Bellabeat Case Study

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1 Introduction

Bellabeat is a high-tech manufacturer of health-focused products for women and is a successful small company, but they have the potential to become a larger player in the global smart device market. My job is to discover the trends and help them become a larger company. In this report I will walk you through the steps that I did to achieve this. These steps are consist of identifying the problems and setting a business task, collecting, cleaning and transforming the data, analyzing the information we gather from the data and visualizing it for a better presentation, lastly the act phase where I share my key findings to help the company.

2 Ask

Our stakeholders want us to answer the following questions:

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

2.1 Business Task

The objective of this case study is to analyze smart device usage data to uncover trends in consumer behavior with non-Bellabeat smart devices.

3 Prepare

Data Source: FitBit Fitness Tracker Dataset

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

Dataset Summary: This dataset consist of 2 months. First month has 35, second month has 33 unique people that participated in this dataset. Some datasets have even lower participation then that. Although small number of users, we will help the company as much as we can. With this low sample size, we cannot be so sure about the insights in this analysis are representative of our total population. There are so many missing values in 'weightLogInfo_merged' such as 'Fat' column is mostly NaN. The absence of gender and age details is a significant concern, since our target audience is women, we need those details to land more accurate inferences.

4 Process

This section is mostly about data cleaning and transformation. We will start with importing libraries and data, later on we will add new columns to data for a better understanding and visualization.

[5]:
```
# Importing libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import datetime as dt
pd.set_option('display.max.rows', 100)
```

[6]:
```
# Importing data
daily_activity_1 = pd.read_csv(r"C:
 ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_3.12.16-4.11.16\Fitabase␣
 ↪Data 3.12.16-4.11.16\dailyActivity_merged.csv")
daily_activity_2 = pd.read_csv(r"C:
 ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_4.12.16-5.12.16\Fitabase␣
 ↪Data 4.12.16-5.12.16\dailyActivity_merged.csv")

heartrate_seconds_1 = pd.read_csv(r"C:
 ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_3.12.16-4.11.16\Fitabase␣
 ↪Data 3.12.16-4.11.16\heartrate_seconds_merged.csv")
heartrate_seconds_2 = pd.read_csv(r"C:
 ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_4.12.16-5.12.16\Fitabase␣
 ↪Data 4.12.16-5.12.16\heartrate_seconds_merged.csv")

hourly_calories_1 = pd.read_csv(r"C:
 ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_3.12.16-4.11.16\Fitabase␣
 ↪Data 3.12.16-4.11.16\hourlyCalories_merged.csv")
hourly_calories_2 = pd.read_csv(r"C:
 ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_4.12.16-5.12.16\Fitabase␣
 ↪Data 4.12.16-5.12.16\hourlyCalories_merged.csv")

hourly_intensities_1 = pd.read_csv(r"C:
 ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_3.12.16-4.11.16\Fitabase␣
 ↪Data 3.12.16-4.11.16\hourlyIntensities_merged.csv")
hourly_intensities_2 = pd.read_csv(r"C:
 ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_4.12.16-5.12.16\Fitabase␣
 ↪Data 4.12.16-5.12.16\hourlyIntensities_merged.csv")
```

```
hourly_steps_1 = pd.read_csv(r"C:
  ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_3.12.16-4.11.16\Fitabase␣
  ↪Data 3.12.16-4.11.16\hourlySteps_merged.csv")
hourly_steps_2 = pd.read_csv(r"C:
  ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_4.12.16-5.12.16\Fitabase␣
  ↪Data 4.12.16-5.12.16\hourlySteps_merged.csv")

met_minute_1 = pd.read_csv(r"C:
  ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_3.12.16-4.11.16\Fitabase␣
  ↪Data 3.12.16-4.11.16\minuteMETsNarrow_merged.csv")
met_minute_2 = pd.read_csv(r"C:
  ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_4.12.16-5.12.16\Fitabase␣
  ↪Data 4.12.16-5.12.16\minuteMETsNarrow_merged.csv")

minute_sleep_1 = pd.read_csv(r"C:
  ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_3.12.16-4.11.16\Fitabase␣
  ↪Data 3.12.16-4.11.16\minuteSleep_merged.csv")
minute_sleep_2 = pd.read_csv(r"C:
  ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_4.12.16-5.12.16\Fitabase␣
  ↪Data 4.12.16-5.12.16\minuteSleep_merged.csv")

weight_log_1 = pd.read_csv(r"C:
  ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_3.12.16-4.11.16\Fitabase␣
  ↪Data 3.12.16-4.11.16\weightLogInfo_merged.csv")
weight_log_2 = pd.read_csv(r"C:
  ↪\Users\volka\OneDrive\Masaüstü\Case_Study_2\fitbit_4.12.16-5.12.16\Fitabase␣
  ↪Data 4.12.16-5.12.16\weightLogInfo_merged.csv")
```

[7]:
```
# Adding first and second month the data
daily_activity_all = pd.concat([daily_activity_1, daily_activity_2])
heartrate_seconds_all = pd.concat([heartrate_seconds_1, heartrate_seconds_2])
hourly_calories_all = pd.concat([hourly_calories_1, hourly_calories_2])
hourly_intensities_all = pd.concat([hourly_intensities_1, hourly_intensities_2])
hourly_steps_all = pd.concat([hourly_steps_1, hourly_steps_2])
met_minute_all = pd.concat([met_minute_1, met_minute_2])
minute_sleep_all = pd.concat([minute_sleep_1, minute_sleep_2])
weight_log_all = pd.concat([weight_log_1, weight_log_2])
```

[8]:
```
# Resetting index so added data index doesn't start with 0
daily_activity_all.reset_index(drop = True, inplace = True)
heartrate_seconds_all.reset_index(drop = True, inplace = True)
hourly_calories_all.reset_index(drop = True, inplace = True)
hourly_intensities_all.reset_index(drop = True, inplace = True)
hourly_steps_all.reset_index(drop = True, inplace = True)
met_minute_all.reset_index(drop = True, inplace = True)
```

```
minute_sleep_all.reset_index(drop = True, inplace = True)
weight_log_all.reset_index(drop = True, inplace = True)
```

After binding the data, we will look through it using info() and head() functions to see if there is anything to be done.

[10]:
```
daily_activity_all.info() # ActivityDate should be in datetime format
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1397 entries, 0 to 1396
Data columns (total 15 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Id                        1397 non-null   int64
 1   ActivityDate              1397 non-null   object
 2   TotalSteps                1397 non-null   int64
 3   TotalDistance             1397 non-null   float64
 4   TrackerDistance           1397 non-null   float64
 5   LoggedActivitiesDistance  1397 non-null   float64
 6   VeryActiveDistance        1397 non-null   float64
 7   ModeratelyActiveDistance  1397 non-null   float64
 8   LightActiveDistance       1397 non-null   float64
 9   SedentaryActiveDistance   1397 non-null   float64
 10  VeryActiveMinutes         1397 non-null   int64
 11  FairlyActiveMinutes       1397 non-null   int64
 12  LightlyActiveMinutes      1397 non-null   int64
 13  SedentaryMinutes          1397 non-null   int64
 14  Calories                  1397 non-null   int64
dtypes: float64(7), int64(7), object(1)
memory usage: 163.8+ KB
```

[11]:
```
heartrate_seconds_all.info() #Time should be in datetime format
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3638339 entries, 0 to 3638338
Data columns (total 3 columns):
 #   Column  Dtype
---  ------  -----
 0   Id      int64
 1   Time    object
 2   Value   int64
dtypes: int64(2), object(1)
memory usage: 83.3+ MB
```

[12]:
```
hourly_calories_all.info() # ActivityHour should be in datetime format
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46183 entries, 0 to 46182
Data columns (total 3 columns):
```

```
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Id            46183 non-null  int64
 1   ActivityHour  46183 non-null  object
 2   Calories      46183 non-null  int64
dtypes: int64(2), object(1)
memory usage: 1.1+ MB
```

[13]:
```
hourly_intensities_all.info() # ActivityHour should be in datetime format
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46183 entries, 0 to 46182
Data columns (total 4 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Id                46183 non-null  int64
 1   ActivityHour      46183 non-null  object
 2   TotalIntensity    46183 non-null  int64
 3   AverageIntensity  46183 non-null  float64
dtypes: float64(1), int64(2), object(1)
memory usage: 1.4+ MB
```

[14]:
```
hourly_steps_all.info() # ActivityHour should be in datetime format
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46183 entries, 0 to 46182
Data columns (total 3 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Id            46183 non-null  int64
 1   ActivityHour  46183 non-null  object
 2   StepTotal     46183 non-null  int64
dtypes: int64(2), object(1)
memory usage: 1.1+ MB
```

[15]:
```
met_minute_all.info() # ActivityMinute should be in datetime format
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2770620 entries, 0 to 2770619
Data columns (total 3 columns):
 #   Column          Dtype
---  ------          -----
 0   Id              int64
 1   ActivityMinute  object
 2   METs            int64
dtypes: int64(2), object(1)
memory usage: 63.4+ MB
```

[16]:
```
minute_sleep_all.info() # date should be in datetime format
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 387080 entries, 0 to 387079
Data columns (total 4 columns):
 #   Column  Non-Null Count   Dtype 
---  ------  --------------   ----- 
 0   Id      387080 non-null  int64 
 1   date    387080 non-null  object
 2   value   387080 non-null  int64 
 3   logId   387080 non-null  int64 
dtypes: int64(3), object(1)
memory usage: 11.8+ MB
```

