Google Data Analytics Certificate Capstone (Bellabeat Case Study)

Gabriel Fernandez

```r
# Set default options for code chunks
knitr::opts_chunk$set(
  echo = TRUE,          # Display R code and its output
  comment=NA,           # Suppress code comments in output
  warning = FALSE,      # Suppress warning messages
  fig.align='center',   # Align figures in the center
  eval = TRUE           # Evaluate R code
)
```

Prepare and preprocess phase

```r
# Import libraries
library(tidyverse) # includes ggplot2
library(skimr) #  provides a compact and informative summary of your dataframe or dataset
library(lubridate)
library(janitor) # set of utility functions for data cleaning and data frame tidying tasks
library(RColorBrewer) # Color palettes for data visualization
library(ggcorrplot) # Visualize correlation matrices using ggplot2
library(scales) # formatting and transforming data for visualizations


# display.brewer.all(colorblindFriendly = TRUE)
```

Load datasets

- Datasets:

These datasets originate from a survey distributed on Amazon Mechanical Turk from 03.12.2016 to 05.12.2016. They include personal tracker data from 30 Fitbit users, covering physical activity, heart rate, and sleep monitoring, with differentiation based on Fitbit types and user behavior.

- Metadata: Fitbit data dictionary

```r
# Clean environment
rm(list = ls())

daily_activity <-
  read_csv("original_data/dailyActivity_merged.csv",
    trim_ws = TRUE,
    show_col_types = FALSE
  )

daily_sleep <- read_csv("original_data/sleepDay_merged.csv",
  trim_ws = TRUE,
```

```r
  show_col_types = FALSE
)

hourly_calories <-
  read_csv("original_data/hourlyCalories_merged.csv",
    trim_ws = TRUE,
    show_col_types = FALSE
  )

hourly_intensities <-
  read_csv("original_data/hourlyIntensities_merged.csv",
    trim_ws = TRUE,
    show_col_types = FALSE
  )
hourly_steps <-
  read_csv("original_data/hourlySteps_merged.csv",
    trim_ws = TRUE,
    show_col_types = FALSE
  )

minute_sleep <-
  read_csv("original_data/minuteSleep_merged.csv",
    trim_ws = TRUE,
    show_col_types = FALSE
  )

seconds_heartrate <-
  read_csv("original_data/heartrate_seconds_merged.csv",
    trim_ws = TRUE,
    show_col_types = FALSE
  )

weight_logs <-
  read_csv("original_data/weightLogInfo_merged.csv",
    trim_ws = TRUE,
    show_col_types = FALSE
  )

# Remove trailing spaces (trim_ws = TRUE)
```

dataset

Clean datasets

Clean the daily_activity dataset

```r
# Check daily_activity dataset before cleaning
glimpse(daily_activity)
```

```
Rows: 940
Columns: 15
$ Id                       <dbl> 1503960366, 1503960366, 1503960366, 150396036~
$ ActivityDate             <chr> "4/12/2016", "4/13/2016", "4/14/2016", "4/15/~
$ TotalSteps               <dbl> 13162, 10735, 10460, 9762, 12669, 9705, 13019~
```

```
$ TotalDistance            <dbl> 8.50, 6.97, 6.74, 6.28, 8.16, 6.48, 8.59, 9.8~
$ TrackerDistance          <dbl> 8.50, 6.97, 6.74, 6.28, 8.16, 6.48, 8.59, 9.8~
$ LoggedActivitiesDistance <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ VeryActiveDistance       <dbl> 1.88, 1.57, 2.44, 2.14, 2.71, 3.19, 3.25, 3.5~
$ ModeratelyActiveDistance <dbl> 0.55, 0.69, 0.40, 1.26, 0.41, 0.78, 0.64, 1.3~
$ LightActiveDistance      <dbl> 6.06, 4.71, 3.91, 2.83, 5.04, 2.51, 4.71, 5.0~
$ SedentaryActiveDistance  <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ VeryActiveMinutes        <dbl> 25, 21, 30, 29, 36, 38, 42, 50, 28, 19, 66, 4~
$ FairlyActiveMinutes      <dbl> 13, 19, 11, 34, 10, 20, 16, 31, 12, 8, 27, 21~
$ LightlyActiveMinutes     <dbl> 328, 217, 181, 209, 221, 164, 233, 264, 205, ~
$ SedentaryMinutes         <dbl> 728, 776, 1218, 726, 773, 539, 1149, 775, 818~
$ Calories                 <dbl> 1985, 1797, 1776, 1745, 1863, 1728, 1921, 203~
```

```r
# Check missing values and duplicates
cat(
  "\n",
  "Missing values:",
  sum(is.na(daily_activity)),
  "\n",
  "Duplicate values:",
  sum(duplicated(daily_activity)),
  "\n",
  "Unique Ids:",
  n_distinct(daily_activity$Id)
)
```

```
 Missing values: 0
 Duplicate values: 0
 Unique Ids: 33
```

Let us clean:

- Change column names to lower case because R is case sensitive.
- Change "Id" from double to a character because the number represents a category.
- Change "ActivityDate" from char to date.

```r
# Clean daily_activity dataset

daily_activity <-
  # Clean column names
  clean_names(daily_activity) %>%
  # Correct column types
  mutate(id = as.character(id)) %>% # from double to chr
  mutate(activity_date = as.Date(activity_date,
                                 format = "%m/%d/%Y")) %>% # from chr to date
  # Remove duplicate rows
  distinct()

# Check daily_activity dataset after cleaning
glimpse(daily_activity)
```

```
Rows: 940
Columns: 15
$ id                         <chr> "1503960366", "1503960366", "1503960366", "~
$ activity_date              <date> 2016-04-12, 2016-04-13, 2016-04-14, 2016-0~
```

```
$ total_steps                <dbl> 13162, 10735, 10460, 9762, 12669, 9705, 130~
$ total_distance             <dbl> 8.50, 6.97, 6.74, 6.28, 8.16, 6.48, 8.59, 9~
$ tracker_distance           <dbl> 8.50, 6.97, 6.74, 6.28, 8.16, 6.48, 8.59, 9~
$ logged_activities_distance <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0~
$ very_active_distance       <dbl> 1.88, 1.57, 2.44, 2.14, 2.71, 3.19, 3.25, 3~
$ moderately_active_distance <dbl> 0.55, 0.69, 0.40, 1.26, 0.41, 0.78, 0.64, 1~
$ light_active_distance      <dbl> 6.06, 4.71, 3.91, 2.83, 5.04, 2.51, 4.71, 5~
$ sedentary_active_distance  <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0~
$ very_active_minutes        <dbl> 25, 21, 30, 29, 36, 38, 42, 50, 28, 19, 66,~
$ fairly_active_minutes      <dbl> 13, 19, 11, 34, 10, 20, 16, 31, 12, 8, 27, ~
$ lightly_active_minutes     <dbl> 328, 217, 181, 209, 221, 164, 233, 264, 205~
$ sedentary_minutes          <dbl> 728, 776, 1218, 726, 773, 539, 1149, 775, 8~
$ calories                   <dbl> 1985, 1797, 1776, 1745, 1863, 1728, 1921, 2~
```

```r
# Check missing values and duplicates after cleaning
cat("\n",
    "Missing values:",
    sum(is.na(daily_activity)),
    "\n",
    "Duplicate values:",
    sum(duplicated(daily_activity)))
```

```
 Missing values: 0
 Duplicate values: 0
```

```r
# Let us print summary statistics to have a better idea of the dataset
daily_activity %>%
  summary()
```

```
      id            activity_date         total_steps    total_distance
 Length:940         Min.   :2016-04-12   Min.   :    0   Min.   : 0.000
 Class :character   1st Qu.:2016-04-19   1st Qu.: 3790   1st Qu.: 2.620
 Mode  :character   Median :2016-04-26   Median : 7406   Median : 5.245
                    Mean   :2016-04-26   Mean   : 7638   Mean   : 5.490
                    3rd Qu.:2016-05-04   3rd Qu.:10727   3rd Qu.: 7.713
                    Max.   :2016-05-12   Max.   :36019   Max.   :28.030
 tracker_distance logged_activities_distance very_active_distance
 Min.   : 0.000   Min.   :0.0000             Min.   : 0.000
 1st Qu.: 2.620   1st Qu.:0.0000             1st Qu.: 0.000
 Median : 5.245   Median :0.0000             Median : 0.210
 Mean   : 5.475   Mean   :0.1082             Mean   : 1.503
 3rd Qu.: 7.710   3rd Qu.:0.0000             3rd Qu.: 2.053
 Max.   :28.030   Max.   :4.9421             Max.   :21.920
 moderately_active_distance light_active_distance sedentary_active_distance
 Min.   :0.0000             Min.   : 0.000        Min.   :0.000000
 1st Qu.:0.0000             1st Qu.: 1.945        1st Qu.:0.000000
 Median :0.2400             Median : 3.365        Median :0.000000
 Mean   :0.5675             Mean   : 3.341        Mean   :0.001606
 3rd Qu.:0.8000             3rd Qu.: 4.782        3rd Qu.:0.000000
 Max.   :6.4800             Max.   :10.710        Max.   :0.110000
 very_active_minutes fairly_active_minutes lightly_active_minutes
 Min.   :  0.00      Min.   :  0.00        Min.   :  0.0
 1st Qu.:  0.00      1st Qu.:  0.00        1st Qu.:127.0
 Median :  4.00      Median :  6.00        Median :199.0
 Mean   : 21.16      Mean   : 13.56        Mean   :192.8
```

```
 3rd Qu.: 32.00      3rd Qu.: 19.00        3rd Qu.:264.0
 Max.   :210.00      Max.   :143.00        Max.   :518.0
 sedentary_minutes    calories
 Min.   :   0.0    Min.   :   0
 1st Qu.: 729.8    1st Qu.:1828
 Median :1057.5    Median :2134
 Mean   : 991.2    Mean   :2304
 3rd Qu.:1229.5    3rd Qu.:2793
 Max.   :1440.0    Max.   :4900
```

- This summary helps us explore each attribute quickly. We notice that some attributes have a minimum value of zero (total_step, total_distance, calories). Let us explore this observation.

```r
# Check where total_steps is zero
filter(daily_activity, total_steps == 0)
```

```
# A tibble: 77 x 15
   id         activity~1 total~2 total~3 track~4 logge~5 very_~6 moder~7 light~8
   <chr>      <date>       <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1 1503960366 2016-05-12       0       0       0       0       0       0       0
 2 1844505072 2016-04-24       0       0       0       0       0       0       0
 3 1844505072 2016-04-25       0       0       0       0       0       0       0
 4 1844505072 2016-04-26       0       0       0       0       0       0       0
 5 1844505072 2016-05-02       0       0       0       0       0       0       0
 6 1844505072 2016-05-07       0       0       0       0       0       0       0
 7 1844505072 2016-05-08       0       0       0       0       0       0       0
 8 1844505072 2016-05-09       0       0       0       0       0       0       0
 9 1844505072 2016-05-10       0       0       0       0       0       0       0
10 1844505072 2016-05-11       0       0       0       0       0       0       0
# ... with 67 more rows, 6 more variables: sedentary_active_distance <dbl>,
#   very_active_minutes <dbl>, fairly_active_minutes <dbl>,
#   lightly_active_minutes <dbl>, sedentary_minutes <dbl>, calories <dbl>, and
#   abbreviated variable names 1: activity_date, 2: total_steps,
#   3: total_distance, 4: tracker_distance, 5: logged_activities_distance,
#   6: very_active_distance, 7: moderately_active_distance,
#   8: light_active_distance
```

- We found 77 observations where total_steps is zero. We should delete these observations so they do not affect our mean and median. If the total_step is zero, the person did not wear the Fitbit.

```r
# Check where calories is zero
filter(daily_activity, calories == 0)
```

```
# A tibble: 4 x 15
  id         activity_~1 total~2 total~3 track~4 logge~5 very_~6 moder~7 light~8
  <chr>      <date>        <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
1 1503960366 2016-05-12        0       0       0       0       0       0       0
2 6290855005 2016-05-10        0       0       0       0       0       0       0
3 8253242879 2016-04-30        0       0       0       0       0       0       0
4 8583815059 2016-05-12        0       0       0       0       0       0       0
# ... with 6 more variables: sedentary_active_distance <dbl>,
#   very_active_minutes <dbl>, fairly_active_minutes <dbl>,
#   lightly_active_minutes <dbl>, sedentary_minutes <dbl>, calories <dbl>, and
#   abbreviated variable names 1: activity_date, 2: total_steps,
#   3: total_distance, 4: tracker_distance, 5: logged_activities_distance,
#   6: very_active_distance, 7: moderately_active_distance,
#   8: light_active_distance
```

```r
# Check where total_distance is zero
filter(daily_activity, total_distance == 0)
```

```
# A tibble: 78 x 15
   id         activity~1 total~2 total~3 track~4 logge~5 very_~6 moder~7 light~8
   <chr>      <date>       <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1 1503960366 2016-05-12       0       0       0       0       0       0       0
 2 1844505072 2016-04-24       0       0       0       0       0       0       0
 3 1844505072 2016-04-25       0       0       0       0       0       0       0
 4 1844505072 2016-04-26       0       0       0       0       0       0       0
 5 1844505072 2016-04-27       4       0       0       0       0       0       0
 6 1844505072 2016-05-02       0       0       0       0       0       0       0
 7 1844505072 2016-05-07       0       0       0       0       0       0       0
 8 1844505072 2016-05-08       0       0       0       0       0       0       0
 9 1844505072 2016-05-09       0       0       0       0       0       0       0
10 1844505072 2016-05-10       0       0       0       0       0       0       0
# ... with 68 more rows, 6 more variables: sedentary_active_distance <dbl>,
#   very_active_minutes <dbl>, fairly_active_minutes <dbl>,
#   lightly_active_minutes <dbl>, sedentary_minutes <dbl>, calories <dbl>, and
#   abbreviated variable names 1: activity_date, 2: total_steps,
#   3: total_distance, 4: tracker_distance, 5: logged_activities_distance,
#   6: very_active_distance, 7: moderately_active_distance,
#   8: light_active_distance
```

From our inspection above, we can see that we just need to delete the entries where total_steps is zero and will take take care of the rest.

```r
daily_activity_clean <-
  filter(daily_activity,
         total_steps != 0,
         total_distance != 0,
         calories != 0)
daily_activity_clean
```

```
# A tibble: 862 x 15
   id         activity~1 total~2 total~3 track~4 logge~5 very_~6 moder~7 light~8
   <chr>      <date>       <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1 1503960366 2016-04-12   13162    8.5     8.5        0    1.88   0.550    6.06
 2 1503960366 2016-04-13   10735    6.97    6.97       0    1.57   0.690    4.71
 3 1503960366 2016-04-14   10460    6.74    6.74       0    2.44   0.400    3.91
 4 1503960366 2016-04-15    9762    6.28    6.28       0    2.14   1.26     2.83
 5 1503960366 2016-04-16   12669    8.16    8.16       0    2.71   0.410    5.04
 6 1503960366 2016-04-17    9705    6.48    6.48       0    3.19   0.780    2.51
 7 1503960366 2016-04-18   13019    8.59    8.59       0    3.25   0.640    4.71
 8 1503960366 2016-04-19   15506    9.88    9.88       0    3.53   1.32     5.03
 9 1503960366 2016-04-20   10544    6.68    6.68       0    1.96   0.480    4.24
10 1503960366 2016-04-21    9819    6.34    6.34       0    1.34   0.350    4.65
# ... with 852 more rows, 6 more variables: sedentary_active_distance <dbl>,
#   very_active_minutes <dbl>, fairly_active_minutes <dbl>,
#   lightly_active_minutes <dbl>, sedentary_minutes <dbl>, calories <dbl>, and
#   abbreviated variable names 1: activity_date, 2: total_steps,
#   3: total_distance, 4: tracker_distance, 5: logged_activities_distance,
#   6: very_active_distance, 7: moderately_active_distance,
#   8: light_active_distance
```

```r
names(daily_activity)
```

```
 [1] "id"                          "activity_date"
 [3] "total_steps"                 "total_distance"
 [5] "tracker_distance"            "logged_activities_distance"
 [7] "very_active_distance"        "moderately_active_distance"
 [9] "light_active_distance"       "sedentary_active_distance"
[11] "very_active_minutes"         "fairly_active_minutes"
[13] "lightly_active_minutes"      "sedentary_minutes"
[15] "calories"
```

```r
# Check the attributes again

cat("Before deleting the entries\n\n")
```

```
Before deleting the entries
```

```r
select(daily_activity,total_steps,total_distance,calories) %>%
  summary()
```

```
  total_steps    total_distance      calories
 Min.   :    0   Min.   : 0.000   Min.   :   0
 1st Qu.: 3790   1st Qu.: 2.620   1st Qu.:1828
 Median : 7406   Median : 5.245   Median :2134
 Mean   : 7638   Mean   : 5.490   Mean   :2304
 3rd Qu.:10727   3rd Qu.: 7.713   3rd Qu.:2793
 Max.   :36019   Max.   :28.030   Max.   :4900
```

```r
cat("\n\n\n",
    "\t\t vs",
    "\n\n\n")
```

```



         vs



```

```r
cat("After deleting the entries\n\n")
```

```
After deleting the entries
```

```r
select(daily_activity_clean, total_steps, total_distance, calories) %>%
  summary()
```

```
  total_steps    total_distance      calories
 Min.   :    8   Min.   : 0.010   Min.   :  52
 1st Qu.: 4927   1st Qu.: 3.373   1st Qu.:1857
 Median : 8054   Median : 5.590   Median :2220
 Mean   : 8329   Mean   : 5.986   Mean   :2362
 3rd Qu.:11096   3rd Qu.: 7.905   3rd Qu.:2832
 Max.   :36019   Max.   :28.030   Max.   :4900
```

We can see that the observation we removed affected our mean and median.

Clean the daily_sleep dataset

```r
# Check daily_sleep dataset before cleaning
glimpse(daily_sleep)
```

```
Rows: 413
Columns: 5
$ Id                 <dbl> 1503960366, 1503960366, 1503960366, 1503960366, 150~
$ SleepDay           <chr> "4/12/2016 12:00:00 AM", "4/13/2016 12:00:00 AM", "~
$ TotalSleepRecords  <dbl> 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ~
$ TotalMinutesAsleep <dbl> 327, 384, 412, 340, 700, 304, 360, 325, 361, 430, 2~
$ TotalTimeInBed     <dbl> 346, 407, 442, 367, 712, 320, 377, 364, 384, 449, 3~
```

```r
# Check missing values and duplicates
cat("\n",
    "Missing values:",
    sum(is.na(daily_sleep)),
    "\n",
    "Duplicate values:",
    sum(duplicated(daily_sleep)),
  "\n",
  "Unique Ids:",
  n_distinct(daily_sleep$Id)
    )
```

```
 Missing values: 0
 Duplicate values: 3
 Unique Ids: 24
```

Let us clean:

- Change column names to lower case because R is case sensitive
- Change "Id" from double to a character because the number represents a category
- Change "SleepDay" from char to date. Since the time component of this column is the same for each observation"12:00:00 AM", we can remove it. This will helps us merged this dataset with daily_activity later
- Delete duplicates (3 observations are duplicates)

```r
# Clean daily_sleep dataset

daily_sleep_clean <-
  # Clean column names
  clean_names(daily_sleep) %>%
  # Correct column types
  mutate(id = as.character(id)) %>% # from double to chr
  mutate(sleep_day = as.Date(sleep_day,
                             format = "%m/%d/%Y")) %>% # from chr to date
  # Remove duplicate rows
  distinct()

# Check clean daily_sleep dataset
glimpse(daily_sleep_clean)
```

```
Rows: 410
Columns: 5
$ id                   <chr> "1503960366", "1503960366", "1503960366", "150396~
$ sleep_day            <date> 2016-04-12, 2016-04-13, 2016-04-15, 2016-04-16, ~
$ total_sleep_records  <dbl> 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ total_minutes_asleep <dbl> 327, 384, 412, 340, 700, 304, 360, 325, 361, 430,~
```

```
$ total_time_in_bed    <dbl> 346, 407, 442, 367, 712, 320, 377, 364, 384, 449,~
```

```r
# Check missing values and duplicates after cleaning
cat("\n",
    "Missing values:",
    sum(is.na(daily_sleep_clean)),
    "\n",
    "Duplicate values:",
    sum(duplicated(daily_sleep_clean)))
```

```
 Missing values: 0
 Duplicate values: 0
```

Clean the hourly datasets (hourly__calories, hourly__intensities, and hourly__steps)

```r
# Check hourly_calories dataset before cleaning
glimpse(hourly_calories)
```

```
Rows: 22,099
Columns: 3
$ Id           <dbl> 1503960366, 1503960366, 1503960366, 1503960366, 150396036~
$ ActivityHour <chr> "4/12/2016 12:00:00 AM", "4/12/2016 1:00:00 AM", "4/12/20~
$ Calories     <dbl> 81, 61, 59, 47, 48, 48, 48, 47, 68, 141, 99, 76, 73, 66, ~
```

```r
# Check missing values and duplicates
cat("\n",
    "Missing values:",
    sum(is.na(hourly_calories)),
    "\n",
    "Duplicate values:",
    sum(duplicated(hourly_calories)))
```

```
 Missing values: 0
 Duplicate values: 0
```

```r
# Check hourly_intensities dataset before cleaning
glimpse(hourly_intensities)
```

```
Rows: 22,099
Columns: 4
$ Id               <dbl> 1503960366, 1503960366, 1503960366, 1503960366, 15039~
$ ActivityHour     <chr> "4/12/2016 12:00:00 AM", "4/12/2016 1:00:00 AM", "4/1~
$ TotalIntensity   <dbl> 20, 8, 7, 0, 0, 0, 0, 0, 13, 30, 29, 12, 11, 6, 36, 5~
$ AverageIntensity <dbl> 0.333333, 0.133333, 0.116667, 0.000000, 0.000000, 0.0~
```

```r
# Check missing values and duplicates
cat("\n",
    "Missing values:",
    sum(is.na(hourly_intensities)),
    "\n",
    "Duplicate values:",
    sum(duplicated(hourly_intensities)))
```

```
 Missing values: 0
```

```
 Duplicate values: 0
```

```r
# Check hourly_steps dataset before cleaning
glimpse(hourly_steps)
```

```
Rows: 22,099
Columns: 3
$ Id           <dbl> 1503960366, 1503960366, 1503960366, 1503960366, 150396036~
$ ActivityHour <chr> "4/12/2016 12:00:00 AM", "4/12/2016 1:00:00 AM", "4/12/20~
$ StepTotal    <dbl> 373, 160, 151, 0, 0, 0, 0, 0, 250, 1864, 676, 360, 253, 2~
```

```r
# Check missing values and duplicates
cat("\n",
    "Missing values:",
    sum(is.na(hourly_steps)),
    "\n",
    "Duplicate values:",
    sum(duplicated(hourly_steps)))
```

```
 Missing values: 0
 Duplicate values: 0
```

Join hourly datasets to create a hourly_actitvity dataset

These datasets shared the same Id and Activity_hour, let us join them into a new dataset (hourly_activity) before we clean them.

```r
# Join the hourly datasets (hourly_calories, hourly_intensities, and hourly_steps)

hourly_activity <-
  inner_join(hourly_calories,
             hourly_intensities,
             by = c("Id", "ActivityHour"))

hourly_activity <-
  inner_join(hourly_activity, hourly_steps, by = c("Id", "ActivityHour"))
```

```r
# Check hourly_activity dataset before cleaning
glimpse(hourly_activity)
```

```
Rows: 22,099
Columns: 6
$ Id               <dbl> 1503960366, 1503960366, 1503960366, 1503960366, 15039~
$ ActivityHour     <chr> "4/12/2016 12:00:00 AM", "4/12/2016 1:00:00 AM", "4/1~
$ Calories         <dbl> 81, 61, 59, 47, 48, 48, 48, 47, 68, 141, 99, 76, 73, ~
$ TotalIntensity   <dbl> 20, 8, 7, 0, 0, 0, 0, 0, 13, 30, 29, 12, 11, 6, 36, 5~
$ AverageIntensity <dbl> 0.333333, 0.133333, 0.116667, 0.000000, 0.000000, 0.0~
$ StepTotal        <dbl> 373, 160, 151, 0, 0, 0, 0, 0, 250, 1864, 676, 360, 25~
```

```r
# Check missing values and duplicates
cat("\n",
    "Missing values:",
    sum(is.na(hourly_activity)),
    "\n",
    "Duplicate values:",
    sum(duplicated(hourly_activity)))
```

```
 Missing values: 0
 Duplicate values: 0
```

Let us clean:

- Change column names to lower case because R is case sensitive
- Change "Id" from double to a character because the number represents a category
- Change "ActivityHour" from char to datetime

Note:The default timezone is UTC.

```r
# Clean hourly_activity dataset

hourly_activity_clean <-
  # Clean column names
  clean_names(hourly_activity) %>%
  # Correct column types
  mutate(id = as.character(id)) %>% # from double to chr
  mutate(activity_hour = as_datetime(activity_hour,
                                     format = "%m/%d/%Y %I:%M:%S %p")) %>% # from chr to datetime
  # Remove duplicate rows
  distinct()

# Check clean daily_activity dataset
glimpse(hourly_activity_clean)
```

```
Rows: 22,099
Columns: 6
$ id                <chr> "1503960366", "1503960366", "1503960366", "150396036~
$ activity_hour     <dttm> 2016-04-12 00:00:00, 2016-04-12 01:00:00, 2016-04-1~
$ calories          <dbl> 81, 61, 59, 47, 48, 48, 48, 47, 68, 141, 99, 76, 73,~
$ total_intensity   <dbl> 20, 8, 7, 0, 0, 0, 0, 0, 13, 30, 29, 12, 11, 6, 36, ~
$ average_intensity <dbl> 0.333333, 0.133333, 0.116667, 0.000000, 0.000000, 0.~
$ step_total        <dbl> 373, 160, 151, 0, 0, 0, 0, 0, 250, 1864, 676, 360, 2~
```

```r
# Check missing values and duplicates after cleaning
cat("\n",
    "Missing values:",
    sum(is.na(hourly_activity_clean)),
    "\n",
    "Duplicate values:",
    sum(duplicated(hourly_activity_clean)))
```

```

 Missing values: 0
 Duplicate values: 0
```

```r
# as_datetime() converts with default timezone = "UTC"
```

Clean the minute_sleep dataset

```r
# Check minute_sleep dataset before cleaning
glimpse(minute_sleep)
```

```
Rows: 188,521
Columns: 4
```

```
$ Id    <dbl> 1503960366, 1503960366, 1503960366, 1503960366, 1503960366, 1503~
$ date  <chr> "4/12/2016 2:47:30 AM", "4/12/2016 2:48:30 AM", "4/12/2016 2:49:~
$ value <dbl> 3, 2, 1, 1, 1, 1, 1, 2, 2, 2, 3, 3, 3, 3, 3, 2, 1, 1, 1, 1, 1, 1~
$ logId <dbl> 11380564589, 11380564589, 11380564589, 11380564589, 11380564589,~
```

```
# Check missing values and duplicates
cat("\n",
    "Missing values:",
    sum(is.na(minute_sleep)),
    "\n",
    "Duplicate values:",
    sum(duplicated(minute_sleep)),
    "\n",
  "Unique Ids:",
  n_distinct(minute_sleep$Id))
```

```
 Missing values: 0
 Duplicate values: 543
 Unique Ids: 24
```

Let us clean:

- Change column names to lower case because R is case sensitive.
- Change "Id" from double to a character because the number represents a category.
- Change "date" from char to datetime.
- Change "value" from double to factor. Value indicates the sleep state: 1 = asleep, 2 = restless, 3 = awake. For for details see: Fitbit data dictionary
- Remove duplicate values: 543.

```
# Clean minute_sleep dataset

minute_sleep_clean <-
  # Clean column names
  clean_names(minute_sleep) %>%
  # Correct column types
  mutate(value = as.factor(value)) %>% # from double to chr
  mutate(id = as.character(id)) %>% # from double to chr
  mutate(date = as_datetime(date,
                            format = "%m/%d/%Y %I:%M:%S %p")) %>% # From chr to datetime
  # Remove duplicate rows
  distinct()

# Check clean daily_activity dataset
glimpse(minute_sleep_clean)
```

```
Rows: 187,978
Columns: 4
$ id     <chr> "1503960366", "1503960366", "1503960366", "1503960366", "150396~
$ date   <dttm> 2016-04-12 02:47:30, 2016-04-12 02:48:30, 2016-04-12 02:49:30,~
$ value  <fct> 3, 2, 1, 1, 1, 1, 1, 2, 2, 2, 3, 3, 3, 3, 3, 2, 1, 1, 1, 1, 1, ~
$ log_id <dbl> 11380564589, 11380564589, 11380564589, 11380564589, 11380564589~
```

```
# Check missing values and duplicates after cleaning
cat("\n",
```

```
    "Missing values:",
    sum(is.na(minute_sleep_clean)),
    "\n",
    "Duplicate values:",
    sum(duplicated(minute_sleep_clean)))
```

```
 Missing values: 0
 Duplicate values: 0
```

Clean the seconds_heartrate dataset

```
# Check seconds_heartrate set before cleaning
glimpse(seconds_heartrate)
```

```
Rows: 2,483,658
Columns: 3
$ Id    <dbl> 2022484408, 2022484408, 2022484408, 2022484408, 2022484408, 2022~
$ Time  <chr> "4/12/2016 7:21:00 AM", "4/12/2016 7:21:05 AM", "4/12/2016 7:21:~
$ Value <dbl> 97, 102, 105, 103, 101, 95, 91, 93, 94, 93, 92, 89, 83, 61, 60, ~
```

```
# Check missing values and duplicates
cat(
  "\n",
  "Missing values:", sum(is.na(seconds_heartrate)),
  "\n",
  "Duplicate values:", sum(duplicated(seconds_heartrate))
)
```

```
 Missing values: 0
 Duplicate values: 0
```

Let us clean:

- Change column names to lower case because R is case sensitive
- Change "Id" from double to a character because the number represents a category
- Change "Time" from char to datetime and rename it date_time
- Rename "Value" to heart_rate Fitbit data dictionary

```
# Clean seconds_heartrate dataset

seconds_heartrate_clean <-
  # Clean column names
  clean_names(seconds_heartrate) %>%
  # Correct column types
  mutate(id = as.character(id)) %>% # from double to chr
  mutate(time = as_datetime(time,
                            format = "%m/%d/%Y %I:%M:%S %p")) %>% # from chr to datetime
  # Rename columns
  rename(date_time = time,
         heart_rate = value) %>%
  # Remove duplicate rows
  distinct()

# Check clean daily_activity dataset
```

```r
glimpse(seconds_heartrate_clean)
```

```
Rows: 2,483,658
Columns: 3
$ id         <chr> "2022484408", "2022484408", "2022484408", "2022484408", "20~
$ date_time  <dttm> 2016-04-12 07:21:00, 2016-04-12 07:21:05, 2016-04-12 07:21~
$ heart_rate <dbl> 97, 102, 105, 103, 101, 95, 91, 93, 94, 93, 92, 89, 83, 61,~
```

```r
# Check missing values and duplicates after cleaning

cat("\n",
    "Missing values:",
    sum(is.na(seconds_heartrate_clean)),
    "\n",
    "Duplicate values:",
    sum(duplicated(seconds_heartrate_clean)))
```

```
 Missing values: 0
 Duplicate values: 0
```

```r
# as_datetime() converts with default timezone = "UTC"
```

Clean the weight_logs dataset

```r
# Check weight_logs set before cleaning

glimpse(weight_logs)
```

```
Rows: 67
Columns: 8
$ Id             <dbl> 1503960366, 1503960366, 1927972279, 2873212765, 2873212~
$ Date           <chr> "5/2/2016 11:59:59 PM", "5/3/2016 11:59:59 PM", "4/13/2~
$ WeightKg       <dbl> 52.6, 52.6, 133.5, 56.7, 57.3, 72.4, 72.3, 69.7, 70.3, ~
$ WeightPounds   <dbl> 115.9631, 115.9631, 294.3171, 125.0021, 126.3249, 159.6~
$ Fat            <dbl> 22, NA, NA, NA, NA, 25, NA, NA, NA, NA, NA, NA, NA, NA,~
$ BMI            <dbl> 22.65, 22.65, 47.54, 21.45, 21.69, 27.45, 27.38, 27.25,~
$ IsManualReport <lgl> TRUE, TRUE, FALSE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, ~
$ LogId          <dbl> 1.462234e+12, 1.462320e+12, 1.460510e+12, 1.461283e+12,~
```

```r
# Check missing values and duplicates
cat("\n",
    "Missing values:",
    sum(is.na(weight_logs)),
    "\n",
    "Duplicate values:",
    sum(duplicated(weight_logs)))
```

```
 Missing values: 65
 Duplicate values: 0
```

Let us clean: - Change column names to lower case because R is case sensitive.

- Change “Id” from double to a character because the number represents a category
- Change “Date” from char to datetime and rename it date_time.

- Change NA to 0 in the column "fat."

```
# Clean  weight_logs dataset

weight_logs_clean <-
  # Clean column names
  clean_names(weight_logs) %>%
  # Correct column types
  mutate(id = as.character(id)) %>% # from double to chr
  mutate(date = as_datetime(date,
                            format = "%m/%d/%Y %I:%M:%S %p")) %>% # from chr to datetime
  # Rename columns
  rename(date_time = date) %>%
  # Remove duplicate rows
  distinct()



# Change NA to 0 in the column "fat"
weight_logs_clean$fat[is.na(weight_logs_clean$fat)] <- 0

# Check clean daily_activity dataset
glimpse(weight_logs_clean)
```

```
Rows: 67
Columns: 8
$ id                <chr> "1503960366", "1503960366", "1927972279", "2873212765~
$ date_time         <dttm> 2016-05-02 23:59:59, 2016-05-03 23:59:59, 2016-04-13~
$ weight_kg         <dbl> 52.6, 52.6, 133.5, 56.7, 57.3, 72.4, 72.3, 69.7, 70.3~
$ weight_pounds     <dbl> 115.9631, 115.9631, 294.3171, 125.0021, 126.3249, 159~
$ fat               <dbl> 22, 0, 0, 0, 0, 25, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ bmi               <dbl> 22.65, 22.65, 47.54, 21.45, 21.69, 27.45, 27.38, 27.2~
$ is_manual_report <lgl> TRUE, TRUE, FALSE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE~
$ log_id            <dbl> 1.462234e+12, 1.462320e+12, 1.460510e+12, 1.461283e+1~
```

```
# Check missing values and duplicates after cleaning

cat("\n",
    "Missing values:",
    sum(is.na(weight_logs_clean)),
    "\n",
    "Duplicate values:",
    sum(duplicated(weight_logs_clean)))
```

```

 Missing values: 0
 Duplicate values: 0
```

Distribution of ids across datasets

```
# Loop through each  dataset and print th number o funiqu ids
datasets <- c(
    "daily_activity_clean",
    "daily_sleep_clean",
    "hourly_activity_clean",
```

```r
    "minute_sleep_clean",
    "seconds_heartrate_clean",
    "weight_logs_clean"
)


results_df <- data.frame(Dataset = character(0), distinct_IDs = integer(0))

for (dataset_name in datasets) {
    dataset <- get(dataset_name)  # Retrieve the dataset by its name
    distinct_ids <- length(unique(dataset$id))  # Calculate the number of distinct IDs

    result_row <- data.frame(Dataset = dataset_name, distinct_IDs = distinct_ids)
    results_df <- bind_rows(results_df, result_row)
}

sorted_results <- results_df %>% arrange(- distinct_IDs )

print(sorted_results)
```

```
                  Dataset distinct_IDs
1    daily_activity_clean           33
2   hourly_activity_clean           33
3       daily_sleep_clean           24
4      minute_sleep_clean           24
5 seconds_heartrate_clean           14
6       weight_logs_clean            8
```

- Differences in the number of unique IDs between the datasets can imply discrepancies in data collection methods, data incompleteness, or differing levels of user engagement.

Export clean datasets

```r
# To uncomment the following code, select all the lines and press shift + control + c on Mac


# write.csv(daily_activity_clean,
#           "daily_activity_clean.csv",
#           row.names = FALSE)
#
# write.csv(daily_sleep_clean,
#           "daily_sleep_clean.csv",
#           row.names = FALSE)
#
# write.csv(daily_sleep_clean,
#           "hourly_activity_clean.csv",
#           row.names = FALSE)
#
# write.csv(minute_sleep_clean,
#           "minute_sleep_clean.csv",
#           row.names = FALSE)
#
# write.csv(seconds_heartrate_clean,
#           "seconds_heartrate_clean.csv",
```

```
#           row.names = FALSE)
#
# write.csv(weight_logs_clean ,
#           "weight_logs_clean .csv",
#           row.names = FALSE)
```

Analyze phase: Exploratory data analysis

EDA for daily_activity_clean

```
str(daily_activity_clean)
```

```
tibble [862 x 15] (S3: tbl_df/tbl/data.frame)
 $ id                         : chr [1:862] "1503960366" "1503960366" "1503960366" "1503960366" ...
 $ activity_date              : Date[1:862], format: "2016-04-12" "2016-04-13" ...
 $ total_steps                : num [1:862] 13162 10735 10460 9762 12669 ...
 $ total_distance             : num [1:862] 8.5 6.97 6.74 6.28 8.16 ...
 $ tracker_distance           : num [1:862] 8.5 6.97 6.74 6.28 8.16 ...
 $ logged_activities_distance: num [1:862] 0 0 0 0 0 0 0 0 0 0 ...
 $ very_active_distance       : num [1:862] 1.88 1.57 2.44 2.14 2.71 ...
 $ moderately_active_distance: num [1:862] 0.55 0.69 0.4 1.26 0.41 ...
 $ light_active_distance      : num [1:862] 6.06 4.71 3.91 2.83 5.04 ...
 $ sedentary_active_distance  : num [1:862] 0 0 0 0 0 0 0 0 0 0 ...
 $ very_active_minutes        : num [1:862] 25 21 30 29 36 38 42 50 28 19 ...
 $ fairly_active_minutes      : num [1:862] 13 19 11 34 10 20 16 31 12 8 ...
 $ lightly_active_minutes     : num [1:862] 328 217 181 209 221 164 233 264 205 211 ...
 $ sedentary_minutes          : num [1:862] 728 776 1218 726 773 ...
 $ calories                   : num [1:862] 1985 1797 1776 1745 1863 ...
```

Univariate analysis for daily_activity_clean

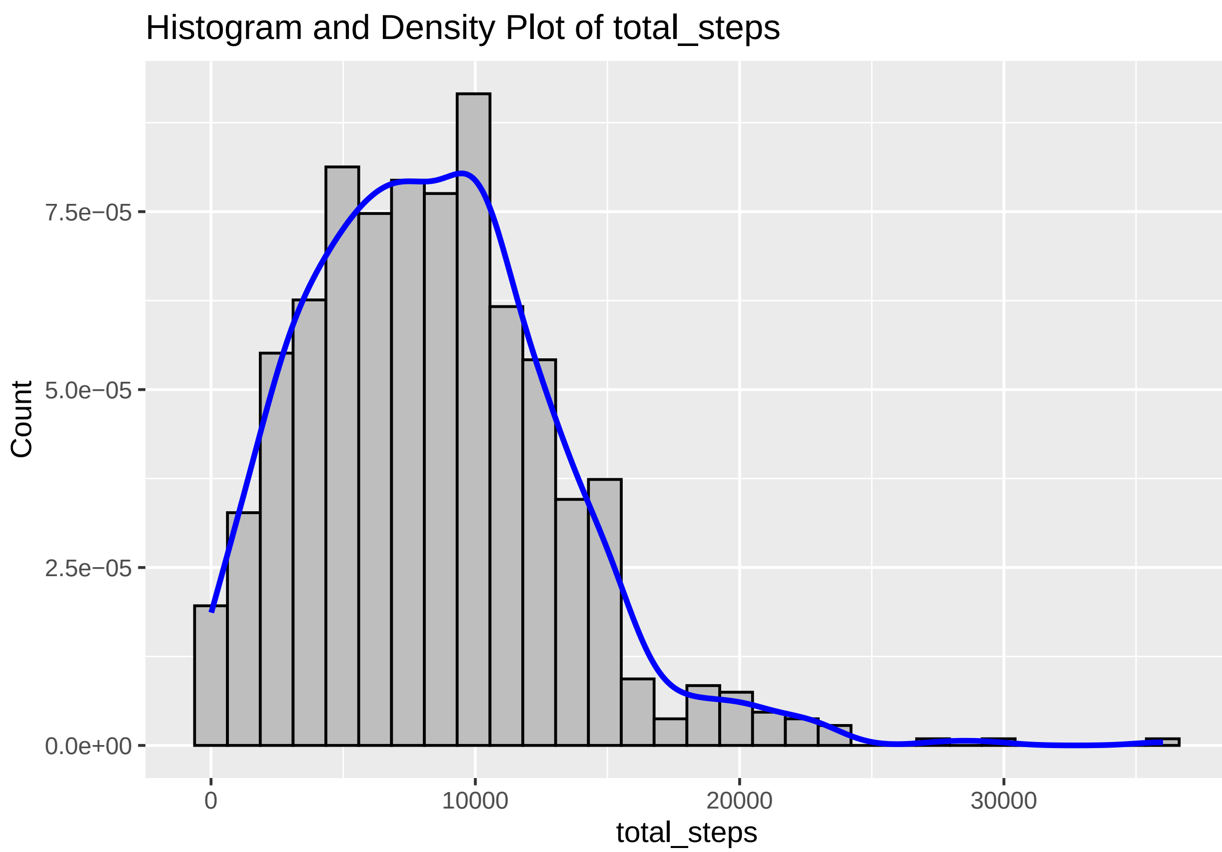
```
# Subset numeric columns
num_df <- select_if(daily_activity_clean, is.numeric)

# Identify numeric columns
colnames(num_df)
```

