Bellabeat Capstone project

Feng-Chiu Tsai-Goss

2024-07-19

Introduction

Bellabeat is a high-tech company with the focus on health products for women, and plans to expand in the global smart device market. Bellabeat designs technology that informs, inspires, and collectas data on activity, sleep, stress and reproductive health to empower women with knowledge about their own health and habits. The company has invested two marketing strategies: traditional media (such as radio, out-of-home billboards, print, and television) and digital marketing (such as Google search and Dispaly Network, active Facebook and Instagram pages, video aids on YouTube, Twitter). The cofounder and Chief Creative Office of Bellabeat, Urska Srsen, asks the marketing analytic team to focus on a Bellabeat product and analyze smart device usage data to gain insight into how people are already using their smart devices. She is seeking the opportunity to growing into a bigger market and would like high-level recommendations for how these trends can inform and guide marketing strategy for the company. Below is my analysis based on the data analysis process: Ask, Prepare, Process, Analyze, Share, Act.

Ask

The project is aiming to identify tends that non-Bellabeat customers use smart fitness devices and further to provide insights to inform Bellabeat's marketing strategy. Here are questions that guided the analysis. a. What are some trends in smart device usage?

b. How could these trends apply to Bellabeat customers?

c. How could these trends help influence Bellabeat marketing strategy?

Our team will provide and present the findings and recommendations to the stakeholders:

Urška Sršen: Bellabeat's cofounder and Chief Creative Officer

Sando Mur: key member of the Bellabeat executive team

Bellabeat marketing analytics team

Prepare

1.Data sources and organization

The data used for this project was collected through a survey via Amazon Mechanical Turk between 03.12.2016-05.12.2016. The data shares thirty Fitbit users who consented to the submission of personal tracker data, including minute-level output for physical activity, heart rate, and sleep monitoring. Thirteen sets of data was organized in long format and the rest was in wide format.https://www.kaggle.com/datasets/arashnic/fitbit

2. Accessibility and privacy of data

The data is open and publicly shared by Mobius on Kaggle. The data is licensed by CCO: Public Domain by waiving all his or her rights to the work worldwide under copyright law. One can copy, modify, distribute,

and perform data without asking permission. In the data, all the participants were assigned an ID number without listing their credentials in the files.

3.ROCCC analysis

To verify the credibility of data, the ROCCC process was conducted.

- (1) Reliable: Low. The dataset includes only 30 participants without knowing their genders, ages, and nationality so it might have concern of the sample selection bias to reflect the overall population.
- (2) Original: Low. The dataset was collected by the third-party Amazon Mechanical Turk and published by Mobius on Kaggle.
- (3) Comprehensive: Medium. The dataset provides information on daily activity intensity, calories used, daily steps taken, daily sleep time, and distance travelled in various levels of activities.
- (4) Current: Low. The data set was collected in 2016, which has been 8 years old. The smart device trackers have been updated for the last 10 years. Functionalities and service might be different between now and then; therefore, it is needed to collect more information to help know better the fitness activities and health life habits.
- (5) Cited: High. The dataset is cited with sources being well documented..

4. Data integrity

Dataset was sorted, organized, and sorted in 18 .cvs files. I firstly open the datasets in Excel and realized that the dataset from 03.12.2016-04.11.2016 is incomplete. Some data frames are in a minute-level output. Thus, several data frames will not be used for the analysis. This project will focus on the data set from 04.12.2016-05.12.2016, with the analysis on dailyActivity_merged and sleepDay_merged to identify trends of people using smart devices as daily habits for fitness purposes.

Process

First, I downloaded the dataset and stored it in OneDrive in Microsoft 365. Then I checked the file names that were already named in a way that we can easily recognize and separate from other files in the same folder.

This project will utilize the R programming in R Studio to clean, analyze, and create visualizations of the data.

1.Install and load the following packages in R Studio, and then open libraries.

```
install.packages("tidyverse")

## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'

## (as 'lib' is unspecified)

install.packages("lubridate")

## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'

## (as 'lib' is unspecified)

install.packages("readr")

## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'

## (as 'lib' is unspecified)

install.packages("ggplot2")
```

```
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'
## (as 'lib' is unspecified)
install.packages("cowplot")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'
## (as 'lib' is unspecified)
install.packages("here")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'
## (as 'lib' is unspecified)
install.packages("janitor")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'
## (as 'lib' is unspecified)
install.packages("skimr")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'
## (as 'lib' is unspecified)
install.packages("dplyr")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.3'
## (as 'lib' is unspecified)
library(tidyverse)
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr
           1.1.4 v readr
                                   2.1.5
## v forcats 1.0.0
                       v stringr 1.5.1
## v ggplot2 3.5.1
                                  3.2.1
                      v tibble
## v lubridate 1.9.3
                                   1.3.1
                        v tidyr
              1.0.2
## v purrr
## -- Conflicts -----
                                         ------tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
                  masks stats::lag()
## x dplyr::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
library(lubridate)
library(readr)
library(ggplot2)
library(cowplot)
## Attaching package: 'cowplot'
## The following object is masked from 'package:lubridate':
##
##
       stamp
library(here)
## here() starts at /cloud/project
library(janitor)
```

##

```
## Attaching package: 'janitor'
##
## The following objects are masked from 'package:stats':
##
## chisq.test, fisher.test
library(skimr)
library(dplyr)
```

2.Import datasets into RStudio

The following datasets are used for this project. * DailyActivity_merged: Daily Activities over 31 days of 33 IDs. Tracking daily steps, distance, intensity, active time, and calories. * sleepDay_merged: Daily sleeping time over 31 days of 24 IDs. Recording daily sleeping time and time in bed.

```
DailyActivity <- read.csv("/cloud/project/Bellabeat/dailyActivity_merged.csv")
Sleep_Activity <- read.csv("/cloud/project/Bellabeat/sleepDay_merged.csv")
```

3. Preview data

After importing data sets, I firstly checked how many rows and columns are in each data frame, and then veiwed the column names. There are 15 columns and 940 rows in the data frame of daily activity, and 5 columns and 413 rows in the data frame of sleeping activity.

glimpse(DailyActivity)

```
## Rows: 940
## Columns: 15
## $ Id
                          <dbl> 1503960366, 1503960366, 1503960366, 150396036~
## $ ActivityDate
                          <chr> "4/12/2016", "4/13/2016", "4/14/2016", "4/15/~
                          <int> 13162, 10735, 10460, 9762, 12669, 9705, 13019~
## $ TotalSteps
                          <dbl> 8.50, 6.97, 6.74, 6.28, 8.16, 6.48, 8.59, 9.8~
## $ TotalDistance
## $ TrackerDistance
                          <dbl> 8.50, 6.97, 6.74, 6.28, 8.16, 6.48, 8.59, 9.8~
<dbl> 1.88, 1.57, 2.44, 2.14, 2.71, 3.19, 3.25, 3.5~
## $ VeryActiveDistance
## $ 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
                          <int> 25, 21, 30, 29, 36, 38, 42, 50, 28, 19, 66, 4~
## $ VeryActiveMinutes
## $ FairlyActiveMinutes
                          <int> 13, 19, 11, 34, 10, 20, 16, 31, 12, 8, 27, 21~
## $ LightlyActiveMinutes
                          <int> 328, 217, 181, 209, 221, 164, 233, 264, 205, ~
                          <int> 728, 776, 1218, 726, 773, 539, 1149, 775, 818~
## $ SedentaryMinutes
## $ Calories
                           <int> 1985, 1797, 1776, 1745, 1863, 1728, 1921, 203~
glimpse(Sleep_Activity)
```

