“Whereabouts”: A Mental Health Intervention Using Location Tracking

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ABSTRACT

This paper discusses how movement data can be collected and framed on a mobile phone platform. This intervention targets Cornell students and aims to help students understand and quantify symptoms of stress.

An algorithm that clusters location data is used to support an application that visualizes data and creates custom feedback for the user. Referencing prior research, a prototype of the mobile intervention is made as a proof of concept of how movement data can indicate stress, and how proper data framing can bring mental health awareness.

INTRODUCTION

As technology becomes increasingly pervasive in our everyday lives, its purpose has expanded beyond professional use to personal use. Ubiquitous technology targets many aspects of a user’s personal lives, and research includes a growing interest in health applications [2, 11, 13]. Health interventions can range from weight management [9], to drug overdose sensing [14], support for elderly loneliness [16], and has stress management [3, 5, 6, 8, 11, 21].

At Cornell University, there is a large community shift to bring focus to the mental health of students, as it can not only negatively affect their academic lives but personal lives as well [19]. The Presiding President of the university, Martha Pollack, declared in late 2019 that “We really … need to be talking about mental health and student wellness very holistically” [23].

Since Pollack’s inauguration in 2017, she has helped establish the Mental Health Review Committee (MHRC), an internal review team dedicated to examining the “academic and social environment, climate, and culture related to mental health”. They will later share their findings with practitioners and specialists to develop strategies for improvement [12].

As mental health awareness becomes ever more prevalent on the Cornell Campus, the focus of our paper is to add to the growing body of research of students’ mental health and provide a technological intervention to help facilitate mental health mindfulness in Cornell students.

Our research delves into the product design and implementation of a platform named “Whereabouts”. This platform leverages mobile device sensors to collect location data of a user and to build a stronger image of their mental health wellbeing. We aim to find a relationship between location movement and stress and to help Cornell students bring awareness to their own stress and mood and what healthy activities help them cope.

HYPOTHESIS

We hypothesize that mental health wellbeing is significantly related to routine physical movement from different locations. The locational movement can help indicate the health of a student, such as, changes in routine, increased visits to a favorite place, and extreme amounts of decreased movement.

Additionally, we predict that a platform that can provide an indication of users’ mental well-being through analysis of locational data, will allow users to self-reflect more effectively about their own wellbeing in real time.

METHODOLOGY

Our study is broken into three separate investigations.

1. What relationship exists between location movement and student stress?

Does there exist a significant relationship between physical activity and stress? If so, what is the correlation?

2. How can location data be collected from a mobile device and processed to predict a general state of mental health?

If stress is correlated to movement, how can we design an algorithm that will help collect such data? We will investigate how sensor data may be collected and processed to produce predictions of mental wellbeing.

3. How can movement information be framed so that our app is an effective intervention?

Lastly, what type of information are students looking for in a mental health awareness application? How can an application be best designed to develop a consistent and reliable repertoire with its users. We will investigate preexisting mental health applications available on the market. Based on our findings, a prototype called “Whereabouts” will be designed for users to interact with, and student feedback will be analyzed for the success of the interface

STRESS AND MOVEMENT

Prior research has investigated the relationship between stress and physical activity in university students [15].

According to Northwestern University’s research team, smartphone sensor data can detect depression by tracking the phone usage and geographical location data.

The time spent on using a smartphone and the likeliness of having depression is closely related. The average daily usage for depressed individuals was about 68 minutes, while for non-depressed individuals it was about 17 minutes [22].

In addition, geographical locational data can be an indicative of depression. Spending too much time at either your home or fewer locations are closely linked to depression. Having an irregular everyday schedule is also linked to depression.

Based on the phone sensor data, Northwestern scientists could identify people with depressive symptoms with 87 percent accuracy [22].

David Mohr, director of the Center for Behavioral Intervention Technologies at Northwestern University Feinberg School of Medicine, stated that “We now have an objective measure of behavior related to depression. And we’re detecting it passively. Phones can provide data unobtrusively and with no effort on the part of the user”.

Compared to daily questionnaires which ask participants to answer their emotional state on a scale of 1 to 10, the smart phone data was more reliable in detecting depression.

Saeb, a postdoctoral fellow and computer scientist in preventive medicine at Feinberg, analyzed the GPS location data and phone usage data for 28 individuals over two weeks. The sensor tracked GPS locations every five minutes [17].

