Helping BellaBeat learn from FitBit

2026-01-26

Contents

1 Introduction

This case study is an integral component of the Google Data Analytics Capstone project. Its objective is to analyze Fitbit Tracker Data to inform the marketing strategy for Bellabeat, a high-technology corporation specializing in health-focused smart products, co-founded by Urška Sršen and Sando Mur.

Note: This project will use R and SQL to explore the Fitness Tracker Data available at Kaggle

1.1 Business task

This analysis aims to inform and guide Bellabeat's marketing strategy by ascertaining trends in smart device utilization and their applicability to Bellabeat's customer base. It aims to answer the following 3 questions

1. What are some trends in smart device usage?
2. How could these trends apply to Bellabeat customers?
3. How could these trends help influence Bellabeat marketing strategy?

1.2 Key stakeholders

Urška Sršen: Bellabeat's cofounder and Chief Creative Officer Sando Mur: Mathematician and Bellabeat's cofounder; key member of the Bellabeat executive team Bellabeat marketing analytics team

1.3 Data Source and Description

Data source

The fitbit data is publicly available on Kaggle and can be downloaded from this link: https://www.kaggle.com/datasets/arashnic/fitbit

The data was sourced using this link: https://zenodo.org/records/53894#.X9oeh3Uzaao

It was collected by

- Furberg, Robert
- Brinton, Julia
- Keating, Michael
- Ortiz, Alexa1

Data Description (as described by Authors)

These datasets were generated by respondents to a distributed survey via Amazon Mechanical Turk between 03.12.2016-05.12.2016. Thirty eligible Fitbit users consented to the submission of personal tracker data, including minute-level output for physical activity, heart rate, and sleep monitoring. Individual reports can be parsed by export session ID (column A) or timestamp (column B). Variation between output represents use of different types of Fitbit trackers and individual tracking behaviors / preferences.

This dataset has a total of 29 files spanning over two time periods:

1. 3-12-16 to 4-11-16
2. 4.12.16 to 5-12-16

Both timeperiods have different CSV files for the following indicators:

- Physical Activities (Daily, Hourly, Minute-level)
- Calories (Daily, Hourly, Minute-level)
- Daily Intensities (Daily, Hourly, Minute-level)
- Daily Steps (Daily, Hourly, Minute-level)
- Heart Rate in Seconds
- Sleep (Daily, Minute)
- Weight

Most of the data is in long format but the minute level output for intensities, steps and calories for the April-May period is available in the form of wide format as well

This case study is divided in two parts: Part 1 will focus on Daily data and Part 2 on Hourly data.

Part 1 will be the main focus of this datastudy. It will only focus on the Daily level data, for the **4.12.16 to 5-12-16** timeperiod, for the following indicators:

- Daily Activity
- Daily Calories
- Daily Intensities
- Daily Steps
- Daily Sleep
- Weight

Part 2 will only focus at hourly level data, for the **4.12.16 to 5-12-16** timeperiod, for the following indicators:

- Hourly Calories
- Hourly Intensities
- Hourly Steps

The relevant datasets will be downloaded and created as tables in a database before being cleaned in this R file using SQL code

1.4 Issues with bias or credibility in this data

The dataset spanning the period of April 12, 2016, to May 12, 2016, is limited in scope, containing information from only **33** respondents, which increases the potential for bias. Furthermore, it lacks demographic data, such as age, gender, education, and occupation. While a dataset for weight exists, it is similarly constrained, covering only eight respondents.

1.5 Privacy concerns

The kaggle data is open source and 38 Fitbit users consented to the submission of personal tracker data removing any privacy concerns

1.6 Using R and SQL

This data study uses a combination of *R* and *SQL.* (via SQlite)

SQL will be used for the following purposes:

- Basic data exploration
- Reviewing Column Names and Data Types
- Creating a Pivot Table
- Shortlisting tables for Join
- Basic Cleaning for Dates
- Joining the data

The rest of the analysis will be done via R. This includes:

- Formatting any SQL data
- Any transformations post the join
- Data Visualization

1.6.1 Setting Up

The code chunk below loads up the relevant libraties and sets up an SQL connection via RSQlite.

```r
#Load libraries
library(tidyverse)
library(readxl)
library(readr)
library(dplyr)
library(ggplot2)
library(ggcorrplot)
library(cowplot)
library(knitr)
library(kableExtra)
library(DBI)
library(RSQLite)

#Set up the SQL connection with a new database created purely in memory.
# I am storing it in memory rather than disk as I do not need these tables
# outside of this Rmd file
con <- dbConnect(RSQLite::SQLite(), dbname = ":memory:")

#General Settings for Code chunks
knitr::opts_chunk$set(connection = con) # Enable the connection for all chunks
knitr::opts_chunk$set(fig.align = "center") # Align output when knitting the document
```

2 Part 1: Daily Level Analysis

2.1 Data Processing and Cleaning

This section outlines the process for data processing and cleaning in preparation for the daily analysis.

Initially, it will identify the tables required for joining to derive information for meaningful insights. Subsequently, it will select the relevant columns from these tables through in-depth examination, data validation, and checks for duplicate and missing values. The final steps will involve cleaning and transforming the data, followed by joining it into a consolidated dataframe.

2.1.1 Shortlisting Tables

As mentioned in the description, individual records in each data file represent an individual at a specific time period. This is significant because it implies that any joins between the tables will necessitate being performed at the individual-datetime level.

We have identified a total of six relevant daily data indicators. We will assess which ones require joining.

- Activity
- Calories
- Intensities
- Steps
- Sleep
- Weight

Dedicated CSV data files exist for each of the indicators mentioned above. All six of these CSV files are loaded as seperate tables for analysis using SQL

```
dbWriteTable(con, "dailyactivity_merged",
             read.csv("Fitbit_Data/dailyActivity_merged.csv"))
dbWriteTable(con, "dailyintensities_merged",
             read.csv("Fitbit_Data/dailyIntensities_merged.csv"))
dbWriteTable(con, "dailycalories_merged",
             read.csv("Fitbit_Data/dailyCalories_merged.csv"))
dbWriteTable(con, "dailysteps_merged",
             read.csv("Fitbit_Data/dailySteps_merged.csv"))
dbWriteTable(con, "sleepday_merged",
             read.csv("Fitbit_Data/sleepDay_merged.csv"))
dbWriteTable(con, "weightLogInfo_merged",
             read.csv("Fitbit_Data/weightLogInfo_merged.csv"))
dbWriteTable(con, "hourlyintensities_merged",
             read.csv("Fitbit_Data/hourlyIntensities_merged.csv"))
dbWriteTable(con, "hourlycalories_merged",
             read.csv("Fitbit_Data/hourlyCalories_merged.csv"))
dbWriteTable(con, "hourlysteps_merged",
             read.csv("Fitbit_Data/hourlySteps_merged.csv"))
```

2.1.1.1 Creating tables from the CSV files

2.1.1.2 Unique ID's in each table The following SQL query checks the number of unique ID's in each table

```
SELECT                            -- Activity Table
    'Activity' AS DataIndicator, -- Data indicators representing each table
    COUNT(DISTINCT Id) AS UniqueIds  -- Count of Unique IDs
```

```
FROM
    dailyactivity_merged
UNION             -- UNION to stack rows for all tables
    SELECT          -- Process Repeated for Weight
        'Weight' AS DataIndicator,
        COUNT(DISTINCT Id) AS UniqueIds
    FROM
        weightloginfo_merged
UNION
    SELECT            -- Process Repeated for Sleep
        'Sleep' AS DataIndicator,
        COUNT(DISTINCT Id) AS UniqueIds
    FROM
        sleepday_merged
UNION
    SELECT      -- Process Repeated for Steps
        'Steps' AS DataIndicator,
        COUNT(DISTINCT Id) AS UniqueIds
    FROM
        dailysteps_merged
UNION
    SELECT        -- Process Repeated for Intensities
        'Intensities' AS DataIndicator,
        COUNT(DISTINCT Id) AS UniqueIds
    FROM
        dailyintensities_merged
UNION
    SELECT              -- Process Repeated for Calories
        'Calories' AS DataIndicator,
        COUNT(DISTINCT Id) AS UniqueIds
    FROM
        dailycalories_merged
ORDER BY        -- Sort by Unique ID's
  UniqueIds
```

Table 1: 6 records

DataIndicator	UniqueIds
Weight	8
Sleep	24
Activity	33
Calories	33
Intensities	33
Steps	33

The results above indicate a maximum sample size of 33 respondents. The weight dataset will need to be dropped from this analysis due to insufficient data. Only 8 respondents provided weight information, making the sample size too small for meaningful insights

After dropping weight, we now have a total of 5 data indicators:

- Activity
- Calories

- Intensities
- Steps
- Sleep

2.1.1.3 Checking for Shared Column Names via a Pivot Table Next, we will determine which data files require joining. Although each indicator has its own dedicated data file, we need to check if any of these already contain combined data from others.

Our first step is to review the column names in each table to identify shared names.

The following code will generate a pivot table with the following details:

- Rows: Combined a list of unique column names
- Columns: The 5 data indicators (Activity, Calories, Intensities, Steps and Sleep) columns.
- Values: 1 if a column is present in the tables as represented by the Data Indicator. 0 othwerwise.

```sql
-- The Outer Query creates a pivot table from the pivot_data created by the subquery

-- Unique values from the Field column represent the rows of the pivot table
-- This is achieved through group aggregation using the GROUP BY clause in
-- conjunction with the SUM function
-- GROUP By groups all rows for a given field together
-- The SUM() function for the CASE statement collapses all rows for a field in one

-- Columns for the Pivot Table and the Values in them are created using CASE
-- For each Field/Column Name, CASE checks if it is present in the table
-- represented by the Data Indicator
-- If a given field is present, a Value of 1 is assigned to the relevant Column
-- If a given field is not present, a value of 0 is assigned instead


SELECT
      Field,
    SUM(CASE WHEN DataIndicator = 'Activity' THEN 1 ELSE 0 END) AS Activity,
    SUM(CASE WHEN DataIndicator = 'Intensities' THEN 1 ELSE 0 END) AS Intensities,
    SUM(CASE WHEN DataIndicator = 'Steps' THEN 1 ELSE 0 END) AS Steps,
    SUM(CASE WHEN DataIndicator = 'Calories' THEN 1 ELSE 0 END) AS Calories,
      SUM(CASE WHEN DataIndicator = 'Sleep' THEN 1 ELSE 0 END) AS Sleep,
    Count(*) as Total -- Count total tables the field column is in
FROM
-- The Inner query below stores column names from each of the 6 tables
-- in a column named Field

-- Column names are retrieved using PRAGMA table_info(table-name)
-- This is a specialized command in SQLite used to retrieve metadata about the
-- columns within a specific table

-- A DataIndicator value was also assigned to each table to represent it.
-- Results from the six tables rows are combined into a single output using the
-- UNION operation and are aliased as pivot_data
    (SELECT
       name AS Field, 'Sleep' AS DataIndicator
    FROM
      PRAGMA_TABLE_INFO('sleepday_merged')
    UNION
```

```
      SELECT
        name AS Field, 'Activity' AS DataIndicator
      FROM
        PRAGMA_TABLE_INFO('dailyactivity_merged')
    UNION
      SELECT
          name AS Field, 'Steps' AS DataIndicator
        FROM
        PRAGMA_TABLE_INFO('dailysteps_merged')
    UNION
      SELECT
          name AS Field, 'Intensities' AS DataIndicator
      FROM
          PRAGMA_TABLE_INFO('dailyintensities_merged')
    UNION
      SELECT
        name AS Field, 'Calories' AS DataIndicator
      FROM
          PRAGMA_TABLE_INFO('dailycalories_merged')) as pivot_data
Group By
    Field -- Group By Field and then use SUM() in the select statement for unqiue rows
Order by
    Activity, Total DESC, Field
    -- Order by the Activity column, then by Total
    -- Count (in descending order) and then by Field for easier visualization.
```

The results derived from the SQL query will be color-coded and formatted to facilitate visualization.

- All rows where 'Activity' is equal to 0, signifying rows for all columns not present in the 'Activity' table, are formatted in bold. Given that the SQL table was ordered by 'Activity,' these rows will appear at the top of the pivot table.
- The row corresponding to the 'ID' field is highlighted in **green**, as this column will serve as the key for joining tables.
- The rows for 'ActivityDay,' 'ActivityDate,' and 'Sleepday' are highlighted in **salmon red**.
- The rows for 'TotalSteps' and 'StepTotal' are highlighted in **yellow**.

```
pivot_table %>%
  kable(caption  = "Presence of a Field in each Table. 1 if Yes, 0 if not",
        booktabs=TRUE) %>% kable_styling("striped")  %>% #For striped rows
  row_spec(which(pivot_table$Activity == 0), bold=TRUE) %>%
  row_spec(which(pivot_table$Field == 'Id'), background ='#C1FFC1') %>%
  row_spec(which(pivot_table$Field == 'ActivityDay' |
                 pivot_table$Field == 'ActivityDate' |
                 pivot_table$Field == 'SleepDay'),background ='#FA8072') %>%
  row_spec(which(pivot_table$Field == 'TotalSteps'|
             pivot_table$Field == 'StepTotal'), background ='#FAFAD2')
```

Table 2: Presence of a Field in each Table. 1 if Yes, 0 if not

Field	Activity	Intensities	Steps	Calories	Sleep	Total
ActivityDay	**0**	**1**	**1**	**1**	**0**	**3**
SleepDay	**0**	**0**	**0**	**0**	**1**	**1**
StepTotal	**0**	**0**	**1**	**0**	**0**	**1**
TotalMinutesAsleep	**0**	**0**	**0**	**0**	**1**	**1**

TotalSleepRecords	**0**	**0**	**0**	**0**	**1**	**1**
TotalTimeInBed	**0**	**0**	**0**	**0**	**1**	**1**
Id	1	1	1	1	1	5
Calories	1	0	0	1	0	2
FairlyActiveMinutes	1	1	0	0	0	2
LightActiveDistance	1	1	0	0	0	2
LightlyActiveMinutes	1	1	0	0	0	2
ModeratelyActiveDistance	1	1	0	0	0	2
SedentaryActiveDistance	1	1	0	0	0	2
SedentaryMinutes	1	1	0	0	0	2
VeryActiveDistance	1	1	0	0	0	2
VeryActiveMinutes	1	1	0	0	0	2
ActivityDate	1	0	0	0	0	1
LoggedActivitiesDistance	1	0	0	0	0	1
TotalDistance	1	0	0	0	0	1
TotalSteps	1	0	0	0	0	1
TrackerDistance	1	0	0	0	0	1

Insights

The following insights were derived from the Pivot Table analysis:

- Most columns are present in the Activity Dataset. Six out of a total of 21 rows exhibit a value of 0 for Activity (the top six rows are highlighted in bold).
- The 'Id' column is common across all five tables, as indicated in the green row.
- A single, consolidated Date Column is absent. Three potential date fields were identified due to their similar naming conventions: 'ActivityDate', 'ActivityDay', and 'SleepDay'. These rows are highlighted in red.
- 'ActivityDay' and 'SleepDay' are included in the six rows highlighted in bold. 'ActivityDay' is found in the Steps, Calories, and Intensities tables, while 'SleepDay' is exclusive to the Sleep table. Further investigation is necessary to ascertain if these are equivalent to 'ActivityDate' in the Activity table.
- 'StepTotal' is another column name not present in the Activity table but found in the Steps table. Scrolling through the pivot table reveals that the Activity table contains 'TotalSteps'. Additional analysis is required to confirm the equivalence of these two columns. See rows highlighted in Yellow
- The remaining three columns not present in the Activity table, 'TotalMinutesAsleep', 'TotalSleepRecords', and 'TotalTimeinBed', lack similarly named alternatives in the Activity dataset and are therefore unique columns from the Sleep table.

2.1.1.4 Resolving Inconsistencies in Column Names and Values Insights form the pivot table show that when compared with the Activity table:

- Steps contains two additional columns; ActivityDay and StepTotal
- Calories contains one additional columns; ActivityDay
- Intensities contains one additional columns; ActivityDay
- Sleep contains 4 additional columns; SleepDay, TotalMinutesAsleep', 'TotalSleepRecords', and 'TotalTimeinBed

The SQL query below will check:

- The number of records when TotalSteps is not the same as StepTotal
- The number of records when ActivityDate is not the same as ActivityDay in each of Calories, Steps and Intensities tables
- The number of records when ActivityDate is not the same as SleepDay

```
WITH step_diff as (   -- Create a temporary table when TotalSteps != StepTotal
SELECT
    Count(*) as StepsDiff, -- Count for total Rows
    1 as UniId       -- 1 set as a uniqueid which will be used for the Join
FROM
    (SELECT
      TotalSteps
     FROM
      dailyactivity_merged
    EXCEPT             -- EXCEPT operator is a set operation that returns distinct
    -- rows from the result set of the first SELECT query that are not present
    -- in the result set of the second
      SELECT
        StepTotal
    FROM
       dailysteps_merged) as tab1
),         -- Repeat for ActivityDate != ActivityDay in Steps
date_diff_step as (
SELECT
    Count(*) as DatesDiffSteps,
    1 as UniId
FROM
    (SELECT
       ActivityDate
    FROM
         dailyactivity_merged
    EXCEPT
    SELECT
        ActivityDay
    FROM
          dailysteps_merged) as tab2
),   -- Repeat for ActivityDate != ActivityDay in Calories
date_diff_cal as (
SELECT
    Count(*) as DatesDiffCal,
    1 as UniId
FROM
    (SELECT
        ActivityDate
    FROM
        dailyactivity_merged
    EXCEPT
    SELECT
      ActivityDay
  FROM
        dailycalories_merged) as tab3
),  -- -- Repeat for ActivityDate != ActivityDay in Intensities
date_diff_inten as (
SELECT
    Count(*) as DatesDiffInten,
    1 as UniId
FROM
    (SELECT
```

```
        ActivityDate
    FROM
        dailyactivity_merged
    EXCEPT
    SELECT
      ActivityDay
  FROM
        dailyintensities_merged) as tab4
), -- Repeat for ActivityDate != SleepDay
date_diff_sleep as (
SELECT
    Count(*) as DatesDiffSleep,
    1 as UniId
FROM
    (SELECT
        ActivityDate
    FROM
        dailyactivity_merged
    EXCEPT
    SELECT
      SleepDay
    FROM
        sleepday_merged) as tab5
)       -- Join rows from all 5 temporary tables in 1 using UniId as the key
SELECT
  A.StepsDiff,
  B.DatesDiffSteps,
  C.DatesDiffCal,
  D.DatesDiffInten,
  E.DatesDiffSleep
FROM
  step_diff as A
JOIN
  date_diff_step as B ON A.UniId=B.UniId
JOIN
 date_diff_cal as C ON A.UniId=C.UniId
JOIN
 date_diff_inten as D ON A.UniId=D.UniId
JOIN
 date_diff_sleep as E ON A.UniId=E.UniId
```

Table 3: 1 records

StepsDiff	DatesDiffSteps	DatesDiffCal	DatesDiffInten	DatesDiffSleep
0	0	0	0	31

There is no supplmentary information in the Steps, Calories and Intensities tables as they already possess corresponding columns in the Activity table. This is because:

- 0 records are returned when TotalSteps in the Activity table is **not** the same as StepTotal in the Steps table.
- 0 records are returned when ActivityDate in the Activitiy table is the **not** the ssame as ActivityDay in the Steps table.