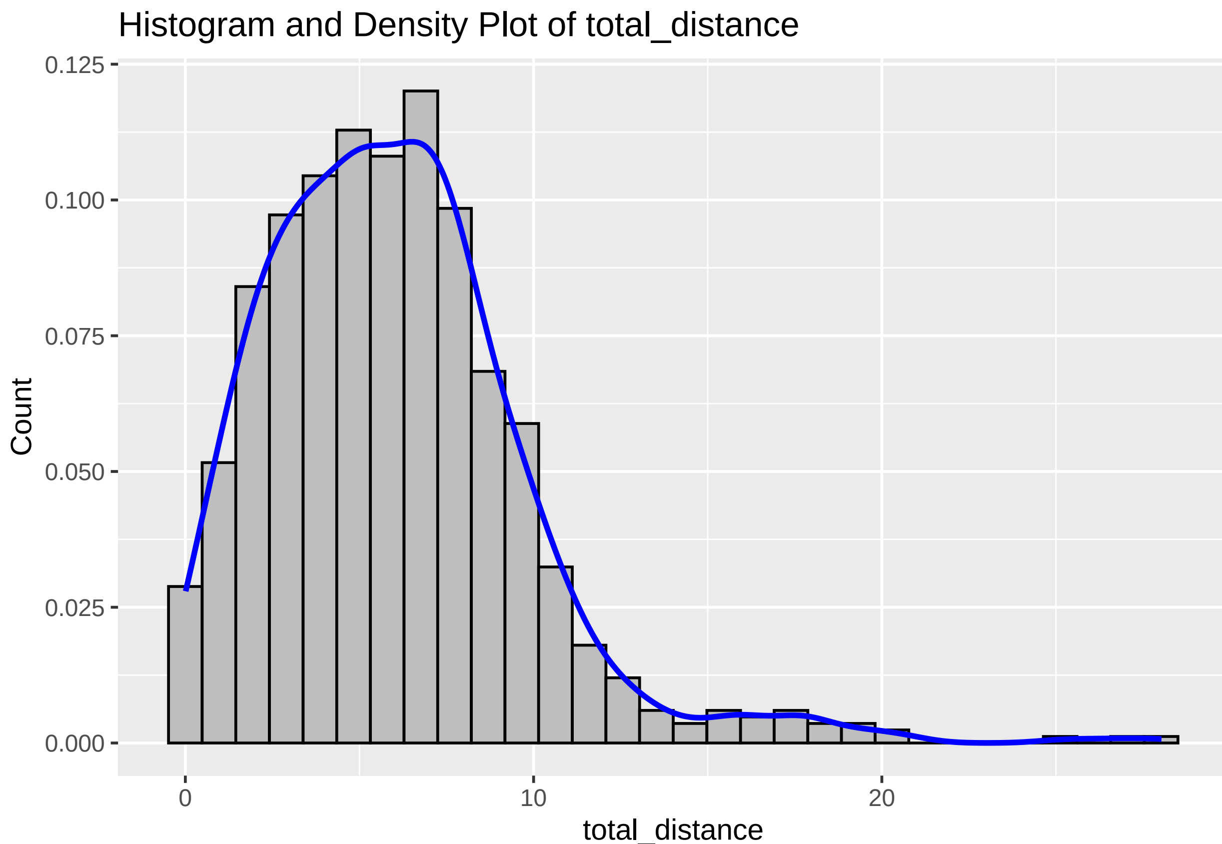
Numerical variables

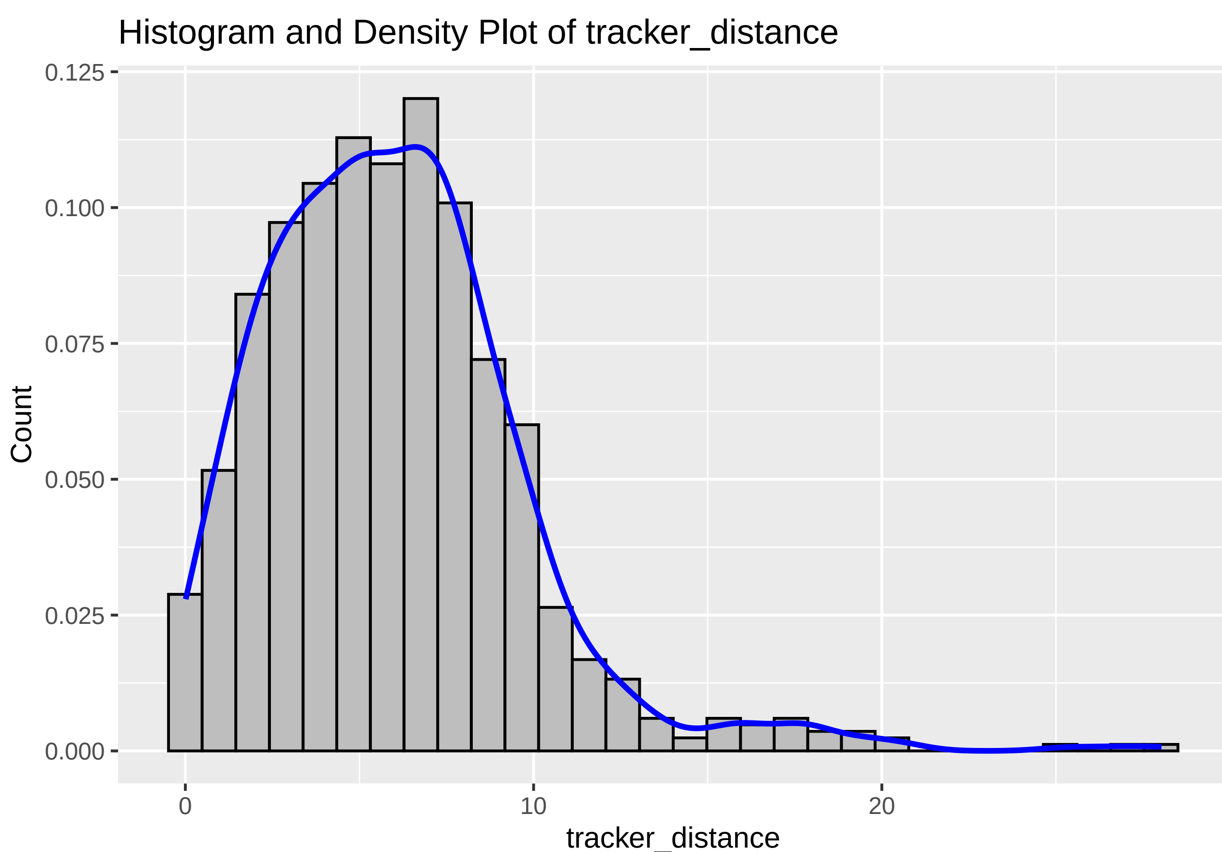
```
 [1] "total_steps"                "total_distance"
 [3] "tracker_distance"           "logged_activities_distance"
 [5] "very_active_distance"       "moderately_active_distance"
 [7] "light_active_distance"      "sedentary_active_distance"
 [9] "very_active_minutes"        "fairly_active_minutes"
[11] "lightly_active_minutes"     "sedentary_minutes"
[13] "calories"
```

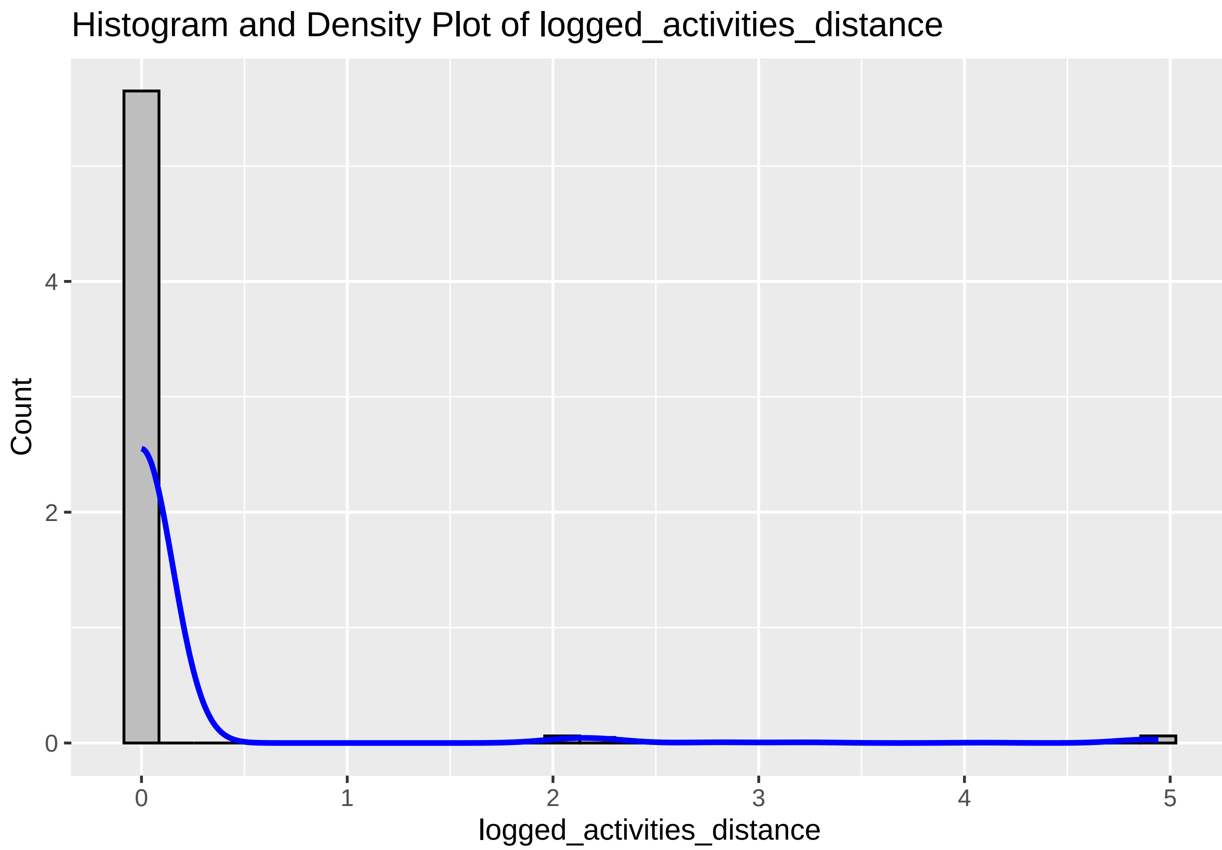
```
# plotting all numerical variables
col_names <- colnames(num_df)
for (i in col_names) {
  suppressWarnings(print(
    ggplot(num_df, aes(num_df[[i]])) +
      geom_histogram(
```

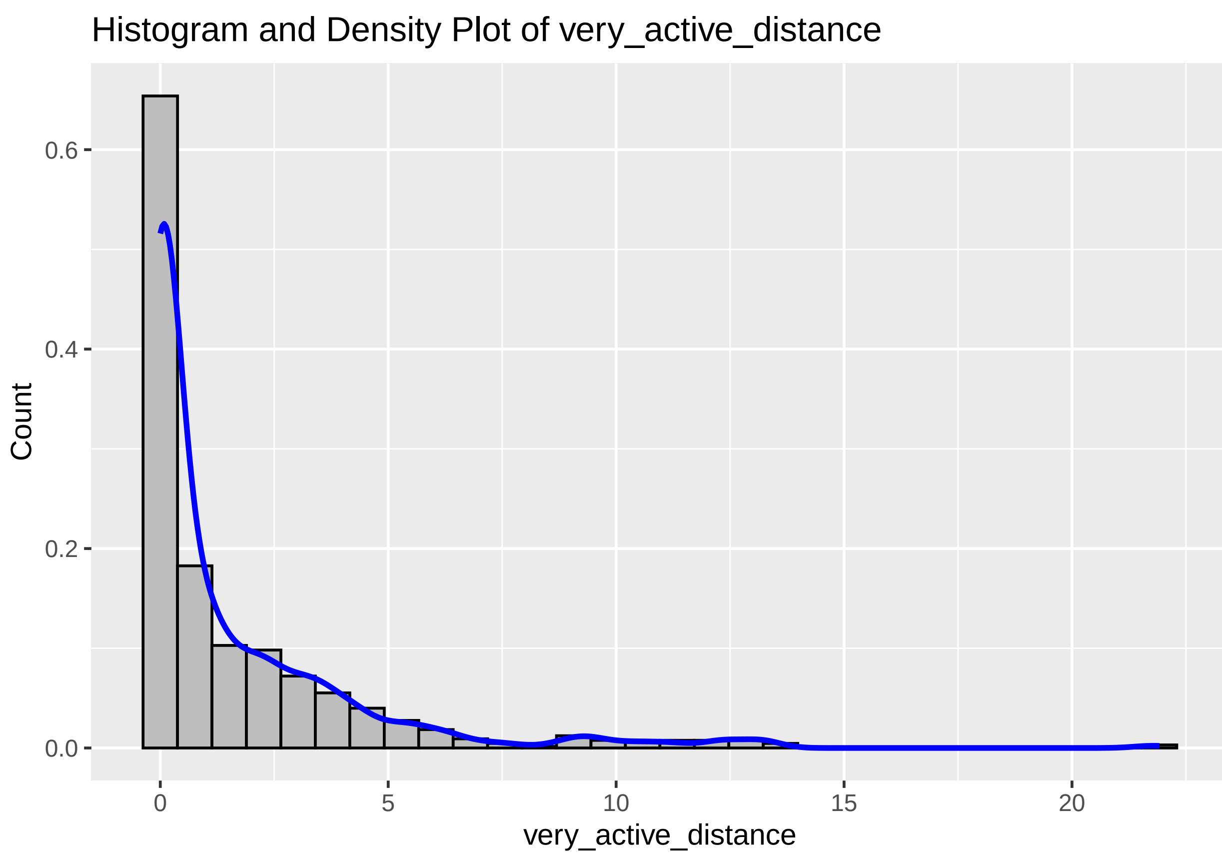
```
        bins = 30,
        color = "black",
        fill = "gray",
        aes(y = ..density..)
      ) +
      geom_density(
        color = "blue",
        size = 1
      ) +
      xlab(i) + ylab("Count") +
      ggtitle(paste("Histogram and Density Plot of", i))
  ))
}
```

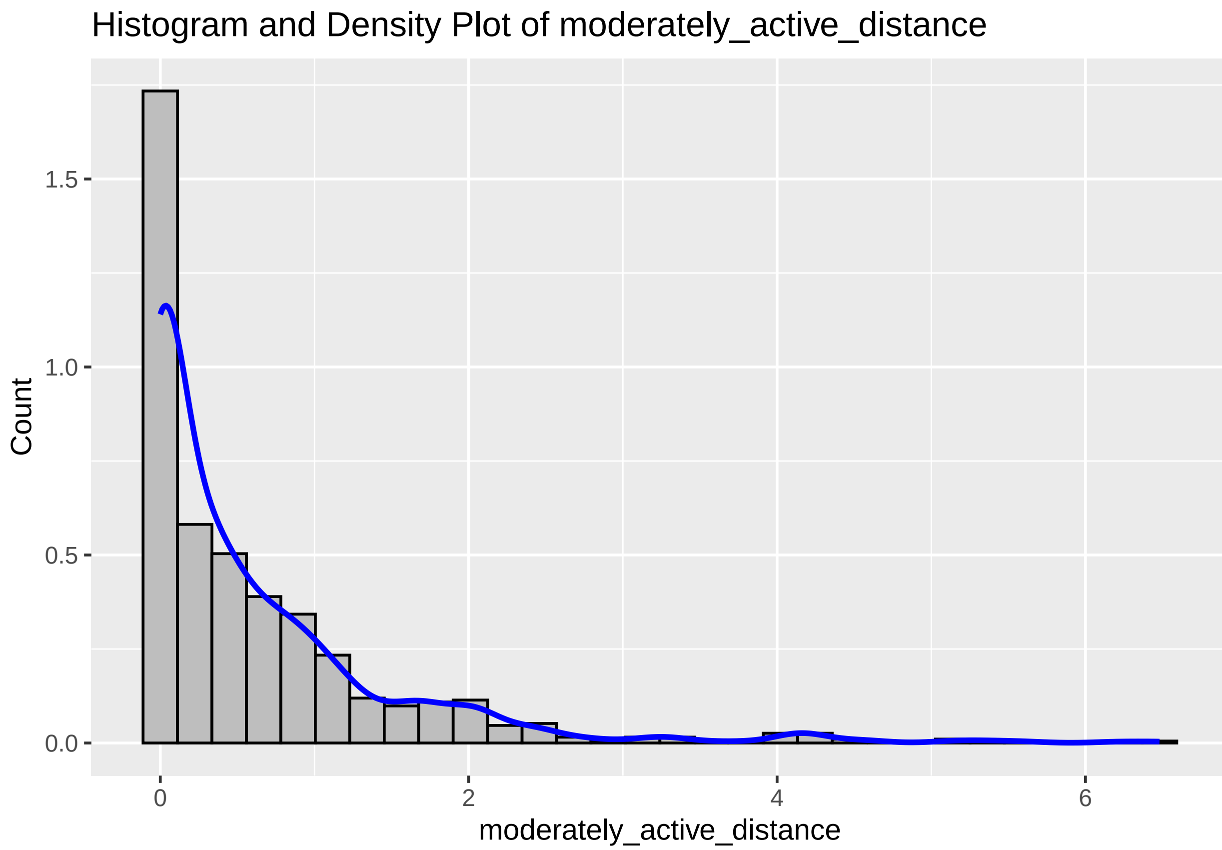


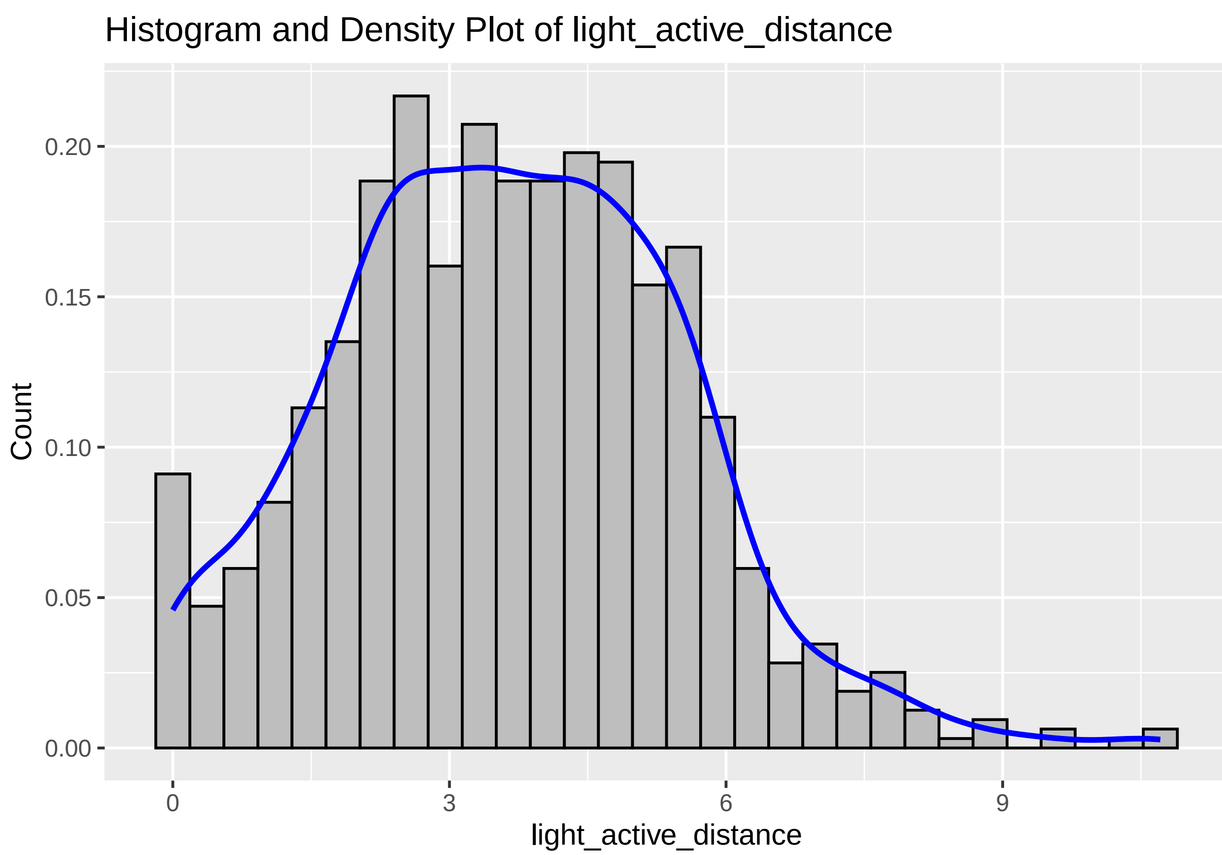

Histogram and Density Plot of total_distance
Count
0.125
0.100
0.075
0.050
0.025
0.000
0
10
20
total_distance

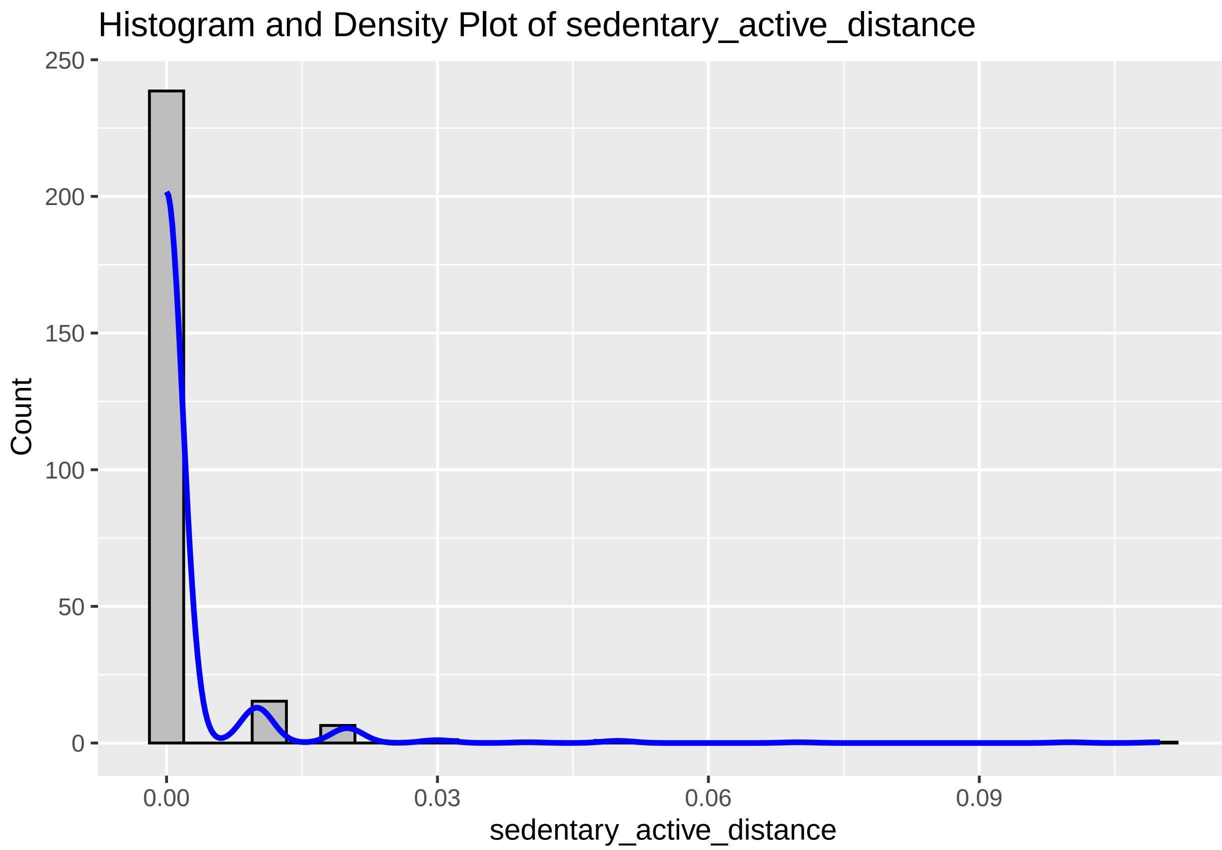

Histogram and Density Plot of tracker_distance
Count
0.125
0.100
0.075
0.050
0.025
0.000
0
10
20
tracker_distance

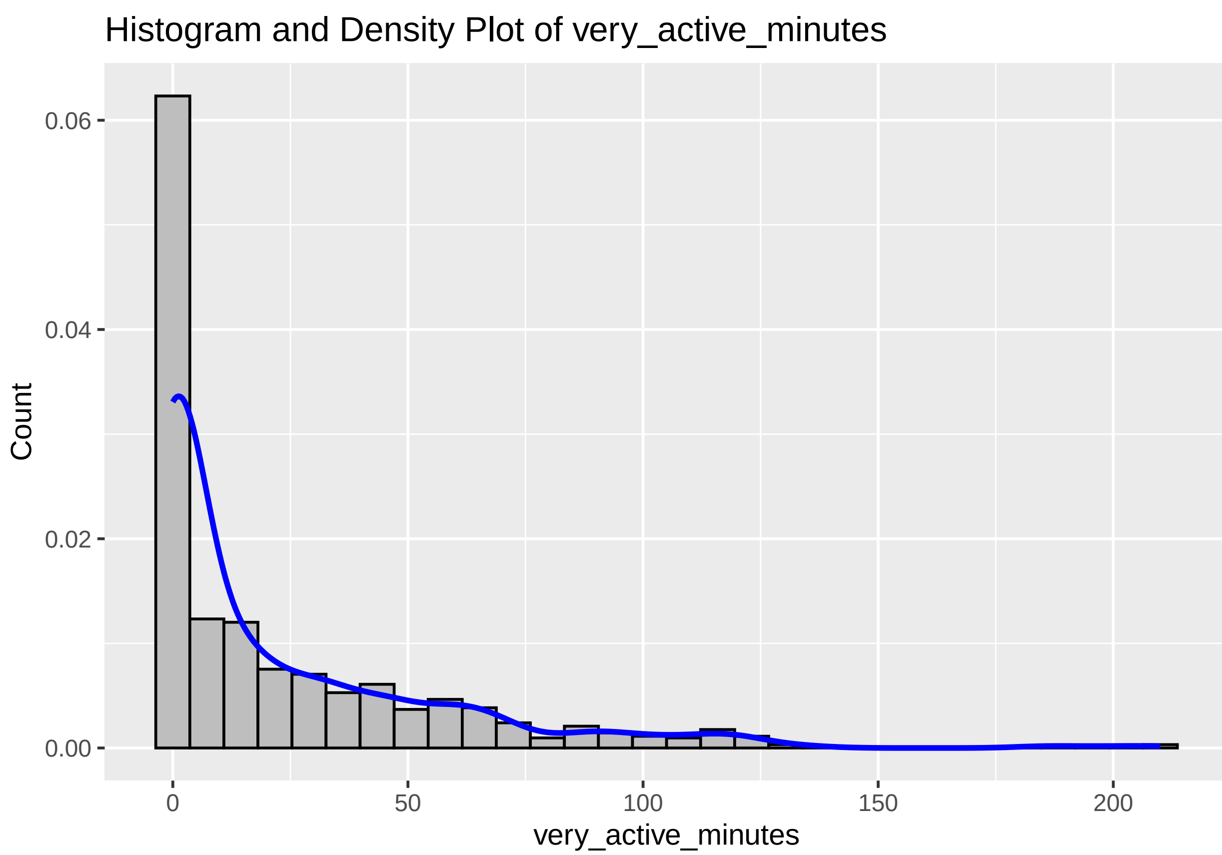

Histogram and Density Plot of logged_activities_distance
Count
0
2
4
0
1
2
3
4
5
logged_activities_distance

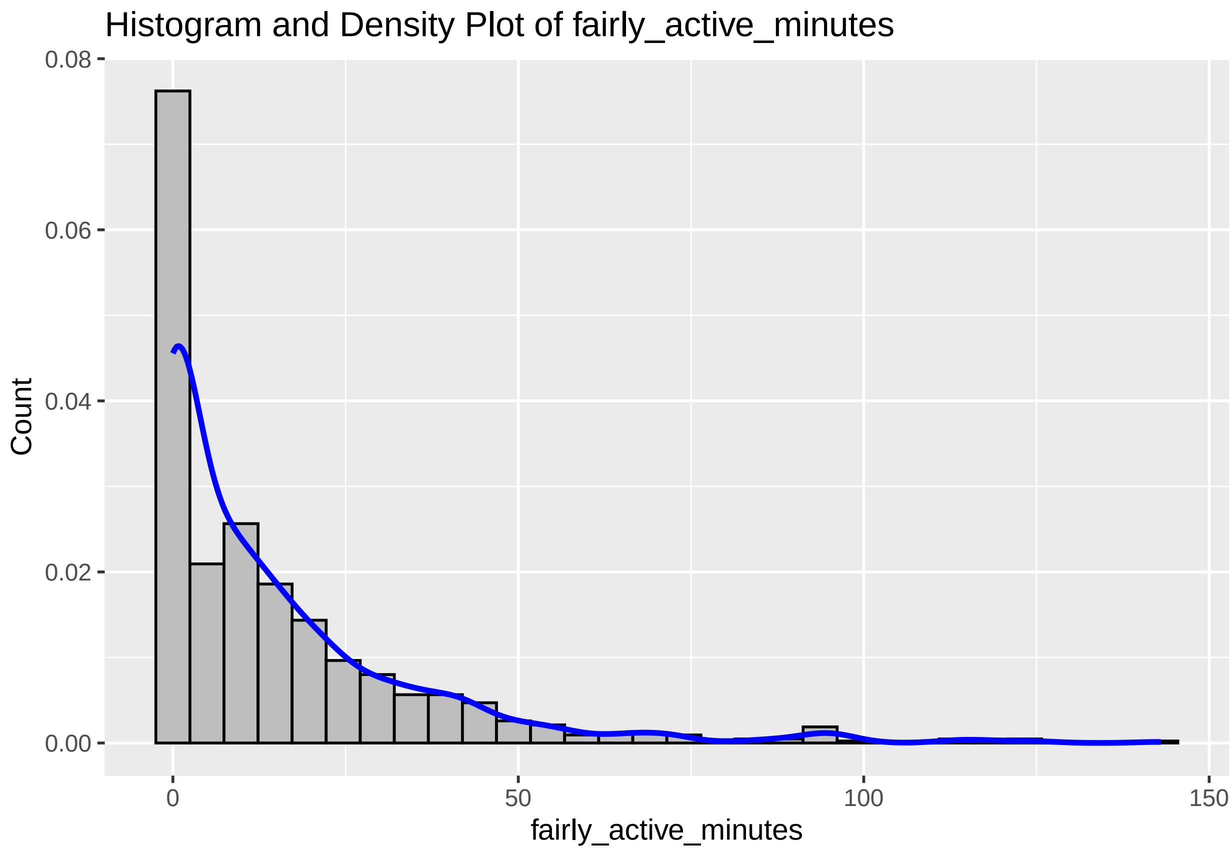

Histogram and Density Plot of very_active_distance
Count
0.0
0.2
0.4
0.6
0
5
10
15
20
very_active_distance

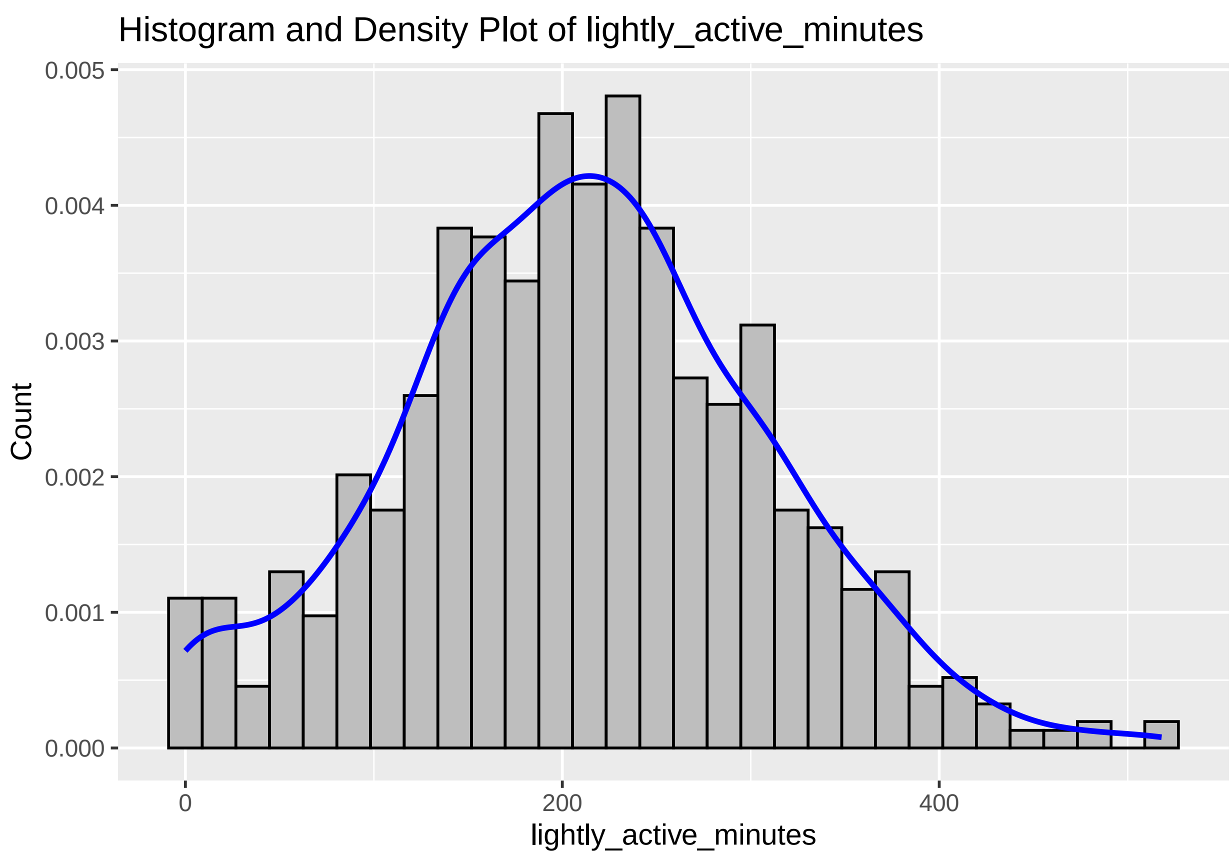

Histogram and Density Plot of moderately_active_distance
Count
1.5
1.0
0.5
0.0
0
2
4
6
moderately_active_distance

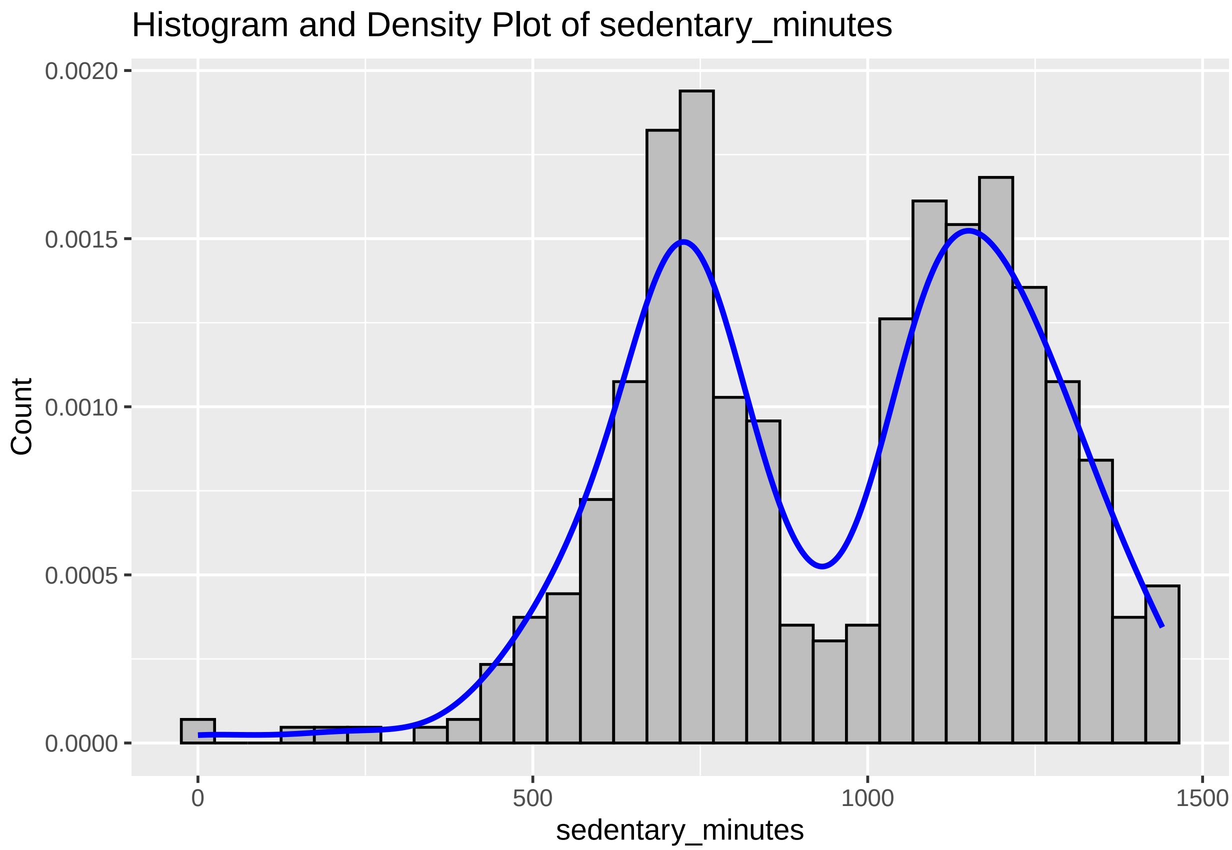

Histogram and Density Plot of light_active_distance
Count
0.20
0.15
0.10
0.05
0.00
0
3
6
9
light_active_distance

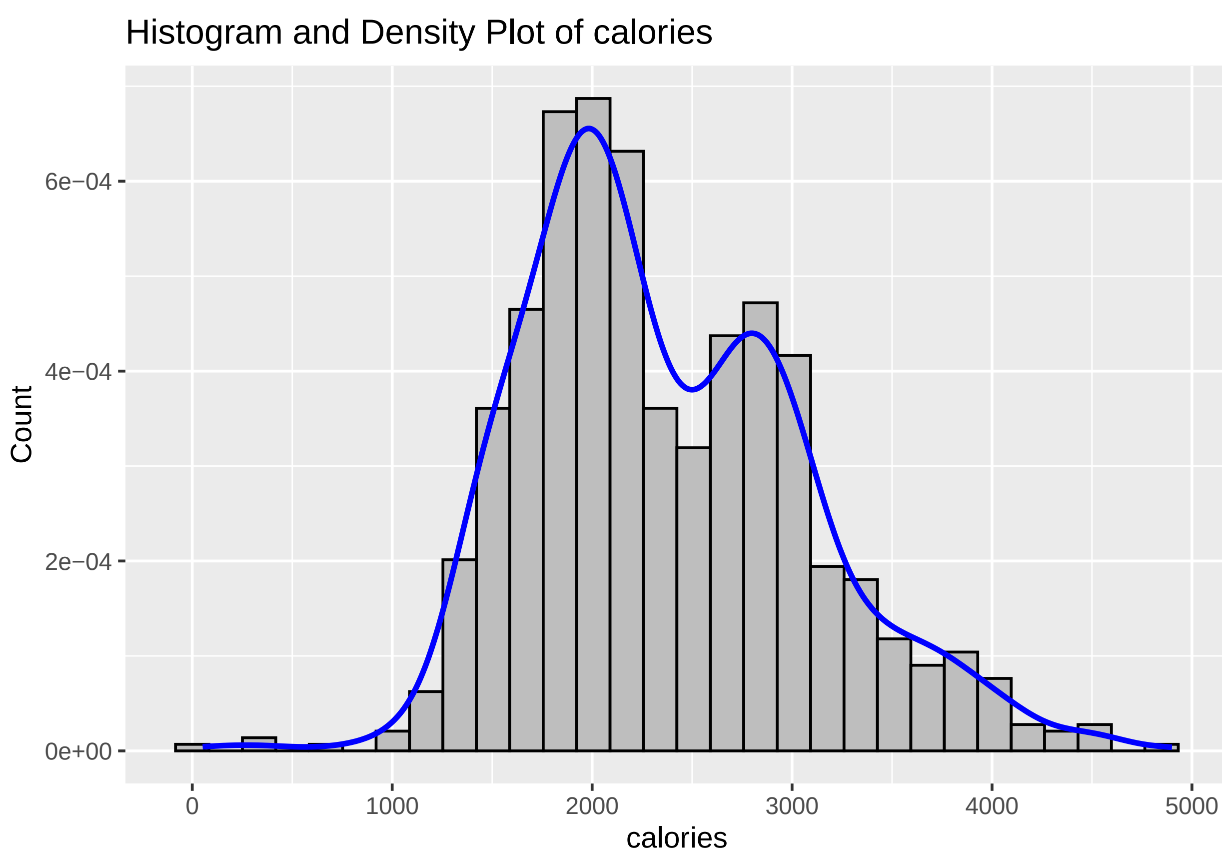

Histogram and Density Plot of sedentary_active_distance
Count
250
200
150
100
50
0
0.00
0.03
0.06
0.09
sedentary_active_distance


Histogram and Density Plot of very_active_minutes
Count
0.06
0.04
0.02
0.00
0
50
100
150
200
very_active_minutes


Histogram and Density Plot of fairly_active_minutes
Count
0.08
0.06
0.04
0.02
0.00
0
50
100
150
fairly_active_minutes


Histogram and Density Plot of lightly_active_minutes
Count
0.005
0.004
0.003
0.002
0.001
0.000
0
200
400
lightly_active_minutes


Histogram and Density Plot of sedentary_minutes
Count
0.0020
0.0015
0.0010
0.0005
0.0000
0
500
1000
1500
sedentary_minutes


Histogram and Density Plot of calories
Count
6e−04
4e−04
2e−04
0e+00
0
1000
2000
3000
4000
5000
calories

Observations:

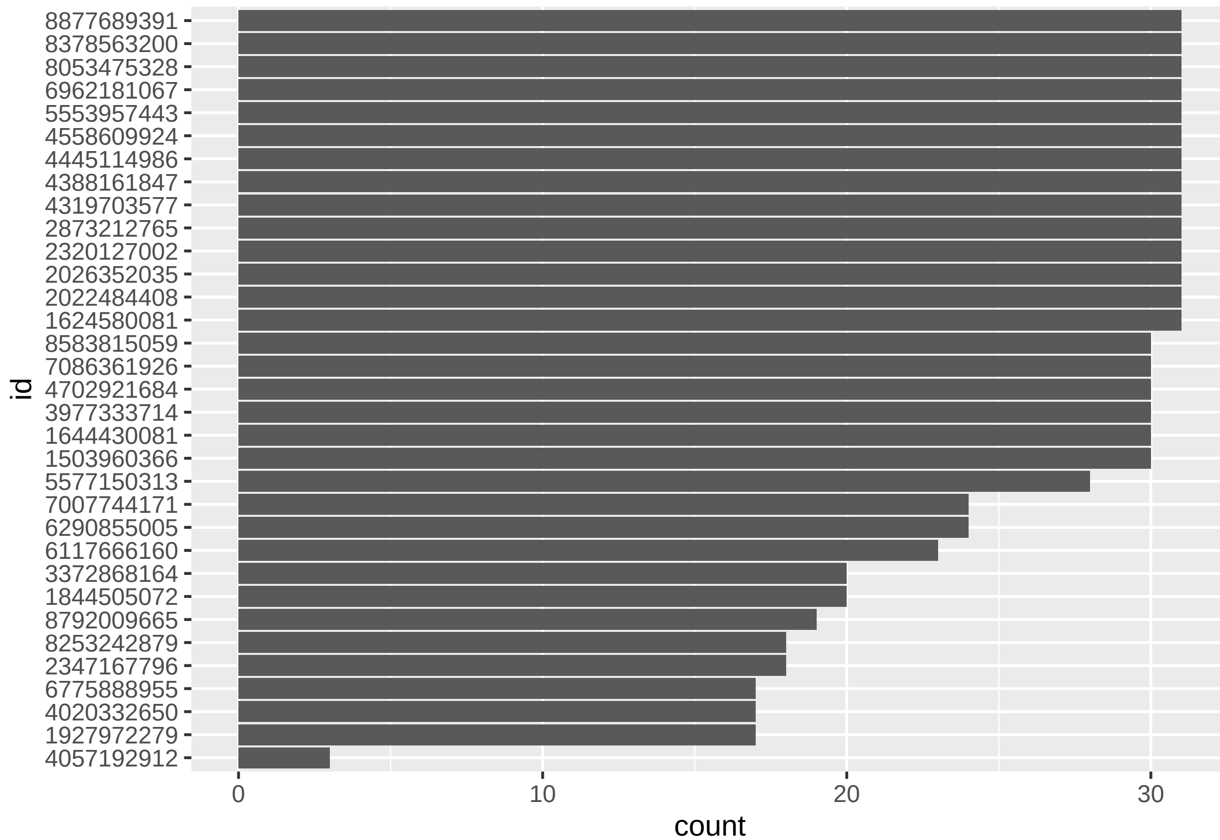
- Many variables show a right-skewed distribution: a larger number of data values are located on the left side of the curve.
- The variables total_steps, total_distance, tracker_distance have a similar distribution. We can explore their correlations later.
- Since the distributions are not normal. The median is a better indicator of central tendency for the numerical variables in these dataset.
- **The variable "logged_activities_distance" and "sedentary_active_distance" might not provide useful information since most of the data points are zero. It seems that the users are not logging the distance frequently.**
- The following variables seem related. We will explore them further in the bivariate analysis section:
  - sedentary_minutes; sedentary_active_distance
  - lightly_active_minutes; light_active_distance
  - fairly_active_minutes; moderately_active_distance
  - very_active_minutes; very_active_distance
- The variables calories and sedentary_minutes exhibit a multimodal distribution, indicating the presence of subpopulations within the data. In this dataset, gender could be a potential variable that would result in a bimodal distribution when examining histograms of calories and sedentary minutes. Unfortunately, the gender of the users is not provided, limiting our ability to confirm this hypothesis.

```
# Subset numeric columns

select_if(daily_activity_clean, negate(is.numeric))
```

