A data analytical approach that tracks daily physical activities and discover routine clusters for a healthy lifestyle

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ABSTRACT

Background: Fitness trackers and smartwatches are equipped with various sensors, algorithms, and accompanying mobile apps to help consumers track their fitness scale, sleep quality, heart rate, general well-being, and much more. These devices can be used in patient diagnostics and treatment. Today, we are amid a pandemic in which a person's physical and mental health is deteriorating, and skipping routine check-ups due to their higher cost causes a slew of issues in dealing with health. As a result, there is a need for effective consumer analysis and clustering that can not only evaluate health but also alert customers of potential sickness at an early stage.

Objective: The goal of this study is to look at a large quantity of data to have a better understanding of how customers utilize their fitness devices and their features. The results of this experiment may be utilized to create campaigns to raise awareness about health and the use of monitoring devices in everyday life. This analysis will not only be helpful for people’s health monitoring but also for helping the marketing team of these devices in planning marketing strategies.

Methods: Throughout the study, I'll be using Kaggle's Fitbit dataset for thirty eligible Fitbit users over a month. I am going to contribute to the existing research and explain the general usage of trackers, as well as periodic and overall changes throughout time, and uncover recurring trends. The core findings in this study are explored using an exploratory approach and searching for trends, patterns, and relationships among variables using regression analysis in the data.

Results: Findings from the above methods contribute to understanding device’s acceptability and usage rate by the users and also provide help to marketing teams to drive better campaigns and awareness about fitness and trackers. I have identified 33 unique consumers out of which 18 consumers used the device in their day-to-day life. I also discovered routine clusters for consumers and performed the KNN classification to detect the set of clusters that matches a new consumer's profile. A strong linear relationship was observed between steps and distance whereas steps and calories burnt showed a weaker relationship, also the active minutes and steps showed surprisingly incorrect relationship due to limitations in data size.

Keywords: physical activity; fitness trackers; data mining; user clusters; fitbit; personal trackers; wearables; health monitoring; usage patterns; quantitative analysis

1. Introduction

The World Health Organization advises that adults should engage in 150 minutes of moderate-intensity physical activity (PA) each week, while children and adolescents should engage in PA for 60 minutes [1]. However, 25% of adults and over 80% of adolescents do not achieve the recommended PA targets [1].

Physical exercise is without a doubt one of the most essential activities in the prevention [1] and treatment [15] of a variety of illnesses, including obesity, diabetes, and cardiovascular disease. At the same time, health and fitness are socially valued, and being fit and active is an important aspect of modern life. Low PA is currently the fourth leading risk factor for mortality worldwide [3]. Even though there is limited evidence that using wearable fitness trackers will improve health [4,5].

Within this context, activity trackers such as those from Fitbit, Garmin, Nike, Jawbone, and other companies have become increasingly popular in recent years. In 2016, vendors shipped 102 million devices worldwide, compared to 82 million in 2015 [6]. Fifty-seven percent of these devices were sold by the top five brands: Fitbit, Xiaomi, Apple, Garmin, and Samsung.

What are wearable devices?

> Wearable devices enable the continuous monitoring of human physical activities and behaviors, along-with physiological parameters during daily life. The most commonly measured data include vital signs such as heart rate, blood pressure, body temperature, along-with blood oxygen saturation, posture, and physical activities through the use of electrocardiogram (ECG), and other devices.

Activity trackers have become a popular study area amongst data scientists, statisticians, medical experts, physiologists, and psychologists. In response to evolving technology and understanding, these gadgets are intended to be more efficient to track daily activities. These devices are used in numerous contexts such as personal wellbeing and fitness, life and health logging, and also in health behavior change interventions and research studies. Despite their popularity, however, the use of activity trackers in health interventions is challenging, and their success is debatable.

Detecting relationships in complex time-series data, such as personal tracker data, can be a way of establishing daily life patterns, and also a way of detecting deviations from these patterns. The robust data that provides steps, heart rate, weight log and sleep data by the day, hour, and sometimes minute and seconds level data, outliers can be easily spotted but hardly classified.

Most of these devices provide basic analytics and predictions which are capable of tracking one's fitness but not health. So, through this study, I will answer how the micro-management of physical activity has implications for human behavior and the macro-issue of health and fitness. I would also classify users into various groups based on their device usage. These clusters can later be used to create a baseline user profile to predict future activities or focus on identifying atypical activities in this established baseline for that user and warn users of their health deterioration and help them in planning a plan to avoid it.

2. Literature Review

Many techniques have been developed to anticipate symptoms/illness in health situations using anomalous activity detection. These investigations are also for assessment of the monitoring devices' accuracy (Benedetto et al., 2018), (Nazari, 2017) and efficacy (Wright et al., 2017).

