The Untapped Opportunity of Mobile Network Data for Mental Health

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ABSTRACT
Smartphone-based mobile health (mHealth) applications have been proposed to unobtrusively sense and analyze human behavior, to deliver medical/lifestyle feedback and to provide behavioral therapy. These mHealth apps enable continuous care extended to the daily life outside of clinical settings and help mitigate existing pressure placed on healthcare systems due partly to the aging of the population and the increased numbers of chronic disease patients. However, despite the enthusiasm brought by this mHealth approach, it faces important shortcomings that could limit its widespread adoption in practice. In this paper, we discuss the limitations of mHealth apps and propose how mobile network data could address these limitations and be exploited to monitor mental health conditions. We highlight both the opportunities and challenges that this kind of data presents for mental health.

Author Keywords
Mobile data; mental health; behavioral analysis;

ACM Classification Keywords
H.1.2. Models and Principles: User/Machine Systems – Human Factors

INTRODUCTION
Mental health problems account for 20% of the disease burden worldwide [1]. One out of four individuals suffers mental health problems in a given year [1]. It is the third most common reason to visit a health center and suicide –with a yearly rate of 800.000 worldwide – is recognized to be a major public health issue [1]. There is a variety of reasons that contribute to such a high burden caused by mental health problems. Firstly, the traditional model of episodic care is suboptimal to prevent mental health outcomes and improve chronic disease outcomes [2, 3]. Secondly, standard clinical practice relies on periodic self-reports to assess behavior and mental state, which suffer from memory dependence, recall bias, and subjectivity. Finally, individuals with mental conditions typically visit doctors when the crisis has already happened or is underway thus reporting limited information about precursors and making it impossible to eventually prevent the crisis onset.

Mobile Health (mHealth) has emerged as a discipline with an high potential value for the healthcare, and in particular for monitoring and treating mental conditions [3]. However, despite the early efforts to develop mHealth applications to monitor and treat mental conditions, a wide adoption of smartphones in clinical practice seems still to be far due to a variety of reasons, including technical barriers and a lack of large scale clinical validations.

In this paper, we identify key technical limitations of mHealth for mental health and outline the immense, yet unexploited, opportunities that mobile network data presents for human behavior monitoring in the context of mental health. We describe the different sources and types of mobile network data available today and describe also their advantages and limitations. Finally, we highlight key challenges that would need to be addressed to be able to realize the potential of this opportunity.

CHALLENGES IN MHEALTH FOR MENTAL HEALTH
Mobile technology in healthcare has been recently emphasized for its opportunity to extend monitoring and health interventions beyond the reach of traditional care – the approach referred to as Mobile Health (mHealth) [3]. While mobile technology can be used for a variety of purposes within mental health, in this paper we focus exclusively on its value to address the limitations of episodic care and self-reporting methods through an automatic monitoring and analysis of human behavior via the analysis of the data captured with the mobile phone.

One of the first initiatives to use smartphones to extend monitoring and treatment of mental conditions outside of clinical settings to daily life was within the EU FP7 project called MONARCA. The main objective was to detect significant changes in the behavior of bipolar disorder patients related to maniac and depressive episodes. Though the sample of patients in their reported study was only 12, Gruenerbl *et al* [10] demonstrated a high accuracy in recognizing the current state (approx. 80%) and in predicting state change (approx. 95%). In a recent study, Saeb *et al* [5] analyzed data sampled from mobile phones that were carried by 28 participants for 2 weeks and modelled their behavior using location and phone usage data. They showed that it is possible to distinguish depressed from non-depressed

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individuals with an accuracy of 86.5%. In a similar line, Canzian and Musolesi [6] analyzed mobility patterns of 28 individuals who suffer depression and demonstrated significant correlations between several mobility trace characteristics and depressive moods. From a commercial perspective, there are a few recent off-the-shelf mobile applications –*e.g.,* Ginger.io, Mobilyze – that aim to detect significant changes in the user's behavior (*e.g.* staying at home for several days) and share the inferred behavioral parameters with the specialists.

Although the recent research progress has shown the potential of mHealth to overcome the limitations of self-reporting methods and of episodic care in mental healthcare, the widespread adoption and usability of mHealth applications faces a number of challenges, including:

(L.1) Lack of historical information about a patient before installing the mobile app. For a new user *i.e.* a patient who has just installed a mHealth app (*e.g.* a newly diagnosed patient), the app lacks historical behavioral data (prior to the time of installing it). This can limit the potential of the app to build a baseline behavior model --*i.e.* typical behavior for that particular user—and use such baseline behavior as a reference to identify significant deviations of behavior which could be attributable to a mental health crisis.

(L.2) User stigmatization and potentially low adherence. Installing an app on a mobile phone and keeping it active may be cumbersome for users who are already becoming overwhelmed with the growing number of apps in their devices. Moreover, an active mHealth app would remind users that they are being monitored, which could affect their natural behavior and ultimately make them decide to stop running the app.

(L.3) Considerable consumption of phone resources by the mHealth app (*e.g.* battery, CPU, memory). The sensors typically used in mHealth apps for mental health may consume significant phone resources such as GPS [6] or accelerometer [4]. Decreased battery life and impaired phone performance may considerably affect the user satisfaction with the app and may result in its uninstalling.

