Capstone 1: Milestone Report

Problem

Fitbit is an electronics company that sells devices that track the user's physical activity and sleep. A few of the common features of Fitbit devices include step counts, calories burnt, heart rate, and quality of sleep. Millions of devices have been sold worldwide, proving the popularity of Fitbit and its products, but how effective, or rather, impactful, are the devices? Fitbit watches do a decent job tracking sleep patterns and physical activities, and users have the option to download their data to view. The data collected is meaningless, though, if they are only represented as just numbers on a spreadsheet.

Effectively transitioning to a healthier lifestyle and achieving fitness goals comes with knowing the appropriate changes to make. Having a thorough analysis and visual representations of the collected data provide insights to an individual's fitness and sleeping habits. Having this piece of knowledge can help an individual gauge what habits they should maintain and what they can change.

Client

As the data used for this project belongs to a particular Fitbit user, the analysis would be of great interest to that user. Another audience this study may attract are fitness enthusiasts.

It is reasonable to assume users who regularly track their physical activities and/or sleep strive for healthy living and have fitness goals. By translating the data into graphs or models, the targeted audience will be provided with an intuitive understanding of Tracy's physical and sleep pattern. The subject of this project, Tracy, is a group exercise instructor and a home health aide. As someone who is constantly up on her feet and moving, it is expected that her activity levels will be higher than that of an average person's.

The outcomes of the data analysis provide details to Tracy on her current fitness and sleeping habits. Based on her reactions to the findings of this report, she can make the appropriate changes to help herself achieve new health/fitness goals.

Data Wrangling

Data was exported via Fitbit's website, and only up to 31 days of data can be collected at a time. Instinctively, I exported the data by month, all of which are Excel files. Activity, Sleep, and Food data were collected for all months, and are saved as separate sheets within an Excel file. In addition, daily food logs are saved as its own sheets, meaning each Excel file has at least 30 sheets. Unfortunately, heart rate information is not made readily available to users like the three set of data mentioned above, so an outside source was used to extract the data.

Fitbit's activity and sleep data are saved in a traditional database format, where each column is a variable and each row is an instance of the data. To consolidate the monthly data into one dataframe, the activity and sleep data were first parsed separately and stored into two lists of dataframes. Second, we concatenate the lists of dataframes to get two big dataframes. Fitbit displays their data in a user-friendly manner, so commas are used for numbers when needed. In Python, unfortunately, numeric data types are strictly just numbers, so the presence of a comma automatically renders the value to be treated as a string. To convert columns of strings into numeric values, commas were removed using regular expressions then converted using Python's handy "pd.to_numeric" function.

Upon analysis of the datasets, it was discovered that on days when Tracy does not use her Fitbit, data will still be displayed for that day with default values (e.g., minimum calories burned value based on Tracy's BMI). A check was performed to determine how many missing values (days Tracy doesn't use her Fitbit) were present in the dataset. It turns out only a small portion of the data contained missing values, so instead of filling in missing values, they were removed instead. The default value for Steps is 0, so we remove instances of data where the Steps column contains 0. Outliers were determined to be any values 2 standard deviations away from the mean. Outliers were easily handled by being replaced with the mean value.

The trickiest dataset to work with was the Food data.

	A	B	C
1	Date	Calories In	
2	2018-08-01	2,310	
3	2018-08-02	759	
4	2018-08-03	0	
5	2018-08-04	0	
6	2018-08-05	0	
7	2018-08-06	2,915	
8	2018-08-07	0	
9	2018-08-08	0	
10	2018-08-09	0	
11	2018-08-10	0	
12	2018-08-11	0	
13	2018-08-12	0	
14	2018-08-13	2,775	
15	2018-08-14	0	
16	2018-08-15	983	
17	2018-08-16	1,266	
18	2018-08-17	734	
19	2018-08-18	0	
20	2018-08-19	0	
21	2018-08-20	1,375	
22	2018-08-21	1,340	
23	2018-08-22	2,535	
24	2018-08-23	266	
25	2018-08-24	545	
26	2018-08-25	907	
27	2018-08-26	0	
28	2018-08-27	0	
29	2018-08-28	0	
30	2018-08-29	1,662	
31	2018-08-30	0	
32	2018-08-31	0	

Foods

	A	B	C	D
1	Meal	Food	Calories	
2	Anytime			
3		String Cheese, 100% Natural String Cheese	80	
4				
5	Breakfast			
6		Egg, Chicken, Hard-boiled	154	
7		Pop Tarts, Strawberry Unfrosted	210	
8				
9	Lunch			
10		Taco Cheese	220	
11		Chicken Breast, Boneless, Roasted, Meat Only	232	
12				
13	Afternoon Snack			
14		Fudge Stripes Cookies, Minis, Original	400	
15		Banana	121	
16		Nectarine, Raw	59	
17				
18	Dinner			
19		Flour Tortilla	134	
20		Ezekiel 4:9 Sprouted Grain Bread, Low Sodium	160	
21		Natural Creamy Peanut Butter Spread	380	
22		Skim Milk	160	
23				
24				
25				
26	Daily Totals			
27		Calories	2,310	
28		Fat	106 g	
29		Fiber	21 g	
30		Carbs	271 g	
31		Sodium	2,544 mg	
32		Protein	136 g	
33		Water	0 fl oz	

Foods | Activities | Sleep | Food Log 20180801 | Food

This kind of data layout is not in a traditional dataset format. In order to transform the data to achieve the desired structure, extensive manipulation of data was involved.