Various studies involve in gathering device data and finding the accuracy of device's data collected when user forgets to wear the device (Tang et al., 2016) or in detecting anomalous sleep patterns (Liang et al., 2016), (Purta et al.,2016), and classifying long-term use behavior (Meyer et al., 2017).

A study was conducted by Gartner to know how and why the users buy "wearable devices", results show that about 34% of people bought this device for its real purpose, while other 26% of users bought this for a gift because it looks good as an accessory and remaining 40% people either didn't buy or didn't find it useful. They explained the reasons why people use activity trackers, and when and why they stopped.

A study conducted by (Emaus A, Degerstrøm) which used user's current and historic Fitbit data for a data-driven predictive model built to generate automated real-time goal planning. In this study, the best results were provided by the Random Forest algorithm.

Another study conducted by (Finkelstein EA) used wearable device data to categorize and predict if a person is anxious, depressed, or infected with influenza. They created a machine learning model for categorization based on heart rate variation (HRV), which includes time-domain, frequency-domain, and non-linear factors.

An advanced prediction was performed that looked at the ability of behavioral risk variables, particularly Fitbit-measured behavior. Objective was to predict re-admission of post-surgical cancer patients. They created a machine learning model by analyzing physical activity data from a Fitbit tracker worn by patients during their in-hospital recovery period.

A study conducted by Altenhoff, Vaigneur, and Caine (2015), evaluated the usage of the wearable and its application and found that the most useful feedback users got from the application. They also said that users are motivated to use the device, if they are confident enough that it will provide proper feedback. Feedback is the only mode of communication from the wearable to the human that aids individuals in their quest to improve their physical health.

A deep learning approach to determining quality of sleep used convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory RNNs (LSTM-RNN) (Sathyanarayana et al., 2016). Also, a clustering approach was taken on general activity tracker data to determine daily patterns (Yürüten, 2014).

To predict the performance during self-regulated learning, one study included FitBit heart rate and steps, along with weather, online browsing activity metrics, and historical user experience ratings, and then analyzed the data using a Linear Mixed Model (Di Mitri et al., 2017). One of the more edifying notes in this particular study was that for LMEM, heart rate is considered fixed, as the participant cannot control it. Steps, on the other hand, are considered to be a random effect, as the participant has liberty in how many steps they wish to achieve. This study was also interesting because it incorporated a second dataset: the weather data, with which to draw predictions.

3. Background

> In the era of non-stop technological innovation, fuzzy wishful thinking has yielded to the hard doctrine of personal optimization. It’s no longer enough to imagine our way to a better state of body or mind. We must now chart our progress, count steps, log sleep rhythms, tweak diets, record weight, heartbeat rate, and negative thoughts — then analyze the data, recalibrate, and repeat.
> **~ Schwarts, 2018**

Fitbit is one of the most commonly used [15]. Fitbit trackers have high user acceptability over a sustained period (5–7 months) [18], and research indicates that they can provide valid estimates for several sleep metrics [15,17,18]. In a recent meta-analysis, Fitbit devices correctly identified sleep episodes with accuracy values between 0.81 and 0.91 and sensitivity values between 0.87 and 0.99 [18]. Thus in our study, we would be using the Fitbit dataset.

3.1. Problem Overview

Today we are in a state of a pandemic where the physical and mental health of a person is decreasing. Avoiding routine check-ups because of higher costs creates various problems in coping up with health. The actual problem arises when people tend to ignore certain symptoms or are unaware of the reason behind their health deteriorations. By the time they get aware of it, it becomes complex.

Self-tracking is a phenomenon that is increasingly accessible and accepted in today's digitized world. Smartphones and wearable devices allow us to capture quantitative self-representation in numbers/visuals. Along with written and visual digital self-representations, they can now shape an extension of themselves.

Consumers tend to assume that simply wearing a fitness tracker, following diet plans, and daily goals will make them healthy. In reality, these devices can help track fitness but not health. These devices due to their limitation in display and size provide limited statistics, also they fail to discover any anomalous activities. Thus lack in providing advanced analytics and predictions from collected data doesn't guarantee a health improvement.

The prime focus behind this case study is to take the raw data as an input and produce insightful analytics and identify routine clusters and user types, which later can be useful for creating awareness of health amongst the people or help the R&D team to plan their strategies.

3.2. Dataset Overview

Throughout this study, I will be using the publicly available data from Zenodo to analyze and correlate personal tracking data of thirty different users over one month. This dataset contains 18 CSV files which were generated by respondents to a distributed survey via Amazon Mechanical Turk between March 12th, 2016, and May 12th, 2016.

