Cyclistic Bike-Share Case Study Report

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Executive Summary

Cyclistic is a Chicago-based bike-share program seeking to increase annual memberships. This case study analyses differences in usage behaviour between annual members and casual riders using Cyclistic trip data from Q1 and Q4 of 2019. Data cleaning and analysis were conducted using SQL in BigQuery, with insights visualized in Tableau.

The analysis shows that annual members account for approximately 88% of total rides and demonstrate consistent weekday usage aligned with commuter behaviour. In contrast, casual riders make up roughly 12% of rides but take significantly longer trips—nearly three times the average duration of members—and exhibit peak usage on weekends. These patterns indicate that members primarily use the service for short, purpose-driven trips, while casual riders engage in longer, leisure-oriented rides.

These behavioural differences highlight clear opportunities to convert casual riders into annual members. By targeting high-engagement periods such as weekends, rewarding long-duration usage, and aligning seasonal marketing efforts with peak casual demand, Cyclistic can drive membership growth while continuing to support its core commuter base.

1. Ask Phase

Business Task

Determine how annual members and casual riders use Cyclistic bikes differently in order to inform a targeted marketing strategy aimed at converting casual riders into annual subscribers.

Primary Research Question

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

Success Metric

Success will be measured by an increase in annual memberships driven by the conversion of casual riders, while maintaining satisfaction and usage levels among existing members.

Stakeholders

- Cyclistic Executive Team
- Marketing Department
- Director of Marketing (Lily Moreno)

2. Prepare Phase

Data Source

The analysis uses publicly available Cyclistic (Divvy) bike-share trip data for the first and fourth quarters of 2019. The dataset was accessed through the BigQuery public data repository.

Data Structure

The data is provided in CSV format with consistent column naming across quarters. Key fields used in the analysis include ride identifiers, start and end timestamps, station information, and user type classifications.

Data Limitations

Due to BigQuery Sandbox storage restrictions, trip data for Q2 and Q3 could not be imported, limiting full-season analysis. As a result, seasonal trends are inferred from partial-year data. Additionally, timestamp formats required standardization during data preparation.

Data Ethics and Security

All data is fully anonymized and contains no personally identifiable information. The dataset is publicly available and approved for analytical use, ensuring compliance with ethical data handling standards.

3. Process Phase

Data Cleaning and Transformation

Trip data from the first and fourth quarters of 2019 were combined into a single dataset using a union operation to enable consolidated analysis. Ride duration was calculated in minutes using the difference between start and end timestamps. Additional features, including day of week and month, were extracted from trip start times to support temporal analysis. Records with negative ride durations or trips exceeding 24 hours were removed to ensure data accuracy and consistency. A cleaned database view was created to support downstream analysis.

Validation and Quality Checks

Post-cleaning validation checks were performed to confirm data integrity. Row counts were compared before and after cleaning to ensure no unintended data loss occurred. Key fields, including ride identifiers, timestamps, and user type classifications, were checked for null values. User type labels were reviewed to confirm consistent categorization across merged datasets.

4. Analyze Phase

4.1 Ride Volume by User Type

As shown in Figure 1, annual members account for approximately 88% of total Cyclistic rides, while casual riders represent the remaining 12%. This substantial difference indicates that members use the bike-share service far more frequently than casual riders. The high ride volume among members suggests strong reliance on Cyclistic for routine and repeat travel, consistent with commuter-oriented usage. In contrast, the lower share of rides among casual users indicates more occasional engagement with the service.

4.2 Ride Duration

As illustrated in Figure 2, casual riders take significantly longer trips than annual members, with an average ride duration of approximately 35 minutes compared to about 11 minutes for subscribers. This pronounced difference suggests that casual riders primarily use Cyclistic bikes for leisure or recreational purposes rather than for time-sensitive travel. In contrast, the shorter and more consistent ride durations among members indicate purpose-driven usage, such as commuting or routine errands. These duration patterns reinforce the behavioral distinction between the two rider segments

4.3 Weekly Ride Patterns

As shown in Figure 3, annual members exhibit the highest ride activity during weekdays, with usage peaking from Monday through Friday and declining sharply over the weekend. This pattern aligns closely with commuter-driven behavior, where bikes are used for regular work-related travel. In contrast, casual riders demonstrate lower usage during weekdays and significantly higher activity on Saturdays and Sundays. The divergence in weekly usage patterns highlights the routine nature of member trips versus the discretionary, leisure-focused usage of casual riders.

