Google Data Analytics Capstone Project - Cyclistic 2024¶

Introduction

This report presents an analysis of Cyclist ride data from 2024, prepared for the Marketing Department to support future business decisions. The goal is to uncover members behaviours and patterns through 2024 and its' influence to the company. The analysis is conducted as part of the Google Data Analytics Professional Certificate capstone, using a hypothetical company ("Cyclist") and real-world ride data from Divvy Bikes a bike-sharing service based in Chicago.

1. Ask

What is the problem trying to be solved?

The problem trying to be solved is to increase conversion from casual members to annual members.

How can insights be used to drive business decisions?

By understanding behaviours and trends from both members (casual and annual), it is expected to identify and correlate patterns that will guide targeting casual members that could benefit more from the annual membership and how this could be done.

Identify the business task

Identifying trends and key information that helps distinguish casual riders from annual members to help the marketing team understand how to set a strategy visioning converting casual members to annual members.

Key stakeholders

Lily Moreno: The director of marketing and "my" manager. Cyclistic marketing analytics team: A team of data analysts who are responsible for collecting, analysing, and reporting data that helps guide Cyclistic's marketing strategy. Cyclistic executive team: The notoriously detail-oriented executive team will decide whether to approve the recommended marketing program. Cyclistic users: • Casual members: Customers who purchase single-ride or full-day passes • Annual members: Customers who purchase annual memberships

2. Prepare

Data Preparation and Overview

Data was downloaded from the Index of bucket "divvy-tripdata" where 2024 data has been downloaded from January to December. All datasets contain the following columns:

1. ride_id: Unique identifier for each ride
2. rideable_type: Type of bike used for the ride
3. started_at: Start time of the ride
4. ended_at: End time of the ride
5. start_station_name: Name of the station where the ride started
6. end_station_name: Name of the station where the ride ended
7. start_station_id: Unique identifier for the start station
8. end_station_id: Unique identifier for the end station
9. start_lat: Latitude of the start station
10. start_lng: Longitude of the start station
11. end_lat: Latitude of the end station
12. end_lng: Longitude of the end station
13. member_casual: Type of membership (member or casual)

Data was downloaded by month (Jan 24 to Dec 24) - 12 csv files were stored appropriately on the local desktop. The files were uploaded to the GCS (Google Cloud Storage) and merged automatically with BigQuery while linking the 2024 bucket when creating a table on BigQuery 'cyclistic_24'.

Credibility of the data.

The data is credible and reliable as it comes directly from the official Divvy Trip Data website, managed by Motivate International Inc. The data is ROCCC because it is Reliable, Original, Comprehensive, Current, and Cited. It represents real user trips collected, covering all of 2024 to ensure an updated, complete year of insights.

License

The data has been made available by Motivate International Inc. under this license. This is public data that can be used to explore how different customer types are using Cyclistic bikes.

Problems with the Data

There are minor limitations, such as the absence of personal or demographic data and the focus solely on the Chicago area, which may slightly limit broader generalisation. The dataset does not include membership pricing or cost information, which caps revenue calculation and profitability assessment, or determining which membership option offers more value to users based on their spending. Each ride_id does not represent the user and channel of purchase. All observations are intended for educational purposes, not real-life business recommendations.

3. Process

3.1 Documenting data cleaning process and manipulation

The process of cleaning was done with SQL using BigQuery, the data cleaning process can be seen on the following file on GitHub.

Clean version and transformation completed.

The clean version was created and named as 'cyclistic_24_cleaned'. There were several columns added in relation to the data from Index of bucket "divvy-tripdata" such as:

- ride_lenght
- day
- month
- weekday

Having now 9 columns as per below:

1. ride_id: Unique identifier for each ride
2. rideable_type: Type of bike used for the ride
3. started_at: Start time of the ride
4. ended_at: End time of the ride
5. ride_length - Duration of the ride
6. day - Day of the month the ride occured
7. month - Month the ride occured
8. weekday - name of the Day of the week the ride occured
9. member_casual: Type of membership (member or casual)

The dataset was fully cleaned no NULLs, no duplicates, and no rides_length with less than 1 min could be found, ending with a total of 4168627 lines.

3.2 Dataset Imported to Kaggle and R summary of data

Final version has been downloaded as csv file and the dataset was uploaded to kaggle as 'cyclistic_24'.

3.3 Preparing my environment

The Analysis part will be done using R, therefore, the environment will need to be set by loading the needed packages, importing the cyclistic_24 dataset and finally checking the information about the dataset imported.

In [1]:

 # 1. Setting up my Environment

 # Notes: setting up my R environment by loading the tidyverse, skimr, janitor, scales, patchwork, lubridate, stringr, forcats and hms packages.

library(tidyverse)

library(skimr)

library(janitor)

library(scales)

library(patchwork)

library(lubridate)

library(stringr)

library(forcats)

library(hms)

── **Attaching core tidyverse packages** ──────────────────────── tidyverse 2.0.0 ──

✔ dplyr 1.1.4 ✔ readr 2.1.5

✔ forcats 1.0.0 ✔ stringr 1.5.1

✔ ggplot2 3.5.1 ✔ tibble 3.2.1

✔ lubridate 1.9.3 ✔ tidyr 1.3.1

✔ purrr 1.0.2

── **Conflicts** ──
tidyverse_conflicts() ──

✖ dplyr::filter() masks stats::filter()

✖ dplyr::lag()   masks stats::lag()

ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors

Attaching package: 'janitor'

The following objects are masked from 'package:stats':

    chisq.test, fisher.test

Attaching package: 'scales'

The following object is masked from 'package:purrr':

    discard

The following object is masked from 'package:readr':

    col_factor

Attaching package: 'hms'

The following object is masked from ‘package:lubridate’:

hms

In [2]:

 # 2. Importing my dataset

file_path <- "//kaggle/input/cyclistic-24-cleanedv2/cyclistic_24_cleanedV2.csv"

cyclistic_24 <- read.csv(file_path)

In [3]:

 # 3. Information about the dataset

colnames(cyclistic_24)

glimpse(cyclistic_24)

summary(cyclistic_24)

1. 'ride_id'
2. 'started_at'
3. 'ended_at'
4. 'ride_length'
5. 'day'
6. 'month'
7. 'weekday'
8. 'rideable_type'
9. 'member_casual'

Rows: 4,168,627

Columns: 9

```
$ ride_id      <chr> "79C40E1E65E476D9", "4C9B4B6F9E226983",
"48FE138D9F08E68...
$ started_at   <chr> "16:10:36", "13:10:55", "15:45:25", "11:18:01", "17:23:1...
$ ended_at     <chr> "16:12:34", "13:12:32", "15:47:21", "11:19:14", "17:24:5...
$ ride_length  <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...
$ day          <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...
$ month        <int> 10, 5, 8, 9, 2, 2, 7, 2, 10, 7, 8, 11, 5, 11, 4, 1, 9, 1...
$ weekday      <chr> "Tuesday", "Wednesday", "Thursday", "Sunday", "Thursday"...
$ rideable_type <chr> "electric_bike", "electric_bike", "classic_bike", "class...
$ member_casual <chr> "member", "member", "member", "member", "member",
"membe...
  ride_id          started_at          ended_at           ride_length
 Length:4168627    Length:4168627    Length:4168627    Min.   :   1.00
 Class :character  Class :character  Class :character  1st Qu.:   5.00
 Mode  :character  Mode  :character  Mode  :character  Median :  10.00
                                                       Mean   :  16.32
                                                       3rd Qu.:  18.00
                                                       Max.   :1509.00
    day           month          weekday           rideable_type
 Min.   : 1.00  Min.   : 1.000  Length:4168627     Length:4168627
 1st Qu.: 8.00  1st Qu.: 5.000  Class :character   Class :character
 Median :15.00  Median : 7.000  Mode  :character   Mode  :character
 Mean   :15.62  Mean   : 6.965
 3rd Qu.:23.00  3rd Qu.: 9.000
 Max.   :31.00  Max.   :12.000
 member_casual
 Length:4168627
 Class :character
 Mode  :character
```

Found the started_at and ended_at were in character format so this was change as per below

In [4]:

```
#formating started_at and ended_at
cyclistic_24 <- cyclistic_24 %>%
 mutate(
  started_at = hms::as_hms(started_at),
  ended_at   = hms::as_hms(ended_at),
  start_hour = hour(started_at),
  end_hour   = hour(ended_at)
 )
```

In [5]:

```
mean(cyclistic_24$ride_length, na.rm = TRUE)


aggregate(
 ride_length ~ member_casual,
 data = cyclistic_24,
 FUN = mean,
 na.rm = TRUE
)
```

16.318226840636

member_casual	ride_length
<chr>	<dbl>
casual	23.79280

member_casual	ride_length
<chr>	<dbl>
member	12.08928

A data.frame: 2 × 2

4. Analysis

Executive Summary

In this stage, we are looking to compare and understand how casual members and annual members use Cyclistic, considering different types of timeframes, the length of rides and the type of ride being used. It is expected that by understanding these patterns, we will be able to make better recommendations on how to convert casual members into annual members.

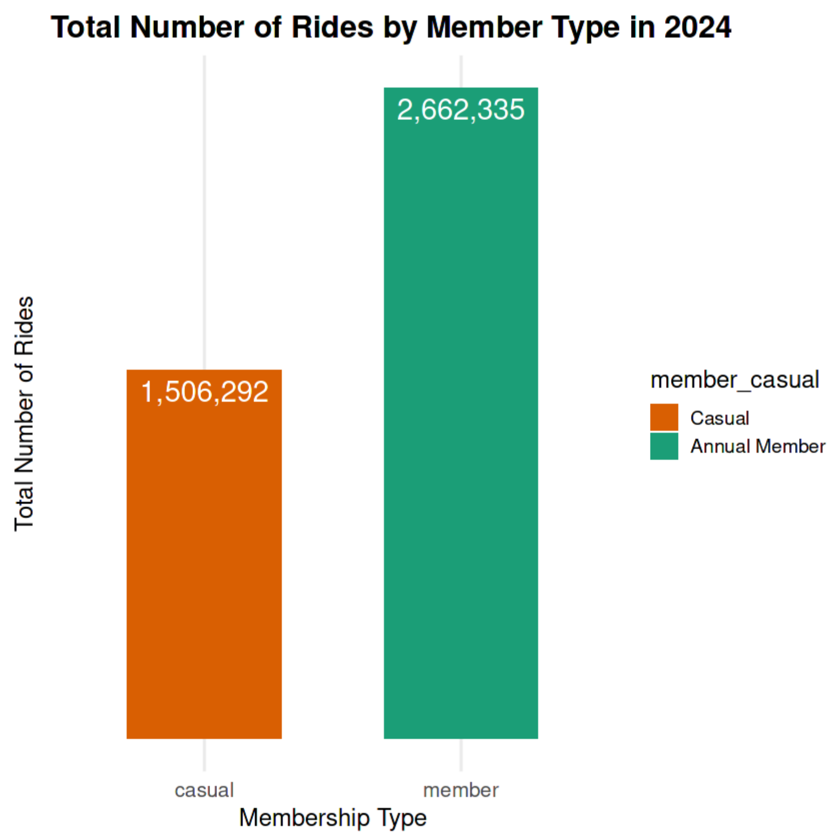
Note: According to the Cyclistic team, Cyclistic users are more likely to ride for leisure, but about 30% use the bikes to commute to work each day.

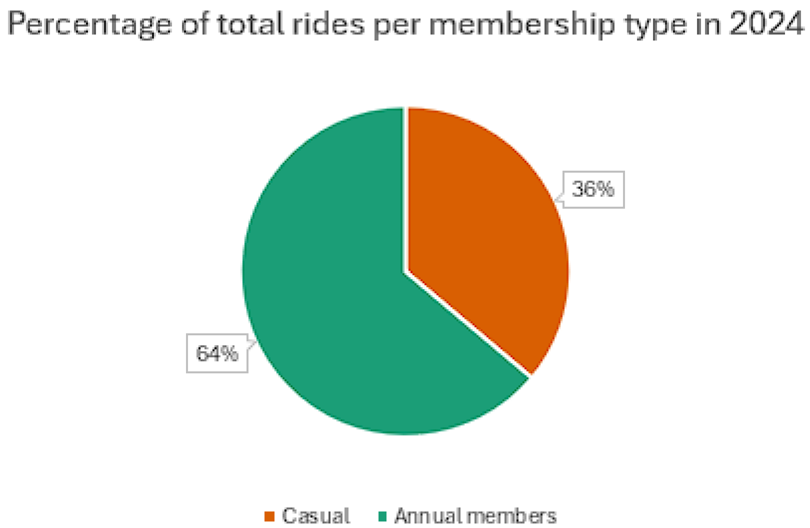
4.1 Analysing Ride Volume

In [6]:

```
# Total number of rides between casual and annual member

total_rides <- cyclistic_24 %>%

 group_by(member_casual) %>%

 summarise(total_rides = n())


print(total_rides)


# Plot

ggplot(total_rides, aes(x = member_casual, y = total_rides, fill = member_casual))
+

 geom_bar(stat = "identity", width = 0.6) +

 geom_text(

    aes(label = label_comma()(total_rides)),  # nicely formatted numbers

   colour = "white",
```

```
    size = 6,
    vjust = 1.5
  ) +
  labs(
    title = "Total Number of Rides by Member Type in 2024",
    x = "Membership Type",
    y = "Total Number of Rides"
  ) +
  theme_minimal() +
  scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77"),
                    labels = c("Casual", "Annual Member"))+
theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(face = "bold", size = 18),
    plot.subtitle = element_text(size = 13),
      axis.text.x = element_text(size = 12),
      axis.text.y  = element_blank(),
    axis.ticks.y = element_blank(),
    panel.grid.major.y = element_blank(),
    panel.grid.minor.y = element_blank()
  )
# A tibble: 2 × 2
  member_casual total_rides
  <chr>           <int>
1 casual        1506292
2 member        2662335
```



