Hemalatha_Subbiah_Project_Step2

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R Markdown

How to import and clean my data :

```
## Set the working directory to the root of your DSC 520 directory
## Load the `data/r4ds/week-6-housing.csv` to
setwd("C:/MastersCourse/RAssignemtents/data")

dailyActivity_data <- read.csv("dailyActivity_merged.csv", header = TRUE)
head(dailyActivity_data)
```

```
##           Id ActivityDate TotalSteps TotalDistance TrackerDistance
## 1 1503960366    4/12/2016      13162          8.50            8.50
## 2 1503960366    4/13/2016      10735          6.97            6.97
## 3 1503960366    4/14/2016      10460          6.74            6.74
## 4 1503960366    4/15/2016       9762          6.28            6.28
## 5 1503960366    4/16/2016      12669          8.16            8.16
## 6 1503960366    4/17/2016       9705          6.48            6.48
##   LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance
## 1                        0               1.88                     0.55
## 2                        0               1.57                     0.69
## 3                        0               2.44                     0.40
## 4                        0               2.14                     1.26
## 5                        0               2.71                     0.41
## 6                        0               3.19                     0.78
##   LightActiveDistance SedentaryActiveDistance VeryActiveMinutes
## 1                6.06                       0                25
## 2                4.71                       0                21
## 3                3.91                       0                30
## 4                2.83                       0                29
## 5                5.04                       0                36
## 6                2.51                       0                38
##   FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes Calories
## 1                  13                  328              728     1985
## 2                  19                  217              776     1797
## 3                  11                  181             1218     1776
## 4                  34                  209              726     1745
## 5                  10                  221              773     1863
## 6                  20                  164              539     1728
```

```r
dailyCalories_data <- read.csv("dailyCalories_merged.csv", header = TRUE)
head(dailyCalories_data)
```

```
##           Id ActivityDay Calories
## 1 1503960366   4/12/2016     1985
## 2 1503960366   4/13/2016     1797
## 3 1503960366   4/14/2016     1776
## 4 1503960366   4/15/2016     1745
## 5 1503960366   4/16/2016     1863
## 6 1503960366   4/17/2016     1728
```

```r
dailySteps_data <- read.csv("dailySteps_merged.csv", header = TRUE)
head(dailySteps_data)
```

```
##           Id ActivityDay StepTotal
## 1 1503960366   4/12/2016     13162
## 2 1503960366   4/13/2016     10735
## 3 1503960366   4/14/2016     10460
## 4 1503960366   4/15/2016      9762
## 5 1503960366   4/16/2016     12669
## 6 1503960366   4/17/2016      9705
```

```r
sleepDay_data <- read.csv("sleepDay_merged.csv", header = TRUE)
head(sleepDay_data)
```

```
##           Id              SleepDay TotalSleepRecords TotalMinutesAsleep
## 1 1503960366 4/12/2016 12:00:00 AM                 1                327
## 2 1503960366 4/13/2016 12:00:00 AM                 2                384
## 3 1503960366 4/15/2016 12:00:00 AM                 1                412
## 4 1503960366 4/16/2016 12:00:00 AM                 2                340
## 5 1503960366 4/17/2016 12:00:00 AM                 1                700
## 6 1503960366 4/19/2016 12:00:00 AM                 1                304
##   TotalTimeInBed
## 1            346
## 2            407
## 3            442
## 4            367
## 5            712
## 6            320
```

```r
weightLogInfo_data <- read.csv("weightLogInfo_merged.csv", header = TRUE)
head(weightLogInfo_data)
```

```
##           Id                  Date WeightKg WeightPounds Fat   BMI
## 1 1503960366  5/2/2016 11:59:59 PM     52.6     115.9631  22 22.65
## 2 1503960366  5/3/2016 11:59:59 PM     52.6     115.9631  NA 22.65
## 3 1927972279  4/13/2016 1:08:52 AM    133.5     294.3171  NA 47.54
## 4 2873212765 4/21/2016 11:59:59 PM     56.7     125.0021  NA 21.45
## 5 2873212765 5/12/2016 11:59:59 PM     57.3     126.3249  NA 21.69
## 6 4319703577 4/17/2016 11:59:59 PM     72.4     159.6147  25 27.45
##   IsManualReport        LogId
```

```
## 1           True 1.462234e+12
## 2           True 1.462320e+12
## 3          False 1.460510e+12
## 4           True 1.461283e+12
## 5           True 1.463098e+12
## 6           True 1.460938e+12
```

1. Clean column names

2.Remove empty column or rows Suppose if you want to remove the column or row if contain completely empty, then you can use remove_empty function.

3. To Exclude duplicates and remove null:

```
dailyActivity_data <- unique(dailyActivity_data)                                    # Exclude duplica
dailyCalories_data <- unique(dailyCalories_data)
dailySteps_data <- unique(dailySteps_data)
sleepDay_data <- unique(sleepDay_data)
weightLogInfo_data <- unique(weightLogInfo_data)

sum(is.na(dailyActivity_data))
```

```
## [1] 0
```

```
sum(is.na(dailyCalories_data))
```

```
## [1] 0
```

```
sum(is.na(dailySteps_data))
```

```
## [1] 0
```

```
sum(is.na(sleepDay_data))
```

```
## [1] 0
```

```
sum(is.na(weightLogInfo_data))
```

```
## [1] 65
```