- 0 records are returned when ActivityDate in the Activity table is not the same as ActivityDay in the Calories table.
- 0 records are returned when ActivityDate in the Activity table is not the same as ActivityDay in the Intensities table

Therefore, any additional joins for these three tables are unnecessary.

However dates in the Activity table are very different from dates in the Sleep table.

- 31 records are returned when ActivityDate is not the same as SleepDay. This includes all 31 days for the whole time-period. This will need to be explored and cleaned further in the next section.

To summarize all columns from the calories, steps and intensities tables already exist in the activities table. However, the sleep table contains additional information related to sleep as well as dates in a different format. Therefore the Sleep and the Activity tables would need to be joined, once the relevant dates columns have been cleaned.

2.1.2 Shortlisting Columns to Include in the Join

Now that we have identified the tables requiring a join, namely the Activity and the Sleep tables, the subsequent step would be to finalize columns in each table that need to be joined and idenftify any cleaning or transformations that need to take place

```
With sleep as ( -- Create a temporary table with the first row of the Sleep table
SELECT
    SleepDay as Dates,    -- Rename as Dates
    'Sleep' as Tablename  -- Tablename to distinguish table
FROM
    sleepday_merged
LIMIT
  1     -- 1st row only
),
activity as (    -- Repeat for Activity with a new temporary table
SELECT
     ActivityDate as Dates,
     'Activity' as Tablename
FROM
     dailyactivity_merged
LIMIT
  1
)
SELECT
  *
FROM
  sleep
UNION      -- Union results from both tables
SELECT
    *
FROM
  activity
```

Table 4: 2 records

Dates	Tablename
4/12/2016	Activity
4/12/2016 12:00:00 AM	Sleep

The results show that while the SleepDay column also represents dates, its values are of a different format. They contain timestamps as well.

We can create new clean columns for both Activity and Sleep

2.1.2.1 Clean Dates

In both tables, we will create new columns, named as RecordedDate, to store cleaned values from the current date fields

Activity Table

```
ALTER TABLE dailyactivity_merged -- Create a new column named as RecordedDate
ADD COLUMN RecordedDate TEXT
```

Currently values in ActivityDate are either in the M/DD/YYYY or M/D/YYYY format. These need to be standardized to YYYY-MM-DD format

```
UPDATE dailyactivity_merged

-- Update RecordedDate with Cleaned Values from the ActivityDate field
-- Last 4 digits as YYYY
-- Month as MM (All months are currently either 4 or 5, these will be formatted
-- to 04 or 05)
-- Day as DD (Dates when Days are represented in single digits eg 1 will need to
-- be treated seperately from Days in double digits eg 10)

SET RecordedDate = (
    SUBSTR(ActivityDate, -4) || '-0' ||  -- Last 4 digits for YYYY
    SUBSTR(ActivityDate, 1,1) || --  0 and First digit for MM
    CASE -- 0 and Third, or, Third and Fourth Digits for DD
        WHEN SUBSTR(ActivityDate, 4, 1) = '/'
        THEN '-0' || SUBSTR(ActivityDate, 3, 1)
        ELSE '-' || SUBSTR(ActivityDate, 3, 2)
    END
)
```

Check that RecordedDate stores the correct values from ActivityDate regardless of the format (M/DD/YYYY or M/D/YYYY)

```
With doubleday as ( -- Create a temporary table with rows where the ActivityDate
SELECT              --format is  M/DD/YYYY
   ActivityDate, RecordedDate
FROM
    dailyactivity_merged
WHERE
  LENGTH(ActivityDate) = 9
LIMIT
  1     -- 1st row only
),
singleday as (    -- Create a temporary table with rows where the ActivityDate
SELECT             --format is  M/D/YYYY
   ActivityDate, RecordedDate
FROM
    dailyactivity_merged
WHERE
  LENGTH(ActivityDate) = 8
LIMIT
  1     -- 1st row only
```

```
)
SELECT
  *
FROM
  doubleday
UNION      -- Union results from both tables
SELECT
    *
FROM
  singleday
```

Table 5: 2 records

ActivityDate	RecordedDate
4/12/2016	2016-04-12
5/1/2016	2016-05-01

Sleep Table

```
ALTER TABLE sleepday_merged -- Create a new column named as RecordedDate
ADD COLUMN RecordedDate TEXT
```

Currently values in SleepDay are either in the M/DD/YYYY hh:mm:s or M/D/YYYY hh:mm:s format. These need to be standardized to YYYY-MM-DD format

```
-- Update RecordedDate with Cleaned Values from the SleepyDaty field

-- When Day are in Single Digits:
-- Digits 5-9 as YYYY
-- 0 and First digit for MM
-- 0 and Third Digit, or , Third and Fourth Digit DDD
-- Day as DD (Dates when Days are represented in single digits eg 1 will need to
-- be treated seperately from Days in double digits eg 10)


UPDATE sleepday_merged
SET RecordedDate = (
    CASE
        WHEN SUBSTR(SleepDay, 4, 1) = '/'
        THEN SUBSTR(SleepDay, 5,4) || '-0' || SUBSTR(SleepDay, 1,1) ||
        '-0' || SUBSTR(SleepDay, 3, 1)
        ELSE  SUBSTR(SleepDay, 6,4) || '-0' || SUBSTR(SleepDay, 1,1) ||
        '-' || SUBSTR(SleepDay, 3, 2)
    END
)
```

Check that RecordedDate stores the correct values from SleepDay regardless of the format (M/DD/YYYY or M/D/YYYY)

```
With doubleday as ( -- Create a temporary table with rows where the SleepDay
SELECT              --format is  M/DD/YYYY hh:mm:ss
   SleepDay, RecordedDate
FROM
    SleepDay_merged
```

```
WHERE
  LENGTH(SleepDay) = 21
LIMIT
  1      -- 1st row only
),
singleday as (     -- Create a temporary table with rows where the ActivityDate
SELECT              --format is  M/D/YYYY hh:mm:ss
   SleepDay, RecordedDate
FROM
    sleepday_merged
WHERE
  LENGTH(SleepDay) = 20
LIMIT
  1      -- 1st row only
)
SELECT
  *
FROM
  doubleday
UNION      -- Union results from both tables
SELECT
    *
FROM
  singleday
```

Table 6: 2 records

SleepDay	RecordedDate
4/12/2016 12:00:00 AM	2016-04-12
5/1/2016 12:00:00 AM	2016-05-01

Now that we have created new date fields with cleaned data, we will exclude the ActivityDate and SleepDay fields from the Join and any relevant code below

Next we will see if any other columns in the two tables would need to be dropped or transformed.

First let's get some brief description of the columns in the two tables

```
PRAGMA table_info(dailyactivity_merged)
```

Table 7: 16 records

cid	name	type	notnull	dflt_value	pk
0	Id	REAL	0	NA	0
1	ActivityDate	TEXT	0	NA	0
2	TotalSteps	INTEGER	0	NA	0
3	TotalDistance	REAL	0	NA	0
4	TrackerDistance	REAL	0	NA	0
5	LoggedActivitiesDistance	REAL	0	NA	0
6	VeryActiveDistance	REAL	0	NA	0
7	ModeratelyActiveDistance	REAL	0	NA	0
8	LightActiveDistance	REAL	0	NA	0
9	SedentaryActiveDistance	REAL	0	NA	0

cid	name	type	notnull	dflt_value	pk
10	VeryActiveMinutes	INTEGER	0	NA	0
11	FairlyActiveMinutes	INTEGER	0	NA	0
12	LightlyActiveMinutes	INTEGER	0	NA	0
13	SedentaryMinutes	INTEGER	0	NA	0
14	Calories	INTEGER	0	NA	0
15	RecordedDate	TEXT	0	NA	0

```
PRAGMA table_info(sleepday_merged)
```

Table 8: 6 records

cid	name	type	notnull	dflt_value	pk
0	Id	REAL	0	NA	0
1	SleepDay	TEXT	0	NA	0
2	TotalSleepRecords	INTEGER	0	NA	0
3	TotalMinutesAsleep	INTEGER	0	NA	0
4	TotalTimeInBed	INTEGER	0	NA	0
5	RecordedDate	TEXT	0	NA	0

Let's also review their descriptions. The table below lists descriptions for the relevant columns from the Fitabase data dictionary

```
datadescription <- read_excel("datadescription.xlsx", sheet='Daily')
kable(datadescription, booktabs=TRUE) %>%  kable_styling("striped") %>%
  column_spec(2, width = "12cm")
```

Data Header	Data Description
ActivityDate	Date value in mm/dd/yyyy format.
TotalSteps	Total number of steps taken.
TotalDistance	Total kilometers tracked.
TrackerDistance	Total kilometers tracked by Fitbit device.
LoggedActivitiesDistance	Total kilometers from logged activities.
VeryActiveDistance	Kilometers travelled during very active activity.
ModeratelyActiveDistance	Kilometers travelled during moderate activity.
LightActiveDistance	Kilometers travelled during light activity.
SedentaryActiveDistance	Kilometers travelled during sedentary activity.
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.
Calories	Total estimated energy expenditure (in kilocalories).
SleepDay	Date on which the sleep event started. (in mm/dd/yyyy hh:mm:ss format)
TotalSleepRecords	Number of recorded sleep periods for that day. Includes naps > 60min
TotalMinutesAsleep	Total number of minutes classified as being "asleep".
TotalTimeInBed	Total minutes spent in bed, including asleep, restless, and awake, that occurred during a defined sleep record.

2.1.2.2 Finalize and Validate Columns from the Activity table We will investigate the distance and minutes columns from the Activity table to finalize which ones to keep.

Variables name are renamed below for easier analysis and visualization. This renaming will be repeatedly used in other codes as well including the Join

2.1.2.2.1 Validate Distance and Minutes Columns** The distance columns

```sql
SELECT
   LoggedActivitiesDistance as LogActDist,
   TotalDistance as TotalDist,
   TrackerDistance as TrackDist,
   SedentaryActiveDistance as SedActDist,
   LightActiveDistance as LightActDist,
   VeryActiveDistance as VeryActDist,
   ModeratelyActiveDistance as ModActDist
FROM
  dailyactivity_merged
LIMIT
  5
```

Table 10: 5 records

LogActDist	TotalDist	TrackDist	SedActDist	LightActDist	VeryActDist	ModActDist
0	8.50	8.50	0	6.06	1.88	0.55
0	6.97	6.97	0	4.71	1.57	0.69
0	6.74	6.74	0	3.91	2.44	0.40
0	6.28	6.28	0	2.83	2.14	1.26
0	8.16	8.16	0	5.04	2.71	0.41

The minutes columns

```sql
SELECT
   VeryActiveMinutes as VeryActMin,
   FairlyActiveMinutes as FairlyActMin,
   LightlyActiveMinutes as LightlyActMin,
   SedentaryMinutes as SedMin
FROM
  dailyactivity_merged
LIMIT
  5
```

Table 11: 5 records

VeryActMin	FairlyActMin	LightlyActMin	SedMin
25	13	328	728
21	19	217	776
30	11	181	1218
29	34	209	726
36	10	221	773

It appears that Tracker Distance and Total Distance are largely equivalent. To confirm this, we can calculate the difference between these two variables and then compute summary statistics to check if the difference is zero.

Additionally, LoggedActivitiesDistance and Sedentary Active Distance appear to be mostly zero. We can calculate summary statistics to verify this observation.

The following query calculates the average difference between Tracker Distance and Total Distance and determines the percentage of rows where the difference is zero. It also computes the average values for LoggedActivitiesDistance and Sedentary Active Distance and counts the percentage of rows where these values are zero

```
SELECT
  avg(DistDiff) as AvgDistDiff,  -- Mean of the difference
  COUNT(CASE WHEN DistDiff=0 THEN 1 END)*100/940 as PerDistDiffZero, -- % when 0
  avg(LogActDist) as AvgLogActDist, -- Mean of LoggedActivitiesDistance
  COUNT(CASE WHEN LogActDist=0 THEN 1 END)*100/940 as PerLogActDistZero, -- % when 0
  avg(SedActDist) as AvgSedActDist, -- Mean of SedentaryActiveDistance
  COUNT(CASE WHEN SedActDist=0 THEN 1 END)*100/940 as PedActDistZero -- % when 0
  FROM -- Inner query to select relevant columns
  (SELECT
    TrackerDistance,
    TotalDistance,
    LoggedActivitiesDistance as LogActDist,
    SedentaryActiveDistance as SedActDist,
      TrackerDistance - TotalDistance as DistDiff -- Difference the two
  FROM
      dailyactivity_merged) as table1
```

Table 12: 1 records

AvgDistDiff	PerDistDiffZero	AvgLogActDist	PerLogActDistZero	AvgSedActDist	PedActDistZero
-0.0143511	98	0.1081709	96	0.0016064	91

The mean difference between 'Tracker distance' and 'total distance' is negligible, averaging approximately -0.01. The difference is precisely zero in 98.4% of instances.

Similarly, the mean of 'LoggedActivitiesDistance' is close to zero, registering as zero in 96.6% of cases. The Sedentary Active Distance is consistently zero (0) across all observations. This anomaly may be attributed to an import error; however, it has been confirmed that the actual values were so minuscule—only negligibly above zero—that the data import process rounded them down to zero.

Given the preceding analysis, Tracker Distance, LoggedActivitiesDistance, and SedentaryActiveDistance can be excluded from the scope of our analysis.

It is also apparent that the Total Distance is the sum of VeryActiveDistance, ModeratelyActiveDistance, and LightActiveDistance (disregarding Sedentary Active Distance, as its value is uniformly zero).

We can assess the discrepancy by summing the values for VeryActiveDistance, ModeratelyActiveDistance, and LightActiveDistance and subsequently calculating the difference from the Total Distance.

The subsequent query calculates the difference between the sum of VeryActiveDistance, ModeratelyActiveDistance, and LightActiveDistance and the TotalDistance. It then computes the minimum, maximum, and average values for this difference.

```
SELECT
  'TotalDistanceDifference' as Field,
  min((TotalDistance_Diff)) as Minimum,
  avg(TotalDistance_Diff) as Average,
  max((TotalDistance_Diff)) as Maximum
FROM
(SELECT
    VeryActiveDistance + ModeratelyActiveDistance +
```

```
    LightActiveDistance - TotalDistance as TotalDistance_Diff
FROM
    dailyactivity_merged) as table1
```

Table 13: 1 records

Field	Minimum	Average	Maximum
TotalDistanceDifference	-9.37	-0.0786596	0.0100006

The "Total distance" metric is not precisely equivalent to the sum of "VeryActiveDistance," "ModeratelyActiveDistance," and "LightActiveDistance"; however, it is highly comparable. Consequently, the "TotalDistance" column will be excluded, and a new, comprehensive total will be calculated by aggregating the three active distance categories.

Furthermore, it would be beneficial to introduce columns for "Total Active Minutes" and "Total Minutes." The creation of these aggregate values will be advantageous for conducting a composition breakdown. We will keep this in mind while constructing the SQL query for the join

2.1.2.3 Finalize and Validate Columns from the Sleep table Now let's explore the first few rows from the Sleep table

```
SELECT
  *
FROM
  sleepday_merged
LIMIT 5
```

Table 14: 5 records

Id	SleepDay	TotalSleepRecords	TotalMinutesAsleep	TotalTimeInBed	RecordedDate
1503960366	4/12/2016 12:00:00 AM	1	327	346	2016-04-12
1503960366	4/13/2016 12:00:00 AM	2	384	407	2016-04-13
1503960366	4/15/2016 12:00:00 AM	1	412	442	2016-04-15
1503960366	4/16/2016 12:00:00 AM	2	340	367	2016-04-16
1503960366	4/17/2016 12:00:00 AM	1	700	712	2016-04-17

The Sleep table just contains 5 columns. As discussed earlier, the SleepDay variable would need to be cleaned to make it consistent with the ActivityDate column in the Activity table.

Lets explore the TotalSleepRecords column with some summary statistics.

```
SELECT
  'TotalSleepRecords' as Field,
  min(TotalSleepRecords) as Minimum,
  avg(TotalSleepRecords) as Average,
  max(TotalSleepRecords) as Maximum,
  COUNT(CASE WHEN TotalSleepRecords = 1 THEN 1 END)*100/413 as PerEqualOne
FROM
```

```
(SELECT
  TotalSleepRecords
FROM
  sleepday_merged) as table1
```

Table 15: 1 records

Field	Minimum	Average	Maximum	PerEqualOne
TotalSleepRecords	1	1.118644	3	88

The TotalSleepRecords variable ranges from 1 to 3, with a value of 1 occurring approximately 89% of the time. As this variable does not appear to provide meaningful data, it will be excluded from the analysis.

Next, we will verify whether "minutes asleep" is consistently less than "time in bed."

```
SELECT
  count(*) as AsleepMoreThanInBed
FROM
  sleepday_merged
WHERE
  TotalMinutesAsleep > TotalTimeInBed
```

Table 16: 1 records

AsleepMoreThanInBed
0

Yes, we can confirm that time spent asleep is always less than the time spent in bed

2.1.3 Checking for Duplicates and Missing Values

Next we will check for any duplicates and missing values that exist for our finalized column lists for both activities and sleep,

```
WITH dup_act as (      -- Create a temporary table to calculate Duplicates
SELECT
  1 as UniId,     -- Define UniId in each temporary table to facilitate the join
  COUNT(*) -      -- Calculate the difference between the count of total rows
(SELECT           -- and distinct rows. This difference will be the # of duplicates
  count(*)
FROM
(SELECT DISTINCT       -- This inner query counts distinct rows
  RecordedDate,
  Id,
    Calories,
    TotalSteps,
    LightlyActiveMinutes,
    FairlyActiveMinutes,
    VeryActiveMinutes,
    SedentaryMinutes,
    LightActiveDistance,
    ModeratelyActiveDistance,
    VeryActiveDistance
```

```sql
FROM
  dailyactivity_merged) as t1) as DuplicatesActivity
FROM
  dailyactivity_merged
),
miss_act as ( -- Create a temporary table to calculate Missing Values
SELECT
    COUNT(*) AS MissingValuesActivity,  -- Count values when any one of the columns
    1 as UniId                          -- specified is null. See where
FROM
    dailyactivity_merged
WHERE
    RecordedDate IS NULL OR
  Id IS NULL OR
    Calories IS NULL OR
    TotalSteps IS NULL OR
    LightlyActiveMinutes IS NULL OR
    FairlyActiveMinutes IS NULL OR
    VeryActiveMinutes IS NULL OR
    SedentaryMinutes IS NULL OR
    LightActiveDistance IS NULL OR
    ModeratelyActiveDistance IS NULL OR
    VeryActiveDistance IS NULL
),
dup_sleep as (     -- Repeat the process for the sleep table
SELECT
  1 as UniId,
  COUNT(*) -
(SELECT
  count(*)
FROM
(SELECT DISTINCT
  Id,
  RecordedDate,
  TotalMinutesAsleep,
  TotalTimeInBed
FROM
  sleepday_merged) as t2) as DuplicatesSleep
FROM
  sleepday_merged
),
miss_sleep as (
SELECT
    COUNT(*) AS MissingValuesSleep,
    1 as UniId
FROM
  sleepday_merged
WHERE
    Id IS NULL OR
  RecordedDate IS NULL OR
  TotalMinutesAsleep IS NULL OR
    TotalTimeInBed IS NULL
)
```

```
SELECT                -- Join results from all tables into one
  A.DuplicatesActivity,
  B.MissingValuesActivity,
  C.DuplicatesSleep,
  D.MissingValuesSleep
FROM
  dup_act as A
JOIN
  miss_act as B on A.UniId=B.UniId
JOIN
  dup_sleep as C on A.UniId=C.UniId
JOIN
  miss_sleep as D on A.UniId=D.UniId
```

Table 17: 1 records

DuplicatesActivity	MissingValuesActivity	DuplicatesSleep	MissingValuesSleep
0	0	3	0

We have 0 missing values in both tables. We also have 0 duplicates in the activity table. However, we have 3 duplicate rows in our Sleep Dataset. We will exclude these while constructing the SQL query for the join

2.1.4 Joining the Activity and Sleep tables

With the columns finalized, the Activity and Sleep tables can be joined.

