Case Study: BellaBeat

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NOTE: code and files can be found in the full Github Repository

Overview

I completed the following case study as a part of the Google Data Analytics Professionals course. It is based on the fictional Company BellaBeat, a high-tech manufacturer of health-focused products for women.

In this scenario, the instructors tasked me as a data analysis to help Bellabeat become a potential big player in the global smart device market. The co-founder and Chief Creative Officer (CEO), Urška Sršen, believes that analyzing smart device fitness data could help unlock new growth opportunities for the company. Along with Sršen, another key stakeholder is Sando Mur, a mathematician and Bellabeat's co-founder.

The company offers a variety of products such as:

- Bellabeat App
- Leaf: a classic wellness tracker
- Time: a wellness watch combines timeless look of a classic timepiece with smart technology to track user activity
- Spring: This is a water bottle that tracks daily water intake using smart technology
- Bellabeat membership: a subscription-based membership program for users.

Buisness Task

In this scenario, Sršen and Mur have tasked me with completing the following requirements:

1. Analyze smart device usage data in order to gain insight into how consumers use non-Bellabeat smart devices
2. Select one Bellabeat product to apply these insights

Through completing the tasks this report will explain to key stakeholders:

1. What are some trends in smart device usage?
2. How could the trends apply to the Bellabeat customer?
3. How can both my team members and stakeholders use these insights to make data driven decisions?

Analysis

For my analysis, I focused on the fitness tracker to complete this report. I completed the analysis using the FitBit Fitness Tracker Data (FFTD). The FFTD dataset is open to the public and can be found on the Kaggle website.

Data gathering and cleaning phase

Before analyzing the data, I first cleaned and organized the data using excel when I pulled the raw data file from FFTD. I noticed there were multiple spread sheets that had overlapping data. To make sure I was not looking at repeated data, I combined all of them into one file using the XLOOKUP function. With the one excel sheet I imported it to a relational databases.

During this stage of the analysis, I noticed something interesting about data. When it came to users logging their data with the fitness tracker, it was either rare or none at all. There were also inconsistent metrics being recorded when users were very active or moderately active. However, for light activity metric, there was plenty of data recorded. At this stage, it's easy to determine that every day the users were engaging in some form of activity.

Analysis phase

How anlaysis was conducted

For the analysis portion of this case study, I completed it using SQL and the BigQuery database.

I broke the large data down to answer the query's below:

- What was the Average activity per day?
- What was each users Average Activity?
- What was the Average of all the users?

I stored these results into a seperate folder, then used a combination of R and Tableau to visualize the results.

Results

The following metrics were used to complete analysis:

- Total Calories Burned
- Total Steps taken
- Total Distance Traveled
- Total Distance Tracked

Through analysis of these metrics, I found something interesting in the data. I noticed that in each of the datasets there was an outlier throwing off the trendline of my scatterplot. The error came from a single point on May 12th. For each metric, there was a significant drop in the data recorded on that day. There are no significant reasons or holidays on this day that would make the drop in activity seem reasonable across all users. Unless a vast majority of people celebrate National Limerick Day & World Migratory Bird Day, and I am just unaware. I decided it was safe to remove this data point.

From the data I found that the average user:

- Burned 2,304 Calories
- Took 7,638 Steps
- Traveled 5 miles
- Tracked 5 miles

It is a good sign that the average total distance traveled and the total distance tracked are the same because that means that the fitness tracker works properly and tracking all the miles the users are active.

After reviewing the overall averages across each metric, I analyzed the results per day. The first metric I analyzed was calories per day.