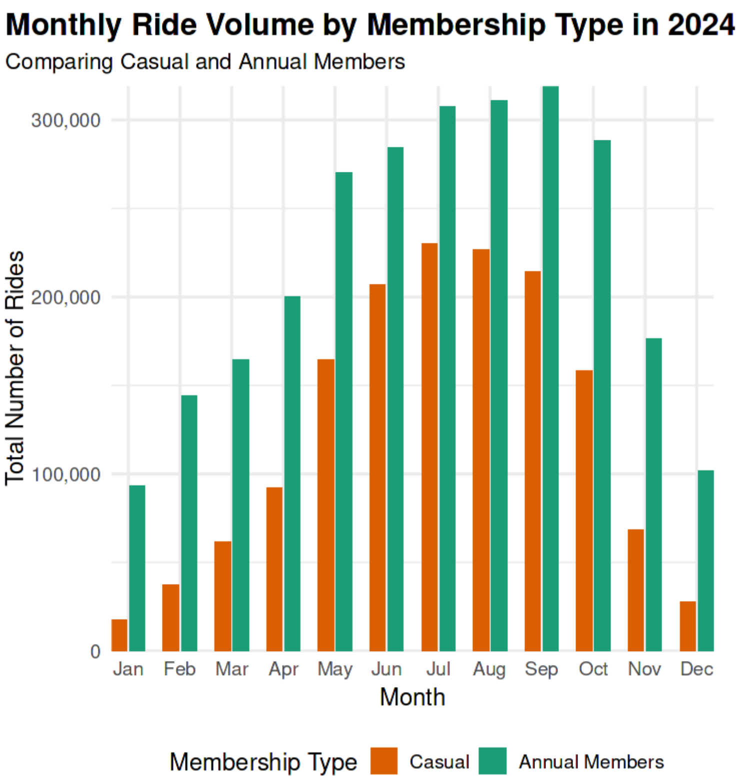


In [7]:

```
monthly_rides <- cyclistic_24 %>%
  group_by(month, member_casual) %>%
  summarise(total_rides = n(), .groups = "drop") %>%
  mutate(
    month = factor(month, levels = 1:12, labels = month.abb, ordered = TRUE)
```

```r
 )

#plot
ggplot(monthly_rides, aes(x = month, y = total_rides, fill = member_casual)) +
 geom_col(position = position_dodge(width = 0.7), width = 0.6) +

 labs(
  title = "Monthly Ride Volume by Membership Type in 2024",
  subtitle = "Comparing Casual and Annual Members",
  x = "Month",
  y = "Total Number of Rides",
  fill = "Membership Type"
 ) +

 scale_fill_manual(
  values = c("casual" = "#d95f02", "member" = "#1b9e77"),
  labels = c("Casual", "Annual Members")
 ) +

 scale_y_continuous(labels = label_comma()) +

 theme_minimal(base_size = 14) +
 theme(
    plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",
  plot.margin = margin(20, 40, 20, 40)  # top, right, bottom, left margins larger
```

```
 ) +

 coord_cartesian(expand = FALSE)  # Avoid default padding, making bars span wider
```



member_casual	total_rides	%
casual	1506292	36%
member	2662335	64%
total	4168627	

The last two plots reflect that the Annual members had a higher number of rides throughout the year, representing 64% of the total rides. Also, when we look to how the volume is spreaded monthly we can see the peak of riding is between June and October, which could correlate with Summer season and the number of rides seem to decrease more from the casual riders than from the annual members, for instance in November the casual riders had a decrease of 57% in relation to the previous month while the annual members had a deecrease of 39%.

month	member_casual	total_rides	Previous month(%)
Jan	casual	17373.00	-38%
Jan	member	93550.00	-8%
Feb	casual	37619.00	117%
Feb	member	144471.00	54%
Mar	casual	61805.00	64%
Mar	member	164709.00	14%
Apr	casual	92244.00	49%
Apr	member	200342.00	22%
May	casual	164362.00	78%
May	member	270051.00	35%
Jun	casual	206717.00	26%
Jun	member	284528.00	5%
Jul	casual	230176.00	11%
Jul	member	307502.00	8%
Aug	casual	226827.00	-1%
Aug	member	311129.00	1%
Sep	casual	214299.00	-6%
Sep	member	319104.00	3%
Oct	casual	158455.00	-26%
Oct	member	288466.00	-10%
Nov	casual	68404.00	-57%
Nov	member	176421.00	-39%
Dec	casual	28011.00	-59%
Dec	member	102062.00	-42%

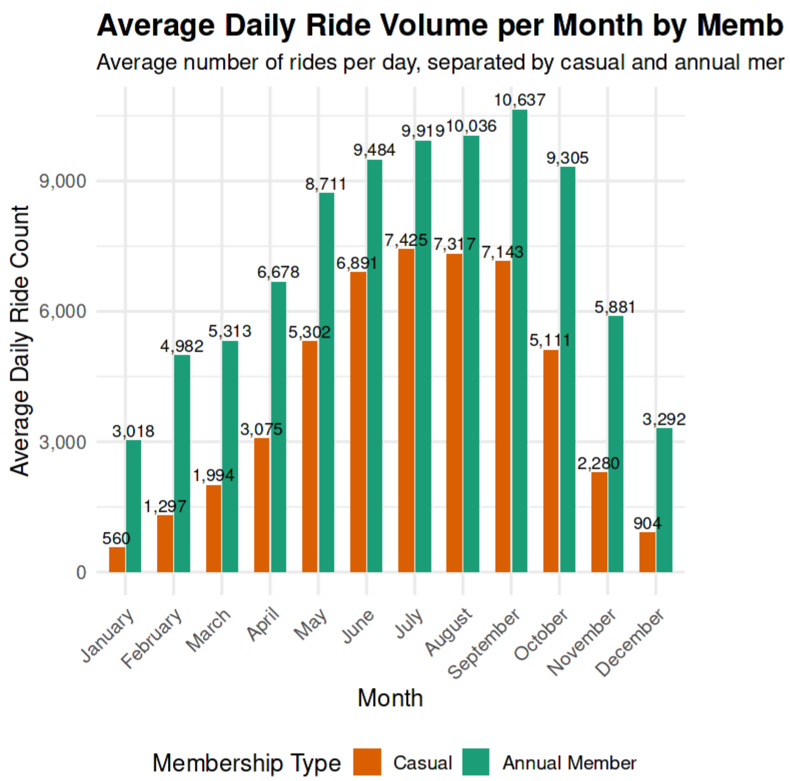
The level of decrease mentioned above between casual and annual members is pointed out in the table above, where we can see the highest declines happening in November, followed by December. And the casual members have a larger decrease than the annual members, suggesting the volume of rides on the annual members is more stable throughout the year.

In [8]:

```
# Calculate average rides per month per membership type

avg_monthly_rides_member <- cyclistic_24 %>%

 group_by(month, member_casual) %>%

 summarise(avg_rides = n() / n_distinct(day), .groups = "drop") %>%

 mutate(

  month = factor(month, levels = 1:12, labels = month.name, ordered = TRUE)

 )
```

```r
# Plot: Average Monthly Ride Volume per Membership Type
ggplot(avg_monthly_rides_member, aes(x = month, y = avg_rides, fill = member_casual)) +
  geom_col(position = position_dodge(width = 0.7), width = 0.6) + # Side-by-side bars
  geom_text(
    aes(label = scales::comma(round(avg_rides, 0))),
    position = position_dodge(width = 0.7),
    vjust = -0.3,
    size = 3.5,
    color = "black"
  ) +
  labs(
    title = "Average Daily Ride Volume per Month by Membership Type (2024)",
    subtitle = "Average number of rides per day, separated by casual and annual members",
    x = "Month",
    y = "Average Daily Ride Count",
    fill = "Membership Type"
  ) +
  scale_fill_manual(
    values = c("casual" = "#d95f02", "member" = "#1b9e77"),
    labels = c("Casual", "Annual Member")
  ) +
  scale_y_continuous(labels = scales::label_comma()) +
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(face = "bold", size = 18),
    plot.subtitle = element_text(size = 13),
```

```
  legend.position = "bottom",
  axis.text.x = element_text(angle = 45, hjust = 1),
  axis.text.y = element_text(size = 11),
  plot.margin = margin(20, 60, 20, 40)
 )
```

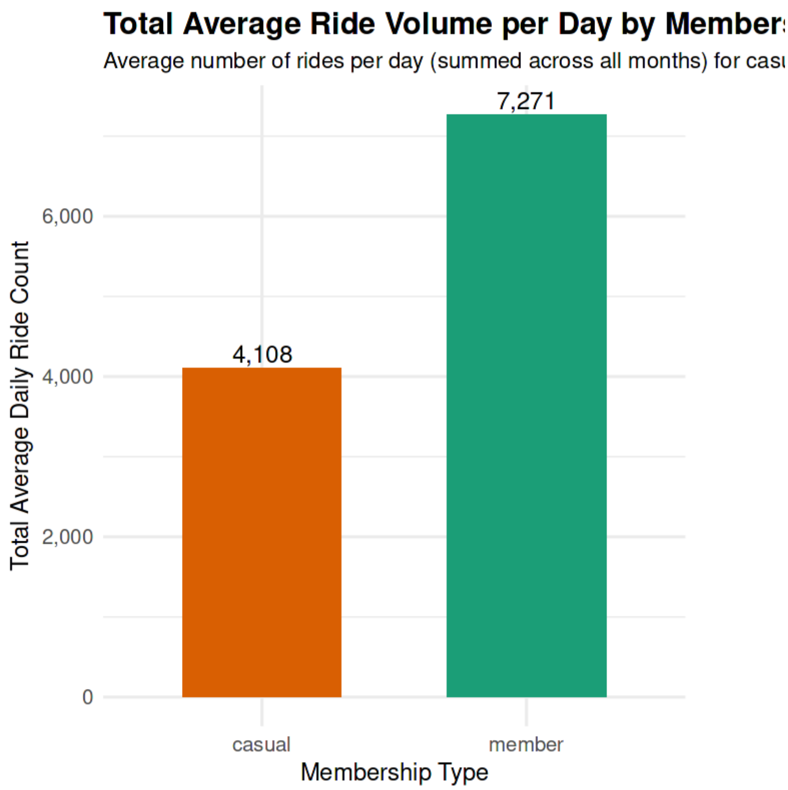


In [9]:

```
# Calculate total rides per membership type, grouped by month and day
avg_rides_per_day_by_month_member <- cyclistic_24 %>%
 group_by(month, day, member_casual) %>%  # Group by month and day to correctly calculate the average
 summarise(total_rides = n(), .groups = "drop") %>%  # Count the rides per day
 group_by(month, member_casual) %>%  # Now group by month and membership type for final average calculation
 summarise(
  total_rides = sum(total_rides),  # Sum the total rides for each month and membership type
```

```
    total_days = n_distinct(day),    # Count distinct days per month
    avg_rides_per_day = total_rides / total_days,  # Calculate the average rides per day
    .groups = "drop"
  ) %>%
  mutate(month = factor(month, levels = 1:12, labels = month.name, ordered = TRUE))  # Convert month to a factor for plotting


# Calculate the total average rides per day across all months for each membership type
avg_total_rides_per_day <- avg_rides_per_day_by_month_member %>%
  group_by(member_casual) %>%
  summarise(
    total_avg_rides_per_day = mean(avg_rides_per_day),  # Average the daily averages across the 12 months
    .groups = "drop"
  )


# Plot: Total Average Ride Volume per Day by Membership Type
ggplot(avg_total_rides_per_day, aes(x = member_casual, y = total_avg_rides_per_day, fill = member_casual)) +
  geom_col(width = 0.6) +  # Bar chart for total average rides per day by membership type
  geom_text(
    aes(label = scales::comma(round(total_avg_rides_per_day, 0))),
    vjust = -0.3,  # Place the label above the bar
    size = 5,
    color = "black"
  ) +
  labs(
```

```
    title = "Total Average Ride Volume per Day by Membership Type in 2024",
    subtitle = "Average number of rides per day (summed across all months) for casual and annual members",
    x = "Membership Type",
    y = "Total Average Daily Ride Count",
    fill = "Membership Type"
  ) +
  scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77")) +  # Custom colors for membership types
  scale_y_continuous(labels = scales::label_comma()) +  # Format the y-axis with commas
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(face = "bold", size = 18),
    plot.subtitle = element_text(size = 13),
    legend.position = "none",  # No legend needed, as membership types are labeled directly
    axis.text.x = element_text(size = 12),
    axis.text.y = element_text(size = 12),
    plot.margin = margin(20, 60, 20, 40)
  )
```

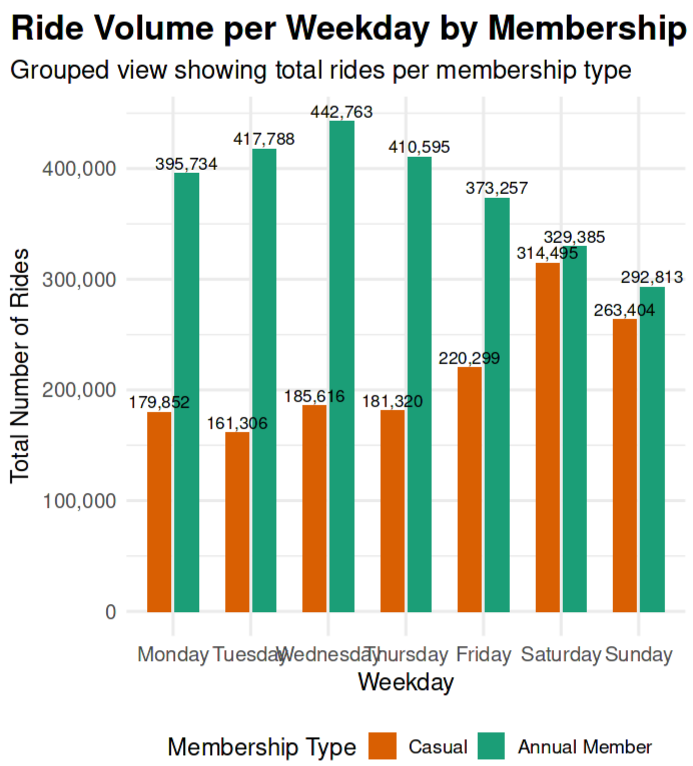


In [10]:

```
weekday_rides <- cyclistic_24 %>%
  group_by(weekday, member_casual) %>%
  summarise(total_rides = n(), .groups = "drop")

print(weekday_rides)

weekday_rides$weekday <- factor(
  weekday_rides$weekday,
  levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday",
"Sunday"),
  ordered = TRUE
)

# Grouped Column Chart: Ride Volume per Weekday by Membership Type
```

```
ggplot(weekday_rides, aes(x = weekday, y = total_rides, fill = member_casual)) +
 geom_col(width = 0.6, position = position_dodge(width = 0.7)) +
 geom_text(
  aes(label = scales::comma(total_rides)),
  position = position_dodge(width = 0.7),
  vjust = -0.3,        # Slightly above the bar
  size = 3.5,
  color = "black"
 ) +
 labs(
  title = "Ride Volume per Weekday by Membership Type in 2024",
  subtitle = "Grouped view showing total rides per membership type",
  x = "Weekday",
  y = "Total Number of Rides",
  fill = "Membership Type"
 ) +
 scale_fill_manual(
  values = c("casual" = "#d95f02", "member" = "#1b9e77"),
  labels = c("Casual", "Annual Member")
 ) +
 scale_y_continuous(labels = scales::label_comma()) +
 theme_minimal(base_size = 14) +
 theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 20),  # Increase title size
  plot.subtitle = element_text(size = 15),  # Increase subtitle size
  legend.position = "bottom",
  plot.margin = margin(30, 60, 20, 40),  # Increase margin for better spacing
```

```
    axis.text.x = element_text(size = 12),
    axis.text.y = element_text(size = 12)
  ) +
  coord_cartesian(expand = TRUE)

# Save the plot with larger dimensions for better readability
ggsave("weekday_ride_volume.png", width = 12, height = 8, dpi = 300, limitsize = FALSE)
# A tibble: 14 × 3
   weekday   member_casual total_rides
   <chr>     <chr>               <int>
 1 Friday    casual             220299
 2 Friday    member             373257
 3 Monday    casual             179852
 4 Monday    member             395734
 5 Saturday  casual             314495
 6 Saturday  member             329385
 7 Sunday    casual             263404
 8 Sunday    member             292813
 9 Thursday  casual             181320
10 Thursday  member             410595
11 Tuesday   casual             161306
12 Tuesday   member             417788
13 Wednesday casual             185616
14 Wednesday member             442763
```



