How Much Do People Sleep?

Final Project Report
Anonymous Author(s)

1. INTRODUCTION

The objective of this project is to analyze Twitter data to get insights and answer the following questions:

- Gender effects: Do sleep schedules vary significantly between male and female users?
- Weekend effects: How do weekends change a person's sleep schedule, and how long does it take for them to recover?
- Novel question: Sentiment and mental health effects: How does a user's sentiment and mental health affect their sleeping schedule?

Our work has the following main contributions:

1) Our study finds interesting insights for the questions specified above, that we believe will be useful for psychologists and sociologists for future studies about a person's sleep.
2) We propose **Sleep Schedule Detector**: which is a simple algorithm to predict the sleeping pattern of each user on twitter, that performs surprisingly well with high accuracy on sample tests (people we know and celebrities for whom information is available online), and have been validated by previous studies on sleep.
3) We also propose **Mean-Variance Clustering**: a new and simple way to study a twitter user's sentiment and mental health which uses both the mean and variance of the sentiments for each of the user's tweets instead of just using the mean as in previous studies. Mean-Variance Clustering gives a more robust set of user clusters (each cluster has large differences in sleeping pattern with respect to other clusters, and significantly smaller within-cluster-variance compared to the variance of all users) than Only-Mean Clustering or Only-Variance Clustering.

Figure 1 is the road map we have used to successfully complete all steps of our project.
It is also our hope that this project can lead to published work.

2. DATA COLLECTING AND MUNGING

2.1. CrowdFlower Gender Dataset

We used the CrowdFlower Gender Dataset [1], an external dataset that provided us with the usernames of 20,000 Twitter users, along with their gender, location, time zone, whether they were a human, a brand or a bot, and their total number of tweets. Because each Twitter profile was viewed and judged by contributors, the users' information has much higher accuracy and confidence than we could achieve through modeling. The current state-of-the-art model for predicting gender has an accuracy of only around 80% [2], while models to predict whether an account is an actual human (not a bot) is 90% (or lower if we have to additionally detect whether it is a human or a brand) [3].

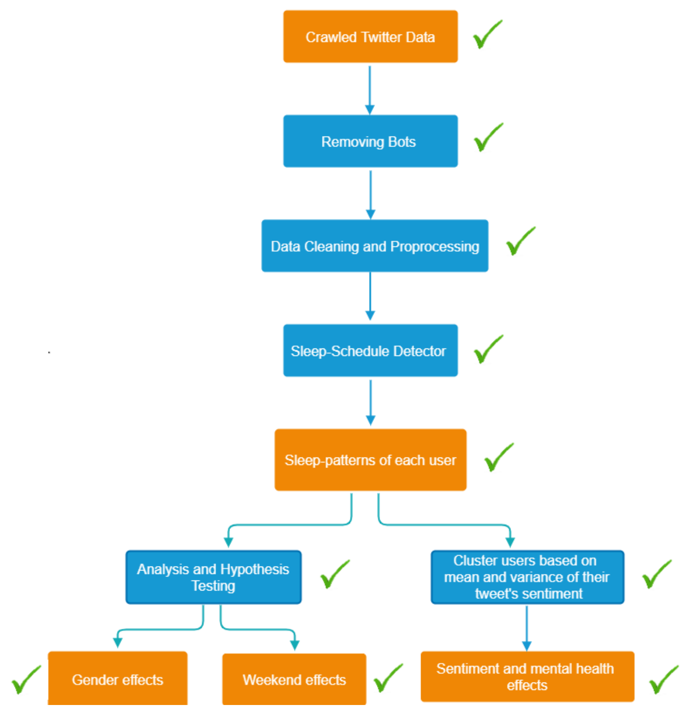


Figure 1: Completed Project Road Map

2.2. Cleaning the Gender Dataset

Next step, we did some cleaning of the Gender Dataset to fit the objectives of this project:

- Removing Brand/Bot:
  We are only interested in the accounts that are actually operated by a human, not by a brand or bot. This eliminated about 7000 users. See Figure 2 for the full gender distribution of the CrowdFlower Dataset.
- Removing less active users:
  To ensure users have enough tweet history for inferring sleep schedule, we also remove users that have less than 1000 tweets in total. This eliminated an additional

2000 users. Figure 3 shows number of users in each tweet_count bucket for the CrowdFlower Dataset.

- Fixing the non-uniform ‘user_timezone’ column:
  This is one of the most important steps in our data cleaning. Because the crawling process returns any given users’ tweet history with a UTC based timestamp, we need to find the correct native time zones of our users. If we do not correct this we cannot know the exact time of each tweet, which would lead to the breakdown of our whole project’s architecture.
  The ‘user_timezone’ column was labeled by contributors. In many cases, instead of putting in the standard time zone name, they just put in the location of the users that is available on their profile (.i.e New York, Indiana, Chennai...). To solve this, we corrected the time zones of the 30 most common locations, updated them in our data, and removed users in less frequent locations which constituted only 10% of the total number.