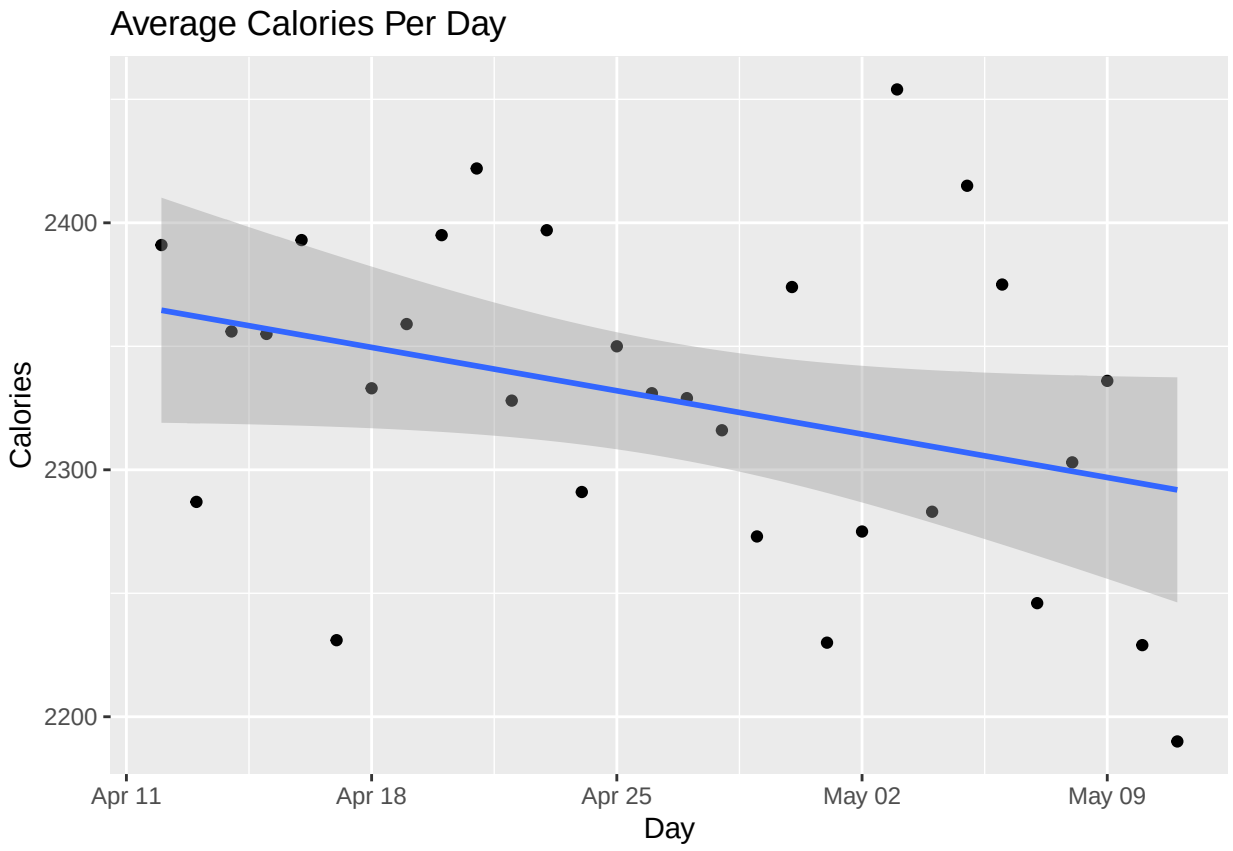
After isolating just the calories in SQL, I used the code below to plot a scatterplot and included a trend line to see what direction the data was moving. The plot shows a downward trend revealing that as time goes on, users burn fewer calories.

```
# loads calories file
  library(readxl)
  calories <- read_excel("/Users/kahlyllwilson/Desktop/excel sheets/Average Calories per day.xls")
  calo = data.frame(calories)


  #Filters out the outlier
  filt_calo = filter(calo, Calories_Per_day > 1900)

  # Makes scatter plot for the Average Calories per day
  ggplot(data= filt_calo, mapping = aes(x=ActivityDate, y=Calories_Per_day)) +geom_point() +
  geom_smooth(method = lm) + ggtitle('Average Calories Per Day') +
    labs(x = 'Day', y ='Calories')
```