(L.4) Limited reach. Although the adoption of smartphones is increasing steadily, only 1 out of 5 individuals worldwide owns a smartphone required to install mHealth apps, and among 4.5bn of mobile phone subscribers, there are still more than 2 bn worldwide without a smartphone[1].

(L.5) Lack of portability. Smartphone users may encounter difficulties when migrating to different phones or operating systems (*e.g.* from Android to iPhone) as mHealth apps do not necessarily support inter-platform compatibility.

(L.6) Lack of contextual information. Analyzing solely behavioral parameters extracted from sensor readings without a broader context can be insufficient to assess behavior, mainly for two reasons, 1) the difficulty in establishing a reference point for the behavior considered to be "normal" (baseline) for the monitored patient; and 2) the difficulty to determine if a significant change in behavior is due to a mental health factor or due to some other contextual factor. For instance, a significant reduction in the mobility of a depressed patient can be interpreted as the start of a depression episode whereas the reason could lie in an external factor such as a bad weather or a strike in the public transport system.

Passively collected mobile network data is insensitive to the challenges listed above while still acting as an accurate proxy of human behavior [7]. The robustness to the listed challenges mostly comes from the fact that the logs are captured and stored for all the subscribers regardless of the phone model (for any kind of smartphone and also for non-smartphones); such data collection is invisible and fully passive from the user's perspective and it does not require any phone resources. In the next section we briefly describe the main types of mobile network data and underline their potential to model human behavior in the context of mental health monitoring.

PASSIVELY COLLECTED MOBILE NETWORK DATA

Description of Mobile Network Logs

A mobile (cellular) network is a wireless network composed of cell towers, called Base Transceiver Stations (BTS), which give coverage to a specific geographic area called a *cell*. BTS are typically grouped in Location Area Networks (LACs) which are groups of 10 to more than 100 BTS, depending on the communication needs of a certain region.

When a mobile phone is connected to the network, it notifies the BTS where it is located. There are two types of notifications which generate two different types of mobile network data: (1) *event-driven* notifications, which are generated when a service (e.g. a call, SMS, MMS, data access, etc.) is requested by the users. Traditionally the data generated by voice and SMS event-driven notifications is called Call Detail Records (CDRs). The notifications generated by data access are usually referred to as Internet access logs; and (2) *network-driven* notifications, which are periodically triggered by the network in order to locate the mobile phone and deliver the services (every 2-4 hours or when the user changes LAC or switches off the phone).

Call Detail Records (CDRs) store phone usage logs for invoicing purposes. The structure of the CDRs can vary among different operators, however in most cases it contains the encrypted originating and destination phone numbers, a timestamp, the call duration, and the identifier of the sector

[1] http://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/ [accessed: Jan 2016]

and the cell tower that provided the communication for both cell phones. These identifiers give an indication of an approximate geographical location of the mobile phone at that specific moment in time. No information about the position of the mobile phone within a cell is known. *Table 1* shows an example of three calls logged in CDRs.

Originating	Destination	Date/Time	Op-Orig	Op-Dest	Duration	Sector-Orig	Sector-Dest	Code
65464165114	12345678910	15-Dec-15	1	3	134	13683481	3541547	0
36151571541	65464165114	15-Dec-15	1	1	26		4564782	0
65464165114	91245687867	16-Dec-15	3	1	84	13683481		0

Table 1 CDRs Example

Moreover, when a mobile phone connects to the Internet, the BTS also creates a record of the data connection events. As in the case of CDRs the content is not necessarily standard, but basically contains an encrypted identifier of the mobile phone, the time and date of the event, information about the website, number of bytes transferred, control codes, etc. (Table 2 presents an example of three data connection events in the log structure that contain an identifier - as an IP number, session reference, web-page address, and date & time stamp).

IP	SessionCD	HTTPS Request Date	HTTP Request Time	Web Page
10.101.55.352	532655265	01/07/14	12:45	www.njuz.net
10.61.17.193	346236363	01/07/14	13:01	www.gmail.com
10.54.112.142	164363146	02/07/14	22:43	www.instagram.com

Table 2 Data Logs Example

Despite its poor spatial and temporal granularity, mobile network data can enable unprecedented insights into how people and populations behave [7]. The value of modeling population behavior using mobile network data has been demonstrated in various studies (e.g. for modeling disease spread [8]). However, its benefits have not been exploited to model human behavior at an individual level in the context of mental health conditions.