4. Convert data type

```
sapply(dailyActivity_data, class)
```

```
##                       Id             ActivityDate                TotalSteps
##                "numeric"              "character"                 "integer"
##            TotalDistance          TrackerDistance LoggedActivitiesDistance
##                "numeric"                "numeric"                 "numeric"
```

```
##       VeryActiveDistance ModeratelyActiveDistance      LightActiveDistance
##                "numeric"                "numeric"                "numeric"
##  SedentaryActiveDistance        VeryActiveMinutes      FairlyActiveMinutes
##                "numeric"                "integer"                "integer"
##     LightlyActiveMinutes         SedentaryMinutes                 Calories
##                "integer"                "integer"                "integer"
```

```
sapply(dailyCalories_data, class)
```

```
##          Id ActivityDay    Calories
##   "numeric" "character"   "integer"
```

```
sapply(dailySteps_data, class)
```

```
##          Id ActivityDay   StepTotal
##   "numeric" "character"   "integer"
```

```
sapply(sleepDay_data, class)
```

```
##                 Id           SleepDay  TotalSleepRecords TotalMinutesAsleep
##          "numeric"        "character"          "integer"          "integer"
##     TotalTimeInBed
##          "integer"
```

```
sapply(weightLogInfo_data, class)
```

```
##             Id           Date       WeightKg   WeightPounds            Fat
##      "numeric"    "character"      "numeric"      "numeric"      "integer"
##            BMI IsManualReport          LogId
##      "numeric"    "character"      "numeric"
```

```
dailyActivity_data <- type.convert(dailyActivity_data, as.is = TRUE)
dailyCalories_data <- type.convert(dailyCalories_data, as.is = TRUE)
dailySteps_data <- type.convert(dailySteps_data, as.is = TRUE)
sleepDay_data <- type.convert(sleepDay_data, as.is = TRUE)
weightLogInfo_data <- type.convert(weightLogInfo_data, as.is = TRUE)
```

5. Detect & Remove Outliers

```
weightLogInfo_data$weight_kg[weightLogInfo_data$weight_kg%in% boxplot.stats(weightLogInfo_data$weight_kg
```

```
## NULL
```

```
head(dailyActivity_data)
```

```
##           Id ActivityDate TotalSteps TotalDistance TrackerDistance
## 1 1503960366    4/12/2016      13162          8.50            8.50
## 2 1503960366    4/13/2016      10735          6.97            6.97
```

```
## 3 1503960366    4/14/2016      10460          6.74            6.74
## 4 1503960366    4/15/2016       9762          6.28            6.28
## 5 1503960366    4/16/2016      12669          8.16            8.16
## 6 1503960366    4/17/2016       9705          6.48            6.48
##   LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance
## 1                        0              1.88                     0.55
## 2                        0              1.57                     0.69
## 3                        0              2.44                     0.40
## 4                        0              2.14                     1.26
## 5                        0              2.71                     0.41
## 6                        0              3.19                     0.78
##   LightActiveDistance SedentaryActiveDistance VeryActiveMinutes
## 1                6.06                       0                25
## 2                4.71                       0                21
## 3                3.91                       0                30
## 4                2.83                       0                29
## 5                5.04                       0                36
## 6                2.51                       0                38
##   FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes Calories
## 1                  13                  328              728     1985
## 2                  19                  217              776     1797
## 3                  11                  181             1218     1776
## 4                  34                  209              726     1745
## 5                  10                  221              773     1863
## 6                  20                  164              539     1728
```

What does the final data set look like?

It might be difficult to understand at first what the data means and what column names to use, but after couple of analysis was able to figure out the data.

#preparing daily activity dataset,

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

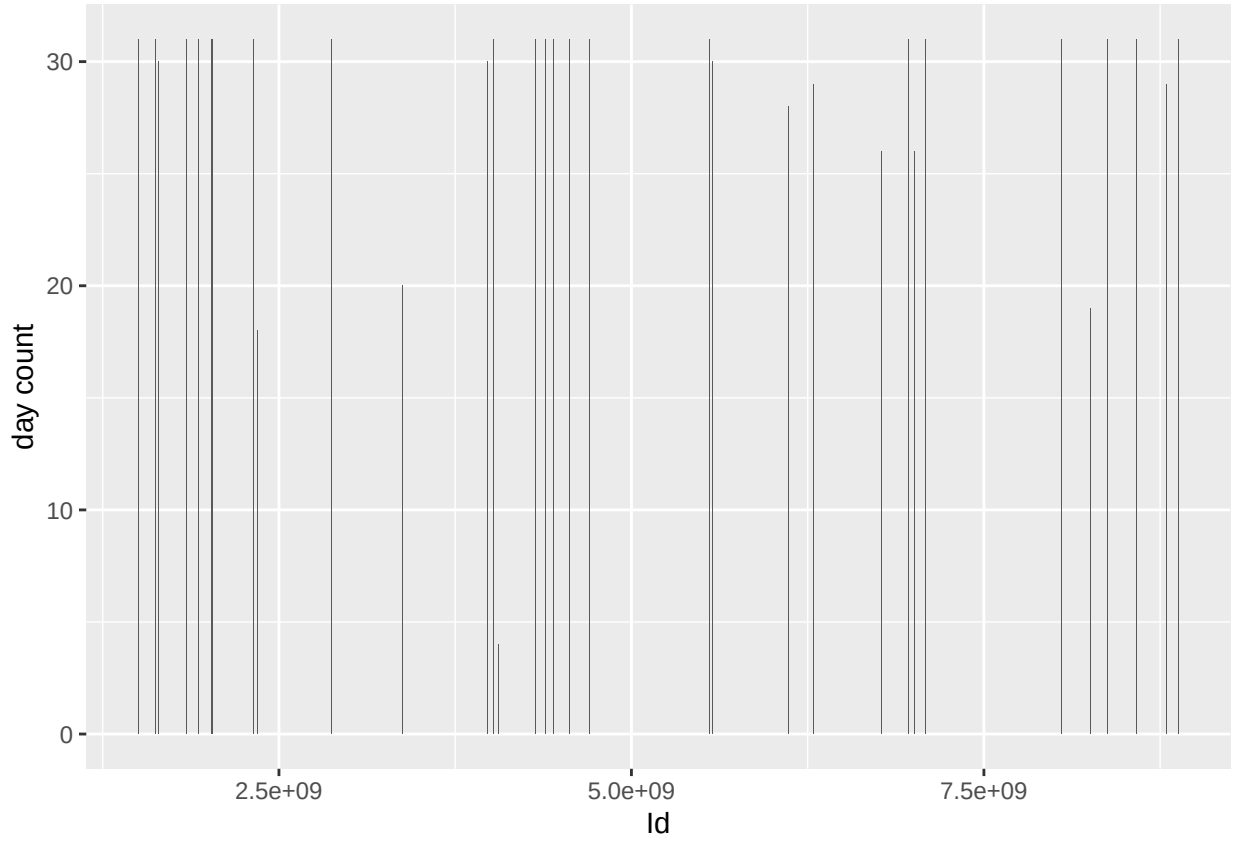
```
library(ggplot2)
dailyActivity_data <- dailyActivity_data %>% mutate(day = as.Date(ActivityDate)) %>% select(-c(2,5:9))
print(paste(c("Rows: ", "Columns: "), dim(dailyActivity_data)))
```

```
## [1] "Rows:  940"   "Columns:  10"
```

```
dailyactivity <- distinct(dailyActivity_data)
print(paste(c("Rows: ", "Columns: "), dim(dailyActivity_data)))
```

```
## [1] "Rows:  940"   "Columns:  10"
```

```
ggplot(data=dailyActivity_data,aes(x=Id)) +
  geom_bar() + ylab("day count")
```




```
library(lubridate)
library(dplyr)
library(ggplot2)
head(weightLogInfo_data)
```

```
##           Id                  Date WeightKg WeightPounds Fat   BMI
## 1 1503960366  5/2/2016 11:59:59 PM     52.6     115.9631  22 22.65
## 2 1503960366  5/3/2016 11:59:59 PM     52.6     115.9631  NA 22.65
## 3 1927972279  4/13/2016 1:08:52 AM    133.5     294.3171  NA 47.54
## 4 2873212765 4/21/2016 11:59:59 PM     56.7     125.0021  NA 21.45
## 5 2873212765 5/12/2016 11:59:59 PM     57.3     126.3249  NA 21.69
## 6 4319703577 4/17/2016 11:59:59 PM     72.4     159.6147  25 27.45
##   IsManualReport        LogId
## 1           True 1.462234e+12
## 2           True 1.462320e+12
## 3          False 1.460510e+12
## 4           True 1.461283e+12
## 5           True 1.463098e+12
## 6           True 1.460938e+12
```

```
weightLogInfo_data <- weightLogInfo_data %>% mutate (time = mdy_hms(as.Date(Date)))%>% mutate(day = dat
```

```
## Warning: All formats failed to parse. No formats found.
```

```
print(paste(c("Rows: ", "Columns: "), dim(weightLogInfo_data)))
```

```
## [1] "Rows:  67"   "Columns:  6"
```