4.4 Daily Composition

Figure 4 illustrates the daily composition of rides by user type. During weekdays, annual members dominate total ride volume, accounting for more than 90% of all trips. On weekends, however, the share of casual riders increases substantially, reaching approximately 35–40% of total rides. This shift indicates that casual riders contribute disproportionately to weekend demand, while members remain the primary users during the workweek. The contrasting composition further reinforces the distinction between commuter-oriented members and leisure-oriented casual riders.

4.5 Monthly Trends

As shown in Figure 5, average ride duration trends differ between user types within the available Q1 and Q4 data range. Casual riders exhibit longer average ride durations during warmer periods, particularly in October, suggesting increased leisure activity during more favorable weather conditions. In contrast, annual members maintain relatively consistent ride durations across months, indicating stable, purpose-driven usage regardless of seasonality. Although full seasonal analysis is limited by missing Q2 and Q3 data, the observed pattern highlights the greater sensitivity of casual riders to seasonal conditions compared to members.

5. Share Phase

Insights from the analysis were communicated to stakeholders through a series of Tableau visualizations designed to highlight key differences in behaviour between annual members and casual riders. The dashboards were structured to support executive-level decision-making by clearly linking usage patterns to potential membership conversion opportunities. Each visualization focuses on a specific dimension of rider behaviour and reinforces the overall analytical narrative.

The following visuals were included in the final presentation:

Figure 1: Total Rides by User Type — Compares overall ride volume between annual members and casual riders.

Figure 2: Average Ride Duration by User Type — Highlights differences in trip length between rider segments.

Figure 3: Weekly Usage Patterns — Shows variation in ride activity across days of the week for each user type.

Figure 4: Daily Ride Composition — Illustrates shifts in user type contribution between weekdays and weekends.

Figure 5: Monthly Ride Duration Trends — Displays seasonal variation in average ride length within the available data range.