When joining, we will exclude the column names for the previously discussed variables.

- A column for TotalActiveMinutes (LightlyActiveMinutes + FairlyActiveMinutes + VeryActiveMinutes) will be created.
- A column for TotalMinutes (TotalActiveMinutes + SedentaryMinutes) will be created.
- A column for TotalActiveDistance (LightActiveDistance + ModeratelyActiveDistance + VeryActiveDistance) will be created.
- A column for Day is created based on the date
- A column for DayType (Weekend or Weekday)
- The cleaned date columns for both datasets are used
- A left join will be utilized to combine the two tables.
- Unique rows will be selected from the Right i.e. Sleep table in order to account for the duplicate rows in this table.

As disucssed earlier, variables name are renamed for easier analysis and visualization.

2.1.4.1 Constructing the Join The subsequent SQL query employs a left join on the Id and date columns to merge the two tables. It also generates the three identified columns and cleans the date columns. This code chunk will produce a dataframe named daily_activity_sleep, containing the results of the query.

```
-- This SQL Query will output a dataframe named as named as daily_activity_sleep
-- with the results of the query.

SELECT
    A.Id,
    A.RecordedDate,       -- Cleaned Date variable
    --STRFTIME('%', A.RecordedDate) AS DayName,  -- Day Name
    CASE CAST(STRFTIME('%w', A.RecordedDate) AS INTEGER)
```

```
      WHEN 0 THEN 'Weekend'
      WHEN 6 THEN 'Weekend'
      ELSE 'Weekday' -- DayType; Weekday or Weekend
    END AS DayType,
    A.Calories,
  A.TotalSteps as Steps,
    A.LightlyActiveMinutes as LightlyActMin,
    A.FairlyActiveMinutes as FairlyActMin,
    A.VeryActiveMinutes VeryActMin,
    A.LightlyActiveMinutes + A.FairlyActiveMinutes +
    A.VeryActiveMinutes as TotalActMin,  -- Add all active minutes
    A.SedentaryMinutes as SedMin,
    A.LightlyActiveMinutes + A.FairlyActiveMinutes + A.VeryActiveMinutes +
    A.SedentaryMinutes as TotalMin,   -- Add all active and sedentary minutes
    A.LightActiveDistance as LightActDist,
    A.ModeratelyActiveDistance as ModActDist,
    A.VeryActiveDistance as VeryActDist,
    A.LightActiveDistance + A.ModeratelyActiveDistance +
    A.VeryActiveDistance as TotalDist, -- Add all distance
    B.TotalMinutesAsleep as AsleepMin,
    B.TotalTimeInBed as TimeInBed
FROM
    dailyactivity_merged as A
LEFT JOIN
    (SELECT DISTINCT        -- Select Distinct rows to drop duplicates
        Id,
        TotalMinutesAsleep,
        TotalTimeInBed,
        RecordedDate -- Cleaned Date variable
    FROM
        sleepday_merged) as B
ON
    A.Id = B.Id  -- Join on ID and Date
    AND
    A.RecordedDate = B.RecordedDate
```

2.1.4.2 Validating the Join In this section we will review he daily_activity_sleep dataframe that contains the results from the Join. We will confirm that the join happened correctly.

Review Data First we will preview, the first few rows of the dataframe. We will split the view for easier visualization

```
kable(head(daily_activity_sleep,5)[,1:6]) %>%
  kable_styling("striped")
```

Id	RecordedDate	DayType	Calories	Steps	LightlyActMin
1503960366	2016-04-12	Weekday	1985	13162	328
1503960366	2016-04-13	Weekday	1797	10735	217
1503960366	2016-04-14	Weekday	1776	10460	181
1503960366	2016-04-15	Weekday	1745	9762	209
1503960366	2016-04-16	Weekend	1863	12669	221

```
kable(head(daily_activity_sleep,5)[,7:12]) %>%
  kable_styling("striped")
```

FairlyActMin	VeryActMin	TotalActMin	SedMin	TotalMin	LightActDist
13	25	366	728	1094	6.06
19	21	257	776	1033	4.71
11	30	222	1218	1440	3.91
34	29	272	726	998	2.83
10	36	267	773	1040	5.04

```
kable(head(daily_activity_sleep,5)[,13:17]) %>%
  kable_styling("striped")
```

ModActDist	VeryActDist	TotalDist	AsleepMin	TimeInBed
0.55	1.88	8.49	327	346
0.69	1.57	6.97	384	407
0.40	2.44	6.75	NA	NA
1.26	2.14	6.23	412	442
0.41	2.71	8.16	340	367

All of the columns appear to be error-free.

Review Summary Statistics

Next we will display some summary statistics for the joined dataframe. We will split the view easier visualization

```
kable(daily_activity_sleep[,1:6] %>% summary()) %>%
  kable_styling("striped")
```

Id	RecordedDate	DayType	Calories	Steps	LightlyActMin
Min. :1.504e+09	Length:940	Length:940	Min. : 0	Min. : 0	Min. : 0.0
1st Qu.:2.320e+09	Class :character	Class :character	1st Qu.:1828	1st Qu.: 3790	1st Qu.:127.0
Median :4.445e+09	Mode :character	Mode :character	Median :2134	Median : 7406	Median :199.0
Mean :4.855e+09	NA	NA	Mean :2304	Mean : 7638	Mean :192.8
3rd Qu.:6.962e+09	NA	NA	3rd Qu.:2793	3rd Qu.:10727	3rd Qu.:264.0
Max. :8.878e+09	NA	NA	Max. :4900	Max. :36019	Max. :518.0

The mean for Calories is within the general dietary guidelines of 2000-2500 daily value. The mean for Steps is slightly above the top range for the general average of 5000-7000

```
kable(daily_activity_sleep[,7:12] %>% summary()) %>%
  kable_styling("striped")
```

FairlyActMin	VeryActMin	TotalActMin	SedMin	TotalMin	LightActDist
Min. : 0.00	Min. : 0.00	Min. : 0.0	Min. : 0.0	Min. : 2.0	Min. : 0.000
1st Qu.: 0.00	1st Qu.: 0.00	1st Qu.:146.8	1st Qu.: 729.8	1st Qu.: 989.8	1st Qu.: 1.945
Median : 6.00	Median : 4.00	Median :247.0	Median :1057.5	Median :1440.0	Median : 3.365
Mean : 13.56	Mean : 21.16	Mean :227.5	Mean : 991.2	Mean :1218.8	Mean : 3.341

3rd Qu.: 19.00	3rd Qu.: 32.00	3rd Qu.:317.2	3rd Qu.:1229.5	3rd Qu.:1440.0	3rd Qu.: 4.783
Max. :143.00	Max. :210.00	Max. :552.0	Max. :1440.0	Max. :1440.0	Max. :10.710

Lightly Active Minutes have very high values as compared to fairly active and very active minutes. The mean for lightly active minutes is around 193, around 14 times that of Fairly Active Minutes and 9 times that of Very Active Minutes

Sedentary minutes have very high values as compared to the Total Active Minutes. The Mean for sedentary minutes is around 4 times that of total active minutes.

```
kable(daily_activity_sleep[,13:17] %>% summary()) %>%
  kable_styling("striped")
```

ModActDist	VeryActDist	TotalDist	AsleepMin	TimeInBed
Min. :0.0000	Min. : 0.000	Min. : 0.000	Min. : 58.0	Min. : 61.0
1st Qu.:0.0000	1st Qu.: 0.000	1st Qu.: 2.540	1st Qu.:361.0	1st Qu.:403.8
Median :0.2400	Median : 0.210	Median : 5.175	Median :432.5	Median :463.0
Mean :0.5675	Mean : 1.503	Mean : 5.411	Mean :419.2	Mean :458.5
3rd Qu.:0.8000	3rd Qu.: 2.052	3rd Qu.: 7.638	3rd Qu.:490.0	3rd Qu.:526.0
Max. :6.4800	Max. :21.920	Max. :28.020	Max. :796.0	Max. :961.0
NA	NA	NA	NA's :530	NA's :530

The means for time in bed are and minutes asleep are very close to each other as expected.

The dataset sourced from the Sleep table exhibits 530 missing values. This discrepancy is logical, given that the Sleep table contained a total of 410 rows (after dropping the 3 duplicates), in contrast to the 940 rows present in the activities dataset.

The join operation was successful, as indicated by the presence of relevant columns and reasonably associated statistics. Furthermore, the data preview confirmed the accurate matching of the relevant columns.

2.2 Data Visualizations and Plots

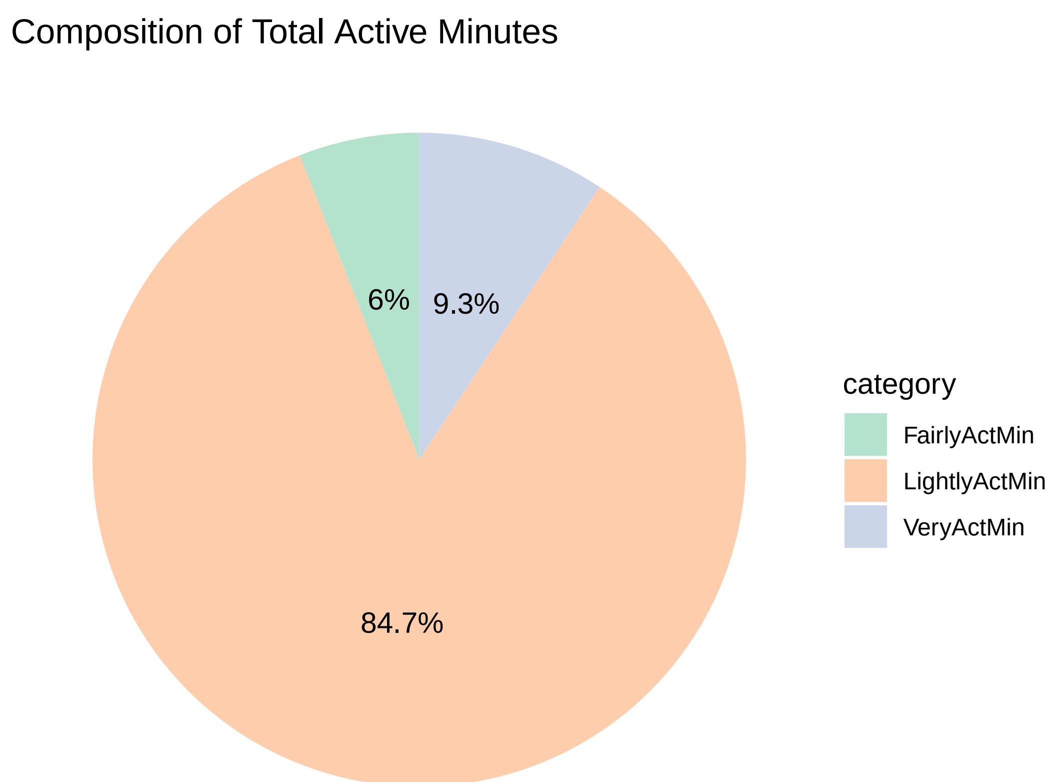
Noe that we have our data consolidated and cleaned, we can move forward with the Data Visualization

2.2.1 Reviewing Composition of Total Min, TotalActiveMin and TotalDist

2.2.1.1 Composition of Total Active Min

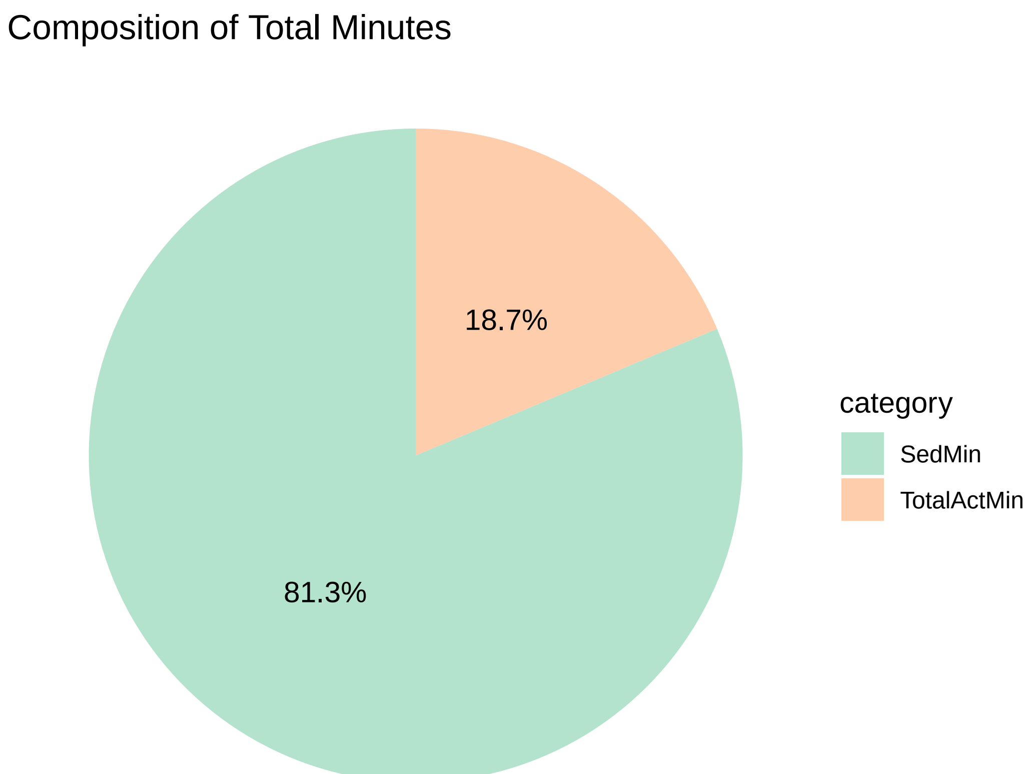
Recall that Total Active Minutes was created in the Join statement as the sum of Fairly Active Minutes, Lightly Active Miutes and Very Active Minutes .

```
# Identify data for the plot

# Select FairlyActMin, LightlyActMin, VeryActMin
# Use the apply function to sum all rows in each of the columns
# Add percentage as well
plot_data <- daily_activity_sleep[,c("FairlyActMin","LightlyActMin","VeryActMin")] %>%
  apply(2,sum) %>% as.data.frame() %>% setNames("value") %>%
  rownames_to_column("category") %>%
  mutate(percentage = value / sum(value) * 100) %>%
  arrange(value)

#Plot the data using geom_bar
ggplot(plot_data, aes(x = "", y = value, fill = category)) +
  geom_bar(stat = "identity", width = 1) + #stacked bar chart
  coord_polar(theta = "y") + #To convert the chart into a piechart
  theme_void() + # Removes background grid and axes
  labs(title = "Composition of Total Active Minutes") + #Add title
  geom_text(aes(label = paste0(round(percentage, 1), "%")),
            position = position_stack(vjust = 0.5)) + #Add labels for %age
  scale_fill_brewer(palette = "Pastel2")
```



2.2.1.2 Composition of Total Min Recall that Total Minutes was created in the Join statement as the sum of Total Active Minutes and Sedentary Minutes

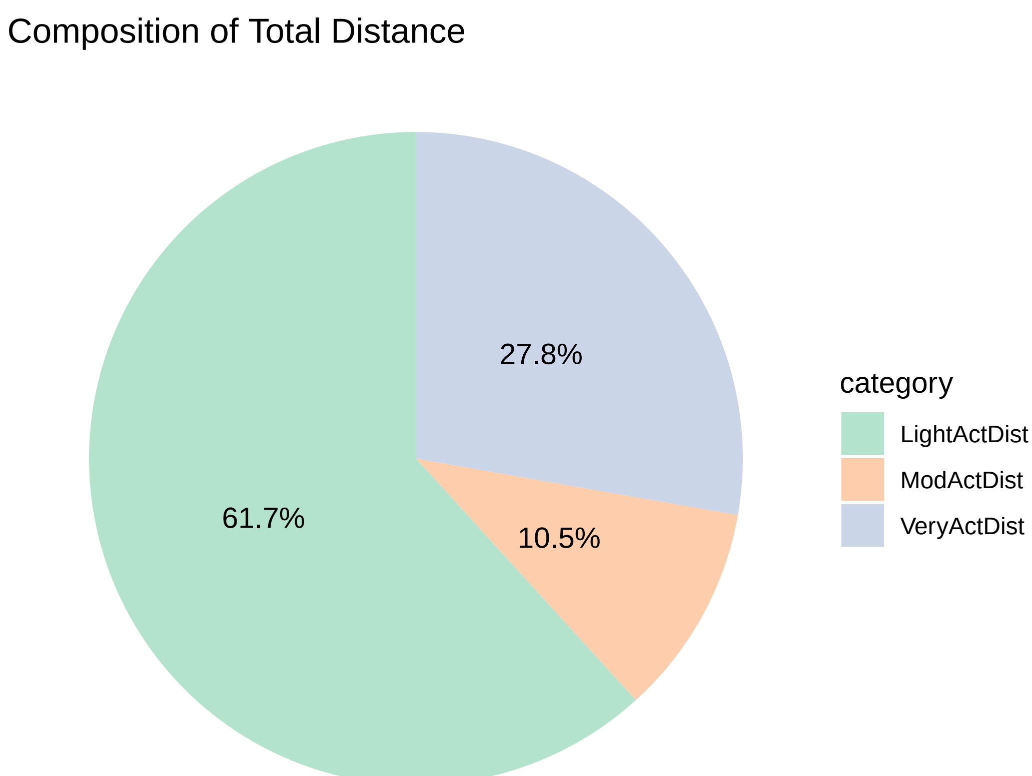
```
# Identify data for the plot

# Select TotalActiveMinutes and SedentaryMinutes
# Use the apply function to sum all rows in each of the columns
# Add percentage as well
plot_data <- daily_activity_sleep[,c("TotalActMin","SedMin")] %>%
  apply(2,sum) %>% as.data.frame() %>% setNames("value") %>%
  rownames_to_column("category") %>%
  mutate(percentage = value / sum(value) * 100) %>%
  arrange(value)

#Plot the data using geom_bar
ggplot(plot_data, aes(x = "", y = value, fill = category)) +
  geom_bar(stat = "identity", width = 1) + #stacked bar chart
  coord_polar(theta = "y") + #To convert the chart into a piechart
  theme_void() + # Removes background grid and axes
  labs(title = "Composition of Total Minutes") + #Add title
  geom_text(aes(label = paste0(round(percentage, 1), "%")),
            position = position_stack(vjust = 0.5)) + #Add labels for %age
  scale_fill_brewer(palette = "Pastel2")
```