Thirty eligible Fitbit users consented to submit personal tracker data, including minute-level output for physical activity, heart rate, and sleep monitoring. It includes information about daily activity, steps, and heart rate that can be used to explore users' habits. It's a database segmented in several tables with different aspects of the data of the device with lots of details about the user behavior.

For detecting high-level usage trends, the most interesting data is all the daily activity and the sleep data as they will probably show some interesting patterns but I'll have to merge some tables to do my analysis.

To track health, only a few of the important parameters are needed like, steps count, calories burnt, hours slept, hours awake, distance covered, weight logged and heart rate, etc. Parameters like Active minutes and distance helps in creating clusters and classifying user's active time and distance in a day.

Table structure and parameters

1.) Weight data:

Columns	Description
Id	User ID
Date	Date and Time on which task was performed
WeightKg	Weight in KG
WeightPounds	Weight in Pounds
Fat	FAT
BMI	BMI Value

2.) Heart rate data:

Columns	Description
Id	User ID
Time	Date and Time on which task was performed
Value	Heartbeat count

3.) Sleep table:

Columns	Description
Id	User ID
SleepDay	Date on which task was performed
TotalSleepRecords	Total record of sleeps for that user
TotalMinutesAsleep	Total Minutes asleep
TotalTimeInBed	Total Minutes in bed without sleep

4.) Daily activity table:

Columns	Description
Id	User ID
ActivityDate	Date on which task was performed
TotalSteps	Total Steps taken
TotalDistance	Total Distance travelled
TrackerDistance	Total Distance measured
LoggedActivitiesDistance	Difference in distance travelled and measured
VeryActiveDistance	Distance travelled when active
ModeratelyActiveDistance	Distance travelled when moderately active
LightActiveDistance	Distance travelled when lightly active
SedentaryActiveDistance	Distance travelled when sedentarily active
VeryActiveMinutes	Minutes user was Very active
FairlyActiveMinutes	Minutes user was Fairly active
LightlyActiveMinutes	Minutes user was Lightly active
SedentaryMinutes	Minutes user was Sedentarily active
Calories	Total Calories burnt

4. Research Methodology

As previously said, a significant amount of study has already been done on personal fitness monitors. Prior findings focused on either establishing normal patterns of use or forecasting outliers, this study will use both baseline usage and anomalies to inform observers about when non-baseline activity is most likely to occur.

In the dataset, there are 2 folders each for one-month data starting from 12th March 2016 to 12th May 2016. There are 18 CSV files in each directory. Out of these 18 files, I would be concentrating on daily level activities (sleep quality, heart rate, weight-log, steps-count, calories burnt, etc.) in this scope. As I am concerned about trends daily, I would discard minute level or hourly level data points.

Research methodology will take the quantitative approach to find the answers to the questions, this section includes Data cleaning, Feature Exploration, routine clusters, Correlations and Relationship Analysis.

4.1. Data Cleaning and Preparation

For ease of analysis and results, I would have to clean and merge datatables that would be required for analysis or classification. Using R and its packages, I would perform below task:

- Cleaning Variable names
- Transforming the date from %m-%d-%Y format to %Y-%m-%d
- Removing redundant/unnecessary variables after transforming and merging data

Merging the **daily activity** with **sleep** and **weight** data, to see how the daily activity parameters affect sleep and weight. We would also be interested in finding the correlation between those parameters and the relation.

4.2. Features Exploration

We are going to plot a Venn-diagram that would show which features the users use most and which features are less used. This Venn-diagram will aid in the discovery of data-driven parameters, as well as the creation of a user survey to learn why a specific feature isn't being used. The survey findings and this matrix may then be analyzed to determine why people aren't using the product/feature, allowing them to improve it and attract more consumers.

4.3. Routine clusters Identification

In this section we are going to categories users into different buckets based on different parameters. The parameters can be “Distance traveled”, “Usage Rate”, “Steps taken”, “Calories burnt”, “No. of hours slept”, etc..

A valid day was determined as having at least 10 hr valid wear. The active minutes variable was the sum of the “very active” and “fairly active” minutes. The sedentary minutes variable was computed by subtracting the active and light activity minutes from the total valid wear time.

Valid sleep data were defined as having nonnap sleep duration >3 hr. We defined nap as a sleep episode with a start time between 8 am to 5 pm. Sleep duration was computed by subtracting total nap minutes from “total minutes asleep.”

Usage Rate was defined as the number of days a user was active given the total number of days in observation. **Usage rate = Active days / Total day observed**

4.3.1 Based on Usage

According to the definition, the customer who has used the product daily is considered as a **“Committed Customer”**, the customer whose usage rate goes below 70% are considered as **“Dormant Customers of Fitbit”**.