Figure 1. Total Rides by User Type

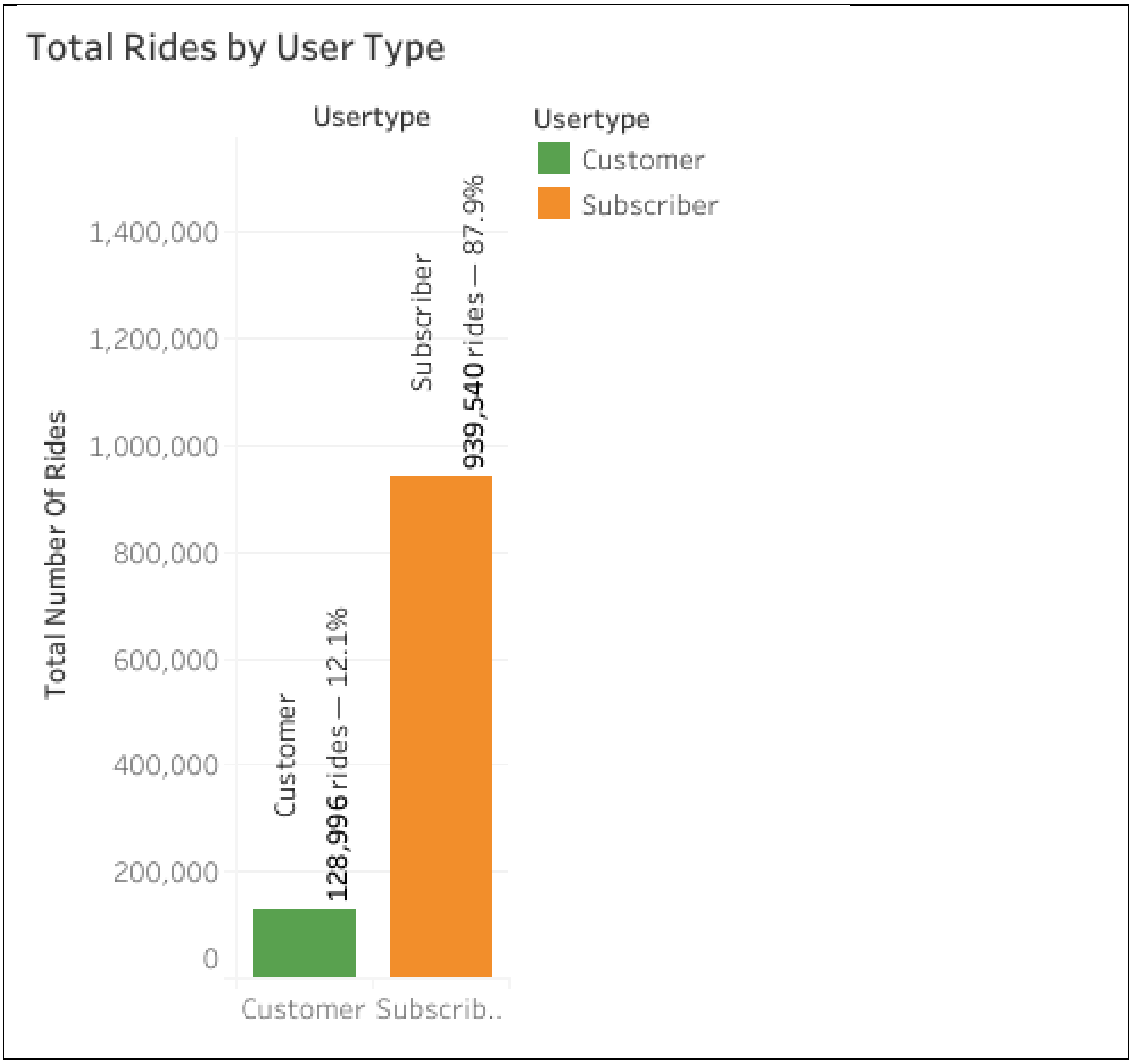


Figure 2. Average