To discover the link between phone usage data, geographical location data, and depression, the participants were assigned with a widely-used questionnaire measuring depression, the PHQ-9. The PHQ-9 measures common symptoms used to determine depression such as anxiety, excessive stress, sleeping or eating disorder, hopelessness, and social isolation. Then, Saeb collected phone usage data and GPS data from participants and developed an algorithm that correlated the results of those data with the subjects’ PHQ-9 results. Out of 14 participants who were found to have mild to strong depression, it was found that PHQ-9 results and phone data had strong correlation.

The relationship between depression and different levels of emotional states and phone data has been made. We plan to advance our hypothesis that ubiquitous computing technology could be used to monitor people who are at risk of depression using such concepts.

GPS DATA CLUSTERING ALGORITHM

We hypothesize that location data can be collected through students’ phones and process that data to find how much they have moved that day. By clustering latitude and longitude data, their daily routines can be derived and depressive symptoms can be highlighted. Additionally, ambient tracking will be beneficial because it requires minimum effort for those with depressive symptoms to report.

The algorithm will cluster a spatial data set of GPS latitude and longitude coordinates using Python and its Scikit-Learn implementation of the DBSCAN clustering algorithm. In this paper, we have implemented the function using the data set provided from the StudentLife study conducted at Dartmouth [20].

Although the k-means algorithm is one of the most common clustering algorithms, the DBSCAN algorithm is superior for clustering a set of spatial data. Because the k-means algorithm clusters N observations into k clusters, it is not suited for clustering latitude and longitude spatial data because it minimizes the variance between data, not the actual geographic distance [4].

On the other hand, the DBSCAN clustering algorithm clusters a set of spatial data based on two parameters. First, the actual geographic distance from each point, and the minimum cluster size. Compared to the k-means algorithm, this method does not distort geographic data and therefore is suited better for spatial latitude-longitude data.

First, the necessary Python modules and the data set are imported to the notebook. Spatial data of latitude and longitude coordinate columns are converted into a two-dimensional Numpy array (Figure 1).

```
In [59]: #impoting necessary functions
         import pandas as pd, numpy as np, matplotlib.pyplot as plt, time
         from sklearn.cluster import DBSCAN
         from sklearn import metrics
         from geopy.distance import great_circle
         from shapely.geometry import MultiPoint
         %matplotlib inline

In [60]: # define the number of kilometers in one radian
         kms_per_radian = 6371.0088

In [72]: # load the data set
         df = pd.read_csv('gps/gps_u30.csv', encoding='utf-8')
         df.head()

Out[72]:
```

	time	provider	network_type	accuracy	latitude	longitude	altitude	bearing	speed	travelstate
1364404322	network	wifi	20.000	43.706599	-72.286978	0.0	0.0	0.0	NaN	NaN
1364405529	network	wifi	24.247	43.706588	-72.287015	0.0	0.0	0.0	NaN	NaN
1364406729	network	wifi	25.446	43.706607	-72.286991	0.0	0.0	0.0	stationary	NaN
1364407929	network	wifi	20.000	43.706606	-72.286981	0.0	0.0	0.0	stationary	NaN
1364409811	network	wifi	23.712	43.706607	-72.287017	0.0	0.0	0.0	NaN	NaN

Figure 1. Modules and datasets imported.

Next, DBSCAN is computed. The *epsilon* variable indicates the maximum distance that a single point can be away from another point to be classified as a cluster. The *min_samples* variable indicates the minimum cluster size. This variable is set to 1 so that every single point of data belongs to a cluster or serves as its own cluster with size 1.

The DBSCAN haversine distance metric works with data presented in the form or latitude and longitude, with both inputs and outputs in radian units. (Figure 2).

The *Eps* variable indicates the actual geographic distance that each data point forms its cluster. Therefore, latitude and longitude data are presented in a form of Numpy matrix of coordinates, then they are converted into radians to be used for the haversine metric. Then, the haversine metric is used to calculate distance of greater cluster circles between points.

```
# represent points consistently as (lat, lon)
coords = df.as_matrix(columns=['latitude', 'longitude'])

# define epsilon as 1.5 kilometers, converted to radians for use by haversine
epsilon = 1.5 / kms_per_radian
```

```
start_time = time.time()
db = DBSCAN(eps=epsilon, min_samples=1, algorithm='ball_tree', metric='haversine').fit
(np.radians(coords))
cluster_labels = db.labels_

# get the number of clusters
num_clusters = len(set(cluster_labels))

# all done, print the outcome
message = 'Clustered {:,} points down to {:,} clusters, for {:.1f}% compression in {:,
.2f} seconds'
print(message.format(len(df), num_clusters, 100*(1 - float(num_clusters) / len(df)),
time.time()-start_time))
print('Silhouette coefficient: {:0.03f}'.format(metrics.silhouette_score(coords,
cluster_labels)))
# turn the clusters in to a pandas series, where each element is a cluster of points
clusters = pd.Series([coords[cluster_labels==n] for n in range(num_clusters)])
```

Figure 2. DBSCAN is computed, clusters are found.

