Google Data Analytics Professional Certificate Capstone Project

The **6 steps of Data Analysis** are used to present this analysis.

Title: **Bellabeat Case Study**

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Bellabeat: How Can a Wellness Technology Company Play It Smart?

STEP 1: ASK

1.0 Background

Bellabeat is a high-tech manufacturer of beautifully designed health-focused smart products for women since 2013. Inspiring and empowering women with knowledge about their own health and habits, Bellabeat has grown rapidly and quickly positioned itself as a tech-driven wellness company for females.

The co-founder and Chief Creative Officer, Urška Sršen is confident that an analysis of non-Bellebeat consumer data (ie. FitBit fitness tracker usage data) would reveal more opportunities for growth.

1.2 Business Task:

> **Analyze FitBit Fitness Tracker Data to gain insights into how consumers are using the FitBit app and discover trends and insights for Bellabeat marketing strategy.**

1.3 Business Objectives:

1. **What are the trends identified?**
2. **How could these trends apply to Bellabeat customers?**
3. **How could these trends help influence Bellabeat marketing strategy?**

1.4 Deliverables:

1. **A clear summary of the business task**
2. **A description of all data sources used**
3. **Documentation of any cleaning or manipulation of data**
4. **A summary of analysis**
5. **Supporting visualizations and key findings**
6. **High-level content recommendations based on the analysis**

1.5 Key Stakeholders:

1. **Urška Sršen: Bellabeat's cofounder and Chief Creative Officer**
2. **Sando Mur: Mathematician, Bellabeat's cofounder and key member of the Bellabeat executive team**
3. **Bellabeat marketing analytics team: A team of data analysts guiding Bellabeat's marketing strategy.**

STEP 2: PREPARE

2.1 Information on Data Source:

1. **The data is publicly available on Kaggle: FitBit Fitness Tracker Data and stored in 18 csv files.**
2. **Generated by respondents from a distributed survey via Amazon Mechanical Turk between 12 March 2016 to 12 May 2016.**
3. **30 FitBit users who consented to the submission of personal tracker data.**
4. **Data collected includes (1) physical activity recorded in minutes, (2) heart rate, (3) sleep monitoring, (4) daily activity and (5) steps.**

2.2 Limitations of Data Set:

1. **Data collected from year 2016. Users' daily activity, fitness and sleeping habits, diet and food consumption may have changed since then, hence data may not be timely or relevant.**
2. **Sample size of 30 female FitBit users is not representative of the entire female population.**
3. **As data is collected in a survey, hence unable to ascertain the integrity or accuracy of data.**

2.3 Is Data ROCCC?

A good data source is ROCCC which stands
for Reliable, Original, Comprehensive, Current, and Cited.

1. **Reliable - LOW - Not reliable as it only has 30 respondents**
2. **Original - LOW - Third party provider (Amazon Mechanical Turk)**
3. **Comprehensive - MED - Parameters match most of Bellabeat's products' parameters**
4. **Current - LOW - Data is 5 years old and is not relevant**
5. **Cited - LOW - Data collected from third party, hence unknown**

Overall, the dataset is considered bad quality data and it is not recommended to produce business recommendations based on this data.

2.4 Data Selection:

The following file is selected and copied for analysis.

- **dailyActivity_merged.csv**

STEP 3: PROCESS

We are using Python to prepare and process the data.

3.1 Preparing the Environment

The numPy, pandas, matplotlib, datetime packages are installed and aliased for easy reading.

In [1]: *# import packages and alias*

```
import numpy as np # data arrays
import pandas as pd # data structure and data analysis
import matplotlib as plt # data visualization
import datetime as dt # date time
```

3.2 Importing data set

Reading in the selected file.

In [2]: *# read_csv function to read the required CSV file*

```
daily_activity = pd.read_csv("../input/fitbit/Fitabase Data 4.12.16-
5.12.16/dailyActivity_merged.csv")
```

3.3 Data cleaning and manipulation

Steps

1. **Observe and familiarize with data**
2. **Check for null or missing values**
3. **Perform sanity check of data**

Previewing using head function to show the first 10 rows of daily activity to familiarise with the data.