Categorical variables

```
# A tibble: 862 x 2
   id         activity_date
   <chr>      <date>
 1 1503960366 2016-04-12
 2 1503960366 2016-04-13
 3 1503960366 2016-04-14
 4 1503960366 2016-04-15
 5 1503960366 2016-04-16
 6 1503960366 2016-04-17
 7 1503960366 2016-04-18
 8 1503960366 2016-04-19
 9 1503960366 2016-04-20
10 1503960366 2016-04-21
# ... with 852 more rows
```

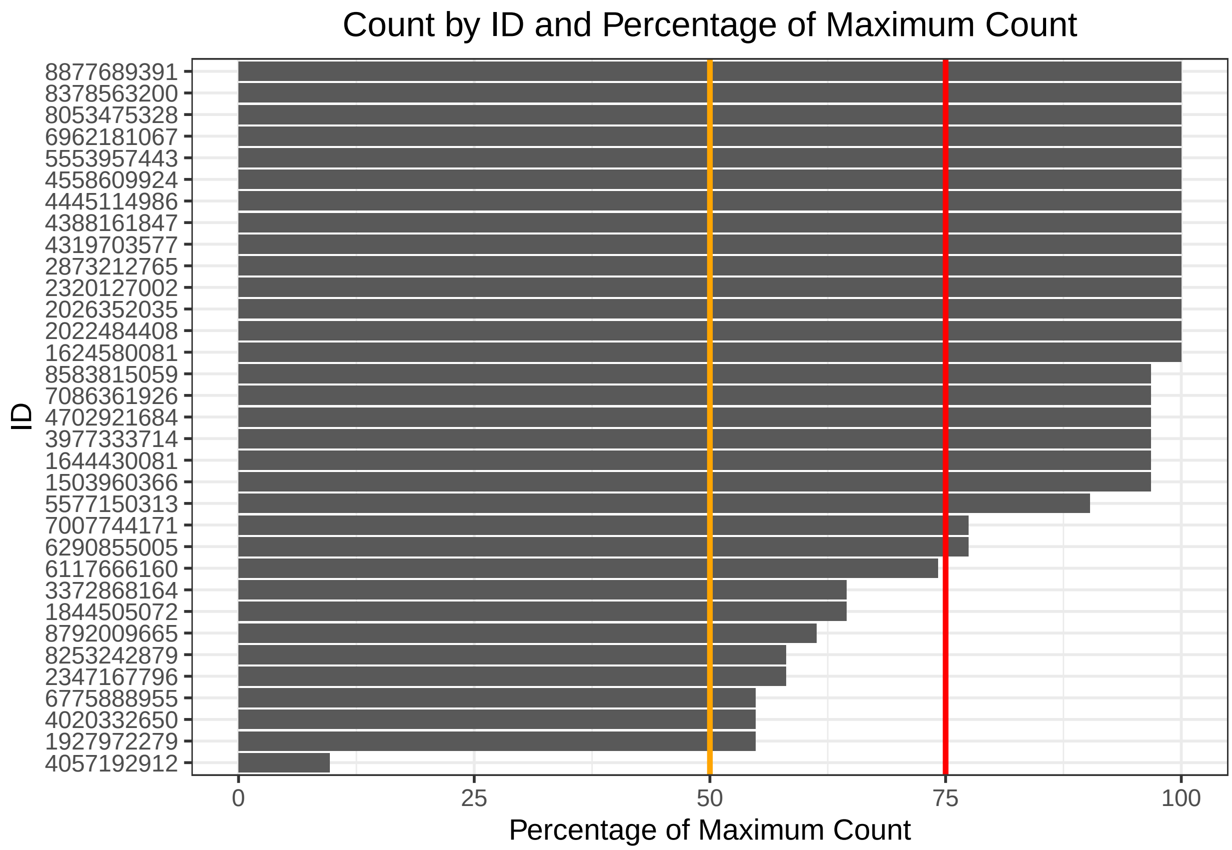
```
# Check counts by id
ggplot(data=daily_activity_clean) +
  geom_bar(mapping = aes (x= reorder(id, id,length)))+
  xlab("id") +
  coord_flip()
```




```
#https://stackoverflow.com/a/9231857/15333580

#reorder(id, id, length) takes the id variable, uses itself to determine the order, and uses the length
```

```
count_max_ratio <- daily_activity_clean %>%
  count(id) %>%
  rename(id = "id", count = "n") %>%
  mutate(percent_of_max = count / max(count) * 100) %>%
  arrange(desc(percent_of_max))
```

```
# Create bar graph with percentage of entries compared to maximum
ggplot(count_max_ratio, aes(x = reorder(id, percent_of_max), y = percent_of_max)) +
  geom_bar(stat = "identity") +
  xlab("ID") +
  ylab("Percentage of Maximum Count") +
  ggtitle("Count by ID and Percentage of Maximum Count") +
  theme_bw() +
  theme(plot.title = element_text(hjust = 0.5)) +
  geom_hline(yintercept=50, color="orange", linewidth=1)+
  geom_hline(yintercept=75, color="red", linewidth=1)+
  coord_flip()
```




```r
# percent_of_max > 75%

percent_of_max_top_75 <- filter(count_max_ratio, percent_of_max >=75)
percent_of_max_top_75
```

```
# A tibble: 23 x 3
   id         count percent_of_max
   <chr>      <int>          <dbl>
 1 1624580081    31            100
 2 2022484408    31            100
 3 2026352035    31            100
 4 2320127002    31            100
 5 2873212765    31            100
 6 4319703577    31            100
 7 4388161847    31            100
 8 4445114986    31            100
 9 4558609924    31            100
10 5553957443    31            100
# ... with 13 more rows
```

```r
# percent_of_max < 75

percent_of_max_under_75 <- filter(count_max_ratio, percent_of_max < 75)
percent_of_max_under_75
```

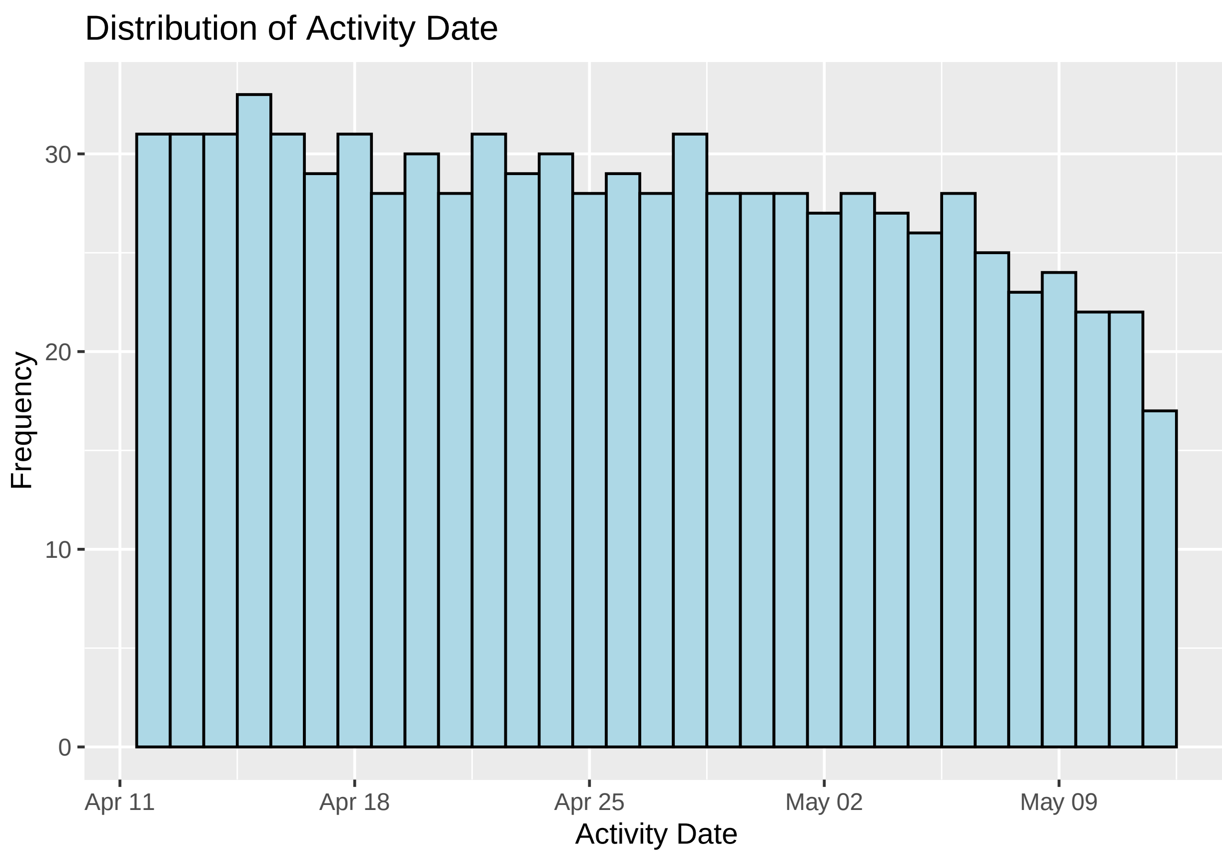
```
# A tibble: 10 x 3
   id         count percent_of_max
   <chr>      <int>          <dbl>
```

```
 1 6117666160    23          74.2
 2 1844505072    20          64.5
 3 3372868164    20          64.5
 4 8792009665    19          61.3
 5 2347167796    18          58.1
 6 8253242879    18          58.1
 7 1927972279    17          54.8
 8 4020332650    17          54.8
 9 6775888955    17          54.8
10 4057192912     3           9.68
```

```r
daily_activity_clean$activity_date %>% summary()
```

```
        Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
"2016-04-12" "2016-04-18" "2016-04-26" "2016-04-26" "2016-05-03" "2016-05-12"
```

```r
ggplot(data=daily_activity_clean , aes(x = activity_date)) +
  geom_histogram(binwidth = 1, color = "black", fill = "lightblue") +
  labs(x = "Activity Date", y = "Frequency", title = "Distribution of Activity Date")
```

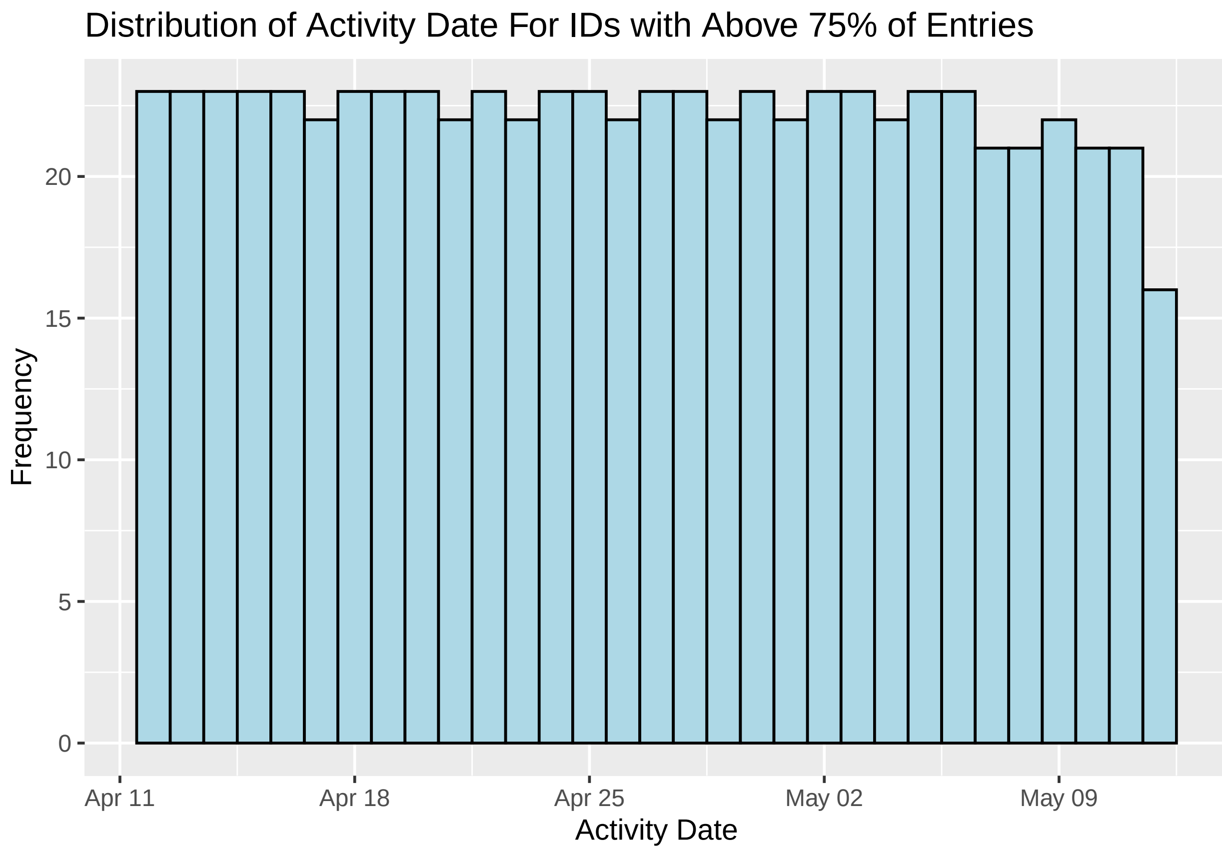


Observations:

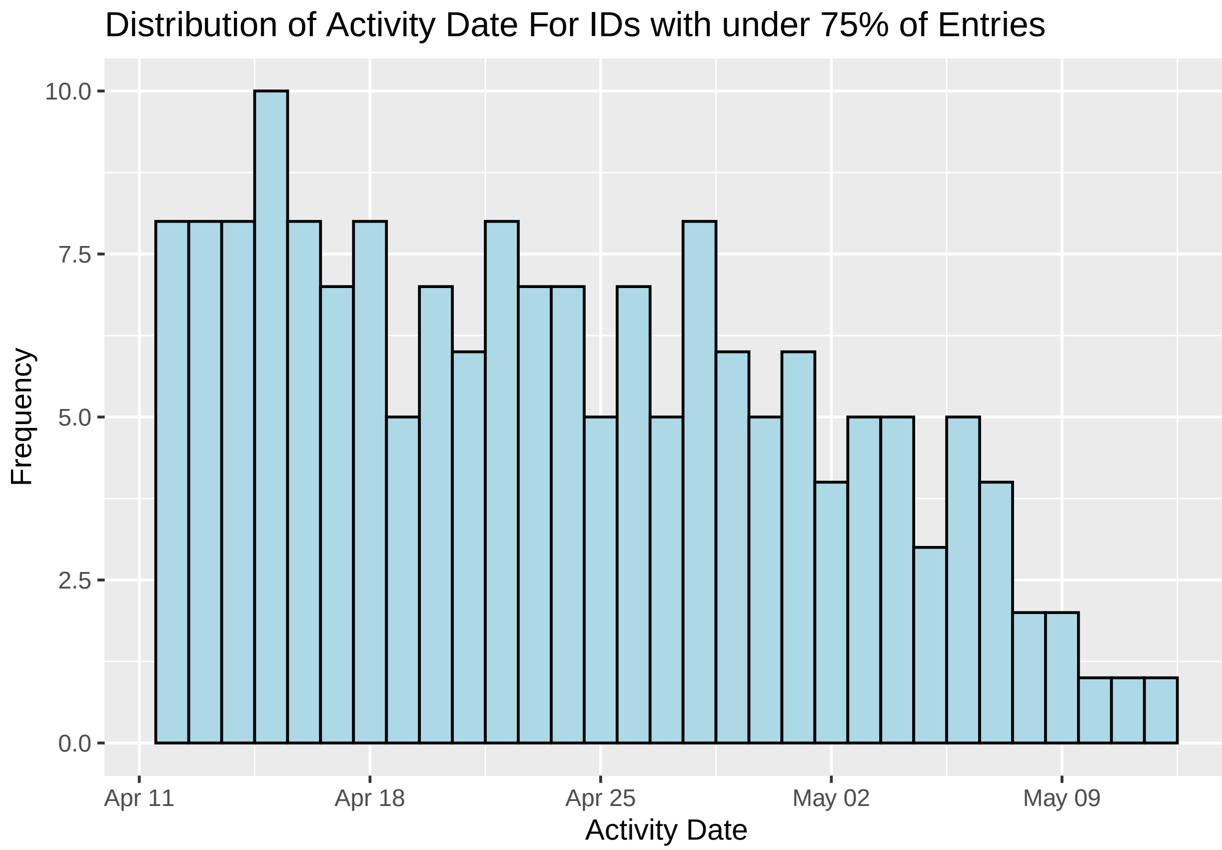
- It appears that there is missing activity data towards the end of the available period, specifically in the beginning of May.

```r
# Investigate if the missing activity data coincides with the absence of entries for certain user IDs.

ggplot(data=subset(daily_activity_clean, id %in% percent_of_max_top_75$id), aes(x = activity_date)) +
  geom_histogram(binwidth = 1, color = "black", fill = "lightblue") +
```

```
  labs(x = "Activity Date", y = "Frequency", title = "Distribution of Activity Date For IDs with Above 
```




```
ggplot(data=subset(daily_activity_clean, id %in% percent_of_max_under_75$id), aes(x = activity_date)) +
  geom_histogram(binwidth = 1, color = "black", fill = "lightblue") +
  labs(x = "Activity Date", y = "Frequency", title = "Distribution of Activity Date For IDs with under 
```

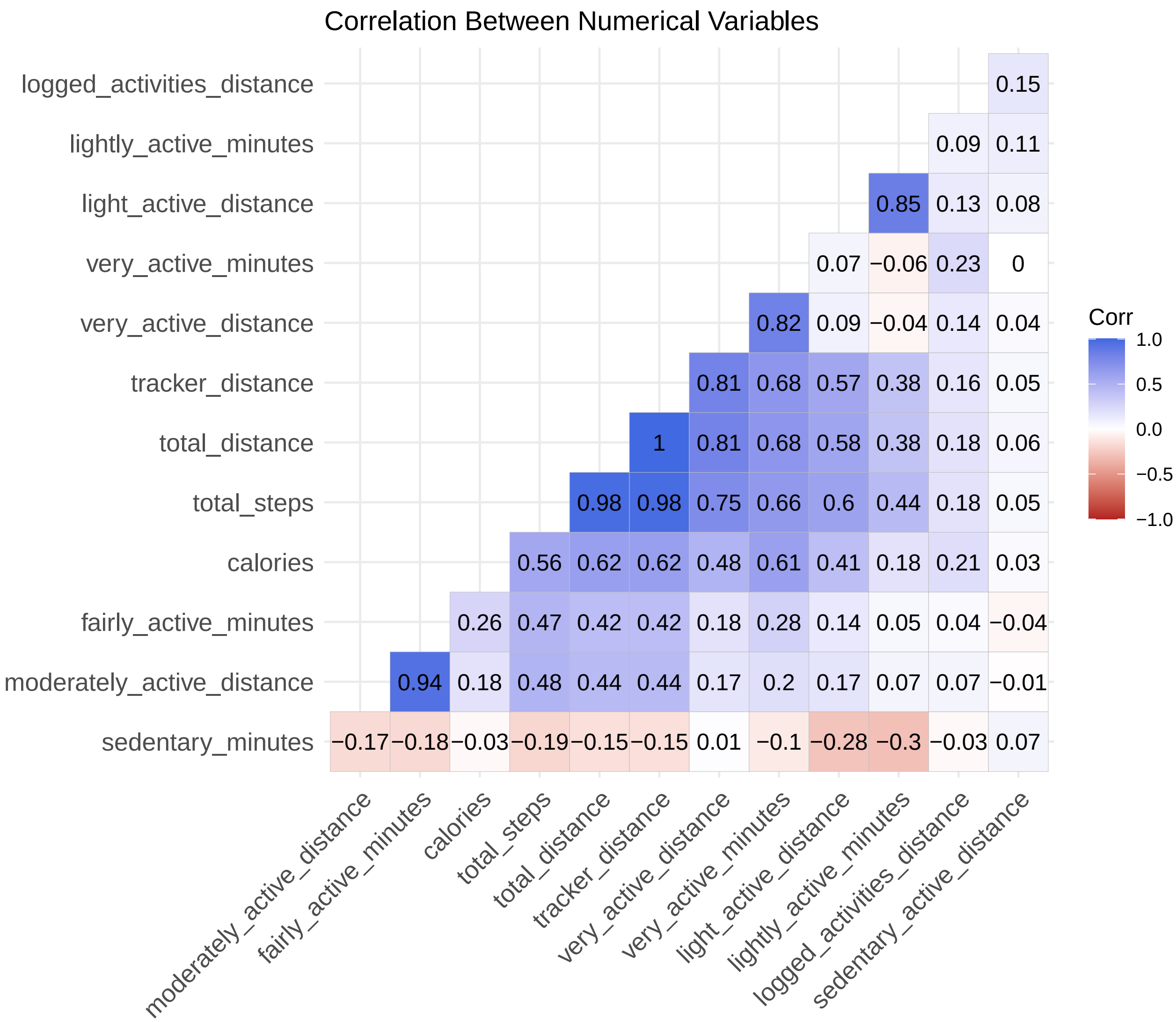


- Users with more than 75% of data consistently report activity dates, while those with less than 75% of data show a decline in reporting starting from the end of April. The decline in Activity Date seems to be primarily due to a lack of data reporting from some users during that period.

Bivariate analysis

```
corr <- cor(select_if(daily_activity_clean, is.numeric))

ggcorrplot(corr,
           hc.order = TRUE,
           type = "lower",
           lab = TRUE,
           colors = c("firebrick", "white", "royalblue"),
           lab_size = 4,
           lab_col = "black",
           title = "Correlation Between Numerical Variables")
```

Correlation between numerical variables




```
#https://rdrr.io/github/microresearcher/MicroVis/man/ggcorrplot.html
```

sedentary__minutes; sedentary__active__distance lightly__active__minutes; light__active__distance
fairly__active__minutes; moderately__active__distance very__active__minutes; very__active__distance

```
# Compute correlation matrix
corr_matrix <- corr

# Set the threshold for correlation
threshold <- 0.60

# Find pairs of highly correlated variables
high_cor_pairs <- which(abs(corr_matrix) > threshold & lower.tri(corr_matrix, diag = FALSE), arr.ind = 

# Extract the variable names and correlation coefficients for the correlated pairs
variable_names <- colnames(corr_matrix)
cor_values <- as.vector(corr_matrix[high_cor_pairs])

# Create a data frame to store the correlated pairs and their correlation coefficients
cor_data <- data.frame(
```

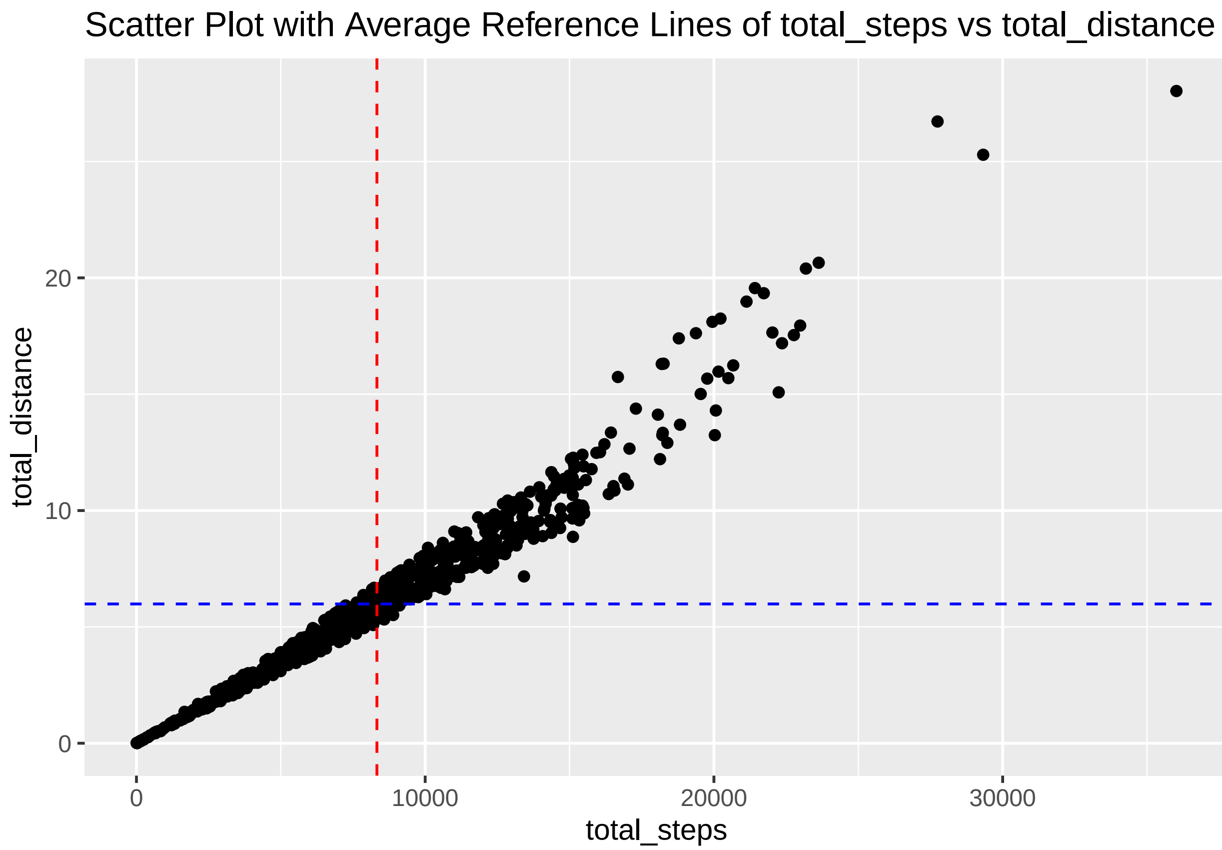
```r
  Variable1 = variable_names[high_cor_pairs[, 1]],
  Variable2 = variable_names[high_cor_pairs[, 2]],
  Correlation = cor_values
)

# Sort the correlated pairs by correlation coefficient in descending order
sorted_cor_data <- cor_data[order(-cor_data$Correlation), ]

# Remove the index
row.names(sorted_cor_data) <- NULL

# Display the sorted correlated variable pairs in the dataframe
print(sorted_cor_data)
```

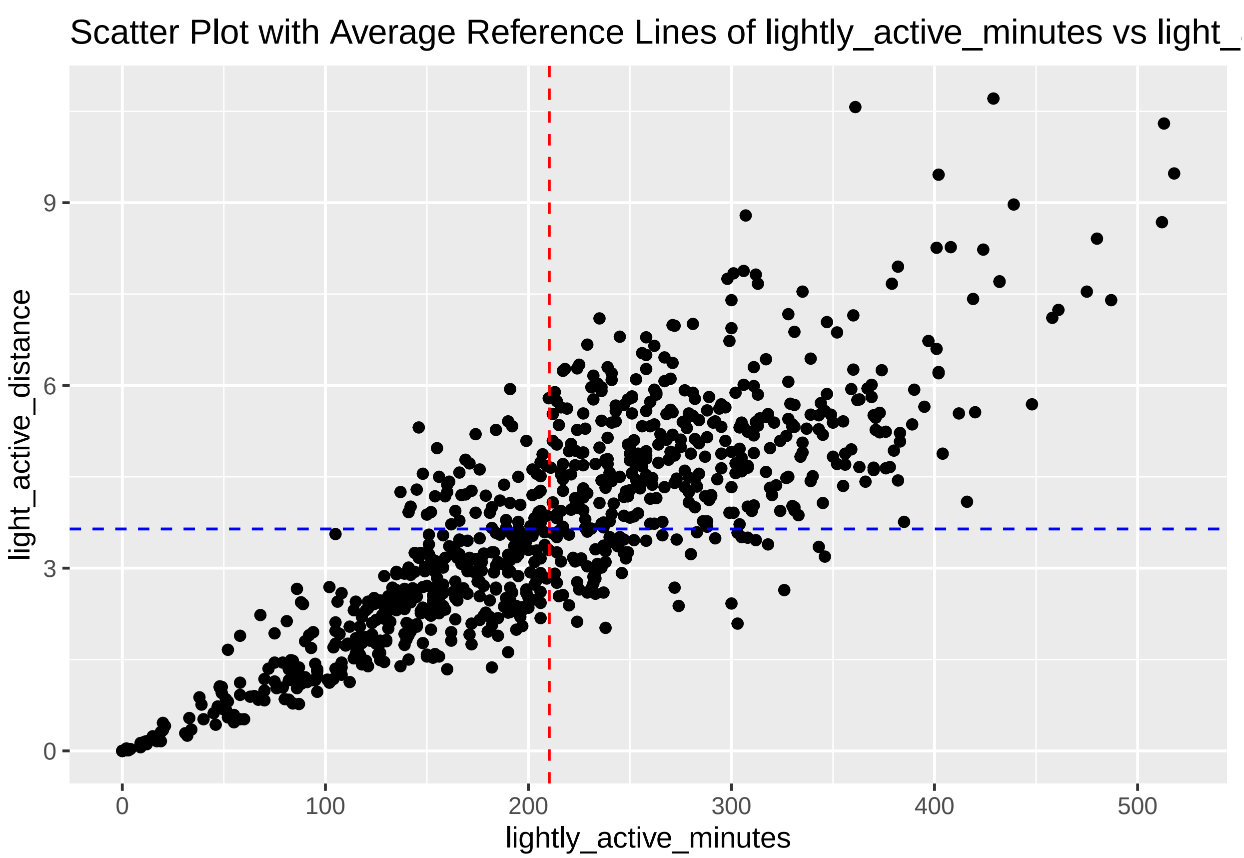
```
                Variable1                 Variable2 Correlation
1        tracker_distance            total_distance   0.9993982
2          total_distance               total_steps   0.9826464
3        tracker_distance               total_steps   0.9819287
4    fairly_active_minutes moderately_active_distance   0.9448137
5   lightly_active_minutes     light_active_distance   0.8463101
6      very_active_minutes      very_active_distance   0.8215184
7     very_active_distance            total_distance   0.8088356
8     very_active_distance          tracker_distance   0.8087337
9     very_active_distance               total_steps   0.7544861
10     very_active_minutes            total_distance   0.6755673
11     very_active_minutes          tracker_distance   0.6751272
12     very_active_minutes               total_steps   0.6639646
13                calories          tracker_distance   0.6246510
14                calories            total_distance   0.6242380
15                calories       very_active_minutes   0.6122349
16   light_active_distance               total_steps   0.6048838
```

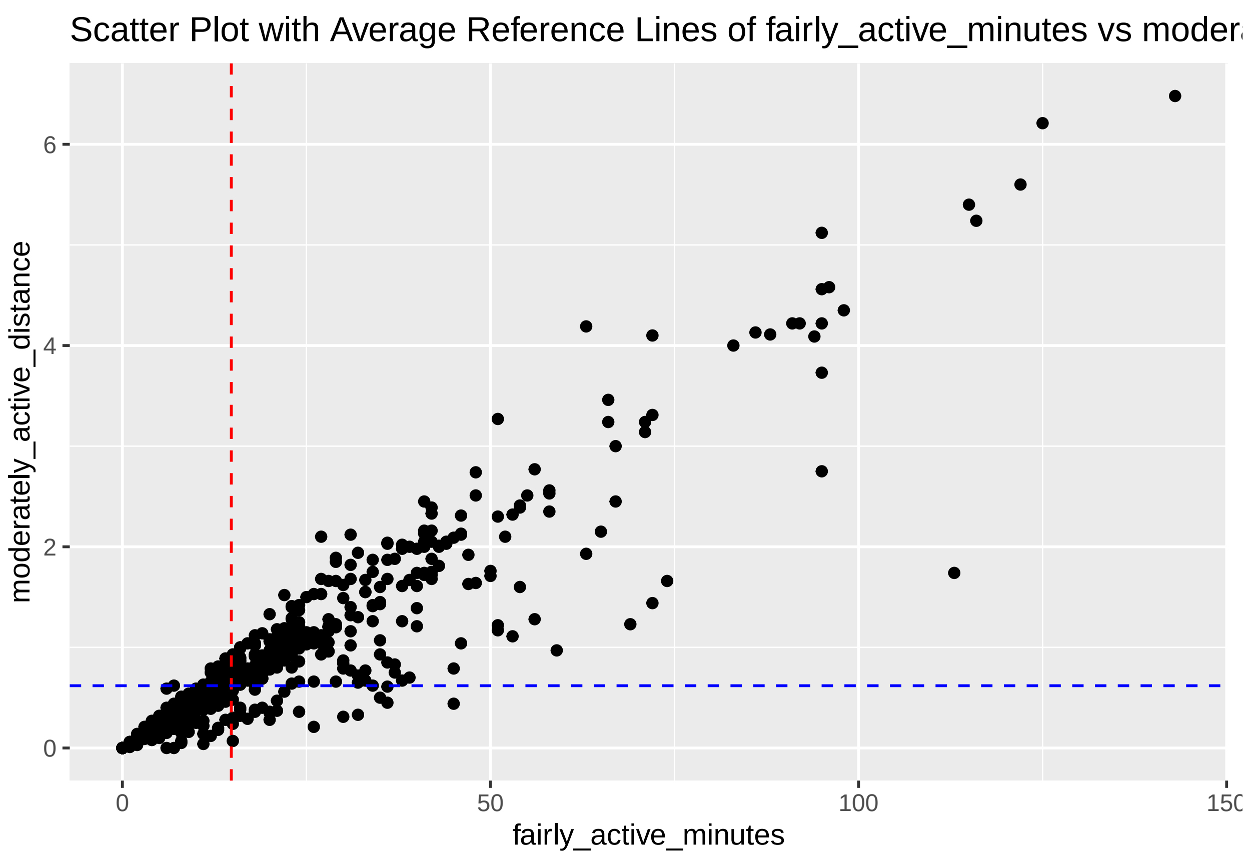
- Total_distance, tracker_distance, and total steps are highly correlated, so we will retain only total distance and total steps as they provide similar information.
- The following minute and distance types are correlated. Which indicates that they report different aspects of the same activity, this is time or distance:
  - lightly_active_minutes and light_active_distance (corr = 0.85)
  - fairly_active_minutes and moderately_active_distance (corr = 0.94)
  - very_active_minutes and very_active_distance (corr = 0.82)
- There is a moderately high correlation between the time spent during very active periods and the total number of steps/total distance:
  - The correlation between very_active_minutes and total_distance is 0.68
  - The correlation between very_active_minutes and total_steps is 0.66
- There is a moderate correlation of 0.61 between the total duration of very active minutes and the estimated daily calories consumed.
- There is a moderate correlation of 0.62 between the total distance covered and the estimated daily calories consumed.
- There is a moderate correlation coefficient of 0.60 between the distance covered during light activity (light_active_distance) and the total number of steps taken (total_steps).

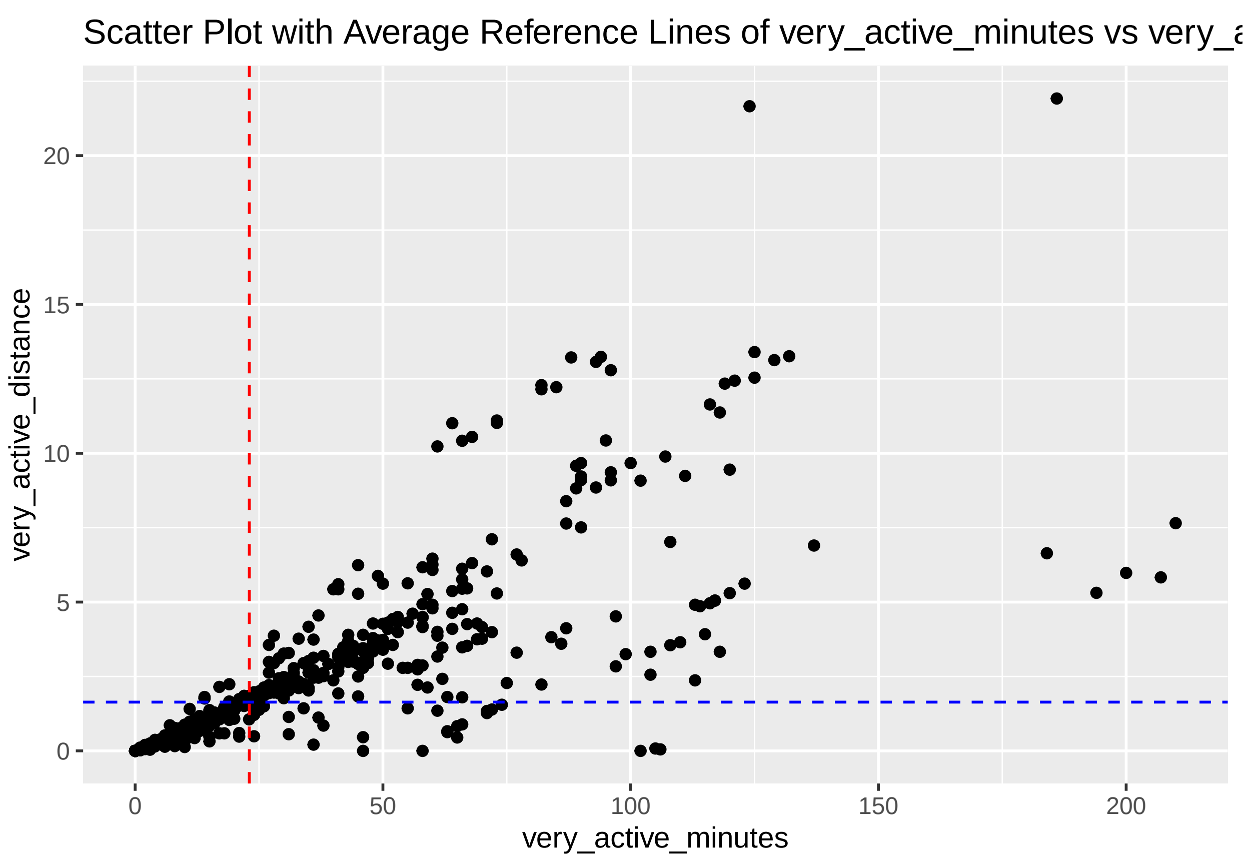
```r
# List of correlated variable pairs
correlated_pairs <- list(c("total_steps", "total_distance"),
                         c("lightly_active_minutes", "light_active_distance"),
                         c("fairly_active_minutes", "moderately_active_distance"),
                         c("very_active_minutes", "very_active_distance"),
                         c("very_active_minutes", "total_distance"),
                         c("very_active_minutes", "total_steps"),
                         c("very_active_minutes", "calories"),
                         c("total_distance", "calories"),
                         c("light_active_distance", "total_steps"))

# Loop over each pair and create scatter plot
for (pair in correlated_pairs) {
  var1 <- pair[1]
  var2 <- pair[2]

  # Calculate averages
  avg_var1 <- mean(daily_activity_clean[[var1]], na.rm = TRUE)
  avg_var2 <- mean(daily_activity_clean[[var2]], na.rm = TRUE)

  # Create scatter plot using ggplot2 with aes()
  print(ggplot(data = daily_activity_clean, aes(x = !!sym(var1), y = !!sym(var2))) +
    geom_point() +
    geom_vline(xintercept = avg_var1, linetype = "dashed", color = "red") +
    geom_hline(yintercept = avg_var2, linetype = "dashed", color = "blue") +
    xlab(var1) + ylab(var2) +
    ggtitle(paste("Scatter Plot with Average Reference Lines of", var1, "vs", var2)))
}
```

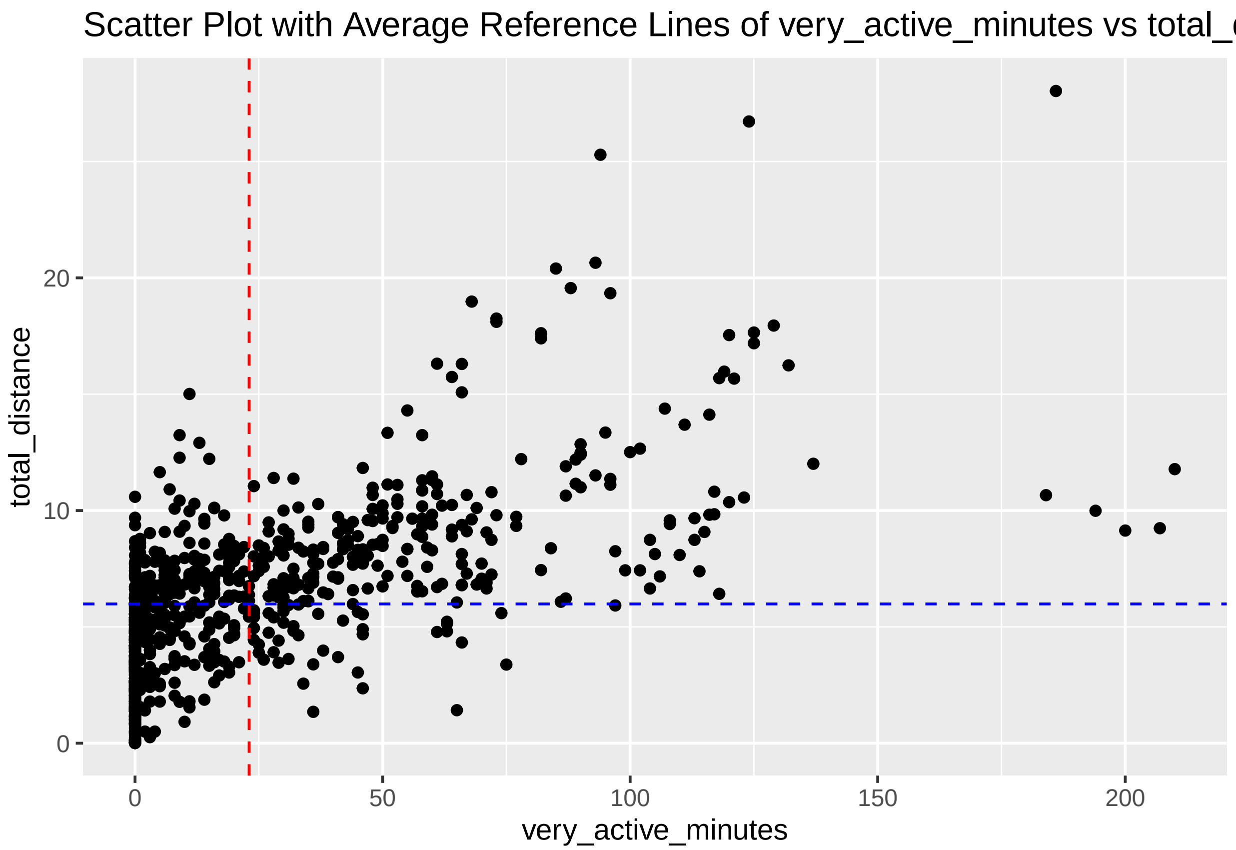
Scatterplots of selected highly correlated variables pairs (>0.60)

