Using Heart Rate and Body Movement Data to Determine the Optimal Wake-up Time

Giorgi Kharshiladze
Department of Computer Science
Earlham College
Richmond, Indiana
gkhars15@earlham.edu

ABSTRACT

What is the optimal time to wake up? To answer this question, we analyze the sleep data using a Fitbit wearable device and apply supervised machine learning algorithms to find the best sleeping stage. Wearable device provided the heart rate, body movement and labeled sleep stage of each thirty-second interval. Using these features, we classify the given data point into the corresponding label.

KEYWORDS

Sleep Pattern Classification, Supervised Machine Learning, Optimal Wake-up Time

ACM Reference Format:
Giorgi Kharshiladze. 2019. Using Heart Rate and Body Movement Data to Determine the Optimal Wake-up Time. In *Proceedings of ACM Conference (Conference'17).* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Getting enough sleep might have been a problem for everyone at some point in their lives. Some people go to bed early; others wake up late, but sometimes still wake up tired, restless and dizzy. Even though seven or eight hours of sleep should be enough because of the human body's natural circadian rhythm [6], wake-up time is also a huge factor. When someone gets ten hours of sleep, if the alarm rings in the deep sleep stage, they might still have trouble feeling restful and energized. In general, sleep consists of several sleeping cycles, and each cycle is divided into several stages. There are two main categories of sleep stages: REM (Rapid Eye Movement) and Non-REM (Consists of light and deep sleep stages) [8]. Deep sleep is the most difficult stage from which to wake up and provides the most restorative sleep of all the sleep stages [25]. If not satisfied with their sleep, humans have a hard time enjoying their lives and simply being productive throughout the day [9]. Sleep remains one of the most critical aspects of our lives which we need to regulate and wake up the easiest way possible.

Conference'17, July 2017, Washington, DC, USA

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

As students, we always try to figure out how to balance our life and find efficient time-management strategies. There is a notable trade-off between being awake and being productive. The goal is to minimize the amount of time we are asleep and maximize working efficiency, learn faster and enjoy life. If someone woke up tired and cranky after a reasonably good amount of sleep, they might be "sleeping wrong" [15]. It would be helpful to track sleep using a wearable device and figure out what can be done differently. Looking at the heart rate data, the number of sleeping cycles per night and movements between different stages can tell us enough to turn a regular day into a productive one.

In this paper, we overview the specifics of sleep stages, related work about sleep pattern recognition, existing algorithms that determine the sleeping stage using different features (heart rate, body movement, brain activity, cardio-respiratory activity, etc.) and how to find the optimal wake-up time. There exist projects developed by huge companies like Samsung, Apple, Fitbit. They use a wearable device or a smart-watch to get the necessary data for sleep pattern classification. Fitbit analyzed data from around 4 billion nights of sleep stages across the world and said that "its results supported long-standing sleep scientists theories" [5]. Even though we do not have access to their algorithm, we have access to their data. Therefore, we can let the machine learn how to classify the sleep stage using the data they provide. For data collection purposes of this research, I use Fitbit Alta HR, which provides a way to access the labeled data about sleep stages, heart rates, body movements, etc. We can use several supervised machine learning (machine learning that has labeled data) algorithms like K-Nearest-Neighbor, Decision Tree, Random Forest, Support Vector Machine and Neural Network for this classification problem and see how accurately they can perform. The main goal of this research is to use heart rate and body movement data to predict the best wake time to wake up.