Figure 2: Gender Distribution of Crowd Flower Dataset

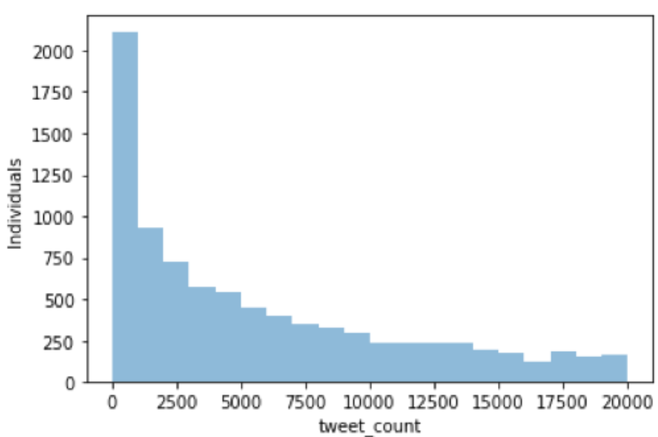


Figure 3: Users Per Tweet Count

2.3. Scraping Twitter

After finishing all the data cleaning, we had around 12,000 ‘qualified’ twitter users. We then start to scrape these users’ information. With each user, we scraped the tweets history: the timestamp, text, number of favorites, number of retweets of their own tweets, retweets of other people’s tweets. In total, we scraped the tweet history of 12,000 users with a total of around 30 million tweets (It took us around 72 hours, which was much longer than anticipated)

3. SLEEP-SCHEDULE DETECTOR

How to infer the sleep schedule of users based on their activities on Twitter?
We went through two steps to design a Sleep-Schedule Detector for this task.
Step 1: From the tweet history of each user, we calculated the distribution of these tweets for every hour of the day.

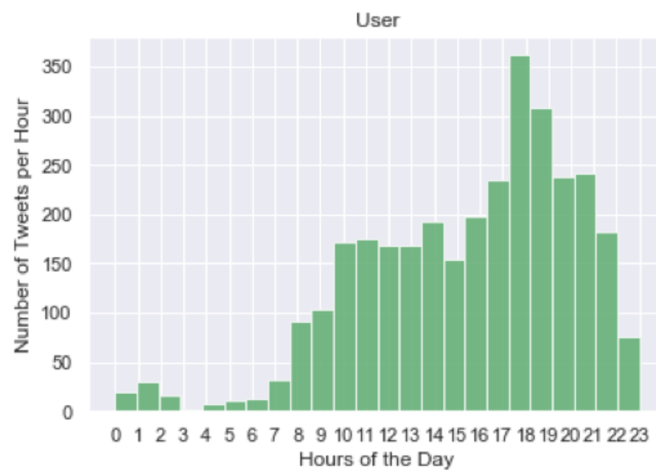


Figure 4: Tweet-per-hour Distribution of One Sample User

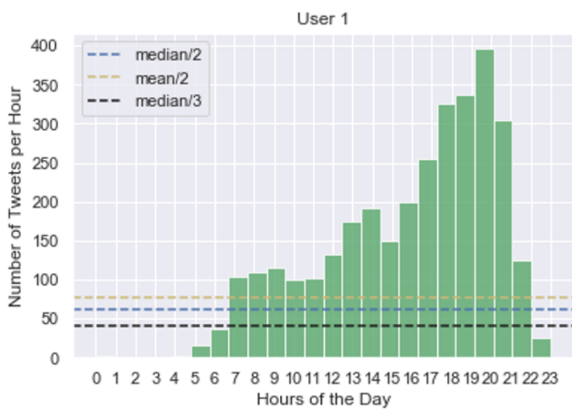
For example, with the user in Figure 4, we can see that he tweets the most at 6pm (362 tweets) and the least at 3am (2 tweets).

Step 2: Find a way to infer the wake-up hour and go-to-bed hour of the user from the user’s Tweet-per-hour Distribution.
Observation from exploring the data: the sleeping hours tend to be a long list of consecutive hours in which users have very little activity on Twitter, meaning that the number of tweets during each hour in this period is very low (below a certain threshold).
For example, with the user above, his sleep hours are likely to be from 0 to 7am, where the number of tweets is very low for every hour within [0 am, 7 am].
From this observation, we build an algorithm: for each user, find the longest period of consecutive hours in which the number of tweets per hour is smaller than an appropriate threshold. These consecutive hours are regarded as the period when the user sleeps.

	Revealed Sleep Schedule	Predicted with $t = median/2$	Predicted with $t = median/3$	Predicted with $t = mean/2$
Donald Trump	12am to 5am	12am to 5am	**12am to 5am**	12am to 6am
Elon Musk	1am to 7am	11am to 7am	**12am to 7am**	11am to 7am
Tim Cook	10pm to 5pm	10pm to 6pm	**10pm to 5pm**	10pm to 5pm
Barack Obama	1am to 8am	1am to 8am	**1am to 8am**	1am to 8am
Oprah Winfrey	10pm to 7am	10pm to 7am	**10pm to 7am**	10pm to 8am
Our 20 samples	20	15/20	**18/20**	12/20

TABLE 1: Results of Three Different Thresholds

Now the question becomes: **What should be the appropriate threshold?**
We test on our dataset with different thresholds (that seem appropriate intuitively), for example: half of median, half of mean, one third of median.



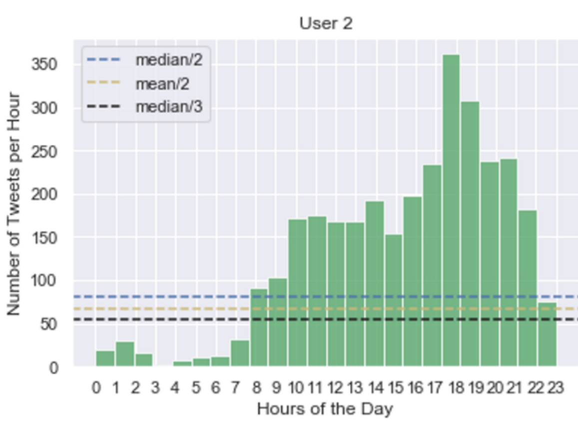


Figure 5: Tweet-per-hour Distribution of Two Sample Users with Each of the Three Thresholds

With each of these thresholds, we plot the Tweet-per-hour Distribution for sample users (20 users who's real-life sleep schedule is known: ourselves and our friends). See Figure 5 for two sample user plots.