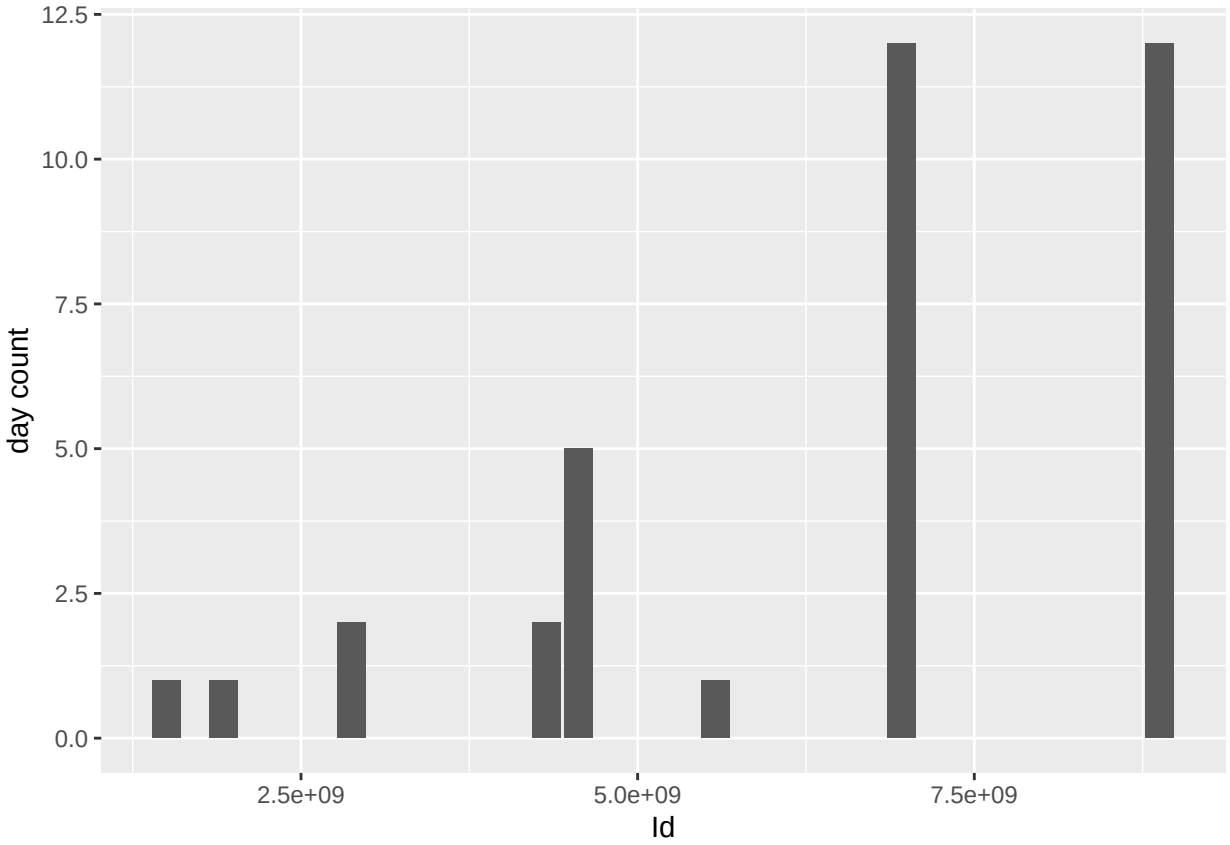
```
weightLogInfo_data <- distinct(weightLogInfo_data)
print(paste(c("Rows: ", "Columns: "), dim(weightLogInfo_data)))
```

```
## [1] "Rows:  36"   "Columns:  6"
```

```
head(weightLogInfo_data)
```

```
##           Id WeightKg WeightPounds   BMI IsManualReport  day
## 1 1503960366     52.6     115.9631 22.65           True <NA>
## 2 1927972279    133.5     294.3171 47.54          False <NA>
## 3 2873212765     56.7     125.0021 21.45           True <NA>
## 4 2873212765     57.3     126.3249 21.69           True <NA>
## 5 4319703577     72.4     159.6147 27.45           True <NA>
## 6 4319703577     72.3     159.3942 27.38           True <NA>
```

```
ggplot(data=weightLogInfo_data, aes(x=Id)) +
  geom_bar() + ylab("day count")
```