Ride Duration Comparison

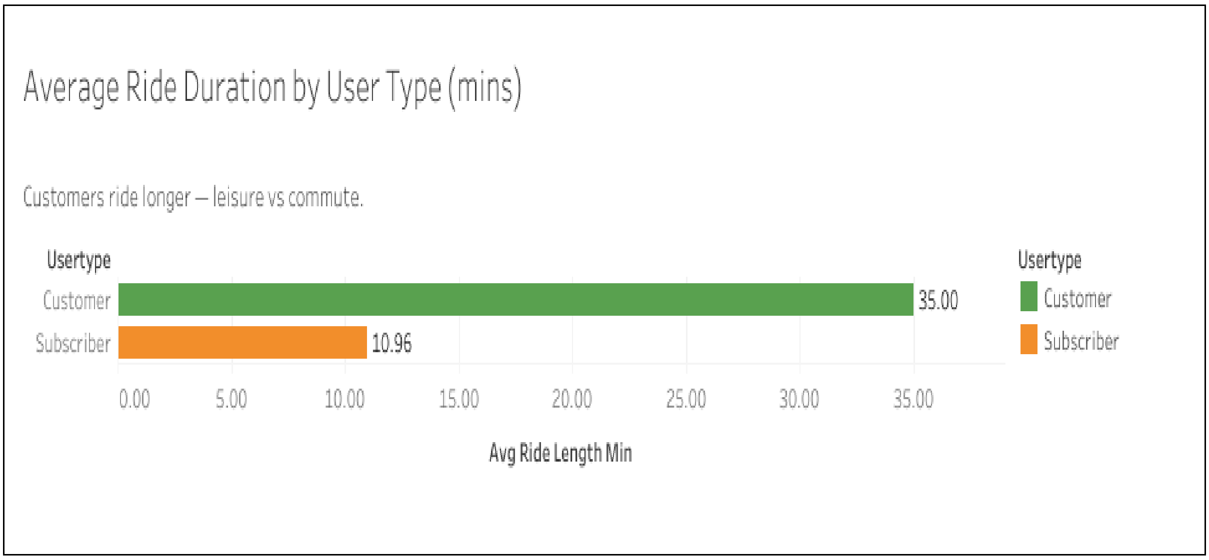


Figure 3. Ride Frequency