2 RELATED WORK

Everyone has a different sleeping schedule, and each sleep has a different pattern [22]. In this section, we compare some existing approaches for sleep pattern recognition. Our night sleep consists of several sleeping cycles. Usually, healthy people experience four to five sleeping cycles per night [1]. Before we dive into the science of sleep pattern recognition, it would be helpful to overview the stages and define each phase. One sleep cycle consists of five stages that fall into two major categories: Non-REM and REM [8]. Non-REM sleeping stages include light sleep of stage one and two and deep sleep of stage three. Stage one is a transition phase between being awake (when the heart rate is relatively high, breathing is intense, and brain waves are more active than during sleep) and falling asleep. Stage two is the first actual stage of light sleep. Brain waves slow down, eyes stop moving, and the body dives deeper into sleep; however, we might still experience occasional bursts of sleep spindles (bursts of rapid brain rhythmic activity [24]) and rapid brain waves. Stage three is deep Non-REM stage. The brain starts producing delta waves and muscle and eye activity completely stops. It is the most difficult to wake up from this stage. REM (Rapid Eye Movement), stage four is when brain waves are very similar to awake. In this stage, breathing becomes more intense; the eyes move rapidly in various direction and blood pressure and heart rate rise. People mostly dream at this stage. It is the final stage of the sleeping cycle. Generally, the cycle starts with stage one, goes to stage two and three, then returns to stage two before going into stage four or Rapid Eye Movement stage and finally back to stage one. The amount of time spent in each stage depends on the age of a person and how long they have been asleep [14]. Getting enough rest at night depends on how much deep sleep we get; however, teenagers need more deep sleep than older people [4]. Various studies found out that infants need 16 hours of sleep on average, and as their age increases, they demand less sleep. For example, teenagers need around 9 hours and people in their forties demand only 7 hours of sleep [15].

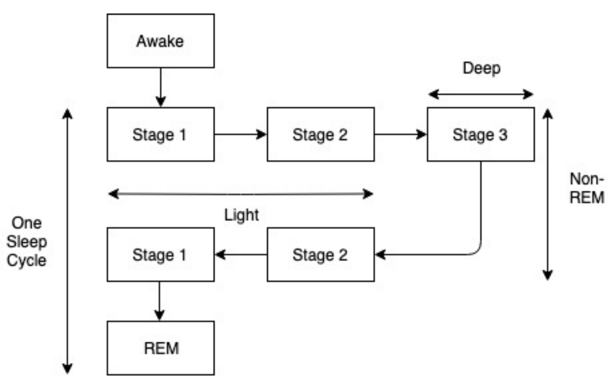

Figure 1: One sleep cycle from Awake to the end of REM

Sleep tracking can be done in lots of different ways. There are multiple wearable devices available today that can be used to track our sleep [20]. For example, Fitbit device uses accelerometers to track movements and directions of motion of a person wearing it. These accelerometers, along with heart rate data are used to determine the sleeping stage. This method of using a device to measure sleep is called actigraphy [3]. Actigraph is a device very similar to Fitbit, mainly used in clinics as it is more convenient to study patients' sleep patterns without having them to sleep in the lab. However, sleep researchers use polysomnography, or PSG, for studying sleep in a lab. A basic polysomnography test requires sleeping in a lab where researchers monitor brain waves by Electroencephalography or EEG test, where electrodes aligned on a patient's scalp measure brain activity. Sleep researchers have agreed that PSG is a "gold standard" and "the definitive way to measure sleep." Most of the studies, which use methodology other than PSG, compare their results to PSG data to check the accuracy [3]. Fitbit is not a replacement for a high-level sleep analysis, but it uses heart rate and body movement to make predictions based on these two factors [21].

In most of the prior work that we reviewed, researchers who used actigraphy in their studies compared the result accuracy against a PSG test. For the most part "actigraphy is generally accurate enough to track sleep in healthy adults with normal sleep patterns." This means that actigraph accuracy decreases for people with sleeping disorders. It can be explained by not having eye movement and brain activity data when we use the actigraph device (since it only tracks the movement and the heart rate) [3]. Michael Scullin asserted in 2014 that fitness trackers could not accurately determine sleep stages since "they rely on movements, whereas sleep stages are defined primarily by brain activity" [18]. However, in 2017, a new study commissioned by Fitbit showed that wrist-worn devices could determine wake, light, deep and REM stages in healthy adults "with a reasonable degree of accuracy." The study involved 60 adults wearing two fitness trackers and Type III home sleep testing device (Which is used for patients with sleeping disorders [23]) to compare the accuracy. Dr. Conor Heneghan, lead sleep research scientist at Fitbit, said that the performance was either similar or better than EEG-based sleep studies done earlier [5]. The question arises if we can trust results of these wearable devices. They get better every day because big companies like Samsung, Apple, and Fitbit collect more data, and therefore more trends and insights about sleep. As mentioned earlier, their sleep classification algorithm is already accurate enough for people without sleep disorders, and their labeled data can lead us to more meaningful results.