In [3]:
```
# preview first 10 rows with all columns
daily_activity.head(10)
```

Out[3]:

	Id	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	Calories
0	1503960366	4/12/2016	13162	8.50	8.50	0.0	1.88	0.55	6.06	0.0	25	13	328	728	1985
1	1503960366	4/13/2016	10735	6.97	6.97	0.0	1.57	0.69	4.71	0.0	21	19	217	776	1797
2	1503960366	4/14/2016	10460	6.74	6.74	0.0	2.44	0.40	3.91	0.0	30	11	181	1218	1776
3	1503960366	4/15/2016	9762	6.28	6.28	0.0	2.14	1.26	2.83	0.0	29	34	209	726	1745
4	1503960366	4/16/2016	12669	8.16	8.16	0.0	2.71	0.41	5.04	0.0	36	10	221	773	1863

	Id	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	Calories
5	1503960366	4/17/2016	9705	6.48	6.48	0.0	3.19	0.78	2.51	0.0	38	20	164	539	1728
6	1503960366	4/18/2016	13019	8.59	8.59	0.0	3.25	0.64	4.71	0.0	42	16	233	1149	1921
7	1503960366	4/19/2016	15506	9.88	9.88	0.0	3.53	1.32	5.03	0.0	50	31	264	775	2035
8	1503960366	4/20/2016	10544	6.68	6.68	0.0	1.96	0.48	4.24	0.0	28	12	205	818	1786
9	1503960366	4/21/2016	9819	6.34	6.34	0.0	1.34	0.35	4.65	0.0	19	8	211	838	1775

Then, finding out whether there is any null or missing values in daily_activity.

In [4]:

```
# obtain the # of missing data points per column
missing_values_count = daily_activity.isnull().sum()

# look at the # of missing points in all columns
missing_values_count[:]
```

Out[4]:

```
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
```

Finding out the basic information of daily_activity:

- **no. of rows and columns**
- **name of columns**
- **type of value**

In [5]:

```
# show basic information of data
daily_activity.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 940 entries, 0 to 939
Data columns (total 15 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Id                         940 non-null    int64
 1   ActivityDate               940 non-null    object
 2   TotalSteps                 940 non-null    int64
 3   TotalDistance              940 non-null    float64
 4   TrackerDistance            940 non-null    float64
 5   LoggedActivitiesDistance   940 non-null    float64
 6   VeryActiveDistance         940 non-null    float64
 7   ModeratelyActiveDistance   940 non-null    float64
 8   LightActiveDistance        940 non-null    float64
 9   SedentaryActiveDistance    940 non-null    float64
 10  VeryActiveMinutes          940 non-null    int64
 11  FairlyActiveMinutes        940 non-null    int64
 12  LightlyActiveMinutes       940 non-null    int64
 13  SedentaryMinutes           940 non-null    int64
 14  Calories                   940 non-null    int64
dtypes: float64(7), int64(7), object(1)
memory usage: 110.3+ KB
```

Counting the unique ID and to confirm whether data set has 30 IDs.

In [6]:

```
# count distinct value of "Id"
unique_id = len(pd.unique(daily_activity["Id"]))

print("# of unique Id: " + str(unique_id))
# of unique Id: 33
```

From the above observation, noted that

1. **There is no typo, Null or missing values.**
2. **Data frame has 940 rows and 15 columns.**
3. ***ActivityDate* is wrongly classified as object dtype and has to be converted to datetime64 dtype.**
4. **There are 33 unique IDs, instead of 30 unique IDs as expected from 30 fitness tracker users.**

The following data manipulation is performed:

1. **Convert *ActivityDate* to datatime64 dtype.**
2. **Convert format of *ActivityDate* to yyyy-mm-dd.**
3. **Create new column *DayOfTheWeek* by separating the date into day of the week for further analysis.**
4. **Create new column *TotalMins* being the sum of *VeryActiveMinutes*, *FairlyActiveMinutes*, *LightlyActiveMinutes* and *SedentaryMinutes*.**
5. **Create new column *TotalHours* by converting new column in #4 to number of hours.**
6. **Rearrange and rename columns.**

Converting *ActivityDate* from object to datatime64 dtype and converting format of *ActivityDate* to yyyy-mm-dd. Then, printing head to confirm whether it has been updated to datatime64 dtype and dates to yyyy-mm-dd.