by Day of Week

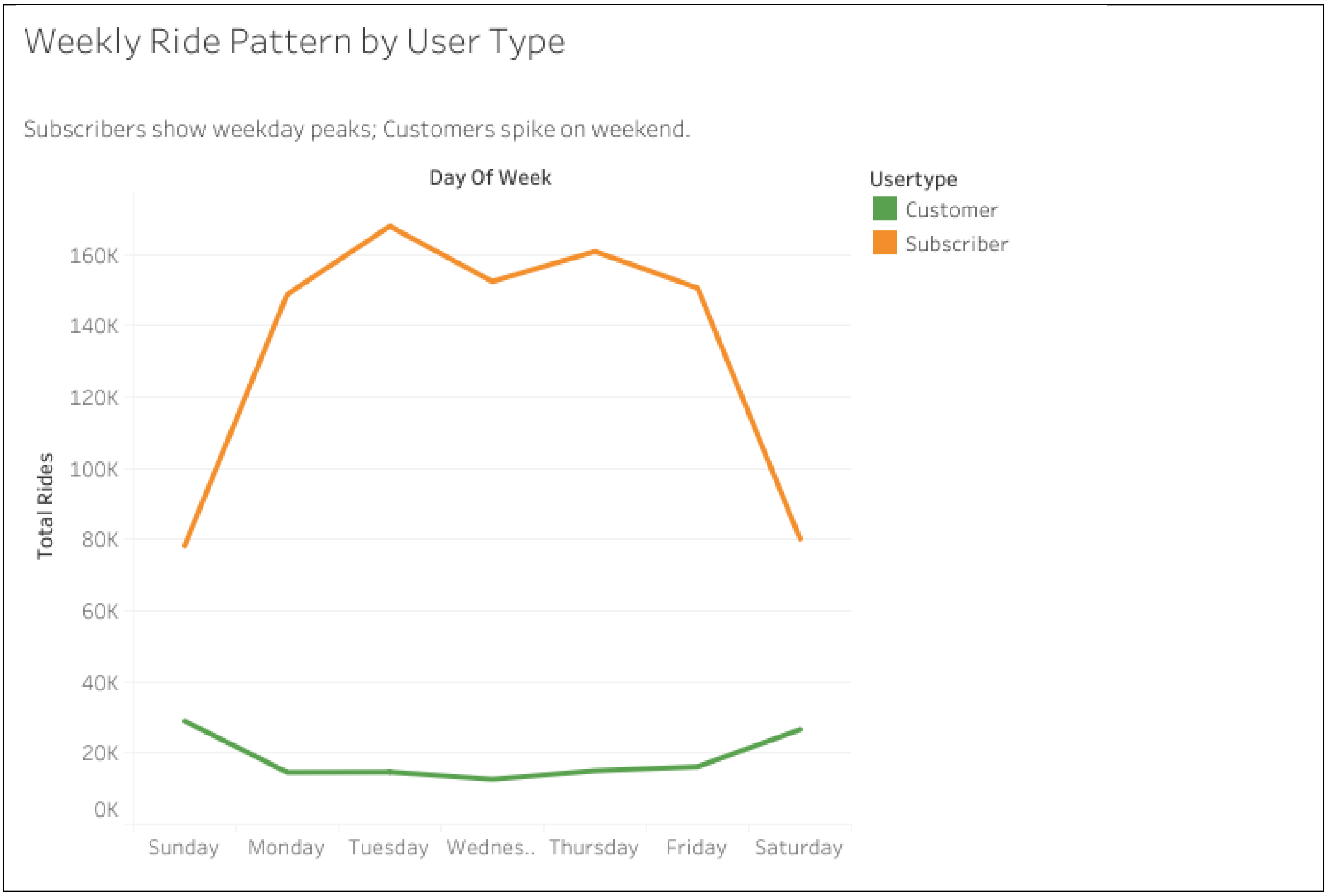


Figure 4. Daily Composition of User Types