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



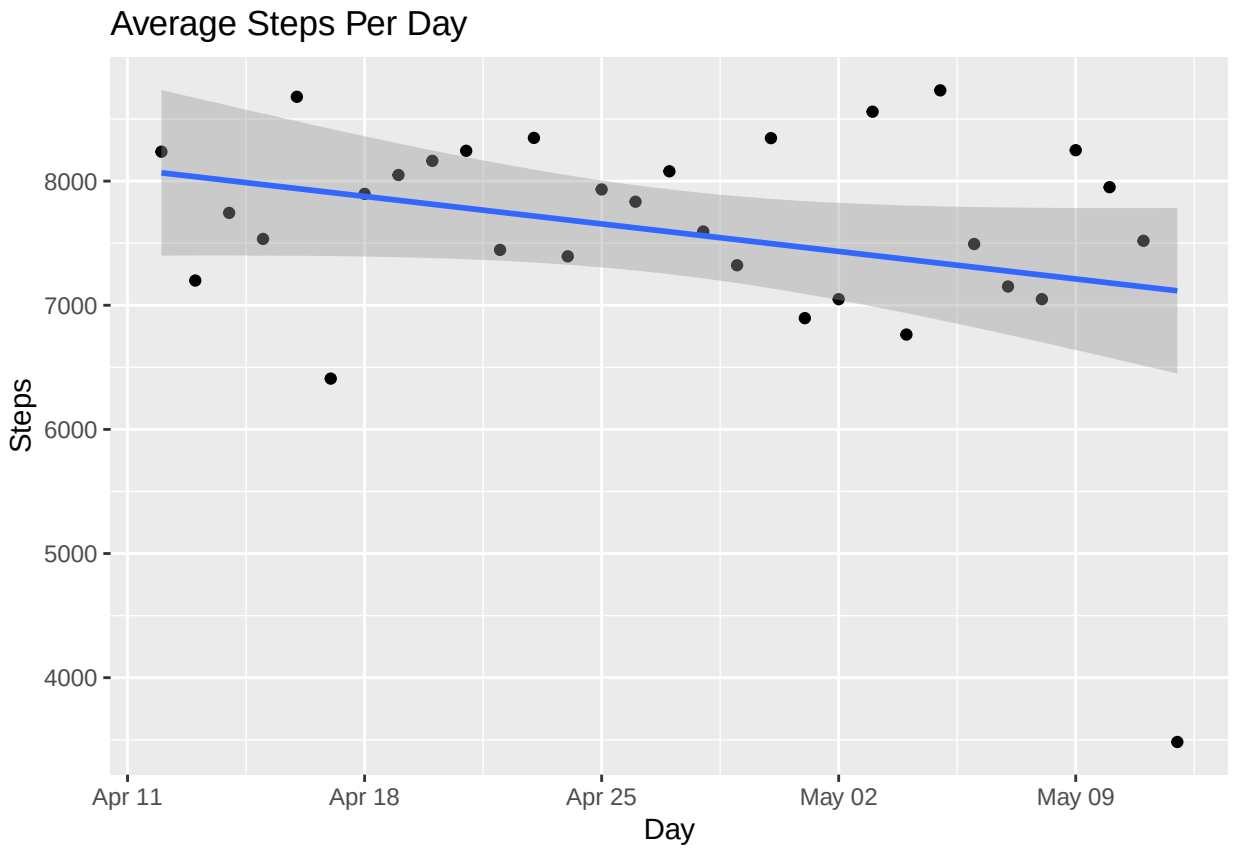
When viewing the results for the steps. The data showed as time went on, users were taking fewer steps per day.

```
  # loads steps file
  library(readxl)
  steps <- read_excel("/Users/kahlyllwilson/Desktop/excel sheets/Average steps per day.xls")
  ste = data.frame(steps)

  #Filters out the outlier
  filt_ste = filter(ste, Average_Total_steps > 2.5)

  # Makes scatter plot for the Average Tracked Distance per day
  ggplot(data=filt_ste, mapping = aes(x=ActivityDate, y=Average_Total_steps)) +geom_point() +
    geom_smooth(method = lm) + ggtitle('Average Steps Per Day') +
    labs(x = 'Day', y ='Steps')
```