Based on Tweet-per-hour Distributions with each of the three thresholds, we find that 'one third of median' perform the best (Please see Table 1 for the detailed results). It accurately predicts the sleep hours of 18 out of 20 sample users. Next is 'half of median' with 15 out of 20 accurately predicted. The worst is 'half of mean' with only 12 out of 20 accurately predicted.
Based on this sample test and also our intuition when looking at the Tweet-per-hour plots of users, we decide to choose 'one third of median' as the threshold for our Sleep-Schedule Detector.

4. DATA EXPLORATION

4.1. Analyzing General Sleeping Pattern of Americans

We compare the our plots to the sleep survey by TheGoodBody.com [4]
Comparing the two statistics, it seems that our findings align with the sleep survey by TheGoodBody.com pretty well. Our findings also provide some other interesting information about how Americans sleep: only 15% of Americans sleep more than 8 hours per day, and more than half of Americans sleep from 7 to 8 hours each night (Figure 6).

For Go-to-Bed hours, 12:00 am and 11:00 pm are the most frequent and second most frequent hours when people go to sleep (Figure 7). For Wake-up hour, 7am is the hour where most Americans wake up. More than 80% wake up before 9 (Figure 8).

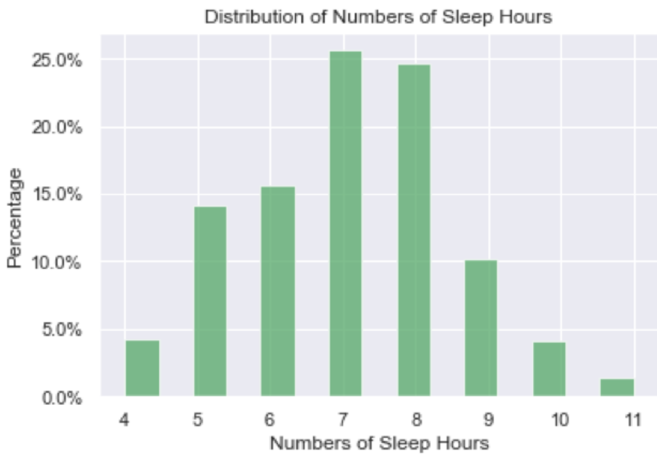


Figure 6: Distribution of Numbers of Sleep Hours

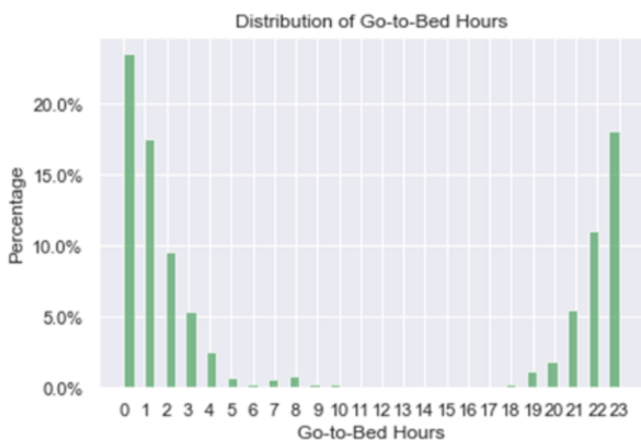


Figure 7: Distribution of Numbers of Go-to-Bed Hours

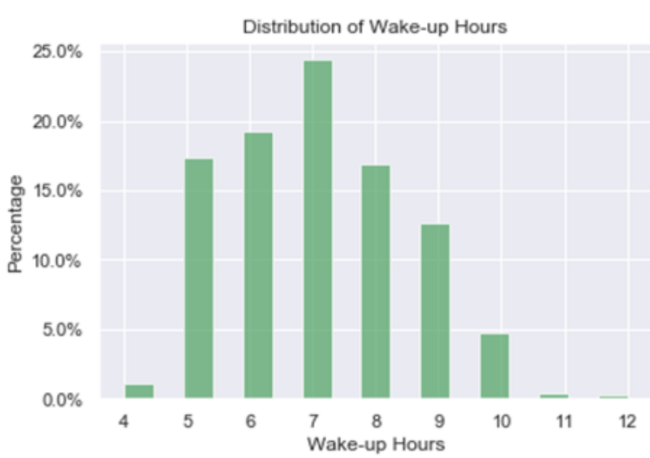


Figure 8: Distribution of Numbers of Wake-up Hours

4.2. Gender effects: Do sleep schedules vary significantly between males and females?

In order to see whether there are differences between male and female sleep schedules, we consider two aspects:

- **Mean**: Is there any differences between the mean of male and female sleep schedules: On average, who sleeps more? Who wakes up earlier? Who goes to bed later?
  To investigate this aspect, we apply the T-TEST.
- **Variances**: Do male and female sleep schedules have the same variances?
  To investigate this aspect, we apply the F-TEST.

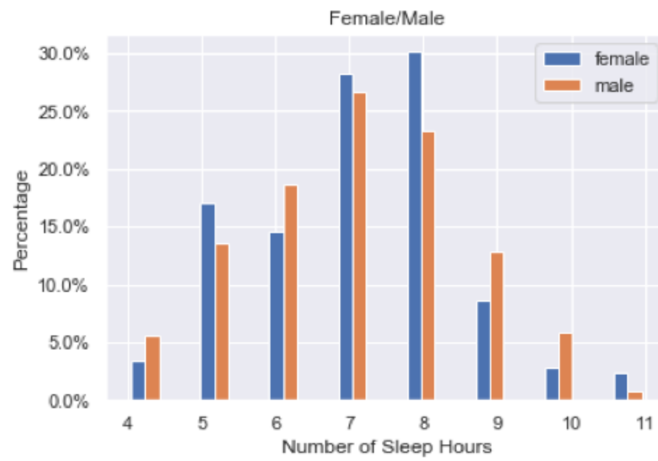


Figure 9: Probability Distribution of Number of Sleep Hours

Women, on average, sleep 7.06 hours with the variance of 2.25 hours. Men sleep 7.07 hours with 2.45 hours variance. 8 ranks 1st among numbers of sleep hour of Women. For men, it's 7. (See Figure 9) So both genders have similar number of sleep hours on average. T-Test in this case give us only p = 4% that the above difference of 0.01 hour is actually significant.