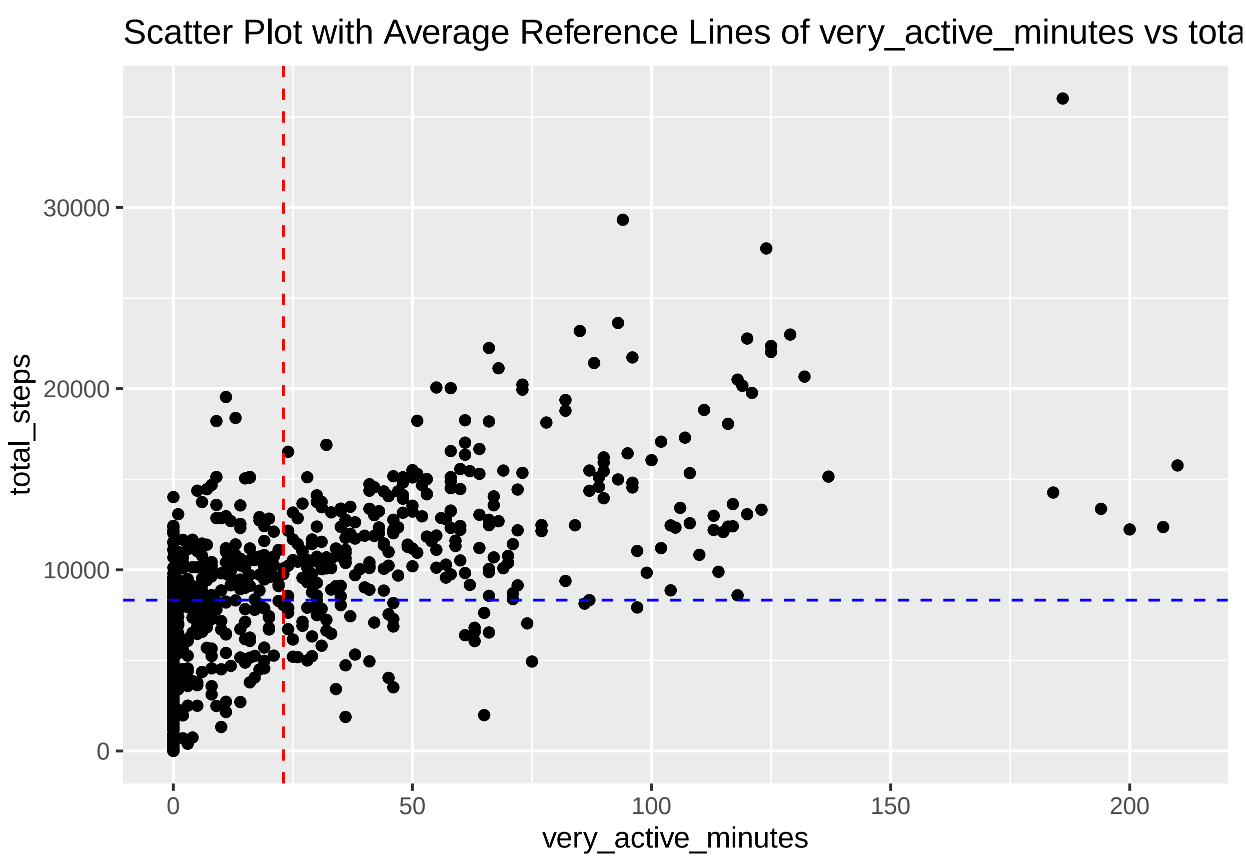

Scatter Plot with Average Reference Lines of total_steps vs total_distance
total_distance
20
10
0
0
10000
20000
30000
total_steps

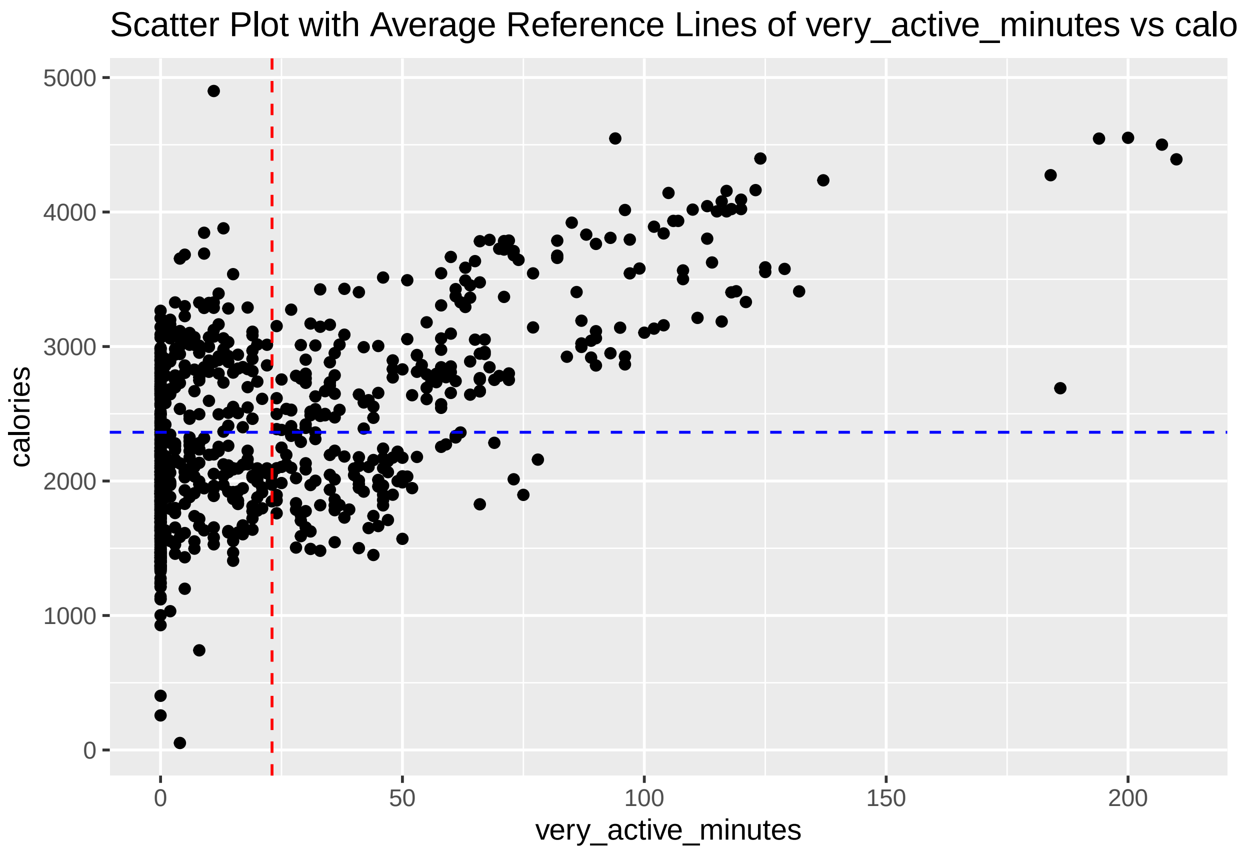

Scatter Plot with Average Reference Lines of lightly_active_minutes vs light_
light_active_distance
9
6
3
0
0
100
200
300
400
500
lightly_active_minutes

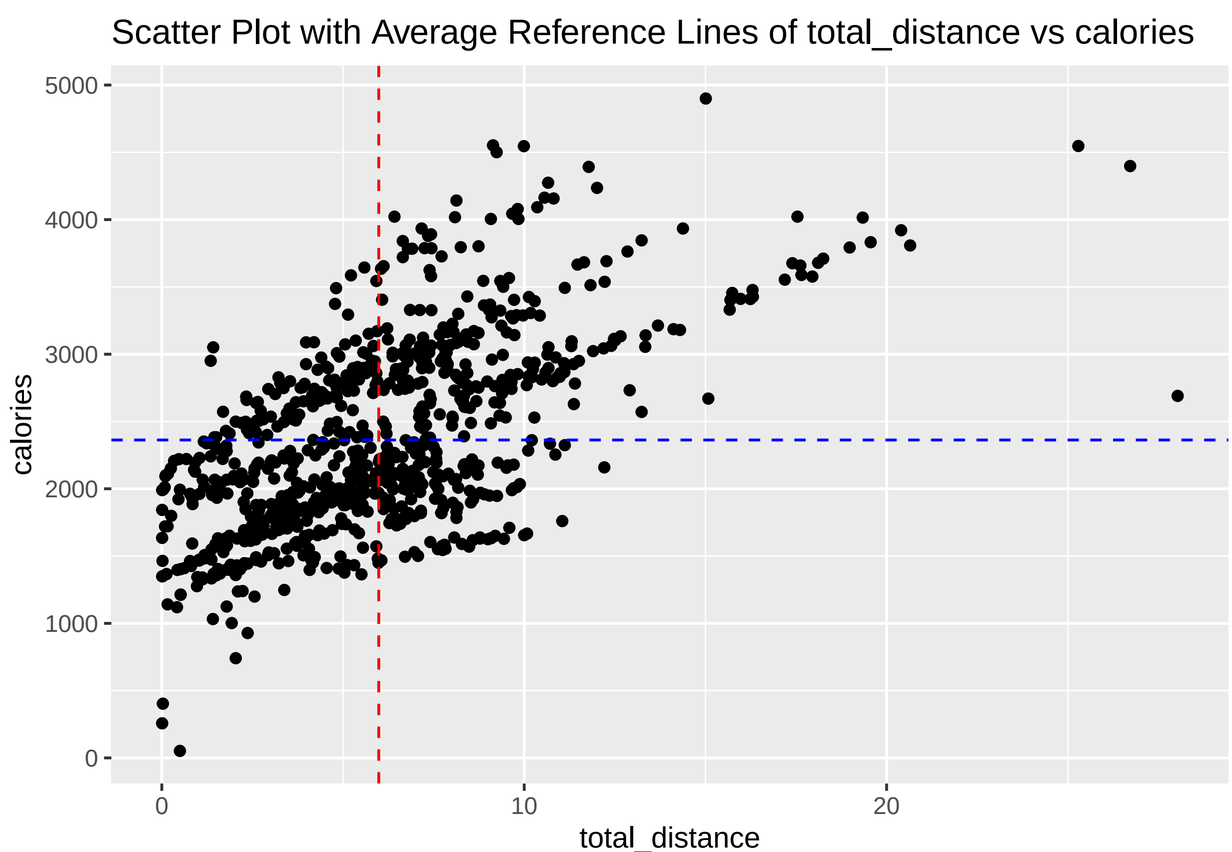

Scatter Plot with Average Reference Lines of fairly_active_minutes vs moder
moderately_active_distance
fairly_active_minutes
0
2
4
6
0
50
100
150

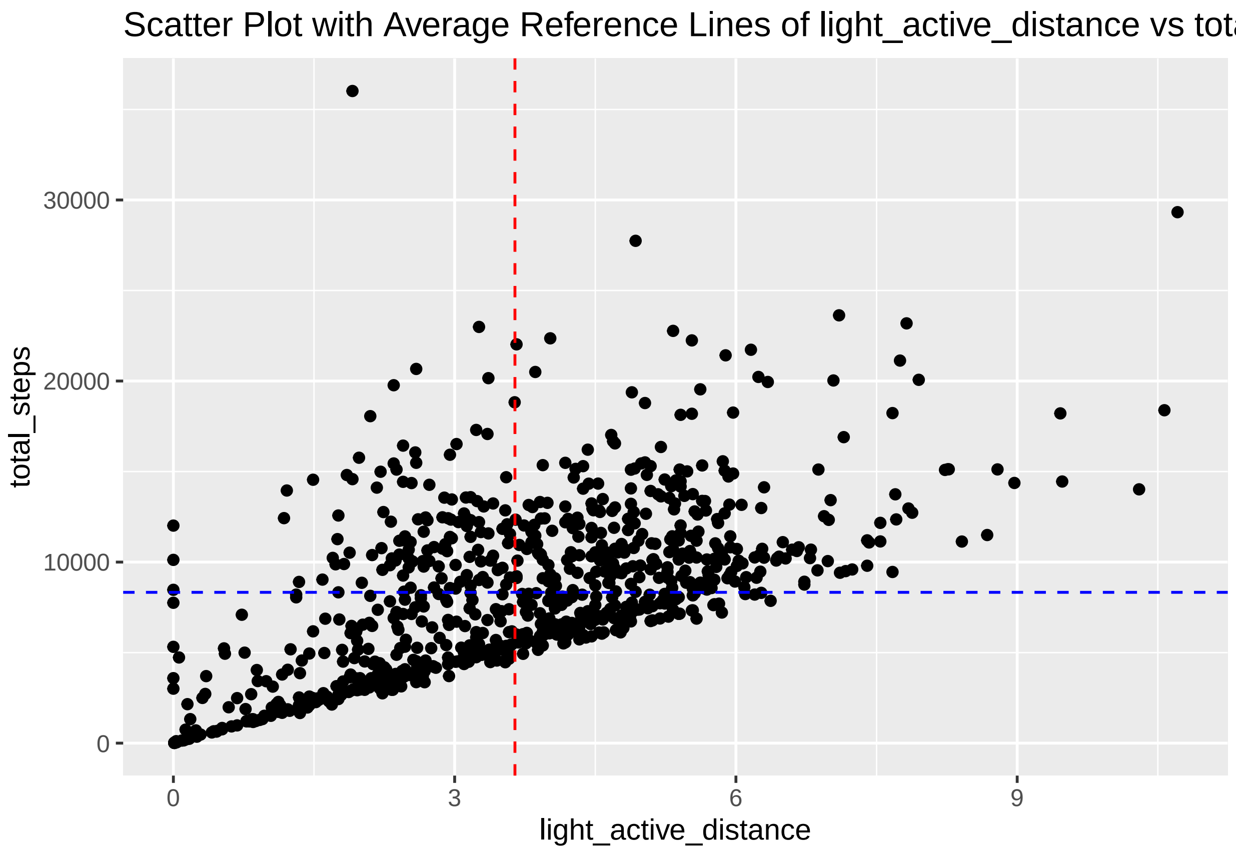

Scatter Plot with Average Reference Lines of very_active_minutes vs very_a
very_active_distance
very_active_minutes
0
5
10
15
20
0
50
100
150
200


Scatter Plot with Average Reference Lines of very_active_minutes vs total_c
total_distance
0
10
20
0
50
100
150
200
very_active_minutes


Scatter Plot with Average Reference Lines of very_active_minutes vs tota
total_steps
0
10000
20000
30000
0
50
100
150
200
very_active_minutes


Scatter Plot with Average Reference Lines of very_active_minutes vs calor
calories
5000
4000
3000
2000
1000
0
0
50
100
150
200
very_active_minutes

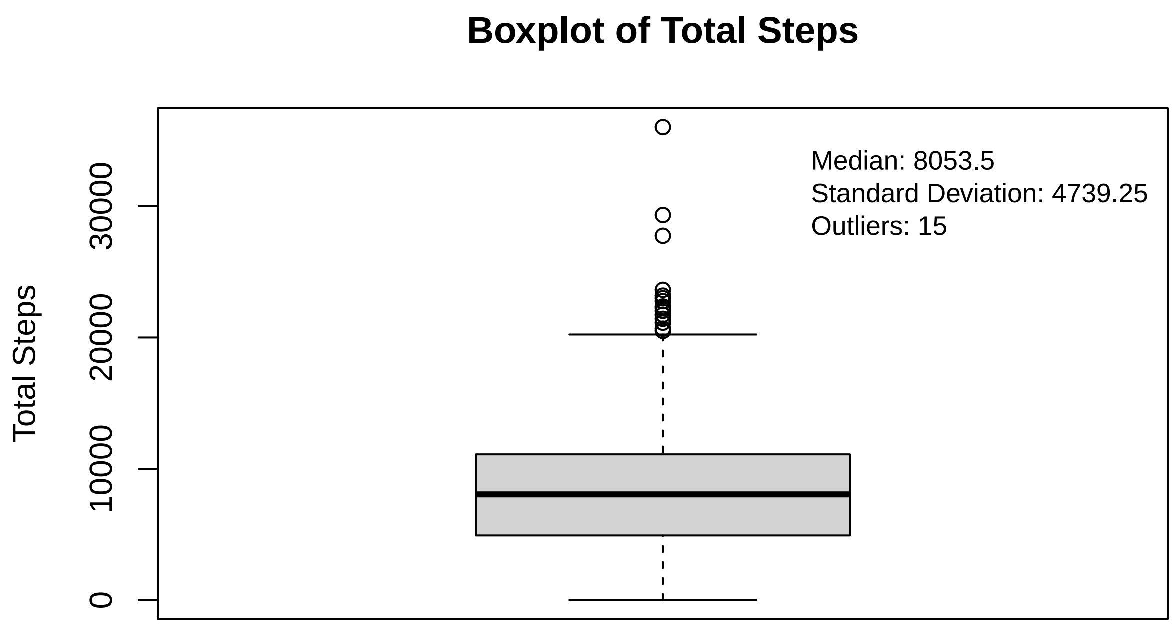

Scatter Plot with Average Reference Lines of total_distance vs calories
calories
5000
4000
3000
2000
1000
0
0
10
20
total_distance



User Behavior for the daily activity dataset

```
# Create a boxplot for total_steps
boxplot(daily_activity_clean$total_steps,
        main = "Boxplot of Total Steps",
        ylab = "Total Steps")

# Calculate the median and standard deviation
median_value <- median(daily_activity_clean$total_steps)
std_dev <- round(sd(daily_activity_clean$total_steps),2)

# Identify outliers
outliers <- boxplot.stats(daily_activity_clean$total_steps)$out

# Count the number of outliers
num_outliers <- length(outliers)

# Create the legend label with median, standard deviation, and outlier count
legend_label <- paste("Median:", median_value,
                      "\nStandard Deviation:", std_dev,
                      "\nOutliers:", num_outliers)

# Add the legend with median, standard deviation, and outlier count
legend("topright", legend = legend_label, pch = "", col = "black", bty = "n", cex = 0.85)
```

Total steps: Total number of steps taken.




```r
# Steps averages by IDs
steps_df <- daily_activity_clean %>%
  group_by(id) %>%
  summarise(average_steps = mean(total_steps), median_steps =median(total_steps), n = n())

steps_df
```

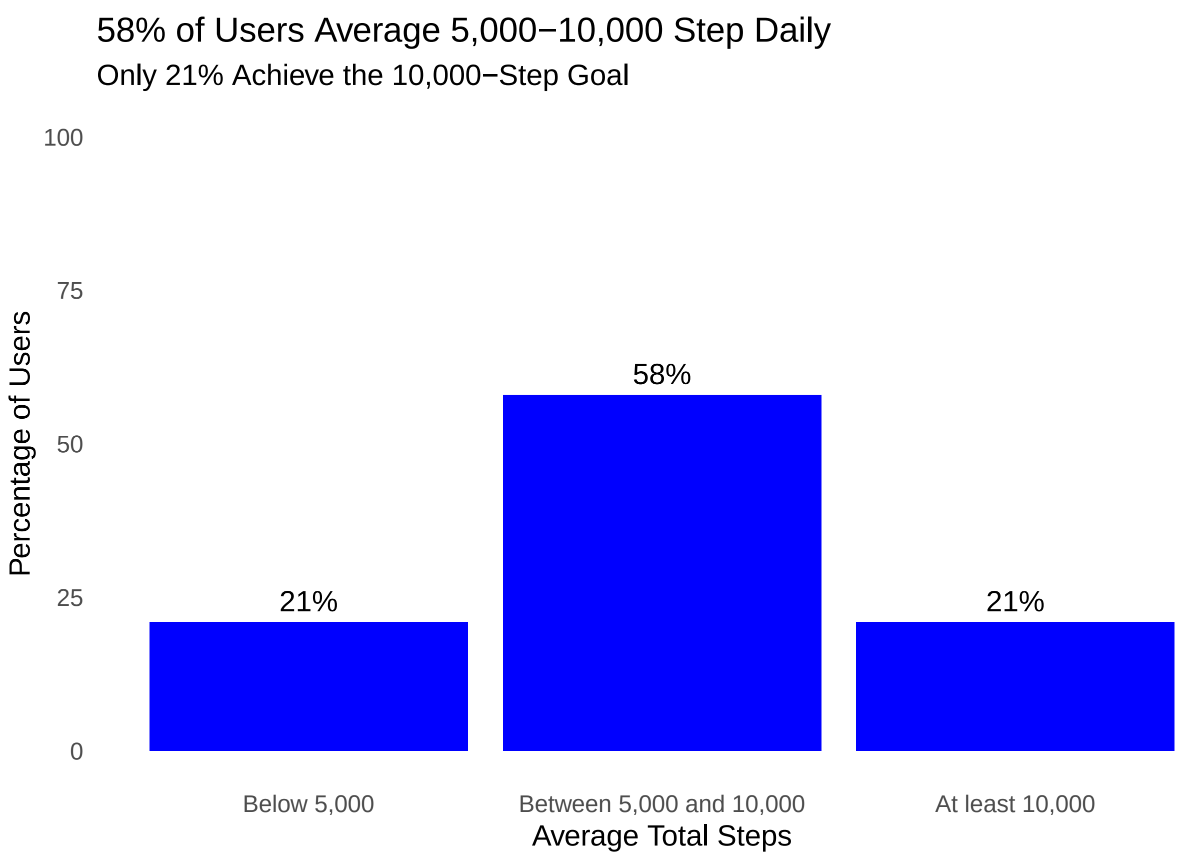
```
# A tibble: 33 x 4
   id          average_steps median_steps     n
   <chr>               <dbl>        <dbl> <int>
 1 1503960366         12521.        12438    30
 2 1624580081          5744.         4026    31
 3 1644430081          7283.         6684.   30
 4 1844505072          3999.         4036.   20
 5 1927972279          1671.         1675    17
 6 2022484408         11371.        11548    31
 7 2026352035          5567.         5528    31
 8 2320127002          4717.         5057    31
 9 2347167796          9520.         9781    18
10 2873212765          7556.         7762    31
# ... with 23 more rows
```

```r
# Calculate percentages for the average column
at_least_10k_avg <- sum(steps_df$average_steps >= 10000) / nrow(steps_df) * 100
between_5K_10K_avg <- sum(steps_df$average_steps >= 5000 & steps_df$average_steps < 10000) / nrow(steps_
below_5k_avg <- sum(steps_df$average_steps < 5000) / nrow(steps_df) * 100

# Calculate percentages for the median column
at_least_10k_med <- sum(steps_df$median_steps >= 10000) / nrow(steps_df) * 100
between_5K_10K_med <- sum(steps_df$median_steps >= 5000 & steps_df$median_steps < 10000) / nrow(steps_d
below_5k_med <- sum(steps_df$median_steps < 5000) / nrow(steps_df) * 100

# Create a data frame for the steps categories
percentage_steps_df<- data.frame(
  Category = c("Below 5,000", "Between 5,000 and 10,000", "At least 10,000"),
```

```
  Percentage_Average = round(c(below_5k_avg, between_5K_10K_avg, at_least_10k_avg)),
  Percentage_Median = round(c(below_5k_med, between_5K_10K_med, at_least_10k_med)))
percentage_steps_df
```

```
                  Category Percentage_Average Percentage_Median
1              Below 5,000                 21                21
2 Between 5,000 and 10,000                 58                52
3           At least 10,000                21                27
```

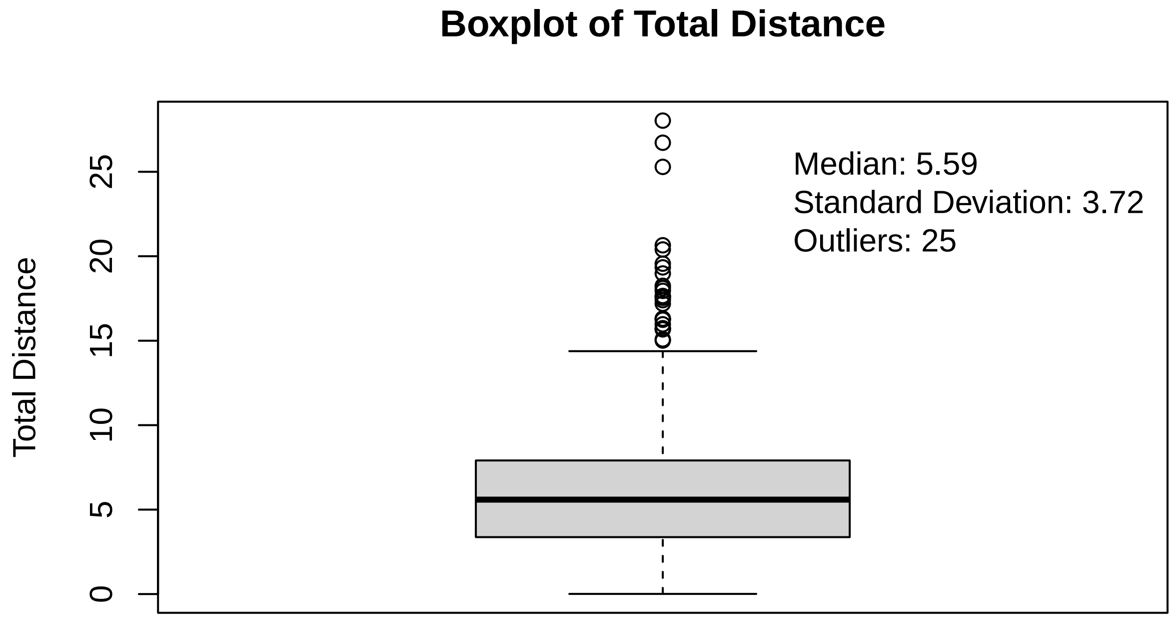
```
# Convert Category to a factor with custom factor levels
percentage_steps_df$Category <- factor(percentage_steps_df$Category, levels = c("Below 5,000", "Between

# Create a bar plot using ggplot
ggplot(percentage_steps_df, aes(x = Category, y = Percentage_Average)) +
  geom_bar(stat = "identity", fill = "blue") +
  labs(x = "Average Total Steps", y = "Percentage of Users", title = "58% of Users Average 5,000-10,000
  geom_text(aes(label = paste0(Percentage_Average, "%")), vjust = -0.5, color = "black") +
  ylim(0, 100) +  theme_minimal() + theme(panel.grid = element_blank())
```




```
# Create a boxplot for total_distance
boxplot(daily_activity_clean$total_distance,
        main = "Boxplot of Total Distance",
        ylab = "Total Distance")

# Calculate the median and standard deviation
median_value <- median(daily_activity_clean$total_distance)
```

```
std_dev <- sd(daily_activity_clean$total_distance)

# Identify outliers
outliers <- boxplot.stats(daily_activity_clean$total_distance)$out

# Count the number of outliers
num_outliers <- length(outliers)

# Create the legend label with median, standard deviation, and outlier count
legend_label <- paste("Median:", round(median_value, 2),
                      "\nStandard Deviation:", round(std_dev, 2),
                      "\nOutliers:", num_outliers)

# Add the legend with median, standard deviation, and outlier count
legend("topright", legend = legend_label, pch = "", col = "black", bty = "n")
```

Total Distance: Total kilometers tracked.




```
# Total distance by IDs
t_distance_df <- daily_activity_clean %>%
  group_by(id) %>%
  summarise(average_t_distance = mean(total_distance ), median_t_distance =median(total_distance), n = 

t_distance_df
```

```
# A tibble: 33 x 4
   id         average_t_distance median_t_distance     n
   <chr>                   <dbl>             <dbl> <int>
 1 1503960366               8.07              8.08    30
 2 1624580081               3.91              2.62    31
 3 1644430081               5.30              4.86    30
 4 1844505072               2.64              2.68    20
 5 1927972279               1.16              1.16    17
 6 2022484408               8.08              8.29    31
 7 2026352035               3.45              3.45    31
```

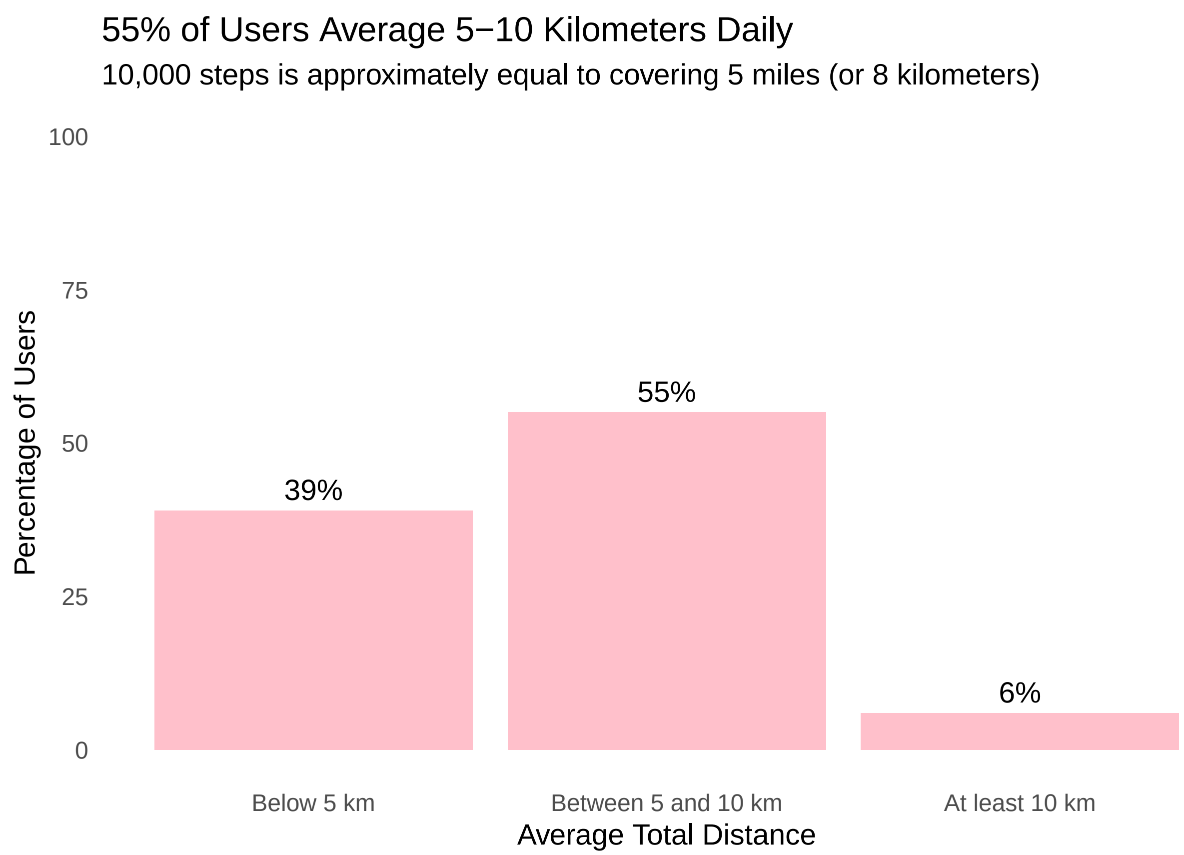
```
 8 2320127002                3.19               3.41    31
 9 2347167796                6.36               6.54    18
10 2873212765                5.10               5.24    31
# ... with 23 more rows
```

```r
# Calculate percentages for the average column
at_least_10_avg<- sum(t_distance_df$average_t_distance>= 10) / nrow(t_distance_df) * 100
between_5_10_avg <- sum(t_distance_df$average_t_distance >= 5 & t_distance_df$average_t_distance < 10) /
below_5_avg <- sum(t_distance_df$average_t_distance < 5) / nrow(t_distance_df) * 100


# Create a data frame for the distance categories
percentage_t_distance_df<- data.frame(
  Category = c("Below 5 km", "Between 5 and 10 km", "At least 10 km"),
  Percentage_Average = round(c(below_5_avg, between_5_10_avg , at_least_10_avg)))
percentage_t_distance_df
```

```
             Category Percentage_Average
1          Below 5 km                 39
2 Between 5 and 10 km                 55
3      At least 10 km                  6
```

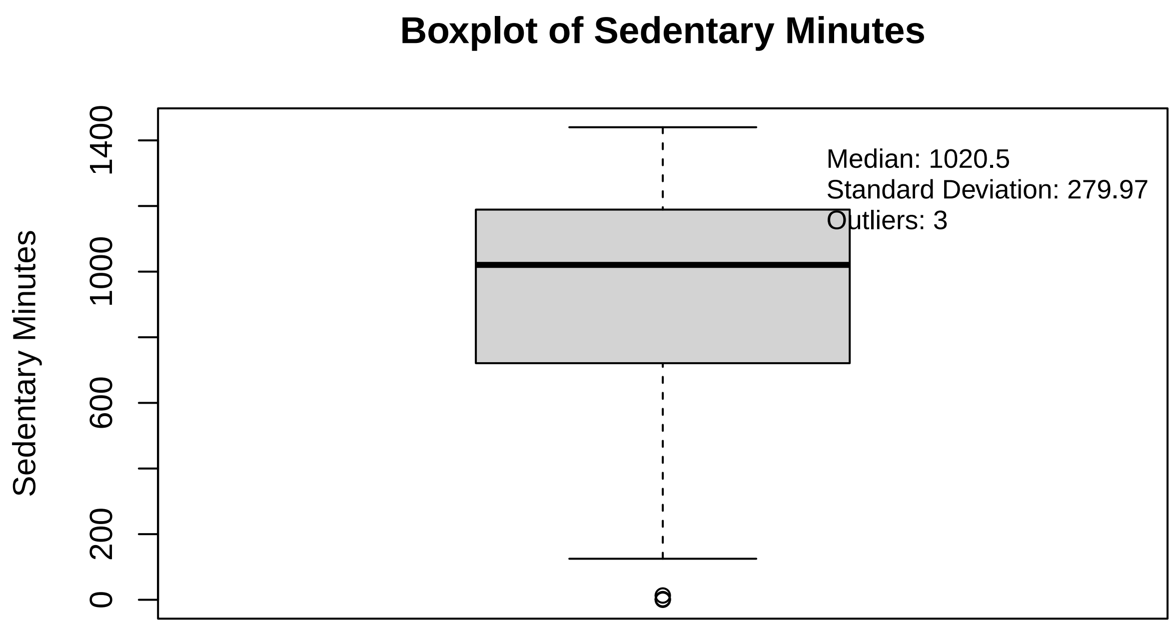
```r
# Convert Category to a factor with custom factor levels
percentage_t_distance_df$Category <- factor(percentage_t_distance_df$Category, levels = c("Below 5 km",
```

```r
# Create a bar plot using ggplot
ggplot(percentage_t_distance_df, aes(x = Category, y = Percentage_Average)) +
  geom_bar(stat = "identity", fill = "pink") +
  labs(x = "Average Total Distance", y = "Percentage of Users", title = "55% of Users Average 5-10 Kilom
  geom_text(aes(label = paste0(Percentage_Average, "%")), vjust = -0.5, color = "black") +
  ylim(0, 100) +  theme_minimal() +theme(panel.grid = element_blank())
```




```r
# Create a boxplot for sedentary_minutes
boxplot(daily_activity_clean$sedentary_minutes,
        main = "Boxplot of Sedentary Minutes",
        ylab = "Sedentary Minutes")

# Calculate the median and standard deviation
median_value <- median(daily_activity_clean$sedentary_minutes)
std_dev <- sd(daily_activity_clean$sedentary_minutes)

# Identify outliers
outliers <- boxplot.stats(daily_activity_clean$sedentary_minutes)$out

# Count the number of outliers
num_outliers <- length(outliers)

# Create the legend label with median, standard deviation, and outlier count
legend_label <- paste("Median:", round(median_value, 2),
                      "\nStandard Deviation:", round(std_dev, 2),
                      "\nOutliers:", num_outliers)

# Add the legend with median, standard deviation, and outlier count
legend("topright", legend = legend_label, pch = "", col = "black", bty = "n", cex = 0.80)
```

Sedentary Minutes: Total minutes spent in sedentary activity.



- These are high values for sedentary minutes. For instance, 1020 minutes is equivalent to 17 hours, and 1400 minutes is equivalent to 24 hours. After performing a quick search, it seems that the Fitbit uses 1400 as default for sedentary minutes when the device is not worn and it includes the sleeping time. SedentaryMinutes is total minutes spent in sedentary activity according to the data dictionary. See meta data section. Therefore, we need to substract the times sleeping to obtain an more accurate estimate of daily sedentary minutes.

Sleep time is not considered sedentary time, so it was removed to determine the waking day and to allow the proportion of the day spent sedentary to be calculated

```
# Check sedentary_minutes stats
daily_activity_clean$sedentary_minutes %>% summary()
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    0.0   721.2  1020.5   955.2  1189.0  1440.0
```

```
outliers
```

```
[1]  2 13  0
```

```
# Count entries where sedentary minutes equal 1440
count_1440 <- sum(daily_activity_clean$sedentary_minutes == 1440)

# Output the count
count_1440
```

```
[1] 7
```

```
# Remove rows with sedentary minutes equal to the default value (1440) and outliers

daily_activity_clean <- filter(daily_activity_clean, !(sedentary_minutes %in% c(0, 2, 13, 1440)))
```

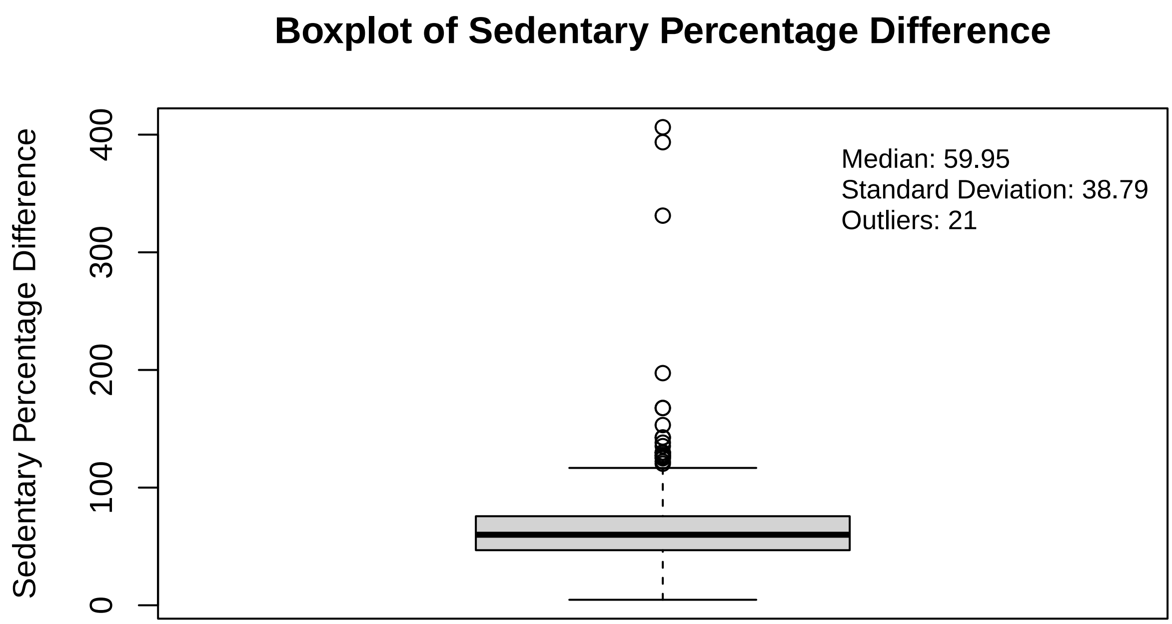
```
# Rename the column
daily_sleep_clean <- rename(daily_sleep_clean, activity_date = sleep_day)

# Join the datasets
joined_activity_sleep <- inner_join(daily_activity_clean, daily_sleep_clean, by = c("id", "activity_dat
```

```r
# Check missing values and duplicates
cat(
  "\n",
  "Missing values:",
  sum(is.na(joined_activity_sleep )),
  "\n",
  "Duplicate values:",
  sum(duplicated(joined_activity_sleep )),
  "\n",
  "Unique Ids:",
  n_distinct(joined_activity_sleep $id)
)
```

```
 Missing values: 0
 Duplicate values: 0
 Unique Ids: 24
```

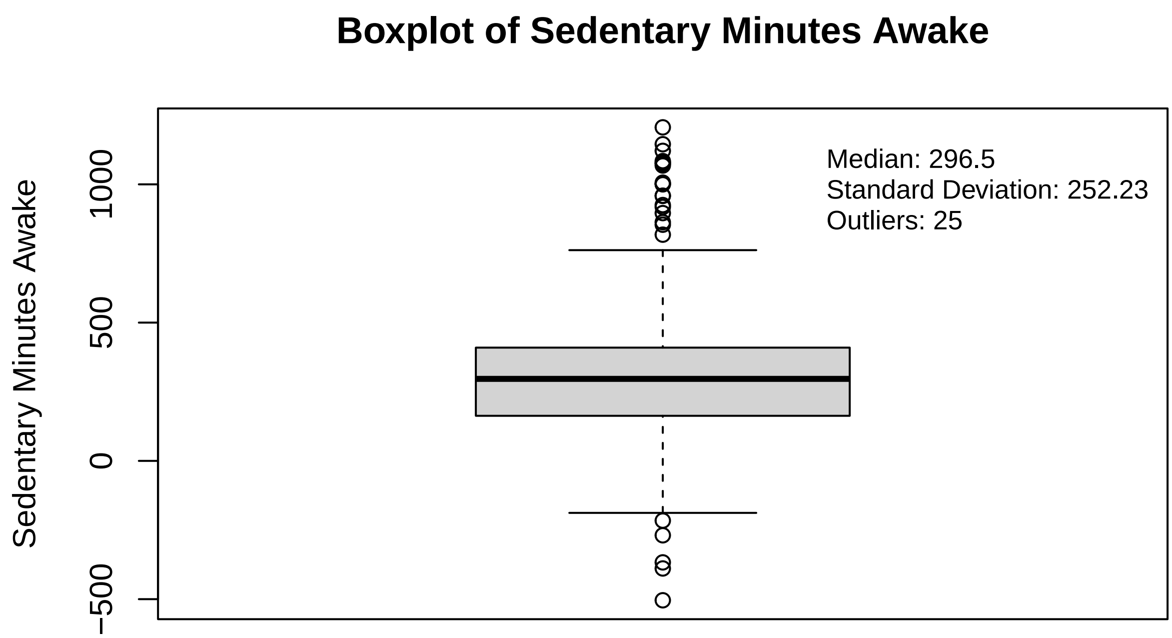
```r
# Create a derived column for sedentary minutes that does not include sleep time
joined_activity_sleep <- joined_activity_sleep %>%
  mutate(
    sedentary_min_awake = sedentary_minutes - total_minutes_asleep,
    sedentary_hours_awake = sedentary_min_awake / 60,
    sedentary_percentage_diff = (sedentary_minutes - sedentary_min_awake) / sedentary_minutes * 100
  )
```

```r
# Let us check the percentage difference of sedentary_minutes and the new column "sedentary_min_awake

# Create a boxplot for sedentary_percentage_diff
boxplot(joined_activity_sleep$sedentary_percentage_diff,
        main = "Boxplot of Sedentary Percentage Difference",
        ylab = "Sedentary Percentage Difference")

# Calculate the median and standard deviation
median_value <- median(joined_activity_sleep$sedentary_percentage_diff)
std_dev <- sd(joined_activity_sleep$sedentary_percentage_diff)

# Identify outliers
outliers <- boxplot.stats(joined_activity_sleep$sedentary_percentage_diff)$out

# Count the number of outliers
num_outliers <- length(outliers)

# Create the legend label with median, standard deviation, and outlier count
legend_label <- paste("Median:", round(median_value, 2),
                      "\nStandard Deviation:", round(std_dev, 2),
                      "\nOutliers:", num_outliers)

# Add the legend with median, standard deviation, and outlier count
legend("topright", legend = legend_label, pch = "", col = "black", bty = "n", cex = 0.80)
```



- The sedentary percentage difference has a median value of 59.95%, indicating a significant distinction between sedentary_minutes and sedentary_min_awake. This suggest that the original column “sedentary_minutes” included the time asleep.

```
# Create a boxplot for sedentary_min_awake
boxplot(joined_activity_sleep$sedentary_min_awake,
        main = "Boxplot of Sedentary Minutes Awake",
        ylab = "Sedentary Minutes Awake")

# Calculate the median and standard deviation
median_value <- median(joined_activity_sleep$sedentary_min_awake)
std_dev <- sd(joined_activity_sleep$sedentary_min_awake)

# Identify outliers
outliers <- boxplot.stats(joined_activity_sleep$sedentary_min_awake)$out

# Count the number of outliers
num_outliers <- length(outliers)

# Create the legend label with median, standard deviation, and outlier count
legend_label <- paste("Median:", round(median_value, 2),
                      "\nStandard Deviation:", round(std_dev, 2),
                      "\nOutliers:", num_outliers)

# Add the legend with median, standard deviation, and outlier count
legend("topright", legend = legend_label, pch = "", col = "black", bty = "n", cex = 0.80)
```



