Monitoring Social Anxiety from Mobility and Communication Patterns

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Abstract
Mental health problems are a leading cause of disease burden and disability worldwide. The use of mobile and wireless technologies to support the achievement of health objectives (mHealth) has the potential to transform the face of health service delivery. In this paper, we demonstrate how non-invasive mobile sensing technology can be used to passively assess and predict social anxiety among college students. The collected data enhances understanding of how students' social anxiety levels are associated with their mobility and communication patterns. Our analysis based on GPS location, text messages, and call data collected from 54 college students over a two-week period indicates that social anxiety level can be predicted with an accuracy of up to 85%.

Author Keywords
mobile sensing, social anxiety, mobile health, mobility patterns, communication patterns

ACM Classification Keywords
H.1.2 [Models and Principles]: User/Machine Systems; J.3 [Life and Medical Sciences]: Health; J.4 [Social and Behavioral Sciences]: Psychology

Introduction

Social anxiety is the extreme fear of being scrutinized and judged by others in social or performance situations [6]. Social anxiety disorder can interfere with occupational and social functioning, making it difficult to complete school, get a job, as well as develop and maintain relationships. Current techniques to identify social anxiety are typically based on self-report via questionnaires or interviews in traditional clinical settings, where only small numbers of people can be monitored and client motivation to seek out an assessment is required. This approach is inadequate given the high prevalence of social anxiety. For example, according to the Anxiety and Depression Association of America , 36 percent of people with social anxiety disorder report symptoms for 10 or more years before seeking help [6].

Thanks to the ubiquity and the emerging sensing capabilities of smartphones, researchers are able to non-invasively assess markers of mental health disorders through *in situ* data collection and analysis. By leveraging the various sensors embedded in commodity mobile phones (e.g., GPS, accelerometer and light sensors), a rich data set can be collected to better understand the relations between human behavior and mental health status.

The purpose of this research is to demonstrate the feasibility of predicting social anxiety levels from passively generated smartphone data. We examine the correlation between social anxiety symptoms and both passively sensed indicators of mobility and communication (calls and texts) patterns, then propose a classification model to predict social anxiety levels. This work may ultimately help researchers and clinicians learn how social anxiety symptoms manifest in the daily lives of college students, so that more precise and personalized interventions can be developed.

Related Work

Anxiety and depression research has traditionally relied on laboratory-based approaches. More recently, significant efforts have been undertaken to monitor and understand mental health status using Ecological Momentary Assessment (EMA). While these approaches allow a more direct assessment of people's social-emotional daily lives [2], regularly prompting individuals to answer questions also raises challenges of participation burden. Advances in mobile technology have now made it possible to monitor people's states both remotely and unobtrusively through passive sensing of behavior. Several recent studies have been conducted using personal smartphones and wearable sensors to unobtrusively sense mental health state [5].

For instance, the StudentLife project [7] used smartphones to assess the impact of workload on stress, sleep, activity, mood, sociability, mental well-being and academic performance of students. In another study [4], researchers used a broad array of built-in mobile phone sensors to predict mood, finding that decreases in calls, SMS messaging, Bluetooth-detected contacts, and location entropy were strongly related to feeling sad and stressed among students.

In the following section, we introduce the design of our study and data collection procedures. We then present the data preprocessing and feature extraction approach. Finally, we highlight the results of our predictive model.

Proposed Study

N=54 undergraduate students with varying levels of social anxiety were recruited for a two-week study. University students were examined because there are high rates of social anxiety among young adults, and because recruiting young adults in a university setting provides a relatively