4. Cleaning data

Now inspect the data to see if there are any duplicates, null values, formatting errors or any inconsistencies.

```
sum(duplicated(DailyActivity))
(1) check and remove duplicates and N/A values
## [1] O
sum(duplicated(Sleep_Activity))
## [1] 3
n_unique(DailyActivity$Id)
## [1] 33
n_unique(Sleep_Activity$Id)
## [1] 24
sum(!complete.cases(DailyActivity))
## [1] 0
sum(!complete.cases(Sleep_Activity))
## [1] 0
cleaned_sleep <- Sleep_Activity %>%
  distinct( )
sum(duplicated(cleaned sleep))
## [1] 0
(2) clean and rename columns names Then I want to ensure that all the columns names are unique
and consistent, including numbers, letter, underscores in the name only.
DailyActivity_cleaned <- DailyActivity %>%
  distinct( ) %>%
  drop_na
head(DailyActivity_cleaned)
             Id ActivityDate TotalSteps TotalDistance TrackerDistance
## 1 1503960366
                   4/12/2016
                                   13162
                                                   8.50
                                                                    8.50
## 2 1503960366
                   4/13/2016
                                                   6.97
                                                                    6.97
                                   10735
                   4/14/2016
                                                                    6.74
## 3 1503960366
                                   10460
                                                   6.74
                   4/15/2016
## 4 1503960366
                                    9762
                                                   6.28
                                                                    6.28
## 5 1503960366
                   4/16/2016
                                   12669
                                                   8.16
                                                                    8.16
                                    9705
                                                   6.48
                                                                    6.48
## 6 1503960366
                    4/17/2016
     LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance
##
## 1
                             0
                                              1.88
                                                                        0.55
## 2
                             0
                                              1.57
                                                                        0.69
## 3
                             0
                                              2.44
                                                                        0.40
                             0
## 4
                                              2.14
                                                                        1.26
## 5
                             0
                                              2.71
                                                                        0.41
                                                                        0.78
## 6
                             0
                                              3.19
##
    LightActiveDistance SedentaryActiveDistance VeryActiveMinutes
## 1
                    6.06
## 2
                    4.71
                                                 0
                                                                   21
```

```
## 3
                    3.91
                                                                30
## 4
                    2.83
                                               0
                                                                 29
## 5
                    5.04
                                               0
                                                                36
## 6
                                               0
                    2.51
                                                                38
##
    FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes Calories
## 1
                                                           728
                      13
                                          328
## 2
                                                           776
                                                                    1797
                      19
                                          217
## 3
                                                          1218
                                                                   1776
                      11
                                          181
## 4
                      34
                                          209
                                                           726
                                                                    1745
## 5
                      10
                                          221
                                                           773
                                                                   1863
## 6
                      20
                                          164
                                                           539
                                                                    1728
cleaned_sleep <- Sleep_Activity %>%
  distinct( )
sum(duplicated(cleaned_sleep))
## [1] 0
(3) check errors of formatting Then I ensure column names are in the consistent format across data
frames for the later merging.
str(DailyActivity_cleaned)
## 'data.frame':
                    940 obs. of 15 variables:
## $ Id
                              : num 1.5e+09 1.5e+09 1.5e+09 1.5e+09 ...
                                     "4/12/2016" "4/13/2016" "4/14/2016" "4/15/2016" ...
## $ ActivityDate
                              : chr
                                     13162 10735 10460 9762 12669 9705 13019 15506 10544 9819 ...
## $ TotalSteps
                              : int
## $ TotalDistance
                              : num 8.5 6.97 6.74 6.28 8.16 ...
## $ TrackerDistance
                              : num 8.5 6.97 6.74 6.28 8.16 ...
## $ LoggedActivitiesDistance: num 0 0 0 0 0 0 0 0 0 0 ...
## $ VeryActiveDistance
                              : num
                                     1.88 1.57 2.44 2.14 2.71 ...
## $ ModeratelyActiveDistance: num 0.55 0.69 0.4 1.26 0.41 ...
## $ LightActiveDistance
                              : num 6.06 4.71 3.91 2.83 5.04 ...
                                     0 0 0 0 0 0 0 0 0 0 ...
## $ SedentaryActiveDistance : num
## $ VeryActiveMinutes
                                     25 21 30 29 36 38 42 50 28 19 ...
                              : int
                              : int 13 19 11 34 10 20 16 31 12 8 ...
## $ FairlyActiveMinutes
## $ LightlyActiveMinutes
                              : int 328 217 181 209 221 164 233 264 205 211 ...
                                     728 776 1218 726 773 539 1149 775 818 838 ...
## $ SedentaryMinutes
                              : int
## $ Calories
                                     1985 1797 1776 1745 1863 1728 1921 2035 1786 1775 ...
                              : int
str(cleaned_sleep)
                    410 obs. of 5 variables:
## 'data.frame':
## $ Id
                        : num 1.5e+09 1.5e+09 1.5e+09 1.5e+09 ...
## $ SleepDay
                        : chr
                              "4/12/2016 12:00:00 AM" "4/13/2016 12:00:00 AM" "4/15/2016 12:00:00 AM"
## $ TotalSleepRecords : int 1 2 1 2 1 1 1 1 1 1 ...
## $ TotalMinutesAsleep: int 327 384 412 340 700 304 360 325 361 430 ...
                        : int 346 407 442 367 712 320 377 364 384 449 ...
## $ TotalTimeInBed
I noticed that I need to correct the date format in the frames that should be a date form.
DailyActivity_cleaned$ActivityDate <- as.Date(DailyActivity_cleaned$ActivityDate, '%m/%d/%y')
cleaned_sleep$SleepDay <- as.Date(cleaned_sleep$SleepDay, '%m/%d/%y')</pre>
```

str(DailyActivity)

```
## 'data.frame':
                   940 obs. of 15 variables:
##
   $ Td
                             : num 1.5e+09 1.5e+09 1.5e+09 1.5e+09 ...
  $ ActivityDate
##
                                    "4/12/2016" "4/13/2016" "4/14/2016" "4/15/2016" ...
                                   13162 10735 10460 9762 12669 9705 13019 15506 10544 9819 ...
  $ TotalSteps
##
                             : int
##
   $ TotalDistance
                             : num
                                    8.5 6.97 6.74 6.28 8.16 ...
##
  $ TrackerDistance
                             : num 8.5 6.97 6.74 6.28 8.16 ...
  $ LoggedActivitiesDistance: num 00000000000...
   $ VeryActiveDistance
##
                             : num
                                    1.88 1.57 2.44 2.14 2.71 ...
##
   $ ModeratelyActiveDistance: num   0.55   0.69   0.4   1.26   0.41   ...
## $ LightActiveDistance
                             : num 6.06 4.71 3.91 2.83 5.04 ...
## $ SedentaryActiveDistance : num 0 0 0 0 0 0 0 0 0 ...
## $ VeryActiveMinutes
                                    25 21 30 29 36 38 42 50 28 19 ...
                             : int
## $ FairlyActiveMinutes
                             : int
                                    13 19 11 34 10 20 16 31 12 8 ...
                                    328 217 181 209 221 164 233 264 205 211 ...
## $ LightlyActiveMinutes
                             : int
## $ SedentaryMinutes
                                    728 776 1218 726 773 539 1149 775 818 838 ...
                             : int
## $ Calories
                                    1985 1797 1776 1745 1863 1728 1921 2035 1786 1775 ...
str(cleaned_sleep)
## 'data.frame':
                   410 obs. of 5 variables:
   $ Id
                        : num 1.5e+09 1.5e+09 1.5e+09 1.5e+09 1.5e+09 ...
##
   $ SleepDay
                        : Date, format: "2020-04-12" "2020-04-13" ...
   $ TotalSleepRecords : int
                             1 2 1 2 1 1 1 1 1 1 ...
## $ TotalMinutesAsleep: int
                              327 384 412 340 700 304 360 325 361 430 ...
                              346 407 442 367 712 320 377 364 384 449 ...
  $ TotalTimeInBed
                       : int
```

Then I separated date and time in the SleepDay column into two different columns so that I can combine merge the frames next.

(4) Adding a new column I also add a new column in the data frame of sleeping activity that finds the difference between the total time in bed and total minute asleep by the code below. That might help me to study the relation to other factors in activities.

```
New_Sleep <- cleaned_sleep %>%
  mutate(diff = TotalTimeInBed - TotalMinutesAsleep)
view(New_Sleep)
```

Before merging, I rename columns regarding dates and identifications to be consistent between these two data sets so that I can combine them into one data frame to further investigate the relationship between daily activities and sleeping pattern.

```
New_Sleep_cleaned <- New_Sleep %>%
    rename(
        Date = SleepDay,
        Id = Id
)

view(New_Sleep_cleaned)

Activity_cleaned <- DailyActivity_cleaned %>%
    rename (
        Date = ActivityDate,
        Id = Id
)

view(Activity_cleaned)
```

```
DailyActivity_Sleep_merged <- merge(Activity_cleaned, New_Sleep_cleaned, by= c ("Id", "Date"))
head(DailyActivity_Sleep_merged)</pre>
```

			_						
##		Id		_	TotalDistan		cerDist		
##		1503960366		13162	8.			8.50	
		1503960366		10735	6.9			6.97	
		1503960366		9762	6.3			6.28	
		1503960366		12669	8.			8.16	
##	5	1503960366	2020-04-17	9705	6.	48		6.48	
##	6	1503960366		15506	9.			9.88	
##		LoggedActiv	vitiesDistar	ce VeryAct	iveDistance 1	Moderate	elyActi	veDistance	
##	1			0	1.88			0.55	
##	2			0	1.57			0.69	
##	3			0	2.14			1.26	
##	4			0	2.71			0.41	
##	5			0	3.19			0.78	
##	6			0	3.53			1.32	
##		LightActive	eDistance Se	edentaryAct	iveDistance '	VeryActi	veMinu	ites	
##	1		6.06		0			25	
##	2		4.71		0			21	
##	3		2.83		0			29	
##	4		5.04		0			36	
##	5		2.51		0			38	
##	6		5.03		0			50	
##		FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes Calories							
##	1		13		328		728	1985	
##	2		19		217		776	1797	
##	3		34		209		726	1745	
##	4		10		221		773	1863	
##	5		20		164		539	1728	
##	6		31		264		775	2035	
##		TotalSleepH	Records Tota	alMinutesAsl	leep TotalTi	meInBed	diff		
##	1		1		327	346	19		
##	2		2		384	407	23		
##	3		1		412	442	30		
##	4		2		340	367	27		
##	5		1		700	712	12		
##	6		1		304	320	16		

After merging, there are 24 participants that are on the final list for this project since they are the overlap between these two data sets.