[17]:
```
weight_log_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Id              100 non-null    int64  
 1   Date            100 non-null    object 
 2   WeightKg        100 non-null    float64
 3   WeightPounds    100 non-null    float64
 4   Fat             4 non-null      float64
 5   BMI             100 non-null    float64
 6   IsManualReport  100 non-null    bool   
 7   LogId           100 non-null    int64  
dtypes: bool(1), float64(4), int64(2), object(1)
memory usage: 5.7+ KB
```

[18]:
```
daily_activity_all.head()
```

[18]:
```
           Id ActivityDate  TotalSteps  TotalDistance  TrackerDistance  \
0  1503960366    3/25/2016       11004           7.11             7.11   
1  1503960366    3/26/2016       17609          11.55            11.55   
2  1503960366    3/27/2016       12736           8.53             8.53   
3  1503960366    3/28/2016       13231           8.93             8.93   
4  1503960366    3/29/2016       12041           7.85             7.85   

   LoggedActivitiesDistance  VeryActiveDistance  ModeratelyActiveDistance  \
0                       0.0                2.57                      0.46   
1                       0.0                6.92                      0.73   
2                       0.0                4.66                      0.16   
3                       0.0                3.19                      0.79   
4                       0.0                2.16                      1.09   

   LightActiveDistance  SedentaryActiveDistance  VeryActiveMinutes  \
0                 4.07                      0.0                 33   
```

```
1             3.91                 0.0              89
2             3.71                 0.0              56
3             4.95                 0.0              39
4             4.61                 0.0              28

   FairlyActiveMinutes  LightlyActiveMinutes  SedentaryMinutes  Calories
0                   12                   205               804      1819
1                   17                   274               588      2154
2                    5                   268               605      1944
3                   20                   224              1080      1932
4                   28                   243               763      1886
```

[19]:
```
heartrate_seconds_all.head()
```

[19]:
```
           Id                  Time  Value
0  2022484408  4/1/2016 7:54:00 AM     93
1  2022484408  4/1/2016 7:54:05 AM     91
2  2022484408  4/1/2016 7:54:10 AM     96
3  2022484408  4/1/2016 7:54:15 AM     98
4  2022484408  4/1/2016 7:54:20 AM    100
```

[20]:
```
hourly_calories_all.head()
```

[20]:
```
           Id            ActivityHour  Calories
0  1503960366  3/12/2016 12:00:00 AM        48
1  1503960366   3/12/2016 1:00:00 AM        48
2  1503960366   3/12/2016 2:00:00 AM        48
3  1503960366   3/12/2016 3:00:00 AM        48
4  1503960366   3/12/2016 4:00:00 AM        48
```

[21]:
```
hourly_intensities_all.head()
```

[21]:
```
           Id            ActivityHour  TotalIntensity  AverageIntensity
0  1503960366  3/12/2016 12:00:00 AM               0               0.0
1  1503960366   3/12/2016 1:00:00 AM               0               0.0
2  1503960366   3/12/2016 2:00:00 AM               0               0.0
3  1503960366   3/12/2016 3:00:00 AM               0               0.0
4  1503960366   3/12/2016 4:00:00 AM               0               0.0
```

[22]:
```
hourly_steps_all.head()
```

[22]:
```
           Id            ActivityHour  StepTotal
0  1503960366  3/12/2016 12:00:00 AM          0
1  1503960366   3/12/2016 1:00:00 AM          0
2  1503960366   3/12/2016 2:00:00 AM          0
3  1503960366   3/12/2016 3:00:00 AM          0
4  1503960366   3/12/2016 4:00:00 AM          0
```

[23]:
```
met_minute_all.head()
```

[23]:
```
           Id         ActivityMinute  METs
0  1503960366  3/12/2016 12:00:00 AM    10
1  1503960366  3/12/2016 12:01:00 AM    10
2  1503960366  3/12/2016 12:02:00 AM    10
3  1503960366  3/12/2016 12:03:00 AM    10
4  1503960366  3/12/2016 12:04:00 AM    10
```

[24]:
```
minute_sleep_all.head()
```

[24]:
```
           Id                  date  value        logId
0  1503960366  3/13/2016 2:39:30 AM      1  11114919637
1  1503960366  3/13/2016 2:40:30 AM      1  11114919637
2  1503960366  3/13/2016 2:41:30 AM      1  11114919637
3  1503960366  3/13/2016 2:42:30 AM      1  11114919637
4  1503960366  3/13/2016 2:43:30 AM      1  11114919637
```

[25]:
```
weight_log_all.head()
```

[25]:
```
           Id                  Date    WeightKg  WeightPounds   Fat  \
0  1503960366  4/5/2016 11:59:59 PM   53.299999    117.506384  22.0
1  1927972279  4/10/2016 6:33:26 PM  129.600006    285.719105   NaN
2  2347167796  4/3/2016 11:59:59 PM   63.400002    139.773078  10.0
3  2873212765  4/6/2016 11:59:59 PM   56.700001    125.002104   NaN
4  2873212765  4/7/2016 11:59:59 PM   57.200001    126.104416   NaN

         BMI  IsManualReport          LogId
0  22.969999            True  1459900799000
1  46.169998           False  1460313206000
2  24.770000            True  1459727999000
3  21.450001            True  1459987199000
4  21.650000            True  1460073599000
```

Checking the null and duplicate values with is.null().sum() and duplicated() functions.

[27]:
```
daily_activity_all.isnull().sum()
```

[27]:
```
Id                          0
ActivityDate                0
TotalSteps                  0
TotalDistance               0
TrackerDistance             0
LoggedActivitiesDistance    0
VeryActiveDistance          0
ModeratelyActiveDistance    0
LightActiveDistance         0
SedentaryActiveDistance     0
```

```
VeryActiveMinutes           0
FairlyActiveMinutes         0
LightlyActiveMinutes        0
SedentaryMinutes            0
Calories                    0
dtype: int64
```

[28]:
```
heartrate_seconds_all.isnull().sum()
```

[28]:
```
Id       0
Time     0
Value    0
dtype: int64
```

[29]:
```
hourly_calories_all.isnull().sum()
```

[29]:
```
Id              0
ActivityHour    0
Calories        0
dtype: int64
```

[30]:
```
hourly_intensities_all.isnull().sum()
```

[30]:
```
Id                  0
ActivityHour        0
TotalIntensity      0
AverageIntensity    0
dtype: int64
```

[31]:
```
hourly_steps_all.isnull().sum()
```

[31]:
```
Id              0
ActivityHour    0
StepTotal       0
dtype: int64
```

[32]:
```
met_minute_all.isnull().sum()
```

[32]:
```
Id                0
ActivityMinute    0
METs              0
dtype: int64
```

[33]:
```
minute_sleep_all.isnull().sum()
```

[33]:
```
Id       0
date     0
value    0
```

```
logId    0
dtype: int64
```

[34]:
```
weight_log_all.isnull().sum()
```

[34]:
```
Id                 0
Date               0
WeightKg           0
WeightPounds       0
Fat               96
BMI                0
IsManualReport     0
LogId              0
dtype: int64
```

[35]:
```
daily_activity_all.loc[daily_activity_all.duplicated()] # There are no␣
↪duplicate values
```

[35]:
```
Empty DataFrame
Columns: [Id, ActivityDate, TotalSteps, TotalDistance, TrackerDistance,
LoggedActivitiesDistance, VeryActiveDistance, ModeratelyActiveDistance,
LightActiveDistance, SedentaryActiveDistance, VeryActiveMinutes,
FairlyActiveMinutes, LightlyActiveMinutes, SedentaryMinutes, Calories]
Index: []
```

[36]:
```
heartrate_seconds_all.loc[heartrate_seconds_all.duplicated()] # There are 23424␣
↪duplicated values
```

[36]:
```
                 Id                  Time  Value
1154681  2022484408  4/12/2016 7:21:00 AM     97
1154682  2022484408  4/12/2016 7:21:05 AM    102
1154683  2022484408  4/12/2016 7:21:10 AM    105
1154684  2022484408  4/12/2016 7:21:20 AM    103
1154685  2022484408  4/12/2016 7:21:25 AM    101
…               …                   …    …
3410816  8877689391  4/12/2016 9:46:25 AM    113
3410817  8877689391  4/12/2016 9:46:30 AM    108
3410818  8877689391  4/12/2016 9:46:35 AM    102
3410819  8877689391  4/12/2016 9:46:40 AM     99
3410820  8877689391  4/12/2016 9:46:45 AM     98

[23424 rows x 3 columns]
```

[37]:
```
hourly_calories_all.loc[hourly_calories_all.duplicated()] # There are 175␣
↪duplicated values
```

[37]:
```
                Id           ActivityHour  Calories
24801  1624580081  4/12/2016 12:00:00 AM        55
24802  1624580081   4/12/2016 1:00:00 AM        51
24803  1624580081   4/12/2016 2:00:00 AM        50
24804  1624580081   4/12/2016 3:00:00 AM        51
24805  1624580081   4/12/2016 4:00:00 AM        50
…             …                      …       …
45452  8877689391   4/12/2016 4:00:00 AM        73
45453  8877689391   4/12/2016 5:00:00 AM        73
45454  8877689391   4/12/2016 6:00:00 AM        96
45455  8877689391   4/12/2016 7:00:00 AM       169
45456  8877689391   4/12/2016 8:00:00 AM       136

[175 rows x 3 columns]
```