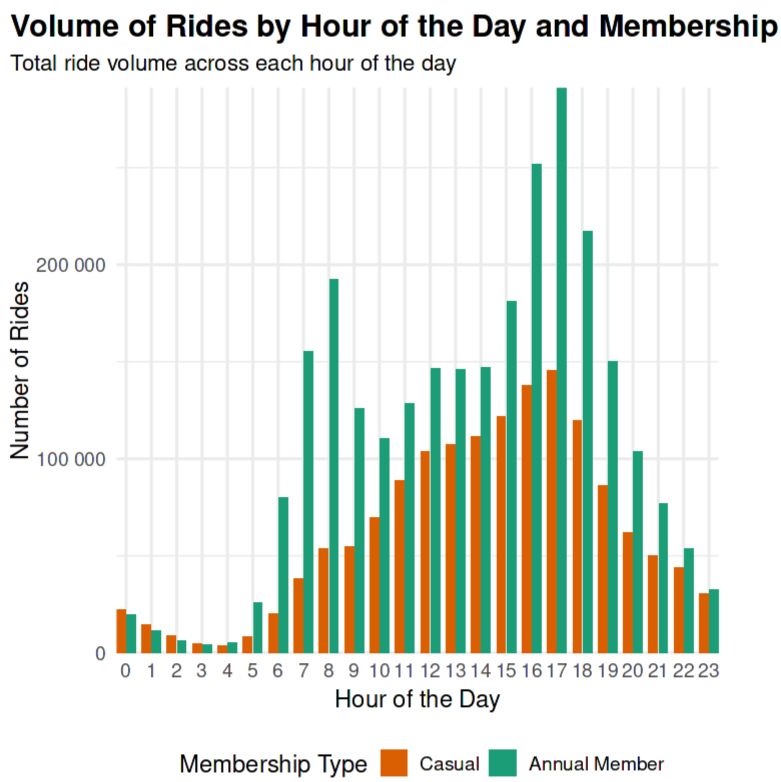
In terms of rides per weekday, although the annual members have a higher volume of rides than the casual members during the working days, the rides of casual members during the weekend seem to increase considerably. This can suggest that the annual members may use Cyclistic as a way to commute to their jobs, schools/universities, etc… while the casual riders may use it whenever convenient, or in their spare time. At the same time, this makes us reflect on whether the casual members ride as a hobby or for convenience, and why they would not opt for the annual membership plan? We hope to dismantle that during further analysis.

In [11]:

```
# Ride Count by Hour of the Day


# Create dataset with hour-based categorization

cyclistic_hourly <- cyclistic_24 %>%

  mutate(

    hour = hour(started_at)  # Extract hour from the timestamp

  )
```

```r
# Compute ride count per hour and member type
hourly_count <- cyclistic_hourly %>%
  group_by(hour, member_casual) %>%
  summarise(ride_count = n(), .groups = "drop")  # Count rides per hour

# Plot: Ride Count by Hour of the Day
ggplot(hourly_count, aes(x = factor(hour), y = ride_count, fill = member_casual)) +
  geom_col(position = position_dodge(width = 0.8), width = 0.7) +

  labs(
    title = "Volume of Rides by Hour of the Day and Membership Type in 2024",
    subtitle = "Total ride volume across each hour of the day",
    x = "Hour of the Day",
    y = "Number of Rides",
    fill = "Membership Type"
  ) +

  scale_fill_manual(
    values = c("casual" = "#d95f02", "member" = "#1b9e77"),
    labels = c("Casual", "Annual Member")
  ) +

  scale_y_continuous(
    labels = label_number(accuracy = 1),
    expand = expansion(mult = c(0, 0.05))
  ) +
```

```
theme_minimal(base_size = 14) +
theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",
  plot.margin = margin(20, 40, 20, 40)
) +

coord_cartesian(expand = FALSE)
```



Considering the volume of rides per hour, we can observe that the annual members volumes are higher than the casual members and that two periods stand: in the morning from 7am to 9am and in the afternoon from 4pm to 6pm. This could reflect periods during the working days where a considerable number of people are commuting to their workplace, school and universities, and the afternoon as the period they return back home. That in correlation with the people riding for other reasons, for example, doing exercise could be one of the reasons for those higher peaks.

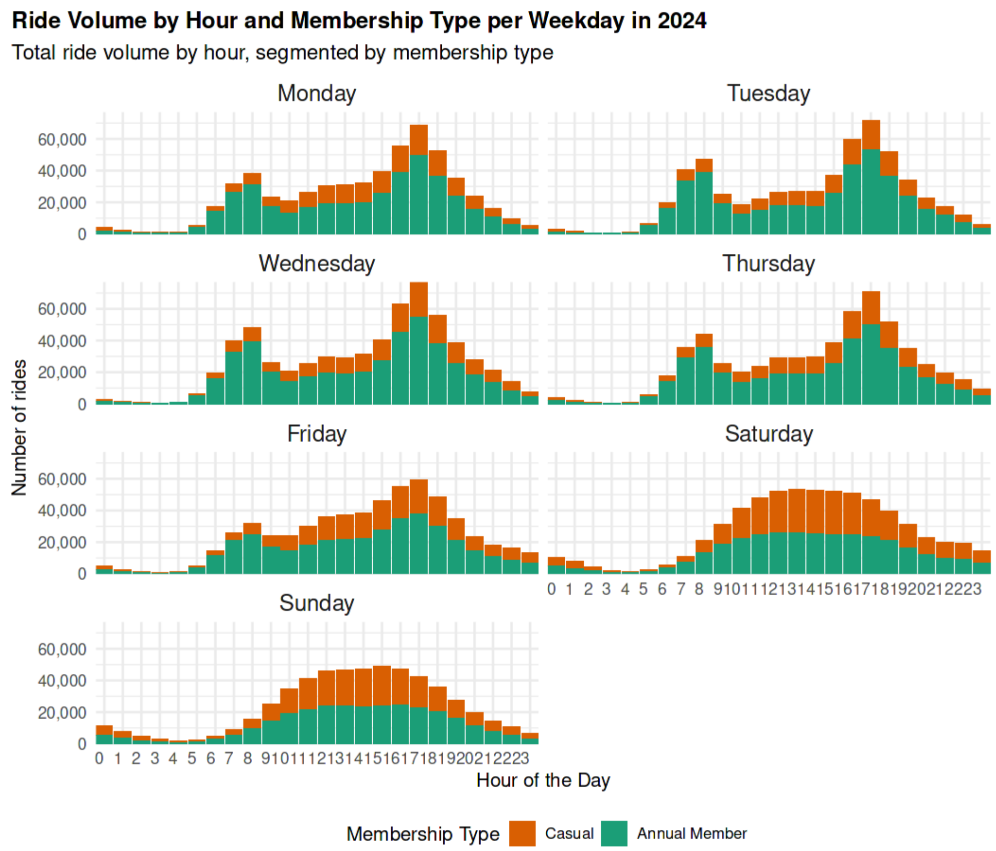
In [12]:

```
# Stacked Bar Chart of Ride Volume by Hour and Weekday


# Compute ride count per hour, weekday, and member type
hourly_weekday_count <- cyclistic_24 %>%
  mutate(hour = lubridate::hour(started_at)) %>%
  group_by(hour, weekday, member_casual) %>%
  summarise(ride_count = n(), .groups = "drop")


#ensuring the plots order of the weekdays
hourly_weekday_count$weekday <- factor(
  hourly_weekday_count$weekday,
  levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday"),
  ordered = TRUE
)


# Set plot dimensions for this specific plot
options(repr.plot.width = 10, repr.plot.height = 8)


# Plot: Stacked Bar Chart of Ride Volume by Hour and Weekday
ggplot(hourly_weekday_count, aes(x = factor(hour), y = ride_count, fill = member_casual)) +
  geom_bar(stat = "identity") +   # Stacked bar chart


  labs(
    title = "Ride Volume by Hour and Membership Type per Weekday in 2024",
```

```r
  subtitle = "Total ride volume by hour, segmented by membership type",
  x = "Hour of the Day",
  y = "Number of rides",
  fill = "Membership Type"
) +

scale_fill_manual(
  values = c("casual" = "#d95f02", "member" = "#1b9e77"),
  labels = c("Casual", "Annual Member")
) +

scale_y_continuous(labels = scales::label_comma()) +

theme_minimal(base_size = 12) +
theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 14),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",
  plot.margin = margin(20, 60, 20, 40),
  strip.text = element_text(size = 14),  # Larger weekday labels
  axis.text.x = element_text(size = 10, hjust = 1),  # Smaller hour labels on x-axis
  axis.text.y = element_text(size = 10)   # Adjust y-axis text size
) +

facet_wrap(~ weekday, ncol = 2) +  # Facet by weekday with 3 columns for better
layout
coord_cartesian(expand = FALSE)  # Remove extra space around the plot
```

 # Save the plot with larger dimensions for better readability

ggsave("ride_volume_plot.png", width = 20, height = 40, dpi = 300, limitsize = FALSE)



These plots reflect the volume of rides per hour for each day of the week, and here we get a confirmation on what was stated above, that during the working days, the morning periods from 7am-9am and afternoon periods from 4pm-6pm have higher values. Nevertheless, we notice that during the weekend, the number of rides and especially from casual members are higher, and remain slightly consistent from 11 am until 6pm. This could aggregate the rides that have more spare time during the weekend and use it for a ride.

4.2 Analysing Ride Duration

In [13]:

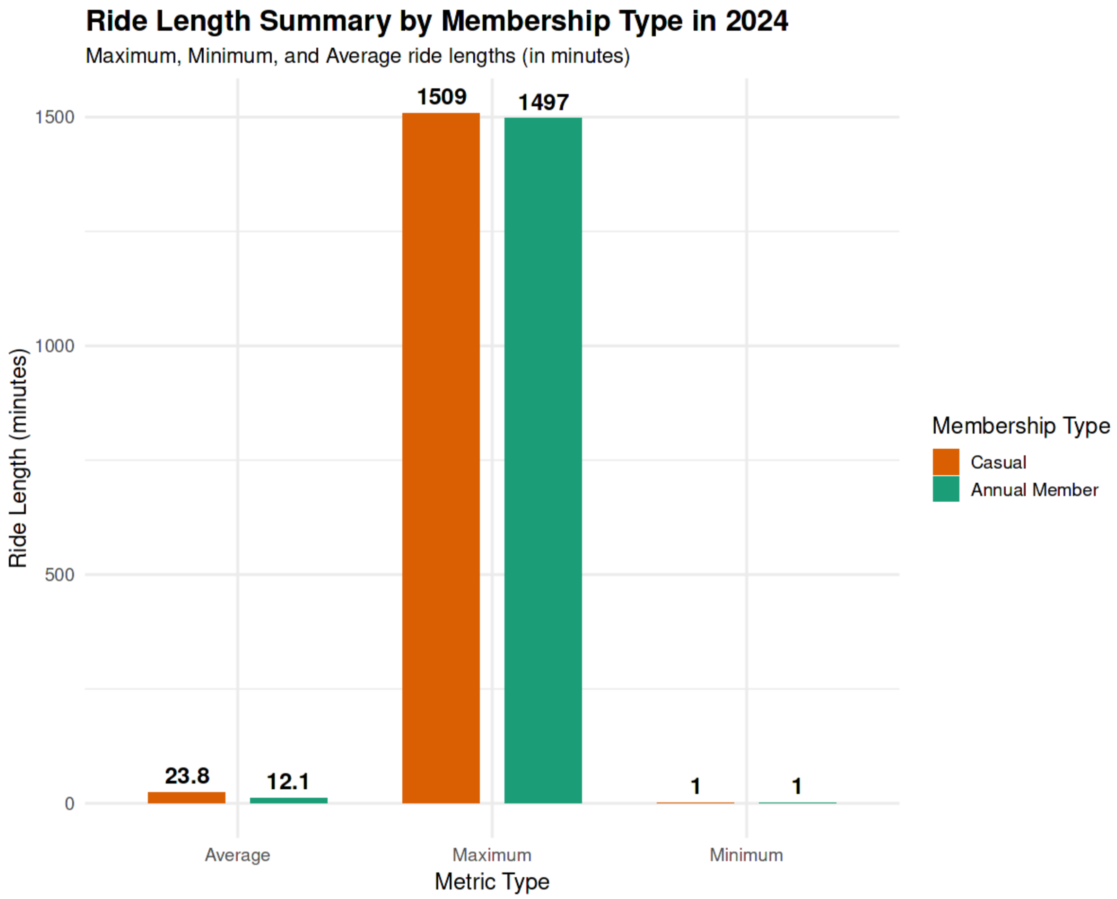
 # Summary of ride length stats by member type