But what about variance? F-Test on these two variances produce a p-value of 0.17, meaning that there is a 83% probability that numbers of sleep hours of men vary more than women. On average, women wake up at 7:09 am, men wake up at 7:19 am, with both genders most likely waking up at 7 am (See Figure 10). The T-Test tells us that there is an 84% probability that women wake up earlier than men in real life. The F-Test produces very high P-value of 0.91, meaning that there is only a 9% probability that wake-up hours of men vary more than those of women.

On average, female go to bed at 23:55 pm, and male to to bed at 0:22 am. 12am is the most frequent Go-to-Bed hour for both genders (See Figure 11). There is a strong possibility of 82% (according to T-Test) that women Go-to-Bed earlier than men. There are also a strong 79%

possibility (according to F-Test) that the time men go to bed varies more than women.

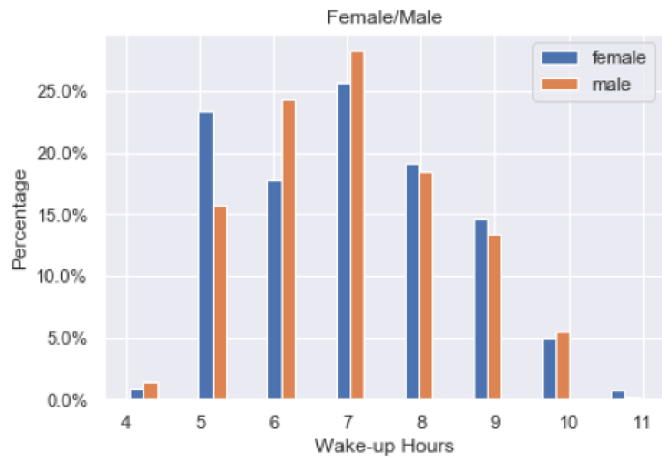


Figure 10: Probability Distribution of Wake-Up Hours

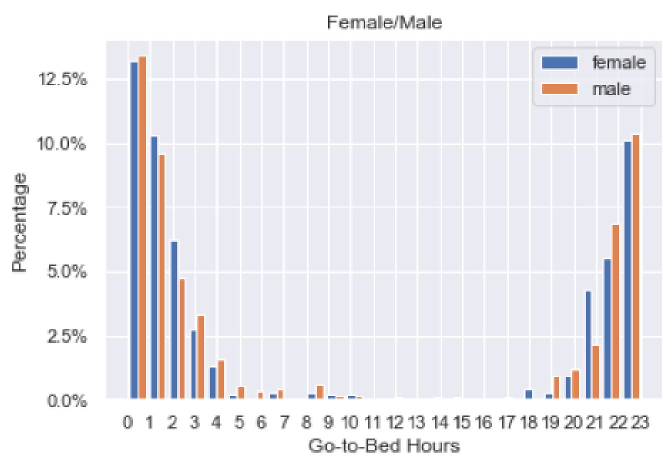


Figure 11: Probability Distribution of Go-To-Bed Hours

4.3. Weekend Effects

(a) How to get user sleep schedule for a specific day of the week?
To find a user's sleep schedule of a specific day of the week, we collect all tweets of that user from 5pm on the previous day to 5pm that day.
For example, to study sleeping hours of Elon Musk for Monday, we collect all of his tweets that from 5pm Sunday to 5pm Monday of every week. Then, we apply our Sleep Schedule Detector to these tweets to find out when he goes to bed the night before Monday and when he wakes up on Monday morning.

(b) How does a person's sleeping pattern change throughout the week?
Below is the average wake-up hour, average go-to-bed hour, and average total sleeping hour of all users throughout the week (See Figures 12 and 13).

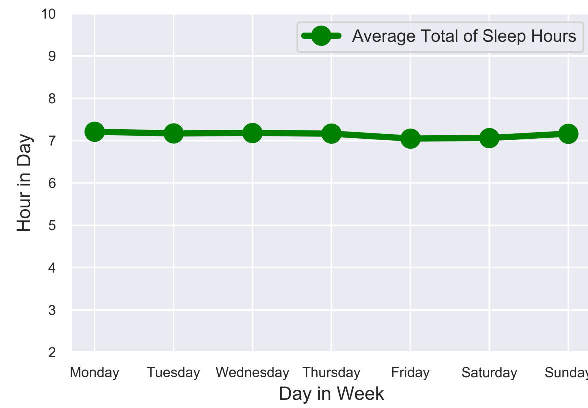


Figure 12: Average Number of Sleep Hours each Day in Week

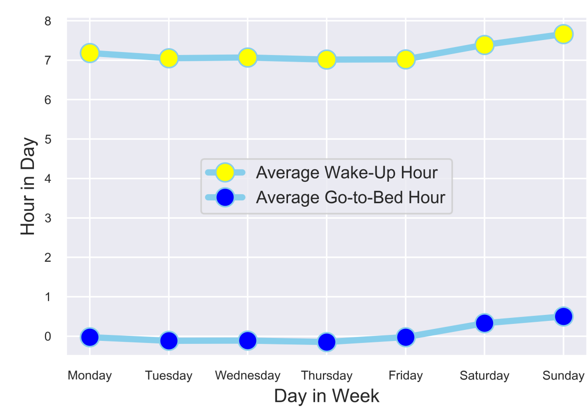


Figure 13: Average Wake-up vs Go-to-Bed Hour each Day in Week

Even though the figures 12 and 13 only show the average of all users, it still gives us a strong sense that that while the total number of sleep hours is pretty stable throughout the week, people go to bed and wake up significantly later on weekends than on weekdays (approximately 1 hour later).