- Observation: There appears to be an inconsistency in the data. The sedentary_minutes value is smaller than the total_minutes_asleep value, which is unexpected.

```r
# Count the number of cases where sedentary_minutes is smaller than total_minutes_asleep
count <- sum(joined_activity_sleep$sedentary_minutes < joined_activity_sleep$total_minutes_asleep)

# Print the count
count
```

```
[1] 42
```

```r
# Subset the dataset
subset_data <- joined_activity_sleep[joined_activity_sleep$sedentary_minutes < joined_activity_sleep$to

# View the subsetted data
subset_data
```

```
# A tibble: 42 x 21
   id          activity~1 total~2 total~3 track~4 logge~5 very_~6 moder~7 light~8
   <chr>       <date>       <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1 1503960366 2016-04-17     9705   6.48    6.48        0 3.19      0.780   2.51
 2 1503960366 2016-05-08    10060   6.58    6.58        0 3.53      0.320   2.73
 3 1644430081 2016-05-02     3758   2.73    2.73        0 0.0700    0.310   2.35
 4 1844505072 2016-04-15     3844   2.54    2.54        0 0         0       2.54
 5 1844505072 2016-04-30     4014   2.67    2.67        0 0         0       2.65
 6 1844505072 2016-05-01     2573   1.70    1.70        0 0         0.260   1.45
 7 1927972279 2016-04-12      678   0.470   0.470       0 0         0       0.470
 8 2026352035 2016-04-23    12357   7.71    7.71        0 0         0       7.71
 9 2026352035 2016-05-04     6564   4.07    4.07        0 0         0       4.07
10 2026352035 2016-05-06     8198   5.08    5.08        0 0         0       5.08
# ... with 32 more rows, 12 more variables: sedentary_active_distance <dbl>,
#   very_active_minutes <dbl>, fairly_active_minutes <dbl>,
#   lightly_active_minutes <dbl>, sedentary_minutes <dbl>, calories <dbl>,
#   total_sleep_records <dbl>, total_minutes_asleep <dbl>,
#   total_time_in_bed <dbl>, sedentary_min_awake <dbl>,
#   sedentary_hours_awake <dbl>, sedentary_percentage_diff <dbl>, and
```

```
#   abbreviated variable names 1: activity_date, 2: total_steps, ...
```

```r
# Check column names of the subsetted data
subset_data %>%
select(sedentary_minutes, total_minutes_asleep, sedentary_min_awake, calories,id, activity_date, total_s
```

```
# A tibble: 42 x 9
   sedentary_~1 total~2 seden~3 calor~4 id    activity~5 total~6 total~7 very_~8
          <dbl>   <dbl>   <dbl>   <dbl> <chr> <date>       <dbl>   <dbl>   <dbl>
 1          539     700    -161    1728 1503~ 2016-04-17    9705   6.48       38
 2          574     594     -20    1740 1503~ 2016-05-08   10060   6.58       44
 3          682     796    -114    2580 1644~ 2016-05-02    3758   2.73        1
 4          527     644    -117    1725 1844~ 2016-04-15    3844   2.54        0
 5          218     722    -504    1763 1844~ 2016-04-30    4014   2.67        0
 6          585     590      -5    1541 1844~ 2016-05-01    2573   1.70        0
 7          734     750     -16    2220 1927~ 2016-04-12     678   0.470       0
 8          458     522     -64    1916 2026~ 2016-04-23   12357   7.71        0
 9          530     538      -8    1658 2026~ 2016-05-04    6564   4.07        0
10          511     524     -13    1736 2026~ 2016-05-06    8198   5.08        0
# ... with 32 more rows, and abbreviated variable names 1: sedentary_minutes,
#   2: total_minutes_asleep, 3: sedentary_min_awake, 4: calories,
#   5: activity_date, 6: total_steps, 7: total_distance, 8: very_active_minutes
```

```r
dim(subset_data)
```

```
[1] 42 21
```

```r
dim(joined_activity_sleep)
```

```
[1] 408  21
```

```r
# Use anti_join() to return a new dataset that includes all rows from the first dataset except for the 
 clean_subset<- anti_join(joined_activity_sleep, subset_data)
```

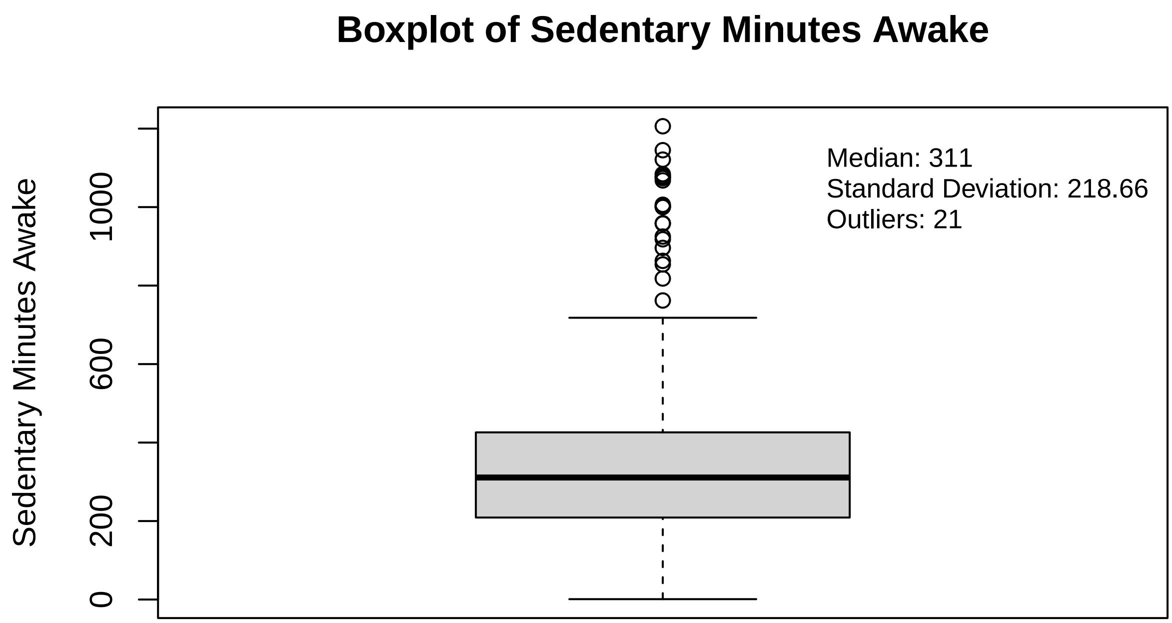
```
Joining with `by = join_by(id, activity_date, total_steps, total_distance,
tracker_distance, logged_activities_distance, very_active_distance,
moderately_active_distance, light_active_distance, sedentary_active_distance,
very_active_minutes, fairly_active_minutes, lightly_active_minutes,
sedentary_minutes, calories, total_sleep_records, total_minutes_asleep,
total_time_in_bed, sedentary_min_awake, sedentary_hours_awake,
sedentary_percentage_diff)`
```

```r
dim(clean_subset)
```

```
[1] 366  21
```

```r
# Create a boxplot for sedentary_min_awake
boxplot(clean_subset$sedentary_min_awake,
        main = "Boxplot of Sedentary Minutes Awake",
        ylab = "Sedentary Minutes Awake")

# Calculate the median and standard deviation
median_value <- median(clean_subset$sedentary_min_awake)
std_dev <- sd(clean_subset$sedentary_min_awake)

# Identify outliers
outliers <- boxplot.stats(clean_subset$sedentary_min_awake)$out
```

```r
# Count the number of outliers
num_outliers <- length(outliers)

# Create the legend label with median, standard deviation, and outlier count
legend_label <- paste("Median:", round(median_value, 2),
                      "\nStandard Deviation:", round(std_dev, 2),
                      "\nOutliers:", num_outliers)

# Add the legend with median, standard deviation, and outlier count
legend("topright", legend = legend_label, pch = "", col = "black", bty = "n", cex = 0.80)
```



Observation: By eliminating negative values from "sedentary_min_awake," the resulting values now reflect a more realistic scenario.

```r
# Total sedentary minutes awake by IDs
t_sedentary_df <- clean_subset %>%
  group_by(id) %>%
  summarise(average_sedentary_min_awake = mean(sedentary_min_awake),
            median_sedentary_min_awake = median(sedentary_min_awake), n = n())

t_sedentary_df
```

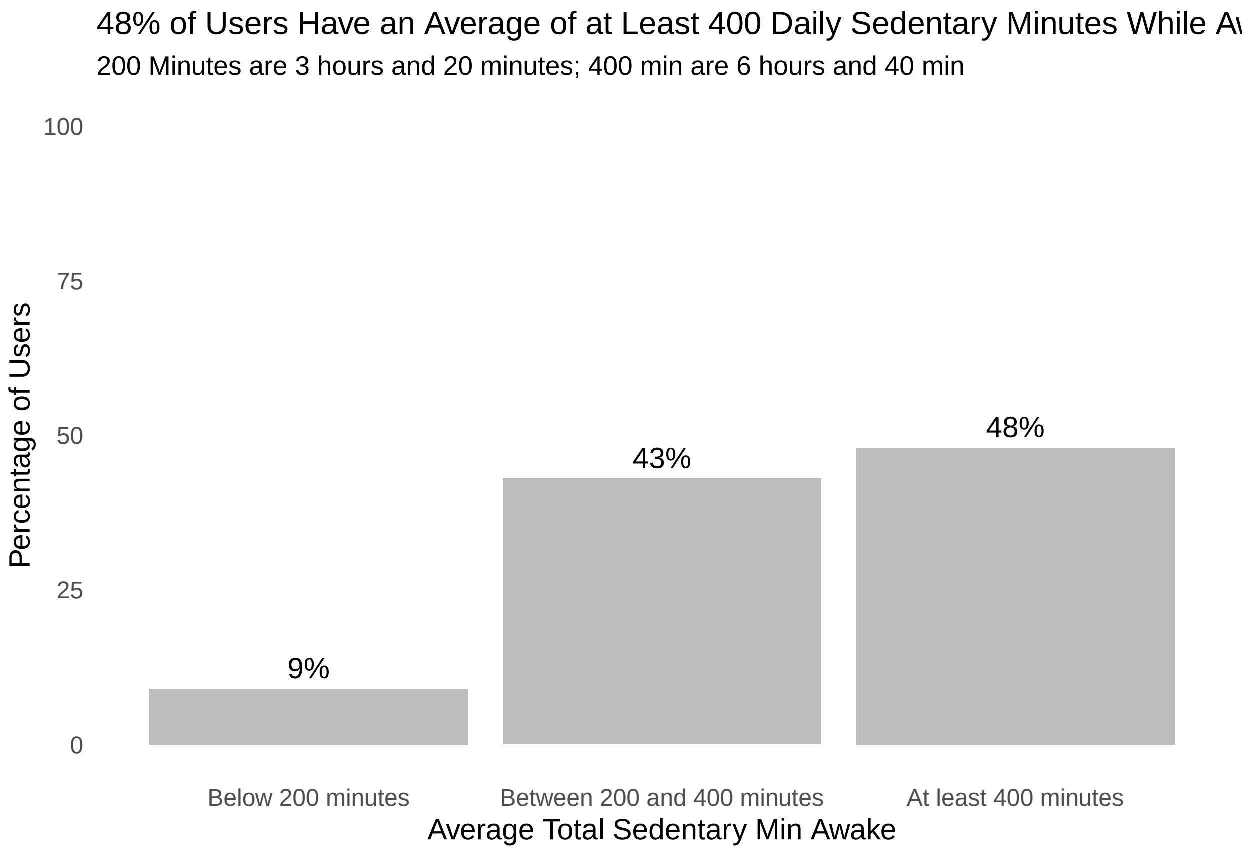
```
# A tibble: 23 x 4
   id         average_sedentary_min_awake median_sedentary_min_awake     n
   <chr>                            <dbl>                      <dbl> <int>
 1 1503960366                        442.                        433    23
 2 1644430081                        873.                        854     3
 3 1927972279                        704.                        675     4
 4 2026352035                        181.                        158    24
 5 2320127002                       1068                        1068     1
 6 2347167796                        245.                        220    13
 7 3977333714                        423.                        420    28
 8 4020332650                        492.                        440.    8
 9 4319703577                        209.                        148    23
10 4388161847                        345                         294    23
```

```
# ... with 13 more rows
```

```r
dataset <- t_sedentary_df
column <- "average_sedentary_min_awake"
new_categories <- c("Below 200 minutes", "Between 200 and 400 minutes", "At least 400 minutes")

# Calculate percentages for the average column
below_200_avg <- sum(dataset[[column]] < 200) / nrow(dataset) * 100
between_200_400_avg <- sum(dataset[[column]] >= 200 & dataset[[column]] <= 400) / nrow(dataset) * 100
at_least_400_avg <- sum(dataset[[column]] >= 400) / nrow(dataset) * 100

# Create a data frame for the categories
percentage_sedentary_awake_df <- data.frame(
  Category = new_categories,
  Percentage_Average = round(c(below_200_avg, between_200_400_avg, at_least_400_avg))
)

# Convert Category to a factor with custom factor levels
percentage_sedentary_awake_df$Category <- factor(percentage_sedentary_awake_df$Category, levels = new_ca

percentage_sedentary_awake_df
```

```
                     Category Percentage_Average
1           Below 200 minutes                  9
2 Between 200 and 400 minutes                 43
3        At least 400 minutes                 48
```

```r
# Create a bar plot using ggplot
ggplot(percentage_sedentary_awake_df, aes(x = Category, y = Percentage_Average)) +
  geom_bar(stat = "identity", fill = "gray") +
  labs(x = "Average Total Sedentary Min Awake", y = "Percentage of Users",
       title = "48% of Users Have an Average of at Least 400 Daily Sedentary Minutes While Awake",
       subtitle = "200 Minutes are 3 hours and 20 minutes; 400 min are 6 hours and 40 min") +
  geom_text(aes(label = paste0(Percentage_Average, "%")), vjust = -0.5, color = "black") +
  ylim(0, 100) +
  theme_minimal() +
  theme(panel.grid = element_blank(), plot.title = element_text(size = 12), plot.subtitle = element_tex
```



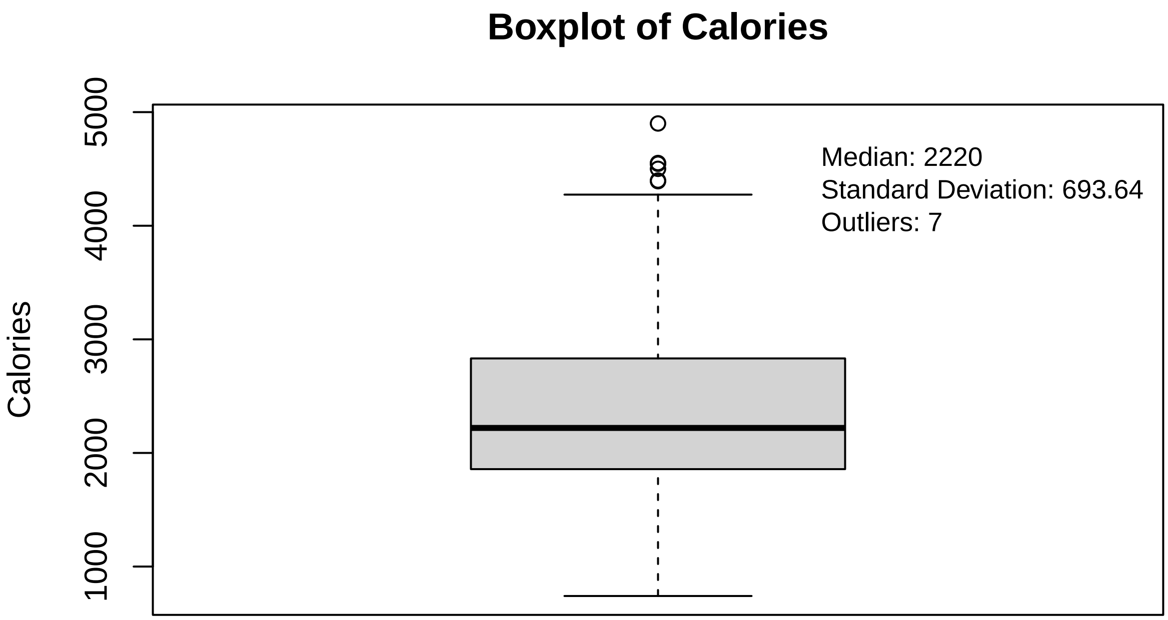
In a representative sample of U.S. adults, over two-thirds spent 6 + hours/day sitting, and more than half did not meet the recommended 150 min/week of physical activity. The study discovered that prolonged sitting for 6+ hours/day was associated with higher body fat percentages. While exceeding 150 min/week of physical activity was linked to lower body fat percentages, achieving recommended activity levels may not fully offset the increased body fat from prolonged sitting.

Jingwen Liao, Min Hu, Kellie Imm, Clifton J. Holmes, Jie Zhu, Chao Cao, Lin Yang. Association of daily sitting time and leisure-time physical activity with body fat among U.S. adults. Journal of Sport and Health Science, 2022. ISSN 2095-2546. https://doi.org/10.1016/j.jshs.2022.10.001. (https://www.sciencedirect.com/science/article/pii/S2095254622001016)

```r
# Create a boxplot for calories
boxplot(daily_activity_clean$calories,
        main = "Boxplot of Calories",
        ylab = "Calories")

# Calculate the median and standard deviation
median_value <- median(daily_activity_clean$calories)
std_dev <- round(sd(daily_activity_clean$calories),2)

# Identify outliers
outliers <- boxplot.stats(daily_activity_clean$calories)$out

# Count the number of outliers
num_outliers <- length(outliers)
```

```r
# Create the legend label with median, standard deviation, and outlier count
legend_label <- paste("Median:", median_value,
                      "\nStandard Deviation:", std_dev,
                      "\nOutliers:", num_outliers)

# Add the legend with median, standard deviation, and outlier count
legend("topright", legend = legend_label, pch = "", col = "black", bty = "n", cex = 0.85)
```

Calories:Total estimated energy expenditure (in kilocalories).




```r
outliers
```

```
[1] 4552 4392 4501 4546 4900 4547 4398
```

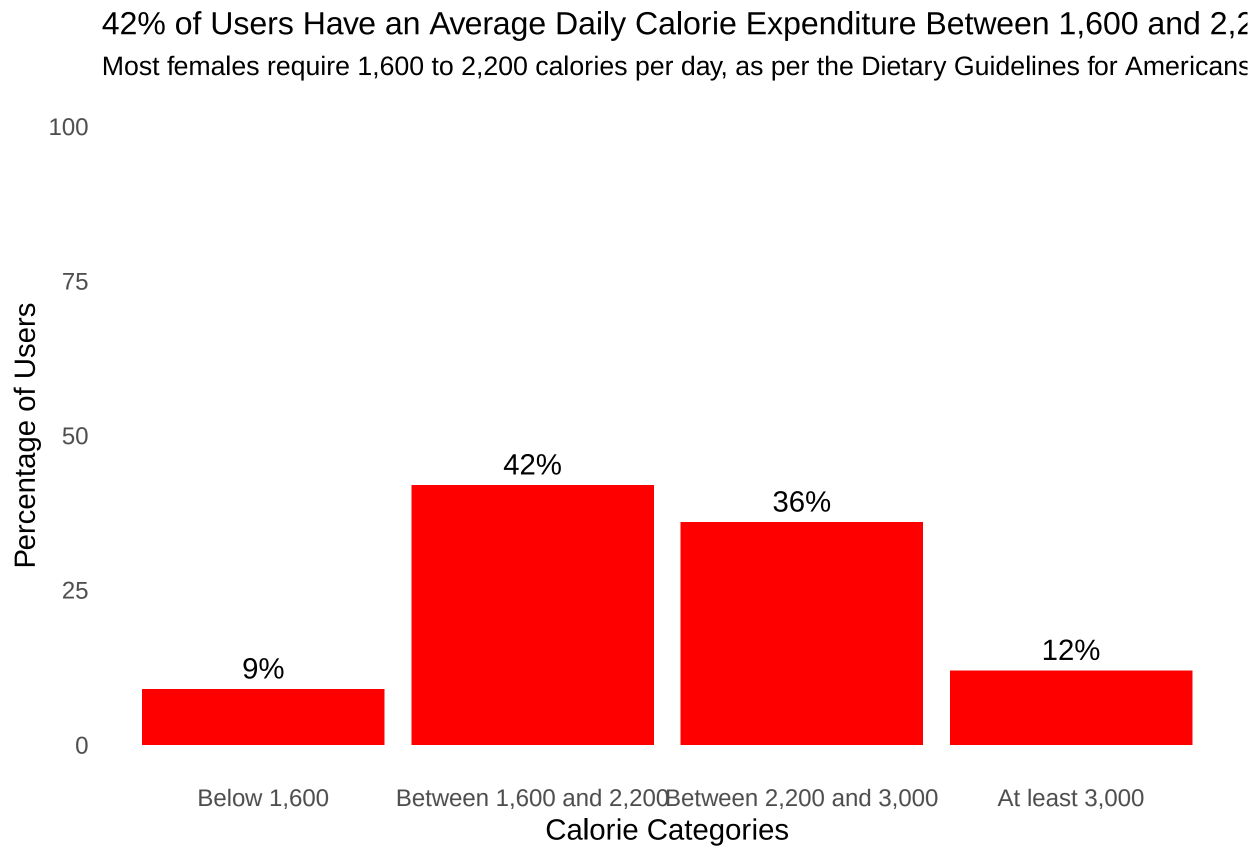
```r
# Calories averages by IDs
calories_df <- daily_activity_clean %>%
  group_by(id) %>%
  summarise(average_calories = mean(calories), median_calories = median(calories))

calories_df
```

```
# A tibble: 33 x 3
   id          average_calories median_calories
   <chr>                  <dbl>           <dbl>
 1 1503960366             1877.           1848
 2 1624580081             1483.           1435
 3 1644430081             2811.           2802.
 4 1844505072             1732.           1752.
 5 1927972279             2303.           2324
 6 2022484408             2510.           2529
 7 2026352035             1541.           1521
 8 2320127002             1724.           1779
 9 2347167796             2140.           2095
10 2873212765             1917.           1907
# ... with 23 more rows
```

```r
# Calculate percentages for the average column
below_1600_avg <- sum(calories_df$average_calories < 1600) / nrow(calories_df) * 100
between_1600_2200_avg <- sum(calories_df$average_calories >= 1600 & calories_df$average_calories < 2200
between_2200_3000_avg <- sum(calories_df$average_calories >= 2200 & calories_df$average_calories < 3000
at_least_3000_avg <- sum(calories_df$average_calories >= 3000) / nrow(calories_df) * 100

# Calculate percentages for the median column
below_1600_med <- sum(calories_df$median_calories < 1600) / nrow(calories_df) * 100
between_1600_2200_med <- sum(calories_df$median_calories >= 1600 & calories_df$median_calories < 2200) /
between_2200_3000_med <- sum(calories_df$median_calories >= 2200 & calories_df$median_calories < 3000) /
at_least_3000_med <- sum(calories_df$median_calories >= 3000) / nrow(calories_df) * 100

# Create a data frame for the calories categories
percentage_calories_df <- data.frame(
  Category = c("Below 1,600", "Between 1,600 and 2,200", "Between 2,200 and 3,000", "At least 3,000"),
  Percentage_Average = round(c(below_1600_avg, between_1600_2200_avg, between_2200_3000_avg, at_least_3
  Percentage_Median = round(c(below_1600_med, between_1600_2200_med, between_2200_3000_med, at_least_30
)

# Convert Category to a factor with custom factor levels
percentage_calories_df$Category <- factor(percentage_calories_df$Category, levels = c("Below 1,600", "Be

percentage_calories_df
```

```
                 Category Percentage_Average Percentage_Median
1             Below 1,600                  9                 9
2 Between 1,600 and 2,200                 42                36
3 Between 2,200 and 3,000                 36                36
4          At least 3,000                 12                18
```

```r
# Create a bar plot using ggplot
ggplot(percentage_calories_df, aes(x = Category, y = Percentage_Average)) +
  geom_bar(stat = "identity", fill = "red") +
  labs(x = "Calorie Categories", y = "Percentage of Users",
       title = "42% of Users Have an Average Daily Calorie Expenditure Between 1,600 and 2,200.",
       subtitle = "Most females require 1,600 to 2,200 calories per day, as per the Dietary Guidelines f
  geom_text(aes(label = paste0(Percentage_Average, "%")), vjust = -0.5, color = "black") +
  ylim(0, 100) +
  theme_minimal() +
  theme(panel.grid = element_blank(),
        plot.title = element_text(size = 12),
        plot.subtitle = element_text(size = 10))
```



"Females ages 19 through 30 require about 1,800 to 2,400 calories a day. Males in this age group have higher calorie needs of about 2,400 to 3,000 a day. Calorie needs for adults ages 31 through 59 are generally lower; most females require about 1,600 to 2,200 calories a day and males require about 2,200 to 3,000 calories a day."

U.S. Department of Agriculture and U.S. Department of Health and Human Services. Dietary Guidelines for Americans, 2020-2025. 9th Edition. December 2020. Available at DietaryGuidelines.gov/

Intensity Minutes: Time spent in one of four intensity categories.

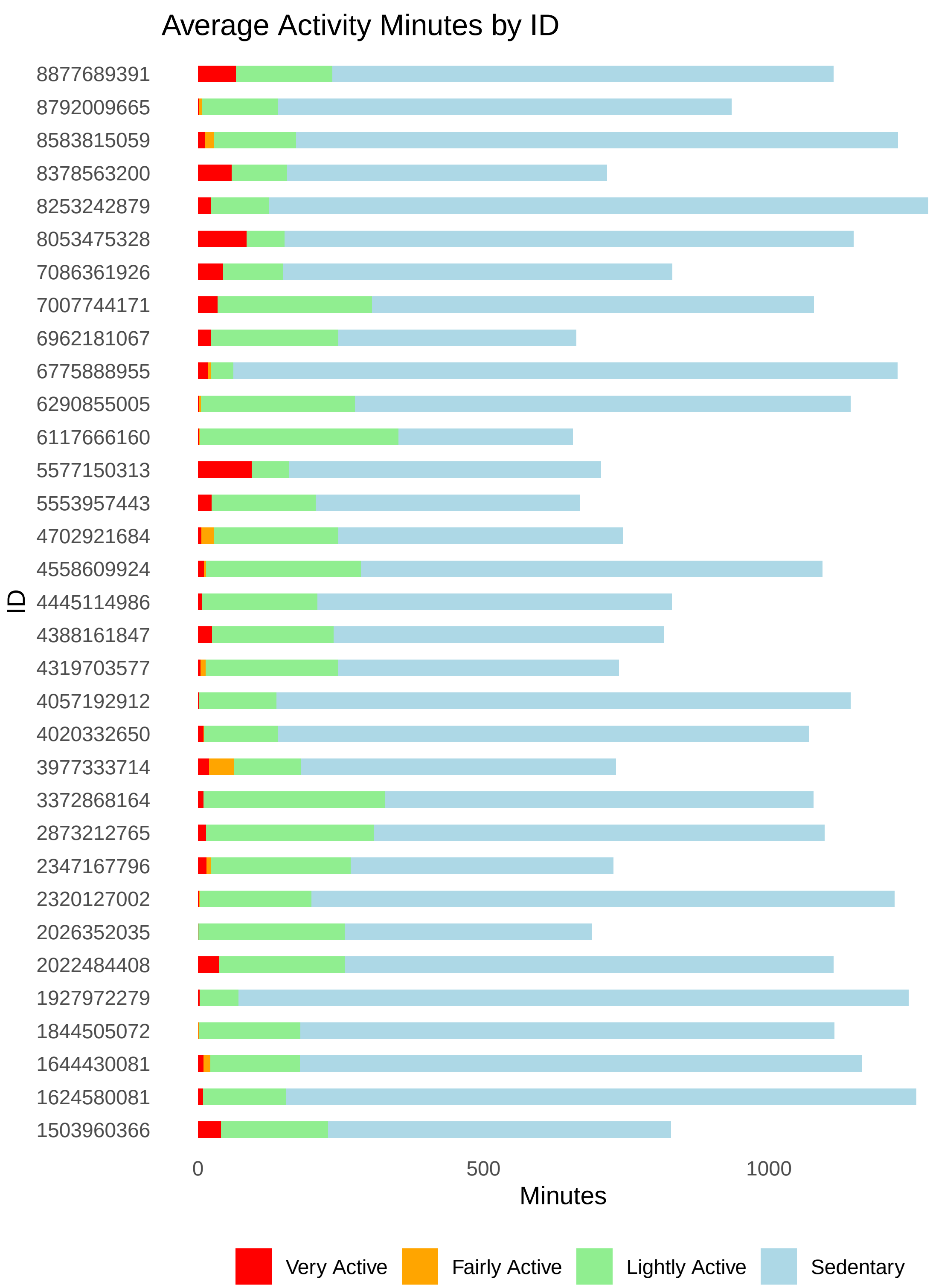
- VeryActiveMinutes: Total minutes spent in very active activity
- FairlyActiveMinutes: Total minutes spent in moderate activity
- LightlyActiveMinutes: Total minutes spent in light activity
- SedentaryMinutes: Total minutes spent in sedentary activity

```
activity_minutes_df <- daily_activity_clean %>%
  group_by(id) %>%
  summarise(
    average_very_active_minutes = mean(very_active_minutes),
    average_fairly_active_minutes = mean(fairly_active_minutes),
    average_lightly_active_minutes = mean(lightly_active_minutes),
    average_sedentary_minutes = mean(sedentary_minutes)
  )

activity_minutes_df
```

```
# A tibble: 33 x 5
```

```
   id         average_very_active_minutes average_fairly_activ~1 avera~2 avera~3
   <chr>                            <dbl>                  <dbl>   <dbl>   <dbl>
 1 1503960366                     40                      19.8     227.     828.
 2 1624580081                      8.68                    5.81    153.    1258.
 3 1644430081                      9.57                   21.4     178.    1162.
 4 1844505072                      0.2                     2       179.    1115.
 5 1927972279                      2.41                    1.41     70.4   1244.
 6 2022484408                     36.3                    19.4     257.    1113.
 7 2026352035                      0.0968                  0.258   257.     689.
 8 2320127002                      1.35                    2.58    198.    1220.
 9 2347167796                     14.3                    21.8     267.     727.
10 2873212765                     14.1                     6.13    308     1097.
# ... with 23 more rows, and abbreviated variable names
#   1: average_fairly_active_minutes, 2: average_lightly_active_minutes,
#   3: average_sedentary_minutes
```

```r
# Define the custom order of legend items
custom_order <- c( "Very Active", "Fairly Active", "Lightly Active", "Sedentary")

# Create the stacked bar plot
ggplot(activity_minutes_df, aes(y = id)) +
  geom_bar(aes(x = average_sedentary_minutes, fill = "Sedentary"), stat = "identity", width = 0.5) +
  geom_bar(aes(x = average_lightly_active_minutes, fill = "Lightly Active"), stat = "identity", width =
  geom_bar(aes(x = average_fairly_active_minutes, fill = "Fairly Active"), stat = "identity", width = 0
  geom_bar(aes(x = average_very_active_minutes, fill = "Very Active"), stat = "identity", width = 0.5) +
  xlab("Minutes") +
  ylab("ID") +
  ggtitle("Average Activity Minutes by ID") +
  scale_fill_manual(name = "", values = c("Very Active" = "red", "Fairly Active" = "orange", "Lightly Ac
  theme_minimal() +
  theme(legend.position = "bottom", panel.grid = element_blank())
```

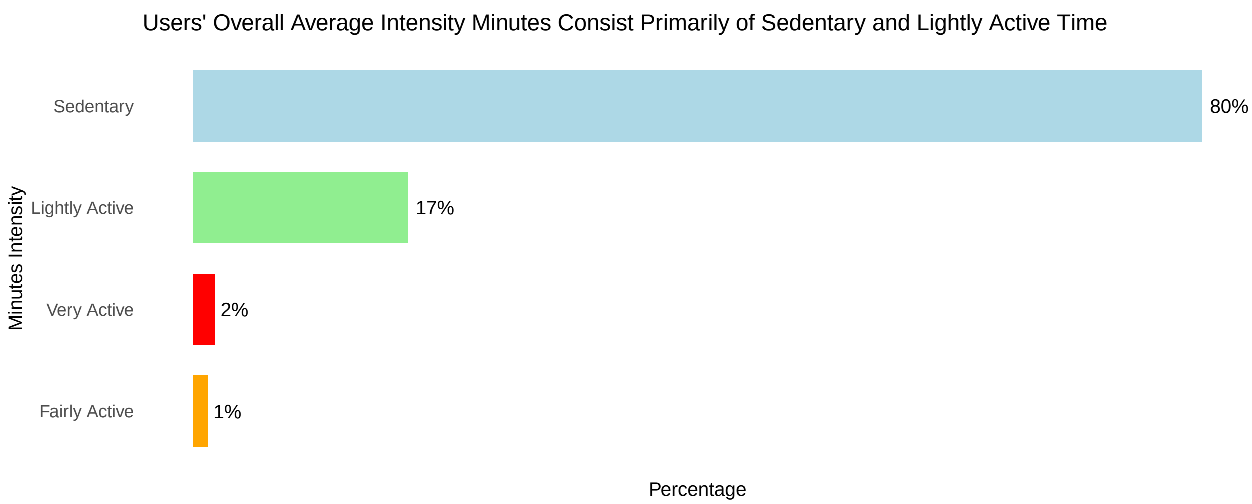



```r
# Calculate the average for each column
averages <- colMeans(activity_minutes_df[, c("average_very_active_minutes",
                                              "average_fairly_active_minutes",
                                              "average_lightly_active_minutes",
                                              "average_sedentary_minutes")])
```

```r
# Calculate the total average
total_average <- sum(averages)

# Calculate the proportions
proportions <- averages / total_average

# Create the new dataframe with modified row names
overall_average_df<- data.frame(Average = averages,
                                Percentage = proportions * 100)

# Modify the row names
row_names <- c("Very Active", "Fairly Active", "Lightly Active", "Sedentary")
row.names(overall_average_df) <- row_names

# Print the new dataframe
overall_average_df
```

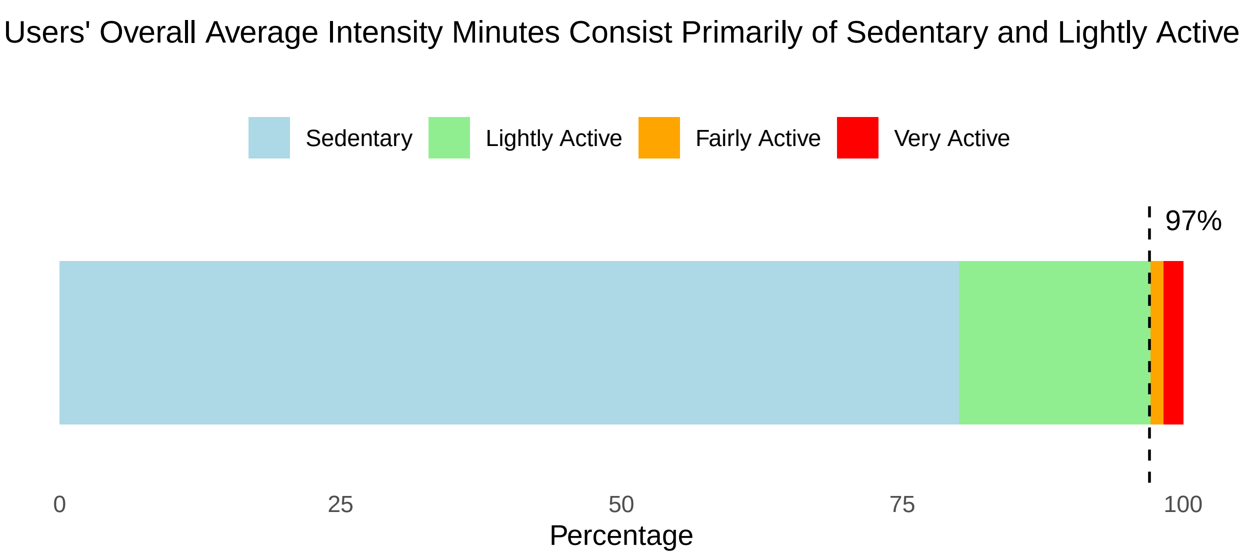
```
                 Average Percentage
Very Active     21.18923   1.744450
Fairly Active   14.29851   1.177156
Lightly Active 206.97366  17.039558
Sedentary      972.20431  80.038837
```

```r
ggplot(overall_average_df, aes(x = Percentage, y = reorder(row.names(overall_average_df), Percentage), 
  geom_bar(stat = "identity", width = 0.7, show.legend = FALSE) +
  geom_text(aes(label = paste0(round(Percentage), "%")), hjust = -0.2, color = "black", size = 4) +
  ylab("Minutes Intensity") +
  xlab("Percentage") +
  ggtitle("Users' Overall Average Intensity Minutes Consist Primarily of Sedentary and Lightly Active Ti
  scale_fill_manual(values = c("Very Active" = "red", "Fairly Active" = "orange", "Lightly Active" = "li
 scale_x_continuous(labels = NULL) +
  theme_minimal() +
  theme(legend.position = "none", panel.grid = element_blank(), axis.text.y = element_text(size = 10))
```



"Analyzing each individual's average calorie intake can provide insights into their individual dietary habits and patterns. By comparing the individual averages to the overall average, you can identify individuals who consume more or fewer calories compared to the group average. This comparison can help in understanding variations in calorie intake and potential factors influencing individual differences."

```r
# Define the custom order of legend items

custom_order <- c("Very Active", "Fairly Active", "Lightly Active", "Sedentary")


# Create the stacked horizontal bar chart
ggplot(overall_average_df, aes(x = Percentage, y = factor(1), fill = factor(row.names(overall_average_d
  geom_bar(stat = "identity", width = 0.7) +
  xlab("Percentage") +
  ylab("") +
  ggtitle("Users' Overall Average Intensity Minutes Consist Primarily of Sedentary and Lightly Active T
  scale_fill_manual(
    name = "",
    values = c(
      "Very Active" = "red",
      "Fairly Active" = "orange",
      "Lightly Active" = "lightgreen",
      "Sedentary" = "lightblue"
    ),
    breaks = custom_order
  ) +
  guides(fill = guide_legend(reverse = TRUE)) +  # Reverse the order of the legend
  theme_minimal() +
  theme(legend.position = "top",
        panel.grid = element_blank(),
         axis.text.y = element_blank(),  # Remove the y-axis text
         plot.title = element_text(size = 12, margin = margin(b = 20))) + # Adjust the title size and m
  geom_vline(xintercept = 97, color = "black", linetype = "dashed") +
  annotate("text", x = 97, y = 1, label = "   97%", vjust = -5.5, hjust = 0.1)
```



These indicators provide insights into activity levels, sedentary behavior, and calorie burn. They can help track progress, set goals, and evaluate user behavior over time. Remember to consider the specific context and goals of your analysis to select and customize the most relevant KPIs for your use case. The context I will use is the guidelines for physical activity and diet for Americans:

- U.S. Department of Health and Human Services. (2019). Physical Activity Guidelines for Americans (2nd ed.). Available at https://health.gov/sites/default/files/2019-09/Physical_Activity_Guidelines_2nd_edition.pdf

- U.S. Department of Agriculture and U.S. Department of Health and Human Services. Dietary Guidelines for Americans, 2020-2025. 9th Edition. December 2020. Available at DietaryGuidelines.gov/

EDA for daily_sleep_clean

```
str(daily_sleep_clean)
```

```
tibble [410 x 5] (S3: tbl_df/tbl/data.frame)
 $ id                  : chr [1:410] "1503960366" "1503960366" "1503960366" "1503960366" ...
 $ activity_date       : Date[1:410], format: "2016-04-12" "2016-04-13" ...
 $ total_sleep_records : num [1:410] 1 2 1 2 1 1 1 1 1 1 ...
 $ total_minutes_asleep: num [1:410] 327 384 412 340 700 304 360 325 361 430 ...
 $ total_time_in_bed   : num [1:410] 346 407 442 367 712 320 377 364 384 449 ...
```

- activity_date (sleep_day): Date on which the sleep event started.
- total_sleep_records: Number of recorded sleep periods for that day. Includes naps > 60 min.
- total_minutes_asleep: Total number of minutes classified as being "asleep".
- total_time_in_bed: Total minutes spent in bed, including asleep, restless, and awake, that occurred during a defined sleep record.