In this study, we attempted to predict the best time to wake up. It is not deep sleep, because if awoken during this time, we are most probably disoriented. The final stage of the sleep cycle, REM sleep, where most of the dreams occur, is also not the ideal option. Even though our brain activity is similar to its awake state, our body is paralyzed [14]. The best time to wake up is the during sleep [12] but with several conditions: we need to experience around four or five sleep cycles during the night [1], and we need to get enough of deep sleep to wake up fully refreshed and well rested. Going to bed early is another critical factor as people experience more Non-REM sleep between 11 p.m. to 3 a.m. of their circadian rhythm and more REM sleep between 3am-7am [2]. This means that waking up in the morning would feel much better if we go to bed early, since our Non-REM sleep will be longer.

3 METHODOLOGY

The project consists of three major parts: The labeled data collection using Fitbit Alta HR wearable device, the supervised machine learning algorithms to predict the wake-up time, and the web application for user interactions to see the results based on users' heart rate data. In the following paragraphs, we explain each part separately.

3.1 DATA COLLECTION

Unfortunately, heart rate data is not available online, especially the type we need (labeled data which consists of the body movement, sleep stage at a specific time and average heart beat per minute). Luckily, however, there are certain devices like Fitbit that give us Web API access [13] to our data collection. Getting access to the data is just the beginning. It is essential to investigate how Fitbit provides the data to the users (format, request limitations, etc.) Fitbit Web API uses the OAuth 2.0 protocol to authenticate users. Thus, whenever we need to send a request to their servers, the user credentials should be given in advance. For security reasons, this API tool provides a temporary token with an expiration time and refresh token to maintain a connection to the data when a temporary token expires. These tokens are securely stored in our JSON file. This way, we can automate the authentication process from the back-end application [11]. After authorization, we had to understand what type of data can be retrieved from this API and how it can be organized. We could download the sleep data of every thirty-second interval, as well as the heart beats per thirty seconds. Another helpful feature for the machine learning algorithms could be an activity(how active is a body on a scale of 1-5) and calories burned during that period. Once API call is made, we retrieve the data in JSON format. Therefore, using the Pandas library in python [16] was helpful to organize this non-relational structure into a CSV (Comma separated value) format and merge sleeping, heart-rate and activity data based on time. Another alternative was to use a third-party Fitbit python library which had some built-in functions that could simplify the entire process. However, because of the lack of flexibility in terms of the format of data, it became necessary to implement data collection methods from scratch. Finally, each API call downloaded one-day data and stored in a separate CSV file.

3.2 DATA ANALYSIS

This is one of the significant parts of the project. After we have all the necessary data collected, we could import as pandas dataframe and divide into training and testing data sets. The problem we are going to solve is the classification problem - given the heart rate per thirty seconds, the time passed after falling asleep, and the body movement activity (On a scale of 1-5) predict and classify in which sleep stage could a person be at that time. To make the classification easier and more accurate, we can convert the problem into binary classification. Stage values can be either light or non-light (deep, rem, awake). Machine learning algorithms that are used for this project are K-nearest-neighbor, Decision Tree, Random Forest, Neural Networks and Support vector machine. Instead of implementing these algorithms from scratch, we use python Scikit-learn library [19] where we pass the training set, compare the results to the testing set and return the accuracy score of a particular algorithm.