2.2.1.3 Composition of Total Distance Recall that Total Minutes was created in the Join statement as the sum of Light Active Distance, Moderately Active Distance and Very Active Distance

```
# Identify data for the plot

# Select LightActDist, ModActDist, VeryActDist
```

```r
# Use the apply function to sum all rows in each of the columns
# Add percentage as well
plot_data <- daily_activity_sleep[,c("LightActDist","ModActDist","VeryActDist")] %>%
  apply(2,sum) %>% as.data.frame() %>% setNames("value") %>%
  rownames_to_column("category") %>%
  mutate(percentage = value / sum(value) * 100) %>%
  arrange(value)

#Plot the data using geom_bar
ggplot(plot_data, aes(x = "", y = value, fill = category)) +
  geom_bar(stat = "identity", width = 1) + #stacked bar chart
  coord_polar(theta = "y") + #To convert the chart into a piechart
  theme_void() + # Removes background grid and axes
  labs(title = "Composition of Total Distance") + #Add title
  geom_text(aes(label = paste0(round(percentage, 1), "%")),
            position = position_stack(vjust = 0.5)) + #Add labels for %age
  scale_fill_brewer(palette = "Pastel2")
```



2.2.2 Reviewing Distribution

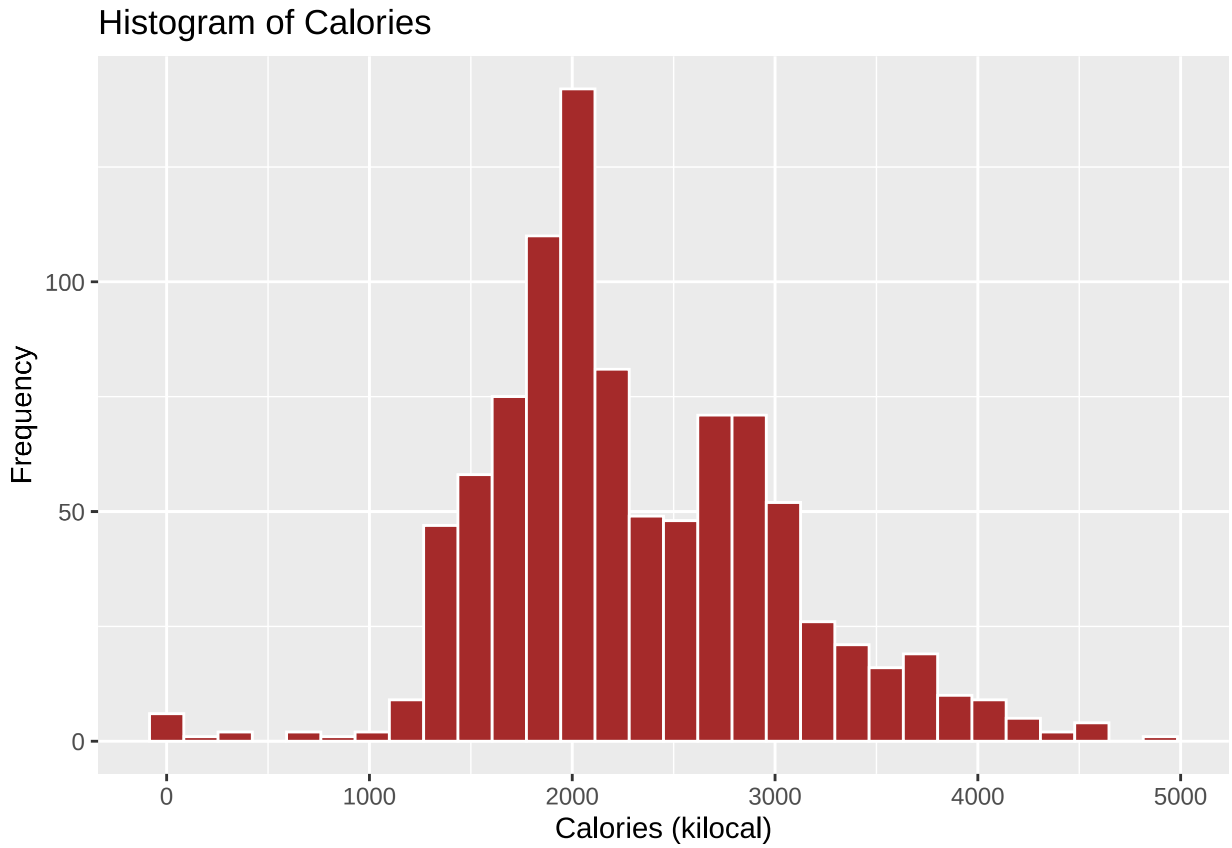
This section uses histograms to visually display the frequency distribution of different numerical indicators

[Compare to global avergaes] [Add line for global average]

```r
ggplot(daily_activity_sleep, aes(Calories)) +
 geom_histogram(fill = 'brown', color = 'white') +
  labs(title ="Histogram of Calories",
  x = 'Calories (kilocal)',
```

```
  y = "Frequency")
```

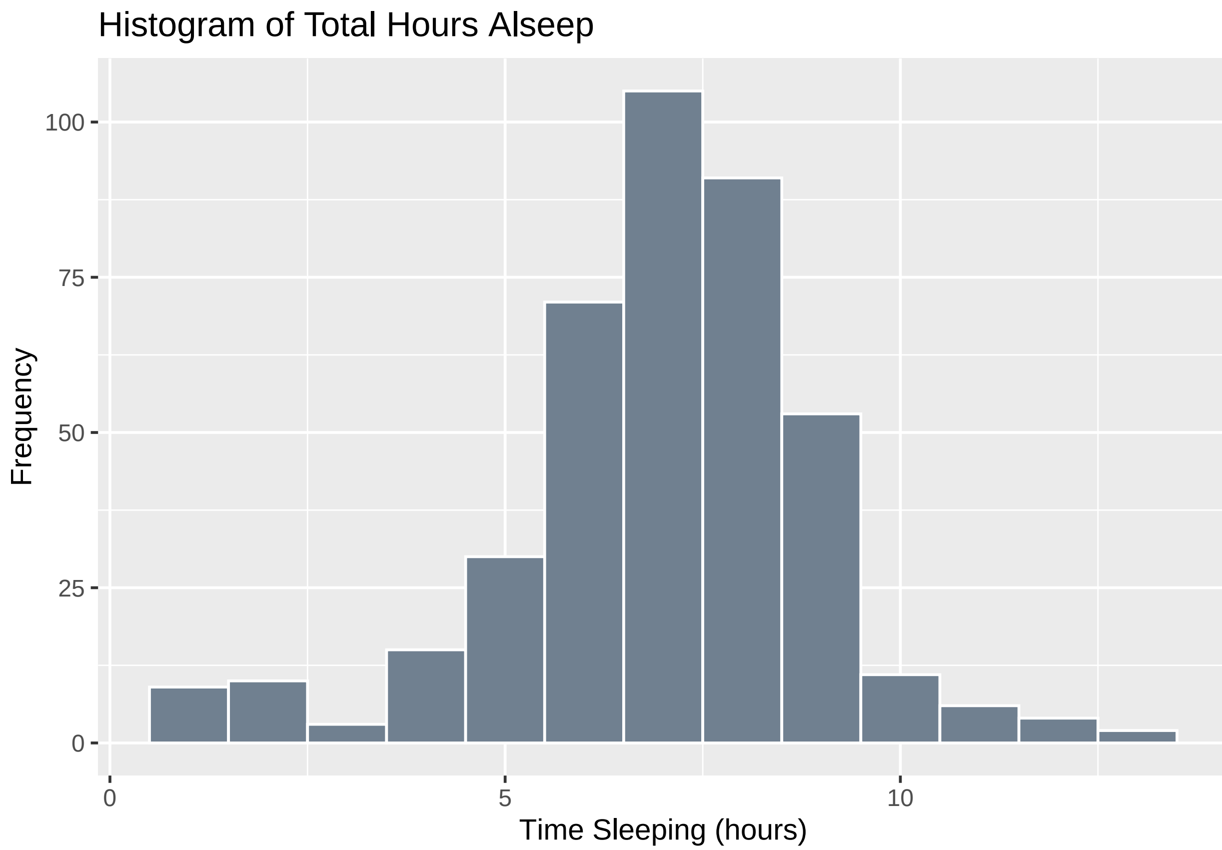
2.2.2.1 Calories



2.2.2.2 Total Hours Asleep

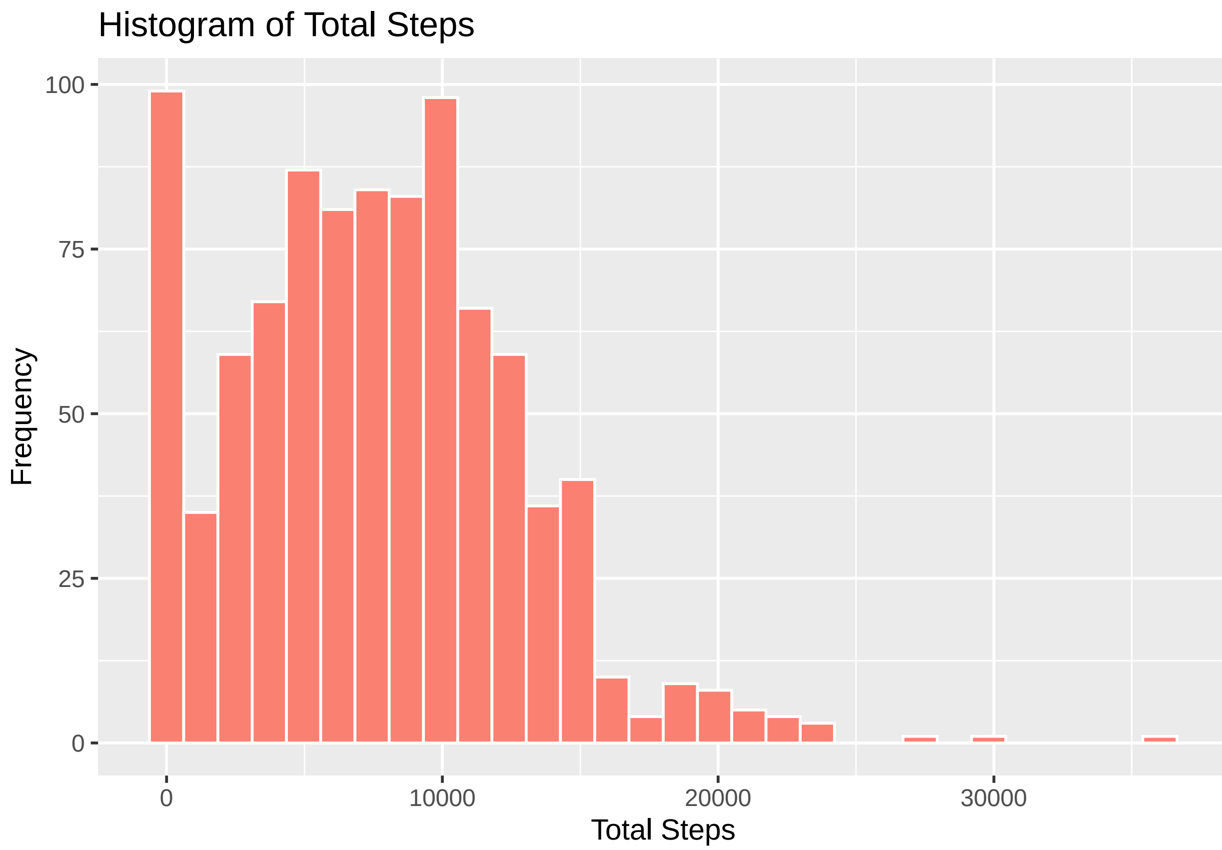
7-8 hours as recommended

```
ggplot(daily_activity_sleep, aes(AsleepMin/60)) +
 geom_histogram(fill = 'slategray', color = 'white', binwidth = 1) +
  labs(title ="Histogram of Total Hours Alseep",
  x = 'Time Sleeping (hours)',
  y = "Frequency")
```



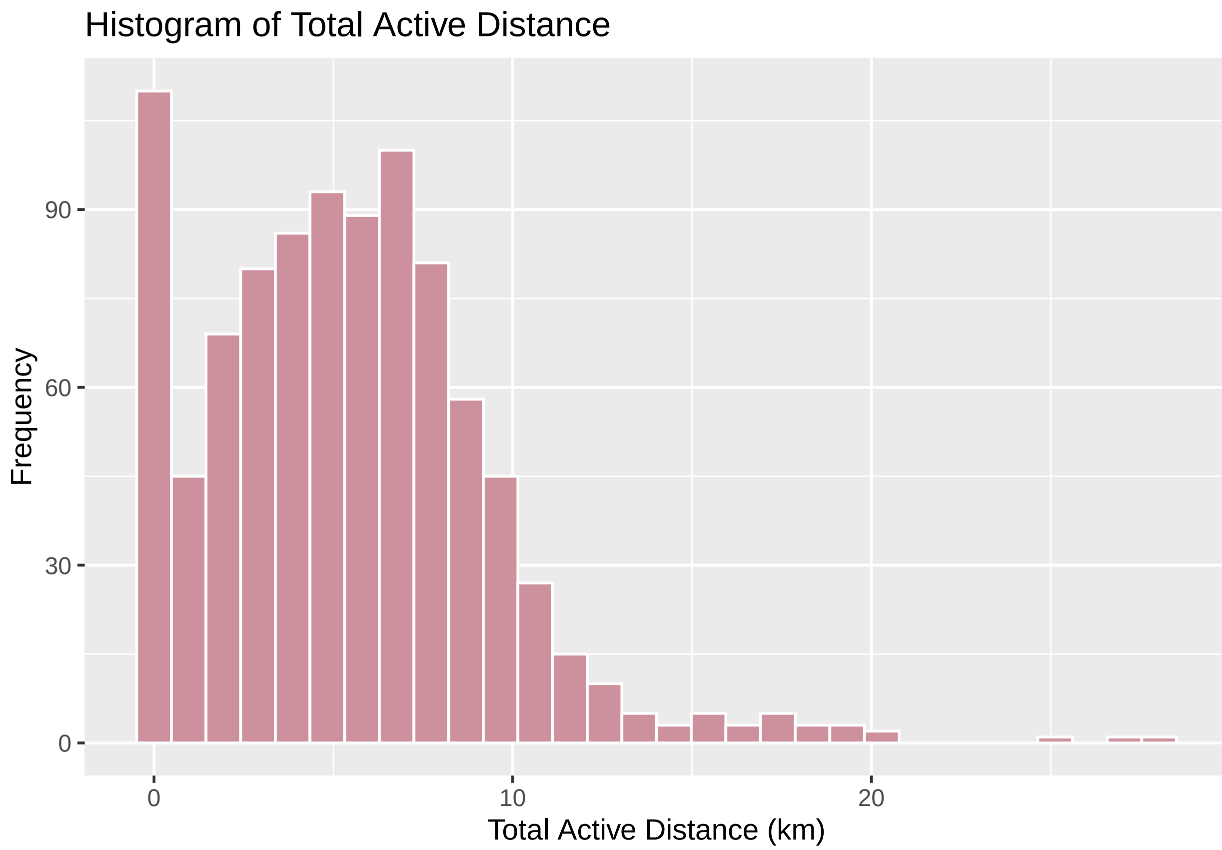
2.2.2.3 Total Steps Most people are covering the daily goal of 5000-7000 steps

```
ggplot(daily_activity_sleep, aes(Steps)) +
 geom_histogram(fill = 'salmon', color = 'white') +
  labs(title ="Histogram of Total Steps",
  x = 'Total Steps',
  y = "Frequency")
```




```
ggplot(daily_activity_sleep, aes(TotalDist)) +
 geom_histogram(fill = 'pink3', color = 'white') +
  labs(title ="Histogram of Total Active Distance",
  x = "Total Active Distance (km)",
  y = "Frequency")
```

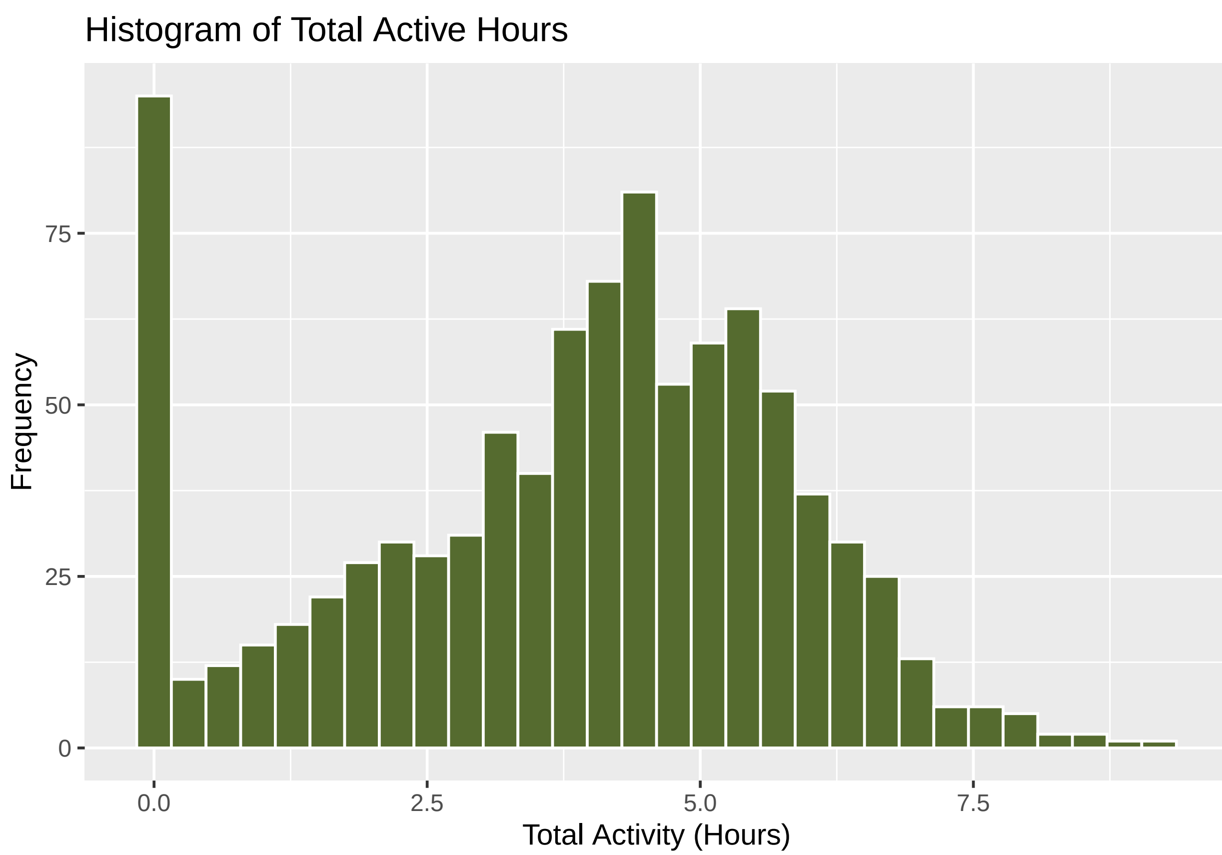
2.2.2.4 Total Active Distance




```
ggplot(daily_activity_sleep, aes(TotalActMin/60)) +
 geom_histogram(fill = 'darkolivegreen', color = 'white') +
  labs(title ="Histogram of Total Active Hours",
  x = "Total Activity (Hours)",
  y = "Frequency")
```