Analyze

At the analyze phase, I will analyze the patterns and trends of these thirties Fit Bit users by providing statistical calculation information.

1.Summarize and explore data sets

```
DailyActivity_Sleep_merged %>%
select(TotalSteps,
```

```
TotalDistance,

TotalMinutesAsleep,

TotalTimeInBed,

diff,

Calories) %>%

summary()
```

```
##
      TotalSteps
                     TotalDistance
                                       TotalMinutesAsleep TotalTimeInBed
##
           :
                17
                     Min.
                            : 0.010
                                              : 58.0
                                                           Min.
                                                                   : 61.0
##
    1st Qu.: 5189
                     1st Qu.: 3.592
                                       1st Qu.:361.0
                                                           1st Qu.:403.8
##
   Median : 8913
                     Median : 6.270
                                       Median :432.5
                                                           Median :463.0
          : 8515
                           : 6.012
                                              :419.2
##
    Mean
                     Mean
                                       Mean
                                                           Mean
                                                                   :458.5
##
    3rd Qu.:11370
                     3rd Qu.: 8.005
                                       3rd Qu.:490.0
                                                           3rd Qu.:526.0
##
    Max.
           :22770
                            :17.540
                                              :796.0
                                                           Max.
                                                                   :961.0
                     Max.
                                       Max.
##
         diff
                         Calories
                             : 257
##
           : 0.00
                      Min.
   \mathtt{Min}.
   1st Qu.: 17.00
                      1st Qu.:1841
##
##
   Median : 25.50
                      Median:2207
   Mean
           : 39.31
                      Mean
                             :2389
    3rd Qu.: 40.00
##
                      3rd Qu.:2920
   Max.
           :371.00
                      Max.
                             :4900
```

Findings:

*The average of daily total steps is 8515. It is recommended that an adult should aim to walk 10,000 steps in a day for health benefits.

*The average daily total distance is 6.012 kilometers and the median is 6.27 kilometers. That means, half of the participants moved less than 6.27 miles in a day.

*The average daily total asleep time is 419.2 minutes, which approximately equals to 7 hours a day. Also, average time that people stay on bed while not asleep is 39.31 minutes. It is recommended that staying for 15-30 minutes on bed after waking up should be enough for most people. Using few minutes to stretch body before getting out of your bed will benefit making your day better.

*The average calories burn is 2389 per day.

```
##
    VeryActiveDistance ModeratelyActiveDistance LightActiveDistance
          : 0.000
                               :0.0000
##
   Min.
                        Min.
                                                  Min.
                                                         :0.010
##
   1st Qu.: 0.000
                        1st Qu.:0.0000
                                                  1st Qu.:2.540
## Median: 0.570
                                                  Median :3.665
                        Median : 0.4200
##
  Mean
           : 1.446
                        Mean
                               :0.7439
                                                  Mean
                                                         :3.791
##
    3rd Qu.: 2.360
                        3rd Qu.:1.0375
                                                  3rd Qu.:4.918
##
           :12.540
                        Max.
                               :6.4800
                                                  Max.
                                                         :9.480
  {\tt Max.}
```

```
## SedentaryActiveDistance
## Min. :0.0000000
## 1st Qu.:0.0000000
## Median :0.0000000
## Mean :0.0009268
## 3rd Qu.:0.0000000
## Max. :0.1100000
```

*The average sedentary active distance is almost close to 0 miles per day whereas the average moderately active distance is 0.74 miles. This needs to be improved.

```
VeryActiveMinutes FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes
## Min.
         : 0.00
                     Min.
                          : 0.00
                                         Min. : 2.0
                                                             Min.
                                                                    :
                                                                        0.0
##
  1st Qu.: 0.00
                     1st Qu.: 0.00
                                         1st Qu.:158.0
                                                              1st Qu.: 631.2
## Median: 9.00
                     Median : 11.00
                                         Median :208.0
                                                             Median : 717.0
                           : 17.92
                                                                    : 712.1
## Mean
          : 25.05
                     Mean
                                         Mean
                                                :216.5
                                                             Mean
##
                     3rd Qu.: 26.75
   3rd Qu.: 38.00
                                         3rd Qu.:263.0
                                                              3rd Qu.: 782.8
  Max.
          :210.00
                     Max.
                            :143.00
                                         Max.
                                                :518.0
                                                             Max.
                                                                    :1265.0
```

2.Summarize weekday distance and activity time

I will find a summary of total distance and active time from the datasets and then display data in bar graphs.

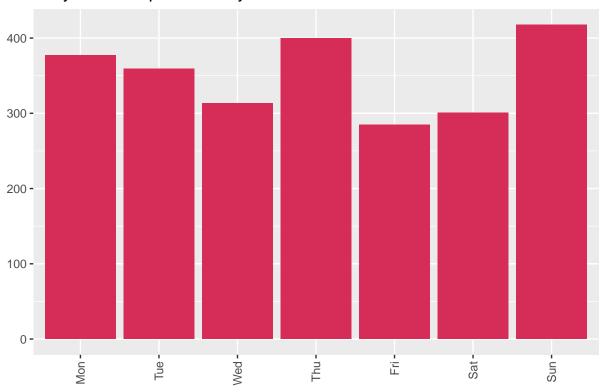
```
DailyActivity_Sleep_merged <- DailyActivity_Sleep_merged %>%
  mutate(day = format(ymd(Date), format = '%a'))
head(DailyActivity_Sleep_merged)
```

## 2 0 1.57 0 ## 3 0 2.14 ## 4 0 2.71 0 ## 5 0 3.19						
## 3 1503960366 2020-04-15 9762 6.28 6.28 ## 4 1503960366 2020-04-16 12669 8.16 8.16 ## 5 1503960366 2020-04-17 9705 6.48 6.48 ## 6 1503960366 2020-04-19 15506 9.88 9.88 ## LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance ## 1 0 1.88 (## 2 0 1.57 (## 3 0 2.14						
## 4 1503960366 2020-04-16 12669 8.16 8.16 ## 5 1503960366 2020-04-17 9705 6.48 6.48 ## 6 1503960366 2020-04-19 15506 9.88 9.88 ## LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance ## 1 0 1.88 (## 2 0 1.57 (## 3 0 2.14 ## 4 0 2.71 (## 5 0 3.19						
## 5 1503960366 2020-04-17 9705 6.48 6.48 ## 6 1503960366 2020-04-19 15506 9.88 9.88 ## LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance ## 1 0 1.88 0 ## 2 0 1.57 0 ## 3 0 2.14 1 ## 4 0 2.71 0 ## 5 0 3.19						
6 1503960366 2020-04-19 15506 9.88 9.88 ## LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance ## 1 0 1.88 (## 2 0 1.57 (## 3 0 2.14 (## 4 0 2.71 (## 5 0 3.19 (
## LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance ## 1						
## 1 0 1.88 0 1 1.88 0 1 1.88 0 1 1.57 0 1 1.57 0 1 1.57 0 1 1 1.57 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1						
## 2 0 1.57 0 ## 3 0 2.14 ## 4 0 2.71 0 ## 5 0 3.19	ince					
## 3 0 2.14 ## 4 0 2.71 0 4 1 5 1 6 1 6 1 6 1 6 1 6 1 6 1 6 1 6 1 6	0.55					
## 4 0 2.71 0 ## 5 0 3.19	0.69					
## 5 0 3.19	1.26					
	0.41					
## 6 0 3.53	0.78					
	1.32					
LightActiveDistance SedentaryActiveDistance VeryActiveMinutes						
## 1 6.06 0 25						
## 2 4.71 0 21						
## 3 2.83 0 29						
## 4 5.04 0 36						

