Autonomously Sensing Loneliness and Its Interactions with Personality Traits using Smartphones

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***Abstract*— One in five Americans is lonely and loneliness disproportionately affects senior citizens and international students. In this paper, we propose Socialoscope, a smartphone app that passively senses user loneliness from their communication and interaction patterns (e.g. calls, SMS, browsing patterns and social media usage), while factoring in different personality types. Data was gathered from 9 international students over 2 weeks to train machine learning classifiers for loneliness. Using smartphone-sensed data, we show that of the big 5 personality traits, extraversion and emotional stability features were strongly correlated with smartphone-sensed loneliness. We synthesized machine learning classifiers that classified user smartphone interaction and communication features into ranges of loneliness with an accuracy of 98%, while factoring in user personality types.**

I. Introduction

Healthy relationships with family members, friends, colleagues and community members are important for mental wellbeing. A lonely person feels disconnected from the world and has no one to discuss important matters with. Loneliness and social isolation seriously impacts one's mental health, increasing their levels of stress, anxiety, and drug or alcohol addiction [1]. Loneliness increases the death rate of older people, weakens the immune system, and increases the risk of stroke and cardiovascular disease [1].

Loneliness is on this rise. One in five Americans is lonely and more than a third of the population has felt depressed as a result of chronic loneliness. The recent increase in loneliness is due to a rise in one-person households, increased divorce rates, longer work hours and longer commutes [1]. Older adults and international students are particularly susceptible to loneliness. Strategies to treat loneliness include helping lonely people connect with others, medication, meditation and yoga, exercise classes, walking groups, and cognitive behavioral therapy [2]. However, these treatments reach less than half of those afflicted with loneliness worldwide due to several factors including the social stigma associated with mental disorders, lack of resources, lack of skilled therapists and misdiagnosis [2].

In this paper, we propose Socialoscope, a smartphone app that passively detects the loneliness in smartphone users based on their communication (e.g. phone calls, SMS text, web browser, app, email and social media usage) and social interaction (e.g. number of other people seen via Bluetooth, locations visited via Wi-Fi SSID) patterns passively sensed by their smartphones. Socialoscope is intended as an early warning system that informs caregivers of patients that require more careful examination. Since smartphones are widely owned, loneliness sensing using smartphones will likely be cost effective and have global reach.

Prior work by Hojat [3] showed that the loneliness levels experienced by various people depended on their personality types and that some personality types (e.g. extroverts) were more vulnerable to loneliness. This means that if two people with different personality types each make 5 calls per day, depending on their personalities, one person may feel lonely while the other might not. In this paper, like prior work, our goal was to detect loneliness levels of smartphone users passively. However, we also explored interactions of loneliness with personality, which enabled us to factor in personality into our loneliness inferences. Hojat [3] established a statistical relationship between loneliness and personality. Personality variables such as depression, anxiety, neuroticism, psychoticism, misanthropy were found to positively predict loneliness, while, personality variables such as self-esteem and extraversion negatively contributed to loneliness. This work made the following specific research contributions:

1. Investigated what smartphone features (call logs, contacts, SMS logs, location, Bluetooth, Wi-Fi devices, app usage, browser usage, emails and social media) are statistically correlated with questions on the clinically validated UCLA loneliness scale [8].
2. Extended the list of features explored by prior work on smartphone loneliness and personality sensing by including new Internet (browser usage) and social media features (e.g. Facebook).
3. Explored whether smartphone sensed loneliness is statistically correlated with certain big five personality traits (extraversion agreeableness, conscientiousness, neuroticism, and openness to experience) [9].
4. Synthesized machine learning classifiers that detect lonely smartphone users more accurately by factoring in differences in their personality types.
5. Researched and developed Socialoscope, an intelligent smartphone application, which detects lonely smartphone users, while factoring in differences in their personality types.

