Prediction of Happy-Sad Mood from Daily Behaviors and Previous Sleep History

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Abstract— We collected and analyzed subjective and objective data using surveys and wearable sensors worn day and night from 68 participants, for 30 days each, to address questions related to the relationships among sleep duration, sleep irregularity, self-reported Happy-Sad mood and other factors in college students. We analyzed daily and monthly behavior and physiology and identified factors that affect mood, including how accurately sleep duration and sleep regularity for the past 1-5 days classified the participants into high/low mood using support vector machines. We found statistically significant associations among sad mood and poor health-related factors. Behavioral factors such as the percentage of neutral social interactions and the total academic activity hours showed the best performance in separating the Happy-Sad mood groups. Sleep regularity was a more important discriminator of mood than sleep duration for most participants, although both variables predicted happy/sad mood with from 70-82% accuracy. The number of nights giving the best prediction of happy/sad mood varied for different groups of individuals.

I. INTRODUCTION

Positive mood is linked to improved performance, cognition, and memory. These results are based on studies with either depressed or healthy individuals undergoing emotional induction (e.g.., inducing emotion from stimuli such as videos and music) or sleep deprivation in a laboratory [1][2]. New technology makes it possible to objectively measure sleep and other behaviors and examine their association with daily mood changes. We have conducted a study to examine sleep and behavior influences on mood for college students in their daily lives at home, work, and school.

Multiple studies have shown that sleep influences mood [3][4]. One study investigated the association among sociability, sleep quality and good-poor mood (good: happy or content, relaxed or peaceful, poor: stressed or anxious, angry or frustrated) with self-reported surveys and mobile phone proximity data from 54 participants for one month [3]: Based on self-reported data from participants, they found that the good mood group had longer sleep duration (average ~7 hours) than the poor mood group (6.4 hours) and lower sociability was related to poorer mood. Another study showed a relationship among self-reported fatigue, mood (negative mood: apathy, irritability, tension, and nervousness), and the difference between preferred sleep length and actual self-reported sleep length school children, students and employees [4]. The goal of the study is to understand whether changing sleep tonight will impact mood in the future.

We collected and analyzed 30 days of multi-modal wearable sensor and self-report data from undergraduate students. We aim to identify (1) which behavioral factors in daily life or internal factors separate happy/sad self-reported mood groups and (2) how accurately we can classify daily happy or sad mood from sleep parameters from the previous one to five days. One goal is to identify behaviors that an individual can control - for example sleep timing- that will improve self-reported happy – sad mood.

II. PROCEDURE

A. Data Collection

Sixty-eight undergraduate students participated in a 30-day experiment (49 males, 19 females, aged 20.1 ± 1.5, mean ± SD) providing 1,980 days of data. Participants were recruited through email. Participants completed the Pittsburgh Sleep Quality Index (PSQI) [5], the Big Five Inventory Personality Test [6], and the Horne-Ostberg Morningness-Eveningness Questionnaire (MEQ) [7]. During the 30-day experiment, participants wore a wrist sensor on their dominant hand (Q-sensor, Affectiva, USA) to measure three-axis accelerometer data (ACC) at 8 Hz and a wrist actigraphy monitor on their non-dominant hand (Motion Logger, AMI, USA) to measure activity and light exposure levels. Participants also installed an Android phone application adapted by the first author from the funf open source framework [8] to measure call, SMS, location, and "screen on" timing. During the study period, they completed surveys every morning and evening about academic, extracurricular, and exercise activities, sleep, caffeinated drink intake, social interaction, and self-reported general health, mood, alertness, tiredness and stress level. Data types collected are listed in Table 1. Mood was evaluated using visual non-numeric 0-100 scales (0: sad, 100: happy). At the end of the study, they completed the Perceived Stress

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Scale (PSS) [9], the SF-12 Physical and Mental Health Composite Scale (PCS and MCS) [10] and, State-Trait Anxiety Index [11]. Grade point average (GPA) was reported by the participants at the end of the semester in which the experiment occurred. Email usage during the experiment (to, from, cc and timestamps) was collected through the MIT website *Immersion* at the end of the study. In addition, based on their call, short message service (SMS) and email usage during the experiment, participants were asked to characterize the interactions with their frequent contacts. The Massachusetts Institute of Technology Committee On the Use of Humans as Experimental Subjects approved this study and all participants gave informed consent.