Merging data

Before beginning to visualize the data, I need to merge two data sets. I'm going to merge (inner join) activity and sleep on columns Id and date (that I previously created after converting data to date time format).

```
merged_data <- merge(sleepDay_data, dailyActivity_data,  by=c('Id'))
head(merged_data)
```

```
##           Id              SleepDay TotalSleepRecords TotalMinutesAsleep
## 1 1503960366 4/12/2016 12:00:00 AM                 1                327
## 2 1503960366 4/12/2016 12:00:00 AM                 1                327
## 3 1503960366 4/12/2016 12:00:00 AM                 1                327
## 4 1503960366 4/12/2016 12:00:00 AM                 1                327
## 5 1503960366 4/12/2016 12:00:00 AM                 1                327
## 6 1503960366 4/12/2016 12:00:00 AM                 1                327
##   TotalTimeInBed TotalSteps TotalDistance SedentaryActiveDistance
## 1            346      11992          7.71                       0
## 2            346      12159          8.03                       0
## 3            346      10602          6.81                       0
## 4            346      14673          9.25                       0
## 5            346      13162          8.50                       0
## 6            346      10735          6.97                       0
##   VeryActiveMinutes FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes
## 1                37                  46                  175              833
```

```
## 2                24                  6                289              754
## 3                33                 35                246              730
## 4                52                 34                217              712
## 5                25                 13                328              728
## 6                21                 19                217              776
##   Calories        day
## 1     1821 0005-07-20
## 2     1896 0005-06-20
## 3     1820 0005-01-20
## 4     1947       <NA>
## 5     1985 0004-12-20
## 6     1797       <NA>
```

```
merged_data <- merge(dailyActivity_data,  weightLogInfo_data, by=c('Id'))
head(merged_data)
```

```
##           Id TotalSteps TotalDistance SedentaryActiveDistance VeryActiveMinutes
## 1 1503960366      12669          8.16                       0                36
## 2 1503960366      13019          8.59                       0                42
## 3 1503960366       9762          6.28                       0                29
## 4 1503960366      10060          6.58                       0                44
## 5 1503960366       9705          6.48                       0                38
## 6 1503960366      15506          9.88                       0                50
##   FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes Calories      day.x
## 1                  10                  221              773     1863       <NA>
## 2                  16                  233             1149     1921       <NA>
## 3                  34                  209              726     1745       <NA>
## 4                   8                  203              574     1740 0005-08-20
## 5                  20                  164              539     1728       <NA>
## 6                  31                  264              775     2035       <NA>
##   WeightKg WeightPounds   BMI IsManualReport day.y
## 1     52.6     115.9631 22.65           True  <NA>
## 2     52.6     115.9631 22.65           True  <NA>
## 3     52.6     115.9631 22.65           True  <NA>
## 4     52.6     115.9631 22.65           True  <NA>
## 5     52.6     115.9631 22.65           True  <NA>
## 6     52.6     115.9631 22.65           True  <NA>
```