^{*}The average active minutes is close to the average fairly active minutes, but much shorter than the average lightly active time and sedentary minutes. This needs to be improved. However, there is a need to investigate whether the sedentary minutes includes the measurement of asleep time.

```
## 5
                    2.51
                                                0
                                                                  38
## 6
                    5.03
                                                 0
                                                                  50
    FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes Calories
##
## 1
                       13
                                           328
                                                             728
                                                                      1985
## 2
                       19
                                           217
                                                             776
                                                                      1797
## 3
                       34
                                           209
                                                             726
                                                                      1745
## 4
                       10
                                           221
                                                             773
                                                                      1863
## 5
                       20
                                                             539
                                                                     1728
                                           164
## 6
                       31
                                           264
                                                             775
                                                                      2035
##
     TotalSleepRecords TotalMinutesAsleep TotalTimeInBed diff day
## 1
                     1
                                       327
                                                       346
                                                             19 Sun
## 2
                     2
                                       384
                                                             23 Mon
                                                       407
## 3
                                       412
                                                       442
                                                             30 Wed
                     1
## 4
                     2
                                       340
                                                       367
                                                             27 Thu
## 5
                                       700
                                                       712
                                                             12 Fri
                     1
## 6
                     1
                                       304
                                                       320
                                                             16 Sun
activitydistance_daily <- DailyActivity_Sleep_merged %>%
  group_by(day) %>%
  drop_na() %>%
  summarise(VeryActiveDistance = sum(VeryActiveDistance),
            ModeratelyActiveDistance = sum(ModeratelyActiveDistance),
            LightActiveDistance = sum(LightActiveDistance),
            SedentaryActiveDistance = sum(SedentaryActiveDistance))
weekday_steps <- activitydistance_daily %>%
 mutate(weekday = day)
weekday_steps$weekday <- ordered(weekday_steps$weekday, levels = c("Mon", "Tue", "Wed", "Thu", "Fri", "</pre>
weekday_steps <- weekday_steps %>%
 group_by(weekday) %>%
summarize(daily_distance = sum(VeryActiveDistance, ModeratelyActiveDistance, LightActiveDistance, Sede:
ggplot(weekday_steps, aes(x = weekday, y = daily_distance)) +
 geom_col(fill = "#d62d58") +
labs(title = "Daily Distance per weekday", x ="", y = "") +
theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))
```

Daily Distance per weekday



Findings:

1 Mon

2 Tue

3 Wed

4 Thu

63393

60162

57086

55717

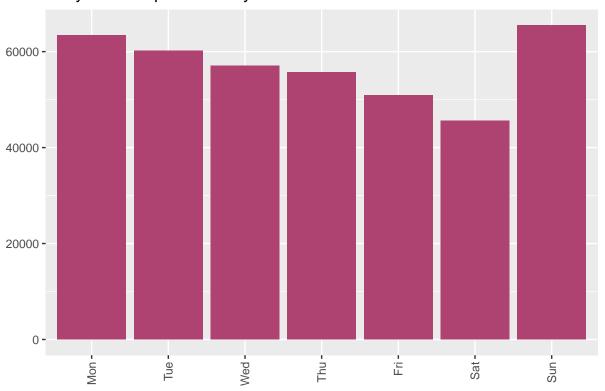
*In the observations, Thursday and Sunday are the days during the week that people tend to walk more, but less on Friday and Saturday. It is interesting to further investigate why the Thursdays cumulates longer walk distance than the rest of weekdays.

```
dailyactivity_time<- DailyActivity_Sleep_merged %>%
  group_by(day) %>%
  drop_na() %>%
  summarise(VeryActiveMinutes = sum(VeryActiveMinutes),
           FairlyActiveMinutes = sum(FairlyActiveMinutes),
            LightlyActiveMinutes = sum(LightlyActiveMinutes),
            SedentaryMinutes = sum(SedentaryMinutes))
weekday_minutes <- dailyactivity_time %>%
mutate(weekday = day)
 weekday_minutes$weekday <- ordered(weekday_minutes$weekday, levels = c("Mon", "Tue", "Wed", "Thu", "Fr
weekday_minutes <- weekday_minutes %>%
 group_by(weekday) %>%
 summarize(daily_minutes = sum(VeryActiveMinutes, FairlyActiveMinutes, LightlyActiveMinutes, SedentaryM
head(weekday_minutes)
## # A tibble: 6 x 2
##
     weekday daily_minutes
##
     <ord>
                     <int>
```

```
## 5 Fri 50962
## 6 Sat 45567

ggplot(weekday_minutes, aes(x = weekday, y = daily_minutes)) +
    geom_col(fill = "#AE4371") +
    labs(title = "Daily Minutes per weekday", x ="", y = "") +
    theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))
```

Daily Minutes per weekday



*The graph shows that, during the observation, people spend more time being active on Sunday and Monday. It displays a declining trend from Tuesday to Saturday being active.

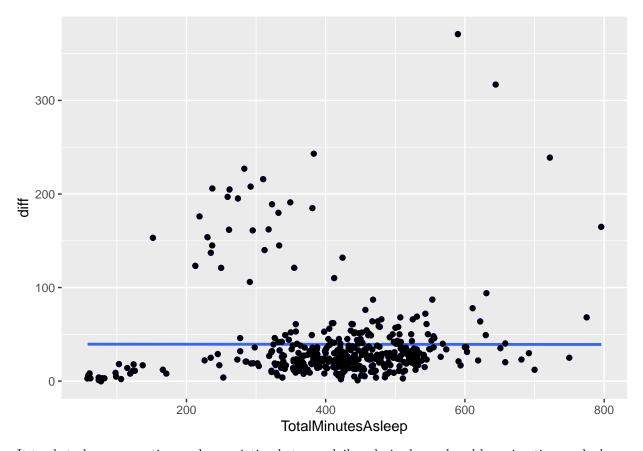
Share

More visualizations are created to share our findings.

1. Association between sleeping time, calories, and intensity distance

```
ggplot(data = DailyActivity_Sleep_merged, aes(TotalMinutesAsleep, diff)) +
geom_point(color = "blue") + geom_smooth(method = "lm", se = FALSE) + geom_jitter()
```

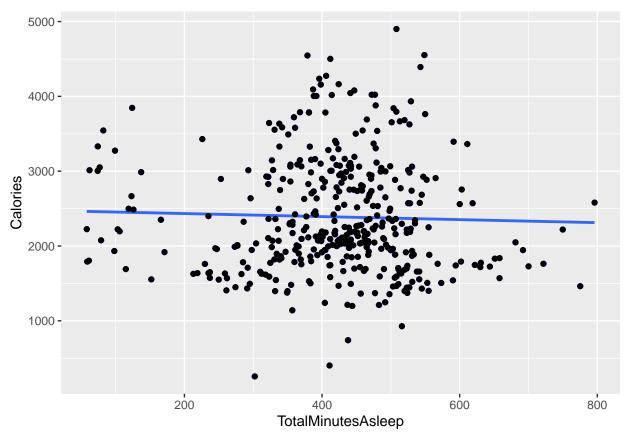
```
## `geom_smooth()` using formula = 'y ~ x'
```



It tends to have a negative weak association between daily calories burned and lounging time on bed.

```
ggplot(data = DailyActivity_Sleep_merged, aes(TotalMinutesAsleep, Calories)) +
geom_point(color = "blue") + geom_smooth(method = "lm", se = FALSE) + geom_jitter()
```

`geom_smooth()` using formula = 'y ~ x'



It tends to have a week negative relation between daily sleeping duration and daily calories burned. The TotalAsleepTime data will be divided into groups to help further investigate the relation between sleep pattern, calories burned, and intensity.

2. Sleeping type

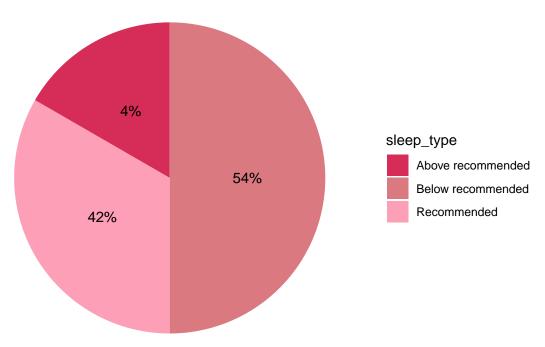
We will assign data into the following groups based on the length of total asleep time in a day. This categorization is based on CDC recommendations for health benefits.