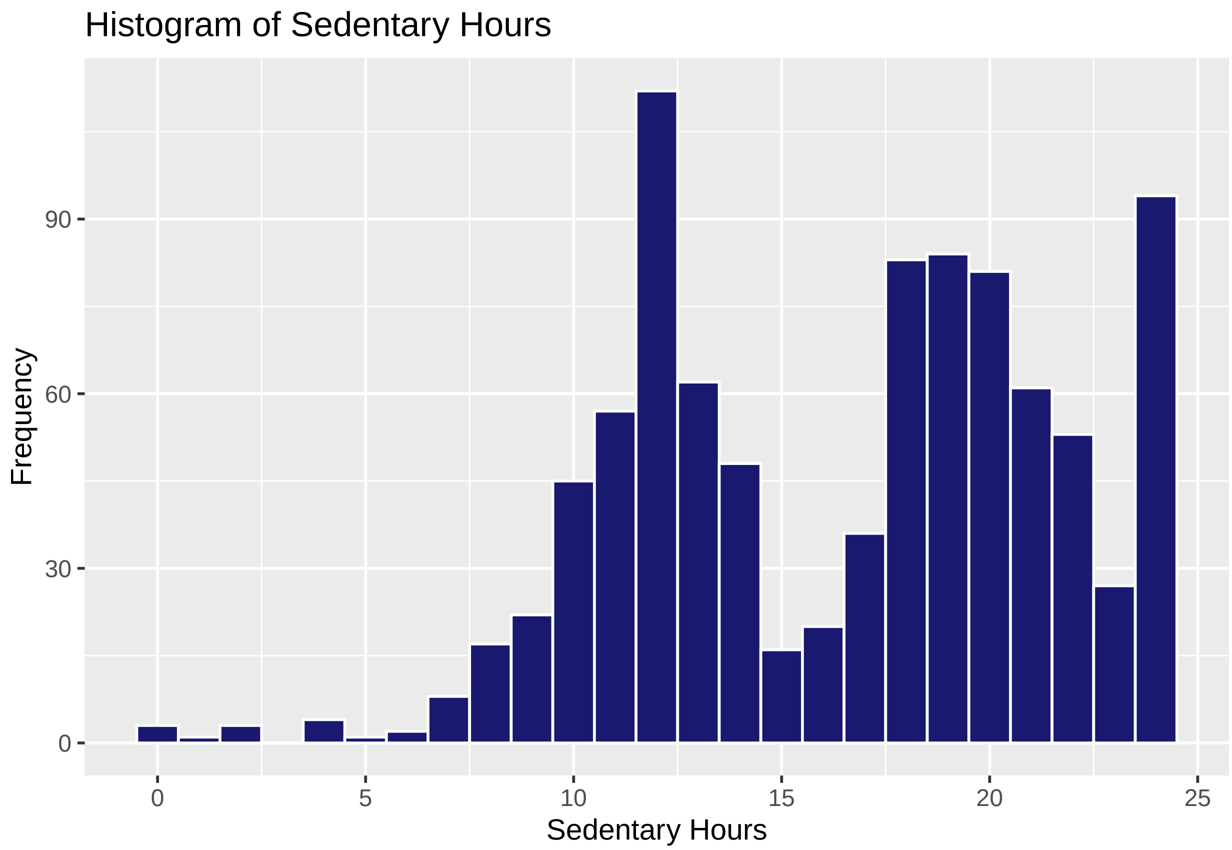
2.2.2.5 Total Active Hours

```
## `stat_bin()` using `bins = 30`. Pick better value `binwidth`.
```




```r
ggplot(daily_activity_sleep, aes(SedMin/60)) +
 geom_histogram(fill = 'midnightblue', color = 'white', binwidth = 1) +
  labs(title ="Histogram of Sedentary Hours",
  x = "Sedentary Hours",
  y = "Frequency")
```

2.2.2.6 Total Sedentary Hours

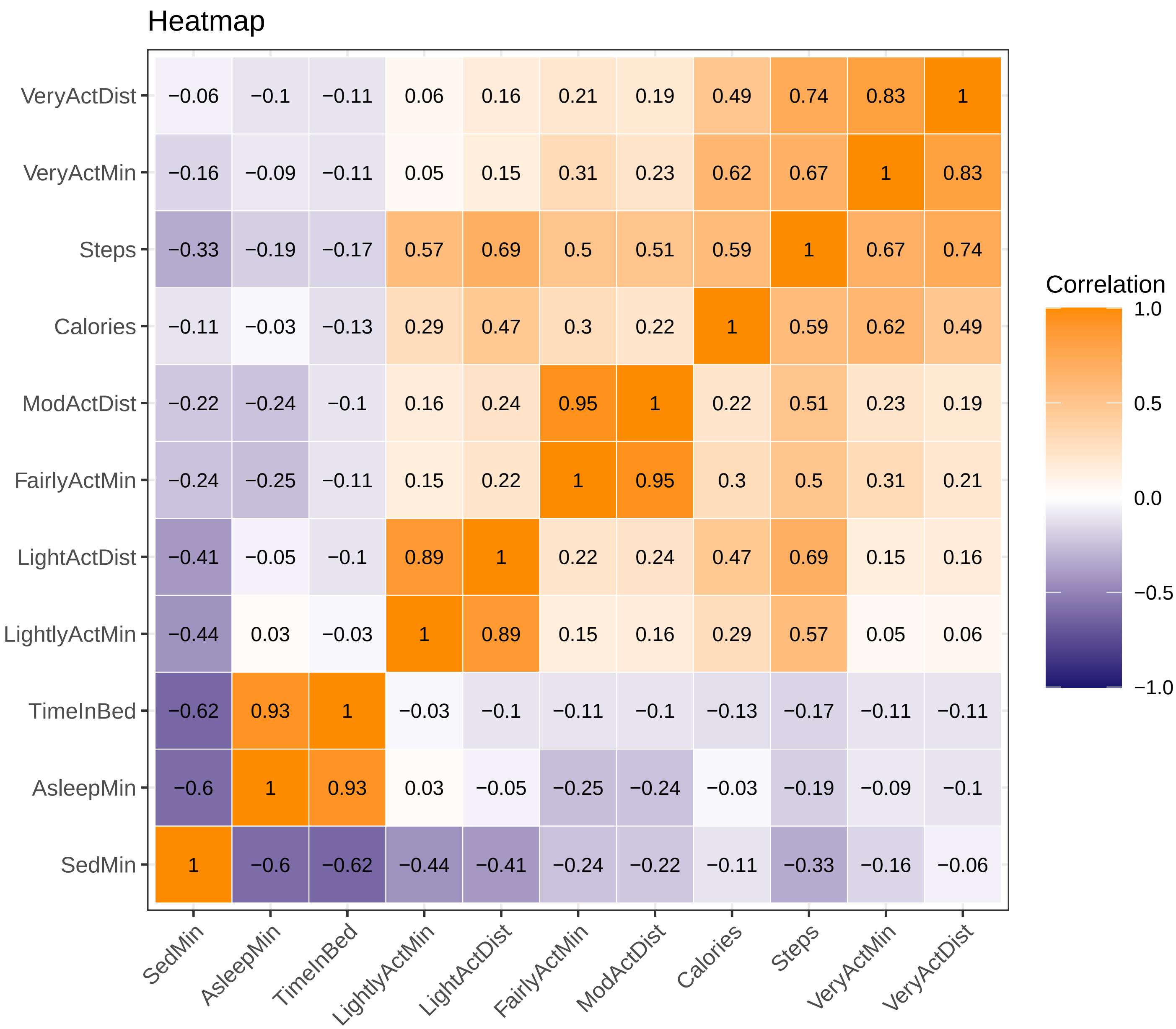


2.2.3 Identifying Relationships

2.2.3.1 Correlation Matrix Heat Map

Exlcude columns we created that are a sum of other variables

```
data_corr <- daily_activity_sleep %>%
  relocate(TotalMin, TotalDist, TotalActMin) #relocate columns to be excluded
                                            # to the beginning
# Create correlation matrix
corr_matrix <- cor(data_corr[,7:17], #Only select numeric data
                   use="pairwise.complete.obs") %>%
  round(2) #round correlation matrix

ggcorrplot(corr_matrix,
           method='square',
           hc.order = TRUE,    # Automatic hierarchical clustering
           colors = c("midnightblue", "white", "darkorange"),
           lab = TRUE,         # Add correlation coefficients
           outline.color='white', #Add outline color
           lab_size = 3.2,      # Adjust label size
           tl.cex = 10,   # Adjust textlabel size
           legend.title='Correlation', #Add legend title
           ggtheme = ggplot2::theme_bw, # Set theme
           title= 'Heatmap') +
           theme(legend.key.size = unit(1.2, "cm")) #Set legend size
```



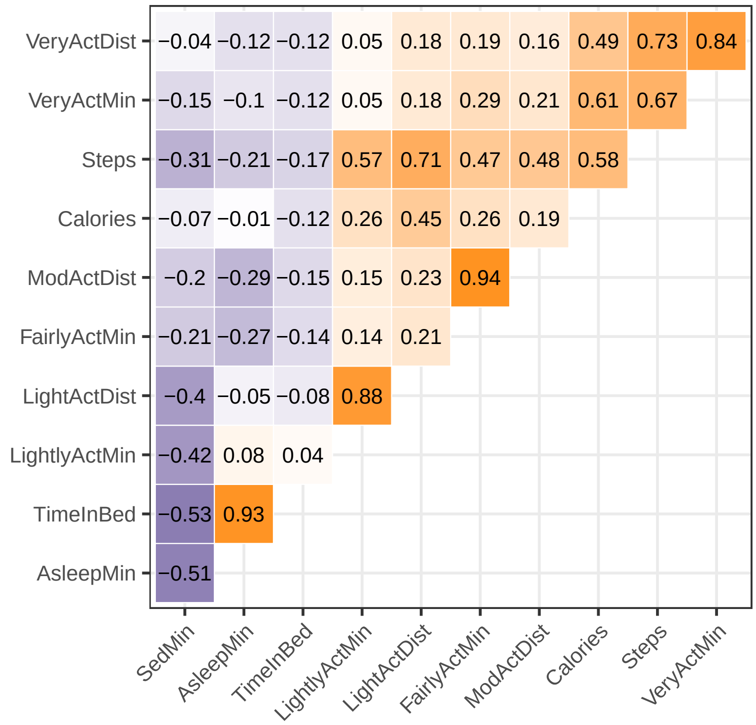
sed minutes has strongest corr with light active min, negative correlations with all fairlyact min with asleep in bed calories and vactive min, steps and vactivemin (plots) strong corr with min and distance shows that people are walkers (plot total act min and distance)

Weekdays Vs Weekend

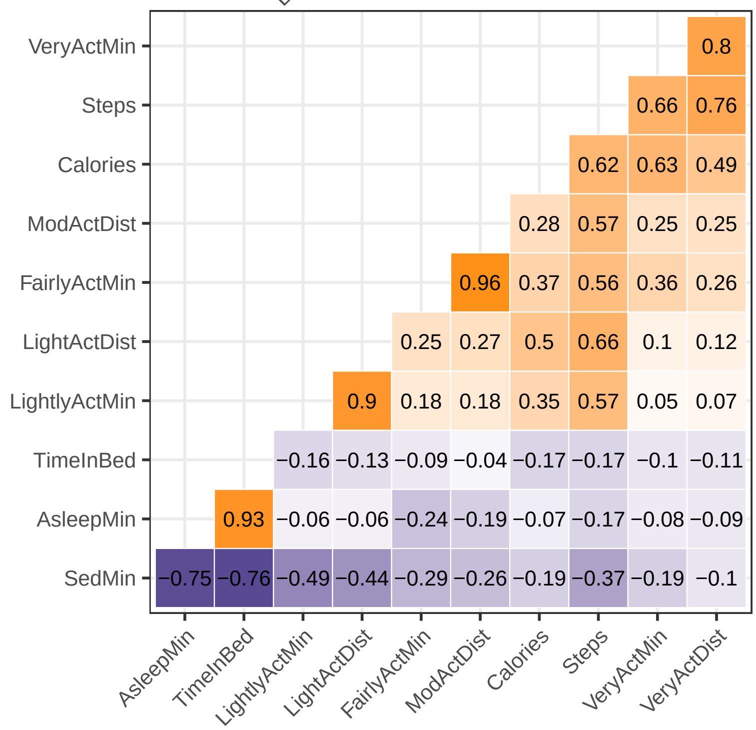
```
# correlation matrix with data filtered for weekday
corr_mat_wd <- cor(data_corr %>% filter(DayType == 'Weekday')  %>% .[,7:17],
                   use="pairwise.complete.obs")  %>% round(2)

#fcorrelation matrix with data filtered for weekend
corr_mat_wend <- cor(data_corr %>% filter(DayType == 'Weekend') %>% .[,7:17],
                     use="pairwise.complete.obs") %>% round(2)

p1 <- ggcorrplot(corr_mat_wd,
           method='square',
```

```
           type='upper',
           hc.order = TRUE,
           colors = c("midnightblue", "white", "darkorange"),
           lab = TRUE,
           outline.color='white',
           lab_size = 2.8,
           tl.cex = 8,
           ggtheme = ggplot2::theme_bw,
           show.legend=FALSE) + theme(plot.margin = unit(c(0, 0, 0, 0), "cm"))

p2 <- ggcorrplot(corr_mat_wend,
           method='square',
           type='lower',
           hc.order = TRUE,
           colors = c("midnightblue", "white", "darkorange"),
           lab = TRUE,
           outline.color='white',
           lab_size = 2.8,
           tl.cex = 8,
           ggtheme = ggplot2::theme_bw,
           show.legend = FALSE) + theme(plot.margin = unit(c(0, 0, 0, 0), "cm"))

plot_grid(p1, p2, ncol = 1, labels = c('Weekday', 'Weekend'), label_size = 12)
```

Weekday



Weekend



Calories and sed minutes; relationship stronger on weekends

Maximum differentials of correlations

```
data.frame(Max=apply(abs(corr_mat_wend-corr_mat_wd),2,max)) %>%
  arrange(desc(Max)) %>% kable(booktabs=TRUE) %>% kable_styling("striped")  %>%
  row_spec(1:5, bold=TRUE , background ='#FA8072') #highlight top 5 rows
```

	Max
SedMin	**0.24**
AsleepMin	**0.24**
TimeInBed	**0.23**
LightlyActMin	**0.20**
Calories	**0.12**
FairlyActMin	0.11
ModActDist	0.11
Steps	0.09
VeryActDist	0.09
VeryActMin	0.08
LightActDist	0.08

as expected sed min, min asleep and time in bed have biggest changes

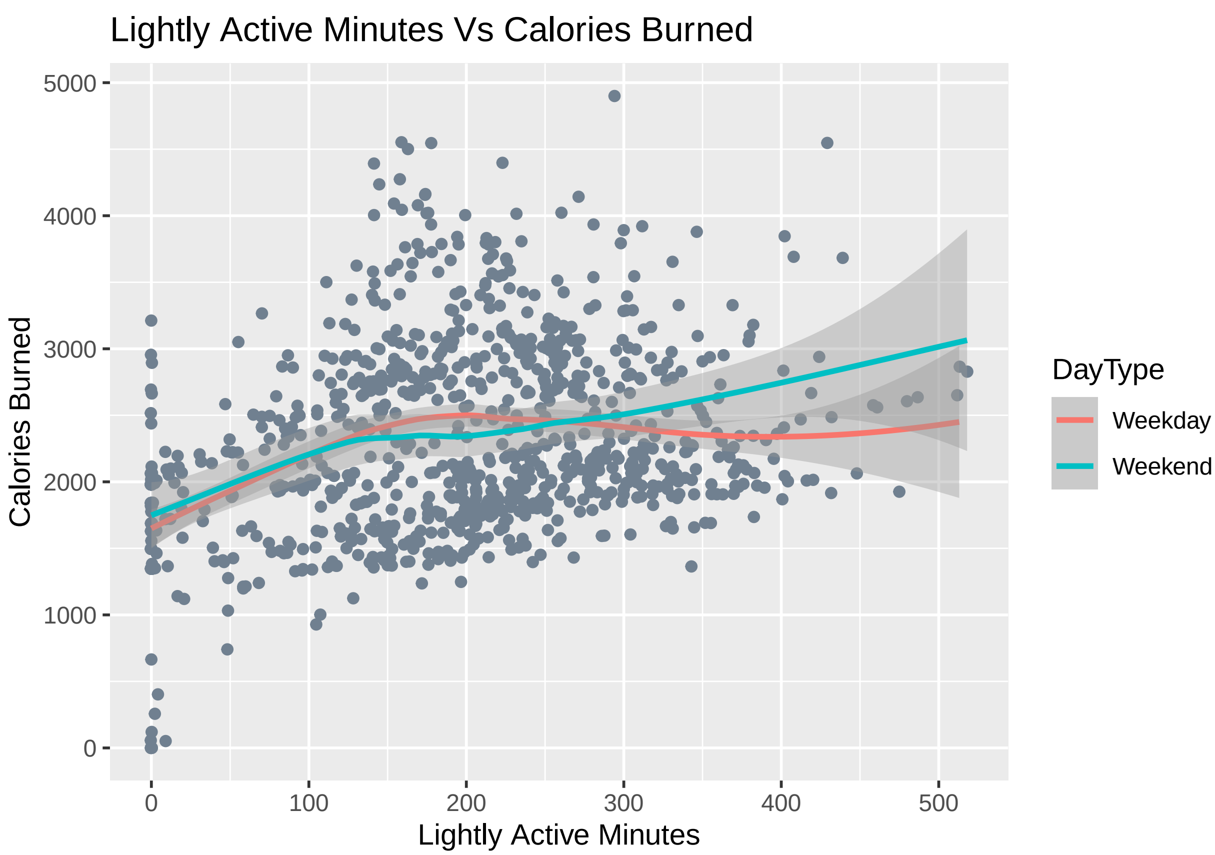
light act min and calories also saw come changes

```
# Calculate differences in correlations
# Sort by sedentary minutes as this is the column that showed the highest changes
# Once sorted all the relevant information was in the top 3 rows for sedentary
# minutes and lightlyactiveminutes so we will limit our view to that

data.frame(abs(corr_mat_wend-corr_mat_wd)) %>% arrange(desc(SedMin)) %>%
 .[1:5,c("SedMin","LightlyActMin")] %>%
   kable() %>%  kable_styling("striped")
```