[38]:
```
hourly_intensities_all.loc[hourly_intensities_all.duplicated()] #There are 175 duplicated values
```

[38]:
```
                Id           ActivityHour  TotalIntensity  AverageIntensity
24801  1624580081  4/12/2016 12:00:00 AM               4          0.066667
24802  1624580081   4/12/2016 1:00:00 AM               1          0.016667
24803  1624580081   4/12/2016 2:00:00 AM               0          0.000000
24804  1624580081   4/12/2016 3:00:00 AM               1          0.016667
24805  1624580081   4/12/2016 4:00:00 AM               0          0.000000
…             …                      …             …                …
45452  8877689391   4/12/2016 4:00:00 AM               0          0.000000
45453  8877689391   4/12/2016 5:00:00 AM               0          0.000000
45454  8877689391   4/12/2016 6:00:00 AM               7          0.116667
45455  8877689391   4/12/2016 7:00:00 AM              26          0.433333
45456  8877689391   4/12/2016 8:00:00 AM              17          0.283333

[175 rows x 4 columns]
```

[39]:
```
hourly_steps_all.loc[hourly_steps_all.duplicated()] #There are 175 duplicated values
```

[39]:
```
                Id           ActivityHour  StepTotal
24801  1624580081  4/12/2016 12:00:00 AM         31
24802  1624580081   4/12/2016 1:00:00 AM          0
24803  1624580081   4/12/2016 2:00:00 AM          0
24804  1624580081   4/12/2016 3:00:00 AM          7
24805  1624580081   4/12/2016 4:00:00 AM          0
…             …                      …        …
45452  8877689391   4/12/2016 4:00:00 AM          0
45453  8877689391   4/12/2016 5:00:00 AM          0
45454  8877689391   4/12/2016 6:00:00 AM        209
45455  8877689391   4/12/2016 7:00:00 AM        964
```

```
45456  8877689391   4/12/2016 8:00:00 AM       834

[175 rows x 3 columns]
```

[40]:
```
met_minute_all.loc[met_minute_all.duplicated()] #There are 10500 duplicated␣
 ↪values
```

[40]:
```
                  Id          ActivityMinute  METs
1488060  1624580081  4/12/2016 12:00:00 AM    10
1488061  1624580081  4/12/2016 12:01:00 AM    10
1488062  1624580081  4/12/2016 12:02:00 AM    10
1488063  1624580081  4/12/2016 12:03:00 AM    10
1488064  1624580081  4/12/2016 12:04:00 AM    10
…               …                     …    …
2727115  8877689391   4/12/2016 8:55:00 AM    10
2727116  8877689391   4/12/2016 8:56:00 AM    10
2727117  8877689391   4/12/2016 8:57:00 AM    10
2727118  8877689391   4/12/2016 8:58:00 AM    11
2727119  8877689391   4/12/2016 8:59:00 AM    10

[10500 rows x 3 columns]
```

[41]:
```
minute_sleep_all.loc[minute_sleep_all.duplicated()] #There are 4300  duplicated␣
 ↪values
```

[41]:
```
                Id                  date  value        logId
80158   4319703577  4/5/2016 10:50:00 PM      3  11344563687
80159   4319703577  4/5/2016 10:51:00 PM      3  11344563687
80160   4319703577  4/5/2016 10:52:00 PM      2  11344563687
80161   4319703577  4/5/2016 10:53:00 PM      2  11344563687
80162   4319703577  4/5/2016 10:54:00 PM      2  11344563687
…              …                     …    …          …
365560  8378563200  4/12/2016 4:10:00 AM      1  11373088895
365561  8378563200  4/12/2016 4:11:00 AM      1  11373088895
365562  8378563200  4/12/2016 4:12:00 AM      1  11373088895
365563  8378563200  4/12/2016 4:13:00 AM      1  11373088895
365564  8378563200  4/12/2016 4:14:00 AM      1  11373088895

[4300 rows x 4 columns]
```

[42]:
```
weight_log_all.loc[weight_log_all.duplicated()] #There are 2 duplicates
```

[42]:
```
            Id                   Date   WeightKg  WeightPounds  Fat  \
46  6962181067  4/12/2016 11:59:59 PM  62.500000    137.788914  NaN
76  8877689391   4/12/2016 6:47:11 AM  85.800003    189.156628  NaN

          BMI  IsManualReport         LogId
```

```
46  24.389999            True  1460505599000
76  25.680000           False  1460443631000
```

4.1 Removing Nulls and Duplicates

We see that in weight_log_all there is a column that have mostly null values, we remove it since it is no use to us. Almost all tables have duplicated rows. Some have 23424 some have 10500 duplicate values. We get rid of them too. Below code chunks provide that.

[45]:
```
# Removing 'Fat' column
weight_log_all.drop(columns='Fat', inplace=True)
```

[46]:
```
#Removing all duplicates
heartrate_seconds_all = heartrate_seconds_all.loc[~heartrate_seconds_all.
 ↪duplicated()]
hourly_calories_all = hourly_calories_all.loc[~hourly_calories_all.duplicated()]
hourly_intensities_all = hourly_intensities_all.loc[~hourly_intensities_all.
 ↪duplicated()]
hourly_steps_all = hourly_steps_all.loc[~hourly_steps_all.duplicated()]
met_minute_all = met_minute_all.loc[~met_minute_all.duplicated()]
minute_sleep_all = minute_sleep_all.loc[~minute_sleep_all.duplicated()]
weight_log_all = weight_log_all.loc[~weight_log_all.duplicated()]
```

4.2 Transforming and Merging Data

4.2.1 Changing Objects to Datetime

Datetime related columns should be in datetime format, that way we can make calculations on them.

[48]:
```
daily_activity_all['ActivityDate'] = pd.
 ↪to_datetime(daily_activity_all['ActivityDate'])
```

[49]:
```
heartrate_seconds_all['Time'] = pd.to_datetime(heartrate_seconds_all['Time'],␣
 ↪format='%m/%d/%Y %I:%M:%S %p')
```

[50]:
```
hourly_calories_all['ActivityHour'] = pd.
 ↪to_datetime(hourly_calories_all['ActivityHour'], format='%m/%d/%Y %I:%M:%S␣
 ↪%p')
```

[51]:
```
hourly_intensities_all['ActivityHour'] = pd.
 ↪to_datetime(hourly_intensities_all['ActivityHour'], format='%m/%d/%Y %I:%M:
 ↪%S %p')
```

[52]:
```
hourly_steps_all['ActivityHour'] = pd.
 ↪to_datetime(hourly_steps_all['ActivityHour'], format='%m/%d/%Y %I:%M:%S %p')
```

[53]:
```
met_minute_all['ActivityMinute'] = pd.
↪to_datetime(met_minute_all['ActivityMinute'], format='%m/%d/%Y %I:%M:%S %p')
```

[54]:
```
minute_sleep_all['date'] = pd.to_datetime(minute_sleep_all['date'], format='%m/
↪%d/%Y %I:%M:%S %p')
```

[55]:
```
weight_log_all['Date'] = pd.to_datetime(weight_log_all['Date'], format='%m/%d/
↪%Y %I:%M:%S %p')
```

4.2.2 Adding Columns and Aggregations

Here we convert minute data into hourly data to execute merging.

[57]:
```
# Adding day column to help visualization
daily_activity_all['day'] = daily_activity_all['ActivityDate'].dt.day_name()
```

[58]:
```
# Converting heartrate_seconds_all to hourly version
heartrate_seconds_all['ActivityHour'] = heartrate_seconds_all['Time'].dt.
↪floor('h')
```

[59]:
```
hourly_heartrate_all = heartrate_seconds_all.groupby(['Id', 'ActivityHour']).
↪agg({'Value':'mean'}).reset_index()
```

[60]:
```
hourly_heartrate_all['Value'] = hourly_heartrate_all['Value'].round().
↪astype(int)
```

[61]:
```
hourly_heartrate_all.rename(columns = {'Value':'heartrate'}, inplace=True)
```

[62]:
```
# Converting heartrate_seconds_all to hourly version
met_minute_all['ActivityHour'] = met_minute_all['ActivityMinute'].dt.floor('h')
```

[63]:
```
hourly_met_all = met_minute_all.groupby(['Id', 'ActivityHour']).agg({'METs':
↪'mean'}).round(1).reset_index()
```

[64]:
```
hourly_met_all.rename(columns = {'METs':'avg_met_h'}, inplace=True)
```

[65]:
```
# Converting minute_sleep_all to hourly version
minute_sleep_all['hour'] = minute_sleep_all['date'].dt.floor('h')
```

[66]:
```
hourly_sleep_all = minute_sleep_all.groupby(['logId', 'Id', 'hour']).agg(
    slept_minute=('value', lambda x: (x == 1).sum())
).reset_index()
```

[67]:
```
hourly_sleep_all.rename(columns = {'hour':'ActivityHour'}, inplace = True)
```

4.2.3 Merging Data

[69]:
```
hourly_merged = pd.merge(hourly_heartrate_all, hourly_calories_all, on = ['Id',␣
↪'ActivityHour'], how = 'outer')
```

[70]:
```
hourly_merged = pd.merge(hourly_merged, hourly_intensities_all, on = ['Id',␣
↪'ActivityHour'], how = 'outer')
```