ride_length_summary <- cyclistic_24 %>%

 group_by(member_casual) %>%

```
  summarise(
    max_ride_length  = max(ride_length, na.rm = TRUE),
    min_ride_length  = min(ride_length, na.rm = TRUE),
    avg_ride_length  = mean(ride_length, na.rm = TRUE)
  )

#plot
# Reshape data from wide → long for plotting
ggplot(ride_length_summary) +
  geom_col(aes(x = "Maximum", y = max_ride_length, fill = member_casual),
           position = position_dodge(width = 0.8), width = 0.6) +
  geom_col(aes(x = "Minimum", y = min_ride_length, fill = member_casual),
           position = position_dodge(width = 0.8), width = 0.6) +
  geom_col(aes(x = "Average", y = avg_ride_length, fill = member_casual),
           position = position_dodge(width = 0.8), width = 0.6) +

  # Add text labels on top of bars
  geom_text(aes(x = "Maximum", y = max_ride_length, label = round(max_ride_length, 1), group = member_casual),
            position = position_dodge(width = 0.8), vjust = -0.5, size = 5, fontface = "bold") +
  geom_text(aes(x = "Minimum", y = min_ride_length, label = round(min_ride_length, 1), group = member_casual),
            position = position_dodge(width = 0.8), vjust = -0.5, size = 5, fontface = "bold") +
  geom_text(aes(x = "Average", y = avg_ride_length, label = round(avg_ride_length, 1), group = member_casual),
            position = position_dodge(width = 0.8), vjust = -0.5, size = 5, fontface = "bold") +
```

```r
# Labels and theme
labs(
  title = "Ride Length Summary by Membership Type in 2024",
  subtitle = "Maximum, Minimum, and Average ride lengths (in minutes)",
  x = "Metric Type",
  y = "Ride Length (minutes)",
  fill = "Membership Type"
) +
scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77"),
                  labels = c("Casual", "Annual Member")) +
theme_minimal(base_size = 14) +
theme(
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "right"
)
```



This plot reflects the summary by membership type, in which we can see that although both have long-duration rides, the casual members seem to have a significantly higher number of long rides, which is reflected in their high average value of 23.8 min per ride against 12.1 min average ride from the annual members.

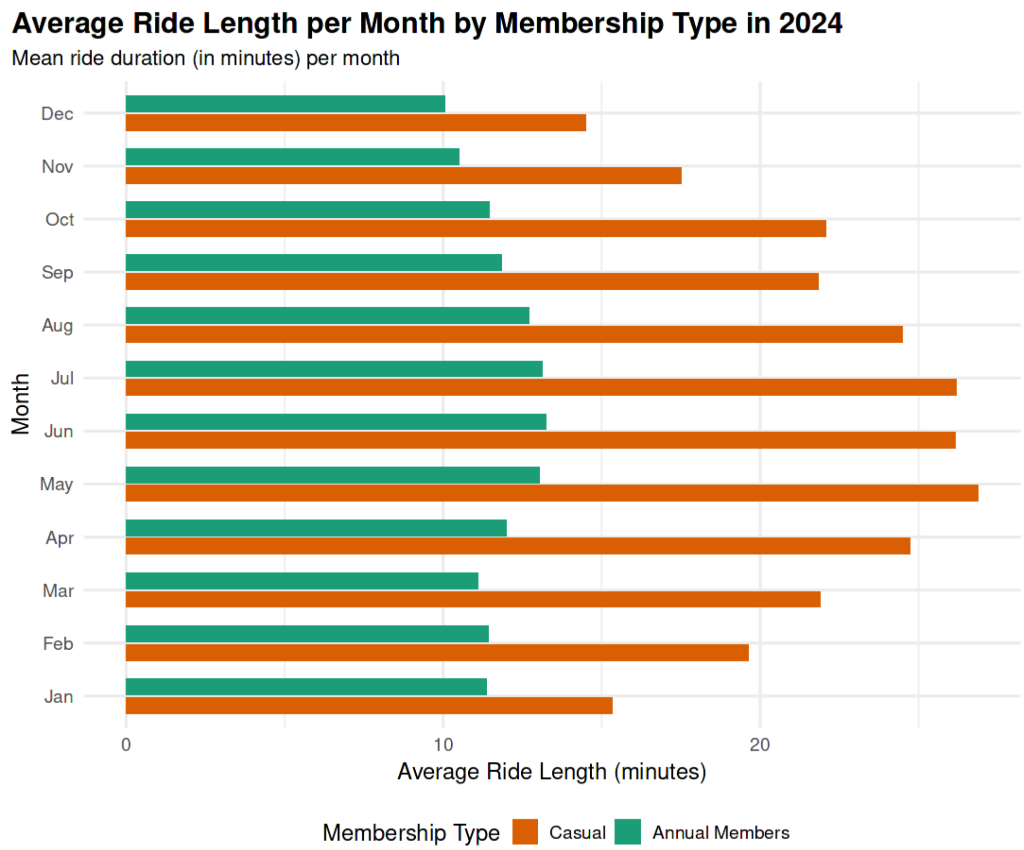
In [14]:

```
# Average ride length

avg_ride_length_month <- cyclistic_24 %>%

 mutate(month = month(month)) %>%

 group_by(month, member_casual) %>%

 summarise(avg_ride_length = mean(ride_length, na.rm = TRUE), .groups = "drop")
%>%

 mutate(

  month = factor(month, levels = 1:12, labels = month.abb, ordered = TRUE)

 )
```

#AVG ride length plot

```
ggplot(avg_ride_length_month, aes(x = month, y = avg_ride_length, fill = member_casual)) +
 geom_col(position = position_dodge(width = 0.7), width = 0.6) +

 labs(
  title = "Average Ride Length per Month by Membership Type in 2024",
  subtitle = "Mean ride duration (in minutes) per month",
  x = "Month",
  y = "Average Ride Length (minutes)",
  fill = "Membership Type"
 ) +

 scale_fill_manual(
  values = c("casual" = "#d95f02", "member" = "#1b9e77"),
  labels = c("Casual", "Annual Members")
 ) +

 scale_y_continuous(labels = label_comma()) +

 theme_minimal(base_size = 14) +
 theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",
  plot.margin = margin(20, 40, 20, 40)
 ) +
```

```
coord_flip()
```



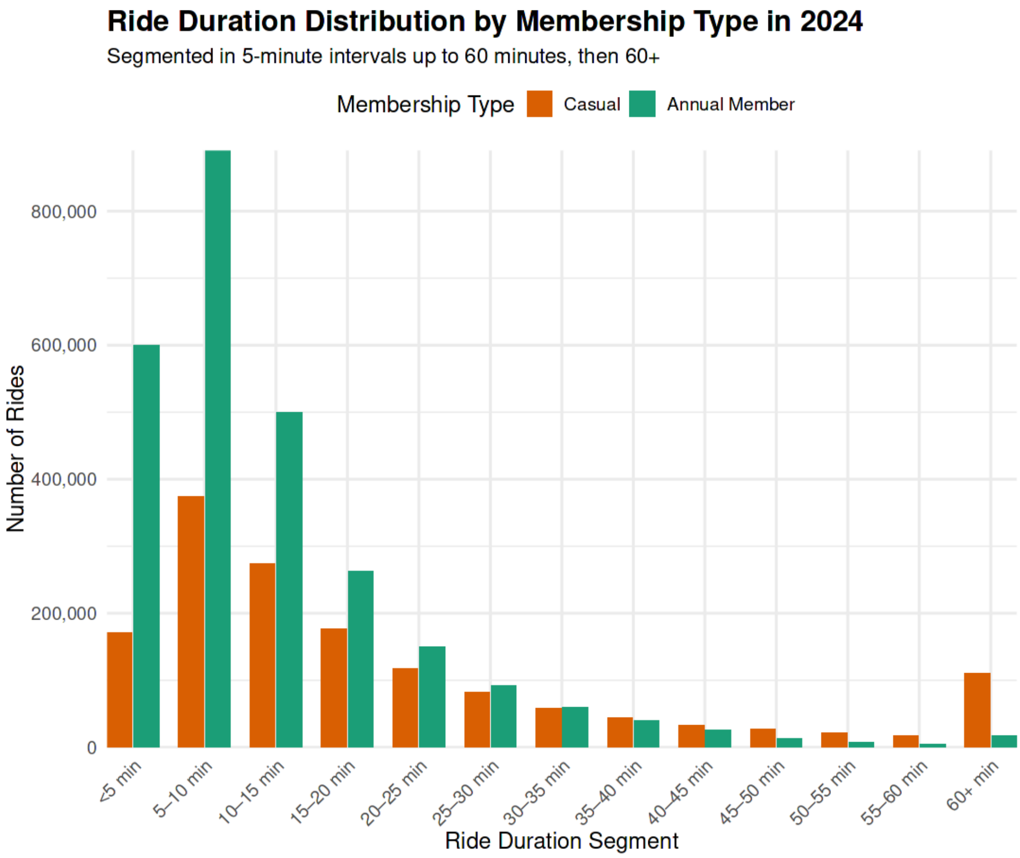
As previously mentioned, the casual riders on average ride for longer periods of time, having higher peaks in Summer, while the average ride duration for the annual members remains constant throughout the year, with a slight increase in the summer. This could reflect that the annual membership is used for shorter rides. For a better understanding, breaking down the ride duration into segments could enable a better analysis.

In [15]:

```
# Creating dataset for ride duration distribution by segment and membership type

ride_length_distribution <- cyclistic_24 %>%

 mutate(

  duration_segment = case_when(

   ride_length < 5 ~ "<5 min",

   ride_length >= 5 & ride_length < 10 ~ "5–10 min",

   ride_length >= 10 & ride_length < 15 ~ "10–15 min",
```

```
    ride_length >= 15 & ride_length < 20 ~ "15–20 min",
    ride_length >= 20 & ride_length < 25 ~ "20–25 min",
    ride_length >= 25 & ride_length < 30 ~ "25–30 min",
    ride_length >= 30 & ride_length < 35 ~ "30–35 min",
    ride_length >= 35 & ride_length < 40 ~ "35–40 min",
    ride_length >= 40 & ride_length < 45 ~ "40–45 min",
    ride_length >= 45 & ride_length < 50 ~ "45–50 min",
    ride_length >= 50 & ride_length < 55 ~ "50–55 min",
    ride_length >= 55 & ride_length < 60 ~ "55–60 min",
    ride_length >= 60 ~ "60+ min"
   )
  ) %>%
  group_by(duration_segment, member_casual) %>%
  summarise(total_rides = n(), .groups = "drop")


# - Organize duration_segment by a predefined order -
ride_length_distribution$duration_segment <- factor(
  ride_length_distribution$duration_segment,
  levels = c("<5 min", "5–10 min", "10–15 min", "15–20 min",
        "20–25 min", "25–30 min", "30–35 min", "35–40 min",
        "40–45 min", "45–50 min", "50–55 min", "55–60 min", "60+ min"),
  ordered = TRUE
   )

# - Plot: Ride Duration Distribution by Membership Type -
ggplot(ride_length_distribution, aes(x = duration_segment, y = total_rides, fill = member_casual)) +
```

```r
geom_col(position = position_dodge(width = 0.75), width = 0.7) +
labs(
  title = "Ride Duration Distribution by Membership Type in 2024",
  subtitle = "Segmented in 5-minute intervals up to 60 minutes, then 60+",
  x = "Ride Duration Segment",
  y = "Number of Rides",
  fill = "Membership Type"
) +
scale_fill_manual(
  values = c("casual" = "#d95f02", "member" = "#1b9e77"),
  labels = c("Casual", "Annual Member")
) +
scale_y_continuous(labels = scales::label_comma()) +
theme_minimal(base_size = 14) +
theme(
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "top",
  axis.text.x = element_text(angle = 45, hjust = 1),
  plot.margin = margin(20, 40, 20, 40)
) +
coord_cartesian(expand = FALSE)
```



In this plot, we can see that the highest volume of rides happens between rides under 5 min and rides under 15 min. This plot confirms what was being suggested before, that the annual members tend to ride more in shorter periods of time, having the highest volumes of rides lasting between 5 to 10 min. The segment 5 to 10 min of ride also has the highest volume of casual members' rides. At the same time, after 35-40 min the volume of casual members' rides surpasses the annual members, and has a significant increase in rides with over 60 min long. Also, it is important to distinguish the lowest amounts of rides the annual members have between 50-60 min segments. This could suggest that the end of the free duration allowance ends here, although difficult to conclude as there are some ride