3.3 DATA VISUALIZATION

This part of the project is responsible for representing the results of our algorithms visually. We use python flask framework [10] that helps us create an interactive web application, where users can select features of our dataset, and see some changes in accuracy based on their selections. In addition, we use ChartJS library [7] on the front-end to display charts in the web browser. To load the algorithm results in the browser faster, we run each model and the web server on a separate thread. Collected data and results will be securely stored in the remote MySQL database. This way, I would be able to shorten the running time of the model since I will not have to parse and clean data all the time.

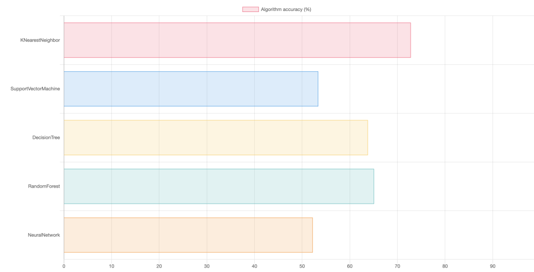

Figure 2: Comparison chart of the algorithm accuracy

4 RESULTS

After collecting 20 days of labeled data, the K-Nearest-Neighbor algorithm had the accuracy score of 73% which was the highest compared to others. Even though 20 days is not enough to make any reasonable conclusions, there is a similar project done using Huawei Watch 2 wearable device which classifies each sleep stage individually with an average accuracy of 98%. This makes us believe that using a binary classification it would be easier to get to high accuracy while having a smaller amount of data points. The models used on the Huawei device data are Decision Trees, Random Forest, and Logistic Regression [17]. One of the most significant benefits of using a supervised machine learning algorithm is more data I collect, more accurate results will become. In the figure below, we can see some changes that occur to the accuracy as we collect more data.

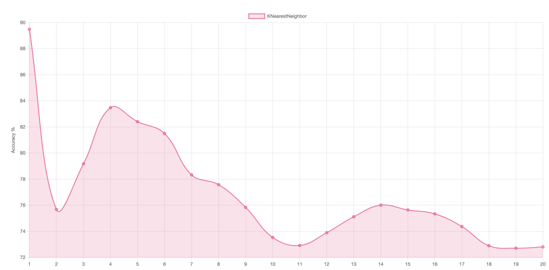

Figure 3: KNN Accuracy over time

5 ANALYSIS OF THE RESULTS

Results of this research turns out to be promising. At this point, looking at the 20 days with the average accuracy of 73% might not be the same as the final result as we collect more data. However, as we see the pattern from KNN over time, there are days when machine learns more and shows higher accuracy, compared to the previous. The hypothesis is that after about one year of data collection, our algorithm have more stable results without significantly changing the accuracy and precision score. Having a stable algorithm allows us to get the measures of only heart rate and the body movement using a lower budget hardware and get the appropriate classification of the sleeping stage.

6 FUTURE WORK

After having an accurate algorithm, we could build a low-budget sleep tracking system. It could consist of consisting of three parts: an Arduino device that tracks the heart rate and accelerometer data, a mobile app that collects data from the Arduino device via Bluetooth connection and sends an API request to our remote algorithm that returns the wake-up time from the back-end. This Arduino device can be placed inside the pillow to get the measurement from a neck of a person and take ease of waking up to the next level.