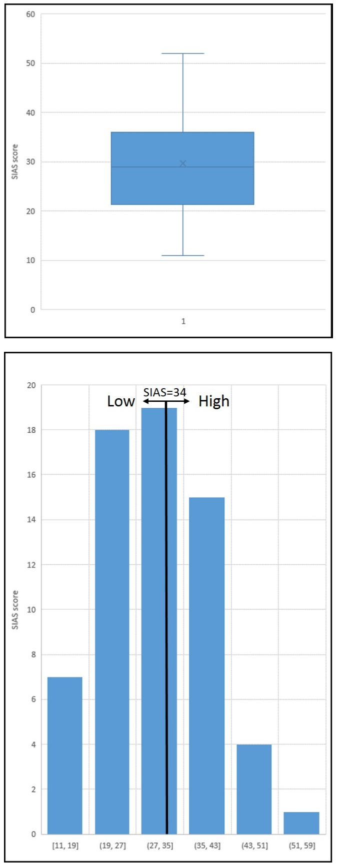

Figure 1: SIAS score distribution for recruited participants. Our 54 participants' SIAS scores have a mean of 29.67 and a standard deviation of 9.19.

homogeneous sample in terms of life phase and common psychological stressors, thereby mitigating the impact of a wide variety of potential nuisance factors.

We first assessed the social anxiety level of each participant using the Social Interaction Anxiety Scale (SIAS [2]), which contains 20 items (rated from 0=not at all to 4=extremely). A higher SIAS score (specifically, higher than 34 [2]) indicates a higher probability of clinically significant social anxiety (see Figure 1). A custom mobile app was installed on participants' personal android smartphones to passively collect both GPS location (every 150 seconds) and communication patterns (SMS texts and calls), as well as upload the data to an Amazon Web Services server. (Note, these measures and procedures were part of a larger study that also included two lab visits; full details on the larger study are available from the authors.)

Feature Extraction

We parsed participants' raw GPS data by semantic locations (e.g., restaurant, campus area, and shops), by combining a spatiotemporal clustering algorithm [3] and OpenStreetMap geodatabase. Our label taxonomy includes the following types: home, other houses, education (e.g., university and libraries), leisure (e.g., cinemas), food (e.g., restaurants), supermarket, religious, shopping, service (e.g., bank), out of town, and in transition (going from one place to another). Thereafter, we used the semantic labels to identify participants': (1) distribution of cumulative staying time in each location (e.g., a participant may have 35% of time spent at home, 30% in education areas, 20% in leisure places and 15% in restaurants), (2) distribution of communications in each type of location, (3) location entropy based on the number of different places that the user has visited during the study, and (4) average daily amount of calls and SMS texts.

Correlation Analysis

We examined the correlation between participants' sensed behavior and their SIAS score. The aim was to investigate if high socially anxious students have any unique mobility and/or communication patterns that distinguish them from low socially anxious students. We calculated the Pearson correlation between each mobility and communication feature and the SIAS score to identify the direction (positive or negative) and strength of the correlation. To assess the reliability of the correlations, we also calculated significance levels (p-value).

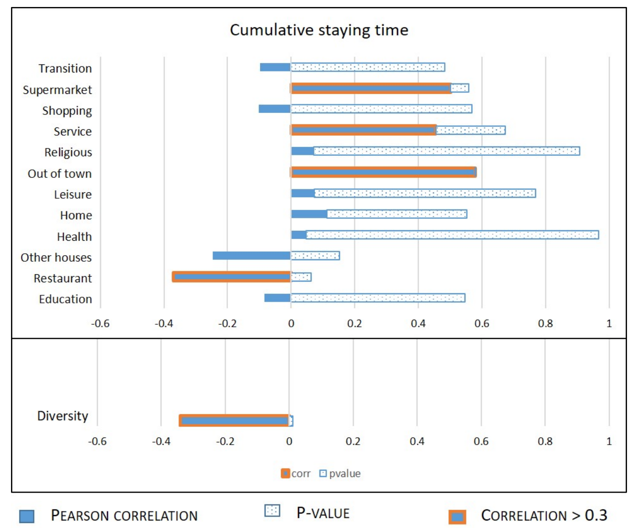

Figure 2: Correlation and significance analysis of mobility (based on GPS location) with social anxiety (based on SIAS).