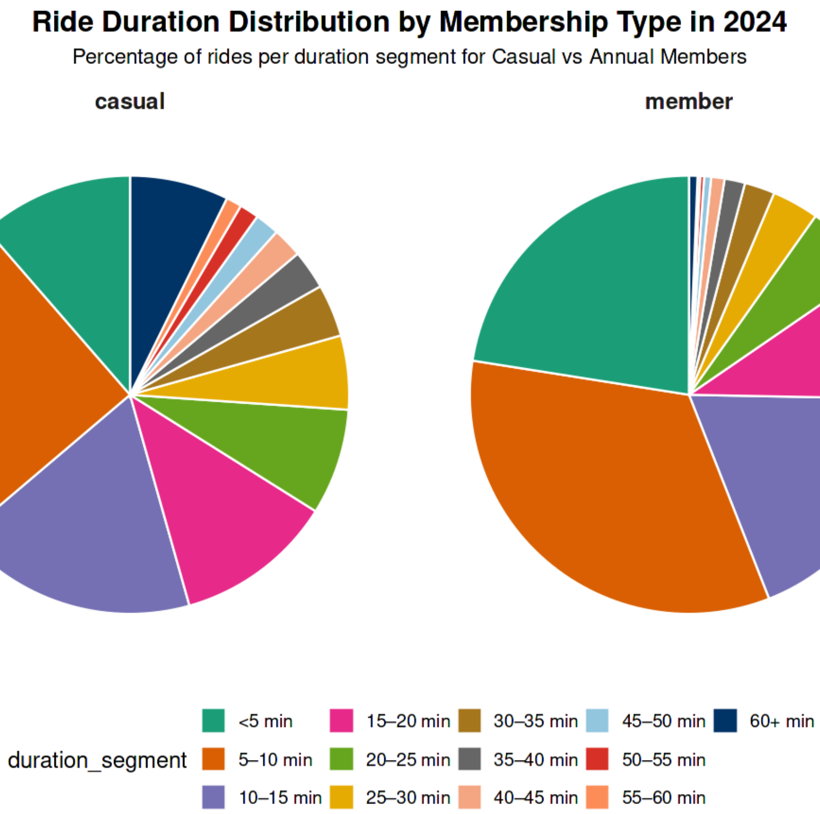
In [16]:

```
# Create dataset for ride duration distribution by segment and membership type

ride_length_distribution <- cyclistic_24 %>%

 mutate(

  duration_segment = case_when(

   ride_length < 5 ~ "<5 min",

   ride_length >= 5 & ride_length < 10 ~ "5–10 min",
```

```
    ride_length >= 10 & ride_length < 15 ~ "10–15 min",
    ride_length >= 15 & ride_length < 20 ~ "15–20 min",
    ride_length >= 20 & ride_length < 25 ~ "20–25 min",
    ride_length >= 25 & ride_length < 30 ~ "25–30 min",
    ride_length >= 30 & ride_length < 35 ~ "30–35 min",
    ride_length >= 35 & ride_length < 40 ~ "35–40 min",
    ride_length >= 40 & ride_length < 45 ~ "40–45 min",
    ride_length >= 45 & ride_length < 50 ~ "45–50 min",
    ride_length >= 50 & ride_length < 55 ~ "50–55 min",
    ride_length >= 55 & ride_length < 60 ~ "55–60 min",
    ride_length >= 60 ~ "60+ min"
   )
  ) %>%
  group_by(duration_segment, member_casual) %>%
  summarise(total_rides = n(), .groups = "drop") %>%
  group_by(member_casual) %>%
  mutate(percentage = total_rides / sum(total_rides) * 100) %>%
  ungroup()

# - Order segments chronologically -
ride_length_distribution$duration_segment <- factor(
  ride_length_distribution$duration_segment,
  levels = c("<5 min", "5–10 min", "10–15 min", "15–20 min",
        "20–25 min", "25–30 min", "30–35 min", "35–40 min",
        "40–45 min", "45–50 min", "50–55 min", "55–60 min", "60+ min"),
  ordered = TRUE
)
```

```
# Custom color palette with more colors
custom_colors <- c("#1b9e77", "#d95f02", "#7570b3", "#e7298a", "#66a61e", "#e6ab02",
          "#a6761d", "#666666", "#f4a582", "#92c5de", "#d73027", "#fc8d59",
          "#003366", "#4575b4", "#313695", " #a6761d")  # New color for 45-50 min and 60+ min

# - Plot: Two Pie Charts (one per membership type) showing percentage -
ggplot(ride_length_distribution, aes(x = "", y = percentage, fill = duration_segment)) +
 geom_bar(stat = "identity", width = 1, color = "white") +
 coord_polar(theta = "y") +

 facet_wrap(~ member_casual, ncol = 2) +  # Separate pie charts for each membership type
 scale_fill_manual(values = custom_colors) +  # Use custom color palette
 labs(
  title = "Ride Duration Distribution by Membership Type in 2024",
  subtitle = "Percentage of rides per duration segment for Casual vs Annual Members",
  x = NULL,
  y = NULL
 ) +
 theme_minimal(base_size = 14) +
 theme(
  plot.title = element_text(face = "bold", size = 18, hjust = 0.5),
  plot.subtitle = element_text(size = 13, hjust = 0.5),
  legend.position = "bottom",
  axis.text = element_blank(),
```

```
  axis.ticks = element_blank(),
  panel.grid = element_blank(),
  strip.text = element_text(size = 14, face = "bold")
)
```



According to the pie charts above, we can see that as the duration increases the volume of rides decrease, however, if we see the segment of +60 min we can see that the casual members have a higher volume of rides than the annual members. This is better represented in the table below, where we can see that this segment represents 7.3% of the total rides of the casual member rides, and 2,6% for the total rides overall. Differently, for the annual members, this represents 0.6% of the total rides of the annual members and 0.4% for the total rides overall.

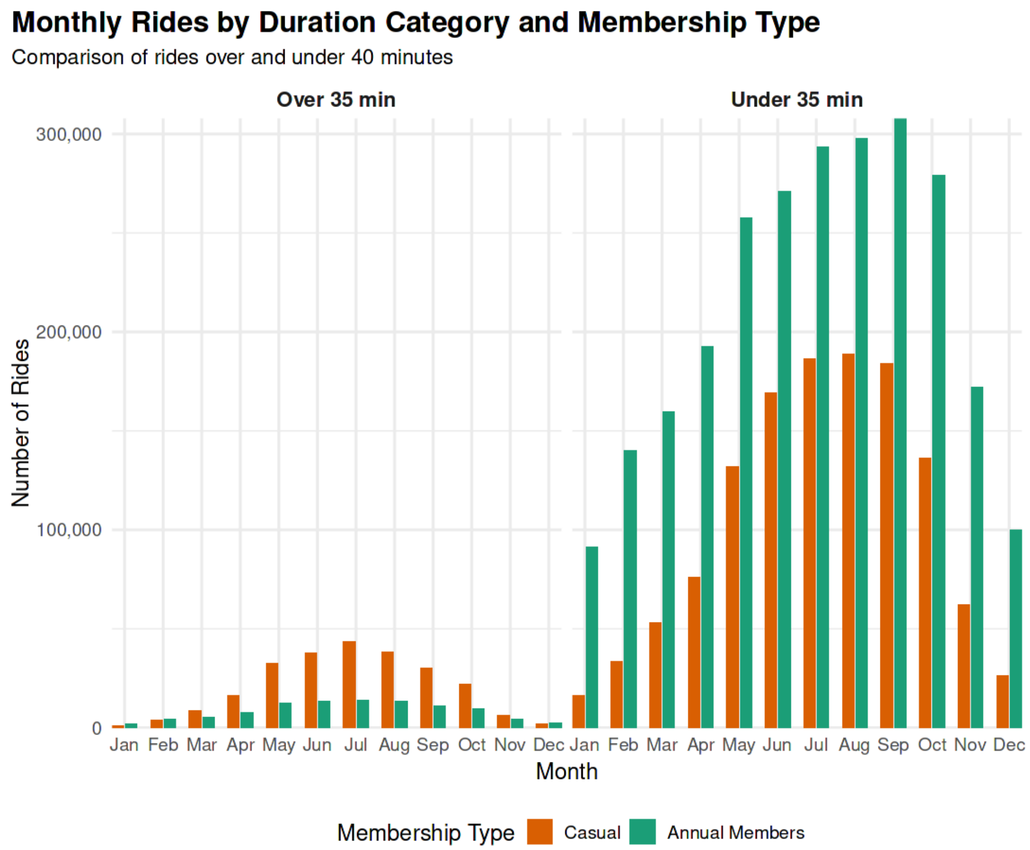
duration_segment	member_casual	total_rides	percentage per membership	% total rides
<5 min	casual	171452	11.4%	4.1%
<5 min	member	599220	22.5%	14.4%
5–10 min	casual	373896	24.8%	9.0%
5–10 min	member	890528	33.4%	21.4%
10–15 min	casual	273649	18.2%	6.6%
10–15 min	member	499115	18.7%	12.0%
15–20 min	casual	176373	11.7%	4.2%
15–20 min	member	262774	9.9%	6.3%
20–25 min	casual	117890	7.8%	2.8%
20–25 min	member	149429	5.6%	3.6%
25–30 min	casual	82238	5.5%	2.0%
25–30 min	member	91995	3.5%	2.2%
30–35 min	casual	58426	3.9%	1.4%
30–35 min	member	59523	2.2%	1.4%
35–40 min	casual	43529	2.9%	1.0%
35–40 min	member	40228	1.5%	1.0%
40–45 min	casual	33176	2.2%	0.8%
40–45 min	member	26253	1.0%	0.6%
45–50 min	casual	27021	1.8%	0.6%
45–50 min	member	13727	0.5%	0.3%
50–55 min	casual	21486	1.4%	0.5%
50–55 min	member	7771	0.3%	0.2%
55–60 min	casual	17317	1.1%	0.4%
55–60 min	member	5012	0.2%	0.1%
60+ min	casual	109839	7.3%	2.6%
60+ min	member	16760	0.6%	0.4%

In [17]:

```
# Volume of Rides with duration over 35 min vs under 35 min

long_rides_over_35 <- cyclistic_24 %>%

 filter(ride_length > 35) %>%

 mutate(

  month = month(month),  # Use started_at to extract month

  ride_category = "Over 35 min"

 ) %>%

 group_by(month, member_casual, ride_category) %>%

 summarise(total_rides = n(), .groups = "drop") %>%

 mutate(month = factor(month, levels = 1:12, labels = month.abb, ordered =
TRUE))


# - Rides under 35 min -

long_rides_less_35 <- cyclistic_24 %>%
```

```r
  filter(ride_length <= 35) %>%
  mutate(
    month = month(month),
    ride_category = "Under 35 min"
  ) %>%
  group_by(month, member_casual, ride_category) %>%
  summarise(total_rides = n(), .groups = "drop") %>%
  mutate(month = factor(month, levels = 1:12, labels = month.abb, ordered =
TRUE))

# - Combine datasets -
combined_rides <- bind_rows(long_rides_over_35, long_rides_less_35)

# - Plot: Facet Wrap -
ggplot(combined_rides, aes(x = month, y = total_rides, fill = member_casual)) +
  geom_col(position = position_dodge(width = 0.7), width = 0.6) +
  facet_wrap(~ ride_category) +
  labs(
    title = "Monthly Rides by Duration Category and Membership Type",
    subtitle = "Comparison of rides over and under 40 minutes",
    x = "Month",
    y = "Number of Rides",
    fill = "Membership Type"
  ) +
  scale_fill_manual(
    values = c("casual" = "#d95f02", "member" = "#1b9e77"),
    labels = c("Casual", "Annual Members")
  ) +
```

```
scale_y_continuous(labels = scales::label_comma()) +
theme_minimal(base_size = 14) +
theme(
  strip.text = element_text(face = "bold", size = 13),
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",
  plot.title.position = "plot",
  plot.margin = margin(20, 40, 20, 40)
) +
coord_cartesian(expand = FALSE)
```



The 45 min, could be the breaking point in which it's more valuable to have a casual membership rather than being an annual member. Unfortunately, we cannot develop our analysis on this hypothesis as we have no access to any monetary value in this scenario. But we can use this period up to 35 min as the ideal target for acquiring an annual membership.

A tibble: 2 × 5

member_casual	rides_over_35	rides_under_35	percentage_over_35	percentage_under_35
<chr>	<int>	<int>	<dbl>	<dbl>
casual	242558	1263734	70.74013	33.0324
member	100328	2562007	29.25987	66.9676

As per the above table, we can see that 33% of the rides with a duration under 35 min were done by casual members. This number can be associated with the potential value to analyse how many people could be converted to annual members.

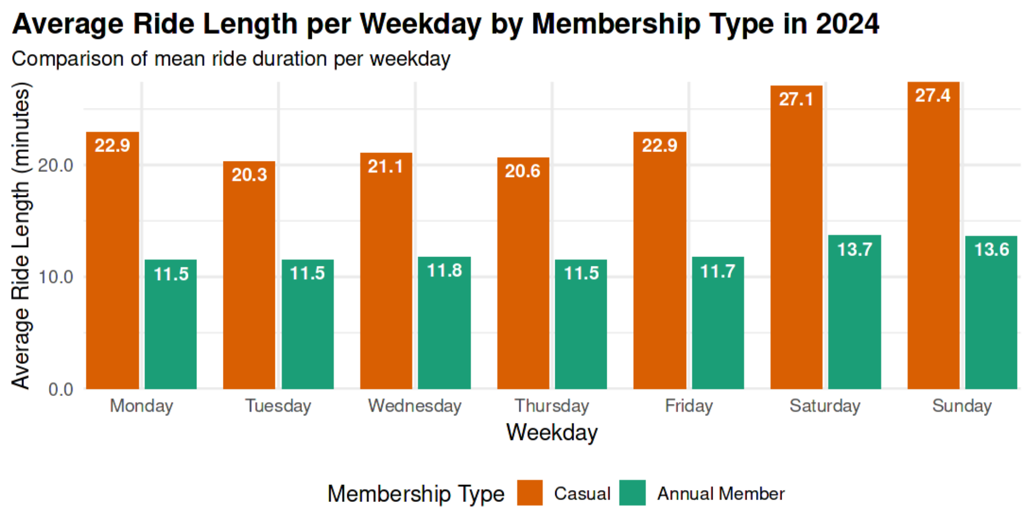
Note: 35 min segment was chosen for being a moment where the volume of casual member rides surpasses the annual members.

In [18]:

```
# Compute average ride length per weekday

weekday_avg_length <- cyclistic_24 %>%

  group_by(weekday, member_casual) %>%

  summarise(avg_ride_length = mean(ride_length, na.rm = TRUE), .groups = "drop")


weekday_avg_length$weekday <- factor(

  weekday_avg_length$weekday,

  levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday"),

  ordered = TRUE

)


# - Plot: Average Ride Length per Weekday -

p1 <- ggplot(weekday_avg_length, aes(x = weekday, y = avg_ride_length, fill = member_casual)) +

  geom_col(position = position_dodge(width = 0.85), width = 0.75) +  # 🔧 reduced gap between bars
```

```
# Add text labels inside bars
geom_text(
  aes(label = round(avg_ride_length, 1)),
  position = position_dodge(width = 0.85),
  vjust = 1.5,
  size = 4,
  fontface = "bold",
  color = "white"
) +

labs(
  title = "Average Ride Length per Weekday by Membership Type in 2024",
  subtitle = "Comparison of mean ride duration per weekday",
  x = "Weekday",
  y = "Average Ride Length (minutes)",
  fill = "Membership Type"
) +
scale_fill_manual(
  values = c("casual" = "#d95f02", "member" = "#1b9e77"),
  labels = c("Casual", "Annual Member")
) +
scale_y_continuous(
  labels = label_number(accuracy = 0.1),
  expand = expansion(mult = c(0, 0.05))
) +
theme_minimal(base_size = 14) +
theme(
```

```
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",
  plot.margin = margin(20, 40, 20, 40)
 ) +
 coord_cartesian(expand = FALSE)

options(repr.plot.width = 10, repr.plot.height = 5)
print(p1)
```



In this plot, we understand that not only the casual members ride for a longer time than the annual members but they also ride longer at the weekends. Regarding the annual members, it is noticeable a tendency to ride for longer times during the weekends, which is an interesting correlation with the casual members and could be a point to explore to track those casual members who ride more on the weekend and turn them into annual members.