Below Recommended type: less than 7 hours Recommended type: $7 \sim 9$ hours Above Recommended type: more than 9 hours. Below provides more analysis that might help us understand the different trends underlying each sleep type.

```
sleep_type <-DailyActivity_Sleep_merged %>%
group_by(Id) %>%
summarize(minutes_sleep = round(mean(TotalMinutesAsleep))) %>%
mutate(sleep_type = case_when(
    minutes_sleep >=0 & minutes_sleep < 420 ~ "Below Recommended",
    minutes_sleep >=420 & minutes_sleep < 540 ~ "Recommended",
    minutes_sleep >=540 & minutes_sleep < 1000 ~ "Above Recommended"
))
head(sleep_type)</pre>
```

```
## 4 1927972279
                         417 Below Recommended
                          506 Recommended
## 5 2026352035
## 6 2320127002
                          61 Below Recommended
table_sleep_type <-DailyActivity_Sleep_merged %>%
  left_join(sleep_type, by = "Id") %>%
  group_by(sleep_type) %>%
  summarise(participants = n_distinct(Id)) %>%
  mutate(perc = participants/sum(participants)) %>%
  arrange(perc) %>%
  mutate(perc = scales::percent(perc))
head(table_sleep_type)
## # A tibble: 3 x 3
                       participants perc
##
     sleep_type
##
     <chr>
                              <int> <chr>
## 1 Above Recommended
                                 1 4%
## 2 Recommended
                                 10 42%
## 3 Below Recommended
                                 13 54%
table_sleep_type %>%
  ggplot(aes(x = "", y = perc, fill = sleep_type,)) +
  geom_bar(stat = "identity", width = 2) +
  coord_polar("y", start = 0) +
  theme minimal() +
  theme(axis.title.x = element_blank(),
       axis.title.y = element_blank(),
        panel.border = element_blank(),
       panel.grid = element_blank(),
        axis.ticks = element blank(),
       axis.text.x = element_blank(),
       plot.title = element_text(hjust = 0.5, size = 14, face = "bold")) +
  geom_text(aes(label = perc),
            position = position_stack(vjust = 0.5)) +
  scale_fill_manual(values = c("#d62d58", "#db7980", "#fc9fb7"),
                    labels = c("Above recommended",
                               "Below recommended",
                               "Recommended"))+
  labs(title = "Sleep Types Distribution")
```

Sleep Types Distribution



Findings:

More than half of the participants sleep less than 7 hours a night. From health benefits, it is recommended an adult should sleep between 7-9 hours a night. Adults who sleep less than 7 hours a night may have more health issues than those who sleep 7 or more hours a night. If you regularly need more than 9 hours of sleep per night to feel rested, it might be a sign of a sleep or medical problem.

3. Average daily distance, day, and sleep type

3.1 Average daily distance by day To know what day during the week participants are active the most.

```
weekday_average_distance <- DailyActivity_Sleep_merged %>%
  mutate (day)
weekday_average_distance$day <- ordered(weekday_average_distance$day, levels = c("Mon", "Tue", "Wed","
weekday_average_distance <- weekday_average_distance %>%
  group_by(day) %>%
  summarize(average_daily_distance = mean(TotalDistance))
head(weekday_average_distance)
```

```
## # A tibble: 6 x 2
           average_daily_distance
##
     day
##
     <ord>
                             <dbl>
                              5.72
## 1 Mon
## 2 Tue
                              5.77
## 3 Wed
                              5.51
## 4 Thu
                              7.02
## 5 Fri
                              5.18
```

^{*4%} of participants usually sleep MORE than 7 hours a night.

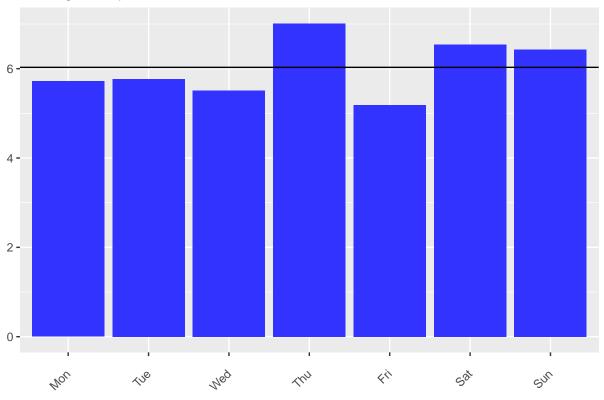
^{*42%} of them usually sleep between 7-9 hours a night.

^{*54%} of them usually sleep Less than 7 hours recommended.

6 Sat 6.54

```
ggplot(weekday_average_distance, aes(day,average_daily_distance)) +
geom_col(fill = "#3333FF") +
geom_hline(yintercept = 6.03) +
labs(title = "Average Daily Distance", x = "", y ="") +
theme (axis.text.x = element_text(angle = 45, vjust = 0.5, hjust = 1))
```

Average Daily Distance



Findings:

*The highest average daily activity distance is Thursday, followed by Saturday and Sunday. People might have more time to enjoy activities with friends and family and become more active.

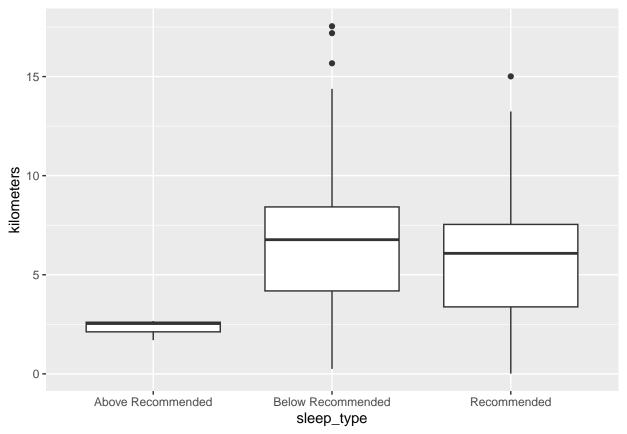
*The lowest average daily activity distance is Friday. It might be the end of the working week and most of us just want to go home and rest.

*It will be interesting to analyze the reasons behind a very active Thursday.

3.2 Daily distance by sleep type To know what sleep type of people travelled the most during activities.

```
daily_distance_sleep <- DailyActivity_Sleep_merged %>%
  left_join(sleep_type, by = 'Id') %>%
  group_by(day, sleep_type) %>%
  select(sleep_type, TotalDistance, day) %>%
  mutate(day = factor(day, levels = c("Mon", "Tue", "Wed", "Thu", "Fri", "Sat", "Sun")))
head(daily_distance_sleep)
```

```
8.5 Sun
## 1 Below Recommended
## 2 Below Recommended
                                6.97 Mon
                                6.28 Wed
## 3 Below Recommended
## 4 Below Recommended
                                8.16 Thu
## 5 Below Recommended
                                 6.48 Fri
## 6 Below Recommended
                                9.88 Sun
p <- ggplot(daily_distance_sleep, aes(x=sleep_type, y=TotalDistance))+</pre>
      geom boxplot() + labs(y="kilometers")+
      theme(legend.position="none")
plot(p)
```



Findings:

*The group of sleeping hours above recommended has a much lower median than the other two groups. This suggests that people who sleep longer than 9 hours a night tends to be less active than the ones who sleep less than 9 hours.

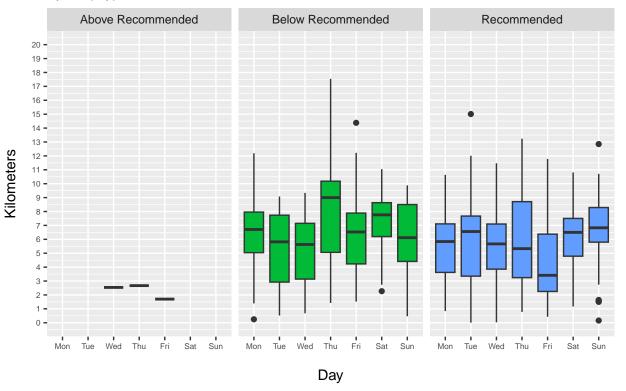
*The distribution for the group of sleeping hours by recommendation is similar to the group of sleeping hours below recommendation. The data of the group of the below recommendation is more spread out than the group of recommended.

3.3 Daily Distance by day, sleep type To make visualization to compare sleeping groups in terms of daily distance across a week.

```
ggtitle("A boxplot with jitter") +
    xlab("") +
    labs(title=("Daily Distance"), subtitle=("By sleep type"), x="Day", y="Kilometers") +
    theme(plot.title=element_text(size = 12,hjust = 0))+
    theme(plot.subtitle=element_text(size = 10,hjust = 0))+
    theme(axis.text.y=element_text(size=6)) +
    theme(axis.text.x=element_text(size=6,hjust= 0.5))+
    theme(axis.title.x = element_text(margin = margin(t = 14, r = 0, b = 0, l = 0)))+
    theme(axis.title.y = element_text(margin = margin(t = 0, r = 10, b = 0, l = 0)))+
    theme(legend.title=element_text(size=10))+
    theme(legend.text=element_text(size=8))+
    facet_grid(~sleep_type)
plot(p1)
```

Daily Distance

By sleep type



Findings:

^{*}It tends to have a trailing off the week from Monday to Friday among the three groups.