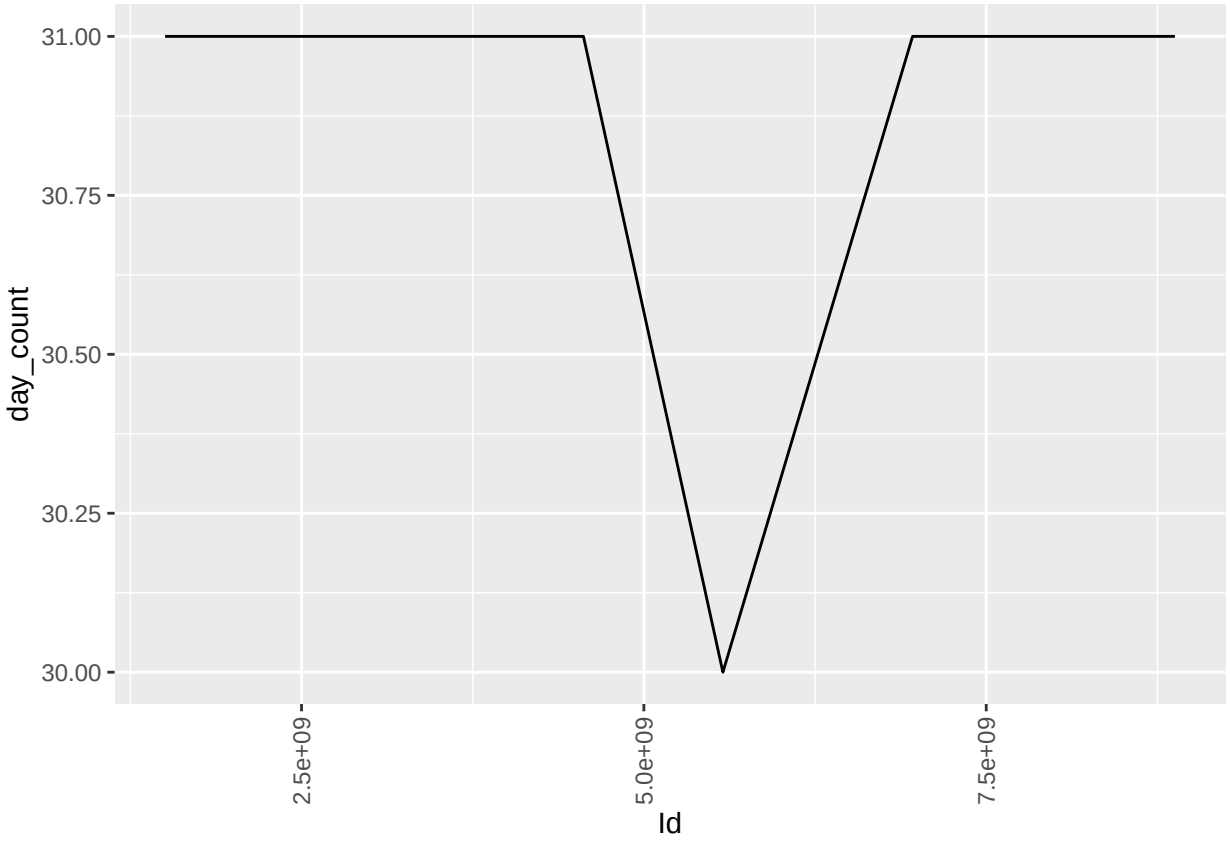
```
#joining the essential data frames earlier read above
head(dailyCalories_data)
```

```
##           Id ActivityDay Calories
## 1 1503960366   4/12/2016     1985
## 2 1503960366   4/13/2016     1797
## 3 1503960366   4/14/2016     1776
## 4 1503960366   4/15/2016     1745
## 5 1503960366   4/16/2016     1863
## 6 1503960366   4/17/2016     1728
```

```
all_tables <- dailyActivity_data %>% full_join(sleepDay_data, by = c("Id")) %>% full_join(dailyCalories_
head(all_tables)
```

```
##           Id TotalSteps TotalDistance SedentaryActiveDistance VeryActiveMinutes
## 1 1503960366      13162           8.5                       0                25
## 2 1503960366      13162           8.5                       0                25
## 3 1503960366      13162           8.5                       0                25
## 4 1503960366      13162           8.5                       0                25
## 5 1503960366      13162           8.5                       0                25
## 6 1503960366      13162           8.5                       0                25
##   FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes Calories.x
## 1                  13                  328              728       1985
## 2                  13                  328              728       1985
## 3                  13                  328              728       1985
## 4                  13                  328              728       1985
## 5                  13                  328              728       1985
## 6                  13                  328              728       1985
##        day.x              SleepDay TotalSleepRecords TotalMinutesAsleep
## 1 0004-12-20 4/12/2016 12:00:00 AM                 1                327
## 2 0004-12-20 4/12/2016 12:00:00 AM                 1                327
## 3 0004-12-20 4/12/2016 12:00:00 AM                 1                327
## 4 0004-12-20 4/12/2016 12:00:00 AM                 1                327
## 5 0004-12-20 4/12/2016 12:00:00 AM                 1                327
## 6 0004-12-20 4/12/2016 12:00:00 AM                 1                327
##   TotalTimeInBed ActivityDay Calories.y WeightKg WeightPounds   BMI
## 1            346   4/12/2016       1985     52.6     115.9631 22.65
## 2            346   4/13/2016       1797     52.6     115.9631 22.65
## 3            346   4/14/2016       1776     52.6     115.9631 22.65
## 4            346   4/15/2016       1745     52.6     115.9631 22.65
## 5            346   4/16/2016       1863     52.6     115.9631 22.65
## 6            346   4/17/2016       1728     52.6     115.9631 22.65
##   IsManualReport day.y
## 1           True  <NA>
## 2           True  <NA>
## 3           True  <NA>
## 4           True  <NA>
## 5           True  <NA>
## 6           True  <NA>
```

```
#day count for users who tracked their calories, checking frequency of daily use
calories<-filter(all_tables,BMI!=0)%>% group_by(Id)%>% summarise(day_count= n_distinct(ActivityDay), .g
ggplot(data=calories, mapping=aes(x=Id, y=day_count)) + geom_line()+ theme(axis.text.x = element_text(a
```



From the analysis I did the people are generally using fitness tracker to track activities and calories burned.And used it for sleep ans rest as well/

What information is not self-evident?

1.Key demographics data such as gender, age, were not identified. This is a crucial missing how far women use activity trackers.

2.User's exercise habits differ between summer and winter as the data is just for 31 days limited.

3.Health and lifestyle data is varied across different facets of society ,the data set is collected from small sample size.

What are different ways you could look at this data?

When I started analyzing the data, I want to set clear goals and expectations for what I wanted to learn and what insights you were expecting to find. I see that outliers in the data may skew the results. Significant outliers can easily skew averages in the data, so I may need to track the median rather than the mean. The median uses the middle value of the numerical data set, so it's less skewed by outliers. Alternatively, I may need to discount these outliers from your analysis altogether.

How do you plan to slice and dice the data?

Slicing means filtering rows from the data set and dicing means select set of columns from the data set.

With daily_activity data set,we will assume that days with < 200 TotalSteps taken, are days where users have not used their watches. We will filter out these inactive day and assign the following designations:

Low Use - 1 to 14 days o Moderate Use - 15 to 21 days High Use - 22 to 31 days

```
#data transformation to create df for 'Usage Types'
dailyActivity_data_group <- dailyActivity_data %>%
  filter(TotalSteps >200 ) %>%
  group_by(Id) %>%
  summarize(ActivityDate=sum(n())) %>%
  mutate(Usage = case_when(
    ActivityDate >= 1 & ActivityDate <= 14 ~ "Low Use",
    ActivityDate >= 15 & ActivityDate <= 21 ~ "Moderate Use",
    ActivityDate >= 22 & ActivityDate <= 31 ~ "High Use")) %>%
  mutate(Usage = factor(Usage, level = c('Low Use','Moderate Use','High Use'))) %>%
  rename(daysused = ActivityDate) %>%
  group_by(Usage)
head(dailyActivity_data_group)
```

```
## # A tibble: 6 x 3
## # Groups:   Usage [2]
##           Id daysused Usage
##        <dbl>    <int> <fct>
## 1 1503960366       30 High Use
## 2 1624580081       31 High Use
## 3 1644430081       30 High Use
## 4 1844505072       17 Moderate Use
## 5 1927972279       15 Moderate Use
## 6 2022484408       31 High Use
```

```
daily_use <- dailyActivity_data %>%
  left_join(dailyActivity_data_group, by = 'Id') %>%
  group_by(Usage) %>%
  summarise(participants = n_distinct(Id)) %>%
  mutate(perc = participants/sum(participants)) %>%
  arrange(perc) %>%
  mutate(perc = scales::percent(perc))
head(daily_use)
```

```
## # A tibble: 3 x 3
##   Usage        participants perc
##   <fct>               <int> <chr>
## 1 Low Use                 2 6%
## 2 Moderate Use            7 21%
## 3 High Use               24 73%
```

Above analysis ascertain how often the participants use their watches.We will filter out these how the activity trackers are used by the participant and categorized in to 3 parts.