In [19]:

```
# Distribution of ride duration volume by weekday and membership type
weekday_duration_distribution <- cyclistic_24 %>%
 mutate(
  duration_segment = case_when(
```

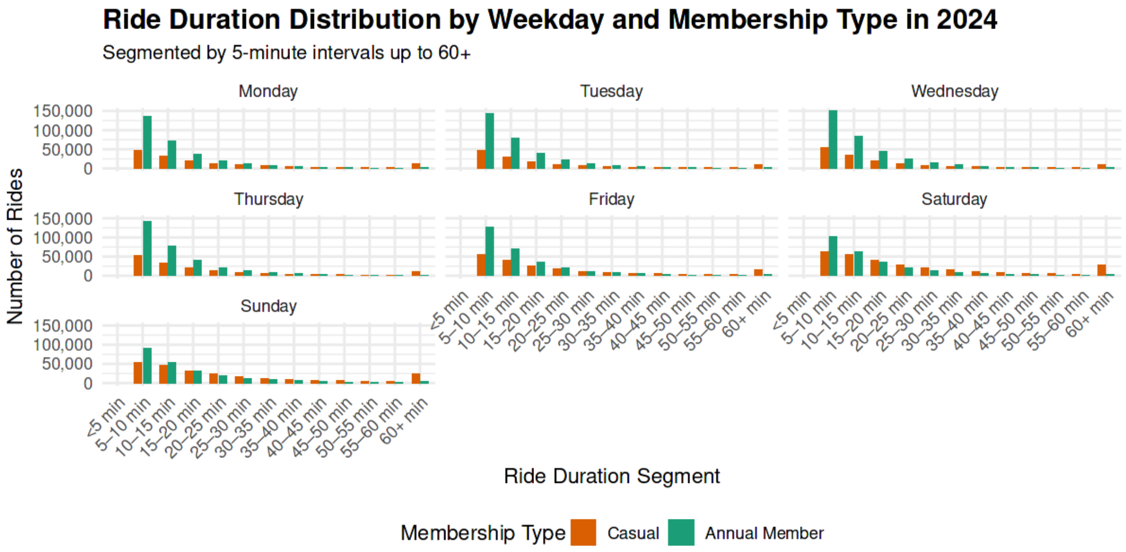
```
    ride_length < 5 ~ "< 5 min",
   ride_length >= 5 & ride_length < 10 ~ "5–10 min",
    ride_length >= 10 & ride_length < 15 ~ "10–15 min",
    ride_length >= 15 & ride_length < 20 ~ "15–20 min",
    ride_length >= 20 & ride_length < 25 ~ "20–25 min",
    ride_length >= 25 & ride_length < 30 ~ "25–30 min",
    ride_length >= 30 & ride_length < 35 ~ "30–35 min",
    ride_length >= 35 & ride_length < 40 ~ "35–40 min",
    ride_length >= 40 & ride_length < 45 ~ "40–45 min",
    ride_length >= 45 & ride_length < 50 ~ "45–50 min",
    ride_length >= 50 & ride_length < 55 ~ "50–55 min",
    ride_length >= 55 & ride_length < 60 ~ "55–60 min",
    ride_length >= 60 ~ "60+ min"
  )
 ) %>%
 group_by(weekday, member_casual, duration_segment) %>%
 summarise(total_rides = n(), .groups = "drop")

# Ensure weekday order from Monday to Sunday
weekday_duration_distribution$weekday <- factor(
 weekday_duration_distribution$weekday,
 levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday",
"Sunday"),
 ordered = TRUE
)

# Pivot the data to have total_rides for each membership type in separate columns
weekday_duration_distribution_wide <- weekday_duration_distribution %>%
```

```r
  pivot_wider(
    names_from = member_casual,   # Create columns for 'casual' and 'member'
    values_from = total_rides,     # The total rides for each membership type
      # Fill missing values with 0 if there are any missing combinations
  )

# - Ordering duration segments correctly -
weekday_duration_distribution_wide$duration_segment <- factor(
  weekday_duration_distribution_wide$duration_segment,
  levels = c("< 5 min", "5–10 min", "10–15 min", "15–20 min",
           "20–25 min", "25–30 min", "30–35 min", "35–40 min",
           "40–45 min", "45–50 min", "50–55 min", "55–60 min", "60+ min"),
  ordered = TRUE
)

# Arrange by weekday and duration segment
weekday_duration_distribution_wide <- weekday_duration_distribution_wide %>%
  arrange(weekday, duration_segment)

# Plot of the ride duration for each day of the week
ggplot(weekday_duration_distribution,
      aes(x = duration_segment, y = total_rides, fill = member_casual)) +
  geom_col(position = position_dodge(width = 0.7), width = 0.6) +
  facet_wrap(~ weekday, ncol = 3) +
  labs(
    title = "Ride Duration Distribution by Weekday and Membership Type in 2024",
    subtitle = "Segmented by 5-minute intervals up to 60+",
    x = "Ride Duration Segment",
```

```
  y = "Number of Rides",
  fill = "Membership Type"
 ) +
 scale_fill_manual(
  values = c("casual" = "#d95f02", "member" = "#1b9e77"),
  labels = c("Casual", "Annual Member")
 ) +
 scale_y_continuous(labels = scales::label_comma()) +
 theme_minimal(base_size = 13) +
 theme(
  plot.title = element_text(face = "bold", size = 17),
  plot.subtitle = element_text(size = 12),
  legend.position = "bottom",
  axis.text.x = element_text(angle = 45, hjust = 1)
 ) +
 # Ensure the segments are ordered correctly (small to large)
 scale_x_discrete(
  limits = c("<5 min", "5–10 min", "10–15 min", "15–20 min",
       "20–25 min", "25–30 min", "30–35 min", "35–40 min",
       "40–45 min", "45–50 min", "50–55 min", "55–60 min", "60+ min")
 )
```

Warning message:

“Removed 14 rows containing missing values or values outside the scale range (`geom_col()`).”



Furthermore, with these charts, it is possible to have a better perspective on the volumes of the ride durations across the week, where it is observable a consistent pattern between both volume and ride duration from Monday to Friday, not changing much between those days. The segment under 5 min had the highest volume on rides for both casual and annual members. During the weekend, there was a small decrease on the rides overall rides for the annual members and in contrast, the casual members had an overall increase across many segments in particular from under 5 min to 25 min, and they had also a notable increase for the rides longer than 60 min, concluding that these longer rides tend to happen the most during the weekends.

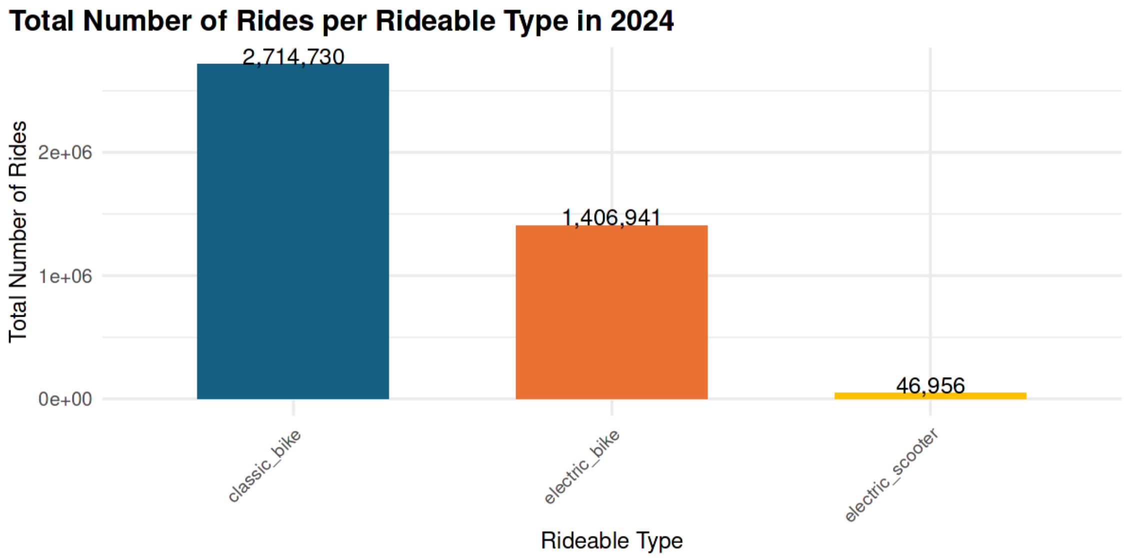
4.3 Analysing Type of Rides

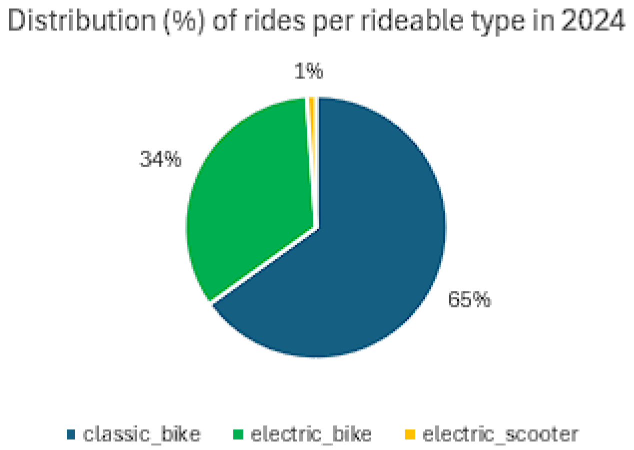
4.3.1 Overview of the Type of Rides

In [20]:

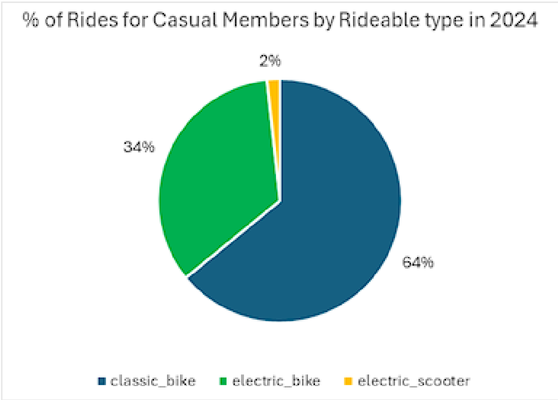
```
# Total ride volume by rideable_type

total_rideable_type_rides <- cyclistic_24 %>%

  group_by(rideable_type) %>%

  summarise(total_rides = n(), .groups = "drop")


# Plot: Total Ride Volume by Rideable Type

ggplot(total_rideable_type_rides, aes(x = rideable_type, y = total_rides, fill = rideable_type)) +

  geom_bar(stat = "identity", position = "dodge", width = 0.6) +  # Side-by-side bars for each rideable type
```

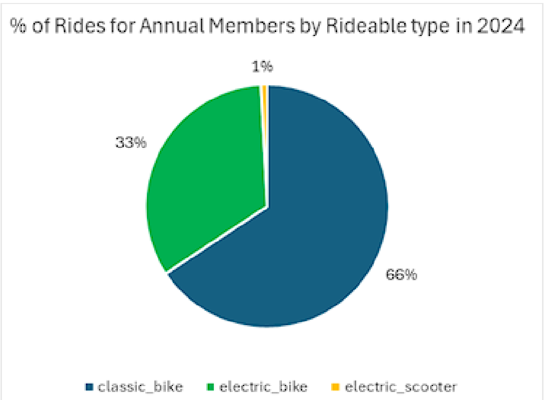
```r
  geom_text(
    aes(label = scales::label_comma()(total_rides)),  # Nicely formatted numbers
    colour = "black",  # Text color inside the bar
    size = 5,
    position = position_dodge(width = 0.6),  # Ensure text is aligned with the bars
    vjust = 0  # Place the text just above the bars
  ) +
  labs(
    title = "Total Number of Rides per Rideable Type in 2024",
    x = "Rideable Type",
    y = "Total Number of Rides"
  ) +
  scale_fill_manual(values = c("classic_bike" = "#156082", "electric_bike" =
"#E97132", "electric_scooter" = "#FFC000")) +  # Custom colors for rideable types
  theme_minimal(base_size = 14) +
  theme(
    plot.title.position = "plot",
    plot.title = element_text(face = "bold", size = 18),
    plot.subtitle = element_text(size = 13),
    axis.text.x = element_text(angle = 45, hjust = 1),  # Rotate x-axis labels for better
readability
    axis.text.y = element_text(size = 12),
    axis.ticks.y = element_blank(),  # Remove y-axis ticks
    legend.position = "none"  # No legend needed for this plot
  )
```





Considering the overall volume of rides, 65% were rides using classic bikes, reflecting a higher tendency to use casual bikes; 34% using the electric bikes and 1% using electric scooters. Assessing this distribution per membership type will enable an understanding of how casual members and annual members use these three rideable types.





In the percentage of rideable types' distribution per membership type, we can see that casual bikes take the lead as the preferred rideable type by both casual and annual members representing 64% and 66% respectively. Then, followed by the electric bikes with 34% and 33% respectively. In terms of shared distribution, it's interesting that both casual and annual members have a very similar representation.