^{*}The group below recommended tends to have a slightly higher median across the weekday than the rest two groups. That means, people sleeping below 7 hours a night might walk longer distance than the rest two groups.

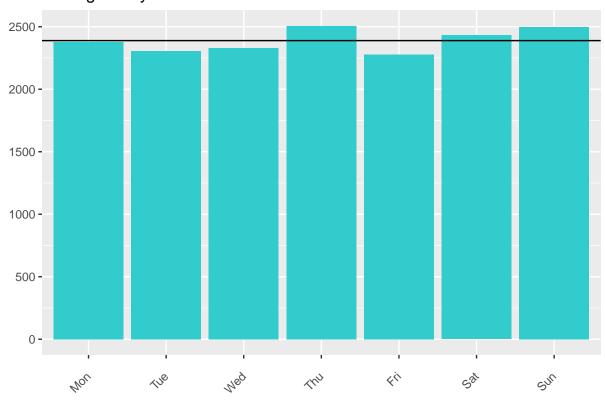
^{*}Also, it seems there is more spread out on Thursday on both groups of below recommended and recommended.

^{*}Among all three groups, people seem to be involved in less active activities on Friday.

- 4. Daily calories, day, and sleep type
- **4.1 Average daily calories by day** To know what day during a week participants burned calories the most.

```
average_daily_calories <- DailyActivity_Sleep_merged %>%
  mutate(day)
average_daily_calories$day <- ordered(average_daily_calories$day, levels = c("Mon", "Tue", "Wed", "Thu"
average_daily_calories <- average_daily_calories %>%
  group_by(day) %>%
  summarize(weekday_calories = mean(Calories))
head(average_daily_calories)
## # A tibble: 6 x 2
##
    day
           weekday_calories
##
     <ord>
                      <dbl>
## 1 Mon
                      2378.
## 2 Tue
                      2307.
## 3 Wed
                      2330.
## 4 Thu
                      2507.
## 5 Fri
                      2277.
## 6 Sat
                      2432.
ggplot(average_daily_calories, aes(day, weekday_calories)) +
  geom_col(fill = "#33CCCC") +
  geom_hline(yintercept = 2389) +
  labs(title = "Average Daily Calories", x = "", y = "") +
  theme(axis.text.x = element_text(angle = 45, vjust = 0.5, hjust = 1))
```

Average Daily Calories



Findings:

*The graph shows that participants burned calories on Thursday the most on average, followed by Sunday and Saturday. The least on Friday. This is consistent with the finding that participants are the least active on Friday.

*The weekdays that have average daily calories burned less than the mean are on Tuesday, Wednesday, and Friday.

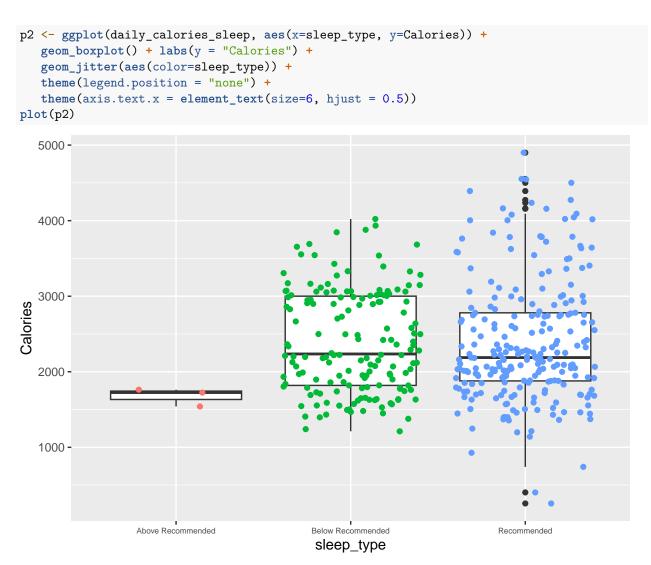
4.2 Daily calories by sleep type

To know what sleep type of people burned calories the most.

```
daily_calories_sleep <- DailyActivity_Sleep_merged %>%
  left_join(sleep_type, by = 'Id') %>%
  group_by(day, sleep_type) %>%
  select(sleep_type, Calories, day) %>%
  mutate(day = factor(day, levels = c("Mon", "Tue", "Wed", "Thu", "Fri", "Sat", "Sun")))
head(daily_calories_sleep)

## # A tibble: 6 x 3
## # Groups: day, sleep_type [5]
```

```
##
     sleep_type
                        Calories day
     <chr>
                           <int> <fct>
##
## 1 Below Recommended
                            1985 Sun
## 2 Below Recommended
                            1797 Mon
## 3 Below Recommended
                            1745 Wed
## 4 Below Recommended
                            1863 Thu
## 5 Below Recommended
                            1728 Fri
## 6 Below Recommended
                            2035 Sun
```



Findings:

*The group sleeping below recommended hours has a slightly higher median than the group sleeping 7-9 hours a night. That means, the group of people who sleep below 7 hours a night might take part in more activities, thus burning more calories.

*The data of the group sleeping 7-9 hours a night more spread out than the rest two groups. Several of them are even exceeding the maximum of the group sleeping below 7 hours a night.

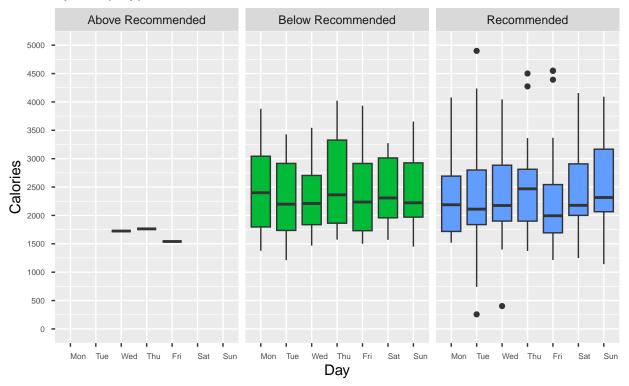
*The group sleeping over 9 hours a night seems to burn less calories with lowest median and less variability.

4.3 Daily calories by day, sleep type

```
p3 <- ggplot(daily_calories_sleep, aes(x = day, y = Calories, fill = sleep_type)) +
geom_boxplot() +
scale_y_continuous(breaks = seq(0, 5000, by = 500), limits = c(0, 5000)) +
theme(legend.position = "none", plot.title = element_text(size = 9)) +
ggtitle("A boxplot with jitter") +
xlab("") +
labs(title = ("Weekday Calories"), subtitle = ("by Sleep Type"), x = "Day", y = "Calories") +
theme(plot.title = element_text(size = 14, hjust = 0)) +
```

```
theme(plot.subtitle = element_text(size = 12, hjust = 0)) +
theme(axis.text.x = element_text(size = 6, hjust = 0)) +
theme(axis.text.y = element_text(size = 6)) +
theme(axis.text.x = element_text(margin = margin(t = 5, r = 1, b = 0, l = 0))) +
theme(axis.text.y = element_text(margin = margin(t = 0, r = 5, b = 0, l = 0))) +
theme(legend.title = element_text(size = 6)) +
theme(legend.text = element_text(size = 6)) +
facet_grid(~sleep_type)
plot(p3)
```

Weekday Calories by Sleep Type



Findings:

*Both groups of sleeping below 7 hours a night and between 7-9 hours a night share a similar distribution that the median tends to go down from Monday to Friday, except Thursday, and then slightly increase over the weekend. That indicates that participants who sleep less than 9 hours a night tend to burn more calories over the weekend and may be more active.

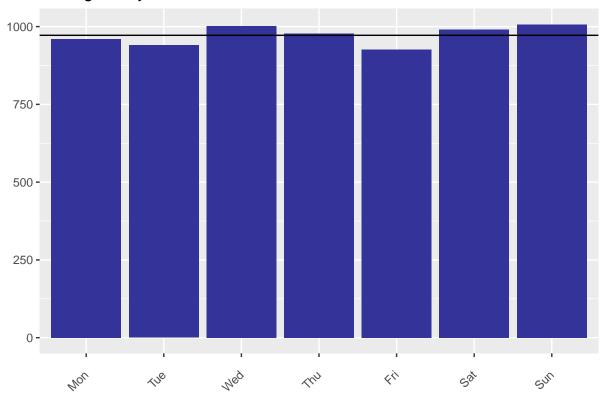
*However, all three groups showed burning more calories on Thursday than the rest weekdays. Further study is needed to discuss the reason behind this.