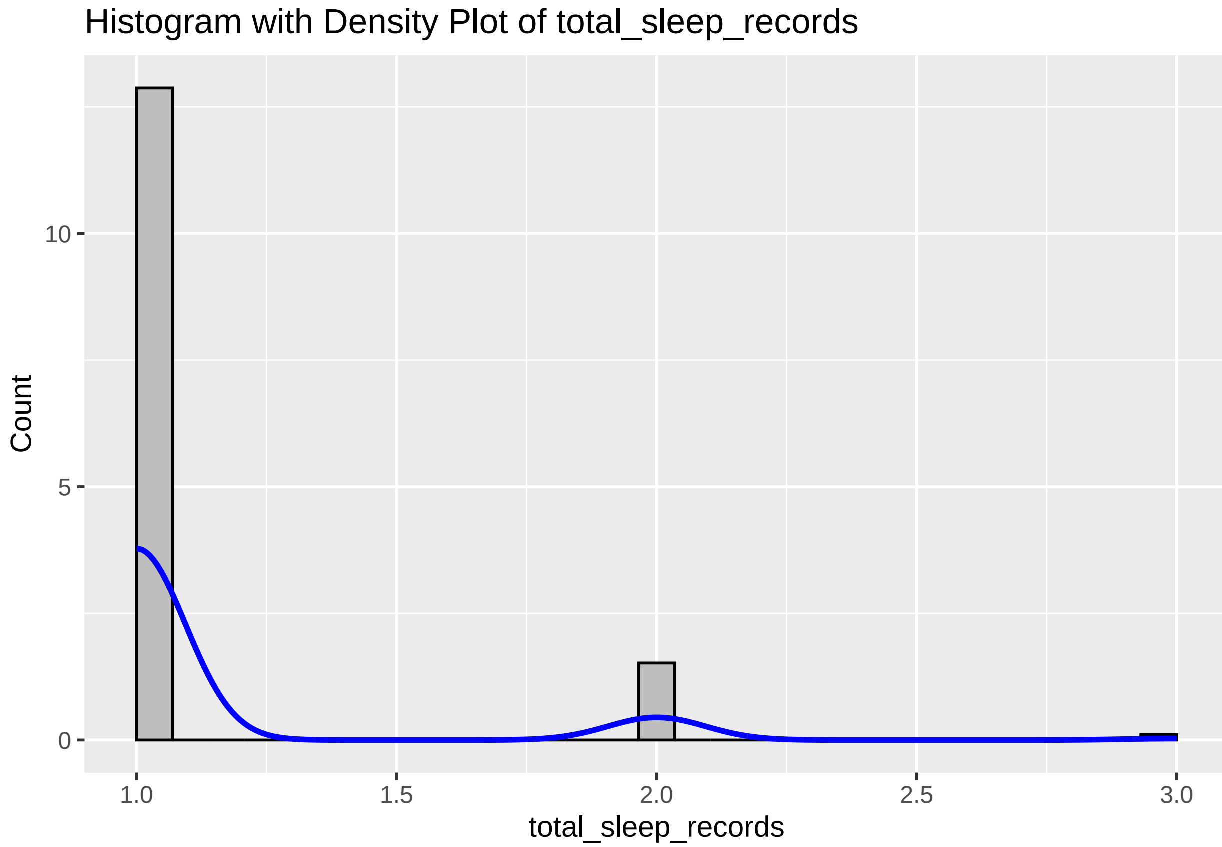
```
#Sanity check: Verify that the value of total_time_in_bed is greater than total_minutes_asleep, as we w
daily_sleep_clean[daily_sleep_clean$total_time_in_bed < daily_sleep_clean$total_minutes_asleep,]
```

```
# A tibble: 0 x 5
# ... with 5 variables: id <chr>, activity_date <date>,
#   total_sleep_records <dbl>, total_minutes_asleep <dbl>,
#   total_time_in_bed <dbl>
```

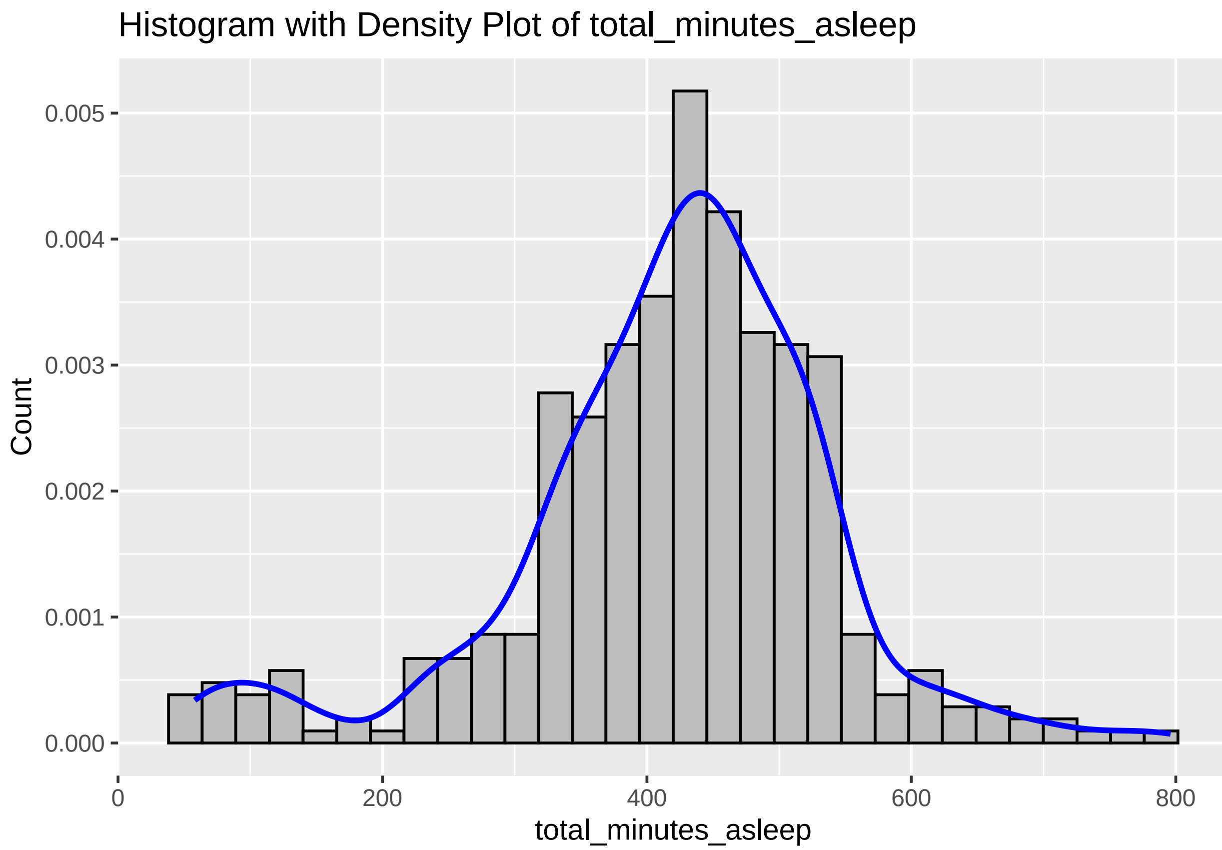
Univariate analysis

```
numerical_cols <- daily_sleep_clean%>%
  select_if(is.numeric)

# plotting all numerical variables
col_names <- colnames(numerical_cols )
for (i in col_names) {
  suppressWarnings(print(
    ggplot(numerical_cols , aes(numerical_cols [[i]])) +
      geom_histogram(
        bins = 30,
        color = "black",
        fill = "gray",
        aes(y = ..density..)
      ) +
      geom_density(
        color = "blue",
        size = 1
      ) +
      xlab(i) + ylab("Count") +
      ggtitle(paste("Histogram with Density Plot of", i))
```

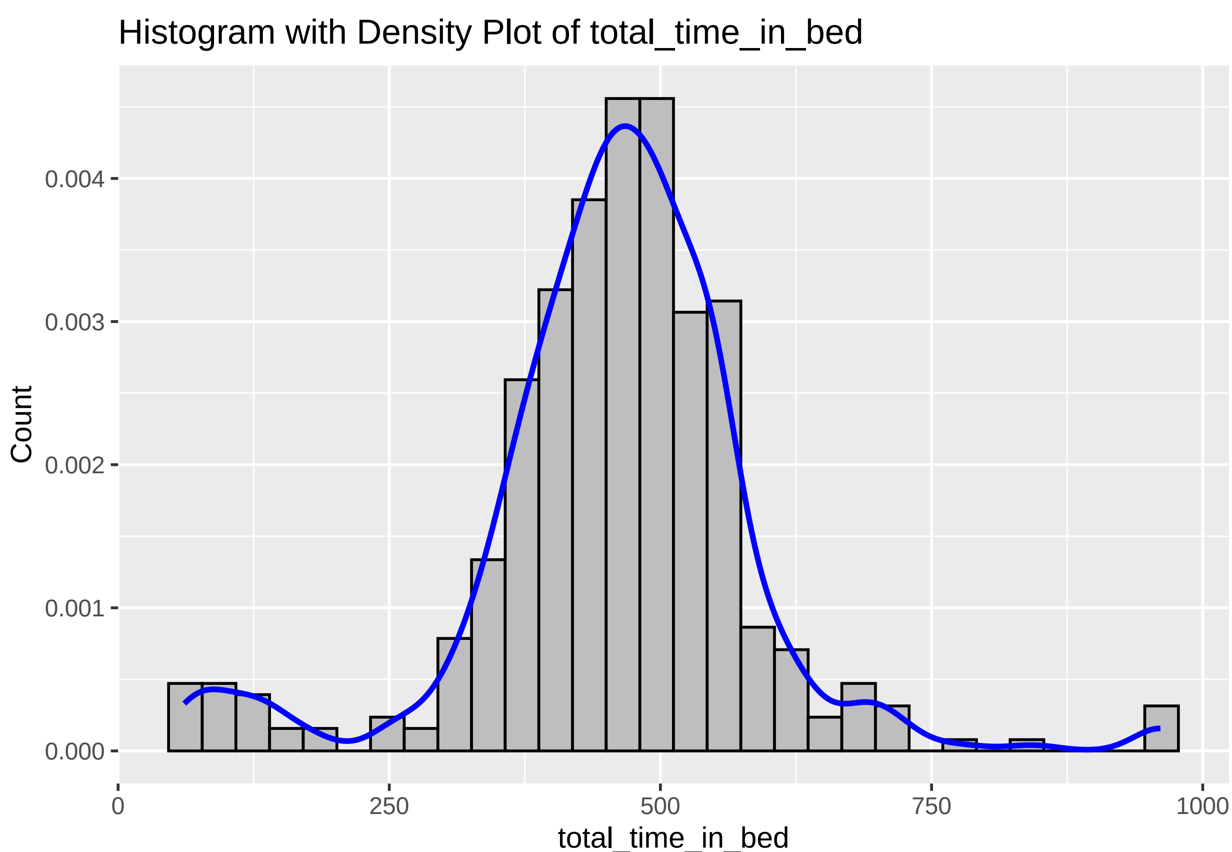
```
  ))
}
```



Histogram with Density Plot of total_sleep_records
Count
10
5
0
1.0
1.5
2.0
2.5
3.0
total_sleep_records



Histogram with Density Plot of total_minutes_asleep
Count
0.005
0.004
0.003
0.002
0.001
0.000
0
200
400
600
800
total_minutes_asleep

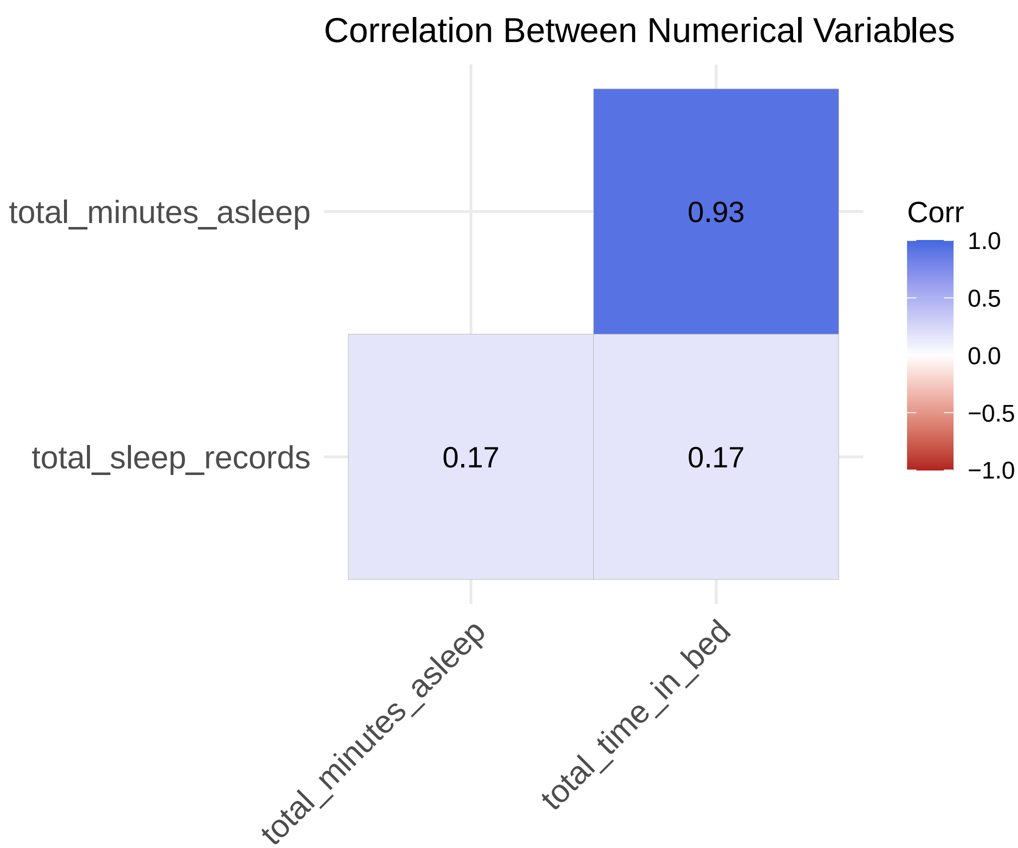


Histogram with Density Plot of total_time_in_bed
Count
0.004
0.003
0.002
0.001
0.000
0
250
500
750
1000
total_time_in_bed

Bivariate analysis

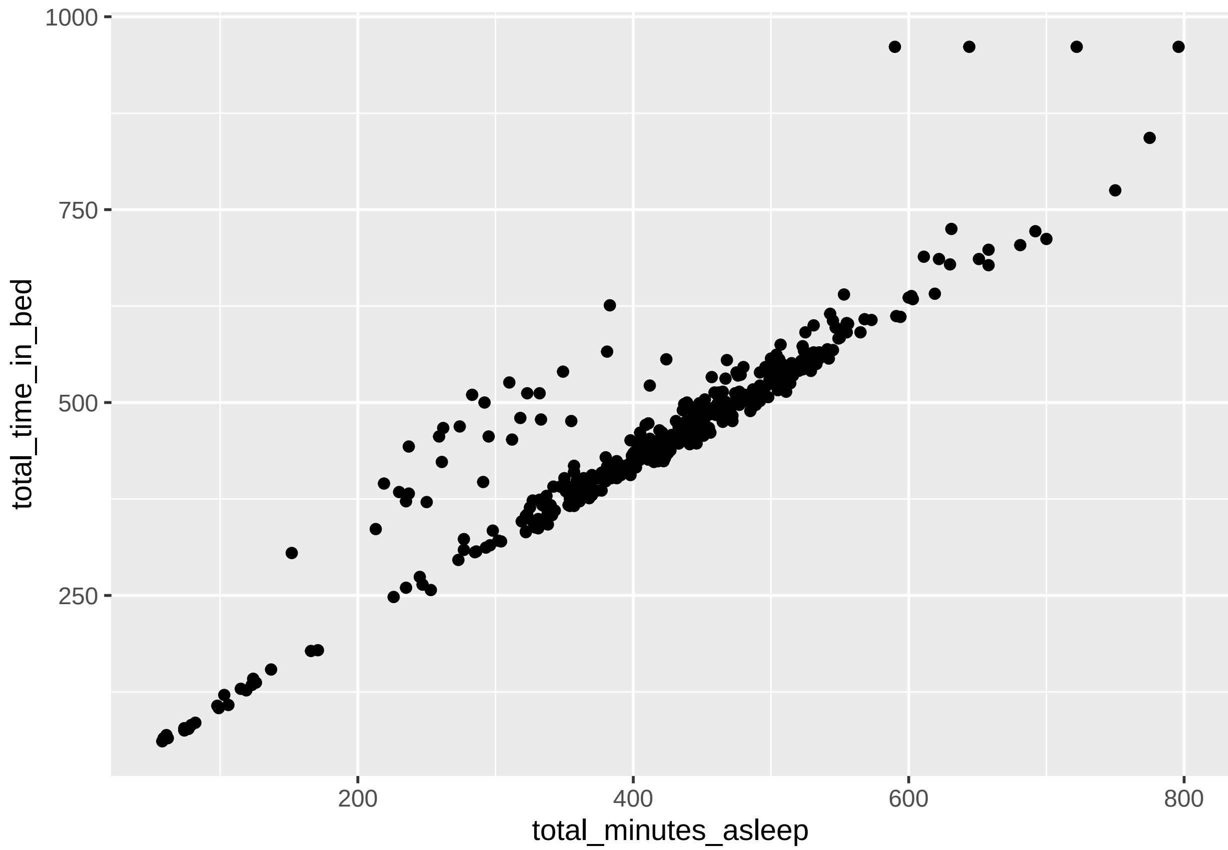
```r
# Correlation between numerical variables
corr <- cor(select_if(daily_sleep_clean, is.numeric))

ggcorrplot(corr,
           hc.order = TRUE,
           type = "lower",
           lab = TRUE,
           colors = c("firebrick", "white", "royalblue"),
           lab_size = 4,
           lab_col = "black",
           title = "Correlation Between Numerical Variables")
```

Correlation between numerical variables



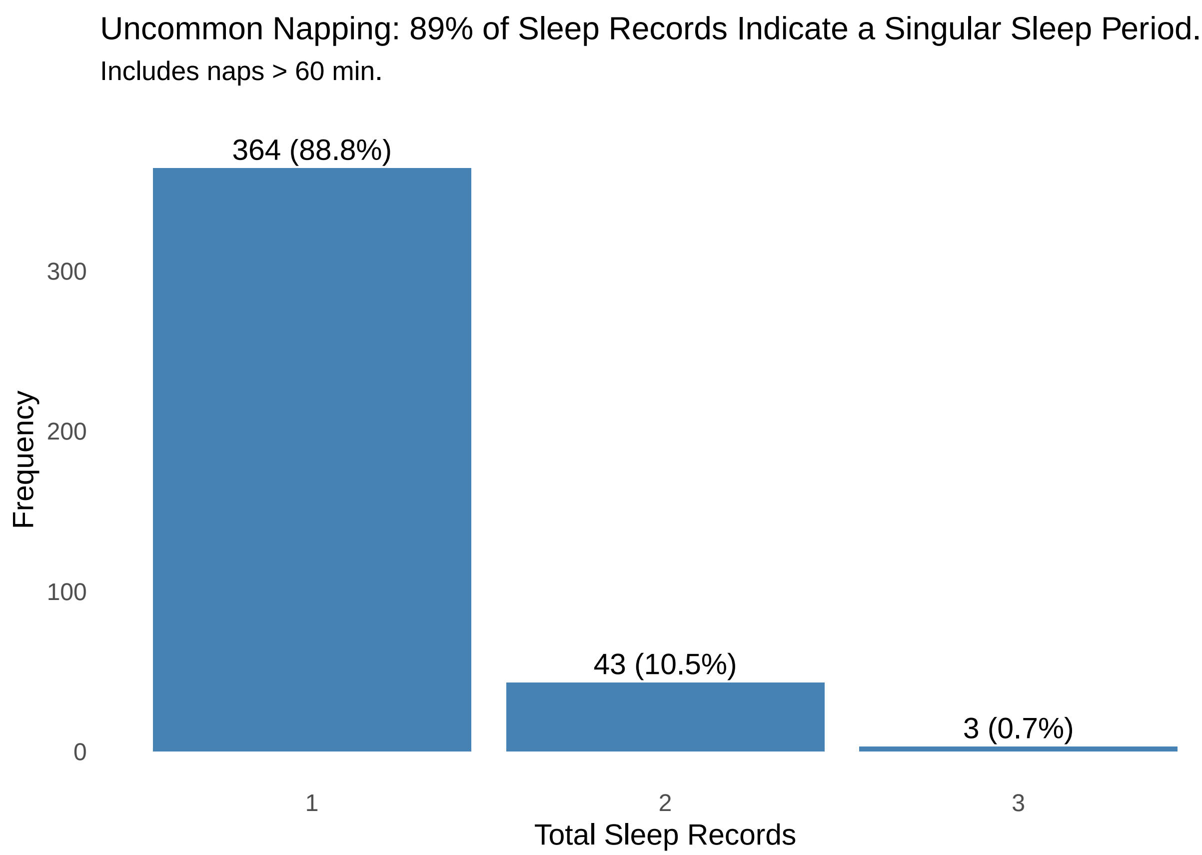

```r
ggplot(data = daily_sleep_clean, aes(x = total_minutes_asleep, y = total_time_in_bed)) +
  geom_point()
```

Scatterplots of total_minutes_asleep vs total_time_in_bed



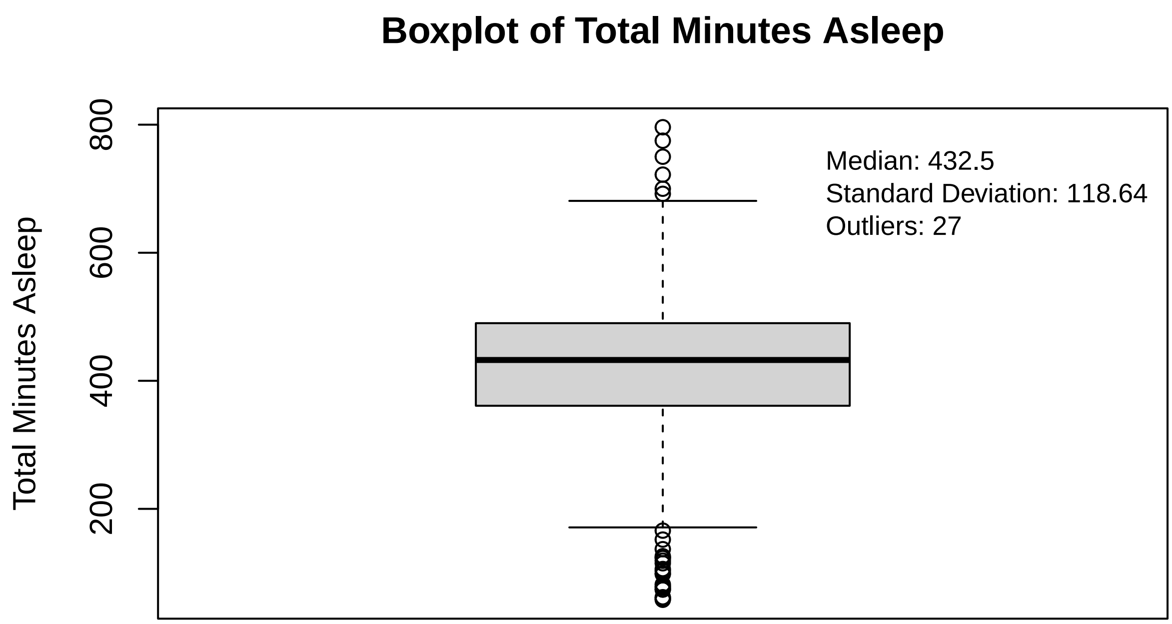
User Behavior for daily sleep dataset

```
frequency_table <- as.data.frame(table(daily_sleep_clean$total_sleep_records))
frequency_table$Percentage <- frequency_table$Freq / sum(frequency_table$Freq) * 100

ggplot(data = frequency_table, aes(x = Var1, y = Freq)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  geom_text(aes(label = paste(Freq, " (", percent(Percentage / 100), ")", sep = "")),
            hjust = 0.5,  vjust = -0.4, color = "black") +
  labs(x = "Total Sleep Records", y = "Frequency",
       title = "Uncommon Napping: 89% of Sleep Records Indicate a Singular Sleep Period.",
       subtitle = "Includes naps > 60 min.")+
  theme_minimal() +
  theme(panel.grid = element_blank(),
        plot.title = element_text(size = 12),
        plot.subtitle = element_text(size = 10, margin = margin(b = 20)))
```




```r
# Create a boxplot for total_minutes_asleep
boxplot(daily_sleep_clean$total_minutes_asleep,
        main = "Boxplot of Total Minutes Asleep",
        ylab = "Total Minutes Asleep")

# Calculate the median and standard deviation
median_value <- median(daily_sleep_clean$total_minutes_asleep)
std_dev <- round(sd(daily_sleep_clean$total_minutes_asleep), 2)

# Identify outliers
outliers <- boxplot.stats(daily_sleep_clean$total_minutes_asleep)$out

# Count the number of outliers
num_outliers <- length(outliers)

# Create the legend label with median, standard deviation, and outlier count
legend_label <- paste("Median:", median_value,
                      "\nStandard Deviation:", std_dev,
                      "\nOutliers:", num_outliers)

# Add the legend with median, standard deviation, and outlier count
legend("topright", legend = legend_label, pch = "", col = "black", bty = "n", cex = 0.85)
```

Total minutes asleep




```
# Sleep duration averages by IDs with standard deviation and count (n)
sleep_df <- daily_sleep_clean %>%
  group_by(id) %>%
  summarise(average_sleep_minutes = mean(total_minutes_asleep),
            standard_deviation_sleep_minutes = sd(total_minutes_asleep),
            n = n())

sleep_df
```

```
# A tibble: 24 x 4
   id         average_sleep_minutes standard_deviation_sleep_minutes     n
   <chr>                      <dbl>                            <dbl> <int>
 1 1503960366                  360.                            100.     25
 2 1644430081                  294                             335.      4
 3 1844505072                  652                              66.4     3
 4 1927972279                  417                             219.      5
 5 2026352035                  506.                             42.3    28
 6 2320127002                   61                              NA       1
 7 2347167796                  447.                             43.0    15
 8 3977333714                  294.                             63.9    28
 9 4020332650                  349.                            141.      8
10 4319703577                  477.                            114.     26
# ... with 14 more rows
```

```
# Drop ID "2320127002" due to insufficient data for computing mean and standard deviation.
sleep_df <- sleep_df %>%
filter(id != "2320127002")
```

```
sleep_df
```

```
# A tibble: 23 x 4
   id         average_sleep_minutes standard_deviation_sleep_minutes     n
   <chr>                      <dbl>                            <dbl> <int>
 1 1503960366                  360.                            100.     25
 2 1644430081                  294                             335.      4
 3 1844505072                  652                              66.4     3
```

```
 4 1927972279                  417                           219.      5
 5 2026352035                  506.                           42.3    28
 6 2347167796                  447.                           43.0    15
 7 3977333714                  294.                           63.9    28
 8 4020332650                  349.                          141.      8
 9 4319703577                  477.                          114.     26
10 4388161847                  400.                          146.     23
# ... with 13 more rows
```

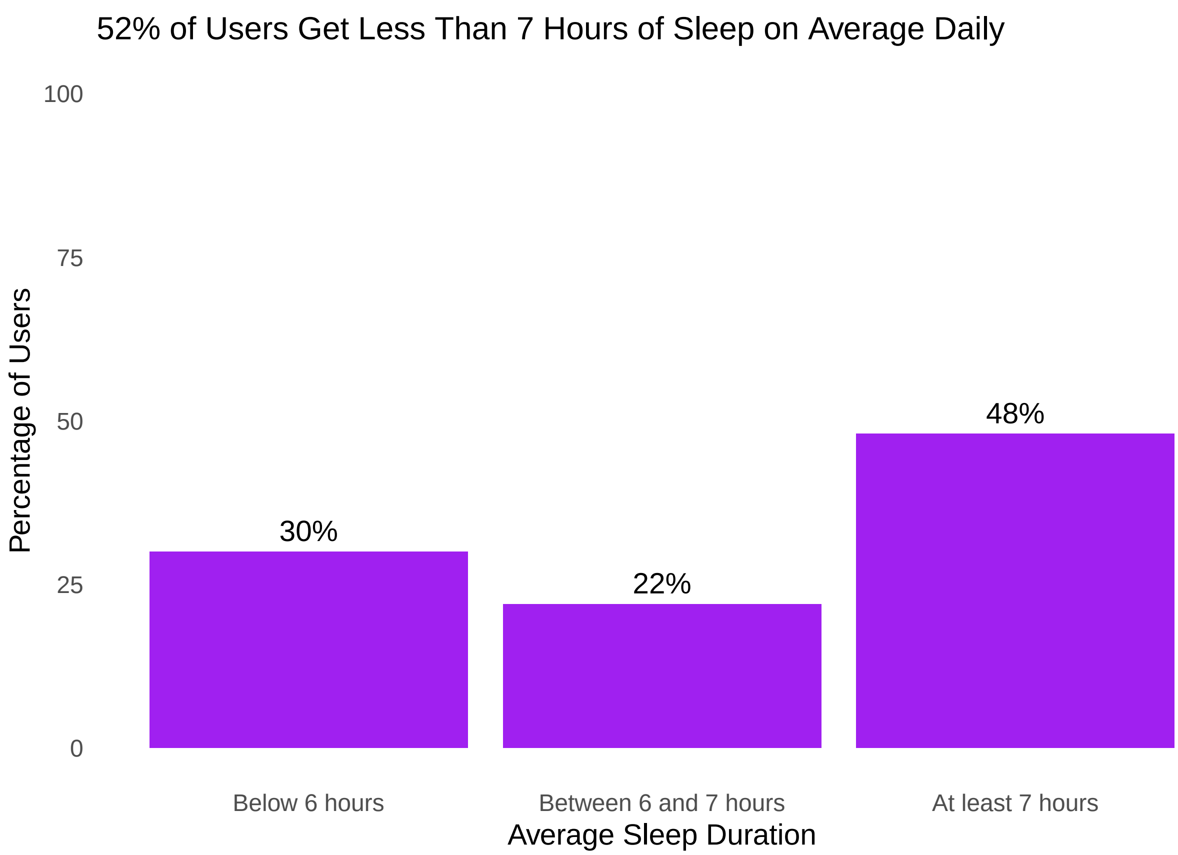
```r
# Calculate percentages for the average column
below_6_hours <- sum(sleep_df$average_sleep_minutes < 360) / nrow(sleep_df) * 100
between_6_7_hours <- sum(sleep_df$average_sleep_minutes >= 360 & sleep_df$average_sleep_minutes < 420) /
at_least_7_hours <- sum(sleep_df$average_sleep_minutes >= 420) / nrow(sleep_df) * 100

# Create a data frame for the sleep duration categories
percentage_sleep_df <- data.frame(
  Category = c("Below 6 hours", "Between 6 and 7 hours", "At least 7 hours"),
  Percentage_Average = round(c(below_6_hours, between_6_7_hours, at_least_7_hours))
)

# Convert Category to a factor with custom factor levels
percentage_sleep_df$Category <- factor(percentage_sleep_df$Category, levels = c("Below 6 hours", "Betwee

percentage_sleep_df
```

```
               Category Percentage_Average
1         Below 6 hours                 30
2 Between 6 and 7 hours                 22
3      At least 7 hours                 48
```

```r
str(percentage_sleep_df)
```

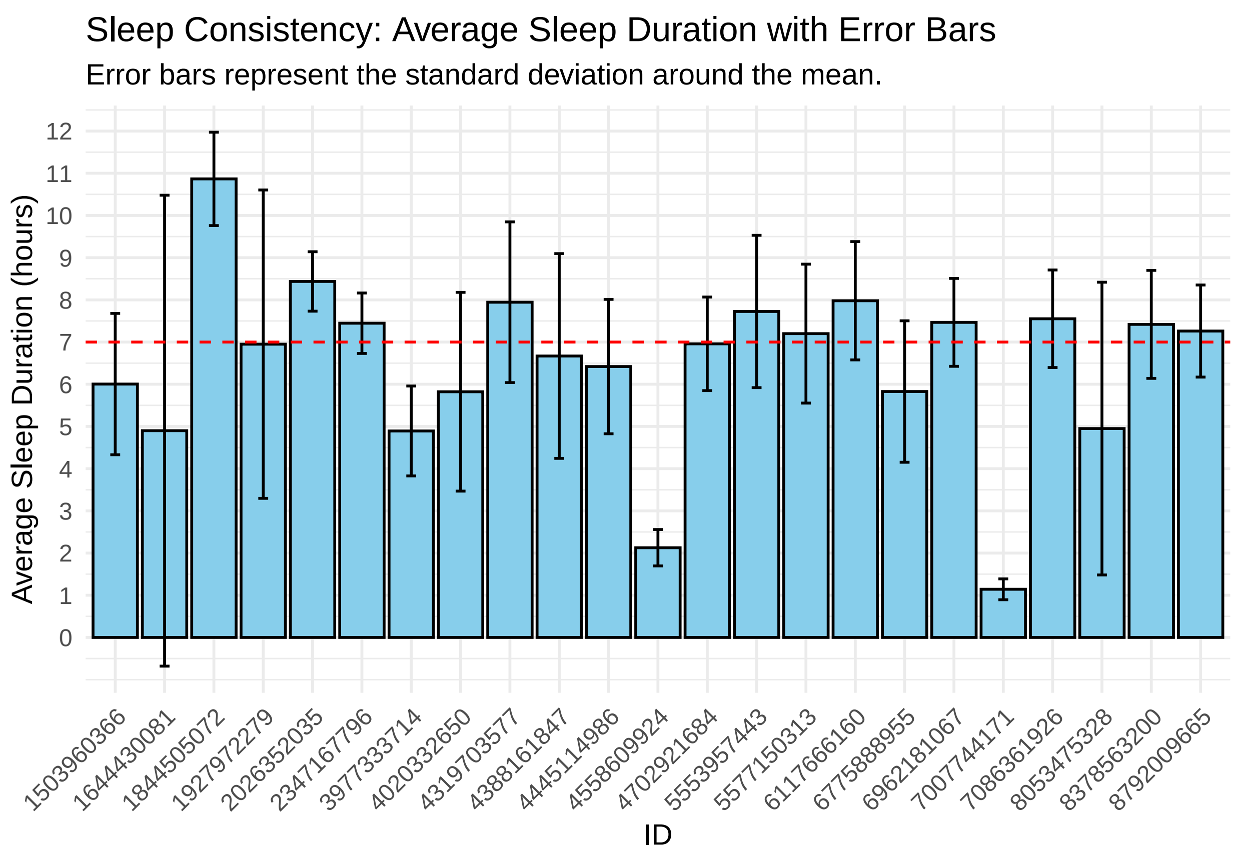
```
'data.frame':   3 obs. of  2 variables:
 $ Category          : Factor w/ 3 levels "Below 6 hours",..: 1 2 3
 $ Percentage_Average: num  30 22 48
```

```r
ggplot(percentage_sleep_df, aes(x = Category, y = Percentage_Average)) +
  geom_bar(stat = "identity", fill = "purple") +
  labs(x = "Average Sleep Duration", y = "Percentage of Users",
       title = "52% of Users Get Less Than 7 Hours of Sleep on Average Daily") +
  geom_text(aes(label = paste0(Percentage_Average, "%")), vjust = -0.5, color = "black") +
  ylim(0, 100) +
  theme_minimal() +
  theme(panel.grid = element_blank(), plot.title = element_text(size = 12), plot.subtitle = element_tex
```




```
#Error bars

# Convert average_sleep_minutes and standard_deviation_sleep_minutes to hours
sleep_df$average_sleep_hours <- sleep_df$average_sleep_minutes / 60
sleep_df$standard_deviation_sleep_hours <- sleep_df$standard_deviation_sleep_minutes / 60


# Create a bar plot for each 'id' with error bars representing standard deviation
ggplot(sleep_df, aes(x = id, y = average_sleep_hours)) +
  geom_bar(stat = "identity", fill = "skyblue", color = "black") +
  geom_errorbar(aes(ymin = average_sleep_hours - standard_deviation_sleep_minutes / 60,
                    ymax = average_sleep_hours + standard_deviation_sleep_minutes / 60),
                width = 0.2, position = position_dodge(0.9), color = "black") +
  labs(x = "ID", y = "Average Sleep Duration (hours)",
       title = "Sleep Consistency: Average Sleep Duration with Error Bars",
       subtitle = "Error bars represent the standard deviation around the mean.") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  geom_hline(yintercept = 7, linetype = "dashed", color = "red") +
  scale_y_continuous(breaks = seq(0, 12, 1))  # Adjust the range as needed
```

Sleep duration consistency




```r
# Calculate sleep duration averages and standard deviations in hours
sleep_df <- daily_sleep_clean %>%
  group_by(id) %>%
  summarise(n = n(),
            average_sleep_hours = mean(total_minutes_asleep) / 60,        # Convert minutes to hours
            average_time_in_bed_hours = mean(total_time_in_bed) / 60,
            standard_deviation_sleep_hours = sd(total_minutes_asleep) / 60,
            standard_deviation_time_in_bed_hours = sd(total_time_in_bed) / 60,
           ) %>%
  mutate(time_difference_hours = average_time_in_bed_hours - average_sleep_hours,  # Calculate the time
         average_awake_in_bed_hours = time_difference_hours,  # Rename column "awake_in_bed"
         sd_awake_in_bed_hours = sd(time_difference_hours))  # Calculate SD for "awake_in_bed" in hours


sleep_df
```

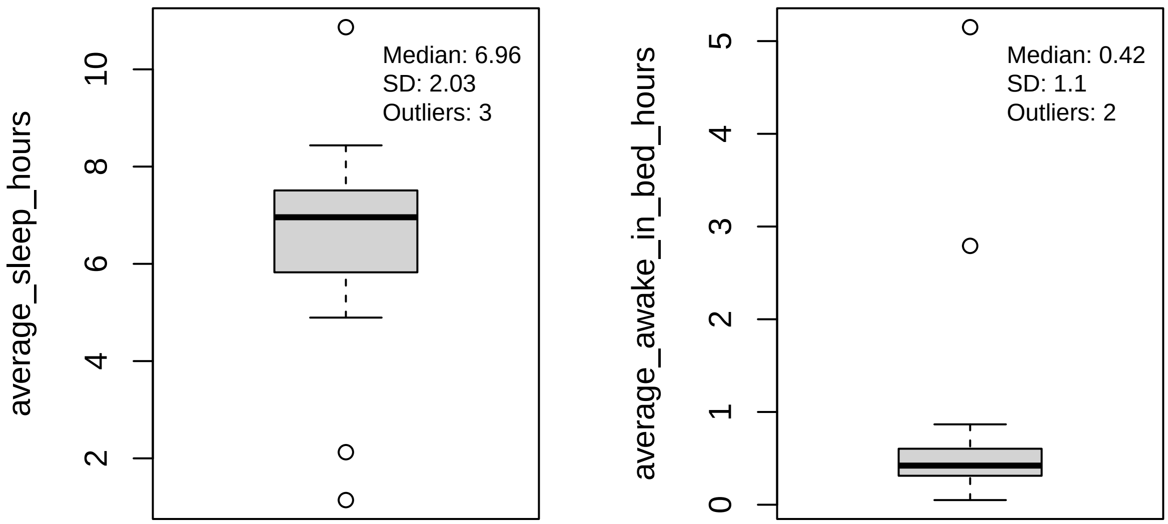
```
# A tibble: 24 x 9
   id             n average_sl~1 avera~2 stand~3 stand~4 time_~5 avera~6 sd_aw~7
   <chr>      <int>        <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1 1503960366    25         6.00    6.39   1.67    1.63    0.382   0.382    1.08
 2 1644430081     4         4.9     5.77   5.58    6.84    0.867   0.867    1.08
 3 1844505072     3        10.9    16.0    1.11    0       5.15    5.15     1.08
 4 1927972279     5         6.95    7.30   3.65    3.73    0.347   0.347    1.08
 5 2026352035    28         8.44    8.96   0.704   0.707   0.524   0.524    1.08
 6 2320127002     1         1.02    1.15  NA      NA       0.133   0.133    1.08
 7 2347167796    15         7.45    8.19   0.716   0.827   0.742   0.742    1.08
 8 3977333714    28         4.89    7.69   1.07    1.24    2.79    2.79     1.08
```

```
 9 4020332650     8          5.82     6.33    2.35     2.64     0.506    0.506     1.08
10 4319703577    26          7.94     8.37    1.90     1.97     0.422    0.422     1.08
# ... with 14 more rows, and abbreviated variable names 1: average_sleep_hours,
#   2: average_time_in_bed_hours, 3: standard_deviation_sleep_hours,
#   4: standard_deviation_time_in_bed_hours, 5: time_difference_hours,
#   6: average_awake_in_bed_hours, 7: sd_awake_in_bed_hours
```

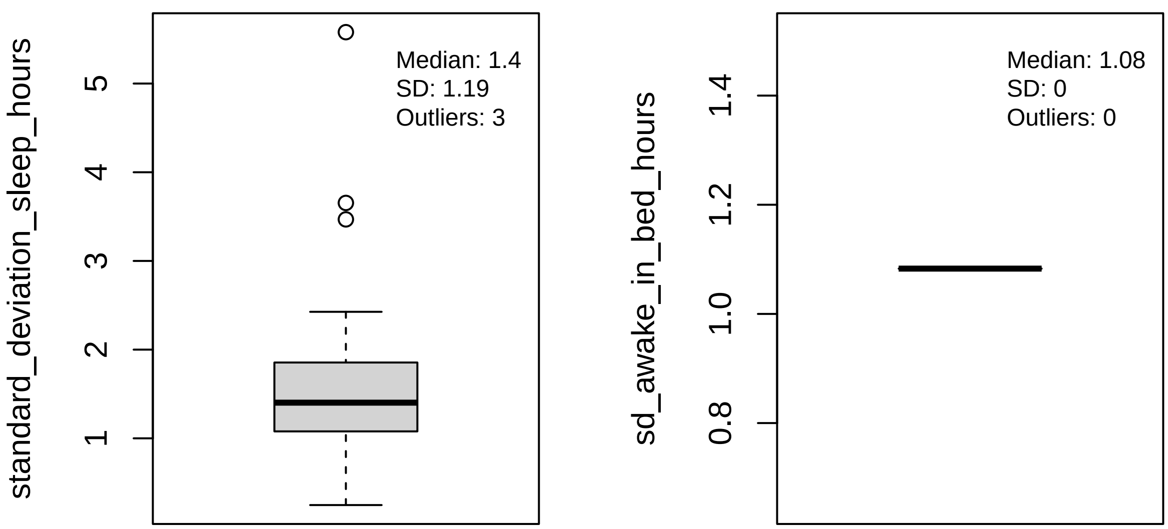
```r
# Drop ID "2320127002" due to insufficient data for computing mean and standard deviation.
sleep_df <- sleep_df %>%
filter(id != "2320127002")
dim(sleep_df)
```

```
[1] 23  9
```

```r
create_boxplots_in_one_output <- function(data_frame, columns_to_analyze, decimal_places = 2) {
  num_columns <- length(columns_to_analyze)
  num_rows <- ceiling(num_columns / 2)

  par(mfrow = c(num_rows, 2))  # Set the plotting layout

  for (i in 1:num_columns) {
    column_name <- columns_to_analyze[i]
    boxplot(data_frame[[column_name]],
            ylab = column_name)

    median_value <- median(data_frame[[column_name]])
    std_dev <- round(sd(data_frame[[column_name]]), decimal_places)
    outliers <- boxplot.stats(data_frame[[column_name]])$out
    num_outliers <- length(outliers)

    legend_label <- paste("Median:", round(median_value, decimal_places),
                          "\nSD:", std_dev,
                          "\nOutliers:", num_outliers)

    legend("topright", legend = legend_label, pch = "", col = "black", bty = "n", cex = 0.75)
  }

  par(mfrow = c(1, 1))  # Reset the plotting layout to default
}

# Columns to analyze
columns_to_analyze <- c("average_sleep_hours", "average_awake_in_bed_hours")

# Call the function to create boxplots in one output
create_boxplots_in_one_output(sleep_df, columns_to_analyze, decimal_places = 2)
```




```
# Columns to analyze
columns_to_analyze <- c("standard_deviation_sleep_hours", "sd_awake_in_bed_hours")

# Call the function
create_boxplots_in_one_output(sleep_df, columns_to_analyze, decimal_places = 2)
```