In [7]:

```
# convert "ActivityDate" to datatime64 dtype and format to yyyy-mm-dd
daily_activity["ActivityDate"] =
pd.to_datetime(daily_activity["ActivityDate"], format="%m/%d/%Y")

# re-print information to confirm
daily_activity.info()

# print the first 5 rows of "ActivityDate" to confirm
daily_activity["ActivityDate"].head()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 940 entries, 0 to 939
Data columns (total 15 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
```

```
 0   Id                        940 non-null    int64
 1   ActivityDate              940 non-null    datetime64[ns]
 2   TotalSteps                940 non-null    int64
 3   TotalDistance             940 non-null    float64
 4   TrackerDistance           940 non-null    float64
 5   LoggedActivitiesDistance  940 non-null    float64
 6   VeryActiveDistance        940 non-null    float64
 7   ModeratelyActiveDistance  940 non-null    float64
 8   LightActiveDistance       940 non-null    float64
 9   SedentaryActiveDistance   940 non-null    float64
 10  VeryActiveMinutes         940 non-null    int64
 11  FairlyActiveMinutes       940 non-null    int64
 12  LightlyActiveMinutes      940 non-null    int64
 13  SedentaryMinutes          940 non-null    int64
 14  Calories                  940 non-null    int64
dtypes: datetime64[ns](1), float64(7), int64(7)
memory usage: 110.3 KB
```

Out[7]:

```
0   2016-04-12
1   2016-04-13
2   2016-04-14
3   2016-04-15
4   2016-04-16
Name: ActivityDate, dtype: datetime64[ns]
```

Creating new list with rearranged column names and renaming daily_activity to a shorter name df_activity.

In [8]:

```
#r create new list of rearranged columns
new_cols = ['Id', 'ActivityDate', 'DayOfTheWeek', 'TotalSteps',
'TotalDistance', 'TrackerDistance', 'LoggedActivitiesDistance',
'VeryActiveDistance', 'ModeratelyActiveDistance', 'LightActiveDistance',
'SedentaryActiveDistance', 'VeryActiveMinutes', 'FairlyActiveMinutes',
'LightlyActiveMinutes', 'SedentaryMinutes', 'TotalExerciseMinutes',
'TotalExerciseHours', 'Calories']

# reindex function to rearrange columns based on "new_cols"
df_activity = daily_activity.reindex(columns=new_cols)

# print 1st 5 rows to confirm
df_activity.head(5)
```

Out[8]:

	Id	ActivityDate	DayOfTheWeek	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	TotalExerciseMinutes	TotalExerciseHours	Calories
0	1503960366	2016-04-12	NaN	13162	8.50	8.50	0.0	1.88	0.55	6.06	0.0	25	13	328	728	NaN	NaN	1985
1	1503960366	2016-04-13	NaN	10735	6.97	6.97	0.0	1.57	0.69	4.71	0.0	21	19	217	776	NaN	NaN	1797
2	1503960366	2016-04-14	NaN	10460	6.74	6.74	0.0	2.44	0.40	3.91	0.0	30	11	181	1218	NaN	NaN	1776
3	1503960366	2016-04-15	NaN	9762	6.28	6.28	0.0	2.14	1.26	2.83	0.0	29	34	209	726	NaN	NaN	1745

	Id	ActivityDate	DayOfTheWeek	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	TotalExerciseMinutes	TotalExerciseHours	Calories
4	1503960366	2016-04-16	NaN	12669	8.16	8.16	0.0	2.71	0.41	5.04	0.0	36	10	221	773	NaN	NaN	1863

Creating new column by separating the date into day of the week for further analysis.

In [9]:

```
# create new column "day_of_the_week" to represent day of the week
df_activity["DayOfTheWeek"] = df_activity["ActivityDate"].dt.day_name()

# print 1st 5 rows to confirm
df_activity["DayOfTheWeek"].head(5)
```

Out[9]:

```
0      Tuesday
1    Wednesday
2     Thursday
3       Friday
4     Saturday
Name: DayOfTheWeek, dtype: object
```

Rearranging and renaming columns from XxxYyy to xxx_yyy.

In [10]:

```
# rename columns
df_activity.rename(columns = {"Id":"id", "ActivityDate":"date",
"DayOfTheWeek":"day_of_the_week", "TotalSteps":"total_steps",
"TotalDistance":"total_dist", "TrackerDistance":"track_dist",
"LoggedActivitiesDistance":"logged_dist",
"VeryActiveDistance":"very_active_dist",
"ModeratelyActiveDistance":"moderate_active_dist",
"LightActiveDistance":"light_active_dist",
"SedentaryActiveDistance":"sedentary_active_dist",
"VeryActiveMinutes":"very_active_mins",
```

```
"FairlyActiveMinutes":"fairly_active_mins",
"LightlyActiveMinutes":"lightly_active_mins",
"SedentaryMinutes":"sedentary_mins",
"TotalExerciseMinutes":"total_mins","TotalExerciseHours":"total_hours","Calor
ies":"calories"}, inplace = True)

# print column names to confirm
print(df_activity.columns.values)
df_activity.head(5)
['id' 'date' 'day_of_the_week' 'total_steps' 'total_dist' 'track_dist'
 'logged_dist' 'very_active_dist' 'moderate_active_dist'
 'light_active_dist' 'sedentary_active_dist' 'very_active_mins'
 'fairly_active_mins' 'lightly_active_mins' 'sedentary_mins' 'total_mins'
 'total_hours' 'calories']
```