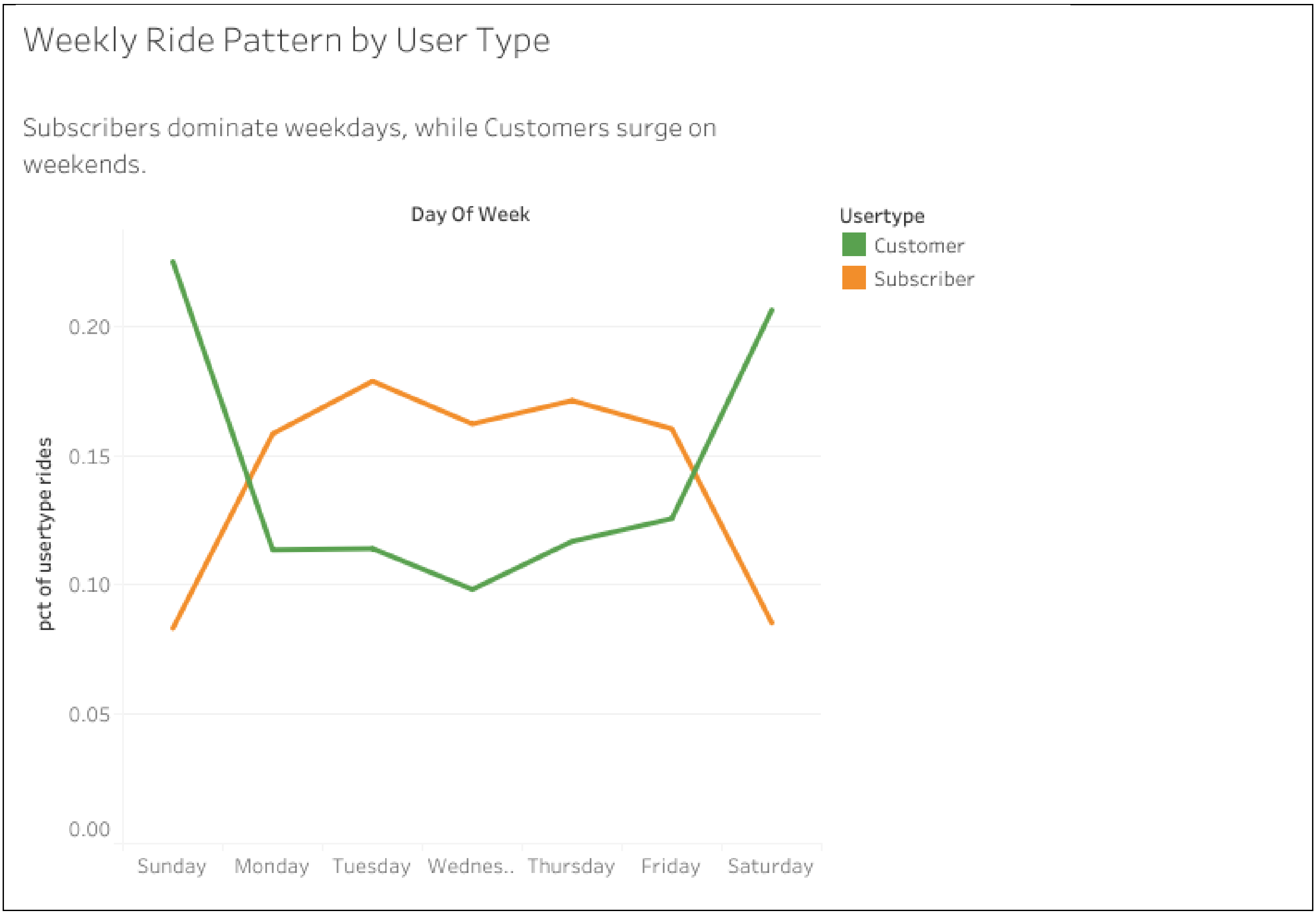
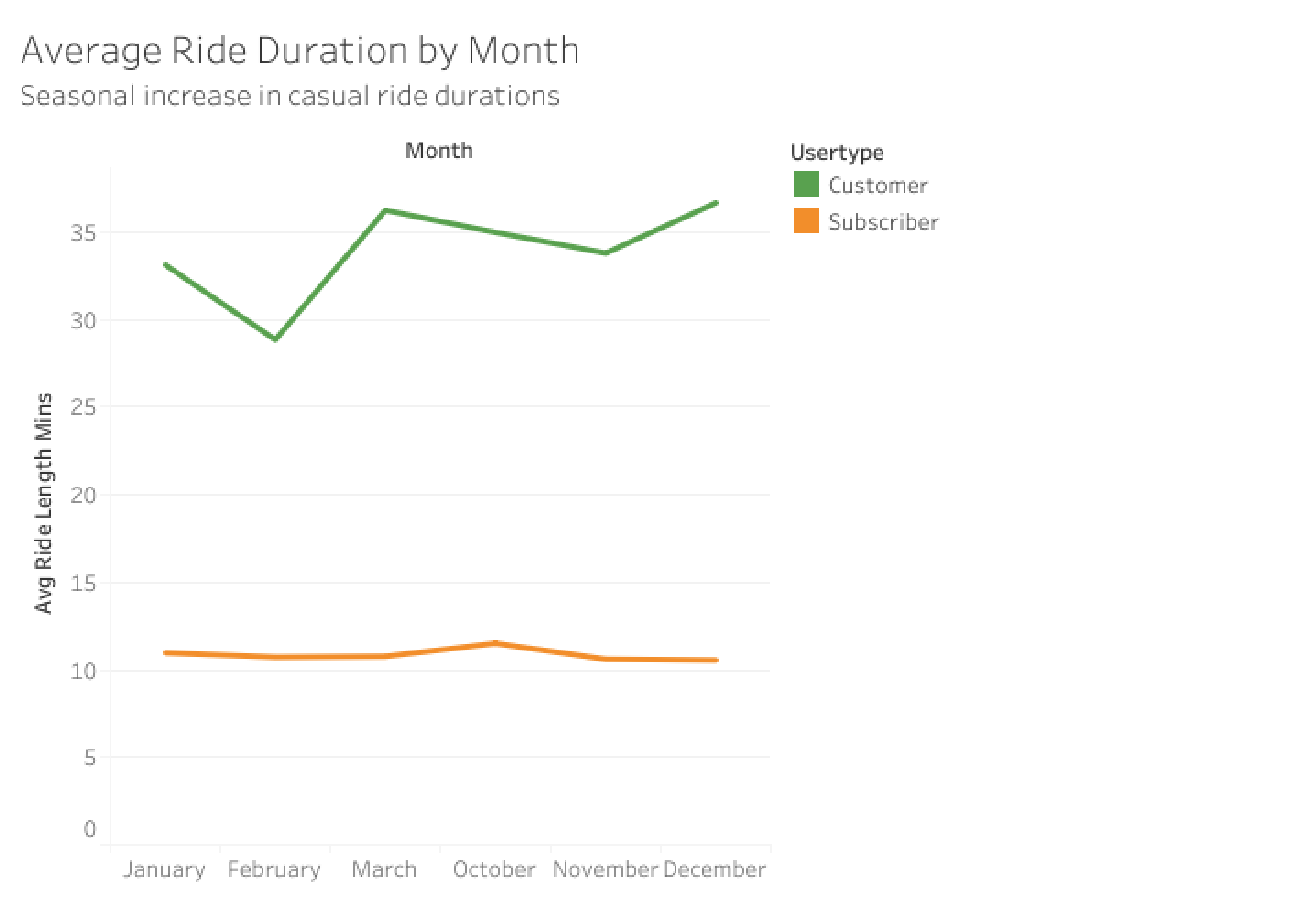