II. Related Work

SociableSense [4] and Vive [5] are two previously proposed smartphone sensing apps that detect loneliness. SociableSense detects the sociability levels of smartphone users and the strengths of their relations with their co-workers. SociableSense uses data from the smartphone's accelerometer, Bluetooth, microphone that are classified using machine learning classifiers and decision theory. Our proposed Socialoscope app, on the other hand, uses a more comprehensive set of sensors including social media usage, and is not restricted to a workplace environment. Moreover, Socialoscope also investigates the interactions of loneliness with personality traits. Vive [5] is a smartphone app that senses loneliness in senior citizens. Vive had four main modules derived from four psychological factors of loneliness - family, spouse, social and existential crisis. Vive did not explore personality and focused on older adults, while our Socialoscope app senses loneliness in all ages.

Chittaranjan et al [6] classified the Big-five personality scores of smartphone users from their usage patterns, but did not infer user loneliness. The smartphone user's personality type was inferred from their cell phone usage. Features such as number and length of SMS messages, Call duration and count, associated contact, missed calls, physical proximity via Bluetooth Scans and application Usage were considered.

Wang et al [7] presented StudentLife a smartphone sensing system that predicts students' academic performance from smartphone sensor data but does not explicitly detect loneliness or its interactions with personality.

III. OUR SOCIALOSCOPE SMARTPHONE APP

Figure 1 Features Tracked by Our Socialoscope App

Figure 1 summarizes smartphone communications and sensors continuously sensed by our Socialoscope app, from which features are extracted as inputs to machine learning classifiers of loneliness. These include app usage, emails, messages, phone calls, Wi-Fi connectivity, Bluetooth devices sensed, contacts, and social media and browser usage.

IV. OUR METHODOLOGY FOR SYNTHESIZING MACHINE LEARNING CLASSIFIERS FOR LONELINESS AND PERSONALITY

Our workflow for synthesizing machine learning classifiers for Socialoscope is shown in figure 2. These classifiers run in real time on the Socialoscope app, continuously monitoring and classifying the user's daily communications and social interactions, to infer their loneliness levels. Our steps to synthesize loneliness classifiers are now described.

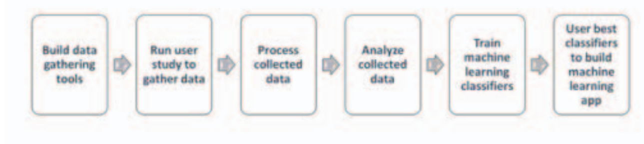

Figure 2 Workflow to synthesize Socialoscope's Machine Learning Classifiers

A. *Study to Gather Loneliness and Personality Data*

In an IRB approved study, the communications, social interactions and smartphone usage of 9 international students (6 males, 3 females aged 23-28 years) were continuously logged for two weeks. Two data gathering apps were installed on subjects' phones for this purpose. A summary of the user communications and interactions monitored are shown in table 1.

Table 1 Sensors and features used in Socialoscope

Sensor Type	**Features extracted**
Phone Calls	Call count, duration, caller, Is caller a close friend?
SMS Text	SMS count, character count, sender, Is sender close friend? SMS type
App Usage	Number of launches, use duration, app category
Bluetooth (BT) devices sensed	Number of unique BT IDs, Number of times saved BT IDs are seen, duration of availability
Wi-Fi SSIDs sensed	Number of SSIDs, duration of SSID connectivity, Wi-Fi type (Public/Home/Work)
Browser usage	Browser history, favorites, browsing time of day, browsing duration, category of website browsed
Social Media usage	Number of times social media app is launched

1) *Big-Five Personality Traits*

To capture their personality traits, at the beginning of the 2-week data gathering study, subjects were given a one-time personality survey based on the Big-Five Personality Traits [9]. Psychologists in this school of thought believe that there are five basic dimensions of personality namely Extraversion, Agreeableness, Conscientiousness, Emotional Stability or Neuroticism, and Intellect or Openness to Experience. These traits are called the Big-Five personality traits, and are commonly used to describe human personality.

2) *UCLA Loneliness Scale*

To capture the subjects' loneliness levels, they were made to answer questions from the UCLA Loneliness Scale [8] every 4 hours for the entire 2 weeks. The UCLA Loneliness Scale is commonly used for quantitatively measuring one's subjective feelings of loneliness and feelings of social isolation. It has 20 questions including questions about how often users felt they lacked companionship, felt alone and how often they felt people did not really understand them. Participants responded to each question on the scale as Never (1), rarely (2), Sometimes (3), or Often (4).