Out[10]:

	id	date	day_of_the_week	total_steps	total_dist	track_dist	logged_dist	very_active_dist	moderate_active_dist	light_active_dist	sedentary_active_dist	very_active_mins	fairly_active_mins	lightly_active_mins	sedentary_mins	total_mins	total_hours	calories
0	1503960366	2016-04-12	Tuesday	13162	8.50	8.50	0.0	1.88	0.55	6.06	0.0	25	13	328	728	NaN	NaN	1985
1	1503960366	2016-04-13	Wednesday	10735	6.97	6.97	0.0	1.57	0.69	4.71	0.0	21	19	217	776	NaN	NaN	1797
2	1503960366	2016-04-	Thursday	10460	6.74	6.74	0.0	2.44	0.40	3.91	0.0	30	11	181	1218	NaN	NaN	1776

	id	date	day_of_the_week	total_steps	total_dist	track_dist	logged_dist	very_active_dist	moderate_active_dist	light_active_dist	sedentary_active_dist	very_active_mins	fairly_active_mins	lightly_active_mins	sedentary_mins	total_mins	total_hours	calories
		14																
3	1503960366	2016-04-15	Friday	9762	6.28	6.28	0.0	2.14	1.26	2.83	0.0	29	34	209	726	NaN	NaN	1745
4	1503960366	2016-04-16	Saturday	12669	8.16	8.16	0.0	2.71	0.41	5.04	0.0	36	10	221	773	NaN	NaN	1863

Creating new column *total_mins* being the sum of total time logged.

In [11]:

```
# create new column "total_mins" containing sum of total minutes.
df_activity["total_mins"] = df_activity["very_active_mins"] +
df_activity["fairly_active_mins"] + df_activity["lightly_active_mins"] +
df_activity["sedentary_mins"]
df_activity["total_mins"].head(5)
```

Out[11]:

```
0    1094
1    1033
2    1440
3     998
4    1040
Name: total_mins, dtype: int64
```

Creating new column by converting *total_mins* to number of hours.

In [12]:

```
# create new column *total_hours* by converting to hour and round float to
two decimal places
df_activity["total_hours"] = round(df_activity["total_mins"] / 60)

# print 1st 5 rows to confirm
df_activity["total_hours"].head(5)
```

Out[12]:

```
0    18.0
1    17.0
2    24.0
3    17.0
4    17.0
Name: total_hours, dtype: float64
```

Data cleaning and manipulation is completed. Hence, data is now ready to be analysed.

STEP 4: ANALYZE

4.1 Perform calculations

Pulling the statistics of df_activity for analysis:

- **count - no. of rows**
- **mean (average)**
- **std (standard deviation)**
- **min and max**
- **percentiles 25%, 50%, 75%**

In [13]:

```
# pull general statistics
df_activity.describe()
```

Out[13]:

	id	total_steps	total_dist	track_dist	logged_dist	very_active_dist	moderate_active_dist	light_active_dist	sedentary_active_dist	very_active_mins	fairly_active_mins	lightly_active_mins	sedentary_mins	total_mins	total_hours	calories
count	9.400000e+02	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000	940.000000
mean	4.855407e+09	7637.910638	5.489702	5.475351	0.108171	1.502681	0.567543	3.340819	0.001606	21.164894	13.564894	192.812766	991.210638	1218.753191	20.313830	2303.609574
std	2.424805e+09	5087.150742	3.924606	3.907276	0.619897	2.658941	0.883580	2.040655	0.007346	32.844803	19.987404	109.174700	301.267437	265.931767	4.437283	718.166862
min	1.503960e+09	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	2.000000	0.000000	0.000000
25%	2.320127e+09	3789.750000	2.620000	2.620000	0.000000	0.000000	0.000000	1.945000	0.000000	0.000000	0.000000	127.000000	729.750000	989.750000	16.000000	1828.500000
50%	4.445115e+09	7405.500000	5.245000	5.245000	0.000000	0.210000	0.240000	3.365000	0.000000	4.000000	6.000000	199.000000	1057.500000	1440.000000	24.000000	2134.000000
75%	6.962181e+09	10727.000000	7.712500	7.710000	0.000000	2.052500	0.800000	4.782500	0.000000	32.000000	19.000000	264.000000	1229.500000	1440.000000	24.000000	2793.250000

	id	total_steps	total_dist	track_dist	logged_dist	very_active_dist	moderate_active_dist	light_active_dist	sedentary_active_dist	very_active_mins	fairly_active_mins	lightly_active_mins	sedentary_mins	total_mins	total_hours	calories
max	8.877689e+09	36019.000000	28.030001	28.030001	4.942142	21.920000	6.480000	10.710000	0.110000	210.000000	143.000000	518.000000	1440.000000	1440.000000	24.000000	4900.000000