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



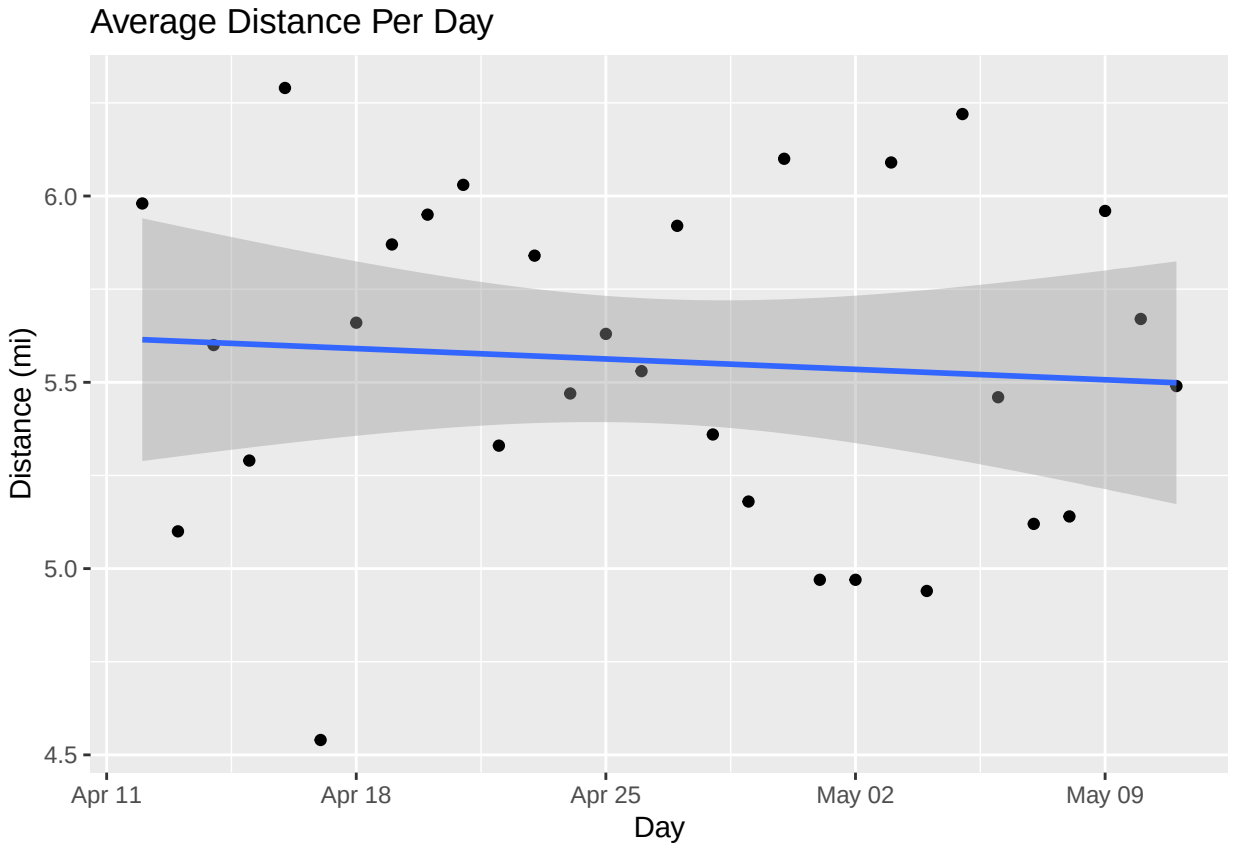
When viewing the results for the distance traveled. The data showed as time went on, the distance users traveled was mostly the same.

```
# loads distance file
library(readxl)
distance <- read_excel("/Users/kahlyllwilson/Desktop/excel sheets/Average Distance Traveled.xls")
dis = data.frame(distance)

#Filters out the outlier
filt_dis= filter(dis, Distance_traveled_Per_Day > 2.5)

# Makes scatter plot for the Average Tracked Distance per day
ggplot(data=filt_dis, mapping = aes(x=ActivityDate, y=Distance_traveled_Per_Day)) +geom_point() +
  geom_smooth(method = lm) + ggtitle('Average Distance Per Day') +
  labs(x = 'Day', y ='Distance (mi)')
```