We collected 3-axis acceleration data from wrist-worn devices to estimate activity patterns (percentages of sitting, walking and running; details are described in the analysis section) as exercise has been shown to enhance mood [12]. Sleep/wake onsets were determined by a combination of wrist actigraphy and sleep diaries. We computed sleep regularity as a value of 0 - 1 using cross correlation of sleep wake episodes, because sleep researchers have suggested the importance of sleep regularity [13] in addition to sleep duration.

We collected phone and email usage as an estimate of participants' social interaction, social factors are believed to be involved in both mood and sleep [3, 15]. The timing of mobile phone calls, SMS, emails and "screen on" provide an estimate of how often participants interact with their phone during the day and the night, while the number of calls, SMS and emails and the number of people they interact with helps quantify social interaction. In addition, lighting from the interaction with mobile phones or emailing late at night could disturb the biological circadian clock and increase alertness, both of which can influence mood [16].

III. Analysis

A. Feature Extraction

We extracted features from the collected data (Table 1). For ACC, we computed the mean activity level based on the root square values of the 3-axis accelerometer. For ACC data in wakefulness, we separated the data into sit, walk and run episodes based on thresholds we computed with another set of ACC data from 48 people who did sitting, walking and running with the same sensor on their non-dominant wrist.

B. Clustering participants based on Mood vs Mood Variation

For mood, we computed mean and coefficient of variance (CV = mean/SD) of daily morning and evening mood. The average morning and evening mood ratings over the month for each person and their CV's were used with k-nearest neighbor clustering to define three types of participants (Figure 2). For the two extreme clusters (happy mood and low CV group and sad mood and high CV group), we applied an unpaired t- test to compare their behaviors and traits from surveys and ambulatory monitoring. Next, in order to understand which behavioral features work best in classifying happy and sad mood groups, we focused on only behavioral features (bold items in Table 2) and applied sequential forward feature selection to find the best combinations of 1-5 features and SVM (linear) classifiers.

TABLE I. COMPUTED FEATURES

Surveys	
Sleep	PSQI score, MEQ, **sleep time**, **wake time**, **sleep latency**, **sleep regularity**, **how they wake up (alarm or spontaneously)**, **# of awakenings**, **duration of awakenings**, **# of naps**, **duration of naps**
Stress	Perceived Stress Scale (PSS)
Anxiety	State and Trait Anxiety Score
Personality Traits	Big Five Test (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism)
Physical and Mental Health	Physical and mental health composite scores (PCS and MCS) from SF-12
Academic Performance	Grade point average (GPA)
Daily Diary	Alertness, happiness, sluggishness, healthiness and calmness when wake up and before sleep (0-100 scales)
Social Interactions	**Social interactions before sleep (with person in person or through electronic devices), frequency of memorable positive and negative and very negative social interactions, and social interactions in the past one month (# of the top 20 people to interact through face to face, email, SMS and phone, total # of people with positive, neutral and negative interactions, # of family members, friends, work-related colleagues each participant interacted frequently in the past one month)**
Activities	**Total hours of academic, exercise, and extracurricular activities, # of cups of caffetinated drinks**
Monitoring using phones or wearable sensors	
Email (10 features)	**Total # of sent emails, mean and SD of # of daily received/sent emails, # of people to send emails, mean and SD of timestamps of received and sent emails**
Phone (CALL) (3 features)	**Time of each call, duration for each call, total # of people called**
Phone (SMS) (3 features)	**Time of each SMS message, total # of SMS messages, total # of people SMS messaged**
Phone (Screen on/off) (10 features)	**Time of each screen on/off, total # of screen on/off, total duration % of screen on between 0-3am, 3-6am, 6-9am, 9am-12pm, 12-3pm, 3-6pm, 6-9pm and 9pm-0am**
Phone (MOB: mobility) (2 features)	**Total distance per day and standard deviation of the distance**
Wearable sensor (ACC) (19 features)	**Mean % of sit, walk and run activities per day, mean, median and SD of RMS values for day time, sit, walk, run and entire sleep and mean objective sleep quality from actigraphy**