The Go-to-Bed and Wake-Up hour is stable from Tuesday to Friday and then suddenly increases significantly on Saturday, peaks on Sunday, and then start to decrease significantly on Monday (but still is later than the other four weekdays: giving us a sense that there are still some considerable hangover from weekend effects on Monday).

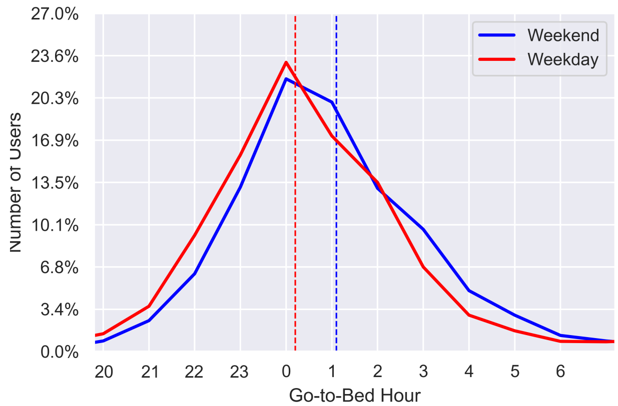


Figure 14: Weekend Effects on Go-To-Bed Hour

(c) Are there really weekend effects? If yes, how big are these effects?
The average sleep pattern of all users throughout the week gives us a good sense of how users sleep each day of the week, but it's not clear and not reliable enough: outliers like people work at night shifts,.. can greatly affect the average and make it unreliable. So in order to see in detail, we study at the individual user level.
With each user, we use Sleep-Schedule Detector to get their sleep schedule on weekdays vs on weekends, and plot the distribution of their schedules:

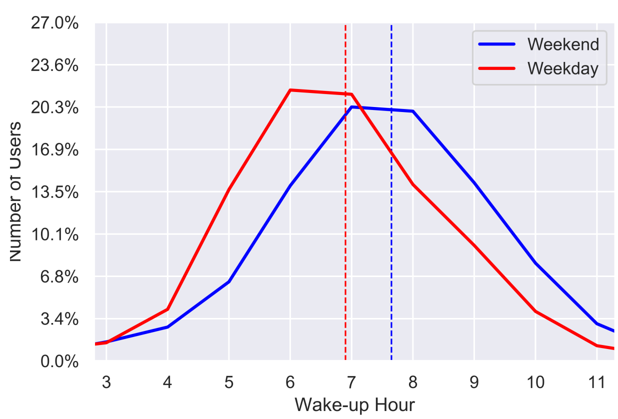


Figure 15: Weekend Effects on Wake-Up Hour

To test whether the distribution of sleep schedules on weekdays and weekends are actually different and not a result of randomness, we use T-test and F-test.

T-test gives us very strong possibilities of there are actually weekend effects: with a possibility of 91% that users go to sleep later on weekends than on weekdays, and a possibility of 96% that users wake up later on weekends than on weekdays.

So, in conclusion: based on the above analysis and statistical testing, we concluded that there are weekend effects which makes people go to bed and wake up later on weekends than on weekdays: 46 minutes for going to bed, and 41 minutes late for waking up.

From the sleep schedules on weekdays and weekends of each user, we calculate the difference of weekends' sleep schedule compared to weekdays' for each user. Below is the distribution of the difference :

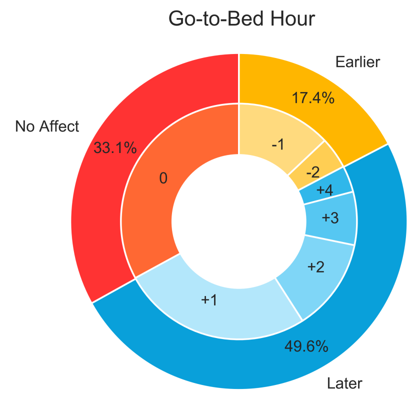


Figure 16: Distribution of changes to Go-to-Bed Hour of weekdays on weekends

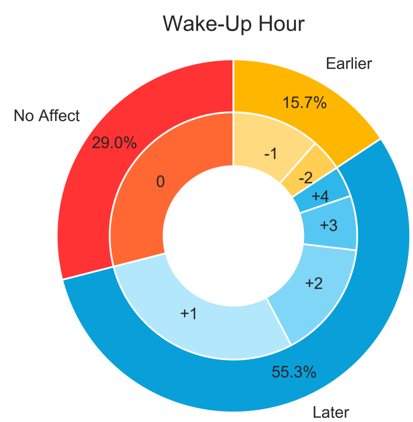


Figure 17: Distribution of changes to Wake-Up Hour of weekdays on weekends

Figures 16 and 17 above show that:

- Nearly half of all users go to bed later on weekends: 27.5% of all users go to bed 1 hour later compared to weekdays, 13.3% with 2 hours late, 6.1% with 3 hours late, and only 2.7% with 4 hours late.
- One-third of all users do not change Go-to-Bed hour on weekends compared with weekdays.
- 17.1% actually go to bed earlier on weekends than on weekdays: 14.4% go to bed 1 hour earlier, while 3.2% go to bed 2 hours earlier.

Our takes and potential explanations of the above results:

- A large portion of all users going to bed later on weekends is likely due to many of them not having to go to work on the weekends. Therefore, they're free to stay up late without worrying that they won't be able to get up in time the following day.

- More people wake up late than go to bed late (55.3% vs 49.6%): This can be due to multiple factors. First, people who go to bed later will likely wake up later. In addition to that, there are people who might go to bed the same time or earlier on weekends than on weekdays, and force themselves to wake up earlier than they desire in order to go to work. Since they do have to work on the weekends, they can freely sleep their desired amount of hours and wake up late.

