset
combined_data_2019_2020 <- bind_rows(cleaned_data_2019, cleaned_data_2020) %>%
  mutate(
    # Add a 'year' column extracted from the 'start_time' field
    year = format(start_time, "%Y"),

    # Add a 'ride_duration' column that converts 'ride_length' to HH:MM:SS format
    ride_duration = sprintf("%02d:%02d:%02d",
                            ride_length %/% 3600,  # Hours
                            (ride_length %% 3600) %/% 60,  # Minutes
                            ride_length %% 60)  # Seconds
  )
```

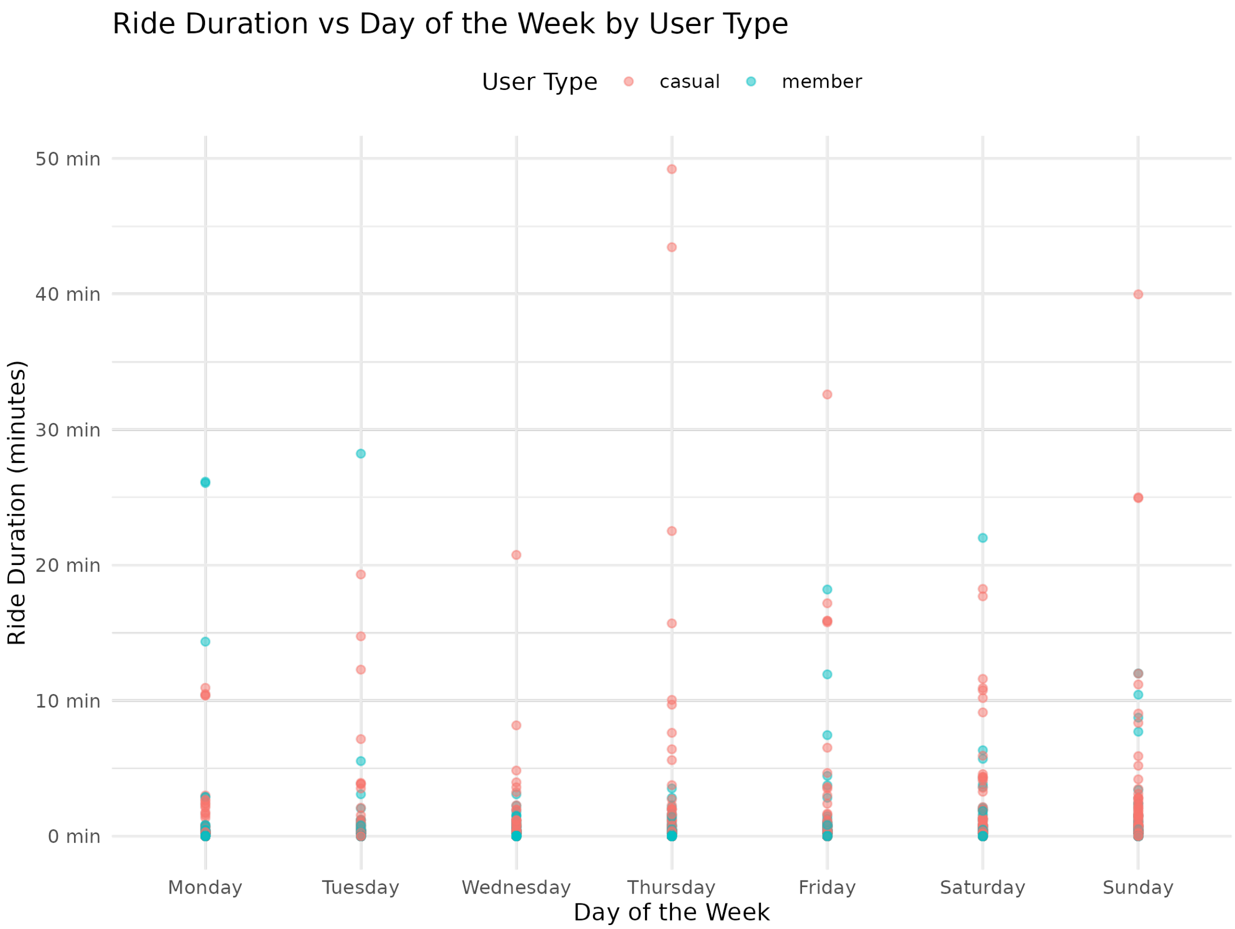
Now the data is clean, unified across years, and enriched with additional columns like day_of_week, ride_length, ride_duration, and year. These will be useful for further analysis and visualization.

Visualization of Users by User Type per Year



As shown in the data, in both 2019 and 2020, the number of casual users significantly surpassed that of members, with a considerable gap between the two groups. This trend highlights the dominance of casual users in comparison to registered members during these years.

Visualization Ride Duration vs Day of the Week by User Type



Casual Users:

- The longest ride durations for casual users occur on Thursdays, Fridays, Sundays, and Wednesdays.
- The peak ride duration is observed on Thursday, reaching almost 50 minutes on average.
- This suggests that casual users tend to take longer rides closer to or during the weekend, possibly for leisure or recreational purposes.

Member Users:

- The longest ride durations for members are recorded on Mondays, Tuesdays, and Saturdays.
- The highest average for member users is seen on Tuesday, with a duration close to 30 minutes.
- This pattern may reflect more consistent, utility-based use such as commuting or routine travel.

Comparison Between User Types:

- Casual users consistently have longer ride durations compared to member users across most days.
- The difference in ride duration between casual and member users is especially noticeable on weekends and Thursdays.
- Member ride durations are relatively stable and shorter, indicating a more predictable usage pattern.

Overall Insight:

- Members may be using the service more for commuting or quick trips, reflected in shorter and steadier durations throughout the week.

Conclusion

- The analysis reveals a significant difference in ride behavior between casual and member users.
- Casual users consistently take longer rides, especially on Thursdays, Fridays, and weekends, often reaching up to 50 minutes.
- In contrast, member users have shorter and more consistent ride durations, likely due to routine commuting.

Implication

- Since casual users ride for longer durations, there is an opportunity to encourage them to convert to membership.
- One potential strategy is to offer a membership discount or promotion for casual users who often exceed a certain ride duration (e.g., more than 30 minutes).
- This could provide better value for users while increasing the number of registered members and enhancing user retention.