Figure 3 computes the centroid cluster's coordinates. Python's built-in Min function finds the smallest member of the cluster in terms of distance to that centroid. The function returns each data point's distance from the centroid in unit of meters, based on Geopy's great circle function. Finally, the latitude and longitude coordinates of the point which had the least distance from the centroid is computed

This function is visualized by being mapped to a Pandas series of clusters. Each cluster in the series receives the center-most point of the cluster and then these points form a new series *centermost_points*. Finally, these points are presented through a Pandas data frame of points. This data frame is a spatial representative of clusters from the original dataset.

```
def get_centermost_point(cluster):
    centroid = (MultiPoint(cluster).centroid.x, MultiPoint(cluster).centroid.y)
    centermost_point = min(cluster, key=lambda point: great_circle(point, centroid).m)
    return tuple(centermost_point)

centermost_points = clusters.map(get_centermost_point)
```

```
# unzip the list of centermost points (lat, lon) tuples into separate lat and lon lists
lats, lons = zip(*centermost_points)

# from these lats/lons create a new df of one representative point for each cluster
rep_points = pd.DataFrame({'longitude':lons, 'latitude':lats})
rep_points.tail()
```

	longitude	latitude
47	149.699997	-72.286899
48	150.100006	-72.290418
49	161.199997	-72.272580
50	140.300003	-72.287930
51	123.900002	-72.289579

```
# pull row from original data set where lat/lon match the lat/lon of each row of
representative points
# that way we get the full details like city, country, and date from the original
dataframe
rs = rep_points.apply(lambda row: df[(df['latitude']==row['latitude']) & (df
['longitude']==row['longitude'])].iloc[0], axis=1)
rs.to_csv('gps/gps_u21.csv', encoding='utf-8')
rs.tail()
```

Figure 3. Mapping data to spatial representation using a cluster's centroid.

The original data set is reduced down to a spatially representative set of points and plotted to the final reduced set to observe clusters based on locational data (Figure 4).

In order to consider possible outliers, the most isolated points, or clusters of points, will be identified based on some threshold distance. If the user travels somewhere, those locational data clusters are very concentrated in terms of distance between each other, but will be far away from other locational data which represent daily locations.

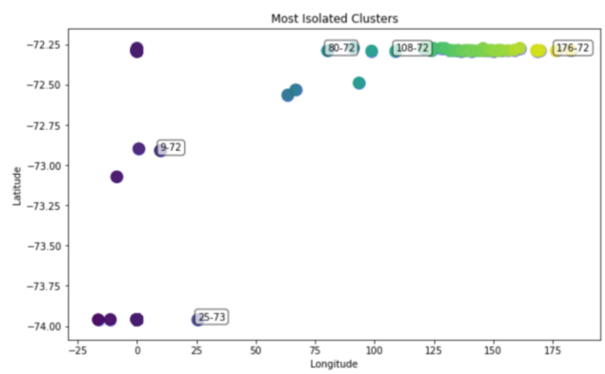

Figure 4. The results of the clustering algorithm.

BUILDING THE INTERFACE

The algorithm of code developed focuses primarily on locations students heavily spend in a day. We have developed a proof of concept that data can be collected from smartphones, but now that there is data, what should be done with it?

We hypothesize that proper framing of movement and emotional information on mobile devices would promote attention to mental mindfulness and healthier behaviors.

Recent research varies in their conclusions about the effectiveness of mobile mental health interventions. John Torous and his team has found by random-effects meta-analysis that smartphone interventions led to significantly greater reductions in total anxiety scores were observed from smartphone interventions, [6]. However, they also found that the effectiveness was significantly lower in studies that controlled user attention and engagement.

Furthermore, studies have also found that there have been no significant benefits to mental health interventions [3, 5, 21].

In light of the recent findings, it appears that the most effective affordance of a mobile intervention that targets stress management is "to enhance and support the delivery of existing face-to-face or internet-based therapy programs" [6]. Providing resources rather than focusing on engagement with the application appears to be the most useful affordance of stress management platforms.