Interpreting statistical findings:

1. **On average, users logged 7,637 steps or 5.4km which is not adequate. As recommended by CDC, an adult female has to aim at least 10,000 steps or 8km per day to benefit from general health, weight loss and fitness improvement. Source: Medical News Today article**

2. **Sedentary users are the majority logging on average 991 minutes or 20 hours making up 81% of total average minutes.**

3. **Noting that average calories burned is 2,303 calories equivalent to 0.6 pound. Could not interpret into detail as calories burned depend on several factors such as the age, weight, daily tasks, exercise, hormones and daily calorie intake. Source: Health Line article**

STEP 5: SHARE

In this step, we are creating visualizations and communicating our findings based on our analysis.

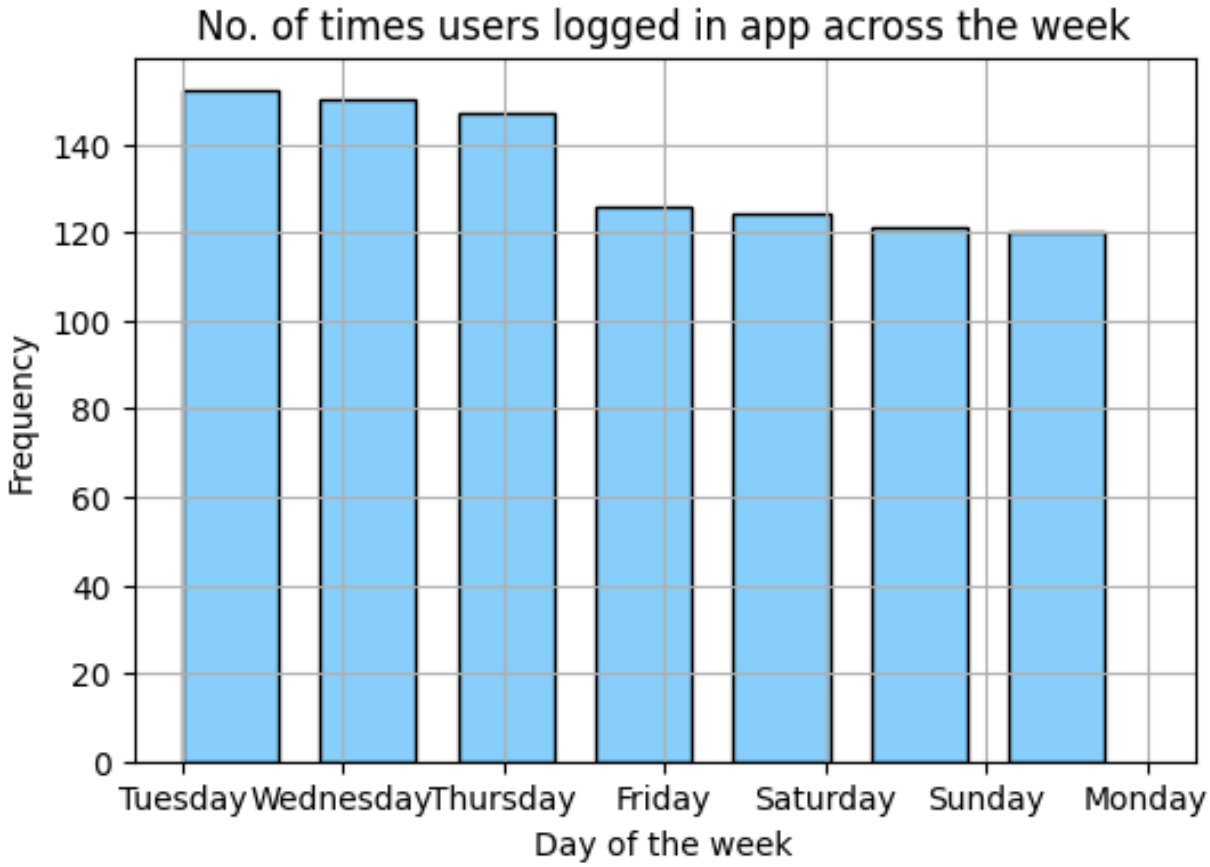
5.1 Data Visualisation and Findings

In [14]:

```
# import matplotlib package
import matplotlib.pyplot as plt

# plotting histogram
plt.style.use("default")
plt.figure(figsize=(6,4)) # specify size of the chart
plt.hist(df_activity.day_of_the_week, bins = 7,
         width = 0.6, color = "lightskyblue", edgecolor = "black")
```

```
# adding annotations and visuals
plt.xlabel("Day of the week")
plt.ylabel("Frequency")