Figure 2 shows the Pearson correlations between cumulative staying time and SIAS score, as well as the corresponding p-value. It appears that time spent in some locations is associated with SIAS. For instance, time spent in food locations, such as restaurants, is negatively correlated with SIAS. However, time spent in supermarkets is positively correlated with SIAS. This suggests that high socially anxious students may be more likely to buy food so they can eat at home, thereby avoiding social interactions in restaurants. Figure 2 also shows that the diversity of places visited is negatively correlated with SIAS, which suggests that socially anxious students visit fewer different places and have a narrower range of activities.

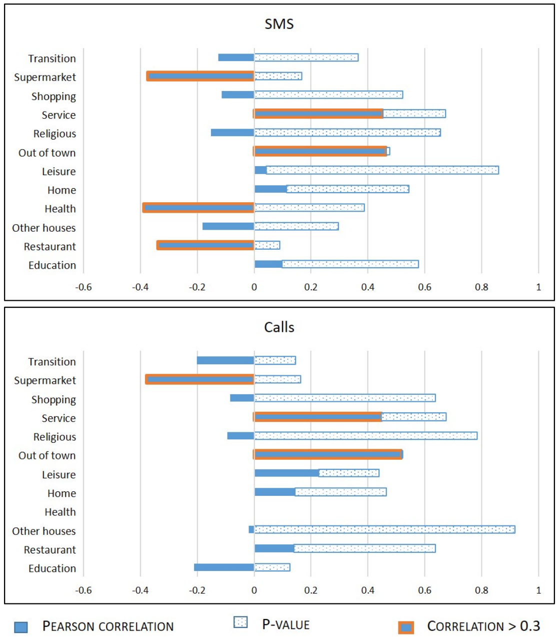

Figure 3: Correlation and significance analysis of communication (based on distribution of calls and SMS in each location) with social anxiety (based on SIAS).

The distribution of calls and SMS texts among the different locations was correlated with SIAS in a number of expected ways (see Figure 3). For instance, more communication in public places such as restaurants, where one might expect fears of negative evaluation to be heightened, was negatively correlated with SIAS, suggesting that high (relative to low) socially anxious people are less likely to call and send texts in such places.

Predictive Model

Using the extracted mobility and communication features, we aim to investigate if the extracted features can predict students' SIAS levels. We first classified SIAS scores as low (SIAS < 34) or high (SIAS ≥ 34). While we recognize that a dichotomous split is a somewhat simplistic and artificial way to create groups, we felt that a two-group classification was most appropriate given the novelty of the test and our relatively small sample. Notably, we used an established clinical cutoff for the SIAS so the classification would have some known groups validity. Then, we used the GPS location and SMS texts and call features to predict the SIAS group by using a decision tree algorithm (C4.5 [1]). The classification results are presented in Table 1.

Table 1: Accuracy and F1 rate for both low and high social anxiety levels. We performed two types of tests: 10-fold cross-validation and split validation (2/3 for training and 1/3 for testing). Com=Communication features.

	Cross-validation		**Split validation**	
	Mobility	**+Com**	Mobility	**+Com**
Accuracy	67%	**85%**	61%	**77%**
F1 high	42%	**77%**	54%	**62%**
F1 low	77%	**89%**	67%	**84%**

We first calculated the accuracy of the classification by using only participants' mobility patterns, then we added communication patterns to investigate if it improved the model results. From table 1, we notice, indeed, that combining both mobility and communication patterns improved the model predictions to reach an accuracy of up to 85% for the cross-validation test and 77% for the split validation test while keeping a good F1 score for both low and high classes.

Conclusions

Social anxiety monitoring methods are typically based on self-report in traditional clinical settings, where clinicians rely on client motivation to seek an assessment. These methods suffer from recall biases and fail to capture fine-grained, ecologically valid details of *in situ* social anxiety-linked, real world behavior. In this paper, we investigate the feasibility of assessing and predicting college students' social anxiety level through mobile technology. Although replication in a larger sample is needed, our study demonstrates that combining mobility and communication patterns may help to reveal how social anxiety symptoms manifest in the daily lives of college students, especially given the predictive model classified participants as high or low socially anxious with an accuracy of 85%. Further work will investigate the importance of mobility and communication patterns in a larger population and extend the approach to other mental health disorders.

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