- There are some people who go to bed earlier on the weekend. One possible explanation is that on weekdays, these people have to stay up late for work or homework to prepare for the following day. So finally, on the weekends, they have the freedom to sleep earlier. These people will also be more likely to wake up earlier on the weekends.

(d) How long does it take for users to recover from weekend effects?
To know how long it takes for a specific user to recover from the weekend effect:

- First, we remove the users that have no weekend effect (33% for Go-to-Bed hour, 29% for Wake-Up hour)

- Of those remaining users, we want to find out how many of them recover in no time, which means that: their Monday's sleeping schedule is similar to the overall weekday sleeping schedule. We use T-test for this task with the threshold of 70%: if T-test gives us less than 70% confidence that Monday's sleeping schedule of a user differs from his or her overall weekday sleeping schedule, then we'll consider that the user recovers in no time.

- Of those remaining users who need at least one day to recover, we want to find out how many of them recover in one day, which means that: their Tuesday's sleeping schedule is similar to the overall weekday sleeping schedule. We also use T-test for this task with a threshold of 70%.

- The same test is performed with Wednesday to determine how many of the remaining users recover in two days and 100% of the remaining users recover by Wednesday.

Based on the above steps, we get the results below:

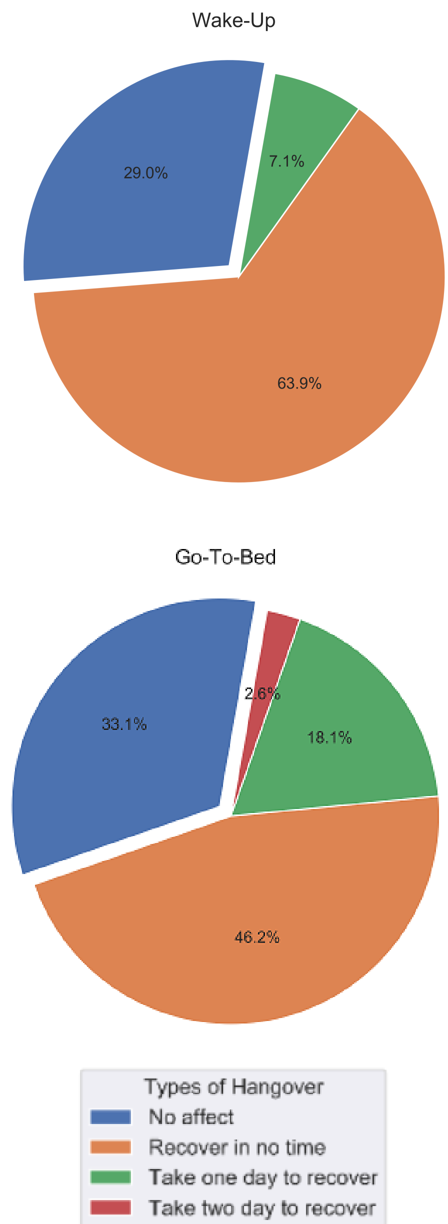


Figure 18: Recovery Time From Weekend Effects

Our result shows that 46.2% of all users take no time to recover from the go-to-bed hour weekend effect while a whopping 63.9% take no time to recover from the wake-up hour weekend effect. This can be explained by the fact that many people have to wake up at the right time to work on Monday.

18.1% of all users need one day to recover go-to-bed from the go-to-bed hour weekend effect why only

7.1% for wake- up. 2.6% take two days to recover from go-to-bed hour weekend effect while no one needs two days to recover wake up.

So, we can conclude that users tend to recover from wake-up hour weekend effect faster than from go-to-bed hour weekend effect.

4.4. Sentiment and mental health effects

How does users' sentiment and mental health affect their sleep schedule?

Many studies have been done regarding users' sentiment on twitter [13]. The way these studies being conducted is that they come up with different ways for 'averaging' the sentiments of a user' tweets to analyse that user's sentiment overall or mental health. To the best of our knowledge, none of these studies have taken into account the variance of the sentiments of the user's tweets.

Let's take a simple example. There are two users A and B. The mean sentiment of A's tweets and B's tweets are the same. But, Tweets of A are always kind of neutral, potentially a little bit negative or positive sometimes but nothing extreme. On the other hand, tweets of B fluctuate heavily, one day B was very positive, the next day B become extremely negative and vice versa. So who do you think have better mental health given they have the means of the sentiments are the same?

Psychologists agree that the mental health of B is worse than A, and B has a much higher chance of being depressed. Based on the intuition of the above example, besides the mean, we want to use the variance of the sentiments of the user's tweets to study Sentiment and mental health effects.

To do this:

- First we use [14] to get the sentiment score of each tweet of each user.
- Then, for each user, we calculate the mean and standard deviation of the sentiment score of their tweets.
- Next, we will cluster users based their (mean, std) using K-means
- Analyse the resulting clusters from K-means: How does each cluster sleep and why does each cluster sleep the way it does? What does that tell us about the effects of (mean, std) to users' sleep schedule?

Mean-Variance Clustering

How to determine the optimal number of clusters K for K-Means for this task?

The basic idea behind k-means consists of defining k clusters such that total within-cluster variation (or error) is minimum. Within-Cluster-Sum of Squared Errors sounds a bit complex. Let's break it down:

- The Squared Error for each point is the square of the distance of the point from its representation i.e. its predicted cluster center.
- The WSS score is the sum of these Squared Errors for all the points.
- Any distance metric like the Euclidean Distance or the Manhattan Distance can be used.

Therefore, in order to find the optimal k, we employ the "Elbow" method:
Calculate the Within-Cluster-Sum of Squared Errors (WSS) for different values of k, and choose the k for which WSS becomes first starts to diminish. In the plot of WSS-versus-k, this is visible as an elbow.
We obtain the following plot for WSS-vs-k for our dataset.