[71]:
```
hourly_merged = pd.merge(hourly_merged, hourly_steps_all, on = ['Id',␣
↪'ActivityHour'], how = 'outer')
```

[72]:
```
hourly_merged = pd.merge(hourly_merged, hourly_met_all, on = ['Id',␣
↪'ActivityHour'], how = 'outer')
```

[73]:
```
hourly_merged = pd.merge(hourly_merged, hourly_sleep_all, on = ['Id',␣
↪'ActivityHour'], how = 'outer')
```

5 Analyze & Share

Now we have 3 data tables to analyze. These are :

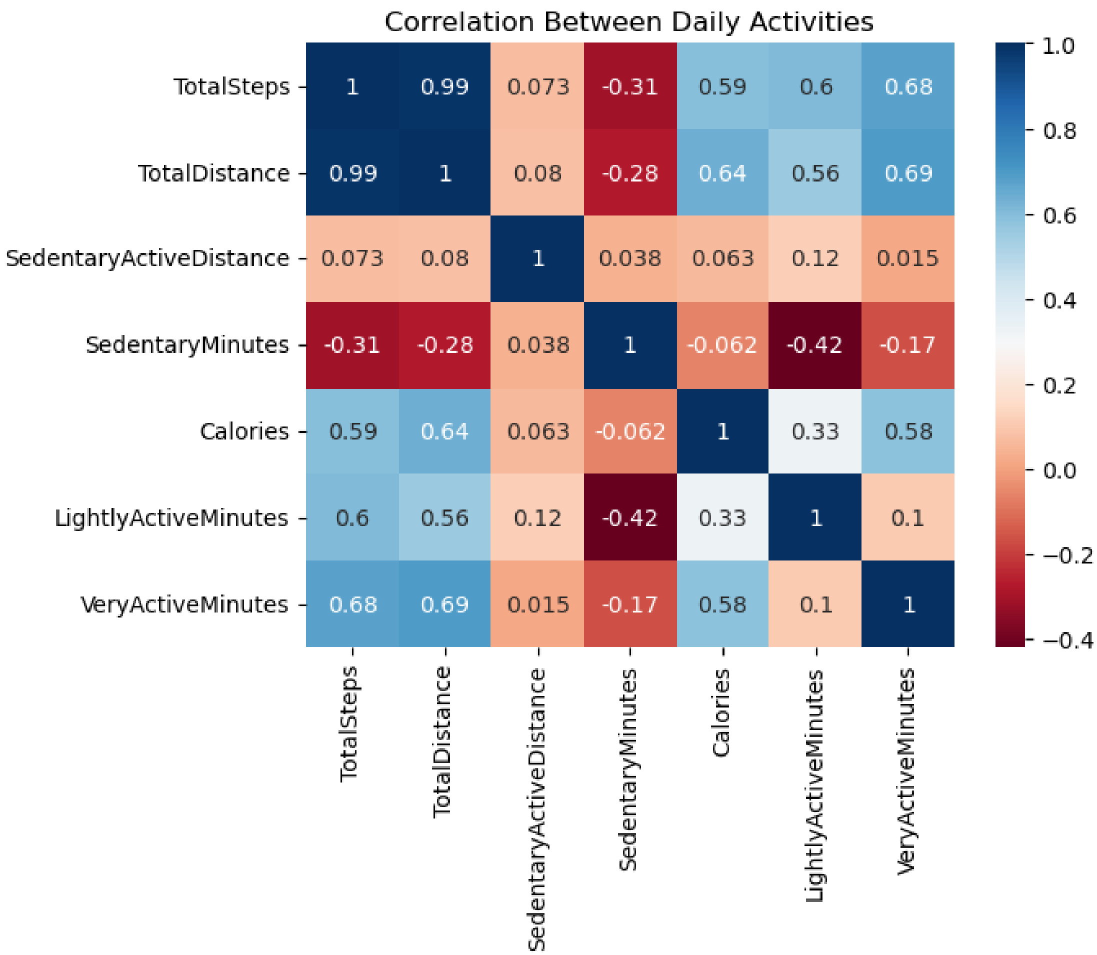
1. daily_activity_all
2. hourly_merged
3. weight_log_all

[75]:
```
print('There are ' + str(daily_activity_all['Id'].nunique()) + ' unique people␣
↪that are in daily_activity_all.')
print('There are ' + str(hourly_merged['Id'].nunique()) + ' unique people that␣
↪are in hourly_merged.')
print('There are ' + str(weight_log_all['Id'].nunique()) + ' unique people that␣
↪are in weight_log_all.')
```

```
There are 35 unique people that are in daily_activity_all.
There are 35 unique people that are in hourly_merged.
There are 13 unique people that are in weight_log_all.
```

These numbers are so low that, they don't represent the total population of fitness tracker users. Let's begin our visualizations with finding correlation between data.

[77]:
```
sns.heatmap(daily_activity_all[['TotalSteps', 'TotalDistance',␣
↪'SedentaryActiveDistance',
            'SedentaryMinutes', 'Calories', 'LightlyActiveMinutes',␣
↪'VeryActiveMinutes']].corr(), annot=True, cmap='RdBu')
plt.title('Correlation Between Daily Activities')
plt.show()
```



There are:

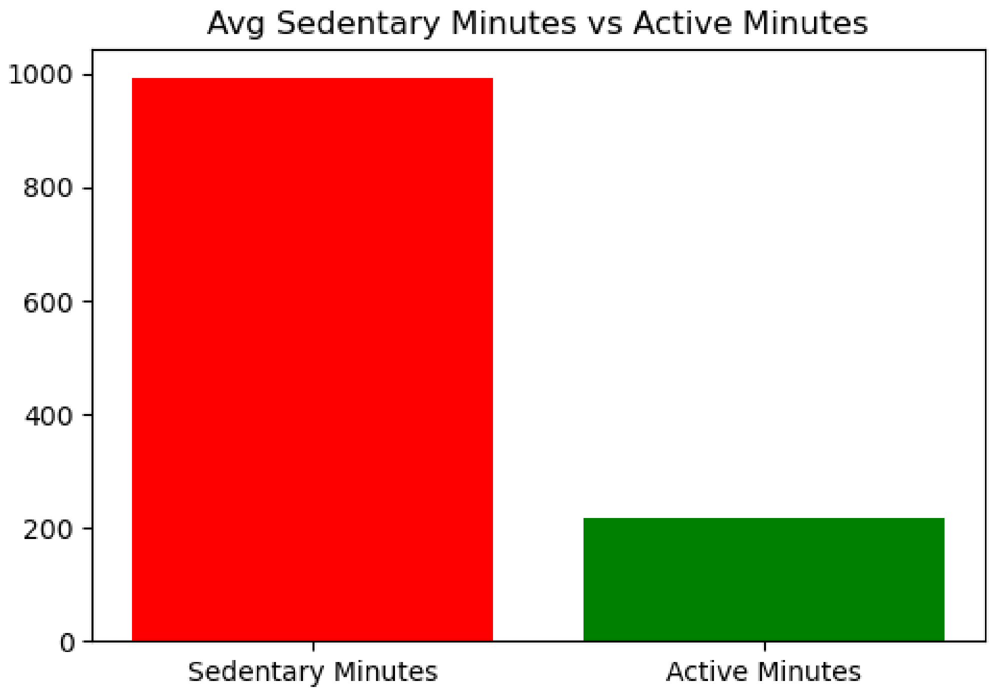
- Positive correlation between [‘Calories’, ‘ActiveMinutes’, ‘TotalSteps’,‘Total Distance’]
- Negative correlation between [‘SedentaryMinutes’, ‘TotalSteps’], [‘SedentaryMinutes’, ‘TotalDistance’], [‘SedentaryMinutes’, ‘ActiveMinutes’]

Which means one has positive or negative impact on other.

[79]:
```
daily_activity_all['active_total'] = (daily_activity_all['VeryActiveMinutes'] +␣
↪daily_activity_all['FairlyActiveMinutes'] +␣
↪daily_activity_all['LightlyActiveMinutes'])
```

