# Cyclistic Bike-Share Case Study (Google Data Analytics Capstone)

**Tools:** R (tidyverse, lubridate, janitor, ggplot2), SQL (for sanity checks), Excel (spot checks).

**Data:** 12 months of Cyclistic trips (CSV, millions of rows).

**Goal:** Understand how **casual riders** vs **annual members** use bikes differently to inform a campaign that **converts casuals to members**.

#### **ASK**

#### **Business task:**

Identify behavioral differences between casual riders and members to recommend **data-driven tactics** that increase annual memberships.

#### **Primary question:**

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

#### Stakeholders:

Director of Marketing (Lily Moreno), Marketing Analytics Team, Executive Team.

### **PREPARE**

Data source: Cyclistic historical trip data (12 months).

Format: CSV; typical columns include:

• ride\_id, rideable\_type, started\_at, ended\_at, start\_station\_name, end\_station\_name, member\_casual, etc.

Storage: Local data/ folder; sample data for repo, full data kept locally (files are large).

#### **Quality & limitations:**

Missing station names/IDs for some rows.

- Outliers (negative or extremely long ride durations) must be removed.
- Time fields in local timezone; confirm and normalize.

## PROCESS (Cleaning & feature engineering with R)

```
# packages
library(tidyverse)
library(lubridate)
library(janitor)
# load multiple months (example pattern)
files <- list.files("data", pattern = "\\.csv$", full.names = TRUE)</pre>
trips_raw <- files %>% map_df(read_csv)
# basic cleaning
trips <- trips_raw %>%
 clean_names() %>%
 mutate(
    started_at = ymd_hms(started_at),
    ended_at = ymd_hms(ended_at),
    ride_length_min = as.numeric(difftime(ended_at, started_at, units
= "mins")),
    day_of_week = wday(started_at, label = TRUE, week_start = 1),
    month = floor_date(started_at, "month"),
    hour = hour(started_at)
  ) %>%
  # keep valid rows only
 filter(
    !is.na(started_at), !is.na(ended_at),
    ride_length_min > 0,
                                   # remove negative/zero durations
    ride_length_min <= 1440  # cap at 24h to remove extreme
outliers
  ) %>%
 # trim whitespace in station names
 mutate(
    start_station_name = str_squish(start_station_name),
```

```
end_station_name = str_squish(end_station_name)
)
```

#### Sanity checks with SQL (optional):

```
-- avg ride length by member type
SELECT member_casual, AVG(TIMESTAMPDIFF(MINUTE, started_at, ended_at))
AS avg_mins
FROM trips
WHERE ended_at > started_at AND TIMESTAMPDIFF(MINUTE, started_at, ended_at) <= 1440
GROUP BY member_casual;</pre>
```

# **ANALYZE** (Key comparisons)

#### 1) Ride duration & frequency

```
duration_summary <- trips %>%
  group_by(member_casual) %>%
  summarise(
    rides = n(),
    avg_mins = mean(ride_length_min),
    median_mins = median(ride_length_min)
)
print(duration_summary)
```

#### 2) Day-of-week & hour patterns

```
dow_pattern <- trips %>%
  count(member_casual, day_of_week, name = "rides")
hour_pattern <- trips %>%
  count(member_casual, hour, name = "rides")
```

#### 3) Seasonality (monthly trend)

```
monthly <- trips %>%
  count(member_casual, month, name = "rides")
```

#### 4) Start stations (top locations)

```
top_stations <- trips %>%
  filter(!is.na(start_station_name), start_station_name != "") %>%
  count(member_casual, start_station_name, sort = TRUE, name =
"rides") %>%
  group_by(member_casual) %>%
  slice_head(n = 10)
```

## **SHARE (Visuals for stakeholders)**

Export plots to images/ and embed them below.

#### Ride duration distribution (members vs casuals)

#### Rides by day of week

```
ggplot(dow_pattern, aes(x = day_of_week, y = rides, fill =
member_casual)) +
  geom_col(position = "dodge") +
  labs(title = "Rides by Day of Week", x = "", y = "Rides")
ggsave("images/rides_by_dow.png", width = 8, height = 5, dpi = 300)
```

#### Hourly usage pattern

```
ggplot(hour_pattern, aes(x = hour, y = rides, color = member_casual))
+
    geom_line(linewidth = 1) +
    labs(title = "Hourly Usage Pattern", x = "Hour of Day", y = "Rides")
ggsave("images/hourly_usage.png", width = 8, height = 5, dpi = 300)
```

#### Monthly seasonality

```
ggplot(monthly, aes(x = month, y = rides, color = member_casual)) +
  geom_line(linewidth = 1) +
  labs(title = "Monthly Rides by Rider Type", x = "Month", y =
  "Rides")
ggsave("images/monthly_trend.png", width = 8, height = 5, dpi = 300)
```

#### Top start stations (table preview)

```
top_stations %>% print(n = 20)
```

## **INSIGHTS** (example findings—validate with your results)

- Casual riders tend to have longer average ride durations and higher weekend usage (leisure behavior).
- Members ride shorter, more consistent trips concentrated on weekday peaks (commute behavior).
- There's strong seasonality (summer spikes) for both, but casual riders show bigger seasonal swings.
- Top casual stations cluster near tourist/recreation areas; member stations cluster near transit/work hubs.

## **ACT (Recommendations)**

#### 1. Convert casuals with targeted offers:

- Weekend → Weekday trial: "Ride to work free for 2 weeks if you rode this weekend."
- o **Bundle**: multi-month discounted membership during peak season.

#### 2. Geo-targeting & creatives:

- o Promote at top casual stations with QR codes and membership benefits.
- Messaging focused on cost savings + convenience for frequent riders.

#### 3. Product nudges in app:

 If a casual rider takes ≥3 rides/month, show in-app calculator comparing per-ride vs membership.

#### 4. Measure & iterate:

- A/B test landing pages and in-app banners.
- Track conversion rate, CAC, 30/90-day retention.

#### Success metrics:

Membership conversion rate, churn rate, average rides per member, revenue per user.

## Repo Structure (suggested)

```
| L viz.R
|- images/
| L duration_hist.png
| L rides_by_dow.png
| L hourly_usage.png
| L monthly_trend.png
| .gitignore
```