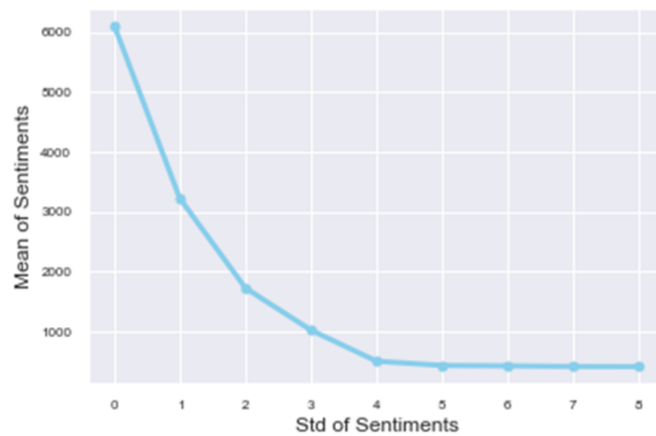


Figure 19: Within-Cluster-Sum of Squared Errors (WSS) with respect to Number of Clusters

Based on the results above (Figure 19), we choose k = 4 as our number of clusters.

What each cluster represents?

Using K-means with k = 4 to cluster users based on (mean of their sentiments, standard deviation of their sentiments), we have the below result.

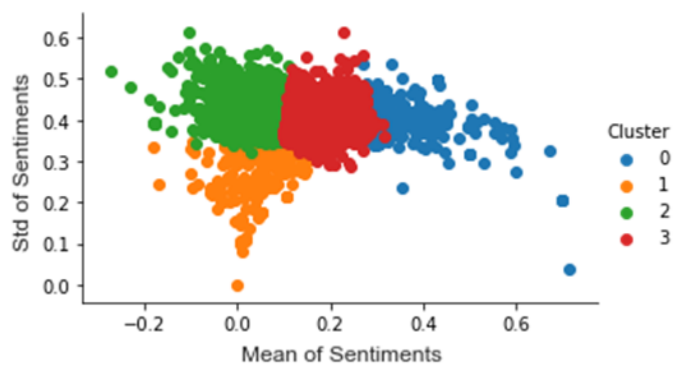


Figure 20: K-Clusters with 4 clusters

Looking at the plot above (Figure 20), we can see that K-mean group users into 4 groups as follows:

- Group 0 consists of users who have high mean: these users tend to have positive sentiment in their tweets.

	All Users	Group 0 high mean	Group 3 medium mean	Group 1 low mean, low std	Group 2 low mean, high std
Std of number of sleep hours	**1.48**	0.46	0.51	<u>0.38</u>	0.66
Std of wake-up hour	**2.18**	<u>0.69</u>	0.83	0.70	1.02
Std of go-to-bed hour	**2.31**	1.17	1.21	<u>0.75</u>	1.39
Mean of number of sleep hours	7.13	<u>6.56</u>	**7.34**	7.26	6.83
Mean of wake-up hour	7.45	<u>5.92</u>	7.23	7.56	**7.74**
Mean of go-to-bed hour	0.32	<u>23.46</u>	23.89	0.30	**0.81**

TABLE 2: How Each Cluster Sleeps

- Group 3 consists of users who have medium mean: these users tend to have more neutral sentiment in their tweets.
- Group 1 of users who have low mean and low standard deviation: these users tend to have negative sentiment in their tweets. Their low standard deviation indicates that the sentiments in their tweets do not vary much: they are a bit little negative most of the time, their mood/sentiment do not fluctuate much as time went by.
- Group 2 of users who have low mean and high standard deviation: these users tend to have negative sentiment in their tweets. But unlike group 1, this group's high standard deviation indicates that their sentiments are not stable and fluctuate heavily: they can be more positive than Group 0 at one moment and then suddenly become more negative than Group 1. According to psychologists, group 2 is the one with the highest chance of having mental health problems.

How each cluster sleeps?

One very interesting observation of ours is that these four groups have their within-group standard deviation of sleep schedule significantly smaller than the overall sleep schedule's standard deviation of all users. This sends a strong signal to us that the (mean, std) of users relates to how they sleep: users that have similar (mean of sentiments, std of sentiments) tend to sleep a more similar schedules.

- For go-to-bed hours, it indicates that the more positive a user are the more likely he/she go to sleep early. Of those who are more negative, those with high std sleep significantly later than those with low std. This result aligns with one sleep laboratory study which found that youngsters with an anxiety disorder took longer to fall asleep, and slept less deeply, when compared with a control group of healthy children. [34]
- For wake-up hour, users who are more positive (Group 0) is by far the group who wake up earliest. So it either "Waking up earlier makes you more positive" or "Being positive make it easier for you to wake up early". Group 2 wake up the latest (make sense because they go to bed the latest)
- For standard deviation, it seem that group 1 (Low Mean, Low Std) have users that sleep most similar to each other. Come in a close second is Group 0 (High Mean). All the groups have much smaller std than 'All User'.

5. CONCLUSION

In this report, we have successfully developed a Sleep Schedule Detector to approximate a person's sleep schedules based on their activities on Twitter, and have achieved high accuracy on our sample tests. Based on the accuracy of this detector, we have been able to study, analyze and obtain many interesting findings of how people sleep (gender effect, weekend effects, etc.). We also proposed a new way to study and cluster users' mental health to discover the mutual relation between sleep and mental health. In the near future, we plan to extend this report to focus on the mutual relation between sleep and mental health and submit a paper based on this report to a conferences in psychology, sociology, and mental health.

REFERENCES

[1] J. Tenuto, "Using machine learning to predict gender", figure-eight, 2015.