How could you summarize your data to answer key questions?

```
# activity
dailyActivity_data %>%
  select(TotalSteps,
         TotalDistance,
         SedentaryMinutes, Calories) %>%
  summary()
```

```
##    TotalSteps    TotalDistance    SedentaryMinutes    Calories
##  Min.   :    0   Min.   : 0.000   Min.   :   0.0   Min.   :   0
##  1st Qu.: 3790   1st Qu.: 2.620   1st Qu.: 729.8   1st Qu.:1828
##  Median : 7406   Median : 5.245   Median :1057.5   Median :2134
##  Mean   : 7638   Mean   : 5.490   Mean   : 991.2   Mean   :2304
##  3rd Qu.:10727   3rd Qu.: 7.713   3rd Qu.:1229.5   3rd Qu.:2793
##  Max.   :36019   Max.   :28.030   Max.   :1440.0   Max.   :4900
```

```
# explore num of active minutes per category
dailyActivity_data %>%
  select(VeryActiveMinutes, FairlyActiveMinutes, LightlyActiveMinutes) %>%
  summary()
```

```
##  VeryActiveMinutes FairlyActiveMinutes LightlyActiveMinutes
##  Min.   :  0.00    Min.   :  0.00      Min.   :  0.0
##  1st Qu.:  0.00    1st Qu.:  0.00      1st Qu.:127.0
##  Median :  4.00    Median :  6.00      Median :199.0
##  Mean   : 21.16    Mean   : 13.56      Mean   :192.8
##  3rd Qu.: 32.00    3rd Qu.: 19.00      3rd Qu.:264.0
##  Max.   :210.00    Max.   :143.00      Max.   :518.0
```

```
# calories
dailyCalories_data %>%
  select(Calories) %>%
  summary()
```

```
##     Calories
##  Min.   :   0
##  1st Qu.:1828
##  Median :2134
##  Mean   :2304
##  3rd Qu.:2793
##  Max.   :4900
```

```
# sleep
sleepDay_data %>%
  select(TotalSleepRecords, TotalMinutesAsleep, TotalTimeInBed) %>%
  summary()
```

```
##  TotalSleepRecords TotalMinutesAsleep TotalTimeInBed
##  Min.   :1.00      Min.   : 58.0      Min.   : 61.0
```

```
##  1st Qu.:1.00      1st Qu.:361.0      1st Qu.:403.8
##  Median :1.00      Median :432.5      Median :463.0
##  Mean   :1.12      Mean   :419.2      Mean   :458.5
##  3rd Qu.:1.00      3rd Qu.:490.0      3rd Qu.:526.0
##  Max.   :3.00      Max.   :796.0      Max.   :961.0
```

```
# weight
weightLogInfo_data %>%
  select(WeightKg, BMI) %>%
  summary()
```

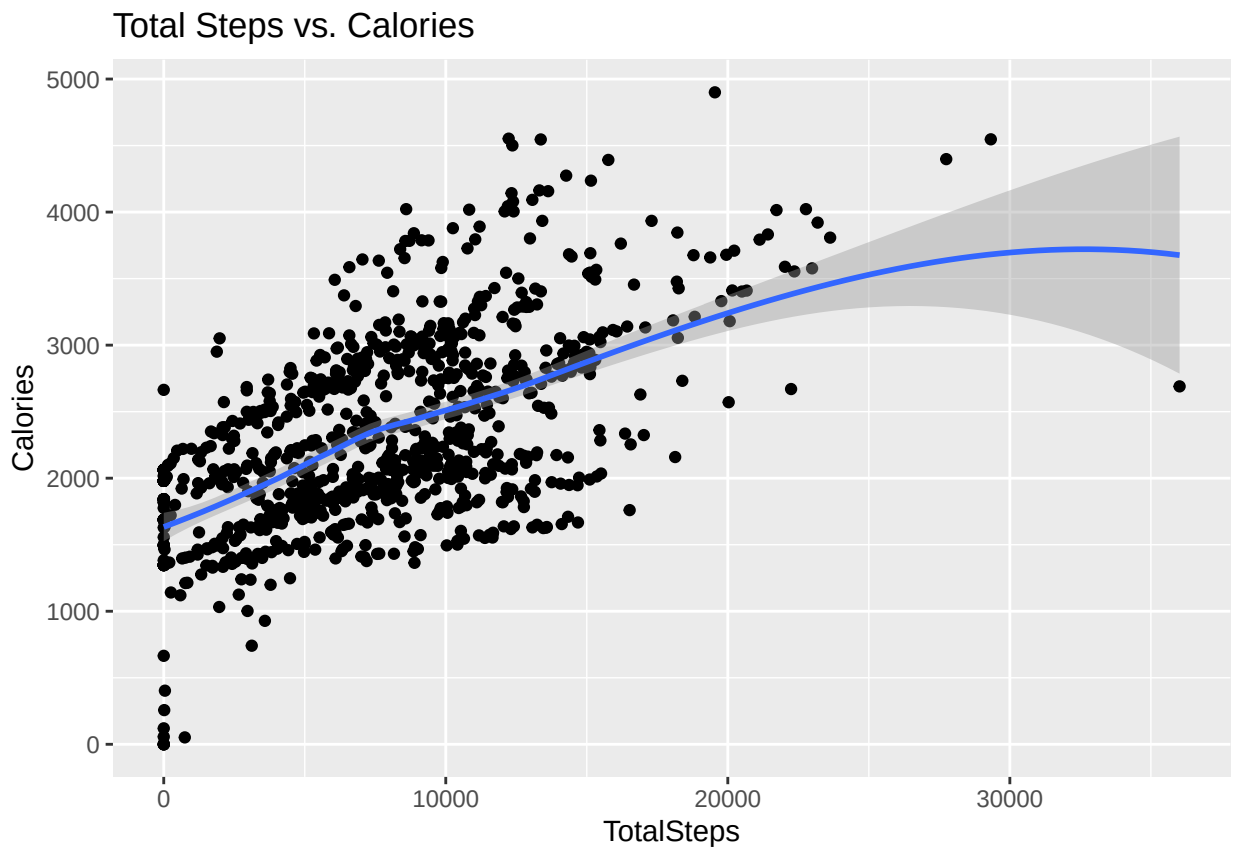
```
##     WeightKg           BMI
##  Min.   : 52.60   Min.   :21.45
##  1st Qu.: 61.65   1st Qu.:24.07
##  Median : 69.80   Median :25.30
##  Mean   : 73.44   Mean   :25.73
##  3rd Qu.: 84.92   3rd Qu.:26.01
##  Max.   :133.50   Max.   :47.54
```