Figure 5. Monthly Ride Duration Trends



6. Act Phase

Based on the behavioural differences identified between annual members and casual riders, several targeted actions are recommended to support Cyclistic's goal of increasing annual memberships. These actions focus on converting high-engagement casual riders while continuing to support the needs of existing members. Each recommendation is directly aligned with observed usage patterns and includes a measurable success indicator.

Recommendation 1: Launch Weekend Conversion Campaigns

Casual rider activity peaks on weekends, indicating strong engagement during leisure periods. Cyclistic should introduce weekend-focused membership promotions, such as limited-time weekend trial memberships and discounted first-month offers for riders who primarily use the service on Saturdays and Sundays. These initiatives leverage existing usage behaviour to encourage commitment without disrupting weekday commuter patterns.

KPI:

Increase weekend-driven annual membership sign-ups by 10% within 90 days.

Recommendation 2: Introduce Loyalty Incentives for Long-Duration Riders

Casual riders consistently record longer trip durations, making them strong candidates for conversion. Cyclistic should implement loyalty incentives such as point-based reward systems, ride bundles, or discounts triggered by repeated long-duration usage. These incentives reward high engagement while gradually encouraging riders to transition to membership plans.

KPI:

Achieve a 5% increase in casual-to-member conversions during peak riding seasons.

Recommendation 3: Strengthen Commuter Support for Annual Members

Annual members display stable, weekday usage patterns consistent with commuter behaviour. To maintain member satisfaction and retention, Cyclistic should improve bike availability during morning peak hours and optimize docking station density in high-demand business districts. Supporting core commuter needs ensures that growth initiatives do not negatively impact existing members.

KPI:

Improve bike availability at key commuter stations by 15% during weekday morning peak hours.

Recommendation 4: Implement Seasonal Marketing Campaigns

Casual rider engagement increases during warmer months, particularly in late summer and early fall. Cyclistic should deploy seasonal marketing campaigns during spring and summer, with tailored messaging for tourists and recreational riders. Aligning promotions with favourable weather conditions maximizes exposure and conversion potential.

KPI:

Increase seasonal casual rider engagement by 12% year-over-year.

Appendix A: SQL Queries and Tableau Dashboards

SQL Queries

The following SQL queries were used for data cleaning, transformation, and analysis using Google BigQuery. Queries shown are representative of the core logic applied during the analysis.

Data Cleaning and Consolidation Query

```
CREATE OR REPLACE VIEW trips_cleaned_view AS
SELECT
  ride_id,
  start_time,
  end_time,
  usertype,
  TIMESTAMP_DIFF(end_time, start_time, MINUTE) AS ride_length,
  FORMAT_DATE('%A', DATE(start_time)) AS day_of_week,
  FORMAT_DATE('%B', DATE(start_time)) AS month
FROM (
  SELECT * FROM cyclistic_q1_2019
  UNION ALL
  SELECT * FROM cyclistic_q4_2019
)
WHERE
  TIMESTAMP_DIFF(end_time, start_time, MINUTE) > 0
  AND TIMESTAMP_DIFF(end_time, start_time, MINUTE) < 1440;
```

Analysis Query: Ride Volume by User Type

```
SELECT
  usertype,
  COUNT(*) AS total_rides
FROM trips_cleaned_view
GROUP BY usertype;
```

Analysis Query: Average Ride Duration by User Type

```
SELECT
  usertype,
  AVG(ride_length) AS avg_ride_duration_minutes
FROM trips_cleaned_view
GROUP BY usertype;
```