Similarly, Sebastian Scherr and Mark Goering investigated the opportunities for smartphone applications that facilitate mental health self-monitoring. They assessed 6,675 users of a mood-tracking platform called Moodpath. They studied two different purposes of mental health apps, the ability to inform users with mental health resources as well as collecting data for health providers [18].

They found that users who were reporting more depressive symptoms would seek information more frequently. They attributed this outcome due to the privacy that the platform provides to users. However, they pointed out that even though activity was positively correlated with depressive symptoms, there was an overabundance of affordances for those who did not report symptoms. The primary affordance that the application appeared to provide to its users was the ability to find information on "combined causes or detailed descriptions of the experiential facets of depression" [18].

Moodpath is one of the most popular public applications targeted at mental health tracking with over one million users globally. The application tracks self-reported data over two-week intervals and provides over 150 personal exercises to alleviate depressive symptoms. Additionally, it can help users contact a professional by drafting a letter to a doctor for a consultation. In their documentation, Moodpath is supposed to counteract recall bias–bias through recalling events after they have happened–by allowing its users to immediately record their feelings as they happen. This real-time data can help psychologists and practitioners understand what the patient is undergoing, without as much subjectivity [8].

Taking prior research into account, as well as similar platforms on the market, our team developed a prototype that would frame the locational data. Whereabouts gathers self-reported information by using a mood selector option on a sliding scale to combat the complexity of mood characterization (Figure 5). In addition, users are allowed to comment on what they are thinking and allocate "tags" to their documentation.

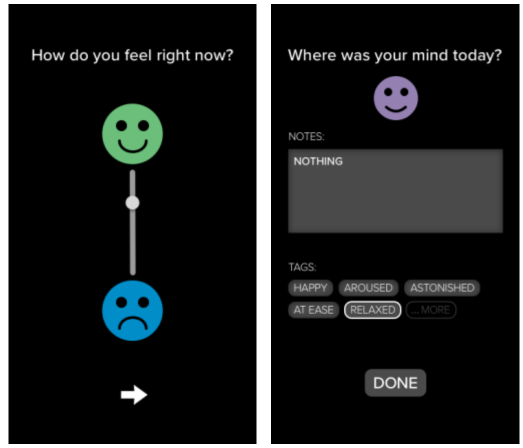

Figure 5. Mood selection screen and comment screen. Users can select from "mood scale" and then comment to be more specific.

Tags will be generated from a more detailed list of emotions related to the emotion users selected, if they cannot find one they like, they can search for a specific one.

The application is able to combine location data through our algorithm as well as self-reported data to help draw a more detailed understanding of what the person is experiencing.

Users will create a personal profile to log into for customized feedback. Their profile will include self-reported data about their identity, where they live, and their health. Whereabouts will also access medical information through other phone applications that specialize in collecting such data (e.g. Google Fit for Androids) (Figure 6).

Because users with depressive symptoms were found to seek more information, Whereabouts will have an "Explore" feature where various different personal exercises, articles, resources, and more can be found. Although our investigation does not delve into the exact type of resources to be provided, the Whereabouts prototype provides a few examples of what type of resources it would provide and how (Figure 7).

Additionally, because recent findings argue that a stress management application cannot focus solely on user engagement for self-reported data, we aim to use location data as well as mood history to provide custom resources that would be similar to what resources a professional would give. There will be a "POPULAR" section for users to explore, but also have a "RECOMMENDED" list (Figure 6) of resources that would allow a user to learn coping mechanisms for what they are personally experiencing.

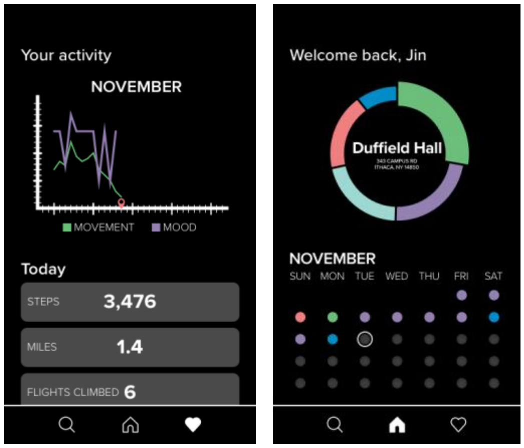

Figure 6. Personal feedback derived from 3rd party health applications as location tracking algorithm. Whereabouts provides information about where you have spent most of your day as well as a history diagram of movement and mood.