Total Average step per day is 7638.They found that taking 8,000 steps per day was associated with a 51% lower risk for all-cause mortality (or death from all causes). Taking 12,000 steps per day was associated with a 65% lower risk compared with taking 4,000 steps. The majority of the participants are lightly active.

What types of plots and tables will help you to illustrate the findings to your questions?

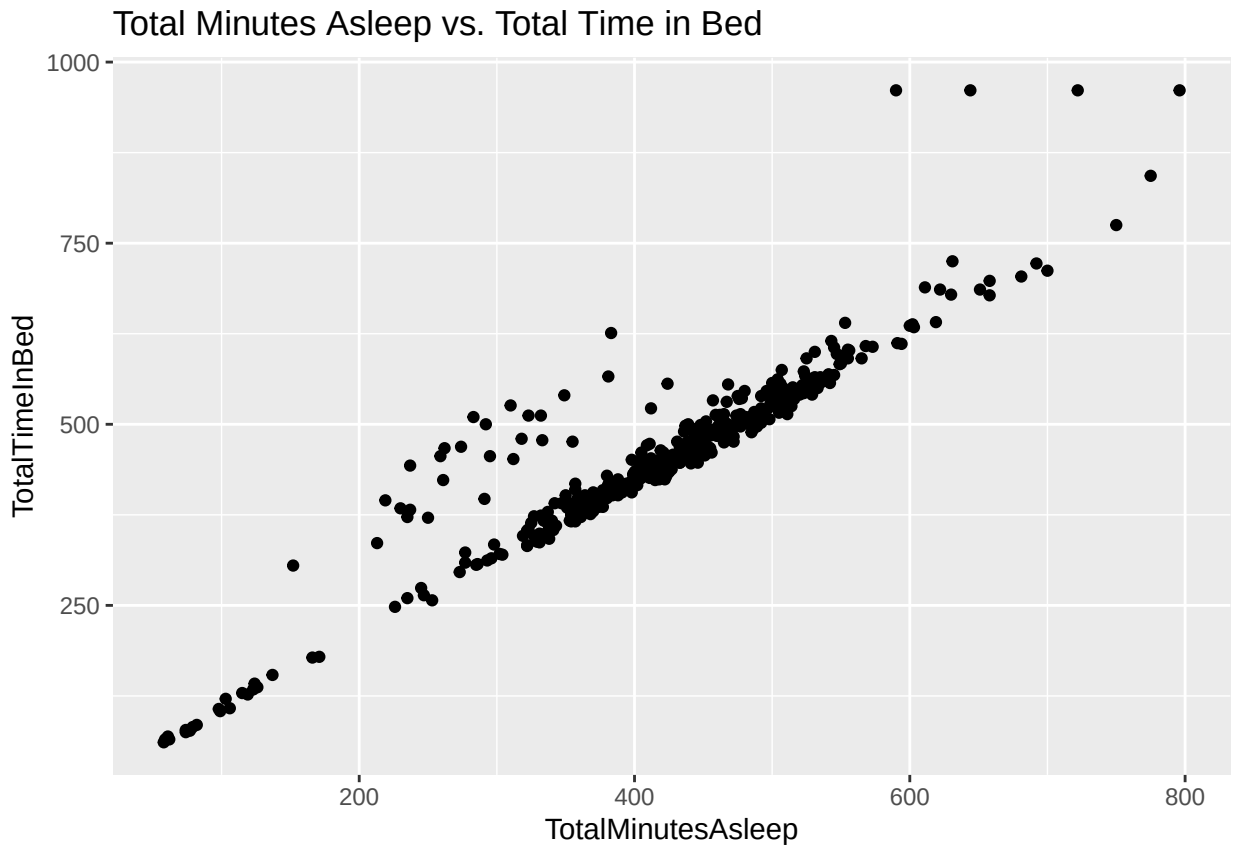
```
ggplot(data=dailyActivity_data, aes(x=TotalSteps, y=Calories)) +
  geom_point() + geom_smooth() + labs(title="Total Steps vs. Calories")
```

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



I see positive correlation here between Total Steps and Calories, which is obvious - the more active we are, the more calories we burn.

```
ggplot(data=sleepDay_data, aes(x=TotalMinutesAsleep, y=TotalTimeInBed)) +
  geom_point()+ labs(title="Total Minutes Asleep vs. Total Time in Bed")
```



The relationship between Total Minutes Asleep and Total Time in Bed looks linear. So if the Activity tracker users want to improve their sleep, we should consider using notification to go to sleep.