B. Feature Extraction

The raw logs of smartphone-sensed user communications and interactions were processed to extract the features listed in table 1. User responses to the UCLA loneliness scale and Big-Five personality questionnaire were also coded.

C. Correlation Analysis

The first analysis step was to determine which extracted features were strongly correlated with user loneliness and personality scores. The most correlated features were then selected to train machine learning classifiers. This feature selection methodology based on correlations is called Correlation-based Feature Selection (CFS).

D. Classification

The most correlated features were imported into the Weka machine learning library along with user loneliness and personality scores. Various machine learning types (e.g. SVM, Naïve Bayes,) were tested. The best performing classifiers were exported and programmed into the real time version of the Socialoscope app, which detects the loneliness of smartphone users in real time based on sensed interactions and personality traits.

V. RESULTS

A. UCLA Loneliness Score of Subjects

The loneliness scores of all subjects were computed along with box plots of sensed features. Figure 3 shows the total number of calls (incoming and outgoing) per subject. User 1 had a high loneliness score and also had low numbers of interactions (SMS messages, outgoing calls, total calls).

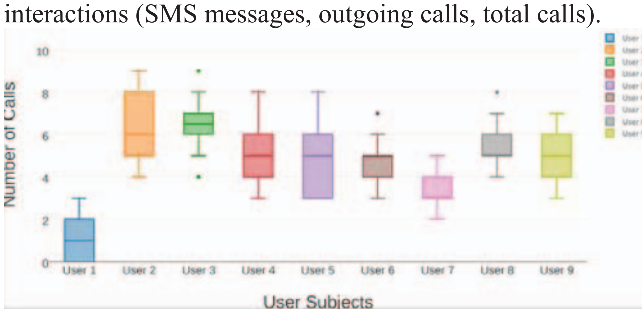

Figure 3 Total number of calls per subject

We calculated the correlation coefficient, standard error of the correlation coefficient, t-score followed by p-values for each of these features with UCLA Loneliness Levels (table 2). The significant factors are listed first, followed by the non-significant ones, in decreasing order of their absolute value of correlation coefficient. From this table, we conclude that features such as the number of messages, number of calls, number of late night searches and the difference between number of outgoing and incoming messages, difference between the number of outgoing and incoming calls and percentage of calls that are missed are the features that are strongly correlated to UCLA Loneliness Levels.

Table 2 Correlation coefficient and p-values of features with UCLA Loneliness Scores

Feature	Correlation Coefficient	p-value
No of messages	-0.793	< 0.00001
No of outgoing calls	-0.681	< 0.00001
No of Calls	-0.626	< 0.00001
No of short incoming or outgoing calls	-0.548	< 0.00001
No of late night browser searches	0.51	0.00001
No of long incoming or outgoing calls	-0.448	< 0.00001
Moving Travel State	-0.412	< .00001
No of Contacts	-0.386	< .00001
No of incoming calls	-0.363	0.000029
Difference between no of outgoing and incoming messages	-0.338	0.000107
Difference between no of outgoing and incoming calls	-0.327	0.000186
Percentage of calls that are missed	0.326	0.000193
No of auto-joined trusted Wi-Fi SSIDS	-0.297	0.000734
No of missed calls	0.162	0.069893
No of browser searches	0.078	0.3853
Low Activity Level	0.022	0.80686
High Activity Level	0.001	0.99116

B. Personality Scores of Subjects

The total Big-Five personality score of all subjects were computed along with their scores for individual traits (agreeableness, conscientiousness, emotional stability, extraversion and intellect personality traits). The extraversion and emotional stability scores of User 1 (lonely user) was significantly different from those of other users. No similar conclusions could be made for the agreeableness, conscientiousness and intellect traits.