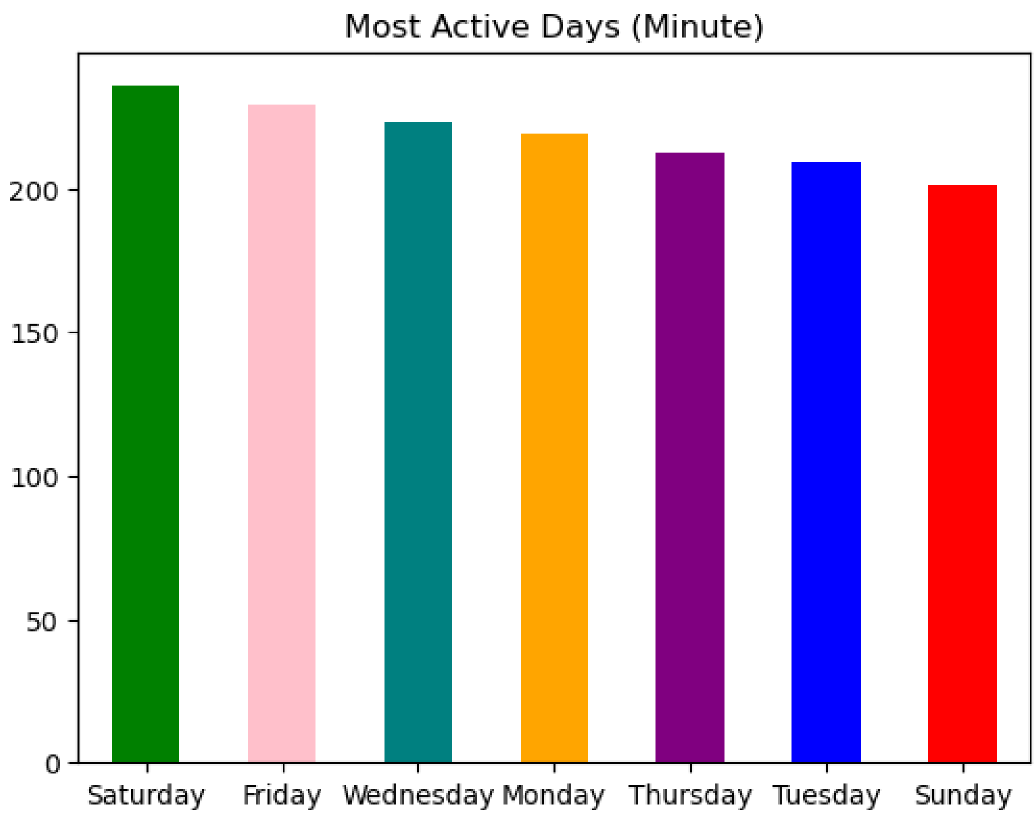
[80]:
```
x = np.array(['Sedentary Minutes', 'Active Minutes'])
y = np.array([daily_activity_all['SedentaryMinutes'].mean(),␣
↪daily_activity_all['active_total'].mean()])

fig, ax = plt.subplots(figsize=(6,4))
ax.bar(x, y, color = ['red','green'])
```

```
plt.title('Avg Sedentary Minutes vs Active Minutes')
plt.show()
```



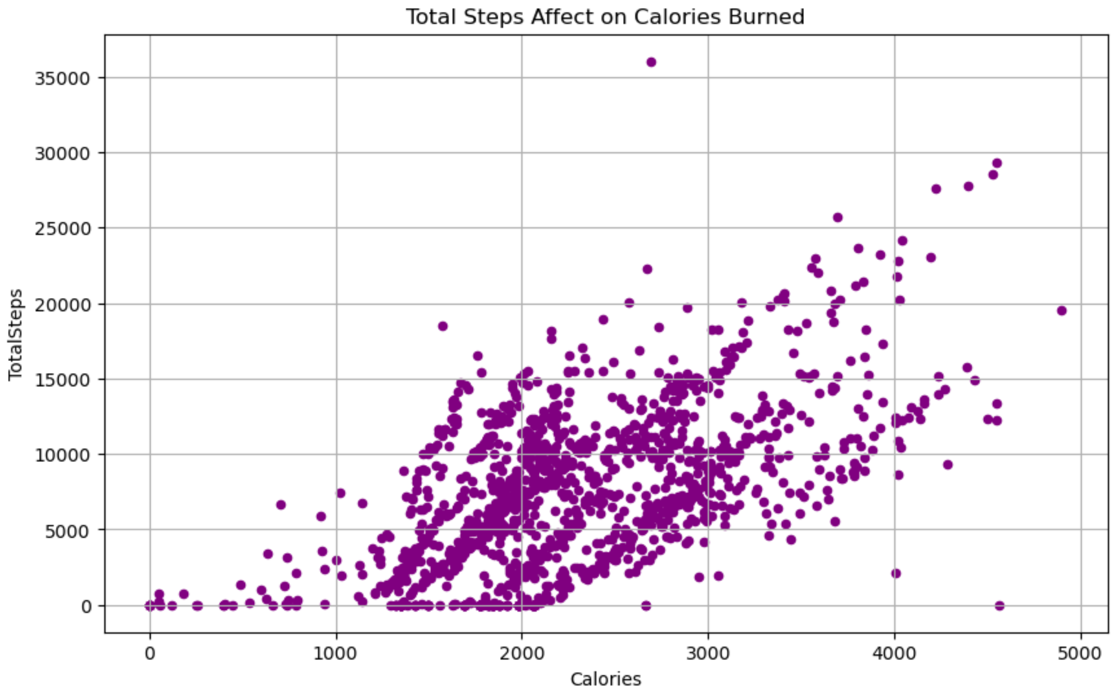
People spent most of their time standing still including their sleep around 992 minute (16.5 hour) and 218 minute (3.6 hour) as active which we will see if it is better to stay active or not.

[82]:
```
#most active day
ax = daily_activity_all.groupby('day')['active_total'].mean().
 ↪sort_values(ascending=False)
ax.plot(kind = 'bar', x='day', y = 'active_total', color =␣
 ↪['green','pink','teal','orange','purple','blue','red'])
plt.title('Most Active Days (Minute)')
plt.xticks(rotation=0)
plt.xlabel('')
plt.show()
```



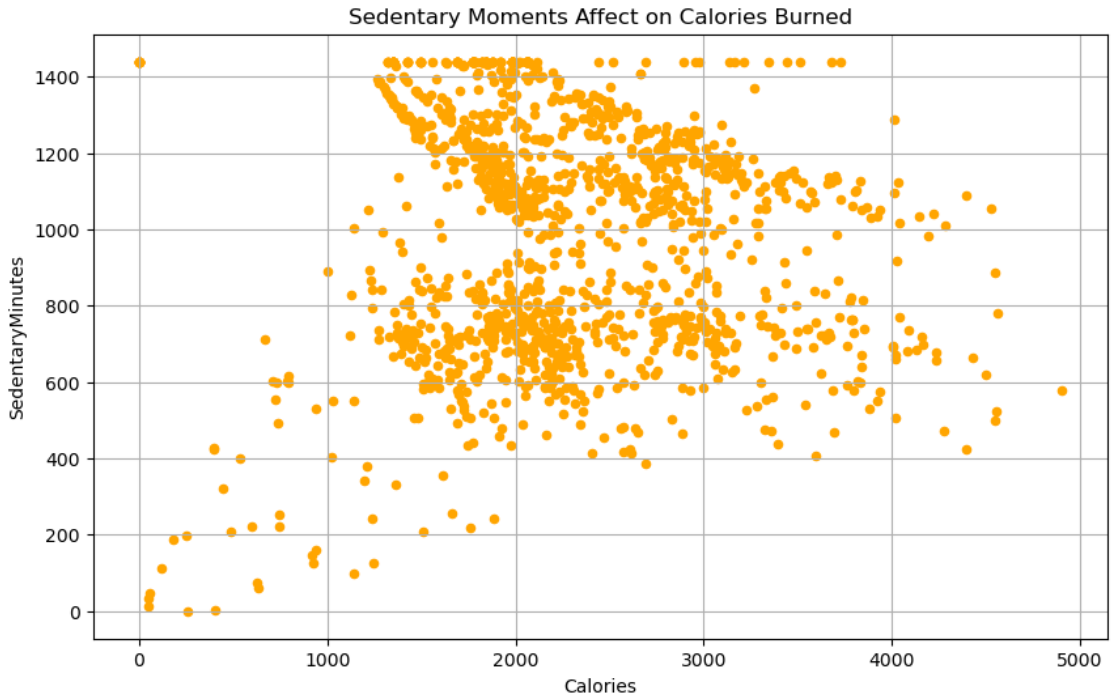
Most active days are saturdays and fridays. Since it is weekend people most likely do exercise or travel. People tend to stay less active on sundays because they want to rest and prepare themselves for the monday.

[84]:
```
ax = daily_activity_all.plot(kind = 'scatter',
                        x = 'Calories', y = 'TotalSteps',
                        figsize = (10,6),
                        color = 'purple',
                        title = 'Total Steps Affect on Calories Burned'
                        )
ax.set_xlabel = 'Calories'
ax.set_ylabel = 'TotalSteps'
plt.grid(True)
plt.show()
```



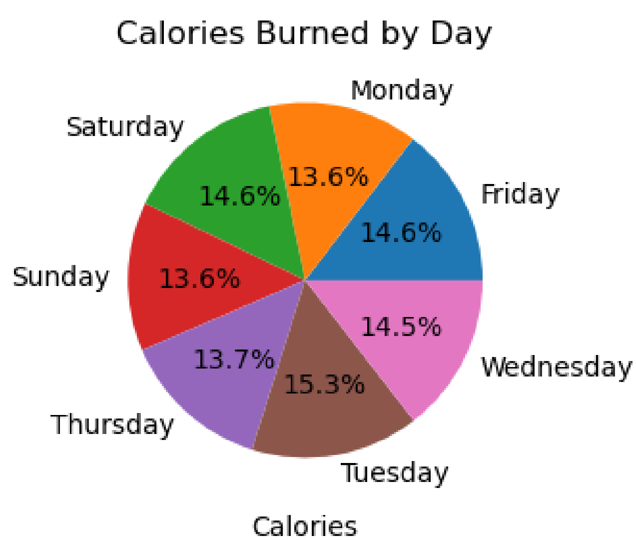
We found out that the more steps we take the more calories we burn.