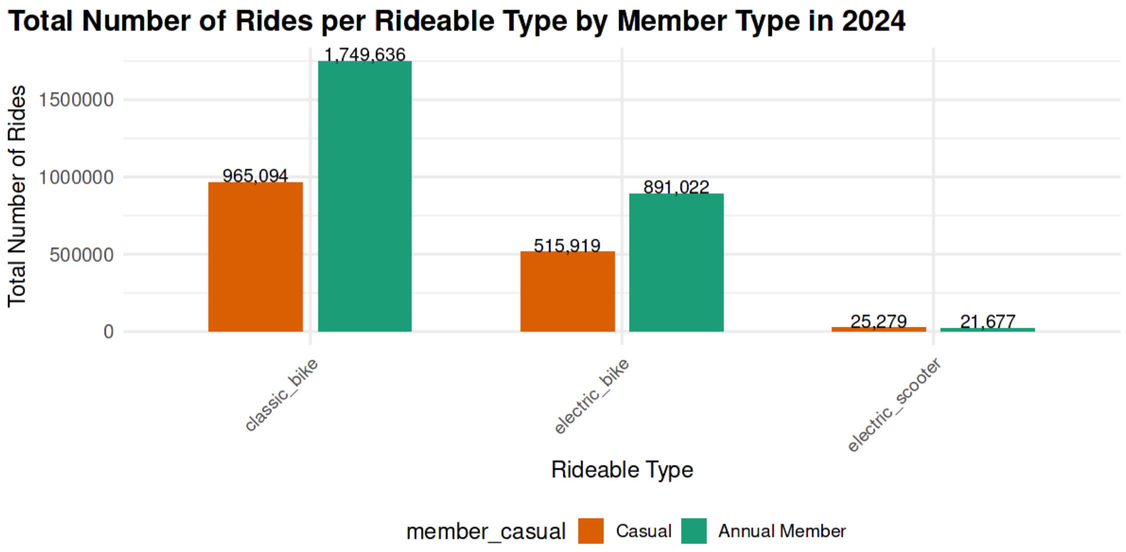
In [21]:

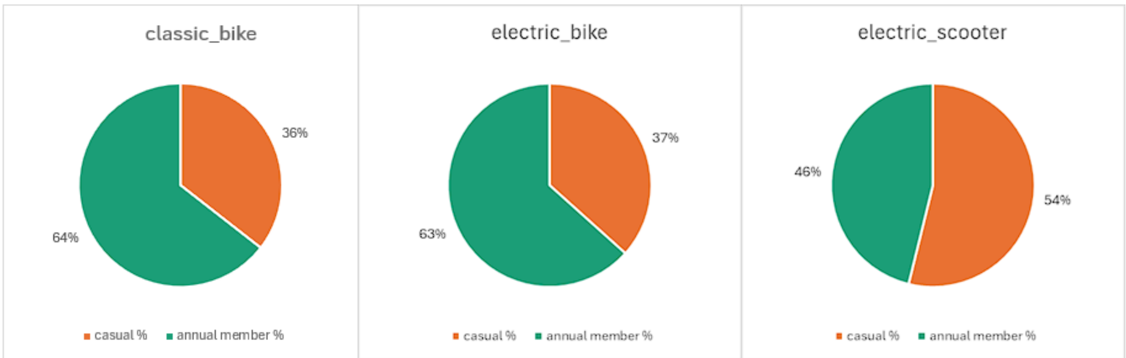
```
# Calculate total ride volume by rideable_type and member_casual

ride_volume_by_type <- cyclistic_24 %>%
  group_by(rideable_type, member_casual) %>%
  summarise(total_rides = n(), .groups = "drop")


ride_volume_by_type


# Plot: Total Ride Volume by Rideable Type and Member Type
ggplot(ride_volume_by_type, aes(x = rideable_type, y = total_rides, fill = member_casual)) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.7), width = 0.6) +  # Side-by-side bars for each member type
  geom_text(
    aes(label = scales::label_comma()(total_rides)),  # Nicely formatted numbers
    colour = "black",
    size = 4,
    position = position_dodge(width = 0.7),  # Ensure text is aligned with the bars
    vjust = 0  # Center the text vertically inside the bars
  ) +
  labs(
    title = "Total Number of Rides per Rideable Type by Member Type in 2024",
    x = "Rideable Type",
    y = "Total Number of Rides"
```

```r
 ) +
 scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77"),
                   labels = c("Casual", "Annual Member")) +  # Custom colors for membership types
 theme_minimal(base_size = 14) +
 theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",  # Move legend to the bottom
  axis.text.x = element_text(angle = 45, hjust = 1),  # Rotate x-axis labels for readability
  axis.text.y = element_text(size = 12),
  axis.ticks.y = element_blank(),  # Remove y-axis ticks
  strip.text = element_text(size = 14)  # Larger facet labels
 )
```

rideable_type	member_casual	total_rides
<chr>	<chr>	<int>
classic_bike	casual	965094
classic_bike	member	1749636
electric_bike	casual	515919
electric_bike	member	891022
electric_scooter	casual	25279
electric_scooter	member	21677

A tibble: 6 × 3



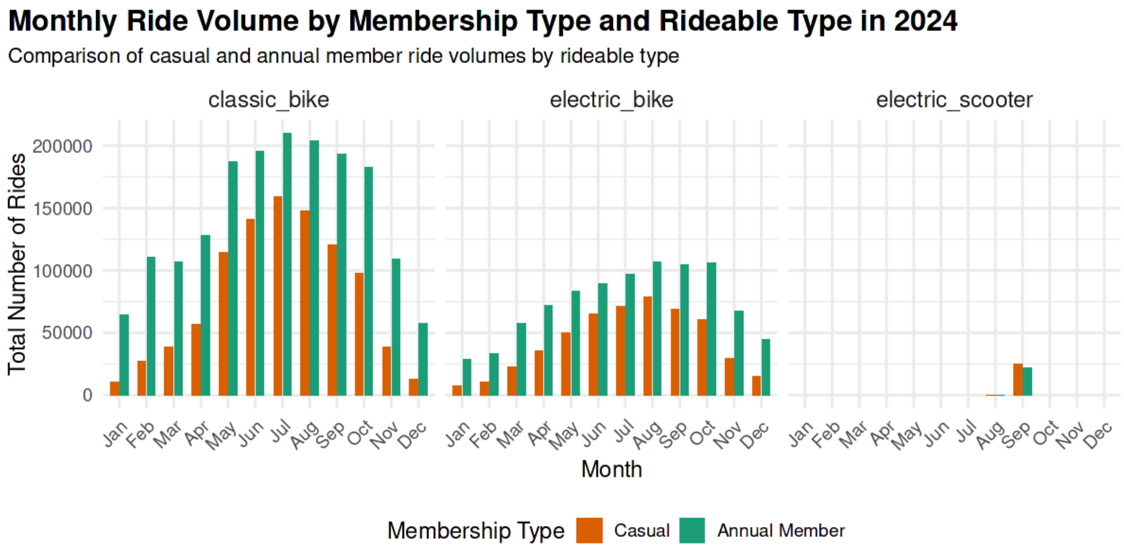


In terms of volume of rides, we see annual members with a significantly higher volume of rides than the casual members, in both casual bikes and electric bikes, having the annual members 64% and 63% respectively. Nevertheless, the electric scooter, although it had a lower volume of rides, the casual members had 8% more rides than the annual members.

In [22]:

```
# Calculate total ride volume by month, membership type, and rideable type
monthly_ride_volume <- cyclistic_24 %>%
 group_by(month, rideable_type, member_casual) %>%
 summarise(total_rides = n(), .groups = "drop") %>%
 mutate(
  month = factor(month, levels = 1:12, labels = month.abb, ordered = TRUE)  # Convert month to labels (Jan-Dec)
 )
```

```r
# Plot: Monthly Ride Volume by Membership Type and Rideable Type

ggplot(monthly_ride_volume, aes(x = month, y = total_rides, fill = member_casual))
+

  geom_bar(stat = "identity", position = position_dodge(width = 0.7), width = 0.6) +  #
Side-by-side bars for each member type

  labs(

    title = "Monthly Ride Volume by Membership Type and Rideable Type in 2024",

    subtitle = "Comparison of casual and annual member ride volumes by rideable
type",

    x = "Month",

    y = "Total Number of Rides",

    fill = "Membership Type"

  ) +

  scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77"),

                    labels = c("Casual", "Annual Member")) +  # Custom colors for
membership types

  theme_minimal(base_size = 14) +

  theme(

    plot.title.position = "plot",

    plot.title = element_text(face = "bold", size = 18),

    plot.subtitle = element_text(size = 13),

    legend.position = "bottom",

    axis.text.x = element_text(angle = 45, hjust = 1),

    strip.text = element_text(size = 14)  # Larger facet labels for rideable types

  ) +

  # Facet by rideable type (classic_bike, electric_bike, electric_scooter)

  facet_wrap(~ rideable_type, scales = "fixed")  # Separate by rideable type
```



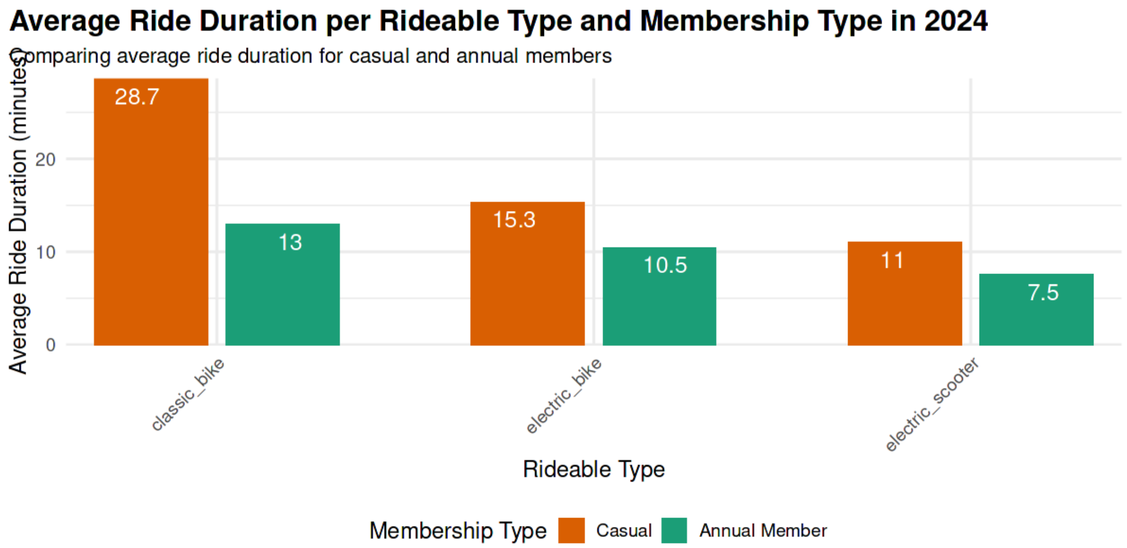
Starting with the electric scooter, and considering they were available for just around 1 month and for that reason it should be excluded from our analysis.

In terms of volume of rides, the annual members had higher volumes of rides than the casual members across all years. Additionally, it is notable that the peak of volume for both casual bikes and electric bikes is during May until October, reflecting the Summer and the middle of Fall seasons, having a significant decrease during Winter times.

In [23]:

```
# Calculate the average ride duration by rideable_type and member_casual

avg_ride_duration_by_type <- cyclistic_24 %>%

  group_by(rideable_type, member_casual) %>%

  summarise(avg_ride_duration = mean(ride_length, na.rm = TRUE), .groups = "drop")


# Plot: Average Ride Duration per Rideable Type and Membership Type

ggplot(avg_ride_duration_by_type, aes(x = rideable_type, y = avg_ride_duration, fill = member_casual)) +

  geom_bar(stat = "identity", position = position_dodge(width = 0.7), width = 0.6) +  # Bar chart with dodged bars for each membership type

  labs(

    title = "Average Ride Duration per Rideable Type and Membership Type in 2024",

    subtitle = "Comparing average ride duration for casual and annual members",
```

```
  x = "Rideable Type",
  y = "Average Ride Duration (minutes)",
  fill = "Membership Type"
 ) +
 scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77"),
          labels = c("Casual", "Annual Member")) +  # Customize colors for casual and member
 theme_minimal(base_size = 14) +
 theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",
  axis.text.x = element_text(angle = 45, hjust = 1),
  strip.text = element_text(size = 14)  # Larger facet labels
 ) +
 # Add labels in the middle of each bar (inside the bar)
 geom_text(aes(label = round(avg_ride_duration, 1)),
      position = position_dodge(width = 0.8, preserve = "total"),  # Position the label inside the bar
      size = 5,
      color = "white",  # White text for contrast against the bars
      fontface = "plain",
      vjust = 1.5,  # Center the text vertically inside the bar
      hjust = 0.6) +  # Center the text horizontally inside the bar
 coord_cartesian(expand = FALSE)  # Remove extra space around the plot
```

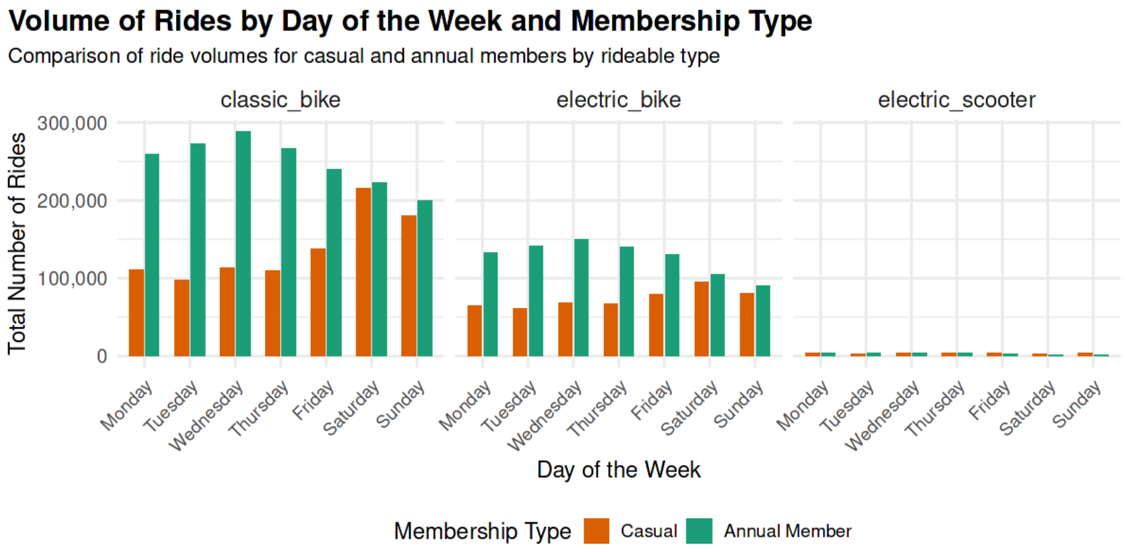


The average duration of the ride per rideable type reflects that casual members engage with longer rides on the overall, especially using casual bikes, having an average 28.7 min per ride. Although the annual members also seem to use the casual bikes for slightly longer times than the electric bikes, having on average 13 min per ride.