For each classification, we examined the accuracy using 10-fold cross validation: we trained the model with 90% of the data, tested with the remaining 10% and repeated this procedure 10 times.

C. Daily mood prediction using sleep parameters

We classified happy vs sad daily morning mood within each participant using the previous 1-5 nights of sleep duration, and the previous 2-5 nights of sleep regularity. Within each participant, we defined the top and the bottom 20% of their morning mood distribution as happy or sad mood. As in the previous classification, we examined the accuracy using 10-fold cross validation.

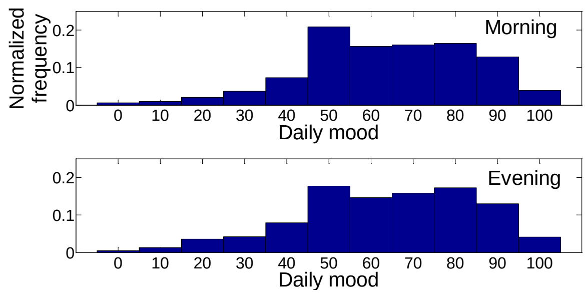

Figure 1. Distribution of mood scores in morning and evning surveys

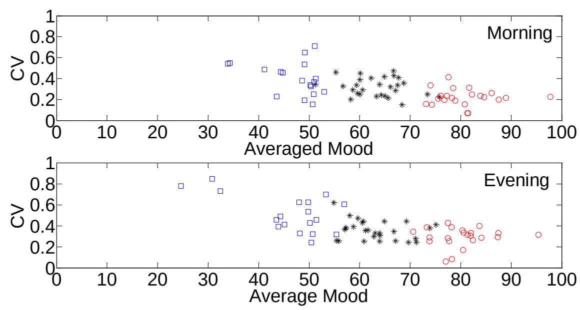

Figure 2. Average of mood vs coefficient variance (Morning and Evening). Different colors indicate different clusters from k-nearest neighbor clustering

IV. RESULTS

A. Mood distribution and clusters

Morning and evening mood distributions are similar (Figure 1): Morning mood mean: 64.7, median: 65, SD: 19.9; Evening mood mean: 64.1, median: 66, SD: 21.0. A Kolmogorov-Smirnov test showed that there was no statistically significant difference between these two distributions. Mood vs CV plots in the morning and evening and three clusters (Figure 2, red, black and blue). The happy mood group (red) has a lower CV than the sad mood group (blue) both in the morning and evening.

B. Daily behavior and trait difference in happy mood & low CV vs sad mood & high CV groups

Table 2 shows that we found statistically significant differences in features between the happy and sad mood groups. The sad mood group showed a higher PSQI score (poor sleep quality), higher anxiety state and trait scores, higher stress scale, higher morning and evening sleepiness, sluggishness, sickness and stress level, longer academic hours, lower conscientiousness, extraversion and agreeableness, higher neuroticism and lower MCS score. From ambulatory monitoring, we found that the sad mood group had a later mean SMS timestamp, more frequent total neutral social contact, and more frequent face to face neutral social contacts. We did not find any significant differences in exercise and GPA. Furthermore, there was no significant difference in mood between the high/low GPA groups – top and bottom 20%. Among behavioral factors, three measures – daily total hours of academic activities (including classes, e-classes, sections, seminars, labs, study groups), total positive contacts and neutral face to face interactions – showed 91 ± 0.1% accuracy in discriminating these two groups.