[86]:
```
ax = daily_activity_all.plot(kind = 'scatter',
                        x = 'Calories', y = 'SedentaryMinutes',
                        figsize = (10,6),
                        color = 'orange',
                        title = 'Sedentary Moments Affect on Calories Burned'
                       )
plt.grid(True)
ax.set_xlabel = 'Calories'
ax.set_ylabel = 'SedentaryMinutes'
plt.show()
```



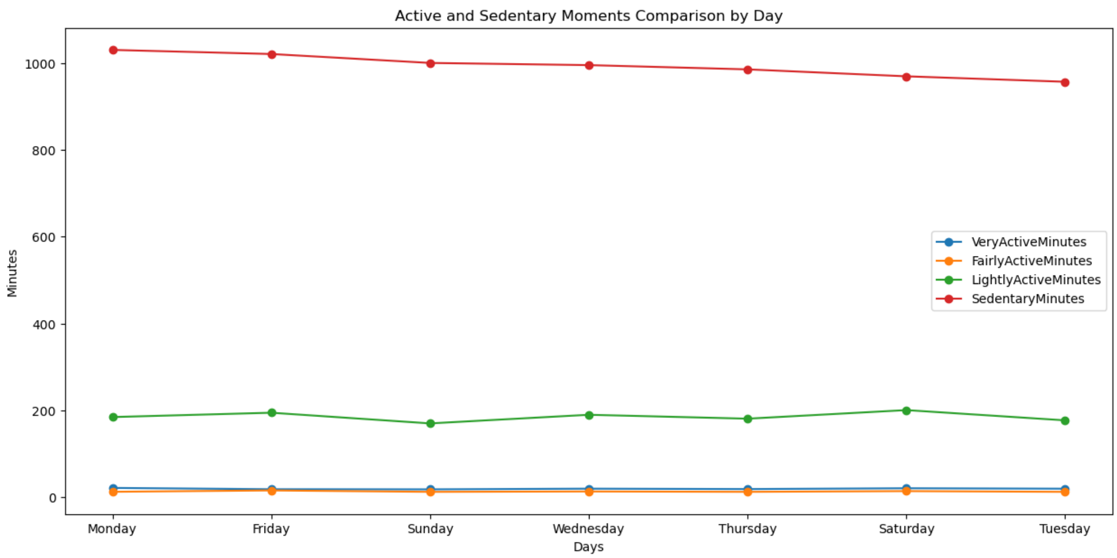
The more time spent as sedentary means the less calories burned in time.

[88]:
```
ax = daily_activity_all.groupby('day')['Calories'].sum().plot(kind = 'pie', y =
  'day', autopct = '%1.1f%%', figsize = (3,3))
ax.set_ylabel('')
ax.set_xlabel('Calories')
ax.set_title('Calories Burned by Day')
plt.show()
```

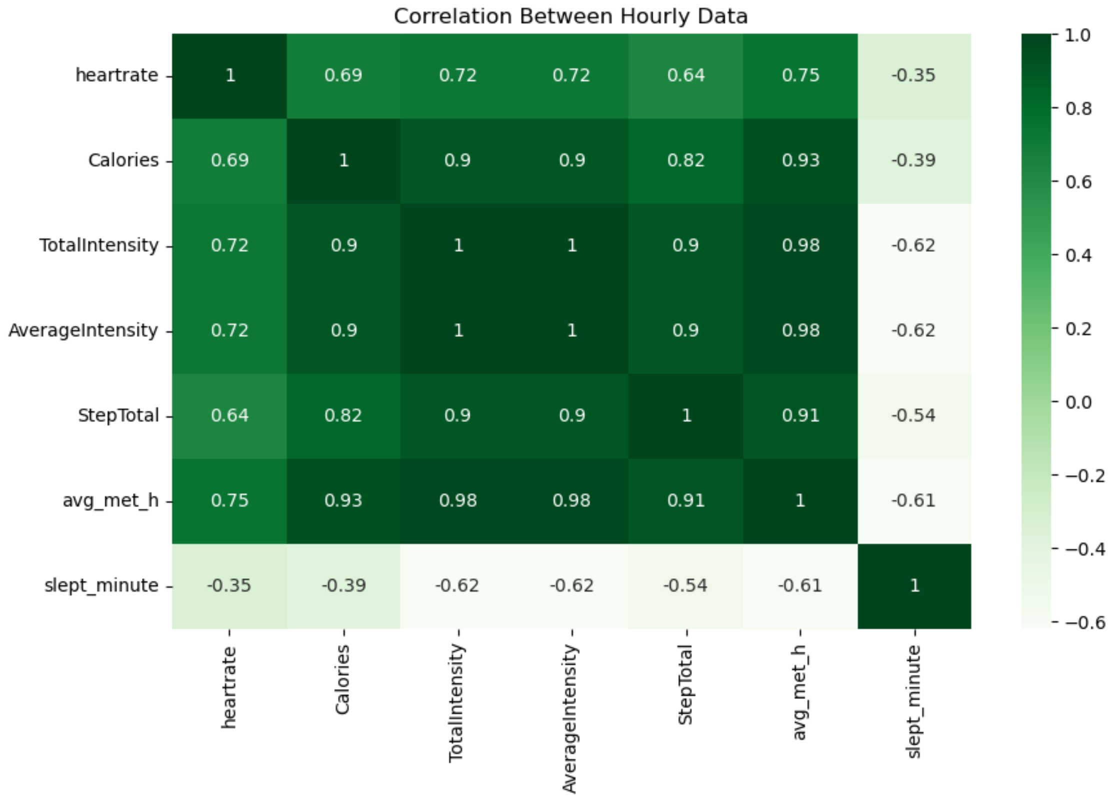


There is no exact correlation between calories burned and each day.

[90]:
```
ax = daily_activity_all.groupby('day')[['VeryActiveMinutes',
                    'FairlyActiveMinutes',
                    'LightlyActiveMinutes',
                    'SedentaryMinutes'
                    ]].mean().sort_values('SedentaryMinutes', ascending=False).
 ↪plot(kind='line', marker='o', figsize = (15,7))
ax.set_xlabel('Days')
ax.set_ylabel('Minutes')
ax.set_title('Active and Sedentary Moments Comparison by Day')
plt.show()
```

