Importance of Sleep Data in Predicting Next-Day Stress, Happiness, and Health in College Students

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Introduction
The ability to model and predict self-reported stress, happiness, and health could be beneficial for individual and public health, for education, and in the treatment and prevention of mental illness.

Importance:
- Self-reported health strongly relates to actual health and all-cause mortality [1]
- Stress increases susceptibility to infection and illness [2]
- Self-reported happiness is indicative of clinical depression [3], and has as strong an effect on longevity as cigarette smoking [4].
- Automated mood recognition and prediction are hard: accuracies range from 55-80% (e.g. [5,6]), including the data we use in this work here [7,8].

We show the accuracy for predicting next-day wellbeing is improved when including simple sleep features.

Data
144 college students participated in a 30-day study. Total of 2,769 days of data were used.

Physiology: Accel., skin temp., Electrodermal Activity (EDA)

Actigraphy

Smartphone logs (call, sms, screen, location)

Behavioral surveys

Wellbeing reported on visual analog scale
Stressed out – Calm Relaxed
Sad – Happy
Sick – Healthy

Methods
The top and bottom 40% of scores were assigned positive and negative labels, respectively.

Figure 1: Distributions: Stressed-Calm, Sad-Happy, and Sick-Healthy
A hierarchical Bayes machine learning algorithm [9] was trained to predict each next-day wellbeing label on two data sets:
1. including self-reported sleep features (i.e., self-reported sleep latency, bedtime, and wake time), and
2. discarding sleep features.

Both data sets include ~20 features computed from wearable sensors, phone, and online surveys. These features include changes in physical activity that are often associated with sleep/wake.

Results
Hold-out Test accuracies on self-reported stress, happiness, and health:
- Without self-reported sleep features:
  - 79.62%, 78.24%, 83.55%, respectively.
- When including self-reported sleep features:
  - 80.67%, 80.40%, 83.12%, respectively.

Using McNemar’s test we find that including self-reported sleep features does not significantly improve the classifiers for the stress or healthy prediction, but does significantly improve the classifier for the happy prediction (p<0.15).

Conclusions
The inclusion of self-reported sleep features improved the prediction of tomorrow’s state of self-reported of sad or happy above the accuracy achieved using features from smartphones and wearables. Changes in stress and health prediction were not statistically significant.

Future studies of personalized prediction of mood ought to consider including self-reported sleep features in order to improve prediction.

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References