4.3.2. Clustering users based on various parameters

To make it simpler, the following variables have been categorized:

- **Sleep (by hours):** < 6h , 6h - 8h , > 8h
- **Calories (by number of calories burnt):** < 1500, 1500 - 2500, > 2500
- **Steps (by number of steps):** < 5000, 5000 - 10000, > 10000
- **Distance (by Kilometers):** < 5km, 5km - 10 km, > 10km
- **Total Inactivity in bed :** < 100 mins, 100 - 200 mins, > 200 mins

Based on the above clusters, we then identified consumers and their activity twin. With introduction to new customers, I used the KNN classifier to detect the clusters that profiles that customer.

4.3.3. Association and Correlation of Parameters w.r.t Health

This section is used for analyzing the relationship between parameters and effect of one parameter on another (correlation). This study can identify the indicators of anomalous behavior by identifying which data is strongly correlated (TotalSteps and TotalDistance) and data that is not (ActiveMinutes and SleepQualtiy).

A sparse matrix is formed with columns representing clusters they lie in and their strength in that cluster. Strength in the cluster is defined by their average value divided by the cluster's range of value, strength is always normalized and stored so that it can be used for predictions and classification. For example (steps taken by a user daily are 3800, he lies in < 5000 categories, so his strength will be 0.76.)

Through this association of parameters, I have found out the possible reasons for the people having insufficient sleep which indirectly affects their health. Then I used the correlation plot to plot the relation of parameters and also individually identified the relations with Pearson coefficient and p-value.

Based on the p-value and coefficient, I then applied linear regression and multilevel regression models to compare their actual and estimated values. If anything wrong is identified a notification will be triggered warning users about possible health deterioration.

5. Key Findings

A total of 33 participants took part. Out of which 24 users had valid Fitbit data with more than a feature used and having more than 90% activity rate. Thus, the analytical sample included 24 participants for further analysis and clustering.

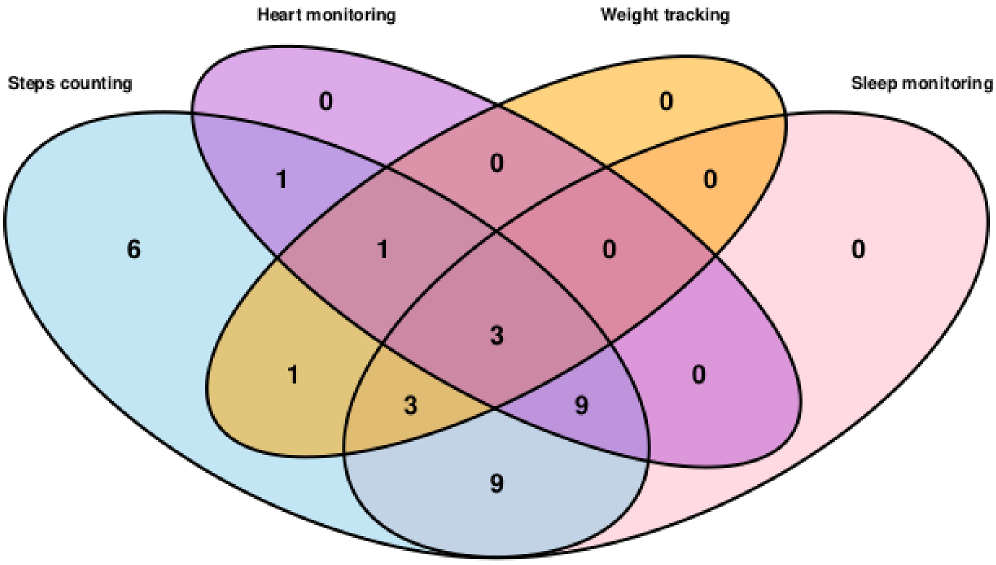


Fig 1: Venn-diagram for feature exploration

Users who have used all 4 features - 9% (3 Ids) have all four featured records of STEPS - SLEEP - HEARTBEATS - WEIGHT

Based on the diagram, we could conclude: Step is the core function that includes data of all users and Sleep monitoring is the 2nd most used feature.