5. Total active time, day and sleep type

5.1 Total active time by day Before this analysis, I add a new column that shows the total active time from four categories of active times.

```
average_daily_time <- DailyActivity_Sleep_merged %>%
  mutate(day)
average_daily_time$day <- ordered(average_daily_time$day, levels = c("Mon", "Tue",
 "Wed", "Thu", "Fri", "Sat", "Sun"))
average_daily_time <- average_daily_time %>%
  group_by(day) %>%
  summarize(active_time = mean(TotalActiveTime))
head(average_daily_time)
## # A tibble: 6 x 2
##
     day
           active_time
##
     <ord>
                 <dbl>
## 1 Mon
                  960.
                  940.
## 2 Tue
## 3 Wed
                 1002.
## 4 Thu
                  977.
## 5 Fri
                  927.
                  991.
## 6 Sat
ggplot(average_daily_time, aes(day, active_time)) +
  geom_col(fill = "#333399") +
  geom_hline(yintercept = 972) +
  labs(title = "Average Daily Active Time", x = "", y = "") +
  theme(axis.text.x = element_text(angle = 45, vjust = 0.5, hjust = 1))
```

Average Daily Active Time



Findings:

^{*}Wednesday, Saturday, and Sunday are the days with the highest average daily active time. Participants

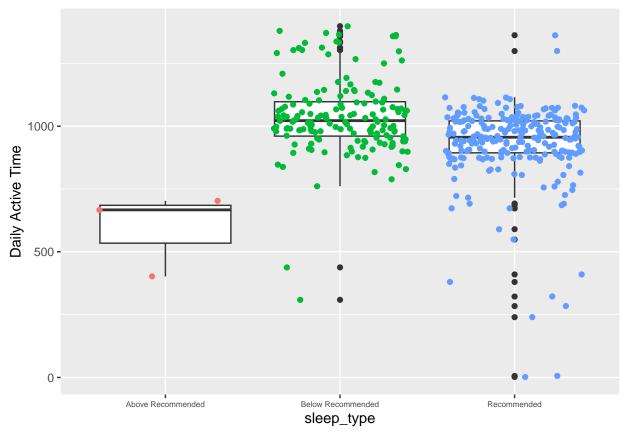
spent at least 16.2 hours on Wednesday, Saturday, and Sunday being active on various tensity of activities.

*The lowest is on Tuesday and Friday. Participants on average spent 15 hours on four different intensity levels of activities.

```
daily_time_sleep <- DailyActivity_Sleep_merged %>%
  left_join(sleep_type, by = "Id") %>%
  group_by(day, sleep_type) %>%
  select(sleep_type, TotalActiveTime, day) %>%
  mutate(day = factor(day, levels = c("Mon", "Tue", "Wed", "Thu", "Fri", "Sat", "Sun")))
head(daily_time_sleep)
```

5.2 Total active time by sleep type

```
## # A tibble: 6 x 3
## # Groups:
               day, sleep_type [5]
                       TotalActiveTime day
##
     sleep_type
                                 <dbl> <fct>
     <chr>
##
## 1 Below Recommended
                                  1094 Sun
## 2 Below Recommended
                                  1033 Mon
## 3 Below Recommended
                                   998 Wed
## 4 Below Recommended
                                  1040 Thu
## 5 Below Recommended
                                   761 Fri
## 6 Below Recommended
                                  1120 Sun
p4 <- ggplot(daily_time_sleep, aes(x = sleep_type, y = TotalActiveTime)) +
  geom_boxplot() + labs(y = "Daily Active Time") +
  geom_jitter(aes(color = sleep_type)) +
  theme(legend.position = "none") +
  theme(axis.text.x = element_text(size = 6, hjust = 0.5))
plot(p4)
```



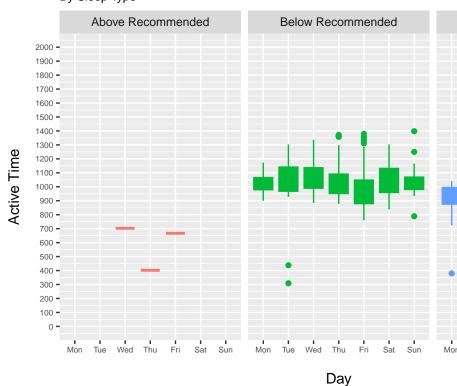
Findings:

- *The group sleeping less than 7 hours a night has the highest median than the other two groups. That means half of the group spend at least 1000 minutes (about 16 and a half hours) a day engaging in activities.
- *However, the group sleeping 7-9 hours a night has a greater variability. Participants in this group spent time on activities in very various spectrums.
- *The group sleeping more than 9 hours has the lowest median and the smallest range. This provides a indicator that participants in this group spent the least amount of time in a day on partaking activities.

```
p5 <- ggplot(daily_time_sleep, aes(x = day, y = TotalActiveTime, fill = sleep_type, colour = sleep_type
  geom_boxplot() +
  scale_y_continuous(breaks = seq(0, 2000, by = 100), limits = <math>c(0, 2000)) +
  theme(legend.position = "none", plot.title = element_text(size = 9)) +
  ggtitle("A boxplot with jitter") +
  xlab("") +
  labs(title = ("Daily Active Time"), subtitle = ("By Sleep Type"), x= "Day", y = "Active Time") +
  theme(plot.title = element_text(size = 12, hjust = 0)) +
  theme(plot.subtitle = element_text(size = 9, hjust = 0)) +
  theme(axis.text.x = element_text(size = 6, hjust = 0.5)) +
  theme(axis.text.y = element_text(size = 6)) +
  theme(axis.title.x = element text(margin = margin(t= 14, r = 0, b = 0, 1 = 0))) +
  theme(axis.title.y = element_text(margin = margin(t = 0, r = 10, b = 0, l = 0))) +
  theme(legend.title = element_text(size = 12)) +
  theme(legend.text = element_text(size = 8)) +
  facet_grid(~sleep_type)
```

plot(p5)

Daily Active Time By Sleep Type



5.3 Total active time by day, sleep type

Findings:

- *Overall, the group sleeping less than 7 hours a night has a higher median throughout the week than the other two groups as well as a greater variability. This suggests that people who sleep less than 7 hours a night spend more time daily of a week joining in different levels of intensity activities.
- *Also, all three groups show a trend that daily active time goes down from Monday to Friday and slightly move back up over the weekend. This might not be surprising. It's a resting day and people intend to go out to hang out with friends and/or family, taking care of chores.

6. Awake time, day, and sleep type

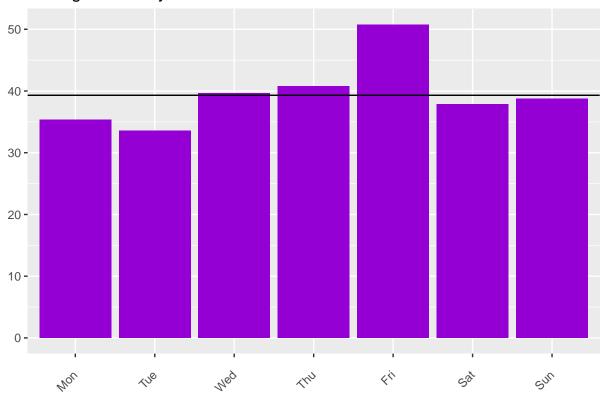
Awake time is the difference between the total asleep time and total time in bed. We will investigate how sleep type relates to awake time on bed across the week.

6.1 Awake time by day To know how participants stay in bed over a week after sleeping.

```
average_awake <- DailyActivity_Sleep_merged %>%
  mutate(day)
average_awake$day <- ordered(average_awake$day, levels = c("Mon", "Tue", "Wed", "Thu", "Fri", "Sat", "Suaverage_awake <- average_awake %>%
  group_by(day) %>%
  summarise(dailyawaketime = mean(diff))
ggplot(average_awake, aes(day, dailyawaketime))+
  geom_col(fill = "#9400D3") +
  geom_hline(yintercept = 39.31) +
```

```
labs(title = "Average Weekday Awake time on bed", x = "", y = "") +
theme(axis.text.x = element_text(angle =45, vjust = 0.5, hjust = 1))
```

Average Weekday Awake time on bed



Findings:

```
awake <- DailyActivity_Sleep_merged %>%
  left_join(sleep_type, by ='Id') %>%
  group_by(day, sleep_type) %>%
  select(sleep_type, diff, day) %>%
  mutate(day = factor(day, levels = c("Mon", "Tue", "Wed", "Thu", "Fri", "Sat", "Sun")))
head(awake)
```

6.2 Awake time by sleep types

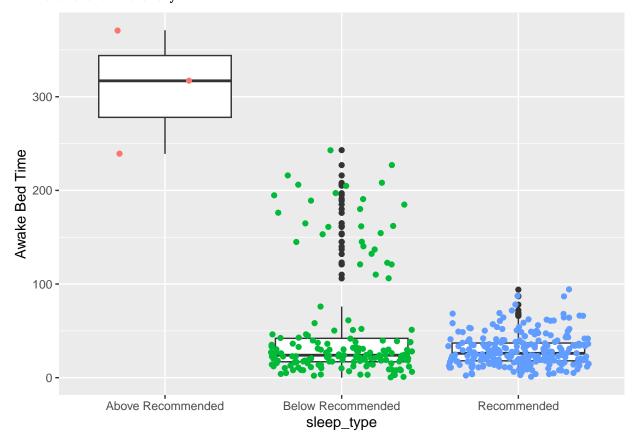
```
## # A tibble: 6 x 3
## # Groups:
               day, sleep_type [5]
##
     sleep_type
                        diff day
##
     <chr>
                       <int> <fct>
## 1 Below Recommended
                          19 Sun
## 2 Below Recommended
                          23 Mon
## 3 Below Recommended
                          30 Wed
## 4 Below Recommended
                          27 Thu
## 5 Below Recommended
                          12 Fri
## 6 Below Recommended
                          16 Sun
```

^{*}The weekday that participants lounged on bed the longest after waking up from sleeping is on Friday.