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



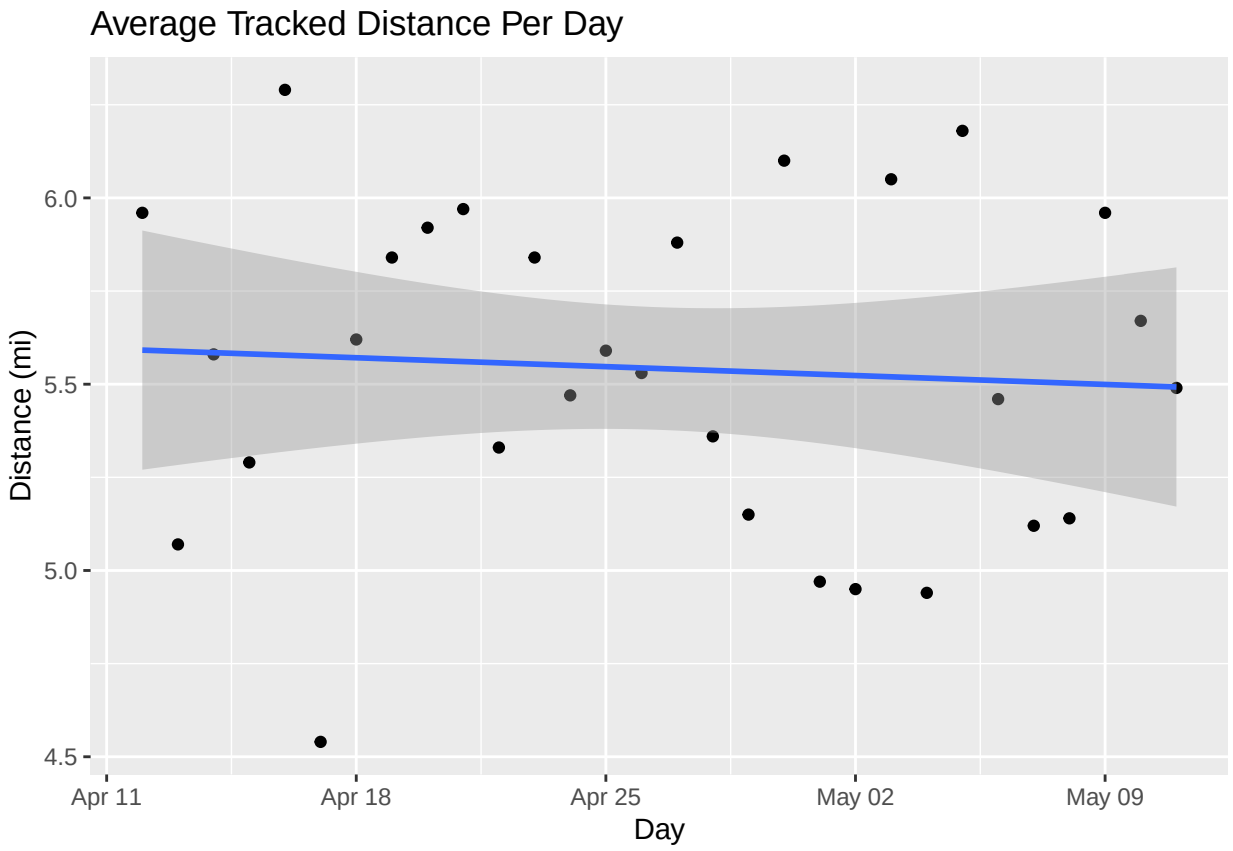
When viewing the results for the distance traveled. The data showed as time went on; the distance being tracked was constant with the distance traveled. This is a positive result, as it shows the tracking on the fitness tracker is accurate.

```
  # loads tracked distance file
  library(readxl)
  tracked_distance <- read_excel("/Users/kahlyllwilson/Desktop/excel sheets/Average Distance Tracked.xls
  trac = data.frame(tracked_distance)

  #Filters out the outlier
  filt_trac = filter(trac, Distance_tracked_Per_Day > 2.5)

  # Makes scatter plot for the Average Tracked Distance per day
  ggplot(data=filt_trac, mapping = aes(x=ActivityDate, y=Distance_tracked_Per_Day)) +geom_point() +
    geom_smooth(method = lm) + ggtitle('Average Tracked Distance Per Day') +
    labs(x = 'Day', y ='Distance (mi)')
```