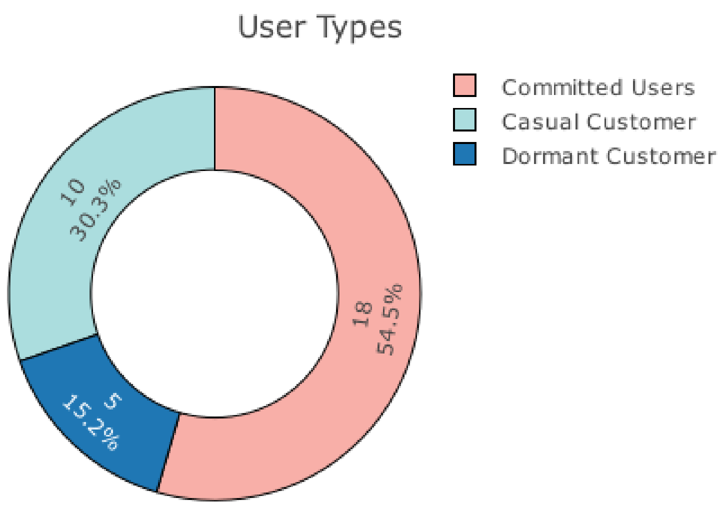


Fig 2: User Type based on usage rate

All the data is very useful for the marketing and research team, so that they can create a survey and figure out challenges the user face while using the product and based on the feedback they can improve their product.

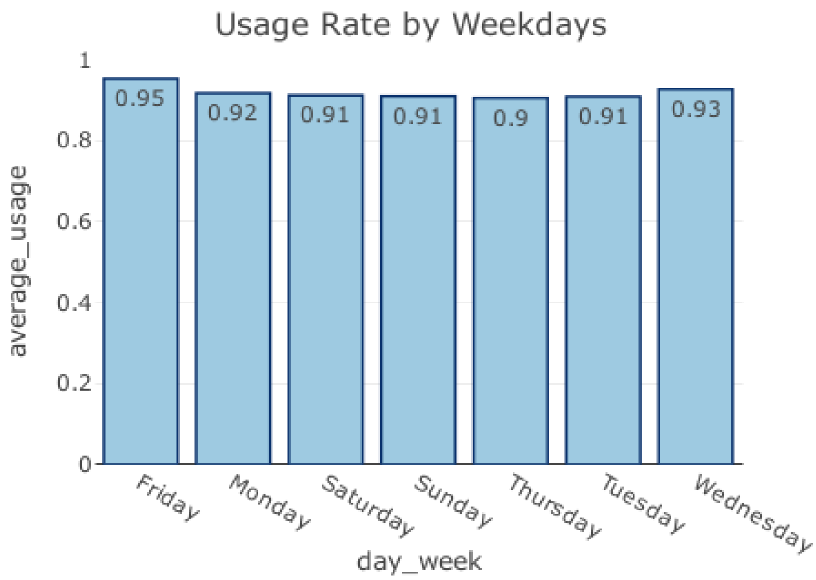
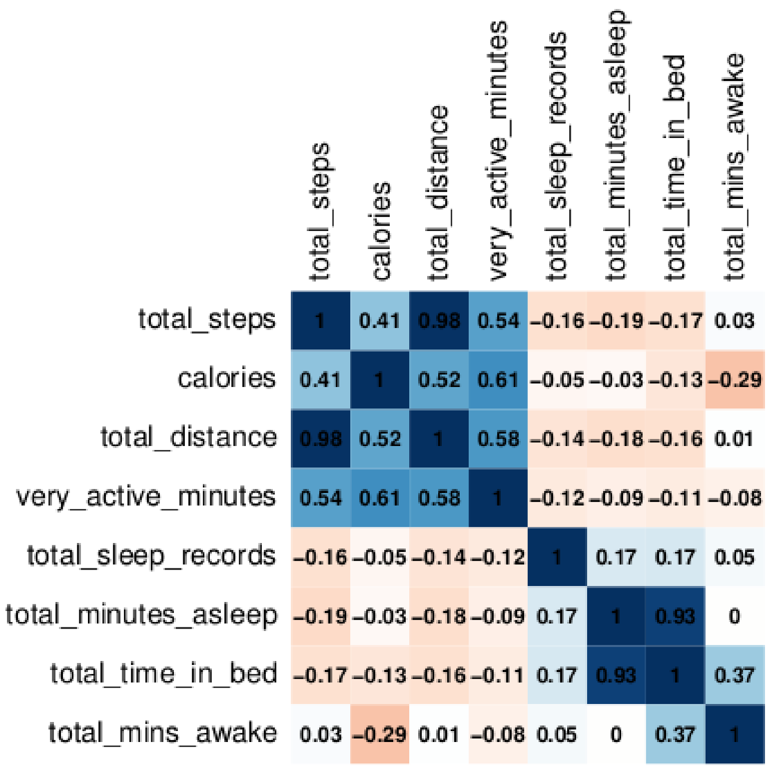


Fig 3: Usage of device based on week days

Secondly, the users who have used their product daily, what changes they have noticed in their health, productivity, etc., should be gathered and used as a marketing tactic to create awareness about health and increase their sales.