plt.title("No. of times users logged in app across the week")
plt.grid(True)
plt.show()
```



Frequency of usage across the week

In this histogram, we are looking at the frequency of FitBit app usage in terms of days of the week.

1. **We discovered that users prefer or remember (giving them the doubt of benefit that they forgotten) to track their activity on the app during midweek from Tuesday to Friday.**

2. **Noting that the frequency dropped on Friday and continue on weekends and Monday.**

In [15]:

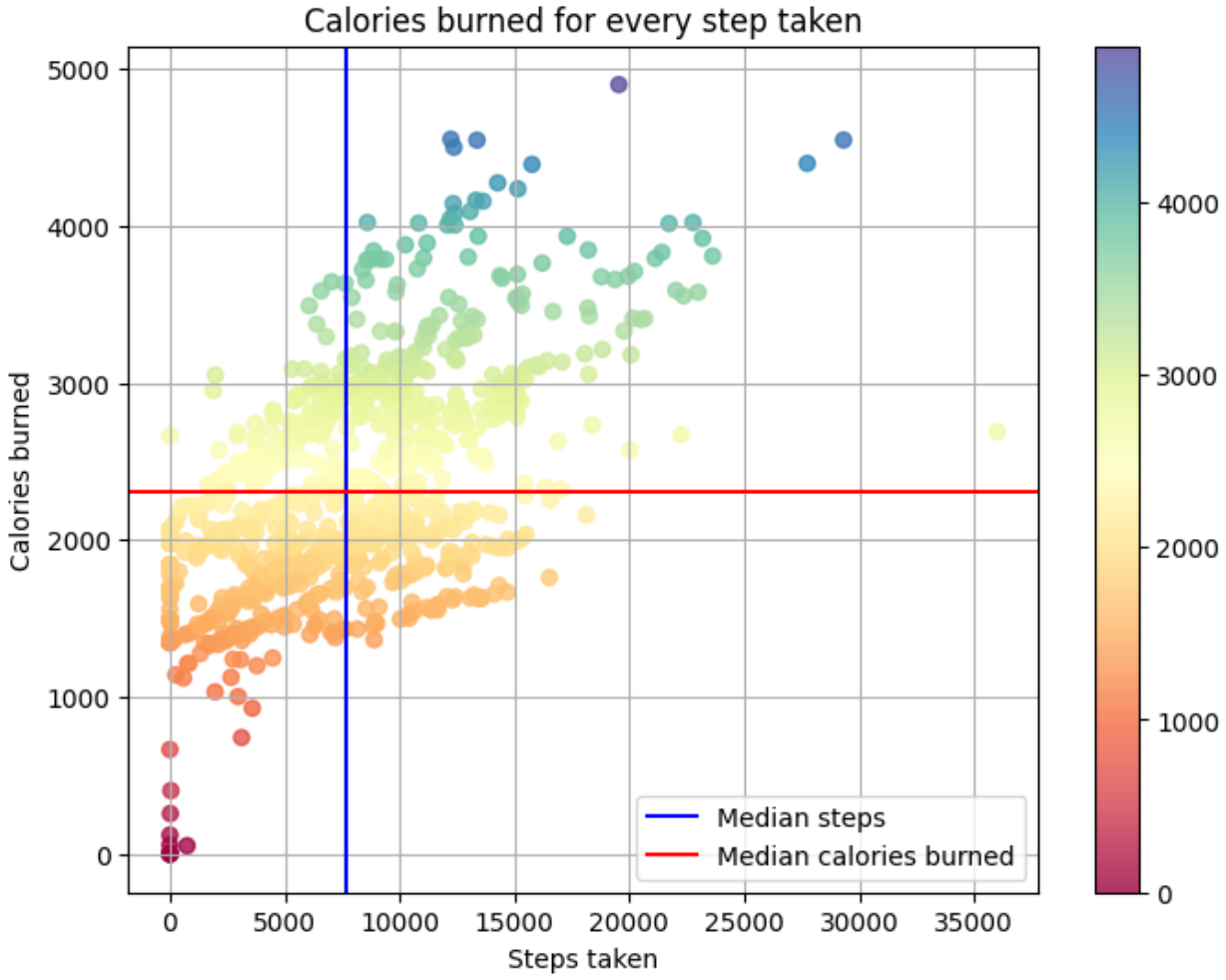
```
# import matplotlib package
import matplotlib.pyplot as plt

# plotting scatter plot
plt.style.use("default")
plt.figure(figsize=(8,6)) # specify size of the chart
```

```
plt.scatter(df_activity.total_steps, df_activity.calories,
            alpha = 0.8, c = df_activity.calories,
            cmap = "Spectral")

# add annotations and visuals
median_calories = 2303
median_steps = 7637

plt.colorbar(orientation = "vertical")
plt.axvline(median_steps, color = "Blue", label = "Median steps")
plt.axhline(median_calories, color = "Red", label = "Median calories burned")
plt.xlabel("Steps taken")
plt.ylabel("Calories burned")
plt.title("Calories burned for every step taken")
plt.grid(True)
plt.legend()
plt.show()
```