In the "Foods" sheet, it should be intuitive that no food data is entered for a particular day if the value in "Calories In" is 0. Since there is a sheet for each day of the month (for daily food log), we are only interested in the sheets where food data is entered--when "Calories In" is not 0. We store the dates of interest in a list and use it to get the corresponding daily food log sheets. Each sheet is converted into a dataframe, where further manipulation is done. We associate each food item with the type of meal it was eaten as (e.g., Breakfast, Lunch, etc.) by taking the existing “Meal” column and forward filling each value. Any rows with missing values are removed.

Fitbit includes daily food composition totals within each sheet, which has sufficient information to be a separate dataframe itself. These data were extracted out of the food dataframe and put into its own dataframe. As a result of manipulating the food data, two dataframes were created.

	Meal	Food	Calories	Date	Weekday
0	Breakfast	American Cheese	61	2015-11-09	Monday
1	Breakfast	Bagel thins, Everything	110	2015-11-09	Monday
2	Breakfast	Egg, Chicken, Fried	184	2015-11-09	Monday
3	Breakfast	Ham Steak, Traditional	30	2015-11-09	Monday
4	Morning Snack	Dark Chocolate Dreams	170	2015-11-09	Monday
5	Morning Snack	Banana	90	2015-11-09	Monday
6	Morning Snack	Rice Cakes, Salt Free	70	2015-11-09	Monday
7	Breakfast	English Muffin, Original	129	2015-11-11	Wednesday
8	Breakfast	Egg, Chicken, Fried	184	2015-11-11	Wednesday
9	Breakfast	Bacon Pre-Cooked (S)	75	2015-11-11	Wednesday
10	Breakfast	American Cheese	79	2015-11-11	Wednesday

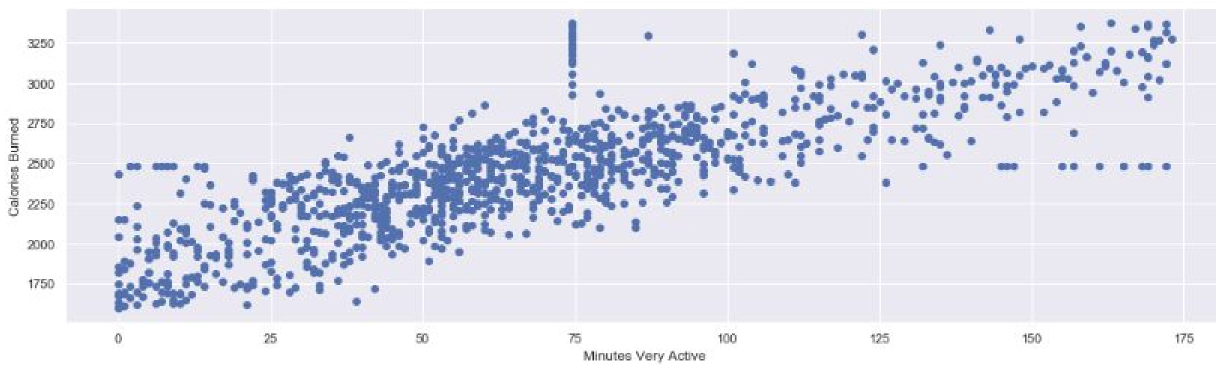
Dataframe containing food consumption data

Food	Calories	Carbs	Fat	Fiber	Protein	Sodium	Water	Weekday
Date								
2015-11-09	715	72	34	8	35	943	0	Monday
2015-11-11	797	74	39	4	37	1064	0	Wednesday
2015-11-12	1049	108	45	11	53	1216	0	Thursday
2015-11-30	90	20	0	1	1	2	0	Monday
2015-12-02	240	29	6	3	17	152	0	Wednesday
2015-12-09	860	101	35	8	37	1105	0	Wednesday
2015-12-10	1054	135	40	26	58	1210	0	Thursday
2015-12-11	1157	155	35	23	68	679	0	Friday
2015-12-15	1162	142	44	13	57	1402	0	Tuesday