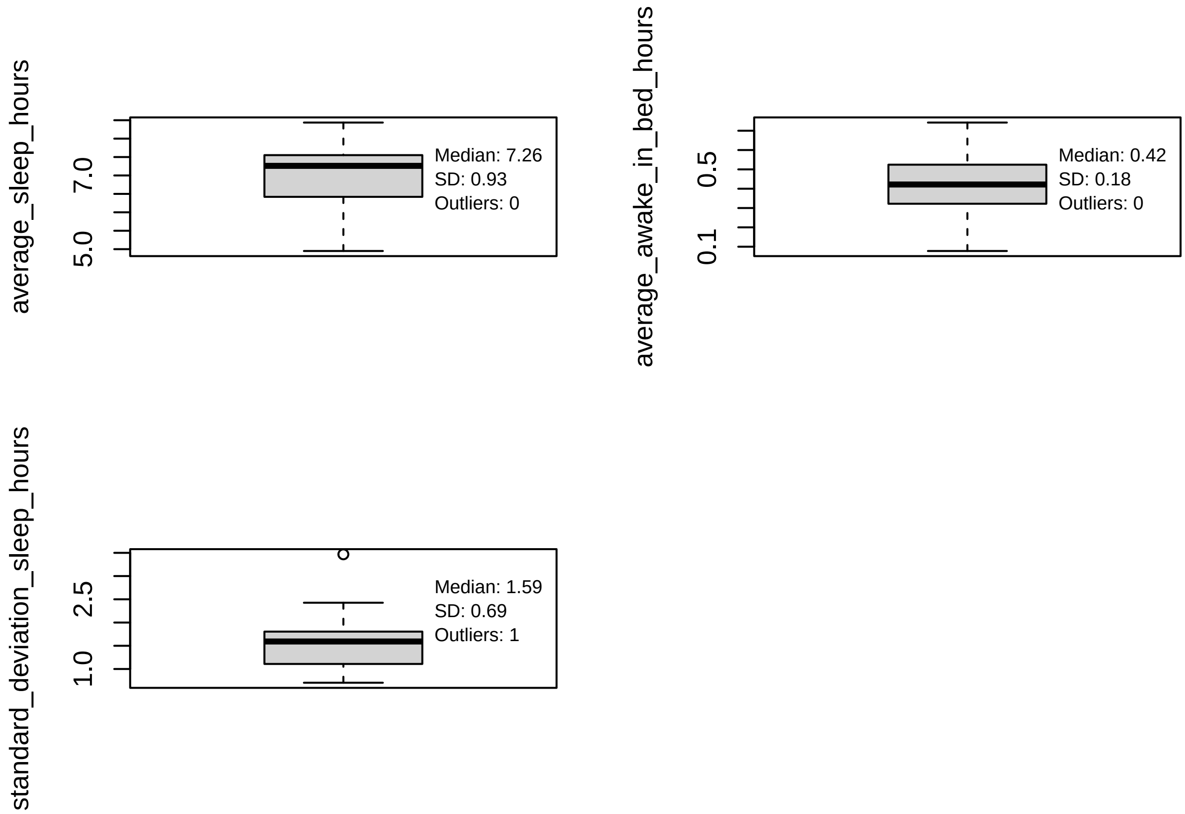



```
#Columns with outliers to remove
columns_with_outliers <- c("average_sleep_hours", "average_awake_in_bed_hours", "standard_deviation_sle

# Function to remove outliers from a column
remove_outliers <- function(data, column_name) {
  outlier_bounds <- boxplot.stats(data[[column_name]])$out
  data_no_outliers<- data[!(data[[column_name]] %in% outlier_bounds), ]
  return(data_no_outliers)
}

# Loop through each column and remove outliers
for (col in columns_with_outliers) {
  sleep_df <- remove_outliers(sleep_df, col)
}
```

```r
sleep_df
```

```
# A tibble: 17 x 9
   id             n average_sl~1 avera~2 stand~3 stand~4 time_~5 avera~6 sd_aw~7
   <chr>      <int>        <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1 1503960366    25         6.00    6.39   1.67    1.63   0.382   0.382     1.08
 2 2026352035    28         8.44    8.96   0.704   0.707  0.524   0.524     1.08
 3 2347167796    15         7.45    8.19   0.716   0.827  0.742   0.742     1.08
 4 4020332650     8         5.82    6.33   2.35    2.64   0.506   0.506     1.08
 5 4319703577    26         7.94    8.37   1.90    1.97   0.422   0.422     1.08
 6 4388161847    23         6.67    7.05   2.43    2.58   0.384   0.384     1.08
 7 4445114986    28         6.42    6.95   1.59    1.73   0.527   0.527     1.08
 8 4702921684    27         6.96    7.30   1.11    1.13   0.346   0.346     1.08
 9 5553957443    31         7.72    8.43   1.80    1.91   0.706   0.706     1.08
10 5577150313    26         7.2     7.68   1.65    1.79   0.477   0.477     1.08
11 6117666160    18         7.98    8.50   1.40    1.55   0.523   0.523     1.08
12 6775888955     3         5.83    6.15   1.68    1.60   0.322   0.322     1.08
13 6962181067    31         7.47    7.77   1.04    1.11   0.302   0.302     1.08
14 7086361926    24         7.55    7.77   1.16    1.18   0.222   0.222     1.08
15 8053475328     3         4.95    5.03   3.47    3.52   0.0778  0.0778    1.08
16 8378563200    31         7.42    8.10   1.28    1.45   0.680   0.680     1.08
17 8792009665    15         7.26    7.56   1.09    1.15   0.302   0.302     1.08
# ... with abbreviated variable names 1: average_sleep_hours,
#   2: average_time_in_bed_hours, 3: standard_deviation_sleep_hours,
#   4: standard_deviation_time_in_bed_hours, 5: time_difference_hours,
#   6: average_awake_in_bed_hours, 7: sd_awake_in_bed_hours
```

```r
# Check if outliers were removed
columns_to_analyze <- c("average_sleep_hours", "average_awake_in_bed_hours", "standard_deviation_sleep_h


# Call the function to create boxplots in one output
create_boxplots_in_one_output(sleep_df, columns_to_analyze, decimal_places = 2)
```




```r
#Let us divide the users into irregular sleepers and regular sleepers. We will use the 75th percentile 

# Define the Threshold (e.g., using the 75th percentile)
threshold <- quantile(sleep_df$standard_deviation_sleep_hours, 0.75)

# Create a new column "sleeper_type" based on the threshold
sleep_df$sleeper_type <- ifelse(sleep_df$standard_deviation_sleep_hours > threshold, "irregular", "regul
```

```r
sleep_df
```

```
# A tibble: 17 x 10
   id            n avera~1 avera~2 stand~3 stand~4 time_~5 avera~6 sd_aw~7 sleep~8
   <chr>     <int>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl> <chr>
 1 150396~      25    6.00    6.39   1.67    1.63   0.382   0.382      1.08 regular
 2 202635~      28    8.44    8.96   0.704   0.707  0.524   0.524      1.08 regular
 3 234716~      15    7.45    8.19   0.716   0.827  0.742   0.742      1.08 regular
 4 402033~       8    5.82    6.33   2.35    2.64   0.506   0.506      1.08 irregu~
 5 431970~      26    7.94    8.37   1.90    1.97   0.422   0.422      1.08 irregu~
 6 438816~      23    6.67    7.05   2.43    2.58   0.384   0.384      1.08 irregu~
 7 444511~      28    6.42    6.95   1.59    1.73   0.527   0.527      1.08 regular
 8 470292~      27    6.96    7.30   1.11    1.13   0.346   0.346      1.08 regular
 9 555395~      31    7.72    8.43   1.80    1.91   0.706   0.706      1.08 regular
10 557715~      26    7.2     7.68   1.65    1.79   0.477   0.477      1.08 regular
11 611766~      18    7.98    8.50   1.40    1.55   0.523   0.523      1.08 regular
12 677588~       3    5.83    6.15   1.68    1.60   0.322   0.322      1.08 regular
13 696218~      31    7.47    7.77   1.04    1.11   0.302   0.302      1.08 regular
14 708636~      24    7.55    7.77   1.16    1.18   0.222   0.222      1.08 regular
15 805347~       3    4.95    5.03   3.47    3.52   0.0778  0.0778     1.08 irregu~
16 837856~      31    7.42    8.10   1.28    1.45   0.680   0.680      1.08 regular
```

```
17 879200~    15    7.26    7.56   1.09    1.15   0.302   0.302     1.08 regular
# ... with abbreviated variable names 1: average_sleep_hours,
#   2: average_time_in_bed_hours, 3: standard_deviation_sleep_hours,
#   4: standard_deviation_time_in_bed_hours, 5: time_difference_hours,
#   6: average_awake_in_bed_hours, 7: sd_awake_in_bed_hours, 8: sleeper_type
```

```r
# sleep_type counts
table(sleep_df$sleeper_type)
```

```
irregular   regular
        4        13
```

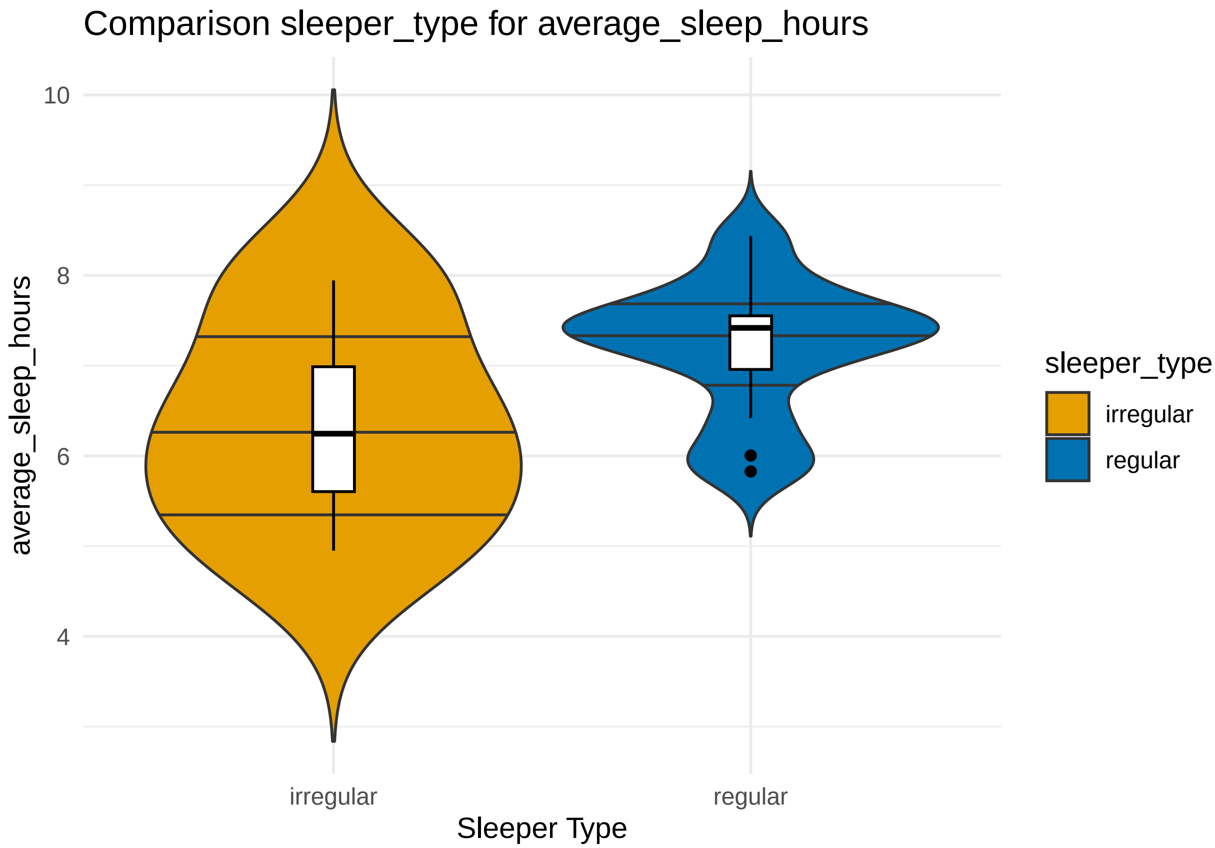
```r
sleep_df
```

```
# A tibble: 17 x 10
   id           n avera~1 avera~2 stand~3 stand~4 time_~5 avera~6 sd_aw~7 sleep~8
   <chr>    <int>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl> <chr>
 1 150396~    25    6.00    6.39   1.67    1.63   0.382   0.382     1.08 regular
 2 202635~    28    8.44    8.96   0.704   0.707  0.524   0.524     1.08 regular
 3 234716~    15    7.45    8.19   0.716   0.827  0.742   0.742     1.08 regular
 4 402033~     8    5.82    6.33   2.35    2.64   0.506   0.506     1.08 irregu~
 5 431970~    26    7.94    8.37   1.90    1.97   0.422   0.422     1.08 irregu~
 6 438816~    23    6.67    7.05   2.43    2.58   0.384   0.384     1.08 irregu~
 7 444511~    28    6.42    6.95   1.59    1.73   0.527   0.527     1.08 regular
 8 470292~    27    6.96    7.30   1.11    1.13   0.346   0.346     1.08 regular
 9 555395~    31    7.72    8.43   1.80    1.91   0.706   0.706     1.08 regular
10 557715~    26    7.2     7.68   1.65    1.79   0.477   0.477     1.08 regular
11 611766~    18    7.98    8.50   1.40    1.55   0.523   0.523     1.08 regular
12 677588~     3    5.83    6.15   1.68    1.60   0.322   0.322     1.08 regular
13 696218~    31    7.47    7.77   1.04    1.11   0.302   0.302     1.08 regular
14 708636~    24    7.55    7.77   1.16    1.18   0.222   0.222     1.08 regular
15 805347~     3    4.95    5.03   3.47    3.52   0.0778  0.0778    1.08 irregu~
16 837856~    31    7.42    8.10   1.28    1.45   0.680   0.680     1.08 regular
17 879200~    15    7.26    7.56   1.09    1.15   0.302   0.302     1.08 regular
# ... with abbreviated variable names 1: average_sleep_hours,
#   2: average_time_in_bed_hours, 3: standard_deviation_sleep_hours,
#   4: standard_deviation_time_in_bed_hours, 5: time_difference_hours,
#   6: average_awake_in_bed_hours, 7: sd_awake_in_bed_hours, 8: sleeper_type
```

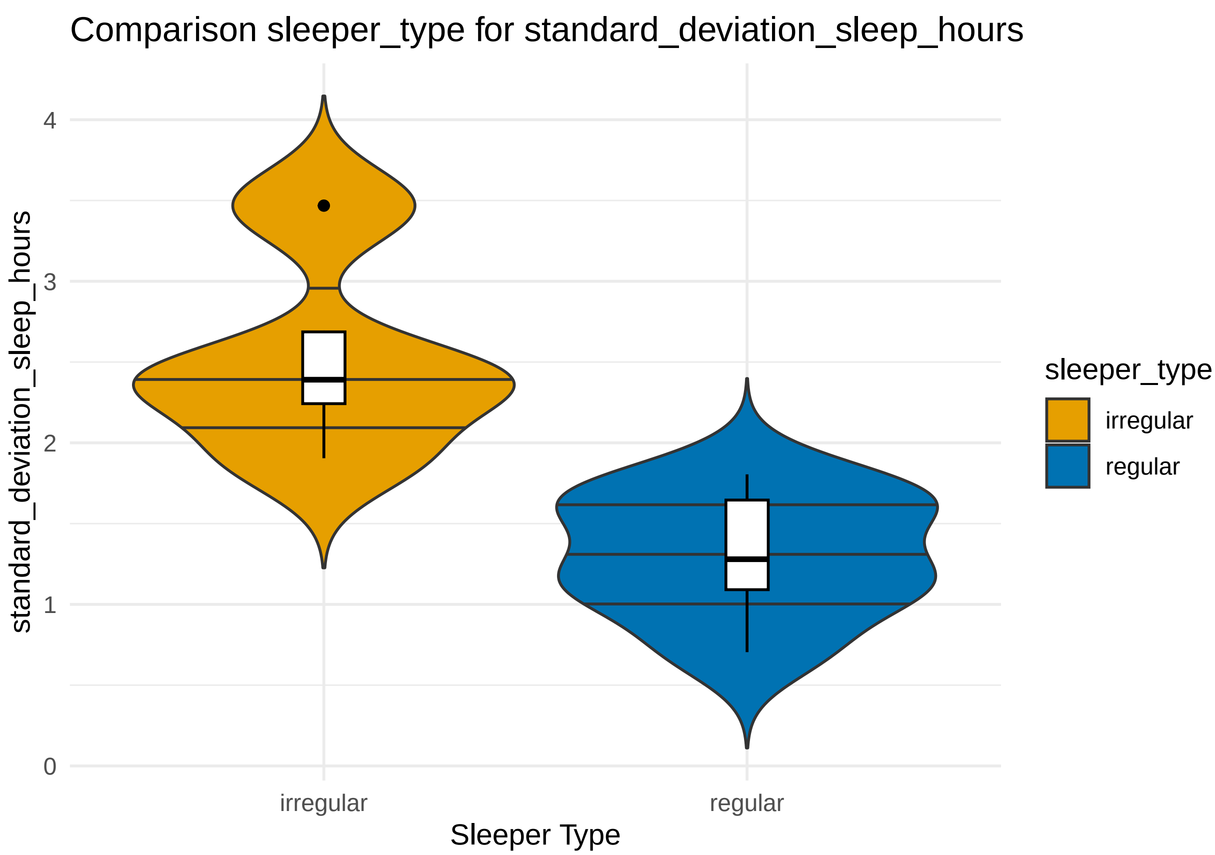
```r
color_options <- c("#E69F00", "#0072B2") # Blue: "#0072B2", Orange: "#E69F00"

# Function to create the violin plot for a given y-axis column
create_violin_plot <- function(data, x_axis_col, y_axis_col) {
  ggplot(data, aes_string(x = x_axis_col, y = y_axis_col, fill = x_axis_col)) +
    geom_violin(scale = "width", draw_quantiles = c(0.25, 0.5, 0.75), trim = FALSE) +
    geom_boxplot(width = 0.1, fill = "white", color = "black") +
    labs(x = "Sleeper Type", y = y_axis_col, title = paste("Comparison",x_axis_col,"for", y_axis_col)) +
    scale_fill_manual(values = color_options) +
    theme_minimal()
}
```

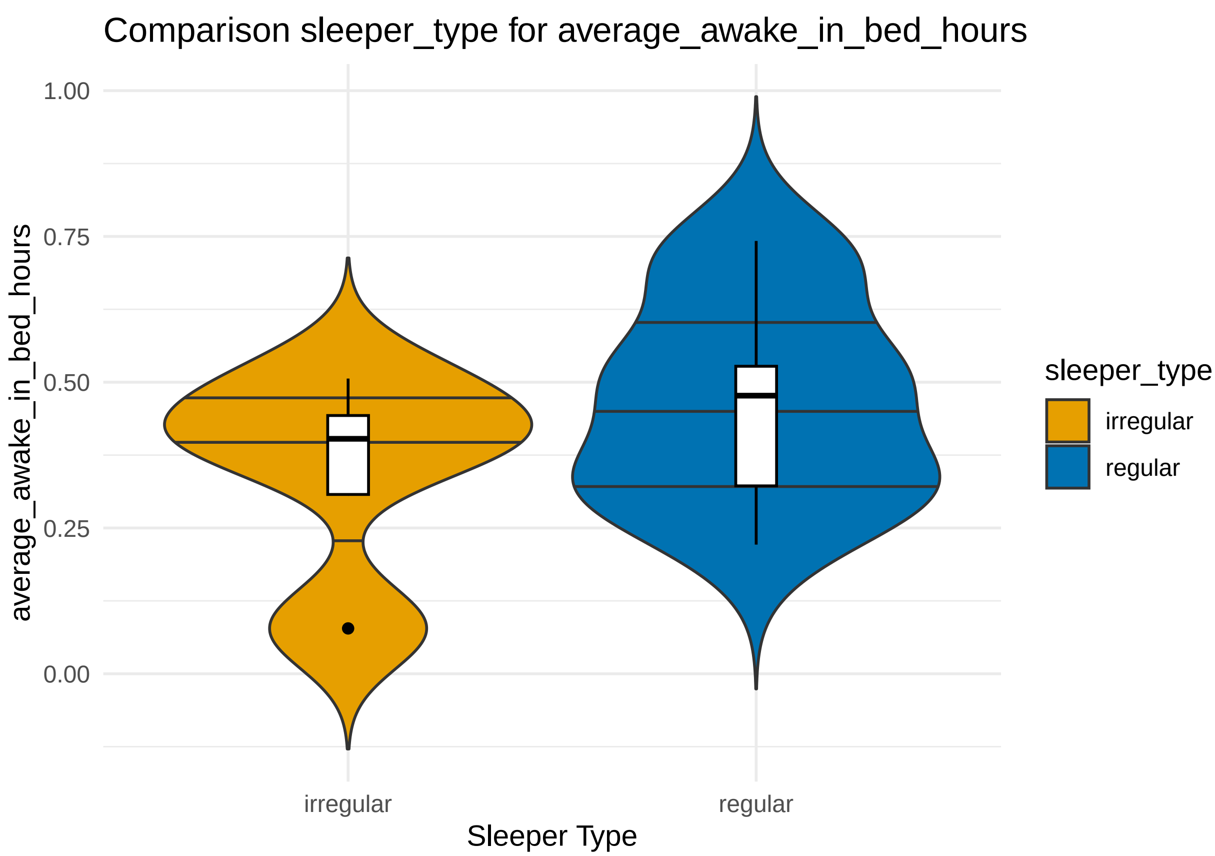
```r
# Call the function to create the violin plots for each column
for (col in c("average_sleep_hours", "standard_deviation_sleep_hours", "average_awake_in_bed_hours","sd_
  plot <- create_violin_plot(sleep_df, "sleeper_type", col)
  print(plot)
```

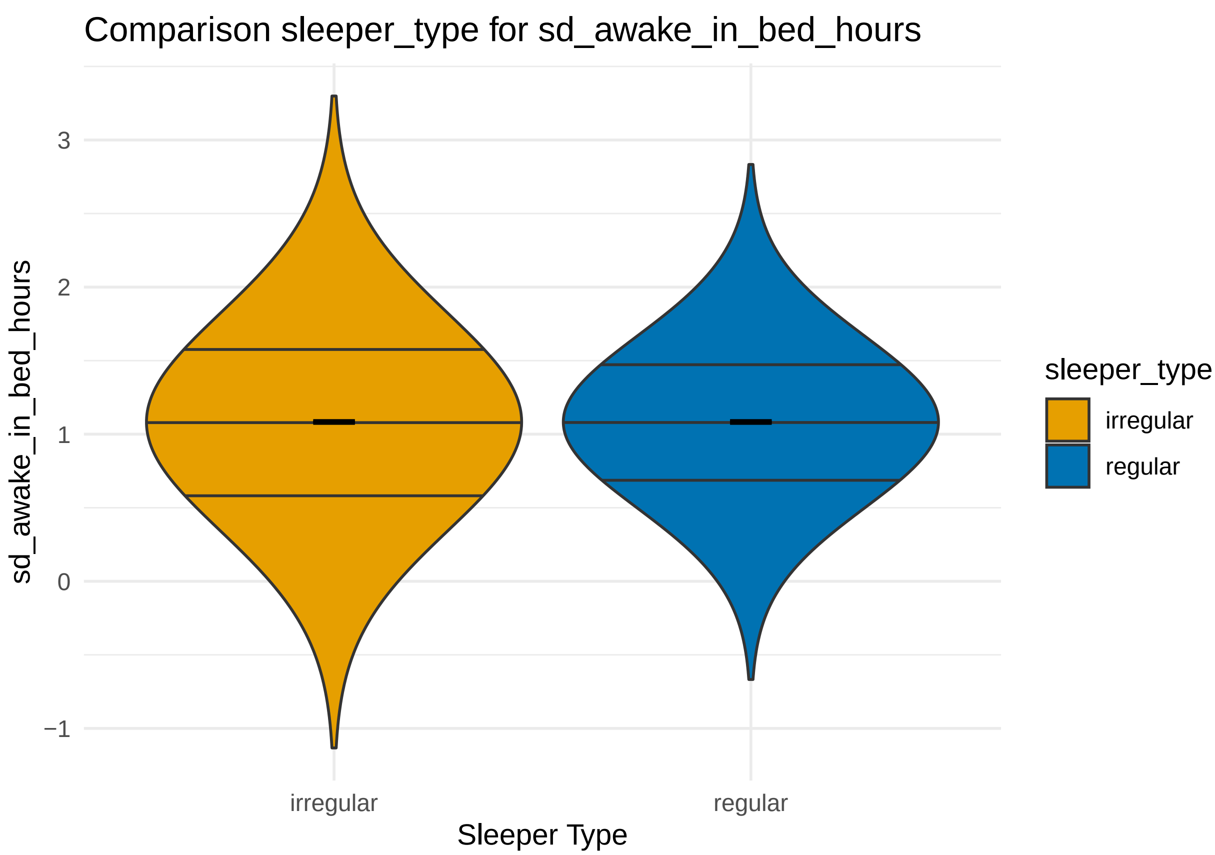
```
}
```



Comparison sleeper_type for average_sleep_hours
10
8
6
4
average_sleep_hours
irregular
regular
Sleeper Type
sleeper_type
irregular
regular


Comparison sleeper_type for standard_deviation_sleep_hours
standard_deviation_sleep_hours
4
3
2
1
0
irregular
regular
Sleeper Type
sleeper_type
irregular
regular


Comparison sleeper_type for average_awake_in_bed_hours
average_awake_in_bed_hours
1.00
0.75
0.50
0.25
0.00
irregular
regular
Sleeper Type
sleeper_type
irregular
regular



Observations:

- Regular sleepers tend to have higher median average sleep hours compared to irregular sleepers.This suggests that individuals classified as regular sleepers are likely getting more sleep on average than those categorized as irregular sleepers.
- Additionally, the spread of the "average_sleep_hours" for irregular sleepers appears to be wider, indicating more variability in their sleep duration. In contrast, the violin plot for regular sleepers shows a narrower spread, suggesting that their sleep duration is more consistent.
- Regular sleepers exhibit a slightly higher median average awake-in-bed duration compared to irregular sleepers.

Summary: Regular sleepers get more sleep on average, have a more consistent sleep duration, and slightly higher median awake-in-bed duration than irregular sleepers.

EDA minute_sleep_clean

```
str(minute_sleep_clean)
```

```
tibble [187,978 x 4] (S3: tbl_df/tbl/data.frame)
 $ id    : chr [1:187978] "1503960366" "1503960366" "1503960366" "1503960366" ...
 $ date  : POSIXct[1:187978], format: "2016-04-12 02:47:30" "2016-04-12 02:48:30" ...
 $ value : Factor w/ 3 levels "1","2","3": 3 2 1 1 1 1 1 2 2 2 ...
 $ log_id: num [1:187978] 1.14e+10 1.14e+10 1.14e+10 1.14e+10 1.14e+10 ...
```

This data seems to come from the Classic Sleep Log (1 minute)

Value indicating the sleep state. 1 = asleep, 2 = restless, 3 = awake

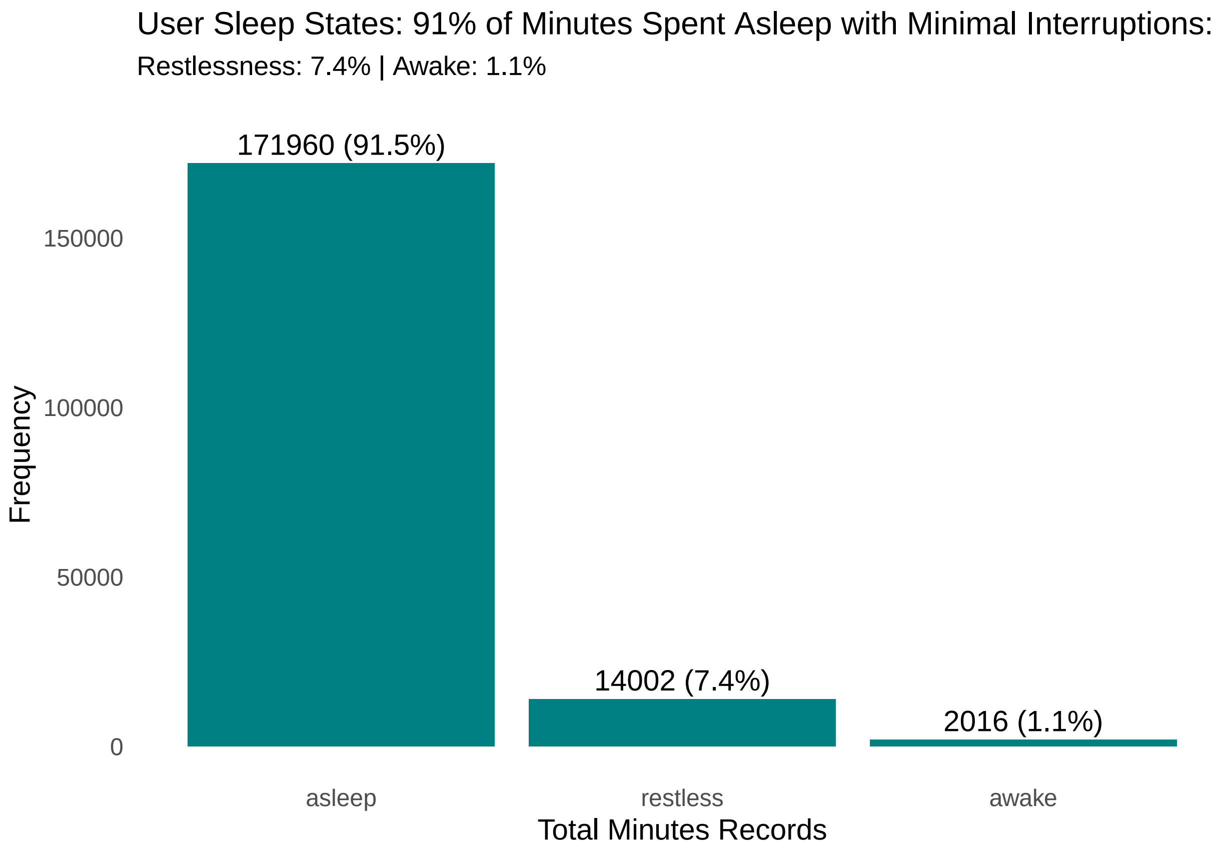
For more detail check : Fitbit data dictionary

```r
# Add labels to the velue column
minute_sleep_clean$value <- factor(minute_sleep_clean$value, levels = c("1", "2", "3"), labels = c("asle
```

```r
minute_sleep_clean %>% summary()
```

```
      id                 date                             value       
 Length:187978      Min.   :2016-04-11 20:48:00.00   asleep   :171960  
 Class :character   1st Qu.:2016-04-19 02:48:00.00   restless: 14002  
 Mode  :character   Median :2016-04-26 21:48:00.00   awake    :  2016  
                    Mean   :2016-04-26 13:31:23.11                     
                    3rd Qu.:2016-05-03 23:47:00.00                     
                    Max.   :2016-05-12 09:56:00.00                     
     log_id         
 Min.   :1.137e+10  
 1st Qu.:1.144e+10  
 Median :1.150e+10  
 Mean   :1.150e+10  
 3rd Qu.:1.155e+10  
 Max.   :1.162e+10  
```

```r
# Assuming "value" column represents total sleep records
frequency_table <- as.data.frame(table(minute_sleep_clean$value))
frequency_table$Percentage <- frequency_table$Freq / sum(frequency_table$Freq) * 100

ggplot(data = frequency_table, aes(x = Var1, y = Freq)) +
  geom_bar(stat = "identity", fill = "#008080") +
  geom_text(aes(label = paste(Freq, " (", percent(Percentage / 100), ")", sep = "")),
            hjust = 0.5,  vjust = -0.4, color = "black") +
  labs(x = "Total Minutes Records", y = "Frequency",
       title = "User Sleep States: 91% of Minutes Spent Asleep with Minimal Interruptions:",
       subtitle = "Restlessness: 7.4% | Awake: 1.1%") +
  theme_minimal() +
  theme(panel.grid = element_blank(),
        plot.title = element_text(size = 12),
        plot.subtitle = element_text(size = 10, margin = margin(b = 20)))
```



EDA for hourly_activity_clean

```
str(hourly_activity_clean)
```

```
tibble [22,099 x 6] (S3: tbl_df/tbl/data.frame)
 $ id                : chr [1:22099] "1503960366" "1503960366" "1503960366" "1503960366" ...
 $ activity_hour     : POSIXct[1:22099], format: "2016-04-12 00:00:00" "2016-04-12 01:00:00" ...
 $ calories          : num [1:22099] 81 61 59 47 48 48 48 47 68 141 ...
 $ total_intensity   : num [1:22099] 20 8 7 0 0 0 0 0 13 30 ...
 $ average_intensity: num [1:22099] 0.333 0.133 0.117 0 0 ...
 $ step_total        : num [1:22099] 373 160 151 0 0 ...
```

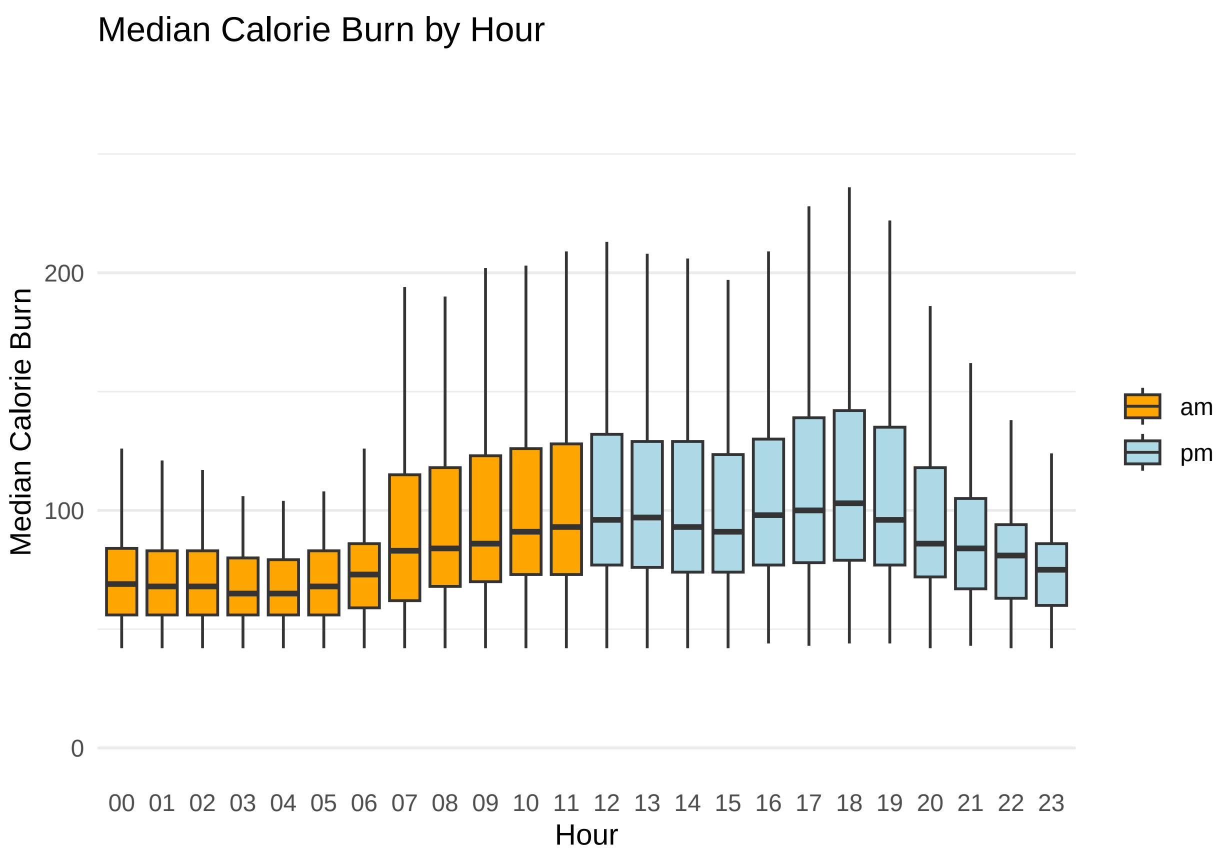
- Calories integer Total number of estimated calories burned.
- TotalIntensity: integer Value calculated by adding all the minute-level intensity values that occurred within the hour.
- AverageIntensity: intensity state exhibited during that hour (TotalIntensity for that ActivityHour divided by 60)
- StepTotal: Total number of steps taken.

For more detail check : Fitbit data dictionary

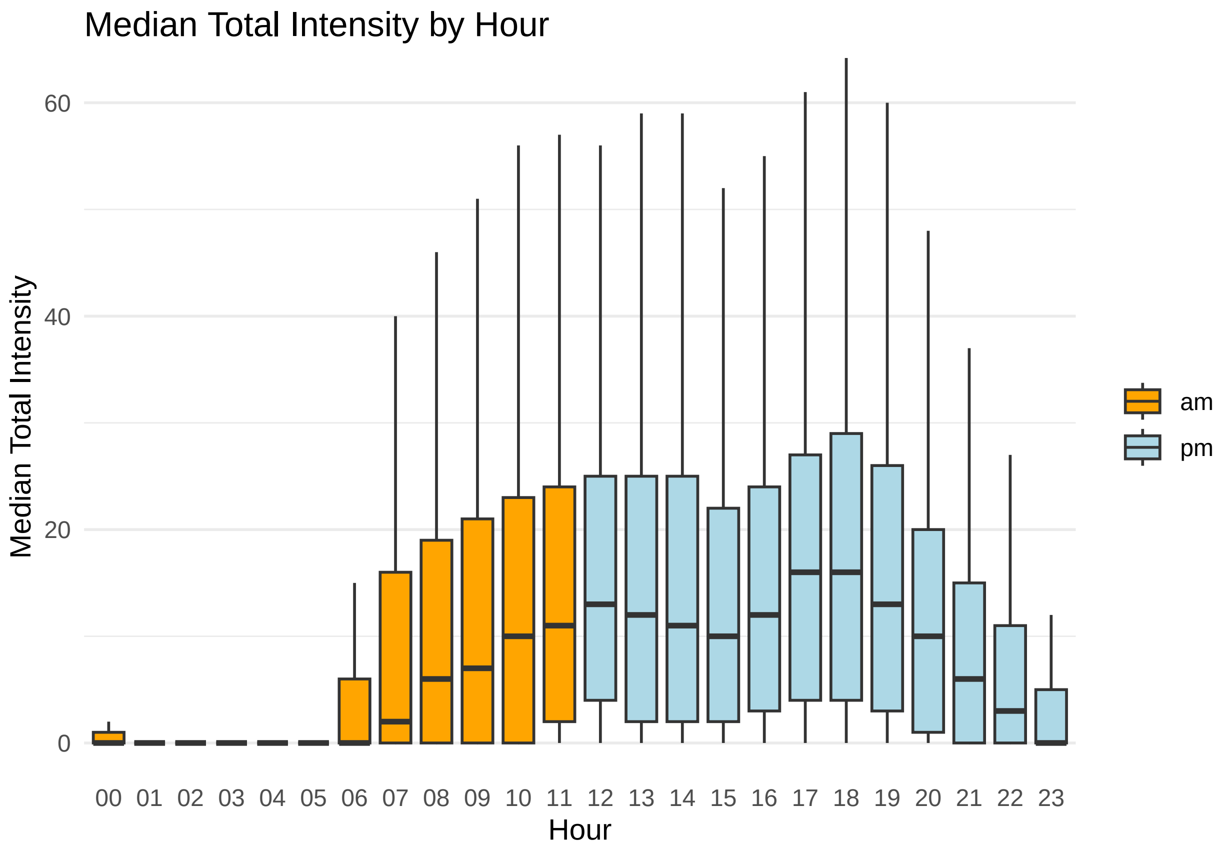
```
hourly_df <-hourly_activity_clean


# Extract "am" or "pm" from the activity_hour column
hourly_df$am_pm <- ifelse(format(hourly_df$activity_hour, "%p") == "AM", "am", "pm")
```

```r
#Add a column for the hour
hourly_df$hour <- format(hourly_df$activity_hour, "%H")
```

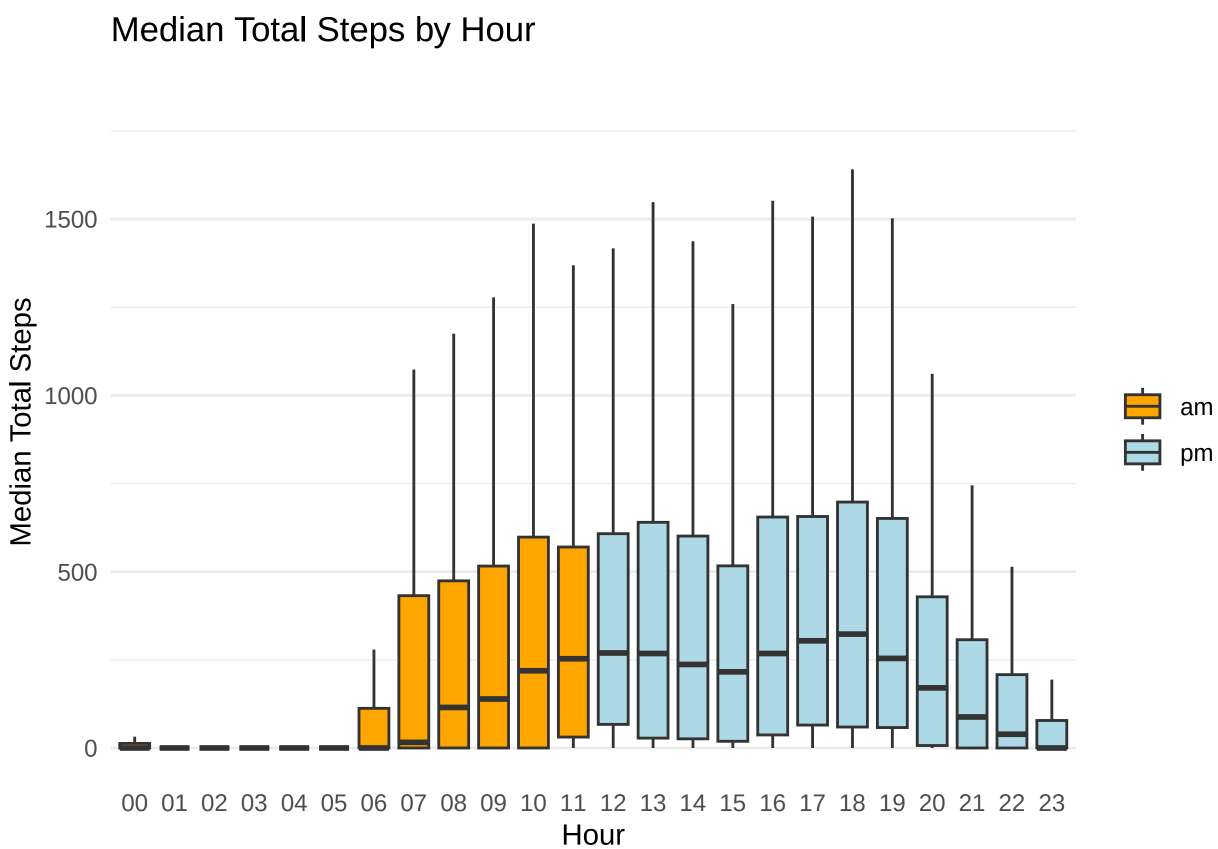
```r
# Define colors for AM and PM
color_palette <- c("#FFA500", "#ADD8E6")  # Orange for AM, Light Blue for PM

# Custom function to generate the boxplot with dynamically set y-axis limits
generate_boxplot <- function(data, y_var, y_label, limit_factor) {
  y_limit <- quantile(data[[y_var]], 0.95) * limit_factor

  ggplot(data, aes(x = hour, y = get(y_var), fill = am_pm)) +
    geom_boxplot(position = position_dodge(0.9), outlier.shape = NA) +
    scale_fill_manual(values = color_palette) +
    labs(title = paste("Median", y_label, "by Hour"),
         x = "Hour",
         y = paste("Median", y_label)) +
    guides(fill = guide_legend(title = NULL)) +  # Remove legend title
    theme_minimal() +
    theme(panel.grid.major.x = element_blank()) +
    coord_cartesian(ylim = c(0, y_limit))
}

# Assuming your dataset is named 'hourly_df1'
data <- hourly_df

# Create the plots with dynamically adjusted y-axis limits
# Adjust the limit_factor as needed (e.g., 1.1, 1.2, etc.)
calories_plot <- generate_boxplot(data, "calories", "Calorie Burn", limit_factor = 1.4)
total_intensity_plot <- generate_boxplot(data, "total_intensity", "Total Intensity", limit_factor = 1.3)
step_total_avg_plot <- generate_boxplot(data, "step_total", "Total Steps", limit_factor = 1.3)

# Print the plots
print(calories_plot)
```




```
print(total_intensity_plot)
```




```
print(step_total_avg_plot)
```

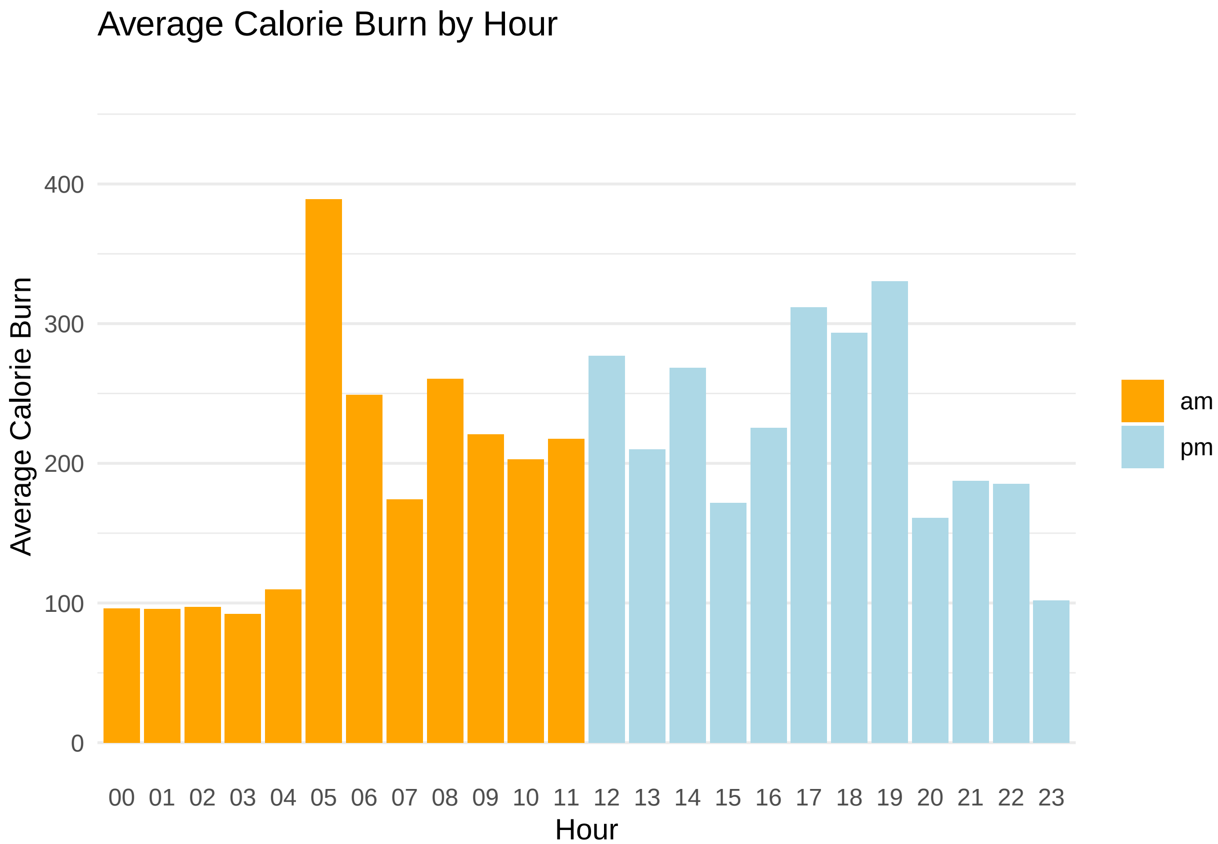



```
# Group by id, hour, and am_pm and summarize the columns
summary_data <- hourly_df %>%
  group_by(id, hour, am_pm) %>%
  summarize(
    calories_avg = mean(calories),
    calories_max = max(calories),
    calories_min = min(calories),
    total_intensity_avg = mean(total_intensity),
    total_intensity_max = max(total_intensity),
    total_intensity_min = min(total_intensity),
    average_intensity_avg = mean(average_intensity),
    step_total_avg = mean(step_total),
    observations_count = n()
  )
```