Analysis Query: Weekly Usage Patterns

```
SELECT
  usertype,
  day_of_week,
  COUNT(*) AS total_rides
FROM trips_cleaned_view
GROUP BY usertype, day_of_week
ORDER BY usertype, total_rides DESC;
```

Analysis Query: Monthly Ride Duration Trends

```
SELECT
  usertype,
  month,
  AVG(ride_length) AS avg_ride_duration_minutes
FROM trips_cleaned_view
GROUP BY usertype, month
ORDER BY usertype, avg_ride_duration_minutes DESC;
```

Tableau Dashboards

Interactive Tableau dashboards were developed to support exploration and communication of key findings from the analysis. The dashboards were designed for executive and marketing stakeholders, emphasizing clarity, comparability, and ease of interpretation.

The dashboards include the following visual components:

- A comparative bar chart showing total ride volume by user type.
- A summary view comparing average ride duration between annual members and casual riders.
- A weekly usage visualization highlighting differences in ride activity across days of the week.
- A 100% stacked bar chart illustrating daily ride composition by user type.
- A monthly trend view displaying changes in average ride duration within the available data range.

These dashboards enable stakeholders to quickly identify behavioural differences between rider segments and support data-driven decision-making related to membership conversion strategies.

Appendix B: Project Limitations and Challenges

This appendix summarizes key challenges encountered during the Cyclistic case study and how they were addressed.

BigQuery Sandbox Constraints

The analysis was conducted within the BigQuery Sandbox, which imposed storage and feature limitations. Trip data for Q2 and Q3 exceeded allowable size limits, preventing a full-year analysis. To address this, the scope was adjusted to Q1 and Q4 2019, with emphasis placed on behavioural patterns—such as ride duration and weekday versus weekend usage—rather than full seasonal trends.

Applying SQL in a Real-World Dataset

Although familiar with SQL concepts, working with real trip data introduced challenges related to query structure, aggregation logic, and percentage calculations. Iterative validation was required to ensure queries produced results that aligned with the business question, reinforcing the importance of writing intentional and accurate SQL.

Query Design and View Management

While creating cleaned views, issues related to excessive view nesting and circular references occurred. These were resolved by consolidating transformations into fewer, more efficient views, improving both performance and query clarity.

Interpreting Behavioural Patterns

Some metrics showed minimal numerical variation, particularly across months. The challenge was addressed by focusing on contextual patterns—such as commuter versus leisure behaviour—rather than isolated numeric differences.

From Analysis to Action

Translating analytical findings into actionable business recommendations required shifting from technical thinking to strategic reasoning. Linking each recommendation directly to an insight and measurable KPI helped bridge this gap.

Visualization Workflow Challenges

Exporting SQL outputs into Tableau required careful organization. Separating each query result into individual CSV files and creating one visualization per insight improved clarity and consistency.

Appendix C: Key Learnings

This case study provided practical experience across the full data analysis lifecycle.

Structuring Analysis Around a Business Question

I learned how to translate an open-ended business question into focused analytical components, including ride frequency, duration, and temporal usage patterns.

Adapting to Tool Limitations

Working within the BigQuery Sandbox highlighted the need to adapt scope and make trade-offs while still delivering meaningful insights.

Data Inspection and Preparation

The project reinforced the importance of inspecting datasets for consistency and validity before cleaning, ensuring reliable downstream analysis.

SQL for Data Cleaning and Analysis

I gained hands-on experience combining datasets, creating calculated fields, extracting time-based features, and filtering invalid records using SQL.

Writing Purpose-Driven SQL

A key takeaway was learning to write SQL that answers the correct question, understanding how aggregation logic and window functions affect results.

Interpreting Patterns, Not Just Numbers

The analysis emphasized identifying behavioural patterns—such as commuter versus leisure usage—rather than focusing solely on large numerical differences.

Designing Effective Visualizations

I learned how to select visualization types that support a narrative, ensuring clarity and alignment with analytical insights.

Communicating Insights and Driving Action

Finally, the project strengthened my ability to communicate insights clearly and translate analysis into actionable recommendations supported by measurable KPIs.