	SedMin	LightlyActMin
AsleepMin	0.24	0.14
TimeInBed	0.23	0.20
Calories	0.12	0.09
FairlyActMin	0.08	0.04
LightlyActMin	0.07	0.00

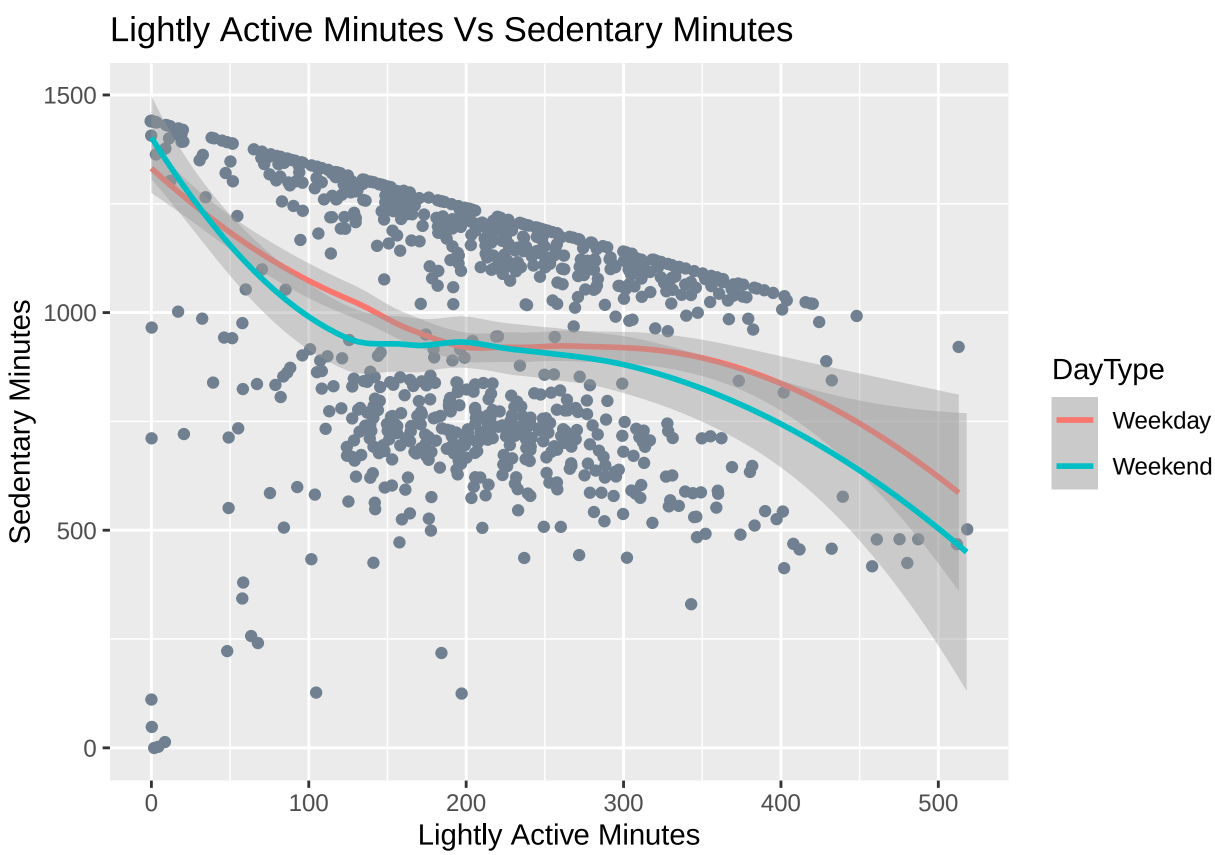
```
ggplot(data=daily_activity_sleep) +
geom_jitter(aes(x=LightlyActMin,y=Calories), color='slategray') +
geom_smooth(aes(x=LightlyActMin,y=Calories, color=DayType)) +
#coord_cartesian(xlim = c(0, 25000), ylim = c(0, 820)) +
labs(
    x = "Lightly Active Minutes", # New x-axis title
    y = "Calories Burned", # New y-axis title
    title = "Lightly Active Minutes Vs Calories Burned"
  )
```

2.2.3.2 Lightly Active Minutes and Calories Burned



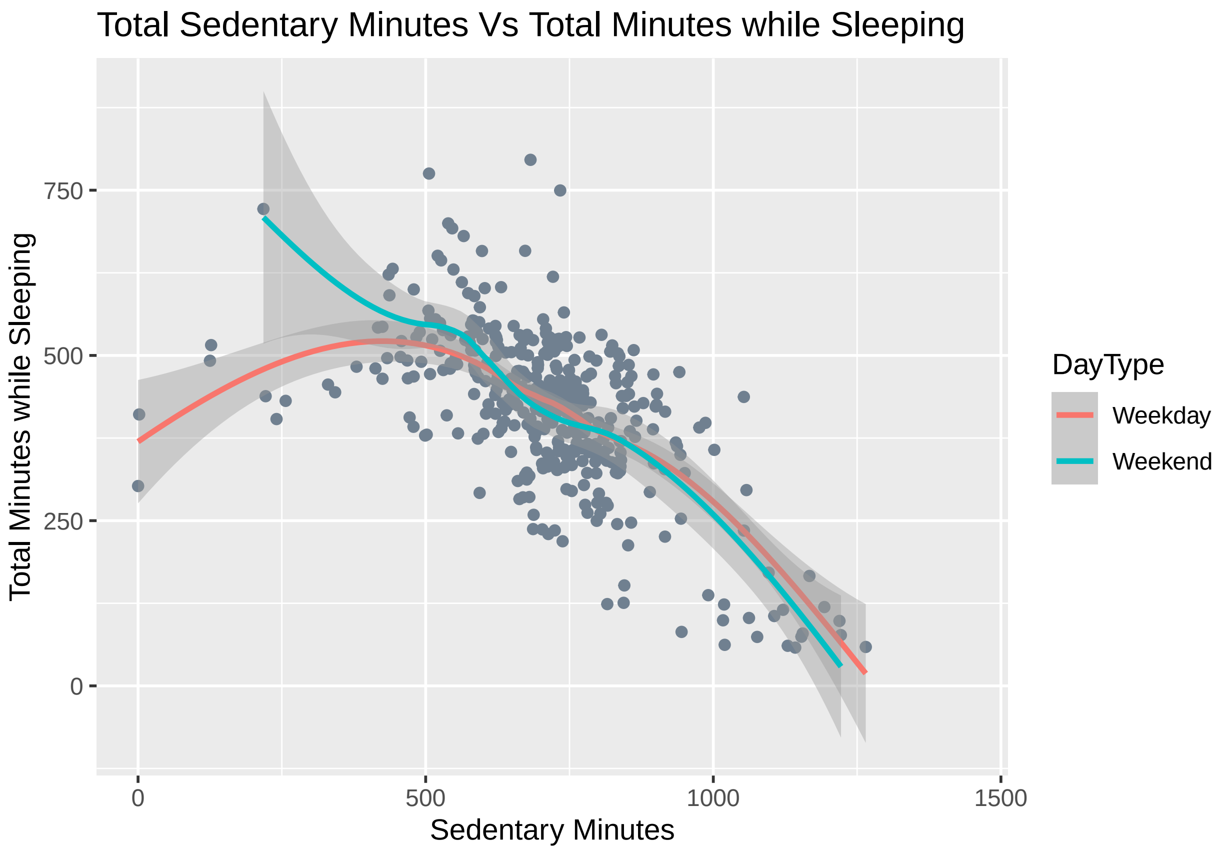

```
ggplot(data=daily_activity_sleep) +
geom_jitter(aes(x=LightlyActMin,y=SedMin), color='slategray') +
geom_smooth(aes(x=LightlyActMin,y=SedMin, color=DayType)) +
#coord_cartesian(xlim = c(0, 25000), ylim = c(0, 820)) +
labs(
    x = "Lightly Active Minutes", # New x-axis title
    y = "Sedentary Minutes", # New y-axis title
    title = "Lightly Active Minutes Vs Sedentary Minutes"
  )
```

2.2.3.3 Lightly Active Minutes and Sedentary Minutes




```
ggplot(data=daily_activity_sleep) +
geom_jitter(aes(x=SedMin,y=AsleepMin),color='slategray') +
geom_smooth(aes(x=SedMin,y=AsleepMin,color=DayType)) +
labs(
    x = "Sedentary Minutes", # New x-axis title
    y = "Total Minutes while Sleeping", # New y-axis title
    title = "Total Sedentary Minutes Vs Total Minutes while Sleeping"
  )
```

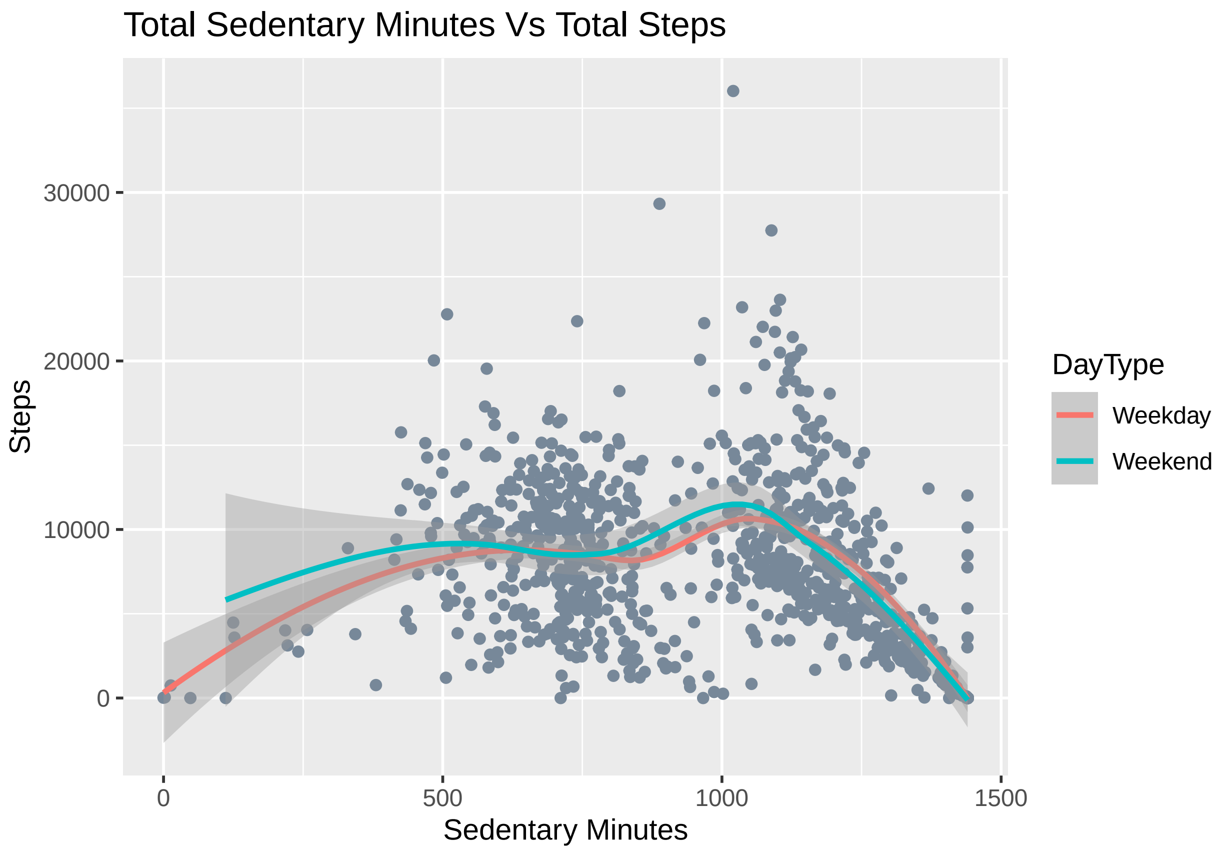
2.2.3.4 Total Minutes Asleep and Sedentary Minutes



very strong for weekends as compared to weekday. sharp fall for both for those days when an indivdual had high amount of sdeneatrt minutes. weekends: relaxing, watching movies, reading books, scrolling social media

```
ggplot(data=daily_activity_sleep) +
geom_jitter(aes(x=SedMin, y=Steps), color='lightslategray') +
geom_smooth(aes(x=SedMin, y=Steps, color=DayType)) +
  labs(
    x = "Sedentary Minutes", # New x-axis title
    y = "Steps", # New y-axis title
    title = "Total Sedentary Minutes Vs Total Steps"
  )
```

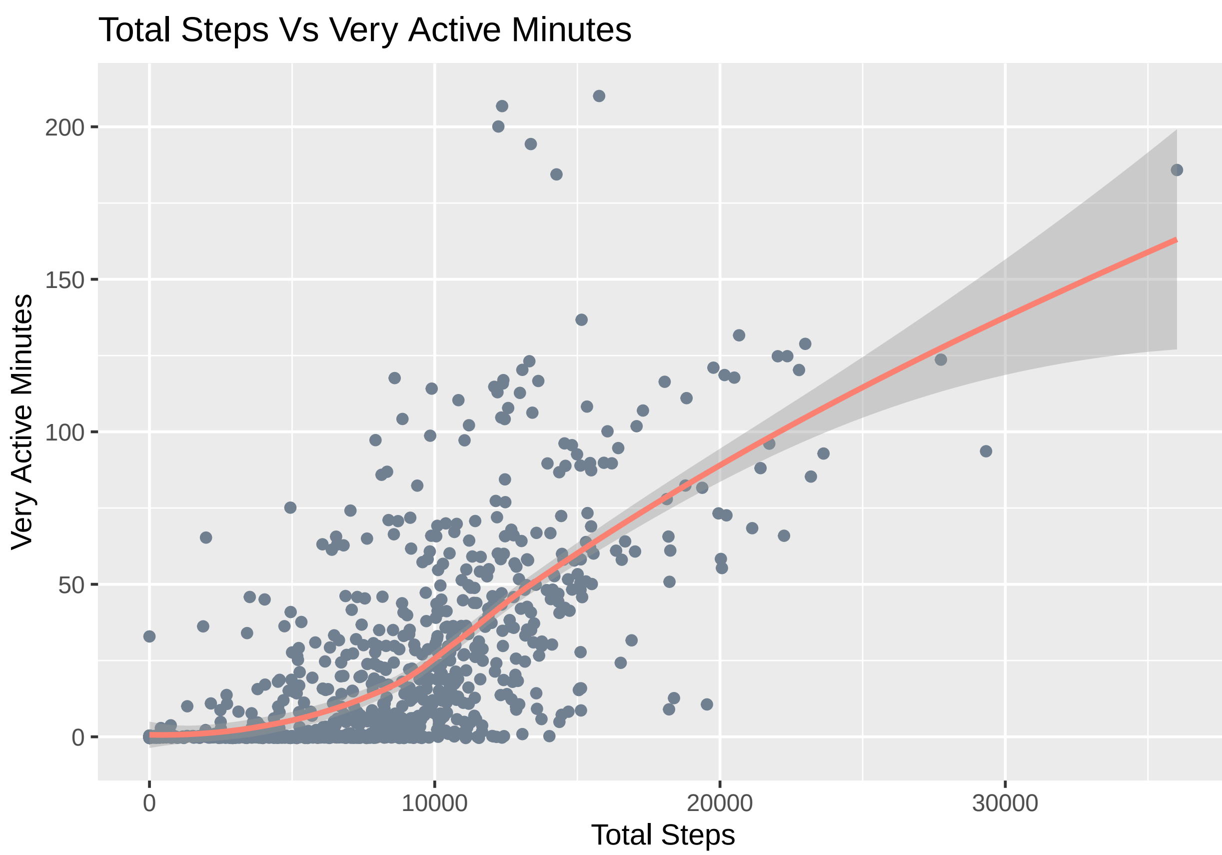
2.2.3.5 Sedentary Minutes and Total Steps



- Days when sedenatry minutes are upto 500, total steps also increase and total time asleep also increases
- Days when sedenatry minutes are more 1000, total steps also decrease and total time asleep also increases

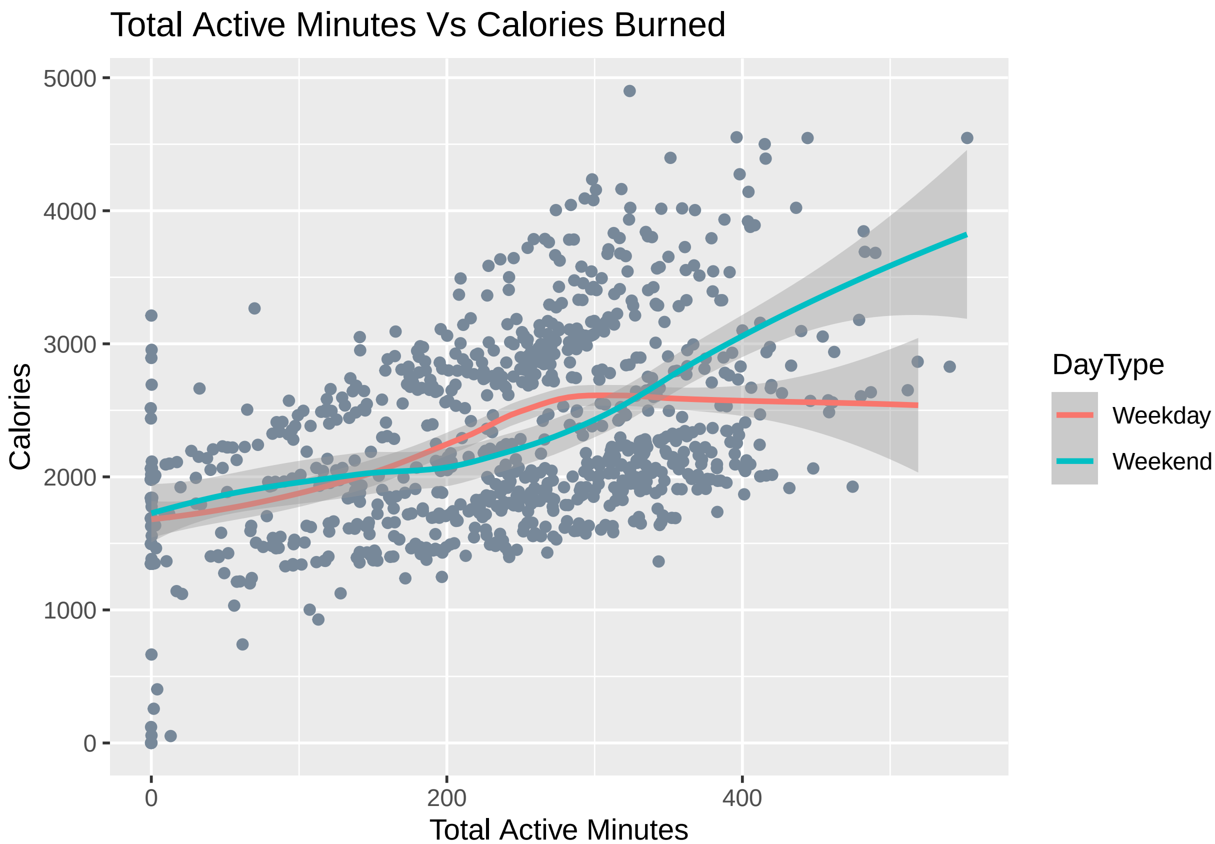
```
ggplot(data=daily_activity_sleep) +
geom_jitter(aes(x=Steps,y=VeryActMin), color='slategray') +
geom_smooth(aes(x=Steps,y=VeryActMin), color='salmon',) +
labs(
    x = "Total Steps", # New x-axis title
    y = "Very Active Minutes", # New y-axis title
    title = "Total Steps Vs Very Active Minutes"
  )
```