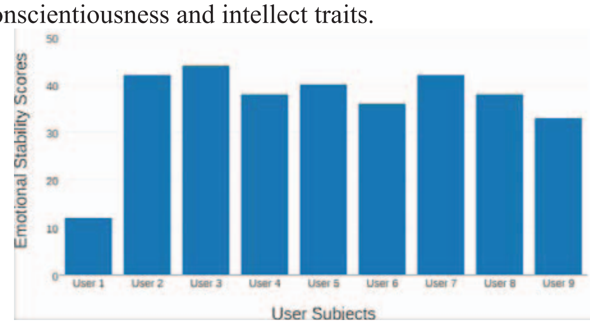

Figure 4 Emotional Stabilty Scores of Subjects

To understand the significance of the above conclusions, we performed statistical analysis of the feature values with each of these personality traits. We calculated the correlation coefficient, standard error of correlation coefficient, t-score followed by p-value for each of the five traits for all the features values. We found that the Emotional Stability and Extraversion personality traits are strongly correlated with most of the smartphone-sensed features (table 3), while Agreeableness personality trait, Conscientiousness personality trait and Intellect personality trait are weakly correlated with most of the features. This result proves the finding by Hojat that the feeling of loneliness is accompanied by depression, anxiety, neuroticism and that loneliness is linked inversely to self-esteem and extraversion [3].

Table 3 Correlation coefficient and p-values of features with Extraversion Score

Feature	Correlation Coefficient	p-value
No of messages	0.795	< 0.00001
No of late night browser searches	-0.601	< 0.00001
No of outgoing calls	0.589	< 0.00001
No of Calls	0.584	< 0.00001
No of short incoming or outgoing calls	0.505	< 0.00001
No of auto-joined trusted Wi-Fi SSIDS	0.484	< 0.00001
Moving Travel State	0.458	< 0.00001
No of long incoming or outgoing calls	0.442	< 0.00001
No of incoming calls	0.393	< 0.00001
Percentage of calls that are missed	-0.379	0.000012
Difference between no of outgoing and incoming messages	0.368	0.000025
No of browser searches	-0.231	0.0089
Difference between no of outgoing and incoming calls	0.216	0.1547
No of Contacts	-0.211	0.0179
No of missed calls	-0.176	0.5015
No of Bluetooth devices around	-0.108	0.227
High Activity Level	0.099	0.268
Low Activity Level	0.009	0.919

C. Classification Results

We classified the statistically significant smartphone-sensed features into loneliness levels with and without using personality traits as features (see tables 4 and 5). UCLA Loneliness scores range from 20 to 80. We used three ranges to classify the UCLA loneliness scores into loneliness categories. These were class 1: 20-40, class 2: 40-60 and class 3: 60-80. Users with scores 60-80 are considered lonely. Average values fall in the range 40-60 and users with scores 20-40 are not lonely. Our goal was to classify features generated from subjects' smartphone communication and interactions into these loneliness categories. We did not aim to infer subjects' precise scores on the UCLA loneliness scale.

Table 4 Classifier Accuracy without Using Personality Traits as Features

	Correctly Classified Instances	Incorrectly Classified Instances	Kappa statistic
J48	90%	10%	0.8258
Random Forest	86%	14%	0.7611
Bayes Net	88%	12%	0.7973
AdaBoostM1	88%	12%	0.7973
Naive Bayes	80%	20%	0.6479

Table 5 Classifying Accuracy using Personality Traits as Features

	Correctly Classified Instances	Incorrectly Classified Instances	Kappa statistic
J48	98%	2%	0.8258
Random Forest	94%	6%	0.7611
Bayes Net	94%	6%	0.7973
AdaBoostM1	92%	8%	0.7973
Naive Bayes	82%	18%	0.6479

Our results show that J48 is the best performing classifier type with an accuracy of 98%. Using the subject's personality as a feature increases classifier accuracy by about 8%.

VI. CONCLUSION

One in five Americans is lonely and loneliness disproportionately affects senior citizens and international students. In this paper, we proposed Socialoscope, a smartphone app that sensed user loneliness from their communication and interaction patterns (e.g. calls, SMS, browsing patterns and social media usage). Data was gathered from 9 international students over 2 weeks to train machine learning classifiers for loneliness. We showed that extraversion and emotional stability personality features were strongly correlated with smartphone-sensed loneliness. We synthesized machine learning classifiers that classified user interactions into ranges of loneliness with an accuracy of 98%, while factoring in user personality types. These classifiers were used to develop the real-time version of the Socialoscope app.

In future, we would like to continue to validate our approach in a larger study with more users. We would also like to capture user communications that use VoIP applications such as WhatsApp and Skype. Finally, we would also like to explore privacy concerns raised by gathering sensitive communication and interaction data.

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