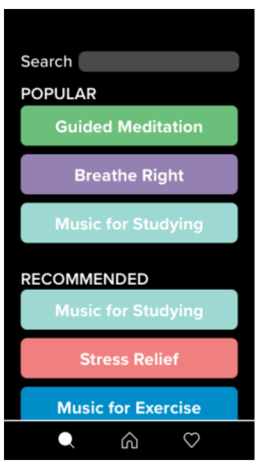

Figure 7. Explore page helps users view different resources available to help cope.

ETHICS

Whereabouts collects personal information about a user daily; the ethical concerns that arise from storing such data must be considered.

The possibility of theft or malfunction of the mobile device, which can lead to possible exploitation of important data, that could be used to harm the user whom it was supposed to benefit [7]. Similar to other fitness tracker applications in the market, Whereabouts would require and collect various personally identifiable data, such as demographics, medical information, location data, etc. There are no guarantees that these private data would be properly protected, which means that someone with malicious purpose could potentially exploit the data for his or her own benefits. Hackers can easily attempt to crack or bypass the security walls of the main server to locate and steal private data. Other than using secured connections (e.g. proxy, VPN), users do not have many choices to protect their private information.

Stress can also take serious effect after a prolonged period of time. Whereabouts cannot supplement for professional help and it will have to be made clear to users. As a personal intervention, Whereabouts's utmost purpose is to help users cope with stress and should provide information to do so in the healthiest way possible. In future iterations of this product, we look to consult with professionals to understand to a larger extent what information should be made available to the user and framed in a beneficial way.

Additionally, we would like to discuss the accessibility of our product for Cornell students as our target audience.

The median family income for Cornell is $151,600 and 64% of students are from family incomes of the top 20%, there is decent reason to assume that most students own a mobile device [1].

However, a mobile device may be a smaller investment compared to therapy. The average cost to visit a therapist, once, would be about $60 to $250 with the national average cost being around $90 a visit [10]. Often times multiple visits must be made to acquire treatment, which will easily add up to the cost of a mobile device and more. Our application will help users receive a similar type of treatment through a mobile device that they most likely already own for free. This platform will give the disadvantaged access to resources that could have been otherwise unattainable. Users will also be able to understand when would be the right time to seek a professional, which would lead to more effective sessions and a better investment.

LIMITATIONS

Whereabouts uses strictly location tracking. A mobile device affords many other sensing opportunities to help develop a better understanding of a user.

It is clear that more research will be required in the future to further develop the correlation between mobile phone data and mental health illness. There are previous scholarly papers that have investigated the relationship between human behavior and phone data usage, mobile phone data cannot serve as the only indicator of the user's mental health. Although the dataset suggests some correlation, there is not enough research conducted on how the information should be presented to the users and health professionals who can potentially provide feedback.

Our algorithm and product are based on the revelation from previous research that correlates depression and mobile phone data. However, these studies have only examined the relationship between self-reported mental health issues and locational data. Therefore, we cannot conclude that there is a definite causal relationship between two variables. There could be other intermediary variables that affect this particular correlation, and self-reported symptoms are sometimes unreliable.

In addition, the dataset used in this product is only a small sample of college students, not a representative of typical trends we observe from people with mental health issues. Therefore, future researchers should obtain more data or recruit more participants with depression to determine whether the participant's tracked data of movements through geographic locations actually indicates the participant's state or if there are any other variables affecting the results. (e.g. occupational status, size of social network, or chronic health problems).

CONCLUDING STATEMENTS

Despite these limitations, utilizing ubiquitous computing technology to detect correlation between behavioral factors and mental health can further develop into the invention of new behavioral detecting technologies that successfully tracks and detects the user's behavioral patterns, and positively reinforce or provide support to the user by suggesting various solutions. Especially, with the assistance of medical professionals, these technologies have potential to make the identification of depression easier and the health care services to appropriately allocate resources to those in need. Therefore, patients with mental health issues could capitalize on these technologies to overcome the existing barriers of conventional psychological treatment settings.

Unlike questionnaires or special devices, mobile phones are an essential part of life for most people in the 21st century. People keep phones with them all the time, and therefore data can be automatically obtained without the user having to manually record the data. Utilization of phone sensors will make the capturing of information easier than conventional methods. Phones fit into the fabric of people's lives. As the correlation between phone usage data and depression become better understood and researched, they may serve as a pivotal role in understanding the symptoms of depression and its appropriate treatment.

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