[2] Sezerer, Erhan, Ozan Polatbilek, and Selma Tekir. "Gender Prediction from Tweets: Improving Neural Representations with Hand-Crafted Features." arXiv preprint arXiv:1908.09919 (2019).

[3] Färber, Michael, Agon Qurdina, and Lule Ahmedi. "Identifying Twitter Bots Using a Convolutional Neural Network." (2019).

[4] The Good Body, "Sleep Statistics Reveal The (Shocking) Cost To Health And Society", (2018)

[5] Jones, Jason J., et al. "Association between late-night tweeting and next-day game performance among professional basketball players." Sleep health 5.1 (2019): 68-71.

[6] McIver, David J., et al. "Characterizing sleep issues using Twitter." Journal of medical Internet research 17.6 (2015): e140.

[7] C. Sheehan et al. Are U.S. adults reporting less sleep?: Findings from sleep duration trends in the National Health Interview Survey, 2004-2017. Sleep. Published online November 17, 2018. doi: 10.1093/sleep/zsy221.

[8] Ásgeirsdóttir, Tinna Laufey, and Sigurur Páll Ólafsson. "An empirical analysis of the demand for sleep: Evidence from the american time use survey." Economics & Human Biology 19 (2015): 265-274.

[9] Score, S. H. I. "Sleep Health & Scheduling."

[10] Hausmann, Jonathan S., et al. "Adolescent and young adult use of social media for health and its implications." Journal of Adolescent Health 60.6 (2017): 714-719.

[11] Akbar, Fatema, and Ingmar Weber. "Sleep as Android: Feasibility of Using Sleep Logs on Twitter for Sleep Studies." 2016 IEEE International Conference on Healthcare Informatics (ICHI). IEEE, 2016.

[12] Hansen, Martha, et al. "The impact of school daily schedule on adolescent sleep." Pediatrics 115.6 (2005): 1555-1561.

[13] McIver, David J., et al. "Characterizing sleep issues using Twitter." Journal of medical Internet research 17.6 (2015): e140.

[14] Powell, Gregory E., Harry A. Seifert, Tjark Reblin, Phil J. Burstein, James Blowers, J. Alan Menius, Jeffery L. Painter et al. "Social media listening for routine post-marketing safety surveillance." Drug safety 39, no. 5 (2016): 443-454.

[15] Sathyanarayana, Aarti, et al. "Sleep quality prediction from wearable data using deep learning." JMIR mHealth and uHealth 4.4 (2016): e125.

[16] Roccetti, Marco, et al. "Attitudes of Crohn's disease patients: infodemiology case study and sentiment analysis of facebook and twitter posts." JMIR public health and surveillance 3.3 (2017): e51.

[17] Nguyen, Quynh C., et al. "Geotagged US tweets as predictors of county-level health outcomes, 2015–2016." American journal of public health 107.11 (2017): 1776-1782.

[18] Levenson, Jessica C., et al. "The association between social media use and sleep disturbance among young adults." Preventive medicine 85 (2016): 36-41.

[19] Hicks, Robert A., and Robert J. Pellegrini. "The changing sleep habits of college students." Perceptual and Motor Skills 72.3suppl (1991): 1106-1106.

[20] Shochat, Tamar, Ofra Flint-Bretler, and Orna Tzischinsky. "Sleep patterns, electronic media exposure and daytime sleep-related behaviours among Israeli adolescents." Acta Paediatrica 99.9 (2010): 1396-1400.

[21] Harvey, Allison G. "Sleep hygiene and sleep-onset insomnia." The Journal of nervous and mental disease 188.1 (2000): 53-55.

[22] Tavernier, Royette, and Teena Willoughby. "Sleep problems: predictor or outcome of media use among emerging adults at university?." Journal of sleep research 23.4 (2014): 389-396.

[23] Afandi, Omar, et al. "Sleep quality among university students: Evaluating the impact of smoking, social media use, and energy drink consumption on sleep quality and anxiety." Inquiries Journal 5.06 (2013).

[24] Woods, Heather Cleland, and Holly Scott. " Sleepyteens: Social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem." Journal of adolescence 51 (2016): 41-49.

[25] Long Xu, X., et al. "The influence of social media on sleep quality: a study of undergraduate students in Chongqing." China. J Nurs Care 4.253 (2015): 2167-1168.

[26] Levenson, Jessica C., et al. "Social media use before bed and sleep disturbance among young adults in the United States: A nationally representative study." Sleep 40.9 (2017).

[27] Keyes, Katherine M., et al. "The great sleep recession: changes in sleep duration among US adolescents, 1991–2012." Pediatrics 135.3 (2015): 460-468.

[28] Scott, Holly, Stephany M. Biello, and Heather Cleland Woods. "Identifying drivers for bedtime social media use despite sleep costs: the adolescent perspective." Sleep Health (2019).

[29] Chaput, Jean-Philippe, and Ian Janssen. "Sleep duration estimates of Canadian children and adolescents." Journal of sleep research 25.5 (2016): 541-548.

[30] Pallesen, Ståle, et al. "The effects of sleep deprivation on soccer skills." Perceptual and motor skills 124.4 (2017): 812-829.

[31] Gariépy, Geneviève, et al. "School start time and sleep in Canadian adolescents." Journal of sleep research 26.2 (2017): 195-201.

[32] Johnson, Nathan L., et al. "Sleep estimation using wrist actigraphy in adolescents with and without sleep disordered breathing: a comparison of three data modes." Sleep 30.7 (2007): 899-905.

[33] Ciesielczyk, K., et al. "Changes of sleep quality and mood disorders under the influence of phototherapy in patients with seasonal affective disorders SAD." Psychiatria polska 38.6 (2004): 1105-1114.

[34] Forbes, Erika E., et al. "Objective sleep in pediatric anxiety disorders and major depressive disorder." Journal of the American Academy of Child Adolescent Psychiatry 47.2 (2008): 148-155. .