Mobile Network Data for Mental Health

CDRs, Internet access logs and network events constitute longitudinal *digital traces* of human behavior from which we can infer different kinds of variables, including:

Consumption variables. These variables capture aspects related to social activities, data usage patterns and service-spending habits by computing *e.g.* the total number of incoming and outgoing calls received by a user, the average duration of incoming and outgoing calls, the total expenses in phone calls, the total number of messages, the ratio of incoming/outgoing SMS versus all communications, the amount of data transferred and received, the amount of time spent on the Internet, etc. All of these variables can be computed to characterize behavior over a specific time period (*e.g.* day, week, month...) or a specific time of the day (*e.g.* morning, afternoon, evening, night);

Social variables. The user's *call graph* can be built by taking into account the unique contacts that the user has been communicating within a specific time period. A number of social variables can be derived from the call graph, including the in and out degree and the centrality and total degree of the graph;

Mobility variables. Approximate locations collected periodically in *network events* or in the CDRs enable the characterization of the user's mobility over a specific time period by means of variables such as the radius of gyration (i.*e.* the root mean squared distance between the set of BTS's and their center of masses), the total distance traveled and the diameter of the area of influence (*i.e.,* the geographical area where the user spends his/her time doing daily activities which is computed as the maximum distance between the set of BTS's used to make/receive calls);

Personal interests. Internet browsing logs give insights into the topics or categories of the most accessed Web services and mobile apps over a specific time period;

Derived variables; In addition to the variables above, other aspects of human behavior can be inferred from these logs, such as **sleep patterns** (obtained from the timestamps of the last/first entries in a day) and **commuting routines and distances** as well as **time spent at home and at work** (obtained after inferring the user's home and work locations).

The variations in behavior related to mobility, social activities, spending, interests, sleep, time spent at home, *etc.* may be indicative of a certain mental health state. Mobility patterns have been shown to be relevant to assess depression levels [5, 6] and detect bipolar episodes [10]. Mobile phone call patterns have been demonstrated to be a good predictor of depression [5] and bipolar state transition [4]. Sleep disturbances represent one of the basic symptoms of an affective disorder, taking place in depression and bipolar disorder [1]. Significant changes in the spectrum of interests or developing new interests are associated with mental state [11].

Therefore, mobile network data would enable to build models of individual and aggregated human behavior that are relevant for mental health conditions, particularly to analyze aspects of daily routine and lifestyle that may be valuable to a) monitor the condition, and b) detect behavioral deviations that are indicative of a crisis [12].

Comparative and Contextual Behavioral Assessment

Most of the state-of-the-art in behavioral quantification (in various domains, not limited only to mental health applications, such as fitness monitoring) either reports behavioral performance regardless of its assessment or in some cases reports an assessment of the user's behavior and wellbeing status when compared to his/her typical behavior or to general guidelines (*i.e.* what is a considered to be a "normal" behavior, such as a number of steps, mobility patterns, etc.). However, performing behavioral assessments in such an isolated manner, and with little regard to the wider context, may be misleading. In this regard, mobile network data provides a unique advantage by providing insights into the behavior not only of a monitored individual but also of a larger population from *e.g.* from the same geographical area (district, city, country, etc.). Establishing a model of “typical” behavior with respect to the individual’s environment (cultural, geographical, demographical, etc.) in a specific time period (*e.g.* summer *vs* winter, weekends *vs* weekdays) may yield a better understanding of the underlying factors affecting behavioral changes *i.e.* whether they are personal (*e.g.* due to the mental health condition) or contextual (thus being reflected also in the behavior of other people in the context and over the same time period) factors. This contextual information could also provide the foundation for a persuasive computing strategy: comparing the user’s behavior to that of others may stimulate positive behavioral changes through social pressure.

CHALLENGES OF USING MOBILE NETWORK DATA

Given the lack of prior work on using passively collected mobile network data for mental health, we believe there is a tremendous opportunity to have positive impact in this domain. However, such an impact will only be achieved when technical, regulatory, legal and ethical challenges are addressed, as described below.

Technical and Research Challenges. Mobile network data is a subject to limitations in data collection (*e.g.* gaps in location tracking, no access to the phone sensors such as accelerometers, light sensor, *etc*.); in user-interaction (*e.g.* instead of interactive interfaces provided by an app or an online dashboard the interaction is reduced to mobile network communication channels such as SMS messages or calls); and in temporal and spatial granularity. Therefore it is required to develop novel methods that consider and try to overcome such limitations.

Privacy, Regulation and Data Security. Storing, accessing and processing data that contains personal sensitive information, such as location and mobility, Internet logs, call and messaging patterns, as well as information related an individual's social network must adhere to data privacy laws and a clear ethical code of conduct. Such challenges apply to almost any application that rely on the use of personal data, hence ownership, transparency and control of personal data are important topics that would need to be addressed [13] both in mHealth applications and in using mobile network data for mental health.

Despite these limitations, given the many advantages of passively collected mobile data, we are excited about the potential of using this data (or combining it with the mobile app data) for advancing mental healthcare.

ONGOING WORK

We are currently exploring the value of mobile network data in the context of affective disorders. We plan to carry out at least two clinical trials in collaboration with two hospitals to empirically assess the value of this type of data for mental health monitoring and for the detection and prediction of significant changes in the mental health condition of patients.

CONCLUSION

In this paper we have described the potential of mobile network data for monitoring and characterizing human behavior in the context of mental health. Given that this data is passively collected, it overcomes many of the challenges associated with mobile apps. However, since the acquisition of this data was not designed for mental applications, its analysis entails regulatory, security and technical challenges that need to be addressed to realize this opportunity.

We are actively exploring the potential that this data has in the context of mental health [9].

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