When conducting correlation performance analysis, I found the below parameters to be highly or loosely correlated to each other.



	total_steps	calories	total_distance	very_active_minutes	total_sleep_records	total_minutes_asleep	total_time_in_bed	total_mins_awake
total_steps	1	0.41	0.98	0.54	-0.16	-0.19	-0.17	0.03
calories	0.41	1	0.52	0.61	-0.05	-0.03	-0.13	-0.29
total_distance	0.98	0.52	1	0.58	-0.14	-0.18	-0.16	0.01
very_active_minutes	0.54	0.61	0.58	1	-0.12	-0.09	-0.11	-0.08
total_sleep_records	-0.16	-0.05	-0.14	-0.12	1	0.17	0.17	0.05
total_minutes_asleep	-0.19	-0.03	-0.18	-0.09	0.17	1	0.93	0
total_time_in_bed	-0.17	-0.13	-0.16	-0.11	0.17	0.93	1	0.37
total_mins_awake	0.03	-0.29	0.01	-0.08	0.05	0	0.37	1

Fig 4: Correlation coefficients of various parameters

Firstly, there is a strong correlation between TotalSteps and TotalDistance with a coefficient of 0.98. This makes sense because the more a user walks, the further they will travel. Surprisingly, TotalSteps and ActiveMinutes have a considerably weaker relationship. Any user who takes "more steps" and travels "more distance" was predicted to have "Most Active Minutes" going into this research. That is not the case in this database.

A good relationship is defined between Total Distance traveled(0.58), Total Calories burnt (0.61), Total Steps taken(0.54), and Very Active Minutes

TotalSteps does not correlate with QualitySleep, and also weaker relations are observed between ActiveMinutes and Sleep parameters.

NOTE:- The active minutes represent that users are doing some physical exercise, thus we get a strong relationship with all physical factors. The QualitySleep is defined as sufficient amount of sleep with fewer minutes awake in bed.

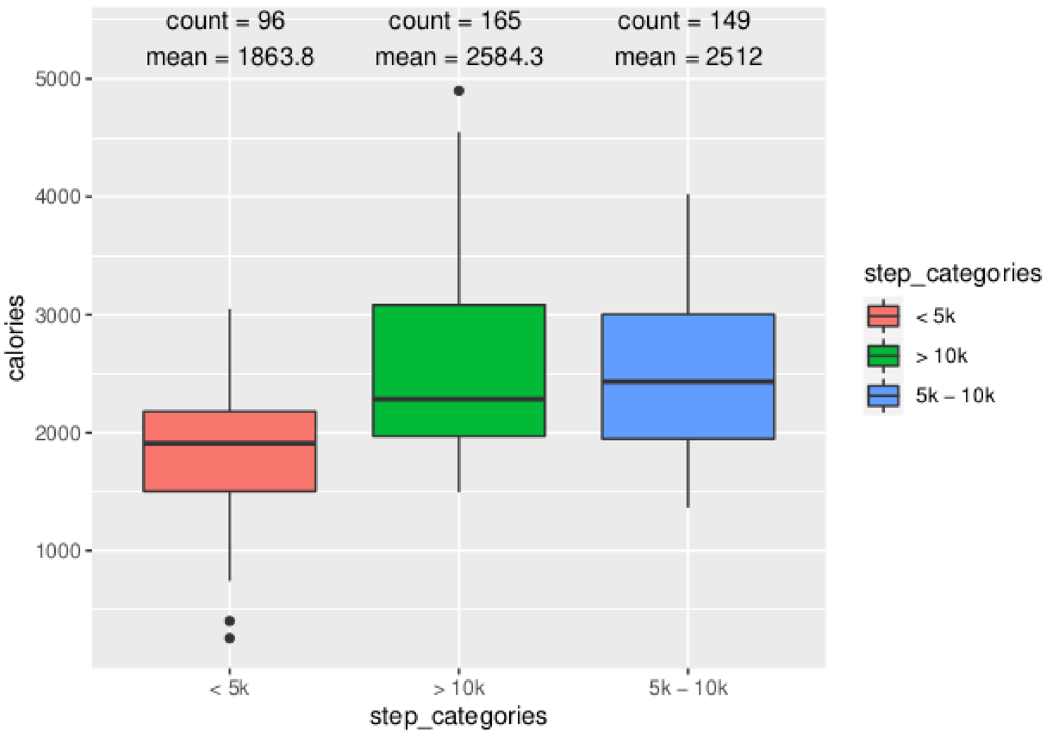


Fig 5: Relation between steps and calories (Linear relation)
[Outlier found in <5k category]

The average number of calories burnt ranges from 1800 to 2600 per day. This average states that users in all the groups are following the recommended steps and calories burned. Though we can see there are some outliers which have less than 500 steps a day, these users can be considered as inactive and can be warned for their health deterioration reasons and help them plan their diet goals accordingly.