Calories burned for every step taken

From the scatter plot, we discovered that:

1. **It is a positive correlation.**

2. **We observed that intensity of calories burned increase when users are at the range of > 0 to 15,000 steps with calories burn rate cooling down from 15,000 steps onwards.**

3. **Noted a few outliers:**

    - **Zero steps with zero to minimal calories burned.**
    - **1 observation of > 35,000 steps with < 3,000 calories burned.**
    - **Deduced that outliers could be due to natural variation of data, change in user's usage or errors in data collection (ie. miscalculations, data contamination or human error).**

In [16]:

```
# import matplotlib package
import matplotlib.pyplot as plt

# plotting scatter plot
plt.style.use("default")
plt.figure(figsize=(8,6)) # Specify size of the chart
plt.scatter(df_activity.total_hours, df_activity.calories,
            alpha = 0.8, c = df_activity.calories,
            cmap = "Spectral")

# adding annotations and visuals
median_calories = 2303
median_hours = 20
median_sedentary = 991 / 60

plt.colorbar(orientation = "vertical")
plt.axvline(median_hours, color = "Blue", label = "Median steps")
plt.axvline(median_sedentary, color = "Purple", label = "Median sedentary")
plt.axhline(median_calories, color = "Red", label = "Median hours")
plt.xlabel("Hours logged")
plt.ylabel("Calories burned")
plt.title("Calories burned for every hour logged")
plt.legend()
plt.grid(True)
plt.show()
```

Calories burned for every hour logged

The scatter plot is showing:

1. **A weak positive correlation whereby the increase of hours logged does not translate to more calories being burned. That is largely due to the average sedentary hours (purple line) plotted at the 16 to 17 hours range.**