In [24]:

```
# Calculate total rides by day of the week, rideable type, and membership type

rides_by_day_type <- cyclistic_24 %>%

  group_by(weekday, rideable_type, member_casual) %>%

  summarise(total_rides = n(), .groups = "drop") %>%

  mutate(

    weekday = factor(weekday, levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday"),

             ordered = TRUE)  # Ensure weekdays are ordered from Monday to Sunday

  )


# Plot: Total Rides by Day of the Week, Rideable Type, and Membership Type

ggplot(rides_by_day_type, aes(x = weekday, y = total_rides, fill = member_casual)) +

  geom_bar(stat = "identity", position = position_dodge(width = 0.7), width = 0.6) +  # Stacked bars for casual and annual members
```

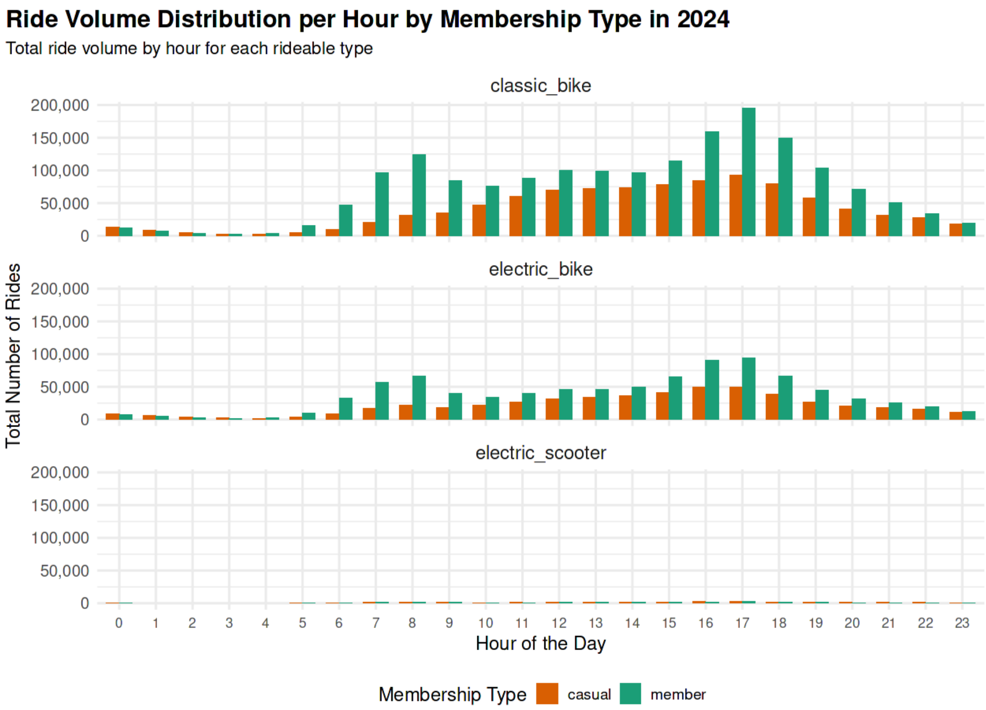
```
 labs(
  title = "Volume of Rides by Day of the Week and Membership Type",
  subtitle = "Comparison of ride volumes for casual and annual members by rideable type",
  x = "Day of the Week",
  y = "Total Number of Rides",
  fill = "Membership Type"
 ) +
 scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77"),  # Custom colors for membership types
                labels = c("Casual", "Annual Member")) +
 theme_minimal(base_size = 14) +
 theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",  # Move the legend to the bottom
  axis.text.x = element_text(angle = 45, hjust = 1),  # Rotate x-axis labels for readability
  axis.text.y = element_text(size = 12),
  strip.text = element_text(size = 14)  # Larger facet labels for rideable types
 ) +
 # Format y-axis labels with commas
 scale_y_continuous(labels = scales::label_comma()) +  # Adds commas to large numbers like 100,000
 facet_wrap(~ rideable_type, scales = "fixed")  # Separate by rideable type (classic_bike, electric_bike, electric_scooter)
```



In [25]:

```
# Increase the plot size for better readability in Kaggle

options(repr.plot.width = 12, repr.plot.height = 8)


# - Calculate total ride volume per hour, rideable type, and membership type -

hourly_ride_distribution <- cyclistic_24 %>%

  mutate(hour = factor(lubridate::hour(started_at), levels = 0:23)) %>%  # Use factor to ensure hours are ordered

  group_by(hour, rideable_type, member_casual) %>%

  summarise(total_rides = n(), .groups = "drop")


# - Plot: Ride Volume Distribution per Hour, Facet Wrap by Rideable Type -

ggplot(hourly_ride_distribution, aes(x = hour, y = total_rides, fill = member_casual)) +

  geom_bar(stat = "identity", position = "dodge", width = 0.7) +  # Side-by-side bars for casual and annual members

  labs(

    title = "Ride Volume Distribution per Hour by Membership Type in 2024",

    subtitle = "Total ride volume by hour for each rideable type",

    x = "Hour of the Day",
```

```
  y = "Total Number of Rides",
  fill = "Membership Type"
 ) +
 scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77")) +  # Custom colors for membership types
 theme_minimal(base_size = 14) +
 theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",  # Move legend to the bottom
  axis.text.x = element_text(size = 10),  # Rotate x-axis labels for readability
  axis.text.y = element_text(size = 12),
  strip.text = element_text(size = 14),  # Larger facet labels for rideable types
  plot.margin = margin(20, 80, 20, 40)  # Adjust plot margins for better readability
 ) +
 scale_y_continuous(labels = scales::label_comma()) +  # Format the y-axis with commas for readability
 facet_wrap(~ rideable_type, scales = "fixed", ncol = 1)  # Facet by rideable type, 2 columns for better layout
```

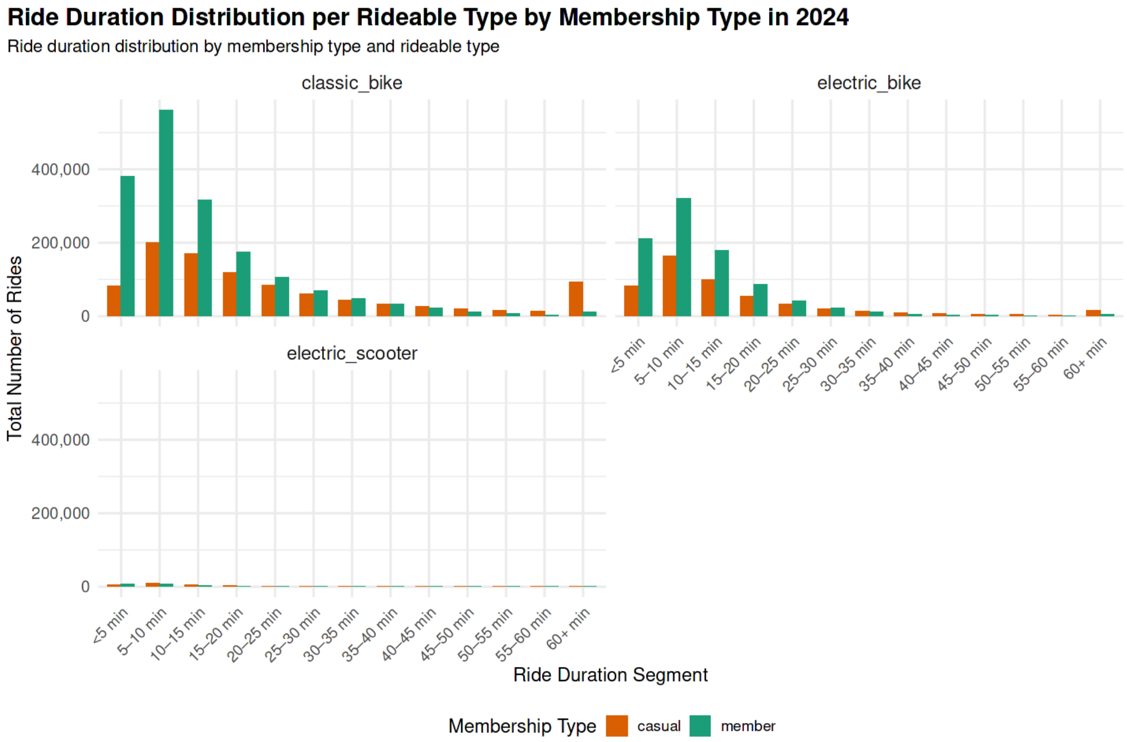


In [26]:

```
# Create ride duration segments and store in a new data frame
ride_duration_distribution_data <- cyclistic_24 %>%
 mutate(
  duration_segment = case_when(
   ride_length < 5 ~ "<5 min",
   ride_length >= 5 & ride_length < 10 ~ "5–10 min",
   ride_length >= 10 & ride_length < 15 ~ "10–15 min",
   ride_length >= 15 & ride_length < 20 ~ "15–20 min",
   ride_length >= 20 & ride_length < 25 ~ "20–25 min",
   ride_length >= 25 & ride_length < 30 ~ "25–30 min",
   ride_length >= 30 & ride_length < 35 ~ "30–35 min",
   ride_length >= 35 & ride_length < 40 ~ "35–40 min",
   ride_length >= 40 & ride_length < 45 ~ "40–45 min",
   ride_length >= 45 & ride_length < 50 ~ "45–50 min",
   ride_length >= 50 & ride_length < 55 ~ "50–55 min",
```

```
    ride_length >= 55 & ride_length < 60 ~ "55–60 min",
    ride_length >= 60 ~ "60+ min"
  )
 ) %>%
 mutate(
  duration_segment = factor(duration_segment,
                 levels = c("<5 min", "5–10 min", "10–15 min", "15–20 min",
                       "20–25 min", "25–30 min", "30–35 min", "35–40 min",
                       "40–45 min", "45–50 min", "50–55 min", "55–60 min", "60+ min"),
                 ordered = TRUE)  # Ensure segments are ordered by duration
 )

# - Calculate total rides per duration segment, rideable type, and membership type
-
ride_duration_distribution <- ride_duration_distribution_data %>%
 group_by(duration_segment, rideable_type, member_casual) %>%
 summarise(total_rides = n(), .groups = "drop")

# - Plot: Ride Duration Distribution per Rideable Type by Membership Type -
ggplot(ride_duration_distribution, aes(x = duration_segment, y = total_rides, fill =
member_casual)) +
 geom_bar(stat = "identity", position = "dodge", width = 0.7) +  # Side-by-side bars
for each membership type
 labs(
  title = "Ride Duration Distribution per Rideable Type by Membership Type in
2024",
  subtitle = "Ride duration distribution by membership type and rideable type",
  x = "Ride Duration Segment",
  y = "Total Number of Rides",
```

```
  fill = "Membership Type"
 ) +
 scale_fill_manual(values = c("casual" = "#d95f02", "member" = "#1b9e77")) +  # Custom colors for membership types
 theme_minimal(base_size = 14) +
 theme(
  plot.title.position = "plot",
  plot.title = element_text(face = "bold", size = 18),
  plot.subtitle = element_text(size = 13),
  legend.position = "bottom",  # Move the legend to the bottom
  axis.text.x = element_text(angle = 45, hjust = 1),  # Rotate x-axis labels for readability
  axis.text.y = element_text(size = 12),
  strip.text = element_text(size = 14)  # Larger facet labels for rideable types
 ) +
 scale_y_continuous(labels = scales::label_comma()) +  # Use commas to format the y-axis labels
 facet_wrap(~ rideable_type, scales = "fixed", ncol = 2)  # Facet by rideable type with 2 columns
```



5. Share

In this phase, it is expected to share the most relevant findings, key findings, in ways that will enable replying to the following questions:

- What were the similarities found between the casual and annual members?
- What were the differences found between the casual and annual members?

This analysis was presented to Lily Moreno and the Cyclistic Marketing analytics team via a presentation accessible through the following link:

- Cyclistic 2024 - Presentation.pdf

6. Act

Recommendations

1. **Launching marketing campaigns before the Summer-time:**

Considering that ride activity peaks during the summer, the marketing team should begin allocating marketing efforts one to two months before the season starts, when ride volume begins to increase. This timing could make the annual membership appear as a more valuable and timely offer, which could appear as a great moment to engage with promotions.

2. **Offer Higher Ride Allowances on the Weekends to Match Riding Patterns**

Since a considerable number of casual members ride more on weekends than on weekdays, introducing to the plan different ride allowances, with a standard limit during weekdays and a higher one on weekends, could better match riding patterns and increase casual members' interest in upgrading to an annual plan.

3. **Extend Ride Duration Limits to Encourage Membership Upgrades**

The longer rides over 60 min represent around 7.3% of the total rides for the casual members, and only 0.6% for the annual members. Increasing the overall duration of the current allowance could support long riders and increase their intention to acquire the annual plan. At the same time, using in-app prompts as "You've ridden 6 times during this month, you could have saved x£ with the annual plan" could make the customers understand more about their usage and support their conversion to become annual members.

To sum up, these recommendations were mainly focused on the differences between casual and annual members; however, it would be essential to convert those casual members who often ride to commute to work, for example, and who are still casual customers, and therefore they should be made aware of the advantages of the annual plan and the benefits considering their usage.

7. Conclusion

This project was a way to solidify my learnings throughout the Google Data Analytics Course, and although it was approached as a real business problem, it should not be interpreted as a professional recommendation. There are several considerations and data limitations that were not addressed, as well as potential strategies previously implemented by the organisation, which were unknown and could have influenced the overall outcome. The recommendations presented aim to solve a fictitious business challenge within the context and information provided.

Beyond the analytical results, this project represented a valuable learning experience that allowed me to apply key concepts in R, SQL, and Tableau while following the structured data analysis process — from data cleaning and exploration to visualisation and insight generation. It was both challenging and rewarding to translate raw data into meaningful business insights.

Through this project, I gained a deeper understanding of how data-driven thinking supports decision-making, and I developed a greater appreciation for the importance of clarity, precision, and ethical consideration in analytics. Overall, it was an enriching experience that strengthened my confidence and passion for working with data and solving real-world problems through analytical approaches.