2.2.3.6 Very Active Min and Total Steps




```
ggplot(data=daily_activity_sleep) +
geom_jitter(aes(x=TotalActMin,y=Calories), color='lightslategray') +
geom_smooth(aes(x=TotalActMin,y=Calories, color=DayType)) +
  labs(
    x = "Total Active Minutes", # New x-axis title
    y = "Calories", # New y-axis title
    title = "Total Active Minutes Vs Calories Burned"
  )
```

2.2.3.7 Total Active Minutes and Calories



steep rise on weekends

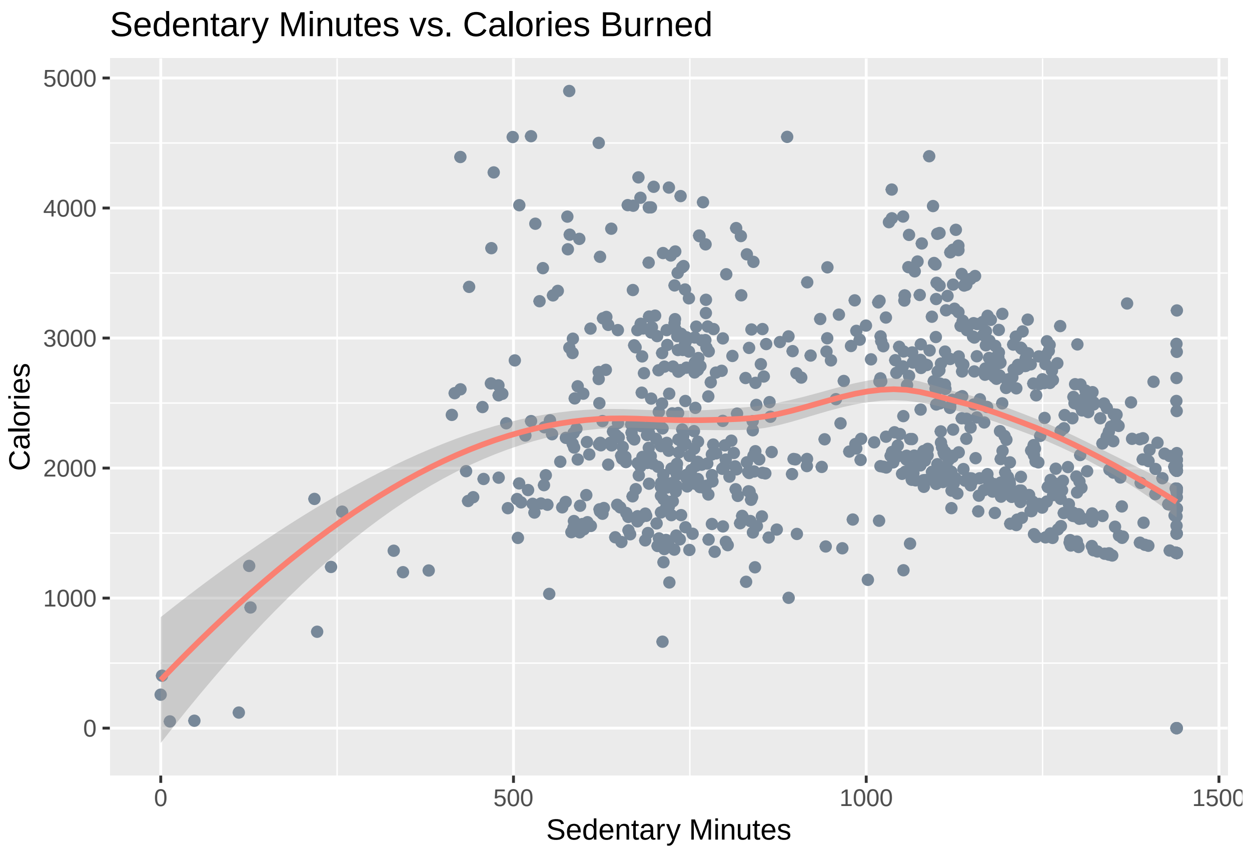
```
ggplot(data=daily_activity_sleep,) +
geom_jitter(aes(x=Steps,y=Calories), color='lightslategray') +
geom_smooth(aes(x=Steps,y=Calories), color='salmon') +
  labs(title = "Total Steps vs. Calories Burned")
```

2.2.3.8 Total Steps and Calories

very sharp trend

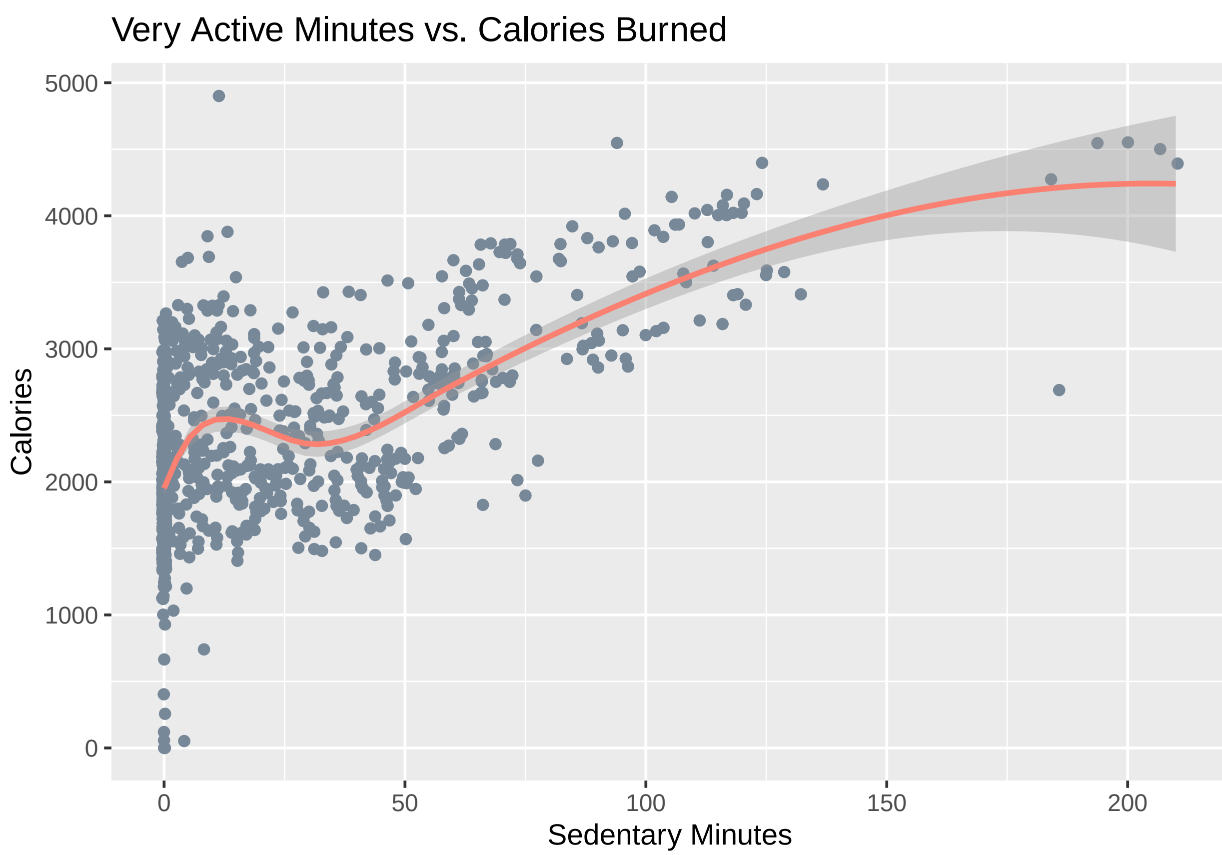
```
ggplot(data=daily_activity_sleep,) +
geom_jitter(aes(x=SedMin,y=Calories), color='lightslategray') +
geom_smooth(aes(x=SedMin,y=Calories), color='salmon') +
  labs(title = "Sedentary Minutes vs. Calories Burned", x="Sedentary Minutes")
```

2.2.3.9 Sedentary Minutes and Calories




```
ggplot(data=daily_activity_sleep,) +
geom_jitter(aes(x=VeryActMin,y=Calories), color='lightslategray') +
geom_smooth(aes(x=VeryActMin,y=Calories), color='salmon') +
  labs(title = "Very Active Minutes vs. Calories Burned", x="Sedentary Minutes")
```

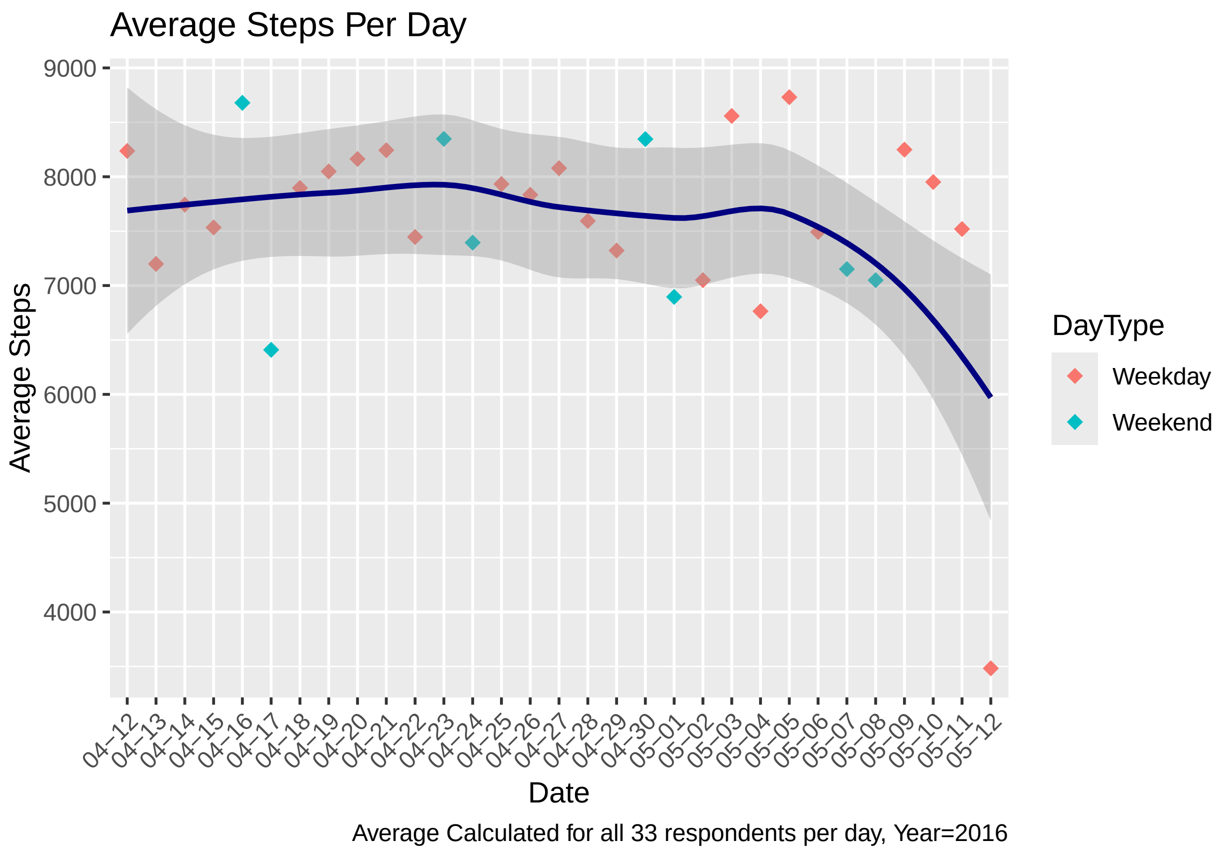
2.2.3.10 Very Active Minutes and Calories



2.2.4 Looking at Time Trends

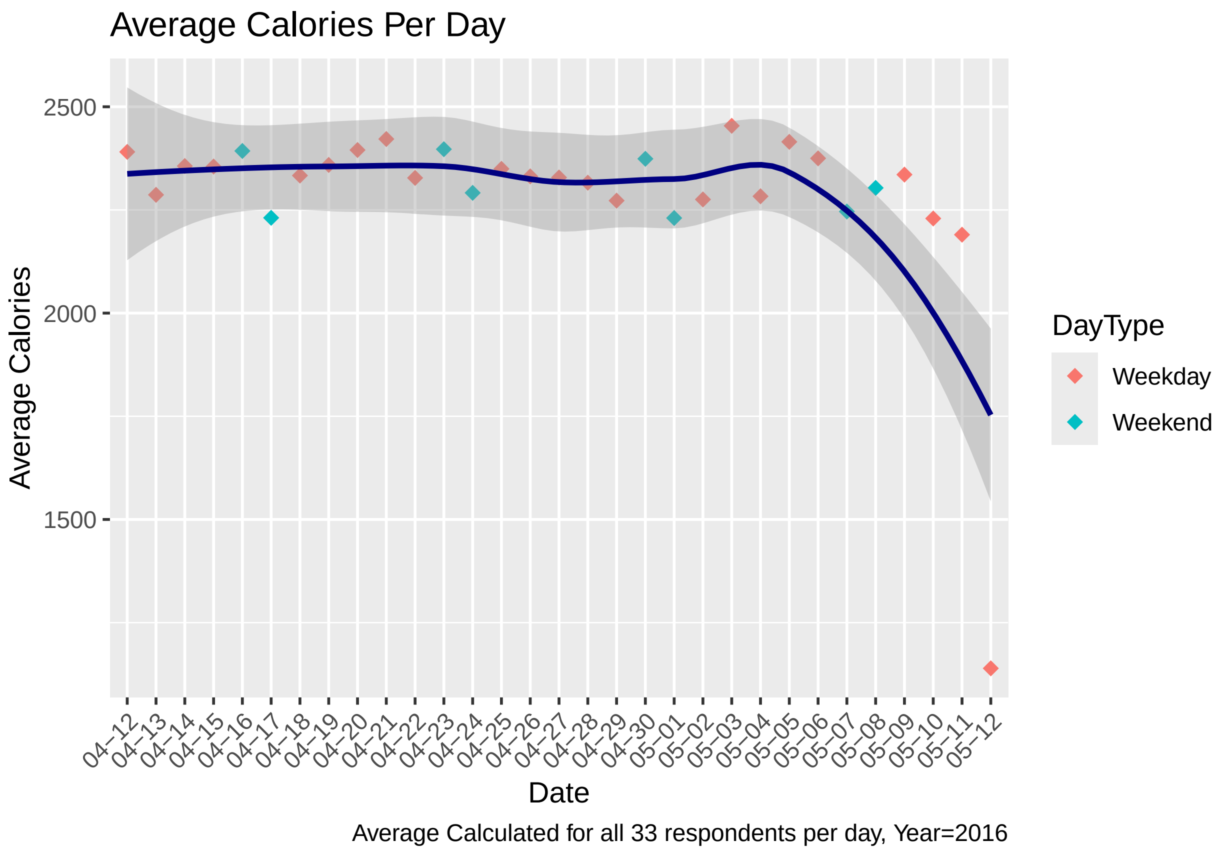
```
daily_activity_sleep %>% group_by(RecordedDate,DayType) %>%
  summarise(daily_avg= mean(Steps), .groups = 'drop') %>% #Calculate mean per day
  ggplot(aes(x=format(as.Date(RecordedDate), format = "%m-%d"), #format date to just month-day as 2016
             y=daily_avg, group = 1, color=DayType)) +
  geom_point(shape=18, size=2.5) +
  geom_smooth(color = "navyblue") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1)) +
  labs(
    x = "Date", # New x-axis title
    y = "Average Steps", # New y-axis title
    title = "Average Steps Per Day",
    caption = "Average Calculated for all 33 respondents per day, Year=2016"
  )
```

2.2.4.1 Daily Mean of Total Steps



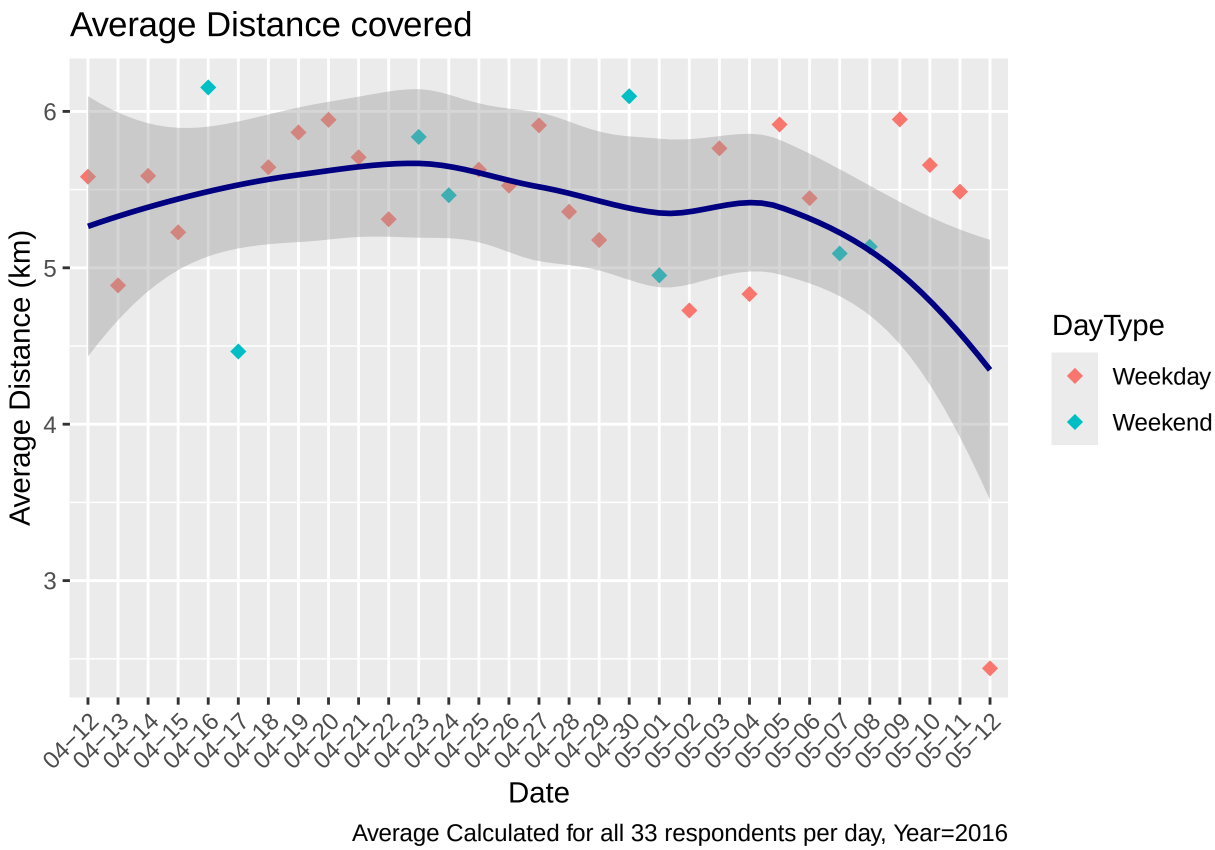

```
daily_activity_sleep %>% group_by(RecordedDate,DayType) %>%
  summarise(daily_avg= mean(Calories), .groups = 'drop') %>% #Calculate mean per day
  ggplot(aes(x=format(as.Date(RecordedDate), format = "%m-%d"), #format date to just month-day as 2016
             y=daily_avg, group = 1, color=DayType)) +
  geom_point(shape=18, size=2.5) +
  geom_smooth(color = "navyblue") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1)) +
  labs(
    x = "Date", # New x-axis title
    y = "Average Calories", # New y-axis title
    title = "Average Calories Per Day",
    caption = "Average Calculated for all 33 respondents per day, Year=2016"
  )
```