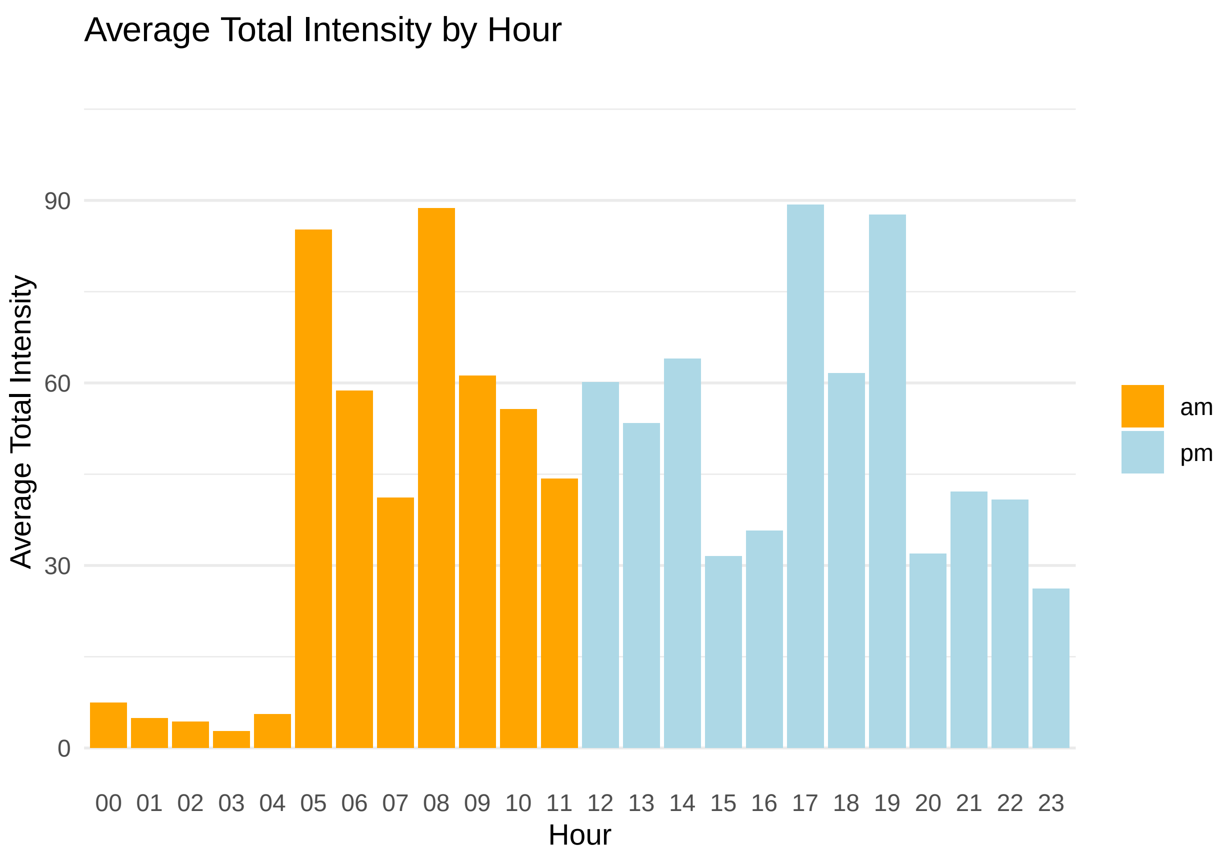
```
`summarise()` has grouped output by 'id', 'hour'. You can override using the
`.groups` argument.
```

```
# Define colors for AM and PM
color_palette <- c("#FFA500", "#ADD8E6")  # Orange for AM, Light Blue for PM

# Custom function to generate the bar plot with dynamically set y-axis limits
generate_bar_plot <- function(data, y_var, y_label, limit_factor) {
  y_limit <- max(data[[paste0(y_var, "_avg")]]) * limit_factor

  ggplot(data, aes(x = hour, y = get(paste0(y_var, "_avg")), fill = am_pm)) +
    geom_bar(stat = "identity", position = "dodge") +
    scale_fill_manual(values = color_palette) +
```

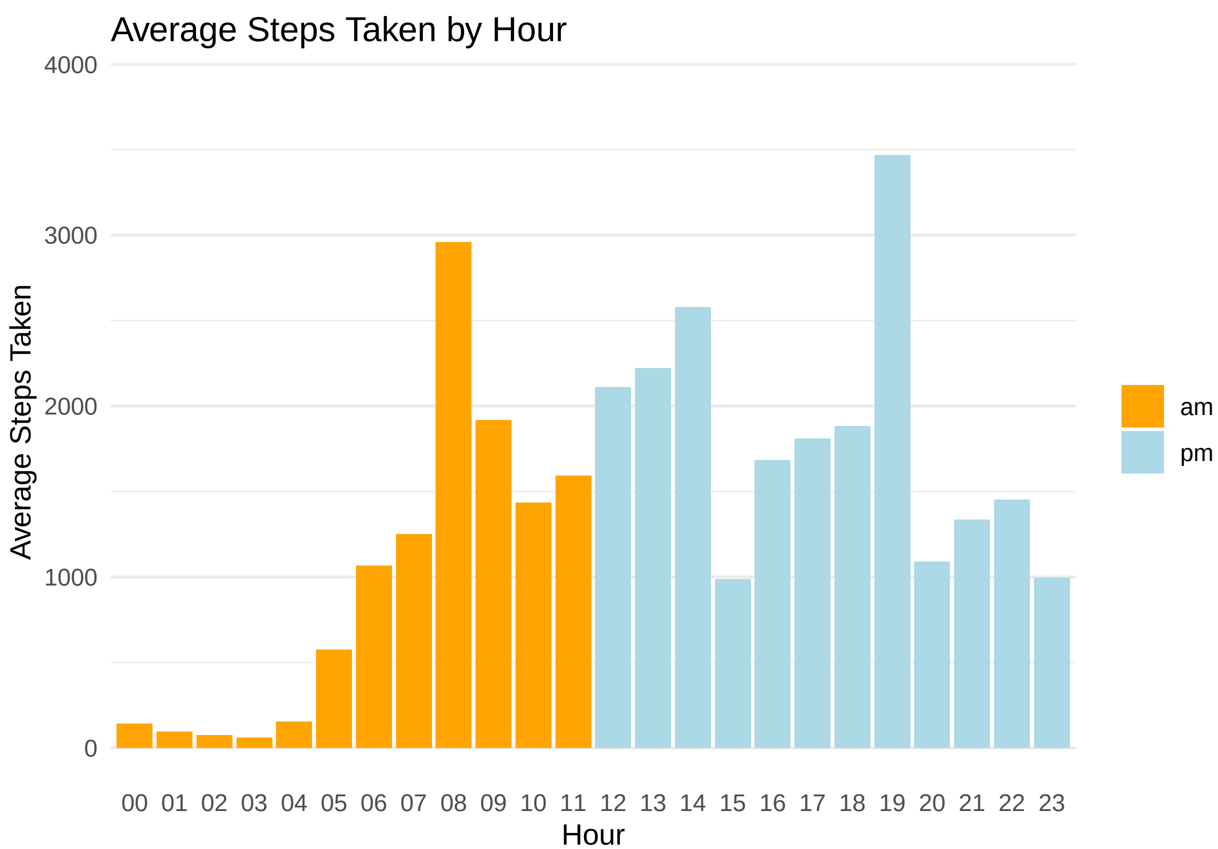
```r
    labs(title = paste("Average", y_label, "by Hour"),
         x = "Hour",
         y = paste("Average", y_label)) +
    guides(fill = guide_legend(title = NULL)) +  # Remove legend title
    theme_minimal() +
    theme(panel.grid.major.x = element_blank()) +
    coord_cartesian(ylim = c(0, y_limit))
}


# Assuming your dataset is named 'summary_data'
data <- summary_data

# Create the bar plots with dynamically adjusted y-axis limits
calories_plot <- generate_bar_plot(data, "calories", "Calorie Burn", limit_factor = 1.2)
total_intensity_plot <- generate_bar_plot(data, "total_intensity", "Total Intensity", limit_factor = 1.
steps_plot <- generate_bar_plot(data, "step_total", "Steps Taken", limit_factor = 1.1)

# Print the plots
print(calories_plot)
```



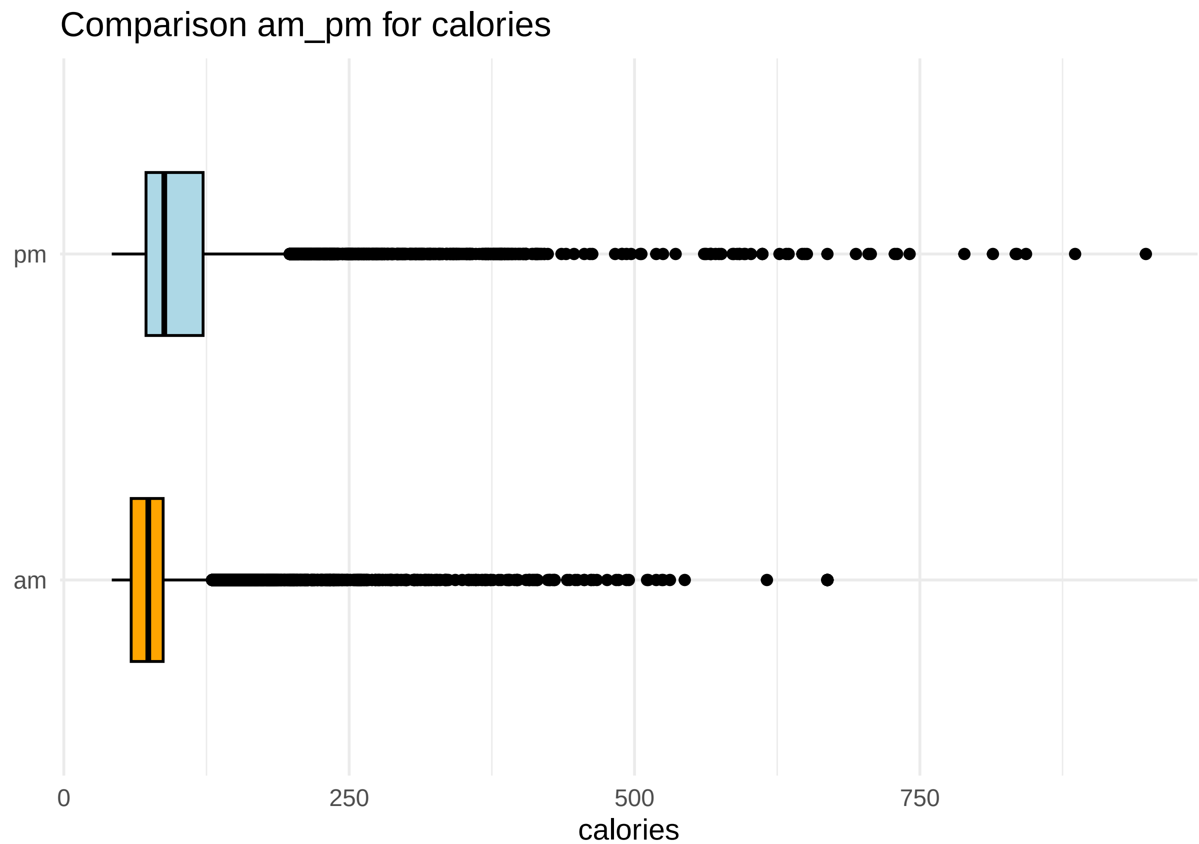

```r
print(total_intensity_plot)
```

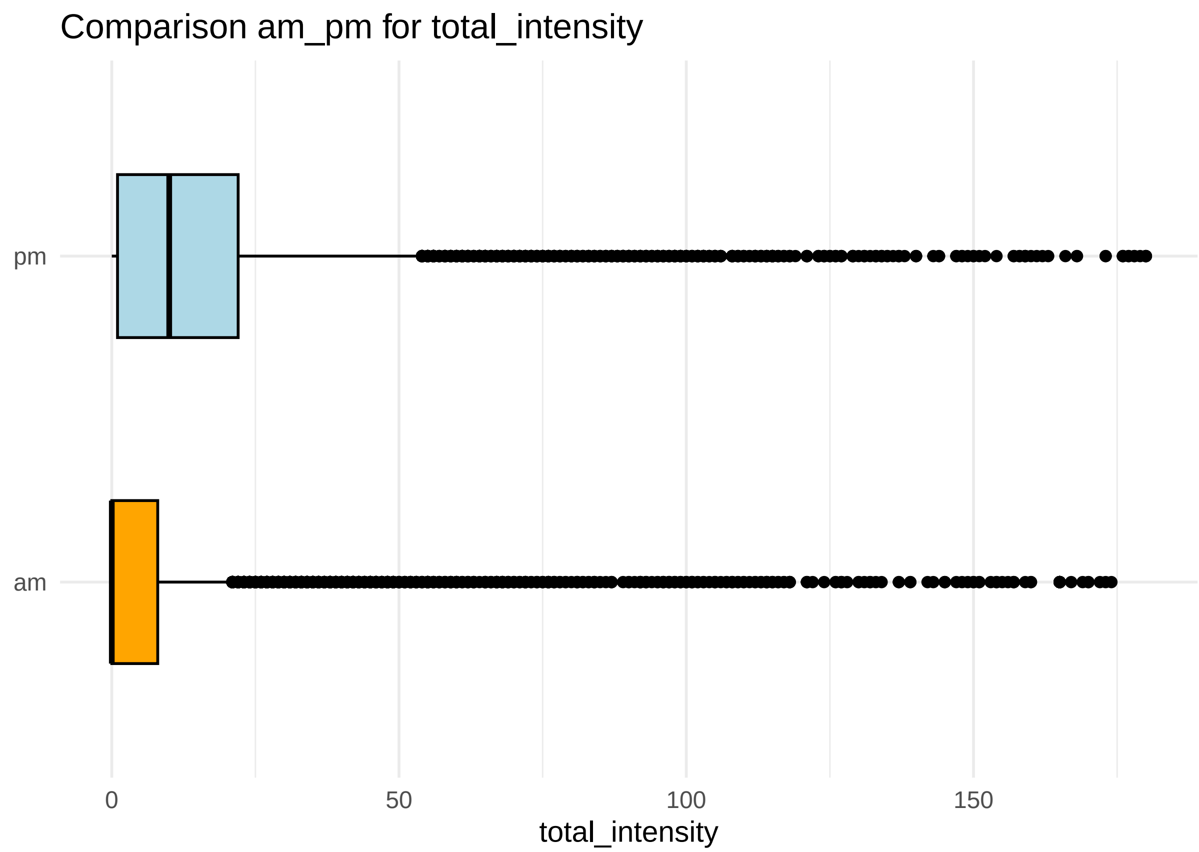


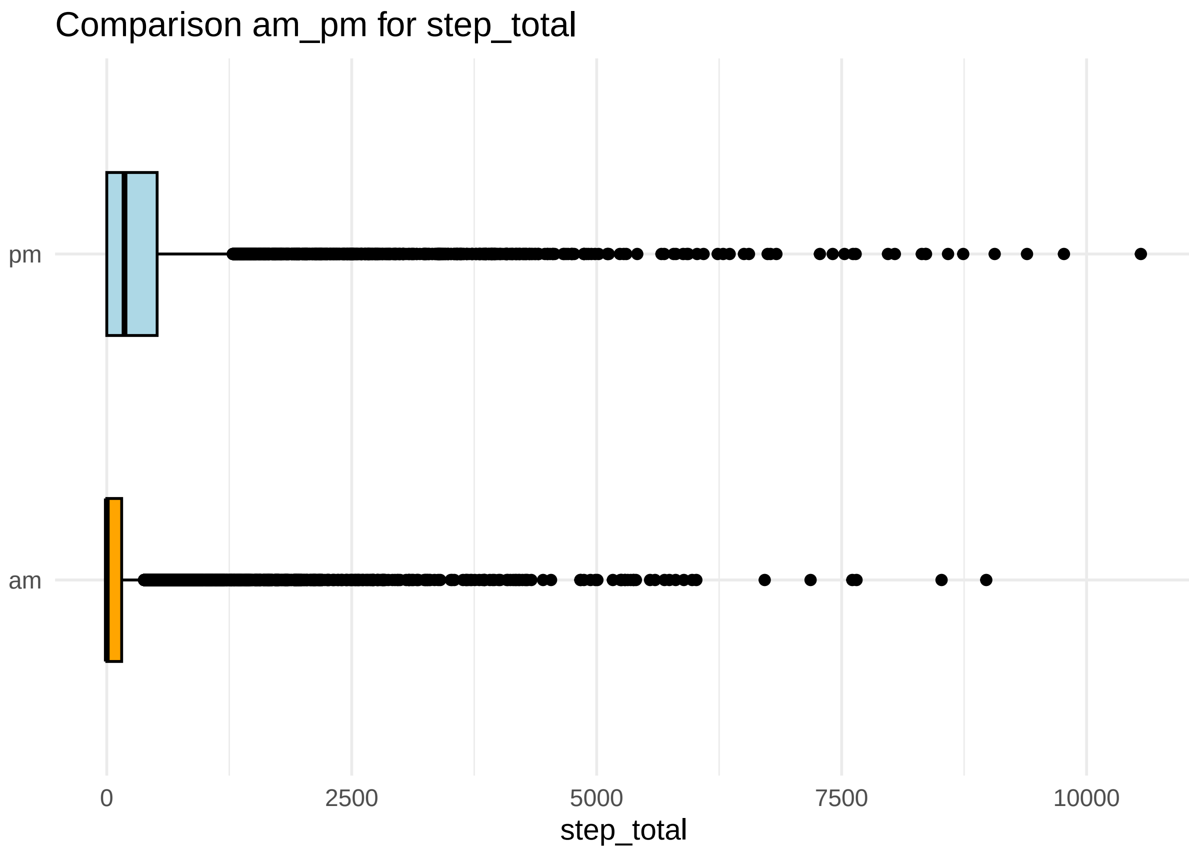

```
print(steps_plot)
```




```r
# Function to create a box plot with customizable orientation and colors for a given y-axis column
create_custom_box_plot <- function(data, x_axis_col, y_axis_col, orientation = "ver", colors) {
  ggplot(data, aes_string(x = x_axis_col, y = y_axis_col, fill = x_axis_col)) +
    geom_boxplot(width = ifelse(orientation == "ver", 0.2, 0.5),
                 color = "black") +  # Remove fill = "white"
    labs(x = "", y = y_axis_col,
         title = paste("Comparison", x_axis_col, "for", y_axis_col)) +
    scale_fill_manual(values = colors) +
     guides(fill = "none") +  # Remove the legend for fill color
    theme_minimal() +
    if (orientation == "hor") coord_flip()
}

# Call the function with custom colors as a tuple and specify the x-axis label
custom_colors <- c("#FFA500", "#ADD8E6")  # Orange for AM, Light Blue for PM


for (col in c("calories", "total_intensity", "step_total")) {
  plot <- create_custom_box_plot(hourly_df, x_axis_col = "am_pm", y_axis_col = col, orientation = "hor"
  print(plot)
}
```


Comparison am_pm for calories
pm
am
0
250
500
750
calories


Comparison am_pm for total_intensity
pm
am
0
50
100
150
total_intensity



With the code provided, you can gain several insights into user behavior and activity patterns based on the "hourly_df" dataset. Some of the insights you can obtain are:

Hourly Activity Patterns: You can observe how user activity varies throughout the day. The calories_avg, total_intensity_avg, and average_intensity_avg columns will give you the average calorie burn, total intensity, and average intensity for each hour, respectively. This can help identify peak activity hours and periods of lower activity.

Variability in Activity: The calories_max, calories_min, total_intensity_max, and total_intensity_min columns will provide information about the maximum and minimum values of calorie burn and total intensity recorded during each hour. This can help you understand the range of activity levels and how much the activity varies from hour to hour.

Average Steps per Hour: The step_total_avg column will give you the average number of steps taken during each hour. This can help you identify the typical step count during different times of the day.

Observations Count: The observations_count column will show the number of data points (observations) available for each "id," "hour," and "am_pm" group. This can help you assess the data density and identify hours with more or fewer data points, which may influence the reliability of the insights.

AM vs. PM Activity: The "am_pm" column indicates whether the activity occurred during the morning (AM) or afternoon/evening (PM). You can compare the activity patterns between these two periods and explore any differences in user behavior during these times.

Individual User Insights: By grouping the data by "id," you can also gain insights into each individual user's activity patterns. You can assess their average calorie burn, intensity, and steps during various hours.

Overall, these insights can help you understand how users engage in physical activity throughout the day, identify peak activity hours, and detect any patterns or trends in their behavior. This information can be valuable for designing personalized fitness plans, optimizing activity programs, and making data-driven decisions to improve health and well-being.

EDA for seconds_heartrate_clean

```
str(seconds_heartrate_clean)
```

```
tibble [2,483,658 x 3] (S3: tbl_df/tbl/data.frame)
 $ id        : chr [1:2483658] "2022484408" "2022484408" "2022484408" "2022484408" ...
 $ date_time : POSIXct[1:2483658], format: "2016-04-12 07:21:00" "2016-04-12 07:21:05" ...
 $ heart_rate: num [1:2483658] 97 102 105 103 101 95 91 93 94 93 ...
```

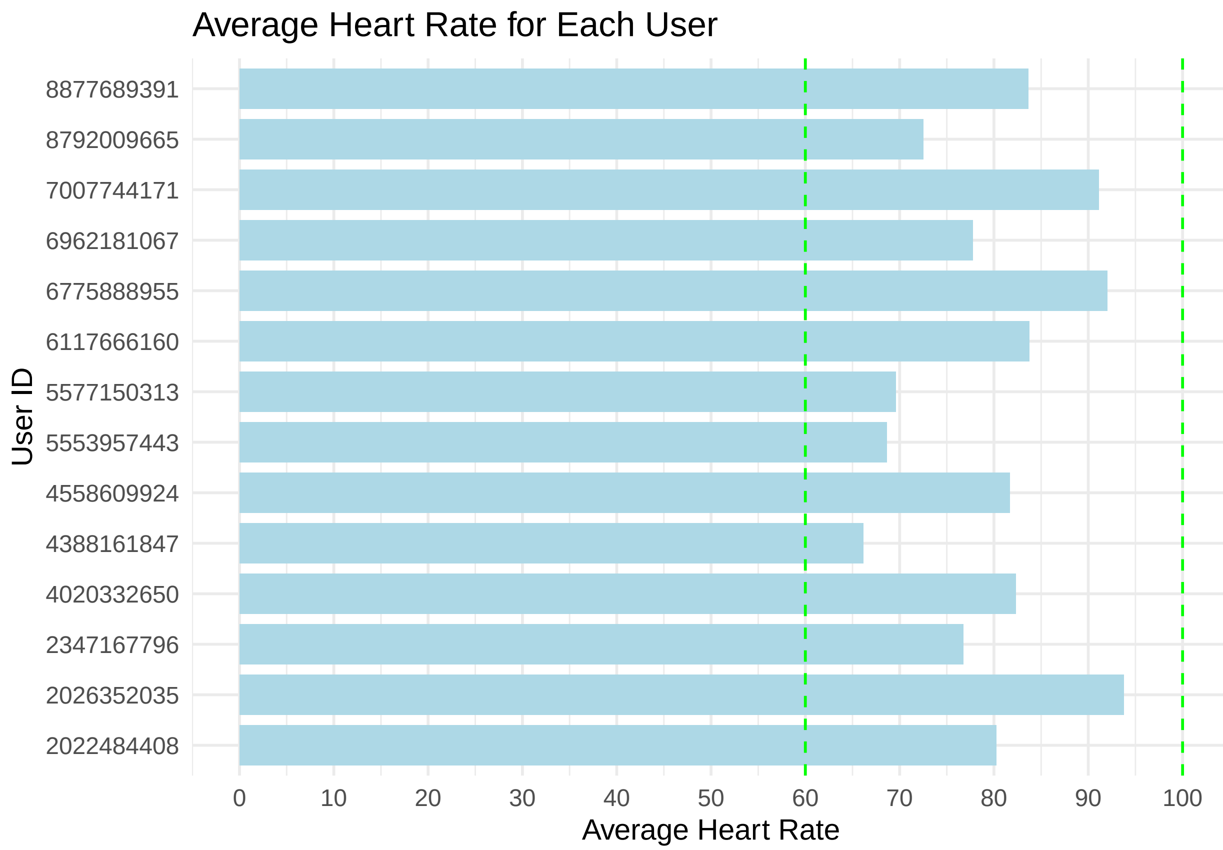
```
seconds_heartrate_clean %>% summary()
```

```
      id              date_time                        heart_rate
 Length:2483658     Min.   :2016-04-12 00:00:00.00   Min.   : 36.00
 Class :character   1st Qu.:2016-04-19 06:18:10.00   1st Qu.: 63.00
 Mode  :character   Median :2016-04-26 20:28:50.00   Median : 73.00
                    Mean   :2016-04-26 19:43:52.24   Mean   : 77.33
                    3rd Qu.:2016-05-04 08:00:20.00   3rd Qu.: 88.00
                    Max.   :2016-05-12 16:20:00.00   Max.   :203.00
```

```
n_distinct(seconds_heartrate_clean$id)
```

```
[1] 14
```

```
# Group by 'id' and calculate the average heart rate for each user
average_heart_rate <- seconds_heartrate_clean %>%
  group_by(id) %>%
  summarise(average_heart_rate = mean(heart_rate, na.rm = TRUE))

# Bar Plot with smaller bars and custom breaks on the heart rate axis
bar_plot <- ggplot(average_heart_rate, aes(x = id, y = average_heart_rate)) +
  geom_bar(stat = "identity", fill = "#ADD8E6", width = 0.8) +  # Adjust the width here (e.g., 0.5 for
  labs(x = "User ID", y = "Average Heart Rate", title = "Average Heart Rate for Each User") +
  theme_minimal() + coord_flip() +
  scale_y_continuous(breaks = seq(0, 100, 10), limits = c(0, 100))+ # Set custom breaks and limits for
  geom_hline(yintercept = 60, linetype = "dashed", color = "green") +
  geom_hline(yintercept = 100, linetype = "dashed", color = "green")

# Display the bar plot
print(bar_plot)
```



EDA for weight_logs_clean

```
str(weight_logs_clean)
```

```
tibble [67 x 8] (S3: tbl_df/tbl/data.frame)
 $ id               : chr [1:67] "1503960366" "1503960366" "1927972279" "2873212765" ...
 $ date_time        : POSIXct[1:67], format: "2016-05-02 23:59:59" "2016-05-03 23:59:59" ...
 $ weight_kg        : num [1:67] 52.6 52.6 133.5 56.7 57.3 ...
 $ weight_pounds    : num [1:67] 116 116 294 125 126 ...
 $ fat              : num [1:67] 22 0 0 0 0 25 0 0 0 0 ...
 $ bmi              : num [1:67] 22.6 22.6 47.5 21.5 21.7 ...
 $ is_manual_report: logi [1:67] TRUE TRUE FALSE TRUE TRUE TRUE ...
 $ log_id           : num [1:67] 1.46e+12 1.46e+12 1.46e+12 1.46e+12 1.46e+12 ...
```

- Fat:Body fat percentage recorded.
- BMI: Measure of body mass index based on the height and weight in the participant's Fitbit.com profile.
- isManualReport: If the data for this weigh-in was done manually (TRUE), or if data was measured and synced directly to Fitbit.com from a connected scale (FALSE).

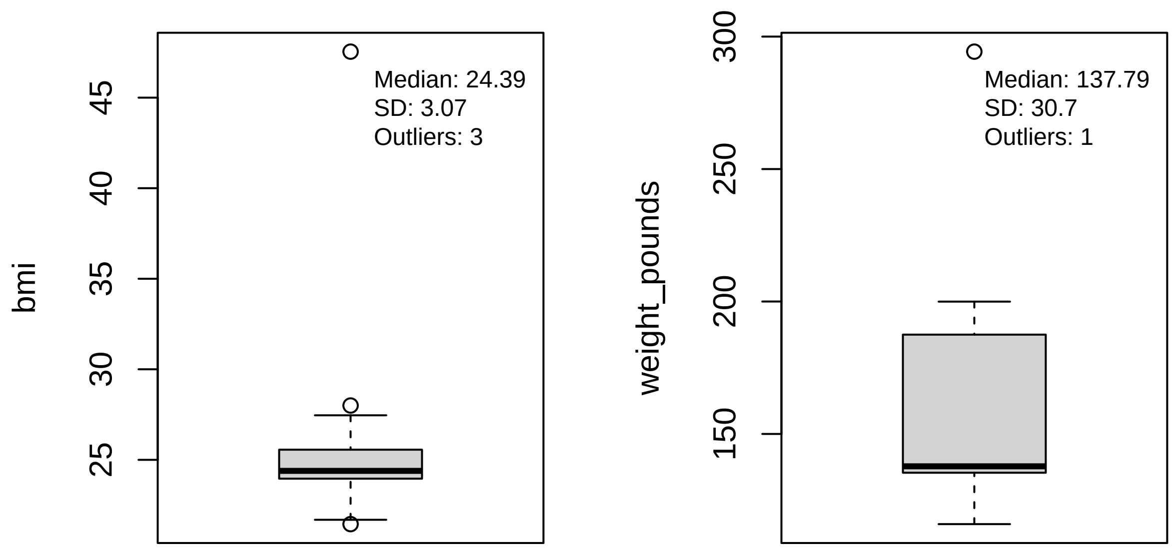
For more detail check : Fitbit data dictionary

```
weight_logs_clean %>% summary()
```

```
      id              date_time                         weight_kg
 Length:67          Min.   :2016-04-12 06:47:11.00   Min.   : 52.60
 Class :character   1st Qu.:2016-04-19 15:19:45.00   1st Qu.: 61.40
 Mode  :character   Median :2016-04-27 23:59:59.00   Median : 62.50
```

```
                   Mean   :2016-04-27 15:39:54.27   Mean   : 72.04
                   3rd Qu.:2016-05-04 15:24:10.50   3rd Qu.: 85.05
                   Max.   :2016-05-12 23:59:59.00   Max.   :133.50
 weight_pounds        fat                 bmi         is_manual_report
 Min.   :116.0   Min.   : 0.0000   Min.   :21.45   Mode :logical
 1st Qu.:135.4   1st Qu.: 0.0000   1st Qu.:23.96   FALSE:26
 Median :137.8   Median : 0.0000   Median :24.39   TRUE :41
 Mean   :158.8   Mean   : 0.7015   Mean   :25.19
 3rd Qu.:187.5   3rd Qu.: 0.0000   3rd Qu.:25.56
 Max.   :294.3   Max.   :25.0000   Max.   :47.54
     log_id
 Min.   :1.460e+12
 1st Qu.:1.461e+12
 Median :1.462e+12
 Mean   :1.462e+12
 3rd Qu.:1.462e+12
 Max.   :1.463e+12
```

```r
# Create boxplots for "bmi" and "weight_pounds"

columns_to_analyze <- c("bmi", "weight_pounds")

# Call the function to create boxplots
create_boxplots_in_one_output(weight_logs_clean, columns_to_analyze, decimal_places = 2)
```




```r
entry_count <- weight_logs_clean %>%
  group_by(id, is_manual_report) %>%
  summarize(entry_count = n(), .groups = "keep") %>%
  arrange (- entry_count)

print(entry_count)
```

```
# A tibble: 8 x 3
# Groups:   id, is_manual_report [8]
  id         is_manual_report entry_count
  <chr>      <lgl>                  <int>
1 6962181067 TRUE                      30
2 8877689391 FALSE                     24
```

```
3 4558609924 TRUE                        5
4 1503960366 TRUE                        2
5 2873212765 TRUE                        2
6 4319703577 TRUE                        2
7 1927972279 FALSE                       1
8 5577150313 FALSE                       1
```

```
# Check users that reported fat percentage
weight_logs_clean %>% filter(fat != 0)
```

```
# A tibble: 2 x 8
  id         date_time           weight_kg weight_~1   fat   bmi is_ma~2  log_id
  <chr>      <dttm>                  <dbl>     <dbl> <dbl> <dbl> <lgl>     <dbl>
1 1503960366 2016-05-02 23:59:59      52.6      116.    22  22.6 TRUE    1.46e12
2 4319703577 2016-04-17 23:59:59      72.4      160.    25  27.5 TRUE    1.46e12
# ... with abbreviated variable names 1: weight_pounds, 2: is_manual_report
```

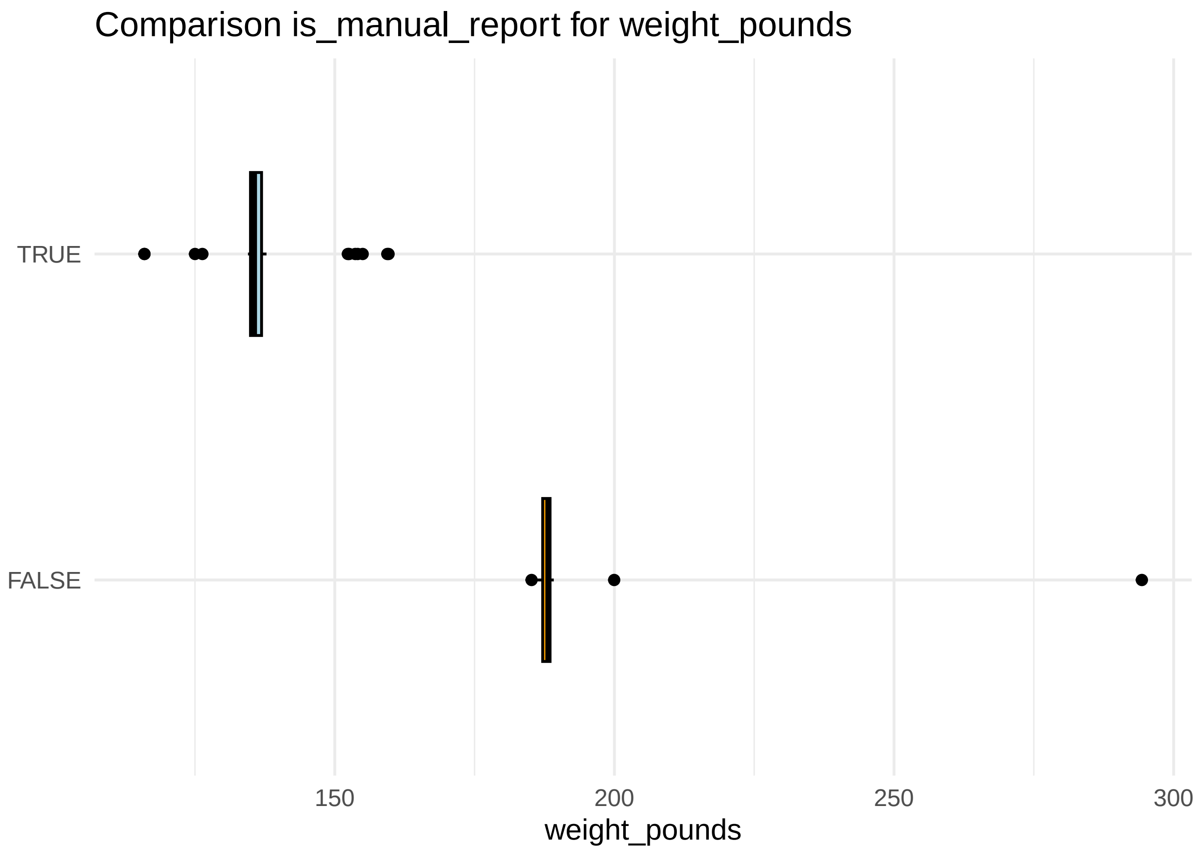
Observation: - Only two users reported fat percentage

```
# Calculate total entries
total_entries <- sum(entry_count$entry_count)


average_bmi_weight <- weight_logs_clean %>%
  group_by(is_manual_report) %>%
  summarize(mean_bmi = mean(bmi, na.rm = TRUE),
            mean_weight_pounds = mean(weight_pounds, na.rm = TRUE),
            entry_count = n(),
            entry_count_percentage = round((n()/total_entries)*100,2),
            .groups = "keep")

print(average_bmi_weight)
```

```
# A tibble: 2 x 5
# Groups:   is_manual_report [2]
  is_manual_report mean_bmi mean_weight_pounds entry_count entry_count_percent~1
  <lgl>               <dbl>              <dbl>       <int>                 <dbl>
1 FALSE                26.4               192.          26                  38.8
2 TRUE                 24.4               138.          41                  61.2
# ... with abbreviated variable name 1: entry_count_percentage
```

Observation: - 61% of users log their weight manually, while 39% sync their weight from other devices

```
create_custom_box_plot(weight_logs_clean , x_axis_col = "is_manual_report", y_axis_col = "weight_pounds
```

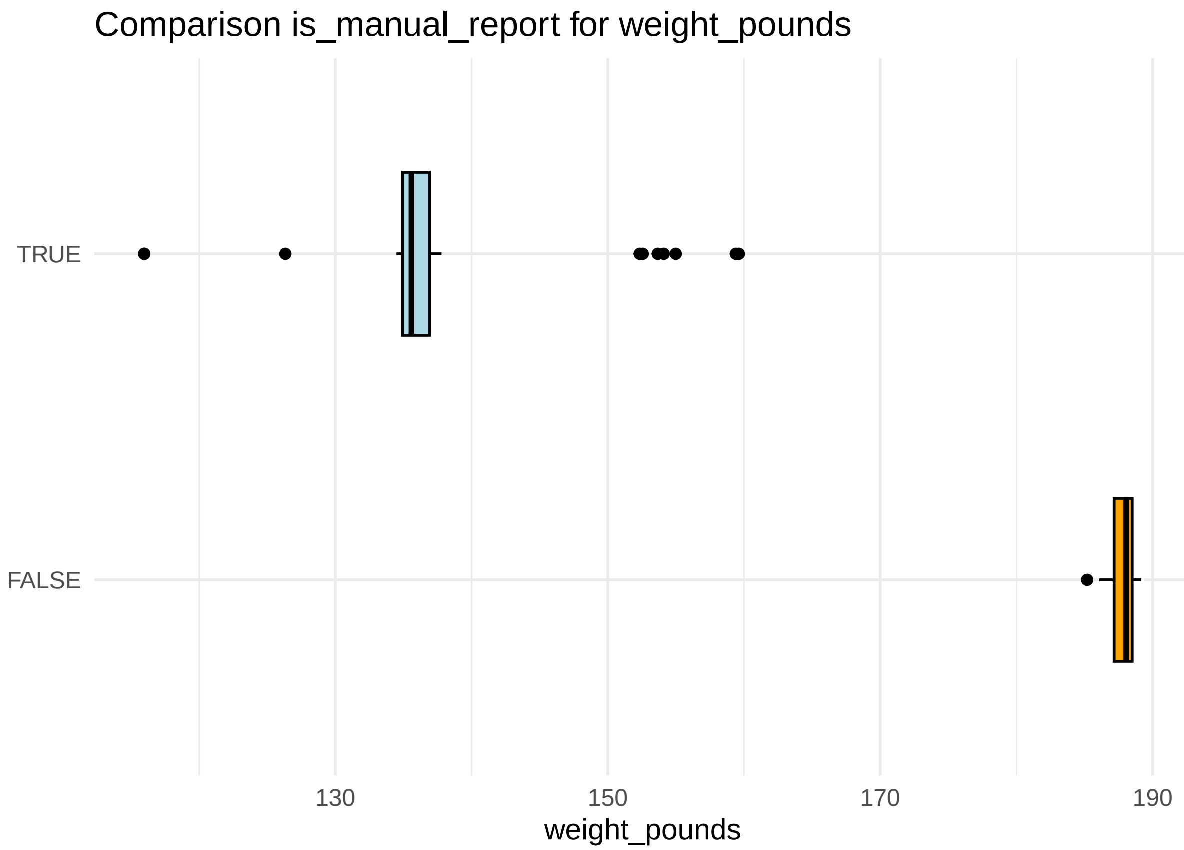



```
# Use the remove_outliers function we created previously to remove the outliers

columns_with_outliers <- c("weight_pounds", "bmi")


# Loop through each column and remove outliers
for (col in columns_with_outliers) {
  weight_logs_clean <- remove_outliers(weight_logs_clean, col)
}
```

```
dim(weight_logs_clean)
```

```
[1] 64  8
```

```
create_custom_box_plot(weight_logs_clean , x_axis_col = "is_manual_report", y_axis_col = "weight_pounds
```



Observations:

- It appears that users who log their weight data manually have a lower median weight than users who sync their weight from other devices.
- The previous observation should be viewed as exploratory and could benefit from additional data. The weight log dataset only has 68 entries; more data would be needed to evaluate these hunches.
- The lack of completeness in the weight log dataset could indicate a lack of user engagement.

next

- add percentages of entries
- Revise notebook -Check for grammar
- Organize references and check headings and formatting
- Write final recommendations _ Write limitations
- Work on report and final recommendations
- Check knit and convert to jupyternotebook
-

Reference:

- EDA: https://rpubs.com/jovial/r
- Histograms: https://statisticsbyjim.com/basics/histograms/ https://blog.minitab.com/en/3-things-a-histogram-can-tell-you

Categorical, ordinal, interval, and ratio variables : https://www.graphpad.com/guides/prism/latest/statistics/the_different_kinds_of_variabl.htm

Add density line to histogram: https://r-coder.com/density-plot-r

- Error bars vs CI: https://blogs.sas.com/content/iml/2019/10/09/statistic-error-bars-mean.html

1. Plotting histograms with ggplot2:1.0,

Insights and recommendations

https://www.cdc.gov/mmwr/volumes/68/wr/mm6823a1.htm

https://stackoverflow.com/questions/13035834/plot-every-column-in-a-data-frame-as-a-histogram-on-one-page-using-ggplot

https://stackoverflow.com/questions/13035834/plot-every-column-in-a-data-frame-as-a-histogram-on-one-page-using-ggplot

Another source:

https://www.kaggle.com/datasets/arashnic/fitbit/discussion/313589?search=data

#paper https://dl.acm.org/doi/pdf/10.1145/3339825.3394926

this is it: physical innactivity. Plot a barplot with percentages. https://www.cdc.gov/physicalactivity/data/inactivity-prevalence-maps/index.html#Race-Ethnicity

information about physical activity guidlines (sex and age):

https://www.cdc.gov/nchs/products/databriefs/db443.htm Elgaddal N, Kramarow EA, Reuben C. Physical activity among adults aged 18 and over: United States, 2020. NCHS Data Brief, no 443. Hyattsville, MD: National Center for Health Statistics. 2022. DOI: https://dx.doi.org/10.15620/cdc:120213

———————— showing notebook in github

convert to jupyter notbook option: https://medium.datadriveninvestor.com/transforming-your-rmd-to-ipynb-file-r-markdown-to-python-jupyter-b1306646f50b

Hey all,

Sorry if I'm misunderstanding here, but I have been knitting the .Rmd notebook to a .md file within RStudio, and it seems to display very well in GitHub. You can see an example in my repo to see if I'm on track with this thread.

The links below give the explanation. Short Version:

change "output=html_document" to "output=github_document"

knit the document push the .md file to GitHub instead of the .Rmd be sure to push the '_files' folder to include any images https://rmarkdown.rstudio.com/github_document_format.html https://gist.github.com/JoshuaTPierce/b919168421b40e06481080eb53c3fb2f