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



The full combined graph can be viewed below or on Tableu

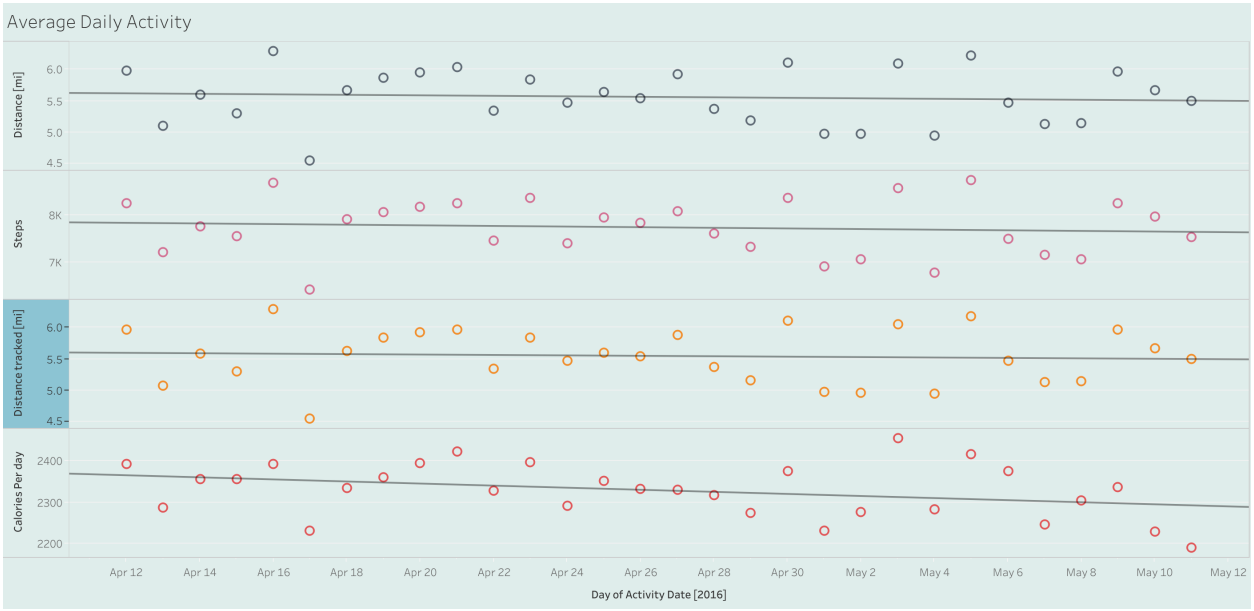


Figure 1: Tableu Table: Activity Over Time

Conclusions

The analysis of the fitness tracker was a success. The data showed some valuable insights and gave important information regarding our users and how they interact with the fitness tracker.

From our sample size, we gathered users are more likely to engage in light activity (i.e. walking, light bike ride, etc.) than engaging with activities that are considered moderate or very active (i.e. running, rock climbing, etc.).

I also noticed that users were not inclined to log this activity. A possible reason for users not logging their activity could be that they simply did not feel the need to log the data or they may have forgotten to log the activity.

A way that we could improve this metric is by adding a setting that automatically logs the data for the user. This option can be toggled on and off depending on the user's preference, and they will still have the choice to manually log activity.

Another insight I found was that as time went on, the calories burned decrease. This could result from the users' activity decreasing and the distance remaining constant, which leads to burning fewer calories to perform the same tasks. This may be a potential issue because our customers bought our product with the goal to lose weight or maintain their healthy lifestyle. If the users are noticing that they are not losing weight or have trouble tracking their fitness metrics, it could lead to the loss of customers.

A potential solution would be to integrate a weekly fitness goal feature in our app that could be tracked by the fitness tracker. We could have the users create their own goals or give them a few generic goals such as walking 10,000 steps for the week, running 5 miles for the week, weight loss goals, and so on. The fitness tracker would track these goals on a day-to-day basis. Then every Sunday the user can read a report of their activity and ways to improve if they fell short. But regardless, the report encourages them to move forward with their fitness goals.

Apart from the weekly goals, we could have daily advice blogs to help promote healthy living. The articles would be short and take the average reader no longer that 2 minutes to read. This will help to encourage our users to stay the course and reach their fitness goals.