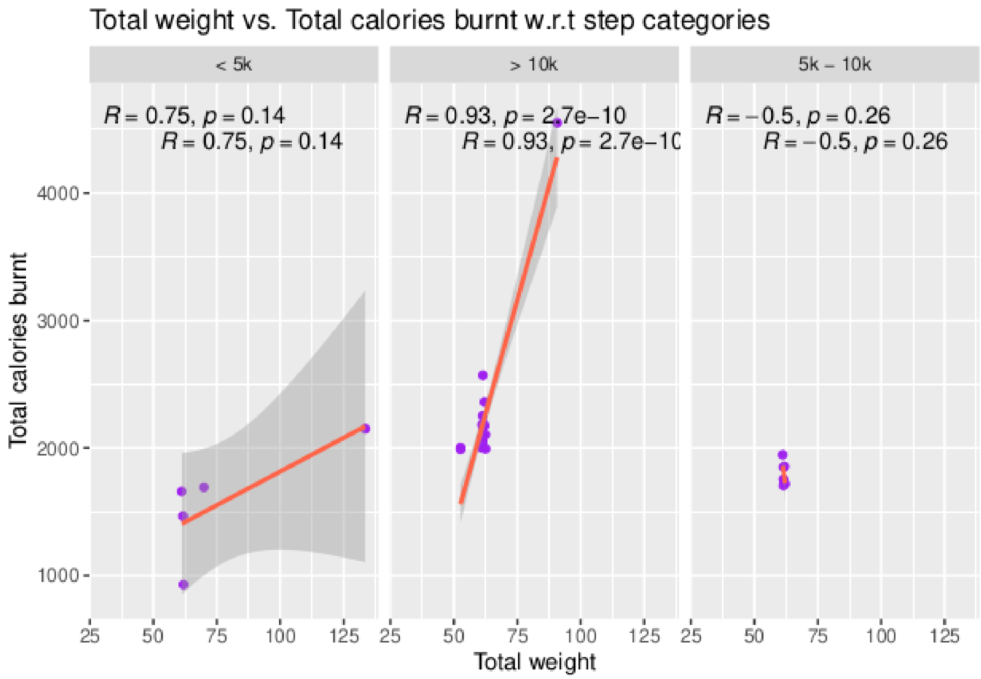


Fig 6: Relation between weight (kgs) and calories burnt w.r.t steps taken

Out of all 3 categories, there's strong association and positive relationship between these two variables when total steps taken is greater than 10k because we get R(co-efficient) as 0.93 and p-value as 2.7e-10(i.e. it is less than 0.05). Thus we can conclude that, Calories burnt are dependent on Weight of the person if he/she takes approx 10k steps a day.

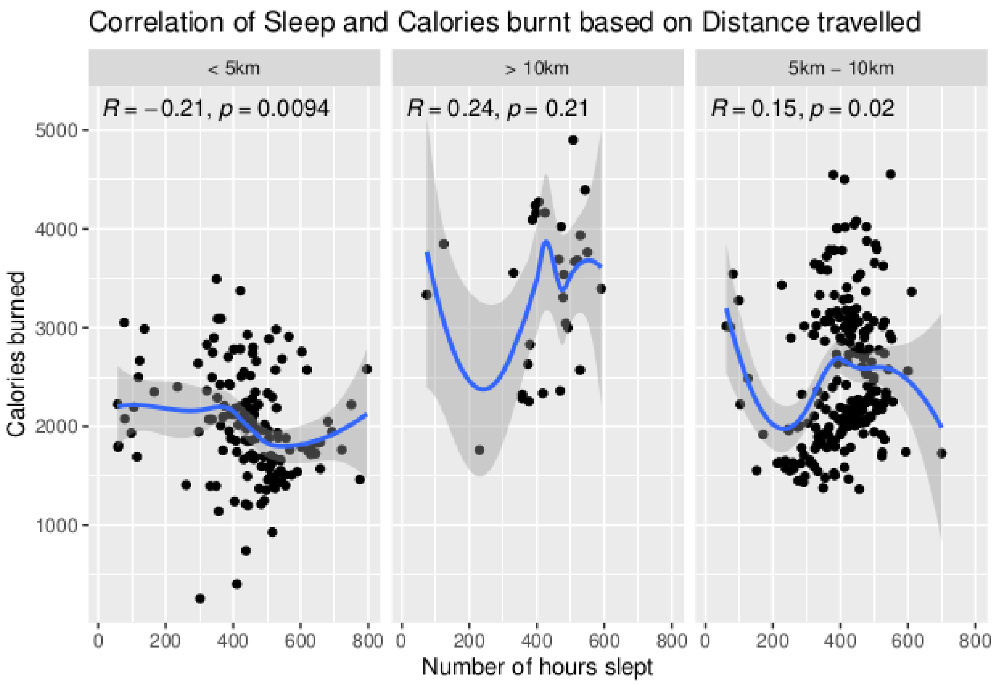


Fig 7: Relation between sleep hours (kgs) and calories burnt w.r.t distance travelled