REFERENCES

[1] Ronald M Aarts. 2016. Heart rate analysis for sleep detection. (2016), 37.
[2] Ph.D. Amie M. Gordon. 2013. Your Sleep Cycle Revealed. http://www.psychologytoday.com/blog/between-you-and-me/201307/your-sleep-cycle-revealed
[3] Belle. 2014. How does your fitness tracker know when you're asleep? https://exist.io/blog/fitness-tracker-sleep/
[4] Emily Bertha. 2017. The Difference Between Light and Deep Sleep: How Much Do You Really Ne âĂŞ Eight Sleep. https://eightsleep.com/blogs/news/the-difference-between-light-and-deep-sleep-how-much-do-you-really-need
[5] Jen Booton. 2017. Fitbit Study: Fitness Devices Accurately Track Sleep Stages – Unlike Calories. https://www.sporttechie.com/fitbit-study-fitness-devices-accurately-track-sleep-stages-unlike-calories/
[6] Byrdie. 2017. Scientific Studies Say THIS Is the Best Time to Sleep. https://www.byrdie.com/best-time-to-sleep
[7] ChartJS. 2019. Chart.js Âů Chart.js documentation. https://www.chartjs.org/docs/latest/
[8] Rich Crane. 2016. Enhance Your Sleep Cycles. https://www.alaskasleep.com/blog/enhance-your-sleep-cycles
[9] Philadelphia 19104-6021 USA. Department of Psychiatry, University of Pennsylvania School of Medicine. 1997. Cumulative sleepiness, mood disturbance, and psychomotor vigilance performance decrements during a week of sleep restricted to 4-5 hours per night. https://www.ncbi.nlm.nih.gov/pubmed/9231952
[10] Flask. 2019. Welcome | Flask (A Python Microframework). http://flask.pocoo.org/
[11] Stephen Hsu. 2018. Collect Your Own Fitbit Data with Python. https://towardsdatascience.com/collect-your-own-fitbit-data-with-python-ff145fa10873
[12] Azumio Inc. 2017. Wake Up During Your Lightest Sleep. https://www.azumio.com/blog/health/sleep-cycle-why-you-should-wake-up-during-your-lightest-sleep
[13] Fitbit Inc. 2019. Fitbit Development: Web API. https://dev.fitbit.com/build/reference/web-api/
[14] Carole Yue khanacademymedicine. 2014. Sleep stages and circadian rhythms | Processing the Environment | MCAT | Khan Academy. https://www.youtube.com/watch?v=fNlp0UMqUtM
[15] Danielle Kosecki. 2018. REM, Light, Deep: How Much of Each Stage of Sleep Are You Getting? https://blog.fitbit.com/sleep-stages-explained/
[16] Pandas. 2018. Python Data Analysis Library âĂŤ pandas: Python Data Analysis Library. https://pandas.pydata.org/
[17] Brittany Pine. 2018. Using acceleration and heart rate data to classify awake, deep, and light sleep: bpine0/Sleep-Stages-Classification. https://github.com/bpine0/Sleep-Stages-Classification original-date: 2017-12-19T16:52:26Z.
[18] Rachael Rettner, Senior writer | January 20, and 2014 08:37am ET. 2014. Fitness Trackers & Sleep: How Accurate Are They? https://www.livescience.com/42710-fitness-trackers-sleep-monitoring-accuracy.html
[19] Scikit-Learn. 2019. scikit-learn: machine learning in Python âĂŤ scikit-learn 0.20.3 documentation. https://scikit-learn.org/stable/
[20] Sarah Silbert. 2018. All the Things You Can Track with Wearables. https://www.lifewire.com/what-wearables-can-track-4121040
[21] Sarah Silbert An editor who loves smartwatches, Fitness Trackers, and Other Wearable Smart Devices. 2018. What Exactly Can a Wearable Help You Track? https://www.lifewire.com/what-wearables-can-track-4121040
[22] Lori Smith. 2017. Biphasic and polyphasic sleep: What is it and is it good for you? https://www.medicalnewstoday.com/articles/319425.php
[23] Kirk Scovill Thomas D. Schwieterman MD, Hani Kayyali. 2011. What is Home Sleep Testing? Resources, Tips, Guides. https://clevemed.com/home-sleep-testing/
[24] Tuck. 2017. Sleep Spindles and K-Complex Sleep. https://www.tuck.com/sleep-spindles/
[25] Tuck. 2018. Stages of Sleep - Non-REM and REM Sleep Cycles | Tuck Sleep. https://www.tuck.com/stages/