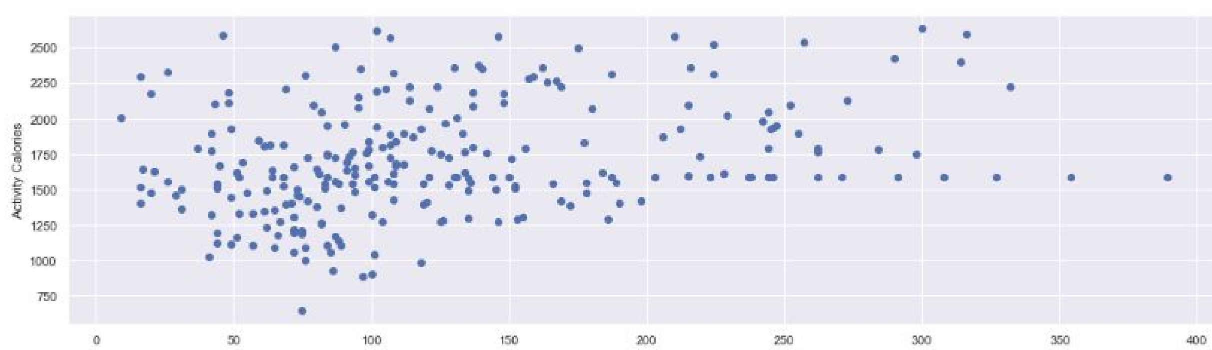
Dataframe containing nutritional facts data

Inferential Statistics

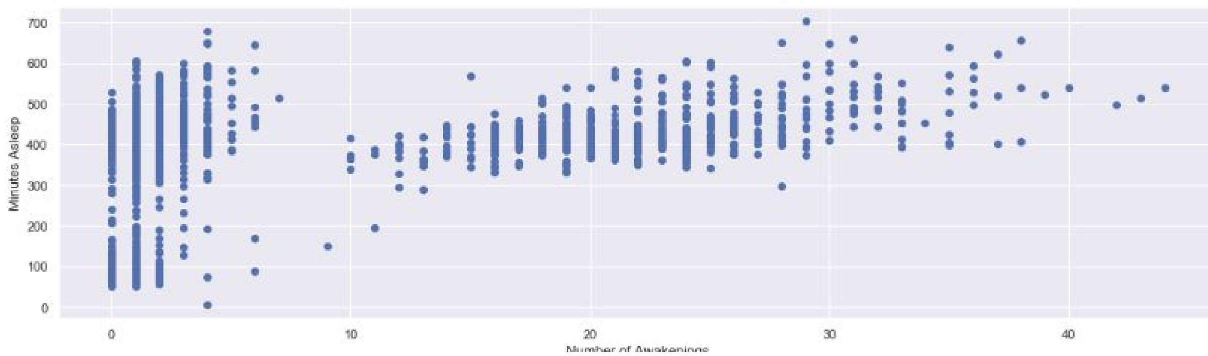
Two variables that obviously have a strong correlation are “Minutes Very Active” and “Calories Burned”, as exercising burns calories. Creating a scatter plot with “Minutes Very Active” as the independent variable and “Calories Burned” as the dependent variable, an upward trend is formed. This means that the longer Tracy is active, the more calories she burns. It is important to note that there is a separate variable called “Activity Calories” in the dataset, but was not chosen as it is more interesting to see if there are other factors that contribute to calorie expenditure. The calculated pearson correlation coefficient is 0.786, indicating a moderately strong linear relationship between active minutes and daily burned calories. Since the coefficient is not enough to represent an almost linear relationship, there are still other factors that contribute to the total amount of calories Tracy burns in a day.



Other variables that were tested for correlation include “Activity Calories” with “Carb (g)” and “Number of Awakenings” with “Minutes Asleep”. With the former, the correlation was tested to determine if Tracy is an athlete who tends to load up on carbs on her activity-heavy days. The r-value is calculated to be 0.3, which is a somewhat weak correlation, but is still a positive one nonetheless. One thing to note is that the food data is incomplete (e.g., there are instances where dinner is not recorded). It is reasonable to assume that the r-value might actually be greater if all food intake is logged, but with the data we have available, it is still plausible to say there is a weak positive relationship between how many calories are burned from exercising and how much carbs Tracy eats.



When looking at Tracy’s sleep data, it was intriguing -- maybe even shocking -- to see nights where she wakes up more than 30 times. According to a study, the average number of awakenings per night for an adult is around 6. Tracy’s number is quintuple the average, which is astounding. However, the r-value for “Number of Awakenings” and “Minutes Asleep” is 0.381. This indicates a weak, but nonetheless positive correlation. The more awakenings Tracy experiences, the longer her sleeps. It would be more worrying if the upward trend is absent because that would indicate a low quantity in sleep, which would be a health concern.



Only the pearson correlation test was performed, as the above three examples asks how strongly related the two variables are to each other. As an afterthought, it is possible to separate her data into winter and summer and see how her stats compare. For now, we are able to assume that Tracy is an active individual who has trouble staying asleep.