2.2.4.2 Daily Mean of Total Calories Burned




```r
daily_activity_sleep %>% group_by(RecordedDate,DayType) %>%
  summarise(daily_avg= mean(TotalDist), .groups = 'drop') %>% #Calculate mean per day
  ggplot(aes(x=format(as.Date(RecordedDate), format = "%m-%d"), #format date to just month-day as 2016
             y=daily_avg, group = 1, color=DayType)) +
  geom_point(shape=18, size=2.5) +
  geom_smooth(color = "navyblue") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1)) +
  labs(
    x = "Date", # New x-axis title
    y = "Average Distance (km)", # New y-axis title
    title = "Average Distance covered",
    caption = "Average Calculated for all 33 respondents per day, Year=2016"
  )
```

2.2.4.3 Daily Mean of Total Distance Covered




```
daily_activity_sleep %>%
  group_by(RecordedDate, DayType) %>%
  summarize(Observations = n(), .groups = 'drop') %>% arrange(Observations) %>%
  head(8) %>% kable(booktabs = TRUE) %>% kable_styling("striped")
```

RecordedDate	DayType	Observations
2016-05-12	Weekday	21
2016-05-11	Weekday	24
2016-05-10	Weekday	26
2016-05-08	Weekend	27
2016-05-09	Weekday	27
2016-05-02	Weekday	29
2016-05-03	Weekday	29
2016-05-04	Weekday	29

3 Part 2: Hourly Level Analysis

3.1 Data Processing and Cleaning

3.1.1 Column Types and Descriptions

Review column names in all 3 tables

```
PRAGMA table_info(hourlyintensities_merged)
```

Table 27: 4 records

cid	name	type	notnull	dflt_value	pk
0	Id	REAL	0	NA	0
1	ActivityHour	TEXT	0	NA	0
2	TotalIntensity	INTEGER	0	NA	0
3	AverageIntensity	REAL	0	NA	0

```
PRAGMA table_info(hourlysteps_merged)
```

Table 28: 3 records

cid	name	type	notnull	dflt_value	pk
0	Id	REAL	0	NA	0
1	ActivityHour	TEXT	0	NA	0
2	StepTotal	INTEGER	0	NA	0

```
PRAGMA table_info(hourlycalories_merged)
```

Table 29: 3 records

cid	name	type	notnull	dflt_value	pk
0	Id	REAL	0	NA	0
1	ActivityHour	TEXT	0	NA	0
2	Calories	INTEGER	0	NA	0

Id and ActivityHour are in all 3 tables which can be used to join the tables

Description obtained from this link

```
datadescription <- read_excel("datadescription.xlsx", sheet='Hourly')
kable(datadescription) %>%
  kable_styling("striped") %>% column_spec(2, width = "12cm")
```

Data Header	Data Description
ActivityHour	Date and hour value in mm/dd/yyyy hh:mm:ss format.
TotalIntensity	Value calculated by adding all the minute-level intensity values that occurred within the hour
AverageIntensity	Average intensity state exhibited during that hour (TotalIntensity for that ActivityHour divided by 60).
StepTotal	Total number of steps taken.

Calories	Total number of estimated calories burned.

[add table for describing column names]

3.1.2 Unique ID's in each table

The following SQL query checks the number of unique ID's in each table

```
SELECT        -- Intensities Table
  'HourlyIntensities' AS DataIndicator, -- Data indicators representing each table
    COUNT(DISTINCT Id) AS UniqueIds  -- Count of Unique IDs
FROM
    hourlyintensities_merged
UNION
SELECT      -- Process Repeated for Steps
    'HourlySteps' AS DataIndicator,
    COUNT(DISTINCT Id) AS UniqueIds
FROM
        hourlysteps_merged
UNION
SELECT             -- Process Repeated for Calories
    'Calories' AS DataIndicator,
    COUNT(DISTINCT Id) AS UniqueIds
FROM
    hourlycalories_merged
ORDER BY        -- Sort by Unique ID's
  UniqueIds
```

Table 31: 3 records

DataIndicator	UniqueIds
Calories	33
HourlyIntensities	33
HourlySteps	33

Data for all 33 respondents in all 3 tables

3.1.3 Duplicates and missing values

Next we will check for any duplicates and missing values for the 3 hourly tables

```
WITH dup_inten as (     -- Create a temporary table to calculate Duplicates
SELECT
  1 as UniId,    -- Define UniId in each temporary table to facilitate the join
  COUNT(*) -     -- Calculate the difference between the count of total rows
(SELECT          -- and distinct rows. This difference will be the # of duplicates
  count(*)
FROM
(SELECT DISTINCT      -- This inner query counts distinct rows
  Id,
  ActivityHour,
  TotalIntensity,
  AverageIntensity
```

```sql
FROM
  hourlyintensities_merged) as t1) as DuplicatesIntensities
FROM
  hourlyintensities_merged
),
miss_inten as ( -- Create a temporary table to calculate Missing Values
SELECT
    COUNT(*) AS MissingIntensities,  -- Count values when any one of the columns
    1 as UniId                          -- specified is null.
FROM
    hourlyintensities_merged
WHERE
    Id IS NULL OR
  ActivityHour IS NULL OR
  TotalIntensity IS NULL OR
  AverageIntensity IS NULL
),
dup_steps as (     -- Repeat the process for the steps table
SELECT
  1 as UniId,
  COUNT(*) -
(SELECT
  count(*)
FROM
(SELECT DISTINCT
  Id,
  ActivityHour,
  StepTotal
FROM
  hourlysteps_merged) as t2) as DuplicatesSteps
FROM
  hourlysteps_merged
),
miss_steps as (
SELECT
    COUNT(*) AS MissingSteps,
    1 as UniId
FROM
  hourlysteps_merged
WHERE
    Id IS NULL OR
  ActivityHour IS NULL OR
  StepTotal IS NULL
),
dup_cals as (     -- Repeat the process for the calories table
SELECT
  1 as UniId,
  COUNT(*) -
(SELECT
  count(*)
FROM
(SELECT DISTINCT
  Id,
```

```
  ActivityHour,
  Calories
FROM
  hourlycalories_merged) as t2) as DuplicatesCals
FROM
  hourlycalories_merged
),
miss_cals as (
SELECT
    COUNT(*) AS MissingCals,
    1 as UniId
FROM
  hourlycalories_merged
WHERE
    Id IS NULL OR
  ActivityHour IS NULL OR
  Calories IS NULL
)
SELECT               -- Join results from all tables into one
  A.DuplicatesIntensities,
  B.MissingIntensities,
  C.DuplicatesSteps,
  D.MissingSteps,
  E.DuplicatesCals,
  F.MissingCals
FROM
  dup_inten as A
JOIN
  miss_inten as B on A.UniId=B.UniId
JOIN
  dup_steps as C on A.UniId=C.UniId
JOIN
  miss_steps as D on A.UniId=D.UniId
JOIN
  dup_cals as E on A.UniId=E.UniId
JOIN
  miss_cals as F on A.UniId=F.UniId
```

Table 32: 1 records

DuplicatesIntensities	MissingIntensities	DuplicatesSteps	MissingSteps	DuplicatesCals	MissingCals
0	0	0	0	0	0

0 duplicates and missing values in all 3 tables

3.1.4 Join

```
SELECT
  I.*,
  S.StepTotal,
  C.Calories
FROM hourlyintensities_merged as I
```

```
JOIN
    hourlysteps_merged as S
ON
    I.Id = S.Id
AND
    I.ActivityHour = S.ActivityHour
JOIN
    hourlycalories_merged as C
ON
    I.Id = C.Id
AND
    I.ActivityHour = C.ActivityHour
```

```
kable(head(hourly_activity,5)) %>%
  kable_styling("striped")
```

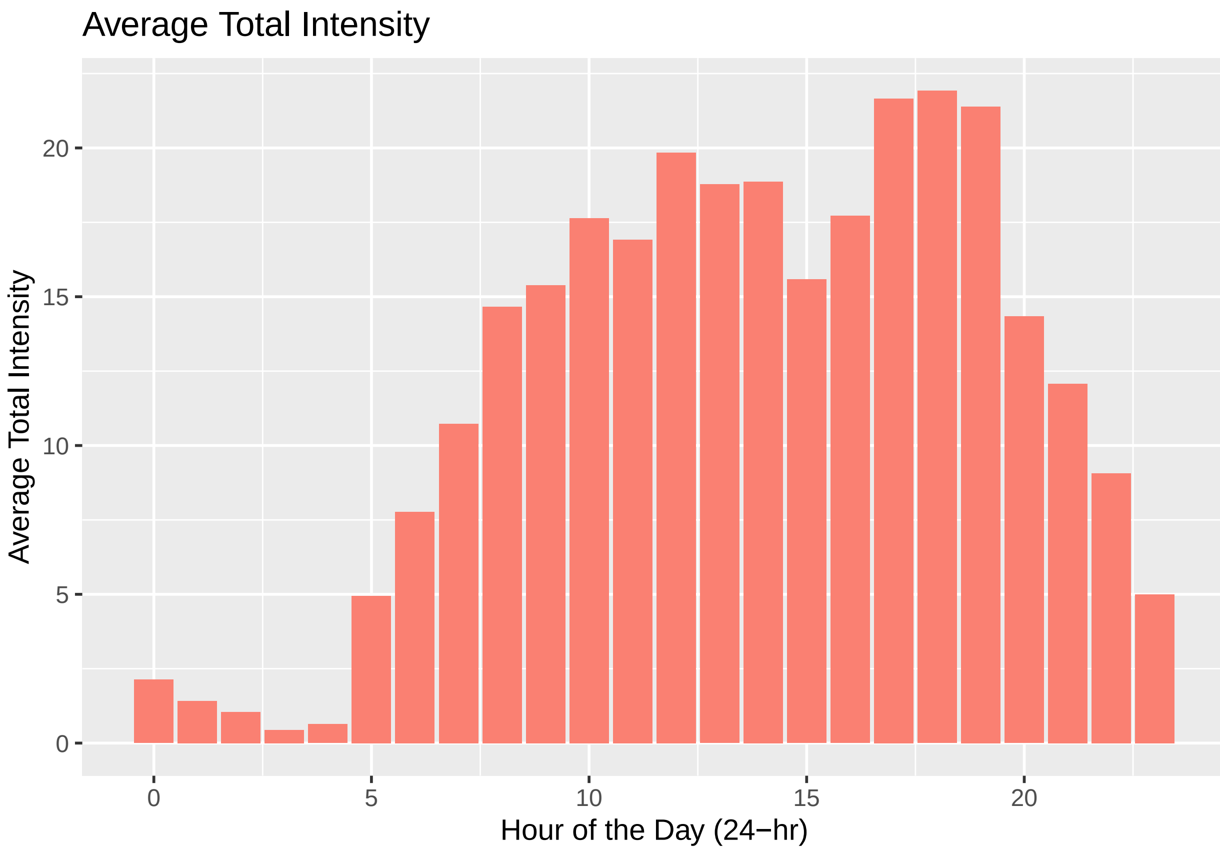
Id	ActivityHour	TotalIntensity	AverageIntensity	StepTotal	Calories
1503960366	4/12/2016 12:00:00 AM	20	0.333333	373	81
1503960366	4/12/2016 1:00:00 AM	8	0.133333	160	61
1503960366	4/12/2016 2:00:00 AM	7	0.116667	151	59
1503960366	4/12/2016 3:00:00 AM	0	0.000000	0	47
1503960366	4/12/2016 4:00:00 AM	0	0.000000	0	48

```
kable(hourly_activity %>% summary()) %>%
  kable_styling("striped")
```

Id	ActivityHour	TotalIntensity	AverageIntensity	StepTotal	Calories
Min. :1.504e+09	Length:22099	Min. : 0.00	Min. :0.0000	Min. : 0.0	Min. : 42.00
1st Qu.:2.320e+09	Class :character	1st Qu.: 0.00	1st Qu.:0.0000	1st Qu.: 0.0	1st Qu.: 63.00
Median :4.445e+09	Mode :character	Median : 3.00	Median :0.0500	Median : 40.0	Median : 83.00
Mean :4.848e+09	NA	Mean : 12.04	Mean :0.2006	Mean : 320.2	Mean : 97.39
3rd Qu.:6.962e+09	NA	3rd Qu.: 16.00	3rd Qu.:0.2667	3rd Qu.: 357.0	3rd Qu.:108.00
Max. :8.878e+09	NA	Max. :180.00	Max. :3.0000	Max. :10554.0	Max. :948.00

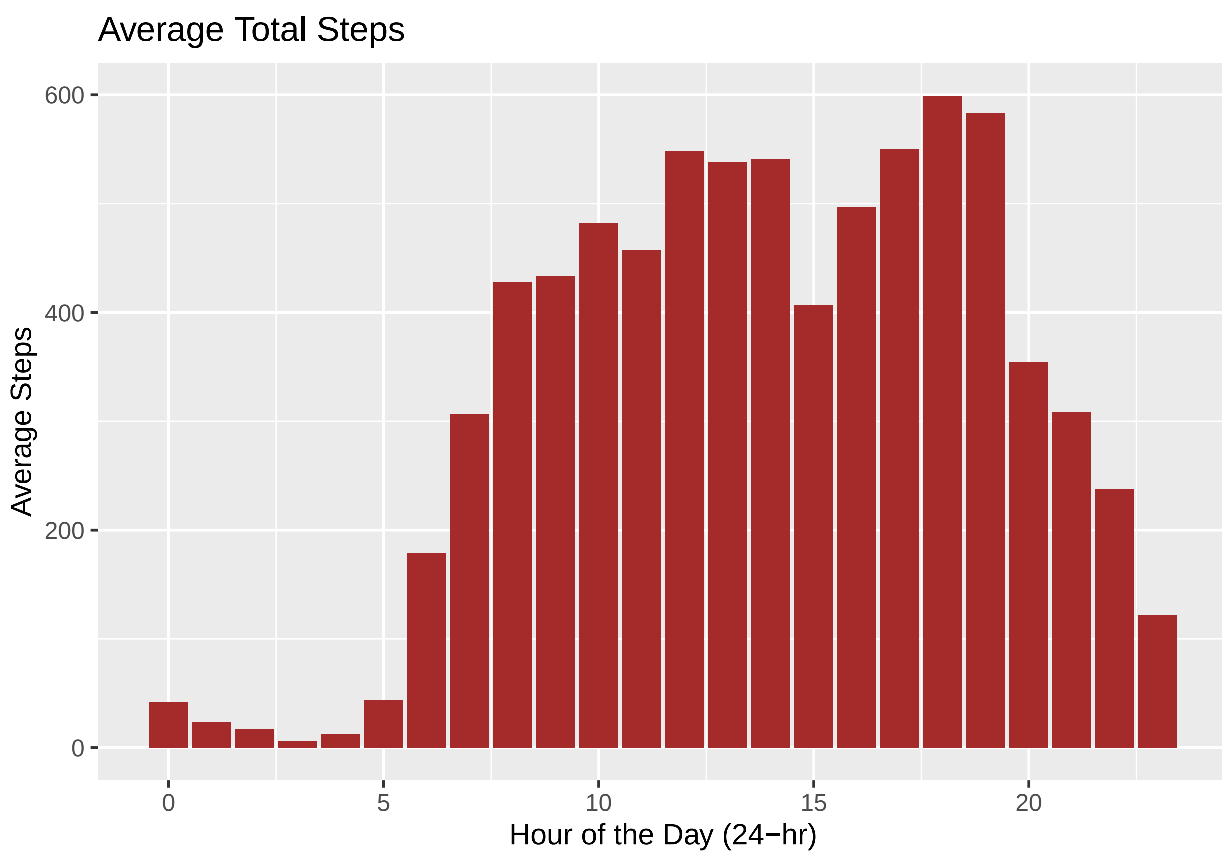
3.2 Data Visualization and Plots

```
hourly_activity %>%
  mutate(activity_time = mdy_hms(ActivityHour), time = hour(activity_time)) %>%
  group_by(time) %>% summarise(hourly_avg = mean(TotalIntensity)) %>%
ggplot(aes(x=time, y=hourly_avg)) + geom_col(fill='salmon') +
  labs(title="Average Total Intensity", x='Hour of the Day (24-hr)',
       y='Average Total Intensity')
```




```
hourly_activity %>%
  mutate(activity_time = mdy_hms(ActivityHour), time = hour(activity_time)) %>%
  group_by(time) %>% summarise(hourly_avg = mean(Calories)) %>%
ggplot(aes(x=time, y=hourly_avg)) + geom_col(fill='pink4') +
  labs(title="Average Calories", x='Hour of the Day (24-hr)',
       y='Average Calories Burned')
```


```
hourly_activity %>%
  mutate(activity_time = mdy_hms(ActivityHour), time = hour(activity_time)) %>%
  group_by(time) %>% summarise(hourly_avg = mean(StepTotal)) %>%
ggplot(aes(x=time, y=hourly_avg)) + geom_col(fill='brown') +
  labs(title="Average Total Steps", x='Hour of the Day (24-hr)',
       y='Average Steps')
```



4 Conclusion and Recommendations

```
# Code to close database connection
DBI::dbDisconnect(con)
```