2. **Again, we can see a few outliers:**

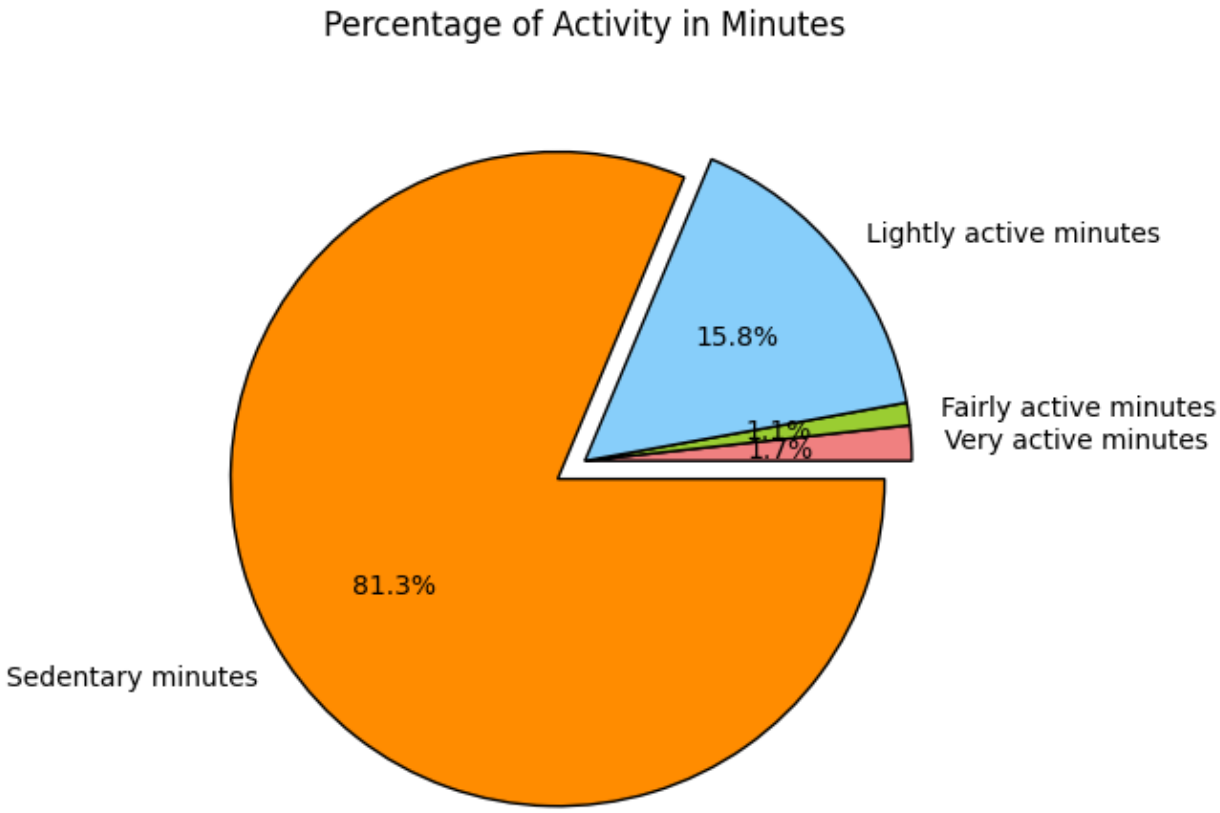
    - **The same zero value outliers**
    - **An unusual red dot at the 24 hours with zero calorie burned which may be due to the same reasons as above.**
    -

In [17]:

```
# import packages
import matplotlib.pyplot as plt
import numpy as np
```

```
# calculating total of individual minutes column
very_active_mins = df_activity["very_active_mins"].sum()
fairly_active_mins = df_activity["fairly_active_mins"].sum()
lightly_active_mins = df_activity["lightly_active_mins"].sum()
sedentary_mins = df_activity["sedentary_mins"].sum()

# plotting pie chart
slices = [very_active_mins, fairly_active_mins, lightly_active_mins,
sedentary_mins]
labels = ["Very active minutes", "Fairly active minutes", "Lightly active
minutes", "Sedentary minutes"]
colours = ["lightcoral", "yellowgreen", "lightskyblue", "darkorange"]
explode = [0, 0, 0, 0.1]
plt.style.use("default")
plt.pie(slices, labels = labels,
        colors = colours, wedgeprops = {"edgecolor": "black"},
        explode = explode, autopct = "%1.1f%%")
plt.title("Percentage of Activity in Minutes")
plt.tight_layout()
plt.show()
```



Percentage of Activity in Minutes

As seen from the pie chart,

1. **Sedentary minutes takes the biggest slice at 81.3%.**

2. **This indicates that users are using the FitBit app to log daily activities such as daily commute, inactive movements (moving from one spot to another) or running errands.**

3. **App is rarely being used to track fitness (ie. running) as per the minor percentage of fairly active activity (1.1%) and very active activity (1.7%). This is highly discouraging as FitBit app was developed to encourage fitness.**

STEP 6: ACT

In the final step, we will be delivering our insights and providing recommendations based on our analysis.

Here, we revisit our business questions and share with you our high-level business recommendations.

1. What are the trends identified?

- **Majority of users (81.3%) are using the FitBit app to track sedentary activities and not using it for tracking their health habits.**

- **Users prefer to track their activities during weekdays as compared to weekends - perhaps because they spend more time outside on weekdays and stay in on weekends.**

2. How could these trends apply to Bellabeat customers?

- **Both companies develop products focused on providing women with their health, habit and fitness data and encouraging them to understand their current habits and make healthy decisions. These common trends surrounding health and fitness can very well be applied to Bellabeat customers.**

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

- **Bellabeat marketing team can encourage users by educating and equipping them with knowledge about fitness benefits, suggest different types of exercise (ie. simple 10 minutes exercise on weekday and a more intense exercise on weekends) and calories intake and burnt rate information on the Bellabeat app.**
- **On weekends, Bellabeat app can also prompt notification to encourage users to exercise.**