^{*}Participants stay awake in bed on Monday, Tuesday, and Saturday shorter than the rest weekdays.

```
p6 <- ggplot(awake, aes(x = sleep_type, y = diff)) +
   geom_boxplot() + labs (y = "Awake Bed Time") +
   geom_jitter(aes(color = sleep_type)) +
   theme(legend.position = "none") +
   theme(asix.text.x = element_text(size = 6, hjust = 0.5))
plot(p6)</pre>
```

Warning in plot_theme(plot): The `asix.text.x` theme element is not defined in ## the element hierarchy.



Findings:

*The group sleeping more than 9 hours a night shows a greater median, which means they stay in bed longer after waking up from sleeping than the other two groups.

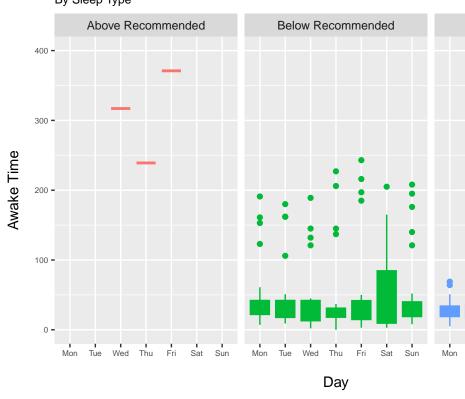
*The majority of groups sleep 7-9 hours or below a night is below 100 minutes. The means that those participants will stay in bed about one hour and half when not asleep.

*Some people who sleep below recommended might stay in bed longer than 100 minutes, but less than 250 minutes (about 4 hours).

```
p7 <- ggplot(awake, aes(x = day, y = diff, fill = sleep_type, colour = sleep_type))+
    geom_boxplot() +
    scale_y_continuous(breaks = seq(0, 400, by = 100), limits = c(0, 400)) +
    theme(legend.position = "none", plot.title = element_text(size = 9)) +
    ggtitle("A boxplot with jitter") +
    xlab("") +</pre>
```

```
labs(title = ("Daily awake time on bed"), subtitle = ("By Sleep Type"), x= "Day", y = "Awake Time"
theme(plot.title = element_text(size = 12, hjust = 0)) +
theme(plot.subtitle = element_text(size = 9, hjust = 0)) +
theme(axis.text.x = element_text(size = 6, hjust = 0.5)) +
theme(axis.text.y = element_text(size = 6)) +
theme(axis.title.x = element_text(margin = margin(t= 14, r = 0, b = 0, l = 0))) +
theme(axis.title.y = element_text(margin = margin(t = 0, r = 10, b = 0, l = 0))) +
theme(legend.title = element_text(size = 12)) +
theme(legend.text = element_text(size = 8)) +
facet_grid(~sleep_type)
plot(p7)
```

Daily awake time on bed By Sleep Type



6.3 Awake time by day, by sleep types

Findings:

*The distributions of groups sleeping 7-9 hours a night and sleeping below 7 hours a night is close to each other. Their daily median seems to be lower than 50 minutes through the week.

*But the group sleeping below 7 hours a night seems to have more outlier on daily awake time than the group sleeping 7-9 hours a night. This implies it is more consistent that people who sleep 7-9 hours a night would not stay in bed long after they have a overnight sleeping and might get up to take part in activities that require more energy expenditures.

Act

Conclusion

*Bellabeat is a high-tech company that focus on health products for woman and collect health data to empower them with knowledge about their health and habits. The goal of this project is to analyze data

from Fitbit smart device users and, ultimately, to use the results to inform the marketing strategies for the company's next global expansion. Below are the conclusions from this project:

*Overall, participants would travel (walk or move around) more distance and spend more time on activities on Monday and during the weekend. But the trend is trailing off from Tuesday to Friday.

*54% of participants sleep less than 7 hours a night, 42% of them between 7- 9 hours, and 4% is above 9 hours. Those who sleep less than 7 hours a night tends to travel more distance in kilometers daily, but those who sleep between 7-9 hours a night tends to burn more calories daily. This implies people who sleep between 7-9 hours a night engage in more active activities than lightly active or sedentary.

*For participants who sleep less than 7 hours a night, the pattern of daily active time spent is like the one from participants who sleep between 7 and 9 hours a night.

*The participants who sleep more than 9 hours a night tends to have a pattern of lowest daily distance travelled, daily calories burned, and shortest daily active time. This might correspond to the finding that this group seems to have daily longest awake time in bed. This might indicate that those participants sleeping more than 9 hours a night join mostly lightly active or sedentary distance and minutes. In addition, some of participants who sleep less than 7 hours a night would choose to lounge longer in bed than those sleep by recommended.

*Limitation is noted in this project. We have a small sample size, and datasets can be biased since demographic information is lacking.

Recommendations

*The Bellabeat company aims to empower woman with knowledge about their own health and habits. Regardless of ages, getting enough sleep and getting active have been recommended to stay healthy for woman. Here are my recommendations for the marketing strategy to expand globally.

*Bellabeat app. should put out more notifications or reminders to encourage more engagement in active activities during the weekdays, emphasizing consistently getting active throughout a week could get a better result to build a healthy habit and lifestyle.

*Bellabeat app. should allow users to flexibly personalize their settings on their smart devices based on their health information (sleeping status, diet restriction, illness, and etc.) and needs (such as stay healthy, lose weight, or others), and provide real-time feedback to users based on their personalization.

*The company should consider cooperating with devices that have AI functions (such as ALEXA) that users can set up alarm for or schedule a lightly workout or stretch in bed before or after sleeping since people tends to stay awake in bed almost 40 minutes daily.

*Bellabeat company should build a communication system between smart devices and their users. This system can be delivered by email, text, or other means so that a daily or weekly summary will be sent to users in terms of activities engaged, calories burned, sleeping status, and etc. Suggestions or tips will be followed at the end of the summary to remind users to maintain a healthy habit or behaviors.

*Marketing could deliver that Bellabeat smart devices are more than just a fitness tracker. It provides a means to depict the quality of a woman's life and to motivate and educate them to become better and healthier themselves.

*More further studies are needed with datasets from Bellabeat smart device users. The current project is analyzed with Fitbit datasets that target audiences are more than just woman. With Bellabeat's very own datasets, we can analyze patterns of womans' usage on smart devices for wellness purposes and compare them with Fitbit users to explore similarities and differences. From that, we can make suggestions and improve Bellabest smart devices so that we can more holistically take care of woman's wellness.

Resource:

https://www.cdc.gov/healthequity/features/nwhw/index.html

 $https://www.medicalnewstoday.com/articles/how-many-steps-should-you-take-a-day\#for-general-health \\ https://www.nytimes.com/2024/02/17/well/bed-rotting-hurkle-durkle.html$

https://www.nbcnews.com/better/pop-culture/make-your-day-better-stay-bed-longer-really-ncna837176

 $https://www.nhlbi.nih.gov/health/sleep/how-much-sleep\#:\sim:text=Experts\%20 recommend\%20 that\%20 adults\%20 sleep, or\%20 more\%20 hours\%20 a\%20 night$

A special thank you to the following authors that have completed their Bellabeat capstone project and share their work. Their work provides a light to guide me through the tunel of navigating data analysis as a first-time R programming user.

https://www.kaggle.com/code/zulkhaireesulaiman/bellabeat-capstone-project-in-r/notebook

https://medium.com/@shogbaikeadeola/google-data-analytics-capstone-project-bellabeat-case-study-48431571702