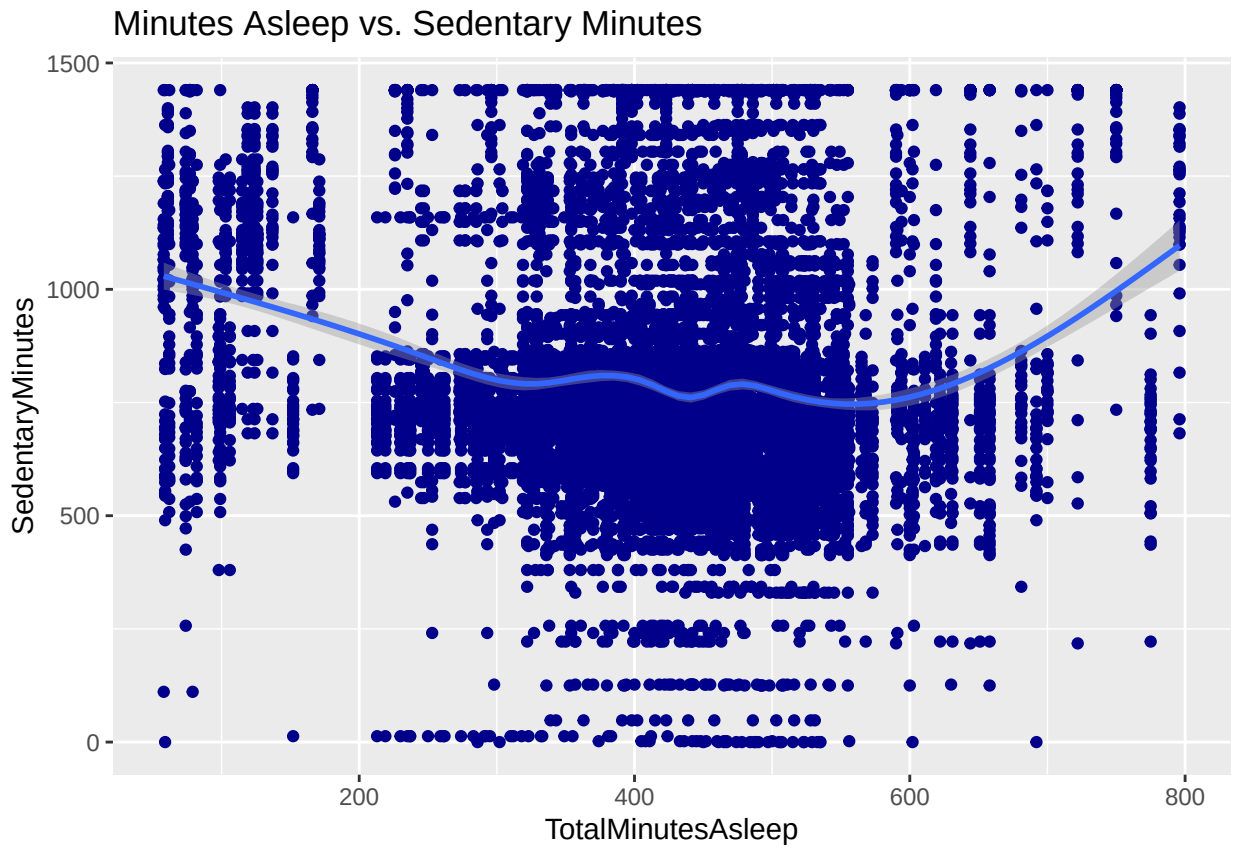
```
merged_data <- merge(sleepDay_data, dailyActivity_data,  by=c('Id'))
head(merged_data)
```

```
##           Id              SleepDay TotalSleepRecords TotalMinutesAsleep
## 1 1503960366 4/12/2016 12:00:00 AM                 1                327
## 2 1503960366 4/12/2016 12:00:00 AM                 1                327
## 3 1503960366 4/12/2016 12:00:00 AM                 1                327
## 4 1503960366 4/12/2016 12:00:00 AM                 1                327
## 5 1503960366 4/12/2016 12:00:00 AM                 1                327
## 6 1503960366 4/12/2016 12:00:00 AM                 1                327
##   TotalTimeInBed TotalSteps TotalDistance SedentaryActiveDistance
## 1            346      11992          7.71                       0
## 2            346      12159          8.03                       0
## 3            346      10602          6.81                       0
## 4            346      14673          9.25                       0
## 5            346      13162          8.50                       0
## 6            346      10735          6.97                       0
##   VeryActiveMinutes FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes
## 1                37                  46                  175              833
## 2                24                   6                  289              754
## 3                33                  35                  246              730
## 4                52                  34                  217              712
## 5                25                  13                  328              728
```

```
## 6               21                  19                  217              776
##   Calories        day
## 1     1821 0005-07-20
## 2     1896 0005-06-20
## 3     1820 0005-01-20
## 4     1947       <NA>
## 5     1985 0004-12-20
## 6     1797       <NA>
```

```
ggplot(data=merged_data, aes(x=TotalMinutesAsleep, y=SedentaryMinutes)) +
geom_point(color='darkblue') + geom_smooth() +
  labs(title="Minutes Asleep vs. Sedentary Minutes")
```

```
## `geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



Do you plan on incorporating any machine learning techniques to answer your research questions? Explain :

Machine learning uses two techniques: supervised learning, which trains a model on known input and output data to predict future outputs, and unsupervised learning, which uses hidden patterns or internal structures in the input data.

In my use case its using Supervised machine learning creates a model that makes predictions based on evidence in the presence of uncertainty. A supervised learning algorithm takes a known set of input data and

known responses to the data (output) and trains a model to generate reasonable predictions for the response to the new data. Use supervised learning if you have known data for the output you are trying to estimate.

Planning to use classification and regression techniques to develop machine learning models for my use case.

Regression analysis is used to estimate the relationship between a set of variables. When conducting any type of regression analysis, you're looking to see if there's a correlation between a dependent variable (that's the variable or outcome you want to measure or predict) and any number of independent variables (factors which may have an impact on the dependent variable). The aim of regression analysis is to estimate how one or more variables might impact the dependent variable, in order to identify trends and patterns. This is especially useful for making predictions and forecasting future trends.

Questions for future steps :

1.What are the effects of using these devices and correlating them to Relationship satisfaction or quality of life?

2. What changes to dietary and life style choices after watching the data ?

3.Predicting cholestrol depending on factors like calorie in take, weight, no. of steps walked every day, distance covered, heart rate bpm, types of type of physical excercise,Although one of these activities you have to track outside of Activity Trackers. What all more factors as you see fit?

4.What type of decisions will our data science feature drive?

5.What metric will we use to call this project a success and how will we measure it?

6.what do they currently use and what is the baseline (current) value of that metric?

7.What the outcome of this project success?