TABLE II. CHARACTERISTICS IN THE SAD MOOD GROUP

Statistically significant features		***p***
Sleep	High PSQI score	*< 0 05*
Stress	High PSS score	*< 0.01*
Anxiety	High State Anxiety score	*< 0.01*
	High Trait Anxiety score	*< 0.01*
Personality traits	Low Conscientiousness	*< 0.01*
	Low Exterversion	*< 0.01*
	Low Agreeableness	*< 0.01*
	High Neuroticism	*< 0.01*
Physical and mental health	Low MCS	*< 0.01*
Daily diary	High Morning sleepiness	*< 0.01*
	High Morning sluggishness	*< 0.01*
	High Morning sichness	*< 0.01*
	High Morning stress level	*< 0.01*
	High Evening sleepiness	*< 0.01*
	High Evening sluggishness	*< 0.01*
	High Evening sickness	*< 0.01*
	High Evening stress level	*< 0.01*
Social interactions	Large # of total neutral contacts	*< 0.05*
	Large # of face to face neutral contacts	*< 0.05*
Activities	Long academic hours	*< 0.05*
SMS	Late timestamp	*< 0.05*

TABLE III. SLEEP PARAMETERS AND DAILY MOOD CLASSIFICATION

Parameters	Mean Best Accuracy	# of participants
Sleep duration (previous night)	0.71	7
Sleep duration (previous 2 nights)	0.75	6
Sleep duration (previous 3 nights)	0.82	3
Sleep duration (previous 4 nights)	0.73	5
Sleep duration (previous 5 nights)	0.79	8
Sleep regularity (previous 2 nights)	0.70	9
Sleep regularity (previous 3 nights)	0.73	5
Sleep regularity (previous 4 nights)	0.73	11
Sleep regularity (previous 5 nights)	0.72	14

C. Daily mood classification using sleep parameters

We compared accuracies in classifying individual daily happy or sad mood using the previous 1-5 nights of sleep duration and sleep regularity. Individuals showed their best accuracy over a range of different parameters. We summarize the mean best accuracies and the number of participants who showed the best accuracy with each parameter (Table 3). All the parameters discriminated the two groups from 70-82%, with sleep regularity showing the highest accuracy in over half of the participants. Regularity from the previous 4 and 5 nights accounted for 70% of these. For sleep duration, the results showed a U-shaped curve: more people's moods were classified accurately using either the previous night or the previous 4 or 5 nights of sleep.

V. Discussion

Our data provide further evidence of an association in college students between sad mood and many health-related factors, including high anxiety, stress level, sickness and sluggishness, and low mental health score. Our findings related to personality types are similar to previously reported of links between high conscientiousness, low neuroticism and reduced negative mood [17]. In terms of sleep, contrary to our expectations, we did not find significant differences in averaged bed time, wake time, duration and regularity over the month between the happy/sad mood groups; however, the PSQI scores were significantly different, with happy mood associated with a better sleep quality score (lower PSQI). It is interesting that neither positive nor negative social interactions were related to mood while the frequency of neutral was important: more neutral face to face interactions reported was related to sadder mood.

Multiple nights of sleep duration and regularity affect mood for over half of the participants. As the next analysis, we will include daily sleep quality based on actigraphy for classifying daily happy or sad mood. The current study could only address correlation. For our next steps, we will apply methods to understand causality and interactions among variables. Other aspects of mood and other influences (e.g., sex) also need to be studied.

VI. Conclusion

In this paper, we analyzed the associations between self-reported happy-sad mood and daily behaviors from 30-days of data from each of 68 undergraduate students. The sad mood group showed larger variation of their mood both in the morning and in the evening. Statistical analysis showed that the happy mood group had better health-related behaviors such as high sleep quality index score and low stress level. Machine learning techniques showed that the frequency of neutral interactions and total academic hours are behavioral factors that help differentiate the happy mood group from the sad mood group. In daily mood classification using sleep duration and regularity parameters, different sets of parameters are optimal for different participants. Over the group, the previous one night to five nights of sleep duration and sleep regularity classified happy and sad mood with 70-82% accuracy.

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