In each category of distance, the value of r is less than 0.7. This is why the relationship here is either weak or could be considered as nothing.
In the category of 5km - 10 km, the value “r” is small, representing a weak relationship but the value of p is 0.02 (less than 0.05), it signifies a good correlation and this creates confusion. Why is it so can be explained as below.

In our case, the effect size (the Pearson’s r) is the strength of a relationship between two variables, which is relatively small, but the significant p-value refers to the fact that, given our sample size, the error measurement associated with these variables is small enough so we are getting the correlation as reliable.

6. Discussion

The size of the test set used is very small which consists of only 33 unique users and the data is available for about 2 months span, which is a very small time-series data. This is the reason why there were some discrepancies observed in the analysis. Apart from the size of data, a major issue which was found is that the table weight log contained more null values than data-points. The reason behind this was the manual logging of weight for the users thus making the data too sparse.

We are unaware of user’s basic information and thus providing insights in-general. To get proper and detailed insights that are very user-specific, it would have been great if the data could have contained some extra columns like “age”, “gender”, “geographic location”, “device used”, “brand name”. These parameters when taken into consideration could have enhanced the analysis to a very specific user.

Also, the dataset I used was quite outdated as compared to present technological advancements, precise accuracy, and predictions. With proper dataset, we could have achieved higher f1-score for classification and higher accuracy in predicting future activities/anomalous activities of users.

Future Work

Data mining plays a significant role in discovery and prediction of many types of metabolic syndromes, and therefore different kinds of disease can be identified.

Using this approach, we can build a model that can predict the occurrence of events related to each patient record, current vitality and prevention of risk factors with its associated cost metrics and an improvement in overall prediction accuracy. With a good prediction accuracy, we will develop an Interface for user’s one-time interaction so that they can add their past medical history and basic information and later be notified on WhatsApp whenever their health deteriorates.

7. Conclusion

To summarize, through all the advanced analysis and routine clustering I have observed, how the behaviour changes in each cluster. This behavioural change has helped in predicting anomalous activities and detecting user clusters based on various parameters. The users are associated with a cluster using KNN classifier where a sparse matrix is taken as an input for all past data of all users and new users are classified into clusters with the help of classifier. Based on these classifications the user's twin is identified and goal planning and diet plans are suggested accordingly to help maximize the health benefit of this device.

Apart from this, when it comes to finding the list of features that influences health, we have bucketed users into different categories and analyzed each bucket to get the influential health factor.

1.) Sleep and factors responsible for Insufficient sleep

   We have approx 33% of Insufficient sleepers out of which approx 90% of the users have Insufficient amount of sleep because of their behavior where they spend average of 2.5 hours on bed lying around doing nothing or using phone. Quality of sleep/Inactivity in bed does affect our health and mind.

2.) Steps taken and Calories burnt

   The average amount of steps walked by a healthy adult per day is 10,000. Also, as we've shown in the preceding, there's a clear link between steps done and calories burned. The more steps you take, the farther you'll walk and the more calories you'll burn. The more calories we burn, the less likely we are to develop heart-related health problems, and we also stay in shape.

3.) Weight and Calories Burnt

   People who are overweight should take more steps each day to burn more calories. When persons who are overweight walk more than 10,000 steps per day, they burn more calories. The Coefficient value (r=0.93) and p-value (p=2.77e-10) are used to demonstrate this.

Last question for us to conclude this finding is: How does this analysis be helpful for fitbit to market their product. We can say that each section has its own significance and has its own term for understanding. This case study will help the team evaluate their customers using various buckets that we created like usage rate, sleep quality, steps taken, calories burnt.

The team can create a survey and take help from NGOs to run campaigns and create awareness of the product and it's benefit on health. This will not only help them target their monthly/yearly sales but also make citizens aware about their health with such cool and handy health monitoring devices.

So according to clusters, some analysis and WHO recommendations, we came to a general definition of parameters for Healthy users. A Healthy user takes on an average 5k - 10k steps a day and burns 1800 to 2500 calories a day. A healthy user also takes a sufficient amount of sleep of 8 hours and stays less active in bed.

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