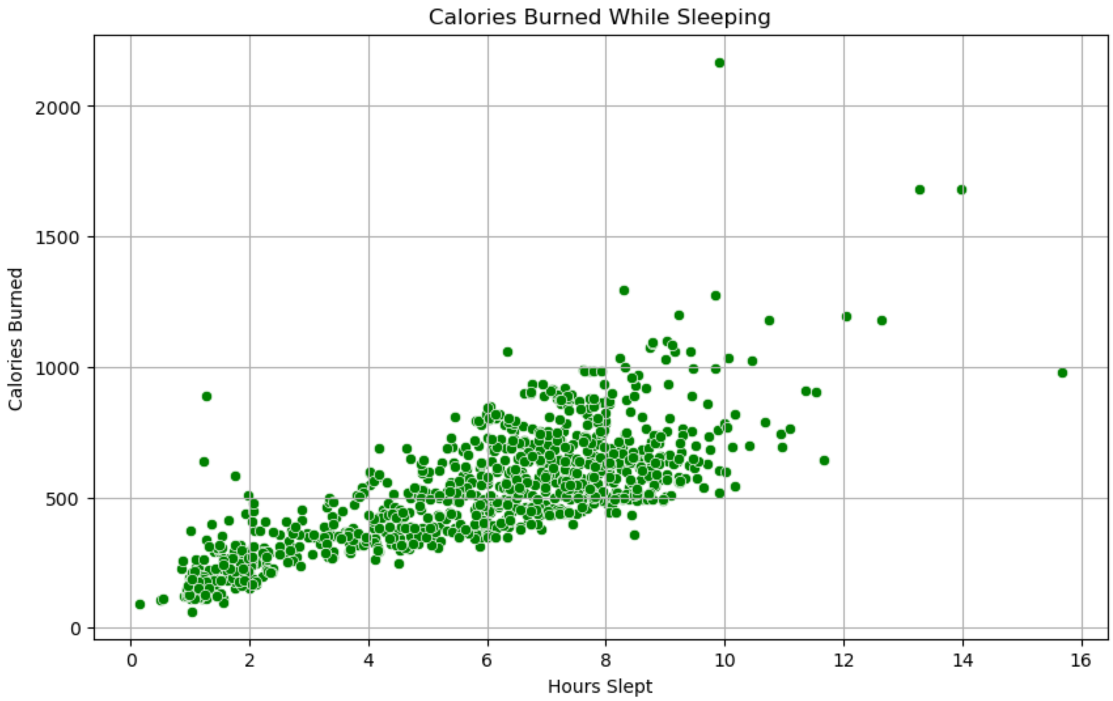


[91]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(hourly_merged[['heartrate', 'Calories', 'TotalIntensity',
            'AverageIntensity', 'StepTotal', 'avg_met_h', 'slept_minute']].
 ↪corr(), annot=True, cmap='Greens')
plt.title('Correlation Between Hourly Data')
plt.show()
```



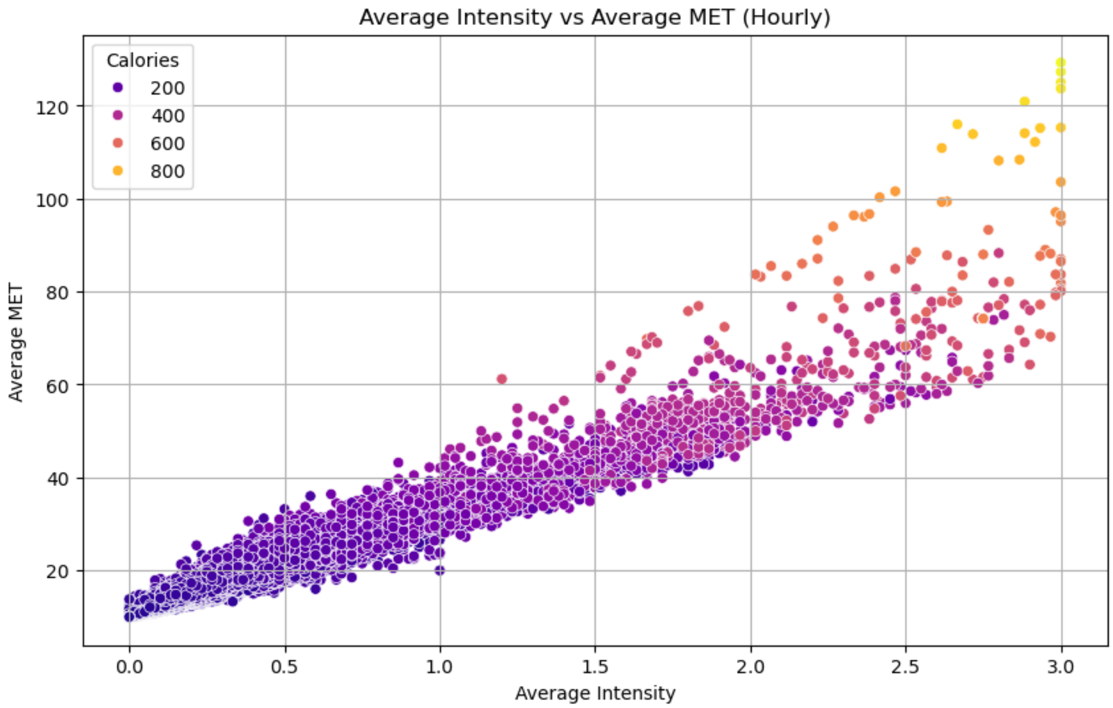
Almost all values have positive correlation except sleep time.

[93]:
```
ax = hourly_merged.groupby('logId')[['slept_minute','Calories']].
 ↪agg({'slept_minute': lambda x: x.sum()/60, 'Calories':'sum'})
plt.figure(figsize=(10, 6))
sns.scatterplot(data=ax, x='slept_minute', y='Calories', color = 'green')
plt.title('Calories Burned While Sleeping')
plt.xlabel('Hours Slept')
plt.ylabel('Calories Burned')
plt.grid(True)
plt.show()
```

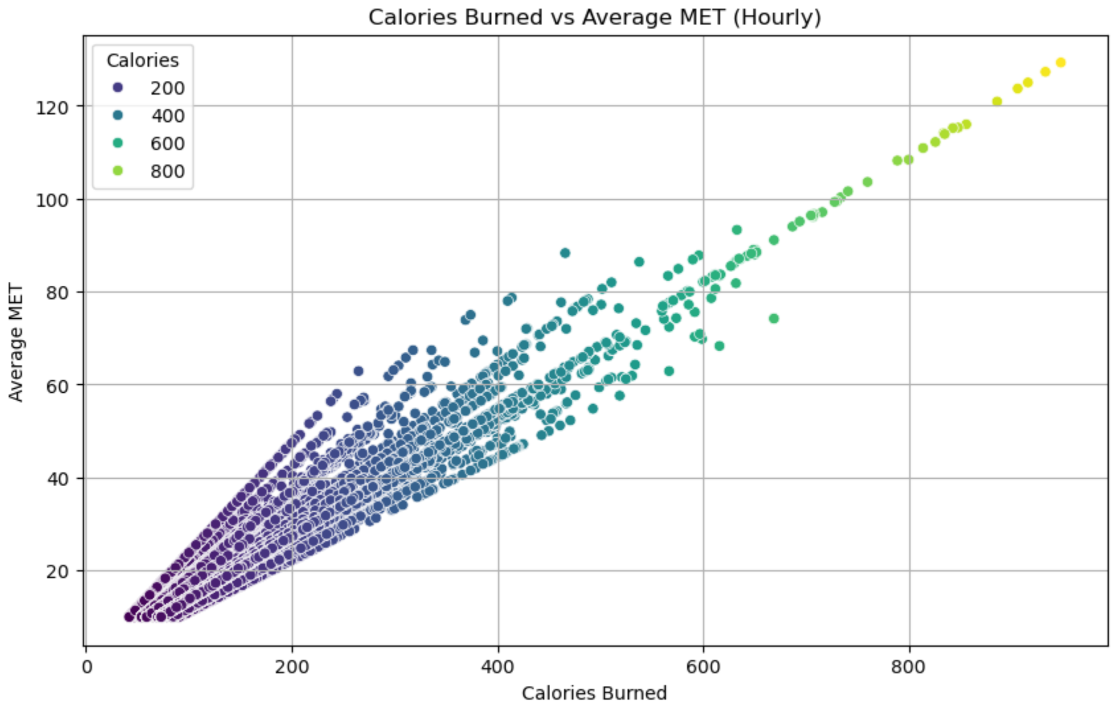


We see that our bodies continue to burn calories even though we sleep.

[95]:
```
plt.figure(figsize = (10,6))
sns.scatterplot(hourly_merged, x = 'AverageIntensity', y = 'avg_met_h',␣
↪hue='Calories', palette = 'plasma')
plt.title('Average Intensity vs Average MET (Hourly)')
plt.xlabel('Average Intensity')
plt.ylabel('Average MET')
plt.grid(True)
plt.show()
```

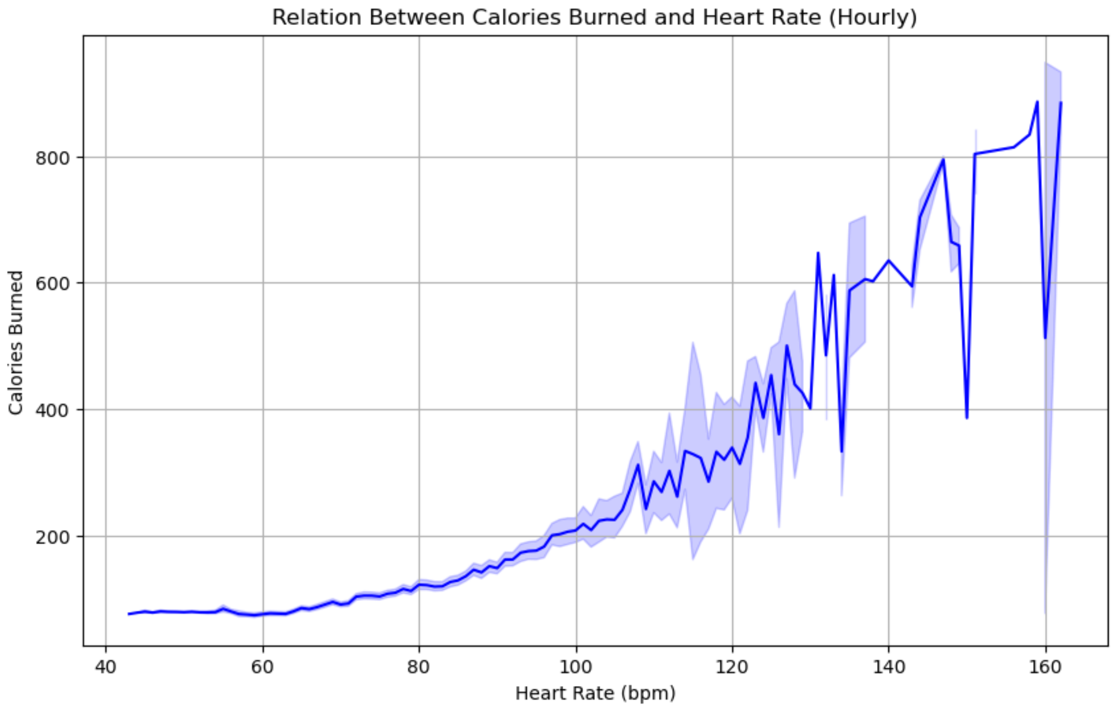


[96]:
```
plt.figure(figsize = (10,6))
sns.scatterplot(hourly_merged, x = 'Calories', y = 'avg_met_h', hue='Calories',␣
  ↪palette = 'viridis')
plt.title('Calories Burned vs Average MET (Hourly)')
plt.xlabel('Calories Burned')
plt.ylabel('Average MET')
plt.grid(True)
plt.show()
```

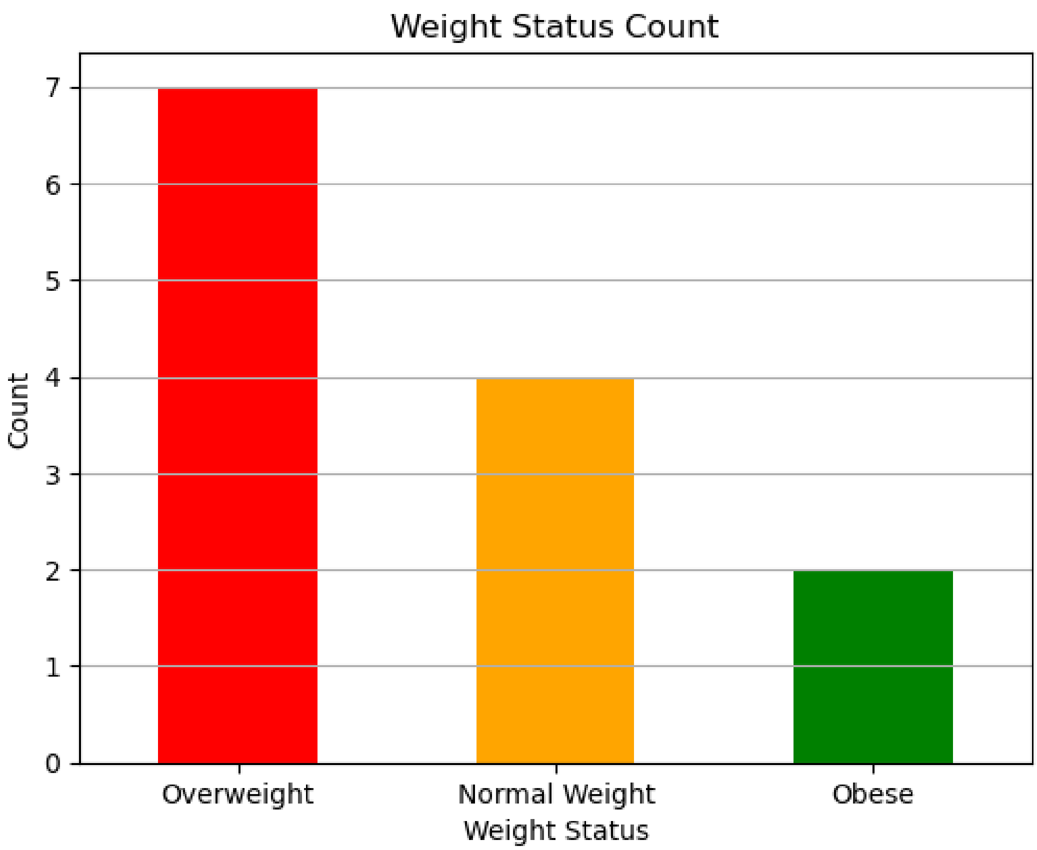


The more calories a person burns, the more energy they expend.

[98]:
```
plt.figure(figsize=(10,6))
sns.lineplot(hourly_merged, x = 'heartrate', y = 'Calories', color = 'blue')
plt.grid()
plt.xlabel('Heart Rate (bpm)')
plt.ylabel('Calories Burned')
plt.title('Relation Between Calories Burned and Heart Rate (Hourly)')
plt.show()
```



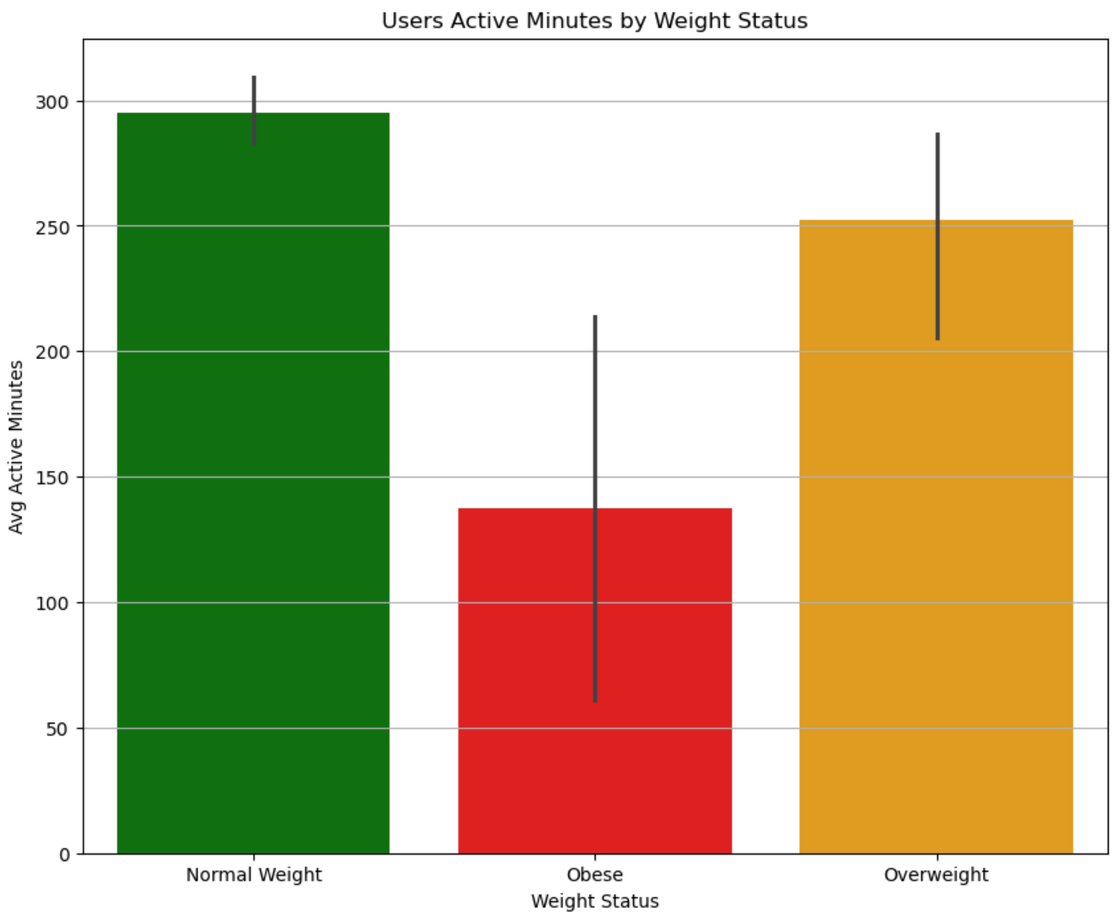
[99]:
```
ax = weight_log_all.groupby('Id').agg({'BMI': 'mean'}).reset_index()
def bmi_status(BMI):
    if BMI < 18.5:
        return 'Underweight'
    elif 18.5 <= BMI < 24.9:
        return 'Normal Weight'
    elif 25 <= BMI < 29.9:
        return 'Overweight'
    else:
        return 'Obese'
ax['weight_status'] = ax['BMI'].apply(bmi_status)
ax['count'] = 1
ax.groupby('weight_status')['count'].sum().sort_values(ascending = False)\
.plot(kind = 'bar', x = 'weight_status', y = 'count', color = ['red', 'orange',␣
 ↪'green', 'blue'])
plt.title('Weight Status Count')
plt.xlabel('Weight Status')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.grid(axis='y')
```



This data includes only 13 people but still it tells us something about the smart device users. Users are most likely have some weight problems and want to lose weight. There are no underweight people in this data but company should do advertisement for underweight people to gain weight. We will discuss this later in the act phase.

[101]:
```
ax = weight_log_all.groupby('Id').agg({'BMI': 'mean'}).reset_index()
def bmi_status(BMI):
    if BMI < 18.5:
        return 'Underweight'
    elif 18.5 <= BMI < 24.9:
        return 'Normal Weight'
    elif 25 <= BMI < 29.9:
        return 'Overweight'
    else:
        return 'Obese'
ax['weight_status'] = ax['BMI'].apply(bmi_status)
ay = daily_activity_all.groupby('Id')['active_total'].mean()
ax.drop(columns = 'BMI', inplace = True)
az = pd.merge(ax, ay, on = 'Id', how = 'inner')
color_mapping = {
```

```
    'Underweight': 'green',
    'Normal Weight': 'green',
    'Overweight': 'orange',
    'Obese': 'red'
}
az['color'] = az['weight_status'].map(color_mapping)

plt.figure(figsize = (10,8))
sns.barplot(az, x = 'weight_status', y = 'active_total', hue='weight_status',␣
↪palette=color_mapping, dodge=False, legend=False)
plt.xlabel('Weight Status')
plt.ylabel('Avg Active Minutes')
plt.title('Users Active Minutes by Weight Status')
plt.grid(axis = 'y')
plt.show()
```



Obese people spend their time less active then normal weight people.

6 Act

6.1 Key Findings & Recommendation

- Since Bellabeat is a woman focused company, the absence of gender and age informations make it hard to come to conclusion. Looking at a data where users are female can lead to more accurate decisions. Or even knowing if the user is pregnant, child or mature can be useful.
- Most of the users tend to have weight issues but non of them are underweight. Company should show interest to people who wants to gain weight (underweight). They should prepare meal plans and workout programs to gain weight. This can be applies to every group of people (overweight, obese, normal weight). I must recommand a fitness tracker app that tracks all calories intake and substract it with calories burned. The result will show if a person gained weight or not that day. People will be informed about their progress and it will keep them motivated.
- According to the data, people that are more active burns more calories. As well as how intense their day is, total steps count, even their heartrate have an effect on calories burned. Inspiring them to be more active via companies products will be benefical to company.
- People spend huge amount of time as sedentary which means they burn less calories. Company should detect and sell devices that tracks the daily lifestyle states. This devices job is to alert people when they don't move so often or stay active as they should be. So they can be aware of the situation and take action against it.
- And lastly advertisement plays a huge role in companies growth. It's best to stay in contact with their successful users and encourage them to give inspirational talks about their journeys. Preparing speeches about healthy lifestyle, planning races, orginizing events with giveaways will influence people and interacting with the audience creates a sincere environment.